1 Chainer at a Glance
  1.1 Mushrooms – tasty or deadly? ......................................................... 3
  1.2 Code Breakdown ................................................................. 3
  1.3 Output ............................................................................... 8

2 Concepts Walkthrough
  2.1 Define-by-Run ................................................................. 13
  2.2 Variables and Derivatives .................................................. 15
  2.3 Links ............................................................................. 17
  2.4 Define your own function ................................................ 35
  2.5 Creating Models ............................................................. 36
  2.6 Optimizer ..................................................................... 37
  2.7 Trainer .......................................................................... 38
  2.8 Trainer Extensions ........................................................ 42
  2.9 Using GPU(s) in Chainer ............................................... 48
  2.10 Type Checks ............................................................... 52
  2.11 Serializers – saving and loading .................................... 53
  2.12 Customize your own logging .......................................... 57

3 Neural Net Examples
  3.1 MNIST using Trainer ....................................................... 57
  3.2 MNIST with a Manual Training Loop .............................. 66
  3.3 Convolutional Network for Visual Recognition Tasks ....... 74
  3.4 DCGAN: Generate images with Deep Convolutional GAN .. 80
  3.5 Recurrent Nets and their Computational Graph ................. 91
  3.6 RNN Language Models .................................................. 97
  3.7 Word2Vec: Obtain word embeddings ............................ 107
  3.8 Write a Sequence to Sequence (seq2seq) Model ............... 116

4 API Reference
  4.1 Variable and Parameter .................................................. 133
  4.2 Functions .................................................................... 154
  4.3 Link and Chains ........................................................... 322
  4.4 Probability Distributions .............................................. 823
  4.5 Optimizers .................................................................. 885
  4.6 Weight Initializers ........................................................ 949
  4.7 Snapshot Writers .......................................................... 963
  4.8 Training Tools ............................................................... 971
  4.9 Datasets .................................................................... 1035
  4.10 Iterator .................................................................... 1081
### 11 Tips and FAQs
- **11.1** It takes too long time to compile a computational graph. Can I skip it? ........................................ 1383
- **11.2** MNIST example does not converge in CPU mode on Mac OS X ......................................................... 1383
- **11.3** How do I fix InvalidType error? ............................................................................................................. 1384
- **11.4** How do I accelerate my model using Chainer Backend for Intel Architecture? ................................. 1385
- **11.5** My training process gets stuck when using MultiprocessIterator ....................................................... 1386

### 12 Performance Best Practices
- **12.1** Use the Latest Version ....................................................................................................................... 1387
- **12.2** Enable Hardware Accelerations ........................................................................................................ 1387
- **12.3** Migrate Data Preprocessing Code from NumPy to CuPy ....................................................................... 1388
- **12.4** Avoid Data Transfer ......................................................................................................................... 1388
- **12.5** Optimize cuDNN Convolution .......................................................................................................... 1389
- **12.6** Fine-Tune Configuration ................................................................................................................ 1389
- **12.7** Load Datasets Concurrently .............................................................................................................. 1390
- **12.8** Use Multiple GPUs ........................................................................................................................ 1390
- **12.9** Use Multiple Nodes ........................................................................................................................ 1390

### 13 Upgrade Guide
- **13.1** Chainer v7 ........................................................................................................................................ 1391
- **13.2** Chainer v6 ........................................................................................................................................ 1391
- **13.3** Chainer v5 ........................................................................................................................................ 1392
- **13.4** Chainer v4 ........................................................................................................................................ 1394
- **13.5** Chainer v3 ........................................................................................................................................ 1396
- **13.6** Chainer v2 ........................................................................................................................................ 1397

### 14 License ............................................................................................................................................... 1413

### 15 Indices and tables .............................................................................................................................. 1415

**Bibliography** ........................................................................................................................................ 1417

**Python Module Index** ............................................................................................................................ 1419

**Index** ................................................................................................................................................ 1421
Chainer is a powerful, flexible and intuitive deep learning framework.

- Chainer supports CUDA computation. It only requires a few lines of code to leverage a GPU. It also runs on multiple GPUs with little effort.
- Chainer supports various network architectures including feed-forward nets, convnets, recurrent nets and recursive nets. It also supports per-batch architectures.
- Forward computation can include any control flow statements of Python without lacking the ability of back-propagation. It makes code intuitive and easy to debug.

Note: As announced, Chainer is under the maintenance phase and further development will be limited to bug-fixes and maintenance only.
Welcome to Chainer!

Chainer is a rapidly growing neural network platform. The strengths of Chainer are:

- Python-based – Chainer is developed in Python, allowing for inspection and customization of all code in python and understandable python messages at run time
- Define by Run – neural networks definitions are defined on-the-fly at run time, allowing for dynamic network changes
- NumPy based syntax for working with arrays, thanks to CuPy implementation
- Fully customizable – since Chainer is pure python, all classes and methods can be adapted to allow for the latest cutting edge or specialized approaches
- Broad and deep support – Chainer is actively used for most of the current approaches for neural nets (CNN, RNN, RL, etc.), aggressively adds new approaches as they’re developed, and provides support for many kinds of hardware as well as parallelization for multiple GPUs

1.1 Mushrooms – tasty or deadly?

Let’s take a look at a basic program of Chainer to see how it works. For a dataset, we’ll work with Kaggle’s edible vs. poisonous mushroom dataset, which has over 8,000 examples of mushrooms, labelled by 22 categories including odor, cap color, habitat, etc., in a mushrooms.csv file.

How will Chainer learn which mushrooms are edible and which mushrooms will kill you? Let’s see!

The code below is from the glance example in the examples/glance directory.

1.2 Code Breakdown

1.2.1 Initialization

Let’s start the program. Here are the typical imports for a Chainer program. `chainer.links` contain trainable parameters and `chainer.functions` do not.

```python
import chainer as ch
from chainer import datasets
import chainer.functions as F
import chainer.links as L
from chainer import training
```

(continues on next page)
We’ll use Matplotlib for the graphs to show training progress.

1.2.2 Trainer Structure

A trainer is used to set up our neural network and data for training. The components of the trainer are generally hierarchical, and are organized as follows:

Each of the components is fed information from the components within it. Setting up the trainer starts at the inner components, and moves outward, with the exception of extensions, which are added after the trainer is defined.

1.2.3 Dataset

Our first step is to format the dataset. From the raw mushrooms.csv, we format the data into a Chainer TupleDataset.
mushroomsfile = 'mushrooms.csv'
data_array = np.genfromtxt(
    mushroomsfile, delimiter=’,’, dtype=str, skip_header=1)
for col in range(data_array.shape[1]):
    data_array[:, col] = np.unique(data_array[:, col], return_inverse=True)[1]
X = data_array[:, 1:].astype(np.float32)
Y = data_array[:, 0].astype(np.int32)[:,
    None]
train, test = datasets.split_dataset_random(
    datasets.TupleDataset(X, Y), int(data_array.shape[0] * .7))

1.2.4 Iterator

Configure *iterators* to step through batches of the data for training and for testing validation. In this case, we’ll use a batch size of 100. For the training iterator, repeating and shuffling are implicitly enabled, while they are explicitly disabled for the testing iterator.

train_iter = ch.iterators.SerialIterator(train, 100)
test_iter = ch.iterators.SerialIterator(
    test, 100, repeat=False, shuffle=False)

1.2.5 Model

Next, we need to define the neural network for inclusion in our model. For our mushrooms, we’ll chain together two fully-connected, *Linear*, hidden layers between the input and output layers.

As an activation function, we’ll use standard Rectified Linear Units (*relu()*).

Using *Sequential* allows us to define the neural network model in a compact format.
# Network definition

```python
def MLP(n_units, n_out):
    layer = ch.Sequential(L.Linear(n_units), F.relu)
    model = layer.repeat(2)
    model.append(L.Linear(n_out))
    return model
```

Since mushrooms are either edible or poisonous (no information on psychedelic effects!) in the dataset, we’ll use a Link Classifier for the output, with 44 units (double the features of the data) in the hidden layers and a single edible/poisonous category for classification.

```python
model = L.Classifier(
    MLP(44, 1), lossfun=F.sigmoid_cross_entropy, accfun=F.binary_accuracy)
```

Note that in the two code snippets above we have not specified the size of the input layer. Once we start feeding the neural network with samples, Chainer will recognize the dimensionality of the input automatically and initialize the matrix for each layer with the appropriate shape. In the example above, that is 44×22 for the first hidden layer, 44×44 for the second hidden layer, and 1×44 for the output layer.

## 1.2.6 Optimizer

Pick an optimizer, and set up the model to use it.

```python
# Setup an optimizer
optimizer = ch.optimizers.SGD().setup(model)
```

## 1.2.7 Updater
Now that we have the training iterator and optimizer set up, we link them both together into the updater. The updater uses the minibatches from the iterator, does the forward and backward processing of the model, and updates the parameters of the model according to the optimizer. Setting the device=-1 sets the device as the CPU. To use a GPU, set device equal to the number of the GPU, usually device=0.

```python
# Create the updater, using the optimizer
updater = training.StandardUpdater(train_iter, optimizer, device=-1)
```

Finally we create a Trainer object. The trainer processes minibatches using the updater defined above until a certain stop condition is met and allows the use of extensions during the training. We set it to run for 50 epochs and store all files created by the extensions (see below) in the result directory.

```python
# Set up a trainer
trainer = training.Trainer(updater, (50, 'epoch'), out='result')
```

### 1.2.8 Extensions

Extensions can be used to execute code at certain events during the training, such as every epoch or every 1000 iterations. This mechanism is used in Chainer to evaluate models during training, print progress messages, or dump intermediate model files.

First, use the testing iterator defined above for an Evaluator extension to the trainer to provide test scores. If using a GPU instead of the CPU, set device to the ID of the GPU, usually 0.

```python
# Evaluate the model with the test dataset for each epoch
trainer.extend(extensions.Evaluator(test_iter, model, device=-1))
```

Save a computational graph from loss variable at the first iteration. main refers to the target link of the main optimizer. The graph is saved in the Graphviz’s dot format. The output location (directory) to save the graph is set by the out argument of trainer.

```python
# Dump a computational graph from 'loss' variable at the first iteration
trainer.extend(extensions.DumpGraph('main/loss'))
```

Take a snapshot of the trainer object every 20 epochs.

```python
trainer.extend(extensions.snapshot(), trigger=(20, 'epoch'))
```

Write a log of evaluation statistics for each epoch.

```python
# Write a log of evaluation statistics for each epoch
trainer.extend(extensions.LogReport())
```
Save two plot images to the result directory.

```python
# Save two plot images to the result dir
trainer.extend(
    extensions.PlotReport(['main/loss', 'validation/main/loss'],
        'epoch', file_name='loss.png'))

trainer.extend(
    extensions.PlotReport(
        ['main/accuracy', 'validation/main/accuracy'],
        'epoch', file_name='accuracy.png'))
```

Print selected entries of the log to standard output.

```python
# Print selected entries of the log to stdout
trainer.extend(extensions.PrintReport(
    ['epoch', 'main/loss', 'validation/main/loss',
     'main/accuracy', 'validation/main/accuracy', 'elapsed_time']))
```

### 1.2.9 Main Loop

Finally, with the `trainer` and all the extensions set up, we can add the line that actually starts the main loop:

```python
# Run the training
trainer.run()
```

### 1.2.10 Inference

Once the training is complete, only the model is necessary to make predictions. Let’s check that a random line from the test data set and see if the inference is correct:

```python
x, t = test[np.random.randint(len(test))]
predict = model.predictor(x[None]).array
predict = predict[0][0]

if predict >= 0:
    print('Predicted Poisonous, Actual ' + ['Edible', 'Poisonous'][t[0]])
else:
    print('Predicted Edible, Actual ' + ['Edible', 'Poisonous'][t[0]])
```

### 1.3 Output

Output for this instance will look like:

```
epoch   main/loss  validation/main/loss  main/accuracy  validation/main/accuracy elapsed_time
        0.550724       0.502818          0.733509         0.752821       0.215426
        0.454206       0.446234          0.805439         0.786926       0.902108
        0.402783       0.395893          0.838421         0.835979       1.504141
```

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<td>0.973333</td>
<td>0.969747</td>
</tr>
<tr>
<td>→ 22.3328</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>0.0860733</td>
<td>0.0984015</td>
<td>0.975263</td>
<td>0.971747</td>
</tr>
<tr>
<td>→ 22.8447</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>41</td>
<td>0.0829282</td>
<td>0.0942095</td>
<td>0.977544</td>
<td>0.974947</td>
</tr>
<tr>
<td>→ 23.5113</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>42</td>
<td>0.082219</td>
<td>0.0947418</td>
<td>0.975965</td>
<td>0.969347</td>
</tr>
<tr>
<td>→ 24.0427</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>43</td>
<td>0.0773362</td>
<td>0.0906804</td>
<td>0.977857</td>
<td>0.977747</td>
</tr>
<tr>
<td>→ 24.5252</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>44</td>
<td>0.0751769</td>
<td>0.0886449</td>
<td>0.977895</td>
<td>0.972147</td>
</tr>
<tr>
<td>→ 25.1722</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>45</td>
<td>0.072056</td>
<td>0.0916797</td>
<td>0.978246</td>
<td>0.977495</td>
</tr>
<tr>
<td>→ 26.0778</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>46</td>
<td>0.0708111</td>
<td>0.0811359</td>
<td>0.98</td>
<td>0.979347</td>
</tr>
<tr>
<td>→ 26.6648</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>47</td>
<td>0.0671919</td>
<td>0.0783265</td>
<td>0.982456</td>
<td>0.978947</td>
</tr>
<tr>
<td>→ 27.2929</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>48</td>
<td>0.0658817</td>
<td>0.0772342</td>
<td>0.981754</td>
<td>0.977747</td>
</tr>
<tr>
<td>→ 27.8119</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>49</td>
<td>0.0634615</td>
<td>0.0762576</td>
<td>0.983333</td>
<td>0.974947</td>
</tr>
<tr>
<td>→ 28.3876</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>50</td>
<td>0.0622394</td>
<td>0.0710278</td>
<td>0.982321</td>
<td>0.981747</td>
</tr>
<tr>
<td>→ 28.9067</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Our prediction was correct. Success!

The loss function:
And the accuracy
CHAPTER TWO

CONCEPTS WALKTHROUGH

2.1 Define-by-Run

As mentioned on the top page, Chainer is a flexible framework for neural networks. One major goal is flexibility, so it must enable us to write complex architectures simply and intuitively.

Most existing deep learning frameworks are based on the “Define-and-Run” scheme. That is, first a network is defined and fixed, and then the user periodically feeds it with mini-batches of training data. Since the network is statically defined before any forward/backward computation, all the logic must be embedded into the network architecture as data. Consequently, defining a network architecture in such systems (e.g. Caffe) follows a declarative approach. Note that one can still produce such a static network definition using imperative languages (e.g. torch.nn, Theano-based frameworks, and TensorFlow).

In contrast, Chainer adopts a “Define-by-Run” scheme, i.e., the network is defined dynamically via the actual forward computation. More precisely, Chainer stores the history of computation instead of programming logic. This strategy enables us to fully leverage the power of programming logic in Python. For example, Chainer does not need any magic to introduce conditionals and loops into the network definitions. The Define-by-Run scheme is the core concept of Chainer. We will show in this tutorial how to define networks dynamically.

This strategy also makes it easy to write multi-GPU parallelization, since logic comes closer to network manipulation. We will review such amenities in later sections of this tutorial.

2.2 Variables and Derivatives

In the example code of this tutorial, we assume for simplicity that the following symbols are already imported.

```python
import math
import numpy as np
import chainer
from chainer import backend
from chainer import backends
from chainer.backends import cuda
from chainer import Function, FunctionNode, gradient_check, report, training, utils,
Variable
from chainer import datasets, initializers, iterators, optimizers, serializers
from chainer import Link, Chain, ChainList
import chainer.functions as F
import chainer.links as L
from chainer.training import extensions
```
As described previously, Chainer uses the “Define-by-Run” scheme, so forward computation itself defines the network. In order to start forward computation, we have to set the input array to a `chainer.Variable` object. Here we start with a simple `ndarray` with only one element:

```python
>>> x_data = np.array([5], dtype=np.float32)
>>> x = Variable(x_data)
```

A Variable object supports basic arithmetic operators. In order to compute \( y = x^2 - 2x + 1 \), just write:

```python
>>> y = x**2 - 2 * x + 1
```

The resulting \( y \) is also a Variable object, whose value can be extracted by accessing the `array` attribute:

```python
>>> y.array
array([16.], dtype=float32)
```

**Note:** `Variable` has two attributes to represent the underlying array: `array` and `data`. There is no difference between the two; both refer to exactly the same object. However it is not recommended that you use `.data` because it might be confused with `numpy.ndarray.data` attribute.

What \( y \) holds is not only the result value. It also holds the history of computation (or computational graph), which enables us to compute its derivative. This is done by calling its `backward()` method:

```python
>>> y.backward()
```

This runs error backpropagation (a.k.a. backprop or reverse-mode automatic differentiation). Then, the gradient is computed and stored in the `grad` attribute of the input variable \( x \):

```python
>>> x.grad
array([8.], dtype=float32)
```

Also we can compute gradients of intermediate variables. Note that Chainer, by default, releases the gradient arrays of intermediate variables for memory efficiency. In order to preserve gradient information, pass the `retain_grad` argument to the backward method:

```python
>>> z = 2*x
>>> y = x**2 - z + 1
>>> y.backward,retain_grad=True
>>> z.grad
array([-1.], dtype=float32)
```

All these computations can be generalized to a multi-element array input. While single-element arrays are automatically initialized to [1], to start backward computation from a variable holding a multi-element array, we must set the initial error manually. This is done simply by setting the `grad` attribute of the output variable:

```python
>>> x = Variable(np.array([[1, 2, 3], [4, 5, 6]], dtype=np.float32))
>>> y = x**2 - 2*x + 1
>>> y.grad = np.ones((2, 3), dtype=np.float32)
>>> y.backward()
>>> x.grad
array([[ 0.,  2.,  4.],
       [ 6.,  8., 10.]], dtype=float32)
```

**Note:** Many functions taking `Variable` object(s) are defined in the `chainer.functions` module. You can
combine them to realize complicated functions with automatic backward computation.

Note: Instead of using `backward()`, you can also calculate gradients of any variables in a computational graph w.r.t. any other variables in the graph using the `chainer.grad()` function.

### 2.2.1 Higher-Order Derivatives

`Variable` also supports higher-order derivatives (a.k.a. double backpropagation).

Let's see a simple example. First calculate the first-order derivative. Note that `enable_double_backprop=True` is passed to `y.backward()`.

```python
>>> x = chainer.Variable(np.array([[0, 2, 3], [4, 5, 6]], dtype=np.float32))
>>> y = x ** 3
>>> y.grad = np.ones((2, 3), dtype=np.float32)
>>> y.backward(enable_double_backprop=True)
>>> x.grad_var
variable([[-0., 12., 27.],
          [48., 75., 108.]])
>>> assert x.grad_var.array is x.grad
>>> assert (x.grad == (3 * x**2).array).all()
```

`chainer.Variable.grad_var` is a `Variable` for `chainer.Variable.grad` (which is an `ndarray`). By passing `enable_double_backprop=True` to `backward()`, a computational graph for the backward calculation is recorded. So, you can start backpropagation from `x.grad_var` to calculate the second-order derivative.

```python
>>> gx = x.grad_var
>>> x.cleargrad()
>>> gx.grad = np.ones((2, 3), dtype=np.float32)
>>> gx.backward()
>>> x.grad
array([[ 0., 12., 18.],
        [24., 30., 36.]], dtype=float32)
>>> assert (x.grad == (6 * x).array).all()
```

### 2.3 Links

In order to write neural networks, we have to combine functions with parameters and optimize the parameters. You can use the class `Link` to do this. A `Link` is an object that holds parameters (i.e. optimization targets).

The most fundamental ones are links that behave like regular functions while replacing some arguments by their parameters. We will introduce higher level links, but here think of links as simply functions with parameters.

One of the most frequently used links is the `Linear` link (a.k.a. fully-connected layer or affine transformation). It represents a mathematical function \( f(x) = Wx + b \), where the matrix \( W \) and the vector \( b \) are parameters. This link corresponds to its pure counterpart `linear()`, which accepts \( x, W, b \) as arguments. A linear link from three-dimensional space to two-dimensional space is defined by the following line:

```python
>>> f = L.Linear(3, 2)
```
Note: Most functions and links only accept mini-batch input, where the first dimension of the input array is considered as the *batch dimension*. In the above Linear link case, input must have shape of \((N, 3)\), where \(N\) is the mini-batch size.

The parameters of a link are stored as attributes. Each parameter is an instance of *Variable*. In the case of the Linear link, two parameters, \(W\) and \(b\), are stored. By default, the matrix \(W\) is initialized randomly, while the vector \(b\) is initialized with zeros. This is the preferred way to initialize these parameters.

```python
>>> f.W.array
array([[ 1.0184761 , 0.23103087, 0.5650746 ],
       [ 1.2937803 , 1.0782351 , -0.56423163]], dtype=float32)
```

An instance of the Linear link acts like a usual function:

```python
>>> x = Variable(np.array([[1, 2, 3], [4, 5, 6]], dtype=np.float32))
>>> y = f(x)
>>> y.array
array([[3.1757617, 1.7575557],
       [8.619507 , 7.1809077]], dtype=float32)
```

**Note:** Sometimes it is cumbersome to compute the dimension of the input space. The linear link and some of (de)convolution links can omit the input dimension in their instantiation and infer it from the first mini-batch.

For example, the following line creates a linear link whose output dimension is two:

```python
>>> f = L.Linear(2)
```

If we feed a mini-batch of shape \((2, M)\), the input dimension will be inferred as \(M\), which means \(l.W\) will be a 2 x \(M\) matrix. Note that its parameters are initialized in a lazy manner at the first mini-batch. Therefore, \(l\) does not have \(W\) attribute if no data is put to the link.

Gradients of parameters are computed by the *backward()* method. Note that gradients are *accumulated* by the method rather than overwritten. So first you must clear the gradients to renew the computation. It can be done by calling the *cleargrads()* method.

```python
>>> f.cleargrads()
```

Now we can compute the gradients of parameters by simply calling the backward method and access them via the *grad* property.

```python
>>> y.grad = np.ones((2, 2), dtype=np.float32)
>>> y.backward()
>>> f.W.grad
array([[5., 7., 9.],
       [5., 7., 9.]], dtype=float32)
>>> f.b.grad
array([2., 2.], dtype=float32)
```
2.4 Define your own function

In this section, you will learn about the following things:

- How to define a function on variables
- Useful tools to write a function using a GPU
- How to test the function definition

After reading this section, you will be able to:

- Write your own functions
- Define simple kernels in the function definition

In the example code of this tutorial, we assume for simplicity that the following symbols are already imported.

```python
import math
import numpy as np
import chainer
from chainer import backend
from chainer.backends import cuda
from chainer import Function, FunctionNode, gradient_check, report, training, utils, Variable
from chainer import datasets, initializers, iterators, optimizers, serializers
from chainer import Link, Chain, ChainList
import chainer.functions as F
import chainer.links as L
from chainer.training import extensions
```

2.4.1 Differentiable Functions

Chainer provides a collection of functions in the `chainer.functions` module. It covers typical use cases in deep learning, so many existing works can be implemented with them. On the other hand, deep learning is evolving rapidly and we cannot cover all possible functions to define unseen architectures. So it is important to learn how to define your own functions.

2.4.2 New-Style v.s. Old-Style Functions

In Chainer, you can define a function in two ways: new-style and old-style.

- New-style functions inherit from `chainer.FunctionNode` class (introduced in Chainer v3). Forward computation can be implemented using NumPy/CuPy. Backward computation needs to be implemented by using (possibly a composition of) other new-style functions.

- Old-style functions inherit from `chainer.Function` class. Forward and backward computation can be implemented using NumPy/CuPy.

The primary advantage of using new-style functions is that they support computation of higher-order gradients (a.k.a. higher-order derivative or double backpropagation). Higher-order gradients are used in some models e.g., recently-proposed GAN architectures. New-style functions are also better in terms of performance of backward, as the interface allows an implementation to skip the computation of unneeded input gradients.
Currently, most of built-in functions are implemented in new-style (with a few exceptions listed in #4449). Basically, we recommend you use new-style when implementing new functions. However, you can still continue to use existing old-style functions for the foreseeable future.

In the following sections, we describe steps to implement user-defined functions in new-style. You can also refer to Implementing Old-Style Functions and Migrating From Old-Style Functions To New-Style Functions if you have interest.

### 2.4.3 Implementing New-Style Functions

First, suppose we want to define an elementwise function \( f(x, y, z) = x \times y + z \). While it is possible to implement this equation using a combination of the \( \times \) and \( + \) functions, defining it as a single function may reduce memory consumption, so it is not only a toy example. Here we call this function `MulAdd`.

Let’s start with defining `MulAdd` working on the CPU. New-style functions must inherit the `chainer.FunctionNode` class. The skeleton of a function looks like:

```python
class MulAdd(FunctionNode):
    def forward_cpu(self, inputs):
        # do forward computation on CPU
        return some_tuple
    def backward(self, target_input_indexes, grad_outputs):
        # do backward computation
        return some_tuple
```

We must implement `forward_cpu()` and `backward()` methods.

- In `forward_cpu()` function, `inputs` is a tuple of array(s). You need to return a tuple of array(s), which is a result of forward computation.

- In `backward()` function, `grad_outputs` is a tuple of `Variable(s)` which are gradients with regard to each output(s), i.e., the length of `grad_outputs` tuple equals to the number of outputs returned by `forward_cpu`). You need to return a tuple of `Variable(s)` which are gradients with regard to each input(s), i.e., the length of returned tuple equals to the number of inputs to `forward_cpu`. You can optionally use `target_input_indexes` (a tuple of indices required to compute gradients) to omit computing unnecessary gradients. We will show you the usage of `target_input_indexes` later.

**Warning:** Be careful to return a tuple even if you have just one array or Variable to return.

**Note:** Unlike old-style functions, inputs and outputs of backward method in new-style functions are `Variables`. In other words, the backward method is device agnostic; there are no `backward_cpu` or `backward_gpu` in `FunctionNode`.

`MulAdd` is simple and can be implemented as follows:

```python
class MulAdd(FunctionNode):
    def forward_cpu(self, inputs):
        # Unpack input arrays (``numpy.ndarray``).
        x, y, z = inputs
        # Mark inputs (``x`` and ``y``) as retained so that it can be accessed during the backward process.
        return some_tuple
```

(continues on next page)
As per the warning above, the `forward_cpu()` method returns a tuple of single element. Note that all arrays appearing in `forward_cpu` are `numpy.ndarray`. The forward function is straightforward; it unpacks the input tuple, computes the output, and packs it into a tuple. The backward function is a bit more complicated. Recall the rule of differentiation of multiplication. This example just implements the rule. Look at the return values, the function just packs the gradient of each input in the same order and returns them.

By just defining the core computation of forward and backward, `FunctionNode` class provides a chaining logic on it (i.e., storing the history of computation, etc.).

---

### Note:
Assuming we implement a (forward) function \( y = f(x) \) which takes as input the vector \( x \in \mathbb{R}^n \) and produces as output a vector \( y \in \mathbb{R}^m \). Then the `backward` method has to compute

\[
\lambda_i = \sum_{j=1}^{m} \frac{\partial y_j}{\partial x_i} \gamma_j \quad \text{for } i = 1 \ldots n
\]

where \( \gamma \) is the `grad_outputs`. Note, that the resulting vector \( \lambda \) must have the same shape as the arguments of the `forward` method.

---

Now let’s define the corresponding GPU method. You can easily predict that the method we have to write is named `forward_gpu()`:

```python
class MulAdd(FunctionNode):
    def forward_cpu(self, inputs):
        ...

    def forward_gpu(self, inputs):
        # Unpack input arrays (``cupy.ndarray``).
        x, y, z = inputs

        # Mark inputs (``x`` and ``y``) as retained so that it can be accessed during the backward process.
```

(continues on next page)
In `forward_gpu` method, arrays are of type `cupy.ndarray`. We use arithmetic operators defined for this class. These operators implement the basic elementwise arithmetics.

You may find that the definitions of `forward_gpu` is exactly same as `forward_cpu`. In that case, we can reduce them to `forward()`.

```python
class MulAdd(FunctionNode):
    def forward(self, inputs):
        # Unpack input arrays (``numpy.ndarray`` or ``cupy.ndarray``).
        x, y, z = inputs

        # Mark inputs (``x`` and ``y``) as retained so that it can be
        # accessed during the backward process.
        self.retain_inputs((0, 1))

        # Compute results.
        w = x * y + z

        # Return the result as a tuple.
        return w,

    def backward(self, inputs, grad_outputs):
        x, y, z = inputs
        gw, = grad_outputs
        gx = y * gw
        gy = x * gw
        gz = gw
        return gx, gy, gz
```

Since the `cupy.ndarray` class implements many methods of `numpy.ndarray`, we can write these unified methods in most cases.

The `MulAdd` function can be used as follows:

```python
x = Variable(np.random.uniform(-1, 1, (3, 2)).astype(np.float32))
y = Variable(np.random.uniform(-1, 1, (3, 2)).astype(np.float32))
z = Variable(np.random.uniform(-1, 1, (3, 2)).astype(np.float32))
w, = MulAdd().apply((x, y, z))
```

It looks a bit ugly: we have to explicitly instantiate `MulAdd` before applying it to variables. We also have to be careful that one instance of `MulAdd` must not be used multiple times, since it acts as a node in the computational graph. In Chainer, we often define a thin wrapper Python function that hide the instantiation:

```python
def muladd(x, y, z):
    return MulAdd().apply((x, y, z))
```
w = muladd(x, y, z)

All functions under `chainer.functions` are implemented as wrapper functions like this.

**Unified forward/backward methods with NumPy/CuPy functions**

CuPy implements many functions that are compatible to those of NumPy. We can write unified forward/backward methods with them. Consider that we want to write a backprop-able function $f(x, y) = \exp(x) + \exp(y)$. We name it `ExpAdd` here. It can be written straight-forward as follows:

```python
from chainer.backends import cuda

class ExpAdd(FunctionNode):
    def forward_cpu(self, inputs):
        self.retain_inputs((0, 1))
        x, y = inputs
        z = np.exp(x) + np.exp(y)
        return z,

    def forward_gpu(self, inputs):
        self.retain_inputs((0, 1))
        cupy = cuda.cupy
        x, y = inputs
        z = cupy.exp(x) + cupy.exp(y)
        return z,

    def backward(self, target_input_indexes, grad_outputs):
        x, y = self.get_retained_inputs()
        gz, = grad_outputs
        gx = gz * F.exp(x)
        gy = gz * F.exp(y)
        return gx, gy

def expadd(x, y):
    z, = ExpAdd().apply((x, y))
    return z
```

**Note:** Here we used `chainer.backends.cuda.cupy` instead of directly accessing `cupy`. This is because the `cupy` module cannot be imported if the CUDA is not installed. In order to keep the implementation valid in non-CUDA environment, we have to defer the access to the `cupy` module. Note that the `chainer.backends.cuda` module can be imported even if the CUDA is not installed. Of course, the module in such environment is almost useless, but if the interpreter does not run through the code accessing CUDA-dedicated functions, the code is still valid.

The CPU and GPU implementations are almost same, except that `numpy` is replaced by `cupy` in `forward_gpu`. We can unify these functions using the `chainer.backend.get_array_module()` function. This function accepts arbitrary number of arrays, and returns an appropriate module for them. See the following code:

```python
class ExpAdd(FunctionNode):
    def forward(self, inputs):
        self.retain_inputs((0, 1))
```

(continues on next page)
xp = backend.get_array_module(*inputs)
x, y = inputs
z = xp.exp(x) + xp.exp(y)
return z,

def backward(self, target_input_indexes, grad_outputs):
x, y = self.get_retained_inputs()
gz, = grad_outputs
gx = gz * F.exp(x)
gy = gz * F.exp(y)
return gx, gy

def expadd(x, y):
z, = ExpAdd().apply((x, y))
return z

Note that this code works correctly even if CUDA is not installed in the environment. If CUDA is not found, `get_array_module()` function always returns `numpy`. We often use the name `xp` for the variadic module name, which is analogous to the abbreviation `np` for NumPy and `cp` for CuPy.

**Write an Elementwise Kernel Function**

Let’s turn back to the MulAdd example.

The GPU implementation of MulAdd as shown above is already fast and parallelized on GPU cores. However, it invokes two kernels during each of forward ($w = x \times y + z$) and backward ($gx = y \times gw$ and $gy = x \times gw$) computations. It might hurt performance, since the intermediate temporary arrays are read and written by possibly different GPU cores, which consumes much bandwidth. We can reduce the number of invocations by defining our own kernel. It also reduce the memory consumption.

CuPy provides a useful tool to define elementwise kernels, the `cupy.ElementwiseKernel` class, and Chainer wraps it by `chainer.backends.cuda.elementwise()` function. Our MulAdd implementation can be improved as follows:

class MulAdd(FunctionNode):
    def forward_cpu(self, inputs):
        self.retain_inputs((0, 1))
x, y, z = inputs
w = x * y + z
return w,

def forward_gpu(self, inputs):
    self.retain_inputs((0, 1))
x, y, z = inputs
w = cuda.cupy.elementwise(
    'float32 x, float32 y, float32 z',
    'float32 w',
    'w = x * y + z',
    'muladd_fwd')((x, y, z))
return w,

def backward(self, target_input_indexes, grad_outputs):
x, y, z = self.get_retained_inputs()
gw, = grad_outputs
(continues on next page)
return MulAddGrad().apply((x, y, z, gw))

class MulAddGrad(FunctionNode):
    def forward_cpu(self, inputs):
        x, y, z, gw = inputs
        gx = y * gw
        gy = x * gw
        gz = gw
        return gx, gy, gz

    def forward_gpu(self, inputs):
        x, y, z, gw = inputs
        gx, gy = cuda.elementwise(
            'float32 x, float32 y, float32 gw',
            'float32 gx, float32 gy',
            '''
            gx = y * gw;
            gy = x * gw;
            ..
            'muladd_bwd')(x, y, gw)

        gz = gw
        return gx, gy, gz

    def backward(self, target_input_indexes, grad_outputs):
        # You can leave this unimplemented unless you need to compute
        # higher-order derivative using this function.
        raise NotImplementedError()

chainer.backends.cuda.elementwise() function accepts the essential implementation of the kernel function, and returns a kernel invocation function (actually, it returns ElementwiseKernel object, which is callable). In typical usage, we pass four arguments to this function as follows:

1. Input argument list. This is a comma-separated string each entry of which consists of a type specification and an argument name.
2. Output argument list in the same format as the input argument list.
3. Body of parallel loop. We can use the input/output argument names as an element of these arrays.
4. Name of the kernel function, which is shown in debuggers and profilers.

Above code is not compiled on every forward/backward computation thanks to two caching mechanisms provided by chainer.backends.cuda.elementwise().

The first one is binary caching: chainer.backends.cuda.elementwise() function caches the compiled binary in the ${HOME}/.cupy/kernel_cache directory with a hash value of the CUDA code, and reuses it if the given code matches the hash value. This caching mechanism is actually implemented in CuPy.

The second one is upload caching: Given a compiled binary code, we have to upload it to the current GPU in order to execute it. chainer.backends.cuda.elementwise() function memoizes the arguments and the current device, and if it is called with the same arguments for the same device, it reuses the previously uploaded kernel code.

The above MulAdd code only works for float32 arrays. The ElementwiseKernel also supports the type-variadic kernel definition. In order to define variadic kernel functions, you can use type placeholder by placing a single character as type specifier:

class MulAdd(Function):
    def forward_cpu(self, inputs):

2.4. Define your own function 23
The type placeholder $T$ indicates an arbitrary data type that CuPy supports.

There are more functionalities on user-defined kernels in CuPy. See the CuPy documentation on user-defined kernels for more details.

### 2.4.4 Advanced Topics

#### Write a function with training/test mode

We sometimes want to make a function behave differently in training and test modes. The training/test mode in Chainer is configured by `chainer.config`. This is a thread-local configuration object, and users can substitute True or False to its `train` attribute. You can refer to [Configuring Chainer](#) to see how to configure this flag as well as other configuration items.

Here, we just show how to use this flag to make a function support training/test mode. You will need to check the value of the boolean flag `chainer.config.train` and branch appropriately.

For example, consider the following simple dropout function:

```python
def dropout(x):
    xp = backend.get_array_module(x.array)
    mask = 2 * (xp.random.rand(*x.shape) > 0.5).astype(x.dtype)
    return x * mask
```
This function applies dropout to each element and doubles survived elements to preserve the scale. The above implementation applies dropout even in test mode, but it is not a desired behavior. We can fix it as follows:

```
def dropout(x):
    if not chainer.config.train:
        return x

    xp = backend.get_array_module(x.array)
    mask = 2 * (xp.random.rand(*x.shape) > 0.5).astype(x.dtype)
    return x * mask
```

The function now supports test mode. Note that you usually do not have to implement your own dropout function because `dropout()` is officially provided.

## Testing Functions

In order to isolate the cause of learning failure from implementation bugs, it is important to test function implementations. Chainer provides simple utilities to help writing unit tests. They are defined in the `gradient_check` module.

The most important test utility is the `numerical_grad()` function. This function computes the numerical gradient of given function using finite differences. It can be used as follows:

```
x = np.random.randn(4, 3).astype(np.float32)
gy = np.ones((4, 3), dtype=np.float32)
f = lambda: (x * x,)
gx = gradient_check.numerical_grad(f, (x,), (gy,))
```

`f` is a closure that returns a tuple of array(s) computed from input arrays. The second and third arguments of `numerical_grad()` are tuples of input arrays and output gradient arrays, respectively. The code above computes the numerical gradients of `sum(f(x))`, where `sum` indicates the summation over all elements. The summation can be weighted by changing `gy`. `numerical_grad()` function also accepts additional `eps` argument, which indicates the quantization width of finite differences.

**Note:** `numerical_grad()` function accepts both CPU and GPU arrays. Note that we cannot mix CPU and GPU arrays.

Another utility is `chainer.testing.assert_allclose()` function. This is similar to `numpy.testing.assert_allclose()` function. The difference is that Chainer’s version accepts CPU and GPU arrays as inputs. We can mix them in one invocation of `chainer.testing.assert_allclose()`. The default values of optional arguments are also different.

Here is a typical usage of gradient checking utilities. This is a test example of `functions.relu()` function:

```
import unittest

from chainer import testing

class TestReLU(unittest.TestCase):
    def test_backward_cpu(self):
        x = Variable(np.random.randn(3, 2).astype(np.float32))
        y = F.relu(x)
        y.grad = np.random.randn(3, 2).astype(np.float32)
        y.backward(retain_grad=True)
```

(continues on next page)
The first four lines of the test code are simple forward and backward computation of ReLU function. The next two lines compute numerical gradient using the same forward function without backward routine. And at last, we compare these two results elementwise. Note that the above test code can be easily modified to test GPU version just by replacing CPU arrays to GPU arrays.

In most cases, we do not write the code like the above explicitly because Chainer offers a utility function `chainer.gradient_check.check_backward()` that follows this procedure.

```python
import unittest
from chainer import gradient_check

class TestReLU(unittest.TestCase):
    def test_backward_cpu(self):
        def f(x):
            return F.relu(x)
        x = np.random.randn(3, 2).astype(np.float32)
        y_grad = np.random.randn(3, 2).astype(np.float32)
        gradient_check.check_backward(f, x, y_grad, atol=1e-4, rtol=1e-4)
```

You can find many examples of function tests under `tests/chainer_tests/functions_tests` directory.

You can use `chainer.gradient_check.check_double_backward()` to run gradient check for the second order gradient computed by new-style functions. This function runs two backpropagations; first to compute the gradient `gx` of `y` w.r.t. `x`, and second to compute the gradient of `gx` w.r.t. `x`. It can be used like `check_backward()`, but `check_double_backward()` expects an additional argument `x_grad_grad`, which is an array or a tuple of arrays used for initializing the gradient array of each gradient w.r.t. an input. In other words, this argument is used to initialize `gx.grad` for the second backprop.

### 2.4.5 Implementing User-Defined Links

Some functions are meant to be combined with parameters. In such case, it is useful to write a small link that wraps the function. We have already seen how to define a chain that wraps other links (by inheriting `Chain` class) in `Creating Models`. Here we study how to define a link that does not hold any other links.

As the first example, suppose that we want to implement elementwise product function between the input array and the parameter array. It can be defined as follows:

```python
class EltwiseParamProduct(Link):
    def __init__(self, shape):
        super(EltwiseParamProduct, self).__init__()
        with self.init_scope():
            self.W = chainer.Parameter(initializers.Normal(scale=1.), shape)

    def __call__(self, x):
        return self.W * x
```
For another example, assume we want to define a simple linear layer. It is already defined as `chainer.links.Linear`, so this is an educational example. The linear layer is divided into two parts: a function and its wrapper link. First, we have to define a function on variables:

```python
class LinearFunction(FunctionNode):
    def forward(self, inputs):
        x, W, b = inputs
        return x.dot(W.T) + b,

    def backward(self, inputs, grad_outputs):
        x, W, b = inputs
        gy, = grad_outputs
        gx = gy.dot(W)
        gW = gy.T.dot(x)
        gb = gy.sum(axis=0)
        return gx, gW, gb

def linear(x, W, b):
    return LinearFunction().apply((x, W, b))
```

This function takes three arguments: input, weight, and bias. It can be used as a part of model definition, though is inconvenient since the user have to manage the weight and bias parameters directly. In order to make a convenient module, let’s wrap it into a link:

```python
class Linear(Link):
    def __init__(self, in_size, out_size):
        super(Linear, self).__init__()
        with self.init_scope():
            self.W = chainer.Parameter(
                initializers.Normal(1. / math.sqrt(in_size)),
                (out_size, in_size))
            self.b = chainer.Parameter(0, (out_size,))

    def __call__(self, x):
        return linear(x, self.W, self.b)
```

This link hides the parameters of the linear layer.

**Note:** An advanced tip to implement functions: if you want to preserve some information between forward and backward computations (e.g. to cache some arrays), you can store it as attributes. Be careful that it might increase the memory consumption during the whole forward-backward computation. If you want to train very large networks on a GPU with limited memory, it is not recommended that you cache arrays between forward and backward. There is one exception for this: caching the output arrays does not change the memory consumption, because they are also held by the output Variable objects.

**Warning:** You should not assume a one-to-one match of calls of forward and backward. Some users may call backward more than once after one forward call.
2.4.6 Migrating From Old-Style Functions To New-Style Functions

Here are the key differences between `Function` and `FunctionNode`.

- Implementing forward computation (difference between `chainer.Function.forward()` and `chainer.FunctionNode.forward()`)
  - There are no difference between `Function` and `FunctionNode` except that the input arrays are NOT retained by default.

    If you want the inputs to be retained to use them in `backward`, call `retain_inputs()` explicitly. In other words, `self.retain_inputs()` has no effect in `FunctionNode`.

- Implementing backward computation (difference between `chainer.Function.backward()` and `chainer.FunctionNode.backward()`)

  - Arguments to the method has been changed.
    - `inputs` argument is no longer passed.
      You can use `get_retained_inputs()` and `get_retained_outputs()` to retrieve the inputs/outputs retained in the forward method. Note that `grad_outputs` and these retained inputs/outputs are all given as `Variable` objects, and `backward` method must return a tuple of `Variable` objects.
    - `target_input_index`es argument has been added.

      It contains a sorted indices of the input variables w.r.t. which the gradients are required. You can use it to skip calculation of unneeded gradients. The use of `target_input_index`es is optional; it is acceptable to calculate and return all gradients.

  - All inputs (`grad_outputs`) and retained values are given in `Variable` in `FunctionNode`, whereas `ndarray` in `Function`.

- Invoking forward computation

  - `Function` is a callable, whereas `FunctionNode` is not.

    You need to use `f.apply((x,))` instead of `f(x)`. Note that `apply()` always returns outputs as `tuple` even if the function generates only one output value.

When migrating from old-style to new-style, typically you will need to write a new function class that implements the first-order gradient of the original function. Here is an example of rewriting old-style `MyOldFunc` unary function to new-style `MyFunc` function.

```python
class MyOldFunc(chainer.Function):
    def forward(self, inputs):
        x, = inputs
        ...  # forward computation code
        return y,
    
def backward(self, inputs, grad_outputs):
        x, = inputs
        gy, = grad_outputs
        ...  # backward computation code
        return gx,

class MyFunc(chainer.FunctionNode):
    def forward(self, inputs):
        (continues on next page)
```
self.retain_inputs((0,))
    x, = inputs
    ...  # forward computation code in MyOldFunc
    return y,

def backward(self, target_input_indexes, grad_outputs):
    x, = self.get_retained_inputs()
    gy, = grad_outputs
    gx, = MyFuncGrad().apply((x, gy))
    return gx,

class MyFuncGrad(chainer.FunctionNode):

    def forward(self, inputs):
        x, gy = inputs
        ...  # backward computation code in MyOldFunc
        return gx,

    def backward(self, target_input_indexes, grad_outputs):
        # You can leave this unimplemented unless you need to compute
        # higher-order derivative using this function.
        raise NotImplementedError()

2.4.7 Implementing Old-Style Functions

Note: As noted in the New-Style v.s. Old-Style Functions, we recommend that you use new-style for newly imple-
mented functions. This section uses the same example as in Implementing New-Style Functions but using old-style.

First, suppose we want to define an elementwise function $f(x, y, z) = x \cdot y + z$. While it is possible to implement 
this equation using a combination of the $\times$ and $+$ functions, defining it as a single function may reduce memory 
consumption, so it is not only a toy example. Here we call this function MulAdd.

Let’s start with defining MulAdd working on the CPU. Old-style functions must inherit the Function class. The 
skeleton of a function looks like:

class MulAdd(Function):
    def forward_cpu(self, inputs):
        # do forward computation on CPU
        return some_tuple

    def backward_cpu(self, inputs, grad_outputs):
        # do backward computation on CPU
        return some_tuple

We must implement forward_cpu() and backward_cpu() methods. The non-self arguments of these functions 
are tuples of array(s), and these functions must return a tuple of array(s).

Warning: Be careful to return a tuple of arrays even if you have just one array to return.

MulAdd is simple and implemented as follows:
class MulAdd(Function):
    def forward_cpu(self, inputs):
        x, y, z = inputs
        w = x * y + z
        return w,

    def backward_cpu(self, inputs, grad_outputs):
        x, y, z = inputs
        gw, = grad_outputs
        gx = y * gw
        gy = x * gw
        gz = gw
        return gx, gy, gz

As per the warning above, the forward_cpu method returns a tuple of single element. Note that all arrays appearing in CPU functions are `numpy.ndarray`. The forward function is straightforward; it unpacks the input tuple, computes the output, and packs it into a tuple. The backward function is a bit more complicated. Recall the rule of differentiation of multiplication. This example just implements the rule. Look at the return values, the function just packs the gradient of each input in the same order and returns them.

By just defining the core computation of forward and backward, Function class provides a chaining logic on it (i.e., storing the history of computation, etc.).

**Note:** Assuming we implement a (forward) function \( y = f(x) \) which takes as input the vector \( x \in \mathbb{R}^n \) and produces as output a vector \( y \in \mathbb{R}^m \). Then the backward method has to compute

\[
\lambda_i = \sum_{j=1}^{m} \frac{\partial y_i}{\partial x_j} \gamma_j \quad \text{for} \quad i = 1 \ldots n
\]

where \( \gamma \) is the `grad_outputs`. Note, that the resulting vector \( \lambda \) must have the same shape as the arguments of the forward method.

Now let’s define the corresponding GPU methods. You can easily predict that the methods we have to write are named `forward_gpu()` and `backward_gpu()`:

class MulAdd(Function):
    def forward_cpu(self, inputs):
        ...

    def backward_cpu(self, inputs, grad_outputs):
        ...

    def forward_gpu(self, inputs):
        x, y, z = inputs
        w = x * y + z
        return w,

    def backward_gpu(self, inputs, grad_outputs):
        x, y, z = inputs
        gw, = grad_outputs
        gx = y * gw
        gy = x * gw
        gz = gw
        return gx, gy, gz
In GPU methods, arrays are of type `cupy.ndarray`. We use arithmetic operators defined for this class. These operators implement the basic elementwise arithmetics.

You may find that the definitions of GPU methods are exactly same as those of CPU methods. In that case, we can reduce them to `forward()` and `backward()` methods.

```python
class MulAdd(Function):
    def forward(self, inputs):
        x, y, z = inputs
        w = x * y + z
        return w,

    def backward(self, inputs, grad_outputs):
        x, y, z = inputs
        gw, = grad_outputs
        gx = y * gw
        gy = x * gw
        gz = gw
        return gx, gy, gz
```

Since the `cupy.ndarray` class implements many methods of `numpy.ndarray`, we can write these unified methods in most cases.

The MulAdd function can be used as follows:

```python
x = Variable(np.random.uniform(-1, 1, (3, 2)).astype(np.float32))
y = Variable(np.random.uniform(-1, 1, (3, 2)).astype(np.float32))
z = Variable(np.random.uniform(-1, 1, (3, 2)).astype(np.float32))
w = MulAdd()(x, y, z)
```

It looks a bit ugly: we have to explicitly instantiate MulAdd before applying it to variables. We also have to be careful that one instance of MulAdd must not be used multiple times, since it acts as a node in the computational graph. In Chainer, we often define a thin wrapper Python function that hide the instantiation:

```python
def muladd(x, y, z):
    return MulAdd()(x, y, z)
w = muladd(x, y, z)
```

All functions under `chainer.functions` are implemented as wrapper functions like this.

**Unified forward/backward methods with NumPy/CuPy functions**

CuPy implements many functions that are compatible to those of NumPy. We can write unified forward/backward methods with them. Consider that we want to write a backprop-able function $f(x, y) = \exp(x) + \exp(y)$. We name it `ExpAdd` here. It can be written straight-forward as follows:

```python
from chainer.backends import cuda

class ExpAdd(Function):
    def forward_cpu(self, inputs):
        x, y = inputs
        z = np.exp(x) + np.exp(y)
        return z,

    def backward_cpu(self, inputs, grad_outputs):
        (continues on next page)
```

2.4. Define your own function
x, y = inputs
gz, = grad_outputs

gx = gz * np.exp(x)
gy = gz * np.exp(y)
return gx, gy

def forward_gpu(self, inputs):
cupy = cuda.cupy
x, y = inputs
z = cupy.exp(x) + cupy.exp(y)
return z,

def backward_gpu(self, inputs, grad_outputs):
cupy = cuda.cupy
x, y = inputs
gz, = grad_outputs

gx = gz * cupy.exp(x)
gy = gz * cupy.exp(y)
return gx, gy

def expadd(x, y):
    return ExpAdd()(x, y)

Note: Here we used chainer.backends.cuda.cupy instead of directly accessing cupy. This is because the cupy module cannot be imported if the CUDA is not installed. In order to keep the implementation valid in non-CUDA environment, we have to defer the access to the cupy module. Note that the chainer.backends.cuda module can be imported even if the CUDA is not installed. Of course, the module in such environment is almost useless, but if the interpreter does not run through the code accessing CUDA-dedicated functions, the code is still valid.

The CPU and GPU implementations are almost same, except that numpy is replaced by cupy in GPU methods. We can unify these functions using the chainer.backend.get_array_module() function. This function accepts arbitrary number of arrays, and returns an appropriate module for them. See the following code:

class ExpAdd(Function):
    def forward(self, inputs):
xp = backend.get_array_module(*inputs)
x, y = inputs
z = xp.exp(x) + xp.exp(y)
return z,

    def backward(self, inputs, grad_outputs):
xp = backend.get_array_module(*inputs)
x, y = inputs
gz, = grad_outputs

gx = gz * xp.exp(x)
gy = gz * xp.exp(y)
return gx, gy

def expadd(x, y):
    return ExpAdd()(x, y)
Note that this code works correctly even if CUDA is not installed in the environment. If CUDA is not found, `get_array_module()` function always returns `numpy`. We often use the name `xp` for the variadic module name, which is analogous to the abbreviation `np` for NumPy and `cp` for CuPy.

**Write an Elementwise Kernel Function**

Let’s turn back to the MulAdd example.

The GPU implementation of MulAdd as shown above is already fast and parallelized on GPU cores. However, it invokes two kernels during each of forward ($w = x \times y + z$) and backward ($gx = y \times gw$ and $gy = x \times gw$) computations. It might hurt performance, since the intermediate temporary arrays are read and written by possibly different GPU cores, which consumes much bandwidth. We can reduce the number of invocations by defining our own kernel. It also reduce the memory consumption.

Most functions only require elementwise operations like MulAdd. CuPy provides a useful tool to define elementwise kernels, the `cupy.ElementwiseKernel` class, and Chainer wraps it by `chainer.backends.cuda.elementwise()` function. Our MulAdd implementation can be improved as follows:

```python
class MulAdd(Function):
    def forward_cpu(self, inputs):
        ...

    def backward_cpu(self, inputs, grad_outputs):
        ...

    def forward_gpu(self, inputs):
        cupy = cuda.cupy
        x, y, z = inputs
        w = cuda.elementwise(
            'float32 x, float32 y, float32 z',
            'float32 w',
            'w = x * y + z',
            'muladd_fwd')(x, y, z)
        return w,

    def backward_gpu(self, inputs, grad_outputs):
        x, y, z = inputs
        gw, = grad_outputs
        gx, gy = cuda.elementwise(
            'float32 x, float32 y, float32 gw',
            'float32 gx, float32 gy',
            '''
            gx = y * gw;
            gy = x * gw;
            ''',
            'muladd_bwd')(x, y, gw)
        gz = gw
        return gx, gy, gz
```

`chainer.backends.cuda.elementwise()` function accepts the essential implementation of the kernel function, and returns a kernel invocation function (actually, it returns `ElementwiseKernel` object, which is callable). In typical usage, we pass four arguments to this function as follows:

1. Input argument list. This is a comma-separated string each entry of which consists of a type specification and an argument name.
2. Output argument list in the same format as the input argument list.
3. Body of parallel loop. We can use the input/output argument names as an element of these arrays.
4. Name of the kernel function, which is shown in debuggers and profilers.

Above code is not compiled on every forward/backward computation thanks to two caching mechanisms provided by \texttt{chainer.backends.cuda.elementwise()}. The first one is binary caching: \texttt{chainer.backends.cuda.elementwise()} function caches the compiled binary in the $\$(HOME) /.cupy/kernel_cache directory with a hash value of the CUDA code, and reuses it if the given code matches the hash value. This caching mechanism is actually implemented in CuPy.

The second one is upload caching: Given a compiled binary code, we have to upload it to the current GPU in order to execute it. \texttt{chainer.backends.cuda.elementwise()} function memoizes the arguments and the current device, and if it is called with the same arguments for the same device, it reuses the previously uploaded kernel code.

The above MulAdd code only works for float32 arrays. The \texttt{ElementwiseKernel} also supports the type-variadic kernel definition. In order to define variadic kernel functions, you can use type placeholder by placing a single character as type specifier:

```python
class MulAdd(Function):
    def forward_cpu(self, inputs):
        ...

    def backward_cpu(self, inputs, grad_outputs):
        ...

    def forward_gpu(self, inputs):
        cupy = cuda.cupy
        x, y, z = inputs
        w = cuda.elementwise(
            'T x, T y, T z',
            'T w',
            'w = x * y + z',
            'muladd_fwd')(x, y, z)
        return w,

    def backward_gpu(self, inputs, grad_outputs):
        x, y, z = inputs
        gw, = grad_outputs
        gx, gy = cuda.elementwise(
            'T x, T y, T gw',
            'T gx, T gy',
            'gx = y * gw;
            gy = x * gw;
            ',
            'muladd_bwd')(x, y, gw)
        gz = gw
        return gx, gy, gz
```

The type placeholder \texttt{T} indicates an arbitrary data type that CuPy supports.

There are more functionalities on user-defined kernels in CuPy. See the CuPy documentation on user-defined kernels for more details.
2.5 Creating Models

In the example code of this tutorial, we assume for simplicity that the following symbols are already imported.

```python
import math
import numpy as np
import chainer
from chainer import backend
from chainer.backends import cuda
from chainer import Function, FunctionNode, gradient_check, report, training, utils, Variable, datasets, initializers, iterators, optimizers, serializers
from chainer import Link, Chain, ChainList
import chainer.functions as F
import chainer.links as L
from chainer.training import extensions
```

Most neural network architectures contain multiple links. For example, a multi-layer perceptron consists of multiple linear layers. We can write complex procedures with parameters by combining multiple links like this:

```python
>>> l1 = L.Linear(4, 3)
>>> l2 = L.Linear(3, 2)

>>> def my_forward(x):
...     h = l1(x)
...     return l2(h)
```

Here the `L` indicates the `links` module. A procedure with parameters defined in this way is hard to reuse. More Pythonic way is combining the links and procedures into a class:

```python
>>> class MyProc(object):
...     def __init__(self):
...         self.l1 = L.Linear(4, 3)
...         self.l2 = L.Linear(3, 2)

...     def forward(self, x):
...         h = self.l1(x)
...         return self.l2(h)
```

In order to make it more reusable, we want to support parameter management, CPU/GPU migration, robust and flexible save/load features, etc. These features are all supported by the `Chain` class in Chainer. Then, what we have to do here is just define the above class as a subclass of Chain:

```python
>>> class MyChain(Chain):
...     def __init__(self):
...         super(MyChain, self).__init__()

...         with self.init_scope():
...             self.l1 = L.Linear(4, 3)
...             self.l2 = L.Linear(3, 2)

...     def forward(self, x):
...         h = self.l1(x)
...         return self.l2(h)
```

It shows how a complex chain is constructed by simpler links. Links like `l1` and `l2` are called `child links` of `MyChain`. 
Note that Chain itself inherits Link. It means we can define more complex chains that hold MyChain objects as their child links.

Note: We often define a single forward method of a link by the forward operator. Such links and chains are callable and behave like regular functions of Variables.

Another way to define a chain is using the ChainList class, which behaves like a list of links:

```python
>>> class MyChain2(ChainList):
...     def __init__(self):
...         super(MyChain2, self).__init__(
...             L.Linear(4, 3),
...             L.Linear(3, 2),
...         )
...     def forward(self, x):
...         h = self[0](x)
...         return self[1](h)
```

ChainList can conveniently use an arbitrary number of links, however if the number of links is fixed like in the above case, the Chain class is recommended as a base class.

### 2.6 Optimizer

In the example code of this tutorial, we assume for simplicity that the following symbols are already imported:

```python
import math
import numpy as np
import chainer
from chainer import backend
from chainer import backends
from chainer.backends import cuda
from chainer import Function, FunctionNode, gradient_check, report, training, utils,
    Variable
from chainer import datasets, initializers, iterators, optimizers, serializers
from chainer import Link, Chain, ChainList
import chainer.functions as F
import chainer.links as L
from chainer.training import extensions
```

From the previous guide on Creating Models, let’s use the MyChain class:

```python
>>> class MyChain(Chain):
...     def __init__(self):
...         super(MyChain, self).__init__()
...         with self.init_scope():
...             self.l1 = L.Linear(4, 3)
...             self.l2 = L.Linear(3, 2)
...     def forward(self, x):
...         h = self.l1(x)
...         return self.l2(h)
```
To tune parameters values to minimize loss, etc., we have to optimize them by the `Optimizer` class. It runs a numerical optimization algorithm on a given link. Many algorithms are implemented in the `optimizers` module. Here we use the simplest one, called Stochastic Gradient Descent (SGD):

```python
>>> model = MyChain()
>>> optimizer = optimizers.SGD().setup(model)
```

The method `setup()` prepares for the optimization given a link.

Some parameter/gradient manipulations, e.g. weight decay and gradient clipping, can be done by setting hook functions to the optimizer. Hook functions are called after the gradient computation and right before the actual update of parameters. For example, we can set weight decay regularization by running the next line beforehand:

```python
>>> optimizer.add_hook(chainer.optimizer_hooks.WeightDecay(0.0005))
```

Of course, you can write your own hook functions. It should be a function or a callable object.

There are two ways to use the optimizer. One is using it via `Trainer`, which we will see in the following sections. The other way is using it directly. We here review the latter case. To use the optimizer in an automated fashion, see the `Trainer` guide.

There are two further ways to use the optimizer directly. One is manually computing gradients and then calling the `update()` method with no arguments. Do not forget to clear the gradients beforehand!

```python
>>> x = np.random.uniform(-1, 1, (2, 4)).astype(np.float32)
>>> model.cleargrads()
>>> # compute gradient here...
>>> loss = F.sum(model(chainer.Variable(x)))
>>> loss.backward()
>>> optimizer.update()
```

The other way is just passing a loss function to the `update()` method. In this case, `cleargrads()` is automatically called by the update method, so the user does not have to call it manually.

```python
>>> def lossfun(arg1, arg2):
...     # calculate loss
...     loss = F.sum(model(chainer.Variable(arg1) - arg2))
...     return loss

>>> arg1 = np.random.uniform(-1, 1, (2, 4)).astype(np.float32)
>>> arg2 = np.random.uniform(-1, 1, (2, 4)).astype(np.float32)
>>> optimizer.update(lossfun, chainer.Variable(arg1), chainer.Variable(arg2))
```

See `chainer.Optimizer.update()` for the full specification.

### 2.7 Trainer

When we want to train neural networks, we have to run training loops that update the parameters many times. A typical training loop consists of the following procedures:

1. Iterations over training datasets
2. Preprocessing of extracted mini-batches
3. Forward/backward computations of the neural networks
4. Parameter updates
5. Evaluations of the current parameters on validation datasets
6. Logging and printing of the intermediate results

Chainer provides a simple yet powerful way to make it easy to write such training processes. The training loop abstraction mainly consists of two components:

- **Dataset abstraction.** It implements 1 and 2 in the above list. The core components are defined in the `dataset` module. There are also many implementations of datasets and iterators in `datasets` and `iterators` modules, respectively.

- **Trainer.** It implements 3, 4, 5, and 6 in the above list. The whole procedure is implemented by Trainer. The way to update parameters (3 and 4) is defined by `Updater`, which can be freely customized. 5 and 6 are implemented by instances of `Extension`, which appends an extra procedure to the training loop. Users can freely customize the training procedure by adding extensions. Users can also implement their own extensions.

### 2.8 Trainer Extensions

In this section, you will learn about the following topics:

- **How to create your own trainer extension**
  - by defining a simple function
  - by defining a function decorated with `@make_extension`
  - by defining a class inherited from `Extension` class

In the example code of this tutorial, we assume for simplicity that the following symbols are already imported.

```python
import math
import numpy as np
import chainer
from chainer import backend
from chainer import backends
from chainer.backends import cuda
from chainer import Function, FunctionNode, gradient_check, report, training, utils,
...Variable
from chainer import datasets, initializers, iterators, optimizers, serializers
from chainer import Link, Chain, ChainList
import chainer.functions as F
import chainer.links as L
from chainer.training import extensions
```

### 2.8.1 What is trainer Extension?

`Extension` is a callable object that takes a `Trainer` object as an argument. By adding an `Extension` to a `Trainer` using the `extend()` method, the `Extension` will be called according to the schedule specified by using a `trigger` object (See the details in `l. trigger`)

The `Trainer` object contains all information used in a training loop, e.g., models, optimizers, updaters, iterators, and datasets, etc. This makes it possible to change settings such as the learning rate of an optimizer.
2.8.2 Write a simple function

You can make a new `Extension` by writing a simple function which takes a `Trainer` object as its argument. For example, when you want to reduce the learning rate periodically during training, an `lr_drop` extension can be written as follows:

```python
def lr_drop(trainer):
    trainer.updater.get_optimizer('main').lr *= 0.1
```

Then you can add this function to a `Trainer` object via `extend()` method.

```python
trainer.extend(lr_drop, trigger=(10, 'epoch'))
```

It lowers the learning rate every 10 epochs by multiplying 0.1 with the current learning rate.

2.8.3 Write a function decorated with `@make_extension`

`make_extension()` is a decorator that adds some attributes to a given function. For example, the simple extension we created above can be written in this form:

```python
@training.make_extension(trigger=(10, 'epoch'))
def lr_drop(trainer):
    trainer.updater.get_optimizer('main').lr *= 0.1
```

The difference between the above example and this is whether it has a default `trigger` or not. In the latter case, `lr_drop()` has its default `trigger` so that unless another `trigger` is specified via `extend()` method, the `trigger` specified in `make_extension()` is used by default. The code below acts the same as the former example, i.e., it reduces the learning rate every 10 epochs.

```python
trainer.extend(lr_drop)
```

There are several attributes you can add using the `make_extension()` decorator.

1. trigger

`trigger` is an object that takes a `Trainer` object as an argument and returns a boolean value. If a tuple in the form `(period, unit)` is given as a trigger, it will be considered as an `IntervalTrigger` that invokes the extension every `period` unit. For example, when the given tuple is `(10, 'epoch')`, the extension will run every 10 epochs.

`trigger` can also be given to the `extend()` method that adds an extension to a `Trainer` object. The priority of triggers is as follows:

- When both `extend()` and a given `Extension` have triggers, the `trigger` given to `extend()` is used.
- When `None` is given to `extend()` as the `trigger` argument and a given `Extension` has `trigger`, the `trigger` given to the `Extension` is used.
- When both `trigger` attributes in `extend()` and `Extension` are `None`, the `Extension` will be fired every iteration.

See the details in the documentation of `get_trigger()` for more information.
2. default_name

An Extension is kept in a dictionary which is a property in a Trainer. This argument gives the name of the Extension. Users will see this name in the keys of the snapshot which is a dictionary generated by serialization.

3. priority

As a Trainer object can be assigned multiple Extension objects, the execution order is defined according to the following three values:

- **PRIORITY_WRITER**: The priority for extensions that write some records to the observation dictionary. It includes cases that the extension directly adds values to the observation dictionary, or the extension uses the chainer.report() function to report values to the observation dictionary. Extensions which write something to reporter should go first because other Extensions which read those values may be added.

- **PRIORITY_EDITOR**: The priority for extensions that edit the observation dictionary based on already reported values. Extensions which edit some values of reported ones should go after the extensions which write values to reporter but before extensions which read the final values.

- **PRIORITY_READER**: The priority for extensions that only read records from the observation dictionary. This is also suitable for extensions that do not use the observation dictionary at all. Extensions which read the reported values should be fired after all the extensions which have other priorities, e.g., PRIORITY_WRITER and PRIORITY_EDITOR because it should read the final values.

See the details in the documentation of Trainer for more information.

4. finalizer

You can specify a function to finalize the extension. It is called once at the end of the training loop, i.e., when run() has finished.

5. initializer

You can specify a function which takes a Trainer object as an argument to initialize the extension. It is called once before the training loop begins.

2.8.4 Write a class inherited from the Extension class

This is the way to define your own extension with the maximum degree of freedom. You can keep any values inside of the extension and serialize them.

As an example, let's make an extension that drops the learning rate polynomially. It calculates the learning rate by this equation:

\[ \eta = \eta_{\text{init}} \left( 1 - \frac{t}{t_{\text{max}}} \right)^{\text{power}} \]

The learning rate will be dropped according to the curve below with power = 0.5:
class PolynomialShift(training.Extension):

    def __init__(self, attr, power, stop_trigger, batchsize=None, len_dataset=None):
        self._attr = attr
        self._power = power
        self._init = None
        self._t = 0
        self._last_value = 0

        if stop_trigger[1] == 'iteration':
            self._maxiter = stop_trigger[0]
        elif stop_trigger[1] == 'epoch':
            if batchsize is None or len_dataset is None:
                raise ValueError('When the unit of `stop_trigger` is `epoch`, '
                                 '`batchsize` and `len_dataset` should be '
                                 'specified to calculate the maximum iteration."
            n_iter_per_epoch = len_dataset / float(batchsize)
            self._maxiter = float(stop_trigger[0] * n_iter_per_epoch)

    def initialize(self, trainer):
        optimizer = trainer.updater.get_optimizer('main')
        # ensure that _init is set
        if self._init is None:
            self._init = getattr(optimizer, self._attr)

    def __call__(self, trainer):
        (continues on next page)
```python
self._t += 1

optimizer = trainer.updater.get_optimizer('main')
value = self._init * ((1 - (self._t / self._maxiter)) ** self._power)
setattr(optimizer, self._attr, value)
self._last_value = value

def serialize(self, serializer):
    self._t = serializer('_t', self._t)
    self._last_value = serializer('_last_value', self._last_value)
    if isinstance(self._last_value, np.ndarray):
        self._last_value = self._last_value.item()

stop_trigger = (10000, 'iteration')
trainer.extend(PolynomialShift('lr', 0.5, stop_trigger))
```

This extension `PolynomialShift` takes five arguments.

- **attr**: The name of the optimizer property you want to update using this extension.
- **power**: The power of the above equation to calculate the learning rate.
- **stop_trigger**: The trigger given to the `Trainer` object to specify when to stop the training loop.
- **batchsize**: The training mini-batchsize.
- **len_dataset**: The length of the dataset, i.e., the number of data in the training dataset.

This extension calculates the number of iterations which will be performed during training by using `stop_trigger`, `batchsize`, and `len_dataset`, then stores it as a property `_maxiter`. This property will be used in the `__call__()` method to update the learning rate. The `initialize()` method obtains the initial learning rate from the optimizer given to the `Trainer` object. The `serialize()` method stores or recovers the properties, `_t` (number of iterations) and `_last_value` (the latest learning rate), belonging to this extension.

### 2.9 Using GPU(s) in Chainer

In the example code of this tutorial, we assume for simplicity that the following symbols are already imported.

```python
import math
import numpy as np
import chainer
from chainer import backend
from chainer import backends
from chainer.backends import cuda
from chainer import Function, FunctionNode, gradient_check, report, training, utils,
˓→Variable
from chainer import datasets, initializers, iterators, optimizers, serializers
from chainer import Link, Chain, ChainList
import chainer.functions as F
import chainer.links as L
from chainer.training import extensions
```

In this section, you will learn about the following topics:

- Relationship between Chainer and CuPy
• Basics of CuPy
• Single-GPU usage of Chainer
• Multi-GPU usage of model-parallel computing
• Multi-GPU usage of data-parallel computing

After reading this section, you will be able to:
• Use Chainer on a CUDA-enabled GPU
• Write model-parallel computing in Chainer
• Write data-parallel computing in Chainer

2.9.1 Relationship between Chainer and CuPy

Note: Even if you have CUDA installed in your environment, you have to install CuPy separately to use GPUs. See Working with Custom CUDA Installation for the way to set up CUDA support.

Chainer uses CuPy as its backend for GPU computation. In particular, the `cupy.ndarray` class is the GPU array implementation for Chainer. CuPy supports a subset of features of NumPy with a compatible interface. It enables us to write a common code for CPU and GPU. It also supports PyCUDA-like user-defined kernel generation, which enables us to write fast implementations dedicated to GPU.

Note: The `chainer.backends.cuda` module imports many important symbols from CuPy. For example, the `cupy` namespace is referred as `cuda.cupy` in the Chainer code. Note that the `chainer.backends.cuda` module can be imported even if CUDA is not installed.

Chainer uses a memory pool for GPU memory allocation. As shown in the previous sections, Chainer constructs and destructs many arrays during learning and evaluating iterations. It is not well suited for CUDA architecture, since memory allocation and release in CUDA (i.e. `cudaMalloc` and `cudaFree` functions) synchronize CPU and GPU computations, which hurts performance. In order to avoid memory allocation and deallocation during the computation, Chainer uses CuPy’s memory pool as the standard memory allocator. Chainer changes the default allocator of CuPy to the memory pool, so user can use functions of CuPy directly without dealing with the memory allocator.

2.9.2 Basics of `cupy.ndarray`

See the documentation of CuPy for the basic usage of `cupy.ndarray`

CuPy is a GPU array backend that implements a subset of NumPy interface. The `cupy.ndarray` class is in its core, which is a compatible GPU alternative of `numpy.ndarray`. CuPy implements many functions on `cupy.ndarray` objects. See the reference for the supported subset of NumPy API. Understanding NumPy might help utilizing most features of CuPy. See the NumPy documentation for learning it.

The main difference of `cupy.ndarray` from `numpy.ndarray` is that the content is allocated on the device memory. The allocation takes place on the current device by default. The current device can be changed by `cupy.cuda.Device` object as follows:

```python
with cupy.cuda.Device(1):
    x_on_gpu1 = cupy.array([1, 2, 3, 4, 5])
```
Most operations of CuPy is done on the current device. Be careful that it causes an error to process an array on a non-current device.

Chainer provides some convenient functions to automatically switch and choose the device. For example, the `chainer.backends.cuda.to_gpu()` function copies a `numpy.ndarray` object to a specified device:

```python
x_cpu = np.ones((5, 4, 3), dtype=np.float32)
x_gpu = cuda.to_gpu(x_cpu, device=1)
```

It is equivalent to the following code using CuPy:

```python
x_cpu = np.ones((5, 4, 3), dtype=np.float32)
with cupy.cuda.Device(1):
    x_gpu = cupy.array(x_cpu)
```

Moving a device array to the host can be done by `chainer.backends.cuda.to_cpu()` as follows:

```python
x_cpu = cuda.to_cpu(x_gpu)
```

It is equivalent to the following code using CuPy:

```python
with x_gpu.device:
    x_cpu = x_gpu.get()
```

**Note:** The `with` statements in these codes are required to select the appropriate CUDA device. If user uses only one device, these device switching is not needed. `chainer.backends.cuda.to_gpu()` and `chainer.backends.cuda.to_cpu()` functions automatically switch the current device correctly.

Chainer also provides a convenient function `chainer.backends.cuda.get_device_from_id()` and `chainer.backends.cuda.get_device_from_array()` to select a device. The former function accepts an integer or `None`. When `None` is given, it returns a dummy device object. Otherwise, it returns a corresponding device object. The latter function accepts CuPy array or NumPy array. When a NumPy array is given, it returns a dummy device object. Otherwise, it returns a corresponding device object to the give CuPy array. The dummy device object also supports `with` statements like the above example but does nothing. Here are some other examples:

```python
cuda.get_device_from_id(1).use()
x_gput = cupy.empty((4, 3), dtype=cupy.float32)
with cuda.get_device_from_id(1):
    x_gput = cupy.empty((4, 3), dtype=cupy.float32)
with cuda.get_device_from_array(x_gput):
    y_gput = x_gpu + 1
```

Since it accepts NumPy arrays, we can write a function that accepts both NumPy and CuPy arrays with correct device switching:

```python
def add1(x):
    with cuda.get_device_from_array(x):
        return x + 1
```

The compatibility of CuPy with NumPy enables us to write CPU/GPU generic code. It can be made easy by the `chainer.backend.get_array_module()` function. This function returns the `numpy` or `cupy` module based on arguments. A CPU/GPU generic function is defined using it like follows:
# Stable implementation of \(\log(1 + \exp(x))\)

```python
def softplus(x):
    xp = backend.get_array_module(x)
    return xp.maximum(0, x) + xp.log1p(xp.exp(-abs(x)))
```

## 2.9.3 Run Neural Networks on a Single GPU

Single-GPU usage is very simple. What you have to do is transferring Link and input arrays to the GPU beforehand. In this subsection, the code is based on our first MNIST example in this tutorial.

A Link object can be transferred to the specified GPU using the `to_gpu()` method.

This time, we make the number of input, hidden, and output units configurable. The `to_gpu()` method also accepts a device ID like `model.to_gpu(0)`. In this case, the link object is transferred to the appropriate GPU device. The current device is used by default.

If we use `chainer.training.Trainer`, what we have to do is just let the updater know the device ID to send each mini-batch.

```python
updater = training.updaters.StandardUpdater(train_iter, optimizer, device=0)
trainer = training.Trainer(updater, (20, 'epoch'), out='result')

trainer.extend(extensions.Evaluator(test_iter, model, device=0))
```

We also have to specify the device ID for an evaluator extension as well.

```python
trainer.extend(extensions.Evaluator(test_iter, model, device=0))
```

When we write down the training loop by hand, we have to transfer each mini-batch to the GPU manually:

```python
model.to_gpu()
batchsize = 100
datasize = len(x_train)
for epoch in range(20):
    print('epoch %d' % epoch)
    indexes = np.random.permutation(datasize)
    for i in range(0, datasize, batchsize):
        x = Variable(cuda.to_gpu(x_train[indexes[i : i + batchsize]]))
        t = Variable(cuda.to_gpu(y_train[indexes[i : i + batchsize]]))
        optimizer.update(model, x, t)
```

## 2.9.4 Model-parallel Computation on Multiple GPUs

Parallelization of machine learning is roughly classified into two types called “model-parallel” and “data-parallel”. Model-parallel means parallelizations of the computations inside the model. In contrast, data-parallel means parallelizations using data sharding. In this subsection, we show how to use the model-parallel approach on multiple GPUs in Chainer.

Recall the MNIST example. Now suppose that we want to modify this example by expanding the network to 6 layers with 2000 units each using two GPUs. In order to make multi-GPU computation efficient, we only make the two GPUs communicate at the third and sixth layer. The overall architecture looks like the following diagram:

```
(GPU0) input --+-+ 11 --> 12 --> 13 --+-+ 14 --> 15 --> 16 --+-+ output  
    |                  |                  |
(GPU1)     --+-+ 11 --> 12 --> 13 --+-+ 14 --> 15 --> 16 --+-+
```

We can use the above MLP chain as following diagram:
Let's write a link for the whole network.

```python
class ParallelMLP(Chain):
    def __init__(self):
        super(ParallelMLP, self).__init__()
        with self.init_scope():
            # the input size, 784, is inferred
            self.mlp1_gpu0 = MLP(1000, 2000).to_gpu(0)
            self.mlp1_gpu1 = MLP(1000, 2000).to_gpu(1)

            # the input size, 2000, is inferred
            self.mlp2_gpu0 = MLP(1000, 10).to_gpu(0)
            self.mlp2_gpu1 = MLP(1000, 10).to_gpu(1)

    def forward(self, x):
        # assume x is on GPU 0
        z0 = self.mlp1_gpu0(x)
        z1 = self.mlp1_gpu1(F.copy(x, 1))

        # sync
        h0 = F.relu(z0 + F.copy(z1, 0))
        h1 = F.relu(z1 + F.copy(z0, 1))

        y0 = self.mlp2_gpu0(h0)
        y1 = self.mlp2_gpu1(h1)

        # sync
        y = y0 + F.copy(y1, 0)
        return y  # output is on GPU0
```

Recall that the `Link.to_gpu()` method returns the link itself. The `copy()` function copies an input variable to specified GPU device and returns a new variable on the device. The copy supports backprop, which just reversely transfers an output gradient to the input device.

**Note:** Above code is not parallelized on CPU, but is parallelized on GPU. This is because all the functions in the above code run asynchronously to the host CPU.

An almost identical example code can be found at `examples/mnist/train_mnist_model_parallel.py`.

### 2.9.5 Data-parallel Computation on Multiple GPUs with Trainer

Data-parallel computation is another strategy to parallelize online processing. In the context of neural networks, it means that a different device does computation on a different subset of the input data. In this subsection, we review the way to achieve data-parallel learning on two GPUs.

Suppose again our task is the MNIST example. This time we want to directly parallelize the three-layer network. The most simple form of data-parallelization is parallelizing the gradient computation for a distinct set of data. First, define a model and optimizer instances:
model = L.Classifier(MLP(1000, 10))  # the input size, 784, is inferred
optimizer = optimizers.SGD()
optimizer.setup(model)

Recall that the MLP link implements the multi-layer perceptron, and the Classifier link wraps it to provide a classifier interface. We used StandardUpdater in the previous example. In order to enable data-parallel computation with multiple GPUs, we only have to replace it with ParallelUpdater.

updater = training.updaters.ParallelUpdater(train_iter, optimizer,
   devices={'main': 0, 'second': 1})

The devices option specifies which devices to use in data-parallel learning. The device with name 'main' is used as the main device. The original model is sent to this device, so the optimization runs on the main device. In the above example, the model is also cloned and sent to GPU 1. Half of each mini-batch is fed to this cloned model. After every backward computation, the gradient is accumulated into the main device, the parameter update runs on it, and then the updated parameters are sent to GPU 1 again.

See also the example code in examples/mnist/train_mnist_data_parallel.py.

## 2.9.6 Data-parallel Computation on Multiple GPUs without Trainer

We here introduce a way to write data-parallel computation without the help of Trainer. Most users can skip this section. If you are interested in how to write a data-parallel computation by yourself, this section should be informative. It is also helpful to, e.g., customize the ParallelUpdater class.

We again start from the MNIST example. At this time, we use a suffix like _0 and _1 to distinguish objects on each device. First, we define a model.

model_0 = L.Classifier(MLP(1000, 10))  # the input size, 784, is inferred

We want to make two copies of this instance on different GPUs. The Link.to_gpu() method runs in place, so we cannot use it to make a copy. In order to make a copy, we can use Link.copy() method.

model_1 = model_0.copy()
model_0.to_gpu(0)
model_1.to_gpu(1)

The Link.copy() method copies the link into another instance. It just copies the link hierarchy, and does not copy the arrays it holds.

Then, set up an optimizer:

optimizer = optimizers.SGD()
optimizer.setup(model_0)

Here we use the first copy of the model as the master model. Before its update, gradients of model_1 must be aggregated to those of model_0.

Then, we can write a data-parallel learning loop as follows:

batchsize = 100
datasize = len(x_train)
for epoch in range(20):
   print('epoch %d' % epoch)
   indexes = np.random.permutation(datasize)
   for i in range(0, datasize, batchsize):
   (continues on next page)
x_batch = x_train[indexes[i : i + batchsize]]
y_batch = y_train[indexes[i : i + batchsize]]

x0 = Variable(cuda.to_gpu(x_batch[:batchsize//2], 0))
t0 = Variable(cuda.to_gpu(y_batch[:batchsize//2], 0))
x1 = Variable(cuda.to_gpu(x_batch[batchsize//2:], 1))
t1 = Variable(cuda.to_gpu(y_batch[batchsize//2:], 1))

loss_0 = model_0(x0, t0)
loss_1 = model_1(x1, t1)

model_0.cleargrads()
model_1.cleargrads()

loss_0.backward()
loss_1.backward()

model_0.addgrads(model_1)
optimizer.update()

model_1.copyparams(model_0)

Do not forget to clear the gradients of both model copies! One half of the mini-batch is forwarded to GPU 0, the other half to GPU 1. Then the gradients are accumulated by the Link.addgrads() method. This method adds the gradients of a given link to those of the self. After the gradients are prepared, we can update the optimizer in usual way. Note that the update only modifies the parameters of model_0. So we must manually copy them to model_1 using Link.copyparams() method.

**Note:** If the batch size used in one model remain the same, the scale of the gradient is roughly proportional to the number of models, when we aggregate gradients from all models by chainer.Link.addgrads(). So you need to adjust the batch size and/or learning rate of the optimizer accordingly.

Now you can use Chainer with GPUs. All examples in the examples directory support GPU computation, so please refer to them if you want to know more practices on using GPUs. In the next section, we will show how to define a differentiable (i.e. backpropable) function on Variable objects. We will also show there how to write a simple (elementwise) CUDA kernel using Chainer’s CUDA utilities.

### 2.10 Type Checks

In this section, you will learn about the following things:

- Basic usage of type check
- Detail of type information
- Internal mechanism of type check
- More complicated cases
- Call functions
- Typical type check example

After reading this section, you will be able to:
• Write a code to check types of input arguments of your own functions

### 2.10.1 Basic usage of type check

When you call a function with an invalid type of array, you sometimes receive no error, but get an unexpected result by broadcasting. When you use CUDA with an illegal type of array, it causes memory corruption, and you get a serious error. These bugs are hard to fix. Chainer can check preconditions of each function, and helps to prevent such problems. These conditions may help a user to understand specification of functions.

Each implementation of `Function` has a method for type check, `check_type_forward()`. This function is called just before the `forward()` method of the `Function` class. You can override this method to check the condition on types and shapes of arguments.

`check_type_forward()` gets an argument `in_types`:

```python
def check_type_forward(self, in_types):
    ...
```

`in_types` is an instance of `TypeInfoTuple`, which is a sub-class of `tuple`. To get type information about the first argument, use `in_types[0]`. If the function gets multiple arguments, we recommend to use new variables for readability:

```python
x_type, y_type = in_types
```

In this case, `x_type` represents the type of the first argument, and `y_type` represents the second one.

We describe usage of `in_types` with an example. When you want to check if the number of dimension of `x_type` equals to 2, write this code:

```python
utils.type_check.expect(x_type.ndim == 2)
```

When this condition is true, nothing happens. Otherwise this code throws an exception, and the user gets a message like this:

```
Traceback (most recent call last):
...  
chainer.utils.type_check.InvalidType: Expect: in_types[0].ndim == 2
Actual: 3 != 2
```

This error message means that “`ndim` of the first argument expected to be 2, but actually it is 3”.

### 2.10.2 Detail of type information

You can access three information of `x_type`.

- `.shape` is a tuple of ints. Each value is size of each dimension.
- `.ndim` is int value representing the number of dimensions. Note that `ndim == len(shape)`
- `.dtype` is `numpy.dtype` representing data type of the value.

You can check all members. For example, the size of the first dimension must be positive, you can write like this:

```python
utils.type_check.expect(x_type.shape[0] > 0)
```

You can also check data types with `.dtype`:
 utils.type_check.expect(x_type.dtype == np.float64)

And an error is like this:

```
Traceback (most recent call last):
...  
chainer.utils.type_check.InvalidType: Expect: in_types[0].dtype == <class 'numpy.float64'>
Actual: float32 != <class 'numpy.float64'>
```

You can also check kind of dtype. This code checks if the type is floating point:

```
utils.type_check.expect(x_type.dtype.kind == 'f')
```

You can compare between variables. For example, the following code checks if the first argument and the second argument have the same length:

```
utils.type_check.expect(x_type.shape[1] == y_type.shape[1])
```

### 2.10.3 Internal mechanism of type check

How does it show an error message like "in_types[0].ndim == 2"? If x_type is an object containing ndim member variable, we cannot show such an error message because this equation is evaluated as a boolean value by Python interpreter.

Actually x_type is a Expr objects, and doesn’t have a ndim member variable itself. Expr represents a syntax tree. x_type.ndim makes a Expr object representing (getattr, x_type, 'ndim').x_type.ndim == 2 makes an object like (eq, (getattr, x_type, 'ndim'), 2). expect() gets a Expr object and evaluates it. When it is True, it causes no error and shows nothing. Otherwise, this method shows a readable error message.

If you want to evaluate a Expr object, call eval() method:

```
actual_type = x_type.eval()
```

actual_type is an instance of TypeInfo, while x_type is an instance of Expr. In the same way, x_type.shape[0].eval() returns an int value.

### 2.10.4 More powerful methods

Expr class is more powerful. It supports all mathematical operators such as + and *. You can write a condition that the first dimension of x_type is the first dimension of y_type times four:

```
utils.type_check.expect(x_type.shape[0] == y_type.shape[0] * 4)
```

When x_type.shape[0] == 3 and y_type.shape[0] == 1, users can get the error message below:

```
Traceback (most recent call last):
...
chainer.utils.type_check.InvalidType: Expect: in_types[0].shape[0] == in_types[1].shape[0] * 4
Actual: 3 != 4
```

To compare a member variable of your function, wrap a value with Variable to show readable error message:
x_type.shape[0] == utils.type_check.Variable(self.in_size, "in_size")

This code can check the equivalent condition below:

x_type.shape[0] == self.in_size

However, the latter condition doesn’t know the meaning of this value. When this condition is not satisfied, the latter code shows unreadable error message:

cruncher.utils.type_check.OutOfRange: Expect: in_types[0].shape[0] == 4  # what does '4' mean?
Actual: 3 != 4

Note that the second argument of `utils.type_check.Variable` is only for readability. The former shows this message:

cruncher.utils.type_check.OutOfRange: Expect: in_types[0].shape[0] == in_size  # OK,
→'in_size' is a value that is given to the constructor
Actual: 3 != 4  # You can also check actual value here

### 2.10.5 Call functions

How to check summation of all values of shape? `Expr` also supports function call:

```python
sum = utils.type_check.Variable(np.sum, 'sum')
utils.type_check.expect(sum(x_type.shape) == 10)
```

Why do we need to wrap the function `numpy.sum` with `utils.type_check.Variable`? `x_type.shape` is not a tuple but an object of `Expr` as we have seen before. Therefore, `numpy.sum(x_type.shape)` fails. We need to evaluate this function lazily.

The above example produces an error message like this:

```
Traceback (most recent call last):
...
chainer.utils.type_check.OutOfRange: Expect: sum(in_types[0].shape) == 10
Actual: 7 != 10
```

### 2.10.6 More complicated cases

How to write a more complicated condition that can’t be written with these operators? You can evaluate `Expr` and get its result value with `eval()` method. Then check the condition and show warning message by hand:

```python
x_shape = x_type.shape.eval()  # get actual shape (int tuple)
if not more_complicated_condition(x_shape):
    expect_msg = 'Shape is expected to be ...
    actual_msg = 'Shape is ...
    raise utils.type_check.OutOfRange(expect_msg, actual_msg)
```

Please write a readable error message. This code generates the following error message:
2.10.7 Typical type check example

We show a typical type check for a function.

First check the number of arguments:

```python
utils.type_check.expect(in_types.size() == 2)
```

`in_types.size()` returns a `Expr` object representing the number of arguments. You can check it in the same way.

And then, get each type:

```python
x_type, y_type = in_types
```

Don’t get each value before checking `in_types.size()`. When the number of argument is illegal, `type_check.expect` might output unuseful error messages. For example, this code doesn’t work when the size of `in_types` is 0:

```python
utils.type_check.expect(
    in_types.size() == 2,
    in_types[0].ndim == 3,
)
```

After that, check each type:

```python
utils.type_check.expect(
    x_type.dtype == np.float32,
    x_type.ndim == 3,
    x_type.shape[1] == 2,
)
```

The above example works correctly even when `x_type.ndim == 0` as all conditions are evaluated lazily.

2.11 Serializers – saving and loading

Serializer is a simple interface to serialize or deserialize an object. `Link`, `Optimizer`, and `Trainer` support serialization.

Concrete serializers are defined in the `serializers` module. It supports NumPy NPZ and HDF5 formats.

For example, we can serialize a link object into NPZ file by the `save_npz()` function:

```python
>>> from chainer import serializers
>>> serializers.save_npz('my.model', model)
```

This saves the parameters of `model` into the file `my.model` in NPZ format. The saved model can be read back from `my.model` back into `model` by the `load_npz()` function:
>>> serializers.load_npz('my.model', model)

**Note:** Note that only the parameters and the persistent values are serialized by this serialization code. Other attributes are not saved automatically. You can register arrays, scalars, or any serializable objects as persistent values by the `add_persistent()` method. The registered values can be accessed by attributes of the name passed to the add_persistent method.

The state of an optimizer can also be saved by the same functions:

```python
>>> serializers.save_npz('my.state', optimizer)
>>> serializers.load_npz('my.state', optimizer)
```

**Note:** Note that serialization of optimizer only saves its internal states including number of iterations, momentum vectors of MomentumSGD, etc. It does not save the parameters and persistent values of the target link. We have to explicitly save the target link with the optimizer to resume the optimization from saved states. This can be done by saving the entire Trainer object, like this:

```python
>>> serializers.save_npz('my.state', trainer)
```

Support of the HDF5 format is enabled if the h5py package is installed. Serialization and deserialization with the HDF5 format are almost identical to those with the NPZ format; just replace `save_npz()` and `load_npz()` by `save_hdf5()` and `load_hdf5()`, respectively.

## 2.12 Customize your own logging

In this section, you will learn about the following things:

- What is `chainer.Reporter`?
- How to report logging with `chainer.Reporter`?
  - The naming rule for the reported values.

After reading this section, you will be able to:
- Write your own report.

### 2.12.1 What is Reporter?

`chainer.Reporter` is used to collect values that users want to watch. The reporter object manipulates a dictionary from value names to the actually observed values. We call this dictionary as `observation`.

See the following example:

```python
>>> from chainer import Reporter, report, report_scope

>>> reporter = Reporter()

>>> observer = object()  # it can be an arbitrary (reference) object

>>> reporter.add_observer('my_observer:', observer)

>>> observation = {}

>>> with reporter.scope(observation):

(continues on next page)
When a value is passed to the `reporter`, an object called `observer` can be optionally attached. In this case, the name of the `observer` is added as the prefix of the value name. The `observer` name should be registered beforehand. Using `reporter.scope`, you can select which `observation` to save the observed values.

There are also a global API `chainer.report()`, which reports observed values with the current reporter object. In this case, `current` means which `with` statement scope the current code line is in. This function calls the `Reporter.report()` method of the current reporter.

```
>>> observation = {}
>>> with reporter.scope(observation):
...     report({'x': 1}, observer)
...     observation
...     {'my_observer:/x': 1}
```

### 2.12.2 Use report in Chain or Link

The most important application of `Reporter` is to report observed values from each `Link` or `Chain` in the training and validation procedures.

But, how to report the observed values from each link or chain? Should we prepare the `Reporter`? No, you only need to call `report()` in chain or link, because `Trainer` and some extensions prepare their own `Reporter` object with the hierarchy of the target link registered as observers. We can use `report()` function inside any links and chains to report the observed values (e.g., training loss, accuracy, activation statistics, etc.).

See the following example:

```
>>> class Classifier(Chain):
...     def __init__(self, predictor):
...         super(Classifier, self).__init__()
...         with self.init_scope():
...             self.predictor = predictor
...     def forward(self, x, t):
...         y = self.predictor(x)
...         loss = F.softmax_cross_entropy(y, t)
...         accuracy = F.accuracy(y, t)
...         report({'loss': loss, 'accuracy': accuracy}, self)
...         return loss
```

If the link is named 'main' in the hierarchy (which is the default name of the target link in the `StandardUpdater`), these reported values are named 'main/loss' and 'main/accuracy'. If these values are reported inside the `Evaluator` extension, 'validation/' is added at the head of the link name, thus the item names are changed to 'validation/main/loss' and 'validation/main/accuracy' ('validation' is the default name of the Evaluator extension).
2.12.3 Naming rule for the reported values

So, you know almost everything about Reporter. However, there is one more thing. It is what is the naming rule for the reported values, especially when the values are reported from a link that is not the root of the link hierarchy.

As we explained in the previous section, the root of links is named as 'main' by the the StandardUpdater and the names of reported values in the root have the prefix 'main/'. When the values are reported from a link that is not the root of the link hierarchy, the prefix of the names are determined by the link hierarchy, or namedlinks().

See the following example:

```python
>>> class MLP(Chain):
...     def __init__(self, n_units, n_out):
...         super(MLP, self).__init__()
...         with self.init_scope():
...             # the size of the inputs to each layer will be inferred
...             self.l1 = L.Linear(None, n_units)  # n_in -> n_units
...             self.l2 = L.Linear(None, n_units)  # n_units -> n_units
...             self.l3 = L.Linear(None, n_out)   # n_units -> n_out
...         ...  
...     def forward(self, x):
...         h1 = F.relu(self.l1(x))
...         h2 = F.relu(self.l2(h1))
...         y = self.l3(h2)
...         report({'sum_y': F.sum(y)}, self)
...         return y
...  
>>> model = Classifier(MLP(100, 10))
>>> for name, observer in model.namedlinks(skipself=True):
...     print(name)
/predictor
/predictor/l1
/predictor/l2
/predictor/l3

You can get the parameters of the link hierarchy by namedlinks(). In this example, we report 'loss' and 'accuracy' in the root of links, and 'sum_y' in the link of '/predictor'. So, you can access the reported values by 'main/accuracy', 'main/accuracy', and 'main/predictor/sum_y'.

See what we explained is correct:

```python
>>> train, test = datasets.get_mnist()
>>> train_iter = iterators.SerialIterator(train, batch_size=100, shuffle=True)
>>> test_iter = iterators.SerialIterator(test, batch_size=100, repeat=False, shuffle=False)
>>> optimizer = optimizers.SGD()
>>> optimizer.setup(model)
>>> updater = training.StandardUpdater(train_iter, optimizer)
>>> trainer = training.Trainer(updater, (1, 'epoch'), out='result')
>>> trainer.extend(extensions.Evaluator(test_iter, model))
>>> trainer.extend(extensions.LogReport())
>>> trainer.run()
```

<table>
<thead>
<tr>
<th>epoch</th>
<th>main/accuracy</th>
<th>main/loss</th>
<th>main/predictor/sum_y</th>
<th>validation/main/accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.662317</td>
<td>1.38345</td>
<td>47.9927</td>
<td>0.8498</td>
</tr>
</tbody>
</table>
3.1 MNIST using Trainer

In the example code of this tutorial, we assume for simplicity that the following symbols are already imported.

```python
import math
import numpy as np
import chainer
from chainer import backend
from chainer import backends
from chainer.backends import cuda
from chainer import Function, FunctionNode, gradient_check, report, training, utils,
        Variable
from chainer import datasets, initializers, iterators, optimizers, serializers
from chainer import Link, Chain, ChainList
import chainer.functions as F
import chainer.links as L
from chainer.training import extensions
```

By using Trainer, you don’t need to write the training loop explicitly any more. Furthermore, Chainer provides many useful extensions that can be used with Trainer to visualize your results, evaluate your model, store and manage log files more easily.

This example will show how to use the Trainer to train a fully-connected feed-forward neural network on the MNIST dataset.

**Note:** If you would like to know how to write a training loop without using the Trainer, please check MNIST with a Manual Training Loop instead of this tutorial.

### 3.1.1 1. Prepare the dataset

Load the MNIST dataset, which contains a training set of images and class labels as well as a corresponding test set.

```python
from chainer.datasets import mnist
train, test = mnist.get_mnist()
```

**Note:** You can use a Python list as a dataset. That’s because Iterator can take any object as a dataset whose elements can be accessed via [] accessor and whose length can be obtained with len() function. For example,
train = [(x1, t1), (x2, t2), ...]

a list of tuples like this can be used as a dataset.

There are many utility dataset classes defined in `datasets`. It is recommended that you utilize them in the actual applications.

For example, if your dataset consists of a number of image files, it would take a large amount of memory to load those data into a list like above. In that case, you can use `ImageDataset`, which just keeps the paths to image files. The actual image data will be loaded from the disk when the corresponding element is requested via `[]` accessor. Until then, no images are loaded to the memory to reduce memory use.

3.1.2 2. Prepare the dataset iterations

`Iterator` creates a mini-batch from the given dataset.

```python
batchsize = 128

train_iter = iterators.SerialIterator(train, batchsize)
test_iter = iterators.SerialIterator(test, batchsize, False, False)
```

3.1.3 3. Prepare the model

Here, we are going to use the same model as the one defined in `MNIST with a Manual Training Loop`.

```python
class MLP(Chain):
    
    def __init__(self, n_mid_units=100, n_out=10):
        super(MLP, self).__init__()
        with self.init_scope():
            self.l1 = L.Linear(None, n_mid_units)
            self.l2 = L.Linear(None, n_mid_units)
            self.l3 = L.Linear(None, n_out)

    def forward(self, x):
        h1 = F.relu(self.l1(x))
        h2 = F.relu(self.l2(h1))
        return self.l3(h2)

gpu_id = 0  # Set to -1 if you use CPU

model = MLP()
if gpu_id >= 0:
    model.to_gpu(gpu_id)
```
3.1.4 4. Prepare the Updater

*Trainer* is a class that holds all of the necessary components needed for training. The main components are shown below.

Basically, all you need to pass to *Trainer* is an *Updater*. However, *Updater* contains an *Iterator* and *Optimizer*. Since *Iterator* can access the dataset and *Optimizer* has references to the model, *Updater* can access to the model to update its parameters.

So, *Updater* can perform the training procedure as shown below:

1. Retrieve the data from dataset and construct a mini-batch (*Iterator*)
2. Pass the mini-batch to the model and calculate the loss
3. Update the parameters of the model (*Optimizer*)

Now let’s create the *Updater* object!

```python
max_epoch = 10

# Wrap your model by Classifier and include the process of loss calculation within your model.
# Since we do not specify a loss function here, the default 'softmax_cross_entropy' is used.
model = L.Classifier(model)
```

(continues on next page)
# selection of your optimizing method
optimizer = optimizers.MomentumSGD()

# Give the optimizer a reference to the model
optimizer.setup(model)

# Get an updater that uses the Iterator and Optimizer
updater = training.updaters.StandardUpdater(train_iter, optimizer, device=gpu_id)

Note: Here, the model defined above is passed to Classifier and changed to a new Chain. Classifier, which in fact inherits from the Chain class, keeps the given Chain model in its predictor attribute. Once you give the input data and the corresponding class labels to the model by the () operator,

1. forward() of the model is invoked. The data is then given to predictor to obtain the output $y$.
2. Next, together with the given labels, the output $y$ is passed to the loss function which is determined by lossfun argument in the constructor of Classifier.
3. The loss is returned as a Variable.

In Classifier, the lossfun is set to softmax_cross_entropy() as default.

StandardUpdater is the simplest class among several updaters. There are also the ParallelUpdater and the MultiprocessParallelUpdater to utilize multiple GPUs. The MultiprocessParallelUpdater uses the NVIDIA NCCL library, so you need to install NCCL and re-install CuPy before using it.

3.1.5 5. Setup Trainer

Lastly, we will setup Trainer. The only requirement for creating a Trainer is to pass the Updater object that we previously created above. You can also pass a stop_trigger to the second trainer argument as a tuple like (length, unit) to tell the trainer when to stop the training. The length is given as an integer and the unit is given as a string which should be either epoch or iteration. Without setting stop_trigger, the training will never be stopped.

# Setup a Trainer
trainer = training.Trainer(updater, (max_epoch, 'epoch'), out='mnist_result')

The out argument specifies an output directory used to save the log files, the image files of plots to show the time progress of loss, accuracy, etc. when you use PlotReport extension. Next, we will explain how to display or save those information by using trainer Extension.

3.1.6 6. Add Extensions to the Trainer object

The Trainer extensions provide the following capabilities:

- Save log files automatically (LogReport)
- Display the training information to the terminal periodically (PrintReport)
- Visualize the loss progress by plotting a graph periodically and save it as an image file (PlotReport)
- Automatically serialize the state periodically (snapshot() / snapshot_object())
- Display a progress bar to the terminal to show the progress of training (ProgressBar)
To use these wide variety of tools for your training task, pass `Extension` objects to the `extend()` method of your `Trainer` object.

```python
from chainer.training import extensions

trainer.extend(extensions.LogReport())
trainer.extend(extensions.snapshot(filename='snapshot_epoch-{.updater.epoch}'))
trainer.extend(extensions.snapshot_object(model.predictor, filename='model_epoch-{.updater.epoch}'))
trainer.extend(extensions.Evaluator(test_iter, model, device=gpu_id))
trainer.extend(extensions.PlotReport(['main/loss', 'validation/main/loss'], x_key='epoch', file_name='loss.png'))
trainer.extend(extensions.PlotReport(['main/accuracy', 'validation/main/accuracy'], x_key='epoch', file_name='accuracy.png'))
trainer.extend(extensions.DumpGraph('main/loss'))
```

**LogReport**

Collect loss and accuracy automatically every epoch or iteration and store the information under the log file in the directory specified by the `out` argument when you create a `Trainer` object.

**snapshot()**

The `snapshot()` method saves the `Trainer` object at the designated timing (default: every epoch) in the directory specified by `out`. The `Trainer` object, as mentioned before, has an `Updater` which contains an `Optimizer` and a model inside. Therefore, as long as you have the snapshot file, you can use it to come back to the training or make inferences using the previously trained model later.

**snapshot_object()**

However, when you keep the whole `Trainer` object, in some cases, it is very tedious to retrieve only the inside of the model. By using `snapshot_object()`, you can save the particular object (in this case, the model wrapped by `Classifier`) as a separate snapshot. `Classifier` is a `Chain` object which keeps the model that is also a `Chain` object as its `predictor` property, and all the parameters are under the `predictor`, so taking the snapshot of `predictor` is enough to keep all the trained parameters.

This is a list of commonly used trainer extensions:

- **LogReport** This extension collects the loss and accuracy values every epoch or iteration and stores in a log file. The log file will be located under the output directory (specified by `out` argument of the `Trainer` object).
- **snapshot()** This extension saves the `Trainer` object at the designated timing (default: every epoch) in the output directory. The `Trainer` object, as mentioned before, has an `Updater` which contains an `Optimizer` and a model inside. Therefore, as long as you have the snapshot file, you can use it to come back to the training or make inferences using the previously trained model later.
- **snapshot_object()** This extension above saves the whole `Trainer` object. However, in some cases, it is tedious to retrieve only the inside of the model. By using `snapshot_object()`, you can save the particular object (in the example above, the model wrapped by `Classifier`) as a separated snapshot. Taking the snapshot of `predictor` is enough to keep all the trained parameters, because `Classifier` (which is a subclass of `Chain`) keeps the model as its `predictor` property, and all the parameters are under this property.
**DumpGraph()** This extension saves the structure of the computational graph of the model. The graph is saved in Graphviz dot format under the output directory of the *Trainer*.

**Evaluator Iterators** that use the evaluation dataset and the model object are required to use *Evaluator* extension. It evaluates the model using the given dataset (typically it’s a validation dataset) at the specified timing interval.

**PrintReport** This extension outputs the specified values to the standard output.

**PlotReport** This extension plots the values specified by its arguments and saves it as a image file.

This is not an exhaustive list of built-in extensions. Please take a look at *Extensions* for more of them.

### 3.1.7 7. Start Training

Just call *run()* method from *Trainer* object to start training.

```python
trainer.run()
```

<table>
<thead>
<tr>
<th>epoch</th>
<th>elapsed_time</th>
<th>main/loss</th>
<th>main/accuracy</th>
<th>validation/main/loss</th>
<th>validation/main/accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.93409</td>
<td>1.53241</td>
<td>0.638409</td>
<td>0.74935</td>
<td>0.835839</td>
</tr>
<tr>
<td>2</td>
<td>7.72883</td>
<td>0.578334</td>
<td>0.858059</td>
<td>0.444722</td>
<td>0.882812</td>
</tr>
<tr>
<td>3</td>
<td>10.4229</td>
<td>0.418569</td>
<td>0.886844</td>
<td>0.364943</td>
<td>0.899229</td>
</tr>
<tr>
<td>4</td>
<td>13.148</td>
<td>0.362342</td>
<td>0.899089</td>
<td>0.327569</td>
<td>0.905558</td>
</tr>
<tr>
<td>5</td>
<td>15.846</td>
<td>0.331067</td>
<td>0.906517</td>
<td>0.304399</td>
<td>0.911788</td>
</tr>
<tr>
<td>6</td>
<td>18.5395</td>
<td>0.309019</td>
<td>0.911964</td>
<td>0.288295</td>
<td>0.917722</td>
</tr>
<tr>
<td>7</td>
<td>21.2173</td>
<td>0.292312</td>
<td>0.916128</td>
<td>0.272073</td>
<td>0.921776</td>
</tr>
<tr>
<td>8</td>
<td>23.9211</td>
<td>0.278291</td>
<td>0.92059</td>
<td>0.261351</td>
<td>0.923457</td>
</tr>
<tr>
<td>9</td>
<td>26.6612</td>
<td>0.266266</td>
<td>0.923541</td>
<td>0.253195</td>
<td>0.927314</td>
</tr>
<tr>
<td>10</td>
<td>29.466</td>
<td>0.255489</td>
<td>0.926739</td>
<td>0.242415</td>
<td>0.929094</td>
</tr>
</tbody>
</table>

Let’s see the plot of loss progress saved in the *mnist_result* directory.
How about the accuracy?

Furthermore, let’s visualize the computational graph saved with `DumpGraph()` using Graphviz.

```bash
dot -Tpng mnist_result/cg.dot -o mnist_result/cg.png
```
From the top to the bottom, you can see the data flow in the computational graph. It basically shows how data and parameters are passed to the *Functions*.

### 3.1.8 8. Evaluate a pre-trained model

Evaluation using the snapshot of a model is as easy as what explained in the *MNIST with a Manual Training Loop*.

```python
import matplotlib.pyplot as plt

model = MLP()
serializers.load_npz('mnist_result/model_epoch-10', model)

# Show the output
x, t = test[0]
plt.imshow(x.reshape(28, 28), cmap='gray')
plt.show()
print('label:', t)

y = model(x[None, ...])
print('predicted_label:', y.array.argmax(axis=1)[0])
```

![Image of handwritten digit 7]

```
label: 7
predicted_label: 7
```

The prediction looks correct. Success!
3.2 MNIST with a Manual Training Loop

In the example code of this tutorial, we assume for simplicity that the following symbols are already imported.

```python
import math
import numpy as np
import chainer
from chainer import backend
from chainer.backends import cuda
from chainer.functions import gradient_check, report, training, utils,
from chainer import datasets, initializers, iterators, optimizers, serializers
from chainer import Link, Chain, ChainList
import chainer.functions as F
import chainer.links as L
from chainer.training import extensions
```

In this tutorial section, we will learn how to train a deep neural network to classify images of hand-written digits in the popular MNIST dataset. This dataset contains 50,000 training examples and 10,000 test examples. Each example is a set of a 28 x 28 greyscale image and a corresponding class label. Since the digits from 0 to 9 are used, there are 10 classes for the labels.

Chainer provides a feature called `Trainer` that can simplify the training procedure of your model. However, it is also good to know how the training works in Chainer before starting to use the useful `Trainer` class that hides the actual processes. Writing your own training loop can be useful for learning how `Trainer` works or for implementing features not included in the standard trainer.

The complete training procedure consists of the following steps:

1. **Prepare a dataset**
2. **Create a dataset iterator**
3. **Define a network**
4. **Select an optimization algorithm**
5. **Write a training loop**
   a. Retrieve a set of examples (mini-batch) from the training dataset.
   b. Feed the mini-batch to your network.
   c. Run a forward pass of the network and compute the loss.
   d. Just call the `backward()` method from the loss `Variable` to compute the gradients for all trainable parameters.
   e. Run the optimizer to update those parameters.
6. **Save the trained model**
7. **Perform classification by the saved model** and check the network performance on validation/test sets.
3.2.1 1. Prepare a dataset

Chainer contains some built-in functions to use some popular datasets like MNIST, CIFAR10/100, etc. Those can automatically download the data from servers and provide dataset objects which are easy to use.

The code below shows how to retrieve the MNIST dataset from the server and save an image from its training split to make sure the images are correctly obtained.

```python
from __future__ import print_function
import matplotlib.pyplot as plt
from chainer.datasets import mnist

# Download the MNIST data if you haven't downloaded it yet
train, test = mnist.get_mnist(withlabel=True, ndim=1)

# Display an example from the MNIST dataset.
# 'x' contains the input image array and 't' contains that target class
# label as an integer.
x, t = train[0]
plt.imshow(x.reshape(28, 28), cmap='gray')
plt.savefig('5.png')
plt.show()
print('label:', t)

label: 5
```

The saved image 5.png will look like:
3.2.2 2. Create a dataset iterator

Although this is an optional step, we’d like to introduce the `Iterator` class that retrieves a set of data and labels from the given dataset to easily make a mini-batch. There are some subclasses that can perform the same thing in different ways, e.g., using multi-processing to parallelize the data loading part, etc.

Here, we use `SerialIterator`, which is also a subclass of `Iterator` in the example code below. The `SerialIterator` can provide mini-batches with or without shuffling the order of data in the given dataset.

All `Iterators` produce a new mini-batch by calling its `next()` method. All `Iterators` also have properties to know how many times we have taken all the data from the given dataset (`epoch`) and whether the next mini-batch will be the start of a new epoch (`is_new_epoch`), and so on.

The code below shows how to create a `SerialIterator` object from a dataset object.

```python
from chainer import iterators

# Choose the minibatch size.
batchsize = 128

train_iter = iterators.SerialIterator(train, batchsize)

# A list of tuples
train_iter = iterators.SerialIterator(train, batchsize)

where x1, x2, ... denote the input data and t1, t2, ... denote the corresponding labels.
```

**Note:** `Iterators` can take a built-in Python list as a given dataset. It means that the example code below is able to work,

```python
train = [(x1, t1), (x2, t2), ...]  # A list of tuples

train_iter = iterators.SerialIterator(train, batchsize)
```

Details of `SerialIterator`

- `SerialIterator` is a built-in subclass of `Iterator` that can retrieve a mini-batch from a given dataset in either sequential or shuffled order.
- The `Iterator`’s constructor takes two arguments: a dataset object and a mini-batch size.
- If you want to use the same dataset repeatedly during the training process, set the `repeat` argument to `True` (default). Otherwise, the dataset will be used only one time. The latter case is actually for the evaluation.
- If you want to shuffle the training dataset every epoch, set the `shuffle` argument to `True`. Otherwise, the order of each data retrieved from the dataset will be always the same at each epoch.

In the example code shown above, we set `batchsize = 128` in both `train_iter` and `test_iter`. So, these iterators will provide 128 images and corresponding labels at a time.
3.2.3 3. Define a network

Now let’s define a neural network that we will train to classify the MNIST images. For simplicity, we use a three-layer perceptron here. We set each hidden layer to have 100 units and set the output layer to have 10 units, which is corresponding to the number of class labels of the MNIST.

Create your network as a subclass of Chain

You can create your network by writing a new subclass of Chain. The main steps are twofold:

1. Register the network components which have trainable parameters to the subclass. Each of them must be instantiated and assigned to a property in the scope specified by init_scope():

2. Define a forward() method that represents the actual forward computation of your network. This method takes one or more Variable, numpy.ndarray, or cupy.ndarray as its inputs and calculates the forward pass using them.

```python
class MyNetwork(Chain):

    def __init__(self, n_mid_units=100, n_out=10):
        super(MyNetwork, self).__init__()
        with self.init_scope():
            self.l1 = L.Linear(None, n_mid_units)
            self.l2 = L.Linear(n_mid_units, n_mid_units)
            self.l3 = L.Linear(n_mid_units, n_out)

    def forward(self, x):
        h = F.relu(self.l1(x))
        h = F.relu(self.l2(h))
        return self.l3(h)

model = MyNetwork()
```

Link, Chain, ChainList, and those subclass objects which contain trainable parameters should be registered to the model by assigning it as a property inside the init_scope(). For example, a FunctionNode does not contain any trainable parameters, so there is no need to keep the object as a property of your network. When you want to use relu() in your network, using it as a function in forward() works correctly.

In Chainer, the Python code that implements the forward computation itself represents the network. In other words, we can conceptually think of the computation graph for our network being constructed dynamically as this forward computation code executes. This allows Chainer to describe networks in which different computations can be performed in each iteration, such as branched networks, intuitively and with a high degree of flexibility. This is the key feature of Chainer that we call Define-by-Run.
3.2.4 4. Select an optimization algorithm

Chainer provides a wide variety of optimization algorithms that can be used to optimize the network parameters during training. They are located in `optimizers` module.

Here, we are going to use the stochastic gradient descent (SGD) method with momentum, which is implemented by `MomentumSGD`. To use the optimizer, we give the network object (typically it’s a `Chain` or `ChainList`) to the `setup()` method of the optimizer object to register it. In this way, the `Optimizer` can automatically find the model parameters and update them during training.

You can easily try out other optimizers as well. Please test and observe the results of various optimizers. For example, you could try to change `MomentumSGD` to `Adam`, `RMSprop`, etc.

```python
from chainer import optimizers

# Choose an optimizer algorithm
optimizer = optimizers.MomentumSGD(lr=0.01, momentum=0.9)

# Give the optimizer a reference to the model so that it
# can locate the model's parameters.
optimizer.setup(model)
```

**Note:** In the above example, we set `lr` to 0.01 in the constructor. This value is known as the “learning rate”, one of the most important hyperparameters that need to be adjusted in order to obtain the best performance. The various optimizers may each have different hyperparameters and so be sure to check the documentation for the details.

3.2.5 5. Write a training loop

We now show how to write the training loop. Since we are working on a digit classification problem, we will use `softmax_cross_entropy()` as the loss function for the optimizer to minimize. For other types of problems, such as regression models, other loss functions might be more appropriate. See the Chainer documentation for detailed information on the various loss functions for more details.

Our training loop will be structured as follows.

1. We will first get a mini-batch of examples from the training dataset.
2. We will then feed the batch into our network by calling it (a `Chain` object) like a function. This will execute the forward-pass code that are written in the `forward()` method.
3. This will return the network output that represents class label predictions. We supply it to the loss function along with the true (that is, target) values. The loss function will output the loss as a `Variable` object.
4. We then clear any previous gradients in the network and perform the backward pass by calling the `backward()` method on the loss variable which computes the parameter gradients. We need to clear the gradients first because the `backward()` method accumulates gradients instead of overwriting the previous values.
5. Since the optimizer already has a reference to the network, it has access to the parameters and the computed gradients so that we can now call the `update()` method of the optimizer which will update the model parameters.

In addition to the above steps, you might want to check the performance of the network with a validation dataset. This allows you to observe how well it is generalized to new data so far, namely, you can check whether it is overfitting to the training data. The code below checks the performance on the test set at the end of each epoch. The code has the same structure as the training code except that no backpropagation is performed and we also compute the accuracy on the test data using the `accuracy()` function.
The training loop code is as follows:

```python
import numpy as np
from chainer.dataset import concat_examples
from chainer.backends.cuda import to_cpu

max_epoch = 10

while train_iter.epoch < max_epoch:
    # ---------- One iteration of the training loop ----------
    train_batch = train_iter.next()
    image_train, target_train = concat_examples(train_batch, gpu_id)

    # Calculate the prediction of the network
    prediction_train = model(image_train)

    # Calculate the loss with softmax_cross_entropy
    loss = F.softmax_cross_entropy(prediction_train, target_train)

    # Calculate the gradients in the network
    model.cleargrads()
    loss.backward()

    # Update all the trainable parameters
    optimizer.update()

    # --------------------- until here ---------------------

    # Check the validation accuracy of prediction after every epoch
    if train_iter.is_new_epoch:  # If this iteration is the final iteration of the current epoch
        # Display the training loss
        print('epoch: {:02d} train_loss: {:.04f}'.format(train_iter.epoch, float(to_cpu(loss.array))), end='')

        test_losses = []
        test_accuracies = []
        for test_batch in test_iter:
            image_test, target_test = concat_examples(test_batch, gpu_id)

            # Forward the test data
            prediction_test = model(image_test)

            # Calculate the loss
            loss_test = F.softmax_cross_entropy(prediction_test, target_test)
            test_losses.append(to_cpu(loss_test.array))

            # Calculate the accuracy
            accuracy = F.accuracy(prediction_test, target_test)
            accuracy.to_cpu()
            test_accuracies.append(accuracy.array)

        test_iter.reset()

        print('val_loss: {:.04f} val_accuracy: {:.04f}'.format(np.mean(test_losses), np.mean(test_accuracies)))
```
Output

```plaintext
<table>
<thead>
<tr>
<th>epoch</th>
<th>train_loss</th>
<th>val_loss</th>
<th>val_accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>0.8072</td>
<td>0.7592</td>
<td>0.8289</td>
</tr>
<tr>
<td>02</td>
<td>0.5021</td>
<td>0.4467</td>
<td>0.8841</td>
</tr>
<tr>
<td>03</td>
<td>0.3539</td>
<td>0.3673</td>
<td>0.9007</td>
</tr>
<tr>
<td>04</td>
<td>0.2524</td>
<td>0.3307</td>
<td>0.9067</td>
</tr>
<tr>
<td>05</td>
<td>0.4232</td>
<td>0.3076</td>
<td>0.9136</td>
</tr>
<tr>
<td>06</td>
<td>0.3033</td>
<td>0.2910</td>
<td>0.9167</td>
</tr>
<tr>
<td>07</td>
<td>0.2004</td>
<td>0.2773</td>
<td>0.9222</td>
</tr>
<tr>
<td>08</td>
<td>0.2885</td>
<td>0.2679</td>
<td>0.9239</td>
</tr>
<tr>
<td>09</td>
<td>0.2818</td>
<td>0.2579</td>
<td>0.9266</td>
</tr>
<tr>
<td>10</td>
<td>0.2403</td>
<td>0.2484</td>
<td>0.9307</td>
</tr>
</tbody>
</table>
```

3.2.6 6. Save the trained model

Chainer provides two types of serializers that can be used to save and restore model state. One supports the HDF5 format and the other supports the NumPy NPZ format. For this example, we are going to use the NPZ format to save our model since it is easy to use with NumPy and doesn’t need to install any additional dependencies or libraries.

```python
serializers.save_npz('my_mnist.model', model)
```

3.2.7 7. Perform classification by the saved model

Let’s use the saved model to classify a new image. In order to load the trained model parameters, we need to perform the following two steps:

1. Instantiate the same network as what you trained.
2. Overwrite all parameters in the model instance with the saved weights using the `load_npz()` function.

Once the model is restored, it can be used to predict image labels on new input data.

```python
from chainer import serializers

# Create an instance of the network you trained
model = MyNetwork()

# Load the saved parameters into the instance
serializers.load_npz('my_mnist.model', model)

# Get a test image and label
x, t = test[0]
plt.imshow(x.reshape(28, 28), cmap='gray')
plt.savefig('7.png')
print('label:', t)
```

```
label: 7
```

The saved test image looks like:
# Change the shape of the minibatch.
# In this example, the size of minibatch is 1.
# Inference using any mini-batch size can be performed.

```python
print(x.shape, end=' -> ')  
x = x[None, ...]  
print(x.shape)
```

```python
# Forward calculation of the model by sending X  
y = model(x)  

# The result is given as Variable, then we can take a look at the contents by the -attribute, .array.

y = y.array  

# Look up the most probable digit number using argmax  
pred_label = y.argmax(axis=1)

print('predicted label:', pred_label[0])
```

```
(784,) -> (1, 784)  
predicted label: 7
```

The prediction result looks correct. Yay!
3.3 Convolutional Network for Visual Recognition Tasks

In this section, you will learn how to write

• A small convolutional network with a model class that is inherited from Chainer,
• A large convolutional network that has several building block networks with ChainList.

After reading this section, you will be able to:

• Write your own original convolutional network in Chainer

A convolutional network (ConvNet) is mainly comprised of convolutional layers. This type of network is commonly used for various visual recognition tasks, e.g., classifying hand-written digits or natural images into given object classes, detecting objects from an image, and labeling all pixels of an image with the object classes (semantic segmentation), and so on.

In such tasks, a typical ConvNet takes a set of images whose shape is \((N, C, H, W)\), where

- \(N\) denotes the number of images in a mini-batch,
- \(C\) denotes the number of channels of those images,
- \(H\) and \(W\) denote the height and width of those images,

respectively. Then, it typically outputs a fixed-sized vector as membership probabilities over the target object classes. It also can output a set of feature maps that have the corresponding size to the input image for a pixel labeling task, etc.

In the example code of this tutorial, we assume for simplicity that the following symbols are already imported.

```python
import math
import numpy as np
import chainer
from chainer import backend
from chainer import backends
cuda
from chainer import Function, FunctionNode, gradient_check, report, training, utils,
˓→Variable
from chainer import datasets, initializers, iterators, optimizers, serializers
from chainer import Link, Chain, ChainList
import chainer.functions as F
import chainer.links as L
from chainer.training import extensions
```

3.3.1 LeNet5

Here, let’s start by defining LeNet5 [LeCun98] in Chainer. In this example, we show a simplified version of LeNet5 introduced in Deep Learning Tutorials. This is a ConvNet model that has 5 layers comprised of 3 convolutional layers and 2 fully-connected layers. This was proposed to classify hand-written digit images in 1998. In Chainer, the model can be written as follows:

```python
class LeNet5(Chain):
    def __init__(self):
        super(LeNet5, self).__init__()
        with self.init_scope():
            self.conv1 = L.Convolution2D(
                in_channels=1, out_channels=6, ksize=5, stride=1)
```
A typical way to write your network is creating a new class inherited from `Chain` class. When defining your model in this way, typically, all the layers which have trainable parameters are registered to the model by assigning the objects of `Link` as an attribute.

The model class is instantiated before the forward and backward computations. To give input images and label vectors simply by calling the model object like a function, `forward()` is usually defined in the model class. This method performs the forward computation of the model. Chainer uses the powerful autograd system for any computational graphs written with `FunctionNode` and `Link` (actually a `Link` calls a corresponding `FunctionNode` inside of it), so that you don’t need to do explicitly write the code for backward computations in the model. Just prepare the data, then give it to the model. The way this works is the resulting output `Variable` from the forward computation has a `backward()` method to perform autograd. In the above model, `forward()` has a `if` statement at the end to switch its behavior by the Chainer’s running mode, i.e., training mode or not. Chainer presents the running mode as a global variable `chainer.config.train`. When it’s in training mode, `forward()` returns the output value of the last layer as is to compute the loss later on, otherwise it returns a prediction result by calculating `softmax()`.

It is recommended that you use the global configuration `chainer.config.train` to switch the running mode.

If you don’t want to write `conv1` and the other layers more than once, you can also write the same model like in this way:

```python
from functools import partial

class LeNet5(Chain):
    def __init__(self):
        super(LeNet5, self).__init__()
        net = [('conv1', L.Convolution2D(1, 6, 5, 1))]
        net += [('sigm1', F.sigmoid)]
        net += [('mpool1', partial(F.max_pooling_2d, ksize=2, stride=2))]
        net += [('conv2', L.Convolution2D(6, 16, 5, 1))]
        net += [('sigm2', F.sigmoid)]
        net += [('mpool2', partial(F.max_pooling_2d, ksize=2, stride=2))]
        net += [('conv3', L.Convolution2D(16, 120, 4, 1))]
        net += [('sigm3', F.sigmoid)]
        net += [('mpool3', partial(F.max_pooling_2d, ksize=2, stride=2))]
        net += [('fc4', L.Linear(None, 84))]
        net += [('sigm4', F.sigmoid)]
        net += [('fc5', L.Linear(84, 10))]
        net += [('sigm5', F.sigmoid)]
        with self.init_scope():
            def forward(self, x):
                h = F.sigmoid(self.conv1(x))
                h = F.max_pooling_2d(h, 2, 2)
                h = F.sigmoid(self.conv2(h))
                h = F.max_pooling_2d(h, 2, 2)
                h = F.sigmoid(self.conv3(h))
                h = F.sigmoid(self.fc4(h))
                if chainer.config.train:
                    return self.fc5(h)
                return F.softmax(self.fc5(h))
```

A typical way to write your network is creating a new class inherited from `Chain` class. When defining your model in this way, typically, all the layers which have trainable parameters are registered to the model by assigning the objects of `Link` as an attribute.

The model class is instantiated before the forward and backward computations. To give input images and label vectors simply by calling the model object like a function, `forward()` is usually defined in the model class. This method performs the forward computation of the model. Chainer uses the powerful autograd system for any computational graphs written with `FunctionNode` and `Link` (actually a `Link` calls a corresponding `FunctionNode` inside of it), so that you don’t need to do explicitly write the code for backward computations in the model. Just prepare the data, then give it to the model. The way this works is the resulting output `Variable` from the forward computation has a `backward()` method to perform autograd. In the above model, `forward()` has a `if` statement at the end to switch its behavior by the Chainer’s running mode, i.e., training mode or not. Chainer presents the running mode as a global variable `chainer.config.train`. When it’s in training mode, `forward()` returns the output value of the last layer as is to compute the loss later on, otherwise it returns a prediction result by calculating `softmax()`.

It is recommended that you use the global configuration `chainer.config.train` to switch the running mode.

If you don’t want to write `conv1` and the other layers more than once, you can also write the same model like in this way:

```python
from functools import partial

class LeNet5(Chain):
    def __init__(self):
        super(LeNet5, self).__init__()
        net = [('conv1', L.Convolution2D(1, 6, 5, 1))]
        net += [('sigm1', F.sigmoid)]
        net += [('mpool1', partial(F.max_pooling_2d, ksize=2, stride=2))]
        net += [('conv2', L.Convolution2D(6, 16, 5, 1))]
        net += [('sigm2', F.sigmoid)]
        net += [('mpool2', partial(F.max_pooling_2d, ksize=2, stride=2))]
        net += [('conv3', L.Convolution2D(16, 120, 4, 1))]
        net += [('sigm3', F.sigmoid)]
        net += [('mpool3', partial(F.max_pooling_2d, ksize=2, stride=2))]
        net += [('fc4', L.Linear(None, 84))]
        net += [('sigm4', F.sigmoid)]
        net += [('fc5', L.Linear(84, 10))]
        net += [('sigm5', F.sigmoid)]
        with self.init_scope():
            def forward(self, x):
                h = F.sigmoid(self.conv1(x))
                h = F.max_pooling_2d(h, 2, 2)
                h = F.sigmoid(self.conv2(h))
                h = F.max_pooling_2d(h, 2, 2)
                h = F.sigmoid(self.conv3(h))
                h = F.sigmoid(self.fc4(h))
                if chainer.config.train:
                    return self.fc5(h)
                return F.softmax(self.fc5(h))
```
for n in net:
    if not n[0].startswith('_'):
        setattr(self, n[0], n[1])
self.layers = net

def forward(self, x):
    for n, f in self.layers:
        if not n.startswith('_'):
            x = getattr(self, n)(x)
        else:
            x = f(x)
    if chainer.config.train:
        return x
    return F.softmax(x)

Note: You can also use Sequential to write the above model more simply. Please note that Sequential is an experimental feature introduced in Chainer v4 and its interface may be changed in the future versions.

This code creates a list of pairs of component name (e.g., conv1, _sigm1, etc.) and all Links and functions (e.g., F.sigmoid, which internally invokes FunctionNode) after calling its superclass's constructor. In this case, components whose name start with _ are functions (FunctionNode), which doesn’t have any trainable parameters, so that we don’t register (setattr) it to the model. Others (conv1, fc4, etc.) are Links, which are trainable layers that hold parameters. This operation can be freely replaced with many other ways because those component names are just designed to select Links only from the list net easily. The list net is stored as an attribute layers to refer it in forward(). In forward(), it retrieves all layers in the network from self.forward sequentially and gives the input variable or the intermediate output from the previous layer to the current layer. The last part of the forward() to switch its behavior by the training/inference mode is the same as the former way.

Ways to calculate loss

When you train the model with label vector t, the loss should be calculated using the output from the model. There also are several ways to calculate the loss:

```python
model = LeNet5()

# Input data and label
x = np.random.rand(32, 1, 28, 28).astype(np.float32)
t = np.random.randint(0, 10, size=(32,)).astype(np.int32)

# Forward computation
y = model(x)

# Loss calculation
loss = F.softmax_cross_entropy(y, t)
```

This is a primitive way to calculate a loss value from the output of the model. On the other hand, the loss computation can be included in the model itself by wrapping the model object (Chain or ChainList object) with a class inherited from Chain. The outer Chain should take the model defined above and register it with init_scope(). Chain is actually inherited from Link, so that Chain itself can also be registered as a trainable Link to another Chain. Actually, Classifier class to wrap the model and add the loss computation to the model already exists. Actually, there is already a Classifier class that can be used to wrap the model and include the loss computation as well. It can be used like this:
model = L.Classifier(LeNet5())

# Forward & Loss calculation
loss = model(x, t)

This class takes a model object as an input argument and registers it to a `predictor` property as a trained parameter. As shown above, the returned object can then be called like a function in which we pass `x` and `t` as the input arguments and the resulting loss value (which we recall is a `Variable`) is returned.

See the detailed implementation of `Classifier` from here: `chainer.links.Classifier` and check the implementation by looking at the source.

From the above examples, we can see that Chainer provides the flexibility to write our original network in many different ways. Such flexibility intends to make it intuitive for users to design new and complex models.

### 3.3.2 VGG16

Next, let’s write some larger models in Chainer. When you write a large network consisting of several building block networks, `ChainList` is useful. First, let’s see how to write a VGG16 [Simonyan14] model.

```python
class VGG16(chainer.ChainList):
    def __init__(self):
        super(VGG16, self).__init__(
            VGGBlock(64),
            VGGBlock(128),
            VGGBlock(256, 3),
            VGGBlock(512, 3),
            VGGBlock(512, 3, True))

    def forward(self, x):
        for f in self.children():
            x = f(x)
        if chainer.config.train:
            return x
        return F.softmax(x)

class VGGBlock(chainer.Chain):
    def __init__(self, n_channels, n_convs=2, fc=False):
        w = chainer.initializers.HeNormal()
        super(VGGBlock, self).__init__()
        with self.init_scope():
            self.conv1 = L.Convolution2D(None, n_channels, 3, 1, 1, initialW=w)
            self.conv2 = L.Convolution2D(n_channels, n_channels, 3, 1, 1, initialW=w)
            if n_convs == 3:
                self.conv3 = L.Convolution2D(n_channels, n_channels, 3, 1, 1, initialW=w)
            if fc:
                self.fc4 = L.Linear(None, 4096, initialW=w)
                self.fc5 = L.linear(4096, 4096, initialW=w)
                self.fc6 = L.Linear(4096, 1000, initialW=w)

        self.n_convs = n_convs
        self.fc = fc
```

(continues on next page)
That’s it. VGG16 is a model which won the 1st place in classification + localization task at ILSVRC 2014, and since then, has become one of the standard models for many different tasks as a pre-trained model. This has 16-layers, so it’s called “VGG-16”, but we can write this model without writing all layers independently. Since this model consists of several building blocks that have the same architecture, we can build the whole network by re-using the building block definition. Each part of the network is consisted of 2 or 3 convolutional layers and activation function (relu()) following them, and max_pooling_2d() operations. This block is written as VGGBlock in the above example code. And the whole network just calls this block one by one in sequential manner.

### 3.3.3 ResNet152

How about ResNet? ResNet [He16] came in the following year’s ILSVRC. It is a much deeper model than VGG16, having up to 152 layers. This sounds super laborious to build, but it can be implemented in almost same manner as VGG16. In the other words, it’s easy. One possible way to write ResNet-152 is:

```python
class ResNet152(chainer.Chain):
    def __init__(self, n_blocks=[3, 8, 36, 3]):
        w = chainer.initializers.HeNormal()
        super(ResNet152, self).__init__()
        with self.init_scope():
            self.conv1 = L.Convolution2D(None, 64, 7, 2, 3, initialW=w, nobias=True)
            self.bn1 = L.BatchNormalization(64)
            self.res2 = ResBlock(n_blocks[0], 64, 64, 256, 1)
            self.res3 = ResBlock(n_blocks[1], 256, 128, 512)
            self.res4 = ResBlock(n_blocks[2], 512, 256, 1024)
            self.res5 = ResBlock(n_blocks[3], 1024, 512, 2048)
            self.fc6 = L.Linear(2048, 1000)

    def forward(self, x):
        h = self.bn1(self.conv1(x))
        h = F.max_pooling_2d(F.relu(h), 2, 2)
        h = self.res2(h)
        h = self.res3(h)
        h = self.res4(h)
        h = self.res5(h)
        h = F.average_pooling_2d(h, h.shape[2:], stride=1)
        h = self.fc6(h)
        if chainer.config.train:
            return h
        return F.softmax(h)
```

```python
class ResBlock(chainer.ChainList):
    def __init__(self, n_layers, n_in, n_mid, n_out, stride=2):
```
In the `BottleNeck` class, depending on the value of the `proj` argument supplied to the initializer, it will conditionally compute a convolutional layer `conv1x1r` which will extend the number of channels of the input `x` to be equal to the number of channels of the output of `conv1x1c`, and followed by a batch normalization layer before the final ReLU layer. Writing the building block in this way improves the re-usability of a class. It switches not only the behavior in `__class__()` by flags but also the parameter registration. In this case, when `proj` is `False`, the `BottleNeck` doesn’t have `conv1x1r` and `bn_r` layers, so the memory usage would be efficient compared to the case when it registers both anyway and just ignore them if `proj` is `False`.

Using nested `Chains` and `ChainList` for sequential part enables us to write complex and very deep models easily.
3.3.4 Use Pre-trained Models

Various ways to write your models were described above. It turns out that VGG16 and ResNet are very useful as general feature extractors for many kinds of tasks, including but not limited to image classification. So, Chainer provides you with the pre-trained VGG16 and ResNet-50/101/152 models with a simple API. You can use these models as follows:

```python
from chainer.links import VGG16Layers
model = VGG16Layers()
```

When `VGG16Layers` is instantiated, the pre-trained parameters are automatically downloaded from the author’s server. So you can immediately start to use VGG16 with pre-trained weight as a good image feature extractor. See the details of this model here: `chainer.links.VGG16Layers`.

In the case of ResNet models, there are three variations differing in the number of layers. We have `chainer.links.ResNet50Layers`, `chainer.links.ResNet101Layers`, and `chainer.links.ResNet152Layers` models with easy parameter loading feature. ResNet’s pre-trained parameters are not available for direct downloading, so you need to download the weight from the author’s web page first, and then place it into the dir `$CHAINER_DATSET_ROOT/pfnet/chainer/models` or your favorite place. Once the preparation is finished, the usage is the same as VGG16:

```python
from chainer.links import ResNet152Layers
model = ResNet152Layers()
```

Traceback (most recent call last):
OSErrror: The pre-trained caffemodel does not exist. Please download it from 'https://github.com/KaimingHe/deep-residual-networks', and place it on ...

Please see the details of usage and how to prepare the pre-trained weights for ResNet here: `chainer.links.ResNet50Layers`.

References

3.4 DCGAN: Generate images with Deep Convolutional GAN

3.4.1 0. Introduction

In this tutorial, we generate images with generative adversarial networks (GAN). GAN are kinds of deep neural network for generative modeling that are often applied to image generation. GAN-based models are also used in PaintsChainer, an automatic colorization service.

In this tutorial, you will learn the following things:

1. Generative Adversarial Networks (GAN)
2. Implementation of DCGAN in Chainer
3.4.2 1. Generarive Adversarial Networks (GAN)

1.1 What are GAN?

As explained in GAN tutorial in NIPS 2016 [1], generative models can be classified into the categories as shown in the following figure:

![Generative Models Diagram](image)

Fig. 1: cited from [1]

Besides GAN, other famous generative models include Fully visible belief networks (FVBNs) and Variational autoencoder (VAE). Unlike FVBNs and VAE, GAN do not explicitly model the probability distribution $p(s)$ that generates training data. Instead, we model a generator $G: z \rightarrow s$. The generator $G$ samples $s \sim p(s)$ from the latent variable $z$. Apart from the generator $G$, we create a discriminator $D(x)$ which discriminates between samples from the generator $G$ and examples from training data. While training the discriminator $D$, the generator $G$ tries to maximize the probability of the discriminator $D$ making a mistake. So, the generator $G$ tries to create samples that seem to be drawn from the same distribution as the training data.

The advantages of GAN are low sampling cost and its state-of-the-art performance in image generation. The disadvantage is that we cannot calculate the likelihood $p_{\text{model}}(s)$ because we do not model any probability distribution, and we cannot infer the latent variable $z$ from a sample.
1.2 How GAN work?

As explained above, GAN use the two models, the generator and the discriminator. When training the networks, we should match the data distribution \( p(s) \) with the distribution of the samples \( s = G(z) \) generated from the generator.

The generator \( G \) learns the target distribution, and ideally eventually reaches a Nash equilibrium of game theory. In detail, while training the discriminator \( D \), the generator \( G \) is also trained, so that the discriminator \( D \) makes a mistake.

As an intuitive example, the relationship between counterfeiters of banknotes and the police is frequently used. The counterfeiters try to make counterfeit notes that look like real banknotes. The police try to distinguish real bank notes from counterfeit notes. It is supposed that the ability of the police gradually rises, so that real banknotes and counterfeit notes can be recognized well. Then, the counterfeiters will not be able to use counterfeit banknotes, so they will create counterfeit banknotes that appear more realistic. As the police improve their skill further, they can distinguish real and counterfeit notes... Eventually, the counterfeiter will be able to produce counterfeit banknotes look as real as genuine ones.

The training process is explained by the following mathematical expressions. First, since the discriminator \( D(s) \) is the probability that a sample \( s \) is generated from the data distribution at, it can be expressed as follows:

\[
D(s) = \frac{p(s)}{p(s) + p_{model}(s)}
\]

Then, when we match the data distribution \( s \sim p(s) \) and the distribution of generated samples by \( G \), it means that we should minimize the dissimilarity between the two distributions. It is common to use Jensen-Shannon Divergence \( D_{JS} \) to measure the dissimilarity between distributions[3].

![Diagram of GAN model](image-url)
The $D_{JS}$ of $p_{\text{model}}(s)$ and $p(s)$ can be written as follows by using $D(s)$:

\[
2D_{JS} = D_{KL}(p(s)||\bar{p}(s)) + D_{KL}(p_{\text{model}}(s)||\bar{p}(s))
\]

\[
= E_{p(s)} \left[ \log \frac{2p(s)}{p(s) + p_{\text{model}}(s)} \right] + E_{p_{\text{model}}(s)} \left[ \log \frac{2p_{\text{model}}(s)}{p(s) + p_{\text{model}}(s)} \right]
\]

\[
= E_{p(s)} \log D(s) + E_{p_{\text{model}}(s)} \log(1 - D(s)) + \log 4
\]

\[
= E_{p(s)} \log D(s) + E_{p_{\text{model}}(s)} \log(1 - D(G(z))) + \log 4
\]

where $\bar{p}(s) = \frac{p(s) + p_{\text{model}}(s)}{2}$. The $D_{JS}$ will be maximized by the discriminator $D$ and minimized by the generator $G$, namely, $p_{\text{model}}$. And the distribution $p_{\text{model}}(s)$ generated by $G(s)$ can match the data distribution $p(s)$.

\[
\min_G \max_D E_{p(s)} \log D(s) + E_{p_{\text{model}}(s)} \log(1 - D(G(z)))
\]

When we actually train the model, the above min-max problem is solved by alternately updating the discriminator $D(s)$ and the generator $G(z)$ [4]. The actual training procedures are described as follows:

**Algorithm 1** Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, $k$, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

```
for number of training iterations do
    for $k$ steps do
        ● Sample minibatch of $m$ noise samples $\{z^{(1)}, \ldots, z^{(m)}\}$ from noise prior $p_g(z)$.
        ● Sample minibatch of $m$ examples $\{x^{(1)}, \ldots, x^{(m)}\}$ from data generating distribution $p_{\text{data}}(x)$.
        ● Update the discriminator by ascending its stochastic gradient:

        \[
        \nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[ \log D \left( x^{(i)} \right) + \log \left( 1 - D \left( G \left( z^{(i)} \right) \right) \right) \right].
        \]

    end for

    ● Sample minibatch of $m$ noise samples $\{z^{(1)}, \ldots, z^{(m)}\}$ from noise prior $p_g(z)$.
    ● Update the generator by descending its stochastic gradient:

        \[
        \nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log \left( 1 - D \left( G \left( z^{(i)} \right) \right) \right).
        \]

end for
```

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

Fig. 2: cited from [4]
1.3 What are DCGAN?

In this section, we will introduce the model called DCGAN (Deep Convolutional GAN) proposed by Radford et al. [5]. As shown below, it is a model using CNN (Convolutional Neural Network) as its name suggests.

![DCGAN Diagram](image)

Fig. 3: cited from [5]

In addition, although GAN are known for its difficulty in training, this paper introduces various techniques for successful training:

1. Convert max-pooling layers to convolution layers with larger or fractional strides
2. Convert fully connected layers to global average pooling layers in the discriminator
3. Use batch normalization layers in the generator and the discriminator
4. Use leaky ReLU activation functions in the discriminator

3.4.3 2. Implementation of DCGAN in Chainer

There is an example of DCGAN in the official repository of Chainer, so we will explain how to implement DCGAN based on this: chainer/examples/dcgan

2.1 Define the generator model

First, let’s define a network for the generator.

Listing 1: train_dcgan.py

```python
class Generator(chainer.Chain):
    def __init__(self, n_hidden, bottom_width=4, ch=512, wscale=0.02):
        super(Generator, self).__init__()
        self.n_hidden = n_hidden
        self.ch = ch
        self.bottom_width = bottom_width

        with self.init_scope():
```

(continues on next page)
w = chainer.initializers.Normal(wscale)
self.l0 = L.Linear(self.n_hidden, bottom_width * bottom_width * ch,
    initialW=w)
self.dc1 = L.Deconvolution2D(ch, ch // 2, 4, 2, 1, initialW=w)
self.dc2 = L.Deconvolution2D(ch // 2, ch // 4, 4, 2, 1, initialW=w)
self.dc3 = L.Deconvolution2D(ch // 4, ch // 8, 4, 2, 1, initialW=w)
self.dc4 = L.Deconvolution2D(ch // 8, 3, 3, 1, 1, initialW=w)
self.bn0 = L.BatchNormalization(bottom_width * bottom_width * ch)
self.bn1 = L.BatchNormalization(ch // 2)
self.bn2 = L.BatchNormalization(ch // 4)
self.bn3 = L.BatchNormalization(ch // 8)

def make_hidden(self, batchsize):
    dtype = chainer.get_dtype()
    return numpy.random.uniform(-1, 1, (batchsize, self.n_hidden, 1, 1))
        .astype(dtype)

    def forward(self, z):
        h = F.reshape(F.relu(self.bn0(self.l0(z))),
            (len(z), self.ch, self.bottom_width, self.bottom_width))
        h = F.relu(self.bn1(self.dc1(h)))
        h = F.relu(self.bn2(self.dc2(h)))
        h = F.relu(self.bn3(self.dc3(h)))
        x = F.sigmoid(self.dc4(h))
        return x

When we make a network in Chainer, there are some conventions:

1. Define a network class which inherits Chain.
2. Make chainer.links's instances in the init_scope(): of the initializer __init__.
3. Define network connections in the __call__ operator by using the chainer.links's instances and chainer.functions.

If you are not familiar with constructing a new network, please refer to this tutorial.

As we can see from the initializer __init__, the Generator uses deconvolution layers Deconvolution2D and batch normalization layers BatchNormalization. In __call__, each layer is called and followed by relu except the last layer.

Because the first argument of L.Deconvolution is the channel size of input and the second is the channel size of output, we can find that each layer halves the channel size. When we construct Generator with ch=1024, the network is same as the above image.

Note: Be careful when passing the output of a fully connected layer to a convolution layer, because the convolutional layer needs additional dimensions for inputs. As we can see the 1st line of __call__, the output of the fully connected layer is reshaped by reshape to add the dimensions of the channel, the width and the height of images.
2.2 Define the discriminator model

In addition, let’s define the network for the discriminator.

Listing 2: train_dcgan.py

```python
class Discriminator(chainer.Chain):
    def __init__(self, bottom_width=4, ch=512, wscale=0.02):
        w = chainer.initializers.Normal(wscale)
        super(Discriminator, self).__init__()
        with self.init_scope():
            self.c0_0 = L.Convolution2D(3, ch // 8, 3, 1, 1, initialW=w)
            self.c0_1 = L.Convolution2D(ch // 8, ch // 4, 4, 2, 1, initialW=w)
            self.c1_0 = L.Convolution2D(ch // 4, ch // 4, 3, 1, 1, initialW=w)
            self.c1_1 = L.Convolution2D(ch // 4, ch // 2, 4, 2, 1, initialW=w)
            self.c2_0 = L.Convolution2D(ch // 2, ch // 2, 3, 1, 1, initialW=w)
            self.c2_1 = L.Convolution2D(ch // 2, ch // 1, 4, 2, 1, initialW=w)
            self.c3_0 = L.Convolution2D(ch // 1, ch // 1, 1, 1, 1, initialW=w)
            self.l4 = L.Linear(bottom_width * bottom_width * ch, 1, initialW=w)
            self.bn0_1 = L.BatchNormalization(ch // 4, use_gamma=False)
            self.bn1_0 = L.BatchNormalization(ch // 4, use_gamma=False)
            self.bn1_1 = L.BatchNormalization(ch // 2, use_gamma=False)
            self.bn2_0 = L.BatchNormalization(ch // 2, use_gamma=False)
            self.bn2_1 = L.BatchNormalization(ch // 1, use_gamma=False)
            self.bn3_0 = L.BatchNormalization(ch // 1, use_gamma=False)

    def forward(self, x):
        device = self.device
        h = add_noise(device, x)
        h = F.leaky_relu(add_noise(device, self.c0_0(h)))
        h = F.leaky_relu(add_noise(device, self.bn0_1(self.c0_1(h))))
        h = F.leaky_relu(add_noise(device, self.bn1_0(self.c1_0(h))))
        h = F.leaky_relu(add_noise(device, self.bn1_1(self.c1_1(h))))
        h = F.leaky_relu(add_noise(device, self.bn2_0(self.c2_0(h))))
        h = F.leaky_relu(add_noise(device, self.bn2_1(self.c2_1(h))))
        h = F.leaky_relu(add_noise(device, self.bn3_0(self.c3_0(h))))
        return self.l4(h)
```

The Discriminator network is almost mirrors of the Generator network. However, there are minor different points:

1. Use `leaky_relu` as activation functions
2. Deeper than Generator
3. Add some noise to every intermediate outputs before giving them to the next layers

Listing 3: train_dcgan.py

```python
def add_noise(device, h, sigma=0.2):
    if chainer.config.train:
        xp = device.xp
        # TODO(niboshi): Support random.randn in ChainerX
        if device.xp is chainerx:
            fallback_device = device.fallback_device
            with chainer.using_device(fallback_device):
                randn = device.send(fallback_device.xp.random.randn(*h.shape))
        else:
```

(continues on next page)
randn = xp.random.randn(*h.shape)
return h + sigma * randn
else:
return h

2.3 Prepare dataset and iterator

Let’s retrieve the CIFAR-10 dataset by using Chainer’s dataset utility function `get_cifar10`. CIFAR-10 is a set of small natural images. Each example is an RGB color image of size 32x32. In the original images, each of R, G, B of pixels is represented by one-byte unsigned integer (i.e. from 0 to 255). This function changes the scale of pixel values into \([0, \text{scale}]\) float values.

```python
train, _ = chainer.datasets.get_cifar10(withlabel=False, scale=255.)
```

Listing 4: train_dcgan.py

```python
train_iter = chainer.iterators.SerialIterator(train, args.batchsize)
```

2.4 Prepare model and optimizer

Let’s make the instances of the generator and the discriminator.

```python
gen = Generator(n_hidden=args.n_hidden)
dis = Discriminator()
gen.to_device(device)  # Copy the model to the device
dis.to_device(device)

def make_optimizer(model, alpha=0.0002, beta1=0.5):
    optimizer = chainer.optimizers.Adam(alpha=alpha, beta1=beta1)
    optimizer.setup(model)
    optimizer.add_hook(chainer.optimizer_hooks.WeightDecay(0.0001), 'hook_dec')
    return optimizer

opt_gen = make_optimizer(gen)
opt_dis = make_optimizer(dis)
```

Listing 5: train_dcgan.py

Next, let’s make optimizers for the models created above.

```python
def make_optimizer(model, alpha=0.0002, beta1=0.5):
    optimizer = chainer.optimizers.Adam(alpha=alpha, betal=beta1)
    optimizer.setup(model)
    optimizer.add_hook(chainer.optimizer_hooks.WeightDecay(0.0001), 'hook_dec')
    return optimizer

opt_gen = make_optimizer(gen)
opt_dis = make_optimizer(dis)
```

Listing 6: train_dcgan.py

(continues on next page)

3.4. DCGAN: Generate images with Deep Convolutional GAN

(continues on next page)
opt_gen = make_optimizer(gen)
opd_dis = make_optimizer(dis)

### 2.5 Prepare updater

GAN need the two models: the generator and the discriminator. Usually, the default updaters pre-defined in Chainer take only one model. So, we need to define a custom updater for GAN training.

The definition of `DCGANUpdater` is a little complicated. However, it just minimizes the loss of the discriminator and that of the generator alternately.

As you can see in the class definition, `DCGANUpdater` inherits `StandardUpdater`. In this case, almost all necessary functions are defined in `StandardUpdater`, we just override the functions of `__init__` and `update_core`.

**Note:** We do not need to define `loss_dis` and `loss_gen` because the functions are called only in `update_core`. It aims at improving readability.

Listing 7: train_dcgan.py

```python
class DCGANUpdater(chainer.training.updaters.StandardUpdater):
    def __init__(self, *args, **kwargs):
        self.gen, self.dis = kwargs.pop('models')
        super(DCGANUpdater, self).__init__(*args, **kwargs)

    def loss_dis(self, dis, y_fake, y_real):
        batchsize = len(y_fake)
        L1 = F.sum(F.softplus(-y_real)) / batchsize
        L2 = F.sum(F.softplus(y_fake)) / batchsize
        loss = L1 + L2
        chainer.report({'loss': loss}, dis)
        return loss

    def loss_gen(self, gen, y_fake):
        batchsize = len(y_fake)
        loss = F.sum(F.softplus(-y_fake)) / batchsize
        chainer.report({'loss': loss}, gen)
        return loss

    def update_core(self):
        gen_optimizer = self.get_optimizer('gen')
        dis_optimizer = self.get_optimizer('dis')

        batch = self.get_iterator('main').next()
        device = self.device
        x_real = Variable(self.converter(batch, device)) / 255.

        gen, dis = self.gen, self.dis
        batchsize = len(batch)

        y_real = dis(x_real)
```
In the initializer __init__, an additional keyword argument models is required as you can see the code below. Also, we use keyword arguments iterator, optimizer and device. It should be noted that the optimizer augment takes a dictionary. The two different models require two different optimizers. To specify the different optimizers for the models, we give a dictionary, {'gen': opt_gen, 'dis': opt_dis}, to the optimizer argument. We should input optimizer as a dictionary {'gen': opt_gen, 'dis': opt_dis}. In the DCGANUpdater, you can access the iterator with self.get_iterator('main'). Also, you can access the optimizers with self.get_optimizers('gen') and self.get_optimizers('dis').

In update_core, the two loss functions loss_dis and loss_gen are minimized by the optimizers. At first two lines, we access the optimizers. Then, we create next minibatch of training data by self.get_iterator('main').next(), copy batch to the device by self.converter, and make it a Variable object. After that, we minimize the loss functions with the optimizers.

**Note:** When defining update_core, we may want to manipulate the underlying array of a Variable with numpy or cupy library. Note that the type of arrays on CPU is numpy.ndarray, while the type of arrays on GPU is cupy.ndarray. However, users do not need to write if condition explicitly, because the appropriate array module can be obtained by xp = chainer.backend.get_array_module(variable.array). If variable is on GPU, cupy is assigned to xp, otherwise numpy is assigned to xp.

---

**Listing 8: train_dcgan.py**

```python
updater = DCGANUpdater(
    models=(gen, dis),
    iterator=train_iter,
    optimizer={'gen': opt_gen, 'dis': opt_dis},
    device=device)
```

---

**2.6 Prepare trainer and run**

**Listing 9: train_dcgan.py**

```python
trainer = training.Trainer(updater, (args.epoch, 'epoch'), out=args.out)
snapshot_interval = (args.snapshot_interval, 'iteration')
display_interval = (args.display_interval, 'iteration')
trainer.extend(
    extensions.snapshot(filename='snapshot_iter_{.updater.iteration}.npz'),
    trigger=snapshot_interval)
trainer.extend(extensions.snapshot_object(gen, 'gen_iter_{.updater.iteration}.npz'), trigger=snapshot_interval)
trainer.extend(extensions.snapshot_object(dis, 'dis_iter_{.updater.iteration}.npz'), trigger=snapshot_interval)
```
trainer.extend(extensions.LogReport(trigger=display_interval))
trainer.extend(extensions.PrintReport([  'epoch', 'iteration', 'gen/loss', 'dis/loss',]), trigger=display_interval)
trainer.extend(extensions.ProgressBar(update_interval=10))
trainer.extend(
  out_generated_image(
    gen, dis,
    10, 10, args.seed, args.out),
  trigger=snapshot_interval)

Listing 10: train_dcgan.py
trainer.run()

2.7 Start training

We can run the example as follows.

```bash
$ pwd
/root2chainer/chainer/examples/dcgan
$ python train_dcgan.py --gpu 0
GPU: 0
# Minibatch-size: 50
# n_hidden: 100
# epoch: 1000

epoch iteration gen/loss dis/loss ...............] 0.01%
0 100 1.2292 1.76914

  total [..................................................] 0.02%

this epoch [############################################] 19.00%
  190 iter, 0 epoch / 1000 epochs
  10.121 iters/sec. Estimated time to finish: 1 day, 3:26:26.372445.
```

The results will be saved in the directory `/root2chainer/chainer/examples/dcgan/result/`. The image is generated by the generator trained for 1000 epochs, and the GIF image on the top of this page shows generated images after every 10 epochs.
3.4.4 3. Reference

- [1] NIPS 2016 Tutorial: Generative Adversarial Networks
- [2] Nash equilibrium

3.5 Recurrent Nets and their Computational Graph

In the example code of this tutorial, we assume for simplicity that the following symbols are already imported.

```python
import math
import numpy as np
import chainer
from chainer import backend
from chainer import backends
from chainer.backends import cuda
from chainer import Function, FunctionNode, gradient_check, report, training, utils,Variable
from chainer import datasets, initializers, iterators, optimizers, serializers
```

(continues on next page)
In this section, you will learn how to write
- recurrent nets with full backprop,
- recurrent nets with truncated backprop,
- evaluation of networks with few memory.

After reading this section, you will be able to:
- Handle input sequences of variable length
- Truncate upper stream of the network during forward computation
- Use no-backprop mode to prevent network construction

### 3.5.1 Recurrent Nets

Recurrent nets are neural networks with loops. They are often used to learn from sequential input/output. Given an input stream $x_1, x_2, \ldots, x_t, \ldots$ and the initial state $h_0$, a recurrent net iteratively updates its state by $h_t = f(x_t, h_{t-1})$, and at some or every point in time $t$, it outputs $y_t = g(h_t)$. If we expand the procedure along the time axis, it looks like a regular feed-forward network except that same parameters are repeatedly used within the network.

Here we learn how to write a simple one-layer recurrent net. The task is language modeling: given a finite sequence of words, we want to predict the next word at each position without peeking the successive words. Suppose there are 1,000 different word types, and that we use 100 dimensional real vectors to represent each word (a.k.a. word embedding).

Let’s start from defining the recurrent neural net language model (RNNLM) as a chain. We can use the `chainer.links.LSTM` link that implements a fully-connected stateful LSTM layer. This link looks like an ordinary fully-connected layer. On construction, you pass the input and output size to the constructor:

```python
>>> l = L.LSTM(100, 50)
```

Then, call on this instance `l(x)` executes one step of LSTM layer:

```python
>>> l.reset_state()
>>> x = Variable(np.random.randn(10, 100).astype(np.float32))
>>> y = l(x)
```

Do not forget to reset the internal state of the LSTM layer before the forward computation! Every recurrent layer holds its internal state (i.e. the output of the previous call). At the first application of the recurrent layer, you must reset the internal state. Then, the next input can be directly fed to the LSTM instance:

```python
>>> x2 = Variable(np.random.randn(10, 100).astype(np.float32))
>>> y2 = l(x2)
```

Based on this LSTM link, let’s write our recurrent network as a new chain:

```python
class RNN(Chain):
    def __init__(self):
        super(RNN, self).__init__()
```

(continues on next page)
```python
with self.init_scope():
    self.embed = L.EmbedID(1000, 100)  # word embedding
    self.mid = L.LSTM(100, 50)        # the first LSTM layer
    self.out = L.Linear(50, 1000)     # the feed-forward output layer

def reset_state(self):
    self.mid.reset_state()

def forward(self, cur_word):
    # Given the current word ID, predict the next word.
    x = self.embed(cur_word)
    h = self.mid(x)
    y = self.out(h)
    return y
```

Here `EmbedID` is a link for word embedding. It converts input integers into corresponding fixed-dimensional embedding vectors. The last linear link `out` represents the feed-forward output layer.

The `RNN` chain implements a one-step-forward computation. It does not handle sequences by itself, but we can use it to process sequences by just feeding items in a sequence straight to the chain.

Suppose we have a list of word variables `x_list`. Then, we can compute loss values for the word sequence by simple for loop.

```python
def compute_loss(x_list):
    loss = 0
    for cur_word, next_word in zip(x_list, x_list[1:]):
        loss += model(cur_word, next_word)
    return loss
```

Of course, the accumulated loss is a Variable object with the full history of computation. So we can just call its `backward()` method to compute gradients of the total loss according to the model parameters:

```python
# Suppose we have a list of word variables x_list.
rnn.reset_state()
model.cleargrads()
loss = compute_loss(x_list)
loss.backward()
optimizer.update()
```

Or equivalently we can use the `compute_loss` as a loss function:

```python
rnn.reset_state()
optimizer.update(compute_loss, x_list)
```
3.5.2 Truncate the Graph by Unchaining

Learning from very long sequences is also a typical use case of recurrent nets. Suppose the input and state sequence is too long to fit into memory. In such cases, we often truncate the backpropagation into a short time range. This technique is called truncated backprop. It is heuristic, and it makes the gradients biased. However, this technique works well in practice if the time range is long enough.

How to implement truncated backprop in Chainer? Chainer has a smart mechanism to achieve truncation, called backward unchaining. It is implemented in the Variable.unchain_backward() method. Backward unchaining starts from the Variable object, and it chops the computation history backwards from the variable. The chopped variables are disposed automatically (if they are not referenced explicitly from any other user object). As a result, they are no longer a part of computation history, and are not involved in backprop anymore.

Let’s write an example of truncated backprop. Here we use the same network as the one used in the previous subsection. Suppose we are given a very long sequence, and we want to run backprop truncated at every 30 time steps. We can write truncated backprop using the model defined above:

```python
loss = 0
count = 0
seqlen = len(x_list[1:])

rnn.reset_state()
for cur_word, next_word in zip(x_list, x_list[1:]):
    loss += model(cur_word, next_word)
    count += 1
    if count % 30 == 0 or count == seqlen:
        model.cleargrads()
        loss.backward()
        loss.unchain_backward()
        optimizer.update()

State is updated at model(), and the losses are accumulated to loss variable. At each 30 steps, backprop takes place at the accumulated loss. Then, the unchain_backward() method is called, which deletes the computation history backward from the accumulated loss. Note that the last state of model is not lost, since the RNN instance holds a reference to it.

The implementation of truncated backprop is simple, and since there is no complicated trick on it, we can generalize this method to different situations. For example, we can easily extend the above code to use different schedules between backprop timing and truncation length.

3.5.3 Network Evaluation without Storing the Computation History

On evaluation of recurrent nets, there is typically no need to store the computation history. While unchaining enables us to walk through unlimited length of sequences with limited memory, it is a bit of a work-around.

As an alternative, Chainer provides an evaluation mode of forward computation which does not store the computation history. This is enabled by just calling no_backprop_mode() context:

```python
with chainer.no_backprop_mode():
    x_list = [Variable(...) for _ in range(100)]  # list of 100 words
    loss = compute_loss(x_list)
```

Note that we cannot call loss.backward() to compute the gradient here, since the variable created in the no-backprop context does not remember the computation history.

No-backprop context is also useful to evaluate feed-forward networks to reduce the memory footprint.
We can combine a fixed feature extractor network and a trainable predictor network using `no_backprop_mode()`.

For example, suppose we want to train a feed-forward network `predictor_func`, which is located on top of another fixed pre-trained network `fixed_func`. We want to train `predictor_func` without storing the computation history for `fixed_func`. This is simply done by following code snippets (suppose `x_data` and `y_data` indicate input data and label, respectively):

```python
with chainer.no_backprop_mode():
    x = Variable(x_data)
    feat = fixed_func(x)
    y = predictor_func(feat)
    y.backward()
```

At first, the input variable `x` is in no-backprop mode, so `fixed_func` does not memorize the computation history. Then `predictor_func` is executed in backprop mode, i.e., with memorizing the history of computation. Since the history of computation is only memorized between variables `feat` and `y`, the backward computation stops at the `feat` variable.

### 3.5.4 Making it with Trainer

The above codes are written with plain Function/Variable APIs. When we write a training loop, it is better to use Trainer, since we can then easily add functionalities by extensions.

Before implementing it on Trainer, let’s clarify the training settings. We here use Penn Tree Bank dataset as a set of sentences. Each sentence is represented as a word sequence. We concatenate all sentences into one long word sequence, in which each sentence is separated by a special word `<eos>`, which stands for “End of Sequence”. This dataset is easily obtained by `chainer.datasets.get_ptb_words()`. This function returns train, validation, and test dataset, each of which is represented as a long array of integers. Each integer represents a word ID.

Our task is to learn a recurrent neural net language model from the long word sequence. We use words in different locations to form mini-batches. It means we maintain $B$ indices pointing to different locations in the sequence, read from these indices at each iteration, and increment all indices after the read. Of course, when one index reaches the end of the whole sequence, we turn the index back to 0.

In order to implement this training procedure, we have to customize the following components of Trainer:

- **Iterator.** Built-in iterators do not support reading from different locations and aggregating them into a mini-batch.
- **Update function.** The default update function does not support truncated BPTT.

When we write a dataset iterator dedicated to the dataset, the dataset implementation can be arbitrary; even the interface is not fixed. On the other hand, the iterator must support the `Iterator` interface. The important methods and attributes to implement are `batch_size`, `epoch`, `epoch_detail`, `is_new_epoch`, `iteration`, `__next__`, and `serialize`. Following is a code from the official example in the `examples/ptb` directory.

```python
from __future__ import division

class ParallelSequentialIterator(chainer.dataset.Iterator):
    def __init__(self, dataset, batch_size, repeat=True):
        self.dataset = dataset
        self.batch_size = batch_size
        self.epoch = 0
        self.is_new_epoch = False
        self.repeat = repeat
        self.offsets = [i * len(dataset) // batch_size for i in range(batch_size)]
        self.iteration = 0
```

(continues on next page)
def __next__(self):
    length = len(self.dataset)
    if not self.repeat and self.iteration * self.batch_size >= length:
        raise StopIteration
    cur_words = self.get_words()
    self.iteration += 1
    next_words = self.get_words()
    epoch = self.iteration * self.batch_size // length
    self.is_new_epoch = self.epoch < epoch
    if self.is_new_epoch:
        self.epoch = epoch
    return list(zip(cur_words, next_words))

@property
def epoch_detail(self):
    return self.iteration * self.batch_size / len(self.dataset)

def get_words(self):
    return [self.dataset[(offset + self.iteration) % len(self.dataset)] for offset in self.offsets]

def serialize(self, serializer):
    self.iteration = serializer('iteration', self.iteration)
    self.epoch = serializer('epoch', self.epoch)

train_iter = ParallelSequentialIterator(train, 20)
val_iter = ParallelSequentialIterator(val, 1, repeat=False)

Although the code is slightly long, the idea is simple. First, this iterator creates offsets pointing to positions equally spaced within the whole sequence. The i-th examples of mini-batches refer the sequence with the i-th offset. The iterator returns a list of tuples of the current words and the next words. Each mini-batch is converted to a tuple of integer arrays by the concat_examples function in the standard updater (see the previous tutorial).

Backprop Through Time is implemented as follows.

class BPTTUpdater(training.updaters.StandardUpdater):
    def __init__(self, train_iter, optimizer, bprop_len):
        super(BPTTUpdater, self).__init__(train_iter, optimizer)
        self.bprop_len = bprop_len

        # The core part of the update routine can be customized by overriding.
        def update_core(self):
            loss = 0
            # When we pass one iterator and optimizer to StandardUpdater.__init__,
            # they are automatically named 'main'.
            train_iter = self.get_iterator('main')
            optimizer = self.get_optimizer('main')

            # Progress the dataset iterator for bprop_len words at each iteration.
            for i in range(self.bprop_len):
                # Get the next batch (a list of tuples of two word IDs)
                batch = train_iter.__next__()

                # Concatenate the word IDs to matrices and send them to the device
# self.converter does this job
# (it is chainer.dataset.concat_examples by default)
x, t = self.converter(batch)

# Compute the loss at this time step and accumulate it
loss += optimizer.target(chainer.Variable(x), chainer.Variable(t))

optimizer.target.cleargrads()  # Clear the parameter gradients
loss.backward()  # Backprop
loss.unchain_backward()  # Truncate the graph
optimizer.update()  # Update the parameters

In this case, we update the parameters on every bprop_len consecutive words. The call of unchain_backward cuts the history of computation accumulated to the LSTM links. The rest of the code for setting up Trainer is almost same as one given in the previous tutorial.

In this section we have demonstrated how to write recurrent nets in Chainer and some fundamental techniques to manage the history of computation (a.k.a. computational graph). The example in the examples/ptb directory implements truncated backprop learning of a LSTM language model from the Penn Treebank corpus. In the next section, we will review how to use GPU(s) in Chainer.

### 3.6.1 0. Introduction

The language model is modeling the probability of generating natural language sentences or documents. You can use the language model to estimate how natural a sentence or a document is. Also, with the language model, you can generate new sentences or documents.

Let’s start with modeling the probability of generating sentences. We represent a sentence as \( X = (x_0, x_1, ..., x_T) \), in which \( x_t \) is a one-hot vector. Generally, \( x_0 \) is the one-hot vector of BOS (beginning of sentence), and \( x_T \) is that of EOS (end of sentence).

A language model models the probability of a word occurrence under the condition of its previous words in a sentence. Let \( X_{[i,j]} \) be \( (x_i, x_{i+1}, ..., x_j) \), the occurrence probability of sentence \( X \) can be represented as follows:

\[
P(X) = P(x_0) \prod_{t=1}^{T} P(x_t|X_{[0,t-1]})
\]

So, the language model \( P(X) \) can be decomposed into word probabilities conditioned with its previous words. In this tutorial, we model \( P(x_t|X_{[0,t-1]}) \) with a recurrent neural network to obtain a language model \( P(X) \).
3.6.2 1. Basic Idea of Recurrent Neural Net Language Model

1.1 Recurrent Neural Net Language Model

Recurrent Neural Net Language Model (RNNLM) is a type of neural net language models which contains the RNNs in the network. Since an RNN can deal with the variable length inputs, it is suitable for modeling the sequential data such as sentences in natural language.

We show one layer of an RNNLM with these parameters.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_t$</td>
<td>the one-hot vector of $t$-th word</td>
</tr>
<tr>
<td>$y_t$</td>
<td>the $t$-th output</td>
</tr>
<tr>
<td>$h_i^{(t)}$</td>
<td>the $t$-th hidden layer of $i$-th layer</td>
</tr>
<tr>
<td>$p_t$</td>
<td>the next word’s probability of $t$-th word</td>
</tr>
<tr>
<td>$E$</td>
<td>Embedding matrix</td>
</tr>
<tr>
<td>$W_h$</td>
<td>Hidden layer matrix</td>
</tr>
<tr>
<td>$W_o$</td>
<td>Output layer matrix</td>
</tr>
</tbody>
</table>

The process to get a next word prediction from $i$-th input word $x_t$

1. Get the embedding vector: $h_t^{(0)} = Ex_t$
2. Calculate the hidden layer: $h_t^{(1)} = \tanh \left( W_h \begin{bmatrix} h_t^{(0)} \\ h_{t-1}^{(1)} \end{bmatrix} \right)$
3. Calculate the output layer: $y_t = W_o h_t^{(1)}$
4. Transform to probability: $p_t = \text{softmax}(y_t)$
**Note:**
- Note that \( \tanh \) in the above equation is applied to the input vector in element-wise manner.
- Note that \( \begin{bmatrix} a \\ b \end{bmatrix} \) denotes a concatenated vector of \( a \) and \( b \).
- Note that \( \text{softmax} \) in the above equation converts an arbitrary real vector to a probability vector which the summation over all elements is 1.

### 1.2 Perplexity (Evaluation of the language model)

**Perplexity** is the common evaluation metric for a language model. Generally, it measures how well the proposed probability model \( P_{\text{model}}(X) \) represents the target data \( P^*(X) \). Let a validation dataset be \( D = \{ X^{(n)} \}_{n=1}^{|D|} \), which is a set of sentences, where the \( n \)-th sentence length is \( T^{(n)} \), and the vocabulary size of this dataset is \( |\mathcal{V}| \), the perplexity is represented as follows:

\[
  b^z \text{ s.t. } z = - \frac{1}{|\mathcal{V}|} \sum_{n=1}^{|D|} \sum_{t=1}^{T^{(n)}} \log_b P_{\text{model}}(x^{(n)}_t, X^{(n)}_{[a,t-1]})
\]

We usually use \( b = 2 \) or \( b = e \). The perplexity shows how much varied the predicted distribution for the next word is. When a language model represents the dataset well, it should show a high probability only for the correct next word, so that the entropy should be high. In the above equation, the sign is reversed, so that smaller perplexity means better model.

During training, we minimize the below cross entropy:

\[
  \mathcal{H}(\hat{P}, P_{\text{model}}) = - \hat{P}(X) \log P_{\text{model}}(X)
\]

where \( \hat{P} \) is the empirical distribution of a sequence in the training dataset.

### 3.6.3 2. Implementation of Recurrent Neural Net Language Model

There is an example of RNN language model in the official repository, so we will explain how to implement a RNNLM in Chainer based on that: `examples/ptb`

#### 2.1 Model Overview
The RNNLM used in this notebook is depicted in the above figure. The symbols appeared in the figure are defined as follows:

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_t$</td>
<td>the one-hot vector of $t$-th word</td>
</tr>
<tr>
<td>$y_t$</td>
<td>the $t$-th output</td>
</tr>
<tr>
<td>$h_t^{(i)}$</td>
<td>the $t$-th hidden layer of $i$-th layer</td>
</tr>
<tr>
<td>$p_t$</td>
<td>the next word’s probability of $t$-th word</td>
</tr>
<tr>
<td>$E$</td>
<td>Embedding matrix</td>
</tr>
<tr>
<td>$W_h$</td>
<td>Hidden layer matrix</td>
</tr>
<tr>
<td>$W_o$</td>
<td>Output layer matrix</td>
</tr>
</tbody>
</table>

**LSTMs** (long short-term memory) are used for the connection of hidden layers. A LSTM is one of major recurrent neural net modules. It is designed for remembering the long-term memory, so that it should be able to consider relationships of distant words, such that a word at beginning of sentence and it at the end. We also use **Dropout** before both LSTMs and linear transformations. Dropout is one of regularization techniques for preventing overfitting on training dataset.

### 2.2 Step-by-step Implementation

#### 2.2.1 Import Package

First, let’s import necessary packages.

Listing 11: train_ptb.py

```python
""
from __future__ import division
import argparse
import sys
import numpy as np
```

#### 2.2.2 Define Training Settings

Define all training settings here.

Listing 12: train_ptb.py

```python
parser.add_argument('--batchsize', '-b', type=int, default=20,
                    help='Number of examples in each mini-batch')
parser.add_argument('--bproplen', '-l', type=int, default=35,
                    help='Number of words in each mini-batch ' +
                         ' (= length of truncated BPTT)')
parser.add_argument('--epoch', '-e', type=int, default=39,
                    help='Number of sweeps over the dataset to train')
parser.add_argument('--device', '-d', type=str, default='-1',
                    help='Device specifier. Either ChainerX device ' +
                         'specifier or an integer. If non-negative integer, ' +
                         'CuPy arrays with specified device id are used. If ' +
                         'negative integer, NumPy arrays are used')
```

(continues on next page)
parser.add_argument('--gradclip', '-c', type=float, default=5,  
    help='Gradient norm threshold to clip')
parser.add_argument('--out', '-o', default='result',  
    help='Directory to output the result')
parser.add_argument('--resume', '-r', type=str,  
    help='Resume the training from snapshot')
parser.add_argument('--test', action='store_true',  
    help='Use tiny datasets for quick tests')
parser.set_defaults(test=False)
parser.add_argument('--unit', '-u', type=int, default=650,  
    help='Number of LSTM units in each layer')
parser.add_argument('--model', '-m', default='model.npz',  
    help='Model file name to serialize')

2.2.3 Define Network Structure

An RNNLM written in Chainer is shown below. It implements the model depicted in the above figure.

Listing 13: train_ptb.py

class RNNForLM(chainer.Chain):
    def __init__(self, n_vocab, n_units):
        super(RNNForLM, self).__init__()
        with self.init_scope():
            self.embed = L.EmbedID(n_vocab, n_units)
            self.l1 = L.LSTM(n_units, n_units)
            self.l2 = L.LSTM(n_units, n_units)
            self.l3 = L.Linear(n_units, n_vocab)

            for param in self.params():
                param.array[...] = np.random.uniform(-0.1, 0.1, param.shape)

    def reset_state(self):
        self.l1.reset_state()
        self.l2.reset_state()

    def forward(self, x):
        h0 = self.embed(x)
        h1 = self.l1(F.dropout(h0))
        h2 = self.l2(F.dropout(h1))
        y = self.l3(F.dropout(h2))
        return y

• When we instantiate this class for making a model, we give the vocabulary size to n_vocab and the size of hidden vectors to n_units.

• This network uses chainer.links.LSTM, chainer.links.Linear, and chainer.functions.dropout as its building blocks. All the layers are registered and initialized in the context with self.init_scope().

• You can access all the parameters in those layers by calling self.params().

• In the constructor, it initializes all parameters with values sampled from a uniform distribution $U(-1, 1)$.

• The forward method takes an word ID x, and calculates the word probability vector for the next word by forwarding it through the network, and returns the output.
• Note that the word ID $x$ is automatically converted to a $|V|$-dimensional one-hot vector and then multiplied with the input embedding matrix in `self.embed(x)` to obtain an embed vector $h_0$ at the first line of `forward`.

### 2.2.4 Load the Penn Tree Bank Long Word Sequence Dataset

In this notebook, we use Penn Tree Bank dataset that contains number of sentences. Chainer provides an utility function to obtain this dataset from server and convert it to a long single sequence of word IDs. `chainer.datasets.get_ptb_words()` actually returns three separated datasets which are for train, validation, and test.

Let’s download and make dataset objects using it:

Listing 14: train_ptb.py

```python
# Load the Penn Tree Bank long word sequence dataset
train, val, test = chainer.datasets.get_ptb_words()
```

### 2.2.5 Define Iterator for Making a Mini-batch from the Dataset

Dataset iterator creates a mini-batch of couple of words at different positions, namely, pairs of current word and its next word. Each example is a part of sentences starting from different offsets equally spaced within the whole sequence.

Listing 15: train_ptb.py

```python
class ParallelSequentialIterator(chainer.dataset.Iterator):
    def __init__(self, dataset, batch_size, repeat=True):
        super(ParallelSequentialIterator, self).__init__()
        self.dataset = dataset
        self.batch_size = batch_size  # batch size
        self.repeat = repeat
        length = len(dataset)
        # Offsets maintain the position of each sequence in the mini-batch.
        self.offsets = [i * length // batch_size for i in range(batch_size)]
        self.reset()

    def reset(self):
        # Number of completed sweeps over the dataset. In this case, it is
        # incremented if every word is visited at least once after the last
        # increment.
        self.epoch = 0
        # True if the epoch is incremented at the last iteration.
        self.is_new_epoch = False
        # NOTE: this is not a count of parameter updates. It is just a count of
        # calls of `__next__`.
        self.iteration = 0
        # use -1 instead of None internally
        self._previous_epoch_detail = -1.

    def __next__(self):
        # This iterator returns a list representing a mini-batch. Each item
        # indicates a different position in the original sequence. Each item is
        # represented by a pair of two word IDs. The first word is at the
        # "current" position, while the second word at the next position.
        # At each iteration, the iteration count is incremented, which pushes
(continues on next page)
# forward the "current" position.
length = len(self.dataset)
if not self.repeat and self.iteration * self.batch_size >= length:
    raise StopIteration

cur_words = self.get_words()
sel._previous_epoch_detail = self.epoch_detail
self.iteration += 1
next_words = self.get_words()

epoch = self.iteration * self.batch_size // length
self.is_new_epoch = self.epoch < epoch
if self.is_new_epoch:
    self.epoch = epoch

return list(zip(cur_words, next_words))

@property
def epoch_detail(self):
    # Floating point version of epoch.
    return self.iteration * self.batch_size / len(self.dataset)

@property
def previous_epoch_detail(self):
    if self._previous_epoch_detail < 0:
        return None
    return self._previous_epoch_detail

def get_words(self):
    # It returns a list of current words.
    return [self.dataset[(offset + self.iteration) % len(self.dataset)]
        for offset in self.offsets]

def serialize(self, serializer):
    # It is important to serialize the state to be recovered on resume.
    self.iteration = serializer('iteration', self.iteration)
    self.epoch = serializer('epoch', self.epoch)
    try:
        self._previous_epoch_detail = serializer(  
            'previous_epoch_detail', self._previous_epoch_detail)
    except KeyError:
        # guess previous_epoch_detail for older version
        self._previous_epoch_detail = self.epoch + \
        (self.current_position - self.batch_size) / len(self.dataset)
    if self.epoch_detail > 0:
        self._previous_epoch_detail = max(  
            self._previous_epoch_detail, 0.)
    else:
        self._previous_epoch_detail = -1.
2.2.6 Define Updater

We use Backpropagation through time (BPTT) for optimize the RNNLM. BPTT can be implemented by overriding `update_core()` method of `StandardUpdater`. First, in the constructor of the `BPTTUpdater`, it takes `bprop_len` as an argument in addition to other arguments `StandardUpdater` needs. `bprop_len` defines the length of sequence \( T \) to calculate the loss:

\[
\mathcal{L} = - \sum_{t=0}^{T} \sum_{n=1}^{|V|} \hat{P}(x_{t+1}^{(n)}) \log P_{\text{model}}(x_{t+1}^{(n)} | x_{t}^{(n)})
\]

where \( \hat{P}(x_{t}^{(n)}) \) is a probability for \( n \)-th word in the vocabulary at the position \( t \) in the training data sequence.

Listing 16: train_ptb.py

```python
class BPTTUpdater(training.updaters.StandardUpdater):
    def __init__(self, train_iter, optimizer, bprop_len, device):
        super(BPTTUpdater, self).__init__(train_iter, optimizer, device=device)
        self.bprop_len = bprop_len

        # The core part of the update routine can be customized by overriding.
    def update_core(self):
        loss = 0
        # When we pass one iterator and optimizer to StandardUpdater.__init__,
        # they are automatically named 'main'.
        train_iter = self.get_iterator('main')
        optimizer = self.get_optimizer('main')

        # Progress the dataset iterator for bprop_len words at each iteration.
        for i in range(self.bprop_len):
            batch = train_iter.__next__()

            # Concatenate the word IDs to matrices and send them to the device
            x, t = self.converter(batch, self.device)

            # Compute the loss at this time step and accumulate it
            loss += optimizer.target(x, t)

        optimizer.target.cleargrads()  # Clear the parameter gradients
        loss.backward()  # Backprop
        loss.unchain_backward()  # Truncate the graph
        optimizer.update()  # Update the parameters
```

104 Chapter 3. Neural Net Examples
2.2.7 Define Evaluation Function (Perplexity)

Define a function to calculate the perplexity from the loss value. If we take $e$ as $b$ in the above definition of perplexity, calculating the perplexity is just to give the loss value to the power of $e$:

```
def compute_perplexity(result):
    result['perplexity'] = np.exp(result['main/loss'])
    if 'validation/main/loss' in result:
        result['val_perplexity'] = np.exp(result['validation/main/loss'])
```

2.2.8 Create Iterator

Here, the code below just creates iterator objects from dataset splits (train/val/test).

```
train_iter = ParallelSequentialIterator(train, args.batchsize)
val_iter = ParallelSequentialIterator(val, 1, repeat=False)
test_iter = ParallelSequentialIterator(test, 1, repeat=False)
```

2.2.9 Create RNN and Classification Model

Instantiate RNNLM model and wrap it with `chainer.links.Classifier` because it calculates softmax cross entropy as the loss.

```
rnn = RNNForLM(n_vocab, args.unit)
model = L.Classifier(rnn)
model.compute_accuracy = False  # we only want the perplexity
```

Note that `Classifier` computes not only the loss but also accuracy based on a given input/label pair. To learn the RNN language model, we only need the loss (cross entropy) in the `Classifier` because we calculate the perplexity instead of classification accuracy to check the performance of the model. So, we turn off computing the accuracy by giving `False` to `model.compute_accuracy` attribute.

2.2.10 Setup Optimizer

Prepare an optimizer. Here, we use `GradientClipping` to prevent gradient explosion. It automatically clips the gradient to be used to update the parameters in the model with given constant `gradclip`.

```
optimizer = chainer.optimizers.SGD(lr=1.0)
optimizer.setup(model)
optimizer.add_hook(chainer.optimizer_hooks.GradientClipping(args.gradclip))
```

3.6. RNN Language Models
2.2.11 Setup and Run Trainer

Let’s make a trainer object and start the training! Note that we add an `eval_hook` to the `Evaluator` extension to reset the internal states before starting evaluation process. It can prevent to use training data during evaluating the model.

Listing 21: train_ptb.py

```python
updater = BPTTUpdater(train_iter, optimizer, args.bproplen, device)
trainer = training.Trainer(updater, (args.epoch, 'epoch'), out=args.out)

eval_model = model.copy()  # Model with shared params and distinct states
eval_rnn = eval_model.predictor
trainer.extend(extensions.Evaluator(
    val_iter, eval_model, device=device,
    eval_hook=lambda _: eval_rnn.reset_state()))

interval = 10 if args.test else 500
trainer.extend(extensions.LogReport(postprocess=compute_perplexity,
                                    trigger=(interval, 'iteration')))
trainer.extend(extensions.PrintReport(
    ['epoch', 'iteration', 'perplexity', 'val_perplexity']), trigger=(interval, 'iteration'))
trainer.extend(extensions.ProgressBar(update_interval=1 if args.test else 10))
trainer.extend(extensions.snapshot())
trainer.extend(extensions.snapshot_object(model, 'model_iter_{.updater.iteration}'))

if args.resume is not None:
    chainer.serializers.load_npz(args.resume, trainer)

trainer.run()
```

2.2.12 Evaluate the trained model on test dataset

Let’s see the perplexity on the test split. `Trainer`’s extension can be used as just a normal function outside of `Trainer`.
2.3 Run Example

2.3.1 Training the model

You can train the model with the script: examples/ptb/train_ptb.py

```bash
$ pwd
/root2chainer/chainer/examples/ptb
$ python train_ptb.py --test  # run by test mode. If you want to use all data, remove
   "--test".
   --train.txt...
   --valid.txt...
   --test.txt...
#vocab = 10000
test
test perplexity: 29889.9857364
```

2.3.2 Generating sentences

You can generate the sentence which starts with a word in the vocabulary. In this example, we generate a sentence which starts with the word apple. We use the script in the PTB example of the official repository: examples/ptb/gentxt.py

```bash
$ pwd
/root2chainer/chainer/examples/ptb
$ python gentxt.py -m model.npz -p apple
apple a new u.s. economist with <unk> <unk> fixed more than to N the company said who
   → is looking back to
```

3.7 Word2Vec: Obtain word embeddings

3.7.1 0. Introduction

Word2vec is the tool for generating the distributed representation of words, which is proposed by Mikolov et al[1]. When the tool assigns a real-valued vector to each word, the closer the meanings of the words, the greater similarity the vectors will indicate.
Distributed representation means assigning a real-valued vector for each word and representing the word by the vector. When representing a word by distributed representation, we call the word embeddings. In this tutorial, we aim at explaining how to get the word embeddings from Penn Tree Bank dataset.

Let's think about what the meaning of word is. Since we are human, we can understand that the words “animal” and “dog” are deeply related each other. But what information will Word2vec use to learn the vectors for words? The words “animal” and “dog” should have similar vectors, but the words “food” and “dog” should be far from each other. How to know the features of those words automatically?

3.7.2 1. Basic Idea

Word2vec learns the similarity of word meanings from simple information. It learns the representation of words from sentences. The core idea is based on the assumption that the meaning of a word is affected by the words around it. This idea follows distributional hypothesis[2].

The word we focus on to learn its representation is called center word, and the words around it are called context words. The window size $C$ determines the number of context words which is considered.

Here, let's see the algorithm by using an example sentence: “The cute cat jumps over the lazy dog.”.

- All of the following figures consider “cat” as the center word.
- According to the window size $C$, you can see that the number of context words is changed.

3.7.3 2. Main Algorithm

Word2vec, the tool for creating the word embeddings, is actually built with two models, which are called Skip-gram and CBow.

To explain the models with the figures below, we will use the following symbols.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$</td>
<td>\mathcal{V}</td>
</tr>
<tr>
<td>$D$</td>
<td>The size of embedding vector</td>
</tr>
<tr>
<td>$v_t$</td>
<td>A one-hot center word vector</td>
</tr>
<tr>
<td>$V_t \pm C$</td>
<td>A set of $2C$ context vectors around $v_t$, namely, ${v_{t+c}}_{c=-C}^{C}\backslash v_t$</td>
</tr>
<tr>
<td>$l_H$</td>
<td>An embedding vector of an input word vector</td>
</tr>
<tr>
<td>$l_O$</td>
<td>An output vector of the network</td>
</tr>
<tr>
<td>$W_H$</td>
<td>The embedding matrix for inputs</td>
</tr>
<tr>
<td>$W_O$</td>
<td>The embedding matrix for outputs</td>
</tr>
</tbody>
</table>
2.1 Skip-gram

This model learns to predict context words $V_{t\pm C}$ when a center word $v_t$ is given. In the model, each row of the embedding matrix for input $W_H$ becomes a word embedding of each word.

When you input a center word $v_t$ into the network, you can predict one of context words $\hat{v}_{t+c} \in V_{t\pm C}$ as follows:

1. Calculate an embedding vector of the input center word vector: $l_H = W_Hv_t$
2. Calculate an output vector of the embedding vector: $l_O = W_OL_H$
3. Calculate a probability vector of a context word: $\hat{v}_{t+c} = \text{softmax}(l_O)$

Each element of the $|V|$-dimensional vector $\hat{v}_{t+c}$ is a probability that a word in the vocabulary turns out to be a context word at position $c$. So, the probability $p(v_{t+c} | v_t)$ can be estimated by a dot product of the one-hot vector $v_{t+c}$ which represents the actual word at the position $c$ and the output vector $\hat{v}_{t+c}$.

$$p(v_{t+c} | v_t) = v_{t+c}^T \hat{v}_{t+c}$$

The loss function to predict all the context words $V_{t\pm C}$ given a center word $v_t$ is defined as follows:

$$L(V_{t\pm C} | v_t; W_H, W_O) = \sum_{V_{t\pm C}} - \log (p(v_{t+c} | v_t))$$
$$= \sum_{V_{t\pm C}} - \log(v_{t+c}^T \hat{v}_{t+c})$$

2.2 Continuous Bag of Words (CBoW)

This model learns to predict center word $v_t$ when context words $V_{t\pm C}$ is given. When you give a set of context words $V_{t\pm C}$ to the network, you can estimate the probability of the center word $\hat{v}_t$ as follows:

1. Calculate a mean embedding vector over all context words: $l_H = \frac{1}{2C} \sum_{V_{t\pm C}} W_Hv_{t+c}$
2. Calculate an output vector of the embedding vector: $l_O = W_OL_H$
3. Calculate a probability vector of a center word: $\hat{v}_t = \text{softmax}(l_O)$

Each element of the $|V|$-dimensional vector $\hat{v}_t$ is a probability that a word in the vocabulary turns out to be a center word. So, the probability $p(v_t | V_{t\pm C})$ can be estimated by a dot product of the one-hot vector $v_t$ which represents the actual center word and the output vector $\hat{v}_t$.

$$p(v_t | V_{t\pm C}) = v_t^T \hat{v}_t$$

The loss function to predict the center word $v_t$ given context words $V_{t\pm C}$ is defined as follows:

$$L(v_t | V_{t\pm C}; W_H, W_O) = - \log (p(v_t | V_{t\pm C}))$$
$$= - \log(v_t^T \hat{v}_t)$$

3.7. Word2Vec: Obtain word embeddings
3.7.4 3. Details of Skip-gram

In this tutorial, we mainly explain Skip-gram model because

1. It is easier to understand the algorithm than CBoW.
2. Even if the number of words increases, the accuracy is largely maintained. So, it is more scalable.

So, let’s think about a concrete example of calculating Skip-gram under this setup:

- The size of vocabulary $|\mathcal{V}|$ is 10.
- The size of embedding vector $D$ is 2.
- Center word is “dog”.
- Context word is “animal”.

Since there should be more than one context word, repeat the following process for each context word.

1. The one-hot vector of “dog” is $[0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0]$ and you input it as the center word.
2. The third row of embedding matrix $W_H$ is used for the word embedding of “dog” $l_H$.
3. Then, multiply $W_O$ with $l_H$ to obtain the output vector $l_O$.
4. Give $l_O$ to the softmax function to make it a predicted probability vector $\hat{v}_{t+c}$ for a context word at the position $c$.
5. Calculate the error between $\hat{v}_{t+c}$ and the one-hot vector of “animal”; $[1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0]$.
6. Propagate the error back to the network to update the parameters.
3.7.5 4. Implementation of Skip-gram in Chainer

There is an example of Word2vec in the official repository of Chainer, so we will explain how to implement Skip-gram based on this: examples/word2vec

4.1 Preparation

First, let’s import necessary packages:

```python
import argparse
import collections
import os
import six
import warnings
import numpy as np
import chainer
from chainer.backends import cuda
import chainer.functions as F
import chainer.initializers as I
import chainer.links as L
import chainer.optimizers as O
from chainer import reporter
```

4.2 Define a Skip-gram model

Next, let’s define a network for Skip-gram.

```python
class SkipGram(chainer.Chain):
    """Definition of Skip-gram Model""
    def __init__(self, n_vocab, n_units, loss_func):
        super(SkipGram, self).__init__()
        with self.init_scope():
            self.embed = L.EmbedID(n_vocab, n_units, initialW=I.Uniform(1. / n_units))
            self.loss_func = loss_func

    def forward(self, x, contexts):
        e = self.embed(contexts)
        batch_size, n_context, n_units = e.shape
        x = F.broadcast_to(x[:, None], (batch_size, n_context))
        e = F.reshape(e, (batch_size * n_context, n_units))
        x = F.reshape(x, (batch_size * n_context,))
        loss = self.loss_func(e, x)
        reporter.report({'loss': loss}, self)
        return loss
```

3.7. Word2Vec: Obtain word embeddings
Listing 25: train_word2vec.py

class SoftmaxCrossEntropyLoss(chainer.Chain):
    """Softmax cross entropy loss function preceded by linear transformation."
    """
    def __init__(self, n_in, n_out):
        super(SoftmaxCrossEntropyLoss, self).__init__()
        with self.init_scope():
            self.out = L.Linear(n_in, n_out, initialW=0)
    def forward(self, x, t):
        return F.softmax_cross_entropy(self.out(x), t)

Note:

• The weight matrix self.embed.W is the embedding matrix for input vector x.

• The function call forward takes the word ID of a center word x and word IDs of context words contexts as inputs, and outputs the error calculated by the loss function loss_func SoftmaxCrossEntropyLoss.

• Note that the initial shape of x and contexts are (batch_size,) and (batch_size, n_context), respectively.

• The batch_size means the size of mini-batch, and n_context means the number of context words.

First, we obtain the embedding vectors of contexts by e = self.embed(contexts). Then F
broadcast_to(x[:, None], (batch_size, n_context)) performs broadcasting of x (its shape is
(batch_size,)) to (batch_size, n_context) by copying the same value n_context time to fill the
second axis, and then the broadcasted x is reshaped into 1-D vector (batchsize * n_context,) while e is re-
shaped to (batch_size + n_context, n_units). In Skip-gram model, predicting a context word from the
center word is the same as predicting the center word from a context word because the center word is always a context
word when considering the context word as a center word. So, we create batch_size * n_context center word predictions by applying self.out linear layer to the embedding vectors of context words. Then, calculate softmax
cross entropy between the broadcasted center word ID x and the predictions.

4.3 Prepare dataset and iterator

Let’s retrieve the Penn Tree Bank (PTB) dataset by using Chainer’s dataset utility get_ptb_words() method.

train, val, _ = chainer.datasets.get_ptb_words()
counts = collections.Counter(train)

Then define an iterator to make mini-batches that contain a set of center words with their context words. train and
val means training data and validation data. Each data contains the list of Document IDs:

>>> train
array([ 0,  1,  2, ..., 39, 26, 24], dtype=int32)

>>> val
array([2211, 396, 1129, ..., 108, 27, 24], dtype=int32)
class WindowIterator(chainer.dataset.Iterator):
    '''Dataset iterator to create a batch of sequences at different positions.
    This iterator returns a pair of the current words and the context words.
    '''
    def __init__(self, dataset, window, batch_size, repeat=True):
        self.dataset = np.array(dataset, np.int32)
        self.window = window  # size of context window
        self.batch_size = batch_size
        self._repeat = repeat
        # order is the array which is shuffled \[window, window + 1, \ldots,  
        # len(dataset) - window - 1]\`
        self.order = np.random.permutation(
            len(dataset) - window * 2).astype(np.int32)
        self.order += window
        self.current_position = 0
        # Number of completed sweeps over the dataset. In this case, it is
        # incremented if every word is visited at least once after the last
        # increment.
        self.epoch = 0
        # True if the epoch is incremented at the last iteration.
        self.is_new_epoch = False
    def __next__(self):
        '''This iterator returns a list representing a mini-batch.
        Each item indicates a different position in the original sequence.
        '''
        if not self._repeat and self.epoch > 0:
            raise StopIteration
        i = self.current_position
        i_end = i + self.batch_size
        position = self.order[i:i_end]
        w = np.random.randint(self.window - 1) + 1
        offset = np.concatenate([np.arange(-w, 0), np.arange(1, w + 1)])
        pos = position[:, None] + offset[None, :]
        contexts = self.dataset.take(pos)
        center = self.dataset.take(position)

        if i_end >= len(self.order):
            np.random.shuffle(self.order)
            self.epoch += 1
            self.is_new_epoch = True
            self.current_position = 0
        else:
            self.is_new_epoch = False
            self.current_position = i_end

        return center, contexts

@property
    def epoch_detail(self):
        return self.epoch + float(self.current_position) / len(self.order)

(continues on next page)
def serialize(self, serializer):
    self.current_position = serializer('current_position',
                                       self.current_position)
    self.epoch = serializer('epoch', self.epoch)
    self.is_new_epoch = serializer('is_new_epoch', self.is_new_epoch)
    if self.order is not None:
        serializer('order', self.order)

• In the constructor, we create an array self.order which denotes shuffled indices of [window, window + 1, ..., len(dataset) - window - 1] in order to choose a center word randomly from dataset in a mini-batch.

• The iterator definition __next__ returns batch_size sets of center word and context words.

• The code self.order[i:i_end] returns the indices for a set of center words from the random-ordered array self.order. The center word IDs center at the random indices are retrieved by self.dataset.take.

• np.concatenate([np.arange(-w, 0), np.arange(1, w + 1)]) creates a set of offsets to retrieve context words from the dataset.

• The code position[:, None] + offset[None, :] generates the indices of context words for each center word index in position. The context word IDs context are retrieved by self.dataset.take.

4.4 Prepare model, optimizer, and updater

Listing 27: train_word2vec.py

```python
model = SkipGram(n_vocab, args.unit, loss_func)
```

Listing 28: train_word2vec.py

```python
optimizer = O.Adam()
optimizer.setup(model)
```

Listing 29: train_word2vec.py

```python
train_iter = WindowIterator(train, args.window, args.batchsize)
val_iter = WindowIterator(val, args.window, args.batchsize, repeat=False)

# Set up an updater
updater = training.updaters.StandardUpdater(
    train_iter, optimizer, converter=convert, device=device)
```

Listing 30: train_word2vec.py

```python
trainer = training.Trainer(updater, (args.epoch, 'epoch'), out=args.out)

trainer.extend(extensions.Evaluator(
    val_iter, model, converter=convert, device=device))
trainer.extend(extensions.LogReport())
trainer.extend(extensions.PrintReport((
```
trainer.extend(extensions.ProgressBar())

trainer.extend(
    extensions.snapshot(filename='snapshot_epoch_{.updater.epoch}'),
    trigger=(args.snapshot_interval, 'epoch'))

if args.resume is not None:
    chainer.serializers.load_npz(args.resume, trainer)
trainer.run()

### 4.5 Start training

```
$ pwd
/root2chainer/chainer/examples/word2vec
$ python train_word2vec.py --test # run by test mode. If you want to use all data, remove "--test".
GPU: -1
# unit: 100
Window: 5
Minibatch-size: 1000
# epoch: 20
Training model: skipgram
Output type: hsm

n_vocab: 10000
data length: 100
epoch  main/loss  validation/main/loss
1     4233.75   2495.33
2     1411.14   4990.66
3     4233.11   1247.66
4     2821.66   4990.65
5     4231.94   1247.66
6     5642.04   2495.3
7     5640.82   4990.64
8     5639.31   2495.28
9     2817.89   4990.62
10    1408.03   3742.94
11    5633.11   1247.62
12    4221.71   2495.21
13    4219.3    4990.56
14    4216.57   2495.16
15    4213.52   2495.12
16    5616.03   1247.55
17    5611.34   3742.78
18    2800.31   3742.74
19    1397.79   2494.95
20    2794.1    3742.66
```

### 3.7. Word2Vec: Obtain word embeddings
4.5 Search the similar words

```bash
$ pwd
/root2chainer/chainer/examples/word2vec
$ python search.py
>> apple
query: apple
compaq: 0.6169619560241699
chip: 0.49579331278800964
retailer: 0.4904134273529053
maker: 0.4684058427810669
computer: 0.4652436673641205
>> animal
query: animal
beauty: 0.5680124759674072
human: 0.5404794216156006
insulin: 0.5365156531333923
cell: 0.5186758041381836
photographs: 0.5077002048492432
```

3.7.6 5. Reference

- [2] Distributional Hypothesis

3.8 Write a Sequence to Sequence (seq2seq) Model

3.8.1 0. Introduction

The sequence to sequence (seq2seq) model[1][2] is a learning model that converts an input sequence into an output sequence. In this context, the sequence is a list of symbols, corresponding to the words in a sentence. The seq2seq model has achieved great success in fields such as machine translation, dialogue systems, question answering, and text summarization. All of these tasks can be regarded as the task to learn a model that converts an input sequence into an output sequence.

3.8.2 1. Basic Idea of Seq2seq Model

1.1 Overview of Seq2seq Model

The Notations of Sequence

The seq2seq model converts an input sequence into an output sequence. Let the input sequence and the output sequence be $X$ and $Y$. The $i$-th element of the input sequence is represented as $x_i$, and the $j$-th element of the output sequence is also represented as $y_j$. Generally, each of the $x_i$ and the $y_j$ is the one-hot vector of the symbols. For example, in natural language processing (NLP), the one-hot vector represents the word and its size becomes the vocabulary size.

Let’s think about the seq2seq model in the context of NLP. Let the vocabulary of the inputs and the outputs be $V^{(s)}$ and $V^{(t)}$, all the elements $x_i$ and $y_j$ satisfy $x_i \in \mathbb{R}^{|V^{(s)}|}$ and $y_i \in \mathbb{R}^{|V^{(t)}|}$. The input sequence $X$ and the output sequence...
\( Y \) are represented as the following equations:

\[
X = (x_1, \ldots, x_I) = (x_i)_{i=1}^I \\
Y = (y_1, \ldots, y_J) = (y_j)_{j=1}^J
\]

\( I \) and \( J \) are the length of the input sequence and the output sequence. Using the typical NLP notation, \( y_0 \) is the one-hot vector of \( BOS \), which is the virtual word representing the beginning of the sentence, and \( y_{J+1} \) is that of \( EOS \), which is the virtual word representing the end of the sentence.

**The Notations of Conditional Probability** \( P(Y \mid X) \)

Next, let’s think about the conditional probability \( P(Y \mid X) \) generating the output sequence \( Y \) when the input sequence \( X \) is given. The purpose of seq2seq model is modeling the probability \( P(Y \mid X) \). However, the seq2seq model does not model the probability \( P(Y \mid X) \) directly. Actually, it models the probability \( P(y_j \mid Y_{<j}, X) \), which is the probability of generating the \( j \)-th element of the output sequence \( y_j \) given the \( Y_{<j} \) and \( X \). \( Y_{<j} \) means the output sequence from 1 to \( j - 1 \), or \((y_j)_{j=1}^{j-1}\). In this notation, you can write the model \( P_\theta(Y \mid X) \) with the product of \( P_\theta(y_j \mid Y_{<j}, X) \):

\[
P_\theta(Y \mid X) = \prod_{j=1}^{J+1} P_\theta(y_j \mid Y_{<j}, X)
\]

**Processing Steps in Seq2seq Model**

Now, let’s think about the processing steps in seq2seq model. The feature of seq2seq model is that it consists of the two processes:

1. The process that generates the fixed size vector \( z \) from the input sequence \( X \)
2. The process that generates the output sequence \( Y \) from \( z \)

In other words, the information of \( X \) is conveyed by \( z \), and \( P_\theta(y_j \mid Y_{<j}, X) \) is actually calculated by \( P_\theta(y_j \mid Y_{<j}, z) \).

First, we represent the process which generating \( z \) from \( X \) by the function \( \Lambda \):

\[
z = \Lambda(X)
\]

The function \( \Lambda \) may be the recurrent neural net such as LSTMs.

Second, we represent the process which generating \( Y \) from \( z \) by the following formula:

\[
P_\theta(y_j \mid Y_{<j}, X) = \Upsilon(h_j^{(t)} , y_j) \\
h_j^{(t)} = \Psi(h_{j-1}^{(t)} , y_{j-1})
\]

\( \Psi \) is the function to generate the hidden vectors \( h_j^{(t)} \), and \( \Upsilon \) is the function to calculate the generative probability of the one-hot vector \( y_j \). When \( j = 1 \), \( h_{j-1}^{(t)} \) or \( h_0^{(t)} \) is \( z \) generated by \( \Lambda(X) \), and \( y_{j-1} \) or \( y_0 \) is the one-hot vector of \( BOS \).
1.2 Model Architecture of Seq2seq Model

In this section, we describe the architecture of seq2seq model. To simplify the explanation, we use the most basic architecture. The architecture of seq2seq model can be separated to the five major roles.

1. Encoder Embedding Layer
2. Encoder Recurrent Layer
3. Decoder Embedding Layer
4. Decoder Recurrent Layer
5. Decoder Output Layer

The encoder consists of two layers: the embedding layer and the recurrent layer, and the decoder consists of three layers: the embedding layer, the recurrent layer, and the output layer.

In the explanation, we use the following symbols:
1.2.1 Encoder Embedding Layer

The first layer, or the encoder embedding layer converts the each word in the input sentence to the embedding vector. When processing the $i$-th word in the input sentence, the input and the output of the layer are the following:

- The input is $x_i$: the one-hot vector which represents $i$-th word
- The output is $\bar{x}_i$: the embedding vector which represents $i$-th word

Each embedding vector is calculated by the following equation:

$$\bar{x}_i = E^{(s)}x_i$$

$E^{(s)} \in \mathbb{R}^{D \times |V^{(s)}|}$ is the embedding matrix of the encoder.

1.2.2 Encoder Recurrent Layer

The encoder recurrent layer generates the hidden vectors from the embedding vectors. When processing the $i$-th embedding vector, the input and the output of the layer are the following:

- The input is $\bar{x}_i$: the embedding vector which represents the $i$-th word
- The output is $h_i^{(s)}$: the hidden vector of the $i$-th position

For example, when using the uni-directional RNN of one layer, the process can be represented as the following function $\Psi^{(s)}$:

$$h_i^{(s)} = \Psi^{(s)}(\bar{x}_i, h_{i-1}^{(s)})$$

$$= \tanh \left( W^{(s)} \begin{bmatrix} h_{i-1}^{(s)} \\ \bar{x}_i \end{bmatrix} + b^{(s)} \right)$$

In this case, we use the $\tanh$ as the activation function.

---

### Symbol Table

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H$</td>
<td>the size of the hidden vector</td>
</tr>
<tr>
<td>$D$</td>
<td>the size of the embedding vector</td>
</tr>
<tr>
<td>$x_i$</td>
<td>the one-hot vector of $i$-th word in the input sentence</td>
</tr>
<tr>
<td>$\bar{x}_i$</td>
<td>the embedding vector of $i$-th word in the input sentence</td>
</tr>
<tr>
<td>$E^{(s)}$</td>
<td>Embedding matrix of the encoder</td>
</tr>
<tr>
<td>$h_i^{(s)}$</td>
<td>the $i$-th hidden vector of the encoder</td>
</tr>
<tr>
<td>$y_j$</td>
<td>the one-hot vector of $j$-th word in the output sentence</td>
</tr>
<tr>
<td>$\bar{y}_j$</td>
<td>the embedding vector of $j$-th word in the output sentence</td>
</tr>
<tr>
<td>$E^{(t)}$</td>
<td>Embedding matrix of the decoder</td>
</tr>
<tr>
<td>$h_j^{(t)}$</td>
<td>the $j$-th hidden vector of the decoder</td>
</tr>
</tbody>
</table>
1.2.3 Decoder Embedding Layer

The decoder embedding layer converts each word in the output sentence to the embedding vector. When processing the \( j \)-th word in the output sentence, the input and the output of the layer are the following:

- The input is \( y_{j-1} \): the one-hot vector which represents the \((j - 1)\)-th word generated by the decoder output layer
- The output is \( \bar{y}_j \): the embedding vector which represents the \((j - 1)\)-th word

Each embedding vector is calculated by the following equation:

\[
\bar{y}_j = E(t) y_{j-1}
\]

\( E(t) \in \mathbb{R}^{D \times |\mathcal{V}(t)|} \) is the embedding matrix of the encoder.

1.2.4 Decoder Recurrent Layer

The decoder recurrent layer generates the hidden vectors from the embedding vectors. When processing the \( j \)-th embedding vector, the input and the output of the layer are the following:

- The input is \( \bar{y}_j \): the embedding vector
- The output is \( h_j(t) \): the hidden vector of \( j \)-th position

For example, when using the uni-directional RNN of one layer, the process can be represented as the following function \( \Psi(t) \):

\[
\begin{align*}
    h_j(t) &= \Psi(t)(\bar{y}_j, h_{j-1}(t)) \\
    &= \tanh \left( W(t) \left[ \bar{y}_j h_{j-1}(t) \right] + b(t) \right)
\end{align*}
\]

In this case, we use the \( \tanh \) as the activation function. And we must use the encoder’s hidden vector of the last position as the decoder’s hidden vector of first position as following:

\[
h_0(t) = z = h_s
\]

1.2.5 Decoder Output Layer

The decoder output layer generates the probability of the \( j \)-th word of the output sentence from the hidden vector. When processing the \( j \)-th embedding vector, the input and the output of the layer are the following:

- The input is \( h_j(t) \): the hidden vector of \( j \)-th position
- The output is \( p_j \): the probability of generating the one-hot vector \( y_j \) of the \( j \)-th word

\[
p_j = P_\theta(y_j|Y_{<j}) = \text{softmax}(o_j) \cdot y_j
\]

\[
= \text{softmax}(W_o h_j(t) + b(\theta)) \cdot y_j
\]

Note: There are a lot of varieties of seq2seq models. We can use the different RNN models in terms of: (1) directionality (unidirectional or bidirectional), (2) depth (single-layer or multi-layer), (3) type (a vanilla RNN, a Long Short-term Memory (LSTM), or a gated recurrent unit (GRU)), and (4) additional functionality (s.t. Attention Mechanism).
3.8.3 2. Implementation of Seq2seq Model

The official Chainer repository includes a neural machine translation example using the seq2seq model. We will now provide an overview of the example and explain its implementation in detail. [chainer/examples/seq2seq](https://github.com/chainer/chainer/tree/master/examples/seq2seq)

### 2.1 Model Overview

In this simple example, an input sequence is processed by a stacked **LSTM-RNN** (long short-term memory recurrent neural networks) and it is encoded as a fixed-size vector. The output sequence is also processed by another stacked LSTM-RNN. At decoding time, an output sequence is generated using argmax.

### 2.2 Step-by-step Implementation

#### 2.2.1 Import Package

First, let’s import necessary packages.

Listing 31: seq2seq.py

```python
import io
from nltk.translate import bleu_score
```

---

3.8. Write a Sequence to Sequence (seq2seq) Model 121
import numpy
import progressbar
import six
import chainer
import chainer.functions as F
import chainer.links as L
from chainer import training

2.2.2 Define Training Settings

Define all training settings here.

Listing 32: seq2seq.py

```python
parser.add_argument('SOURCE', help='source sentence list')
parser.add_argument('TARGET', help='target sentence list')
parser.add_argument('SOURCE_VOCAB', help='source vocabulary file')
parser.add_argument('TARGET_VOCAB', help='target vocabulary file')
parser.add_argument('--validation-source',
    help='source sentence list for validation')
parser.add_argument('--validation-target',
    help='target sentence list for validation')
parser.add_argument('--batchsize', '-b', type=int, default=64,
    help='number of sentence pairs in each mini-batch')
parser.add_argument('--epoch', '-e', type=int, default=20,
    help='number of sweeps over the dataset to train')
parser.add_argument('--resume', '-r', type=str,
    help='resume the training from snapshot')
parser.add_argument('--save', '-s', type=str,
    help='save a snapshot of the training')
parser.add_argument('--unit', '-u', type=int, default=1024,
    help='number of units')
parser.add_argument('--layer', '-l', type=int, default=3,
    help='number of layers')
parser.add_argument('--use-dataset-api', default=False,
    action='store_true',
    help='use TextDataset API to reduce CPU memory usage')
parser.add_argument('--min-source-sentence', type=int, default=1,
    help='minimum length of source sentence')
parser.add_argument('--max-source-sentence', type=int, default=50,
    help='maximum length of source sentence')
parser.add_argument('--min-target-sentence', type=int, default=1,
    help='minimum length of target sentence')
parser.add_argument('--max-target-sentence', type=int, default=50,
    help='maximum length of target sentence')
parser.add_argument('--log-interval', type=int, default=200,
    help='number of iteration to show log')
parser.add_argument('--validation-interval', type=int, default=4000,
    help='number of iteration to evaluate the model with validation dataset')
parser.add_argument('--device', '-d', type=str, default='-1',
    help='Device specifier. Either ChainerX device specifier or an integer. If non-negative integer, CuPy arrays with specified device id are used. If
```
2.2.3 Define Network Structure

The Chainer implementation of seq2seq is shown below. It implements the model depicted in the above figure.

Listing 33: seq2seq.py

```python
class Seq2seq(chainer.Chain):
    def __init__(self, n_layers, n_source_vocab, n_target_vocab, n_units):
        super(Seq2seq, self).__init__()
        with self.init_scope():
            self.embed_x = L.EmbedID(n_source_vocab, n_units)
            self.embed_y = L.EmbedID(n_target_vocab, n_units)
            self.encoder = L.NStepLSTM(n_layers, n_units, n_units, 0.1)
            self.decoder = L.NStepLSTM(n_layers, n_units, n_units, 0.1)
            self.W = L.Linear(n_units, n_target_vocab)

            self.n_layers = n_layers
            self.n_units = n_units

    def forward(self, xs, ys):
        xs = [x[::-1] for x in xs]
        eos = self.xp.array([EOS], numpy.int32)
        ys_in = [F.concat([eos, y], axis=0) for y in ys]
        ys_out = [F.concat([y, eos], axis=0) for y in ys]

        # Both xs and ys_in are lists of arrays.
        exs = sequence_embed(self.embed_x, xs)
        eys = sequence_embed(self.embed_y, ys_in)

        batch = len(xs)
        # None represents a zero vector in an encoder.
        hx, cx, _ = self.encoder(None, None, exs)
        _, _, os = self.decoder(hx, cx, eys)

        # It is faster to concatenate data before calculating loss
        # because only one matrix multiplication is called.
        concat_os = F.concat(os, axis=0)
        concat_ys_out = F.concat(ys_out, axis=0)
        loss = F.sum(F.softmax_cross_entropy(self.W(concat_os), concat_ys_out, reduce='no')) / batch

        chainer.report({'loss': loss}, self)
        n_words = concat_ys_out.shape[0]
        perp = self.xp.exp(loss.array * batch / n_words)
        chainer.report({'perp': perp}, self)
```

3.8. Write a Sequence to Sequence (seq2seq) Model
return loss

```python
def translate(self, xs, max_length=100):
    batch = len(xs)
    with chainer.no_backprop_mode(), chainer.using_config('train', False):
        xs = [x[::-1] for x in xs]
        exs = sequence_embed(self.embed_x, xs)
        h, c, _ = self.encoder(None, None, exs)
        ys = self.xp.full(batch, EOS, numpy.int32)
        result = []
        for i in range(max_length):
            eys = self.embed_y(ys)
            eys = F.split_axis(eys, batch, 0)
            h, c, ys = self.decoder(h, c, eys)
            cys = F.concat(ys, axis=0)
            wy = self.W(cys)
            ys = self.xp.argmax(wy.array, axis=1).astype(numpy.int32)
            result.append(ys)

    result = chainer.get_device('@numpy').send(
        self.xp.concatenate([x[:, None, :] for x in result]).T)
    # Remove EOS tags
    outs = []
    for y in result:
        inds = numpy.argwhere(y == EOS)
        if len(inds) > 0:
            y = y[:inds[0, 0]]
        outs.append(y)
    return outs
```

• In Seq2seq, three functions are defined: the constructor `__init__`, the function call `forward`, and the function for translation `translate`.

Listing 34: seq2seq.py

```python
def __init__(self, n_layers, n_source_vocab, n_target_vocab, n_units):
    super(Seq2seq, self).__init__()
    with self.init_scope():
        self.embed_x = L.EmbedID(n_source_vocab, n_units)
        self.embed_y = L.EmbedID(n_target_vocab, n_units)
        self.encoder = L.NStepLSTM(n_layers, n_units, n_units, 0.1)
        self.decoder = L.NStepLSTM(n_layers, n_units, n_units, 0.1)
        self.W = L.Linear(n_units, n_target_vocab)

    self.n_layers = n_layers
    self.n_units = n_units
```

• When we instantiate this class for making a model, we give the number of stacked lstms to `n_layers`, the vocabulary size of the source language to `n_source_vocab`, the vocabulary size of the target language to `n_target_vocab`, and the size of hidden vectors to `n_units`.

• This network uses `chainer.links.NStepLSTM`, `chainer.links.EmbedID`, and `chainer.links.Linear` as its building blocks. All the layers are registered and initialized in the context with `self.init_scope()`.
• You can access all the parameters in those layers by calling `self.params()`.

• In the constructor, it initializes all parameters with values sampled from a uniform distribution $U(-1, 1)$.

Listing 35: seq2seq.py

```python
def forward(self, xs, ys):
    xs = [x[::-1] for x in xs]

    eos = self.xp.array([EOS], numpy.int32)
    ys_in = [F.concat([eos, y], axis=0) for y in ys]
    ys_out = [F.concat([y, eos], axis=0) for y in ys]

    # Both xs and ys_in are lists of arrays.
exs = sequence_embed(self.embed_x, xs)
ey = sequence_embed(self.embed_y, ys_in)

    batch = len(xs)
    # None represents a zero vector in an encoder.
    hx, cx, _ = self.encoder(None, None, exs)
    _, _, os = self.decoder(hx, cx, eys)

    # It is faster to concatenate data before calculating loss
    # because only one matrix multiplication is called.
    concat_os = F.concat(os, axis=0)
    concat_ys_out = F.concat(ys_out, axis=0)
    loss = F.sum(F.softmax_cross_entropy(self.W(concat_os), concat_ys_out, reduce='no')) / batch
    chainer.report({'loss': loss}, self)

    n_words = concat_ys_out.shape[0]
    perp = self.xp.exp(loss.array * batch / n_words)
    chainer.report({'perp': perp}, self)
    return loss
```

• The `forward` method takes sequences of source language’s word IDs `xs` and sequences of target language’s word IDs `ys`. Each sequence represents a sentence, and the size of `xs` is mini-batch size.

• Note that the sequences of word IDs `xs` and `ys` are converted to a vocabulary-size one-hot vectors and then multiplied with the embedding matrix in `sequence_embed` to obtain embedding vectors `exs` and `eys`.

Listing 36: seq2seq.py

```python
def sequence_embed(embed, xs):
    x_len = [len(x) for x in xs]
    x_section = numpy.cumsum(x_len[:-1])
ex = embed(F.concat(xs, axis=0))
exs = F.split_axis(ex, x_section, 0)
return exs
```

• `self.encoder` and `self.decoder` are the encoder and the decoder of the seq2seq model. Each element of the decoder output `os` is $h^{(t)}_{i:[J]}$ in the figure above.

• After calculating the recurrent layer output, the loss `loss` and the perplexity `perp` are calculated, and the values are logged by `chainer.report`.

Note: It is well known that the seq2seq model learns much better when the source sentences are reversed. The paper[1] says that “While the LSTM is capable of solving problems with long term dependencies, we discovered that

3.8. Write a Sequence to Sequence (seq2seq) Model
the LSTM learns much better when the source sentences are reversed (the target sentences are not reversed). By doing so, the LSTM’s test perplexity dropped from 5.8 to 4.7, and the test BLEU scores of its decoded translations increased from 25.9 to 30.6.” So, at the first line in the forward, the input sentences are reversed $xs = [x[:::-1] \text{ for } x \text{ in } xs]$.

Listing 37: seq2seq.py

```python
def translate(self, xs, max_length=100):
    batch = len(xs)
    with chainer.no_backprop_mode(), chainer.using_config('train', False):
        xs = [x[:::-1] for x in xs]
        exs = sequence_embed(self.embed_x, xs)
        h, c, _ = self.encoder(None, None, exs)
        ys = self.xp.full(batch, EOS, numpy.int32)
        result = []
        for i in range(max_length):
            eys = self.embed_y(ys)
            eys = F.split_axis(eys, batch, 0)
            h, c, ys = self.decoder(h, c, eys)
            cys = F.concat(ys, axis=0)
            wy = self.W(cys)
            ys = self.xp.argmax(wy.array, axis=1).astype(numpy.int32)
            result.append(ys)
        result = chainer.get_device('@numpy').send(
            self.xp.concatenate([x[None, :] for x in result]).T)
        # Remove EOS tags
        outs = []
        for y in result:
            inds = numpy.argwhere(y == EOS)
            if len(inds) > 0:
                y = y[:inds[0, 0]]
            outs.append(y)
    return outs
```

- After the model learned the parameters, the function `translate` is called to generate the translated sentences `outs` from the source sentences `xs`.
- So as not to change the parameters, the codes for the translation are nested in the scope `chainer.no_backprop_mode()` and `chainer.using_config('train', False)`.

2.2.4 Load French-English Corpus from WMT15 Dataset

In this tutorial, we use French-English corpus from WMT15 website that contains $10^9$ documents. We must prepare additional libraries, dataset, and parallel corpus. To understand the pre-processing, see 2.3.1 Requirements.

After the pre-processing the dataset, let’s make dataset objects:

Listing 38: seq2seq.py

```python
# Load pre-processed dataset
print('[[/]] Loading dataset... (this may take several minutes)'.format(
(continues on next page)
datetime.datetime.now()))
source_ids = load_vocabulary(args.SOURCE_VOCAB)
target_ids = load_vocabulary(args.TARGET_VOCAB)

if args.use_dataset_api:
    # By using TextDataset, you can avoid loading whole dataset on memory.
    # This significantly reduces the host memory usage.
    def _filter_func(s, t):
        sl = len(s.strip().split())  # number of words in source line
        tl = len(t.strip().split())  # number of words in target line
        return (args.min_source_sentence <= sl <= args.max_source_sentence
                and args.min_target_sentence <= tl <= args.max_target_sentence)

    train_data = load_data_using_dataset_api(
        source_ids, args.SOURCE,
        target_ids, args.TARGET,
        _filter_func,
    )
else:
    # Load all records on memory.
    train_source = load_data(source_ids, args.SOURCE)
    train_target = load_data(target_ids, args.TARGET)
    assert len(train_source) == len(train_target)

    train_data = [
        (s, t)
        for s, t in six.moves.zip(train_source, train_target)
        if (args.min_source_sentence <= len(s) <= args.max_source_sentence
            and args.min_target_sentence <= len(t) <= args.max_target_sentence)
    ]

print('[{}{}] Dataset loaded.'.format(datetime.datetime.now()))

if not args.use_dataset_api:
    # Skip printing statistics when using TextDataset API, as it is slow.
    train_source_unknown = calculate_unknown_ratio([s for s, _ in train_data])
    train_target_unknown = calculate_unknown_ratio([t for _, t in train_data])

    print('Source vocabulary size: %d' % len(source_ids))
    print('Target vocabulary size: %d' % len(target_ids))
    print('Train data size: %d' % len(train_data))
    print('Train source unknown ratio: %2.2f%%' % (train_source_unknown * 100))
    print('Train target unknown ratio: %2.2f%%' % (train_target_unknown * 100))

    target_words = {i: w for w, i in target_ids.items()}
    source_words = {i: w for w, i in source_ids.items()}

• This code uses utility functions below:
Listing 39: seq2seq.py

def load_vocabulary(path):
    with io.open(path, encoding='utf-8') as f:
        # +2 for UNK and EOS
        word_ids = {line.strip(): i + 2 for i, line in enumerate(f)}
    word_ids['<UNK>'] = 0
    word_ids['<EOS>'] = 1
    return word_ids

Listing 40: seq2seq.py

def load_data(vocabulary, path):
    n_lines = count_lines(path)
    bar = progressbar.ProgressBar()
    data = []
    print('loading...: %s' % path)
    with io.open(path, encoding='utf-8') as f:
        for line in bar(f, max_value=n_lines):
            words = line.strip().split()
            array = numpy.array([vocabulary.get(w, UNK) for w in words], numpy.int32)
            data.append(array)
    return data

Listing 41: seq2seq.py

def calculate_unknown_ratio(data):
    unknown = sum((s == UNK).sum() for s in data)
    total = sum(s.size for s in data)
    return unknown / total

2.2.5 Define Evaluation Function (Bleu Score)

BLEU[3] (bilingual evaluation understudy) is the evaluation metric for the quality of text which has been machine-translated from one natural language to another.

Listing 42: seq2seq.py

class CalculateBleu(chainer.training.Extension):
    trigger = 1, 'epoch'
    priority = chainer.training.PRIORITY_WRITER

    def __init__(self, model, test_data, key, device, batch=100, max_length=100):
        self.model = model
        self.test_data = test_data
        self.key = key
        self.batch = batch
        self.device = device
        self.max_length = max_length

    def __call__(self, trainer):
        (continues on next page)
device = self.device

with chainer.no_backprop_mode():
    references = []
    hypotheses = []
    for i in range(0, len(self.test_data), self.batch):
        sources, targets = zip(*self.test_data[i:i + self.batch])
        references.extend([[t.tolist()] for t in targets])

        sources = [device.send(x) for x in sources]
        ys = [y.tolist() for y in self.model.translate(sources, self.max_length)]
        hypotheses.extend(ys)

    bleu = bleu_score.corpus_bleu(
        references, hypotheses,
        smoothing_function=bleu_score.SmoothingFunction().method1)
    chainer.report({self.key: bleu})

2.2.6 Create Iterator

Here, the code below just creates iterator objects.

Listing 43: seq2seq.py

    train_iter = chainer.iterators.SerialIterator(train_data, args.batchsize)

2.2.7 Create RNN and Classification Model

Instantiate Seq2seq model.

Listing 44: seq2seq.py

    model = Seq2seq(args.layer, len(source_ids), len(target_ids), args.unit)

2.2.8 Setup Optimizer

Prepare an optimizer. We use chainer.optimizers.Adam.
optimizer = chainer.optimizers.Adam()
optimizer.setup(model)

2.2.9 Setup and Run Trainer

Let’s make a trainer object.

updater = training.updaters.StandardUpdater(
    train_iter, optimizer, converter=convert, device=device)
trainer = training.Trainer(updater, (args.epoch, 'epoch'), out=args.out)
trainer.extend(extensions.LogReport(
    trigger=(args.log_interval, 'iteration')))
trainer.extend(extensions.PrintReport(
    ['epoch', 'iteration', 'main/loss', 'main/perp',
     'validation/main/bleu', 'elapsed_time']),
    trigger=(args.log_interval, 'iteration'))
trainer.extend(
    extensions.snapshot(filename='snapshot_epoch_{.updater.iteration}'),
    trigger=(args.validation_interval, 'iteration'))

Setup the trainer’s extension to see the BLEU score on the test data.

@chainer.training.make_extension()
def translate(trainer):
    source, target = test_data[numpy.random.choice(len(test_data))]
    result = model.translate([model.xp.array(source)])[0]

    source_sentence = ' '.join([source_words[x] for x in source])
    target_sentence = ' '.join([target_words[y] for y in target])
    result_sentence = ' '.join([target_words[y] for y in result])
print('# source : ' + source_sentence)
print('# result : ' + result_sentence)
print('# expect : ' + target_sentence)

trainer.extend(
    translate, trigger=(args.validation_interval, 'iteration'))
trainer.extend(
    CalculateBleu(
        model, test_data, 'validation/main/bleu', device),
        trigger=(args.validation_interval, 'iteration'))

if args.resume is not None:
    # Resume from a snapshot
    chainer.serializers.load_npz(args.resume, trainer)

Let's start the training!

Listing 48: seq2seq.py

trainer.run()

if args.save is not None:
    # Save a snapshot
    chainer.serializers.save_npz(args.save, trainer)

2.3 Run Example

2.3.1 Requirements

Before running the example, you must prepare additional libraries, dataset, and parallel corpus.

- See the detail description: chainer/examples/seq2seq/README.md

2.3.1 Training the model

You can train the model with the script: chainer/examples/seq2seq/seq2seq.py

$ pwd
/root2chainer/chainer/examples/seq2seq
$ python seq2seq.py --gpu=0 giga-fren.preprocess.en giga-fren.preprocess.fr \ vocab.en vocab.fr \ --validation-source newstest2013.preprocess.en \ --validation-target newstest2013.preprocess.fr > log

100% (22520376 of 22520376) |#############| Elapsed Time: 0:09:20 Time: 0:09:20
100% (22520376 of 22520376) |#############| Elapsed Time: 0:10:36 Time: 0:10:36
100% (3000 of 3000) |#####################| Elapsed Time: 0:00:00 Time: 0:00:00
100% (3000 of 3000) |#####################| Elapsed Time: 0:00:00 Time: 0:00:00

epoch | iteration | main/loss | validation/main/loss | main/perp | validation/main/perp | validation/main/bleu | elapsed_time
0     | 200       | 171.449   | 991.556              | 85.6739   |
Note: Before running the script, be careful the locale and the python’s encoding. Please setup them to use utf-8 encoding.

### 2.3.1 Validate the model

While you are training the model, you can get the validation results:

```plaintext
... # source: We knew the Government had tried many things, like launching <UNK> with 
˓→<UNK> or organising speed dating evenings.
# result: Nous savions que le gouvernement avait <UNK> plusieurs fois, comme le 
˓→<UNK> <UNK>, le <UNK> ou le <UNK> <UNK>
# expect: Nous savions que le gouvernement avait tenté plusieurs choses comme lancer 
˓→des parfums aux <UNK> ou organiser des soirées de <UNK>
...```

### 3.8.4 3. Reference

- [1] Sequence to Sequence Learning with Neural Networks
- [3] BLEU
## 4.1 Variable and Parameter

### 4.1.1 Variable classes and utilities

<table>
<thead>
<tr>
<th>Class/Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.Variable</code></td>
<td>Array with a structure to keep track of computation.</td>
</tr>
<tr>
<td><code>chainer.as_array</code></td>
<td>Returns the underlying array from a variable or an array.</td>
</tr>
<tr>
<td><code>chainer.as_variable</code></td>
<td>Converts an array or a variable into Variable.</td>
</tr>
<tr>
<td><code>chainer.backward</code></td>
<td>Runs backpropagation from variables simultaneously.</td>
</tr>
<tr>
<td><code>chainer.Parameter</code></td>
<td>Parameter variable that can be registered to a link.</td>
</tr>
<tr>
<td><code>chainer.variable.VariableNode</code></td>
<td>Node in the backward computational graph representing a variable.</td>
</tr>
</tbody>
</table>

### chainer.Variable

```python
class chainer.Variable(data=None, *, name=None, grad=None, requires_grad=True)
```

Array with a structure to keep track of computation.

Every variable holds a data array of type either `numpy.ndarray` or `cupy.ndarray`.

A variable object holds a data array and a `VariableNode` object of a computational graph. If the variable is constructed by the user, the node is `root` and does not hold any parent. If the variable is constructed by a `FunctionNode` object (i.e., by calling functions under `chainer.functions` or user-defined functions), or by using operators (see the list below), the node holds a reference to its parent called `creator_node`. This reference is used in backpropagation to backtrack the graph.

Users can disable (resp. enable) this chaining behavior by calling `no_backprop_mode()` (resp. `force_backprop_mode()`). In the former context, a variable never creates a computational graph, whereas in the latter context, it is forced to create.

**Note:** The following operators are defined for variable(s).

- Indexing: `a[slices]` (`__getitem__()`)
- Addition: `a + b` (`__add__(), __radd__()`)
- Subtraction: `a - b` (`__sub__(), __rsub__()`)
- Multiplication: `a * b` (`__mul__(), __rmul__()`)
- Division: `a / b` (`__div__(), __rdiv__(), __truediv__(), __rtruediv__()`)
- Floor Division: `a // b` (`__floordiv__(), __rfloordiv__()`)


• Exponentiation: \( a \times b \) \(_\text{pow}()\), \(_r\text{pow}()\)
• Matrix Multiplication: \( a \times b \) \(_\text{matmul}()\), \(_r\text{matmul}()\)
• Negation (Arithmetic): \(-a\) \(_\text{neg}()\)
• Absolute value: \(\text{abs}(a)\) \(_\text{abs}()\)

Parameters

• **data** (*N-dimensional array*) – Initial data array.
• **name** (*str*) – Name of the variable.
• **grad** (*N-dimensional array*) – Initial gradient array.
• **requires_grad** (*bool*) – Boolean indicating whether \(\text{grad}\) will be set in backward calculation.

Methods

\_\_getitem\_\_(slices)
Extract elements from array with specified shape, axes and offsets.

Parameters

• **x** (*Variable or N-dimensional array*) – A variable to be sliced.
• **slices** (*int, slice, Ellipsis, None, integer array-like, boolean array-like or tuple of them*) – An object to specify the selection of elements.

Returns A \text{Variable} object which contains sliced array of \(x\).

**Note:** It only supports types that are supported by CUDA’s atomicAdd when an integer array is included in \(\text{slices}\). The supported types are \text{numpy.float32}, \text{numpy.int32}, \text{numpy.uint32}, \text{numpy.uint64} and \text{numpy.ulonglong}.

**Note:** It does not support \(\text{slices}\) that contains multiple boolean arrays.

**Note:** See NumPy documentation for details of \textit{indexing}.

Example

```python
>>> x = np.arange(12).reshape((2, 2, 3))
>>> x
array([[[ 0,  1,  2],
       [ 3,  4,  5]],
       [[ 6,  7,  8],
       [ 9, 10, 11]]])
>>> F.get_item(x, 0)
variable([[0, 1, 2],
          [3, 4, 5]],
          grad=None, requires_grad=False)
```

(continues on next page)
[3, 4, 5])
>>> F.get_item(x, (0, 0, slice(0, 2, 1)))  # equals x[0, 0, 0:2:1]
variable([0, 1])
>>> F.get_item(x, (Ellipsis, 2))  # equals x[..., 2]
variable([[2, 5],
         [8, 11]])
>>> F.get_item(x, (1, np.newaxis, 1, 0))  # equals x[1, None, 1, 0]
variable([9])

__len__()
Returns the first dimension of the data array.

Returns  Number of the first dimension of the data array.

Return type  int

__copy__()

addgrad(var)
Accumulates the gradient array from given source variable.

This method adds the gradient of a given variable to the gradient of this variable. The accumulation is even
done across the host and different devices. If this variable has uninitialized data/grad arrays, this method
initializes it with the shape of the given variable and then accumulates the gradient.

Parameters

• var  (Variable) – Source variable.

as_layout(layout)
backward(retain_grad=False, enable_double_backprop=False, loss_scale=None)
Runs error backpropagation (a.k.a. backprop) from this variable.

On backprop, FunctionNode.backward() is called on each FunctionNode object appearing in
the backward graph starting from this variable. The backward graph is represented by backward references
from variable nodes to their creators, and from function nodes to their input variable nodes. The backprop
stops at all root nodes. Some function nodes set None as gradients of some inputs, where further backprop
does not take place at such inputs.

This method uses grad as the initial error array. User can manually set a gradient array before calling this
method. If the shape of data is () (i.e., it is scalar) and grad is None, then this method automatically
complements 1.0 as the initial error. This is useful on starting backprop from some scalar loss value.

From v3, this method supports differentiable backprop (a.k.a. double backprop, grad of grads). To enable
it, pass enable_double_backprop=True.

Parameters

• retain_grad (bool) – If True, the gradient arrays of all intermediate variables are kept. Otherwise, grad of the intermediate variables are set to None on appropriate timing, which may reduce the maximum memory consumption.

In most cases of training some models, the purpose of backprop is to compute gradients of parameters, not of all variables, and therefore it is recommended that this flag be set to False.

• enable_double_backprop (bool) – (Added in v3.0) If True, computational trace of the whole backpropagation procedure is recorded to the computational graph so that one can further do backpropagation from the resulting gradients. Note that enabling it results in larger memory consumption needed to store the gradients w.r.t intermediate variables that are required for the second gradient computation.
• **loss_scale** *(float)* – Loss scaling factor. Loss scaling is a useful technique to mitigate vanishing gradient issue that tends to happen when low precision data type like float16 is used during training. If you set loss scaling factor, gradients of loss values are to be multiplied by the factor before backprop starts. The factor is propagated to whole gradients in a computational graph along the backprop. The gradients of parameters are divided by the factor just before the parameters are to be updated.

**cleargrad()**
Clears the gradient array.

**copydata (var)**
Copies the data array from given source variable.

This method copies the data array from given variable to this variable. The copy is done even if the arrays reside on different devices, including across the host and a GPU device. If this variable has an uninitialized data array, this method initializes it by the data array of the given variable. Similarly, if the given variable has an uninitialized data array, this method initializes it by the data array of this variable *(self)*. If both are uninitialized, this method does nothing.

**Parameters**

- **var** *(Variable)* – Source variable.

**debug_print()**
Display a summary of the stored data and location of the Variable

**from_chx()**
Converts the array and gradient to non-ChainerX arrays without copy.

This method converts the underlying ChainerX array and gradient residing in either a *native* or *cuda* device to NumPy or CuPy arrays respectively, on their same physical device. It does nothing if the array held by the Variable object is not a ChainerX array. The new array is a view of the original one.

Raises an error if such a conversion is not supported for the device.

**item()**
Converts the variable with one element to a Python scalar.

This will incur host-device synchronization.

**Returns**
The element of the array.

**Return type**
int or float

**mean (axis=None, *, weights=None, keepdims=False)**
Calculate weighted average of array elements over a given axis.

**See also:**

- `chainer.functions.average()` for full documentation,

**reshape (*shape)**
Returns a variable of a different shape and the same content.

**See also:**

- `chainer.functions.reshape()` for full documentation,

**retain_data()**
Lets the corresponding variable node keep the underlying array.

**set_creator (gen_func)**
Notifies the variable that the given function is its creator.

**Parameters**

- **gen_func** *(Function)* – Function object that creates this variable as one of its outputs.
set_creator_node (fnode)
   Notifies the variable that the given node is its creator.

   Parameters fnode (FunctionNode) – Function node that has this variable as an output.

summary ()

to_chx ()
   Converts the array and gradient to ChainerX arrays without copy.
   This method converts the underlying array and gradient to chainerx.ndarray on the same physical
device. It does nothing if the array held by the Variable object is already a ChainerX array. The new array
is a view of the original one.

to_cpu ()
   Copies the data and gradient arrays to CPU.

to_device (device)
   Copies the data and gradient arrays to specified device.

   Parameters device – Target device specifier. See get_device() for available values.

to_gpu (device=None)
   Copies the data and gradient arrays to specified GPU.

   Parameters device – Target device specifier. If omitted, the current device is used.

to_intel64 ()
   Copies the data and gradient arrays to intel64 specific mdarray.
   If the array is not suited for intel64, it will be converted to numpy.ndarray.

transpose (*axes)
   Permute the dimensions of an input variable without copy.

   See also:
   chainer.functions.transpose() for full documentation.

unchain ()
   Deletes the reference to the creator of this variable.

   This method deletes the reference to the creator from the corresponding variable node. Unlike
unchain_backward(), it does not backtrack the graph.

   This method is equivalent to self.creator_node = None.

unchain_backward ()
   Deletes references between variable nodes and functions backward.

   After this method completes, intermediate variable nodes and functions that are not referenced from any-
where are deallocated by reference count GC. Also this variable itself deletes the reference to its creator
function from the node, i.e. the node becomes root in the computation graph. It indicates that backprop
after unchaining stops at this variable. This behavior is useful to implement truncated BPTT.

zerograd ()
   Initializes the gradient array by zeros.

   Note that the gradient variable is unchained from the computational graph by this method, because this
operation breaks the backprop validity.

   Deprecated since version v1.15: Use more efficient cleargrads() instead.

   __eq__ (other)
   This operator is not supported in Variables.
__ne__(other)
This operator is not supported in Variables.

__lt__(other)
This operator is not supported in Variables.

__le__(other)
This operator is not supported in Variables.

__gt__(other)
This operator is not supported in Variables.

__ge__(other)
This operator is not supported in Variables.

__nonzero__()  
This operator is not supported in Variables.

__bool__()  
This operator is not supported in Variables.

__neg__()  
Element-wise negation.

    Returns  Output variable.
    Return type  Variable

__abs__()  
Element-wise absolute.

    Returns  Output variable.
    Return type  Variable

__add__()  
Element-wise addition.

    Returns  Output variable.
    Return type  Variable

__radd__()  
Element-wise addition.

    Returns  Output variable.
    Return type  Variable

__sub__(rhs)  
Element-wise subtraction.

    Returns  Output variable.
    Return type  Variable

__rsub__(rhs)  
Element-wise subtraction.

    Returns  Output variable.
    Return type  Variable

__mul__(rhs)  
Element-wise multiplication.

    Returns  Output variable.
Return type  Variable

`__rmul__(rhs)`
Element-wise multiplication.

Returns  Output variable.

Return type  Variable

`__div__(rhs)`
Element-wise division

Returns  Output variable.

Return type  Variable

`__truediv__(rhs)`
Element-wise division

Returns  Output variable.

Return type  Variable

`__rdiv__(rhs)`
Element-wise division.

Returns  Output variable.

Return type  Variable

`__rtruediv__(rhs)`
Element-wise division.

Returns  Output variable.

Return type  Variable

`__floordiv__(rhs)`
Element-wise floor division.

Returns  Output variable.

Return type  Variable

`__rfloordiv__(rhs)`
Element-wise floor division.

Returns  Output variable.

Return type  Variable

`__pow__(rhs)`
Element-wise power function.

Returns  Output variable.

Return type  Variable

`__rpow__(rhs)`
Element-wise power function.

Returns  Output variable.

Return type  Variable

`__matmul__(rhs)`
Matrix multiplication.
Returns Output variable.

Return type Variable

__rmatmul__(rhs)
Matrix multiplication.

Returns Output variable.

Return type Variable

Attributes

T
Transposition of this variable.

array
The underlying data array.

It is either numpy.ndarray or cupy.ndarray object, or None if the variable in an uninitialised state.

chx_array
A view of the raw ChainerX array.

In contrary to Variable.array which is always disconnected, the array represented by this attribute may be connected to the computational graph.

It is a view, so it has a distinct gradient from the original array.

If this attribute is queried on a Variable with a non-ChainerX array, ValueError will be raised.

creator
Function implementation that created this variable.

When this variable has been created by an old-style function (i.e., it is implemented as a subclass of Function), this property returns that Function object.

When this variable has been created by a new-style function (i.e., it is implemented as a subclass of FunctionNode class), this property returns that node object.

creator_node
FunctionNode object that created this variable.

This property has a setter to which None can be set. Setting None to this property is equivalent to call unchain(); it purges the variable from the function that created this variable.

The setter also accepts the original FunctionNode object that created this variable. For example, you can once set None to this property and then set the original value again.

Note: Setting an irrelevant FunctionNode() object does not emit any error immediately, whereas the behavior is undefined. Do not set a FunctionNode() object that did not create this variable object.

data
The underlying data array (equivalent to array).

Note that using this attribute directly is discouraged; use array instead. Using array, you can find an error earlier when your code mixes up Variable and ndarray because ndarray does not have an attribute .array while it has .data.
device
Device on which the data array of this variable reside.

dtype

grad
Gradient array of this variable.

Note that this property returns the underlying array of the gradient variable instead of the gradient variable itself; to get/set gradient variable, use `grad_var` instead.

If the underlying array is a `chainerx.ndarray` and requires_grad is false, trying to access the gradient will results in an error.

grad_var
Gradient variable.

label
Short text that represents the variable.

layout

name

ndim

node

rank

raw_array
The underlying raw data array.

Its shape does not have to be the semantic shape, if the memory layout is non-standard.

requires_grad
It indicates that `grad` will be set in backward calculation.

shape

size

xp
Array module for the data array of this variable.

chainer.as_array

chainer.as_array(obj)
Returns the underlying array from a variable or an array.

This is a convenient function to get the underlying array object transparently from an object that could be either a variable or an array.

Parameters

obj \((N\text{-dimensional array} \text{ or } \sim chainer.Variable)\) – An array or a variable.

Returns
The underlying array object of the argument.

Return type
\(N\text{-dimensional array} \text{ or } \sim chainer.Variable\)
chainer.as_variable

chainer.as_variable(obj)

Converts an array or a variable into Variable.

This is a convenient function to get a Variable object transparently from a raw array or a variable.

Note that this function should only be used for type consistency (i.e., to enforce the return value of an API having type Variable). The requires_grad flag is kept as is; if obj is a raw array, the newly created variable has requires_grad = False. In order to make a variable w.r.t. which you want to compute the gradient, you should use Variable directly.

Parameters  
obj (N-dimensional array or ~chainer.Variable) – An array or a variable that you want to convert to Variable.

Returns  
A variable converted from obj. If obj is a raw array, this is a new Variable object that wraps the array. If obj is already a Variable object, this function returns obj as is.

Return type  
Variable

chainer.backward

chainer.backward(outputs, grad_outputs=None, *, enable_double_backprop=False)

Runs backpropagation from variables simultaneously.

Warning: This feature is experimental. The interface can change in the future.

Parameters

- outputs (tuple or list of Variable) – A sequence of output variables from which backprop starts.
- grad_outputs (None or tuple or list of Variable) – A sequence of variables that gives the initial value of each output gradient. If this argument is None, backprop uses grad_var of outputs.
- enable_double_backprop (bool) – If True, computational trace of the whole backpropagation procedure is recorded to the computational graph so that one can further do backpropagation from the resulting gradients. Note that enabling it results in larger memory consumption needed to store the gradients w.r.t intermediate variables that are required for the second gradient computation.

See also:

chainer.Variable.backward() chainer.grad()
chainer.Parameter

class chainer.Parameter(initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None, shape: Optional[Union[int, Sequence[int]]] = None, name: Optional[str] = None, *, layout=None)

Parameter variable that can be registered to a link.

Parameter is a subclass of Variable. It almost behaves as same as a usual variable except that a parameter can be registered to a Link object just by assigning it to an attribute of the link within an init_scope() context.

Parameter also supports an initialization by an initializer. It can have two initializers: one for the data array, and the other for the gradient array. The initializer only specifies the way of filling the elements of these arrays, and the shape information is specified at the initialization point.

When a link that the parameter has been registered to is passed to an GradientMethod, an update rule is set to the parameter. This update rule specifies how to update the data array of the parameter using its gradient array.

Parameters

- **initializer** (chainer.Initializer or N-dimensional array) – Initializer of the data array. If shape is given, this initializer is immediately used to initialize the data array. Otherwise, if it is an array, it is immediately used as the data array, and otherwise the data array is left uninitialized and will be initialized by this initializer in initialize(). It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.
- **shape** (int or tuple of int or None) – Shape of the parameter. If it is None, the initialization is deferred to the call of initialize().
- **name** (str) – Name of the parameter.

Variables

- **initializer** – Initializer of the data array. It is used for initializing the data array of an uninitialized variable.
- **update_rule** – UpdateRule instance that updates this variable as a parameter. This argument is set to update_rule.

Methods

__getitem__(slices)

Extract elements from array with specified shape, axes and offsets.

Parameters

- **x** (Variable or N-dimensional array) – A variable to be sliced.
- **slices** (int, slice, Ellipsis, None, integer array-like, boolean array-like or tuple of them) – An object to specify the selection of elements.

Returns A Variable object which contains sliced array of x.

Note: It only supports types that are supported by CUDA’s atomicAdd when an integer array is included.
in slices. The supported types are `numpy.float32`, `numpy.int32`, `numpy.uint32`, `numpy.uint64` and `numpy.ulonglong`.

**Note:** It does not support slices that contains multiple boolean arrays.

**Note:** See NumPy documentation for details of indexing.

### Example

```python
>>> x = np.arange(12).reshape((2, 2, 3))
>>> x
array([[ 0,  1,  2],
       [ 3,  4,  5],
       [ 6,  7,  8],
       [ 9, 10, 11]])
>>> F.get_item(x, 0)
variable([[ 0,  1,  2],
          [ 3,  4,  5]])
>>> F.get_item(x, (0, 0, slice(0, 2, 1)))  # equals x[0, 0, 0:2:1]
variable([0, 1])
>>> F.get_item(x, (Ellipsis, 2))  # equals x[..., 2]
variable([[ 2,  5],
          [ 8, 11]])
>>> F.get_item(x, (1, np.newaxis, 1, 0))  # equals x[1, None, 1, 0]
variable([9])
```

__len__()

Returns the first dimension of the data array.

**Returns** Number of the first dimension of the data array.

**Return type** int

__copy__()

addgrad(var)

Accumulates the gradient array from given source variable.

This method adds the gradient of a given variable to the gradient of this variable. The accumulation is even done across the host and different devices. If this variable has uninitialized data/grad arrays, this method initializes it with the shape of the given variable and then accumulates the gradient.

**Parameters** var (Variable) – Source variable.

as_layout (layout)

backward,retain_grad=False, enable_double_backprop=False, loss_scale=None)

Runs error backpropagation (a.k.a. backprop) from this variable.

On backprop, `FunctionNode.backward()` is called on each `FunctionNode` object appearing in the backward graph starting from this variable. The backward graph is represented by backward references from variable nodes to their creators, and from function nodes to their input variable nodes. The backprop stops at all root nodes. Some function nodes set `None` as gradients of some inputs, where further backprop does not take place at such inputs.
This method uses `grad` as the initial error array. User can manually set a gradient array before calling this method. If the shape of `data` is () (i.e., it is scalar) and `grad` is `None`, then this method automatically complements 1.0 as the initial error. This is useful on starting backprop from some scalar loss value.

From v3, this method supports differentiable backprop (a.k.a. double backprop, grad of grads). To enable it, pass `enable_double_backprop=True`.

**Parameters**

- **retain_grad (bool)** – If `True`, the gradient arrays of all intermediate variables are kept. Otherwise, `grad` of the intermediate variables are set to `None` on appropriate timing, which may reduce the maximum memory consumption. In most cases of training some models, the purpose of backprop is to compute gradients of parameters, not of all variables, and therefore it is recommended that this flag be set to `False`.

- **enable_double_backprop (bool)** – (Added in v3.0) If `True`, computational trace of the whole backpropagation procedure is recorded to the computational graph so that one can further do backpropagation from the resulting gradients. Note that enabling it results in larger memory consumption needed to store the gradients w.r.t intermediate variables that are required for the second gradient computation.

- **loss_scale (float)** – Loss scaling factor. Loss scaling is a useful technique to mitigate vanishing gradient issue that tends to happen when low precision data type like float16 is used during training. If you set loss scaling factor, gradients of loss values are to be multiplied by the factor before backprop starts. The factor is propagated to whole gradients in a computational graph along the backprop. The gradients of parameters are divided by the factor just before the parameters are to be updated.

**cleargrad ()**
Clears the gradient array.

**copydata (var)**
Copies the data array from given source variable.

This method copies the data array from given variable to this variable. The copy is done even if the arrays reside on different devices, including across the host and a GPU device. If this variable has an uninitialized data array, this method initializes it by the data array of the given variable. Similarly, if the given variable has an uninitialized data array, this method initializes it by the data array of this variable (`self`). If both are uninitialized, this method does nothing.

**Parameters**

**var** (Variable) – Source variable.

**debug_print ()**
Display a summary of the stored data and location of the Variable

**from_chx ()**
Converts the array and gradient to non-ChainerX arrays without copy.

This method converts the underlying ChainerX array and gradient residing in either a native or cuda device to NumPy or CuPy arrays respectively, on their same physical device. It does nothing if the array held by the Variable object is not a ChainerX array. The new array is a view of the original one.

Raises an error if such a conversion is not supported for the device.

**initialize (shape)**
Initializes the uninitialized variable.

Uninitialized variable is a variable created with the data array set to `None`. This method creates and initializes the data array. The shape of the variable can be left unknown until this method is called.
Parameters shape (tuple of int) – Shape of the data array.

item()
Converts the variable with one element to a Python scalar.
This will incur host-device synchronization.

Returns The element of the array.

Return type int or float

mean (axis=None, *, weights=None, keepdims=False)
Calculate weighted average of array elements over a given axis.

See also: chainer.functions.average() for full documentation,

reshape (*shape)
Returns a variable of a different shape and the same content.

See also: chainer.functions.reshape() for full documentation,

retain_data()
Lets the corresponding variable node keep the underlying array.

set_creator (gen_func)
Notifies the variable that the given function is its creator.

Parameters gen_func (Function) – Function object that creates this variable as one of its
outputs.

set_creator_node (fnode)
Notifies the variable that the given node is its creator.

Parameters fnode (FunctionNode) – Function node that has this variable as an output.

summary()

to_chx()
Converts the array and gradient to ChainerX arrays without copy.
This method converts the underlying array and gradient to chainerx.ndarray on the same physical
device. It does nothing if the array held by the Variable object is already a ChainerX array. The new array
is a view of the original one.

to_cpu()
Copies the data and gradient arrays to CPU.

to_device (device)
Copies the data and gradient arrays to specified device.

Parameters device – Target device specifier. See get_device() for available values.

to_gpu (device=None)
Copies the data and gradient arrays to specified GPU.

Parameters device – Target device specifier. If omitted, the current device is used.

to_intel64()
Copies the data and gradient arrays to intel64 specific mdarray.
If the array is not suited for intel64, it will be converted to numpy.ndarray.
**transpose** (*axes*)

Permute the dimensions of an input variable without copy.

See also:

`chainer.functions.transpose()` for full documentation.

**unchain()**

Deletes the reference to the creator of this variable.

This method deletes the reference to the creator from the corresponding variable node. Unlike `unchain_backward()`, it does not backtrack the graph.

This method is equivalent to `self.creator_node = None`.

**unchain_backward()**

Deletes references between variable nodes and functions backward.

After this method completes, intermediate variable nodes and functions that are not referenced from anywhere are deallocated by reference count GC. Also this variable itself deletes the reference to its creator function from the node, i.e. the node becomes root in the computation graph. It indicates that backprop after unchaining stops at this variable. This behavior is useful to implement truncated BPTT.

**update()**

Updates the data array using the gradient and the update rule.

This method updates the parameter using the attached update rule.

**zerograd()**

Initializes the gradient array by zeros.

Note that the gradient variable is unchained from the computational graph by this method, because this operation breaks the backprop validity.

Deprecated since version v1.15: Use more efficient `cleargrads()` instead.

**__eq__(other)**

This operator is not supported in Variables.

**__ne__(other)**

This operator is not supported in Variables.

**__lt__(other)**

This operator is not supported in Variables.

**__le__(other)**

This operator is not supported in Variables.

**__gt__(other)**

This operator is not supported in Variables.

**__ge__(other)**

This operator is not supported in Variables.

**__nonzero__()**

This operator is not supported in Variables.

**__bool__()**

This operator is not supported in Variables.

**__neg__()**

Element-wise negation.

Returns Output variable.
Return type: `Variable`

__abs__ ()
Element-wise absolute.

Returns: Output variable.

Return type: `Variable`

__add__ ()
Element-wise addition.

Returns: Output variable.

Return type: `Variable`

__radd__ ()
Element-wise addition.

Returns: Output variable.

Return type: `Variable`

__sub__ (rhs)
Element-wise subtraction.

Returns: Output variable.

Return type: `Variable`

__rsub__ (rhs)
Element-wise subtraction.

Returns: Output variable.

Return type: `Variable`

__mul__ (rhs)
Element-wise multiplication.

Returns: Output variable.

Return type: `Variable`

__rmul__ (rhs)
Element-wise multiplication.

Returns: Output variable.

Return type: `Variable`

__div__ (rhs)
Element-wise division.

Returns: Output variable.

Return type: `Variable`

__truediv__ (rhs)
Element-wise division.

Returns: Output variable.

Return type: `Variable`

__rdiv__ (rhs)
Element-wise division.
Returns Output variable.
Return type Variable

____rtruediv____(rhs)
Element-wise division.

Returns Output variable.
Return type Variable

____floordiv____(rhs)
Element-wise floor division.

Returns Output variable.
Return type Variable

____rfloordiv____(rhs)
Element-wise floor division.

Returns Output variable.
Return type Variable

____pow____(rhs)
Element-wise power function.

Returns Output variable.
Return type Variable

____rpow____(rhs)
Element-wise power function.

Returns Output variable.
Return type Variable

____matmul____(rhs)
Matrix multiplication.

Returns Output variable.
Return type Variable

____rmatmul____(rhs)
Matrix multiplication.

Returns Output variable.
Return type Variable

Attributes

T
Transposition of this variable.

array
The underlying data array.

It is either numpy.ndarray or cupy.ndarray object, or None if the variable is in an uninitialized state.
**chx_array**
A view of the raw ChainerX array.

In contrary to `Variable.array` which is always disconnected, the array represented by this attribute may be connected to the computational graph.

It is a view, so it has a distinct gradient from the original array.

If this attribute is queried on a `Variable` with a non-ChainerX array, `ValueError` will be raised.

**creator**
Function implementation that created this variable.

When this variable has been created by an old-style function (i.e., it is implemented as a subclass of `Function`), this property returns that `Function` object.

When this variable has been created by a new-style function (i.e., it is implemented as a subclass of `FunctionNode` class), this property returns that node object.

**creator_node**
`FunctionNode` object that created this variable.

This property has a setter to which `None` can be set. Setting `None` to this property is equivalent to call `unchain()`: it purges the variable from the function that created this variable.

The setter also accepts the original `FunctionNode` object that created this variable. For example, you can once set `None` to this property and then set the original value again.

**data**
The underlying data array (equivalent to `array`).

Note that using this attribute directly is discouraged; use `array` instead. Using `array`, you can find an error earlier when your code mixes up Variable and ndarray because ndarray does not have an attribute `.array` while it has `.data`.

**device**
Device on which the data array of this variable reside.

**dtype**

**grad**
Gradient array of this variable.

Note that this property returns the underlying array of the gradient variable instead of the gradient variable itself; to get/set gradient variable, use `grad_var` instead.

If the underlying array is a `chainerx.ndarray` and requires_grad is false, trying to access the gradient will results in and error.

**grad_var**
Gradient variable.

**initializer = None**

**is_initialized**

**label**
Short text that represents the variable.

**layout**
name
ndim
node
rank
raw_array
The underlying raw data array.
Its shape does not have to be the semantic shape, if the memory layout is non-standard.
requires_grad
It indicates that grad will be set in backward calculation.
shape
size
xp
Array module for the data array of this variable.

chainer.variable.VariableNode
class chainer.variable.VariableNode(variable: chainer.variable.Variable, name: Optional[str], **kwargs: Any)
Node in the backward computational graph representing a variable.
This object represents a variable node in a computational graph. The node is used in error backpropagation (a.k.a. backprop) to determine which gradient to be passed to each function.
A variable node is held by the corresponding Variable object, which is managed by users. FunctionNode objects that take the variable as an input also hold references to the variable node.
Note that the node does not hold a reference to the corresponding data array in general. The data array is actually accessible by the node in the following cases.
1. If there exists a Variable object that holds a reference to the variable node, the variable node holds a weak reference to the variable object, and thus the data array is accessible via the weak reference.
2. If retain_data() is called, the node holds a reference to the data array. It is mainly called by a function that needs the input or output data array in its backprop procedure. See FunctionNode.retain_inputs() and FunctionNode.retain_outputs() for more details.
Users usually do not need to touch this variable node object. The computational graph is automatically managed by Chainer, and any interface that is beneficial for users is also provided by Variable.

Parameters
• variable (Variable) – The corresponding variable object.
• name (str) – Name of the variable node.

Variables
• dtype – Data type of the data array.
• shape – Shape of the data array.
• name (str) – Name of the variable node.
Methods

get_variable()
Returns the corresponding Variable object.

VariableNode object holds a weak reference of the variable object. If the reference is alive, it is returned by
this property. Otherwise, this property creates a new Variable object from this node object and returns
it.

Returns The variable object that refers this node.
Return type Variable

get_variable_or_none()
Returns the holding Variable object or None.

VariableNode object holds a weak reference of the variable object. If the reference is alive, it is returned by
this property. Otherwise, returns None.

Returns The variable object that refers this node.
Return type Variable

retain_data()
Lets the node hold a reference to the underlying data array.

This method gets the data array of the corresponding variable and keeps it. If the weak reference to the
corresponding variable is dead, it raises an error.

set_creator(creator)
Sets a Function object that created this node.

This method is equivalent to self.creator = creator. A FunctionNode object can also be
passed.

Parameters creator (Function or FunctionNode) – Function that has created this
variable.

set_creator_node(creator_node)
Sets a FunctionNode object that created this node.

This method is equivalent to self.creator_node = creator_node. A Function object can
also be passed, in which case the Function.node attribute is used.

Parameters creator_node (FunctionNode or Function) – Function node that has
this variable as an output.

unchain()
Deletes the reference to the creator of this variable node.

This method is equivalent to self.creator_node = None.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.
__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

creator
Function object that created this variable node.

When the function is implemented with the old-style API (i.e., it uses Function class), this property returns the Function object. The object is extracted from the FunctionAdapter object, so the returned object is not the function node, but instead the actual implementation of forward and backward procedures.

When the function is implemented with the new-style API (i.e., it uses FunctionNode class), this property returns the function node object. In this case, the returned object is same as creator_node.

Warning: As of v3.0.0, when the creator is an old-style function, the following code is invalid:

```python
creator = v.creator
v.creator = None
...
v.creator = creator
```

The point is that FunctionNode objects are used as nodes in the computational graph instead of Function, and each Function object only holds a weak reference to the corresponding FunctionNode. Since creator returns the Function object, the FunctionNode object is not kept by preserving creator.

The above code should be fixed as follows.

```python
creator_node = v.creator_node
v.creator_node = None
...
v.creator_node = creator_node
```

creator_node
Function node that has this variable as an output.

See FunctionNode for the definition of a function node.

data
Data array of the corresponding variable.

If the data is not available, it returns None.

dtype = None

g grad
Gradient array of the corresponding variable.

If the variable is not available, it returns None.

grad_var
Gradient variable of the corresponding variable.

If the corresponding variable is not available, it return None.
label
Short text that represents the variable node.

rank
requires_grad
It indicates that grad will be set in backward calculation.

shape = None

4.1.2 N-dimensional array

chainer.Variable holds its value as an n-dimensional array (ndarray). Chainer supports the following classes:

- numpy.ndarray, including ideep4py.mdarray
- cupy.ndarray
- chainerx.ndarray

Note: Python scalars (float, etc.) and NumPy scalars (numpy.float16, numpy.float32, etc.) cannot be used as chainer.Variable.array. See also chainer.utils.force_array().

4.2 Functions

Chainer provides variety of built-in function implementations in chainer.functions package. These functions usually return a Variable object or a tuple of multiple Variable objects. For a Variable argument of a function, an N-dimensional array can be passed if you do not need its gradient. Some functions additionally supports scalar arguments.

Note: Functions implemented in Chainer consists of the following two parts:

- A class that inherits FunctionNode, which defines forward/backward computation.
- A “wrapper” function around the class.

APIs listed in this page are “wrapper” of FunctionNode implementations. In most cases, you don’t have to use FunctionNode classes directly.

For example, chainer.functions.sum() is a wrapper function defined as def sum(...) in chainer/functions/math/sum.py, and it calls its corresponding FunctionNode implementation, Sum. Some functions may not have the corresponding FunctionNode implementation; one example is chainer.functions.average(), which is defined in chainer/functions/math/average.py, which calls other wrapper functions to calculate average.

If you are implementing your own functions, please see Define your own function.
4.2.1 Arithmetic functions

Basic arithmetic operations for Variables are implemented as operators. Refer to the Notes section of Variable for details.

chainer.functions.add() provides better performance when accumulating three or more Variables at once.

<table>
<thead>
<tr>
<th>chainer.functions.add</th>
<th>Element-wise addition.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>chainer.functions.add</strong> (<em>xs</em>)</td>
<td>Element-wise addition.</td>
</tr>
<tr>
<td><strong>Returns</strong></td>
<td>Output variable.</td>
</tr>
<tr>
<td><strong>Return type</strong></td>
<td>Variable</td>
</tr>
</tbody>
</table>

4.2.2 Activation functions

<table>
<thead>
<tr>
<th>chainer.functions.clipped_relu</th>
<th>Clipped Rectifier Unit function.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.functions.crelu</td>
<td>Concatenated Rectified Linear Unit function.</td>
</tr>
<tr>
<td>chainer.functions.elu</td>
<td>Exponential Linear Unit function.</td>
</tr>
<tr>
<td>chainer.functions.leaky_relu</td>
<td>Leaky Rectified Linear Unit function.</td>
</tr>
<tr>
<td>chainer.functions.log_softmax</td>
<td>Channel-wise log-softmax function.</td>
</tr>
<tr>
<td>chainer.functions.lstm</td>
<td>Long Short-Term Memory units as an activation function.</td>
</tr>
<tr>
<td>chainer.functions.maxout</td>
<td>Maxout activation function.</td>
</tr>
<tr>
<td>chainer.functions.prelu</td>
<td>Parametric ReLU function.</td>
</tr>
<tr>
<td>chainer.functions.relu</td>
<td>Rectified Linear Unit function.</td>
</tr>
<tr>
<td>chainer.functions.relu6</td>
<td>Rectifier Unit function clipped at 6.</td>
</tr>
<tr>
<td>chainer.functions.selu</td>
<td>Scaled Exponential Linear Unit function.</td>
</tr>
<tr>
<td>chainer.functions.sigmoid</td>
<td>Element-wise sigmoid logistic function.</td>
</tr>
<tr>
<td>chainer.functions.slstm</td>
<td>S-LSTM units as an activation function.</td>
</tr>
<tr>
<td>chainer.functions.softmax</td>
<td>Softmax function.</td>
</tr>
<tr>
<td>chainer.functions.softplus</td>
<td>Element-wise softplus function.</td>
</tr>
<tr>
<td>chainer.functions.swish</td>
<td>Swish activation function.</td>
</tr>
<tr>
<td>chainer.functions.tanh</td>
<td>Elementwise hyperbolic tangent function.</td>
</tr>
<tr>
<td>chainer.functions.tree_lstm</td>
<td>TreeLSTM unit as an activation function.</td>
</tr>
</tbody>
</table>
chainer.functions.clipped_relu

`chainer.functions.clipped_relu(x, z=20.0)`  
Clipped Rectifier Unit function.

For a clipping value $z > 0$, it computes

$$\text{ClippedReLU}(x, z) = \min(\max(0, x), z).$$

**Parameters**

- `x` (*Variable or N-dimensional array*) – Input variable. A $(s_1, s_2, ..., s_n)$-shaped float array.
- `z` (*float*) – Clipping value. (default = 20.0)

**Returns** Output variable. A $(s_1, s_2, ..., s_n)$-shaped float array.

**Return type** *Variable*

**Example**

```python
>>> x = np.random.uniform(-100, 100, (10, 20)).astype(np.float32)
>>> z = 10.0
>>> np.any(x < 0)
True
>>> np.any(x > z)
True
>>> y = F.clipped_relu(x, z=z)
>>> np.any(y.array < 0)
False
>>> np.any(y.array > z)
False
```

chainer.functions.crelu

`chainer.functions.crelu(x, axis=1)`  
Concatenated Rectified Linear Unit function.

This function is expressed as follows

$$f(x) = (\max(0, x), \max(0, -x)).$$

Here, two output values are concatenated along an axis.

See: https://arxiv.org/abs/1603.05201

**Parameters**

- `x` (*Variable or N-dimensional array*) – Input variable. A $(s_1, s_2, ..., s_n)$-shaped float array.
- `axis` (*int*) – Axis that the output values are concatenated along. Default is 1.

**Returns** Output variable of concatenated array. If the axis is 1, A $(s_1, s_2 \times 2, ..., s_n)$-shaped float array.
**Return type**  
*Variable*

**Example**

```python
>>> x = np.array([[-1, 0], [2, -3]], np.float32)
>>> x
array([[-1., 0.],
       [ 2., -3.]], dtype=float32)
>>> y = F.crelu(x, axis=1)
>>> y.array
array([[ 0.,  0.,  1.,  0.],
       [ 2.,  0.,  0.,  3.]], dtype=float32)
```

---

**chainer.functions.elu**

**chainer.functions.elu**(*x, alpha=1.0*)  
Exponential Linear Unit function.

For a parameter $\alpha$, it is expressed as

$$f(x) = \begin{cases} 
  x & \text{if } x \geq 0 \\
  \alpha(\exp(x) - 1) & \text{if } x < 0,
\end{cases}$$


**Parameters**

- *x* (*Variable* or *N-dimensional array*) – Input variable. A $(s_1, s_2, ..., s_N)$-shaped float array.
- *alpha* (*float*) – Parameter $\alpha$. Default is 1.0.

**Returns**  
Output variable. A $(s_1, s_2, ..., s_N)$-shaped float array.

**Return type**  
*Variable*

**Example**

```python
>>> x = np.array([[-1, 0], [2, -3]], np.float32)
>>> x
array([[-1., 0.],
       [ 2., -3.]], dtype=float32)
>>> y = F.elu(x, alpha=1.)
>>> y.array
array([[-0.63212055,  0.],
       [ 2.19889744, -0.95021296]], dtype=float32)
```
chainer.functions.hard_sigmoid

chainer.functions.hard_sigmoid(x)
Element-wise hard-sigmoid function.

This function is defined as

\[
    f(x) = \begin{cases} 
    0 & \text{if } x < -2.5 \\
    0.2x + 0.5 & \text{if } -2.5 < x < 2.5 \\
    1 & \text{if } 2.5 < x.
    \end{cases}
\]

Parameters

- `x` ([Variable or N-dimensional array]) – Input variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.

Returns

Output variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.

Return type [Variable]

Example

It maps the input values into the range of \([0, 1]\).

```python
>>> x = np.array([-2.6, -1, 0, 1, 2.6])
>>> x
array([-2.6, -1. ,  0. ,  1. ,  2.6])
>>> F.hard_sigmoid(x).array
array([ 0. ,  0.3,  0.5,  0.7,  1. ])
```

chainer.functions.leaky_relu

chainer.functions.leaky_relu(x, slope=0.2)
Leaky Rectified Linear Unit function.

This function is expressed as

\[
    f(x) = \begin{cases} 
    x & \text{if } x \geq 0 \\
    ax & \text{if } x < 0,
    \end{cases}
\]

where \(a\) is a configurable slope value.

Parameters

- `x` ([Variable or N-dimensional array]) – Input variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.
- `slope` (float) – Slope value \(a\).

Returns

Output variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.

Return type [Variable]

Example

```python
>>> x = np.array([[-1, 0], [2, -3], [-2, 1]], np.float32)
>>> x
array([[-1.,  0.],
       [ 2., -3.]])
```
chainer.functions.log_softmax

chainer.functions.log_softmax(x, axis=1)

Channel-wise log-softmax function.

This function computes its logarithm of softmax along the second axis. Let \( c = (c_1, c_2, \ldots, c_D) \) be the slice of \( x \) along with the second axis. For each slice \( c \), it computes the logarithm of the function \( f(c) \) defined as

\[
    f(c) = \frac{\exp(c)}{\sum_d \exp(c_d)}.
\]

This method is theoretically equivalent to \( \log(\text{softmax}(x)) \) but is more stable.

**Note:** \( \log(\text{softmax}(x)) \) may cause underflow when \( x \) is too small, because \( \text{softmax}(x) \) may return 0. log_softmax method is more stable.

**Parameters**

- x (*Variable* or *N-dimensional array*) – Input variable. A \( n \)-dimensional \((n \geq 2)\) float array.
- axis (*int*) – The axis along which the softmax is to be computed.

**Returns** Output variable. A \( n \)-dimensional \((n \geq 2)\) float array, which is the same shape with \( x \).

**Return type** *Variable*

**See also:**

softmax()

**Example**

```python
>>> x = np.array([[0, 1, 2], [0, 2, 4]], np.float32)
>>> x
array([[0., 1., 2.],
       [0., 2., 4.]], dtype=float32)
>>> F.log_softmax(x).array
array([[-2.407606 , -1.4076059 , -0.4076059 ],
       [-4.1429315 , -2.1429315 , -0.14293146]], dtype=float32)
>>> np.allclose(F.log_softmax(x).data, F.log(F.softmax(x)).data)
True
```
Long Short-Term Memory units as an activation function.

This function implements LSTM units with forget gates. Let the previous cell state `c_prev` and the input array `x`.

First, the input array `x` is split into four arrays `a, i, f, o` of the same shapes along the second axis. It means that `x`'s second axis must have 4 times the `c_prev`'s second axis.

The split input arrays are corresponding to:

- `a`: sources of cell input
- `i`: sources of input gate
- `f`: sources of forget gate
- `o`: sources of output gate

Second, it computes the updated cell state `c` and the outgoing signal `h` as:

\[
    c = \tanh(a)\sigma(i) + c_{prev}\sigma(f),
    h = \tanh(c)\sigma(o),
\]

where \(\sigma\) is the elementwise sigmoid function. These are returned as a tuple of two variables.

This function supports variable length inputs. The mini-batch size of the current input must be equal to or smaller than that of the previous one. When mini-batch size of `x` is smaller than that of `c`, this function only updates `c[0:len(x)]` and doesn't change the rest of `c`, `c[len(x):]`. So, please sort input sequences in descending order of lengths before applying the function.

**Parameters**

- `c_prev (Variable or N-dimensional array)` – Variable that holds the previous cell state. The cell state should be a zero array or the output of the previous call of LSTM.

- `x (Variable or N-dimensional array)` – Variable that holds the sources of cell input, input gate, forget gate and output gate. It must have the second dimension whose size is four times that of the cell state.

**Returns** Two `Variable` objects `c` and `h`. `c` is the updated cell state. `h` indicates the outgoing signal.

**Return type** tuple

See the original paper proposing LSTM with forget gates: Long Short-Term Memory in Recurrent Neural Networks.

**See also:**

- `LSTM`

**Example**

Assuming `y` is the current incoming signal, `c` is the previous cell state, and `h` is the previous outgoing signal from an `lstm` function. Each of `y, c` and `h` has `n_units` channels. Most typical preparation of `x` is:

```python
>>> n_units = 100
>>> y = chainer.Variable(np.zeros((1, n_units), np.float32))
>>> h = chainer.Variable(np.zeros((1, n_units), np.float32))
```
>>> c = chainer.Variable(np.zeros((1, n_units), np.float32))
>>> model = chainer.Chain()
>>> with model.init_scope():
...    model.w = L.Linear(n_units, 4 * n_units)
...    model.v = L.Linear(n_units, 4 * n_units)
>>> x = model.w(y) + model.v(h)
>>> c, h = F.lstm(c, x)

It corresponds to calculate the input array $x$, or the input sources $a, i, f, o$, from the current incoming signal $y$ and the previous outgoing signal $h$. Different parameters are used for different kind of input sources.

---

**Note:** We use the naming rule below.

- **incoming signal**  The formal input of the formulation of LSTM (e.g. in NLP, word vector or output of lower RNN layer). The input of `chainer.links.LSTM` is the **incoming signal**.
- **input array**  The array which is linear transformed from **incoming signal** and the previous outgoing signal. The **input array** contains four sources, the sources of cell input, input gate, forget gate and output gate. The input of `chainer.functions.activation.lstm.LSTM` is the **input array**.

---

**chainer.functions.maxout**

**chainer.functions.maxout**$(x, pool_size, axis=1)$  
Maxout activation function.

It accepts an input tensor $x$, reshapes the $axis$ dimension (say the size being $M \times pool\_size$) into two dimensions $(M, pool\_size)$, and takes maximum along the $axis$ dimension.

**Parameters**

- **x** *(Variable or N-dimensional array)*  – Input variable. A $n$-dimensional ($n \geq axis$) float array. In general, its first dimension is assumed to be the *minibatch dimension*. The other dimensions are treated as one concatenated dimension.
- **pool_size** *(int)*  – The size used for downsampling of pooling layer.
- **axis** *(int)*  – The $axis$ dimension to be reshaped. The size of $axis$ dimension should be $M \times pool\_size$.

**Returns**  Output variable. The shape of the output is same as $x$ except that $axis$ dimension is transformed from $M \times pool\_size$ to $M$.

**Return type**  *Variable*

**See also:**

Maxout

**Example**

Typically, $x$ is the output of a linear layer or a convolution layer. The following is the example where we use `maxout()` in combination with a Linear link.
>>> in_size, out_size, pool_size = 10, 10, 10
>>> bias = np.arange(out_size * pool_size).astype(np.float32)
>>> l = L.Linear(in_size, out_size * pool_size, initial_bias=bias)
>>> x = np.zeros((1, in_size), np.float32)  # prepare data
>>> x = l(x)
>>> y = F.maxout(x, pool_size)
>>> x.shape
(1, 100)
>>> y.shape
(1, 10)
>>> x.reshape((out_size, pool_size)).array
array([[ 0.,  1.,  2.,  3.,  4.,  5.,  6.,  7.,  8.,  9.],
       [40., 41., 42., 43., 44., 45., 46., 47., 48., 49.],
       [50., 51., 52., 53., 54., 55., 56., 57., 58., 59.],
       [60., 61., 62., 63., 64., 65., 66., 67., 68., 69.],
       [70., 71., 72., 73., 74., 75., 76., 77., 78., 79.],
       [80., 81., 82., 83., 84., 85., 86., 87., 88., 89.],
       [90., 91., 92., 93., 94., 95., 96., 97., 98., 99.]],
       dtype=float32)
>>> y.array
       dtype=float32)

chainer.functions.prelu

chainer.functions.prelu(x, W)

Parametric ReLU function.

It accepts two arguments: an input x and a weight array W and computes the output as

\[
PReLU(x_i) = \begin{cases} 
    x_i & (x_i > 0) \\
    W_i \times x_i & (\text{otherwise})
\end{cases}
\]

Parameters

- **x** (*Variable* or *N-dimensional array*) – Input variable. Its first axis is assumed to be the minibatch dimension.

- **W** (*Variable* or *N-dimensional array*) – Weight variable.

Returns  Output variable

Return type  Variable

Example

```python
>>> x = np.arange(-3, 3, dtype=np.float32).reshape((2, 3))
>>> x
array([[-3., -2., -1.],
       [ 0.,  1.,  2.]], dtype=float32)
>>> W = np.array([0.01, 0.1, 1], dtype=np.float32)
>>> W
array([0.01, 0.1 , 1. ], dtype=float32)
>>> F.prelu(x, W)
```
variable([[[-0.03, -0.2, -1.], [0., 1., 2.]]])

**Note:** When the PReLU function is combined with two-dimensional convolution, the elements of parameter \(W\) are typically shared across the same filter of different pixels. In order to support such usage, this function supports the shape of parameter array that indicates leading dimensions of input arrays except the batch dimension.

For example, if \(W\) has the shape of \((2, 3, 4)\), \(x\) must have the shape of \((B, 2, 3, 4, S_1, ..., S_N)\) where \(B\) is the batch size and the number of trailing \(S\)'s \(N\) is an arbitrary non-negative integer.

**Warning:** \(W\) is a trainable parameter in the original paper (https://arxiv.org/abs/1502.01852). To train \(W\), use `chainer.links.PReLU` instead.

See also:
`chainer.links.PReLU` to manage the model parameter \(W\).

**chainer.functions.rrelu**

`chainer.functions.rrelu(x, l=1.0/8, u=1.0/3, *, r=None, return_r=False)`

Randomized Leaky Rectified Liner Unit function.

This function is expressed as

\[
f(x) = \max(x, rx),
\]

where \(r\) is a random number sampled from a uniform distribution \(U(l, u)\).

**Note:** The \(r\) corresponds to \(a\) in the original paper (https://arxiv.org/pdf/1505.00853.pdf).

**Parameters**

- \(x\) (**Variable** or **N-dimensional array**) – Input variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.
- \(l\) (**float**) – The lower bound of the uniform distribution.
- \(u\) (**float**) – The upper bound of the uniform distribution.
- \(r\) (**N-dimensional array** or None) – The \(r\) to be used for rrelu. The shape and dtype must be the same as \(x[0]\) and should be on the same device. If \(r\) is not specified or set to None, an \(r\) will be generated randomly according to the given \(l\) and \(u\). If \(r\) is specified, \(l\) and \(u\) will be ignored.
- \(\text{return}_r\) (**bool**) – If True, the \(r\) used for rrelu is returned altogether with the output variable. The returned \(r\) can latter be reused by passing it to \(r\) argument.

**Returns** When \(\text{return}_r\) is False (default), return the output variable. Otherwise returns the tuple of the output variable and \(r\) (**N-dimensional array**). The \(r\) will be on the same device as the input. A \((s_1, s_2, ..., s_N)\)-shaped float array.
Return type  Variable or tuple

Example

```python
>>> x = np.array([[-1, 0], [2, -3], [-2, 1]], np.float32)
>>> x
array([[-1., 0.],
       [ 2., -3.],
       [-2., 1.]], dtype=float32)
>>> F.relu(x).array
array([[-0.24850948, 0.],
       [ 2., -0.50844127],
       [-0.598535 , 1.]], dtype=float32)
```

chainer.functions.relu

chainer.functions.relu(x)

Rectified Linear Unit function.

\[ f(x) = \max(0, x). \]

Parameters  

- **x** *(Variable or N-dimensional array)* – Input variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.

Returns  

Output variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.

Return type  Variable

Example

```python
>>> x = np.array([[-1, 0], [2, -3], [-2, 1]], np.float32)
>>> np.any(x < 0)
True
>>> y = F.relu(x)
>>> np.any(y.array < 0)
False
>>> y.shape
(3, 2)
```

chainer.functions.relu6

chainer.functions.relu6(x)

Rectifier Unit function clipped at 6.

It computes

\[ \text{ReLU6}(x) = \min(\max(0, x), 6). \]

Parameters  

- **x** *(Variable or N-dimensional array)* – Input variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.

Returns  

Output variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.
Return type  Variable

See also:

`chainer.functions.clipped_relu()`

Example

```python
>>> x = np.array([-20, -2, 0, 2, 4, 10, 100]).astype(np.float32)
>>> x
array([-20., -2., 0., 2., 4., 10., 100.], dtype=float32)
>>> F.relu6(x)
variable([0., 0., 0., 2., 4., 6., 6.])
```

`chainer.functions.selu`

`chainer.functions.selu(x, alpha=1.6732632423543772, scale=1.0507009873554805)`

Scaled Exponential Linear Unit function.

For parameters $\alpha$ and $\lambda$, it is expressed as

$$ f(x) = \lambda \begin{cases} 
    x & \text{if } x \geq 0 \\
    \alpha (\exp(x) - 1) & \text{if } x < 0, 
\end{cases} $$

See: https://arxiv.org/abs/1706.02515

Parameters

- `x` *(Variable or N-dimensional array)* – Input variable. A $(s_1, s_2, ..., s_N)$-shaped float array.
- `alpha` *(float)* – Parameter $\alpha$.
- `scale` *(float)* – Parameter $\lambda$.

Returns  Output variable. A $(s_1, s_2, ..., s_N)$-shaped float array.

Return type  Variable

`chainer.functions.sigmoid`

`chainer.functions.sigmoid(x)`

Element-wise sigmoid logistic function.

$$ f(x) = (1 + \exp(-x))^{-1}. $$

Parameters  

- `x` *(Variable or N-dimensional array)* – Input variable. A $(s_1, s_2, ..., s_N)$-shaped float array.

Returns  Output variable. A $(s_1, s_2, ..., s_N)$-shaped float array.

Return type  Variable

Example

It maps the input values into the range of $[0, 1]$.  

4.2. Functions  165
```python
>>> x = np.arange(-2, 3, 2).astype(np.float32)
>>> x
array([-2.,  0.,  2.], dtype=float32)
>>> F.sigmoid(x).array
array([0.11920291, 0.5 , 0.8807971], dtype=float32)
```

### chainer.functions.slstm

`chainer.functions.slstm(c_prev1, c_prev2, x1, x2)`

S-LSTM units as an activation function.

This function implements S-LSTM unit. It is an extension of LSTM unit applied to tree structures. The function is applied to binary trees. Each node has two child nodes. It gets four arguments, previous cell states `c_prev1` and `c_prev2`, and input arrays `x1` and `x2`.

First both input arrays `x1` and `x2` are split into eight arrays `a1`, `i1`, `f1`, `o1`, and `a2`, `i2`, `f2`, `o2`. They have the same shape along the second axis. It means that `x1` and `x2` 's second axis must have 4 times the length of `c_prev1` and `c_prev2`.

The split input arrays are corresponding to:

- `a`: sources of cell input
- `i`: sources of input gate
- `f`: sources of forget gate
- `o`: sources of output gate

It computes the updated cell state `c` and the outgoing signal `h` as:

\[
c = \tanh(a_1 + a_2)\sigma(i_1 + i_2) + c_{\text{prev1}}\sigma(f_1) + c_{\text{prev2}}\sigma(f_2),
\]

\[
h = \tanh(c)\sigma(o_1 + o_2),
\]

where \(\sigma\) is the elementwise sigmoid function. The function returns `c` and `h` as a tuple.

**Parameters**

- `c_prev1 (Variable or N-dimensional array)` – Variable that holds the previous cell state of the first child node. The cell state should be a zero array or the output of the previous call of LSTM.
- `c_prev2 (Variable or N-dimensional array)` – Variable that holds the previous cell state of the second child node.
- `x1 (Variable or N-dimensional array)` – Variable that holds the sources of cell input, input gate, forget gate and output gate from the first child node. It must have the second dimension whose size is four times of that of the cell state.
- `x2 (Variable or N-dimensional array)` – Variable that holds the input sources from the second child node.

**Returns** Two `Variable` objects `c` and `h`. `c` is the cell state. `h` indicates the outgoing signal.

**Return type** `tuple`

See detail in paper: **Long Short-Term Memory Over Tree Structures.**

**Example**
Assuming $c_1, c_2$ is the previous cell state of children, and $h_1, h_2$ is the previous outgoing signal from children. Each of $c_1, c_2, h_1$ and $h_2$ has $n_{\text{units}}$ channels. Most typical preparation of $x_1, x_2$ is:

```python
>>> n_units = 100
>>> h1 = chainer.Variable(np.zeros((1, n_units), np.float32))
>>> h2 = chainer.Variable(np.zeros((1, n_units), np.float32))
>>> c1 = chainer.Variable(np.zeros((1, n_units), np.float32))
>>> c2 = chainer.Variable(np.zeros((1, n_units), np.float32))
>>> model1 = chainer.Chain()
>>> with model1.init_scope():
...    model1.w = L.Linear(n_units, 4 * n_units)
...    model1.v = L.Linear(n_units, 4 * n_units)
>>> model2 = chainer.Chain()
>>> with model2.init_scope():
...    model2.w = L.Linear(n_units, 4 * n_units)
...    model2.v = L.Linear(n_units, 4 * n_units)
>>> x1 = model1.w(c1) + model1.v(h1)
>>> x2 = model2.w(c2) + model2.v(h2)
>>> c, h = F.slstm(c1, c2, x1, x2)
```

It corresponds to calculate the input array $x_1$, or the input sources $a_1, i_1, f_1, o_1$ from the previous cell state of first child node $c_1$, and the previous outgoing signal from first child node $h_1$. Different parameters are used for different kind of input sources.

---

**chainer.functions.softmax**

chainer.functions.softmax($x$, axis\_1)

Softmax function.

This function computes its softmax along an axis. Let $c = (c_1, c_2, \ldots, c_D)$ be the slice of $x$ along with the axis. For each slice $c$, it computes the function $f(c)$ defined as $f(c) = \frac{\exp(c)}{\sum_d \exp(c_d)}$.

**Parameters**

- $x$ (*Variable* or *N-dimensional array*) – Input variable. A $n$-dimensional ($n \geq 2$) float array.
- **axis** (*int*) – The axis along which the softmax is to be computed.

**Returns** Output variable. A $n$-dimensional ($n \geq 2$) float array, which is the same shape with $x$.

**Return type** *Variable*

---

**Example**

```python
>>> x = np.array([[0, 1, 2], [0, 2, 4]], np.float32)
>>> x
array([[0., 1., 2.],
       [0., 2., 4.]], dtype=float32)
>>> y = F.softmax(x, axis=1)
>>> y.array
array([[0.09003057, 0.24472848, 0.66524094],
       [0.01587624, 0.11731043, 0.86681336]], dtype=float32)
>>> F.sum(y, axis=1).array
array([1., 1.], dtype=float32)
```
chainer.functions.softplus

chainer.functions.softplus(x, beta=1.0)

Element-wise softplus function.

The softplus function is the smooth approximation of ReLU.

\[ f(x) = \frac{1}{\beta} \log(1 + \exp(\beta x)), \]

where \( \beta \) is a parameter. The function becomes curved and akin to ReLU as the \( \beta \) is increasing.

**Parameters**

- **x** (*Variable* or *N-dimensional array*) – Input variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.
- **beta** (*float*) – Parameter \( \beta \).

**Returns** Output variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.

**Return type** *Variable*

**Example**

```python
>>> x = np.arange(-2, 3, 2).astype(np.float32)
>>> x
array([-2., 0., 2.], dtype=float32)
>>> F.softplus(x, beta=1.0).array
array([0.1269281, 0.6931472, 2.1269281], dtype=float32)
```

chainer.functions.swish

chainer.functions.swish(x, beta)

Swish activation function.

\[ f(x, \beta) = x \cdot \sigma(\beta x), \]

where \( \sigma(\cdot) \) is the sigmoid function. It has the following properties:

- \( f(x, 0) = \frac{x}{2} \)
- \( \lim_{\beta \to \infty} f(x, \beta) = \max(0, x) \)

**Parameters**

- **x** (*Variable* or *N-dimensional array*) – Input variable of shape \((s_B, s_1, s_2, ..., s_N)\), where \( s_B \) is assumed to be the minibatch dimension.
- **beta** (*Variable* or *N-dimensional array*) – Parameter variable \( \beta \) of shape \((s_1, s_2, ..., s_M)\), where \( M \) is an arbitrary integer between \( 0 \leq M \leq N \). The number of dimensions of beta will be matched with x by reshaping it as \((1, s_1, ..., s_M, 1, ..., 1)\), then beta and x are multiplied together in an element-wise manner.

**Returns** Output variable of the same shape as x.

**Return type** *Variable*
Warning: $\beta$ is a trainable parameter in the original paper (https://arxiv.org/abs/1710.05941). To train $\beta$, use `chainer.links.Swish` instead.

See also:
`chainer.links.Swish` to manage the model parameter $\beta$.

chainer.functions.tanh

chainer.functions.tanh(x)

Elementwise hyperbolic tangent function.

$$f(x) = \tanh(x).$$

**Parameters** $x$ *(Variable or N-dimensional array)* – Input variable. A $(s_1, s_2, ..., s_N)$-shaped float array.

**Returns** Output variable. A $(s_1, s_2, ..., s_N)$-shaped float array.

**Return type** *Variable*

**Example**

```python
>>> x = np.arange(-1, 4, 2).astype(np.float32)
>>> x
array([-1., 1., 3.], dtype=float32)
>>> F.tanh(x).array
array([-0.7615942, 0.7615942, 0.9950548], dtype=float32)
```

chainer.functions.tree_lstm

chainer.functions.tree_lstm(*inputs)

TreeLSTM unit as an activation function.

This function implements TreeLSTM units both for N-ary TreeLSTM and Child-Sum TreeLSTM. Let the children cell states $c_1, c_2, ..., c_N$, and the incoming signal $x$.

First, the incoming signal $x$ is split into $(3 + N)$ arrays $a, i, o, f_1, f_2, ..., f_N$ of the same shapes along the second axis. It means that $x$’s second axis must have $(3 + N)$ times of the length of each $c_n$.

The splitted input signals are corresponding to:
- $a$ : sources of cell input
- $i$ : sources of input gate
- $o$ : sources of output gate
- $f_n$ : sources of forget gate for n-th ary
Second, it computes outputs as:

\[
c = \tanh(a) \cdot \text{sigmoid}(i)
+ c_1 \cdot \text{sigmoid}(f_1),
+ c_2 \cdot \text{sigmoid}(f_2),
+ \ldots,
+ c_N \cdot \text{sigmoid}(f_N),
\]

\[
h = \tanh(c) \cdot \text{sigmoid}(o).
\]

These are returned as a tuple of \((N + 1)\) variables.

**Parameters**

`inputs` (list of *Variable*) – Variable arguments which include all cell vectors from child-nodes, and an input vector. Each of the cell vectors and the input vector is *Variable* or \(N\)-dimensional array. The input vector must have the second dimension whose size is \((N + 3)\) times of that of each cell, where \(N\) denotes the total number of cells.

**Returns**

Two *Variable* objects \(c\) and \(h\). \(c\) is the updated cell state. \(h\) indicates the outgoing signal.

**Return type**

tuple

See the papers for details: Improved Semantic Representations From Tree-Structured Long Short-Term Memory Networks and A Fast Unified Model for Parsing and Sentence Understanding.

Tai et al.’s N-Ary TreeLSTM is little extended in Bowman et al., and this link is based on the variant by Bowman et al. Specifically, eq. 10 in Tai et al. only has one \(W\) matrix to be applied to \(x\), consistently for all children. On the other hand, Bowman et al.’s model has multiple matrices, each of which affects the forget gate for each child’s cell individually.

**Example**

Assuming \(y\) is the current input signal, \(c\) is the previous cell state, and \(h\) is the previous output signal from an `tree_lstm()` function. Each of \(y\), \(c\) and \(h\) has \(n\_units\) channels. Using 2-ary (binary) TreeLSTM, most typical preparation of \(x\) is:

```python
>>> model = chainer.Chain()
>>> with model.init_scope():
...   model.w = L.Linear(10, 5 * 10)
...   model.v1 = L.Linear(10, 5 * 10)
...   model.v2 = L.Linear(10, 5 * 10)
>>> y = np.random.uniform(-1, 1, (4, 10)).astype(np.float32)
>>> h1 = np.random.uniform(-1, 1, (4, 10)).astype(np.float32)
>>> h2 = np.random.uniform(-1, 1, (4, 10)).astype(np.float32)
>>> c1 = np.random.uniform(-1, 1, (4, 10)).astype(np.float32)
>>> c2 = np.random.uniform(-1, 1, (4, 10)).astype(np.float32)
>>> x = model.w(y) + model.v1(h1) + model.v2(h2)
>>> c, h = F.tree_lstm(c1, c2, x)
```

It corresponds to calculate the input sources \(a, i, o, f_1, f_2\) from the current input \(y\) and the children’s outputs \(h_1\) and \(h_2\). Different parameters are used for different kind of input sources.
4.2.3 Array manipulations

- **chainer.functions.as_strided**: Create a new view of array with the given shape, strides, and offset.
- **chainer.functions.broadcast**: Broadcast given variables.
- **chainer.functions.broadcast_to**: Broadcast a given variable to a given shape.
- **chainer.functions.cast**: Cast an input variable to a given type.
- **chainer.functions.concat**: Concatenates given variables along an axis.
- **chainer.functions.copy**: Copies the input variable onto the specified device.
- **chainer.functions.depth2space**: Computes the depth2space transformation for subpixel calculations.
- **chainer.functions.diagonal**: Take diagonal.
- **chainer.functions.dstack**: Concatenate variables along third axis (depth wise).
- **chainer.functions.expand_dims**: Expands dimensions of an input variable without copy.
- **chainer.functions.flatten**: Flatten a given array into one dimension.
- **chainer.functions.flip**: Flips an input variable in reverse order along the given axis.
- **chainer.functions.fliplr**: Flip array in the left/right direction.
- **chainer.functions.flipud**: Flip array in the up/down direction.
- **chainer.functions.get_item**: Extract elements from array with specified shape, axes and offsets.
- **chainer.functions.hstack**: Concatenate variables horizontally (column wise).
- **chainer.functions.im2col**: Extract patches from an image based on the filter.
- **chainer.functions.moveaxis**: Move the source axes to the destination.
- **chainer.functions.pad**: Pad an input variable.
- **chainer.functions.pad_sequence**: Pad given arrays to make a matrix.
- **chainer.functions.permute**: Permutates a given variable along an axis.
- **chainer.functions.repeat**: Construct an array by repeating a given array.
- **chainer.functions.remove_axis**: Remove dimensions of size one from the shape of a variable.
- **chainer.functions.reshape**: Reshape an input variable without copy.
- **chainer.functions.resize_images**: Resize images to the given shape.
- **chainer.functions.rollaxis**: Roll the axis backwards to the given position.
- **chainer.functions.scatter_add**: Adds given values to specified elements of an array.
- **chainer.functions.select_item**: Select elements stored in given indices.
- **chainer.functions.separate**: Separates an array along a given axis.
- **chainer.functions.space2depth**: Computes the space2depth transformation for subpixel calculations.
- **chainer.functions.spatial_transformer_grid**: 2D Spatial Transformer grid.
- **chainer.functions.spatial_transformer_sampler**: 2D Spatial Transformer sampler.
- **chainer.functions.split_axis**: Splits given variables along an axis.
- **chainer.functions.squeeze**: Remove dimensions of size one from the shape of a variable.
- **chainer.functions.stack**: Concatenate variables along a new axis.
- **chainer.functions.swapaxes**: Swap two axes of a variable.
- **chainer.functions.tile**: Construct an array by tiling a given array.
- **chainer.functions.transpose**: Permute the dimensions of an input variable without copy.
- **chainer.functions.transpose_sequence**: Transpose a list of Variables.
- **chainer.functions.vstack**: Concatenate variables vertically (row wise).
- **chainer.functions.where**: Choose elements depending on condition.
chainer.functions.as_strided

Create a new view of array with the given shape, strides, and offset.

Parameters

- **x** (tuple of `Variable` or `numpy.ndarray` or `cupy.ndarray`) – The array pointing a memory buffer. Its view is totally ignored.
- **shape** (tuple of int) – The shape of output.
- **strides** (tuple of int) – The strides of output, given in the unit of steps.
- **storage_offset** (int) – The offset between the head of allocated memory and the pointer of first element, given in the unit of steps.

Returns

The strided variable.

Return type

`Variable`

**Warning:** Users should be aware that this function potentially causes unintended side effects. See `numpy.lib.stride_tricks.as_strided` for the detail.

**Note:** The backward algorithm is borrowed from `torch.Tensor.as_strided`. Therefore, the returned gradient of backward is `layout-agnostic` when `x` contains memory overlap. See notes in pytorch’s source code (as_strided Backward and layout-aware/agnostic autograd) too.

**Note:** In this function `strides` and `storage_offset` are given in the unit of steps instead of bytes. This specification differs from `numpy.lib.stride_tricks.as_strided()`.

**Example**

```python
>>> from chainer import functions as F, Variable
>>> x = Variable(np.arange(4, dtype=np.float32))
>>> x
variable([0., 1., 2., 3.])
>>> y = F.as_strided(x, (3, 2), (1, 1), 0)
>>> y
variable([[0., 1.],
          [1., 2.],
          [2., 3.]])
>>> y.grad = np.ones((3, 2), dtype=np.float32)
>>> y.backward()
>>> x.grad
array([1., 2., 2., 1.], dtype=float32)
```
chainer.functions.broadcast

chainer.functions.broadcast(*args)
Broadcast given variables.

Parameters

- **args** (*Variable* or *N-dimensional array*) – Input variables to be broadcasted. Each dimension of the shapes of the input variables must have the same size.

Returns

- **Variable** or tuple of **Variable** objects which are broadcasted from the given arguments.

Return type

- **Variable**

Example

```python
>>> x = np.random.uniform(0, 1, (3, 2)).astype(np.float32)
>>> y = F.broadcast(x)
>>> np.all(x == y.array)
True
>>> z = np.random.uniform(0, 1, (3, 2)).astype(np.float32)
>>> y, w = F.broadcast(x, z)
>>> np.all(x == y.array) & np.all(z == w.array)
True
```

chainer.functions.broadcast_to

chainer.functions.broadcast_to(x, shape)
Broadcast a given variable to a given shape.

Parameters

- **x** (*Variable* or *N-dimensional array*) – Input variable to be broadcasted. A \((s_1, s_2, ..., s_N)\)-shaped float array.
- **shape** (*tuple*) – Tuple of int of the shape of the output variable.

Returns

- Output variable broadcasted to the given shape.

Return type

- **Variable**

Example

```python
>>> x = np.arange(0, 3)
>>> x
array([0, 1, 2])
>>> y = F.broadcast_to(x, (3, 3))
>>> y.array
array([[0, 1, 2],
        [0, 1, 2],
        [0, 1, 2]])
```
chainer.functions.cast

chainer.functions.cast(x, typ)

Cast an input variable to a given type.

Parameters

- **x** (*Variable* or *N-dimensional array*) – Input variable to be casted. A \((s_1, s_2, \ldots, s_N)\)-shaped array.
- **typ** (*str* of dtype or *numpy.dtype*) – Typecode or data type to cast.

Returns

Variable holding a casted array.

Return type *Variable*

Example

```python
>>> x = np.arange(0, 3, dtype=np.float64)
>>> x.dtype
dtype('float64')
>>> y = F.cast(x, np.float32)
>>> y.dtype
dtype('float32')
>>> y = F.cast(x, 'float16')
>>> y.dtype
dtype('float16')
```

chainer.functions.concat

chainer.functions.concat(xs, axis=1)

Concatenates given variables along an axis.

Parameters

- **xs** (*tuple of Variable* or *N-dimensional array*) – Input variables to be concatenated. The variables must have the same shape, except in the dimension corresponding to axis.
- **axis** (*int*) – The axis along which the arrays will be joined. Default is 1.

Returns

The concatenated variable.

Return type *Variable*

Example

```python
>>> x = np.arange(0, 12).reshape(3, 4)
>>> x
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
>>> y = np.arange(0, 3).reshape(3, 1)
>>> y
array([[0],
       [1],
       [2]])
>>> z = F.concat((x, y), axis=1)
```

chainer.functions.copy

chainer.functions.copy (x, dst)
Copies the input variable onto the specified device.

If the input x already resides on the device specified by dst, no copy will actually take place and the returned variable will hold a view of the input. In other cases, the input will be copied to dst. When dst == -1, the array is copied to the host memory. This function supports copies from host to host, from host to device, from device to device and from device to host.

Parameters
- x ([Variable or N-dimensional array] – Variable to be copied.
- dst – Target device specifier.

Returns Output variable.
Return type Variable

Example

```python
>>> import chainer.backends.cuda as cuda
>>> x_arr = np.random.uniform(-1, 1, (5, 10))
>>> x = chainer.Variable(x_arr)
>>> x.device
<numpy.Device (numpy)>
>>> y = F.copy(x, '@cupy:0') # from CPU (NumPy) to GPU 0 (CuPy)
>>> y.device
<CudaDevice (cupy):0>
```

Note: Copies between non-ChainerX devices and ChainerX devices are not supported.

chainer.functions.depth2space

chainer.functions.depth2space (X, r)
Computes the depth2space transformation for subpixel calculations.

Parameters
- X ([Variable or N-dimensional array] – Variable holding a 4d array of shape (batch, channel * r * r, dim1, dim2).
- r (int) – the upscaling factor.

Returns A variable holding the upscaled array from interspersed depth layers. The shape is (batch, channel, dim1 * r, dim2 * r).

4.2. Functions
Return type *Variable*

**Note:** This can be used to compute super-resolution transformations. See https://arxiv.org/abs/1609.05158 for details.

See also:

`space2depth()`

Example

```python
>>> X = np.arange(24).reshape(1, 4, 2, 3).astype(np.float32)
>>> X.shape
(1, 4, 2, 3)
>>> X
array([[[[ 0., 1., 2.],
          [ 3., 4., 5.]],
         [[ 6., 7., 8.],
          [ 9., 10., 11.]],
         [[12., 13., 14.],
          [15., 16., 17.]],
         [[18., 19., 20.],
          [21., 22., 23.]]],
       dtype=float32)
```

```python
>>> y = F.depth2space(X, 2)
>>> y.shape
(1, 1, 4, 6)
>>> y
array([[[[ 0., 6., 1., 7., 2., 8.],
          [12., 18., 13., 19., 14., 20.],
          [ 3., 9., 4., 10., 5., 11.],
          [15., 21., 16., 22., 17., 23.]]],
       dtype=float32)
```

### chainer.functions.diagonal

**chainer.functions.diagonal** *(x, offset=0, axis1=0, axis2=1)*

Take diagonal

Axes other than `axis1` and `axis2` are regarded as batch dimensions.

**Parameters**

- **x** *(Variable or N-dimensional array)* – A variable to be sliced.
- **offset** *(int)* – Offset from the principal diagonal. An upper diagonal matrix can have nonzero diagonals with nonnegative offsets.
- **axis1** *(int)* – First axis (that has row indices) of matrix
- **axis2** *(int)* – Second axis (that has column indices) of matrix

**Returns** (Batched) diagonal vectors

**Return type** *Variable*
Example

```python
>>> x = chainer.Variable(np.arange(9).reshape(3, 3).astype(np.float32))
>>> x
variable([[0., 1., 2.],
          [3., 4., 5.],
          [6., 7., 8.]])
>>> chainer.functions.diagonal(x, offset=1)
variable([1., 5.])
```

---

**chainer.functions.dstack**

`chainer.functions.dstack(xs)`

Concatenate variables along third axis (depth wise).

**Parameters** `xs` (list of `Variable` or `N-dimensional array`) – Input variables to be concatenated. The variables must have the same ndim. When the variables have the third axis (i.e. `ndim ≥ 3`), the variables must have the same shape along all but the third axis. When the variables do not have the third axis (i.e. `ndim < 3`), the variables must have the same shape.

**Returns** Output variable. When the input variables have the third axis (i.e. `ndim ≥ 3`), the shapes of inputs and output are the same along all but the third axis. The length of third axis is the sum of the lengths of inputs’ third axis. When the shape of variables are `(N1, N2)` (i.e. `ndim = 2`), the shape of output is `(N1, N2, 2)`. When the shape of variables are `(N1,)` (i.e. `ndim = 1`), the shape of output is `(1, N1, 2)`. When the shape of variables are `()` (i.e. `ndim = 0`), the shape of output is `(1, 1, 2).

**Return type** `Variable`

---

Example

```python
>>> x1 = np.array((1, 2, 3))
>>> x1.shape
(3,)
>>> x2 = np.array((2, 3, 4))
>>> x2.shape
(3,)
>>> y = F.dstack((x1, x2))
>>> y.shape
(1, 3, 2)
>>> y.array
array([[1, 2],
       [2, 3],
       [3, 4]])
```

---

```python
>>> x1 = np.arange(0, 6).reshape(3, 2)
>>> x1.shape
(3, 2)
>>> x1
array([[0, 1],
       [2, 3],
       [4, 5]])
>>> x2 = np.arange(6, 12).reshape(3, 2)
```
>>> x2.shape
(3, 2)
>>> x2
array([[ 6,  7],
       [ 8,  9],
       [10, 11]])
>>> y = F.dstack([x1, x2])
>>> y.shape
(3, 2, 2)
>>> y.array
array([[[ 0,  6],
        [ 1,  7]],
       [[ 2,  8],
        [ 3,  9]],
       [[ 4, 10],
        [ 5, 11]]])

>>> x1 = np.arange(0, 12).reshape(3, 2, 2)
>>> x2 = np.arange(12, 18).reshape(3, 2, 1)
>>> y = F.dstack([x1, x2])
>>> y.shape
(3, 2, 3)
>>> y.array
array([[[ 0,  1, 12],
        [ 2,  3, 13]],
       [[ 4,  5, 14],
        [ 6,  7, 15]],
       [[ 8,  9, 16],
        [10, 11, 17]]])

chainer.functions.expand_dims

chainer.functions.expand_dims(x, axis)

Expands dimensions of an input variable without copy.

Parameters

- **x** *(Variable or N-dimensional array)* – Input variable.
- **axis** *(int)* – Position where new axis is to be inserted. The axis parameter is acceptable when \(-ndim - 1 \leq axis \leq ndim\). (ndim is the dimension of input variables). When axis < 0, the result is the same with ndim + 1 – |axis|.

Returns Variable that holds an expanded input. The ndim of output is one greater than that of x.

Return type Variable

Example
```python
>>> x = np.array([1, 2, 3])
>>> x.shape
(3,)
>>> y = F.expand_dims(x, axis=0)
>>> y.shape
(1, 3)
>>> y.array
array([[1, 2, 3]])
>>> y = F.expand_dims(x, axis=1)
>>> y.shape
(3, 1)
>>> y.array
array([[1],
        [2],
        [3]])
>>> y = F.expand_dims(x, axis=-2)
>>> y.shape
(1, 3)
>>> y.array
array([[1, 2, 3]])
```

### chainer.functions.flatten

**Function**

`chainer.functions.flatten(x)`

Flatten a given array into one dimension.

**Parameters**

- `x` *(Variable or N-dimensional array)* – Input variable.

**Returns**

- Output variable flattened to one dimension.

**Return type**

- Variable

**Note:** When you input a scalar array (i.e. the shape is ()), you can also get the one dimension array whose shape is (1,).

**Example**

```python
>>> x = np.array([[1, 2], [3, 4]])
>>> x.shape
(2, 2)
>>> y = F.flatten(x)
>>> y.shape
(4,)
>>> y.array
array([1, 2, 3, 4])
```

```python
>>> x = np.arange(8).reshape(2, 2, 2)
>>> x.shape
(2, 2, 2)
>>> y = F.flatten(x)
>>> y.shape
(8,)
```

(continues on next page)
>>> y.array
array([0, 1, 2, 3, 4, 5, 6, 7])

chainer.functions.flip

chainer.functions.flip(x, axis)
Flips an input variable in reverse order along the given axis.

Parameters
• x (Variable or N-dimensional array) – Input variable.
• axis (int) – Axis along which the input variable is reversed.

Returns Output variable.
Return type Variable

chainer.functions.fliplr

chainer.functions.fliplr(a)
Flip array in the left/right direction.

Parameters a (Variable or N-dimensional array) – Input variable.

Returns Output variable.
Return type Variable

chainer.functions.flipud

chainer.functions.flipud(a)
Flip array in the up/down direction.

Parameters a (Variable or N-dimensional array) – Input variable.

Returns Output variable.
Return type Variable

chainer.functions.get_item

chainer.functions.get_item(x, slices)
Extract elements from array with specified shape, axes and offsets.

Parameters
• x (Variable or N-dimensional array) – A variable to be sliced.
• slices (int, slice, Ellipsis, None, integer array-like, boolean array-like or tuple of them) – An object to specify the selection of elements.

Returns A Variable object which contains sliced array of x.
Note: It only supports types that are supported by CUDA's atomicAdd when an integer array is included in slices. The supported types are `numpy.float32`, `numpy.int32`, `numpy.uint32`, `numpy.uint64` and `numpy.ulonglong`.

Note: It does not support slices that contains multiple boolean arrays.

Note: See NumPy documentation for details of indexing.

Example

```python
>>> x = np.arange(12).reshape((2, 2, 3))
>>> x
array([[0, 1, 2],
       [3, 4, 5],
       [6, 7, 8],
       [9, 10, 11]])
>>> F.get_item(x, 0)
variable([[0, 1, 2],
         [3, 4, 5]])
>>> F.get_item(x, (0, 0, slice(0, 2, 1)))  # equals x[0, 0, 0:2:1]
variable([0, 1])
>>> F.get_item(x, (Ellipsis, 2))  # equals x[..., 2]
variable([[2, 5],
         [8, 11]])
>>> F.get_item(x, (1, np.newaxis, 1, 0))  # equals x[1, None, 1, 0]
variable([9])
```

`chainer.functions.hstack`

`chainer.functions.hstack(xs)`

Concatenate variables horizontally (column wise).

**Parameters** `xs` (list of `Variable` or `N-dimensional array`) – Input variables to be concatenated.

The variables must have the same `ndim`. When the variables have the second axis (i.e. `ndim ≥ 2`), the variables must have the same shape along all but the second axis. When the variables do not have the second axis (i.e. `ndim < 2`), the variables need not to have the same shape.

**Returns** Output variable. When the input variables have the second axis (i.e. `ndim ≥ 2`), the shapes of inputs and output are the same along all but the second axis. The length of second axis is the sum of the lengths of inputs' second axis. When the variables do not have the second axis (i.e. `ndim < 2`), the shape of output is `(N, )` (N is the sum of the input variables' size).

**Return type** `Variable`

Example
```
>>> x1 = np.array((1, 2, 3))
>>> x1.shape
(3,)
>>> x2 = np.array((2, 3, 4))
>>> x2.shape
(3,)
>>> y = F.hstack((x1, x2))
>>> y.shape
(6,)
>>> y.array
array([1, 2, 3, 2, 3, 4])

```
The output size \((h_O, w_O)\) is determined by the following equations when \(\text{cover} \text{ all} = \text{False}\):

\[
\begin{align*}
    h_O &= (h + 2p_H - k_H - (k_H - 1) \cdot (d_Y - 1))/s_Y + 1, \\
    w_O &= (w + 2p_W - k_W - (k_W - 1) \cdot (d_X - 1))/s_X + 1.
\end{align*}
\]

When \(\text{cover} \text{ all} = \text{True}\), the output size is determined by the following equations:

\[
\begin{align*}
    h_O &= (h + 2p_H - k_H - (k_H - 1) \cdot (d_Y - 1) + s_Y - 1)/s_Y + 1, \\
    w_O &= (w + 2p_W - k_W - (k_W - 1) \cdot (d_X - 1) + s_X - 1)/s_X + 1.
\end{align*}
\]

Parameters

- \(x\) (Variable or N-dimensional array) – Input variable of shape \((n, c, h, w)\).
- \(\text{ksize}\) (int or pair of ints) – Size of filters (a.k.a. kernels). \(\text{ksize}=k\) and \(\text{ksize}=(k, k)\) are equivalent.
- \(\text{stride}\) (int or pair of ints) – Stride of filter applications. \(\text{stride}=s\) and \(\text{stride}=(s, s)\) are equivalent.
- \(\text{pad}\) (int or pair of ints) – Spatial padding width for input arrays. \(\text{pad}=p\) and \(\text{pad}=(p, p)\) are equivalent.
- \(\text{cover} \text{ all}\) (bool) – If \(\text{True}\), all spatial locations are rearranged into some output pixels. It may make the output size larger.
- \(\text{dilate}\) (int or pair of ints) – Dilation factor of filter applications. \(\text{dilate}=d\) and \(\text{dilate}=(d, d)\) are equivalent.

Returns Output variable whose shape is \((n, c \cdot k_H \cdot k_W, h_O, w_O)\)

Return type Variable

**chainer.functions.moveaxis**

chainer.functions.moveaxis \((x, \text{source}, \text{destination})\)

Move the source axes to the destination.

This function transpose the input \(x\) by moving the axes \(\text{source}\) to the axes \(\text{destination}\). Other axes remain in their original order.

See also chainer.functions.transpose(), chainer.functions.swapaxes().

Parameters

- \(x\) (Variable or N-dimensional array) – Input variable.
- \(\text{source}\) (int or tuple of int) – Original positions of the axes to move. These must be unique.
- \(\text{destination}\) (int or tuple of int) – Destination positions for each of the original axes. These must also be unique.

Returns Variable whose axis is moved.

Return type Variable

Example
```python
>>> x = np.zeros((2, 3, 4, 5), np.float32)
>>> chainer.functions.moveaxis(x, 0, -1).shape
(3, 4, 5, 2)
>>> chainer.functions.moveaxis(x, (0, 3), (2, 0)).shape
(5, 3, 2, 4)
```

**chainer.functions.pad**

`chainer.functions.pad(x, pad_width, mode, **keywords)`

Pad an input variable.

**Parameters**

- `x` (*Variable* or *N-dimensional array*) – Input data.
- `pad_width` (*int* or *array-like*) – Number of values padded to the edges of each axis.
- `mode` (*str*) – Specifies how the function fills the periphery of the array. The mode is passed to `numpy.pad()` or `cupy.pad()`. If it is `'constant'`, the input is padded by a constant value specified by `constant_values`.
- `constant_values` (*int* or *array-like*) – Constant values to fill the periphery in the `'constant'` mode.

**Returns**  
Output variable.

**Return type**  
*Variable*

**chainer.functions.pad_sequence**

`chainer.functions.pad_sequence(xs, length=None, padding=0)`

Pad given arrays to make a matrix.

**Parameters**

- `xs` (list of ~chainer.Variable or *N-dimensional array*) – Variables you want to concatenate.
- `length` (*None* or *int*) – Size of the first dimension of a padded array. If it is `None`, the longest size of the first dimension of `xs` is used.
- `padding` (*int* or *float*) – Value to fill.

**Returns**  
A padded matrix. Its shape is `(n, length, ...)`, where `n == len(xs)`.

**Return type**  
*Variable*
chainer.functions.permutate

chainer.functions.permutate(x, indices, axis=0, inv=False)
Permutates a given variable along an axis.
This function permutate x with given indices. That means y[i] = x[indices[i]] for all i. Note that this result is same as y = x.take(indices). indices must be a permutation of [0, 1, ..., len(x) - 1].
When inv is True, indices is treated as its inverse. That means y[indices[i]] = x[i].

Parameters
- x (Variable or N-dimensional array) – Variable to permutate. A (s_1, s_2, ..., s_N) -shaped float array.
- indices (Variable or N-dimensional array) – Indices to extract from the variable. A one-dimensional int array.
- axis (int) – Axis that the input array is permutate along.
- inv (bool) – If True, indices is treated as its inverse.

Returns Output variable.
Return type Variable

Example

```python
>>> x = np.arange(6).reshape((3, 2)).astype(np.float32)
>>> x
array([[0., 1.],
       [2., 3.],
       [4., 5.]], dtype=float32)
>>> indices = np.array([2, 0, 1], np.int32)
>>> y = F.permutate(x, indices)
>>> y.array
array([[4., 5.],
       [0., 1.],
       [2., 3.]], dtype=float32)
>>> y = F.permutate(x, indices, inv=True)
>>> y.array
array([[2., 3.],
       [4., 5.],
       [0., 1.]], dtype=float32)
>>> indices = np.array([1, 0], np.int32)
>>> y = F.permutate(x, indices, axis=1)
>>> y.array
array([[1., 0.],
       [3., 2.],
       [5., 4.]], dtype=float32)
```
chainer.functions.repeat

chainer.functions.repeat(x, repeats, axis=None)

Construct an array by repeating a given array.

Parameters

- **x** (*Variable* or *N-dimensional array*) – Input variable.
- **repeats** (*int* or *tuple* of *int*s) – The number of times which each element of *x* is repeated.
- **axis** (*int*) – The axis along which to repeat values.

Returns

The repeated output *Variable*.

Return type

*Variable*

Example

```python
>>> x = np.array([0, 1, 2])
>>> x.shape
(3,)
>>> y = F.repeat(x, 2)
>>> y.shape
(6,)
>>> y.array
array([0, 0, 1, 1, 2, 2])
>>> x = np.array([[1,2], [3,4]])
>>> x.shape
(2, 2)
>>> y = F.repeat(x, 3, axis=1)
>>> y.shape
(2, 6)
>>> y.array
array([[1, 1, 1, 2, 2, 2],
       [3, 3, 3, 4, 4, 4]])
>>> y = F.repeat(x, (1, 2), axis=0)
>>> y.shape
(3, 2)
>>> y.array
array([[1, 2],
       [3, 4],
       [3, 4]])
```
Returns Variable that holds a reshaped version of the input variable.

Return type Variable

See also:
numpy.reshape(), cupy.reshape()

Example

```python
>>> x = np.array([[1, 2, 3, 4], [5, 6, 7, 8]])
>>> y = F.reshape(x, (8,))
>>> y.array
array([1, 2, 3, 4, 5, 6, 7, 8])
>>> y.shape
(8,)
```
```
>>> y = F.reshape(x, (4, -1)) # the shape of output is inferred
>>> y.shape
(4, 2)
```
```
>>> y.array
array([[1, 2],
        [3, 4],
        [5, 6],
        [7, 8]])
```
```
>>> y = F.reshape(x, (4, 3)) # the shape of input and output are not consistent
Traceback (most recent call last):
  ... 
chainer.utils.type_check.InvalidType:
Invalid operation is performed in: Reshape (Forward)
Expect: prod(x.shape) == prod((4, 3))
Actual: 8 != 12
```

chainer.functions.resize_images

```
chainer.functions.resize_images(x, output_shape, *, mode='bilinear', align_corners=True)
```

Resize images to the given shape.

This function resizes 2D data to output_shape.

Notation: here is a notation for dimensionalities.

- **n** is the batch size.
- **c_I** is the number of the input channels.
- **h** and **w** are the height and width of the input image, respectively.
- **h_O** and **w_O** are the height and width of the output image.

Parameters

- **x** *(Variable or N-dimensional array)* – Input variable of shape \((n, c_I, h, w)\).
- **output_shape** *(tuple)* – This is a tuple of length 2 whose values are \((h_O, w_O)\). Note that the order of height and width is opposite of the one in OpenCV.
- **mode** *(\{'bilinear', 'nearest'\})* – Defines the sampling rule.
• **align_corners** *(bool)* – When this value is True, the corners of the input are mapped to the corners of the output. When False, the behavior is the same as OpenCV.

**Returns** Resized image whose shape is \((n, c, h_O, w_O)\).

**Return type** Variable

### chainer.functions.rollaxis

chainer.functions.**rollaxis** *(x, axis, start=0)*

Roll the axis backwards to the given position.

This function continues to be supported for backward compatibility, but you should prefer chainer.functions.moveaxis(x, source, destination). See chainer.functions.moveaxis().

**Parameters**

- **x** *(Variable or N-dimensional array)* – Input variable.
- **axis** *(int)* – The axis to roll backwards.
- **start** *(int)* – The place to which the axis is moved.

**Returns** Variable whose axis is rolled.

**Return type** Variable

### chainer.functions.scatter_add

chainer.functions.**scatter_add** *(a, slices, b)*

Adds given values to specified elements of an array.

This function adds \(b\) to the specified elements of the copy of \(a\), and returns the copy. The value of the original \(a\) is not changed.

**Parameters**

- **a** *(Variable or N-dimensional array)* – A variable.
- **slices** *(int, slice, Ellipsis, None, integer array-like, boolean array-like or tuple of them)* – It is an integer, a slice, an ellipsis, a numpy.newaxis, an integer array-like, a boolean array-like or tuple of them.
- **b** *(Variable or N-dimensional array)* – A variable that is scatter added to \(a\). Its shape has to equal \(a[slices]\) because broadcasting of variables is not supported.

**Returns** A Variable object which is the result of scatter addition.

**Note:** It only supports types that are supported by CUDA’s atomicAdd when an integer array is included in slices. The supported types are numpy.float32, numpy.int32, numpy.uint32, numpy.uint64 and numpy.ulonglong.

**Note:** It does not support slices that contains multiple boolean arrays.

**See also:**

numpy.add.at() and cupyx.scatter_add().
chainer.functions.select_item

chainer.functions.select_item(x, t)
Select elements stored in given indices.

This function returns t.choose(x.T), that means y[i] == x[i, t[i]] for all i.

Parameters
- **x** (*Variable* or *N-dimensional array*) – Variable storing arrays. A two-dimensional float array.
- **t** (*Variable* or *N-dimensional array*) – Variable storing index numbers. A one-dimensional int array. Length of the t should be equal to x.shape[0].

Returns
Variable that holds t-th element of x.

Return type *Variable*

**Example**
```python
>>> x = np.array([[0, 1, 2], [3, 4, 5]], np.float32)
>>> t = np.array([0, 2], np.int32)
>>> y = F.select_item(x, t)
>>> y.shape
(2,)
>>> y.array
array([0., 5.], dtype=float32)
```

chainer.functions.separate

chainer.functions.separate(x, axis=0)
Separates an array along a given axis.

This function separates an array along a given axis. For example, shape of an array is (2, 3, 4). When it separates the array with axis=1, it returns three (2, 4) arrays.

This function is an inverse of `chainer.functions.stack()`.

Parameters
- **x** (*Variable* or *N-dimensional array*) – Variable to be separated. A \((s_1, s_2, ..., s_N)\) -shaped float array.
- **axis** (*int*) – Axis along which variables are separated.

Returns
Output variables.

Return type *tuple of chainer.Variable*

See also:
- `chainer.functions.stack()`

**Example**
```python
```
```python
>>> x = np.arange(6).reshape((2, 3)).astype(np.float32)
>>> x
array([[0., 1., 2.],
       [3., 4., 5.]], dtype=float32)
>>> x.shape
(2, 3)
>>> y = F.separate(x)  # split along axis=0
>>> isinstance(y, tuple)
True
>>> len(y)
2
>>> y[0].shape
(3,)
>>> y[0].array
array([0., 1., 2.], dtype=float32)

```
>>> y = F.space2depth(X, 2)
>>> y.shape
(1, 4, 2, 3)
>>> y.array
array([[[[ 0., 2., 4.],
               [12., 14., 16.]],
           [[ 1., 3., 5.],
               [13., 15., 17.]],
           [[ 6., 8., 10.],
               [18., 20., 22.]],
           [[ 7., 9., 11.],
               [19., 21., 23.]]],
       dtype=float32)

chainer.functions.spatial_transformer_grid

chainer.functions.spatial_transformer_grid(theta, output_shape, **kwargs)

2D Spatial Transformer grid.

This function generates coordinates of the points sampled from an image to perform warping described in Spatial Transformer Networks.

Given a coordinate in the warped image \((x^t_i, y^t_i)\), the point sampled from the source image \((x^s_i, y^s_i)\) are calculated by the following equation.

Note: cuDNN supports SpatialTransformerGrid from version 5.0.0.

\[
\begin{pmatrix}
    x^s_i \\
    y^s_i
\end{pmatrix} =
\begin{pmatrix}
    \theta_{11} & \theta_{12} & \theta_{13} \\
    \theta_{21} & \theta_{22} & \theta_{23}
\end{pmatrix}
\begin{pmatrix}
    x^t_i \\
    y^t_i \\
    1
\end{pmatrix}
\]

Notation: here is a notation for dimensionalities.

- \(n\) is the batch size.
- \(h_O\) and \(w_O\) are the height and the width of the output image.

Parameters

- **theta** *(Variable or N-dimensional array)* – An array of shape \((n, 2, 3)\). This is a batch of \(2 \times 3\) matrix used for the warping described above.
- **output_shape** *(tuple)* – A tuple of 2 elements: \(h_O, w_O\).

Returns A variable of shape \((n, 2, h_O, w_O)\). In the 2nd dimension, the first element is the coordinate along the x axis, and the second element is the coordinate along the y axis. All the coordinates in the image are scaled to fit range \([-1, 1]\). This means that the coordinate \((-1, -1)\) corresponds to the upper-left corner of the input image.
Return type  **Variable**

chainer.functions.spatial_transformer_sampler

chainer.functions.spatial_transformer_sampler $(x, \text{grid}, **\text{kwargs})$

2D Spatial Transformer sampler.

This is a differentiable image sampler. With a set of sampling points $\text{grid}$ and an input feature map $x$, this produces a sampled output feature map.

This function currently only supports bilinear interpolation as a sampling kernel.

When coordinates in $\text{grid}$ is outside range $[-1, 1]$, values are sampled from a zero padded input image.

Notation: here is a notation for dimensionalities.

- $n$ is the batch size.
- $c_I$ is the number of the input channels.
- $h$ and $w$ are the height and width of the input image, respectively.
- $h_O$ and $w_O$ are the height and width of the output image.

See detail in the following paper: Spatial Transformer Networks.

**Note:** cuDNN supports SpatialTransformerSampler from version 5.0.0.

Parameters

- **$x$** (*Variable* or *$N$-dimensional array*) – Input variable of shape $(n, c_I, h, w)$.
- **$\text{grid}$** (*Variable*) – Coordinate variable of shape $(n, 2, h_O, w_O)$. Each coordinate defines the spatial location in the input where a sampling kernel is applied to get the value at a particular pixel in the output. $\text{grid}[\text{idx}, :, i, j]$ corresponds to the coordinate that is used to sample the values for an output pixel at location $(i, j)$.

  In the second dimension, the first coordinate corresponds to the location along the horizontal axis, and the second coordinate corresponds to the location along the vertical axis.

  The coordinate $(-1, -1)$ corresponds to the upper-left corner of the input image.

Returns  Output feature map of shape $(n, c_I, h_O, w_O)$.

Return type  **Variable**

chainer.functions.split_axis

chainer.functions.split_axis $(x, \text{indices_or_sections}, \text{axis}, \text{force_tuple}=True)$

Splits given variables along an axis.

Parameters

- **$x$** (*Variable* or *$N$-dimensional array*) – A variable to be split.
- **$\text{indices_or_sections}$** (*int* or *1-D array*) – If this argument is an integer, $N$, the array will be divided into $N$ equal arrays along axis. If it is a 1-D array of sorted integers, it indicates the positions where the array is split.
- **$\text{axis}$** (*int*) – Axis that the input array is split along.
• **force_tuple** (bool) – If True (the default) this method returns a tuple even when the number of outputs is one. Otherwise, if False a Variable will be returned when the number of outputs is one.

**Returns** Tuple of Variable objects if the number of outputs is more than 1 or Variable otherwise. When force_tuple is True, returned value is always a tuple regardless of the number of outputs.

**Return type** tuple or Variable

### chainer.functions.squeeze

**chainer.functions.squeeze**(*x, axis=None*)

Remove dimensions of size one from the shape of a ndarray.

**Parameters**

- **x** (Variable or N-dimensional array) – Input variable. A \((s_1, s_2, \ldots, s_N)\)-shaped float array.

- **axis** (None or int or tuple of ints) – A subset of the single-dimensional entries in the shape to remove. If None is supplied, all of them are removed. The dimension index starts at zero. If an axis with dimension greater than one is selected, an error is raised.

**Returns** Variable whose dimensions of size 1 are removed.

**Return type** Variable

**Example**

```python
>>> x = np.array([[[[0, 1, 2]], [[[3, 4, 5]]]], np.float32)
>>> x.shape
(2, 1, 1, 3)
>>> y = F.squeeze(x)
>>> y.shape
(2, 3)
>>> y.array
array([[0., 1., 2.],
       [3., 4., 5.]], dtype=float32)
>>> y = F.squeeze(x, axis=1)
>>> y.shape
(2, 1, 3)
>>> y.array
array([[[0., 1., 2.]],
       [[[3., 4., 5.]]]], dtype=float32)
>>> y = F.squeeze(x, axis=(1, 2))
>>> y.shape
(2, 3)
>>> y.array
array([[[0., 1., 2.]],
       [[[3., 4., 5.]]]], dtype=float32)
```
chainer.functions.stack

chainer.functions.stack(xs, axis=0)

Concatenate variables along a new axis.

**Parameters**

- **xs** (list of Variable or N-dimensional array) – Input variables to be concatenated. The variables must have the same shape.

- **axis** (int) – The axis along which the arrays will be stacked. The axis parameter is acceptable when $-\text{ndim} - 1 \leq \text{axis} \leq \text{ndim}$. (ndim is the dimension of input variables). When axis < 0, the result is the same with $\text{ndim} + 1 - |\text{axis}|$.

**Returns** Output variable. Let $x_1$, $x_2$, ..., $x_n$ and $y$ be the input variables and the output variable, $y[\ldots, 0, \ldots, :]$ is $x_1$, $y[\ldots, 1, \ldots, :]$ is $x_2$ and $y[\ldots, n-1, \ldots, :]$ is $x_n$ (The indexed axis indicates the axis).

**Return type** Variable

**Example**

```python
>>> x1 = np.arange(0, 12).reshape(3, 4)
>>> x1.shape
(3, 4)
>>> x1
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
>>> x2 = np.arange(12, 24).reshape(3, 4)
>>> x2.shape
(3, 4)
>>> x2
array([[12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23]])
>>> y = F.stack([x1, x2], axis=0)
>>> y.shape
(2, 3, 4)
>>> y.array
array([[[ 0,  1,  2,  3],
        [ 4,  5,  6,  7],
        [ 8,  9, 10, 11]],
        [[12, 13, 14, 15],
         [16, 17, 18, 19],
         [20, 21, 22, 23]])
>>> y = F.stack([x1, x2], axis=1)
>>> y.shape
(3, 2, 4)
>>> y.array
array([[[ 0,  1,  2,  3],
        [12, 13, 14, 15]],
        [[ 4,  5,  6,  7],
         [16, 17, 18, 19]],
        [[ 8,  9, 10, 11]],
```

(continues on next page)
```
>>> y = F.stack([x1, x2], axis=2)
>>> y.shape
(3, 4, 2)
>>> y.array
array([[[ 0, 12],
        [ 1, 13],
        [ 2, 14],
        [ 3, 15]],
       [[ 4, 16],
        [ 5, 17],
        [ 6, 18],
        [ 7, 19]],
       [[ 8, 20],
        [ 9, 21],
        [10, 22],
        [11, 23]]])
>>> y = F.stack([x1, x2], axis=-1)
>>> y.shape
(3, 4, 2)
```

**chainer.functions.swapaxes**

chainer.functions.swapaxes(x, axis1, axis2)

Swap two axes of a variable.

Parameters

- **x** *(Variable or N-dimensional array)* – Input variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.
- **axis1** *(int)* – The first axis to swap.
- **axis2** *(int)* – The second axis to swap.

Returns Variable whose axes are swapped.

Return type Variable

Example

```python
>>> x = np.array([[[0, 1, 2], [3, 4, 5]]], np.float32)
>>> x.shape
(1, 2, 3)
>>> y = F.swapaxes(x, axis1=0, axis2=1)
>>> y.shape
(2, 1, 3)
>>> y.array
array([[[0., 1., 2.],
        [3., 4., 5.]]], dtype=float32)
```
chainer.functions.tile

chainer.functions.tile(x, reps)

Construct an array by tiling a given array.

Parameters

- **x** *(Variable or N-dimensional array)* – Input variable. Let the length of *reps* be *d*. If *x.ndim < d*, *x* is treated as *d*-dimensional array by prepending new axes. For example, when the shape of *x* is (2,) and tiled with 2-dim repetitions, *x* is treated as the shape (1, 2). If *x.ndim > d*, *reps* is treated as *x.ndim*-dimensional by pre-pending 1’s. For example, when the shape of *x* is (2, 3, 2, 3), the 2-dim *reps* of (2, 2) is treated as (1, 1, 2, 2).

- **reps** *(int or tuple of int s)* – The number of times which *x* is replicated along each axis.

Returns

The tiled output Variable. Let the length of *reps* be *d*, the output has the dimension of \(\max(d, x.ndim)\).

Return type *Variable*

Example

```python
>>> x = np.array([0, 1, 2])
>>> x.shape
(3,)
>>> y = F.tile(x, 2)
>>> y.shape
(6,)
>>> y.array
array([0, 1, 2, 0, 1, 2])
>>> y = F.tile(x, (2, 2))
>>> y.shape
(2, 6)
>>> y.array
array([[0, 1, 2, 0, 1, 2],
       [0, 1, 2, 0, 1, 2]])
>>> y = F.tile(x, (2, 1, 2))
>>> y.shape
(2, 1, 6)
>>> y.array
array([[[0, 1, 2, 0, 1, 2]],
       [[[0, 1, 2, 0, 1, 2]]]])

>>> x = np.array([[1, 2], [3, 4]])
>>> x.shape
(2, 2)
>>> y = F.tile(x, 2)
>>> y.shape
(2, 4)
>>> y.array
array([[1, 2, 1, 2],
       [3, 4, 3, 4]])
>>> y = F.tile(x, (2, 2))
>>> y.shape
(4, 4)
```

(continues on next page)
chainer.functions.transpose

chainer.functions.transpose(x, axes=None)
Permute the dimensions of an input variable without copy.

Parameters

- x (Variable or N-dimensional array) – Input variable to be transposed. A \((s_1, s_2, ..., s_N)\) -shaped float array.
- axes (tuple of ints) – By default, reverse the dimensions, otherwise permute the axes according to the values given.

Returns
Variable whose axes are permuted.

Return type
Variable

Example

```python
chiran # reverse the dimensions

```
chainer.functions.transpose_sequence

chainer.functions.transpose_sequence(xs)
Transpone a list of Variables.

This function transposes a list of Variables and returns a list of Variables. For example a user gives 
\[(0, 1, 2, 3), (4, 5), (6)\], the function returns 
\[(0, 4, 6), (1, 5), (2), (3)\]. Note that a given list needs to be sorted by each length of Variable.

Parameters xs (list of Variable or N-dimensional array) – Variables to transpose.

Returns Transposed list.

Return type tuple of Variable

Example

```python
>>> lst = [chainer.Variable(np.array([1, 1, 1])), ... chainer.Variable(np.array([2, 2])), ... chainer.Variable(np.array([3]))]
>>> transposed = F.transpose_sequence(lst)
>>> transposed
(Variable([1, 2, 3]), Variable([1, 2]), Variable([1]))
```

chainer.functions.vstack

chainer.functions.vstack(xs)
Concatenate variables vertically (row wise).

Parameters xs (list of Variable or N-dimensional array) – Input variables to be concatenated.
The variables must have the same ndim. When the variables have the second axis (i.e. ndim ≥ 2), the variables must have the same shape along all but the first axis. When the variables do not have the second axis (i.e. ndim < 2), the variables must have the same shape.

Returns Output variable. When the input variables have the second axis (i.e. ndim ≥ 2), the shapes of inputs and output are the same along all but the first axis. The length of first axis is the sum of the lengths of inputs first axis. When the variables do not have the second axis (i.e. ndim < 2), the shape of output is (2, N) (N is the size of the input variable).

Return type Variable

Example

```python
>>> x1 = np.array((1, 2, 3))
>>> x1.shape
(3,)```
>>> x2 = np.array((2, 3, 4))
>>> x2.shape
(3,)
>>> y = F.vstack((x1, x2))
>>> y.shape
(2, 3)
>>> y.array
array([[1, 2, 3],
       [2, 3, 4]])

>>> x1 = np.arange(0, 12).reshape(3, 4)
>>> x1.shape
(3, 4)
>>> x1
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])

>>> x2 = np.arange(12, 20).reshape(2, 4)
>>> x2.shape
(2, 4)
>>> x2
array([[12, 13, 14, 15],
       [16, 17, 18, 19]])

>>> y = F.vstack([x1, x2])
>>> y.shape
(5, 4)
>>> y.array
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11],
       [12, 13, 14, 15],
       [16, 17, 18, 19]])

chainer.functions.where

chainer.functions.where(condition, x, y)

Choose elements depending on condition.

This function choose values depending on a given condition. All condition, x, and y must have the same shape.

Parameters

- **condition** (Variable or N-dimensional array) – Input variable containing the condition. A (s₁, s₂, ..., s_N) -shaped boolean array. Only boolean array is permitted.
- **x** (Variable or N-dimensional array) – Input variable chosen when condition is True. A (s₁, s₂, ..., s_N) -shaped float array.
- **y** (Variable or N-dimensional array) – Input variable chosen when condition is False. A (s₁, s₂, ..., s_N) -shaped float array.

Returns Variable containing chosen values.

Return type Variable
```python
>>> cond = np.array([[1, 0], [0, 1]], dtype=np.bool)
>>> cond
array([[ True, False],
       [False,  True]])
```

```python
>>> x = np.array([[1, 2], [3, 4]], np.float32)
>>> y = np.zeros((2, 2), np.float32)
>>> F.where(cond, x, y).array
array([[1., 0.],
       [0., 4.]], dtype=float32)
```

### 4.2.4 Neural network connections

<table>
<thead>
<tr>
<th>chainer.functions.bilinear</th>
<th>Applies a bilinear function based on given parameters.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.functions.convolution_1d</td>
<td>1-dimensional convolution function.</td>
</tr>
<tr>
<td>chainer.functions.convolution_2d</td>
<td>Two-dimensional convolution function.</td>
</tr>
<tr>
<td>chainer.functions.convolution_3d</td>
<td>3-dimensional convolution function.</td>
</tr>
<tr>
<td>chainer.functions.convolution_nd</td>
<td>N-dimensional convolution function.</td>
</tr>
<tr>
<td>chainer.functions.deconvolution_1d</td>
<td>1-dimensional deconvolution function.</td>
</tr>
<tr>
<td>chainer.functions.deconvolution_2d</td>
<td>Two dimensional deconvolution function.</td>
</tr>
<tr>
<td>chainer.functions.deconvolution_3d</td>
<td>3-dimensional deconvolution function.</td>
</tr>
<tr>
<td>chainer.functions.deconvolution_nd</td>
<td>N-dimensional deconvolution function.</td>
</tr>
<tr>
<td>chainer.functions.depthwise_convolution_2d</td>
<td>Two-dimensional depthwise convolution function.</td>
</tr>
<tr>
<td>chainer.functions.deformable_convolution_2d_sampler</td>
<td>Two-dimensional deformable convolution function using computed offset.</td>
</tr>
<tr>
<td>chainer.functions.dilated_convolution_2d</td>
<td>Two-dimensional dilated convolution function.</td>
</tr>
<tr>
<td>chainer.functions.embed_id</td>
<td>Efficient linear function for one-hot input.</td>
</tr>
<tr>
<td>chainer.functions.linear</td>
<td>Linear function, or affine transformation.</td>
</tr>
<tr>
<td>chainer.functions.local_convolution_2d</td>
<td>Two-dimensional local convolution function.</td>
</tr>
<tr>
<td>chainer.functions.n_step_bigru</td>
<td>Stacked Bi-directional Gated Recurrent Unit function.</td>
</tr>
<tr>
<td>chainer.functions.n_step_bilstm</td>
<td>Stacked Bi-directional Long Short-Term Memory function.</td>
</tr>
<tr>
<td>chainer.functions.n_step_birnn</td>
<td>Stacked Bi-directional RNN function for sequence inputs.</td>
</tr>
<tr>
<td>chainer.functions.n_step_gru</td>
<td>Stacked Uni-directional Gated Recurrent Unit function.</td>
</tr>
<tr>
<td>chainer.functions.n_step_lstm</td>
<td>Stacked Uni-directional Long Short-Term Memory function.</td>
</tr>
<tr>
<td>chainer.functions.n_step_rnn</td>
<td>Stacked Uni-directional RNN function for sequence inputs.</td>
</tr>
<tr>
<td>chainer.functions.shift</td>
<td>Shift function.</td>
</tr>
</tbody>
</table>
chainer.functions.bilinear

chainer.functions.bilinear(e1, e2, W=None, V1=None, V2=None, b=None)

Applies a bilinear function based on given parameters.

This is a building block of Neural Tensor Network (see the reference paper below). It takes two input variables and one or four parameters, and outputs one variable.

To be precise, denote six input arrays mathematically by $e_1 \in \mathbb{R}^{I \cdot J}$, $e_2 \in \mathbb{R}^{I \cdot K}$, $W \in \mathbb{R}^{J \cdot K \cdot L}$, $V^1 \in \mathbb{R}^{J \cdot L}$, $V^2 \in \mathbb{R}^{K \cdot L}$, and $b \in \mathbb{R}^{L}$, where $I$ is mini-batch size. In this document, we call $V^1$, $V^2$, and $b$ linear parameters.

The output of forward propagation is calculated as

$$y_{it} = \sum_{jk} e_{ij}^1 e_{ik}^2 W_{jkl} + \sum_j e_{ij}^1 V^1_{jkl} + \sum_k e_{ik}^2 V^2_{kl} + b_l.$$ 

Note that $V^1$, $V^2$, $b$ are optional. If these are not given, then this function omits the last three terms in the above equation.

Note: This function accepts an input variable $e_1$ or $e_2$ of a non-matrix array. In this case, the leading dimension is treated as the batch dimension, and the other dimensions are reduced to one dimension.

Note: In the original paper, $J$ and $K$ must be equal and the author denotes $[V^1V^2]$ (concatenation of matrices) by $V$.

Parameters

- **e1** (Variable or N-dimensional array) – Left input variable.
- **e2** (Variable or N-dimensional array) – Right input variable.
- **W** (Variable or N-dimensional array) – Quadratic weight variable.
- **V1** (Variable or N-dimensional array) – Left coefficient variable.
- **V2** (Variable or N-dimensional array) – Right coefficient variable.
- **b** (Variable or N-dimensional array) – Bias variable.

Returns Output variable.

Return type Variable

See: Reasoning With Neural Tensor Networks for Knowledge Base Completion [Socher+, NIPS2013].

See also:

Bilinear to manage the model parameters $W$, $V^1$, $V^2$, and $b$. 

4.2. Functions
chainer.functions.convolution_1d

chainer.functions.convolution_1d(x, W, b=None, stride=1, pad=0, cover_all=False, dilate=1, groups=1)

1-dimensional convolution function.

Note: This function calls convolution_nd() internally, so see the details of the behavior in the documentation of convolution_nd().

chainer.functions.convolution_2d

chainer.functions.convolution_2d(x, W, b=None, stride=1, pad=0, cover_all=False, *, dilate=1, groups=1)

Two-dimensional convolution function.

This is an implementation of two-dimensional convolution in ConvNets. It takes three variables: the input image x, the filter weight W, and the bias vector b.

Notation: here is a notation for dimensionalities.
- n is the batch size.
- c_I and c_O are the number of the input and output channels, respectively.
- h_I and w_I are the height and width of the input image, respectively.
- h_K and w_K are the height and width of the filters, respectively.
- h_P and w_P are the height and width of the spatial padding size, respectively.

Then the Convolution2D function computes correlations between filters and patches of size (h_K, w_K) in x. Note that correlation here is equivalent to the inner product between expanded vectors. Patches are extracted at positions shifted by multiples of stride from the first position (-h_P, -w_P) for each spatial axis. The right-most (or bottom-most) patches do not run over the padded spatial size.

Let (s_Y, s_X) be the stride of filter application. Then, the output size (h_O, w_O) is determined by the following equations:

\[ h_O = \frac{(h_I + 2h_P - h_K)}{s_Y} + 1, \]
\[ w_O = \frac{(w_I + 2w_P - w_K)}{s_X} + 1. \]

If cover_all option is True, the filter will cover the all spatial locations. So, if the last stride of filter does not cover the end of spatial locations, an additional stride will be applied to the end part of spatial locations. In this case, the output size (h_O, w_O) is determined by the following equations:

\[ h_O = \frac{(h_I + 2h_P - h_K + s_Y - 1)}{s_Y} + 1, \]
\[ w_O = \frac{(w_I + 2w_P - w_K + s_X - 1)}{s_X} + 1. \]

If the bias vector is given, then it is added to all spatial locations of the output of convolution.

The output of this function can be non-deterministic when it uses cuDNN. If chainer.configuration.config.cudnn_deterministic is True and cuDNN version is >= v3, it forces cuDNN to use a deterministic algorithm.

Convolution links can use a feature of cuDNN called autotuning, which selects the most efficient CNN algorithm for images of fixed-size, can provide a significant performance boost for fixed neural nets. To enable, set chainer.using_config('autotune', True)

When the dilation factor is greater than one, cuDNN is not used unless the version is 6.0 or higher.
Parameters

- **x** *(Variable or N-dimensional array)* – Input variable of shape \((n, c_I, h_I, w_I)\).
- **W** *(Variable or N-dimensional array)* – Weight variable of shape \((c_O, c_I, h_K, w_K)\).
- **b** *(None or Variable or N-dimensional array)* – Bias variable of length \(c_O\) (optional).
- **stride** *(int or pair of int s)* – Stride of filter applications. \(\text{stride}=s\) and \(\text{stride}=(s, s)\) are equivalent.
- **pad** *(int or pair of int s)* – Spatial padding width for input arrays. \(\text{pad}=p\) and \(\text{pad}=(p, p)\) are equivalent.
- **cover_all** *(bool)* – If True, all spatial locations are convoluted into some output pixels.
- **dilate** *(int or pair of int s)* – Dilation factor of filter applications. \(\text{dilate}=d\) and \(\text{dilate}=(d, d)\) are equivalent.
- **groups** *(int)* – Number of groups of channels. If the number is greater than 1, input tensor \(W\) is divided into some blocks by this value. For each tensor blocks, convolution operation will be executed independently. Input channel size \(c_I\) and output channel size \(c_O\) must be exactly divisible by this value.

Returns Output variable of shape \((n, c_O, h_O, w_O)\).

Return type **Variable**

See also:

*Convolution2D* to manage the model parameters \(W\) and \(b\).

Example

```python
>>> n = 10
>>> c_i, c_o = 3, 1
>>> h_i, w_i = 30, 40
>>> h_k, w_k = 10, 10
>>> h_p, w_p = 5, 5
>>> x = np.random.uniform(0, 1, (n, c_i, h_i, w_i)).astype(np.float32)
>>> x.shape
(10, 3, 30, 40)
>>> W = np.random.uniform(0, 1, (c_o, c_i, h_k, w_k)).astype(np.float32)
>>> W.shape
(1, 3, 10, 10)
>>> b = np.random.uniform(0, 1, (c_o,)).astype(np.float32)
>>> b.shape
(1,)
>>> s_y, s_x = 5, 7
>>> y = F.convolution_2d(x, W, b, stride=(s_y, s_x), pad=(h_p, w_p))
>>> y.shape
(10, 1, 7, 6)
>>> h_o = int((h_i + 2 * h_p - h_k) / s_y + 1)
>>> w_o = int((w_i + 2 * w_p - w_k) / s_x + 1)
>>> y.shape == (n, c_o, h_o, w_o)
True
>>> y = F.convolution_2d(x, W, b, stride=(s_y, s_x), pad=(h_p, w_p), cover_all=True)
>>> y.shape == (n, c_o, h_o, w_o + 1)
True
```
chainer.functions.convolution_3d

chainer.functions.convolution_3d(x, W, b=None, stride=1, pad=0, cover_all=False, dilate=1, groups=1)

3-dimensional convolution function.

Note: This function calls convolution_nd() internally, so see the details of the behavior in the documentation of convolution_nd().

chainer.functions.convolution_nd

chainer.functions.convolution_nd(x, W, b=None, stride=1, pad=0, cover_all=False, dilate=1, groups=1)

N-dimensional convolution function.

This is an implementation of N-dimensional convolution which is generalized two-dimensional convolution in ConvNets. It takes three variables: the input x, the filter weight W and the bias vector b.

Notation: here is a notation for dimensionalities.

- \( N \) is the number of spatial dimensions.
- \( n \) is the batch size.
- \( c_I \) and \( c_O \) are the number of the input and output channels, respectively.
- \( d_1, d_2, ..., d_N \) are the size of each axis of the input’s spatial dimensions, respectively.
- \( k_1, k_2, ..., k_N \) are the size of each axis of the filters, respectively.
- \( l_1, l_2, ..., l_N \) are the size of each axis of the output’s spatial dimensions, respectively.
- \( p_1, p_2, ..., p_N \) are the size of each axis of the spatial padding size, respectively.

Then the convolution_nd function computes correlations between filters and patches of size \((k_1, k_2, ..., k_N)\) in x. Note that correlation here is equivalent to the inner product between expanded tensors. Patches are extracted at positions shifted by multiples of \(\text{stride} \) from the first position \((-p_1, -p_2, ..., -p_N)\) for each spatial axis.

Let \((s_1, s_2, ..., s_N)\) be the stride of filter application. Then, the output size \((l_1, l_2, ..., l_N)\) is determined by the following equations:

\[
l_n = (d_n + 2p_n - k_n)/s_n + 1 \quad (n = 1, ..., N)
\]

If \(\text{cover_all}\) option is True, the filter will cover the all spatial locations. So, if the last stride of filter does not cover the end of spatial locations, an additional stride will be applied to the end part of spatial locations. In this case, the output size is determined by the following equations:

\[
l_n = (d_n + 2p_n - k_n + s_n - 1)/s_n + 1 \quad (n = 1, ..., N)
\]

Parameters

- \( x \) (Variable or N-dimensional array) – Input variable of shape \((n, c_I, d_1, d_2, ..., d_N)\).
- \( W \) (Variable or N-dimensional array) – Weight variable of shape \((c_O, c_I, k_1, k_2, ..., k_N)\).
- \( b \) (None or Variable or N-dimensional array) – One-dimensional bias variable with length \(c_O\) (optional).
• **stride** (int or tuple of int s) – Stride of filter applications \((s_1, s_2, \ldots, s_N)\).
  
  `stride=s` is equivalent to \((s, s, \ldots, s)\).

• **pad** (int or tuple of int s) – Spatial padding width for input arrays \((p_1, p_2, \ldots, p_N)\).
  
  `pad=p` is equivalent to \((p, p, \ldots, p)\).

• **cover_all** (bool) – If True, all spatial locations are convoluted into some output pixels.
  It may make the output size larger. `cover_all` needs to be False if you want to use cuDNN.

• **dilate** (int or tuple of int s) – Dilation factor of filter applications. `dilate=d` and `dilate=(d, d, \ldots, d)` are equivalent.

• **groups** (int) – The number of groups to use grouped convolution. The default is one, where grouped convolution is not used.

**Returns** Output variable of shape \((n, c_O, l_1, l_2, \ldots, l_N)\).

**Return type** Variable

---

**Note:** This function uses cuDNN implementation for its forward and backward computation if ALL of the following conditions are satisfied:

- `cuda.cudnn_enabled` is True
- `chainer.config.use_cudnn` is 'always' or 'auto'
- The number of spatial dimensions is more than one.
- `cover_all` is False
- The input's `dtype` is equal to the filter weight's.
- The `dtype` is FP16, FP32 or FP64. (FP16 is only available when cuDNN version \(\geq v3\).)

Convolution links can use a feature of cuDNN called autotuning, which selects the most efficient CNN algorithm for images of fixed-size, can provide a significant performance boost for fixed neural nets. To enable, set `chainer.using_config('autotune', True)`

**See also:**

- `ConvolutionND` to manage the model parameters \(W\) and \(b\).

**See also:**

- `convolution_2d()`

---

**Example**

```python
>>> n = 10
>>> c_i, c_o = 3, 1
>>> d1, d2, d3 = 30, 40, 50
>>> k1, k2, k3 = 10, 10, 10
>>> p1, p2, p3 = 5, 5, 5
>>> x = np.random.uniform(0, 1, (n, c_i, d1, d2, d3)).astype(np.float32)
>>> x.shape
(10, 3, 30, 40, 50)
>>> W = np.random.uniform(0, 1, (c_o, c_i, k1, k2, k3)).astype(np.float32)
>>> W.shape
(1, 3, 10, 10, 10)
>>> b = np.random.uniform(0, 1, (c_o)).astype(np.float32)
>>> b.shape
(continues on next page)
```

---

4.2. Functions
```python
(1,)
>>> s1, s2, s3 = 2, 4, 6
>>> y = F.convolution_nd(x, W, b, stride=(s1, s2, s3), pad=(p1, p2, p3))
>>> y.shape
(10, 1, 16, 11, 9)
>>> l1 = int((d1 + 2 * p1 - k1) / s1 + 1)
>>> l2 = int((d2 + 2 * p2 - k2) / s2 + 1)
>>> l3 = int((d3 + 2 * p3 - k3) / s3 + 1)
>>> y.shape == (n, c_o, l1, l2, l3)
True
>>> y = F.convolution_nd(x, W, b, stride=(s1, s2, s3), pad=(p1, p2, p3), cover_all=True)
>>> y.shape == (n, c_o, l1, l2, l3 + 1)
True
```

**chainer.functions.deconvolution_1d**

```python
chainer.functions.deconvolution_1d(x, W, b=None, stride=1, pad=0, outsize=None, dilate=1, groups=1)
```

1-dimensional deconvolution function.

**Note:** This function calls `deconvolution_nd()` internally, so see the details of the behavior in the documentation of `deconvolution_nd()`.

**chainer.functions.deconvolution_2d**

```python
chainer.functions.deconvolution_2d(x, W, b=None, stride=1, pad=0, outsize=None, *, dilate=1, groups=1)
```

Two dimensional deconvolution function.

This is an implementation of two-dimensional deconvolution. In most of deep learning frameworks and papers, this function is called transposed convolution. But because of historical reasons (e.g. paper by Ziller Deconvolutional Networks) and backward compatibility, this function is called deconvolution in Chainer.

It takes three variables: input image `x`, the filter weight `W`, and the bias vector `b`.

**Notation:** here is a notation for dimensionalities.

- `n` is the batch size.
- `c_I` and `c_O` are the number of the input and output channels, respectively.
- `h_I` and `w_I` are the height and width of the input image, respectively.
- `h_K` and `w_K` are the height and width of the filters, respectively.
- `h_P` and `w_P` are the height and width of the spatial padding size, respectively.

Let `(s_Y, s_X)` be the stride of filter application. Then, the output size `(h_O, w_O)` is estimated by the following equations:

\[
\begin{align*}
    h_O &= s_Y(h_I - 1) + h_K - 2h_P, \\
    w_O &= s_X(w_I - 1) + w_K - 2w_P.
\end{align*}
\]
The output of this function can be non-deterministic when it uses cuDNN. If `chainer.configuration. config.deterministic` is `True` and cuDNN version is `>= v3`, it forces cuDNN to use a deterministic algorithm.

Deconvolution links can use a feature of cuDNN called autotuning, which selects the most efficient CNN algorithm for images of fixed-size, can provide a significant performance boost for fixed neural nets. To enable, set `chainer.using_config('autotune', True)`

Parameters

- **x** *(Variable or N-dimensional array)* – Input variable of shape \((n, c_I, h_I, w_I)\).
- **W** *(Variable or N-dimensional array)* – Weight variable of shape \((c_I, c_O, h_K, w_K)\).
- **b** *(None or Variable or N-dimensional array)* – Bias variable of length \(c_O\) (optional).
- **stride** *(int or pair of int s)* – Stride of filter applications. \(\text{stride}=s\) and \(\text{stride}=(s, s)\) are equivalent.
- **pad** *(int or pair of int s)* – Spatial padding width for input arrays. \(\text{pad}=p\) and \(\text{pad}=(p, p)\) are equivalent.
- **outsize** *(None or tuple of int s)* – Expected output size of deconvolutional operation. It should be pair of height and width \((h_O, w_O)\). Default value is `None` and the outsize is estimated by input size, stride and pad.
- **dilate** *(int or pair of int s)* – Dilation factor of filter applications. \(\text{dilate}=d\) and \(\text{dilate}=(d, d)\) are equivalent.
- **groups** *(int)* – The number of groups to use grouped deconvolution. The default is one, where grouped deconvolution is not used.

Returns Output variable of shape \((n, c_O, h_O, w_O)\).

Return type **Variable**

See also: `Deconvolution2D` to manage the model parameters \(W\) and \(b\).

Example

```python
>>> n = 10
>>> c_i, c_o = 1, 3
>>> h_i, w_i = 5, 10
>>> h_k, w_k = 10, 10
>>> h_p, w_p = 5, 5
>>> x = np.random.uniform(0, 1, (n, c_i, h_i, w_i)).astype(np.float32)
>>> x.shape
(10, 1, 5, 10)
>>> W = np.random.uniform(0, 1, (c_i, c_o, h_k, w_k)).astype(np.float32)
>>> W.shape
(1, 3, 10, 10)
>>> b = np.random.uniform(0, 1, c_o).astype(np.float32)
>>> b.shape
(3,)
>>> s_y, s_x = 5, 5
>>> y = F.deconvolution_2d(x, W, b, stride=(s_y, s_x), pad=(h_p, w_p))
>>> y.shape
(10, 3, 20, 45)
>>> h_o = s_y * (h_i - 1) + h_k - 2 * h_p
```

(continues on next page)
w_o = s_x * (w_i - 1) + w_k - 2 * w_p

y.shape == (n, c_o, h_o, w_o)

True

chainer.functions.deconvolution_3d

chainer.functions.deconvolution_3d(x, W=b=None, stride=1, pad=0, outsize=None, dilate=1, groups=1)

3-dimensional deconvolution function.

**Note:** This function calls deconvolution_nd() internally, so see the details of the behavior in the documentation of deconvolution_nd().

chainer.functions.deconvolution_nd

chainer.functions.deconvolution_nd(x, W=b=None, stride=1, pad=0, outsize=None, dilate=1, groups=1)

N-dimensional deconvolution function.

This is an implementation of N-dimensional deconvolution which generalizes two-dimensional one. In most of deep learning frameworks and papers, this function is called **transposed convolution**. But because of historical reasons (e.g. paper by Ziller *Deconvolutional Networks*) and backward compatibility, this function is called **deconvolution** in Chainer.

It takes three variables: the input x, the filter weight W, and the bias vector b.

Notation: here is a notation for dimensionalities.

- N is the number of spatial dimensions.
- n is the batch size.
- c_I and c_O are the number of the input and output channels, respectively.
- d_1, d_2, ..., d_N are the size of each axis of the input’s spatial dimensions, respectively.
- k_1, k_2, ..., k_N are the size of each axis of the filters, respectively.
- p_1, p_2, ..., p_N are the size of each axis of the spatial padding size, respectively.
- s_1, s_2, ..., s_N are the stride of each axis of filter application, respectively.

If outsize option is None, the output size (l_1, l_2, ..., l_N) is determined by the following equations with the items in the above list:

\[ l_n = s_n(d_n - 1) + k_n - 2p_n \quad (n = 1, ..., N) \]

If outsize option is given, the output size is determined by outsize. In this case, the outsize (l_1, l_2, ..., l_N) must satisfy the following equations:

\[ d_n = \lfloor (l_n + 2p_n - k_n)/s_n \rfloor + 1 \quad (n = 1, ..., N) \]

Deconvolution links can use a feature of cuDNN called autotuning, which selects the most efficient CNN algorithm for images of fixed-size, can provide a significant performance boost for fixed neural nets. To enable, set

chainer.using_config('autotune', True)
Parameters

- **x** (*Variable* or *N-dimensional array*) – Input variable of shape \((n, c_I, d_1, d_2, ..., d_N)\).
- **W** (*Variable* or *N-dimensional array*) – Weight variable of shape \((c_I, c_O, k_1, k_2, ..., k_N)\).
- **b** (*None* or *Variable* or *N-dimensional array*) – One-dimensional bias variable with length \(c_O\) (optional).
- **stride** (*int* or *tuple* of *int* *s*) – Stride of filter applications \((s_1, s_2, ..., s_N)\). \(stride=s\) is equivalent to \((s, s, ..., s)\).
- **pad** (*int* or *tuple* of *int* *s*) – Spatial padding width for input arrays \((p_1, p_2, ..., p_N)\). \(pad=p\) is equivalent to \((p, p, ..., p)\).
- **outsize** (*None* or *tuple* of *int* *s*) – Expected output size of deconvolutional operation. It should be a tuple of ints \((l_1, l_2, ..., l_N)\). Default value is *None* and the outsize is estimated by input size, stride and pad.
- **dilate** (*int* or *tuple* of *int* *s*) – Dilation factor of filter applications. \(dilate=d\) and \(dilate=(d, d, ..., d)\) are equivalent.
- **groups** (*int*) – The number of groups to use grouped convolution. The default is one, where grouped convolution is not used.

Returns Output variable of shape \((n, c_O, l_1, l_2, ..., l_N)\).

Return type *Variable*

See also:

*DeconvolutionND* to manage the model parameters *W* and *b*.

See also:

*deconvolution_2d()*

Example

Example1: the case when *outsize* is not given.

```python
>>> n = 10
>>> c_i, c_o = 3, 1
>>> d1, d2, d3 = 5, 10, 15
>>> k1, k2, k3 = 10, 10, 10
>>> p1, p2, p3 = 5, 5, 5
>>> x = np.random.uniform(0, 1, (n, c_i, d1, d2, d3)).astype(np.float32)
>>> x.shape
(10, 3, 5, 10, 15)
>>> W = np.random.uniform(0, 1, (c_i, c_o, k1, k2, k3)).astype(np.float32)
>>> W.shape
(3, 1, 10, 10, 10)
>>> b = np.random.uniform(0, 1, (c_o)).astype(np.float32)
>>> b.shape
(1,)
>>> s1, s2, s3 = 2, 4, 6
>>> y = F.deconvolution_nd(x, W, b, stride=(s1, s2, s3), pad=(p1, p2, p3))
>>> y.shape
(10, 1, 8, 36, 84)
>>> l1 = s1 * (d1 - 1) + k1 - 2 * p1
>>> l2 = s2 * (d2 - 1) + k2 - 2 * p2
>>> l3 = s3 * (d3 - 1) + k3 - 2 * p3
```
Example2: the case when `outsize` is given.

```python
>>> n = 10
>>> c_i, c_o = 3, 1
>>> d1, d2, d3 = 5, 10, 15
>>> k1, k2, k3 = 10, 10, 10
>>> p1, p2, p3 = 5, 5, 5
>>> x = np.random.uniform(0, 1, (n, c_i, d1, d2, d3)).astype(np.float32)
>>> x.shape
(10, 3, 5, 10, 15)
>>> W = np.random.uniform(0, 1, (c_i, c_o, k1, k2, k3)).astype(np.float32)
>>> W.shape
(3, 1, 10, 10, 10)
>>> b = np.random.uniform(0, 1, (c_o)).astype(np.float32)
>>> b.shape
(1,)
>>> s1, s2, s3 = 2, 4, 6
>>> l1, l2, l3 = 9, 38, 87
>>> d1 == int((l1 + 2 * p1 - k1) / s1) + 1
True
>>> d2 == int((l2 + 2 * p2 - k2) / s2) + 1
True
>>> d3 == int((l3 + 2 * p3 - k3) / s3) + 1
True
>>> y = F.deconvolution_nd(x, W, b, stride=(s1, s2, s3), pad=(p1, p2, p3),
→outsize=(l1, l2, l3))
>>> y.shape
(10, 1, 9, 38, 87)
>>> y.shape == (n, c_o, l1, l2, l3)
True
```

**chainer.functions.depthwise_convolution_2d**

**chainer.functions.depthwise_convolution_2d**(*x, W, b=None, stride=1, pad=0*)

Two-dimensional depthwise convolution function.

This is an implementation of two-dimensional depthwise convolution. It takes two or three variables: the input image `x`, the filter weight `W`, and optionally, the bias vector `b`.

Notation: here is a notation for dimensionalities.

- `n` is the batch size.
- `c_i` is the number of the input.
- `c_M` is the channel multiplier.
- `h` and `w` are the height and width of the input image, respectively.
- `h_O` and `w_O` are the height and width of the output image, respectively.
- `k_H` and `k_W` are the height and width of the filters, respectively.

**Parameters**
• \(x\) (Variable or \(N\)-dimensional array) – Input variable of shape \((n, c_I, h, w)\).
• \(W\) (Variable or \(N\)-dimensional array) – Weight variable of shape \((c_M, c_I, k_H, k_W)\).
• \(b\) (Variable or \(N\)-dimensional array) – Bias variable of length \(c_M \times c_I\) (optional).
• \(\text{stride}\) (int or pair of ints) – Stride of filter applications. \(\text{stride}=s\) and \(\text{stride}=(s, s)\) are equivalent.
• \(\text{pad}\) (int or pair of ints) – Spatial padding width for input arrays. \(\text{pad}=p\) and \(\text{pad}=(p, p)\) are equivalent.

Returns  Output variable. Its shape is \((n, c_I \times c_M, h_O, w_O)\).

Return type  Variable

Like Convolution2D, DepthwiseConvolution2D function computes correlations between filters and patches of size \((k_H, k_W)\) in \(x\). But unlike Convolution2D, DepthwiseConvolution2D does not add up input channels of filters but concatenates them. For that reason, the shape of outputs of depthwise convolution are \((n, c_I \times c_M, h_O, w_O)\), \(c_M\) is called channel multiplier.

\((h_O, w_O)\) is determined by the equivalent equation of Convolution2D.

If the bias vector is given, then it is added to all spatial locations of the output of convolution.

See: L. Sifre. Rigid-motion scattering for image classification

See also:
DepthwiseConvolution2D to manage the model parameters \(W\) and \(b\).

Example

```python
>>> x = np.random.uniform(0, 1, (2, 3, 4, 7))
>>> W = np.random.uniform(0, 1, (2, 3, 3, 3))
>>> b = np.random.uniform(0, 1, (6,))
>>> y = F.depthwise_convolution_2d(x, W, b)
>>> y.shape
(2, 6, 2, 5)
```

4.2. Functions 211
• $p_H$ and $p_W$ are the spatial padding sizes.

The output size $(h_O, w_O)$ is determined by the following equations:

$$h_O = (h + 2p_H - k_H)/s_Y + 1,$$
$$w_O = (w + 2p_W - k_W)/s_X + 1.$$

Parameters

- **x** *(Variable or N-dimensional array)* – Input variable of shape $(n, c_I, h, w)$.
- **offset** *(Variable or N-dimensional array)* – Offset variable of shape $(n, 2 \cdot k_H \cdot k_W, h_O, w_O)$. The first $k_H \cdot k_W$ index of the second axis corresponds to the offsets in the horizontal direction. The last $k_H \cdot k_W$ index of the second axis corresponds to the offsets in the vertical direction.
- **W** *(Variable or N-dimensional array)* – Weight variable of shape $(c_O, c_I, k_H, k_W)$.
- **b** *(Variable or N-dimensional array)* – Bias variable of length $c_O$ (optional).
- **stride** *(int or pair of ints)* – Stride of filter applications. `stride=s` and `stride=(s, s)` are equivalent.
- **pad** *(int or pair of ints)* – Spatial padding width for input arrays. `pad=p` and `pad=(p, p)` are equivalent.

**Returns** Output variable.

**Return type** *Variable*

Deformable convolution adds 2D offsets to the regular grid sampling locations in the standard convolution. It enables free form deformation of the sampling grid.

See Jifeng Dai, Haozhi Qi, Yuwen Xiong, Yi Li, Guodong Zhang, Han Hu, Yichen Wei. Deformable Convolutional Networks

If the bias vector is given, then it is added to all spatial locations of the output of convolution.

See also:

*DeformableConvolution2D* to manage the model parameters $W$ and $b$.

**Example**

```python
>>> x = np.random.uniform(0, 1, (2, 3, 4, 7)).astype(np.float32)
>>> offset = np.random.uniform(...
    0, 1, (2, 2 * 3 * 3, 2, 5)).astype(np.float32)
>>> W = np.random.uniform(0, 1, (4, 3, 3, 3)).astype(np.float32)
>>> b = np.random.uniform(0, 1, (4,)).astype(np.float32)
>>> y = F.deformable_convolution_2d_sampler(x, offset, W, b)
>>> y.shape
(2, 4, 2, 5)
```
**chainer.functions.dilated_convolution_2d**

chainer.functions.dilated_convolution_2d(x, W, b=None, stride=1, pad=0, dilate=1, cover_all=False)

Two-dimensional dilated convolution function.

This is an implementation of two-dimensional dilated convolution in ConvNets. It takes three variables: the input image \(x\), the filter weight \(W\), and the bias vector \(b\).

**Note:** You can also perform dilated convolution by passing `dilate` argument to `chainer.functions.convolution_2d`. The functionality is the same.

Notation: here is a notation for dimensionalities.

- \(n\) is the batch size.
- \(c_I\) and \(c_O\) are the number of the input and output, respectively.
- \(h\) and \(w\) are the height and width of the input image, respectively.
- \(k_H\) and \(k_W\) are the height and width of the filters, respectively.

**Parameters**

- \(x\) (**Variable** or **N-dimensional array**) – Input variable of shape \((n, c_I, h, w)\).
- \(W\) (**Variable** or **N-dimensional array**) – Weight variable of shape \((c_O, c_I, k_H, k_W)\).
- \(b\) (**Variable** or **N-dimensional array**) – Bias variable of length \(c_O\) (optional).
- `stride` (**int or pair of ints**) – Stride of filter applications. `stride=s` and `stride=(s, s)` are equivalent.
- `pad` (**int or pair of ints**) – Spatial padding width for input arrays. `pad=p` and `pad=(p, p)` are equivalent.
- `dilate` (**int or pair of ints**) – Dilation factor of filter applications. `dilate=d` and `dilate=(d, d)` are equivalent.
- `cover_all` (**bool**) – If `True`, all spatial locations are convoluted into some output pixels. It may make the output size larger.

**Returns** Output variable.

**Return type** **Variable**

The two-dimensional dilated convolution function is defined as follows. Then the `DilatedConvolution2D` function computes correlations between filters and patches of size \((k_H, k_W)\) in \(x\). Patches here are extracted at intervals of the dilation factor. Note that correlation here is equivalent to the inner product between expanded vectors. Patches are extracted at intervals of the dilation factor and at positions shifted by multiples of `stride` from the first position `−pad` for each spatial axis. The right-most (or bottom-most) patches do not run over the padded spatial size.

Let \((s_Y, s_X)\) be the stride of filter application, \((p_H, p_W)\) the spatial padding size, and \((d_Y, d_X)\) the dilation factor of filter application. Then, the output size \((h_O, w_O)\) is determined by the following equations:

\[
\begin{align*}
h_O &= (h + 2p_H - k_H - (k_H - 1) * (d_Y - 1)) / s_Y + 1, \\
w_O &= (w + 2p_W - k_W - (k_W - 1) * (d_X - 1)) / s_X + 1.
\end{align*}
\]

If the bias vector is given, then it is added to all spatial locations of the output of convolution.
chainer.functions.embed_id

chainer.functions.embed_id(x, W, ignore_label=None)

Efficient linear function for one-hot input.

This function implements so called word embeddings. It takes two arguments: a set of IDs (words) $x$ in $B$ dimensional integer vector, and a set of all ID (word) embeddings $W$ in $V \times d$ float matrix. It outputs $B \times d$ matrix whose $i$-th row is the $x[i]$-th row of $W$.

This function is only differentiable on the input $W$.

Parameters

- **x** *(Variable or N-dimensional array)* – Batch vectors of IDs. Each element must be signed integer.
- **W** *(Variable or N-dimensional array)* – Distributed representation of each ID (a.k.a. word embeddings).
- **ignore_label** *(int or None)* – If ignore_label is an int value, $i$-th row of return value is filled with 0.

Returns

Output variable.

Return type

Variable

See also:

EmbedID to manage the model parameter $W$.

Example

```python
>>> x = np.array([2, 1]).astype(np.int32)
>>> x
array([2, 1], dtype=int32)
>>> W = np.array([[0, 0, 0],
                [1, 1, 1],
                [2, 2, 2]]).astype(np.float32)
>>> W
array([[0., 0., 0.],
       [1., 1., 1.],
       [2., 2., 2.]], dtype=float32)
>>> F.embed_id(x, W).array
array([[2., 2., 2.],
       [1., 1., 1.]], dtype=float32)
>>> F.embed_id(x, W, ignore_label=1).array
array([[2., 2., 2.],
       [0., 0., 0.]], dtype=float32)
```
chainer.functions.linear

**chainer.functions.linear** \((x, W, b=None, n\_batch\_axes=1)\)

Linear function, or affine transformation.

It accepts two or three arguments: an input minibatch \(x\), a weight matrix \(W\), and optionally a bias vector \(b\). It computes

\[
y_i = Wx_i + b.
\]

**Parameters**

- **\(x\)** *(Variable or N-dimensional array)* – Input variable, which is a \((s_1, s_2, \ldots, s_n)\)-shaped float array. Its first \(n\_batch\_axes\) dimensions are handled as **minibatch dimensions**. The other dimensions are handled as concatenated one dimension whose size must be \((s_{n\_batch\_axes} \times \cdots \times s_n = N)\).

- **\(W\)** *(Variable or N-dimensional array)* – Weight variable of shape \((M, N)\), where \((N = s_{n\_batch\_axes} \times \cdots \times s_n)\).

- **\(b\)** *(Variable or N-dimensional array)* – Bias variable (optional) of shape \((M,)\).

- **\(n\_batch\_axes\)** *(int)* – The number of batch axes. The default is 1. The input variable is reshaped into \((n\_batch\_axes + 1)\)-dimensional tensor. This should be greater than 0.

**Returns** Output variable. A float array with shape of \((s_1, \ldots, s_{n\_batch\_axes}, M)\).

**Return type** *Variable*

**See also:** *Linear* to manage the model parameters \(W\) and \(b\).

**Example**

```python
>>> x = np.random.uniform(0, 1, (3, 4)).astype(np.float32)
>>> W = np.random.uniform(0, 1, (5, 4)).astype(np.float32)
>>> b = np.random.uniform(0, 1, (5,)).astype(np.float32)
>>> y = F.linear(x, W, b)
>>> y.shape
(3, 5)
```

chainer.functions.local_convolution_2d

**chainer.functions.local_convolution_2d** \((x, W, b=None, stride=1)\)

Two-dimensional local convolution function.

Locally-connected function for 2D inputs. Works similarly to convolution_2d, except that weights are unshared, that is, a different set of filters is applied at each different patch of the input. It takes two or three variables: the input image \(x\), the filter weight \(W\), and optionally, the bias vector \(b\).

**Notation:** here is a notation for dimensionalities.

- \(n\) is the batch size.
- \(c_I\) is the number of the input.
- \(c_O\) is the number of output channels.
- \(h\) and \(w\) are the height and width of the input image, respectively.
• $h_O$ and $w_O$ are the height and width of the output image, respectively.
• $k_H$ and $k_W$ are the height and width of the filters, respectively.

Parameters

- $x$ (Variable or N-dimensional array) – Input variable of shape $(n, c_I, h, w)$.
- $W$ (Variable or N-dimensional array) – Weight variable of shape $(c_O, h_O, w_O, c_I, k_H, k_W)$.
- $b$ (Variable or N-dimensional array) – Bias variable of shape $(c_O, h_O, w_O)$ (optional).
- $stride$ (int or pair of ints) – Stride of filter applications. $stride=s$ and $stride=(s, s)$ are equivalent.

Returns

Output variable. Its shape is $(n, c_O, h_O, w_O)$.

Return type

Variable

Like Convolution2D, LocalConvolution2D function computes correlations between filters and patches of size $(k_H, k_W)$ in $x$. But unlike Convolution2D, LocalConvolution2D has a separate filter for each patch of the input $(h_O, w_O)$ is determined by the equivalent equation of Convolution2D, without any padding.

If the bias vector is given, then it is added to all spatial locations of the output of convolution.

See also:

LocalConvolution2D to manage the model parameters $W$ and $b$.

Example

```python
>>> x = np.random.uniform(0, 1, (2, 3, 7, 7))
>>> W = np.random.uniform(0, 1, (2, 5, 5, 3, 3, 3))
>>> b = np.random.uniform(0, 1, (2, 5, 5))
>>> y = F.local_convolution_2d(x, W, b)
>>> y.shape
(2, 2, 5, 5)
```

chainer.functions.n_step_bigru

chainer.functions.n_step_bigru($n_layers$, $dropout_ratio$, $hx$, $ws$, $bs$, $xs$)

Stacked Bi-directional Gated Recurrent Unit function.

This function calculates stacked Bi-directional GRU with sequences. This function gets an initial hidden state $h_0$, an input sequence $x$, weight matrices $W$, and bias vectors $b$. This function calculates hidden states $h_t$ for
each time $t$ from input $x_t$.

$$r_t^f = \sigma(W_0^f x_t + W_1^f h_{t-1} + b_0^f + b_1^f)$$
$$z_t^f = \sigma(W_1^f x_t + W_2^f h_{t-1} + b_1^f + b_2^f)$$
$$h_t'' = \tanh(W_2^f x_t + b_2^f + r_t^f \cdot (W_3^f h_{t-1} + b_3^f))$$
$$h_t^f = (1 - z_t^f) \cdot h_t'' + z_t^f \cdot h_{t-1}$$

$h_t$ for all $t$ with one call. Six weight matrices and six bias vectors are required for each layers. So, when $S$ layers exists, you need to prepare $6S$ weight matrices and $6S$ bias vectors.

If the number of layers `n_layers` is greater than 1, input of $k$-th layer is hidden state $h_{-t}$ of $k-1$-th layer. Note that all input variables except first layer may have different shape from the first layer.

**Parameters**

- `n_layers (int)` – Number of layers.
- `dropout_ratio (float)` – Dropout ratio.
- `hx (Variable)` – Variable holding stacked hidden states. Its shape is $(2S, B, N)$ where $S$ is number of layers and is equal to `n_layers`, $B$ is mini-batch size, and $N$ is dimension of hidden units.
- `ws` (list of list of `Variable`) – Weight matrices. `ws[i]` represents weights for `i`-th layer. Each `ws[i]` is a list containing six matrices. `ws[i][j]` is corresponding with $W_j$ in the equation. Only `ws[0][j]` where $0 <= j <= 2$ is $(N, I)$ shape as they are multiplied with input variables. All other matrices has $(N, N)$ shape.
- `bs` (list of list of `Variable`) – Bias vectors. `bs[i]` represents biases for `i`-th layer. Each `bs[i]` is a list containing six vectors. `bs[i][j]` is corresponding with $b_j$ in the equation. Shape of each matrix is $(N,)$ where $N$ is dimension of hidden units.
- `xs` (list of `Variable`) – A list of `Variable` holding input values. Each element `xs[t]` holds input value for time $t$. Its shape is $(B_t, I)$, where $B_t$ is mini-batch size for time $t$, and $I$ is size of input units. Note that this function supports variable length sequences. When sequences has different lengths, sort sequences in descending order by length, and transpose the sorted sequence. `transpose_sequence()` transpose a list of `Variable()` holding sequence. So `xs` needs to satisfy `xs[t].shape[0] >= xs[t + 1].shape[0]`.

- `use_bi_direction (bool)` – If True, this function uses Bi-direction GRU.

**Returns**

This function returns a tuple containing three elements, $hy$ and $ys$.

- $hy$ is an updated hidden states whose shape is same as $hx$. 

ys is a list of `Variable`. Each element `ys[t]` holds hidden states of the last layer corresponding to an input `xs[t]`. Its shape is `(B_t, N)` where `B_t` is mini-batch size for time `t`, and `N` is size of hidden units. Note that `B_t` is the same value as `xs[t]`.

Return type `tuple`

```python
chainer.functions.n_step_bilstm
```
\[chainer.functions.n_step_bilstm(n_layers, dropout_ratio, hx, cx, ws, bs, xs)\]

Stacked Bi-directional Long Short-Term Memory function.

This function calculates stacked Bi-directional LSTM with sequences. This function gets an initial hidden state \(h_0\), an initial cell state \(c_0\), an input sequence \(x\), weight matrices \(W\), and bias vectors \(b\). This function calculates hidden states \(h_t\) and \(c_t\) for each time \(t\) from input \(x_t\).

\[
\begin{align*}
i_t^f &= \sigma(W_0^f x_t + W_4^f h_{t-1} + b_0^f + b_4^f), \\
f_t^f &= \sigma(W_1^f x_t + W_5^f h_{t-1} + b_1^f + b_5^f), \\
o_t^f &= \sigma(W_2^f x_t + W_6^f h_{t-1} + b_2^f + b_6^f), \\
\tilde{c}_t^f &= \tanh(W_3^f x_t + W_7^f h_{t-1} + b_3^f + b_7^f), \\
c_t^f &= f_t^f \cdot c_{t-1}^f + i_t^f \cdot \tilde{c}_t^f, \\
h_t^f &= o_t^f \cdot \tanh(c_t^f),
\end{align*}
\[
\begin{align*}
i_t^b &= \sigma(W_0^b x_t + W_4^b h_{t-1} + b_0^b + b_4^b), \\
f_t^b &= \sigma(W_1^b x_t + W_5^b h_{t-1} + b_1^b + b_5^b), \\
o_t^b &= \sigma(W_2^b x_t + W_6^b h_{t-1} + b_2^b + b_6^b), \\
\tilde{c}_t^b &= \tanh(W_3^b x_t + W_7^b h_{t-1} + b_3^b + b_7^b), \\
c_t^b &= f_t^b \cdot c_{t-1}^b + i_t^b \cdot \tilde{c}_t^b, \\
h_t^b &= o_t^b \cdot \tanh(c_t^b),
\end{align*}
\]

where \(W^f\) is the weight matrices for forward-LSTM, \(W^b\) is weight matrices for backward-LSTM.

As the function accepts a sequence, it calculates \(h_t\) for all \(t\) with one call. Eight weight matrices and eight bias
vectors are required for each layer of each direction. So, when $S$ layers exist, you need to prepare $16S$ weight matrices and $16S$ bias vectors.

If the number of layers $n_layers$ is greater than 1, the input of the $k$-th layer is the hidden state $h_t$ of the $k-1$-th layer. Note that all input variables except the first layer may have different shape from the first layer.

**Parameters**

- **n_layers** *(int)* – The number of layers.
- **dropout_ratio** *(float)* – Dropout ratio.
- **hx** *(Variable)* – Variable holding stacked hidden states. Its shape is $(2S, B, N)$ where $S$ is the number of layers and is equal to $n_layers$, $B$ is the mini-batch size, and $N$ is the dimension of the hidden units. Because of bi-direction, the first dimension length is $2S$.
- **cx** *(Variable)* – Variable holding stacked cell states. It has the same shape as hx.
- **ws** *(list of list of Variable)* – Weight matrices. $ws[2 * l + m]$ represents the weights for the $l$-th layer of the $m$-th direction. (m == 0 means the forward direction and m == 1 means the backward direction.) Each $ws[i]$ is a list containing eight matrices. $ws[i][j]$ corresponds to $W_j$ in the equation. $ws[0][j]$ and $ws[1][j]$ where $0 <= j < 4$ are $(N, I)$-shaped because they are multiplied with input variables, where $I$ is the size of the input. $ws[1][j]$ where $2 <= i$ and $0 <= j < 4$ are $(N, 2N)$-shaped because they are multiplied with two hidden layers $h_t = [h^f_t; h^b_t]$. All other matrices are $(N, N)$-shaped.
- **bs** *(list of list of Variable)* – Bias vectors. $bs[2 * l + m]$ represents the weights for the $l$-th layer of $m$-th direction. (m == 0 means the forward direction and m == 1 means the backward direction.) Each $bs[i]$ is a list containing eight vectors. $bs[i][j]$ corresponds to $b_j$ in the equation. The shape of each matrix is $(N,)$.
- **xs** *(list of Variable)* – A list of Variable holding input values. Each element $xs[t]$ holds input value for time $t$. Its shape is $(B_t, I)$, where $B_t$ is the mini-batch size for time $t$. The sequences must be transposed. transpose_sequence() can be used to transpose a list of Variables each representing a sequence. When sequences has different lengths, they must be sorted in descending order of their lengths before transposing. So $xs$ needs to satisfy $xs[t].shape[0] >= xs[t + 1].shape[0]$.

**Returns**

This function returns a tuple containing three elements, $hy$, $cy$ and $ys$.

- $hy$ is an updated hidden states whose shape is the same as hx.
- $cy$ is an updated cell states whose shape is the same as cx.
- $ys$ is a list of Variable. Each element $ys[t]$ holds hidden states of the last layer corresponding to an input $xs[t]$. Its shape is $(B_t, 2N)$ where $B_t$ is the mini-batch size for time $t$, and $N$ is size of hidden units. Note that $B_t$ is the same value as $xs[t]$.

**Return type** *tuple*

**Example**

```python
>>> batches = [3, 2, 1]  # support variable length sequences
>>> in_size, out_size, n_layers = 3, 2, 2
>>> dropout_ratio = 0.0
>>> xs = [np.ones((b, in_size)).astype(np.float32) for b in batches]
>>> [x.shape for x in xs]
[(3, 3), (2, 3), (1, 3)]
>>> h_shape = (n_layers * 2, batches[0], out_size)
```
```python
>>> hx = np.ones(h_shape).astype(np.float32)
>>> cx = np.ones(h_shape).astype(np.float32)
>>> def w_in(i, j):
...   if i == 0 and j < 4:
...     return in_size
...   elif i > 0 and j < 4:
...     return out_size * 2
...   else:
...     return out_size
...
>>> ws = []
>>> bs = []
>>> for n in range(n_layers):
...   for direction in (0, 1):
...     ws.append([np.ones((out_size, w_in(n, i))).astype(np.float32) for i in range(8)])
...     bs.append([np.ones((out_size,)).astype(np.float32) for _ in range(8)])
...
>>> ws[0][0].shape  # ws[0:2][:4].shape are (out_size, in_size)
(2, 3)
>>> ws[2][0].shape  # ws[2:][4].shape are (out_size, 2 * out_size)
(2, 4)
>>> ws[0][4].shape  # others are (out_size, out_size)
(2, 2)
>>> bs[0][0].shape
(2,)
>>> hy, cy, ys = F.n_step_bilstm(n_layers, dropout_ratio, hx, cx, ws, bs, xs)
>>> hy.shape
(4, 3, 2)
>>> cy.shape
(4, 3, 2)
>>> [y.shape for y in ys]
[(3, 4), (2, 4), (1, 4)]
```

chainer.functions.n_step_birnn

chainer.functions.n_step_birnn(n_layers, dropout_ratio, hx, ws, bs, xs, activation='tanh')

Stacked Bi-directional RNN function for sequence inputs.

This function calculates stacked Bi-directional RNN with sequences. This function gets an initial hidden state $h_0$, an initial cell state $c_0$, an input sequence $x$, weight matrices $W$, and bias vectors $b$. This function calculates hidden states $h_t$ and $c_t$ for each time $t$ from input $x_t$.

\[
\begin{align*}
  h_t^f &= f(W_0^f x_t + W_1^f h_{t-1} + b_0^f + b_1^f), \\
  h_t^b &= f(W_0^b x_t + W_1^b h_{t-1} + b_0^b + b_1^b), \\
  h_t &= [h_t^f; h_t^b],
\end{align*}
\]

where $f$ is an activation function.
Weight matrices $W$ contains two matrices $W^f$ and $W^b$. $W^f$ is weight matrices for forward directional RNN. $W^b$ is weight matrices for backward directional RNN.

$W^f$ contains $W^f_0$ for an input sequence and $W^f_1$ for a hidden state. $W^b$ contains $W^b_0$ for an input sequence and $W^b_1$ for a hidden state.

Bias matrices $b$ contains two matrices $b^f$ and $b^b$. $b^f$ contains $b^f_0$ for an input sequence and $b^f_1$ for a hidden state. $b^b$ contains $b^b_0$ for an input sequence and $b^b_1$ for a hidden state.

As the function accepts a sequence, it calculates $h_t$ for all $t$ with one call. Two weight matrices and two bias vectors are required for each layer. So, when $S$ layers exist, you need to prepare $2S$ weight matrices and $2S$ bias vectors.

If the number of layers $n$ layers is greater than 1, input of $k$-th layer is hidden state $h_t$ of $k-1$-th layer. Note that all input variables except first layer may have different shape from the first layer.

Parameters

- **n_layers** (int) – Number of layers.
- **dropout_ratio** (float) – Dropout ratio.
- **hx** (Variable) – Variable holding stacked hidden states. Its shape is $(2S, B, N)$ where $S$ is number of layers and is equal to n_layers. $B$ is mini-batch size, and $N$ is dimension of hidden units. Because of bi-direction, the first dimension length is $2S$.
- **ws** (list of list of Variable) – Weight matrices. $ws[2 * i + di]$ represents weights for $i$-th layer. Note that $di = 0$ for forward-RNN and $di = 1$ for backward-RNN. Each $ws[2 * i + di]$ is a list containing two matrices. $ws[2 * i + di][j]$ is corresponding with $W^f[j]$ if $di = 0$ and corresponding with $W^b[j]$ in the equation. Only $ws[0][j]$ and $ws[1][j]$ where $0 <= j < 1$ are $(N, I)$ shape as they are multiplied with input variables. All other matrices has $(N, N)$ shape.
- **bs** (list of list of Variable) – Bias vectors. $bs[2 * i + di]$ represents biases for $i$-th layer. Note that $di = 0$ for forward-RNN and $di = 1$ for backward-RNN. Each $bs[2 * i + di]$ is a list containing two vectors. $bs[2 * i + di][j]$ is corresponding with $b^f[j]$ if $di = 0$ and corresponding with $b^b[j]$ in the equation. Shape of each matrix is $(N,)$ where $N$ is dimension of hidden units.
- **xs** (list of Variable) – A list of Variable holding input values. Each element $xs[t]$ holds input value for time $t$. Its shape is $(B_t, I)$, where $B_t$ is mini-batch size for time $t$, and $I$ is size of input units. Note that this function supports variable length sequences. When sequences has different lengths, sort sequences in descending order by length, and transpose the sorted sequence. transpose_sequence() transpose a list of Variable() holding sequence. So $xs$ needs to satisfy $xs[t].shape[0] >= xs[t + 1].shape[0]$.
- **activation** (str) – Activation function name. Please select tanh or relu.

Returns

This function returns a tuple containing three elements, $hy$ and $ys$.

- $hy$ is an updated hidden states whose shape is same as $hx$.
- $ys$ is a list of Variable. Each element $ys[t]$ holds hidden states of the last layer corresponding to an input $xs[t]$. Its shape is $(B_t, N)$ where $B_t$ is mini-batch size for time $t$, and $N$ is size of hidden units. Note that $B_t$ is the same value as $xs[t]$.

Return type  tuple
chainer.functions.n_step_gru

chainer.functions.n_step_gru(n_layers, dropout_ratio, hx, ws, bs, xs)

Stacked Uni-directional Gated Recurrent Unit function.

This function calculates stacked Uni-directional GRU with sequences. This function gets an initial hidden state \( h_0 \), an input sequence \( x \), weight matrices \( W \), and bias vectors \( b \). This function calculates hidden states \( h_t \) for each time \( t \) from input \( x_t \).

\[
\begin{align*}
r_t &= \sigma(W_0 x_t + W_3 h_{t-1} + b_0 + b_3) \\
    z_t &= \sigma(W_1 x_t + W_4 h_{t-1} + b_1 + b_4) \\
    h_t' &= \tanh(W_2 x_t + b_2 + r_t \cdot (W_5 h_{t-1} + b_5)) \\
    h_t &= (1 - z_t) \cdot h_t' + z_t \cdot h_{t-1}
\end{align*}
\]

As the function accepts a sequence, it calculates \( h_t \) for all \( t \) with one call. Six weight matrices and six bias vectors are required for each layers. So, when \( S \) layers exists, you need to prepare \( 6S \) weight matrices and \( 6S \) bias vectors.

If the number of layers \( n\_layers \) is greater than 1, input of \( k \)-th layer is hidden state \( h_t \) of \( k-1 \)-th layer. Note that all input variables except first layer may have different shape from the first layer.

**Parameters**

- **n\_layers (int)** – Number of layers.
- **dropout_ratio (float)** – Dropout ratio.
- **hx (Variable)** – Variable holding stacked hidden states. Its shape is \( (S, B, N) \) where \( S \) is number of layers and is equal to \( n\_layers \), \( B \) is mini-batch size, and \( N \) is dimension of hidden units.
- **ws (list of list of Variable)** – Weight matrices. \( ws[i] \) represents weights for \( i \)-th layer. Each \( ws[i] \) is a list containing six matrices. \( ws[i][j] \) is corresponding with \( W_j \) in the equation. Only \( ws[0][j] \) where \( 0 \leq j < 3 \) is \( (N, I) \) shape as they are multiplied with input variables. All other matrices has \( (N, N) \) shape.
- **bs (list of list of Variable)** – Bias vectors. \( bs[i] \) represents biases for \( i \)-th layer. Each \( bs[i] \) is a list containing six vectors. \( bs[i][j] \) is corresponding with \( b_j \) in the equation. Shape of each matrix is \( (N,) \) where \( N \) is dimension of hidden units.
- **xs (list of Variable)** – A list of Variable holding input values. Each element \( xs[t] \) holds input value for time \( t \). Its shape is \( (B_t, I) \), where \( B_t \) is mini-batch size for time \( t \), and \( I \) is size of input units. Note that this function supports variable length sequences. When sequences has different lengths, sort sequences in descending order by length, and transpose the sorted sequence. \( \text{transpose_sequence}() \) transpose a list of Variable holding sequence. So \( xs \) needs to satisfy \( xs[t].shape[0] \geq xs[t+1].shape[0] \).

**Returns**

This function returns a tuple containing two elements, \( hy \) and \( ys \).

- **hy** is an updated hidden states whose shape is same as \( hx \).
- **ys** is a list of Variable. Each element \( ys[t] \) holds hidden states of the last layer corresponding to an input \( xs[t] \). Its shape is \( (B_t, N) \) where \( B_t \) is mini-batch size for time \( t \), and \( N \) is size of hidden units. Note that \( B_t \) is the same value as \( xs[t] \).

**Return type** tuple
chainer.functions.n_step_lstm

chainer.functions.n_step_lstm(n_layers, dropout_ratio, hx, cx, ws, bs, xs)

Stacked Uni-directional Long Short-Term Memory function.

This function calculates stacked Uni-directional LSTM with sequences. This function gets an initial hidden state \( h_0 \), an initial cell state \( c_0 \), an input sequence \( x \), weight matrices \( W \), and bias vectors \( b \). This function calculates hidden states \( h_t \) and \( c_t \) for each time \( t \) from input \( x_t \).

\[
\begin{align*}
i_t &= \sigma(W_0 x_t + W_4 h_{t-1} + b_0 + b_4) \\
f_t &= \sigma(W_1 x_t + W_5 h_{t-1} + b_1 + b_5) \\
o_t &= \sigma(W_2 x_t + W_6 h_{t-1} + b_2 + b_6) \\
a_t &= \tanh(W_3 x_t + W_7 h_{t-1} + b_3 + b_7) \\
c_t &= f_t \cdot c_{t-1} + i_t \cdot a_t \\
h_t &= o_t \cdot \tanh(c_t)
\end{align*}
\]

As the function accepts a sequence, it calculates \( h_t \) for all \( t \) with one call. Eight weight matrices and eight bias vectors are required for each layer. So, when \( S \) layers exist, you need to prepare \( 8S \) weight matrices and \( 8S \) bias vectors.

If the number of layers \( n\_layers \) is greater than 1, the input of the \( k \)-th layer is the hidden state \( h_{-t} \) of the \( k-1 \)-th layer. Note that all input variables except the first layer may have different shape from the first layer.

Parameters

- **n_layers** (int) – The number of layers.
- **dropout_ratio** (float) – Dropout ratio.
- **hx** (Variable) – Variable holding stacked hidden states. Its shape is \((S, B, N)\) where \( S \) is the number of layers and is equal to \( n\_layers \), \( B \) is the mini-batch size, and \( N \) is the dimension of the hidden units.
- **cx** (Variable) – Variable holding stacked cell states. It has the same shape as \( hx \).
- **ws** (list of list of Variable) – Weight matrices. \( ws[i] \) represents the weights for the \( i \)-th layer. Each \( ws[i] \) is a list containing eight matrices. \( ws[i][j] \) corresponds to \( W_j \) in the equation. Only \( ws[0][j] \) where \( 0 \leq j < 4 \) are \((N, I)\)-shaped as they are multiplied with input variables, where \( I \) is the size of the input and \( N \) is the dimension of the hidden units. All other matrices are \((N, N)\)-shaped.
- **bs** (list of list of Variable) – Bias vectors. \( bs[i] \) represents the biases for the \( i \)-th layer. Each \( bs[i] \) is a list containing eight vectors. \( bs[i][j] \) corresponds to \( b_j \) in the equation. The shape of each matrix is \((N,)\) where \( N \) is the dimension of the hidden units.
- **xs** (list of Variable) – A list of Variable holding input values. Each element \( xs[t] \) holds input value for time \( t \). Its shape is \((B_t, I)\), where \( B_t \) is the mini-batch size for time \( t \). The sequences must be transposed. transpose_sequence() can be used to transpose a list of Variables each representing a sequence. When sequences has different lengths, they must be sorted in descending order of their lengths before transposing. So \( xs \) needs to satisfy \( xs[t].shape[0] >= xs[t + 1].shape[0] \).

Returns

This function returns a tuple containing three elements, \( hy \), \( cy \) and \( ys \).

- **hy** is an updated hidden states whose shape is the same as \( hx \).
- **cy** is an updated cell states whose shape is the same as \( cx \).
• `ys` is a list of `Variable`. Each element `ys[t]` holds hidden states of the last layer corresponding to an input `xs[t]`. Its shape is `(B_t, N)` where `B_t` is the mini-batch size for time `t`, and `N` is size of hidden units. Note that `B_t` is the same value as `xs[t]`.

**Return type** tuple

**Note:** The dimension of hidden units is limited to only one size `N`. If you want to use variable dimension of hidden units, please use `chainer.functions.lstm`.

**See also:**

`chainer.functions.lstm()`

**Example**

```python
def range(n_layers):
    return range(n_layers)

w_in = lambda i, j: in_size if i == 0 and j < 4 else out_size
ws = []
bs = []
for n in range(n_layers):
    ws.append([np.ones((out_size, w_in(n, i))).astype(np.float32) for i in range(8)])
    bs.append([np.ones((out_size,)).astype(np.float32) for _ in range(8)])

hy, cy, ys = F.n_step_lstm(n_layers, dropout_ratio, hx, cx, ws, bs, xs)
```

```python
>>> hy.shape
(2, 3, 2)
>>> cy.shape
(2, 3, 2)
>>> [y.shape for y in ys]
[(3, 2), (2, 2), (1, 2)]
```
chainer.functions.n_step_rnn

chainer.functions.n_step_rnn(n_layers, dropout_ratio, hx, ws, bs, xs, activation='tanh')

Stacked Uni-directional RNN function for sequence inputs.

This function calculates stacked Uni-directional RNN with sequences. This function gets an initial hidden state \( h_0 \), an initial cell state \( c_0 \), an input sequence \( x \), weight matrices \( W \), and bias vectors \( b \). This function calculates hidden states \( h_t \) and \( c_t \) for each time \( t \) from input \( x_t \).

\[
h_t = f(W_0 x_t + W_1 h_{t-1} + b_0 + b_1)
\]

where \( f \) is an activation function.

Weight matrices \( W \) contains two matrices \( W_0 \) and \( W_1 \). \( W_0 \) is a parameter for an input sequence. \( W_1 \) is a parameter for a hidden state. Bias matrices \( b \) contains two matrices \( b_0 \) and \( b_1 \). \( b_0 \) is a parameter for an input sequence. \( b_1 \) is a parameter for a hidden state.

As the function accepts a sequence, it calculates \( h_t \) for all \( t \) with one call. Two weight matrices and two bias vectors are required for each layer. So, when \( S \) layers exist, you need to prepare \( 2S \) weight matrices and \( 2S \) bias vectors.

If the number of layers \( n\text{\_layers} \) is greater than 1, input of \( k \)-th layer is hidden state \( h_{t-1} \) of \( k-1 \)-th layer. Note that all input variables except first layer may have different shape from the first layer.

Parameters

- **n_layers** (int) – Number of layers.
- **dropout_ratio** (float) – Dropout ratio.
- **hx** (Variable) – Variable holding stacked hidden states. Its shape is \((S, B, N)\) where \( S \) is number of layers and is equal to \( n\text{\_layers} \), \( B \) is mini-batch size, and \( N \) is dimension of hidden units.
- **ws** (list of list of Variable) – Weight matrices. \( ws[i] \) represents weights for \( i \)-th layer. Each \( ws[i] \) is a list containing two matrices. \( ws[i][j] \) is corresponding with \( W_j \) in the equation. Only \( ws[0][j] \) where \( 0 \leq j < 1 \) is \((N, I)\) shape as they are multiplied with input variables. All other matrices has \((N, N)\) shape.
- **bs** (list of list of Variable) – Bias vectors. \( bs[i] \) represents biases for \( i \)-th layer. Each \( bs[i] \) is a list containing two vectors. \( bs[i][j] \) is corresponding with \( b_j \) in the equation. Shape of each matrix is \((N,)\) where \( N \) is dimension of hidden units.
- **xs** (list of Variable) – A list of Variable holding input values. Each element \( xs[t] \) holds input value for time \( t \). Its shape is \((B_t, I)\), where \( B_t \) is mini-batch size for time \( t \), and \( I \) is size of input units. Note that this function supports variable length sequences. When sequences has different lengths, sort sequences in descending order by length, and transpose the sorted sequence. \( \text{transpose_sequence()} \) transpose a list of Variable holding sequence. So \( xs \) needs to satisfy \( xs[t].\text{shape}[0] >= xs[t + 1].\text{shape}[0] \).
- **activation** (str) – Activation function name. Please select tanh or relu.

Returns

This function returns a tuple containing two elements, \( hy \) and \( ys \).

- \( hy \) is an updated hidden states whose shape is same as \( hx \).
- \( ys \) is a list of Variable. Each element \( ys[t] \) holds hidden states of the last layer corresponding to an input \( xs[t] \). Its shape is \((B_t, N)\) where \( B_t \) is mini-batch size for time \( t \), and \( N \) is size of hidden units. Note that \( B_t \) is the same value as \( xs[t] \).
Return type: `tuple`

`chainer.functions.shift`

`chainer.functions.shift(x, ksize=3, dilate=1)`

Shift function.

See: Shift: A Zero FLOP, Zero Parameter Alternative to Spatial Convolutions

**Parameters**

- `x` (*Variable* or *N-dimensional array*) – Input variable of shape \((n, c, h, w)\).
- `ksize` (*int* or *pair of ints*) – Size of filters (a.k.a. kernels). `ksize=k` and `ksize=(k, k)` are equivalent.
- `dilate` (*int* or *pair of ints*) – Dilation factor of filter applications. `dilate=d` and `dilate=(d, d)` are equivalent.

**Returns** Output variable of same shape as `x`.

Return type: `Variable`

### 4.2.5 Evaluation functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.functions.accuracy</code></td>
<td>Computes multiclass classification accuracy of the minibatch.</td>
</tr>
<tr>
<td><code>chainer.functions.binary_accuracy</code></td>
<td>Computes binary classification accuracy of the minibatch.</td>
</tr>
<tr>
<td><code>chainer.functions.classification_summary</code></td>
<td>Calculates Precision, Recall, F beta Score, and support.</td>
</tr>
<tr>
<td><code>chainer.functions.f1_score</code></td>
<td></td>
</tr>
<tr>
<td><code>chainer.functions.precision</code></td>
<td></td>
</tr>
<tr>
<td><code>chainer.functions.r2_score</code></td>
<td>Computes R^2(coefficient of determination) regression score function.</td>
</tr>
<tr>
<td><code>chainer.functions.recall</code></td>
<td></td>
</tr>
</tbody>
</table>

`chainer.functions.accuracy`

`chainer.functions.accuracy(y, t, ignore_label=None)`

Computes multiclass classification accuracy of the minibatch.

**Parameters**

- `y` (*Variable* or *N-dimensional array*) – Array whose \((i, j, k, \ldots)\)-th element indicates the score of the class \(j\) at the \((i, k, \ldots)\)-th sample. The prediction label \(\hat{t}\) is calculated by the formula \(\hat{t}(i, k, \ldots) = \arg\max_j y(i, j, k, \ldots)\).
- `t` (*Variable* or *N-dimensional array*) – Array of ground truth labels.
- `ignore_label` (*int* or *None*) – Skip calculating accuracy if the true label is `ignore_label`.

**Returns** A variable holding a scalar array of the accuracy.

Return type: `Variable`
Note: This function is non-differentiable.

Example

We show the most common case, when $y$ is the two dimensional array.

```python
>>> y = np.array([[0.1, 0.7, 0.2],
...                [8.0, 1.0, 2.0],
...                [-8.0, 1.0, 2.0]],
...                [-8.0, -1.0, -2.0]])  # prediction label is 1
>>> t = np.array([1, 0, 2, 1], np.int32)
>>> F.accuracy(y, t).array  # 100% accuracy because all samples are correct
array(1.)
>>> t = np.array([1, 0, 0, 0], np.int32)
>>> F.accuracy(y, t).array  # 50% accuracy because 1st and 2nd samples are correct.
array(0.5)
>>> F.accuracy(y, t, ignore_label=0).array  # 100% accuracy because of ignoring 2nd, 3rd and 4th samples.
array(1.)
```

chainer.functions.binary_accuracy

chainer.functions.binary_accuracy($y$, $t$)

Computes binary classification accuracy of the minibatch.

Parameters

- **$y$** (Variable or N-dimensional array) – Array whose i-th element indicates the score of positive at the i-th sample. The prediction label $\hat{t}[i]$ is 1 if $y[i] \geq 0$, otherwise 0.

- **$t$** (Variable or N-dimensional array) – Array holding a signed integer vector of ground truth labels. If $t[i] == 1$, it indicates that i-th sample is positive. If $t[i] == 0$, it indicates that i-th sample is negative. If $t[i] == -1$, corresponding $y[i]$ is ignored. Accuracy is zero if all ground truth labels are -1.

Returns A variable holding a scalar array of the accuracy.

Return type Variable

Note: This function is non-differentiable.

Example

We show the most common case, when $y$ is the two dimensional array.

```python
>>> y = np.array([[0.1, 0.7, 0.2],
...                [8.0, 1.0, 2.0],
...                [-8.0, 1.0, 2.0]],
...                [-8.0, -1.0, -2.0]])  # prediction label is 1
>>> t = np.array([1, 0, 2, 1], np.int32)
>>> F.accuracy(y, t).array  # 100% accuracy because all samples are correct.
array(1.)
>>> t = np.array([1, 0, 0, 0], np.int32)
>>> F.accuracy(y, t).array  # 50% accuracy because 1st and 2nd samples are correct.
array(0.5)
>>> F.accuracy(y, t, ignore_label=0).array  # 100% accuracy because of ignoring 2nd, 3rd and 4th samples.
array(1.)
```
chainer.functions.classification_summary

chainer.functions.classification_summary(y, t, label_num=None, beta=1.0, ignore_label=-1)

Calculates Precision, Recall, F beta Score, and support.

This function calculates the following quantities for each class.

- **Precision**: \( \frac{tp}{tp+fp} \)
- **Recall**: \( \frac{tp}{tp+fn} \)
- **F beta Score**: The weighted harmonic average of Precision and Recall.
- **Support**: The number of instances of each ground truth label.

Here, \( tp, fp, tn, \) and \( fn \) stand for the number of true positives, false positives, true negatives, and false negatives, respectively.

`label_num` specifies the number of classes, that is, each value in `t` must be an integer in the range of \([0, label_num)\). If `label_num` is `None`, this function regards `label_num` as a maximum of in `t` plus one.

`ignore_label` determines which instances should be ignored. Specifically, instances with the given label are not taken into account for calculating the above quantities. By default, it is set to `-1` so that all instances are taken into consideration, as labels are supposed to be non-negative integers. Setting `ignore_label` to a non-negative integer less than `label_num` is illegal and yields undefined behavior. In the current implementation, it arises `RuntimeWarning` and `ignore_label`-th entries in output arrays do not contain correct quantities.

**Parameters**

- `y` *(Variable or N-dimensional array)* – Variable holding a vector of scores.
- `t` *(Variable or N-dimensional array)* – Variable holding a vector of ground truth labels.
- `label_num` *(int)* – The number of classes.
- `beta` *(float)* – The parameter which determines the weight of precision in the F-beta score.
- `ignore_label` *(int)* – Instances with this label are ignored.

**Returns** 4-tuple of ~chainer.Variable of size \((label_num,)\). Each element represents precision, recall, F beta score, and support of this minibatch.
chainer.functions.f1_score

chainer.functions.f1_score(y, t, label_num=None, ignore_label=-1)

chainer.functions.precision

chainer.functions.precision(y, t, label_num=None, ignore_label=-1)

chainer.functions.r2_score

chainer.functions.r2_score(pred, true, sample_weight=None, multioutput='uniform_average')

Computes R^2(coefficient of determination) regression score function.

Parameters

- **pred** ([Variable or N-dimensional array]) – Variable holding a vector, matrix or tensor of estimated target values.
- **true** ([Variable or N-dimensional array]) – Variable holding a vector, matrix or tensor of correct target values.
- **sample_weight** – This argument is for compatibility with scikit-learn’s implementation of r2_score. Current implementation admits None only.
- **multioutput** ([string]) – ['uniform_average', 'raw_values']. If 'uniform_average', this function returns an average of R^2 score of multiple output. If 'raw_average', this function return a set of R^2 score of multiple output.

Returns A Variable holding a scalar array of the R^2 score if ‘multioutput’ is ‘uniform_average’ or a vector of R^2 scores if ‘multioutput’ is ‘raw_values’.

Return type Variable

Note: This function is non-differentiable.

chainer.functions.recall

chainer.functions.recall(y, t, label_num=None, ignore_label=-1)

4.2.6 Loss functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.functions.absolute_error</td>
<td>Element-wise absolute error function.</td>
</tr>
<tr>
<td>chainer.functions.bernoulli_nll</td>
<td>Computes the negative log-likelihood of a Bernoulli distribution.</td>
</tr>
<tr>
<td>chainer.functions.black_out</td>
<td>BlackOut loss function.</td>
</tr>
<tr>
<td>chainer.functions.connectionist_temporal_classification</td>
<td>Connectionist Temporal Classification loss function.</td>
</tr>
<tr>
<td>chainer.functions.contrastive</td>
<td>Computes contrastive loss.</td>
</tr>
<tr>
<td>chainer.functions.crf1d</td>
<td>Calculates negative log-likelihood of linear-chain CRF.</td>
</tr>
<tr>
<td>chainer.functions.argmax_crf1d</td>
<td>Computes a state that maximizes a joint probability of the given CRF.</td>
</tr>
</tbody>
</table>

continues on next page
Table 7 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.functions.cross_covariance</code></td>
<td>Computes the sum-squared cross-covariance penalty between y and z</td>
</tr>
<tr>
<td><code>chainer.functions.decov</code></td>
<td>Computes the DeCov loss of h</td>
</tr>
<tr>
<td><code>chainer.functions.discriminative_margin_based_clustering_loss</code></td>
<td>Discriminative margin-based clustering loss function</td>
</tr>
<tr>
<td><code>chainer.functions.gaussian_kl_divergence</code></td>
<td>Computes the KL-divergence of Gaussian variables from the standard one.</td>
</tr>
<tr>
<td><code>chainer.functions.gaussian_nll</code></td>
<td>Computes the negative log-likelihood of a Gaussian distribution.</td>
</tr>
<tr>
<td><code>chainer.functions.hinge</code></td>
<td>Computes the hinge loss for a one-of-many classification task.</td>
</tr>
<tr>
<td><code>chainer.functions.huber_loss</code></td>
<td>Computes the Huber loss.</td>
</tr>
<tr>
<td><code>chainer.functions.mean_absolute_error</code></td>
<td>Mean absolute error function.</td>
</tr>
<tr>
<td><code>chainer.functions.mean_squared_error</code></td>
<td>Mean squared error function.</td>
</tr>
<tr>
<td><code>chainer.functions.negative_sampling</code></td>
<td>Negative sampling loss function.</td>
</tr>
<tr>
<td><code>chainer.functions.sigmoid_cross_entropy</code></td>
<td>Computes cross entropy loss for pre-sigmoid activations.</td>
</tr>
<tr>
<td><code>chainer.functions.softmax_cross_entropy</code></td>
<td>Computes cross entropy loss for pre-softmax activations.</td>
</tr>
<tr>
<td><code>chainer.functions.squared_error</code></td>
<td>Squared error function.</td>
</tr>
<tr>
<td><code>chainer.functions.triplet</code></td>
<td>Computes triplet loss.</td>
</tr>
</tbody>
</table>

### `chainer.functions.absolute_error`

**Function**

`chainer.functions.absolute_error(x0, x1)`

Element-wise absolute error function.

Computes the element-wise absolute error $L$ between two inputs $x_0$ and $x_1$ defined as follows.

$$L = |x_0 - x_1|$$

**Parameters**

- **x0** (Variable or N-dimensional array) – First input variable.
- **x1** (Variable or N-dimensional array) – Second input variable.

**Returns**

An array representing the element-wise absolute error between the two inputs.

**Return type**

Variable

### `chainer.functions.bernoulli_nll`

**Function**

`chainer.functions.bernoulli_nll(x, y, reduce='sum')`

Computes the negative log-likelihood of a Bernoulli distribution.

This function calculates the negative log-likelihood of a Bernoulli distribution.

$$-\log B(x; p) = - \sum_i \{x_i \log(p_i) + (1 - x_i) \log(1 - p_i)\},$$

where $p = \sigma(y)$, $\sigma(\cdot)$ is a sigmoid function, and $B(x; p)$ is a Bernoulli distribution.

The output is a variable whose value depends on the value of the option `reduce`. If it is 'no', it holds the elementwise loss values. If it is 'sum' or 'mean', loss values are summed up or averaged respectively.
Note: As this function uses a sigmoid function, you can pass a result of fully-connected layer (that means Linear) to this function directly.

Parameters

• **x** *(Variable or N-dimensional array)* – Input variable.

• **y** *(Variable or N-dimensional array)* – A variable representing the parameter of Bernoulli distribution.

• **reduce** *(str)* – Reduction option. Its value must be either 'sum', 'mean' or 'no'. Otherwise, ValueError is raised.

Returns A variable representing the negative log-likelihood. If reduce is 'no', the output variable holds array whose shape is same as one of (hence both of) input variables. If it is 'sum' or 'mean', the output variable holds a scalar value.

Return type **Variable**

chainer.functions.black_out

chainer.functions.black_out(x, t, W, samples, reduce='mean')

BlackOut loss function.

BlackOut loss function is defined as

\[-\log(p(t)) - \sum_{s \in S} \log(1 - p(s)),\]

where \(t\) is the correct label, \(S\) is a set of negative examples and \(p(\cdot)\) is likelihood of a given label. And, \(p\) is defined as

\[p(y) = \frac{\exp(W^T y)}{\sum_{s \in \text{samples}} \exp(W^T s)},\]

The output is a variable whose value depends on the value of the option reduce. If it is 'no', it holds the no loss values. If it is 'mean', this function takes a mean of loss values.

Parameters

• **x** *(Variable or N-dimensional array)* – Batch of input vectors. Its shape should be \((N, D)\).

• **t** *(Variable or N-dimensional array)* – Vector of ground truth labels. Its shape should be \((N,)\). Each elements \(v\) should satisfy \(0 \geq v \geq V\) or \(-1\) where \(V\) is the number of label types.

• **W** *(Variable or N-dimensional array)* – Weight matrix. Its shape should be \((V, D)\)

• **samples** *(Variable)* – Negative samples. Its shape should be \((N, S)\) where \(S\) is the number of negative samples.

• **reduce** *(str)* – Reduction option. Its value must be either 'no' or 'mean'. Otherwise, ValueError is raised.

Returns A variable object holding loss value(s). If reduce is 'no', the output variable holds an array whose shape is \((N,)\). If it is 'mean', it holds a scalar.

Return type **Variable**

4.2. Functions
See: BlackOut: Speeding up Recurrent Neural Network Language Models With Very Large Vocabularies

See also: 
BlackOut to manage the model parameter $\mathbf{W}$.

**chainer.functions.connectionist_temporal_classification**

```python
chainer.functions.connectionist_temporal_classification(x, t, blank_symbol,
input_length=None,
label_length=None, reduce='mean')
```

Connectionist Temporal Classification loss function.

Connectionist Temporal Classification (CTC) [Graves2006] is a loss function of sequence labeling where the alignment between the inputs and target is unknown. See also [Graves2012]

The output is a variable whose value depends on the value of the option `reduce`. If it is `no`, it holds the samplewise loss values. If it is `mean`, it takes the mean of loss values.

**Parameters**

- **x** (list or tuple of `Variable`) – A list of unnormalized probabilities for labels. Each element of $x$, $x[i]$ is a `Variable` object, which has shape $(B, V)$, where $B$ is the batch size and $V$ is the number of labels. The softmax of $x[i]$ represents the probabilities of the labels at time $i$.

- **t** (`Variable` or `N-dimensional array`) – A matrix including expected label sequences. Its shape is $(B, M)$, where $B$ is the batch size and $M$ is the maximum length of the label sequences. All elements in $t$ must be less than $V$, the number of labels.

- **blank_symbol** (`int`) – Index of blank_symbol. This value must be non-negative.

- **input_length** (`Variable` or `N-dimensional array`) – Length of sequence for each of mini batch $x$ (optional). Its shape must be $(B,)$. If the `input_length` is omitted or `None`, it assumes that all of $x$ is valid input.

- **label_length** (`Variable` or `N-dimensional array`) – Length of sequence for each of mini batch $t$ (optional). Its shape must be $(B,)$. If the `label_length` is omitted or `None`, it assumes that all of $t$ is valid input.

- **reduce** (`str`) – Reduction option. Its value must be either `mean` or `no`. Otherwise, `ValueError` is raised.

**Returns** A variable holding a scalar value of the CTC loss. If `reduce` is `no`, the output variable holds array whose shape is $(B,)$ where $B$ is the number of samples. If it is `mean`, it holds a scalar.

**Return type** `Variable`

**Note:** You need to input $x$ without applying to activation functions (e.g. softmax function), because this function applies softmax functions to $x$ before calculating CTC loss to avoid numerical limitations. You also need to apply softmax function to forwarded values before you decode it.

**Note:** This function is differentiable only by $x$.  

232 Chapter 4. API Reference
chainer.functions.contrastive

chainer.functions.contrastive(x0, x1, y, margin=1, reduce='mean')

Computes contrastive loss.

It takes a pair of samples and a label as inputs. The label is 1 when those samples are similar, or 0 when they are dissimilar.

Let $N$ and $K$ denote mini-batch size and the dimension of input variables, respectively. The shape of both input variables $x_0$ and $x_1$ should be $(N, K)$. The loss value of the $n$-th sample pair $L_n$ is

$$L_n = \frac{1}{2} \left( y_n d_n^2 + (1 - y_n) \max(margin - d_n, 0)^2 \right)$$

where $d_n = \|x_0_n - x_1_n\|_2$, $x_0_n$ and $x_1_n$ are $n$-th $K$-dimensional vectors of $x_0$ and $x_1$.

The output is a variable whose value depends on the value of the option reduce. If it is 'no', it holds the elementwise loss values. If it is 'mean', this function takes a mean of loss values.

Parameters

- $x_0$ (Variable or $N$-dimensional array) – The first input variable. The shape should be $(N, K)$, where $N$ denotes the mini-batch size, and $K$ denotes the dimension of $x_0$.
- $x_1$ (Variable or $N$-dimensional array) – The second input variable. The shape should be the same as $x_0$.
- $y$ (Variable or $N$-dimensional array) – Labels. All values should be 0 or 1. The shape should be $(N,)$, where $N$ denotes the mini-batch size.
- margin (float) – A parameter for contrastive loss. It should be positive value.
- reduce (str) – Reduction option. Its value must be either 'mean' or 'no'. Otherwise, ValueError is raised.

Returns A variable holding the loss value(s) calculated by the above equation. If reduce is 'no', the output variable holds array whose shape is same as one of (hence both of) input variables. If it is 'mean', the output variable holds a scalar value.

Return type Variable

Note: This cost can be used to train siamese networks. See Learning a Similarity Metric Discriminatively, with Application to Face Verification for details.

Example

```
>>> x0 = np.array([[-2.0, 3.0, 0.5], [5.0, 2.0, -0.5]]).astype(np.float32)
>>> x1 = np.array([[-1.0, 3.0, 1.0], [3.5, 0.5, -2.0]]).astype(np.float32)
>>> y = np.array([1, 0]).astype(np.int32)
>>> F.contrastive(x0, x1, y)
variable(0.3125)
>>> F.contrastive(x0, x1, y, margin=3.0)  # harder penalty
variable(0.3528857)
>>> z = F.contrastive(x0, x1, y, reduce='no')
```

(continues on next page)
'z.shape
(2,)
array([0.625, 0.], dtype=float32)

chainer.functions.crf1d

chainer.functions.crf1d(cost, xs, ys, reduce='mean')
Calculates negative log-likelihood of linear-chain CRF.

It takes a transition cost matrix, a sequence of costs, and a sequence of labels. Let $c_{st}$ be a transition cost from a label $s$ to a label $t$, $x_{it}$ be a cost of a label $t$ at position $i$, and $y_i$ be an expected label at position $i$. The negative log-likelihood of linear-chain CRF is defined as

$$L = - \left( \sum_{i=1}^{l} x_{iy_i} + \sum_{i=1}^{l-1} c_{y_i y_{i+1}} - \log(Z) \right) ,$$

where $l$ is the length of the input sequence and $Z$ is the normalizing constant called partition function.

**Note:** When you want to calculate the negative log-likelihood of sequences which have different lengths, sort the sequences in descending order of lengths and transpose the sequences. For example, you have three input sequences:

```python
>>> a1 = a2 = a3 = a4 = np.random.uniform(-1, 1, 3).astype(np.float32)
>>> b1 = b2 = b3 = np.random.uniform(-1, 1, 3).astype(np.float32)
>>> c1 = c2 = np.random.uniform(-1, 1, 3).astype(np.float32)

>>> a = [a1, a2, a3, a4]
>>> b = [b1, b2, b3]
>>> c = [c1, c2]
```

where $a_1$ and all other variables are arrays with $(K,)$ shape. Make a transpose of the sequences:

```python
>>> x1 = np.stack([a1, b1, c1])
>>> x2 = np.stack([a2, b2, c2])
>>> x3 = np.stack([a3, b3])
>>> x4 = np.stack([a4])
```

and make a list of the arrays:

```python
>>> xs = [x1, x2, x3, x4]
```

You need to make label sequences in the same fashion. And then, call the function:

```python
>>> cost = chainer.Variable(
...     np.random.uniform(-1, 1, (3, 3)).astype(np.float32))
>>> ys = [np.zeros(x.shape[0:1], dtype=np.int32) for x in xs]
>>> loss = F.crf1d(cost, xs, ys)
```

It calculates mean of the negative log-likelihood of the three sequences.

The output is a variable whose value depends on the value of the option `reduce`. If it is 'no', it holds the elementwise loss values. If it is 'mean', it holds mean of the loss values.
Parameters

- **cost (Variable or N-dimensional array)** – A $K \times K$ matrix which holds transition cost between two labels, where $K$ is the number of labels.

- **xs (list of Variable)** – Input vector for each label. len(xs) denotes the length of the sequence, and each Variable holds a $B \times K$ matrix, where $B$ is mini-batch size, $K$ is the number of labels. Note that $B$s in all the variables are not necessary the same, i.e., it accepts the input sequences with different lengths.

- **ys (list of Variable)** – Expected output labels. It needs to have the same length as xs. Each Variable holds a $B$ integer vector. When $x$ in xs has the different $B$, corresponding $y$ has the same $B$. In other words, $ys$ must satisfy $ys[i].shape == xs[i].shape[0:1]$ for all $i$.

- **reduce (str)** – Reduction option. Its value must be either 'mean' or 'no'. Otherwise, ValueError is raised.

**Returns** A variable holding the average negative log-likelihood of the input sequences.

**Return type** Variable

---


---

**chainer.functions.argmax_crf1d**

chainer.functions.argmax_crf1d(cost, xs)

Computes a state that maximizes a joint probability of the given CRF.

**Parameters**

- **cost (Variable or N-dimensional array)** – A $K \times K$ matrix which holds transition cost between two labels, where $K$ is the number of labels.

- **xs (list of Variable)** – Input vector for each label. len(xs) denotes the length of the sequence, and each Variable holds a $B \times K$ matrix, where $B$ is mini-batch size, $K$ is the number of labels. Note that $B$s in all the variables are not necessary the same, i.e., it accepts the input sequences with different lengths.

**Returns** A tuple of Variable object $s$ and a list $ps$. The shape of $s$ is $(B,)$, where $B$ is the mini-batch size. i-th element of $s$, $s[i]$, represents log-likelihood of i-th data. $ps$ is a list of N-dimensional array, and denotes the state that maximizes the point probability. len($ps$) is equal to len(xs), and shape of each $ps[i]$ is the mini-batch size of the corresponding $xs[i]$. That means, $ps[i].shape == xs[i].shape[0:1]$.

**Return type** tuple
chainer.functions.cross_covariance

```python
chainer.functions.cross_covariance(y, z, reduce='half_squared_sum')
```

Computes the sum-squared cross-covariance penalty between \( y \) and \( z \).

The output is a variable whose value depends on the value of the option `reduce`. If it is `'no'`, it holds the covariant matrix that has as many rows (resp. columns) as the dimension of \( y \) (resp. \( z \)). If it is `'half_squared_sum'`, it holds the half of the Frobenius norm (i.e. L2 norm of a matrix flattened to a vector) of the covarainct matrix.

**Parameters**

- \( y \) (*Variable* or *N-dimensional array*) – Variable holding a matrix where the first dimension corresponds to the batches.
- \( z \) (*Variable* or *N-dimensional array*) – Variable holding a matrix where the first dimension corresponds to the batches.
- `reduce` (*str*) – Reduction option. Its value must be either `'half_squared_sum'` or `'no'`. Otherwise, `ValueError` is raised.

**Returns** A variable holding the cross covariance loss. If `reduce` is `'no'`, the output variable holds 2-dimensional array matrix of shape \((M, N)\) where \( M \) (resp. \( N \)) is the number of columns of \( y \) (resp. \( z \)). If it is `'half_squared_sum'`, the output variable holds a scalar value.

**Return type** *Variable*

---

**Note:** This cost can be used to disentangle variables. See https://arxiv.org/abs/1412.6583v3 for details.

chainer.functions.decov

```python
chainer.functions.decov(h, reduce='half_squared_sum')
```

Computes the DeCov loss of \( h \).

The output is a variable whose value depends on the value of the option `reduce`. If it is `'no'`, it holds a matrix whose size is same as the number of columns of \( y \). If it is `'half_squared_sum'`, it holds the half of the squared Frobenius norm (i.e. squared of the L2 norm of a matrix flattened to a vector) of the matrix.

**Parameters**

- \( h \) (*Variable* or *N-dimensional array*) – Variable holding a matrix where the first dimension corresponds to the batches.
- `reduce` (*str*) – Reduction option. Its value must be either `'half_squared_sum'` or `'no'`. Otherwise, `ValueError` is raised.

**Returns** A variable holding a scalar of the DeCov loss. If `reduce` is `'no'`, the output variable holds 2-dimensional array matrix of shape \((N, N)\) where \( N \) is the number of columns of \( y \). If it is `'half_squared_sum'`, the output variable holds a scalar value.

**Return type** *Variable*

---

**Note:** See https://arxiv.org/abs/1511.06068 for details.
chainer.functions.discriminative_margin_based_clustering_loss

chainer.functions.discriminative_margin_based_clustering_loss(embeddings, labels, delta_v, delta_d, max_embedding_dim, norm=1, alpha=1.0, beta=1.0, gamma=0.001)

Discriminative margin-based clustering loss function

This is the implementation of the following paper: https://arxiv.org/abs/1708.02551 This method is a semi-supervised solution to instance segmentation. It calculates pixel embeddings, and calculates three different terms based on those embeddings and applies them as loss. The main idea is that the pixel embeddings for same instances have to be closer to each other (pull force), for different instances, they have to be further away (push force). The loss also brings a weak regularization term to prevent overfitting. This loss function calculates the following three parameters:

**Variance Loss**  Loss to penalize distances between pixels which are belonging to the same instance. (Pull force)

**Distance loss**  Loss to penalize distances between the centers of instances. (Push force)

**Regularization loss**  Small regularization loss to penalize weights against overfitting.

**Parameters**

- **embeddings** (*Variable or N-dimensional array*) – predicted embedding vectors (batch size, max embedding dimensions, height, width)
- **labels** (*N-dimensional array*) – instance segmentation ground truth each unique value has to be denoting one instance (batch size, height, width)
- **delta_v** (*float*) – Minimum distance to start penalizing variance
- **delta_d** (*float*) – Maximum distance to stop penalizing distance
- **max_embedding_dim** (*int*) – Maximum number of embedding dimensions
- **norm** (*int*) – Norm to calculate pixels and cluster center distances
- **alpha** (*float*) – Weight for variance loss
- **beta** (*float*) – Weight for distance loss
- **gamma** (*float*) – Weight for regularization loss

**Returns**

- **Variance loss**: Variance loss multiplied by alpha
- **Distance loss**: Distance loss multiplied by beta
- **Regularization loss**: Regularization loss multiplied by gamma

**Return type**  *tuple of chainer.Variable*
chainer.functions.gaussian_kl_divergence

chainer.functions.gaussian_kl_divergence(mean, ln_var, reduce='sum')
Computes the KL-divergence of Gaussian variables from the standard one.
Given two variable mean representing $\mu$ and ln_var representing $\log(\sigma^2)$, this function calculates the KL-divergence in elementwise manner between the given multi-dimensional Gaussian $N(\mu, S)$ and the standard Gaussian $N(0, I)$

$$D_{KL}(N(\mu, S)\|N(0, I)),$$
where $S$ is a diagonal matrix such that $S_{ii} = \sigma_i^2$ and $I$ is an identity matrix.
The output is a variable whose value depends on the value of the option reduce. If it is 'no', it holds the elementwise loss values. If it is 'sum' or 'mean', loss values are summed up or averaged respectively.

**Parameters**
- **mean** (*Variable or N-dimensional array*) – A variable representing mean of given gaussian distribution, $\mu$.
- **ln_var** (*Variable or N-dimensional array*) – A variable representing logarithm of variance of given gaussian distribution, $\log(\sigma^2)$.
- **reduce** (*str*) – Reduction option. Its value must be either 'sum', 'mean' or 'no'. Otherwise, **ValueError** is raised.

**Returns** A variable representing KL-divergence between given gaussian distribution and the standard gaussian. If reduce is 'no', the output variable holds array whose shape is same as one of (hence both of) input variables. If it is 'sum' or 'mean', the output variable holds a scalar value.

**Return type** **Variable**

chainer.functions.gaussian_nll

chainer.functions.gaussian_nll(x, mean, ln_var, reduce='sum')
Computes the negative log-likelihood of a Gaussian distribution.
Given two variable mean representing $\mu$ and ln_var representing $\log(\sigma^2)$, this function computes in elementwise manner the negative log-likelihood of $x$ on a Gaussian distribution $N(\mu, S)$,

$$-\log N(x; \mu, \sigma^2) = \log \left(\sqrt{(2\pi)^D |S|}\right) + \frac{1}{2}(x - \mu)^\top S^{-1}(x - \mu),$$
where $D$ is a dimension of $x$ and $S$ is a diagonal matrix where $S_{ii} = \sigma_i^2$.
The output is a variable whose value depends on the value of the option reduce. If it is 'no', it holds the elementwise loss values. If it is 'sum' or 'mean', loss values are summed up or averaged respectively.

**Parameters**
- **x** (*Variable or N-dimensional array*) – Input variable.
- **mean** (*Variable or N-dimensional array*) – A variable representing mean of a Gaussian distribution, $\mu$.
- **ln_var** (*Variable or N-dimensional array*) – A variable representing logarithm of variance of a Gaussian distribution, $\log(\sigma^2)$.
- **reduce** (*str*) – Reduction option. Its value must be either 'sum', 'mean' or 'no'. Otherwise, **ValueError** is raised.
Returns A variable representing the negative log-likelihood. If reduce is 'no', the output variable holds array whose shape is same as one of (hence both of) input variables. If it is 'sum' or 'mean', the output variable holds a scalar value.

Return type Variable

chainer.functions.hinge

chainer.functions.hinge(x, t, norm='L1', reduce='mean')
Computes the hinge loss for a one-of-many classification task.

\[ L = \frac{1}{N} \sum_{n=1}^{N} \sum_{k=1}^{K} [\max(0, 1 - \delta\{t_n = k\}x_{nk})]^p \]

where \( N \) denotes the batch size and \( K \) is the number of classes of interest,

\[ \delta\{\text{condition}\} = \begin{cases} 1 & \text{if condition is true} \\ -1 & \text{otherwise} \end{cases} \]

and

\[ p = \begin{cases} 1 & \text{if norm = L1} \\ 2 & \text{if norm = L2}. \end{cases} \]

Let the hinge loss function \( l(x, \delta) = [\max(0, 1 - \delta x)]^p \). When \( x \) and \( \delta \) have the same sign (meaning \( x \) predicts the proper score for classification) and \( |x| \geq 1 \), the hinge loss \( l(x, \delta) = 0 \), but when they have opposite sign, \( l(x, \delta) \) increases linearly with \( x \).

The output is a variable whose value depends on the value of the option reduce. If it is 'no', it holds the elementwise loss values. If it is 'mean', it takes the mean of loss values.

Parameters

- \( x \) (Variable or N-dimensional array) – Input variable. The shape of \( x \) should be \((N, K)\).
- \( t \) (Variable or N-dimensional array) – The \( N \)-dimensional label vector with values \( t_n \in \{0, 1, 2, \ldots, K - 1\} \). The shape of \( t \) should be \((N,)\).
- **norm** (string) – Specifies norm type. Either 'L1' or 'L2' is acceptable.
- **reduce** (str) – Reduction option. Its value must be either 'mean' or 'no'. Otherwise, ValueError is raised.

Returns A variable object holding a scalar array of the hinge loss \( L \). If reduce is 'no', the output variable holds array whose shape is same as one of (hence both of) input variables. If it is 'mean', the output variable holds a scalar value.

Return type Variable

Example

In this case, the batch size \( N \) is 2 and the number of classes \( K \) is 3.
chainer.functions.huber_loss

chainer.functions.huber_loss(x, t, delta, reduce='sum_along_second_axis')

Computes the Huber loss.

The Huber loss is similar to the mean_squared_error() but is less sensitive to outliers in the data. It is defined as

\[ L_\delta(a) = \begin{cases} \\
\frac{1}{2}a^2 & \text{if } |a| \leq \delta \\
\delta(|a| - \frac{1}{2}\delta) & \text{otherwise}, \\
\end{cases} \]

where \( a = x - t \) is the difference between the input \( x \) and the target \( t \).

The loss is a variable whose value depends on the value of the option reduce. If it is 'no', it holds the elementwise loss values. If it is 'sum_along_second_axis', loss values are summed up along the second axis (i.e. axis=1).

See: Huber loss - Wikipedia.

Parameters

- x (Variable or N-dimensional array) – Input variable. The shape of x should be (N, K, ...) if reduce='sum_along_second_axis'.
- t (Variable or N-dimensional array) – Target variable for regression. The shape of t should be (N, K, ...) if reduce='sum_along_second_axis'.
- delta (float) – Constant variable for Huber loss function as used in definition.
- reduce (str) – Reduction option. Its value must be either 'sum_along_second_axis' or 'no'. Otherwise, ValueError is raised.

Returns A variable object holding a scalar array of the Huber loss \( L_\delta \). If reduce is 'no', the output variable holds array whose shape is same as one of (hence both of) input variables. If it is 'sum_along_second_axis', the shape of the array is same as the input variables, except the second axis is removed.

Return type Variable

Example

Example without reduction, in which case the output \( y \) will have the same shape as the inputs \( x \) and \( t \).
```python
>>> import numpy as np
>>> from chainer import functions as F

>>> x = np.array([[-2.0, 3.0, 0.5], [5.0, 2.0, -0.5]]).astype(np.float32)
>>> x.shape
(2, 3)

>>> t = np.array([[-2.0, 3.0, 0.0], [10.0, 2.0, -0.5]]).astype(np.float32)
>>> t.shape
(2, 3)

>>> y = F.huber_loss(x, t, delta=1.0, reduce='no')
>>> y.shape
(2, 3)

>>> y
variable([[0. , 0. , 0.125],
          [4.5 , 0. , 0. ]])

Example with reduction along the second axis.

>>> y = F.huber_loss(x, t, delta=1.0, reduce='sum_along_second_axis')
>>> y.shape
(2,)

>>> y
variable([0.125, 4.5 ])

chainer.functions.mean_absolute_error

chainer.functions.<span class="highlight">mean_absolute_error</span>(x0, x1)

Mean absolute error function.

The function computes the mean absolute error between two variables. The mean is taken over the minibatch. Args x0 and x1 must have the same dimensions. This function first calculates the absolute value differences between the corresponding elements in x0 and x1, and then returns the mean of those differences.

Parameters

- x0 (Variable or N-dimensional array) – Input variable.
- x1 (Variable or N-dimensional array) – Input variable.

Returns A variable holding an array representing the mean absolute error of two inputs.

Return type Variable

Example

1D array examples:

```python
code
>>> x = np.array([1, 2, 3]).astype(np.float32)
>>> y = np.array([0, 0, 0]).astype(np.float32)
>>> F.mean_absolute_error(x, y)
variable(2.)
>>> x = np.array([1, 2, 3, 4, 5, 6]).astype(np.float32)
>>> y = np.array([7, 8, 9, 10, 11, 12]).astype(np.float32)
>>> F.mean_absolute_error(x, y)
variable(6.)
```
In this example, there are 4 elements, and thus 4 errors >>> x = np.array([[1, 2], [3, 4]]).astype(np.float32) >>> y = np.array([[8, 8], [8, 8]]).astype(np.float32) >>> F.mean_absolute_error(x, y) variable(5.5)

3D array example:
In this example, there are 8 elements, and thus 8 errors >>> x = np.reshape(np.array([1, 2, 3, 4, 5, 6, 7, 8]), (2, 2, 2)) >>> y = np.reshape(np.array([8, 8, 8, 8, 8, 8, 8, 8]), (2, 2, 2)) >>> x = x.astype(np.float32) >>> y = y.astype(np.float32) >>> F.mean_absolute_error(x, y) variable(3.5)

chainer.functions.mean_squared_error

chainer.functions.mean_squared_error(x0, x1)

Mean squared error function.

The function computes the mean squared error between two variables. The mean is taken over the minibatch. Args x0 and x1 must have the same dimensions. Note that the error is not scaled by 1/2.

Parameters

- **x0** (*Variable or N-dimensional array*) – Input variable.
- **x1** (*Variable or N-dimensional array*) – Input variable.

Returns

A variable holding an array representing the mean squared error of two inputs.

Return type

~chainer.Variable

Example

1D array examples:

```python
>>> x = np.array([1, 2, 3, 4]).astype(np.float32)
>>> y = np.array([0, 0, 0, 0]).astype(np.float32)
>>> F.mean_squared_error(x, y) variable(7.5)
>>> x = np.array([1, 2, 3, 4, 5, 6]).astype(np.float32)
>>> y = np.array([7, 8, 9, 10, 11, 12]).astype(np.float32)
>>> F.mean_squared_error(x, y) variable(36.)
```

2D array example:
In this example, there are 4 elements, and thus 4 errors >>> x = np.array([[1, 2], [3, 4]]).astype(np.float32) >>> y = np.array([[8, 8], [8, 8]]).astype(np.float32) >>> F.mean_squared_error(x, y) variable(31.5)

3D array example:
In this example, there are 8 elements, and thus 8 errors >>> x = np.reshape(np.array([1, 2, 3, 4, 5, 6, 7, 8]), (2, 2, 2)) >>> y = np.reshape(np.array([8, 8, 8, 8, 8, 8, 8, 8]), (2, 2, 2)) >>> x = x.astype(np.float32) >>> y = y.astype(np.float32) >>> F.mean_squared_error(x, y) variable(17.5)
Chainer Documentation, Release 7.7.0

chainer.functions.negative_sampling

chainer.functions.negative_sampling(x, t, W, sampler, sample_size, reduce='sum', *, return_samples=False)

Negative sampling loss function.

In natural language processing, especially language modeling, the number of words in a vocabulary can be very large. Therefore, you need to spend a lot of time calculating the gradient of the embedding matrix.

By using the negative sampling trick you only need to calculate the gradient for a few sampled negative examples.

The loss is defined as follows.

\[ f(x, p) = -\log \sigma(x^\top w_p) - kE_{i \sim P(i)}[\log \sigma(-x^\top w_i)] \]

where \( \sigma(\cdot) \) is a sigmoid function, \( w_i \) is the weight vector for the word \( i \), and \( p \) is a positive example. It is approximated with \( k \) examples \( N \) sampled from probability \( P(i) \).

\[ f(x, p) \approx -\log \sigma(x^\top w_p) - \sum_{n \in N} \log \sigma(-x^\top w_n) \]

Each sample of \( N \) is drawn from the word distribution \( P(w) = \frac{1}{Z} c(w)^\alpha \), where \( c(w) \) is the unigram count of the word \( w \), \( \alpha \) is a hyper-parameter, and \( Z \) is the normalization constant.

Parameters

- \( x \) (Variable or N-dimensional array) – Batch of input vectors.
- \( t \) (Variable or N-dimensional array) – Vector of ground truth labels.
- \( W \) (Variable or N-dimensional array) – Weight matrix.
- sampler (FunctionType) – Sampling function. It takes a shape and returns an integer array of the shape. Each element of this array is a sample from the word distribution. A \( \text{WalkerAlias} \) object built with the power distribution of word frequency is recommended.
- sample_size (int) – Number of samples.
- reduce (str) – Reduction option. Its value must be either 'sum' or 'no'. Otherwise, \( \text{ValueError} \) is raised.
- return_samples (bool) – If True, the sample array is also returned. The sample array is a

Returns

If return_samples is False (default), the output variable holding the loss value(s) calculated by the above equation is returned. Otherwise, a tuple of the output variable and the sample array is returned.

If reduce is 'no', the output variable holds array whose shape is same as one of (hence both of) input variables. If it is 'sum', the output variable holds a scalar value.

Return type  Variable or tuple

See: Distributed Representations of Words and Phrases and their Compositionality

See also:

NegativeSampling to manage the model parameter \( W \).
chainer.functions.sigmoid_cross_entropy

chainer.functions.sigmoid_cross_entropy(x, t, normalize=True, reduce='mean')
Computes cross entropy loss for pre-sigmoid activations.

Parameters

- **x** (Variable or N-dimensional array) – A variable object holding a matrix whose (i, j)-th element indicates the unnormalized log probability of the j-th unit at the i-th example.

- **t** (Variable or N-dimensional array) – A variable object holding a matrix whose (i, j)-th element indicates a signed integer vector of ground truth labels 0 or 1. If t[i, j] == -1, corresponding x[i, j] is ignored. Loss is zero if all ground truth labels are -1.

- **normalize** (bool) – Variable holding a boolean value which determines the normalization constant. If true, this function normalizes the cross entropy loss across all instances. If else, it only normalizes along a batch size.

- **reduce** (str) – Variable holding a str which determines whether to reduce the shape of the input. If it is 'mean', it computes the sum of cross entropy and normalize it according to normalize option. If is is 'no', this function computes cross entropy for each instance and does not normalize it (normalize option is ignored). In this case, the loss value of the ignored instance, which has -1 as its target value, is set to 0.

Returns A variable object holding an array of the cross entropy. If reduce is 'mean', it is a scalar array. If reduce is 'no', the shape is same as those of x and t.

Return type Variable

Note: This function is differentiable only by x.

Example

```python
>>> x = np.array([[-2.0, 3.0, 0.5], [5.0, 2.0, -0.5]]).astype(np.float32)
>>> x
array([[ -2. ,  3. ,  0.5],
       [  5. ,  2. , -0.5]], dtype=float32)
>>> t = np.array([[0, 1, 0], [1, 1, -1]]).astype(np.int32)
>>> t
array([[ 0,  1,  0],
       [ 1,  1, -1]], dtype=int32)
>>> F.sigmoid_cross_entropy(x, t)
variable(0.25664714)
>>> F.sigmoid_cross_entropy(x, t, normalize=False)
variable(0.64161783)
>>> y = F.sigmoid_cross_entropy(x, t, reduce='no')
>>> y.shape
(2, 3)
>>> y.array
array([[ 0.126928 ,  0.04858735,  0.974077 ],
       [ 0.00671535,  0.126928 , -0. ]], dtype=float32)
```
Computes cross entropy loss for pre-softmax activations.

Parameters

- \(x\) (Variable or N-dimensional array) – Variable holding a multidimensional array whose element indicates unnormalized log probability: the first axis of the variable represents the number of samples, and the second axis represents the number of classes. While this function computes a usual softmax cross entropy if the number of dimensions is equal to 2, it computes a cross entropy of the replicated softmax if the number of dimensions is greater than 2.

- \(t\) (Variable or N-dimensional array) – Variable holding a signed integer vector of ground truth labels. If \(t[i] == \text{ignore}\_\text{label}\), corresponding \(x[i]\) is ignored. When the dtype is float, this function treats \(t\) as an array holding probability distribution of labels, in other words, soft targets. In this case, the shape of \(t\) must be the same as the shape of \(x\). Note that the loss is calculated using cross entropy or KL divergence.

- \(\text{normalize}\) (bool) – If True, this function normalizes the cross entropy loss across all instances. If False, it only normalizes along a batch size.

- \(\text{cache}\_\text{score}\) (bool) – When it is True, the function stores result of forward computation to use it on backward computation. It reduces computational cost though consumes more memory. If \(\text{enable}\_\text{double}\_\text{backprop}\) option is True, this option is forcibly turned off and the function does not cache the intermediate value.

- \(\text{class}\_\text{weight}\) (N-dimensional array) – An array that contains constant weights that will be multiplied with the loss values along with the second dimension. The shape of this array should be \((x.\text{shape}[1],)\). If this is not None, each class weight \(\text{class}\_\text{weight}[i]\) is actually multiplied to \(y[:, i]\) that is the corresponding log-softmax output of \(x\) and has the same shape as \(x\) before calculating the actual loss value.

- \(\text{ignore}\_\text{label}\) (int) – Label value you want to ignore. Its default value is \(-1\). See description of the argument \(t\).

- \(\text{reduce}\) (str) – A string that determines whether to reduce the loss values. If it is 'mean', it computes the sum of the individual cross entropy and normalize it according to normalize option. If it is 'no', this function computes cross entropy for each instance and does not normalize it (normalize option is ignored). In this case, the loss value of the ignored instance, which has ignore_label as its target value, is set to 0.

- \(\text{enable}\_\text{double}\_\text{backprop}\) (bool) – If True, this function uses implementation that supports higher order differentiation. If False, it uses single-backprop implementation. This function use the single-backprop version because we expect it is faster. So, if you need second or higher derivatives, you need to turn it on explicitly.

- \(\text{soft}\_\text{target}\_\text{loss}\) (str) – A string that determines what type of method is used to calculate soft target loss. If 'cross-entropy' and 'kl-divergence', cross-entropy and KL divergence are used for loss calculation.

Returns A variable holding a scalar array of the cross entropy loss. If reduce is 'mean', it is a scalar array. If reduce is 'no', the shape is same as that of \(t\).

Return type Variable
Note: This function is differentiable only by \( x \).

Example

```python
>>> x = np.array([[-1, 0, 1, 2], [2, 0, 1, -1]]).astype(np.float32)
>>> x
array([[-1., 0., 1., 2.],
       [ 2., 0., 1., -1.]], dtype=float32)
>>> t = np.array([3, 0]).astype(np.int32)
>>> t
array([3, 0], dtype=int32)
>>> y = F.softmax_cross_entropy(x, t)
>>> y
variable(0.44018972)
>>> log_softmax = -F.log_softmax(x)
>>> expected_loss = np.mean([log_softmax[row, column].data for row, column in enumerate(t)])
>>> y.array == expected_loss
True
```

chainer.functions.squared_error

chainer.functions.squared_error(\( x_0, x_1 \))

Squared error function.

This function computes the squared error between two variables:

\[
(x_0 - x_1)^2
\]

where operation is done in elementwise manner. Note that the error is not scaled by 1/2:

Parameters

- \( x_0 \) (Variable or N-dimensional array) – Input variable.
- \( x_1 \) (Variable or N-dimensional array) – Input variable.

Returns A variable holding an array representing the squared error of two inputs.

Return type Variable

Note: squared_error() and squared_difference() are identical functions, aside from the different argument names. They are both kept for backward compatibility.

See also:

squared_difference()

Example

```python
>>> x1 = np.arange(6).astype(np.float32)
>>> x1
array([0., 1., 2., 3., 4., 5.], dtype=float32)
```
x2 = np.array([5, 4, 3, 2, 1, 0]).astype(np.float32)

y = F.squared_error(x1, x2)

See also:
squared_difference()

chainer.functions.triplet

chainer.functions.triplet (anchor, positive, negative, margin=0.2, reduce='mean')

Computes triplet loss.

It takes a triplet of variables as inputs, a, p and n: anchor, positive example and negative example respectively. The triplet defines a relative similarity between samples. Let N and K denote mini-batch size and the dimension of input variables, respectively. The shape of all input variables should be (N, K).

L(a, p, n) = \frac{1}{N} \sum_{i=1}^{N} \max\{d(a_i, p_i) - d(a_i, n_i) + margin, 0\}

where d(x_i, y_i) = \|x_i - y_i\|_2.

The output is a variable whose value depends on the value of the option reduce. If it is 'no', it holds the elementwise loss values. If it is 'mean', this function takes a mean of loss values.

Parameters

- anchor (Variable or N-dimensional array) – The anchor example variable. The shape should be (N, K), where N denotes the minibatch size, and K denotes the dimension of the anchor.
- positive (Variable or N-dimensional array) – The positive example variable. The shape should be the same as anchor.
- negative (Variable or N-dimensional array) – The negative example variable. The shape should be the same as anchor.
- margin (float) – A parameter for triplet loss. It should be a positive value.
- reduce (str) – Reduction option. Its value must be either 'mean' or 'no'. Otherwise, ValueError is raised.

Returns

A variable holding a scalar that is the loss value calculated by the above equation. If reduce is 'no', the output variable holds array whose shape is same as one of (hence both of) input variables. If it is 'mean', the output variable holds a scalar value.

Return type Variable

Note: This cost can be used to train triplet networks. See Learning Fine-grained Image Similarity with Deep Ranking for details.
Example

```python
>>> anchor = np.array([[-2.0, 3.0, 0.5],
                      [5.0, 2.0, -0.5]]).astype(np.float32)
>>> pos  = np.array([[-2.1, 2.8, 0.5],
                     [4.9, 2.0, -0.4]]).astype(np.float32)
>>> neg  = np.array([[-2.1, 2.7, 0.7],
                     [4.9, 2.0, -0.7]]).astype(np.float32)
>>> F.triplet(anchor, pos, neg)
variable(0.14000003)
>>> y = F.triplet(anchor, pos, neg, reduce='no')
>>> y.shape
(2,)
>>> y.array
array([0.11000005, 0.17], dtype=float32)
>>> F.triplet(anchor, pos, neg, margin=0.5)  # harder penalty
variable(0.44000003)
```

4.2.7 Mathematical functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.functions.absolute</td>
<td>Element-wise absolute.</td>
</tr>
<tr>
<td>chainer.functions.arccos</td>
<td>Elementwise arccosine function.</td>
</tr>
<tr>
<td>chainer.functions.asin</td>
<td>Elementwise arcsine function.</td>
</tr>
<tr>
<td>chainer.functions.atan</td>
<td>Elementwise arctangent function.</td>
</tr>
<tr>
<td>chainer.functions.arctan2</td>
<td>Elementwise arctangent function with two arguments.</td>
</tr>
<tr>
<td>chainer.functions.arctanh</td>
<td>Elementwise inverse hyperbolic tangent function.</td>
</tr>
<tr>
<td>chainer.functions.argmax</td>
<td>Returns index which holds maximum of array elements over a given axis.</td>
</tr>
<tr>
<td>chainer.functions.argmin</td>
<td>Returns index which holds minimum of array elements over a given axis.</td>
</tr>
<tr>
<td>chainer.functions.average</td>
<td>Calculate weighted average of array elements over a given axis.</td>
</tr>
<tr>
<td>chainer.functions.batch_inv</td>
<td>Computes the inverse of a batch of square matrices.</td>
</tr>
<tr>
<td>chainer.functions.batch_matmul</td>
<td>Computes the batch matrix multiplications of two sets of arrays.</td>
</tr>
<tr>
<td>chainer.functions.bias</td>
<td>Elementwise summation with broadcasting.</td>
</tr>
<tr>
<td>chainer.functions.cholesky</td>
<td>Cholesky Decomposition</td>
</tr>
<tr>
<td>chainer.functions.clip</td>
<td>Clips (limits) elements of input variable.</td>
</tr>
<tr>
<td>chainer.functions.cos</td>
<td>Elementwise cos function.</td>
</tr>
<tr>
<td>chainer.functions.cosh</td>
<td>Elementwise hyperbolic cosine function.</td>
</tr>
<tr>
<td>chainer.functions.cumprod</td>
<td>Cumulative prod of array elements over a given axis.</td>
</tr>
<tr>
<td>chainer.functions.cumsum</td>
<td>Cumulative sum of array elements over a given axis.</td>
</tr>
<tr>
<td>chainer.functions.det</td>
<td>Computes the determinant of a single square matrix.</td>
</tr>
<tr>
<td>chainer.functions.batch_det</td>
<td>Computes the determinant of a batch of square matrices.</td>
</tr>
<tr>
<td>chainer.functions.digamma</td>
<td>Digamma function.</td>
</tr>
<tr>
<td>chainer.functions.einsum</td>
<td>Einstein summation</td>
</tr>
<tr>
<td>chainer.functions.erf</td>
<td>Elementwise error function.</td>
</tr>
<tr>
<td>chainer.functions.erfc</td>
<td>Elementwise complementary error function.</td>
</tr>
</tbody>
</table>

continues on next page
<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.functions.erfconv</code></td>
<td>Elementwise inverse function of complementary error function.</td>
</tr>
<tr>
<td><code>chainer.functions.erfcx</code></td>
<td>Elementwise scaled complementary error function.</td>
</tr>
<tr>
<td><code>chainer.functions.erfinv</code></td>
<td>Elementwise inverse function of error function.</td>
</tr>
<tr>
<td><code>chainer.functions.exp</code></td>
<td>Elementwise exponential function.</td>
</tr>
<tr>
<td><code>chainer.functions.expml</code></td>
<td>Elementwise exponential minus one function.</td>
</tr>
<tr>
<td><code>chainer.functions.fft</code></td>
<td>Fast Fourier transform.</td>
</tr>
<tr>
<td><code>chainer.functions.fix</code></td>
<td>Elementwise fix function.</td>
</tr>
<tr>
<td><code>chainer.functions.fmod</code></td>
<td>Elementwise mod function.</td>
</tr>
<tr>
<td><code>chainer.functions.floor</code></td>
<td>Elementwise floor function.</td>
</tr>
<tr>
<td><code>chainer.functions.identity</code></td>
<td>Just returns input variables.</td>
</tr>
<tr>
<td><code>chainer.functions.ifft</code></td>
<td>Inverse fast Fourier transform.</td>
</tr>
<tr>
<td><code>chainer.functions.inv</code></td>
<td>Computes the inverse of square matrix.</td>
</tr>
<tr>
<td><code>chainer.functions.lgamma</code></td>
<td>Logarithm of gamma function.</td>
</tr>
<tr>
<td><code>chainer.functions.linear_interpolate</code></td>
<td>Elementwise linear-interpolation function.</td>
</tr>
<tr>
<td><code>chainer.functions.log</code></td>
<td>Elementwise natural logarithm function.</td>
</tr>
<tr>
<td><code>chainer.functions.log10</code></td>
<td>Elementwise logarithm function to the base 10.</td>
</tr>
<tr>
<td><code>chainer.functions.log1p</code></td>
<td>Elementwise natural logarithm plus one function.</td>
</tr>
<tr>
<td><code>chainer.functions.log2</code></td>
<td>Elementwise logarithm function to the base 2.</td>
</tr>
<tr>
<td><code>chainer.functions.log_ndtr</code></td>
<td>Logarithm of cumulative distribution function of normal distribution.</td>
</tr>
<tr>
<td><code>chainer.functions.logsumexp</code></td>
<td>Log-sum-exp of array elements over a given axis.</td>
</tr>
<tr>
<td><code>chainer.functions.matmul</code></td>
<td>Computes the matrix multiplication of two arrays.</td>
</tr>
<tr>
<td><code>chainer.functions.max</code></td>
<td>Maximum of array elements over a given axis.</td>
</tr>
<tr>
<td><code>chainer.functions.maximum</code></td>
<td>Element-wise maximum of input variables.</td>
</tr>
<tr>
<td><code>chainer.functions.mean</code></td>
<td>Calculate weighted average of array elements over a given axis.</td>
</tr>
<tr>
<td><code>chainer.functions.min</code></td>
<td>Minimum of array elements over a given axis.</td>
</tr>
<tr>
<td><code>chainer.functions.minimum</code></td>
<td>Element-wise minimum of input variables.</td>
</tr>
<tr>
<td><code>chainer.functions.ndtri</code></td>
<td>Elementwise inverse function of ndtr.</td>
</tr>
<tr>
<td><code>chainer.functions.prod</code></td>
<td>Product of array elements over a given axis.</td>
</tr>
<tr>
<td><code>chainer.functions.polygamma</code></td>
<td>Polygamma function.</td>
</tr>
<tr>
<td><code>chainer.functions.rsqrt</code></td>
<td>Computes elementwise reciprocal of square root of input ( x_i ).</td>
</tr>
<tr>
<td><code>chainer.functions.scale</code></td>
<td>Elementwise product with broadcasting.</td>
</tr>
<tr>
<td><code>chainer.functions.sin</code></td>
<td>Elementwise sin function.</td>
</tr>
<tr>
<td><code>chainer.functions.sinh</code></td>
<td>Elementwise hyperbolic sine function.</td>
</tr>
<tr>
<td><code>chainer.functions.sign</code></td>
<td>Elementwise sign function.</td>
</tr>
<tr>
<td><code>chainer.functions.sparse_matmul</code></td>
<td>Computes the batched multiplication of sparse and dense matrix.</td>
</tr>
<tr>
<td><code>chainer.functions.sqrt</code></td>
<td>Elementwise square root function.</td>
</tr>
<tr>
<td><code>chainer.functions.square</code></td>
<td>Elementwise square function.</td>
</tr>
<tr>
<td><code>chainer.functions.squared_difference</code></td>
<td>Squared difference function.</td>
</tr>
<tr>
<td><code>chainer.functions.sum</code></td>
<td>Sum of array elements over a given axis.</td>
</tr>
<tr>
<td><code>chainer.functions.sum_to</code></td>
<td>Sum elements along axes to output an array of a given shape.</td>
</tr>
<tr>
<td><code>chainer.functions.tanh</code></td>
<td>Elementwise hyperbolic tangent function.</td>
</tr>
<tr>
<td><code>chainer.functions.tan</code></td>
<td>Elementwise tan function.</td>
</tr>
</tbody>
</table>

continues on next page
Table 8 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.functions.tensordot</code></td>
<td>Returns the tensor dot product of two arrays along specified axes.</td>
</tr>
<tr>
<td><code>chainer.functions.zeta</code></td>
<td>Zeta function.</td>
</tr>
</tbody>
</table>

**chainer.functions.absolute**

```python
chainer.functions.absolute(self)
```
Element-wise absolute.

- **Returns**: Output variable.
- **Return type**: Variable

**chainer.functions.arccos**

```python
chainer.functions.arccos(x)
```
Elementwise arccosine function.

\[ y_i = \arccos x_i. \]

- **Parameters**: `x` (Variable or N-dimensional array) – Input variable.
- **Returns**: Output variable.
- **Return type**: Variable

**chainer.functions.arcsin**

```python
chainer.functions.arcsin(x)
```
Elementwise arcsine function.

\[ y_i = \arcsin x_i. \]

- **Parameters**: `x` (Variable or N-dimensional array) – Input variable.
- **Returns**: Output variable.
- **Return type**: Variable

**chainer.functions.arctan**

```python
chainer.functions.arctan(x)
```
Elementwise arctangent function.

\[ y_i = \arctan x_i. \]

- **Parameters**: `x` (Variable or N-dimensional array) – Input variable.
- **Returns**: Output variable.
- **Return type**: Variable
chainer.functions.arctan2

chainer.functions.arctan2(x1, x2)

Elementwise arctangent function with two arguments.

Parameters

- x1 (Variable or N-dimensional array) – Y-coordinates.
- x2 (Variable or N-dimensional array) – X-coordinates.

Returns Angles in radians, in the range [-pi, pi].

Return type Variable

chainer.functions.arctanh

chainer.functions.arctanh(x)

Elementwise inverse hyperbolic tangent function.

Parameters x (Variable or N-dimensional array) – Input variable.

Returns Output variable.

Return type Variable

chainer.functions.argmax

chainer.functions.argmax(x, axis=None)

Returns index which holds maximum of array elements over a given axis.

Parameters

- x (Variable or N-dimensional array) – Array to find maximum elements.
- axis (None or int) – Axis over which a max is performed. The default (axis = None) is perform a max over all the dimensions of the input array.

Returns Output variable.

Return type Variable

chainer.functions.argmin

chainer.functions.argmin(x, axis=None)

Returns index which holds minimum of array elements over a given axis.

Parameters

- x (Variable or N-dimensional array) – Array to find minimum elements.
- axis (None or int) – Axis over which a min is performed. The default (axis = None) is perform a min over all the dimensions of the input array.

Returns Output variable.

Return type Variable
chainer.functions.average

chainer.functions.average(x, axis=None, weights=None, keepdims=False)
Calculate weighted average of array elements over a given axis.

Parameters

- **x** (Variable or N-dimensional array) – Elements to sum.
- **axis** (None or int or tuple of int) – Axis which the method is performed. With the default (axis = None) it performs a mean over all the dimensions of the input array.
- **weights** (None or Variable or N-dimensional array) – An array holding weights to calculate weighted average. If it is None, all weights are assumed to be one. When axis is None, weights must have the same shape of x. And when axis is int, it must be 1-D array satisfying weights.shape == (x.shape[axis],).
- **keepdims** (bool) – If True, the specified axes are remained as axes of length one.

Returns Output variable.

Return type Variable

chainer.functions.batch_inv

chainer.functions.batch_inv(a)
Computes the inverse of a batch of square matrices.

Parameters **a** (Variable or N-dimensional array) – Input array to compute the inverse for. Shape of the array should be (m, n, n) where m is the number of matrices in the batch, and n is the dimensionality of a square matrix.

Returns Inverse of every matrix in the batch of matrices.

Return type Variable

chainer.functions.batch_l2_norm_squared

chainer.functions.batch_l2_norm_squared(x)
L2 norm (a.k.a. Euclidean norm) squared.

This function implements the square of L2 norm on a vector. No reduction along batch axis is done.

Parameters **x** (Variable or N-dimensional array) – Input variable. The first dimension is assumed to be the minibatch dimension. If x has more than two dimensions all but the first dimension are flattened to one dimension.

Returns Two dimensional output variable.

Return type Variable
**chainer.functions.batch_matmul**

chainer.functions.batch_matmul(a, b, transa=False, transb=False)

Computes the batch matrix multiplications of two sets of arrays.

**Parameters**

- **a (Variable or N-dimensional array)** – The left operand of the batch matrix multiplications. A 2-D array of shape \((B, N)\) is considered as \(B \times N\) matrices. A 3-D array of shape \((B, M, N)\) is considered as \(B \times M \times N\) matrices.
- **b (Variable or N-dimensional array)** – The right operand of the batch matrix multiplications. Its array is treated as matrices in the same way as a’s array.
- **transa (bool)** – If True, transpose each matrix in a.
- **transb (bool)** – If True, transpose each matrix in b.

**Returns**
The result of the batch matrix multiplications as a 3-D array.

**Return type**
Variable

Deprecated since version v3.0.0: batch_matmul is deprecated. Use matmul instead.

**chainer.functions.bias**

chainer.functions.bias(x, y, axis=1)

Elementwise summation with broadcasting.

Computes a elementwise summation of two input variables, with the shape of the latter variable broadcasted to match the shape of the former. \(\text{axis}\) is the first axis of the first variable along which the second variable is applied.

The term “broadcasting” here comes from Caffe’s bias layer so the “broadcasting” with the following arguments:

\[
\begin{align*}
    \text{x} &: 100 \times 3 \times 40 \times 5 \times 6 \\
    \text{y} &: 3 \times 40 \\
    \text{axis} &: 1
\end{align*}
\]

is equivalent to the following numpy broadcasting:

\[
\begin{align*}
    \text{x} &: 100 \times 3 \times 40 \times 5 \times 6 \\
    \text{y} &: (1 \times) 3 \times 40 \times 1 \times 1
\end{align*}
\]

Note that the axis of \(\text{x}\) to which we apply \(\text{y}\) is specified by the argument \(\text{axis}\), whose meaning is different from numpy’s \(\text{axis}\).

**Parameters**

- **\(\text{x (Variable or N-dimensional array)}\)** – Input variable to be summed.
- **\(\text{y (Variable or N-dimensional array)}\)** – Input variable to sum, broadcasted.
- **\(\text{axis (int)}\)** – The first axis of \(\text{x}\) along which \(\text{y}\) is applied.

**Returns**
Output variable.

**Return type**
Variable
chainer.functions.ceil

chainer.functions.ceil(x)

Elementwise ceil function.

\[ y_i = \lceil x_i \rceil \]

**Parameters**

- **x** (*Variable* or *N-dimensional array*) – Input variable.

**Returns**

Output variable.

**Return type**

*Variable*

chainer.functions.cholesky

chainer.functions.cholesky(a)

Cholesky Decomposition

**Parameters**

- **a** (*Variable* or *N-dimensional array*) – Input variable.

**Returns**

Output variable.

**Return type**

*Variable*

chainer.functions.clip

chainer.functions.clip(x, x_min, x_max)

Clips (limits) elements of input variable.

Given an interval \([x_{\text{min}}, x_{\text{max}}]\), elements outside the interval are clipped to the interval edges. Its gradients at \(x_{\text{min}}\) and \(x_{\text{max}}\) are regarded as 1.

**Parameters**

- **x** (*Variable* or *N-dimensional array*) – Input variable to be clipped.
- **x_min** (*float*) – Minimum value.
- **x_max** (*float*) – Maximum value.

**Returns**

Output variable.

**Return type**

*Variable*

chainer.functions.cos

chainer.functions.cos(x)

Elementwise cos function.

**Parameters**

- **x** (*Variable* or *N-dimensional array*) – Input variable.

**Returns**

Output variable.

**Return type**

*Variable*
chainer.functions.cosh

chainer.functions.cosh(x)
Elementwise hyperbolic cosine function.

\[ y_i = \cosh x_i. \]

Parameters  
\( x \) (Variable or N-dimensional array) – Input variable.

Returns  Output variable.

Return type  Variable

chainer.functions.cumprod

chainer.functions.cumprod(x, axis=None)
Cumulative prod of array elements over a given axis.

Parameters

- \( x \) (Variable or N-dimensional array) – Elements to calculate the cumulative prod.
- \( axis \) (int or None) – Axis along which the cumulative prod is taken. If it is not specified, the input is flattened.

Returns  Output variable.

Return type  Variable

chainer.functions.cumsum

chainer.functions.cumsum(x, axis=None)
Cumulative sum of array elements over a given axis.

Parameters

- \( x \) (Variable or N-dimensional array) – Elements to calculate the cumulative sum.
- \( axis \) (int or None) – Axis along which the cumulative sum is taken. If it is not specified, the input is flattened.

Returns  Output variable.

Return type  Variable

chainer.functions.det

chainer.functions.det(a)
Computes the determinant of a single square matrix.

Parameters  
\( a \) (Variable or N-dimensional array) – Input array to compute the determinant for.

Returns  Scalar determinant of the matrix a.

Return type  Variable
chainer.functions.batch_det

chainer.functions.batch_det(a)
Computes the determinant of a batch of square matrices.

Parameters
a (Variable or N-dimensional array) – Input array to compute the determinant for. The first dimension should iterate over each matrix and be of the batchsize.

Returns
vector of determinants for every matrix in the batch.

Return type
Variable

chainer.functions.digamma

digamma(x)
Digamma function.

Note: Forward computation in CPU can not be done if SciPy is not available.

Parameters
x (Variable or N-dimensional array) – Input variable.

Returns
Output variable.

Return type
Variable

chainer.functions.einsum

einsum(*operands)
Einstein summation

This function supports two formats of inputs:

* einsum(subscripts, op0, op1, ...)
* einsum(op0, sublist0, op1, sublist1, ..., [sublistout])

See also numpy.einsum()

Example

The following example computes a batched application of a bilinear function with weight $w$.

```python
>>> x1 = np.arange(12).reshape(3, 4).astype(np.float32)
>>> x2 = np.arange(15).reshape(3, 5).astype(np.float32)
>>> w = np.arange(120).reshape(4, 5, 6).astype(np.float32)
>>> y = F.einsum('ij,ik,jkl->il', x1, x2, w)
>>> y.shape
(3, 6)
```

The batch axes can be denoted by .... If the string of output subscripts is omitted, the summation is taken over the subscript alphabets with two (or more) occurrences.

```python
>>> np.allclose(y.array, F.einsum('...j,...k,jkl->il', x1, x2, w).array)
True
```

In the other format:
```python
>>> y = F.einsum(x1, [0, 1], x2, [0, 2], w, [1, 2, 3], [0, 3])
>>> y.shape
(3, 6)
```
```python
>>> y = F.einsum(x1, [Ellipsis, 1], x2, [Ellipsis, 2], w, [1, 2, 3])
>>> y.shape
(3, 6)
```

### chainer.functions.erf

**chainer.functions.erf(x)**

Elementwise error function.

**Note:** Forward computation in CPU can be slow if SciPy is not available.

**Parameters**

- `x (Variable or N-dimensional array)` – Input variable.

**Returns**

- Output variable.

**Return type**

- `Variable`

### chainer.functions.erfc

**chainer.functions.erfc(x)**

Elementwise complementary error function.

**Note:** Forward computation in CPU can be slow if SciPy is not available.

**Parameters**

- `x (Variable or N-dimensional array)` – Input variable.

**Returns**

- Output variable.

**Return type**

- `Variable`

### chainer.functions.erfcinv

**chainer.functions.erfcinv(x)**

Elementwise inverse function of complementary error function.

**Note:** Forward computation in CPU cannot be done if SciPy is not available.

**Parameters**

- `x (Variable or N-dimensional array)` – Input variable.

**Returns**

- Output variable.

**Return type**

- `Variable`
chainer.functions.erfcx

chainer.functions.erfcx(x)
Elementwise scaled complementary error function.

Note: Forward computation in CPU cannot be done if SciPy is not available.

Parameters  x (Variable or N-dimensional array) – Input variable.
Returns  Output variable.
Return type  Variable

chainer.functions.erfinv

chainer.functions.erfinv(x)
Elementwise inverse function of error function.

Note: Forward computation in CPU cannot be done if SciPy is not available.

Parameters  x (Variable or N-dimensional array) – Input variable.
Returns  Output variable.
Return type  Variable

chainer.functions.exp

chainer.functions.exp(x)
Elementwise exponential function.

Parameters  x (Variable or N-dimensional array) – Input variable.
Returns  Output variable.
Return type  Variable

chainer.functions.expm1

chainer.functions.expm1(x)
Elementwise exponential minus one function.

Parameters  x (Variable or N-dimensional array) – Input variable.
Returns  Output variable.
Return type  Variable
**chainer.functions.fft**

chainer.functions.fft(x)

Fast Fourier transform.

**Parameters**

- **x (tuple)** – (real, imag) where real is a `Variable` or an `N-dimensional array` storing the real part and imag is a `Variable` or an `N-dimensional array` storing the imaginary part.

**Returns**

Returns (ry, iy) where ry is the real part of the result and iy is the imaginary part of the result.

**Return type**
tuple

**Note:** Currently this function supports a tuple as input. It will support a complex numbers directly in the future.

**chainer.functions.fix**

chainer.functions.fix(x)

Elementwise fix function.

\[ y_i = x_i \]

**Parameters**

- **x** (`Variable` or `N-dimensional array`) – Input variable.

**Returns**

Output variable.

**Return type**
`Variable`

**chainer.functions.fmod**

chainer.functions.fmod(x, divisor)

Elementwise mod function.

\[ y_i = x_i \mod \text{divisor} \]

**Parameters**

- **x** (`Variable` or `N-dimensional array`) – Input variable.
- **divisor** (`Variable` or `N-dimensional array`) – Input divisor.

**Returns**

Output variable.

**Return type**
`Variable`

**chainer.functions.floor**

chainer.functions.floor(x)

Elementwise floor function.

\[ y_i = \lfloor x_i \rfloor \]

**Parameters**

- **x** (`Variable` or `N-dimensional array`) – Input variable.

**Returns**

Output variable.

**Return type**
`Variable`
**chainer.functions.identity**

`chainer.functions.identity(*inputs)`

Just returns input variables.

**chainer.functions.ifft**

`chainer.functions.ifft(x)`

Inverse fast Fourier transform.

**Parameters**

- `x` (*tuple*) – (real, imag) where real is a `Variable` or an `N-dimensional array` storing the real part and imag is a `Variable` or an `N-dimensional array` storing the imaginary part.

**Returns**

Returns `(ry, iy)` where `ry` is the real part of the result and `iy` is the imaginary part of the result.

**Return type**

`tuple`

**Note:** Currently this function supports a tuple as input. It will support a complex numbers directly in the future.

**chainer.functions.inv**

`chainer.functions.inv(a)`

Computes the inverse of square matrix.

**Parameters**

- `a` (*Variable` or `N-dimensional array*) – Input array to compute the inverse for. Shape of the array should be `(n, n)` where `n` is the dimensionality of a square matrix.

**Returns**

Matrix inverse of `a`.

**Return type**

`Variable`

**chainer.functions.lgamma**

`chainer.functions.lgamma(x)`

logarithm of gamma function.

**Note:** Forward computation in CPU can not be done if SciPy is not available.

**Parameters**

- `x` (*Variable` or `N-dimensional array*) – Input variable.

**Returns**

Output variable.

**Return type**

`Variable`
**chainer.functions.linear_interpolate**

chainer.functions.linear_interpolate\( (p, x, y) \)

Elementwise linear-interpolation function.

This function is defined as

\[
f(p, x, y) = px + (1 - p)y.
\]

**Parameters**

- \( p \) (Variable or N-dimensional array) – Input variable.
- \( x \) (Variable or N-dimensional array) – Input variable.
- \( y \) (Variable or N-dimensional array) – Input variable.

**Returns**

Output variable.

**Return type** Variable

**chainer.functions.log**

chainer.functions.log\( (x) \)

Elementwise natural logarithm function.

**Parameters**

- \( x \) (Variable or N-dimensional array) – Input variable.

**Returns**

Output variable.

**Return type** Variable

**chainer.functions.log10**

chainer.functions.log10\( (x) \)

Elementwise logarithm function to the base 10.

\[
y_i = \log_{10} x_i.
\]

**Parameters**

- \( x \) (Variable or N-dimensional array) – Input variable.

**Returns**

Output variable.

**Return type** Variable

**chainer.functions.log1p**

chainer.functions.log1p\( (x) \)

Elementwise natural logarithm plus one function.

**Parameters**

- \( x \) (Variable or N-dimensional array) – Input variable.

**Returns**

Output variable.

**Return type** Variable
chainer.functions.log2

chainer.functions.log2(x)
Elementwise logarithm function to the base 2.

\[ y_i = \log_2 x_i. \]

**Parameters**
- `x` (Variable or N-dimensional array) – Input variable.

**Returns**
Output variable.

**Return type**
Variable

chainer.functions.log_ndtr

chainer.functions.log_ndtr(x)
Logarithm of cumulative distribution function of normal distribution.

**Note:** Forward computation in CPU can not be done if SciPy is not available.

**Parameters**
- `x` (Variable or N-dimensional array) – Input variable.

**Returns**
Output variable.

**Return type**
Variable

chainer.functions.logsumexp

chainer.functions.logsumexp(x, axis=None)
Log-sum-exp of array elements over a given axis.

This function calculates logarithm of sum of exponential of array elements.

\[ y_i = \log \left( \sum_j \exp(x_{ij}) \right) \]

**Parameters**
- `x` (Variable or N-dimensional array) – Elements to log-sum-exp.
- `axis` (None, int, or tuple of int) – Axis which a sum is performed. The default (axis = None) is perform a sum over all the dimensions of the input array.

**Returns**
Output variable.

**Return type**
Variable
chainer.functions.matmul

chainer.functions.matmul(a, b, transa=False, transb=False)

Computes the matrix multiplication of two arrays.

Parameters

- **a** *(Variable or N-dimensional array)* – The left operand of the matrix multiplication. If `a` and `b` are both 1-D arrays, `matmul` returns a dot product of vector `a` and vector `b`. If 2-D arrays, `matmul` returns matrix product of `a` and `b`. If either’s dimension is larger than 2, they are treated as a stack of matrices residing in the last two indexes. `matmul` returns a stack of each two arrays. In this case, `a` and `b` are broadcasted along axes except the last two.

- **b** *(Variable or N-dimensional array)* – The right operand of the matrix multiplication. Its array is treated as a matrix in the same way as `a`’s array.

- **transa** *(bool)* – If True, each matrices in `a` will be transposed. If `a.ndim == 1`, do nothing.

- **transb** *(bool)* – If True, each matrices in `b` will be transposed. If `b.ndim == 1`, do nothing.

Returns

The result of the matrix multiplication.

Return type *Variable*

Example

```python
>>> a = np.array([[1, 0], [0, 1]], np.float32)
>>> b = np.array([[4, 1], [2, 2]], np.float32)
>>> F.matmul(a, b).array
array([[4., 1.],
       [2., 2.]], dtype=float32)
```

chainer.functions.max

chainer.functions.max(x, axis=None, keepdims=False)

Maximum of array elements over a given axis.

Parameters

- **x** *(Variable or N-dimensional array)* – Array to be maximized.

- **axis** *(None, int, or tuple of int)* – Axis over which a max is performed. The default (axis = None) is perform a max over all the dimensions of the input array.

Returns

Output variable.

Return type *Variable*
**chainer.functions.maximum**

chainer.functions.maximum(x1, x2)

Element-wise maximum of input variables.

**Parameters**

- **x1** *(Variable or N-dimensional array)* – Input variables to be compared. A \((s_1, s_2, ..., s_N)\)-shaped float array.

- **x2** *(Variable or N-dimensional array)* – Input variables to be compared. A \((s_1, s_2, ..., s_N)\)-shaped float array.

**Returns** Output variable.

**Return type** *Variable*

**Example**

```python
>>> x1 = np.arange(6).astype(np.float32)
>>> x1
array([0., 1., 2., 3., 4., 5.], dtype=float32)
>>> x2 = np.array([5, 4, 3, 2, 1, 0]).astype(np.float32)
>>> x2
array([5., 4., 3., 2., 1., 0.], dtype=float32)
>>> y = F.maximum(x1, x2)
>>> y.shape
(6,)
>>> y.array
array([5., 4., 3., 3., 4., 5.], dtype=float32)
```

**chainer.functions.mean**

chainer.functions.mean(x, axis=None, weights=None, keepdims=False)

Calculate weighted average of array elements over a given axis.

**Parameters**

- **x** *(Variable or N-dimensional array)* – Elements to sum.

- **axis** *(None or int or tuple of int)* – Axis which the method is performed. With the default (axis = None) it performs a mean over all the dimensions of the input array.

- **weights** *(None or Variable or N-dimensional array)* – An array holding weights to calculate weighted average. If it is None, all weights are assumed to be one. When axis is None, weights must have the same shape of x. And when axis is int, it must be 1-D array satisfying weights.shape == (x.shape[axis],).

- **keepdims** *(bool)* – If True, the specified axes are remained as axes of length one.

**Returns** Output variable.

**Return type** *Variable*
chainer.functions.min

chainer.functions.min(x, axis=None, keepdims=False)
Minimum of array elements over a given axis.

Parameters

- **x** (*Variable* or *N-dimensional array*) – Array to be minimized.
- **axis** (*None*, *int*, or *tuple of int*) – Axis over which a min is performed. The default (*axis = None*) is perform a min over all the dimensions of the input array.

Returns Output variable.

Return type *Variable*

chainer.functions.minimum

chainer.functions.minimum(x1, x2)
Element-wise minimum of input variables.

Parameters

- **x1** (*Variable* or *N-dimensional array*) – Input variables to be compared.
- **x2** (*Variable* or *N-dimensional array*) – Input variables to be compared.

Returns Output variable.

Return type *Variable*

chainer.functions.ndtr

chainer.functions.ndtr(x)
Elementwise cumulative distribution function of normal distribution.

**Note:** Forward computation in CPU can be slow if SciPy is not available.

Parameters **x** (*Variable* or *N-dimensional array*) – Input variable.

Returns Output variable.

Return type *Variable*

chainer.functions.ndtri

chainer.functions.ndtri(x)
Elementwise inverse function of ndtr.

**Note:** Forward computation in CPU can not be done if SciPy is not available.

Parameters **x** (*Variable* or *N-dimensional array*) – Input variable.

Returns Output variable.

Return type *Variable*
chainer.functions.prod

chainer.functions.prod(x, axis=None, keepdims=False)
Product of array elements over a given axis.

Parameters

• `x` (*Variable or N-dimensional array*) – Elements to calculate the product.
• `axis` (*None, int, or tuple of int*) – Axis which a product is performed. The default (axis = None) is perform a product over all the dimensions of the input array.
• `keepdims` (*bool*) – If True, the specified axes are remained as axes of length one.

Returns Output variable.
Return type *Variable*

chainer.functions.polygamma

chainer.functions.polygamma(n, x)
Polygamma function.

Note: Forward computation in CPU cannot be done if SciPy is not available.

Parameters

• `n` (*Variable or N-dimensional array*) – Input variable.
• `x` (*Variable or N-dimensional array*) – Input variable.

Returns Output variable.
Return type *Variable*

chainer.functions.rsqrt

chainer.functions.rsqrt(x)
Computes elementwise reciprocal of square root of input \(x_i\).

\[ y_i = \frac{1}{\sqrt{x_i}}. \]

Parameters `x` (*Variable or N-dimensional array*) – Input variable.

Returns Output variable.
Return type *Variable*

See also:
`sqrt()`
chainer.functions.scale

chainer.functions.scale(x, y, axis=1)
Elementwise product with broadcasting.

Computes a elementwise product of two input variables, with the shape of the latter variable broadcasted to match the shape of the former. axis is the first axis of the first variable along which the second variable is applied.

The term “broadcasting” here comes from Caffe’s scale layer so the “broadcasting” with the following arguments:

\[
\begin{aligned}
  x & : 100 \times 3 \times 40 \times 5 \times 6 \\
  y & : 3 \times 40 \\
  \text{axis} & : 1
\end{aligned}
\]

is equivalent to the following numpy broadcasting:

\[
\begin{aligned}
  x & : 100 \times 3 \times 40 \times 5 \times 6 \\
  y & : (1 \times) 3 \times 40 \times 1 \times 1
\end{aligned}
\]

Note that the axis of \( x \) to which we apply \( y \) is specified by the argument axis, whose meaning is different from numpy’s axis.

Parameters

- \( x \) (Variable or N-dimensional array) – Input variable to be scaled.
- \( y \) (Variable or N-dimensional array) – Input variable to scale, broadcasted.
- \( \text{axis} \) (int) – The first axis of \( x \) along which \( y \) is applied.

Returns Output variable.

Return type Variable

chainer.functions.sin

chainer.functions.sin(x)
Elementwise sin function.

Parameters \( x \) (Variable or N-dimensional array) – Input variable.

Returns Output variable.

Return type Variable

chainer.functions.sinh

chainer.functions.sinh(x)
Elementwise hyperbolic sine function.

\[ y_i = \sinh x_i. \]

Parameters \( x \) (Variable or N-dimensional array) – Input variable.

Returns Output variable.

Return type Variable
chainer.functions.sign

chainer.functions.sign(x)

Elementwise sign function.

For a given input $x$, this function returns $sgn(x)$ defined as

$$sgn(x) = \begin{cases} 
-1 & \text{if } x < 0 \\
0 & \text{if } x = 0 \\
1 & \text{if } x > 0 
\end{cases}$$

**Note:** The gradient of this function is `None` everywhere and therefore unchains the computational graph.

**Parameters**
- `x` (*Variable* or *N-dimensional array*) – Input variable for which the sign is computed.

**Returns**
- Output variable.

**Return type** *Variable*

chainer.functions.sparse_matmul

chainer.functions.sparse_matmul(a, b, transa=False, transb=False)

Computes the batched multiplication of sparse and dense matrix.

The following use cases are supported:

1. C (dense) = A (sparse) * B (dense)
2. C (dense) = A (dense) * B (sparse)

**Parameters**
- `a` (*Variable* or *CooMatrix*) – The left operand of matrix multiplication.
- `b` (*Variable* or *CooMatrix*) – The right operand of matrix multiplication.
- `transa` (*bool*) – If True, each matrix in `a` will be transposed.
- `transb` (*bool*) – If True, each matrix in `b` will be transposed.

**Returns**
- Result of batched mat-mul.

**Return type** *Variable*

**See also:**

See `to_coo()` for how to construct a COO matrix from an array.

**Note:** Performance of this function on GPU can be improved by using the `order` argument of `CooMatrix` when the sparse matrix is created.
chainer.functions.sqrt

chainer.functions.sqrt(x)
Elementwise square root function.

\[ y_i = \sqrt{x_i}. \]

If the value of \( x_i \) is negative, it returns Nan for \( y_i \) respect to underlying numpy and cupy specification.

Parameters:
- **x** (*Variable* or *N-dimensional array*) – Input variable.

Returns:
- Output variable.

Return type: *Variable*

chainer.functions.square

chainer.functions.square(x)
Elementwise square function.

\[ y_i = x_i^2. \]

Parameters:
- **x** (*Variable* or *N-dimensional array*) – Input variable. A \((s_1, s_2, \ldots, s_N)\) -shaped float array.

Returns:
- Output variable. A \((s_1, s_2, \ldots, s_N)\) -shaped float array.

Return type: *Variable*

Example

```python
>>> x = np.arange(6).reshape(2,3).astype(np.float32)
>>> x
array([[ 0.,  1.,  2.],
       [ 3.,  4.,  5.]], dtype=float32)
>>> y = F.square(x)
>>> y.shape
(2, 3)
>>> y.array
array([[ 0.,  1.,  4.],
        [ 9., 16., 25.]], dtype=float32)
```

chainer.functions.squared_difference

chainer.functions.squared_difference(x1,x2)
Squared difference function.

This functions is identical to `squared_error()` except for the names of the arguments.

See also:
- `squared_error()`
**chainer.functions.sum**

chainer.functions.sum(x, axis=None, keepdims=False)

Sum of array elements over a given axis.

**Parameters**

- **x** *(Variable or N-dimensional array)* – Elements to sum. A \((s_1, s_2, \ldots, s_N)\)-shaped float array.

- **axis** *(None, int, or tuple of int)* – Axis along which a sum is performed. The default \((axis = None)\) is perform a sum over all the dimensions of the input array.

- **keepdims** *(bool)* – If True, the specified axes are remained as axes of length one.

**Returns** Output variable.

**Return type** Variable

**Example**

```python
>>> x = np.arange(6).reshape(2,3).astype(np.float32)
>>> x
array([[0., 1., 2.],
       [3., 4., 5.]], dtype=float32)
>>> y = F.sum(x)
>>> y.shape
()  # Output shape
>>> y.array
array(15., dtype=float32)
>>> y = F.sum(x, axis=1)
>>> y.shape
(2,)
>>> y.array
array([ 3., 12.], dtype=float32)
>>> y = F.sum(x, keepdims=True)
>>> y.shape
(1, 1)
>>> y.array
array([[15.]], dtype=float32)
```

**chainer.functions.sum_to**

chainer.functions.sum_to(x, shape)

Sum elements along axes to output an array of a given shape.

**Parameters**

- **x** *(Variable or N-dimensional array)* – Input variable.

- **shape** *(tuple of int)* – The target shape.

**Returns** Output variable of shape \(shape\).

**Return type** Variable

**Example**

```python
```
```
>>> x = np.array([[1., 2., 3.], [4., 5., 6.]])
>>> x
array([[1., 2., 3.],
       [4., 5., 6.]])
>>> y = F.sum_to(x, (1, 3))
>>> y
variable([[5., 7., 9.]])
>>> z = F.sum_to(x, (2, 1))
>>> z
variable([[ 6.],
          [15.]])
```

### `chainer.functions.tan`

**chainer.functions.tan(x)**

Elementwise tan function.

- **Parameters**
  - `x` (*Variable* or *N-dimensional array*) – Input variable.

- **Returns**
  - Output variable.

- **Return type** *Variable*

### `chainer.functions.tensordot`

**chainer.functions.tensordot(a, b, axes=2)**

Returns the tensor dot product of two arrays along specified axes.

This is equivalent to compute dot product along the specified axes which are treated as one axis by reshaping.

- **Parameters**
  - `a` (*Variable* or *N-dimensional array*) – The first argument.
  - `b` (*Variable* or *N-dimensional array*) – The second argument.
  - `axes` –
    - If it is an integer, then `axes` axes at the last of `a` and the first of `b` are used.
    - If it is a pair of sequences of integers, then these two sequences specify the list of axes for `a` and `b`. The corresponding axes are paired for sum-product.

- **Returns**
  - The tensor dot product of `a` and `b` along the axes specified by `axes`.

- **Return type** *Variable*

#### Example

```
>>> a = np.random.rand(5, 3, 2)
>>> b = np.random.rand(3, 2, 4)
>>> c = F.tensordot(a, b, axes=2)
>>> c.shape
(5, 4)
```

**See also:**

4.2. Functions
numpy.tensordot()

chainer.functions.zeta

chainer.functions.zeta(x, q)

Zeta function.

Differentiable only with respect to q

**Note:** Forward computation in CPU can not be done if SciPy is not available.

**Parameters**

- **x** *(Variable or N-dimensional array)* – Input variable.
- **q** *(Variable or N-dimensional array)* – Input variable.

**Returns** Output variable.

**Return type** Variable

### 4.2.8 Noise injections

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.functions.dropout</td>
<td>Drops elements of input variable randomly.</td>
</tr>
<tr>
<td>chainer.functions.gaussian</td>
<td>Gaussian sampling function.</td>
</tr>
<tr>
<td>chainer.functions.gumbel_softmax</td>
<td>Gumbel-Softmax sampling function.</td>
</tr>
<tr>
<td>chainer.functions.simplified_dropconnect</td>
<td>Linear unit regularized by simplified dropconnect.</td>
</tr>
<tr>
<td>chainer.functions.zoneout</td>
<td>Drops elements of input variable and sets to previous variable randomly.</td>
</tr>
</tbody>
</table>

**chainer.functions.dropout**

chainer.functions.dropout(x, ratio=0.5, *, mask=None, return_mask=False)

Drops elements of input variable randomly.

This function drops input elements randomly with probability \( \text{ratio} \) and scales the remaining elements by factor \( \frac{1}{1 - \text{ratio}} \). In testing mode (i.e., chainer.config.train is set to False), it does nothing and just returns \( x \).

**Parameters**

- **x** *(Variable or N-dimensional array)* – Input variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.
- **ratio** *(float)* – Dropout ratio. The ratio must be \( 0.0 \leq \text{ratio} < 1.0 \).
- **mask** *(N-dimensional array or None)* – The mask to be used for dropout. You do not have to specify this value, unless you need to make results deterministic. If mask is not specified or set to None, a mask will be generated randomly according to the given ratio. If mask is specified, ratio will be ignored. The shape and dtype must be the same as \( x \) and should be on the same device. Note that iDeep and cuDNN will not be used for this function if mask is specified, as iDeep and cuDNN do not support it.
• **return_mask** *(bool)* – If True, the mask used for dropout is returned together with the output variable. The returned mask can later be reused by passing it to mask argument.

**Returns** When return_mask is False (default), returns the output variable. When True, returns the tuple of the output variable and mask *(N-dimensional array)*. The mask will be on the same device as the input. The mask will become None when chainer.config.train is set to False.

**Return type** *Variable* or tuple

See the paper by G. Hinton: Improving neural networks by preventing co-adaptation of feature detectors.

```
Example

>>> x = np.array([[[-1, 0], [2, -3], [-2, 1]], np.float32)
>>> with chainer.using_config('train', True):
...    y = F.dropout(x)
>>> y.array
array([[-2., 0.],
       [ 4., -6.],
       [-0., 2.]], dtype=float32)
>>> with chainer.using_config('train', True):
...    y = F.dropout(x, ratio=0.0)  # dropout returns original input if ratio=0.0
>>> (x == y.array).all()
True
>>> with chainer.using_config('train', False):
...    y = F.dropout(x)  # dropout in test mode returns original input
>>> (x == y.array).all()
True
```

chainer.functions.gaussian

chainer.functions.gaussian *(mean, ln_var, *, eps=None, return_eps=False)*

Gaussian sampling function.

This function takes a mean \(\mu\) and the logarithm of a variance \(\log(\sigma^2)\) as inputs and outputs a sample drawn from a Gaussian distribution \(N(\mu, \sigma)\).

The inputs must have the same shape.

**Parameters**

- **mean** *(Variable or N-dimensional array)* – Input variable representing the mean \(\mu\).
- **ln_var** *(Variable or N-dimensional array)* – Input variable representing the logarithm of a variance \(\log(\sigma^2)\).
- **eps** *(N-dimensional array or None)* – The eps value to be used. You do not have to specify this value, unless you need to make results deterministic. If eps is not specified or set to None, an eps value will be generated randomly. The shape and dtype must be the same as ln_var and should be on the same device.
- **return_eps** *(bool)* – If True, the eps value used in this function is returned together with the output variable. The returned eps can later be reused by passing it to the eps argument.
Returns When `return_eps` is `False` (default), returns the output variable with the shape of `mean` and/or `ln_var`. When `True`, returns the tuple of the output variable and `eps` (**N-dimensional array**). The `eps` will be on the same device as the input (`ln_var`).

**Return type**  Variable or tuple

chainer.functions.gumbel_softmax

```
chainer.functions.gumbel_softmax(log_pi, tau=0.1, axis=1)
```

Gumbel-Softmax sampling function.

This function draws samples $y_i$ from Gumbel-Softmax distribution,

$$y_i = \frac{\exp((g_i + \log \pi_i)/\tau)}{\sum_j \exp((g_j + \log \pi_j)/\tau)},$$

where $\tau$ is a temperature parameter and $g_i$ s are samples drawn from Gumbel distribution $Gumbel(0, 1)$

See **Categorical Reparameterization with Gumbel-Softmax.**

**Parameters**

- `log_pi` (**Variable or N-dimensional array**) – Input variable representing pre-normalized log-probability $\log \pi$.
- `tau` (**float or Variable or N-dimensional array**) – Input variable representing temperature $\tau$.

**Returns**  Output variable.

**Return type**  Variable

chainer.functions.simplified_dropconnect

```
chainer.functions.simplified_dropconnect(x, W, b=None, ratio=0.5, train=True, mask=None, use_batchwise_mask=True)
```

Linear unit regularized by simplified dropconnect.

Simplified dropconnect drops weight matrix elements randomly with probability `ratio` and scales the remaining elements by factor $1 / (1 - \text{ratio})$. It accepts two or three arguments: an input minibatch $x$, a weight matrix $W$, and optionally a bias vector $b$. It computes $Y = xW^T + b$.

In testing mode, zero will be used as simplified dropconnect ratio instead of `ratio`.

Notice: This implementation cannot be used for reproduction of the paper. There is a difference between the current implementation and the original one. The original version uses sampling with gaussian distribution before passing activation function, whereas the current implementation averages before activation.

**Parameters**

- `x` (**Variable or N-dimensional array**) – Input variable. Its first dimension $n$ is assumed to be the minibatch dimension. The other dimensions are treated as concatenated one dimension whose size must be $N$.
- `W` (**Variable or N-dimensional array**) – Weight variable of shape $(M, N)$.
- `b` (**Variable or N-dimensional array**) – Bias variable (optional) of shape $(M, )$.
- `ratio` (**float**) – Dropconnect ratio.
- `train` (**bool**) – If `True`, executes simplified dropconnect. Otherwise, simplified dropconnect function works as a linear function.
• **mask** (None or *Variable* or *N-dimensional array*) – If None, randomized dropconnect mask is generated. Otherwise, The mask must be \((n, M, N)\) or \((M, N)\) shaped array, and **use_batchwise_mask** is ignored. Main purpose of this option is debugging. *mask* array will be used as a dropconnect mask.

• **use_batchwise_mask** (*bool*) – If True, dropped connections depend on each sample in mini-batch.

  **Returns** Output variable.

  **Return type** *Variable*

  **See also:**

  Dropconnect

  **See also:**


**chainer.functions.zoneout**

*chainer.functions.zoneout*(*h, x, ratio=0.5*)

Drops elements of input variable and sets to previous variable randomly.

This function drops input elements randomly with probability *ratio* and instead sets dropping element to their previous variable. In testing mode, it does nothing and just returns *x*.

**Parameters**

• **h** (*Variable* or *N-dimensional array*) – Previous variable.

• **x** (*Variable* or *N-dimensional array*) – Input variable.

• **ratio** (*float*) – Zoneout ratio.

**Returns** Output variable.

**Return type** *Variable*

**See the paper:** Zoneout: Regularizing RNNs by Randomly Preserving Hidden Activations.

### 4.2.9 Normalization functions

| **chainer.functions.batch_normalization** | Batch normalization function. |
| **chainer.functions.batch_renormalization** | Batch renormalization function. |
| **chainer.Functions.decorrelated_batch_normalization** | Decorrelated batch normalization function. |
| **chainer.functions.fixed_batch_normalization** | Batch normalization function with fixed statistics. |
| **chainer.functions.fixed_batch_renormalization** | Decorrelated batch normalization function with fixed statistics. |
| **chainer.functions.group_normalization** | Group normalization function. |
| **chainer.functions.layer_normalization** | Layer normalization. |

continues on next page
**Table 10 – continued from previous page**

<table>
<thead>
<tr>
<th>Chainer Documentation, Release 7.7.0</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>chainer.functions.</strong></td>
</tr>
<tr>
<td><strong>local_response_normalization</strong></td>
</tr>
<tr>
<td><strong>chainer.functions.normalize</strong></td>
</tr>
</tbody>
</table>

**chainer.functions.batch_normalization**

**chainer.functions.batch_normalization**(x, gamma, beta, eps=2e-05, running_mean=None, running_var=None, decay=0.9, axis=None)

Batch normalization function.

It takes the input variable x and two parameter variables gamma and beta. The parameter variables must both have the same dimensionality, which is referred to as the channel shape. This channel shape corresponds to the dimensions in the input which are not averaged over. Since the first dimension of the input corresponds to the batch size, the second dimension of x will correspond to the first dimension of the channel shape, the third dimension of x will correspond to the second channel dimension (if it exists) and so on. Therefore, the dimensionality of the input must be at least one plus the number of channel dimensions. The total effective “batch size” will then be considered to be the product of all dimensions in x except for the channel dimensions.

As an example, if the input is four dimensional and the parameter variables are one dimensional, then it is assumed that the first dimension of the input is the batch size, the second dimension is the channel size, and the remaining two dimensions are considered to be spatial dimensions that will be averaged over along with the batch size in the batch normalization computations. That is, the total batch size will be considered to be the product of all input dimensions except the second dimension.

**Parameters**

- x (**Variable** or **N-dimensional array**) – Input variable.
- gamma (**Variable** or **N-dimensional array**) – Scaling parameter of normalized data.
- beta (**Variable** or **N-dimensional array**) – Shifting parameter of scaled normalized data.
- eps (**float**) – Epsilon value for numerical stability.
- running_mean (**N-dimensional array**) – Running average of the mean. This is a running average of the mean over several mini-batches using the decay parameter. The function takes a previous running average, and updates the array in-place by the new running average. If None, the running average is not computed. If this is None, then running_var must also be None.
- running_var (**N-dimensional array**) – Running average of the variance. This is a running average of the variance over several mini-batches using the decay parameter. The function takes a previous running average, and updates the array in-place by the new running average. If None, the running average is not computed. If this is None, then running_mean must also be None.
- decay (**float**) – Decay rate of moving average. It is used during training.
- axis (**int**, **tuple of int** or **None**) – Axis over which normalization is performed. When axis is None, it is determined from input dimensions. For example, if x.ndim is 4, axis becomes (0, 2, 3) and normalization is performed over 0th, 2nd and 3rd axis of input. If it is 2, axis becomes (0) and normalization is performed over 0th axis of input. When a tuple of int is given to this option, numbers in the tuple must be being sorted in ascending order. For example, (0, 2) is OK, but (2, 0) is not.

See: Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift

See also:
**BatchNormalization** to manage the model parameters \((gamma, beta)\) and the statistics \((running\_mean, running\_var)\).

**chainer.functions.batch_renormalization**

```python
chainer.functions.batch_renormalization(x, gamma, beta, rmax, dmax, eps=2e-05, running_mean=None, running_var=None, decay=0.9, update_statistics=False)
```

Batch renormalization function.

This is an extension of batch normalization, which ensures that the training and inference models generate the same outputs that depend on individual examples rather than the entire minibatch.

**Note:** This function does not perform in-place update to \(running\_mean\) and \(running\_var\) by default, contrary to **batch_normalization**(). If the function is called, it will not be possible to access the updated running mean and variance statistics, because they are members of the function object, which cannot be accessed by the caller. If it is desired to update the running statistics, call the function with \(update\_statistics=True\) option.

**Note:** For the consistency with Batch Normalization, this function intentionally ignores some of the theoretical flaws in Algorithm 1 of the Batch Renormalization paper:

- \(F.batch\_renormalization\) maintains the moving average of variances \(\sigma^2\), while the original paper maintains the moving average of standard deviations \(\sigma\).

- \(F.batch\_renormalization\) applies Bessel’s correction to update the moving average of variances.

See: Batch Renormalization: Towards Reducing Minibatch Dependence in Batch-Normalized Models

See also:

**BatchRenormalization** to manage the model parameters \((gamma, beta)\) and the statistics \((running\_mean, running\_var)\).

**chainer.functions.decorrelated_batch_normalization**

```python
chainer.functions.decorrelated_batch_normalization(x, *, groups=16, eps=2e-05, running_mean=None, running_projection=None, decay=0.9)
```

Decorrelated batch normalization function.

It takes the input variable \(x\) and normalizes it using batch statistics to make the output zero-mean and decorrelated.

**Parameters**

- \(x\) (Variable) – Input variable.
- \(groups\) (int) – Number of groups to use for group whitening.
- \(eps\) (float) – Epsilon value for numerical stability.
- \(running\_mean\) (N-dimensional array) – Expected value of the mean. This is a running average of the mean over several mini-batches using the decay parameter. If \(None\), the expected mean is initialized to zero.
• **running_projection** (*N-dimensional array*) – Expected value of the project matrix. This is a running average of the projection over several mini-batches using the decay parameter. If `None`, the expected projected is initialized to the identity matrix.

• **decay** (*float*) – Decay rate of moving average. It is used during training.

**Returns**

The output variable which has the same shape as `x`.

**Return type** *Variable*

See: Decorrelated Batch Normalization

**See also:**

*DecorrelatedBatchNormalization*

---

**chainer.functions.fixed_batch_normalization**

```
chainer.functions.fixed_batch_normalization(x, gamma, beta, mean, var, eps=2e-05, axis=None)
```

Batch normalization function with fixed statistics.

This is a variant of batch normalization, where the mean and variance statistics are given by the caller as fixed variables. This is used on testing mode of the batch normalization layer, where batch statistics cannot be used for prediction consistency.

**Parameters**

• **x** (*Variable or N-dimensional array*) – Input variable.

• **gamma** (*Variable or N-dimensional array*) – Scaling parameter of normalized data.

• **beta** (*Variable or N-dimensional array*) – Shifting parameter of scaled normalized data.

• **mean** (*Variable or N-dimensional array*) – Shifting parameter of input.

• **var** (*Variable or N-dimensional array*) – Square of scaling parameter of input.

• **eps** (*float*) – Epsilon value for numerical stability.

• **axis** (*int, tuple of int or None*) – Axis over which normalization is performed. When axis is `None`, it is determined from input dimensions. For example, if `x.ndim` is 4, axis becomes (0, 2, 3) and normalization is performed over 0th, 2nd and 3rd axis of input. If it is 2, axis becomes (0) and normalization is performed over 0th axis of input. When a tuple of int is given to this option, numbers in the tuple must be being sorted in ascending order. For example, (0, 2) is OK, but (2, 0) is not.

**See also:**

*batch_normalization()*, *BatchNormalization*

---

**chainer.functions.fixed_batch_renormalization**

```
chainer.functions.fixed_batch_renormalization(x, gamma, beta, mean, var, eps=2e-05)
```

278 Chapter 4. API Reference
chainer.functions.fixed_decorrelated_batch_normalization

chainer.functions.fixed_decorrelated_batch_normalization(x, mean, projection, groups=16)

Decorrelated batch normalization function with fixed statistics.

This is a variant of decorrelated batch normalization, where the mean and projection statistics are given by the caller as fixed variables. This is used in testing mode of the decorrelated batch normalization layer, where batch statistics cannot be used for prediction consistency.

Parameters

- **x** (*Variable*) – Input variable.
- **mean** (*Variable* or *N-dimensional array*) – Shifting parameter of input.
- **projection** (*Variable* or *N-dimensional array*) – Projection matrix for decorrelation of input.
- **groups** (*int*) – Number of groups to use for group whitening.

Returns

The output variable which has the same shape as \(x\).

Return type **Variable**

See also: `decorrelated_batch_normalization()`, `DecorrelatedBatchNormalization`

chainer.functions.group_normalization

chainer.functions.group_normalization(x, groups, gamma, beta, eps=1e-05)

Group normalization function.

This function implements a “group normalization” which divides the channels into groups and computes within each group the mean and variance, then normalize by these statistics, scales and shifts them.

Parameters

- **x** (*Variable* or *N-dimensional array*) – Batch tensors. First dimension of this value must be the size of minibatch and second dimension must be the number of channels. Moreover, this value must have one or more following dimensions, such as height and width.
- **groups** (*int*) – The number of channel groups. This value must be a divisor of the number of channels.
- **gamma** (*Variable* or *N-dimensional array*) – Scaling parameter.
- **beta** (*Variable* or *N-dimensional array*) – Shifting parameter.
- **eps** (*float*) – Epsilon value for numerical stability of normalization.

Returns

The output variable which has the same shape as \(x\).

Return type **Variable**

See: Group Normalization

See also: `GroupNormalization` to manage the model parameters `gamma` and `beta`. 

4.2. Functions
chainer.functions.layer_normalization

chainer.functions.layer_normalization($x$, $gamma$, $beta$, $eps=1e-05$)
Layer normalization.

This function implements a “layer normalization” which normalizes the input units by statistics that are computed along the second axis, scales and shifts them.

Parameters

- $x$ (Variable or N-dimensional array) – Batch vectors. Shape of this value must be (batch_size, unit_size), e.g., the output of linear().
- $gamma$ (Variable or N-dimensional array) – Scaling vectors.
- $beta$ (Variable or N-dimensional array) – Shifting vectors.

Returns
The output variable which has the same shape as $x$.

Return type Variable

See: Layer Normalization

See also:
LayerNormalization to manage the model parameters $gamma$ and $beta$.

chainer.functions.local_response_normalization

chainer.functions.local_response_normalization($x$, $n=5$, $k=2$, $alpha=0.0001$, $beta=0.75$)
Local response normalization across neighboring channels.

This function implements normalization across channels. Let $x$ an input image with $N$ channels. Then, this function computes an output image $y$ by following formula:

$$y_i = \frac{x_i}{(k + \alpha \sum_{j=\max(1,i-n/2)}^{\min(N,i+n/2)} x_j^2)^\beta}.$$ 

Parameters

- $x$ (Variable or N-dimensional array) – Input variable.
- $n$ (int) – Normalization window width.
- $k$ (float) – Smoothing parameter.
- $alpha$ (float) – Normalizer scaling parameter.
- $beta$ (float) – Normalizer power parameter.

Returns
Output variable.

Return type Variable

See: Section 3.3 of ImageNet Classification with Deep Convolutional Neural Networks
**chainer.functions.normalize**

\[
\text{chainer.functions.normalize}(x, \text{eps}=1e-05, \text{axis}=1)
\]

Normalize input by L2 norm.

This function implements L2 normalization on a sample along the given axis/axes. No reduction is done along the normalization axis.

In the case when \(\text{axis}=1\) and \(x\) is a matrix of dimension \((N, K)\), where \(N\) and \(K\) denote mini-batch size and the dimension of the input vectors, this function computes an output matrix \(y\) of dimension \((N, K)\) by the following equation:

\[
y_i = \frac{x_i}{\|x_i\|_2 + \epsilon}
\]

\(\epsilon\) is used to avoid division by zero when norm of \(x\) along the given axis is zero.

The default value of \(\text{axis}\) is determined for backward compatibility.

**Parameters**

- **\(x\)** (*Variable or N-dimensional array*) – multi-dimensional output variable. The first dimension is assumed to be the mini-batch dimension.
- **\(\text{eps}\)** (*float*) – Epsilon value for numerical stability.
- **\(\text{axis}\)** (*int or tuple of ints*) – Axis along which to normalize.

**Returns** The output variable which has the same shape as \(x\).

**Return type** *Variable*

### 4.2.10 Spatial pooling

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>chainer.functions.average_pooling_1d</strong></td>
<td>1-dimensional spatial average pooling function.</td>
</tr>
<tr>
<td><strong>chainer.functions.average_pooling_2d</strong></td>
<td>Spatial average pooling function.</td>
</tr>
<tr>
<td><strong>chainer.functions.average_pooling_3d</strong></td>
<td>3-dimensional spatial average pooling function.</td>
</tr>
<tr>
<td><strong>chainer.functions.average_pooling_nd</strong></td>
<td>N-dimensionally spatial average pooling function.</td>
</tr>
<tr>
<td><strong>chainer.functions.max_pooling_1d</strong></td>
<td>1-dimensional spatial max pooling function.</td>
</tr>
<tr>
<td><strong>chainer.functions.max_pooling_2d</strong></td>
<td>Spatial max pooling function.</td>
</tr>
<tr>
<td><strong>chainer.functions.max_pooling_3d</strong></td>
<td>3-dimensional spatial max pooling function.</td>
</tr>
<tr>
<td><strong>chainer.functions.max_pooling_nd</strong></td>
<td>N-dimensionally spatial max pooling function.</td>
</tr>
<tr>
<td><strong>chainer.functions.roi_average_align_2d</strong></td>
<td>Spatial Region of Interest (ROI) average align function.</td>
</tr>
<tr>
<td><strong>chainer.functions.roi_average_pooling_2d</strong></td>
<td>Spatial Region of Interest (ROI) average pooling function.</td>
</tr>
<tr>
<td><strong>chainer.functions.roi_max_align_2d</strong></td>
<td>Spatial Region of Interest (ROI) max align function.</td>
</tr>
<tr>
<td><strong>chainer.functions.roi_max_pooling_2d</strong></td>
<td>Spatial Region of Interest (ROI) max pooling function.</td>
</tr>
<tr>
<td><strong>chainer.functions.roi_pooling_2d</strong></td>
<td>Spatial Region of Interest (ROI) pooling function.</td>
</tr>
<tr>
<td><strong>chainer.functions.spatial_pyramid_pooling_2d</strong></td>
<td>Spatial pyramid pooling function.</td>
</tr>
<tr>
<td><strong>chainer.functions.unpooling_1d</strong></td>
<td>Inverse operation of 1-dimensional spatial pooling.</td>
</tr>
<tr>
<td><strong>chainer.functions.unpooling_2d</strong></td>
<td>Inverse operation of pooling for 2d array.</td>
</tr>
<tr>
<td><strong>chainer.functions.unpooling_3d</strong></td>
<td>Inverse operation of 3-dimensional spatial pooling.</td>
</tr>
<tr>
<td><strong>chainer.functions.unpooling_nd</strong></td>
<td>Inverse operation of N-dimensional spatial pooling.</td>
</tr>
<tr>
<td><strong>chainer.functions.upsampling_2d</strong></td>
<td>Upsampling using pooling indices.</td>
</tr>
</tbody>
</table>

**4.2. Functions**
chainer.functions.average_pooling_1d

chainer.functions.average_pooling_1d(x, ksize, stride=None, pad=0, pad_value=0)
1-dimensional spatial average pooling function.

**Warning:** This feature is experimental. The interface can change in the future.

**Note:** This function calls `average_pooling_nd()` internally, so see the details of the behavior in the documentation of `average_pooling_nd()`.

chainer.functions.average_pooling_2d

chainer.functions.average_pooling_2d(x, ksize, stride=None, pad=0)
Spatial average pooling function.

This function acts similarly to `convolution_2d()`, but it computes the average of input spatial patch for each channel without any parameter instead of computing the inner products.

**Parameters**
- **x** (Variable) – Input variable.
- **ksize** (int or pair of ints) – Size of pooling window. ksize=k and ksize=(k, k) are equivalent.
- **stride** (int or pair of ints or None) – Stride of pooling applications. stride=s and stride=(s, s) are equivalent. If None is specified, then it uses same stride as the pooling window size.
- **pad** (int or pair of ints) – Spatial padding width for the input array. pad=p and pad=(p, p) are equivalent.

**Returns** Output variable.

**Return type** Variable

**Note:** This function currently does not support cover_all mode as `max_pooling_2d()`. Average pooling runs in non-cover-all mode.

**Note:** The values in the padded region is treated as 0, leading the averages biased towards zero. To obtain unbiased averages, use `average_pooling_nd()` with pad_value=None.
chainer.functions.average_pooling_3d

chainer.functions.average_pooling_3d(x, ksize, stride=None, pad=0, pad_value=0)

3-dimensional spatial average pooling function.

**Warning:** This feature is experimental. The interface can change in the future.

**Note:** This function calls average_pooling_nd() internally, so see the details of the behavior in the documentation of average_pooling_nd().

chainer.functions.average_pooling_nd

chainer.functions.average_pooling_nd(x, ksize, stride=None, pad=0, pad_value=0)

N-dimensionally spatial average pooling function.

**Warning:** This feature is experimental. The interface can change in the future.

This function provides a N-dimensionally generalized version of average_pooling_2d(). This acts similarly to convolution_nd(), but it computes the average of input spatial patch for each channel without any parameter instead of computing the inner products.

**Parameters**

- **x** (*Variable*) – Input variable.
- **ksize** (*int or tuple of ints*) – Size of pooling window. ksize=k and ksize=(k, k, ..., k) are equivalent.
- **stride** (*int or tuple of ints or None*) – Stride of pooling applications. stride=s and stride=(s, s, ..., s) are equivalent. If None is specified, then it uses same stride as the pooling window size.
- **pad** (*int or tuple of ints*) – Spatial padding width for the input array. pad=p and pad=(p, p, ..., p) are equivalent.
- **pad_value** (*0 or None*) – Value to fill the padded region when calculating average. If None is specified, such region is ignored. The default value is 0, therefore the averages are biased towards zero.

**Returns** Output variable.

**Return type** *Variable*

**Note:** This function currently does not support cover_all mode as max_pooling_nd(). Average pooling runs in non-cover-all mode.
chainer.functions.max_pooling_1d

chainer.functions.max_pooling_1d(x, ksize, stride=None, pad=0, cover_all=True, return_indices=False)

1-dimensional spatial max pooling function.

**Warning:** This feature is experimental. The interface can change in the future.

**Note:** This function calls max_pooling_nd() internally, so see the details of the behavior in the documentation of max_pooling_nd().

chainer.functions.max_pooling_2d

chainer.functions.max_pooling_2d(x, ksize, stride=None, pad=0, cover_all=True, return_indices=False)

Spatial max pooling function.

This function acts similarly to convolution_2d(), but it computes the maximum of input spatial patch for each channel without any parameter instead of computing the inner products.

**Parameters**

- x (Variable) – Input variable.
- ksize (int or pair of ints) – Size of pooling window. ksize=k and ksize=(k, k) are equivalent.
- stride (int or pair of ints or None) – Stride of pooling applications. stride=s and stride=(s, s) are equivalent. If None is specified, then it uses same stride as the pooling window size.
- pad (int or pair of ints) – Spatial padding width for the input array. pad=p and pad=(p, p) are equivalent.
- cover_all (bool) – If True, all spatial locations are pooled into some output pixels. It may make the output size larger.
- return_indices (bool) – If True, pooling indices array is returned together with the output variable. The returned indices are expected for use by chainer.functions.upsampling_2d(). Note that cuDNN will not be used for this function if return_indices is set to True, as cuDNN does not return indices information.

**Returns**

When return_indices is False (default), returns the output variable. When True, returns the tuple of the output variable and pooling indices (N-dimensional array). Pooling indices will be on the same device as the input.

**Return type** Variable or tuple
chainer.functions.max_pooling_3d

chainer.functions.max_pooling_3d(x, ksize, stride=None, pad=0, cover_all=True, return_indices=False)

3-dimensional spatial max pooling function.

**Warning:** This feature is experimental. The interface can change in the future.

**Note:** This function calls `max_pooling_nd()` internally, so see the details of the behavior in the documentation of `max_pooling_nd()`.

chainer.functions.max_pooling_nd

chainer.functions.max_pooling_nd(x, ksize, stride=None, pad=0, cover_all=True, return_indices=False)

N-dimensionally spatial max pooling function.

**Warning:** This feature is experimental. The interface can change in the future.

This function provides a N-dimensionally generalized version of `max_pooling_2d()`. This acts similarly to `convolution_nd()`, but it computes the maximum of input spatial patch for each channel without any parameter instead of computing the inner products.

**Parameters**

- `x (Variable)` – Input variable.
- `ksize (int or tuple of ints)` – Size of pooling window. `ksize=k` and `ksize=(k, k, ..., k)` are equivalent.
- `stride (int or tuple of ints or None)` – Stride of pooling applications. `stride=s` and `stride=(s, s, ..., s)` are equivalent. If `None` is specified, then it uses same stride as the pooling window size.
- `pad (int or tuple of ints)` – Spatial padding width for the input array. `pad=p` and `pad=(p, p, ..., p)` are equivalent.
- `cover_all (bool)` – If `True`, all spatial locations are pooled into some output pixels. It may make the output size larger.
- `return_indices (bool)` – If `True`, pooling indices array is returned together with the output variable. The returned indices are expected for use by `chainer.functions.upsampling_nd()`. Note that cuDNN will not be used for this function if `return_indices` is set to `True`, as cuDNN does not return indices information.

**Returns**

When `return_indices` is `False` (default), returns the output variable. When `True`, returns the tuple of the output variable and pooling indices (N-dimensional array). Pooling indices will be on the same device as the input.

**Return type** `Variable` or tuple

4.2. Functions
chainer.functions.roi_average_align_2d

**Parameters**

- `x` (Variable) – Input variable. The shape is expected to be 4 dimensional: `(n: batch, c: channel, h, height, w: width)`.
- `rois` (Variable) – Input roi variable. The shape is expected to be `(n: data size, 4)`, and each datum is set as below: `(y_min, x_min, y_max, x_max)`.
- `roi_indices` (Variable) – Input roi variable. The shape is expected to be `(n: data size, )`.
- `outsize` ((int, int) or int) – Expected output size after pooled (height, width). `outsize=o` and `outsize=(o, o)` are equivalent.
- `spatial_scale` (float) – Scale of the roi is resized.
- `sampling_ratio` ((int, int) or int) – Sampling step for the alignment. It must be an integer over 1 or `None`, and the value is automatically decided when `None` is passed. Use of different ratio in height and width axis is also supported by passing tuple of int as `(sampling_ratio_h, sampling_ratio_w)`. `sampling_ratio=s` and `sampling_ratio=(s, s)` are equivalent.

**Returns** Output variable.

**Return type** Variable

See the original paper proposing ROIAlign: Mask R-CNN.

---

chainer.functions.roi_average_pooling_2d

**Parameters**

- `x` (Variable) – Input variable. The shape is expected to be 4 dimensional: `(n: batch, c: channel, h, height, w: width)`.
- `rois` (Variable) – Input roi variable. The shape is expected to be `(n: data size, 4)`, and each datum is set as below: `(y_min, x_min, y_max, x_max)`.
- `roi_indices` (Variable) – Input roi variable. The shape is expected to be `(n: data size, )`.
- `outsize` ((int, int) or int) – Expected output size after pooled (height, width). `outsize=o` and `outsize=(o, o)` are equivalent.
- `spatial_scale` (float) – Scale of the roi is resized.

**Returns** Output variable.
Return type  **Variable**

See the original paper proposing ROIPooling: Fast R-CNN.

chainer.functions.roi_max_align_2d

chainer.functions.roi_max_align_2d(x, rois, roi_indices, outsize, spatial_scale, sampling_ratio=None)

Spatial Region of Interest (ROI) max align function.

This function acts similarly to `roi_max_pooling_2d()`, but it computes maximum of input spatial patch with bilinear interpolation for each channel with the region of interest.

**Parameters**

- **x** *(Variable)* – Input variable. The shape is expected to be 4 dimensional: `(n: batch, c: channel, h, height, w: width)`.
- **rois** *(Variable)* – Input roi variable. The shape is expected to be `(n: data size, 4)`, and each datum is set as below: `(y_min, x_min, y_max, x_max)`.
- **roi_indices** *(Variable)* – Input roi variable. The shape is expected to be `(n: data size, )`.
- **outsize** *(int, int) or int* – Expected output size after pooled (height, width). `outsize=o` and `outsize=(o, o)` are equivalent.
- **spatial_scale** *(float)* – Scale of the roi is resized.
- **sampling_ratio** *(int, int) or int* – Sampling step for the alignment. It must be an integer over 1 or None, and the value is automatically decided when None is passed. Use of different ratio in height and width axis is also supported by passing tuple of int as `(sampling_ratio_h, sampling_ratio_w).sampling_ratio=s` and `sampling_ratio=(s, s)` are equivalent.

**Returns**  Output variable.

**Return type  **Variable**

See the original paper proposing ROIAlign: Mask R-CNN.

chainer.functions.roi_max_pooling_2d

chainer.functions.roi_max_pooling_2d(x, rois, roi_indices, outsize, spatial_scale)

Spatial Region of Interest (ROI) max pooling function.

This function acts similarly to `max_pooling_2d()`, but it computes the maximum of input spatial patch for each channel with the region of interest.

**Parameters**

- **x** *(Variable)* – Input variable. The shape is expected to be 4 dimensional: `(n: batch, c: channel, h, height, w: width)`.
- **rois** *(Variable)* – Input roi variable. The shape is expected to be `(n: data size, 4)`, and each datum is set as below: `(y_min, x_min, y_max, x_max)`.
- **roi_indices** *(Variable)* – Input roi variable. The shape is expected to be `(n: data size, )`.
- **outsize** *(int, int) or int* – Expected output size after pooled (height, width). `outsize=o` and `outsize=(o, o)` are equivalent.
• **spatial_scale** (*float*) – Scale of the roi is resized.

    **Returns**  Output variable.

    **Return type**  Variable

    See the original paper proposing ROIPooling: Fast R-CNN.

**chainer.functions.roi_pooling_2d**

*chainer.functions.roi_pooling_2d*(x, rois, outh, outw, spatial_scale)

Spatial Region of Interest (ROI) pooling function.

This function acts similarly to *max_pooling_2d()*, but it computes the maximum of input spatial patch for each channel with the region of interest.

    **Parameters**

    • *x* (*Variable*) – Input variable. The shape is expected to be 4 dimensional: (n: batch, c: channel, h: height, w: width).

    • *rois* (*Variable*) – Input roi variable. The shape is expected to be (n: data size, 5), and each datum is set as below: (batch_index, x_min, y_min, x_max, y_max).

    • *outh* (*int*) – Height of output image after pooled.

    • *outw* (*int*) – Width of output image after pooled.

    • *spatial_scale* (*float*) – Scale of the roi is resized.

    **Returns**  Output variable.

    **Return type**  Variable

    See the original paper proposing ROIPooling: Fast R-CNN.

**chainer.functions.spatial_pyramid_pooling_2d**

*chainer.functions.spatial_pyramid_pooling_2d*(x, pyramid_height, pooling=None)

Spatial pyramid pooling function.

It outputs a fixed-length vector regardless of input feature map size.

It performs pooling operation to the input 4D-array *x* with different kernel sizes and padding sizes, and then flattens all dimensions except first dimension of all pooling results, and finally concatenates them along second dimension.

At *i*-th pyramid level, the kernel size (*k_h(i), k_w(i)*) and padding size (*p_h(i), p_w(i)*) of pooling operation are calculated as below:

\[
    k_h(i) = \lceil b_h / 2^i \rceil, \\
    k_w(i) = \lceil b_w / 2^i \rceil, \\
    p_h(i) = (2^i k_h(i) - b_h) / 2, \\
    p_w(i) = (2^i k_w(i) - b_w) / 2,
\]

where \(\lceil \cdot \rceil\) denotes the ceiling function, and *b_h, b_w* are height and width of input variable *x*, respectively. Note that index of pyramid level *i* is zero-based.

    **See detail in paper:**  Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition.

    **Parameters**
• **x** *(Variable)* – Input variable. The shape of x should be *(batchsize, # of channels, height, width)*.

• **pyramid_height** *(int)* – Number of pyramid levels

• **pooling** *(str)* – Currently, only *max* is supported, which performs a 2d max pooling operation.

**Returns** Output variable. The shape of the output variable will be *(batchsize, c \( \sum_{h=0}^{H-1} 2^h \), 1, 1)*, where c is the number of channels of input variable x and H is the number of pyramid levels.

**Return type** *Variable*

**chainer.functions.unpooling_1d**

chainer.functions.unpooling_1d(x, ksize, stride=None, pad=0, outsize=None, cover_all=True)

Inverse operation of 1-dimensional spatial pooling.

*Warning:* This feature is experimental. The interface can change in the future.

*Note:* This function calls *unpooling_nd()* internally, so see the details of the behavior in the documentation of *unpooling_nd()*.

**chainer.functions.unpooling_2d**

chainer.functions.unpooling_2d(x, ksize, stride=None, pad=0, outsize=None, cover_all=True)

Inverse operation of pooling for 2d array.

This function acts similarly to *Deconvolution2DFunction*, but it spreads input 2d array’s value without any parameter instead of computing the inner products.

**Parameters**

• **x** *(Variable)* – Input variable.

• **ksize** *(int or pair of ints)* – Size of pooling window. ksize=k and ksize=(k, k) are equivalent.

• **stride** *(int, pair of ints or None)* – Stride of pooling applications. stride=s and stride=(s, s) are equivalent. If None is specified, then it uses same stride as the pooling window size.

• **pad** *(int or pair of ints)* – Spatial padding width for the input array. pad=p and pad=(p, p) are equivalent.

• **outsize** *(None or pair of ints)* – Expected output size (height, width) of array after the operation. If None, the size (height or width) is estimated from the size of input array in first batch with *get_deconv_outsize()*(). If outsize is not None, the result of outsize applied to *get_conv_outsize()* must be equal to the shape of the 2d array in the input batch x.

• **cover_all** *(bool)* – If True, the output size may be smaller than the size if cover_all is False. This flag serves to align behavior to the pooling functions which can cover all input locations, see *max_pooling_2d()* and *convolution_2d()*.

**Returns** Output variable.
Return type **Variable**

### chainer.functions.unpooling_3d

```python
chainer.functions.unpooling_3d(x, ksize, stride=None, pad=0, outsize=None, cover_all=True)
```

Inverse operation of 3-dimensional spatial pooling.

**Warning:** This feature is experimental. The interface can change in the future.

**Note:** This function calls `unpooling_nd()` internally, so see the details of the behavior in the documentation of `unpooling_nd()`.

### chainer.functions.unpooling_nd

```python
chainer.functions.unpooling_nd(x, ksize, stride=None, pad=0, outsize=None, cover_all=True)
```

Inverse operation of N-dimensional spatial pooling.

**Warning:** This feature is experimental. The interface can change in the future.

This function acts similarly to `DeconvolutionND`, but it spreads input N-dimensional array's value without any parameter instead of computing the inner products.

**Parameters**

- **x (Variable)** – Input variable.
- **ksize (int or pair of ints)** – Size of pooling window \((k_1, k_2, \ldots, k_N)\). `ksize=k` is equivalent to \((k, k, \ldots, k)\).
- **stride (int, pair of ints or None)** – Stride of pooling applications \((s_1, s_2, \ldots, s_N)\). `stride=s` is equivalent to \((s, s, \ldots, s)\). If None is specified, then it uses same stride as the pooling window size.
- **pad (int or pair of ints)** – Spatial padding width for the input array \((p_1, p_2, \ldots, p_N)\). `pad=p` is equivalent to \((p, p, \ldots, p)\).
- **outsize (None or pair of ints)** – Expected output size of unpooling operation \((out_1, out_2, \ldots, out_N)\). If None, the size is estimated from input size, stride and padding.
- **cover_all (bool)** – If True, the pooling window is assumed to cover all of the output array, eventually the output size may be smaller than that in the case `cover_all=False`.

**Returns** Output variable.

**Return type** **Variable**
**chainer.functions.upsampling_2d**

chainer.functions.upsampling_2d(x, indexes, ksize, stride=None, pad=0, outsize=None, cover_all=True)

Upsampling using pooling indices.

This function produces an upsampled image using pooling indices.

### Example

```python
>>> x = np.arange(1, 37).reshape(1, 1, 6, 6).astype(np.float32)
>>> x = chainer.Variable(x)
>>> x.array
array([[ 1.,  2.,  3.,  4.,  5.,  6.],
       [ 7.,  8.,  9., 10., 11., 12.],
       [13., 14., 15., 16., 17., 18.],
       [19., 20., 21., 22., 23., 24.],
       [25., 26., 27., 28., 29., 30.],
       [31., 32., 33., 34., 35., 36.]],
      dtype=float32)
```

This is the original $x$ before max pooling.

```python
>>> pooled_x, indexes = F.max_pooling_2d(  ...
... x, ksize=2, stride=2, return_indices=True)
```

```python
>>> pooled_x.array
array([[ 8., 10., 12.],
       [20., 22., 24.],
       [32., 34., 36.]],
      dtype=float32)
```

```python
>>> indexes
array([[3, 3, 3],
       [3, 3, 3],
       [3, 3, 3]]
      )
```

These are the outputs from the max pooling operation including the resulting indices that will be used to upsample pooled_x. Note that the indices all point to the largest, in the case the last, elements in each window.

```python
>>> upsampled_x = F.upsampling_2d(  ...
... pooled_x, indexes, ksize=2, stride=2, outsize=x.shape[2:])
```

```python
>>> upsampled_x.shape
(1, 1, 6, 6)
```

```python
>>> upsampled_x.array
array([[ 0.,  0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0., 10.,  0., 12.],
       [ 0.,  0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.,  0.],
       [ 0., 20.,  0., 22.,  0., 24.],
       [ 0.,  0.,  0.,  0.,  0.,  0.],
       [ 0., 32.,  0., 34.,  0., 36.]],
      dtype=float32)
```

### Parameters

- **x** (Variable) – Input variable.
- **indexes** (*N-dimensional array*) – Index array returned from preceding call to `max_pooling_2d()`.  
- **ksize** (*int or pair of ints*) – Size of pooling window.  

$ksize=k$ and $ksize=(k, k)$ are equivalent.
• **stride** *(int or pair of ints or None)* – Stride of pooling applications. 
  \( \text{stride}=s \) and \( \text{stride}=(s, s) \) are equivalent. If None is specified, then it uses same 
  stride as the pooling window size.

• **pad** *(int or pair of ints)* – Spatial padding width for the input array. \( \text{pad}=p \) and 
  \( \text{pad}=(p, p) \) are equivalent.

• **outsize** *(int, int)* – Expected output size (height, width).

• **cover_all** *(bool)* – Should be set to True if all spatial locations were pooled into 
  some output pixels during the preceding pooling operation. False otherwise. See 
  `max_pooling_2d()`.

Returns Output variable.

Return type *Variable*

4.2.11 Utility functions

<table>
<thead>
<tr>
<th>chainer.functions.forget</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calls a function without storing intermediate results.</td>
</tr>
</tbody>
</table>

**chainer.functions.forget**

**chainer.functions.forget** *(func, *xs)*

Calls a function without storing intermediate results.

On a forward propagation, Chainer normally stores all intermediate results of *VariableNodes* on a computa-

On a forward propagation, `F.forget` calls a given function with given variables without creating a computa-

tional graph. That means, no intermediate results are stored. On a backward propagation, `F.forget` calls the

given function again to create a computational graph for backpropagation.

`F.forget` reduces internal memory usage, whereas it requires more calculation time as it calls the function

twice.

**Example**

Let \( f \) be a function defined as:

```python
>>> def f(a, b):
...     return (a + b) * a
```

and, \( x \) and \( y \) be *Variables*:

```python
>>> x = chainer.Variable(np.random.uniform(-1, 1, 5).astype(np.float32))
>>> y = chainer.Variable(np.random.uniform(-1, 1, 5).astype(np.float32))
```

When \( z \) is calculated as \( z = f(x, y) \), its intermediate result \( x + y \) is stored in memory. Instead, if you 
call \( f \) with `F.forget`:

```python
>>> z = F.forget(f, x, y)
```
intermediate $x + y$ is forgotten.

**Note:** \texttt{F.forget} does not support functions which behave differently in multiple calls with the same inputs, such as \texttt{F.dropout()} and \texttt{F.negative_sampling()}.

**Note:** In case input argument variables are of \texttt{N-dimensional array} objects, arguments will automatically be converted to \texttt{Variable}s. This conversion takes place to ensure that this function is included in the computational graph to enable backward computations.

**Note:** \texttt{F.forget} does not support double backpropagation.

**Note:** If you want to use \texttt{F.forget} to a link which updates the link’s internal information every time the forward computation is called, please ensure that the information is updated just once in a single iteration. You may use the \texttt{chainer.config.in_recomputing} flag to check if the forward computation is the first call in an iteration. Please see the implementation of \texttt{BatchNormalization} for detail.

**Parameters**

- **func** (callable) – A function to call. It needs to be called with \texttt{Variable} object(s) and to return a \texttt{Variable} object or a tuple of \texttt{Variable} objects.

- **xs** (tuple of \texttt{Variable} or \texttt{N-dimensional array}) – Argument variables of the function.

**Returns** A variable \texttt{func} returns. If it returns a tuple, the method returns a tuple too.

**Return type** \texttt{Variable}

### 4.2.12 Function base

<table>
<thead>
<tr>
<th><strong>chainer.Function</strong></th>
<th>Old-style interface of a differentiable function.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>chainer.FunctionAdapter</strong></td>
<td>Adapter class to wrap Function with FunctionNode.</td>
</tr>
<tr>
<td><strong>chainer.FunctionNode</strong></td>
<td>Function node of the computational graph.</td>
</tr>
<tr>
<td><strong>chainer.force_backprop_mode</strong></td>
<td>Make a context manager which enables backpropagation.</td>
</tr>
<tr>
<td><strong>chainer.no_backprop_mode</strong></td>
<td>Make a context manager which disables backpropagation.</td>
</tr>
<tr>
<td><strong>chainer.grad</strong></td>
<td>Computes the gradient of output variables w.r.t. the input variables.</td>
</tr>
</tbody>
</table>

### 4.2. Functions
class chainer.Function

Old-style interface of a differentiable function.

This class provides an interface to implement an old-style differentiable function (i.e., the function application is recorded to the computational graph). The subclass of `Function` that implement `forward()` and `backward()` can be used to run the forward computation and automatically induce the backpropagation procedure.

There is another way to implement such a function: subclassing `FunctionNode`. There are mainly two differences between them.

1. The differentiable backprop is available for `FunctionNode`, while it is not for `Function` because the `backward()` of the latter directly operates on the arrays instead of `Variable` objects so that it cannot record the history of the computation.

2. The information passed to `backward()` is different. In `FunctionNode`, which inputs the function node has to compute the gradients w.r.t. is passed so that it can omit unnecessary computations, while `Function` always has to compute gradients w.r.t. all the input nodes. The `FunctionNode` also accepts the current gradient values of the input nodes so that the accumulation work can be merged with the gradient computation if an efficient kernel is available.

This class uses `FunctionAdapter` to convert the interface to that of `FunctionNode` and adds the `FunctionNode` object to the computational graph.

See `FunctionNode` for the details of building the computational graph in Chainer.

Methods

`__call__`(*inputs)

Applies forward propagation with chaining backward references.

This method creates a new `FunctionAdapter` object and runs the forward propagation using it.

See `FunctionNode` for the detailed behavior of building the computational graph.

Parameters

- **inputs** – Tuple of input `Variable` or `N-dimensional array` objects. If the input is `N-dimensional array`, it is automatically wrapped with `Variable`.

Returns

One `Variable` object or a tuple of multiple `Variable` objects.

`add_hook`(*hook, name=None)

Registers a function hook.

See `FunctionNode.add_hook()` for the detail.

Parameters

- **hook** (`FunctionHook`) – Function hook to be registered.
- **name** (`str`) – Name of the function hook. name must be unique among function hooks registered to the function. If `None`, default name of the function hook is used.

`backward`(*inputs, grad_outputs)

Applies backprop to output gradient arrays.

It delegates the procedure to `backward_cpu()` or `backward_gpu()` by default. Which it selects is determined by the type of input arrays and output gradient arrays. Implementations of `Function` must implement either CPU/GPU methods or this method, if the function is intended to be backprop-ed.

Parameters
• **inputs** – Tuple of input arrays.

• **grad_outputs** – Tuple of output gradient arrays.

**Returns** Tuple of input gradient arrays. Some or all of them can be None, if the function is not differentiable on inputs.

**Return type** tuple

**Warning:** Implementations of *Function* must take care that the return value must be a tuple even if it returns only one array.

**backward_cpu** *(inputs, grad_outputs)*
Applies backprop to output gradient arrays on CPU.

**Parameters**

• **inputs** – Tuple of input `numpy.ndarray` object(s).

• **grad_outputs** – Tuple of output gradient `numpy.ndarray` object(s).

**Returns** Tuple of input gradient `numpy.ndarray` object(s). Some or all of them can be None, if the function is not differentiable on corresponding inputs.

**Return type** tuple

**Warning:** Implementations of *Function* must take care that the return value must be a tuple even if it returns only one array.

**backward_gpu** *(inputs, grad_outputs)*
Applies backprop to output gradient arrays on GPU.

**Parameters**

• **inputs** – Tuple of input `cupy.ndarray` object(s).

• **grad_outputs** – Tuple of output gradient `cupy.ndarray` object(s).

**Returns** Tuple of input gradient `cupy.ndarray` object(s). Some or all of them can be None, if the function is not differentiable on corresponding inputs.

**Return type** tuple

**Warning:** Implementations of *Function* must take care that the return value must be a tuple even if it returns only one array.

**check_type_forward** *(in_types)*
Checks types of input data before forward propagation.

Before *forward()* is called, this function is called. You need to validate types of input data in this function using the type checking utilities.

**Parameters** in_types *(TypeInfoTuple)* – The type information of input data for *forward()*.

**delete_hook** *(name)*
Unregisters the specified function hook.
Parameters `name (str)` – the name of the function hook to be unregistered.

`forward (inputs)`
Applies forward propagation to input arrays.
It delegates the procedure to `forward_cpu()` or `forward_gpu()` by default. Which it selects is determined by the type of input arrays. Implementations of `Function` must implement either CPU/GPU methods or this method.

Parameters `inputs` – Tuple of input array(s).

Returns Tuple of output array(s).

Warning: Implementations of `Function` must take care that the return value must be a tuple even if it returns only one array.

`forward_cpu (inputs)`
Applies forward propagation to input arrays on CPU.

Parameters `inputs` – Tuple of `numpy.ndarray` object(s).

Returns Tuple of `numpy.ndarray` object(s).

Return type `tuple`

Warning: Implementations of `Function` must take care that the return value must be a tuple even if it returns only one array.

`forward_gpu (inputs)`
Applies forward propagation to input arrays on GPU.

Parameters `inputs` – Tuple of `cupy.ndarray` object(s).

Returns Tuple of `cupy.ndarray` object(s).

Return type `tuple`

Warning: Implementations of `Function` must take care that the return value must be a tuple even if it returns only one array.

`retain_inputs (indexes)`
Lets specified input variable nodes keep data arrays.
By calling this method from `forward()`, the function can specify which inputs are required for backprop.
If this method is not called, the function keeps all input arrays. If you want to release all input arrays, call this method by passing an empty sequence. Note that this behavior is different from that of `FunctionNode.retain_inputs()`.

Note that this method must not be called from the outside of `forward()`.

Parameters `indexes (iterable of int)` – Indexes of input variables that the function will require for backprop.

`retain_outputs (indexes, retain_after_backward=False)`
Lets specified output variable nodes keep data arrays.
By calling this method from `forward()`, the function can specify which outputs are required for backprop. If this method is not called, any output variables are not marked to keep the data array at the point of returning from `__call__()`. The retained arrays are stored to `output_data`.

**Note:** It is STRONGLY RECOMMENDED that you use this method if the function requires some or all output arrays in backprop. The function can also use output arrays just by keeping references to them directly, whereas it might influence on the performance of later function applications to the output variables.

Note that **this method must not be called from the outside of `forward()`**.

**Parameters**

- `indexes (iterable of int)` – Indexes of input variables that the function will require for backprop.

- `retain_after_backward (bool)` – This option has no effect. It is left only for the backward compatibility.

**unchain()**

Purges in/out nodes and this function itself from the graph.

See `FunctionNode.unchain()` for the detail.

**__eq__(value, /)**

Return `self==value`.

**__ne__(value, /)**

Return `self!=value`.

**__lt__(value, /)**

Return `self<value`.

**__le__(value, /)**

Return `self<=value`.

**__gt__(value, /)**

Return `self>value`.

**__ge__(value, /)**

Return `self>=value`.

**Attributes**

**inputs**

The input nodes of the function.

**label**

Short text that represents the function.

The default implementation returns its type name. Each function should override it to give more information.

**local_function_hooks**

Ordered Dictionary of registered function hooks.

See `FunctionNode.local_function_hooks` for the detail.

**node**

The `FunctionAdapter` object that wraps this Function.
If the Function does not have a node object, this property automatically creates a new one.

**output_data**
A tuple of the retained output arrays.

It has the same length as the `outputs`. Elements that are not retained are set to `None`.

**outputs**
Weak references to the output nodes of the function.

**rank**
The topological ordinal of the corresponding function node.

**stack**

### chainer.FunctionAdapter

**class** `chainer.FunctionAdapter (function: chainer.function.Function)`

Adapter class to wrap Function with FunctionNode.

While `FunctionNode` provides the interface of new-style differentiable functions, the old-style `Function` can still be used for the backward compatibility. This class provides an adapter of there interface; it adds `FunctionNode` interface to any `Function` object by delegation.

**Note:** The ownership of `FunctionAdapter` and `Function` is a bit tricky. At the initialization, `FunctionAdapter` is owned by the `Function` object. Once the function is applied to variables, the ownership is reversed; the adapter becomes the owner of the `Function` object and the `Function` object changes the reference to a weak one.

**Parameters**

- **function** *(Function)* – The function object to wrap.

New in version 3.0.0.

**Methods**

- **`__call__`** (*args, **kwargs*)
  Call self as a function.

- **`add_hook`** *(hook, name=None)*
  Registers a function hook.

  **Parameters**

  - **hook** *(FunctionHook)* – Function hook to be registered.
  - **name** *(str)* – Name of the function hook. The name must be unique among function hooks registered to this function. If `None`, the default name of the function hook is used.

- **`apply`** *(inputs)*
  Computes output variables and grows the computational graph.

  Basic behavior is expressed in the documentation of `FunctionNode`.

  **Note:** If the `data` attributes of the input variables exist on a GPU device, that device is made current before calling `forward()`, so implementers do not need to take care of device selection in most cases.
Parameters inputs -- Tuple of input variables. Each element can be either Variable or N-dimensional array. If the element is an ndarray, it is automatically wrapped with Variable.

Returns A tuple of output Variable objects.

backward (target_input_indexes, grad_outputs)
Computes gradients w.r.t. specified inputs given output gradients.

This method is used to compute one step of the backpropagation corresponding to the forward computation of this function node. Given the gradients w.r.t. output variables, this method computes the gradients w.r.t. specified input variables. Note that this method does not need to compute any input gradients not specified by target_input_indices.

Unlike Function.backward(), gradients are given as Variable objects and this method itself has to return input gradients as Variable objects. It enables the function node to return the input gradients with the full computational history, in which case it supports differentiable backpropagation or higher-order differentiation.

The default implementation returns None, which means the function is not differentiable.

Parameters

- target_input_indexes (tuple of int) -- Sorted indices of the input variables w.r.t. which the gradients are required. It is guaranteed that this tuple contains at least one element.

- grad_outputs (tuple of Variables) -- Gradients w.r.t. the output variables. If the gradient w.r.t. an output variable is not given, the corresponding element is None.

Returns Tuple of variables that represent the gradients w.r.t. specified input variables. The length of the tuple can be same as either len(target_input_indexe) or the number of inputs. In the latter case, the elements not specified by target_input_indexes will be discarded.

See also:

backward_accumulate() provides an alternative interface that allows you to implement the backward computation fused with the gradient accumulation.

backward_accumulate (target_input_indexes, grad_outputs, grad_inputs)
Computes gradients w.r.t. specified inputs and accumulates them.

This method provides a way to fuse the backward computation and the gradient accumulations in the case that the multiple functions are applied to the same variable.

Users have to override either of this method or backward(). It is often simpler to implement backward() and is recommended if you do not need to provide efficient gradient accumulation.

Parameters

- target_input_indexes (tuple of int) -- Sorted indices of the input variables w.r.t. which the gradients are required. It is guaranteed that this tuple contains at least one element.

- grad_outputs (tuple of Variable) -- Gradients w.r.t. the output variables. If the gradient w.r.t. an output variable is not given, the corresponding element is None.

- grad_inputs (tuple of Variable) -- Gradients w.r.t. the input variables specified by target_input_indexes. These values are computed by other computation paths. If there is no gradient value existing for the variable, the corresponding element is None. See also the note below.
Returns Tuple of variables that represent the gradients w.r.t. specified input variables. Unlike `backward()`, the length of the tuple must be same as that of `target_input_indices`.

Note: Gradient variables in `grad_outputs` are distinct, even if a variable is passed to multiple input arguments of the function. This is an implementation-detail convention to avoid the complication of correctly accumulating gradients in such a case.

Usually, only the first position of `grad_inputs` corresponding to these input arguments may contain the gradient variable corresponding to that input variable, and other entries are set to `None`. This is not the case with the `lazy_grad_sum` feature. This behavior might be changed in a future version.

### check_layout_forward(inputs)

Checks layout information of input data before forward propagation.

### check_type_forward(in_types)

Checks types of input data before forward propagation.

This method is called before `forward()` and validates the types of input variables using the type checking utilities.

Parameters:
- `in_types` (TypeInfoTuple) – The type information of input variables for `forward()`.

### delete_hook(name)

Unregisters the function hook.

Parameters:
- `name` (str) – The name of the function hook to be unregistered.

### forward(inputs)

Computes the output arrays from the input arrays.

It delegates the procedure to `forward_cpu()` or `forward_gpu()` by default. Which of them this method selects is determined by the type of input arrays. Implementations of `FunctionNode` must implement either CPU/GPU methods or this method.

Parameters:
- `inputs` – Tuple of input array(s).

Returns Tuple of output array(s).

Warning: Implementations of `FunctionNode` must take care that the return value must be a tuple even if it returns only one array.

### forward_chainerx(inputs)

Computes the output arrays from the input ChainerX arrays.

This method may check the input arrays and other attributes to see if the computation can be done using ChainerX implementation. If it’s not supported, `chainer.Fallback` should be returned instead of output arrays. In that case, computation using conventional Python implementation will be performed.

Parameters:
- `inputs` – Tuple of input array(s).

Returns Tuple of output array(s) or `chainer.Fallback`.

### forward_cpu(inputs)

Computes the output arrays from the input NumPy arrays.

Parameters:
- `inputs` – Tuple of input `numpy.ndarray` objects.

Returns Tuple of output arrays. Each element can be NumPy or CuPy arrays.
Warning: Implementation of FunctionNode must take care that the return value must be a tuple even if it returns only one array.

**forward_gpu**(inputs)
Computes the output arrays from the input CuPy arrays.

- **Parameters** `inputs` – Tuple of input cupy.ndarray objects.
- **Returns** Tuple of output arrays. Each element can be NumPy or CuPy arrays.

Warning: Implementation of FunctionNode must take care that the return value must be a tuple even if it returns only one array.

**get_retained_inputs()**
Returns a tuple of retained input variables.
This method is used to retrieve the input variables retained in forward().

- **Returns** A tuple of retained input variables, if available. Otherwise return None.

**get_retained_outputs()**
Returns a tuple of retained output variables.
This method is used to retrieve the output variables retained in forward().

- **Returns** A tuple of retained output variables, if available. Otherwise return None.

Note: This method does a tricky thing to support the case of an output node garbage-collected before this method is called; in this case, this method creates a fresh variable node that acts as an output node of the function node.

**retain_inputs**(indexes)
Lets specified input variable nodes keep data arrays.
By calling this method from forward(), the function node can specify which inputs are required for backprop. The input variables with retained arrays can then be obtained by calling get_retained_inputs() from inside backward().

Unlike Function, the function node DOES NOT keep input arrays by default. If you want to keep some or all input arrays, do not forget to call this method.

Note that this method must not be called from the outside of forward().

- **Parameters** `indexes` (iterable of int) – Indexes of input variables that the function will require for backprop.

**retain_outputs**(indexes)
Lets specified output variable nodes keep data arrays.
By calling this method from forward(), the function node can specify which outputs are required for backprop. If this method is not called, no output variables will be marked to keep their data array at the point of returning from apply(). The output variables with retained arrays can then be obtained by calling get_retained_outputs() from inside backward().

Note: It is recommended to use this method if the function requires some or all output arrays in backprop.
The function can also use output arrays just by keeping references to them directly, although it might affect
the performance of later function applications on the output variables.

Note that this method must not be called from the outside of forward().

**Parameters**

indexes *(iterable of int)* – Indexes of output variables that the function will require for backprop.

**uncchain()**

Purges in/out nodes and this function node itself from the graph.

**Attributes**

chainerx_device = None

function

The *Function* object that this adapter is wrapping.

input_layouts

inputs = None

is_elementwise = False

label

lazy_grad_sum = False

local_function_hooks

Ordered dictionary of registered function hooks.

Contrary to `chainer.thread_local.function_hooks`, which registers its elements to all functions, Function hooks in this property is specific to this function.

output_data

A tuple of the retained output arrays.

This property is mainly used by *Function*. Users basically do not have to use this property; use `get_retained_outputs()` instead.

output_layouts

outputs = None

rank = 0

stack = None
**chainer.FunctionNode**

**class chainer.FunctionNode**
Function node of the computational graph.

FunctionNode is a class representing a node in a computational graph. The node corresponds to an application of a differentiable function to input variables.

When a differentiable function is applied to `Variable` objects, it creates an instance of `FunctionNode` implementation and calls its `apply()` method. The `apply()` method basically does the following three things.

1. Adding an edge from the function node to the variable node corresponding to each input. The node of each input is extracted by `Variable.node`.
2. Computing the output arrays of the function.
3. Creating a `Variable` object for each output array and adding an edge from the node of the variable to the function node.

The output variables are then returned.

---

**Example**

Let $x$ be an instance of `Variable` and $f$ be an instance of `FunctionNode` taking only one argument. Then the following code

```python
>>> import numpy, chainer
>>> x = chainer.Variable(numpy.zeros(10))
>>> f = chainer.functions.math.identity.Identity()
>>> y = f.apply((x,))[0]
```

computes a new variable $y$ and creates backward references. The backward references are actually set as per the following diagram:

```
x.node <--- f <--- y.node
```

If an application of another function $g$ occurs as

```python
>>> g = chainer.functions.math.identity.Identity()
>>> z = g.apply((x,))[0]
```

then the graph grows with a branch:

```
|--- f <--- y.node
x.node <---
|--- g <--- z.node
```

Note that the branching is correctly managed on backward computation, i.e. the gradients from $f$ and $g$ are accumulated to the gradient of $x$.

---

Every function-node implementation should provide `forward()` and `backward()`. Instead of overriding `forward()`, one can also implement `forward_cpu()` and `forward_gpu()` when the implementations for CPU and GPU arrays are totally different.

Note that the input and output variables are inaccessible from `backward()` by default. If it needs accesses to these variables, the `forward()` method (or its CPU/GPU variants) has to call `retain_inputs()` and `retain_outputs()` appropriately. The retained input/output variables can be accessed from `backward()` by calling `get_retained_inputs()` and `get_retained_outputs()`.

---

4.2. Functions 303
Note: There are two types of differentiable functions in Chainer (since v3). The first type is of a function using a subclass of `Function`, which is called **old-style differentiable function**. The second type is of a function using a subclass of `FunctionNode`, which is called **new-style differentiable function**. There are several advantages on using the new-style differentiable function.

- The new-style differentiable function supports **differentiable backpropagation**. The backpropagated gradients computed through the new-style differentiable functions themselves support further backpropagations so that the automatic higher-order differentiation is available.

- The backpropagation of the new-style differentiable function can be more computationally efficient because the interface allows an implementation to omit the computation of unneeded input gradients.

Note that the new-style differentiable function is the standard way of defining a function node of the computational graph in Chainer; old-style differentiable functions are implemented as wrappers of the new-style differentiable functions.

### Variables

- **inputs** – A tuple of the input `VariableNode` objects.
- **outputs** – A tuple of weak references to the output `VariableNode` objects.
- **rank** (`int`) – An ordinal following the topological order of the computational graph.
- **stack** – Stack trace retrieved at the forward computation. The stack trace is available only in the debug mode.

New in version 3.0.0.

### Methods

**__call__** (*args, **kwargs)

Call self as a function.

**add_hook** (*hook, name=None*)

Registers a function hook.

**Parameters**

- **hook** (`FunctionHook`) – Function hook to be registered.
- **name** (`str`) – Name of the function hook. The name must be unique among function hooks registered to this function. If `None`, the default name of the function hook is used.

**apply** (*inputs*)

Computes output variables and grows the computational graph.

Basic behavior is expressed in the documentation of `FunctionNode`.

**Note:** If the `data` attributes of the input variables exist on a GPU device, that device is made current before calling `forward()`, so implementers do not need to take care of device selection in most cases.

**Parameters**

- **inputs** – Tuple of input variables. Each element can be either `Variable` or `N-dimensional array`. If the element is an ndarray, it is automatically wrapped with `Variable`.

**Returns**

A tuple of output `Variable` objects.
**backward**\((\text{target\_input\_indexes}, \text{grad\_outputs})\)

Computes gradients w.r.t. specified inputs given output gradients.

This method is used to compute one step of the backpropagation corresponding to the forward computation of this function node. Given the gradients w.r.t. output variables, this method computes the gradients w.r.t. specified input variables. Note that this method does not need to compute any input gradients not specified by \(\text{target\_input\_indices}\).

Unlike \(\text{Function.backward()}\), gradients are given as \(\text{Variable}\) objects and this method itself has to return input gradients as \(\text{Variable}\) objects. It enables the function node to return the input gradients with the full computational history, in which case it supports *differentiable backpropagation* or *higher-order differentiation*.

The default implementation returns \(\text{None}\) s, which means the function is not differentiable.

**Parameters**

- **target_input_indexes** (tuple of int) – Sorted indices of the input variables w.r.t. which the gradients are required. It is guaranteed that this tuple contains at least one element.

- **grad_outputs** (tuple of Variables) – Gradients w.r.t. the output variables. If the gradient w.r.t. an output variable is not given, the corresponding element is \(\text{None}\).

**Returns** Tuple of variables that represent the gradients w.r.t. specified input variables. The length of the tuple can be same as either \(\text{len(target\_input\_indexes)}\) or the number of inputs. In the latter case, the elements not specified by \(\text{target\_input\_indexes}\) will be discarded.

**See also:**

\(\text{backward\_accumulate()}\) provides an alternative interface that allows you to implement the backward computation fused with the gradient accumulation.

**backward\_accumulate**\((\text{target\_input\_indexes}, \text{grad\_outputs}, \text{grad\_inputs})\)

Computes gradients w.r.t. specified inputs and accumulates them.

This method provides a way to fuse the backward computation and the gradient accumulations in the case that the multiple functions are applied to the same variable.

Users have to override either of this method or \(\text{backward()}\). It is often simpler to implement \(\text{backward()}\) and is recommended if you do not need to provide efficient gradient accumulation.

**Parameters**

- **target_input_indexes** (tuple of int) – Sorted indices of the input variables w.r.t. which the gradients are required. It is guaranteed that this tuple contains at least one element.

- **grad_outputs** (tuple of Variable) – Gradients w.r.t. the output variables. If the gradient w.r.t. an output variable is not given, the corresponding element is \(\text{None}\).

- **grad_inputs** (tuple of Variable) – Gradients w.r.t. the input variables specified by \(\text{target\_input\_indexes}\). These values are computed by other computation paths. If there is no gradient value existing for the variable, the corresponding element is \(\text{None}\). See also the note below.

**Returns** Tuple of variables that represent the gradients w.r.t. specified input variables. Unlike \(\text{backward()}\), the length of the tuple must be same as that of \(\text{target\_input\_indices}\).
Gradient variables in grad_outputs are distinct, even if a variable is passed to multiple input arguments of the function. This is an implementation-detail convention to avoid the complication of correctly accumulating gradients in such a case.

Usually, only the first position of grad_inputs corresponding to these input arguments may contain the gradient variable corresponding to that input variable, and other entries are set to None. This is not the case with the lazy_grad_sum feature. This behavior might be changed in a future version.

**check_layout_forward**(inputs)

**check_type_forward**(in_types)
Checks types of input data before forward propagation.

This method is called before forward() and validates the types of input variables using the type checking utilities.

Parameters

- **in_types** (TypeInfoTuple) – The type information of input variables for forward().

**delete_hook**(name)

Unregisters the function hook.

Parameters

- **name** (str) – The name of the function hook to be unregistered.

**forward**(inputs)

Computes the output arrays from the input arrays.

It delegates the procedure to forward_cpu() or forward_gpu() by default. Which of them this method selects is determined by the type of input arrays. Implementations of FunctionNode must implement either CPU/GPU methods or this method.

Parameters

- **inputs** – Tuple of input array(s).

Returns

Tuple of output array(s).

**Warning:** Implementations of FunctionNode must take care that the return value must be a tuple even if it returns only one array.

**forward_chainerx**(inputs)

Computes the output arrays from the input ChainerX arrays.

This method may check the input arrays and other attributes to see if the computation can be done using ChainerX implementation. If it’s not supported, chainer.Fallback should be returned instead of output arrays. In that case, computation using conventional Python implementation will be performed.

Parameters

- **inputs** – Tuple of input array(s).

Returns

Tuple of output array(s) or chainer.Fallback.

**forward_cpu**(inputs)

Computes the output arrays from the input NumPy arrays.

Parameters

- **inputs** – Tuple of input numpy.ndarray objects.

Returns

Tuple of output arrays. Each element can be NumPy or CuPy arrays.

**Warning:** Implementation of FunctionNode must take care that the return value must be a tuple even if it returns only one array.
forward_gpu(inputs)
Computes the output arrays from the input CuPy arrays.

Parameters inputs – Tuple of input cupy.ndarray objects.

Returns Tuple of output arrays. Each element can be NumPy or CuPy arrays.

Warning: Implementation of FunctionNode must take care that the return value must be a tuple even if it returns only one array.

get_retained_inputs()
Returns a tuple of retained input variables.
This method is used to retrieve the input variables retained in forward().

Returns A tuple of retained input variables, if available. Otherwise return None.

get_retained_outputs()
Returns a tuple of retained output variables.
This method is used to retrieve the output variables retained in forward().

Returns A tuple of retained output variables, if available. Otherwise return None.

Note: This method does a tricky thing to support the case of an output node garbage-collected before this method is called; in this case, this method creates a fresh variable node that acts as an output node of the function node.

retain_inputs(indexes)
Lets specified input variable nodes keep data arrays.
By calling this method from forward(), the function node can specify which inputs are required for backprop. The input variables with retained arrays can then be obtained by calling get_retained_inputs() from inside backward().
Unlike Function, the function node DOES NOT keep input arrays by default. If you want to keep some or all input arrays, do not forget to call this method.
Note that this method must not be called from the outside of forward().

Parameters indexes (iterable of int) – Indexes of input variables that the function will require for backprop.

retain_outputs(indexes)
Lets specified output variable nodes keep data arrays.
By calling this method from forward(), the function node can specify which outputs are required for backprop. If this method is not called, no output variables will be marked to keep their data array at the point of returning from apply(). The output variables with retained arrays can then be obtained by calling get_retained_outputs() from inside backward().

Note: It is recommended to use this method if the function requires some or all output arrays in backprop. The function can also use output arrays just by keeping references to them directly, although it might affect the performance of later function applications on the output variables.

Note that this method must not be called from the outside of forward().
Parameters `indexes` *(iterable of int)* – Indexes of output variables that the function will require for backprop.

`unchain()`

Purges in/out nodes and this function node itself from the graph.

`__eq__(value, /)`

`Return self==value`.

`__ne__(value, /)`

`Return self!=value`.

`__lt__(value, /)`

`Return self<value`.

`__le__(value, /)`

`Return self<=value`.

`__gt__(value, /)`

`Return self>value`.

`__ge__(value, /)`

`Return self>=value`.

**Attributes**

`chainerx_device = None`

`input_layouts`

`inputs = None`

`is_elementwise = False`

`label`

Short text that represents the function.

The default implementation returns its type name. Each function should override it to give more information.

`lazy_grad_sum = False`

`local_function_hooks`

Ordered dictionary of registered function hooks.

Contrary to `chainer.thread_local.function_hooks`, which registers its elements to all functions, Function hooks in this property is specific to this function.

`output_data`

A tuple of the retained output arrays.

This property is mainly used by `Function`. Users basically do not have to use this property; use `get_retained_outputs()` instead.

`output_layouts`

`outputs = None`

`rank = 0`

`stack = None`
chainer.force_backprop_mode

chainer.force_backprop_mode()
Make a context manager which enables back-propagation.

When you want to enable back-propagation in no_backprop_mode(), call this method. A Variable created in this context always has a computational graph unless overridden by deeper contexts. If you call this method outside of no_backprop_mode() context, it changes nothing.

In the following example, y has a computational graph and calling backward() on y will compute and accumulate the gradients of the variables in the graph, in this case only x.

```python
>>> x = chainer.Variable(np.array([1,], np.float32))
>>> with chainer.no_backprop_mode():
...   with chainer.force_backprop_mode():
...     y = x + 1
>>> y.backward()
>>> x.grad
array([1.], dtype=float32)
```

Note: chainer.force_backprop_mode() implicitly applies ChainerX's counterpart chainerx.force_backprop_mode(), but not vice versa. Also, setting enable_backprop configuration does not affect ChainerX.

See also:
See chainer.no_backprop_mode() for details on disabled back-propagation mode.

chainer.no_backprop_mode

chainer.no_backprop_mode()
Make a context manager which disables back-propagation.

In this context, Chainer does not make a computational graph. It has the benefit of reducing memory consumption. However, a Variable created in this context does not hold a reference to the FunctionNode that created itself so no gradients are accumulated by backward().

In the following example, y is created in this context, which means that calling backward() on y has no effect on the gradients of x.

```python
>>> x = chainer.Variable(np.array([1,], np.float32))
>>> with chainer.no_backprop_mode():
...   y = x + 1
>>> y.backward()
>>> x.grad is None
True
```

Note: chainer.no_backprop_mode() implicitly applies ChainerX's counterpart chainerx.no_backprop_mode(), but not vice versa. Also, setting enable_backprop configuration does not affect ChainerX.

See also:
See chainer.force_backprop_mode() for details on how to override this context.
**chainer.grad**

```python
chainer.grad(outputs, inputs, grad_outputs=None, grad_inputs=None, set_grad=False, retain_grad=False, enable_double_backprop=False, loss_scale=None)
```

Computes the gradient of output variables w.r.t. the input variables.

This function implements the backpropagation algorithm. While `Variable.backward()` also implements backprop, this function selects the smallest paths in the computational graph needed to compute the gradients w.r.t. inputs. The error is backpropagated only through these selected paths, which may reduce the overall computational cost.

This function also differs from `Variable.backward()` in the way to return the gradients; it directly returns the gradient variables as a list instead of setting gradients to the `Variable.grad_var` attribute of the original variable. It means users do not need to clear the gradient w.r.t. each variable before computing the gradient using this function. If `set_grad` option is set to `True`, the computed gradient is also stored in the `Variable.grad_var` attribute of each variable, in which case any original value of `Variable.grad_var` will be updated even if it had already been set.

**Parameters**

- **outputs** (tuple or list of `Variable`) – A sequence of output variables from which backprop starts.
- **inputs** (tuple or list of `Variable`) – A sequence of input variables each of which this function computes the gradient w.r.t.
- **grad_outputs** (tuple or list of `Variable` or None) – A sequence of variables that gives the initial value of each output gradient. If an element is set to `None`, an array filled with 1 is used. If this argument itself is `None`, it is treated as a sequence of `None`s.
- **grad_inputs** (tuple or list of `Variable` or None) – A sequence of variables that gives the initial value of each input gradient. The gradients computed by the backprop algorithm are accumulated to them (not in-place). If an element is set to `None`, the gradient is not accumulated to this value. If this argument itself is `None`, it is treated as a sequence of `None`s.
- **set_grad** (bool) – If it is `True`, the `Variable.grad_var` attribute of each input variable is set to the corresponding computed gradient variable.
- **retain_grad** (bool) – If it is `True`, the gradients w.r.t. all the intermediate variables are stored in the `Variable.grad_var` attribute. In this case, the `set_grad` option is ignored.
- **enable_double_backprop** (bool) – If it is `True`, the computed gradients can be further backpropagated. Enabling it may increase the memory consumption (and possibly the computational time) to remember the intermediate gradient values for the second backpropagation.
- **loss_scale** (float) – Loss scaling factor. Loss scaling is a useful technique to mitigate vanishing gradient issue that tends to happen when low precision data type like `float16` is used during training. If you set loss scaling factor, gradients of loss values are to be multiplied by the factor before backprop starts. The factor is propagated to whole gradients in a computational graph along the backprop. The gradients of parameters are divided by the factor just before the parameters are to be updated.

**Returns** A list of gradient variables w.r.t. the inputs.
4.2.13 Function hooks

Chainer provides a function-hook mechanism that enriches the behavior of forward and backward propagation of 
`FunctionNode` and `Function`.

<table>
<thead>
<tr>
<th>Function hook</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.function_hooks.&quot;CUDAProfileHook&quot;</code></td>
<td>Function hook for measuring memory usage of functions in cupy memory pool.</td>
</tr>
<tr>
<td><code>chainer.function_hooks.&quot;CupyMemoryProfileHook&quot;</code></td>
<td>Function hook for measuring memory usage of functions in cupy memory pool.</td>
</tr>
<tr>
<td><code>chainer.function_hooks.&quot;PrintHook&quot;</code></td>
<td>Function hook that prints debug information.</td>
</tr>
<tr>
<td><code>chainer.function_hooks.&quot;TimerHook&quot;</code></td>
<td>Function hook for measuring elapsed time of functions.</td>
</tr>
</tbody>
</table>

**chainer.function_hooks.CUDAProfileHook**

class chainer.function_hooks.CUDAProfileHook

**Methods**

**__enter__()**

**__exit__(*)**

**added(function)**

Callback function invoked when the function hook is registered

Parameters

- `function (FunctionNode)` – Function object to which the function hook is added. None if the function hook is registered globally.

**backward_postprocess(function, in_data, out_grad)**

Callback function invoked after backward propagation.

Parameters

- `function (FunctionNode)` – Function object to which the function hook is registered.
- `in_data (tuple of N-dimensional array)` – Input of forward propagation.
- `out_grad (tuple of N-dimensional array)` – Gradient data of backward propagation.

**backward_preprocess(function, in_data, out_grad)**

Callback function invoked before backward propagation.

Parameters

- `function (FunctionNode)` – Function object to which the function hook is registered.
- `in_data (tuple of N-dimensional array)` – Input data of forward propagation.
- `out_grad (tuple of N-dimensional array)` – Gradient data of backward propagation.

**deleted(function)**

Callback function invoked when the function hook is unregistered

Parameters

- `function (FunctionNode)` – Function object from which the function hook is deleted. None if the function hook was registered globally.

**forward_postprocess(function, in_data)**

Callback function invoked after forward propagation.
Parameters

- **function** *(FunctionNode)* – Function object to which the function hook is registered.
- **in_data** *(tuple of N-dimensional array)* – Input data of forward propagation.

**forward_preprocess** *(function, in_data)*
Callback function invoked before forward propagation.

Parameters

- **function** *(FunctionNode)* – Function object to which the function hook is registered.
- **in_data** *(tuple of N-dimensional array)* – Input data of forward propagation.

```python
__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.
```

Attributes

- **name** = 'CUDAProfileHook'

**chainer.function_hooks.CupyMemoryProfileHook**

class chainer.function_hooks.CupyMemoryProfileHook
Function hook for measuring memory usage of functions in cupy memory pool.

**Example**

Code example:

```python
from chainer.function_hooks import CupyMemoryProfileHook
hook = CupyMemoryProfileHook()
with hook:
    trainer.run()
hook.print_report()
```

Output example:
where `FunctionName` is the name of function that calls the hook, and `UsedBytes` is the memory bytes the function used from cupy memory pool, and `AcquiredBytes` is the actual memory bytes the cupy memory pool acquired from GPU device on the function call, and `Occurrence` is the number of calls.

**Variables** `call_history` – List of measurement results. It consists of the name of the function that calls this hook, the memory bytes the function used from cupy memory pool, and the memory bytes the cupy memory pool acquired from GPU device on the function call.

**Methods**

```python
__enter__()
__exit__(*_,*)
added(function=None)
backward_postprocess(function, in_data, out_grad)
backward_preprocess(function, in_data, out_grad)
deleted(function=None)
forward_postprocess(function, in_data)
```

**Parameters**

- `function (FunctionNode)` – Function object to which the function hook is registered.
- `in_data (tuple of N-dimensional array)` – Input of forward propagation.
- `out_grad (tuple of N-dimensional array)` – Gradient data of backward propagation.
• **in_data** (tuple of \(N\)-dimensional array) – Input data of forward propagation.

**forward_preprocess** *(function, in_data)*

Callback function invoked before forward propagation.

**Parameters**

• **function** *(FunctionNode)* – Function object to which the function hook is registered.

• **in_data** (tuple of \(N\)-dimensional array) – Input data of forward propagation.

**print_report** *(unit='auto', file=<_io.TextIOWrapper name='<stdout>' mode='w' encoding='UTF-8'>)*

Prints a summary report of memory profiling in functions.

**Parameters**

- **unit** *(str)* – Supplementary units used for used memories. \(B, KB, MB, GB, TB, PB, EB, ZB, auto' (default) and 'auto_foreach* are supported. If **auto**, units of memories are aligned to the largest values of ‘used_bytes’ and ‘acquired_bytes’. If **auto_foreach**, units of memories are adjusted for each element.

**summary()**

Returns a summary of memory profiling in functions.

**Returns** A summarized dictionary whose keys are function names and values are dictionaries of `used_bytes`, `acquired_bytes`, and `occurrence`.

**total_acquired_bytes()**

Returns total bytes that cupy memory pool acquired from GPU.

**total_used_bytes()**

Returns total bytes that functions used from cupy memory pool.

**__eq__(value, /)**

Return self==value.

**__ne__(value, /)**

Return self!=value.

**__lt__(value, /)**

Return self<value.

**__le__(value, /)**

Return self<=value.

**__gt__(value, /)**

Return self>value.

**__ge__(value, /)**

Return self>=value.

**Attributes**

**name** = 'CupyMemoryProfileHook'
chainer.function_hooks.PrintHook

```python
class chainer.function_hooks.PrintHook(sep=None, end=’\n’, file=_io.TextIOWrapper( name=’<stdout>’ mode=’w’ encoding=’UTF-8’), flush=True)
```

Function hook that prints debug information.

This function hook outputs the debug information of input arguments of `forward` and `backward` methods involved in the hooked functions at preprocessing time (that is, just before each method is called).

Unlike simple “debug print” technique, where users insert print functions at every function to be inspected, we can show the information of all functions involved with single `with` statement.

Further, this hook enables us to show the information of `backward` methods without inserting print functions into Chainer’s library code.

Parameters

- `sep` – *(deprecated since v4.0.0)* Ignored.
- `end` – Character to be added at the end of print function.
- `file` – Output file_like object that that redirect to.
- `flush` – If `True`, this hook forcibly flushes the text stream at the end of preprocessing.

Example

The basic usage is to use it with `with` statement.

```python
>>> from chainer import function_hooks
>>> l = L.Linear(10, 10)
>>> x = chainer.Variable(np.zeros((1, 10), np.float32))
>>> with chainer.function_hooks.PrintHook():
...     y = l(x)
...     z = F.sum(y)
...     z.backward()
```

In this example, `PrintHook` shows the debug information of forward propagation of `LinearFunction` (which is implicitly called by `l`) and `Sum` (called by `F.sum`) and backward propagation of `z` and `y`.

Methods

```python
__enter__()  
__exit__(*args*)
```

`added` *(function)*

Callback function invoked when the function hook is registered

Parameters

- `function` *(FunctionNode)* – Function object to which the function hook is added. None if the function hook is registered globally.

`backward_postprocess` *(function, in_data, out_grad)*

Callback function invoked after backward propagation.

Parameters

- `function` *(FunctionNode)* – Function object to which the function hook is registered.
• **in_data** (tuple of N-dimensional array) – Input of forward propagation.

• **out_grad** (tuple of N-dimensional array) – Gradient data of backward propagation.

**backward_preprocess** (*function, in_data, out_grad*)

Callback function invoked before backward propagation.

**Parameters**

- **function** (*FunctionNode*) – Function object to which the function hook is registered.
- **in_data** (tuple of N-dimensional array) – Input data of forward propagation.
- **out_grad** (tuple of N-dimensional array) – Gradient data of backward propagation.

**deleted** (*function*)

Callback function invoked when the function hook is unregistered.

**Parameters**

- **function** (*FunctionNode*) – Function object from which the function hook is deleted. None if the function hook was registered globally.

**forward_postprocess** (*function, in_data*)

Callback function invoked after forward propagation.

**Parameters**

- **function** (*FunctionNode*) – Function object to which the function hook is registered.
- **in_data** (tuple of N-dimensional array) – Input data of forward propagation.

**forward_preprocess** (*function, in_data*)

Callback function invoked before forward propagation.

**Parameters**

- **function** (*FunctionNode*) – Function object to which the function hook is registered.
- **in_data** (tuple of N-dimensional array) – Input data of forward propagation.

**Methods**

- **__eq__(value, /)**
  
  Return self==value.

- **__ne__(value, /)**
  
  Return self!=value.

- **__lt__(value, /)**
  
  Return self<value.

- **__le__(value, /)**
  
  Return self<=value.

- **__gt__(value, /)**
  
  Return self>value.

- **__ge__(value, /)**
  
  Return self>=value.
Attributes

name = 'PrintHook'

chainer.function_hooks.TimerHook

class chainer.function_hooks.TimerHook

Function hook for measuring elapsed time of functions.

Example

Code example:

```python
from chainer.function_hooks import TimerHook
hook = TimerHook()
with hook:
    trainer.run()
hook.print_report()
```

Output example:

<table>
<thead>
<tr>
<th>FunctionName</th>
<th>ElapsedTime</th>
<th>Occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>LinearFunction</td>
<td>1.24sec</td>
<td>3900</td>
</tr>
<tr>
<td>ReLU</td>
<td>0.59sec</td>
<td>2600</td>
</tr>
<tr>
<td>SoftmaxCrossEntropy</td>
<td>0.82sec</td>
<td>1300</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.18sec</td>
<td>700</td>
</tr>
</tbody>
</table>

where FunctionName is the name of function that calls the hook, and ElapsedTime is the elapsed time the function consumed, and Occurrence is the number of calls.

Variables call_history – List of measurement results. It consists of pairs of the name of the function that calls this hook and the elapsed time the function consumes.

Methods

__enter__()

__exit__(*)

added(function)

Callback function invoked when the function hook is registered

Parameters

function (FunctionNode) – Function object to which the function hook is added. None if the function hook is registered globally.

backward_postprocess (function, in_data, out_grad)

Callback function invoked after backward propagation.

Parameters

• function (FunctionNode) – Function object to which the function hook is registered.

• in_data (tuple of N-dimensional array) – Input of forward propagation.

• out_grad (tuple of N-dimensional array) – Gradient data of backward propagation.
**backward_preprocess** *(function, in_data, out_grad)*  
Callback function invoked before backward propagation.

**Parameters**

- **function** *(FunctionNode)* – Function object to which the function hook is registered.
- **in_data** (tuple of *N*-dimensional array) – Input data of forward propagation.
- **out_grad** (tuple of *N*-dimensional array) – Gradient data of backward propagation.

**deleted** *(function)*  
Callback function invoked when the function hook is unregistered.

**Parameters**

- **function** *(FunctionNode)* – Function object from which the function hook is deleted. *None* if the function hook was registered globally.

**forward_postprocess** *(function, in_data)*  
Callback function invoked after forward propagation.

**Parameters**

- **function** *(FunctionNode)* – Function object to which the function hook is registered.
- **in_data** (tuple of *N*-dimensional array) – Input data of forward propagation.

**forward_preprocess** *(function, in_data)*  
Callback function invoked before forward propagation.

**Parameters**

- **function** *(FunctionNode)* – Function object to which the function hook is registered.
- **in_data** (tuple of *N*-dimensional array) – Input data of forward propagation.

**print_report** *(unit='auto', file=<_io.TextIOWrapper name='<stdout>' mode='w' encoding='UTF-8'>)*  
Prints a summary report of time profiling in functions.

**Parameters**

- **unit** *(str)* – Supplementary units used for computational times. *sec, ms, us, ns, auto*(default) and *auto_foreach* are supported. If *auto*, units of times are aligned to the largest, and if *auto_foreach*, units of times are adjusted for each element.

**summary** *( )*  
Returns a summary of time profiling in functions.

**Returns** A summarized dictionary whose keys are function names and values are dictionaries of *elapsed_time* and *occurrence*.

**total_time** *( )*  
Returns total elapsed time in seconds.

**__eq__**(value, /)  
Return self==value.

**__ne__**(value, /)  
Return self!=value.

**__lt__**(value, /)  
Return self<value.

**__le__**(value, /)  
Return self<=value.
__gt__(value,)
   Return self>value.

__ge__(value,)
   Return self>=value.

Attributes

name = 'TimerHook'

table = {'ms': 1000, 'ns': 1000000000, 'sec': 1, 'us': 100000}

You can also implement your own function-hook to inject arbitrary code before/after the forward/backward propagation.

chainer.FunctionHook

chainer.FunctionHook

class chainer.FunctionHook
   Base class of hooks for Functions.

   FunctionHook is a callback object that is registered to FunctionNode. Registered function hooks are invoked before and after forward and backward operations of each function.

   Function hooks that derive from FunctionHook may override the following methods:
   • added()
   • deleted()
   • forward_preprocess()
   • forward_postprocess()
   • backward_preprocess()
   • backward_postprocess()

   By default, these methods do nothing.

   Specifically, when the __call__() method of some function is invoked, forward_preprocess() (resp. forward_postprocess()) of all function hooks registered to this function are called before (resp. after) forward propagation.

   Likewise, when backward() of some Variable is invoked, backward_preprocess() (resp. backward_postprocess()) of all function hooks registered to the function which holds this variable as a gradient are called before (resp. after) backward propagation.

   added() and deleted() are called when the hook is registered or unregistered, respectively.

   There are two ways to register FunctionHook objects to FunctionNode objects.

   The first one is to use with statement. Function hooks hooked in this way are registered to all functions within with statement and are unregistered at the end of with statement.

Example

The following code is a simple example in which we measure the elapsed time of a part of forward propagation procedure with TimerHook, which is a subclass of FunctionHook.
In this example, we measure the elapsed times for each forward propagation of all functions in `model1` and `model2`. Note that `model3` is not a target of measurement as `TimerHook` is unregistered before forward propagation of `model3`.

Note: Chainer stores the dictionary of registered function hooks as a thread local object. So, function hooks registered are different depending on threads.

The other one is to register it directly to a `FunctionNode` object by calling its `add_hook()` method. Function hooks registered in this way can be removed by `delete_hook()` method. Contrary to the former registration method, function hooks are registered only to the function whose `add_hook()` method is called.

If the hook is registered globally using `with` statement, `None` is passed as the `function` argument of `added()` and `deleted()`.

If the hook is registered in a specific function using `add_hook()`, the `FunctionNode` instance is passed as the function argument of `added()` and `deleted()`.

**Parameters**

- `name (str)` – Name of this function hook.

**Methods**

- `__enter__()`
- `__exit__(*,)`
- `added(function)`
  
  Callback function invoked when the function hook is registered

  **Parameters**

  - `function (FunctionNode)` – Function object to which the function hook is added. None if the function hook is registered globally.

- `backward_postprocess(function, in_data, out_grad)`
  
  Callback function invoked after backward propagation.

  **Parameters**

  - `function (FunctionNode)` – Function object to which the function hook is registered.
• **in_data** (tuple of *N-dimensional array*) – Input of forward propagation.

• **out_grad** (tuple of *N-dimensional array*) – Gradient data of backward propagation.

**backward_preprocess** (*function, in_data, out_grad*)

Callback function invoked before backward propagation.

**Parameters**

• **function** (*FunctionNode*) – Function object to which the function hook is registered.

• **in_data** (tuple of *N-dimensional array*) – Input data of forward propagation.

• **out_grad** (tuple of *N-dimensional array*) – Gradient data of backward propagation.

**deleted** (*function*)

Callback function invoked when the function hook is unregistered.

**Parameters**

• **function** (*FunctionNode*) – Function object from which the function hook is deleted. *None* if the function hook was registered globally.

**forward_postprocess** (*function, in_data*)

Callback function invoked after forward propagation.

**Parameters**

• **function** (*FunctionNode*) – Function object to which the function hook is registered.

• **in_data** (tuple of *N-dimensional array*) – Input data of forward propagation.

**forward_preprocess** (*function, in_data*)

Callback function invoked before forward propagation.

**Parameters**

• **function** (*FunctionNode*) – Function object to which the function hook is registered.

• **in_data** (tuple of *N-dimensional array*) – Input data of forward propagation.

---

```python
__eq__(value, /)
    Return self==value.
__ne__(value, /)
    Return self!=value.
__lt__(value, /)
    Return self<value.
__le__(value, /)
    Return self<=value.
__gt__(value, /)
    Return self>value.
__ge__(value, /)
    Return self>=value.
```
Attributes

name = 'FunctionHook'

4.3 Link and Chains

Chainer provides many Link implementations in the chainer.links package.

Note: Some of the links are originally defined in the chainer.functions namespace. They are still left in the namespace for backward compatibility, though it is strongly recommended that you use them via the chainer.links package.

4.3.1 Learnable connections

<table>
<thead>
<tr>
<th>Link</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.links.Bias</td>
<td>Broadcasted elementwise summation with learnable parameters.</td>
</tr>
<tr>
<td>chainer.links.Bilinear</td>
<td>Bilinear layer that performs tensor multiplication.</td>
</tr>
<tr>
<td>chainer.links.ChildSumTreeLSTM</td>
<td>Child-Sum TreeLSTM unit.</td>
</tr>
<tr>
<td>chainer.links.Convolution1D</td>
<td>1-dimensional convolution layer.</td>
</tr>
<tr>
<td>chainer.links.Convolution2D</td>
<td>Two-dimensional convolutional layer.</td>
</tr>
<tr>
<td>chainer.links.Convolution3D</td>
<td>3-dimensional convolution layer.</td>
</tr>
<tr>
<td>chainer.links.ConvolutionND</td>
<td>N-dimensional convolution layer.</td>
</tr>
<tr>
<td>chainer.links.Deconvolution1D</td>
<td>1-dimensional deconvolution layer.</td>
</tr>
<tr>
<td>chainer.links.Deconvolution2D</td>
<td>Two dimensional deconvolution function.</td>
</tr>
<tr>
<td>chainer.links.Deconvolution3D</td>
<td>3-dimensional deconvolution layer.</td>
</tr>
<tr>
<td>chainer.links.DeconvolutionND</td>
<td>N-dimensional deconvolution function.</td>
</tr>
<tr>
<td>chainer.links.DeformableConvolution2D</td>
<td>Two-dimensional deformable convolutional layer.</td>
</tr>
<tr>
<td>chainer.links.DepthwiseConvolution2D</td>
<td>Two-dimensional depthwise convolutional layer.</td>
</tr>
<tr>
<td>chainer.links.DilatedConvolution2D</td>
<td>Two-dimensional dilated convolutional layer.</td>
</tr>
<tr>
<td>chainer.links.EmbedID</td>
<td>Efficient linear layer for one-hot input.</td>
</tr>
<tr>
<td>chainer.links.GRU</td>
<td>Stateful Gated Recurrent Unit function (GRU)</td>
</tr>
<tr>
<td>chainer.links.Highway</td>
<td>Highway module.</td>
</tr>
<tr>
<td>chainer.links.Inception</td>
<td>Inception module of GoogLeNet.</td>
</tr>
<tr>
<td>chainer.links.InceptionBN</td>
<td>Inception module of the new GoogLeNet with Batch-Normalization.</td>
</tr>
<tr>
<td>chainer.links.Linear</td>
<td>Linear layer (a.k.a. fully-connected layer).</td>
</tr>
<tr>
<td>chainer.links.LocalConvolution2D</td>
<td>Two-dimensional local convolutional layer.</td>
</tr>
<tr>
<td>chainer.links.LSTM</td>
<td>Fully-connected LSTM layer.</td>
</tr>
<tr>
<td>chainer.links.MLPConvolution2D</td>
<td>Two-dimensional MLP convolution layer of Network in Network.</td>
</tr>
<tr>
<td>chainer.links.NaryTreeLSTM</td>
<td>N-ary TreeLSTM unit.</td>
</tr>
<tr>
<td>chainer.links.NStepBiGRU</td>
<td>Stacked Bi-directional GRU for sequences.</td>
</tr>
<tr>
<td>chainer.links.NStepBiLSTM</td>
<td>Stacked Bi-directional LSTM for sequences.</td>
</tr>
<tr>
<td>chainer.links.NStepBiRNNReLU</td>
<td>Stacked Bi-directional RNN for sequences.</td>
</tr>
<tr>
<td>chainer.links.NStepBiRNNTanh</td>
<td>Stacked Bi-directional RNN for sequences.</td>
</tr>
<tr>
<td>chainer.links.NStepGRU</td>
<td>Stacked Uni-directional GRU for sequences.</td>
</tr>
<tr>
<td>chainer.links.NStepLSTM</td>
<td>Stacked Uni-directional LSTM for sequences.</td>
</tr>
</tbody>
</table>

continues on next page
Table 16 – continued from previous page

<table>
<thead>
<tr>
<th>Module</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.links.NStepRNNReLU</code></td>
<td>Stacked Uni-directional RNN for sequences.</td>
</tr>
<tr>
<td><code>chainer.links.NStepRNNTan</code></td>
<td>Stacked Uni-directional RNN for sequences.</td>
</tr>
<tr>
<td><code>chainer.links.Parameter</code></td>
<td>Link that just holds a parameter and returns it.</td>
</tr>
<tr>
<td><code>chainer.links.Scale</code></td>
<td>Broadcasted elementwise product with learnable parameters.</td>
</tr>
<tr>
<td><code>chainer.links.StatefulGRU</code></td>
<td>Stateful Gated Recurrent Unit function (GRU).</td>
</tr>
<tr>
<td><code>chainer.links.StatelessGRU</code></td>
<td>Stateless Gated Recurrent Unit function (GRU).</td>
</tr>
<tr>
<td><code>chainer.links.StatefulMGU</code></td>
<td></td>
</tr>
<tr>
<td><code>chainer.links.StatelessMGU</code></td>
<td></td>
</tr>
<tr>
<td><code>chainer.links.StatefulPeepholeLSTM</code></td>
<td>Fully-connected LSTM layer with peephole connections.</td>
</tr>
<tr>
<td><code>chainer.links.StatefulZoneoutLSTM</code></td>
<td>Stateless LSTM layer.</td>
</tr>
</tbody>
</table>

**chainer.links.Bias**

```python
class chainer.links.Bias(axis=1, shape=None):
    Broadcasted elementwise summation with learnable parameters.

    Computes a elementwise summation as `bias()` function does except that its second input is a learnable bias parameter `b` the link has.

    Parameters

    - `axis (int)` – The first axis of the first input of `bias()` function along which its second input is applied.
    - `shape (tuple of ints)` – Shape of the learnable bias parameter. If `None`, this link does not have learnable parameters so an explicit bias needs to be given to its `forward` method’s second input.

    See also:

    See `bias()` for details.

    Variables `b (Variable)`: Bias parameter if `shape` is given. Otherwise, no attributes.
```

**Methods**

```python
__call__(*args: Any, **kwargs: Any) → Any
    Call self as a function.

add_hook(hook: chainerlink_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
    Registers a link hook.

    Parameters

    - `hook (LinkHook)` – Link hook to be registered.
    - `name (str)`: Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

    Returns self
```

4.3. Link and Chains
add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None

Registers a parameter to the link.

**Parameters**

- name *(str)* – Name of the parameter. This name is also used as the attribute name.
- shape *(int or tuple of ints)* – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- dtype – Data type of the parameter array.
- initializer *(initializer)* – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- name *(str)* – Name of the persistent value. This name is also used for the attribute name.
- value – Value to be registered.

addgrads(link: chainer.link.Link) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- link *(Link)* – Source link object.

children() → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**
A generator object that generates all child links.

cleargrads() → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy(mode: str = 'share') → chainer.link.Link

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- mode *(str)* – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed
independently. `share` means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is `share`.

**Returns**
Copied link object.

**Return type**
`Link`

### copyparams

```python
def copyparams(link: chainer.link.Link, copy_persistent: bool = True) → None
```

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an `ndarray`, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- `link (Link)` – Source link object.
- `copy_persistent (bool)` – If `True`, persistent values are also copied. `True` by default.

### count_params

```python
def count_params() → int
```

Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**
The total size of parameters (int)

### delete_hook

```python
def delete_hook(name: str) → None
```

Unregisters the link hook.

**Parameters**

- `name (str)` – The name of the link hook to be unregistered.

### device_resident_accept

```python
def device_resident_accept(visitor)
```

Applies the visitor to all the device objects in this instance.

**Parameters**

- `visitor (DeviceResidentsVisitor)` – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

### disable_update

```python
def disable_update() → None
```

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

### enable_update

```python
def enable_update() → None
```

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

### forward

```python
def forward(*xs)
```

Applies broadcasted elementwise summation.

**Parameters**

- `xs (list of Variables)` – Input variables whose length should be one if the link has a learnable bias parameter, otherwise should be two.
from_chx()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(*args, **kwargs)
Initialize link with given parameters.
This method initializes the link with given *N-dimensional arrays*. Arguments includes
• some parameters for a specific link.
• constants such as stride width of a convolutional layer.

init_scope() → Iterator[None]
Creates an initialization scope.
This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example
In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))

links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.
**register_persistent** *(name: str) → None*

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name** *(str)* – Name of the attribute to be registered.

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** *(int)* – Number of times to repeat.
- **mode** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters**

- **serializer** *(AbstractSerializer)* – Serializer object.

**to_chx** ()

Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to Chain-
erX, the link implementation must override this method to do so.

Returns: self

to_cpu() ➔ chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], Module-
Type, Tuple[ModuleType, int]]) ➔ DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device() for available values.

Returns: self

to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) ➔ chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64() ➔ chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

zerograds() ➔ None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.
__gt__ (value, /)
    Return self>value.

__ge__ (value, /)
    Return self>=value.

Attributes

device
    Device instance.

local_link_hooks
    Ordered dictionary of registered link hooks.
    Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions,
    link hooks in this property are specific to this link.

printable_specs
    Generator of printable specs of this link.
    Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword
    and value) that are passed to the __init__(). This pair of key and value is used for
    representing this class or subclass with __str__().

update_enabled
    True if at least one parameter has an update rule enabled.

within_init_scope
    True if the current code is inside of an initialization scope.
    See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.
    Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.Bilinear

class chainer.links.Bilinear(left_size, right_size, out_size, nobias=False, initialW=None, initial_bias=None)

Bilinear layer that performs tensor multiplication.

Bilinear is a primitive link that wraps the bilinear() functions. It holds parameters W, V1, V2, and b
    corresponding to the arguments of bilinear().

Parameters

* left_size (int) – Dimension of input vector e^1 (J)
* right_size (int) – Dimension of input vector e^2 (K)
* out_size (int) – Dimension of output vector y (L)
* nobias (bool) – If True, parameters V1, V2, and b are omitted.
* initialW (initializer) – Initializer to initialize the weight. When it is numpy.ndarray,
    its ndim should be 3.
* initial_bias (tuple of initializer) – Initial values of V1, V2 and b. The length of this
    argument must be 3. Each element of this tuple must have the shapes of (left_size, out_size),
    (right_size, out_size), and (out_size,), respectively if they

4.3. Link and Chains
are `numpy.ndarray`. If `None`, $V^1$ and $V^2$ are initialized by the default initializer and $b$ is set to 0.

See also:

See `chainer.functions.bilinear()` for details.

Variables

- $W$ (Variable) – Bilinear weight parameter.
- $V^1$ (Variable) – Linear weight parameter for the first argument.
- $V^2$ (Variable) – Linear weight parameter for the second argument.
- $b$ (Variable) – Bias parameter.

Methods

__call__ (*args: Any, **kwargs: Any) → Any

Call self as a function.

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link

Registers a link hook.

Parameters

- hook (LinkHook) – Link hook to be registered.
- name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

Returns

self

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None

Registers a parameter to the link.

Parameters

- name (str) – Name of the parameter. This name is also used as the attribute name.
- shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- dtype – Data type of the parameter array.
- initializer (initializer) – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent (name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- name (str) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

**addgrads** (*link: chainer.link.Link*) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**
- **link** (*Link*) – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode: str = 'share'*) → chainer.link.Link

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument *mode* below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**
- **mode** (*str*) – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default *mode* is *share*.

**Returns** Copied link object.

**Return type** *Link*

**copyparams** (*link: chainer.link.Link, copy_persistent: bool = True*) → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using *copy.deepcopy()* . The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

**Parameters**
- **link** (*Link*) – Source link object.
- **copy_persistent** (*bool*) – If True, persistent values are also copied. True by default.

**count_params** () → int

Counts the total number of parameters.
This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

### delete_hook

**signature**

```python
delete_hook (name: str) → None
```

**description**

Unregisters the link hook.

**Parameters**

- `name` (str) – The name of the link hook to be unregistered.

### device_resident_accept

**signature**

```python
device_resident_accept (visitor)
```

**description**

Applies the visitor to all the device objects in this instance.

**Parameters**

- `visitor` (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has a custom sub-hierarchy of device resident objects.

### disable_update

**signature**

```python
disable_update () → None
```

**description**

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

### enable_update

**signature**

```python
enable_update () → None
```

**description**

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

### forward

**signature**

```python
forward (e1, e2)
```

**description**

Applies the bilinear function to inputs and the internal parameters.

**Parameters**

- `e1` (Variable) – Left input.
- `e2` (Variable) – Right input.

**Returns** Output variable.

**Return type** Variable

### from_chx

**signature**

```python
from_chx ()
```

**description**

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

### classmethod from_params

**signature**

```python
classmethod from_params (*args, **kwargs)
```

**description**

Initialize link with given parameters.

This method initializes the link with given *N-dimensional arrays*. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

### init_scope

**signature**

```python
init_scope () → Iterator[None]
```

**description**

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

#### Example

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))

links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

    Parameters skipself (bool) – If True, then the generator skips this link and starts with the
    first child link.

    Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

    Parameters skipself (bool) – If True, then the generator skips this link and starts with the
    first child link.

    Returns A generator object that generates all (path, link) pairs.

namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

    Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

    Returns A generator object that generates all (path, parameter) pairs. The paths are relative from
    this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

    Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

    Returns A generator object that generates all parameters.

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already
registered as a parameter, this method removes it from the list of parameter names and re-registers it as a
persistent value.

    Parameters name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The
mode argument means how to copy this link to repeat.

Example
You can repeat the same link multiple times to create a longer Sequential block like this:

class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
with self.init_scope():
    self.conv = L.Convolution2D(
        None, 64, 3, 1, 1, nobias=True)
    self.bn = L.BatchNormalization(64)

def forward(self, x):
    return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')

The `net` object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat** *(int)* – Number of times to repeat.
- **mode** *(str)* – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

serialize *(serializer: chainer.serializer.AbstractSerializer) → None*  
Serializes the link object.

Parameters **serializer** *(AbstractSerializer)* – Serializer object.

to_chx()  
Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

to_cpu() → chainer.device_resident.DeviceResident  
Copies parameter variables and persistent values to CPU.

Depreciated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

to_device *(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident*  
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. See get_device() for available values.
Returns: self

to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Depreciated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

**Parameters**

device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64 () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Depreciated since version v7.0.0: Use to_device() instead.

zero_grads ()
zerograds () → None
Initializes all gradient arrays by zero.

Depreciated since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.

**Attributes**

device
Device instance.

local_link_hooks
Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
Generator of printable specs of this link.
Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.ChildSumTreeLSTM

class chainer.links.ChildSumTreeLSTM(in_size, out_size)
Child-Sum TreeLSTM unit.

Warning: This feature is experimental. The interface can change in the future.

This is a Child-Sum TreeLSTM unit as a chain. This link is a variable arguments function, which compounds the states of all children nodes into the new states of a current (parent) node. states denotes the cell state, c, and the output, h, which are produced by this link. This link doesn’t keep cell and hidden states internally.

For example, this link is called such as func(c1, c2, h1, h2, x) if the number of children nodes is 2, while func(c1, c2, c3, h1, h2, h3, x) if that is 3. This function is independent from an order of children nodes. Thus, the returns of func(c1, c2, h1, h2, x) equal to those of func(c2, c1, h2, h1, x).

Parameters
• in_size (int) – Dimension of input vectors.
• out_size (int) – Dimensionality of cell and output vectors.

Variables
• W_x (chainer.links.Linear) – Linear layer of connections from input vectors.
• W_h_aio (chainer.links.Linear) – Linear layer of connections between (a, i, o) and summation of children’s output vectors. a, i and o denotes input compound, input gate and output gate, respectively. a, input compound, equals to u in the paper by Tai et al.
• W_h_f (chainer.links.Linear) – Linear layer of connections between forget gate f and the output of each child.

See the paper for details: Improved Semantic Representations From Tree-Structured Long Short-Term Memory Networks.
Methods

__call__(\*args: Any, \*\*kwargs: Any) \rightarrow Any
Call self as a function.

__getitem__(name: str) \rightarrow Any
Equivalent to getattr.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) \rightarrow chainer.link.Link
Registers a link hook.

Parameters

- hook (LinkHook) – Link hook to be registered.
- name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns
self

add_link(name: str, link: chainer.link.Link) \rightarrow None
Registers a child link to this chain.

Parameters

- name (str) – Name of the child link. This name is also used as the attribute name.
- link (Link) – The link object to be registered.

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) \rightarrow None
Registers a parameter to the link.

Parameters

- name (str) – Name of the parameter. This name is also used as the attribute name.
- shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- dtype – Data type of the parameter array.
- initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

addPersistent(name: str, value: Any) \rightarrow None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- name (str) – Name of the persistent value. This name is also used for the attribute name.
- value – Value to be registered.

addgrads(link: chainer.link.Link) \rightarrow None
Accumulates gradient values from given link.

4.3. Link and Chains
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link (Link)** – Source link object.

**children () → Iterator[chainer.link.Link]**

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads () → None**

Cleans all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy (mode: str = 'share') → chainer.link.Chain**

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument **mode** below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode (str)** – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their **initialize()** method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default **mode** is share.

**Returns**

Copied link object.

**Return type**

**Link**

**copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None**

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of **BatchNormalization**). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using **copy.deepcopy()**. The old behavior (not copying persistent values) can be reproduced with **copy_persistent=False**.

**Parameters**

- **link (Link)** – Source link object.

- **copy_persistent (bool)** – If True, persistent values are also copied. True by default.

**count_params () → int**

Counts the total number of parameters.

This method counts the total number of scalar values included in all the **Parameters** held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**

The total size of parameters (int)
**delete_hook** *(name: str) → None*

Unregisters the link hook.

**Parameters**

- **name** *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*

Applies the visitor to all the device objects in this instance.

**Parameters**

- **visitor** *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

**enable_update** () → None

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

**forward** (*cshx*)

Returns new cell state and output of Child-Sum TreeLSTM.

**Parameters**

- **cshx** *(list of Variable)* – Variable arguments which include all cell vectors and all output vectors of variable children, and an input vector.

**Returns**

Returns `(c_new, h_new)`, where `c_new` represents new cell state vector, and `h_new` is new output vector.

**Return type**

tuple of ~chainer.Variable

**from_chx**()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** (*args, **kwargs*)

Initialize link with given parameters.

This method initializes the link with given *N*-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope** () → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```
links \(\text{skipself: bool} = \text{False}\) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks \(\text{skipself: bool} = \text{False}\) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

namedparams \(\text{include_uninit: bool} = \text{True}\) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, parameter) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params \(\text{include_uninit: bool} = \text{True}\) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))
```
(continues on next page)
The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

### Parameters

- **n_repeat** *(int)* – Number of times to repeat.
- **mode** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters** serializer *(AbstractSerializer)* – Serializer object.

**to_chx()**

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: `self`

**to_cpu()** → `chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: `self`

**to_device** *(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]])* → `DeviceResident`

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters** device – Target device specifier. See `get_device()` for available values.

Returns: `self`

**to_gpu** *(device: Optional[Union[cuda.Device, int, numpy.integer]] = None)* → `chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

**Parameters**

- `device` – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64()** → `chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

**zerograds()** → None

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

**__eq__(value,/)**

Return `self==value`.

**__ne__(value,/)**

Return `self!=value`.

**__lt__(value,/)**

Return `self<value`.

**__le__(value,/)**

Return `self<=value`.

**__gt__(value,/)**

Return `self>value`.

**__ge__(value,/)**

Return `self>=value`.

**Attributes**

- `device`

  `Device` instance.

- `local_link_hooks`

  Ordered dictionary of registered link hooks.

  Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

- `printable_specs`

  Generator of printable specs of this link.

  Yields `specs (tuple of str and object)` — Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()`. This pair of key and value is used for representing this class or subclass with `__str__()`.

- `update_enabled`

  True if at least one parameter has an update rule enabled.
within_init_scope
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.Convolution1D

class chainer.links.Convolution1D(in_channels, out_channels, ksize, stride=1, pad=0, nobias=False, initialW=None, initial_bias=None, cover_all=False, dilate=1, groups=1)

1-dimensional convolution layer.

Note: This link wraps ConvolutionND by giving 1 to the first argument ndim, so see the details of the behavior in the documentation of ConvolutionND.

Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters
• hook (LinkHook) – Link hook to be registered.
• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters
• name (str) – Name of the parameter. This name is also used as the attribute name.
• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
• dtype – Data type of the parameter array.
• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.
add_persistent \((\text{name}: \text{str}, \text{value}: \text{Any}) \rightarrow \text{None}\)

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- **name** (str) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

addgrads \((\text{link}: \text{chainer.link.Link}) \rightarrow \text{None}\)

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** (Link) – Source link object.

children () \rightarrow \text{Iterator[chainer.link.Link]}

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

cleargrads () \rightarrow \text{None}

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy \(\text{(mode: str = 'share') \rightarrow \text{chainer.link.Link}}\)

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** (str) – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

**Returns**

Copied link object.

**Return type**

Link

copyparams \((\text{link}: \text{chainer.link.Link}, \text{copy_persistent}: \text{bool} = \text{True}) \rightarrow \text{None}\)

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**
• **link** (Link) – Source link object.

• **copy_persistent** (bool) – If True, persistent values are also copied. True by default.

### count_params () ➔ int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

### delete_hook (name: str) ➔ None

Unregisters the link hook.

**Parameters**

- **name** (str) – The name of the link hook to be unregistered.

### device_resident_accept (visitor)

Applies the visitor to all the device objects in this instance.

**Parameters**

- **visitor** (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

### disable_update () ➔ None

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

### enable_update () ➔ None

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

### forward (x)

Applies N-dimensional convolution layer.

**Parameters**

- **x** (Variable) – Input image.

**Returns** Output of convolution.

**Return type** Variable

### from_chx ()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

### classmethod from_params (cls, W, b=None, stride=1, pad=0, nobias=False, *, cover_all=False, dilate=1, groups=1)

Initialize a ConvolutionND with given parameters.

This method uses W and optional b to initialize an N D convolution layer.

**Parameters**

- **W** (Variable or N-dimensional array) – The weight parameter.

- **b** (Variable, N-dimensional array, or None) – The weight parameter.

- **ksize** (int or tuple of ints) – Size of filters (a.k.a. kernels). ksize=k and ksize=(k, k, ..., k) are equivalent.

- **stride** (int or tuple of ints) – Stride of filter application. stride=s and stride=(s, s, ..., s) are equivalent.
• **pad (int or tuple of ints)** – Spatial padding width for input arrays. pad=p and pad=(p, p, ..., p) are equivalent.

• **nobias (bool)** – If True, then this function does not use the bias.

• **cover_all (bool)** – If True, all spatial locations are convoluted into some output pixels. It may make the output size larger. cover_all needs to be False if you want to use cuDNN.

• **dilate (int or tuple of int s)** – Dilation factor of filter applications. dilate=d and dilate=(d, d, ..., d) are equivalent.

• **groups (int)** – The number of groups to use grouped convolution. The default is one, where grouped convolution is not used.

**init_scope () → Iterator[None]**

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for *Chain*) by an assignment. A *Parameter* object can be automatically registered by assigning it to an attribute under this context manager.

---

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a *Parameter* object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

---

**links (skipself: bool = False) → Iterator[chainer.link.Link]**

Returns a generator of all links under the hierarchy.

**Parameters** skipself (bool) – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all links.

**namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]**

Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters** skipself (bool) – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all (path, link) pairs.

**namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]**

Returns a generator of all (path, param) pairs under the hierarchy.

**Parameters** include_uninit (bool) – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]**

Returns a generator of all parameters under the link hierarchy.

**Parameters** include_uninit (bool) – If True, it also generates uninitialized parameters.
Returns A generator object that generates all parameters.

register_persistent \( (\text{name}: \text{str}) \rightarrow \text{None} \)

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If \text{name} has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters \text{name} (\text{str}) – Name of the attribute to be registered.

repeat \( (\text{n\_repeat}: \text{int}, \text{mode}: \text{str} = \text{'init'}) \rightarrow \text{chainer.sequential.Sequential} \)

Repeats this link multiple times to make a \text{Sequential}.

This method returns a \text{Sequential} object which has the same \text{Link} multiple times repeatedly. The \text{mode} argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer \text{Sequential} block like this:

```python
class ConvBNReLU(chainer.Chain):

    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The \text{net} object contains 16 blocks, each of which is \text{ConvBNReLU}. And the \text{mode} was \text{init}, so each block is re-initialized with different parameters. If you give \text{copy} to this argument, each block has same values for its parameters but its object ID is different from others. If it is \text{share}, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- \text{n\_repeat} (\text{int}) – Number of times to repeat.
- \text{mode} (\text{str}) – It should be either \text{init}, \text{copy}, or \text{share}. \text{init} means parameters of each repeated element in the returned \text{Sequential} will be re-initialized, so that all elements have different initial parameters. \text{copy} means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. \text{share} means all the elements which consist the resulting \text{Sequential} object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

serialize \( (\text{serializer}: \text{chainer.serializer.AbstractSerializer}) \rightarrow \text{None} \)

Serializes the link object.

Parameters \text{serializer} (\text{AbstractSerializer}) – Serializer object.
to_chx()
Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.
Returns: self
to_cpu() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Deprecation since version v7.0.0: Use to_device() instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.
Returns: self
to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]] = DeviceResident
Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.
Parameters device – Target device specifier. See get_device() for available values.
Returns: self
to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.
Deprecation since version v7.0.0: Use to_device() instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Deprecation since version v7.0.0: Use to_device() instead.
zerograds() → None
Initializes all gradient arrays by zero.
Deprecation since version v1.15: Use the more efficient cleargrads() instead.
__eq__(value, /)
Return self==value.
__ne__(value, /)
Return self!=value.
__lt__(value, /)
Return self<value.
__le__(value, /)
    Return self<=value.
__gt__(value, /)
    Return self>value.
__ge__(value, /)
    Return self>=value.

Attributes

device
    Device instance.
local_link_hooks
    Ordered dictionary of registered link hooks.
    Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.
printable_specs
    Generator of printable specs of this link.
    Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().
update_enabled
    True if at least one parameter has an update rule enabled.
within_init_scope
    True if the current code is inside of an initialization scope.
    See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.
    Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.Convolution2D

class chainer.links.Convolution2D (self, in_channels, out_channels, ksize=None, stride=1, pad=0, nobias=False, initialW=None, initial_bias=None, *, dilate=1, groups=1)

Two-dimensional convolutional layer.
This link wraps the convolution_2d() function and holds the filter weight and bias vector as parameters.
The output of this function can be non-deterministic when it uses cuDNN. If chainer.configuration.
config.deterministic is True and cuDNN version is >= v3, it forces cuDNN to use a deterministic algorithm.
Convolution links can use a feature of cuDNN called autotuning, which selects the most efficient CNN algorithm for images of fixed-size, can provide a significant performance boost for fixed neural nets. To enable, set chainer.using_config('autotune', True)

Parameters
• **in_channels** (*int or None*) – Number of channels of input arrays. If None, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.

• **out_channels** (*int*) – Number of channels of output arrays.

• **ksize** (*int or pair of ints*) – Size of filters (a.k.a. kernels). ksize=k and ksize=(k, k) are equivalent.

• **stride** (*int or pair of ints*) – Stride of filter applications. stride=s and stride=(s, s) are equivalent.

• **pad** (*int or pair of ints*) – Spatial padding width for input arrays. pad=p and pad=(p, p) are equivalent.

• **nobias** (*bool*) – If True, then this link does not use the bias term.

• **initialW** (*initializer*) – Initializer to initialize the weight. When it is `numpy.ndarray`, its ndim should be 4.

• **initial_bias** (*initializer*) – Initializer to initialize the bias. If None, the bias will be initialized to zero. When it is `numpy.ndarray`, its ndim should be 1.

• **dilate** (*int or pair of ints*) – Dilation factor of filter applications. dilate=d and dilate=(d, d) are equivalent.

• **groups** (*int*) – Number of groups of channels. If the number is greater than 1, input tensor \( W \) is divided into some blocks by this value channel-wise. For each tensor blocks, convolution operation will be executed independently. Input channel size in_channels and output channel size out_channels must be exactly divisible by this value.

See also:

See `chainer.functions.convolution_2d()` for the definition of two-dimensional convolution.

**Variables**

• **W** (*Variable*) – Weight parameter.

• **b** (*Variable*) – Bias parameter.

**Example**

There are several ways to make a Convolution2D link.

Let an input vector \( x \) be:

```python
>>> x = np.arange(1 * 3 * 10 * 10, dtype=np.float32).reshape(...
    1, 3, 10, 10)
```

1. Give the first three arguments explicitly:

```python
>>> l = L.Convolution2D(3, 7, 5)
>>> y = l(x)
>>> y.shape
(1, 7, 6, 6)
```

2. Omit in_channels or fill it with None:

   The below two cases are the same.
```python
>>> l = L.Convolution2D(7, 5)
>>> y = l(x)
>>> y.shape
(1, 7, 6, 6)
```
a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

**add_persistent** (*name: str, value: Any*) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- **name (str)** — Name of the persistent value. This name is also used for the attribute name.
- **value** — Value to be registered.

**addgrads** (*link: chainer.link.Link*) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link (Link)** — Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode: str = 'share'*) → chainer.link.Link

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode (str)** — It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

**Returns**

Copied link object.

**Return type**

Link

**copyparams** (*link: chainer.link.Link, copy_persistent: bool = True*) → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise,
it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** *(Link)* – Source link object.
- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

**count_params** () → int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

- **Returns** The total size of parameters (int)

**delete_hook** *(name: str)* → None

Unregisters the link hook.

- **Parameters** name *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*

Applies the visitor to all the device objects in this instance.

- **Parameters** visitor *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update** () → None

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

**forward** *(x)*

Applies the convolution layer.

- **Parameters** x *(Variable)* – Input image.

- **Returns** Output of the convolution.

- **Return type** Variable

**from_chx** ()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** *(cls, W, b=None, stride=1, pad=0, nobias=False, *, dilate=1, groups=1)*

Initialize a `Convolution2D` with given parameters.

This method uses W and optional b to initialize a 2D convolution layer.

- **Parameters**
  - **W** *(Variable or N-dimensional array)* – The weight parameter.
  - **b** *(Variable, N-dimensional array, or None)* – The bias parameter.
• **stride** (*int or pair of ints*) – Stride of filter applications. `stride=s` and `stride=(s, s)` are equivalent.

• **pad** (*int or pair of ints*) – Spatial padding width for input arrays. `pad=p` and `pad=(p, p)` are equivalent.

• **nobias** (*bool*) – If True, then this link does not use the bias term in spite of whether `b` is given or not.

• **dilate** (*int or pair of ints*) – Dilation factor of filter applications. `dilate=d` and `dilate=(d, d)` are equivalent.

• **groups** (*int*) – Number of groups of channels. If the number is greater than 1, input tensor `W` is divided into some blocks by this value channel-wise. For each tensor blocks, convolution operation will be executed independently. Input channel size `in_channels` and output channel size `out_channels` must be exactly divisible by this value.

**init_scope()** → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links** (*skipself: bool = False*) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

**Parameters** skipself (*bool*) – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all links.

**namedlinks** (*skipself: bool = False*) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters** skipself (*bool*) – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all (path, link) pairs.

**namedparams** (*include_uninit: bool = True*) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

**Parameters** include_uninit (*bool*) – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.
```python
params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.
```

```python
register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.
This is a convenient method to register an existing attribute as a persistent value. If name has been already
registered as a parameter, this method removes it from the list of parameter names and re-registers it as a
persistent value.

Parameters name (str) – Name of the attribute to be registered.
```

```python
repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.
This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Parameters • n_repeat (int) – Number of times to repeat.
• mode (str) – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.
```

Example
You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each
block is re-initialized with different parameters. If you give copy to this argument, each block has same
values for its parameters but its object ID is different from others. If it is share, each block is same to
others in terms of not only parameters but also the object IDs because they are shallow-copied, so that
when the parameter of one block is changed, all the parameters in the others also change.

Parameters
• n_repeat (int) – Number of times to repeat.
• mode (str) – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.
serialize (serializer: chainer.serializer.AbstractSerializer) \to None
Serializes the link object.

Parameters serializer (AbstractSerializer) – Serializer object.

to_chx ()
Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to Chain-
erX, the link implementation must override this method to do so.
Returns: self

to_cpu () \to chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device () instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept () to do so.

Returns: self

to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], Module-
Type, Tuple[ModuleType, int]]) \to DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device () for available values.

Returns: self

to_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) \to
chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device () instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept () to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64 () \to chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device () instead.

zerograds () \to None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads () instead.

__eq__ (value, /)
Return self==value.
__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

device
    Device instance.

local_link_hooks
    Ordered dictionary of registered link hooks.
    Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions,
    link hooks in this property are specific to this link.

printable_specs

update_enabled
    True if at least one parameter has an update rule enabled.

within_init_scope
    True if the current code is inside of an initialization scope.
    See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.
    Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.Convolution3D

class chainer.links.Convolution3D(in_channels, out_channels, ksize, stride=1, pad=0, nobias=False, initialW=None, initial_bias=None, cover_all=False, dilate=1, groups=1)

3-dimensional convolution layer.

Note: This link wraps ConvolutionND by giving 3 to the first argument ndim, so see the details of the behavior in the documentation of ConvolutionND.
Methods

__call__(*args: Any, **kwargs: Any) → Any

Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link

Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.

• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None

Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.

• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• dtype – Data type of the parameter array.

• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.

• value – Value to be registered.

addgrads(link: chainer.link.Link) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters link (Link) – Source link object.

children() → Iterator[chainer.link.Link]

Returns a generator of all child links.

Returns A generator object that generates all child links.
cleargrads () \rightarrow None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode: str = 'share') \rightarrow chainer.link.Link

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters

- **mode** (str) – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

Returns
Copied link object.

Return type
Link

copyparams (link: chainer.link.Link, copy_persistent: bool = True) \rightarrow None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters

- **link** (Link) – Source link object.
- **copy_persistent** (bool) – If True, persistent values are also copied. True by default.

count_params () \rightarrow int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns
The total size of parameters (int)

delete_hook (name: str) \rightarrow None

Unregisters the link hook.

Parameters

- **name** (str) – The name of the link hook to be unregistered.

device_resident_accept (visitor)

Applies the visitor to all the device objects in this instance.

Parameters

- **visitor** (DeviceResidentsVisitor) – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

disable_update() \rightarrow None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to `False`.

enable_update() \rightarrow None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to `True`.

forward(x)
Applies N-dimensional convolution layer.

Parameters

- **x** *(Variable)* – Input image.

Returns
Output of convolution.

Return type
Variable

from_chx()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(cls, W, b=None, stride=1, pad=0, nobias=False, *, cover_all=False, dilate=1, groups=1)
Initialize a `ConvolutionND` with given parameters.

This method uses \( W \) and optional \( b \) to initialize an \( N \) D convolution layer.

Parameters

- **W** *(Variable or N-dimensional array)* – The weight parameter.
- **b** *(Variable, N-dimensional array, or None)* – The weight parameter.
- **ksize** *(int or tuple of ints)* – Size of filters (a.k.a. kernels). \( ksize=k \) and \( ksize=(k, k, \ldots, k) \) are equivalent.
- **stride** *(int or tuple of ints)* – Stride of filter application. \( stride=s \) and \( stride=(s, s, \ldots, s) \) are equivalent.
- **pad** *(int or tuple of ints)* – Spatial padding width for input arrays. \( pad=p \) and \( pad=(p, p, \ldots, p) \) are equivalent.
- **nobias** *(bool)* – If True, then this function does not use the bias.
- **cover_all** *(bool)* – If True, all spatial locations are convoluted into some output pixels. It may make the output size larger. `cover_all` needs to be `False` if you want to use cuDNN.
- **dilate** *(int or tuple of ints)* – Dilation factor of filter applications. \( dilate=d \) and \( dilate=(d, d, \ldots, d) \) are equivalent.
- **groups** *(int)* – The number of groups to use grouped convolution. The default is one, where grouped convolution is not used.

init_scope() \rightarrow Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.
Example

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

`links` *(skipself: bool = False) → Iterator[chainer.link.Link]*

Returns a generator of all links under the hierarchy.

- **Parameters** `skipself` *(bool)* – If True, then the generator skips this link and starts with the first child link.
- **Returns** A generator object that generates all links.

`namedlinks` *(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]*

Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters** `skipself` *(bool)* – If True, then the generator skips this link and starts with the first child link.
- **Returns** A generator object that generates all (path, link) pairs.

`namedparams` *(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]*

Returns a generator of all (path, parameter) pairs. The paths are relative from this link.

- **Parameters** `include_uninit` *(bool)* – If True, it also generates uninitialized parameters.
- **Returns** A generator object that generates all (path, parameter) pairs.

`params` *(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]*

Returns a generator of all parameters under the link hierarchy.

- **Parameters** `include_uninit` *(bool)* – If True, it also generates uninitialized parameters.
- **Returns** A generator object that generates all parameters.

`register_persistent` *(name: str) → None*

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

- **Parameters** `name` *(str)* – Name of the attribute to be registered.

`repeat` *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:
The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat** (`int`) – Number of times to repeat.
- **mode** (`str`) – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

serialize (serializer: chainer.serialization.AbstractSerializer) → None

Serializes the link object.

Parameters serializer (AbstractSerializer) – Serializer object.

to_chx ()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

to_cpu () → chainer.device_resident.Device Resident

Copies parameter variables and persistent values to CPU.

Depreciated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → Device Resident

Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**
- **device** – Target device specifier. See `get_device()` for available values.

Returns: self

**to_gpu**

```python
device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to GPU.

- Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters**
- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64**

```
-> chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

- Deprecated since version v7.0.0: Use `to_device()` instead.

**zerograds**

```
→ None
```

Initializes all gradient arrays by zero.

- Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

**Special Methods**

- `__eq__(value, /)`
  - Return `self==value`

- `__ne__(value, /)`
  - Return `self!=value`

- `__lt__(value, /)`
  - Return `self<value`

- `__le__(value, /)`
  - Return `self<=value`

- `__gt__(value, /)`
  - Return `self>value`

- `__ge__(value, /)`
  - Return `self>=value`
Attributes

**device**
Device instance.

**local_link_hooks**
Ordered dictionary of registered link hooks.
Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

**printable_specs**
Generator of printable specs of this link.
Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

**update_enabled**
True if at least one parameter has an update rule enabled.

**within_init_scope**
True if the current code is inside of an initialization scope.
See init_scope() for the details of the initialization scope.

**xp**
Array module corresponding to the device.
Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

### chainer.links.ConvolutionND

class chainer.links.ConvolutionND(ndim, in_channels, out_channels, ksize=None, stride=1, pad=0, nobias=False, initialW=None, initial_bias=None, cover_all=False, dilate=1, groups=1)

N-dimensional convolution layer.
This link wraps the convolution_nd() function and holds the filter weight and bias vector as parameters.

Convolution links can use a feature of cuDNN called autotuning, which selects the most efficient CNN algorithm for images of fixed-size, can provide a significant performance boost for fixed neural nets. To enable, set chainer.using_config('autotune', True)

**Parameters**

- **ndim** (int) – Number of spatial dimensions.
- **in_channels** (int) – Number of channels of input arrays. If None, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.
- **out_channels** (int) – Number of channels of output arrays.
- **ksize** (int or tuple of ints) – Size of filters (a.k.a. kernels). ksize=k and ksize=(k, k, ..., k) are equivalent.
- **stride** (int or tuple of ints) – Stride of filter application. stride=s and stride=(s, s, ..., s) are equivalent.
- **pad** (int or tuple of ints) – Spatial padding width for input arrays. pad=p and pad=(p, p, ..., p) are equivalent.
- **nobias** *(bool)* – If True, then this function does not use the bias.

- **initialW** *(initializer)* – Initializer to initialize the weight. When it is `numpy.ndarray`, its `ndim` should be \( n + 2 \) where \( n \) is the number of spatial dimensions.

- **initial_bias** *(initializer)* – Initializer to initialize the bias. If None, the bias will be initialized to zero. When it is `numpy.ndarray`, its `ndim` should 1.

- **cover_all** *(bool)* – If True, all spatial locations are convoluted into some output pixels. It may make the output size larger. `cover_all` needs to be False if you want to use cuDNN.

- **dilate** *(int or tuple of int)* – Dilation factor of filter applications. `dilate=d` and `dilate=(d, d, ..., d)` are equivalent.

- **groups** *(int)* – The number of groups to use grouped convolution. The default is one, where grouped convolution is not used.

**See also:**

See `convolution_nd()` for the definition of N-dimensional convolution. See `convolution_2d()` for the definition of two-dimensional convolution.

**Variables**

- **W** *(Variable)* – Weight parameter.

- **b** *(Variable)* – Bias parameter. If `initial_bias` is None, set to None.

**Example**

There are several ways to make a ConvolutionND link.

Let an input vector \( x \) be:

```python
>>> x = np.arange(2 * 5 * 5 * 5, dtype=np.float32).reshape(... 1, 2, 5, 5, 5)
```

1. Give the first four arguments explicitly:

```python
>>> l = L.ConvolutionND(3, 7, 4)
>>> y = l(x)
>>> y.shape
(1, 7, 2, 2, 2)
```

2. Omit `in_channels` or fill it with `None`:

The below two cases are the same.

```python
>>> l = L.ConvolutionND(7, 4)
>>> y = l(x)
>>> y.shape
(1, 7, 2, 2, 2)
```

```python
>>> l = L.ConvolutionND(3, None, 7, 4)
>>> y = l(x)
>>> y.shape
(1, 7, 2, 2, 2)
```
When you omit the second argument, you need to specify the other subsequent arguments from `stride` as keyword arguments. So the below two cases are the same.

```python
>>> l = L.ConvolutionND(3, 7, 4, stride=1, pad=0)
>>> y = l(x)
>>> y.shape
(1, 7, 2, 2, 2)
```

```python
>>> l = L.ConvolutionND(3, None, 7, 4, 1, 0)
>>> y = l(x)
>>> y.shape
(1, 7, 2, 2, 2)
```

## Methods

**__call__** (*args: Any, **kwargs: Any) -> Any

Call self as a function.

**add_hook** (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) -> chainer.link.Link

Registers a link hook.

Parameters

- **hook** (LinkHook) – Link hook to be registered.
- **name** (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

**add_param** (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) -> None

Registers a parameter to the link.

Parameters

- **name** (str) – Name of the parameter. This name is also used as the attribute name.
- **shape** (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer** (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

**add_persistent** (name: str, value: Any) -> None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- **name** (str) – Name of the persistent value. This name is also used for the attribute name.
• **value** – Value to be registered.

**addgrads** ([link: chainer.link.Link] → None)
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** (Link) – Source link object.

**children** () → Iterator[chainer.link.Link]
Returns a generator of all child links.

**Returns**
A generator object that generates all child links.

**cleargrads** () → None
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (mode: str = 'share') → chainer.link.Link
Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument **mode** below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** (str) – It should be either **init**, **copy**, or **share**. **init** means parameter variables under the returned link object is re-initialized by calling their **initialize()** method, so that all the parameters may have different initial values from the original link. **copy** means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. **share** means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default **mode** is **share**.

**Returns**
Copied link object.

**Return type**
Link

**copyparams** ([link: chainer.link.Link, copy_persistent: bool = True]) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of **BatchNormalization**). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using **copy.deepcopy()**. The old behavior (not copying persistent values) can be reproduced with **copy_persistent=False**.

**Parameters**

- **link** (Link) – Source link object.

- **copy_persistent** (bool) – If True, persistent values are also copied. True by default.

**count_params** () → int
Counts the total number of parameters.
This method counts the total number of scalar values included in all the parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**  
The total size of parameters (int)

```python
delete_hook(name: str) → None
```

Unregisters the link hook.

**Parameters**

name (str) – The name of the link hook to be unregistered.

```python
device_resident_accept(visitor)
```

Applies the visitor to all the device objects in this instance.

**Parameters**

visitor (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

```python
disable_update() → None
```

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to `False`.

```python
enable_update() → None
```

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to `True`.

```python
forward(x)
```

Applies N-dimensional convolution layer.

**Parameters**

x (Variable) – Input image.

**Returns**  
Output of convolution.

**Return type**  
Variable

```python
from_chx()
```

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

```python
classmethod from_params(cls, W, b=None, stride=1, pad=0, nobias=False, *, cover_all=False, dilate=1, groups=1)
```

Initialize a `ConvolutionND` with given parameters.

This method uses `W` and optional `b` to initialize an N D convolution layer.

**Parameters**

- W (Variable or N-dimensional array) – The weight parameter.
- b (Variable, N-dimensional array, or None) – The weight parameter.
- ksize (int or tuple of ints) – Size of filters (a.k.a. kernels). ksize=k and ksize=(k, k, ..., k) are equivalent.
- stride (int or tuple of ints) – Stride of filter application. stride=s and stride=(s, s, ..., s) are equivalent.
- pad (int or tuple of ints) – Spatial padding width for input arrays. pad=p and pad=(p, p, ..., p) are equivalent.
- nobias (bool) – If True, then this function does not use the bias.
• **cover_all** (*bool*) – If True, all spatial locations are convoluted into some output pixels. It may make the output size larger. **cover_all** needs to be **False** if you want to use cuDNN.

• **dilate** (*int* or *tuple of int s*) – Dilation factor of filter applications. dilate=d and dilate=(d, d, ..., d) are equivalent.

• **groups** (*int*) – The number of groups to use grouped convolution. The default is one, where grouped convolution is not used.

**init_scope** () → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for *Chain*) by an assignment. A *Parameter* object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the **init_scope** method, we can simply assign a *Parameter* object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links** (*skipself: bool = False*) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

- **Parameters skipself** (*bool*) – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all links.

**namedlinks** (*skipself: bool = False*) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters skipself** (*bool*) – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all (path, link) pairs.

**namedparams** (*include_uninit: bool = True*) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, parameter) pairs under the hierarchy.

- **Parameters include_uninit** (*bool*) – If True, it also generates uninitialized parameters.

- **Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** (*include_uninit: bool = True*) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

- **Parameters include_uninit** (*bool*) – If True, it also generates uninitialized parameters.

- **Returns** A generator object that generates all parameters.
**register_persistent** *(name: str) → None*

Registers an attribute of a given name as a persistent value. This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- `name` *(str)* − Name of the attribute to be registered.

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a `Sequential`. This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- `n_repeat` *(int)* − Number of times to repeat.

- `mode` *(str)* − It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters**

- `serializer` *(AbstractSerializer)* − Serializer object.

**to_chx** ()

Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

to_cpu() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device() for available values.

Returns: self

to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

zerograds() → None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value,/) Return self==value.

__ne__(value,/) Return self!=value.

__lt__(value,/) Return self<value.

__le__(value,/) Return self<=value.
__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

device
    Device instance.

local_link_hooks
    Ordered dictionary of registered link hooks.
    Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
    Generator of printable specs of this link.

    Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
    True if at least one parameter has an update rule enabled.

within_init_scope
    True if the current code is inside of an initialization scope.
    See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.

    Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.Deconvolution1D

class chainer.links.Deconvolution1D(in_channels, out_channels, ksize, stride=1, pad=0, nobias=False, outsize=None, initialW=None, initial_bias=None, dilate=1, groups=1)

    1-dimensional deconvolution layer.

Note: This link wraps DeconvolutionND by giving 1 to the first argument ndim, so see the details of the behavior in the documentation of DeconvolutionND.
Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

  • hook (LinkHook) – Link hook to be registered.
  • name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

  • name (str) – Name of the parameter. This name is also used as the attribute name.
  • shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
  • dtype – Data type of the parameter array.
  • initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

  • name (str) – Name of the persistent value. This name is also used for the attribute name.
  • value – Value to be registered.

addgrads(link: chainer.link.Link) → None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters link (Link) – Source link object.

children() → Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns A generator object that generates all child links.
clearGrads() \rightarrow \text{None}

Cleans all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

\textbf{copy (mode: str = 'share')} \rightarrow \text{chainer.link.Link}

Copies the link hierarchy to a new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument \textit{mode} below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

\textbf{Parameters} \textit{mode} (str) – It should be either \textit{init}, \textit{copy}, or \textit{share}. \textit{init} means parameter variables under the returned link object are re-initialized by calling their \textit{initialize()} method, so that all the parameters may have different initial values from the original link.\textit{copy} means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have the same initial values but can be changed independently. \textit{share} means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default \textit{mode} is \textit{share}.

\textbf{Returns} Copied link object.

\textbf{Return type} Link

\textbf{copyParams (link: chainer.link.Link, copy_persistent: bool = True)} \rightarrow \text{None}

Copies all parameters from the given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

\textit{From v5.0.0:} this method also copies the persistent values (e.g. the moving statistics of \textit{BatchNormalization}). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using \textit{copy.deepcopy()}. The old behavior (not copying persistent values) can be reproduced with \textit{copy_persistent=False}.

\textbf{Parameters}

- \textit{link} (Link) – Source link object.
- \textit{copy_persistent} (bool) – If \text{True}, persistent values are also copied. \text{True} by default.

\textbf{count_params} () \rightarrow \text{int}

Counts the total number of parameters.

This method counts the total number of scalar values included in all the \textit{Parameters} held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

\textbf{Returns} The total size of parameters (int)

delete_hook (name: str) \rightarrow \text{None}

Unregisters the link hook.

\textbf{Parameters} \textit{name} (str) – The name of the link hook to be unregistered.

device_resident_accept (visitor)

Applies the visitor to all the device objects in this instance.

\textbf{Parameters} \textit{visitor} (DeviceResidentsVisitor) – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update() → None**
Disables update rules of all parameters under the link hierarchy.
This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

**enable_update() → None**
Enables update rules of all parameters under the link hierarchy.
This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

**forward(x)**

**from_chx()**
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params(*args, **kwargs)**
Initialize link with given parameters.
This method initializes the link with given N-dimensional arrays. Arguments includes
- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope() → Iterator[None]**
Creates an initialization scope.
This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**
In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links** *(skipself: bool = False) → Iterator[chainer.link.Link]*
Returns a generator of all links under the hierarchy.

**Parameters skipself** *(bool) – If True, then the generator skips this link and starts with the first child link.*

**Returns** A generator object that generates all links.

**namedlinks** *(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]*
Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters skipself** *(bool) – If True, then the generator skips this link and starts with the first child link.*

**Returns** A generator object that generates all (path, link) pairs.
**namedparams** *(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]*

Returns a generator of all (path, param) pairs under the hierarchy.

- **Parameters**
  - **include_uninit** *(bool)* — If True, it also generates uninitialized parameters.

- **Returns**
  - A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** *(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]*

Returns a generator of all parameters under the link hierarchy.

- **Parameters**
  - **include_uninit** *(bool)* — If True, it also generates uninitialized parameters.

- **Returns**
  - A generator object that generates all parameters.

**register_persistent** *(name: str) → None*

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

- **Parameters**
  - **name** *(str)* — Name of the attribute to be registered.

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):

    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** *(int)* — Number of times to repeat.
- **mode** *(str)* — It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all
elements have different initial parameters. copy means that the parameters will not be
re-initialized but object itself will be deep-copied, so that all elements have same initial
parameters but can be changed independently. share means all the elements which con-
sist the resulting Sequential object are same object because they are shallow-copied,
so that all parameters of elements are shared with each other.

```
serialize (serializer: chainer.serializer.AbstractSerializer) → None
```
Serializes the link object.

Parameters serializer (AbstractSerializer) – Serializer object.

```
to_chx ()
```
Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to Chain-
erX, the link implementation must override this method to do so.

Returns: self

```
to_cpu () → chainer.device_resident.DeviceResident
```
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU,
the link implementation should override device_resident_accept() to do so.

Returns: self

```
to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], Module-
Type, Tuple[ModuleType, int]]) → DeviceResident
```
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the
device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device() for available values.

Returns: self

```
to_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
```
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU,
the link implementation must override device_resident_accept() to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use to_device
to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self

```
to_intel64 () → chainer.device_resident.DeviceResident
```
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.
zerograds() → None

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.

__le__(value, /)

Return self<=value.

__gt__(value, /)

Return self>value.

__ge__(value, /)

Return self>=value.

Attributes

device

Device instance.

local_link_hooks

Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs

Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__() . This pair of key and value is used for representing this class or subclass with __str__() .

update_enabled

True if at least one parameter has an update rule enabled.

within_init_scope

True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.
**chainer.links.Deconvolution2D**

```python
class chainer.links.Deconvolution2D(self, in_channels, out_channels, ksize=None, stride=1, pad=0, nobias=False, outsize=None, initialW=None, initial_bias=None, *, dilate=1, groups=1)
```

Two dimensional deconvolution function.

This link wraps the `deconvolution_2d()` function and holds the filter weight and bias vector as parameters.

Deconvolution links can use a feature of cuDNN called autotuning, which selects the most efficient CNN algorithm for images of fixed-size, can provide a significant performance boost for fixed neural nets. To enable, set `chainer.using_config('autotune', True)`

**Parameters**

- **in_channels (int or None)** – Number of channels of input arrays. If `None`, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.
- **out_channels (int)** – Number of channels of output arrays.
- **ksize (int or pair of ints)** – Size of filters (a.k.a. kernels). `ksize=k` and `ksize=(k, k)` are equivalent.
- **stride (int or pair of ints)** – Stride of filter applications. `stride=s` and `stride=(s, s)` are equivalent.
- **pad (int or pair of ints)** – Spatial padding width for input arrays. `pad=p` and `pad=(p, p)` are equivalent.
- **nobias (bool)** – If `True`, then this function does not use the bias term.
- **outsize (tuple)** – Expected output size of deconvolutional operation. It should be pair of height and width `(out_H, out_W)`. Default value is `None` and the outsize is estimated by input size, stride and pad.
- **initialW (initializer)** – Initializer to initialize the weight. When it is `numpy.ndarray`, its `ndim` should be 4.
- **initial_bias (initializer)** – Initializer to initialize the bias. If `None`, the bias will be initialized to zero. When it is `numpy.ndarray`, its `ndim` should be 1.
- **dilate (int or tuple of int)** – Dilation factor of filter applications. `dilate=d` and `dilate=(d, d)` are equivalent.
- **groups (int)** – The number of groups to use grouped deconvolution. The default is one, where grouped deconvolution is not used.

The filter weight has four dimensions `(c_I, c_O, k_H, k_W)` which indicate the number of input channels, output channels, height and width of the kernels, respectively. The filter weight is initialized with i.i.d. Gaussian random samples, each of which has zero mean and deviation $\sqrt{1/(c_I k_H k_W)}$ by default.

The bias vector is of size `c_O`. Its elements are initialized by `bias` argument. If `nobias` argument is set to `True`, then this function does not hold the bias parameter.

The output of this function can be non-deterministic when it uses cuDNN. If `chainer.configuration.config.cudnn_deterministic` is `True` and cuDNN version is `>= v3`, it forces cuDNN to use a deterministic algorithm.

See also:

See `chainer.functions.deconvolution_2d()` for the definition of two-dimensional convolution.

See also:
There are several ways to make a Deconvolution2D link.

Let an input vector $x$ be:

```python
>>> x = np.arange(1 * 3 * 10 * 10, dtype=np.float32).reshape(... 1, 3, 10, 10)
```

1. Give the first three arguments explicitly:
   
   In this case, all the other arguments are set to the default values.
   
   ```python
   >>> l = L.Deconvolution2D(3, 7, 4)
   >>> y = l(x)
   >>> y.shape
   (1, 7, 13, 13)
   ```

2. Omit `in_channels` or fill it with `None`:
   
   The below two cases are the same.
   
   ```python
   >>> l = L.Deconvolution2D(7, 4)
   >>> y = l(x)
   >>> y.shape
   (1, 7, 13, 13)
   ```

   ```python
   >>> l = L.Deconvolution2D(None, 7, 4)
   >>> y = l(x)
   >>> y.shape
   (1, 7, 13, 13)
   ```

   When you omit the first argument, you need to specify the other subsequent arguments from `stride` as keyword arguments. So the below two cases are the same.

   ```python
   >>> l = L.Deconvolution2D(None, 7, 4, 2, 1)
   >>> y = l(x)
   >>> y.shape
   (1, 7, 20, 20)
   ```

   ```python
   >>> l = L.Deconvolution2D(7, 4, stride=2, pad=1)
   >>> y = l(x)
   >>> y.shape
   (1, 7, 20, 20)
   ```
Methods

__call__(*args: Any, **kwargs: Any) → Any
   Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
   Registers a link hook.

   Parameters
     • hook (LinkHook) – Link hook to be registered.
     • name (str) – Name of the link hook. The name must be unique among link hooks
       registered to this link. If None, the default name of the link hook is used.

   Returns self

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types_AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
   Registers a parameter to the link.

   Parameters
     • name (str) – Name of the parameter. This name is also used as the attribute name.
     • shape (int or tuple of ints) – Shape of the parameter array. If it is omitted,
       the parameter variable is left uninitialized.
     • dtype – Data type of the parameter array.
     • initializer (initializer) – If it is not None, the data is initialized with the given
       initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as
       a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a
       scalar, in which case the data array will be filled by this scalar. Note that float32 is used in
       this case.

addPersistent(name: str, value: Any) → None
   Registers a persistent value to the link.

   The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute
   of the link.

   Parameters
     • name (str) – Name of the persistent value. This name is also used for the attribute name.
     • value – Value to be registered.

addgrads(link: chainer.link.Link) → None
   Accumulates gradient values from given link.

   This method adds each gradient array of the given link to corresponding gradient array of this link. The
   accumulation is even done across host and different devices.

   Parameters link (Link) – Source link object.

children() → Iterator[chainer.link.Link]
   Returns a generator of all child links.

   Returns A generator object that generates all child links.
**cleargrads** () → None
Clears all gradient arrays.
This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode: str = 'share'*) → chainer.link.Link
Copies the link hierarchy to new one.
The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument *mode* below.
The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters

- **mode** (str) – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default *mode* is *share*.

Returns Copied link object.

Return type Link

**copyparams** (*link: chainer.link.Link, copy_persistent: bool = True*) → None
Copies all parameters from given link.
This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

Parameters

- **link** (Link) – Source link object.
- **copy_persistent** (bool) – If True, persistent values are also copied. True by default.

**count_params** () → int
Counts the total number of parameters.
This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.
If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

**delete_hook** (*name: str*) → None
Unregisters the link hook.

Parameters

- **name** (str) – The name of the link hook to be unregistered.

**device_resident_accept** (*visitor*)
Applies the visitor to all the device objects in this instance.

Parameters

- **visitor** (DeviceResidentsVisitor) – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update() → None**

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update() → None**

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

**forward(x)**

**from_chx()**

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params(*args, **kwargs)**

Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope() → Iterator[None]**

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links (skipself: bool = False) → Iterator[chainer.link.Link]**

Returns a generator of all links under the hierarchy.

- **Parameters skipself (bool)** – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all links.

**namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]**

Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters skipself (bool)** – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all (path, link) pairs.
**namedparams** (*include_uninit: bool = True*) \(\rightarrow\) Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

**Parameters**

**include_uninit** (*bool*) – If True, it also generates uninitialized parameters.

**Returns**

A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** (*include_uninit: bool = True*) \(\rightarrow\) Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

**Parameters**

**include_uninit** (*bool*) – If True, it also generates uninitialized parameters.

**Returns**

A generator object that generates all parameters.

**register_persistent** (*name: str*) \(\rightarrow\) None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

**name** (*str*) – Name of the attribute to be registered.

**repeat** (*n_repeat: int, mode: str = 'init') \(\rightarrow\) chainer.sequential.Sequential

Repeats this link multiple times to make a Sequential. This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.
elements have different initial parameters. **copy** means that the parameters will not be
re-initialized but object itself will be deep-copied, so that all elements have same initial
parameters but can be changed independently. **share** means all the elements which con-
sist the resulting **Sequential** object are same object because they are shallow-copied,
so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters**

**serializer** *(AbstractSerializer)* – Serializer object.

**to_chx** *

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to Chain-
erX, the link implementation must override this method to do so.

Returns: self

**to_cpu** *

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU,
the link implementation should override **device_resident_accept** to do so.

Returns: self

**to_device** *(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], Module-
Type, Tuple[ModuleType, int]] → DeviceResident)*

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the
device, the link implementation must override this method to do so.

**Parameters**

**device** – Target device specifier. See **get_device** for available values.

Returns: self

**to_gpu** *(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident)*

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use **to_device** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU,
the link implementation must override **device_resident_accept** to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use **to_device**
to perform inter-GPU transfer.

**Parameters**

**device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** *

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device** instead.
zerograds() \rightarrow \text{None}

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

\_\_eq\_\_\_ (value, /)

Return self==value.

\_\_ne\_\_\_ (value, /)

Return self!=value.

\_\_lt\_\_\_ (value, /)

Return self<value.

\_\_le\_\_\_ (value, /)

Return self<=value.

\_\_gt\_\_\_ (value, /)

Return self>value.

\_\_ge\_\_\_ (value, /)

Return self>==value.

**Attributes**

**device**

Device instance.

**local_link_hooks**

Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

**printable_specs**

Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the \_\_init\_\_(). This pair of key and value is used for representing this class or subclass with \_\_str\_\_().

**update_enabled**

True if at least one parameter has an update rule enabled.

**within_init_scope**

True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

**xp**

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.
class chainer.links.Deconvolution3D(in_channels, out_channels, ksize, stride=1, pad=0, nobias=False, outsize=None, initialW=None, initial_bias=None, dilate=1, groups=1)

3-dimensional deconvolution layer.

Note: This link wraps DeconvolutionND by giving 3 to the first argument ndim, so see the details of the behavior in the documentation of DeconvolutionND.

Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.
• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.
• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
• dtype – Data type of the parameter array.
• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.
• value – Value to be registered.

4.3. Link and Chains 387
addgrads (link: chainer.link.Link) \to None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters link (Link) – Source link object.

children () \rightarrow Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads () \rightarrow None
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode: str = 'share') \rightarrow chainer.link.Link
Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters mode (str) – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

Returns Copied link object.

Return type Link

copyparams (link: chainer.link.Link, copy_persistent: bool = True) \rightarrow None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters

* link (Link) – Source link object.

* copy_persistent (bool) – If True, persistent values are also copied. True by default.

count_params () \rightarrow int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.
If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

```python
delete_hook (name: str) → None
```

Unregisters the link hook.

**Parameters**

- `name (str)` – The name of the link hook to be unregistered.

```python
device_resident_accept (visitor)
```

Applies the visitor to all the device objects in this instance.

**Parameters**

- `visitor (DeviceResidentsVisitor) – Visitor`

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

```python
disable_update () → None
```

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

```python
enable_update () → None
```

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

```python
forward (x)
```

```python
from_chx ()
```

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

```python
classmethod from_params (*args, **kwargs)
```

Initialize link with given parameters.

This method initializes the link with given $N$-dimensional arrays. Arguments includes

- some parameters for a specific link.

- constants such as stride width of a convolutional layer.

```python
init_scope () → Iterator[None]
```

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

```python
links (skipself: bool = False) → Iterator[chainer.link.Link]
```

Returns a generator of all links under the hierarchy.
Parameters `skipself` (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

`namedlinks` (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters `skipself` (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

`namedparams` (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters `include_uninit` (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

`params` (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

Parameters `include_uninit` (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

`register_persistent` (name: str) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters `name` (str) – Name of the attribute to be registered.

`repeat` (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same
values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat (int)** – Number of times to repeat.
- **mode (str)** – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** (serializer: chainer.serializer.AbstractSerializer) → None
Serializes the link object.

**Parameters**

- **serialize** (AbstractSerializer) – Serializer object.

**to_chx**()
Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu**() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

**to_device** (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See get_device() for available values.

Returns: self

**to_gpu** (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.
Warning: This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

Parameters

**device** – Target device specifier. If omitted, the current device is used.

Returns: self

`to_intel64()` ➔ `chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

`zerograds()` ➔ `None`

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

___eq__(value, /)

Return `self==value`.

___ne__(value, /)

Return `self!=value`.

___lt__(value, /)

Return `self<value`.

___le__(value, /)

Return `self<=value`.

___gt__(value, /)

Return `self>value`.

___ge__(value, /)

Return `self>=value`.

Attributes

**device**

*Device* instance.

**local_link_hooks**

Ordered dictionary of registered link hooks.

Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

**printable_specs**

Generator of printable specs of this link.

Yields `specs (tuple of str and object)` – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()`. This pair of key and value is used for representing this class or subclass with `__str__()`. 

**update_enabled**

True if at least one parameter has an update rule enabled.

**within_init_scope**

True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.
XP

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.

**chainer.links.DeconvolutionND**

```python
class chainer.links.DeconvolutionND(ndim, in_channels, out_channels, ksize=None, stride=1, pad=0, nobias=False, outsize=None, initialW=None, initial_bias=None, dilate=1, groups=1)
```

N-dimensional deconvolution function.

This link wraps `deconvolution_nd()` function and holds the filter weight and bias vector as its parameters.

Deconvolution links can use a feature of cuDNN called autotuning, which selects the most efficient CNN algorithm for images of fixed-size, can provide a significant performance boost for fixed neural nets. To enable, set `chainer.using_config('autotune', True)`

**Parameters**

- `ndim (int)` – Number of spatial dimensions.
- `in_channels (int)` – Number of channels of input arrays. If `None`, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.
- `out_channels (int)` – Number of channels of output arrays.
- `ksize (int or tuple of ints)` – Size of filters (a.k.a. kernels). `ksize=k` and `ksize=(k, k, ..., k)` are equivalent.
- `stride (int or tuple of ints)` – Stride of filter application. `stride=s` and `stride=(s, s, ..., s)` are equivalent.
- `pad (int or tuple of ints)` – Spatial padding width for input arrays. `pad=p` and `pad=(p, p, ..., p)` are equivalent.
- `nobias (bool)` – If `True`, then this function does not use the bias.
- `outsize (tuple of ints)` – Expected output size of deconvolutional operation. It should be a tuple of ints that represents the output size of each dimension. Default value is `None` and the outsize is estimated with input size, stride and pad.
- `initialW (initializer)` – Initializer to initialize the weight. When it is `numpy.ndarray`, its `ndim` should be `n + 2` where `n` is the number of spatial dimensions.
- `initial_bias (initializer)` – Initializer to initialize the bias. If `None`, the bias will be initialized to zero. When it is `numpy.ndarray`, its `ndim` should be 1.
- `dilate (int or tuple of int)` – Dilation factor of filter applications. `dilate=d` and `dilate=(d, d, ..., d)` are equivalent.
- `groups (int)` – The number of groups to use grouped convolution. The default is one, where grouped convolution is not used.

**See also:**

`deconvolution_nd()`

**Variables**

- `W (Variable)` – Weight parameter.
Example

There are several ways to make a DeconvolutionND link.

Let an input vector $x$ be:

```python
>>> x = np.arange(2 * 5 * 5 * 5, dtype=np.float32).reshape(...
        1, 2, 5, 5, 5)
```

1. Give the first four arguments explicitly:

```python
>>> l = L.DeconvolutionND(3, 2, 7, 4)
>>> y = l(x)
>>> y.shape
(1, 7, 8, 8, 8)
```

2. Omit `in_channels` or fill it with `None`:

The below two cases are the same.

```python
>>> l = L.DeconvolutionND(3, 7, 4)
>>> y = l(x)
>>> y.shape
(1, 7, 8, 8, 8)

>>> l = L.DeconvolutionND(3, None, 7, 4)
>>> y = l(x)
>>> y.shape
(1, 7, 8, 8, 8)
```

When you omit the second argument, you need to specify the other subsequent arguments from `stride` as keyword arguments. So the below two cases are the same.

```python
>>> l = L.DeconvolutionND(3, 7, 4, stride=2, pad=1)
>>> y = l(x)
>>> y.shape
(1, 7, 10, 10, 10)

>>> l = L.DeconvolutionND(3, None, 7, 4, 2, 1)
>>> y = l(x)
>>> y.shape
(1, 7, 10, 10, 10)
```
Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.

• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.

• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• dtype – Data type of the parameter array.

• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.

• value – Value to be registered.

addgrads(link: chainer.link.Link) → None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters link (Link) – Source link object.

children() → Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns A generator object that generates all child links.
**cleargrads () → None**
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy (mode: str = 'share') → chainer.link.Link**
Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

- **Parameters mode (str)** – It should be either `init`, `copy`, or `share`. `init` means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. `copy` means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. `share` means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default `mode` is `share`.

- **Returns** Copied link object.

- **Return type** `Link`

**copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None**
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g., the moving statistics of `BatchNormalization`). If the persistent value is an `ndarray`, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

- **Parameters**
  - **link (Link)** – Source link object.
  - **copy_persistent (bool)** – If `True`, persistent values are also copied. Default: `True`.

**count_params () → int**
Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

- **Returns** The total size of parameters (int)

**delete_hook (name: str) → None**
Unregisters the link hook.

- **Parameters name (str)** – The name of the link hook to be unregistered.

**device_resident_accept (visitor)**
Applies the visitor to all the device objects in this instance.

- **Parameters visitor (DeviceResidentsVisitor)** – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update**() → None

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

**enable_update**() → None

 Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

**forward**(x)

**from_chx**()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params**(\*\*args, **kwargs)

Initialize link with given parameters.

This method initializes the link with given *N*-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope**() → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

### Example

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links**(skipself: bool = False) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

- **Parameters skipself**(bool) – If `True`, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all links.

**namedlinks**(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters skipself**(bool) – If `True`, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all (path, link) pairs.
**namedparams** *(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]*

Returns a generator of all (path, param) pairs under the hierarchy.

**Parameters**

*include_uninit* *(bool) – If True, it also generates uninitialized parameters.*

**Returns**

A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** *(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]*

Returns a generator of all parameters under the link hierarchy.

**Parameters**

*include_uninit* *(bool) – If True, it also generates uninitialized parameters.*

**Returns**

A generator object that generates all parameters.

**register_persistent** *(name: str) → None*

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

*name* *(str) – Name of the attribute to be registered.*

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

* `n_repeat` *(int) – Number of times to repeat.*

* `mode` *(str) – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all
elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** (serializer: chainer.serializer.AbstractSerializer) → None
Serializes the link object.

**Parameters**

- **serializer** (AbstractSerializer) – Serializer object.

**to_chx** ()
Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu** () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

**to_device** (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See `get_device()` for available values.

Returns: self

**to_gpu** (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.
zerograds() → None

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>==value.

Attributes

device
Device instance.

local_link_hooks
Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__() method. This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.
Two-dimensional deformable convolutional layer.

This link wraps the convolution layer for offset prediction and the deformable_convolution_2d_sampler() function. This also holds the filter weights and bias vectors of two convolution layers as parameters.

Parameters

- **in_channels** (*int*) – Number of channels of input arrays. If None, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.

- **out_channels** (*int*) – Number of channels of output arrays.

- **ksize** (*int or pair of ints*) – Size of filters (a.k.a. kernels). ksize=k and ksize=(k, k) are equivalent.

- **stride** (*int or pair of ints*) – Stride of filter applications. stride=s and stride=(s, s) are equivalent.

- **pad** (*int or pair of ints*) – Spatial padding width for input arrays. pad=p and pad=(p, p) are equivalent.

- **offset_nobias** (*bool*) – If True, then this link does not use the bias term for the first convolution layer.

- **offset_initialW** (*initializer*) – Initializer to initialize the weight of the first convolution layer. When it is numpy.ndarray, its ndim should be 4.

- **offset_initial_bias** (*initializer*) – Initializer to initialize the bias of the first convolution layer. If None, the bias will be initialized to zero. When it is numpy.ndarray, its ndim should be 1.

- **deform_nobias** (*bool*) – If True, then this link does not use the bias term for the second convolution layer.

- **deform_initialW** (*initializer*) – Initializer to initialize the weight for the second convolution layer. When it is numpy.ndarray, its ndim should be 4.

- **deform_initial_bias** (*initializer*) – Initializer to initialize the bias for the second convolution layer. If None, the bias will be initialized to zero. When it is numpy.ndarray, its ndim should be 1.

See also:

See chainer.functions.deformable_convolution_2d_sampler().
Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

__getitem__(name: str) → Any
Equivalent to getattr.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.
• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self

add_link(name: str, link: chainer.link.Link) → None
Registers a child link to this chain.

Parameters

• name (str) – Name of the child link. This name is also used as the attribute name.
• link (Link) – The link object to be registered.

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.
• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
• dtype – Data type of the parameter array.
• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.
• value – Value to be registered.

addgrads(link: chainer.link.Link) → None
Accumulates gradient values from given link.
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** (Link) – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (mode: str = 'share') → chainer.link.Chain

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument *mode* below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** (str) – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default *mode* is *share*.

**Returns**

Copied link object.

**Return type** Link

**copyparams** (link: chainer.link.Link, copy_persistent: bool = True) → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** (Link) – Source link object.

- **copy_persistent** (bool) – If True, persistent values are also copied. True by default.

**count_params** () → int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**

The total size of parameters (int)
**delete_hook** *(name: str) → None*

Unregisters the link hook.

**Parameters**

- **name** *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*

Applies the visitor to all the device objects in this instance.

**Parameters**

- **visitor** *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

**enable_update** () → None

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

**forward** *(x)*

Applies the deformable convolution.

**Parameters**

- **x** *(Variable)* – Input image.

**Returns**

Output of the deformable convolution.

**Return type** *(Variable)*

**from_chx** ()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** (*args, **kwargs)*

Initialize link with given parameters.

This method initializes the link with given *N*-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope** () → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()

        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```
**links** *(skipself: bool = False) → Iterator[chainer.link.Link]*

Returns a generator of all links under the hierarchy.

**Parameters**

- **skipself** *(bool)* – If True, then the generator skips this link and starts with the first child link.

**Returns**

A generator object that generates all links.

**namedlinks** *(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]*

Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters**

- **skipself** *(bool)* – If True, then the generator skips this link and starts with the first child link.

**Returns**

A generator object that generates all (path, link) pairs.

**namedparams** *(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]*

Returns a generator of all (path, parameter) pairs under the hierarchy.

**Parameters**

- **include_uninit** *(bool)* – If True, it also generates uninitialized parameters.

**Returns**

A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** *(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]*

Returns a generator of all parameters under the link hierarchy.

**Parameters**

- **include_uninit** *(bool)* – If True, it also generates uninitialized parameters.

**Returns**

A generator object that generates all parameters.

**register_persistent** *(name: str) → None*

Registers a attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name** *(str)* – Name of the attribute to be registered.

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

4.3. Link and Chains 405
The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat** (int) – Number of times to repeat.
- **mode** (str) – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** (serializer: chainer.serializer.AbstractSerializer) → None

Serializes the link object.

Parameters **serializer** (AbstractSerializer) – Serializer object.

**to_chx**()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu**() → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device**() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

**to_device** (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. See **get_device**() for available values.

Returns: self

**to_gpu** (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use **to_device**() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.
Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

zerograd() → None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrad() instead.

__eq__(value,)
Return self==value.

__ne__(value,)
Return self!=value.

__lt__(value,)
Return self<value.

__le__(value,)
Return self<=value.

__gt__(value,)
Return self>value.

__ge__(value,)
Return self>=value.

Attributes

device
Device instance.

local_link_hooks
Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__() . This pair of key and value is used for representing this class or subclass with __str__() .

update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.
xp

Array module corresponding to the device. Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.DepthwiseConvolution2D

class chainer.links.DepthwiseConvolution2D(in_channels, channel_multiplier, ksize, stride=1, pad=0, nobias=False, initialW=None, initial_bias=None)

Two-dimensional depthwise convolutional layer. This link wraps the depthwise_convolution_2d() function and holds the filter weight and bias vector as parameters.

Parameters

• in_channels (int) – Number of channels of input arrays. If None, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.

• channel_multiplier (int) – Channel multiplier number. Number of output arrays equal in_channels * channel_multiplier.

• ksize (int or pair of ints) – Size of filters (a.k.a. kernels). ksize=k and ksize=(k, k) are equivalent.

• stride (int or pair of ints) – Stride of filter applications. stride=s and stride=(s, s) are equivalent.

• pad (int or pair of ints) – Spatial padding width for input arrays. pad=p and pad=(p, p) are equivalent.

• nobias (bool) – If True, then this link does not use the bias term.

• initialW (initializer) – Initializer to initialize the weight. When it is numpy.ndarray, its ndim should be 4.

• initial_bias (initializer) – Initializer to initialize the bias. If None, the bias will be initialized to zero. When it is numpy.ndarray, its ndim should be 1.

See also:

See chainer.functions.depthwise_convolution_2d().

Variables

• W (Variable) – Weight parameter.

• b (Variable) – Bias parameter.
Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.

• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.

• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• dtype – Data type of the parameter array.

• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.

• value – Value to be registered.

addgrads(link: chainer.link.Link) → None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters link (Link) – Source link object.

children() → Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns A generator object that generates all child links.
cleargrads () → None
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode: str = 'share') → chainer.link.Link
Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters

- **mode** (str) – It should be either **init**, **copy**, or **share**. **init** means parameter variables under the returned link object is re-initialized by calling their **initialize()** method, so that all the parameters may have different initial values from the original link. **copy** means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. **share** means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is **share**.

Returns  Copied link object.

Return type  Link

copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of **BatchNormalization**). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using **copy.deepcopy()**. The old behavior (not copying persistent values) can be reproduced with **copy_persistent=False**.

Parameters

- **link** (Link) – Source link object.
- **copy_persistent** (bool) – If True, persistent values are also copied. True by default.

count_params () → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the **Parameters** held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns  The total size of parameters (int)

delete_hook (name: str) → None
Unregisters the link hook.

Parameters

- **name** (str) – The name of the link hook to be unregistered.

device_resident_accept (visitor)
Applies the visitor to all the device objects in this instance.

Parameters

- **visitor** (**DeviceResidentsVisitor**) – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update() → None**
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update() → None**
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

**forward(x)**
Applies the depthwise convolution layer.

**Parameters**
x (chainer.Variable or numpy.ndarray or cupy.ndarray) – Input image.

**Returns**
Output of the depthwise convolution.

**Return type** Variable

**from_chx()**
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params(*args, **kwargs)**
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope() → Iterator[None]**
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

### Example

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links**(skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

**Parameters** skipself(bool) – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all links.

**namedlinks**(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.
Parameters `skipself` (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

`namedparams` (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters `include_uninit` (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

`params` (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

Parameters `include_uninit` (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

`register_persistent` (name: str) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters `name` (str) – Name of the attribute to be registered.

`repeat` (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.
• **n_repeat** *(int)* – Number of times to repeat.

• **mode** *(str)* – It should be either *init*, *copy*, or *share*. *init* means parameters of each repeated element in the returned *Sequential* will be re-initialized, so that all elements have different initial parameters. *copy* means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. *share* means all the elements which consist the resulting *Sequential* object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters** serializer *(AbstractSerializer)* – Serializer object.

**to_chx** ()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override **device_resident_accept()** to do so.

Returns: self

**to_device** *(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]])* → DeviceResident

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters** device – Target device specifier. See **get_device()** for available values.

Returns: self

**to_gpu** *(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident*

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override **device_resident_accept()** to do so.

**Warning**: This method does not transfer the parameters if they are already on GPU. Use **to_device** to perform inter-GPU transfer.

**Parameters** device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Deprecated since version v7.0.0: Use to_device() instead.

zero_grads() → None
Initializes all gradient arrays by zero.
Deprecated since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value,/)  
Return self==value.

__ne__(value,/)  
Return self!=value.

__lt__(value,/)  
Return self<value.

__le__(value,/)  
Return self<=value.

__gt__(value,/)  
Return self>value.

__ge__(value,/)  
Return self>=value.

Attributes

device
Device instance.

local_link_hooks
Ordered dictionary of registered link hooks.
Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.
See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.
Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.
chainer.links.DilatedConvolution2D

class chainer.links.DilatedConvolution2D(
    in_channels, out_channels, ksize=None, stride=1, pad=0, dilate=1, nobias=False,
    initialW=None, initial_bias=None)

Two-dimensional dilated convolutional layer.

This link wraps the dilated_convolution_2d() function and holds the filter weight and bias vector as parameters.

Note: You can also define a dilated convolutional layer by passing dilate argument to chainer.links.Convolution2D. The functionality is the same.

Parameters

- **in_channels** *(int or None)* – Number of channels of input arrays. If None, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.

- **out_channels** *(int)* – Number of channels of output arrays.

- **ksize** *(int or pair of ints)* – Size of filters (a.k.a. kernels). ksize=k and ksize=(k, k) are equivalent.

- **stride** *(int or pair of ints)* – Stride of filter applications. stride=s and stride=(s, s) are equivalent.

- **pad** *(int or pair of ints)* – Spatial padding width for input arrays. pad=p and pad=(p, p) are equivalent.

- **dilate** *(int or pair of ints)* – Dilation factor of filter applications. dilate=d and dilate=(d, d) are equivalent.

- **nobias** *(bool)* – If True, then this link does not use the bias term.

- **initialW** *(initializer)* – Initializer to initialize the weight. When it is numpy.ndarray, its ndim should be 4.

- **initial_bias** *(initializer)* – Initializer to initialize the bias. If None, the bias will be initialized to zero. When it is numpy.ndarray, its ndim should be 1.

See also:

See chainer.functions.dilated_convolution_2d() for the definition of two-dimensional dilated convolution.

Variables

- **W** *(Variable)* – Weight parameter.

- **b** *(Variable)* – Bias parameter.

Example

There are several ways to make a DilatedConvolution2D link.

Let an input vector \( x \) be:
1. Give the first three arguments explicitly:

```python
>>> x = np.arange(1 * 3 * 10 * 10, dtype=np.float32).reshape(1, 3, 10, 10)
>>> l = L.DilatedConvolution2D(3, 7, 5)
>>> y = l(x)
>>> y.shape
(1, 7, 6, 6)
```

2. Omit `in_channels` or fill it with `None`:

   The below two cases are the same.

   ```python
   >>> l = L.DilatedConvolution2D(7, 5)
   >>> y = l(x)
   >>> y.shape
   (1, 7, 6, 6)
   >>> l = L.DilatedConvolution2D(None, 7, 5)
   >>> y = l(x)
   >>> y.shape
   (1, 7, 6, 6)
   ``

   When you omit the first argument, you need to specify the other subsequent arguments from `stride` as keyword arguments. So the below two cases are the same.

   ```python
   >>> l = L.DilatedConvolution2D(None, 7, 5, 1, 0, 2)
   >>> y = l(x)
   >>> y.shape
   (1, 7, 2, 2)
   >>> l = L.DilatedConvolution2D(7, 5, stride=1, pad=0, dilate=2)
   >>> y = l(x)
   >>> y.shape
   (1, 7, 2, 2)
   ```

---

**Methods**

- **`__call__`**`(*args: Any, **kwargs: Any) → Any`
  Call self as a function.

- **`add_hook`**`(*hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link`
  Registers a link hook.

**Parameters**

- **`hook`**(*LinkHook*) – Link hook to be registered.
- **`name`**(*str*) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

**Returns** self
add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None

Registers a parameter to the link.

Parameters

- **name (str)** – Name of the parameter. This name is also used as the attribute name.
- **shape (int or tuple of ints)** – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer (initializer)** – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- **name (str)** – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

addgrads(link: chainer.link.Link) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters **link (Link)** – Source link object.

children() → Iterator[chainer.link.Link]

Returns a generator of all child links.

Returns **A generator object that generates all child links.**

cleargrads () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode: str = 'share') → chainer.link.Link

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters **mode (str)** – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed.

4.3. Link and Chains 417
independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is *share*.

**Returns** Copied link object.

**Return type** *Link*

`copyparams` *(link: chainer.link.Link, copy_persistent: bool = True) → None*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** *(Link)* – Source link object.
- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

`count_params()` *(bool) → int*

Counts the total number of parameters.

This method counts the total number of scalar values included in all the *Parameters* held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

`delete_hook` *(name: str) → None*

Unregisters the link hook.

**Parameters** *name* *(str)* – The name of the link hook to be unregistered.

`device_resident_accept` *(visitor)*

Applies the visitor to all the device objects in this instance.

**Parameters** *visitor* *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

`disable_update()` *(None)*

Disables update rules of all parameters under the link hierarchy.

This method sets the *enabled* flag of the update rule of each parameter variable to False.

`enable_update()` *(None)*

Enables update rules of all parameters under the link hierarchy.

This method sets the *enabled* flag of the update rule of each parameter variable to True.

`forward` *(x)*

Applies the convolution layer.

**Parameters** *x* *(Variable)* – Input image.

**Returns** Output of the convolution.

**Return type** *Variable*
from_chx()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(*args, **kwargs)
Initialize link with given parameters.
This method initializes the link with given N-dimensional arrays. Arguments includes

• some parameters for a specific link.
• constants such as stride width of a convolutional layer.

init_scope() → Iterator[None]
Creates an initialization scope.
This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example
In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

links(skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

namedparams(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.
**register_persistent** *(name: str) → None*

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name** *(str)* – Name of the attribute to be registered.

---

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** *(int)* – Number of times to repeat.

- **mode** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters**

- **serializer** *(AbstractSerializer)* – Serializer object.

**to_chx()**

Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

to_cpu() \rightarrow \text{chainer.device_resident.DeviceResident}
Copies parameter variables and persistent values to CPU.

\text{Deprecated since version v7.0.0: Use} \text{to_device()} \text{ instead.}

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

to_device\text{ } (device: \text{Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]}) \rightarrow \text{DeviceResident}
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device() for available values.

Returns: self

to_gpu\text{ } (device: \text{Optional[Union[cuda.Device, int, numpy.integer]]} = \text{None}) \rightarrow \text{chainer.device_resident.DeviceResident}
Copies parameter variables and persistent values to GPU.

\text{Deprecated since version v7.0.0: Use} \text{to_device()} \text{ instead.}

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64() \rightarrow \text{chainer.device_resident.DeviceResident}
Copies parameter variables and persistent values to CPU.

\text{Deprecated since version v7.0.0: Use} \text{to_device()} \text{ instead.}

zerograds() \rightarrow \text{None}
Initializes all gradient arrays by zero.

\text{Deprecated since version v1.15: Use} \text{cleargrads()} \text{ instead.}

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.
__gt__(value,)
    Return self>value.
__ge__(value,)
    Return self>=value.

Attributes

device
    Device instance.

local_link_hooks
    Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
    Generator of printable specs of this link.

    Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
    True if at least one parameter has an update rule enabled.

within_init_scope
    True if the current code is inside of an initialization scope.

    See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.

    Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.EmbedID

class chainer.links.EmbedID(in_size, out_size, initialW=None, ignore_label=None)
    Efficient linear layer for one-hot input.

This is a link that wraps the embed_id() function. This link holds the ID (word) embedding matrix \( W \) as a parameter.

Parameters

• in_size (int) – Number of different identifiers (a.k.a. vocabulary size).

• out_size (int) – Size of embedding vector.

• initialW (initializer) – Initializer to initialize the weight. When it is numpy.ndarray, its ndim should be 2.

• ignore_label (int or None) – If ignore_label is an int value, \( i \)-th row of return value is filled with 0.

See also:

embed_id()

Variables W (Variable) – Embedding parameter matrix.
Example

```python
>>> W = np.array([[0, 0, 0],
...                [1, 1, 1],
...                [2, 2, 2]]).astype(np.float32)
>>> W
array([[ 0.,  0.,  0.],
       [ 1.,  1.,  1.],
       [ 2.,  2.,  2.]], dtype=float32)
>>> l = L.EmbedID(W.shape[0], W.shape[1], initialW=W)
>>> x = np.array([2, 1]).astype(np.int32)
>>> x
array([2, 1], dtype=int32)
>>> y = l(x)
>>> y.array
array([[2., 2., 2.],
       [1., 1., 1.]], dtype=float32)
```

Methods

```
__call__ (*args: Any, **kwargs: Any) -> Any
Call self as a function.

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) -> chainer.link.Link
Registers a link hook.

Parameters

- **hook** (LinkHook) – Link hook to be registered.
- **name** (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) -> None
Registers a parameter to the link.

Parameters

- **name** (str) – Name of the parameter. This name is also used as the attribute name.
- **shape** (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitializ
- **dtype** – Data type of the parameter array.
- **initializer** (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent (name: str, value: Any) -> None
Registers a persistent value to the link.
```

4.3. Link and Chains 423
The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- **name** *(str)* – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

`addgrads` *(link: chainer.link.Link) → None*

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters

- **link** *(Link)* – Source link object.

`children` *(→ Iterator[chainer.link.Link]*)

Returns a generator of all child links.

Returns

A generator object that generates all child links.

`cleargrads` *(→ None)*

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

`copy` *(mode: str = 'share') → chainer.link.Link*

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters

- **mode** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. `copy` means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. `share` means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default `mode` is `share`.

Returns

Copied link object.

Return type

`Link`

`copyparams` *(link: chainer.link.Link, copy_persistent: bool = True) → None*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an `ndarray`, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

Parameters

- **link** *(Link)* – Source link object.
• **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

count_params () → int
Counts the total number of parameters.
This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.
If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

delete_hook *(name: str) → None*
Unregisters the link hook.

Parameters name *(str)* – The name of the link hook to be unregistered.

device_resident_accept *(visitor)*
Applies the visitor to all the device objects in this instance.

Parameters visitor *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has a custom sub-hierarchy of device resident objects.

disable_update () → None
Disables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to False.

enable_update () → None
Enables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to True.

forward *(x)*
Extracts the word embedding of given IDs.

Parameters x *(Variable)* – Batch vectors of IDs.

Returns Batch of corresponding embeddings.

Return type Variable

from_chx ()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params *(W, ignore_label=None)*
Initialize ~chainer.links.EmbedID with the given parameter.

Parameters

• W *(Variable or N-dimensional array)* – The weight parameter.

• ignore_label *(int or None)* – If ignore_label is an int value, i-th column of return value is filled with 0.

init_scope () → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

4.3. Link and Chains 425
In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

`links (skipself: bool = False) → Iterator[chainer.link.Link]`
Returns a generator of all links under the hierarchy.

**Parameters**

- `skipself (bool)` – If True, then the generator skips this link and starts with the first child link.

**Returns**

A generator object that generates all links.

`namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]`
Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters**

- `skipself (bool)` – If True, then the generator skips this link and starts with the first child link.

**Returns**

A generator object that generates all (path, link) pairs.

`namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]`
Returns a generator of all (path, parameter) pairs under the hierarchy.

**Parameters**

- `include_uninit (bool)` – If True, it also generates uninitialized parameters.

**Returns**

A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

`params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]`
Returns a generator of all parameters under the link hierarchy.

**Parameters**

- `include_uninit (bool)` – If True, it also generates uninitialized parameters.

**Returns**

A generator object that generates all parameters.

`register_persistent (name: str) → None`
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- `name (str)` – Name of the attribute to be registered.

`repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential`
Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')

The `net` object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat**(int) – Number of times to repeat.
- **mode**(str) – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

serialize(serializer: chainer.serializer.AbstractSerializer) → None

Serializes the link object.

Parameters

- **serializer**(AbstractSerializer) – Serializer object.

to_chx() → chainer.device_resident.DeviceResident

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

to_cpu()  → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]])  → DeviceResident

Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device**: Target device specifier. See `get_device()` for available values.

**Returns**: self

```python
to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to GPU.

Depreciated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning**: This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters**

- **device**: Target device specifier. If omitted, the current device is used.

**Returns**: self

```python
to_intel64() → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

Depreciated since version v7.0.0: Use `to_device()` instead.

```python
zerograds() → None
```

Initializes all gradient arrays by zero.

Depreciated since version v1.15: Use the more efficient `cleargrads()` instead.

**__eq__**(value, /)

Return `self==value`.

**__ne__**(value, /)

Return `self!=value`.

**__lt__**(value, /)

Return `self<value`.

**__le__**(value, /)

Return `self<=value`.

**__gt__**(value, /)

Return `self>value`.

**__ge__**(value, /)

Return `self>=value`.
Attributes

device
    Device instance.

ignore_label = None

local_link_hooks
    Ordered dictionary of registered link hooks.
    Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions,
    link hooks in this property are specific to this link.

printable_specs
    Generator of printable specs of this link.
    Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword
    and value) that are passed to the __init__(). This pair of key and value is used for
    representing this class or subclass with __str__().

update_enabled
    True if at least one parameter has an update rule enabled.

within_init_scope
    True if the current code is inside of an initialization scope.
    See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.
    Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.GRU

class chainer.links.GRU(in_size, out_size, init=None, inner_init=None, bias_init=0)
    Stateful Gated Recurrent Unit function (GRU)
    This is an alias of StatefulGRU.

Methods

__call__(*args: Any, **kwargs: Any) → Any
    Call self as a function.

__getitem__(name: str) → Any
    Equivalent to getattr.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
    Registers a link hook.
    Parameters
        • hook (LinkHook) – Link hook to be registered.
        • name (str) – Name of the link hook. The name must be unique among link hooks
          registered to this link. If None, the default name of the link hook is used.
    Returns self
**add_link** *(name: str, link: chainer.link.Link) → None*

 Registers a child link to this chain.

**Parameters**

- **name (str)** – Name of the child link. This name is also used as the attribute name.
- **link (Link)** – The link object to be registered.

**add_param** *(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None*

 Registers a parameter to the link.

**Parameters**

- **name (str)** – Name of the parameter. This name is also used as the attribute name.
- **shape (int or tuple of ints)** – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer (initializer)** – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

**add_persistent** *(name: str, value: Any) → None*

 Registers a persistent value to the link.

 The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- **name (str)** – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

**addgrads** *(link: chainer.link.Link) → None*

 Accumulates gradient values from given link.

 This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**  
**link (Link)** – Source link object.

**children** () → Iterator[chainer.link.Link]

 Returns a generator of all child links.

**Returns**  
A generator object that generates all child links.

**cleargrads** () → None

 Clears all gradient arrays.

 This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode: str = 'share') → chainer.link.Chain*

 Copies the link hierarchy to new one.

 The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.
The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. `copy` means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. `share` means that the link is shallowly copied, so that its parameters' arrays are shared with the original one. Thus, their values are changed synchronously. The default `mode` is `share`.

**Returns**
Copied link object.

**Return type** *Link*

### copyparams

**copyparams** *(link: chainer.link.Link, copy_persistent: bool = True) → None*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an `ndarray`, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** *(Link)* – Source link object.
- **copy_persistent** *(bool)* – If `True`, persistent values are also copied. `True` by default.

### count_params

**count_params() → int**

Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**
The total size of parameters (int)

### delete_hook

**delete_hook(name: str) → None**

Unregisters the link hook.

**Parameters**

- **name** *(str)* – The name of the link hook to be unregistered.

### device_resident_accept

**device_resident_accept(visitor)**

Applies the visitor to all the device objects in this instance.

**Parameters**

- **visitor** *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

### disable_update

**disable_update() → None**

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

### enable_update

**enable_update() → None**

 Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

---

4.3. Link and Chains 431
forward \((self, x)\)  
Does forward propagation.

def from_chx():  
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

def from_params(*args, **kwargs):  
Initialize link with given parameters.

    This method initializes the link with given \textit{N-dimensional arrays}. Arguments includes
    
    \begin{itemize}
    \item some parameters for a specific link.
    \item constants such as stride width of a convolutional layer.
    \end{itemize}

def init_scope(): → Iterator[None]  
Creates an initialization scope.

    This method returns a context manager object that enables registration of parameters (and links for \textit{Chain})
    by an assignment. A \textit{Parameter} object can be automatically registered by assigning it to an attribute
    under this context manager.

Example

In most cases, the parameter registration is done in the initializer method. Using the \textit{init_scope}
method, we can simply assign a \textit{Parameter} object to register it to the link.

```python

class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```


def links(skipself: bool = False): → Iterator[chainer.link.Link]

    Returns a generator of all links under the hierarchy.

    Parameters \textit{skipself} (bool) – If True, then the generator skips this link and starts with the
    first child link.

    Returns A generator object that generates all links.


def namedlinks(skipself: bool = False): → Iterator[Tuple[str, chainer.link.Link]]

    Returns a generator of all (path, link) pairs under the hierarchy.

    Parameters \textit{skipself} (bool) – If True, then the generator skips this link and starts with the
    first child link.

    Returns A generator object that generates all (path, link) pairs.


def namedparams(include_uninit: bool = True): → Iterator[Tuple[str, chainer.variable.Parameter]]

    Returns a generator of all (path, parameter) pairs under the hierarchy.

    Parameters \textit{include_uninit} (bool) – If True, it also generates uninitialized parameters.

    Returns A generator object that generates all (path, parameter) pairs. The paths are relative from
    this link.


def params(include_uninit: bool = True): → Iterator[chainer.variable.Parameter]

    Returns a generator of all parameters under the link hierarchy.
Parameters `include_uninit (bool)` – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example
You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)
    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- `n_repeat (int)` – Number of times to repeat.
- `mode (str)` – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

reset_state ()

serialize (serializer: chainer.serializer.AbstractSerializer) → None
Serializes the link object.
Parameters **serializer** *(AbstractSerializer)* – Serializer object.

**set_state** *(h)* 

**to_chx** ()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override **device_resident_accept()** to do so.

Returns: self

**to_device** *(device: Union[backend.Device, chainerx.Device, cuda.Device, Tuple[str, int], ModuleType, Tuple[ModuleType, int]])* → DeviceResident

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters** **device** – Target device specifier. See **get_device()** for available values.

Returns: self

**to_gpu** *(device: Optional[Union[cuda.Device, int, numpy.integer]] = None)* → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override **device_resident_accept()** to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use **to_device** to perform inter-GPU transfer.

**Parameters** **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device()** instead.

**zerograds** () → None

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient **cleargrads()** instead.

**__eq__** *(value, /)*

Return self==value.
__ne__(value,)
    Return self!=value.
__lt__(value,)
    Return self<value.
__le__(value,)
    Return self<=value.
__gt__(value,)
    Return self>value.
__ge__(value,)
    Return self>=value.

Attributes

device
    Device instance.

local_link_hooks
    Ordered dictionary of registered link hooks.
    Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
    Generator of printable specs of this link.
    Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__() . This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
    True if at least one parameter has an update rule enabled.

within_init_scope
    True if the current code is inside of an initialization scope.
    See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.
    Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.Highway

class chainer.links.Highway(in_out_size, nobias=False, activate=<function relu>,
    init_Wh=None, init_Wt=None, init_bh=None, init_bt=-1)
Highway module.

In highway network, two gates are added to the ordinal non-linear transformation \( H(x) = activate(W_h x + b_h) \). One gate is the transform gate \( T(x) = \sigma(W_t x + b_t) \), and the other is the carry gate \( C(x) \). For simplicity, the author defined \( C = 1 - T \). Highway module returns \( y \) defined as

\[
y = activate(W_h x + b_h) \odot \sigma(W_t x + b_t) + x \odot (1 - \sigma(W_t x + b_t))
\]

The output array has the same spatial size as the input. In order to satisfy this, \( W_h \) and \( W_t \) must be square matrices.
Parameters

- **in_out_size** *(int)* – Dimension of input and output vectors.
- **nobias** *(bool)* – If True, then this function does not use the bias.
- **activate** – Activation function of plain array. \( \tanh \) is also available.
- **init_Wh** *(initializer)* – Initializer to initialize the weight. When it is `numpy.ndarray`, its `ndim` should be 2.
- **init_bh** *(initializer)* – Initializer to initialize the bias. If `None`, the bias will be initialized to zero. When it is `numpy.ndarray`, its `ndim` should be 1.
- **init_Wt** *(initializer)* – Initializer to initialize the weight. When it is `numpy.ndarray`, its `ndim` should be 2.
- **init_bt** *(initializer)* – Initializer to initialize the bias. If `None`, the bias will be initialized to zero. When it is `numpy.ndarray`, its `ndim` should be 1. Negative value is recommended by the author of the paper. (e.g. \(-1, -3, \ldots\)).

See: Highway Networks.

Methods

__call__ *(args: Any, **kwargs: Any) → Any*

Call self as a function.

__getitem__ *(name: str) → Any*

Equivalent to getattr.

add_hook *(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link*

 Registers a link hook.

Parameters

- **hook** *(LinkHook)* – Link hook to be registered.
- **name** *(str)* – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

Returns self

add_link *(name: str, link: chainer.link.Link) → None*

Registers a child link to this chain.

Parameters

- **name** *(str)* – Name of the child link. This name is also used as the attribute name.
- **link** *(Link)* – The link object to be registered.

add_param *(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.typesМАbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None*

 Registers a parameter to the link.

Parameters

- **name** *(str)* – Name of the parameter. This name is also used as the attribute name.
- **shape** *(int or tuple of ints)* – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
• **dtype** – Data type of the parameter array.

• **initializer (initializer)** – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

**add_persistent** (name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

• **name** (str) – Name of the persistent value. This name is also used for the attribute name.

• **value** – Value to be registered.

**addgrads** (link: chainer.link.Link) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

link (Link) – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (mode: str = 'share') → chainer.link.Chain

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

mode (str) – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

**Returns** Copied link object.

**Return type** Link

**copyparams** (link: chainer.link.Link, copy_persistent: bool = True) → None

Copies all parameters from given link.
This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an `ndarray`, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- `link (Link)` – Source link object.
- `copy_persistent (bool)` – If True, persistent values are also copied. True by default.

**count_params () → int**

Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

**delete_hook (name: str) → None**

Unregisters the link hook.

**Parameters** `name (str)` – The name of the link hook to be unregistered.

**device_resident_accept (visitor) -> None**

Applies the visitor to all the device objects in this instance.

**Parameters** `visitor (DeviceResidentsVisitor)` – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update () → None**

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update () → None**

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

**forward (x)**

Computes the output of the Highway module.

**Parameters** `x (Variable)` – Input variable.

**Returns** Output variable. Its array has the same spatial size and the same minibatch size as the input array.

**Return type** `Variable`

**from_chx ()**

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params (*args, **kwargs)**

Initialize link with given parameters.

This method initializes the link with given *N*-dimensional arrays. Arguments includes
• some parameters for a specific link.
• constants such as stride width of a convolutional layer.

init_scope() → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))

links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, parameter) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters name (str) – Name of the attribute to be registered.
**repeat** (*n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential

Repeats this link multiple times to make a **Sequential**.

This method returns a **Sequential** object which has the same **Link** multiple times repeatedly. The mode argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer **Sequential** block like this:

```python
class ConvBNReLU(chainer.Chain):

    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is ConvBNReLU. And the mode was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat (int)** – Number of times to repeat.
- **mode (str)** – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned **Sequential** will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting **Sequential** object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** (*serializer: chainer.serializer.AbstractSerializer*) → None

Serializes the link object.

**Parameters**

- **serializer (AbstractSerializer)** – Serializer object.

**to_chx**

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: `self`

**to_cpu** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

**to_device** (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See `get_device()` for available values.

Returns: self

**to_gpu** (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

**zerograds** () → None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

**__eq__**(value, /)
Return self==value.

**__ne__**(value, /)
Return self!=value.

**__lt__**(value, /)
Return self<value.

**__le__**(value, /)
Return self<=value.

**__gt__**(value, /)
Return self>value.

**__ge__**(value, /)
Return self>=value.
Attributes

device
Device instance.

local_link_hooks
Ordered dictionary of registered link hooks.
Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
Generator of printable specs of this link.
Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__() method. This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.
See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.
Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.Inception

class chainer.links.Inception(in_channels, out1, proj3, out3, proj5, out5, proj_pool,
conv_init=None, bias_init=None)
Inception module of GoogLeNet.
It applies four different functions to the input array and concatenates their outputs along the channel dimension. Three of them are 2D convolutions of sizes 1x1, 3x3 and 5x5. Convolution paths of 3x3 and 5x5 sizes have 1x1 convolutions (called projections) ahead of them. The other path consists of 1x1 convolution (projection) and 3x3 max pooling.
The output array has the same spatial size as the input. In order to satisfy this, Inception module uses appropriate padding for each convolution and pooling.
See: Going Deeper with Convolutions.

Parameters

• in_channels (int or None) – Number of channels of input arrays.
• out1 (int) – Output size of 1x1 convolution path.
• proj3 (int) – Projection size of 3x3 convolution path.
• out3 (int) – Output size of 3x3 convolution path.
• proj5 (int) – Projection size of 5x5 convolution path.
• out5 (int) – Output size of 5x5 convolution path.
• proj_pool (int) – Projection size of max pooling path.
• **conv_init** (*initializer*) – Initializer to initialize the convolution matrix weights. When it is `numpy.ndarray`, its `ndim` should be 4.

• **bias_init** (*initializer*) – Initializer to initialize the convolution matrix weights. When it is `numpy.ndarray`, its `ndim` should be 1.

### Methods

#### __call__(*args: Any, **kwargs: Any) → Any

Call self as a function.

#### __getitem__(name: str) → Any

Equivalent to `getattr`.

#### add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link

Registers a link hook.

**Parameters**

- **hook** (*LinkHook*) – Link hook to be registered.

- **name** (*str*) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

**Returns** self

#### add_link(name: str, link: chainer.link.Link) → None

Registers a child link to this chain.

**Parameters**

- **name** (*str*) – Name of the child link. This name is also used as the attribute name.

- **link** (*Link*) – The link object to be registered.

#### add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None

 Registers a parameter to the link.

**Parameters**

- **name** (*str*) – Name of the parameter. This name is also used as the attribute name.

- **shape** (*int or tuple of int*) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

- **dtype** – Data type of the parameter array.

- **initializer** (*initializer*) – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

#### add_persistent(name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**
• **name** (*str*) – Name of the persistent value. This name is also used for the attribute name.

• **value** – Value to be registered.

### addgrads

**signature**

\[
\text{addgrads}(\text{link}: \text{chainer.link.Link}) \rightarrow \text{None}
\]

**description**

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** (*Link*) – Source link object.

### children

**signature**

\[
\text{children()} \rightarrow \text{Iterator[chainer.link.Link]}
\]

**description**

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

### cleargrads

**signature**

\[
\text{cleargrads()} \rightarrow \text{None}
\]

**description**

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

### copy

**signature**

\[
\text{copy}(\text{mode}: \text{str} = '\text{'share'}') \rightarrow \text{chainer.link.Chain}
\]

**description**

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** (*str*) – It should be either `init`, `copy`, or `share`. `init` means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. `copy` means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. `share` means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default `mode` is `share`.

**Returns**

Copied link object.

**Return type** *Link*

### copyparams

**signature**

\[
\text{copyparams}(\text{link}: \text{chainer.link.Link}, \text{copy_persistent}: \text{bool} = \text{True}) \rightarrow \text{None}
\]

**description**

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

**From v5.0.0:** this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an `ndarray`, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** (*Link*) – Source link object.

- **copy_persistent** (*bool*) – If True, persistent values are also copied. True by default.

### count_params

**signature**

\[
\text{count_params()} \rightarrow \text{int}
\]

Counts the total number of parameters.
This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

del**ete**_**h**ook (**name**: str) → None
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

device_resident_accept (**visitor**)  
Applies the visitor to all the device objects in this instance.

Parameters visitor (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has a custom sub-hierarchy of device resident objects.

disable_update () → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

enable_update () → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

forward (**x**)  
Computes the output of the Inception module.

Parameters x (Variable) – Input variable.

Returns Output variable. Its array has the same spatial size and the same minibatch size as the input array. The channel dimension has size out1 + out3 + out5 + proj_pool.

Return type Variable

from_chx ()  
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params (**args**, **kwargs**)  
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

• some parameters for a specific link.
• constants such as stride width of a convolutional layer.

init_scope () → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example
In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))

links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

    Parameters skipself (bool) – If True, then the generator skips this link and starts with the
    first child link.

    Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

    Parameters skipself (bool) – If True, then the generator skips this link and starts with the
    first child link.

    Returns A generator object that generates all (path, link) pairs.

dnamedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

    Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

    Returns A generator object that generates all (path, parameter) pairs. The paths are relative from
    this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

    Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

    Returns A generator object that generates all parameters.

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.
This is a convenient method to register an existing attribute as a persistent value. If name has been already
registered as a parameter, this method removes it from the list of parameter names and re-registers it as a
persistent value.

    Parameters name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.
This method returns a Sequential object which has the same Link multiple times repeatedly. The
mode argument means how to copy this link to repeat.

Example
You can repeat the same link multiple times to create a longer Sequential block like this:

class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
with self.init_scope():
    self.conv = L.Convolution2D(
        None, 64, 3, 1, 1, nobias=True)
    self.bn = L.BatchNormalization(64)

def forward(self, x):
    return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat (int)** – Number of times to repeat.
- **mode (str)** – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

serialize (serializer: chainer.serializer.AbstractSerializer) → None
Serializes the link object.

Parameters serializer (AbstractSerializer) – Serializer object.

to_chx ()
Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

to_cpu () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecation since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device() for available values.
Returns: self

to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecation since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecation since version v7.0.0: Use to_device() instead.
zerograds() → None
Initializes all gradient arrays by zero.

Deprecation since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.

Attributes

**device**
Device instance.

**local_link_hooks**
Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

**printable_specs**
Generator of printable specs of this link.
Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.InceptionBN

class chainer.links.InceptionBN(in_channels, out1, proj3, out3, proj33, out33, pooltype, proj_pool=None, stride=1, conv_init=None, dtype=None)

Inception module of the new GoogLeNet with BatchNormalization.

This chain acts like Inception, while InceptionBN uses the BatchNormalization on top of each convolution, the 5x5 convolution path is replaced by two consecutive 3x3 convolution applications, and the pooling method is configurable.


Parameters

- **in_channels**(int or None) – Number of channels of input arrays.
- **out1**(int) – Output size of the 1x1 convolution path.
- **proj3**(int) – Projection size of the single 3x3 convolution path.
- **out3**(int) – Output size of the single 3x3 convolution path.
- **proj33**(int) – Projection size of the double 3x3 convolutions path.
- **out33**(int) – Output size of the double 3x3 convolutions path.
- **pooltype**(str) – Pooling type. It must be either 'max' or 'avg'.
- **proj_pool**(int or None) – Projection size in the pooling path. If None, no projection is done.
- **stride**(int) – Stride parameter of the last convolution of each path.
- **conv_init**(initializer) – Initializer to initialize the convolution matrix weights. When it is numpy.ndarray, its ndim should be 4.
- **dtype**(numpy.dtype) – Type to use in BatchNormalization.

See also:

Inception

4.3. Link and Chains
Methods

`__call__(*args: Any, **kwargs: Any) → Any`
Call self as a function.

`__getitem__(name: str) → Any`
Equivalent to getattr.

`add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link`
Registers a link hook.

Parameters

- `hook` (LinkHook) – Link hook to be registered.
- `name` (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns
self

`add_link(name: str, link: chainer.link.Link) → None`
Registers a child link to this chain.

Parameters

- `name` (str) – Name of the child link. This name is also used as the attribute name.
- `link` (Link) – The link object to be registered.

`add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None`
Registers a parameter to the link.

Parameters

- `name` (str) – Name of the parameter. This name is also used as the attribute name.
- `shape` (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- `dtype` – Data type of the parameter array.
- `initializer` (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

`add_persistent(name: str, value: Any) → None`
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- `name` (str) – Name of the persistent value. This name is also used for the attribute name.
- `value` – Value to be registered.

`addgrads(link: chainer.link.Link) → None`
Accumulates gradient values from given link.
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** *(Link)* – Source link object.

**children** () → Iterator[chainer.link.Link]

- Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** () → None

- Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode: str = 'share')* → chainer.link.Chain

- Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument **mode** below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** *(str)* – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

- **Returns**

  Copied link object.

**Return type**

- **Link**

**copyparams** *(link: chainer.link.Link, copy_persistent: bool = True)* → None

- Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g., the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

**Parameters**

- **link** *(Link)* – Source link object.

- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

**count_params** () → int

- Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**

The total size of parameters (int)
**delete_hook** *(name: str) → None*

Unregisters the link hook.

**Parameters**

- **name** *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*

Applies the visitor to all the device objects in this instance.

**Parameters**

- **visitor** *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

**enable_update** () → None

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

**forward** *(x)*

**from_chx** ()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** (*args, **kwargs)*

Initialize link with given parameters.

This method initializes the link with given `N-dimensional arrays`. Arguments include

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope** () → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links** *(skipself: bool = False) → Iterator[chainer.link.Link]*

Returns a generator of all links under the hierarchy.

**Parameters**

- **skipself** *(bool)* – If True, then the generator skips this link and starts with the first child link.

**Returns**

A generator object that generates all links.
**namedlinks** (*skipself: bool = False*) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters

**skipself (bool)** – If True, then the generator skips this link and starts with the first child link.

Returns

A generator object that generates all (path, link) pairs.

**namedparams** (*include_uninit: bool = True*) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters

**include_uninit (bool)** – If True, it also generates uninitialized parameters.

Returns

A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** (*include_uninit: bool = True*) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

Parameters

**include_uninit (bool)** – If True, it also generates uninitialized parameters.

Returns

A generator object that generates all parameters.

**register_persistent** (*name: str*) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters

**name (str)** – Name of the attribute to be registered.

**repeat** (*n_repeat: int*, **mode: str = 'init'*) → chainer.sequential.Sequential

Repeats this link multiple times to make a **Sequential**.

This method returns a **Sequential** object which has the same **Link** multiple times repeatedly. The **mode** argument means how to copy this link to repeat.

### Example

You can repeat the same link multiple times to create a longer **Sequential** block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The **net** object contains 16 blocks, each of which is **ConvBNReLU**. And the **mode** was **init**, so each block is re-initialized with different parameters. If you give **copy** to this argument, each block has same values for its parameters but its object ID is different from others. If it is **share**, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.
Parameters

- **n_repeat** *(int)* – Number of times to repeat.

- **mode** *(str)* – It should be either *init*, *copy*, or *share*. *init* means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. *copy* means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. *share* means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

```python
serialize (serializer: chainer.serializer.AbstractSerializer) → None
```

Serializes the link object.

**Parameters** `serializer` *(AbstractSerializer)* – Serializer object.

```python
to_chx ()
```

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

```python
to_cpu () → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

```python
to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
```

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters** `device` – Target device specifier. See `get_device()` for available values.

Returns: self

```python
to_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters** `device` – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Deprecated since version v7.0.0: Use to_device() instead.

zerograds() → None
Initializes all gradient arrays by zero.
Depreciated since version v1.15: Use the more efficient cleargrads() instead.

Attributes

device
Device instance.

local_link_hooks
Ordered dictionary of registered link hooks.
Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.
See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.
Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.
### chainer.links.Linear

The `chainer.links.Linear` class wraps the `linear()` function, and holds a weight matrix $W$ and optionally a bias vector $b$ as parameters.

If `initialW` is left to the default value of `None`, the weight matrix $W$ is initialized with i.i.d. Gaussian samples, each of which has zero mean and deviation $\sqrt{1/n}$.

#### Parameters

- **in_size** (`int or None`): Dimension of input vectors. If unspecified or `None`, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.
- **out_size** (`int`): Dimension of output vectors. If only one value is passed for `in_size` and `out_size`, that value will be used for the `out_size` dimension.
- **nobias** (`bool`): If True, then this function does not use the bias.
- **initialW** (`initializer`): Initializer to initialize the weight. When it is `numpy.ndarray`, its `ndim` should be 2. If `initialW` is `None`, then the weights are initialized with i.i.d. Gaussian samples, each of which has zero mean and deviation $\sqrt{1/n}$.

#### See also:

- `linear()`

#### Variables

- **$W$** (`Variable`): Weight parameter.
- **$b$** (`Variable`): Bias parameter.

#### Example

There are several ways to make a Linear link.

Define an input vector $x$ as:

```python
>>> x = np.array([0, 1, 2, 3, 4], np.float32)
```

1. Give the first two arguments explicitly:

   Those numbers are considered as the input size and the output size.

   ```python
   >>> l = L.Linear(5, 10)
   >>> y = l(x)
   >>> y.shape
   (1, 10)
   ```

2. Omit `in_size` (give the output size only as the first argument) or fill it with `None`:

   In this case, the size of second axis of $x$ is used as the input size. So the below two cases are the same.

   ```python
   >>> l = L.Linear(10)
   >>> y = l(x)
   >>> y.shape
   (1, 10)
   ```
>>> l = L.Linear(None, 10)
>>> y = l(x)
>>> y.shape
(1, 10)

When you omit the first argument, you need to specify the other subsequent arguments from nobias as keyword arguments. So the below two cases are the same.

>>> l = L.Linear(None, 10, False, None, 0)
>>> y = l(x)
>>> y.shape
(1, 10)

>>> l = L.Linear(10, nobias=False, initialW=None, initial_bias=0)
>>> y = l(x)
>>> y.shape
(1, 10)

Methods

__call__ (*args: Any, **kwargs: Any) → Any
Call self as a function.

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

- **hook** *(LinkHook)* – Link hook to be registered.
- **name** *(str)* – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

- **name** *(str)* – Name of the parameter. This name is also used as the attribute name.
- **shape** *(int or tuple of ints)* – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer** *(initializer)* – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent (name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

4.3. Link and Chains

457
Parameters

- **name** (*str*) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

`addgrads` (*link: chainer.link.Link*) → `None`

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters

- **link** (*Link*) – Source link object.

`children` () → `Iterator[chainer.link.Link]`

Returns a generator of all child links.

Returns

A generator object that generates all child links.

`cleargrads` () → `None`

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

`copy` (*mode: str = 'share'*) → `chainer.link.Link`

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument *mode* below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters

- **mode** (*str*) – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default *mode* is *share*.

Returns

Copied link object.

Return type *Link*

`copyparams` (*link: chainer.link.Link, copy_persistent: bool = True*) → `None`

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using *copy.deepcopy()* . The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

Parameters

- **link** (*Link*) – Source link object.
- **copy_persistent** (*bool*) – If True, persistent values are also copied. True by default.

`count_params` () → `int`

Counts the total number of parameters.
This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

def delete_hook(name: str) -> None
    Unregisters the link hook.

    Parameters name (str) – The name of the link hook to be unregistered.

device_resident_accept(visitor)
    Applies the visitor to all the device objects in this instance.

    Parameters visitor (DeviceResidentsVisitor) – Visitor.

    This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

disable_update() -> None
    Disables update rules of all parameters under the link hierarchy.

    This method sets the enabled flag of the update rule of each parameter variable to False.

enable_update() -> None
    Enables update rules of all parameters under the link hierarchy.

    This method sets the enabled flag of the update rule of each parameter variable to True.

forward(x: chainer.variable.Variable, n_batch_axes: int = 1) -> chainer.variable.Variable
    Applies the linear layer.

    Parameters
        • x (Variable) – Batch of input vectors.
        • n_batch_axes (int) – The number of batch axes. The default is 1. The input variable is reshaped into (n_batch_axes + 1)-dimensional tensor. This should be greater than 0.

    Returns Output of the linear layer.

    Return type Variable

from_chx()
    Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(W, b=None, nobias=False)
    Initialize a Linear with given parameters.

    This method uses W and optional b to initialize a linear layer.

    Parameters
        • W (Variable or N-dimensional array) – The weight parameter.
        • b (Variable, N-dimensional array, or None) – The bias parameter.
        • nobias (bool) – If True, the argument of b is ignored in spite of whether it’s given or not.

init_scope() -> Iterator[None]
    Creates an initialization scope.

    This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.
Example

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**Example**

You can repeat the same link multiple times to create a longer Sequential block like this:
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)
    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat (int)** – Number of times to repeat.
- **mode (str)** – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

serialize (serializer: chainer.serializer.AbstractSerializer) → None
Serializes the link object.

Parameters **serializer (AbstractSerializer)** – Serializer object.

to_chx ()
Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

to_cpu () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device () instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept () to do so.

Returns: self

to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- `device` – Target device specifier. See `get_device()` for available values.

Returns: self

```python
def to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) -> chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

**Parameters**

- `device` – Target device specifier. If omitted, the current device is used.

Returns: self

```python
def to_intel64() -> chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

```python
def zerograds() -> None
```

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

```python
__eq__(value, /)
Return self==value.
__ne__(value, /)
Return self!=value.
__lt__(value, /)
Return self<value.
__le__(value, /)
Return self<=value.
__gt__(value, /)
Return self>value.
__ge__(value, /)
Return self>=value.
```
Attributes

**device**

Device instance.

**local_link_hooks**

Ordered dictionary of registered link hooks.

Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

**printable_specs**

**update_enabled**

True if at least one parameter has an update rule enabled.

**within_init_scope**

True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.

**xp**

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.

**chainer.links.LocalConvolution2D**

class chainer.links.LocalConvolution2D(in_channels, out_channels, in_size=None, ksize=None, stride=1, nobias=False, initialW=None, initial_bias=None, **kwargs)

Two-dimensional local convolutional layer.

This link wraps the `local_convolution_2d()` function and holds the filter weight and bias array as parameters.

**Parameters**

- **in_channels (int)** – Number of channels of input arrays. If either in_channels or in_size is `None`, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.

- **out_channels (int)** – Number of channels of output arrays

- **in_size (int or pair of ints)** – Size of each image channel in_size=k and in_size=(k,k) are equivalent. If either in_channels or in_size is `None`, parameter initialization will be deferred until the first forward data pass when the size will be determined.

- **ksize (int or pair of ints)** – Size of filters (a.k.a. kernels). ksize=k and ksize=(k, k) are equivalent.

- **stride (int or pair of ints)** – Stride of filter applications. stride=s and stride=(s, s) are equivalent.

- **nobias (bool)** – If True, then this link does not use the bias term.

- **initialW (initializer)** – Initializer to initialize the weight. When it is `numpy.ndarray`, its ndim should be 6.

- **initial_bias (initializer)** – Initializer to initialize the bias. If `None`, the bias will be initialized to zero. When it is `numpy.ndarray`, its ndim should be 3.
See also:
See `chainer.functions.local_convolution_2d()`.

Variables

- \( W \) (Variable) – Weight parameter.
- \( b \) (Variable) – Bias parameter.

Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

- **hook** (LinkHook) – Link hook to be registered.
- **name** (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

- **name** (str) – Name of the parameter. This name is also used as the attribute name.
- **shape** (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer** (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- **name** (str) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

addgrads(link: chainer.link.Link) → None
Accumulates gradient values from given link.
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** *(Link)* – Source link object.

**children** *(→ Iterator[chainer.link.Link]*)

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** *(→ None)*

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode: str = 'share') → chainer.link.Link)*

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument *mode* below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** *(str)* – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default *mode* is *share*.

**Returns**

Copied link object.

**Return type**

**Link**

**copyparams** *(link: chainer.link.Link, copy_persistent: bool = True) → None)*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using *copy.deepcopy()*.

The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

**Parameters**

- **link** *(Link)* – Source link object.

- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

**count_params** *(→ int)*

Counts the total number of parameters.

This method counts the total number of scalar values included in all the *Parameters* held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**

The total size of parameters (int)
**delete_hook** *(name: str) → None*
Unregisters the link hook.

Parameters

- **name** *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*
Applies the visitor to all the device objects in this instance.

Parameters

- **visitor** *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to `False`.

**enable_update** () → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to `True`.

**forward** *(x)*
Applies the local convolution layer.

Parameters

- **x** *(Variable)* – Input image.

Returns

Output of the convolution.

Return type

*Variable*

**from_chx** ()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** (*args, **kwargs)*
Initialize link with given parameters.

This method initializes the link with given *N*-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope** () → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for *Chain*) by an assignment. A *Parameter* object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a *Parameter* object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))```
links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the
first child link.

Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the
first child link.

Returns A generator object that generates all (path, link) pairs.

namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from
this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already
registered as a parameter, this method removes it from the list of parameter names and re-registers it as a
persistent value.

Parameters name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The
mode argument means how to copy this link to repeat.

Example
You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

4.3. Link and Chains 467
The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** *(int)* – Number of times to repeat.
- **mode** *(str)* – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters**

- **serializer** *(AbstractSerializer)* – Serializer object.

**to_chx()**

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu() → chainer.device_resident.DeviceResident**

Copies parameter variables and persistent values to CPU.

 Deprecated since version v7.0.0: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override **device_resident_accept()** to do so.

Returns: self

**to_device** *(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident* 

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See **get_device()** for available values.

Returns: self

**to_gpu** *(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident* 

Copies parameter variables and persistent values to GPU.

 Deprecated since version v7.0.0: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override **device_resident_accept()** to do so.
**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters**
- **device** – Target device specifier. If omitted, the current device is used.

Returns: `self`

**to_intel64**() → `chainer.device_resident.DeviceResident`
Copies parameter variables and persistent values to CPU.
Depreciated since version v7.0.0: Use `to_device()` instead.

**zerograds**() → `None`
Initializes all gradient arrays by zero.
Depreciated since version v1.15: Use the more efficient `cleargrads()` instead.

```python
__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.
```

**Attributes**

- **device**
  - `Device` instance.

- **local_link_hooks**
  - Ordered dictionary of registered link hooks.

  Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

- **printable_specs**
  - Generator of printable specs of this link.

  Yields `specs (tuple of str and object)` – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()`. This pair of key and value is used for representing this class or subclass with `__str__()`. 

- **update_enabled**
  - True if at least one parameter has an update rule enabled.

- **within_init_scope**
  - True if the current code is inside of an initialization scope.

  See `init_scope()` for the details of the initialization scope.
xp

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns \texttt{numpy}, \texttt{cupy} or \texttt{chainerx}.

\texttt{chainer.links.LSTM}

class \texttt{chainer.links.LSTM}(in\_size, out\_size=None, lateral\_init=None, upward\_init=None, bias\_init=None, forget\_bias\_init=None)

Fully-connected LSTM layer.

This is a fully-connected LSTM layer as a chain. Unlike the \texttt{lstm()} function, which is defined as a stateless activation function, this chain holds upward and lateral connections as child links.

It also maintains states, including the cell state and the output at the previous time step. Therefore, it can be used as a stateful LSTM.

This link supports variable length inputs. The mini-batch size of the current input must be equal to or smaller than that of the previous one. The mini-batch size of $c$ and $h$ is determined as that of the first input $x$. When mini-batch size of $i$-th input is smaller than that of the previous input, this link only updates $c[0:len(x)]$ and $h[0:len(x)]$ and doesn’t change the rest of $c$ and $h$. So, please sort input sequences in descending order of lengths before applying the function.

**Parameters**

- \texttt{in\_size (int)} – Dimension of input vectors. If it is \texttt{None} or omitted, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.
- \texttt{out\_size (int)} – Dimensionality of output vectors.
- \texttt{lateral\_init} – A callable that takes $N$-dimensional array and edits its value. It is used for initialization of the lateral connections. May be \texttt{None} to use default initialization.
- \texttt{upward\_init} – A callable that takes $N$-dimensional array and edits its value. It is used for initialization of the upward connections. May be \texttt{None} to use default initialization.
- \texttt{bias\_init} – A callable that takes $N$-dimensional array and edits its value. It is used for initialization of the biases of cell input, input gate and output gate and gates of the upward connection. May be a scalar, in that case, the bias is initialized by this value. If it is \texttt{None}, the cell-input bias is initialized to zero.
- \texttt{forget\_bias\_init} – A callable that takes $N$-dimensional array and edits its value. It is used for initialization of the biases of the forget gate of the upward connection. May be a scalar, in that case, the bias is initialized by this value. If it is \texttt{None}, the forget bias is initialized to one.

**Variables**

- \texttt{upward (Linear)} – Linear layer of upward connections.
- \texttt{lateral (Linear)} – Linear layer of lateral connections.
- \texttt{c (Variable)} – Cell states of LSTM units.
- \texttt{h (Variable)} – Output at the previous time step.

**Example**

There are several ways to make a LSTM link.

Let a two-dimensional input array $x$ be:
1. Give both `in_size` and `out_size` arguments:

```python
>>> x = np.zeros((1, 10), dtype=np.float32)
>>> l = L.LSTM(10, 20)
>>> h_new = l(x)
>>> h_new.shape
(1, 20)
```

2. Omit `in_size` argument or fill it with `None`:

The below two cases are the same.

```python
>>> l = L.LSTM(20)
>>> h_new = l(x)
>>> h_new.shape
(1, 20)
```  
```python
>>> l = L.LSTM(None, 20)
>>> h_new = l(x)
>>> h_new.shape
(1, 20)
```

---

### Methods

- **__call__** *(args: Any, **kwargs: Any) → Any*
  
  Call self as a function.

- **__getitem__** *(name: str) → Any*
  
  Equivalent to getattr.

- **add_hook** *(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link*
  
  Registers a link hook.

  **Parameters**

  - `hook` *(LinkHook)* – Link hook to be registered.
  
  - `name` *(str)* – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

  **Returns** `self`

- **add_link** *(name: str, link: chainer.link.Link) → None*
  
  Registers a child link to this chain.

  **Parameters**

  - `name` *(str)* – Name of the child link. This name is also used as the attribute name.
  
  - `link` *(Link)* – The link object to be registered.

- **add_param** *(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None*
  
  Registers a parameter to the link.
Parameters

- **name (str)** – Name of the parameter. This name is also used as the attribute name.
- **shape (int or tuple of ints)** – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer (initializer)** – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

`add_persistent (name: str, value: Any) -> None`

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- **name (str)** – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

`addgrads (link: chainer.link.Link) -> None`

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters **link (Link)** – Source link object.

`children () -> Iterator[chainer.link.Link]`

Returns a generator of all child links.

Returns **A generator object that generates all child links.**

`cleargrads () -> None`

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

`copy (mode: str = 'share') -> chainer.link.Chain`

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters **mode (str)** – It should be either `init`, `copy`, or `share`. `init` means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. `copy` means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. `share` means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default `mode` is `share`.

Returns **Copied link object.**
**Return type**  
*Link*

**copyparams**  
*link: chainer.link.Link, copy_persistent: bool = True*  \(\rightarrow\)  *None*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g., the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** (*Link*) – Source link object.
- **copy_persistent** (*bool*) – If True, persistent values are also copied. True by default.

**count_params**  \(\rightarrow\)  *int*

Counts the total number of parameters.

This method counts the total number of scalar values included in all the *Parameters* held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**  
The total size of parameters (int)

**delete_hook**  
*name: str*  \(\rightarrow\)  *None*

Unregisters the link hook.

**Parameters**  
*name* (*str*) – The name of the link hook to be unregistered.

**device_resident_accept**  
*visitor*

Applies the visitor to all the device objects in this instance.

**Parameters**  
*visitor* (*DeviceResidentsVisitor*) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update**  \(\rightarrow\)  *None*

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update**  \(\rightarrow\)  *None*

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

**forward**  
*x*

Updates the internal state and returns the LSTM outputs.

**Parameters**  
*x* (*Variable*) – A new batch from the input sequence.

**Returns**  
Outputs of updated LSTM units.

**Return type**  
*Variable*

**from_chx**  

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.
classmethod from_params (*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes
- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

init_scope() → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example
In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))

links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, parameter) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.
This is a convenient method to register an existing attribute as a persistent value. If \texttt{name} has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- \texttt{name} (\textit{str}) – Name of the attribute to be registered.

\texttt{repeat}\texttt{(n\_repeat: int, mode: str = ‘init’) → chainer.sequential.Sequential}

Repeats this link multiple times to make a \texttt{Sequential}.

This method returns a \texttt{Sequential} object which has the same \texttt{Link} multiple times repeatedly. The \texttt{mode} argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer \texttt{Sequential} block like this:

```python

class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The \texttt{net} object contains 16 blocks, each of which is \texttt{ConvBNReLU}. And the \texttt{mode} was \texttt{init}, so each block is re-initialized with different parameters. If you give \texttt{copy} to this argument, each block has same values for its parameters but its object ID is different from others. If it is \texttt{share}, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- \texttt{n\_repeat (int)} – Number of times to repeat.
- \texttt{mode} (\textit{str}) – It should be either \texttt{init}, \texttt{copy}, or \texttt{share}. \texttt{init} means parameters of each repeated element in the returned \texttt{Sequential} will be re-initialized, so that all elements have different initial parameters. \texttt{copy} means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. \texttt{share} means all the elements which consist the resulting \texttt{Sequential} object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

\texttt{reset\_state()}

Resets the internal state.

It sets \texttt{None} to the \texttt{c} and \texttt{h} attributes.

\texttt{serialize(serializer: chainer.serializer.AbstractSerializer) → None}

Serializes the link object.

**Parameters**

- \texttt{serializer} (\texttt{AbstractSerializer}) – Serializer object.
**set_state** \((c, h)\)
Sets the internal state.
It sets the \(c\) and \(h\) attributes.

**Parameters**

- \(c\) (*Variable*) – A new cell states of LSTM units.
- \(h\) (*Variable*) – A new output at the previous time step.

**to_chx**()
Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu**() \(\rightarrow\) chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

**to_device**(device: \(\text{Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]}\)) \(\rightarrow\) DeviceResident
Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See `get_device()` for available values.

Returns: self

**to_gpu**(device: \(\text{Optional[Union[cuda.Device, int, numpy.integer]]}\) = None) \(\rightarrow\) chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning**: This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64**() \(\rightarrow\) chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.
**zerograds** () → None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

**__eq__(value,/)**
Return self==value.

**__ne__(value,/)**
Return self!=value.

**__lt__(value,/)**
Return self<value.

**__le__(value,/)**
Return self<=value.

**__gt__(value,/)**
Return self>value.

**__ge__(value,/)**
Return self>=value.

**Attributes**

**device**
Device instance.

**local_link_hooks**
Ordered dictionary of registered link hooks.
Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

**printable_specs**
Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()`. This pair of key and value is used for representing this class or subclass with `__str__()`.

**update_enabled**
True if at least one parameter has an update rule enabled.

**within_init_scope**
True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.

**xp**
Array module corresponding to the device.
Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.
chainer.links.MLPConvolution2D

class chainer.links.MLPConvolution2D(self, in_channels, out_channels, ksize=None, stride=1, pad=0, activation=relu.relu, conv_init=None, bias_init=None):
Two-dimensional MLP convolution layer of Network in Network.
This is an “mlpconv” layer from the Network in Network paper. This layer is a two-dimensional convolution layer followed by 1x1 convolution layers and interleaved activation functions.
Note that it does not apply the activation function to the output of the last 1x1 convolution layer.

Parameters

- **in_channels (int or None)** – Number of channels of input arrays. If it is None or omitted, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.
- **out_channels (tuple of ints)** – Tuple of number of channels. The i-th integer indicates the number of filters of the i-th convolution.
- **ksize (int or pair of ints)** – Size of filters (a.k.a. kernels) of the first convolution layer. ksize=k and ksize=(k, k) are equivalent.
- **stride (int or pair of ints)** – Stride of filter applications at the first convolution layer. stride=s and stride=(s, s) are equivalent.
- **pad (int or pair of ints)** – Spatial padding width for input arrays at the first convolution layer. pad=p and pad=(p, p) are equivalent.
- **activation (callable)** – Activation function for internal hidden units. You can specify one of activation functions from built-in activation functions or your own function. It should not be an activation functions with parameters (i.e., Link instance). The function must accept one argument (the output from each child link), and return a value. Returned value must be a Variable derived from the input Variable to perform backpropagation on the variable. Note that this function is not applied to the output of this link.
- **conv_init** – An initializer of weight matrices passed to the convolution layers. This option must be specified as a keyword argument.
- **bias_init** – An initializer of bias vectors passed to the convolution layers. This option must be specified as a keyword argument.

See: Network in Network.

Variables activation (callable) – Activation function. See the description in the arguments for details.

Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

__getitem__(index)
Returns the child at given index.

Parameters index (int) – Index of the child in the list.

Returns The index-th child link.

Return type Link
__setitem__ (index: Union[int, slice], value: Union[chainer.link.Link, Iterable[chainer.link.Link]]) → None

__len__() → int
Returns the number of children.

__iter__() → Iterator[chainer.link.Link]

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.

• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_link (link: chainer.link.Link) → None
Registers a child link and adds it to the tail of the list.

Parameters link (Link) – The link object to be registered.

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.

• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• dtype – Data type of the parameter array.

• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent (name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.

• value – Value to be registered.

addgrads (link: chainer.link.Link) → None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters link (Link) – Source link object.
append\((value)\)
S.append(value) – append value to the end of the sequence

children() \(\to\) Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns A generator object that generates all child links.

clear() \(\to\) None – remove all items from S

cleargrads() \(\to\) None
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy\((mode: str = ‘share’)\) \(\to\) chainer.link.ChainList
Returns a deep copy of the chainlist.

copyparams\((link: chainer.link.Link, copy_persistent: bool = True)\) \(\to\) None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters

- link (Link) – Source link object.
- copy_persistent (bool) – If True, persistent values are also copied. True by default.

count\((value)\) \(\to\) integer – return number of occurrences of value

count_params() \(\to\) int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

delete_hook\((name: str)\) \(\to\) None
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

device_resident_accept\((visitor)\)
Applies the visitor to all the device objects in this instance.

Parameters visitor (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

disable_update() \(\to\) None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.
enable_update() → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

extend(values)
S.extend(iterable) – extend sequence by appending elements from the iterable

forward(x)
Computes the output of the mlpconv layer.

Parameters:
x (Variable) – Input image.

Returns:
Output of the mlpconv layer.

Return type:
Variable

from_chx()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes
• some parameters for a specific link.
• constants such as stride width of a convolutional layer.

index(value[, start[, stop]]) → integer – return first index of value.
Raises ValueError if the value is not present.
Supporting start and stop arguments is optional, but recommended.

init_scope() → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example
In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))

insert(index: int, link: chainer.link.Link) → None
Insert a child link at the given index.

Parameters:
• index (int) – The position of the list where the new
• is inserted. (link)–
• \textbf{link} (Link) – The link to be inserted.

\textbf{links} (\textit{skipself}: \texttt{bool} = \texttt{False}) \rightarrow \text{Iterator[chainer.link.Link]}

Returns a generator of all links under the hierarchy.

\textbf{Parameters} \textit{skipself} (\texttt{bool}) – If \texttt{True}, then the generator skips this link and starts with the first child link.

\textbf{Returns} A generator object that generates all links.

\textbf{namedlinks} (\textit{skipself}: \texttt{bool} = \texttt{False}) \rightarrow \text{Iterator[Tuple[str, chainer.link.Link]]}

Returns a generator of all (path, link) pairs under the hierarchy.

\textbf{Parameters} \textit{skipself} (\texttt{bool}) – If \texttt{True}, then the generator skips this link and starts with the first child link.

\textbf{Returns} A generator object that generates all (path, link) pairs.

\textbf{namedparams} (\textit{include_uninit}: \texttt{bool} = \texttt{True}) \rightarrow \text{Iterator[Tuple[str, chainer.variable.Parameter]]}

Returns a generator of all (path, parameter) pairs. The paths are relative from this link.

\textbf{Parameters} \textit{include_uninit} (\texttt{bool}) – If \texttt{True}, it also generates uninitialized parameters.

\textbf{Returns} A generator object that generates all (path, parameter) pairs.

\textbf{params} (\textit{include_uninit}: \texttt{bool} = \texttt{True}) \rightarrow \text{Iterator[chainer.variable.Parameter]}

Returns a generator of all parameters under the link hierarchy.

\textbf{Parameters} \textit{include_uninit} (\texttt{bool}) – If \texttt{True}, it also generates uninitialized parameters.

\textbf{Returns} A generator object that generates all parameters.

\textbf{pop} ([\texttt{index}]) \rightarrow \text{item} – remove and return item at index (default last).

Raise IndexError if list is empty or index is out of range.

\textbf{register_persistent} (\textit{name}: \texttt{str}) \rightarrow \text{None}

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If \textit{name} has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

\textbf{Parameters} \textit{name} (\texttt{str}) – Name of the attribute to be registered.

\textbf{remove} (\textit{value})

S.remove(value) – remove first occurrence of value. Raise ValueError if the value is not present.

\textbf{repeat} (\textit{n_repeat}: \texttt{int}, \textit{mode}: \texttt{str} = 'init') \rightarrow \text{chainer.sequential.Sequential}

Repeats this link multiple times to make a \textit{Sequential}.

This method returns a \textit{Sequential} object which has the same \textit{Link} multiple times repeatedly. The \textit{mode} argument means how to copy this link to repeat.

\textbf{Example}

You can repeat the same link multiple times to create a longer \textit{Sequential} block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            # (continues on next page)
```
The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- `n_repeat (int)` – Number of times to repeat.
- `mode (str)` – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

reverse()

S.reverse() – reverse IN PLACE

serialize (serializer: chainer.serializer.AbstractSerializer) → None

Serializes the link object.

Parameters `serializer` (AbstractSerializer) – Serializer object.

to_chx ()

Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to Chain-
erX, the link implementation must override this method to do so.

Returns: self

to_cpu () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.
Parameters **device** – Target device specifier. See `get_device()` for available values.

Returns: self

to_gpu
    device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

    Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64 () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

    Deprecated since version v7.0.0: Use `to_device()` instead.

zerograds () → None
Initializes all gradient arrays by zero.

    Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

__eq__ (value, /)
    Return self==value.

__ne__ (value, /)
    Return self!=value.

__lt__ (value, /)
    Return self<value.

__le__ (value, /)
    Return self<=value.

__gt__ (value, /)
    Return self>value.

__ge__ (value, /)
    Return self>=value.

Attributes

device
    Device instance.

local_link_hooks
    Ordered dictionary of registered link hooks.

    Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
    Generator of printable specs of this link.
Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

cagher.links.NaryTreeLSTM

class chainer.links.NaryTreeLSTM(in_size, out_size, n_ary=2)
N-ary TreeLSTM unit.

Warning: This feature is experimental. The interface can change in the future.

This is a N-ary TreeLSTM unit as a chain. This link is a fixed-length arguments function, which compounds the states of all children nodes into the new states of a current (parent) node. states denotes the cell state, c, and the output, h, which are produced by this link. This link doesn’t keep cell and hidden states internally.

For example, this link is called such as func(c1, c2, h1, h2, x) if the number of children nodes was set 2 (n_ary = 2), while func(c1, c2, c3, h1, h2, h3, x) if that was 3 (n_ary = 3). This function is dependent from an order of children nodes unlike Child-Sum TreeLSTM. Thus, the returns of func(c1, c2, h1, h2, x) are different from those of func(c2, c1, h2, h1, x).

Parameters

• in_size (int) – Dimension of input vectors.
• out_size (int) – Dimensionality of cell and output vectors.
• n_ary (int) – The number of children nodes in a tree structure.

Variables

• W_x (chainer.links.Linear) – Linear layer of connections from input vectors.
• W_h (chainer.links.Linear) – Linear layer of connections between (a, i, o, all f) and the output of each child. a, i, o and f denotes input compound, input gate, output gate and forget gate, respectively. a, input compound, equals to u in the paper by Tai et al.

See the papers for details: Improved Semantic Representations From Tree-Structured Long Short-Term Memory Networks, and A Fast Unified Model for Parsing and Sentence Understanding.

Tai et al.’s N-Ary TreeLSTM is little extended in Bowman et al., and this link is based on the variant by Bowman et al. Specifically, eq. 10 in Tai et al. has only one W matrix to be applied to x, consistently for all children. On the other hand, Bowman et al.’s model has multiple matrices, each of which affects the forget gate for each child’s cell individually.
Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

__getitem__(name: str) → Any
Equivalent to getattr.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

- **hook** (LinkHook) – Link hook to be registered.
- **name** (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self

add_link(name: str, link: chainer.link.Link) → None
Registers a child link to this chain.

Parameters

- **name** (str) – Name of the child link. This name is also used as the attribute name.
- **link** (Link) – The link object to be registered.

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

- **name** (str) – Name of the parameter. This name is also used as the attribute name.
- **shape** (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer** (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- **name** (str) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

addgrads(link: chainer.link.Link) → None
Accumulates gradient values from given link.
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** (*Link*) – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode: str = 'share'*) → chainer.link.Chain

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument *mode* below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** (*str*) – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default *mode* is *share*.

**Returns**

Copied link object.

**Return type** *Link*

**copyparams** (*link: chainer.link.Link, copy_persistent: bool = True*) → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** (*Link*) – Source link object.

- **copy_persistent** (*bool*) – If True, persistent values are also copied. True by default.

**count_params** () → int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**

The total size of parameters (int)

4.3. Link and Chains

487
delete_hook (name: str) → None
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

device_resident_accept (visitor)
Applies the visitor to all the device objects in this instance.

Parameters visitor (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

disable_update () → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

enable_update () → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

forward (*cshsx)
Returns new cell state and output of N-ary TreeLSTM.

Parameters cshsx (list of Variable) – Arguments which include all cell vectors and all output vectors of fixed-length children, and an input vector. The number of arguments must be same as n_ary * 2 + 1.

Returns Returns (cnew, hnew), where cnew represents new cell state vector, and hnew is new output vector.

Return type tuple of ~chainer.Variable

from_chx ()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params (*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

• some parameters for a specific link.

• constants such as stride width of a convolutional layer.

init_scope () → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example
In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.
self.W = chainer.Parameter(0, (10, 5))
self.b = chainer.Parameter(0, (5,))

Links (skipself: bool = False) → Iterator[chainer.Link]

Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

NamedLinks (skipself: bool = False) → Iterator[Tuple[str, chainer.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

NamedParams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.Parameter]]

Returns a generator of all (path, parameter) pairs. The paths are relative from this link.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs.

Params (include_uninit: bool = True) → Iterator[chainer.Parameter]

Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

Register Persistent (name: str) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters name (str) – Name of the attribute to be registered.

Repeat (n_repeat: int, mode: str = 'init') → chainer.Sequential.Sequential

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer Sequential block like this:

class ConvBNReLU(chainer.Chain):

def __init__(self):
    super(ConvBNReLU, self).__init__()
    with self.init_scope():
        self.conv = L.Convolution2D(
            None, 64, 3, 1, 1, nobias=True)
The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

### Parameters

- **`n_repeat`** *(int)* – Number of times to repeat.
- **`mode`** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

### serialize

```python
serialize(serializer: chainer.serializer.AbstractSerializer) → None
```

Serializes the link object.

**Parameters**

- `serializer` *(AbstractSerializer)* – Serializer object.

### to_chx()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

### to_cpu()

```python
to_cpu() → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

### to_device

```python
to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
```

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- `device` *(Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]*) – Target device specifier. See `get_device()` for available values.

Returns: self
to_gpu

\(\text{to_gpu}(\text{device: Optional[Union[cuda.Device, int, numpy.integer]] = None}) \rightarrow \text{chainer.device_resident.DeviceResident}\)

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

**Parameters**

.device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64

\(\text{to_intel64()} \rightarrow \text{chainer.device_resident.DeviceResident}\)

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

zerograds

\(\text{zerograds()} \rightarrow \text{None}\)

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

*__eq__*(value, /)

Return self==value.

*__ne__*(value, /)

Return self!=value.

*__lt__*(value, /)

Return self<value.

*__le__*(value, /)

Return self<=value.

*__gt__*(value, /)

Return self>value.

*__ge__*(value, /)

Return self>=value.

**Attributes**

device

Device instance.

local_link_hooks

Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs

Generator of printable specs of this link.
Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.
See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.
Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.NStepBiGRU

class chainer.links.NStepBiGRU(self, n_layers, in_size, out_size, dropout)
Stacked Bi-directional GRU for sequences.
This link is stacked version of Bi-directional GRU for sequences. It calculates hidden and cell states of all layer at end-of-string, and all hidden states of the last layer for each time.
Unlike chainer.functions.n_step_bigru(), this function automatically sort inputs in descending order by length, and transpose the sequence. Users just need to call the link with a list of chainer.Variable holding sequences.

Parameters
• n_layers (int) – Number of layers.
• in_size (int) – Dimensionality of input vectors.
• out_size (int) – Dimensionality of hidden states and output vectors.
• dropout (float) – Dropout ratio.

See also:
chainer.functions.n_step_bigru()

Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

__getitem__(index)
Returns the child at given index.
Parameters index (int) – Index of the child in the list.
Returns The index-th child link.

Return type Link

__setitem__ (index: Union[int, slice], value: Union[chainer.link.Link, Iterable[chainer.link.Link]]) → None

__len__() → int
Returns the number of children.
__iter__() → Iterator[chainer.link.Link]

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link

Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.

• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_link (link: chainer.link.Link) → None

Registers a child link and adds it to the tail of the list.

Parameters link (Link) – The link object to be registered.

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None

Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.

• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• dtype – Data type of the parameter array.

• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent (name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.

• value – Value to be registered.

addgrads (link: chainer.link.Link) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters link (Link) – Source link object.

append (value)

S.append(value) – append value to the end of the sequence

children () → Iterator[chainer.link.Link]

Returns a generator of all child links.
Returns  A generator object that generates all child links.

clear () → None – remove all items from S

cleargrads () → None
    Clears all gradient arrays.
    This method should be called before the backward computation at every iteration of the optimization.

    copy (mode='share')
    Returns a deep copy of the chainlist.

copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None
    Copies all parameters from given link.
    This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.
    From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

    Parameters
    • link (Link) – Source link object.
    • copy_persistent (bool) – If True, persistent values are also copied. True by default.

count (value) → integer – return number of occurrences of value

count_params () → int
    Counts the total number of parameters.
    This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.
    If the link contains uninitialized parameters, this method raises a warning.

    Returns  The total size of parameters (int)

delete_hook (name: str) → None
    Unregisters the link hook.

    Parameters name (str) – The name of the link hook to be unregistered.

device_resident_accept (visitor)
    Applies the visitor to all the device objects in this instance.

    Parameters visitor (DeviceResidentsVisitor) – Visitor.
    This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

disable_update () → None
    Disables update rules of all parameters under the link hierarchy.
    This method sets the enabled flag of the update rule of each parameter variable to False.

enable_update () → None
    Enables update rules of all parameters under the link hierarchy.
    This method sets the enabled flag of the update rule of each parameter variable to True.

    extend (values)
    S.extend(iterable) – extend sequence by appending elements from the iterable
**forward** *(self, hx, xs)*  
Calculates all of the hidden states and the cell states.

**Parameters**

- **hx** *(Variable or None)* – Initial hidden states. If None is specified zero-vector is used. Its shape is \((S, B, N)\) for uni-directional RNN and \((2S, B, N)\) for bi-directional RNN where \(S\) is the number of layers and is equal to \(n\_layers\), \(B\) is the mini-batch size, and \(N\) is the dimension of the hidden units.

- **xs** *(list of Variable)* – List of input sequences. Each element \(xs[i]\) is a chainer.Variable holding a sequence. Its shape is \((L_i, I)\), where \(L_i\) is the length of a sequence for batch \(i\), and \(I\) is the size of the input and is equal to \(in\_size\).

**Returns**

This function returns a tuple containing two elements, hy and ys.

- **hy** is an updated hidden states whose shape is same as hx.

- **ys** is a list of Variable. Each element \(ys[i]\) holds hidden states of the last layer corresponding to an input \(xs[i]\). Its shape is \((L_i, N)\) for uni-directional RNN and \((L_i, 2N)\) for bi-directional RNN where \(L_i\) is the length of a sequence for batch \(i\), and \(N\) is size of hidden units.

**Return type** tuple

**from_chx()**  
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params(*args, **kwargs)**  
Initialize link with given parameters.

This method initializes the link with given \(N\)-dimensional arrays. Arguments includes

- some parameters for a specific link.

- constants such as stride width of a convolutional layer.

**index(value[, start[, stop]])** \(\rightarrow\) integer – return first index of value.

Raises ValueError if the value is not present.

Supporting start and stop arguments is optional, but recommended.

**init_hx(xs)**

**init_scope()** \(\rightarrow\) Iterator[None]  
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            ...
```

(continues on next page)
### insert (index: int, link: chainer.link.Link) → None
Insert a child link at the given index.

**Parameters**

- **index** (*int*) – The position of the list where the new link is inserted.
- **link** (*Link*) – The link to be inserted.

### links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

**Parameters**

- **skipself** (*bool*) – If True, then the generator skips this link and starts with the first child link.

**Returns**
A generator object that generates all links.

### namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters**

- **skipself** (*bool*) – If True, then the generator skips this link and starts with the first child link.

**Returns**
A generator object that generates all (path, link) pairs.

### namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

**Parameters**

- **include_uninit** (*bool*) – If True, it also generates uninitialized parameters.

**Returns**
A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

### params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

**Parameters**

- **include_uninit** (*bool*) – If True, it also generates uninitialized parameters.

**Returns**
A generator object that generates all parameters.

### pop (index) → item – remove and return item at index (default last).
Raise IndexError if list is empty or index is out of range.

### register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name** (*str*) – Name of the attribute to be registered.

### remove (value)
S.remove(value) – remove first occurrence of value. Raise ValueError if the value is not present.

### repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.
This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** (`int`) – Number of times to repeat.
- **mode** (`str`) – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

** reverse()**

S.reverse() – reverse IN PLACE

**rnn** (*args*)

Calls RNN function.

This function must be implemented in a child class.

**serialize** (**serializer: chainer.serializer.AbstractSerializer**) → None

Serializes the link object.

Parameters `serializer` (`AbstractSerializer`) – Serializer object.

**to_chx()**

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self
to_cpu() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device() for available values.

Returns: self

to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

zerograds() → None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.
__ge__(value, /)
   Return self>value.

Attributes

device
   Device instance.

local_link_hooks
   Ordered dictionary of registered link hooks.

   Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions,
   link hooks in this property are specific to this link.

n_cells

n_weights = 6

printable_specs
   Generator of printable specs of this link.

   Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword
   and value) that are passed to the __init__(). This pair of key and value is used for
   representing this class or subclass with __str__().

update_enabled
   True if at least one parameter has an update rule enabled.

use_bi_direction = True

within_init_scope
   True if the current code is inside of an initialization scope.

   See init_scope() for the details of the initialization scope.

xp
   Array module corresponding to the device.

   Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

crainer.links.NStepBiLSTM

class crainer.links.NStepBiLSTM(self, n_layers, in_size, out_size, dropout)
   Stacked Bi-directional LSTM for sequences.

   This link is stacked version of Bi-directional LSTM for sequences. It calculates hidden and cell states of all
   layer at end-of-string, and all hidden states of the last layer for each time.

   Unlike crainer.functions.n_step_bilstm(), this function automatically sort inputs in descending
   order by length, and transpose the sequence. Users just need to call the link with a list of crainer.Variable
   holding sequences.

   Parameters

   • n_layers (int) – Number of layers.
   • in_size (int) – Dimensionality of input vectors.
   • out_size (int) – Dimensionality of hidden states and output vectors.
   • dropout (float) – Dropout ratio.
See also:

`chainer.functions.n_step_bilstm()`

### Methods

**`__call__`**

```python
__call__(*args: Any, **kwargs: Any) → Any
```

Call self as a function.

**`__getitem__`**

```python
__getitem__(index)
```

Returns the child at given index.

**Parameters**

- `index` (**int**) – Index of the child in the list.

**Returns**

The `index`-th child link.

**Return type**

`Link`

**`__setitem__`**

```python
__setitem__(index: Union[int, slice], value: Union[chainer.link.Link, Iterable[chainer.link.Link]]) → None
```

**`__len__`**

```python
__len__() → int
```

Returns the number of children.

**`__iter__`**

```python
__iter__() → Iterator[chainer.link.Link]
```

**`add_hook`**

```python
add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
```

Registers a link hook.

**Parameters**

- `hook` (**LinkHook**) – Link hook to be registered.

- `name` (**str**) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

**Returns**

`self`

**`add_link`**

```python
add_link(link: chainer.link.Link) → None
```

Registers a child link and adds it to the tail of the list.

**Parameters**

- `link` (**Link**) – The link object to be registered.

**`add_param`**

```python
add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
```

Registers a parameter to the link.

**Parameters**

- `name` (**str**) – Name of the parameter. This name is also used as the attribute name.

- `shape` (**int or tuple of ints**) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

- `dtype` – Data type of the parameter array.

- `initializer` (**initializer**) – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.
add_persistent (name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters
- name (str) – Name of the persistent value. This name is also used for the attribute name.
- value – Value to be registered.

addgrads (link: chainer.link.Link) → None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters
- link (Link) – Source link object.

append (value)
S.append(value) – append value to the end of the sequence

children () → Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns
A generator object that generates all child links.

clear () → None – remove all items from S

cleargrads () → None
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')
Returns a deep copy of the chainlist.

copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters
- link (Link) – Source link object.
- copy_persistent (bool) – If True, persistent values are also copied. True by default.

count (value) → integer – return number of occurrences of value

count_params () → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.
**Returns**  The total size of parameters (int)

`delete_hook(name: str) → None`

Unregisters the link hook.

**Parameters**  `name (str)` – The name of the link hook to be unregistered.

`device_resident_accept(visitor)`  
Applies the visitor to all the device objects in this instance.

**Parameters**  `visitor (DeviceResidentsVisitor)` – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

`disable_update() → None`

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

`enable_update() → None`

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

`extend(values)`  
S.extend(iterable) – extend sequence by appending elements from the iterable

`forward(self, hx, cx, xs)`  
Calculates all of the hidden states and the cell states.

**Parameters**

- `hx (Variable or None)` – Initial hidden states. If `None` is specified zero-vector is used. Its shape is \((S, E, N)\) for uni-directional LSTM and \((2S, E, N)\) for bi-directional LSTM where \(S\) is the number of layers and is equal to `n_layers`, \(E\) is the mini-batch size, and \(N\) is the dimension of the hidden units.

- `cx (Variable or None)` – Initial cell states. If `None` is specified zero-vector is used. It has the same shape as `hx`.

- `xs (list of Variable)` – List of input sequences. Each element `xs[i]` is a `chainer.Variable` holding a sequence. Its shape is \((L_i, I)\), where \(L_i\) is the length of a sequence for batch \(i\), and \(I\) is the size of the input and is equal to `in_size`.

**Returns**

This function returns a tuple containing three elements, `hy`, `cy` and `ys`.

- `hy` is an updated hidden states whose shape is the same as `hx`.

- `cy` is an updated cell states whose shape is the same as `cx`.

- `ys` is a list of `Variable`. Each element `ys[i]` holds hidden states of the last layer corresponding to an input `xs[i]`. Its shape is \((L_i, N)\) for uni-directional LSTM and \((L_i, 2N)\) for bi-directional LSTM where \(L_i\) is the length of a sequence for batch \(i\), and \(N\) is size of hidden units.

**Return type**  `tuple`

`from_chx()`  
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

`classmethod from_params(*args, **kwargs)`  
Initialize link with given parameters.
This method initializes the link with given \(N\)-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

\[
\text{index}(value[, start[, stop]]) \rightarrow \text{integer} \quad \text{return first index of value.}
\]

Raises ValueError if the value is not present.

Supporting start and stop arguments is optional, but recommended.

\[\text{init}_h(x)\]

\[\text{init}_\text{scope}() \rightarrow \text{Iterator}[\text{None}]\]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for \text{Chain}) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example

In most cases, the parameter registration is done in the initializer method. Using the \text{init}_\text{scope} method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

\[\text{insert}(\text{index: int, link: chainer.link.Link}) \rightarrow \text{None}\]

Insert a child link at the given index.

Parameters

- \text{index (int)} – The position of the list where the new
  - \text{is inserted}.
- \text{link (Link)} – The link to be inserted.

\[\text{links}(\text{skipself: bool = False}) \rightarrow \text{Iterator}[\text{chainer.link.Link}]\]

Returns a generator of all links under the hierarchy.

Parameters \text{skipself (bool)} – If True, then the generator skips this link and starts with the
  - \text{first child link}.

Returns A generator object that generates all links.

\[\text{namedlinks}(\text{skipself: bool = False}) \rightarrow \text{Iterator}[\text{Tuple[str, chainer.link.Link]}]\]

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters \text{skipself (bool)} – If True, then the generator skips this link and starts with the
  - \text{first child link}.

Returns A generator object that generates all (path, link) pairs.

\[\text{namedparams}(\text{include_uninit: bool = True}) \rightarrow \text{Iterator}[\text{Tuple[str, chainer.variable.Parameter]}]\]

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters \text{include_uninit (bool)} – If True, it also generates uninitialized parameters.

4.3. Link and Chains
Returns
A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** (*include_uninit: bool = True*) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

**Parameters**

- **include_uninit** (*bool*) – If True, it also generates uninitialized parameters.

**Returns**
A generator object that generates all parameters.

**pop** (*index*) → item – remove and return item at index (default last).

Raise IndexError if list is empty or index is out of range.

**register_persistent** (*name: str*) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If *name* has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name** (*str*) – Name of the attribute to be registered.

**remove** (*value*)

S.remove(value) – remove first occurrence of value. Raise ValueError if the value is not present.

**repeat** (*n_repeat: int, mode: str = 'init'*) → chainer.sequential.Sequential

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** (*int*) – Number of times to repeat.
• **mode** *(str)* – It should be either *init*, *copy*, or *share*. *init* means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. *copy* means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. *share* means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

```python
reverse()
S.reverse() – reverse IN PLACE
```

```python
rnn(*args)
Calls RNN function.
This function must be implemented in a child class.
```

```python
serialize(serializer: chainer.serializer.AbstractSerializer) → None
Serializes the link object.

Parameters

**serializer** *(AbstractSerializer)* – Serializer object.
```

```python
to_chx()
Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.
Returns: self
```

```python
to_cpu() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Deprecated since version v7.0.0: Use `to_device()` instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.
Returns: self
```

```python
to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters

**device** – Target device specifier. See `get_device()` for available values.
Returns: self
```

```python
to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.
Deprecated since version v7.0.0: Use `to_device()` instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.
```

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.
Parameters `device` – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Depreciated since version v7.0.0: Use `to_device()` instead.
zerograds() → None
Initializes all gradient arrays by zero.
Depreciated since version v1.15: Use the more efficient `cleargrads()` instead.

Attributes

device
   `Device` instance.

local_link_hooks
   Ordered dictionary of registered link hooks.
   Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions,
   link hooks in this property are specific to this link.

n_cells
   n_weights = 8

printable_specs
   Generator of printable specs of this link.
   Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword
   and value) that are passed to the `__init__()`. This pair of key and value is used for
   representing this class or subclass with `__str__()`. 

update_enabled
   True if at least one parameter has an update rule enabled.

use_bi_direction = True

within_init_scope
   True if the current code is inside of an initialization scope.
   See `init_scope()` for the details of the initialization scope.
xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.NStepBiRNNReLU

class chainer.links.NStepBiRNNReLU(self, n_layers, in_size, out_size, dropout)
Stacked Bi-directional RNN for sequences.

This link is stacked version of Bi-directional RNN for sequences. Note that the activation function is relu. It
calculates hidden and cell states of all layer at end-of-string, and all hidden states of the last layer for each time.

Unlike chainer.functions.n_step_birnn(), this function automatically sort inputs in descending
order by length, and transpose the sequence. Users just need to call the link with a list of chainer.Variable
holding sequences.

Parameters

• n_layers (int) – Number of layers.
• in_size (int) – Dimensionality of input vectors.
• out_size (int) – Dimensionality of hidden states and output vectors.
• dropout (float) – Dropout ratio.

See also:
chainer.functions.n_step_birnn()

Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

__getitem__(index)
Returns the child at given index.

Parameters index (int) – Index of the child in the list.

Returns The index-th child link.

Return type Link

__setitem__(index: Union[int, slice], value: Union[chainer.link.Link, Iterable[chainer.link.Link]]) → None

__len__() → int
Returns the number of children.

__iter__() → Iterator[chainer.link.Link]

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.

• name (str) – Name of the link hook. The name must be unique among link hooks
registered to this link. If None, the default name of the link hook is used.

Returns self
add_link \( \text{link: chainer.link.Link} \) \( \rightarrow \) None

Registers a child link and adds it to the tail of the list.

**Parameters**

- **link** (Link) – The link object to be registered.

add_param \( \text{name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None} \) \( \rightarrow \) None

Registers a parameter to the link.

**Parameters**

- **name** (str) – Name of the parameter. This name is also used as the attribute name.
- **shape** (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer** (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent \( \text{name: str, value: Any} \) \( \rightarrow \) None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- **name** (str) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

addgrads \( \text{link: chainer.link.Link} \) \( \rightarrow \) None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** (Link) – Source link object.

append \( \text{value} \)

S.append(value) – append value to the end of the sequence

children () \( \rightarrow \) Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

clear () \( \rightarrow \) None – remove all items from S

cleargrads () \( \rightarrow \) None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')

Returns a deep copy of the chainlist.
**copyparams** (link: chainer.link.Link, copy_persistent: bool = True) → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using *copy.deepcopy()*.. The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

**Parameters**

- **link** (Link) – Source link object.
- **copy_persistent** (bool) – If True, persistent values are also copied. True by default.

**count** (*value*) → integer – return number of occurrences of value

**count_params** () → int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the *Parameters* held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

**delete_hook** (*name: str*) → None

Unregisters the link hook.

**Parameters** **name** (str) – The name of the link hook to be unregistered.

**device_resident_accept** (*visitor*)

Applies the visitor to all the device objects in this instance.

**Parameters** **visitor** (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update** () → None

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

**extend** (*values*)

S.extend(iterable) – extend sequence by appending elements from the iterable

**forward** (*self, hx, xs*)

Calculates all of the hidden states and the cell states.

**Parameters**

- **hx** (Variable or None) – Initial hidden states. If None is specified zero-vector is used. Its shape is \((S, B, N)\) for uni-directional RNN and \((2S, B, N)\) for bi-directional RNN where \(S\) is the number of layers and is equal to \(n\_layers\), \(B\) is the mini-batch size, and \(N\) is the dimension of the hidden units.
• \( \mathbf{x}_s \) (list of \( \text{Variable} \)) – List of input sequences. Each element \( \mathbf{x}_s[i] \) is a \chainer.Variable\ holding a sequence. Its shape is \((L_i, I)\), where \( L_i \) is the length of a sequence for batch \( i \), and \( I \) is the size of the input and is equal to \( \text{in}_\text{size} \).

Returns

This function returns a tuple containing two elements, \( \mathbf{h}_y \) and \( \mathbf{y}_s \).

• \( \mathbf{h}_y \) is an updated hidden states whose shape is same as \( \mathbf{h}_x \).

• \( \mathbf{y}_s \) is a list of \( \text{Variable} \). Each element \( \mathbf{y}_s[i] \) holds hidden states of the last layer corresponding to an input \( \mathbf{x}_s[i] \). Its shape is \((L_i, N)\) for uni-directional RNN and \((L_i, 2N)\) for bi-directional RNN where \( L_i \) is the length of a sequence for batch \( i \), and \( N \) is size of hidden units.

Return type tuple

def from_chx()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(*\texttt{args}, **\texttt{kwargs})

Initialize link with given parameters.

This method initializes the link with given \( \text{N-dimensional arrays} \). Arguments includes

• some parameters for a specific link.

• constants such as stride width of a convolutional layer.

\( \text{index}(\text{value}, [\text{start}, \text{stop}]) \) \to \text{integer} – return first index of value.

Raises ValueError if the value is not present.

Supporting start and stop arguments is optional, but recommended.

\( \text{init}_\text{hx}(xs) \)

\( \text{init}_\text{scope}() \) \to \text{Iterator}[\text{None}]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for \chainer\) by an assignment. A \chainer.Parameter\ object can be automatically registered by assigning it to an attribute under this context manager.

Example

In most cases, the parameter registration is done in the initializer method. Using the \text{init}_\text{scope} method, we can simply assign a \text{Parameter} object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

\( \text{insert}(\text{index}, \text{int}; \text{link}, \text{chainer.link.Link}) \) \to \text{None}

Insert a child link at the given index.

Parameters

• \( \text{index}\ (\text{int}) \) – The position of the list where the new
• **is inserted**. (link)

• **link** (Link) – The link to be inserted.

### links (skipself: bool = False) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

- **Parameters skipself (bool)** – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all links.

### namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters skipself (bool)** – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all (path, link) pairs.

### namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, parameter) pairs under the hierarchy.

- **Parameters include_uninit (bool)** – If True, it also generates uninitialized parameters.

- **Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

### params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

- **Parameters include_uninit (bool)** – If True, it also generates uninitialized parameters.

- **Returns** A generator object that generates all parameters.

### pop ([index]) → item – remove and return item at index (default last).

Raise IndexError if list is empty or index is out of range.

### register_persistent (name: str) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

- **Parameters name (str)** – Name of the attribute to be registered.

### remove (value)

S.remove(value) – remove first occurrence of value. Raise ValueError if the value is not present.

### repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential

Repeats this link multiple times to make a **Sequential**.

This method returns a **Sequential** object which has the same **Link** multiple times repeatedly. The mode argument means how to copy this link to repeat.

- **Example**

You can repeat the same link multiple times to create a longer **Sequential** block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
```

(continues on next page)
with self.init_scope():
    self.conv = L.Convolution2D(
        None, 64, 3, 1, 1, nobias=True)
    self.bn = L.BatchNormalization(64)

def forward(self, x):
    return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat (int)** – Number of times to repeat.
- **mode (str)** – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

reverse()
    S.reverse() – reverse IN PLACE

rnn(*args)
    Calls RNN function.
    This function must be implemented in a child class.

serialize (serializer: chainer.serializer.AbstractSerializer) → None
    Serializes the link object.

    Parameters serializer (AbstractSerializer) – Serializer object.

to_chx()
    Converts parameter variables and persistent values to ChainerX without any copy.
    This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.
    Returns: self

to_cpu () → chainer.device_resident.DeviceResident
    Copies parameter variables and persistent values to CPU.
    Deprecated since version v7.0.0: Use to_device() instead.
    This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.
    Returns: self
**to_device** *(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ ModuleType, int]])* → DeviceResident

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See *get_device()* for available values.

Returns: self

**to_gpu** *(device: Optional[Union[cuda.Device, int, numpy.integer]] = None)* → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use *to_device()* instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override *device_resident_accept()* to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use *to_device()* to perform inter-GPU transfer.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use *to_device()* instead.

**zerograds** () → None

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient *cleargrads()* instead.

**__eq__**(value,/) Return self==value.

**__ne__**(value,/) Return self!=value.

**__lt__**(value,/) Return self<value.

**__le__**(value,/) Return self<=value.

**__gt__**(value,/) Return self>value.

**__ge__**(value,/) Return self>=value.
Attributes

device

Device instance.

local_link_hooks

Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

n_cells

n_weights = 2

printable_specs

Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled

True if at least one parameter has an update rule enabled.

use_bi_direction = True

within_init_scope

True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.NStepBiRNNTanh

class chainer.links.NStepBiRNNTanh (self, n_layers, in_size, out_size, dropout)

Stacked Bi-directional RNN for sequences.

This link is stacked version of Bi-directional RNN for sequences. Note that the activation function is tanh. It calculates hidden and cell states of all layer at end-of-string, and all hidden states of the last layer for each time.

Unlike chainer.functions.n_step_birnn(), this function automatically sort inputs in descending order by length, and transpose the sequence. Users just need to call the link with a list of chainer.Variable holding sequences.

Parameters

• n_layers (int) – Number of layers.
• in_size (int) – Dimensionality of input vectors.
• out_size (int) – Dimensionality of hidden states and output vectors.
• dropout (float) – Dropout ratio.

See also:

chainer.functions.n_step_birnn()
Methods

```python
__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.
```

```python
__getitem__(index)
Returns the child at given index.

Parameters

• `index` (int) – Index of the child in the list.

Returns

The `index`-th child link.
```

```python
__setitem__(index: Union[int, slice], value: Union[chainer.link.Link, Iterable[chainer.link.Link]])
→ None
```

```python
__len__() → int
Returns the number of children.
```

```python
__iter__() → Iterator[chainer.link.Link]
```

```python
add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• `hook` (LinkHook) – Link hook to be registered.

• `name` (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self
```

```python
add_link(link: chainer.link.Link) → None
Registers a child link and adds it to the tail of the list.

Parameters

• `link` (Link) – The link object to be registered.
```

```python
add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• `name` (str) – Name of the parameter. This name is also used as the attribute name.

• `shape` (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• `dtype` – Data type of the parameter array.

• `initializer` (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.
```

```python
add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.
```
Parameters

- **name**: A string. Name of the persistent value. This name is also used for the attribute name.

- **value**: Value to be registered.

**addgrads**: Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters

- **link**: Source link object.

**append**: Appends value to the end of the sequence.

Returns: A generator object that generates all child links.

**clear**: Removes all items from the sequence.

**cleargrads**: Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy**: Returns a deep copy of the chainlist.

**copyparams**: Copies all parameters from the given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters

- **link**: Source link object.

- **copy_persistent**: If True, persistent values are also copied. True by default.

**count**: Returns the number of occurrences of value.

**count_params**: Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns: The total size of parameters (int)

**delete_hook**: Unregisters the link hook.

Parameters

- **name**: The name of the link hook to be unregistered.
device_resident_accept(visitor)
Applies the visitor to all the device objects in this instance.

Parameters
visitor(DeviceResidentsVisitor) – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.
disable_update() → None
Disables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to False.
enable_update() → None
Enables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to True.
extend(values)
S.extend(iterable) – extend sequence by appending elements from the iterable
forward(self, hx, xs)
Calculates all of the hidden states and the cell states.

Parameters

- hx (Variable or None) – Initial hidden states. If None is specified zero-vector is used.
  Its shape is \((S, B, N)\) for uni-directional RNN and \((2S, B, N)\) for bi-directional
  RNN where \(S\) is the number of layers and is equal to n_layers, \(B\) is the mini-batch size,
  and \(N\) is the dimension of the hidden units.

- xs (list of Variable) – List of input sequences. Each element \(xs[i]\) is a chainer.Variable
  holding a sequence. Its shape is \((L_i, I)\), where \(L_i\) is the length of a
  sequence for batch \(i\), and \(I\) is the size of the input and is equal to in_size.

Returns
This function returns a tuple containing two elements, \(hy\) and \(ys\).

- \(hy\) is an updated hidden states whose shape is same as \(hx\).
- \(ys\) is a list of Variable. Each element \(ys[i]\) holds hidden states of the last layer
  corresponding to an input \(xs[i]\). Its shape is \((L_i, N)\) for uni-directional RNN and
  \((L_i, 2N)\) for bi-directional RNN where \(L_i\) is the length of a sequence for batch \(i\),
  and \(N\) is size of hidden units.

Return type tuple

from_chx()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any

classmethod from_params(*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

index(value[, start[, stop]]) → integer – return first index of value.
 Raises ValueError if the value is not present.

Supporting start and stop arguments is optional, but recommended.

init_hx(xs)
init_scope() → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

insert(index: int, link: chainer.link.Link) → None

Insert a child link at the given index.

Parameters

- **index (int)** – The position of the list where the new
- **link (Link)** – The link to be inserted.

links(skipself: bool = False) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

namedparams(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, parameter) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

pop(index) → item – remove and return item at index (default last).

Raise IndexError if list is empty or index is out of range.
**register_persistent** *(name: str) → None*

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name** *(str)* – Name of the attribute to be registered.

- **remove** *(value)*
  S.remove(value) – remove first occurrence of value. Raise ValueError if the value is not present.

- **repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*
  Repeats this link multiple times to make a `Sequential`.

  This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** *(int)* – Number of times to repeat.

  - **mode** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

- **reverse** *
  S.reverse() – reverse IN PLACE
rnn (*args)
    Calls RNN function.

    This function must be implemented in a child class.

serialize (serializer: chainer.serializer.AbstractSerializer) → None
    Serializes the link object.

    Parameters serializer (AbstractSerializer) – Serializer object.

to_chx ()
    Converts parameter variables and persistent values to ChainerX without any copy.

    This method does not handle non-registered attributes. If some of such attributes must be copied to Chain-
erX, the link implementation must override this method to do so.

    Returns: self

to_cpu () → chainer.device_resident.DeviceResident
    Copies parameter variables and persistent values to CPU.

    Deprecated since version v7.0.0: Use to_device() instead.

    This method does not handle non-registered attributes. If some of such attributes must be copied to CPU,
    the link implementation should override device_resident_accept() to do so.

    Returns: self

to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], Module-
    Type, Tuple[ModuleType, int]]) → DeviceResident
    Copies parameter variables and persistent values to the specified device.

    This method does not handle non-registered attributes. If some of such attributes must be copied to the
device, the link implementation must override this method to do so.

    Parameters device – Target device specifier. See get_device() for available values.

    Returns: self

to_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) →
    chainer.device_resident.DeviceResident
    Copies parameter variables and persistent values to GPU.

    Deprecated since version v7.0.0: Use to_device() instead.

    This method does not handle non-registered attributes. If some of such attributes must be copied to GPU,
    the link implementation must override device_resident_accept() to do so.

    Warning: This method does not transfer the parameters if they are already on GPU. Use to_device
to perform inter-GPU transfer.

    Parameters device – Target device specifier. If omitted, the current device is used.

    Returns: self

to_intel64 () → chainer.device_resident.DeviceResident
    Copies parameter variables and persistent values to CPU.

    Deprecated since version v7.0.0: Use to_device() instead.

zerograds () → None
    Initializes all gradient arrays by zero.
Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

```python
__eq__(value, /)
    Return self==value.
__ne__(value, /)
    Return self!=value.
__lt__(value, /)
    Return self<value.
__le__(value, /)
    Return self<=value.
__gt__(value, /)
    Return self>value.
__ge__(value, /)
    Return self>=value.
```

## Attributes

**device**

Device instance.

**local_link_hooks**

Ordered dictionary of registered link hooks.

Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

**n_cells**

```
n_cells = 2
```

**printable_specs**

Generator of printable specs of this link.

```
Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()` . This pair of key and value is used for representing this class or subclass with `__str__()`.
```

**update_enabled**

```
update_enabled = True
```

**use_bi_direction = True**

**within_init_scope**

```
within_init_scope = True if the current code is inside of an initialization scope.
```

**xp**

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.

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4.3. Link and Chains  521
chainer.links.NStepGRU

```python
class chainer.links.NStepGRU(self, n_layers, in_size, out_size, dropout)
Stacked Uni-directional GRU for sequences.

This link is stacked version of Uni-directional GRU for sequences. It calculates hidden and cell states of all
layer at end-of-string, and all hidden states of the last layer for each time.

Unlike `chainer.functions.n_step_gru()`, this function automatically sort inputs in descending order
by length, and transpose the sequence. Users just need to call the link with a list of `chainer.Variable`
holding sequences.

Parameters

- `n_layers (int)` – Number of layers.
- `in_size (int)` – Dimensionality of input vectors.
- `out_size (int)` – Dimensionality of hidden states and output vectors.
- `dropout (float)` – Dropout ratio.

See also:

\[ \text{chainer.functions.n_step_gru}() \]
```

Methods

```python
__call__(*args: Any, **kwargs: Any) \rightarrow \text{Any}
Call self as a function.
```

```python
__getitem__(index)
Returns the child at given index.

Parameters

- `index (int)` – Index of the child in the list.

Returns

The `index`-th child link.

Return type

`Link`
```

```python
__setitem__(index: Union[int, slice], value: Union[chainer.link.Link, Iterable[chainer.link.Link]]) \rightarrow \text{None}
```

```python
len() \rightarrow \text{int}
Returns the number of children.
```

```python
iter() \rightarrow \text{Iterator[chainer.link.Link]}
```

```python
add_hook(hook: chainer.link_hook.LinkHook, name: \text{Optional[str]} = \text{None}) \rightarrow \text{chainer.link.Link}
Registers a link hook.

Parameters

- `hook (LinkHook)` – Link hook to be registered.
- `name (str)` – Name of the link hook. The name must be unique among link hooks
  registered to this link. If `None`, the default name of the link hook is used.

Returns

\text{self}
```

```python
add_link(link: chainer.link.Link) \rightarrow \text{None}
Registers a child link and adds it to the tail of the list.

Parameters

- `link (Link)` – The link object to be registered.
```
add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None

Registers a parameter to the link.

Parameters

- **name** (*str*) – Name of the parameter. This name is also used as the attribute name.
- **shape** (*int or tuple of ints*) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer** (*initializer*) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- **name** (*str*) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

addgrads(link: chainer.link.Link) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters **link** (*Link*) – Source link object.

append(*value*)

S.append(value) – append value to the end of the sequence

children() → Iterator[Link]

Returns a generator of all child links.

Returns A generator object that generates all child links.

clear() → None – remove all items from S

cleargrads() → None

Cleans all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy(*mode='share*)

Returns a deep copy of the chainlist.

copyparams(link: chainer.link.Link, copy_persistent: bool = True) → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.
From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters

- **link** (Link) – Source link object.
- **copy_persistent** (bool) – If True, persistent values are also copied. True by default.

**count**(value) → integer – return number of occurrences of value

**count_params**() → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

**delete_hook**(name: str) → None
Unregisters the link hook.

**Parameters** name (str) – The name of the link hook to be unregistered.

**device_resident_accept**(visitor)
Applies the visitor to all the device objects in this instance.

**Parameters** visitor (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update**() → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update**() → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

**extend**(values)
S.extend(iterable) – extend sequence by appending elements from the iterable

**forward**(self, hx, xs)
Calculates all of the hidden states and the cell states.

**Parameters**

- **hx** (Variable or None) – Initial hidden states. If None is specified zero-vector is used. Its shape is \((S, B, N)\) for uni-directional RNN and \((2S, B, N)\) for bi-directional RNN where \(S\) is the number of layers and is equal to n_layers, \(B\) is the mini-batch size, and \(N\) is the dimension of the hidden units.

- **xs** (list of Variable) – List of input sequences. Each element xs[i] is a chainer.Variable holding a sequence. Its shape is \((L_i, I)\), where \(L_i\) is the length of a sequence for batch i, and \(I\) is the size of the input and is equal to in_size.

**Returns**
This function returns a tuple containing two elements, hy and ys.
• $h_y$ is an updated hidden states whose shape is same as $h_x$.

• $y_s$ is a list of Variable. Each element $y_s[i]$ holds hidden states of the last layer corresponding to an input $x_s[i]$. Its shape is $(L_i, N)$ for uni-directional RNN and $(L_i, 2N)$ for bi-directional RNN where $L_i$ is the length of a sequence for batch $i$, and $N$ is size of hidden units.

**Return type** tuple

`from_chx()`
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

`classmethod from_params(*args, **kwargs)`
Initialize link with given parameters.

This method initializes the link with given $N$-dimensional arrays. Arguments includes
- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

`index[value, start, stop] → integer – return first index of value. Raises ValueError if the value is not present.

Supporting start and stop arguments is optional, but recommended.

`init_hx(xs)`

`init_scope() → Iterator[None]`
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

`insert(index: int, link: chainer.link.Link) → None`
Insert a child link at the given index.

**Parameters**
- `index (int) – The position of the list where the new
- `is inserted. (link)–`
- `link (Link) – The link to be inserted.

`links(skipself: bool = False) → Iterator[chainer.link.Link]`
Returns a generator of all links under the hierarchy.

4.3. Link and Chains 525
Parameters `skipself` *(bool)* – If `True`, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

**namedlinks** *(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]*

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters `skipself` *(bool)* – If `True`, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

**namedparams** *(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]*

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters `include_uninit` *(bool)* – If `True`, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** *(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]*

Returns a generator of all parameters under the link hierarchy.

Parameters `include_uninit` *(bool)* – If `True`, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

**pop** *(index)* → item – remove and return item at index (default last).

Raise IndexError if list is empty or index is out of range.

**register_persistent** *(name: str) → None*

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters `name` *(str)* – Name of the attribute to be registered.

**remove** *(value)*

S.remove(value) – remove first occurrence of value. Raise ValueError if the value is not present.

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
```

(continues on next page)
return F.relu(self.bn(self.conv(x)))
net = ConvBNReLU().repeat(16, mode='init')

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat** (*int*) – Number of times to repeat.
- **mode** (*str*) – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

reverse()

S.reverse() – reverse IN PLACE

rnn(*args)

Calls RNN function.

This function must be implemented in a child class.

serialize (*serializer: chainer.serializer.AbstractSerializer*) → None

Serializes the link object.

Parameters **serializer** (*AbstractSerializer*) – Serializer object.

to_chx()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

to_cpu() → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

to_device (*device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]*) → DeviceResident

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.
Parameters **device** – Target device specifier. See `get_device()` for available values.

Returns: self

do_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to GPU.

Depreciated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self

do_intel64 () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Depreciated since version v7.0.0: Use `to_device()` instead.

zerogrdas () → None

Initializes all gradient arrays by zero.

Depreciated since version v1.15: Use the more efficient `cleargrads()` instead.

__eq__(value,/)  
Return self==value.

__ne__(value,/)  
Return self!=value.

__lt__(value,/)  
Return self<value.

__le__(value,/)  
Return self<=value.

__gt__(value,/)  
Return self>value.

__ge__(value,/)  
Return self>=value.

Attributes

device

  `Device` instance.

local_link_hooks

Ordered dictionary of registered link hooks.

Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

n_cells
n_weights = 6

printable_specs
Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
True if at least one parameter has an update rule enabled.

use_bi_direction = False

within_init_scope
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.NStepLSTM

class chainer.links.NStepLSTM(self, n_layers, in_size, out_size, dropout)
Stacked Uni-directional LSTM for sequences.

This link is stacked version of Uni-directional LSTM for sequences. It calculates hidden and cell states of all layer at end-of-string, and all hidden states of the last layer for each time.

Unlike chainer.functions.n_step_lstm(), this function automatically sort inputs in descending order by length, and transpose the sequence. Users just need to call the link with a list of chainer.Variable holding sequences.

Parameters

• n_layers (int) – Number of layers.
• in_size (int) – Dimensionality of input vectors.
• out_size (int) – Dimensionality of hidden states and output vectors.
• dropout (float) – Dropout ratio.

See also:
chainer.functions.n_step_lstm()

Example

Read forward() method below first.

>>> dropout_ratio = 0.0
>>> in_size, seq_len, n_layers, out_size = 2, 4, 2, 3
>>> batch = 5
>>> xs = [
...     Variable(np.random.rand(seq_len, in_size).astype(np.float32))
...     for i in range(batch)]
>>> [x.shape for x in xs]
Without hidden or cell state:

```python
>>> by, cy, ys = lstm(None, None, xs)
>>> hy.shape  # shape should be (n_layers, batch, out_size)
(2, 5, 3)
>>> ys[0].shape  # should be (seq_len, out_size)
(4, 3)
>>> len(ys)  # should be equal to batch
5
```

With hidden and cell states:

```python
>>> h_shape = (n_layers, batch, out_size)
>>> hx = Variable(np.ones(h_shape, np.float32))
>>> cx = Variable(np.ones(h_shape, np.float32))
>>> by, cy, ys = lstm(hx, cx, xs)
>>> hy.shape  # shape should be (n_layers, batch, out_size)
(2, 5, 3)
>>> ys[0].shape  # should be (seq_len, out_size)
(4, 3)
```

### Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>__call__</code></td>
<td>Call self as a function.</td>
</tr>
<tr>
<td><code>__getitem__</code></td>
<td>Returns the child at given index.</td>
</tr>
<tr>
<td><code>__setitem__</code></td>
<td>Registers a link hook.</td>
</tr>
<tr>
<td><code>__len__</code></td>
<td>Returns the number of children.</td>
</tr>
<tr>
<td><code>__iter__</code></td>
<td>Returns an iterator over children.</td>
</tr>
</tbody>
</table>

#### `__call__`(*args: Any, **kwargs: Any) → Any

Call self as a function.

#### `__getitem__`(index)

Returns the child at given index.  

- **Parameters**
  - `index` *(int)*: Index of the child in the list.

- **Returns**
  The `index`-th child link.

- **Return type**
  `Link`

#### `__setitem__`(index: `Union[int, slice]`, value: `Union[chainer.link.Link, Iterable[chainer.link.Link]]`) → None

Registers a link hook.

- **Parameters**
  - `hook` *(LinkHook)*: Link hook to be registered.
  - `name` *(str)*: Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

- **Returns**
  self
**add_link** *(link: chainer.link.Link) → None*

Registers a child link and adds it to the tail of the list.

**Parameters**

- **link** *(Link)* – The link object to be registered.

**add_param** *(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None*

Registers a parameter to the link.

**Parameters**

- **name** *(str)* – Name of the parameter. This name is also used as the attribute name.
- **shape** *(int or tuple of ints)* – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer** *(initializer)* – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

**add_persistent** *(name: str, value: Any) → None*

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- **name** *(str)* – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

**addgrads** *(link: chainer.link.Link) → None*

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** *(Link)* – Source link object.

**append** *(value)*

S.append(value) – append value to the end of the sequence

**children** *(Link)*

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**clear** *(Link)*

clear() → None – remove all items from S

**cleargrads** *(Link)*

cleargrads() → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode='share')*

Returns a deep copy of the chainlist.

---

### 4.3. Link and Chains

531
copyparams \( (\text{link: chainer.link.Link}, \text{copy\_persistent: bool = True}) \rightarrow \text{None} \)

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using \text{copy\_deepcopy}. The old behavior (not copying persistent values) can be reproduced with \text{copy\_persistent=False}.

**Parameters**

- \text{link (Link)} – Source link object.
- \text{copy\_persistent (bool)} – If \text{True}, persistent values are also copied. \text{True} by default.

\text{count (value) → integer \rightarrow return number of occurrences of value}

\text{count\_params () → int}

Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

\text{delete\_hook (name: str) → None}

Unregisters the link hook.

**Parameters** \text{name (str)} – The name of the link hook to be unregistered.

\text{device\_resident\_accept (visitor)}

Applies the visitor to all the device objects in this instance.

**Parameters** \text{visitor (DeviceResidentsVisitor)} – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

\text{disable\_update () → None}

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

\text{enable\_update () → None}

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

\text{extend (values)}

\text{S.extend(iterable) \rightarrow extend sequence by appending elements from the iterable}

\text{forward (self, hx, cx, xs)}

Calculates all of the hidden states and the cell states.

**Parameters**

- \text{hx (Variable or None)} – Initial hidden states. If \text{None} is specified zero-vector is used. Its shape is \((S, B, N)\) for uni-directional LSTM and \((2S, B, N)\) for bi-directional LSTM where \(S\) is the number of layers and is equal to \text{n\_layers}, \(B\) is the mini-batch size, and \(N\) is the dimension of the hidden units.
• \textbf{cx} (\texttt{Variable} or \texttt{None}) – Initial cell states. If \texttt{None} is specified zero-vector is used. It has the same shape as \texttt{hx}.

• \textbf{xs} (list of \texttt{Variable}) – List of input sequences. Each element \texttt{xs[i]} is a chainer. \texttt{Variable} holding a sequence. Its shape is \((L_i, I)\), where \(L_i\) is the length of a sequence for batch \(i\), and \(I\) is the size of the input and is equal to \texttt{in_size}.

**Returns**

This function returns a tuple containing three elements, \(hy\), \(cy\) and \(ys\).

• \(hy\) is an updated hidden states whose shape is the same as \(hx\).

• \(cy\) is an updated cell states whose shape is the same as \(cx\).

• \(ys\) is a list of \texttt{Variable}. Each element \(ys[i]\) holds hidden states of the last layer corresponding to an input \(xs[i]\). Its shape is \((L_i, N)\) for uni-directional LSTM and \((L_i, 2N)\) for bi-directional LSTM where \(L_i\) is the length of a sequence for batch \(i\), and \(N\) is size of hidden units.

**Return type** \texttt{tuple}

\texttt{from_chx}\texttt{()} 
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

\texttt{classmethod from_params(*args, **kwargs)} 
Initialize link with given parameters.

This method initializes the link with given \texttt{N-dimensional arrays}. Arguments includes

• some parameters for a specific link.

• constants such as stride width of a convolutional layer.

\texttt{index(value, start, stop)} \rightarrow \texttt{integer} – return first index of value.

Supporting start and stop arguments is optional, but recommended.

\texttt{init\_hx(xs)}

\texttt{init\_scope()} \rightarrow \texttt{Iterator[None]} 
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for \texttt{Chain}) by an assignment. A \texttt{Parameter} object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the \texttt{init\_scope} method, we can simply assign a \texttt{Parameter} object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

4.3. Link and Chains 533
**insert** *(index: int, link: chainer.link.Link) → None*

Insert a child link at the given index.

**Parameters**

- **index** *(int)* – The position of the list where the new link is inserted.
- **link** *(Link)* – The link to be inserted.

**links** *(skipself: bool = False) → Generator[chainer.link.Link]*

Returns a generator of all links under the hierarchy.

**Parameters** *skipself*(bool) – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all links.

**namedlinks** *(skipself: bool = False) → Generator[Tuple[str, chainer.link.Link]]*

Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters** *skipself*(bool) – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all (path, link) pairs.

**namedparams** *(include_uninit: bool = True) → Generator[Tuple[str, chainer.variable.Parameter]]*

Returns a generator of all (path, parameter) pairs. The paths are relative from this link.

**Parameters** *include_uninit*(bool) – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all parameters.

**params** *(include_uninit: bool = True) → Generator[chainer.variable.Parameter]*

Returns a generator of all parameters under the link hierarchy.

**Parameters** *include_uninit*(bool) – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all parameters.

**pop** *(index)* → item – remove and return item at index (default last).

Raise IndexError if list is empty or index is out of range.

**register_persistent** *(name: str) → None*

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters** *name*(str) – Name of the attribute to be registered.

**remove** *(value)*

S.remove(value) – remove first occurrence of value. Raise ValueError if the value is not present.

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.
You can repeat the same link multiple times to create a longer *Sequential* block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- `n_repeat` (*int*) – Number of times to repeat.
- `mode` (*str*) – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned *Sequential* will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting *Sequential* object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

reverse()

S.reverse() – reverse *IN PLACE*

rnn(*args*)

Calls RNNN function.

This function must be implemented in a child class.

serialize (serializer: chainer.serializer.AbstractSerializer) \(\rightarrow\) None

Serializes the link object.

Parameters serializer (AbstractSerializer) – Serializer object.

to_chx()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

to_cpu() \(\rightarrow\) chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

**to_device** (device: `Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]`) → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**
- **device** – Target device specifier. See `get_device()` for available values.

Returns: self

**to_gpu** (device: `Optional[Union[cuda.Device, int, numpy.integer]]` = `None`) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

**Parameters**
- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

**zerograds** () → `None`
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

---

__eq__(value,)
Return self==value.

__ne__(value,)
Return self!=value.

__lt__(value,)
Return self<value.

__le__(value,)
Return self<=value.

__gt__(value,)
Return self>value.

__ge__(value,)
Return self>=value.
Attributes

**device**

Device instance.

**local_link_hooks**

Ordered dictionary of registered link hooks.

Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

**n_cells**

n_weights = 8

**printable_specs**

Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()`.

This pair of key and value is used for representing this class or subclass with `__str__()`.

**update_enabled**

True if at least one parameter has an update rule enabled.

**use_bi_direction** = False

**within_init_scope**

True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.

**xp**

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.

**chainer.links.NStepRNNReLU**

**class** chainer.links.NStepRNNReLU (self, n_layers, in_size, out_size, dropout)

Stacked Uni-directional RNN for sequences.

This link is stacked version of Uni-directional RNN for sequences. Note that the activation function is `relu`. It calculates hidden and cell states of all layer at end-of-string, and all hidden states of the last layer for each time.

Unlike `chainer.functions.n_step_rnn()`, this function automatically sort inputs in descending order by length, and transpose the sequence. Users just need to call the link with a list of `chainer.Variable` holding sequences.

**Parameters**

- `n_layers (int)` – Number of layers.
- `in_size (int)` – Dimensionality of input vectors.
- `out_size (int)` – Dimensionality of hidden states and output vectors.
- `dropout (float)` – Dropout ratio.

**See also:**

`chainer.functions.n_step_rnn()`
Methods

__call__ (*args: Any, **kwargs: Any) → Any

Call self as a function.

__getitem__ (index)

Returns the child at given index.

Parameters

- **index** (*int*) – Index of the child in the list.

Returns

The index-th child link.

Return type

Link

__setitem__ (index: Union[int, slice], value: Union[chainer.link.Link, Iterable[chainer.link.Link]]) → None

__len__ () → int

Returns the number of children.

__iter__ () → Iterator[chainer.link.Link]

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link

Registers a link hook.

Parameters

- **hook** (*LinkHook*) – Link hook to be registered.
- **name** (*str*) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self

add_link (link: chainer.link.Link) → None

Registers a child link and adds it to the tail of the list.

Parameters

- **link** (*Link*) – The link object to be registered.

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None

Registers a parameter to the link.

Parameters

- **name** (*str*) – Name of the parameter. This name is also used as the attribute name.
- **shape** (*int or tuple of ints*) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer** (*initializer*) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent (name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.
Parameters

- **name** (*str*) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

**addgrads** (*link: chainer.link.Link*) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**
- **link** (*Link*) – Source link object.

**append** (*value*)

S.append(value) – append value to the end of the sequence

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**
A generator object that generates all child links.

**clear** () → None – remove all items from S

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode*='share')

Returns a deep copy of the chainlist.

**copyparams** (*link: chainer.link.Link, copy_persistent: bool = True*) → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using *copy.deepcopy()*.

The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

**Parameters**

- **link** (*Link*) – Source link object.
- **copy_persistent** (*bool*) – If True, persistent values are also copied. True by default.

**count** (*value*) → integer – return number of occurrences of value

**count_params** () → int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the **Parameters** held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**
The total size of parameters (int)

**delete_hook** (*name: str*) → None

Unregisters the link hook.

**Parameters**
- **name** (*str*) – The name of the link hook to be unregistered.
device_resident_accept(visitor)
Applies the visitor to all the device objects in this instance.

Parameters

visitor (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

disable_update() → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

enable_update() → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

extend(values)
S.extend(iterable) – extend sequence by appending elements from the iterable

forward(self, hx, xs)
Calculates all of the hidden states and the cell states.

Parameters

• hx (Variable or None) – Initial hidden states. If None is specified zero-vector is used. Its shape is \((S, B, N)\) for uni-directional RNN and \((2S, B, N)\) for bi-directional RNN where \(S\) is the number of layers and is equal to \(n\_layers\), \(B\) is the mini-batch size, and \(N\) is the dimension of the hidden units.

• xs (list of Variable) – List of input sequences. Each element \(xs[i]\) is a chainer.Variable holding a sequence. Its shape is \((L_i, I)\), where \(L_i\) is the length of a sequence for batch \(i\), and \(I\) is size of the input and is equal to \(in\_size\).

Returns

This function returns a tuple containing two elements, \(hy\) and \(ys\).

• \(hy\) is an updated hidden states whose shape is same as \(hx\).

• \(ys\) is a list of Variable. Each element \(ys[i]\) holds hidden states of the last layer corresponding to an input \(xs[i]\). Its shape is \((L_i, N)\) for uni-directional RNN and \((L_i, 2N)\) for bi-directional RNN where \(L_i\) is the length of a sequence for batch \(i\), and \(N\) is size of hidden units.

Return type
tuple

from_chx()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given \(N\)-dimensional arrays. Arguments includes

• some parameters for a specific link.

• constants such as stride width of a convolutional layer.

index(value[, start, stop]) → integer – return first index of value.

Supporting start and stop arguments is optional, but recommended.

init_hx(xs)
**init_scope**() → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

---

**Example**

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

---

**insert** (index: int, link: chainer.link.Link) → None

Insert a child link at the given index.

- **Parameters**
  - *index* (int) – The position of the list where the new
  - *link* (Link) – The link to be inserted.

**links** (skipself: bool = False) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

- **Parameters** skipself (bool) – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all links.

**namedlinks** (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters** skipself (bool) – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all (path, link) pairs.

**namedparams** (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, parameter) pairs under the hierarchy.

- **Parameters** include_uninit (bool) – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

- **Parameters** include_uninit (bool) – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all parameters.

**pop** ([index]) → item – remove and return item at index (default last).

Raise IndexError if list is empty or index is out of range.
**register_persistent** *(name: str) → None*

 Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- `name (str)` – Name of the attribute to be registered.

**remove** *(value)*

`S.remove(value)` – remove first occurrence of value. Raise ValueError if the value is not present.

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- `n_repeat (int)` – Number of times to repeat.
- `mode (str)` – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**reverse()**

`S.reverse()` – reverse IN PLACE
rnn(*args)
Calls RNN function.
This function must be implemented in a child class.

serialize(serializer: chainer.serializer.AbstractSerializer) → None
Serializes the link object.

Parameters serializer (AbstractSerializer) – Serializer object.

to_chx()
Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self
to_cpu() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self
to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device() for available values.

Returns: self
to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device() instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.
zerograds() → None
Initializes all gradient arrays by zero.
Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

```python
__eq__(value,)
    Return self==value.
__ne__(value,)
    Return self!=value.
__lt__(value,)
    Return self<value.
__le__(value,)
    Return self<=value.
__gt__(value,)
    Return self>value.
__ge__(value,)
    Return self>=value.
```

**Attributes**

- **device**
  - `Device` instance.

- **local_link_hooks**
  - Ordered dictionary of registered link hooks.
  
  Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

- **n_cells**
  - `n_weights = 2`

- **printable_specs**
  - Generator of printable specs of this link.
    
    Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()` method. This pair of key and value is used for representing this class or subclass with `__str__()`.

- **update_enabled**
  - `True` if at least one parameter has an update rule enabled.

- **use_bi_direction** = `False`

- **within_init_scope**
  - `True` if the current code is inside of an initialization scope.
  
  See `init_scope()` for the details of the initialization scope.

- **xp**
  - Array module corresponding to the device.
  
  Depending on the device in which this object resides, this property returns `numpy`, `cupy`, or `chainerx`. 
**chainer.links.NStepRNNTanh**

**class** chainer.links.NStepRNNTanh(self, n_layers, in_size, out_size, dropout)

Stacked Uni-directional RNN for sequences.

This link is stacked version of Uni-directional RNN for sequences. Note that the activation function is \(\tanh\). It calculates hidden and cell states of all layer at end-of-string, and all hidden states of the last layer for each time.

Unlike **chainer.functions.n_step_rnn()**, this function automatically sort inputs in descending order by length, and transpose the sequence. Users just need to call the link with a list of **chainer.Variable** holding sequences.

**Parameters**

- **n_layers** (**int**) – Number of layers.
- **in_size** (**int**) – Dimensionality of input vectors.
- **out_size** (**int**) – Dimensionality of hidden states and output vectors.
- **dropout** (**float**) – Dropout ratio.

**See also:**

**chainer.functions.n_step_rnn()**

**Methods**

- **__call__(***args: Any, **kwargs: Any) → Any**
  
  Call self as a function.

- **__getitem__(**index**)
  
  Returns the child at given index.

  **Parameters**
  
  - **index** (**int**) – Index of the child in the list.

  **Returns**
  
  The \(\text{index}\)-th child link.

  **Return type**
  
  **Link**

- **__setitem__(**index: Union[int, slice], value: Union[chainer.link.Link, Iterable[chainer.link.Link]]) → None**

- **__len__() → int**

  Returns the number of children.

- **__iter__() → Iterator[chainer.link.Link]**

- **add_hook(**hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link**

  Registers a link hook.

  **Parameters**

  - **hook** (**LinkHook**) – Link hook to be registered.

  - **name** (**str**) – Name of the link hook. The name must be unique among link hooks registered to this link. If **None**, the default name of the link hook is used.

  **Returns**

  - **self**

- **add_link(**link: chainer.link.Link) → None**

  Registers a child link and adds it to the tail of the list.

  **Parameters**

  - **link** (**Link**) – The link object to be registered.
add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

- **name (str)** – Name of the parameter. This name is also used as the attribute name.
- **shape (int or tuple of ints)** – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer (initializer)** – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- **name (str)** – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

addgrads(link: chainer.link.Link) → None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters **link (Link)** – Source link object.

append(value)
S.append(value) – append value to the end of the sequence

children() → Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns A generator object that generates all child links.

clear() → None – remove all items from S

cleargrads() → None
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy(mode='share')
Returns a deep copy of the chainlist.

copyparams(link: chainer.link.Link, copy_persistent: bool = True) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.
From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters

- **link** *(Link)* – Source link object.
- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

**count** *(value) → integer* – return number of occurrences of value

**count_params** *(*) → int*

Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

**delete_hook** *(name: str) → None*

Unregisters the link hook.

Parameters **name** *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*

Applies the visitor to all the device objects in this instance.

Parameters **visitor** *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** *(*) → None*

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update** *(*) → None*

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

**extend** *(values)*

S.extend(iterable) – extend sequence by appending elements from the iterable

**forward** *(self, hx, xs)*

Calculates all of the hidden states and the cell states.

Parameters

- **hx** *(Variable or None)* – Initial hidden states. If None is specified zero-vector is used. Its shape is *(S, B, N)* for uni-directional RNN and *(2S, B, N)* for bi-directional RNN where *S* is the number of layers and is equal to n_layers, *B* is the mini-batch size, and *N* is the dimension of the hidden units.

- **xs** (list of Variable) – List of input sequences. Each element xs[i] is a chainer.Variable holding a sequence. Its shape is *(L_i, I)*, where L_i is the length of a sequence for batch *i*, and *I* is the size of the input and is equal to in_size.

Returns

This function returns a tuple containing two elements, *hy* and *ys.*
• `hy` is an updated hidden states whose shape is same as `hx`.
• `ys` is a list of `Variable`. Each element `ys[i]` holds hidden states of the last layer corresponding to an input `xs[i]`. Its shape is `(L_i, N)` for uni-directional RNN and `(L_i, 2N)` for bi-directional RNN where `L_i` is the length of a sequence for batch `i`, and `N` is size of hidden units.

**Return type**  `tuple`

`from_chx()`  
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

`classmethod from_params(*args, **kwargs)`  
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes
• some parameters for a specific link.
• constants such as stride width of a convolutional layer.

`index(value[, start, stop])` → integer – return first index of value.
Raises ValueError if the value is not present.

Supporting start and stop arguments is optional, but recommended.

`init_hx(xs)`  

`init_scope()` → Iterator[None]  
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

`insert(index: int, link: chainer.link.Link) → None`  
Insert a child link at the given index.

**Parameters**
• `index` (`int`) – The position of the list where the new
• `is inserted` (`link`)–
• `link` (`Link`) – The link to be inserted.

`links` (`skipself: bool = False`) → Iterator[chainer.link.Link]  
Returns a generator of all links under the hierarchy.
Parameters **skipself** *(bool)* – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

**namedlinks** *(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]*

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters **skipself** *(bool)* – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

**namedparams** *(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]*

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters **include_uninit** *(bool)* – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** *(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]*

Returns a generator of all parameters under the link hierarchy.

Parameters **include_uninit** *(bool)* – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

**pop** *(index) → item* – remove and return item at index (default last).

Raise IndexError if list is empty or index is out of range.

**register_persistent** *(name: str) → None*

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters **name** *(str)* – Name of the attribute to be registered.

**remove** *(value)*

S.remove(value) – remove first occurrence of value. Raise ValueError if the value is not present.

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):

    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
```

(continues on next page)
The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

### Parameters

- **n_repeat** (`int`) – Number of times to repeat.
- **mode** (`str`) – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

```python
return F.relu(self.bn(self.conv(x)))
```

```python
net = ConvBNReLU().repeat(16, mode='init')
```

### reverse() method

Reverse IN PLACE

### rnn() method

Calls RNN function.

This function must be implemented in a child class.

### serialize() method

Serializes the link object.

#### Parameters

- **serializer** (`AbstractSerializer`) – Serializer object.

### to_chx() method

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

### to_cpu() method

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

### to_device() method

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.
Parameters `device` – Target device specifier. See `get_device()` for available values.

Returns: self

`to_gpu` *(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) -> chainer.device_resident.DeviceResident* 
Copies parameter variables and persistent values to GPU.

Depreciated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

Parameters `device` – Target device specifier. If omitted, the current device is used.

Returns: self

`to_intel64` () -> chainer.device_resident.DeviceResident 
Copies parameter variables and persistent values to CPU.

Depreciated since version v7.0.0: Use `to_device()` instead.

`zerograds` () -> None 
Initializes all gradient arrays by zero.

Depreciated since version v1.15: Use the more efficient `cleargrads()` instead.

`__eq__` *(value, /)* 
Return self==value.

`__ne__` *(value, /)* 
Return self!=value.

`__lt__` *(value, /)* 
Return self<value.

`__le__` *(value, /)* 
Return self<=value.

`__gt__` *(value, /)* 
Return self>value.

`__ge__` *(value, /)* 
Return self>=value.

Attributes

`device` 
Device instance.

`local_link_hooks` 
Ordered dictionary of registered link hooks.

Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

`n_cells`
n_weights = 2

printable_specs
    Generator of printable specs of this link.
    
    **Yields** specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the **__init__()**. This pair of key and value is used for representing this class or subclass with **__str__()**.

update_enabled
    True if at least one parameter has an update rule enabled.

use_bi_direction = False

within_init_scope
    True if the current code is inside of an initialization scope.
    See **init_scope()** for the details of the initialization scope.

xp
    Array module corresponding to the device.
    Depending on the device in which this object resides, this property returns **numpy**, **cupy** or **chainerx**.

chainer.links.Parameter

class chainer.links.Parameter(array)
    Link that just holds a parameter and returns it.
    
    Deprecated since version v1.5: The parameters are stored as variables since v1.5. Use them directly instead.
    
    **Parameters**
    array – Initial parameter array.
    
    **Variables**
    W (Variable) – Parameter variable.

Methods

**__call__(***args: Any, **kwargs: Any) → Any**
    Call self as a function.

**add_hook** (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
    Registers a link hook.
    
    **Parameters**
    
    • hook (LinkHook) – Link hook to be registered.
    
    • name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

    **Returns**
    self

**add_param**(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
    Registers a parameter to the link.
    
    **Parameters**
    
    • name (str) – Name of the parameter. This name is also used as the attribute name.
• **shape** *(int or tuple of ints)* – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• **dtype** – Data type of the parameter array.

• **initializer** *(initializer)* – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

```python
add_persistent*(name: str, value: Any) → None
```
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

• **name** *(str)* – Name of the persistent value. This name is also used for the attribute name.

• **value** – Value to be registered.

```python
addgrads*(link: chainer.link.Link) → None
```
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

• **link** *(Link)* – Source link object.

```python
children() → Iterator[chainer.link.Link]
```
Returns a generator of all child links.

**Returns** A generator object that generates all child links.

```python
cleargrads() → None
```
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

```python
copy*(mode: str = 'share') → chainer.link.Link
```
Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

• **mode** *(str)* – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

**Returns** Copied link object.

**Return type** *Link*
**copyparams** *(link: chainer.link.Link, copy_persistent: bool = True) → None*
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** *(Link)* – Source link object.
- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

**count_params** () → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

**delete_hook** *(name: str) → None*
Unregisters the link hook.

**Parameters** name *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*
Applies the visitor to all the device objects in this instance.

**Parameters** visitor *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to `False`.

**enable_update** () → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to `True`.

**forward** *(volatile='off')*
Returns the parameter variable.

**Parameters** volatile *(Flag)* – The volatility of the returned variable.

**Returns** A copy of the parameter variable with given volatility.

**Return type** `Variable`

**from_chx** ()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** (*args, **kwargs)*
Initialize link with given parameters.
This method initializes the link with given N-dimensional arrays. Arguments includes
- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

```python
def __init__(self):
    super().__init__()
    with self.init_scope():
        self.W = chainer.Parameter(0, (10, 5))
        self.b = chainer.Parameter(0, (5,))
```

### Example
In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()  # line 15
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```
Parameters

- **name** *(str)* – Name of the attribute to be registered.

- **repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

  Repeats this link multiple times to make a **Sequential**.

  This method returns a **Sequential** object which has the same **Link** multiple times repeatedly. The **mode** argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer **Sequential** block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The **net** object contains 16 blocks, each of which is **ConvBNReLU**. And the **mode** was **init**, so each block is re-initialized with different parameters. If you give **copy** to this argument, each block has same values for its parameters but its object ID is different from others. If it is **share**, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat** *(int)* – Number of times to repeat.
- **mode** *(str)* – It should be either **init**, **copy**, or **share**. **init** means parameters of each repeated element in the returned **Sequential** will be re-initialized, so that all elements have different initial parameters. **copy** means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. **share** means all the elements which consist the resulting **Sequential** object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

- **serializer** *(AbstractSerializer)* – Serializer object.

**to_chx** ()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.
Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See `get_device()` for available values.

Returns: self
to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.
zerograds() → None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

___eq__(value, /)  
Return self==value.

___ne__(value, /)  
Return self!=value.

___lt__(value, /)  
Return self<value.

___le__(value, /)  
Return self<=value.

___gt__(value, /)  
Return self>value.

___ge__(value, /)  
Return self>=value.
Attributes

device

Device instance.

local_link_hooks

Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs

Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__() function. This pair of key and value is used for representing this class or subclass with __str__().

update_enabled

True if at least one parameter has an update rule enabled.

within_init_scope

True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.Scale

class chainer.links.Scale(axis=1, W_shape=None, bias_term=False, bias_shape=None)

Broadcasted elementwise product with learnable parameters.

Computes a elementwise product as scale() function does except that its second input is a learnable weight parameter \( W \) the link has.

Parameters

• axis (int) – The first axis of the first input of scale() function along which its second input is applied.

• W_shape (tuple of ints) – Shape of learnable weight parameter. If None, this link does not have learnable weight parameter so an explicit weight needs to be given to its forward method’s second input.

• bias_term (bool) – Whether to also learn a bias (equivalent to Scale link + Bias link).

• bias_shape (tuple of ints) – Shape of learnable bias. If W_shape is None, this should be given to determine the shape. Otherwise, the bias has the same shape W_shape with the weight parameter and bias_shape is ignored.

See also:

See scale() for details.

Variables

• W (Parameter) – Weight parameter if W_shape is given. Otherwise, no W attribute.

• bias (Bias) – Bias term if bias_term is True. Otherwise, no bias attribute.
Methods

__call__(*args: Any, **kwargs: Any) \rightarrow Any
Call self as a function.

__getitem__(name: str) \rightarrow Any
Equivalent to getattr.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) \rightarrow chainer.link.Link
Registers a link hook.

Parameters

- **hook**: LinkHook – Link hook to be registered.
- **name**: str – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self

add_link(name: str, link: chainer.link.Link) \rightarrow None
Registers a child link to this chain.

Parameters

- **name**: str – Name of the child link. This name is also used as the attribute name.
- **link**: Link – The link object to be registered.

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) \rightarrow None
Registers a parameter to the link.

Parameters

- **name**: str – Name of the parameter. This name is also used as the attribute name.
- **shape**: int or tuple of ints – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype**: – Data type of the parameter array.
- **initializer**: initializer – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) \rightarrow None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- **name**: str – Name of the persistent value. This name is also used for the attribute name.
- **value**: Value to be registered.

addgrads(link: chainer.link.Link) \rightarrow None
Accumulates gradient values from given link.
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** *(Link)* – Source link object.

**children** *(→ Iterator[chainer.link.Link])*  
Returns a generator of all child links.

**Returns**  
A generator object that generates all child links.

**cleargrads** *(→ None)*  
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode: str = 'share') → chainer.link.Chain)*  
Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument **mode** below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** *(str)* – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default **mode** is share.

**Returns**  
Copied link object.

**Return type**  
**Link**

**copyparams** *(link: chainer.link.Link, copy_persistent: bool = True) → None)*  
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using *copy.deepcopy()* . The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

**Parameters**

- **link** *(Link)* – Source link object.

- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

**count_params** *(→ int)*  
Counts the total number of parameters.

This method counts the total number of scalar values included in all the **Parameters** held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**  
The total size of parameters (int)
delete_hook (name: str) \rightarrow None

Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

device_resident_accept (visitor)

Applies the visitor to all the device objects in this instance.

Parameters visitor (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

disable_update () \rightarrow None

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

enable_update () \rightarrow None

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

forward (*xs)

Applies broadcasted elementwise product.

Parameters xs (list of Variables) – Input variables whose length should be one if the link has a learnable weight parameter, otherwise should be two.

from_chx ()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params (*args, **kwargs)

Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

• some parameters for a specific link.

• constants such as stride width of a convolutional layer.

init_scope () \rightarrow Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

links (skipself: bool = False) \rightarrow Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.
Parameters `skipself` (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

def namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters `skipself` (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

def namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters `include_uninit` (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

def params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

Parameters `include_uninit` (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

def register_persistent (name: str) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters `name` (str) – Name of the attribute to be registered.

def repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

class ConvBNReLU (chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same
values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- `n_repeat` *(int)* – Number of times to repeat.
- `mode` *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters**

- `serializer` *(AbstractSerializer)* – Serializer object.

**to_chx**

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu** *(→ chainer.device_resident.DeviceResident)*

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override `device_resident_accept()` to do so.

Returns: self

**to_device** *(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]] → DeviceResident)*

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- `device` – Target device specifier. See `get_device()` for available values.

Returns: self

**to_gpu** *(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident)*

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.
Warning: This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

Parameters

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

`to_intel64()` → `chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

`zerograds()` → `None`

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

\[__eq__(value,/)\]

Return `self==value`.

\[__ne__(value,/)\]

Return `self!=value`.

\[__lt__(value,/)\]

Return `self<value`.

\[__le__(value,/)\]

Return `self<=value`.

\[__gt__(value,/)\]

Return `self>value`.

\[__ge__(value,/)\]

Return `self>=value`.

Attributes

- **device**
  - `Device` instance.

- **local_link_hooks**
  - Ordered dictionary of registered link hooks.
  
  Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

- **printable_specs**
  - Generator of printable specs of this link.
  
  Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()`. This pair of key and value is used for representing this class or subclass with `__str__()`.

- **update_enabled**
  - True if at least one parameter has an update rule enabled.

- **within_init_scope**
  - True if the current code is inside of an initialization scope.

  See `init_scope()` for the details of the initialization scope.
XP
Array module corresponding to the device.
Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.StatefulGRU

class chainer.links.StatefulGRU(in_size, out_size, init=None, inner_init=None, bias_init=0)
Stateful Gated Recurrent Unit function (GRU).
Stateful GRU function has six parameters \( W_r, W_z, W, U_r, U_z, \) and \( U \). The three parameters \( W_r, W_z, \) and \( W \) are \( n \times m \) matrices, and the others \( U_r, U_z, \) and \( U \) are \( n \times n \) matrices, where \( m \) is the length of input vectors and \( n \) is the length of hidden vectors.

Given input vector \( x \), Stateful GRU returns the next hidden vector \( h' \) defined as

\[
\begin{align*}
    r &= \sigma(W_r x + U_r h), \\
    z &= \sigma(W_z x + U_z h), \\
    \bar{h} &= \tanh(W x + U (r \odot h)), \\
    h' &= (1 - z) \odot h + z \odot \bar{h},
\end{align*}
\]

where \( h \) is current hidden vector.

As the name indicates, StatefulGRU is stateful, meaning that it also holds the next hidden vector \( h' \) as a state. For a stateless GRU, use StatelessGRU.

Parameters

- \texttt{in\_size (int)} – Dimension of input vector \( x \).
- \texttt{out\_size (int)} – Dimension of hidden vector \( h \).
- \texttt{init} – Initializer for GRU’s input units (\( W \)). It is a callable that takes \( N \)-dimensional array and edits its value. If it is \texttt{None}, the default initializer is used.
- \texttt{inner\_init} – Initializer for the GRU’s inner recurrent units (\( U \)). It is a callable that takes \( N \)-dimensional array and edits its value. If it is \texttt{None}, the default initializer is used.
- \texttt{bias\_init} – Bias initializer. It is a callable that takes \( N \)-dimensional array and edits its value. If \texttt{None}, the bias is set to zero.

Variables \texttt{h (Variable)} – Hidden vector that indicates the state of StatefulGRU.

See also:

- StatelessGRU
- GRU: an alias of StatefulGRU

Example

There are several ways to make a StatefulGRU link. Let \( x \) be a two-dimensional input array:
1. Give only `in_size` and `out_size` arguments:

```python
>>> in_size = 10
>>> out_size = 20
>>> x = np.zeros((1, in_size), dtype=np.float32)

>>> l = L.StatefulGRU(in_size, out_size)
>>> h_new = l(x)
>>> h_new.shape
(1, 20)
```

2. Give all optional arguments:

```python
>>> init = np.zeros((out_size, in_size), dtype=np.float32)
>>> inner_init = np.zeros((out_size, out_size), dtype=np.float32)
>>> bias = np.zeros((1, out_size), dtype=np.float32)

>>> l = L.StatefulGRU(in_size, out_size, init=init, ...
... inner_init=inner_init, bias_init=bias)
>>> h_new = l(x)
>>> h_new.shape
(1, 20)
```

**Methods**

- **__call__** (*args: Any, **kwargs: Any) → Any
  Call self as a function.

- **__getitem__** (name: str) → Any
  Equivalent to getattr.

- **add_hook** (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
  Registers a link hook.

  **Parameters**
  - **hook** (LinkHook) – Link hook to be registered.
  - **name** (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

  **Returns** self

- **add_link** (name: str, link: chainer.link.Link) → None
  Registers a child link to this chain.

  **Parameters**
  - **name** (str) – Name of the child link. This name is also used as the attribute name.
  - **link** (Link) – The link object to be registered.

- **add_param** (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
  Registers a parameter to the link.

  **Parameters**
• **name**: *(str)* – Name of the parameter. This name is also used as the attribute name.

• **shape**: *(int or tuple of ints)* – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• **dtype** – Data type of the parameter array.

• **initializer**: *(initializer)* – If it is not *None*, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

`add_persistent (name: str, value: Any) → None`

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

• **name**: *(str)* – Name of the persistent value. This name is also used for the attribute name.

• **value** – Value to be registered.

`addgrads (link: chainer.link.Link) → None`

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

• **link**: *(Link)* – Source link object.

`children () → Iterator[chainer.link.Link]`

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

`cleargrads () → None`

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

`copy (mode: str = 'share') → chainer.link.Chain`

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

• **mode**: *(str)* – It should be either `init`, `copy`, or `share`. *init* means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default `mode` is *share*.

**Returns**

Copied link object.

**Return type**

*Link*
copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters

• link (Link) – Source link object.
• copy_persistent (bool) – If True, persistent values are also copied. True by default.

count_params () → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)
delete_hook (name: str) → None
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.
device_resident_accept (visitor) → None
Applies the visitor to all the device objects in this instance.

Parameters visitor (DeviceResidentsVisitor) – Visitor.

disable_update () → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

enable_update () → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

forward(x)

from_chx ()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params (*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

• some parameters for a specific link.
• constants such as stride width of a convolutional layer.
**init_scope** () → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links** (skipself: bool = False) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

- **Parameters** skipself (bool) – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all links.

**namedlinks** (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters** skipself (bool) – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all (path, link) pairs.

**namedparams** (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

- **Parameters** include_uninit (bool) – If True, it also generates uninitialized parameters.

- **Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

- **Parameters** include_uninit (bool) – If True, it also generates uninitialized parameters.

- **Returns** A generator object that generates all parameters.

**register_persistent** (name: str) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

- **Parameters** name (str) – Name of the attribute to be registered.

**repeat** (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential

Repeats this link multiple times to make a `Sequential`.  

4.3. Link and Chains
This method returns a **Sequential** object which has the same **Link** multiple times repeatedly. The **mode** argument means how to copy this link to repeat.

### Example

You can repeat the same link multiple times to create a longer **Sequential** block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the **mode** was `'init'`, so each block is re-initialized with different parameters. If you give **copy** to this argument, each block has same values for its parameters but its object ID is different from others. If it is **share**, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

### Parameters

- **n_repeat** *(int)* – Number of times to repeat.
- **mode** *(str)* – It should be either **init**, **copy**, or **share**. **init** means parameters of each repeated element in the returned **Sequential** will be re-initialized, so that all elements have different initial parameters. **copy** means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. **share** means all the elements which consist the resulting **Sequential** object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

### Methods

- **reset_state()**
- **serialize**(serializer: chainer.serializer.AbstractSerializer) → None
  Serializes the link object.
- **set_state**(serializer: AbstractSerializer) – Serializer object.
- **to_chx()**
  Converts parameter variables and persistent values to ChainerX without any copy.
  This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.
  Returns: self
- **to_cpu()** → chainer.device_resident.DeviceResident
  Copies parameter variables and persistent values to CPU.
Deprecated since version v7.0.0: Use \texttt{to\_device()} instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override \texttt{device\_resident\_accept()} to do so.

\textbf{Returns:} self

\textbf{to\_device (device: Union[\texttt{backend.Device}}, \texttt{chainerx.Device}, \texttt{cuda.Device}, \texttt{str}, \texttt{Tuple[str, int]}, \texttt{ModuleType}, \texttt{Tuple[ModuleType, int]}]) -> DeviceResident}

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

\textbf{Parameters} \textbf{device} – Target device specifier. See \texttt{get\_device()} for available values.

\textbf{Returns:} self

\textbf{to\_gpu (device: Optional[Union[\texttt{cuda.Device, int, numpy.integer}]] = None) -> chainer.device\_resident.DeviceResident}

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use \texttt{to\_device()} instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override \texttt{device\_resident\_accept()} to do so.

\textbf{Warning:} This method does not transfer the parameters if they are already on GPU. Use \texttt{to\_device} to perform inter-GPU transfer.

\textbf{Parameters} \textbf{device} – Target device specifier. If omitted, the current device is used.

\textbf{Returns:} self

\textbf{to\_intel64 () -> chainer.device\_resident.DeviceResident}

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use \texttt{to\_device()} instead.

\textbf{zerograds () -> None}

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient \texttt{cleargrads()} instead.

\textbf{__eq__ (value, /)}

Return self==value.

\textbf{__ne__ (value, /)}

Return self!=value.

\textbf{__lt__ (value, /)}

Return self<value.

\textbf{__le__ (value, /)}

Return self<=value.

\textbf{__gt__ (value, /)}

Return self>value.

\textbf{__ge__ (value, /)}

Return self>=value.
Attributes

device
   Device instance.

local_link_hooks
   Ordered dictionary of registered link hooks.
   Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
   Generator of printable specs of this link.
   Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
   True if at least one parameter has an update rule enabled.

within_init_scope
   True if the current code is inside of an initialization scope.
   See init_scope() for the details of the initialization scope.

xp
   Array module corresponding to the device.
   Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.StatelessGRU

class chainer.links.StatelessGRU(in_size, out_size, init=None, inner_init=None, bias_init=None)
   Stateless Gated Recurrent Unit function (GRU).

GRU function has six parameters \( W_r, W_z, W, U_r, U_z, \) and \( U \). The three parameters \( W_r, W_z, \) and \( W \) are \( n \times m \) matrices, and the others \( U_r, U_z, \) and \( U \) are \( n \times n \) matrices, where \( m \) is the length of input vectors and \( n \) is the length of hidden vectors.

Given two inputs a previous hidden vector \( h \) and an input vector \( x \), GRU returns the next hidden vector \( h' \) defined as

\[
\begin{align*}
    r &= \sigma(W_r x + U_r h), \\
    z &= \sigma(W_z x + U_z h), \\
    \hat{h} &= \tanh(W x + U (r \odot h)), \\
    h' &= (1 - z) \odot h + z \odot \hat{h},
\end{align*}
\]

where \( \sigma \) is the sigmoid function, and \( \odot \) is the element-wise product.

As the name indicates, StatelessGRU is stateless, meaning that it does not hold the value of hidden vector \( h \). For a stateful GRU, use StatefulGRU.

Parameters
• **in_size** (*int*) – Dimension of input vector \(x\). If `None`, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.

• **out_size** (*int*) – Dimension of hidden vector \(h, \bar{h}\) and \(h'\).

See:

- Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling [Chung+NIPS2014 DLWorkshop].

See also:

*StatefulGRU*

### Example

There are several ways to make a StatelessGRU link. Let \(x\) be a two-dimensional input array:

```python
>>> in_size = 10
>>> out_size = 20
>>> x = np.zeros((1, in_size), dtype=np.float32)
>>> h = np.zeros((1, out_size), dtype=np.float32)
```

1. Give both `in_size` and `out_size` arguments:

```python
>>> l = L.StatelessGRU(in_size, out_size)
>>> h_new = l(h, x)
>>> h_new.shape
(1, 20)
```

2. Omit `in_size` argument or fill it with `None`:

```python
>>> l = L.StatelessGRU(None, out_size)
>>> h_new = l(h, x)
>>> h_new.shape
(1, 20)
```

### Methods

- **__call__(** `*args: Any, **kwargs: Any`) → Any**
  Call self as a function.

- **__getitem__(** `name: str`) → Any
  Equivalent to getattr.

- **add_hook** (`hook: chainer.link_hook.LinkHook, name: Optional[str] = None`) → chainer.link.Link
  Registers a link hook.

  **Parameters**

  - **hook** (`LinkHook`) – Link hook to be registered.
  - **name** (`str`) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.
Returns self

add_link (name: str, link: chainer.link.Link) → None
Registers a child link to this chain.

Parameters

- name (str) – Name of the child link. This name is also used as the attribute name.
- link (Link) – The link object to be registered.

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

- name (str) – Name of the parameter. This name is also used as the attribute name.
- shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- dtype – Data type of the parameter array.
- initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent (name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- name (str) – Name of the persistent value. This name is also used for the attribute name.
- value – Value to be registered.

addgrads (link: chainer.link.Link) → None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters link (Link) – Source link object.

children () → Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads () → None
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode: str = 'share') → chainer.link.Chain
Copies the link hierarchy to new one.
The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** *(str)* – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

**Returns** Copied link object.

**Return type** *Link*

**copyparams** *(link: chainer.link.Link, copy_persistent: bool = True) → None*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

**Parameters**

- **link** *(Link)* – Source link object.
- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

**count_params** *(()) → int*

Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

**delete_hook** *(name: str) → None*

Unregisters the link hook.

**Parameters** *name** *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*

Applies the visitor to all the device objects in this instance.

**Parameters** *visitor* *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** *(()) → None*

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

### 4.3. Link and Chains

575
**enable_update**() → None

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

**forward**(h, x)

**from_chx**()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params**(*args, **kwargs)

Initialize link with given parameters.

This method initializes the link with given \(N\)-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope**() → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links**(skipself: bool = False) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

- **Parameters** `skipself` (bool) – If `True`, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all links.

**namedlinks**(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters** `skipself` (bool) – If `True`, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all (path, link) pairs.

**namedparams**(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

- **Parameters** `include_uninit` (bool) – If `True`, it also generates uninitialized parameters.

- **Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.
**params** (*include_uninit: bool = True*) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

**Parameters**

- **include_uninit** (*bool*) – If True, it also generates uninitialized parameters.

**Returns**

A generator object that generates all parameters.

**register_persistent** (*name: str*) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If *name* has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name** (*str*) – Name of the attribute to be registered.

**repeat** (*n_repeat: int, mode: str = 'init'*) → chainer.sequential.Sequential

Repeats this link multiple times to make a **Sequential**.

This method returns a **Sequential** object which has the same **Link** multiple times repeatedly. The *mode* argument means how to copy this link to repeat.

**Parameters**

- **n_repeat** (*int*) – Number of times to repeat.
- **mode** (*str*) – It should be either *init*, *copy*, or *share*. *init* means parameters of each repeated element in the returned **Sequential** will be re-initialized, so that all elements have different initial parameters. *copy* means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. *share* means all the elements which consist the resulting **Sequential** object are same object because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Example**

You can repeat the same link multiple times to create a longer **Sequential** block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x))

net = ConvBNReLU().repeat(16, mode='init')
```

The *net* object contains 16 blocks, each of which is **ConvBNReLU**. And the *mode* was *init*, so each block is re-initialized with different parameters. If you give *copy* to this argument, each block has same values for its parameters but its object ID is different from others. If it is *share*, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** (*int*) – Number of times to repeat.
- **mode** (*str*) – It should be either *init*, *copy*, or *share*. *init* means parameters of each repeated element in the returned **Sequential** will be re-initialized, so that all elements have different initial parameters. *copy* means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. *share* means all the elements which consist the resulting **Sequential** object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.
**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters**

- **serializer** *(AbstractSerializer)* – Serializer object.

**to_chx()**

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu() → chainer.device_resident.DeviceResident**

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override **device_resident_accept()** to do so.

Returns: self

**to_device**(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See **get_device()** for available values.

Returns: self

**to_gpu**(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override **device_resident_accept()** to do so.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64() → chainer.device_resident.DeviceResident**

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device()** instead.

**zerograds() → None**

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use **cleargrads()** instead.

**__eq__**(value, /)

Return self==value.
__ne__(value,/)  
Return self!=value.

__lt__(value,/)  
Return self<value.

__le__(value,/)  
Return self<=value.

__gt__(value,/)  
Return self>value.

__ge__(value,/)  
Return self>=value.

**Attributes**

**device**  
Device instance.

**local_link_hooks**  
Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

**printable_specs**  
Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

**update_enabled**  
True if at least one parameter has an update rule enabled.

**within_init_scope**  
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

**xp**  
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

**chainer.links.StatefulMGU**

class chainer.links.StatefulMGU(in_size, out_size)
Methods

__call__(*args: Any, **kwargs: Any) \(\rightarrow\) Any
Call self as a function.

__getitem__(name: str) \(\rightarrow\) Any
Equivalent to getattr.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) \(\rightarrow\) chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.
• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_link(name: str, link: chainer.link.Link) \(\rightarrow\) None
Registers a child link to this chain.

Parameters

• name (str) – Name of the child link. This name is also used as the attribute name.
• link (Link) – The link object to be registered.

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) \(\rightarrow\) None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.
• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
• dtype – Data type of the parameter array.
• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) \(\rightarrow\) None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.
• value – Value to be registered.

addgrads(link: chainer.link.Link) \(\rightarrow\) None
Accumulates gradient values from given link.
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** (`Link`) – Source link object.

**children** () → `Iterator[chainer.link.Link]`

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** () → `None`

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (`mode: str = 'share'`) → `chainer.link.Chain`

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** (`str`) – It should be either `init`, `copy`, or `share`. 
  - `init` means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link.
  - `copy` means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently.
  - `share` means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default `mode` is `share`.

**Returns**

Copied link object.

**Return type**

`Link`

**copyparams** (`link: chainer.link.Link, copy_persistent: bool = True`) → `None`

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** (`Link`) – Source link object.

- **copy_persistent** (`bool`) – If True, persistent values are also copied. True by default.

**count_params** () → `int`

Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**

The total size of parameters (`int`)
**delete_hook** *(name: str) → None*

Unregisters the link hook.

**Parameters**

- **name** *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*

Applies the visitor to all the device objects in this instance.

**Parameters**

- **visitor** *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update** () → None

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

**forward** *(x)*

**from_chx** ()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** (*args, **kwargs)*

Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope** () → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

---

**Example**

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links** *(skipself: bool = False) → Iterator[chainer.link.Link]*

Returns a generator of all links under the hierarchy.

**Parameters**

- **skipself** *(bool)* – If True, then the generator skips this link and starts with the first child link.

**Returns**

A generator object that generates all links.
namedlinks \((\text{skipself}: \text{bool} = \text{False}) \rightarrow \text{Iterator}[	ext{Tuple}[	ext{str}, \text{chainer.link.Link}]]\)

Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters**  
  - **skipself**  
    - **bool** - If True, then the generator skips this link and starts with the first child link.

- **Returns**  
  - A generator object that generates all (path, link) pairs.

namedparams \((\text{include_uninit}: \text{bool} = \text{True}) \rightarrow \text{Iterator}[	ext{Tuple}[	ext{str}, \text{chainer.variable.Parameter}]]\)

Returns a generator of all (path, param) pairs under the hierarchy.

- **Parameters**  
  - **include_uninit**  
    - **bool** - If True, it also generates uninitialized parameters.

- **Returns**  
  - A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params \((\text{include_uninit}: \text{bool} = \text{True}) \rightarrow \text{Iterator}[	ext{chainer.variable.Parameter}]\)

Returns a generator of all parameters under the link hierarchy.

- **Parameters**  
  - **include_uninit**  
    - **bool** - If True, it also generates uninitialized parameters.

- **Returns**  
  - A generator object that generates all parameters.

register_persistent \((\text{name}: \text{str}) \rightarrow \text{None}\)

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

- **Parameters**  
  - **name**  
    - **str** - Name of the attribute to be registered.

repeat \((\text{n_repeat}: \text{int}, \text{mode}: \text{str} = \text{'init'}) \rightarrow \text{chainer.sequential.Sequential}\)

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.
Parameters

- **n_repeat** (*int*) – Number of times to repeat.
- **mode** (*str*) – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**reset_state()**

**serialize** (*serializer: chainer.serializer.AbstractSerializer*) → None

Serializes the link object.

**Parameters**

- **serializer** (*AbstractSerializer*) – Serializer object.

**set_state** (*h*)

**to_chx()**

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu()** → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

**to_device** (*device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]*) → DeviceResident

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See `get_device()` for available values.

Returns: self

**to_gpu** (*device: Optional[Union[cuda.Device, int, numpy.integer]] = None*) →

chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.
**Parameters**

**device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device()** instead.

**zerograds** () → None

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient **cleargrads()** instead.

**__eq__**(value, /)

Return self==value.

**__ne__**(value, /)

Return self!=value.

**__lt__**(value, /)

Return self<value.

**__le__**(value, /)

Return self<=value.

**__gt__**(value, /)

Return self>value.

**__ge__**(value, /)

Return self>=value.

**Attributes**

**device**

Device instance.

**local_link_hooks**

Ordered dictionary of registered link hooks.

Contrary to **chainer.thread_local.link_hooks**, which registers its elements to all functions, link hooks in this property are specific to this link.

**printable_specs**

Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the **__init__()**. This pair of key and value is used for representing this class or subclass with **__str__()**.

**update_enabled**

True if at least one parameter has an update rule enabled.

**within_init_scope**

True if the current code is inside of an initialization scope.

See **init_scope()** for the details of the initialization scope.

**xp**

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns **numpy**, **cupy** or **chainerx**.
chainer.links.StatelessMGU

class chainer.links.StatelessMGU(n_inputs, n_units)

Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

__getitem__(name: str) → Any
Equivalent to getattr.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.

• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_link(name: str, link: chainer.link.Link) → None
Registers a child link to this chain.

Parameters

• name (str) – Name of the child link. This name is also used as the attribute name.

• link (Link) – The link object to be registered.

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.

• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• dtype – Data type of the parameter array.

• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.
• **value** – Value to be registered.

### addgrads

```python
addgrads(link: chainer.link.Link) → None
```

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- `link` *(Link)* – Source link object.

### children

```python
children() → Iterator[chainer.link.Link]
```

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

### cleargrads

```python
cleargrads() → None
```

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

### copy

```python
mode: str = 'share') → chainer.link.Chain
```

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- `mode` *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. `copy` means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. `share` means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is `share`.

**Returns**

Copied link object.

**Return type** *(Link)*

### copyparams

```python
copyparams(link: chainer.link.Link, copy_persistent: bool = True) → None
```

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- `link` *(Link)* – Source link object.

- `copy_persistent` *(bool)* – If True, persistent values are also copied. True by default.

### count_params

```python
count_params() → int
```

Counts the total number of parameters.

---

4.3. Link and Chains | 587
This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

### delete_hook

```python
def delete_hook(name: str) -> None
```

Unregisters the link hook.

**Parameters**

- **name (str)** – The name of the link hook to be unregistered.

### device_resident_accept

```python
def device_resident_accept(visitor)
```

Applies the visitor to all the device objects in this instance.

**Parameters**

- **visitor (DeviceResidentsVisitor)** – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

### disable_update

```python
def disable_update() -> None
```

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

### enable_update

```python
def enable_update() -> None
```

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

### forward

```python
def forward(h, x)
```

### from_chx

```python
def from_chx()
```

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

### classmethod from_params

```python
classmethod from_params(*args, **kwargs)
```

Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

### init_scope

```python
def init_scope() -> Iterator[None]
```

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

### Example

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```
links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, parameter) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example
You can repeat the same link multiple times to create a longer Sequential block like this:

class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat** (int) – Number of times to repeat.
- **mode** (str) – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** (serializer: chainer.serializer(AbstractSerializer) → None

Serializes the link object.

Parameters 

 serializer (AbstractSerializer) – Serializer object.

**to_chx** ()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu** () → chainer.device.resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecate since version v7.0.0: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override **device_resident_accept()** to do so.

Returns: self

**to_device** (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters 

 device – Target device specifier. See **get_device()** for available values.

Returns: self

**to_gpu** (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to GPU.

Deprecate since version v7.0.0: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override **device_resident_accept()** to do so.
**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

### `to_intel64()` → `chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

### `zerograds()` → `None`

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

### `__eq__`(value,)

Return `self==value`.

### `__ne__`(value,)

Return `self!=value`.

### `__lt__`(value,)

Return `self<value`.

### `__le__`(value,)

Return `self<=value`.

### `__gt__`(value,)

Return `self>value`.

### `__ge__`(value,)

Return `self>=value`.

**Attributes**

- **device**

  `Device` instance.

- **local_link_hooks**

  Ordered dictionary of registered link hooks.

  Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

- **printable_specs**

  Generator of printable specs of this link.

  **Yields** specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()` method. This pair of key and value is used for representing this class or subclass with `__str__()`.

- **update_enabled**

  True if at least one parameter has an update rule enabled.

- **within_init_scope**

  True if the current code is inside of an initialization scope.

  See `init_scope()` for the details of the initialization scope.
Array module corresponding to the device. Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.

### chainer.links.StatefulPeepholeLSTM

**class** `chainer.links.StatefulPeepholeLSTM(in_size, out_size)`

Fully-connected LSTM layer with peephole connections.

This is a fully-connected LSTM layer with peephole connections as a chain. Unlike the `LSTM` link, this chain holds `peep_i`, `peep_f` and `peep_o` as child links besides `upward` and `lateral`.

Given a input vector $x$, Peephole returns the next hidden vector $h'$ defined as

$$
\begin{align*}
    a &= \tanh(upwardx + lateralth), \\
    i &= \sigma(upwardx + lateralth + peepic), \\
    f &= \sigma(upwardx + lateralth + peepfc), \\
    c' &= a \odot i + f \odot c, \\
    o &= \sigma(upwardx + lateralth + peepoc'), \\
    h' &= o \tanh(c'),
\end{align*}
$$

where $\sigma$ is the sigmoid function, $\odot$ is the element-wise product, $c$ is the current cell state, $c'$ is the next cell state and $h$ is the current hidden vector.

**Parameters**

- `in_size` (*int*) — Dimension of the input vector $x$.
- `out_size` (*int*) — Dimension of the hidden vector $h$.

**Variables**

- `upward` (*Linear*) — Linear layer of upward connections.
- `lateral` (*Linear*) — Linear layer of lateral connections.
- `peep_i` (*Linear*) — Linear layer of peephole connections to the input gate.
- `peep_f` (*Linear*) — Linear layer of peephole connections to the forget gate.
- `peep_o` (*Linear*) — Linear layer of peephole connections to the output gate.
- `c` (*Variable*) — Cell states of LSTM units.
- `h` (*Variable*) — Output at the current time step.
Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

__getitem__(name: str) → Any
Equivalent to getattr.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.
• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self

add_link(name: str, link: chainer.link.Link) → None
Registers a child link to this chain.

Parameters

• name (str) – Name of the child link. This name is also used as the attribute name.
• link (Link) – The link object to be registered.

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.
• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
• dtype – Data type of the parameter array.
• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.
• value – Value to be registered.

addgrads(link: chainer.link.Link) → None
Accumulates gradient values from given link.
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**
- **link** ([Link]) – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**
A generator object that generates all child links.

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode: str = 'share')* → chainer.link.Chain

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument **mode** below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**
- **mode** (str) – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

**Returns**
Copied link object.

**Return type** [Link]

**copyparams** *(link: chainer.link.Link, copy_persistent: bool = True)* → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

**Parameters**
- **link** ([Link]) – Source link object.
- **copy_persistent** (bool) – If True, persistent values are also copied. True by default.

**count_params** () → int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**
The total size of parameters (int)
delete_hook (name: str) → None
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

device_resident_accept (visitor)
Applies the visitor to all the device objects in this instance.

Parameters visitor (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

disable_update () → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

enable_update () → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

forward (x)
Updates the internal state and returns the LSTM outputs.

Parameters x (Variable) – A new batch from the input sequence.

Returns Outputs of updated LSTM units.

Return type Variable

from_chx ()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params (*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given \(N\)-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

init_scope () → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for \(Chain\)) by an assignment. A \(Parameter\) object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink (chainer.Link):
    def __init__ (self):
        super ().__init__ ()
        with self.init_scope ():
            self.W = chainer.Parameter (0, \(10, 5\))
            self.b = chainer.Parameter (0, \(5,\))
```

4.3. Link and Chains 595
links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.
  
  Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.
  
  Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.
  
  Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.
  
  Returns A generator object that generates all (path, link) pairs.

namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, parameter) pairs under the hierarchy.
  
  Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.
  
  Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

def forward(self, x):
    return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** *(int)* – Number of times to repeat.
- **mode** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**reset_state** ()

Resets the internal states.

It sets `None` to the `c` and `h` attributes.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters** `serializer` *(AbstractSerializer)* – Serializer object.

**to_chx** ()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

**to_device** *(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident*

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters** `device` – Target device specifier. See `get_device()` for available values.

Returns: self

**to_gpu** *(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident*

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

---

```python
__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.
```

---

**Attributes**

- **device**
  
  *Device* instance.

- **local_link_hooks**
  
  Ordered dictionary of registered link hooks.

  Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

- **printable_specs**
  
  Generator of printable specs of this link.

  **Yields** *specs (tuple of str and object)* – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()`. This pair of key and value is used for representing this class or subclass with `__str__()`.

- **update_enabled**
  
  True if at least one parameter has an update rule enabled.
Chainer Documentation, Release 7.7.0

within_init_scope
True if the current code is inside of an initialization scope.
See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.
Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.StatefulZoneoutLSTM

class chainer.links.StatefulZoneoutLSTM(in_size, out_size, c_ratio=0.5, h_ratio=0.5, **kwargs)

Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

__getitem__ (name: str) → Any
Equivalent to getattr.

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.
• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_link (name: str, link: chainer.link.Link) → None
Registers a child link to this chain.

Parameters

• name (str) – Name of the child link. This name is also used as the attribute name.
• link (Link) – The link object to be registered.

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.
• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
• dtype – Data type of the parameter array.
• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a

4.3. Link and Chains 599
Chainer Documentation, Release 7.7.0

scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

**add_persistent** *(name: str, value: Any) → None*

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- **name**(str) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

**addgrads** *(link: chainer.link.Link) → None*

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link**(Link) – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode: str = 'share') → chainer.link.Chain*

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode**(str) – It should be either *init, copy, or share*. *init* means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default `mode` is `share`.

**Returns** Copied link object.

**Return type** Link

**copyparams** *(link: chainer.link.Link, copy_persistent: bool = True) → None*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise,
it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** (*Link*) – Source link object.
- **copy_persistent** (*bool*) – If `True`, persistent values are also copied. `True` by default.

**count_params** () → int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**
The total size of parameters (int)

**delete_hook** (*name: str*) → None

Unregisters the link hook.

**Parameters**

- **name** (*str*) – The name of the link hook to be unregistered.

**device_resident_accept** (*visitor*)

Applies the visitor to all the device objects in this instance.

**Parameters**

- **visitor** (*DeviceResidentsVisitor*) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

**enable_update** () → None

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

**forward** (*x*)

Updates the internal state and returns the LSTM outputs.

**Parameters**

- **x** (*Variable*) – A new batch from the input sequence.

**Returns**

Outputs of updated LSTM units.

**Return type**

*Variable*

**from_chx** ()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** (**args, **kwargs*)

Initialize link with given parameters.

This method initializes the link with given `N-dimensional arrays`. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope** () → Iterator[None]

Creates an initialization scope.
This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links**

`links(skipself: bool = False) → Iterator[chainer.link.Link]`

Returns a generator of all links under the hierarchy.

**Parameters**

- **skipself (bool) –** If `True`, then the generator skips this link and starts with the first child link.

**Returns**

A generator object that generates all links.

**namedlinks**

`namedlinks(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]`

Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters**

- **skipself (bool) –** If `True`, then the generator skips this link and starts with the first child link.

**Returns**

A generator object that generates all (path, link) pairs.

**namedparams**

`namedparams(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]`

Returns a generator of all (path, parameter) pairs under the hierarchy.

**Parameters**

- **include_uninit (bool) –** If `True`, it also generates uninitialized parameters.

**Returns**

A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params**

`params(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]`

Returns a generator of all parameters under the link hierarchy.

**Parameters**

- **include_uninit (bool) –** If `True`, it also generates uninitialized parameters.

**Returns**

A generator object that generates all parameters.

**register_persistent**

`register_persistent(name: str) → None`

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name (str) –** Name of the attribute to be registered.

**repeat**

`repeat(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential`

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.
Example

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the mode was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat** (`int`) – Number of times to repeat.
- **mode** (`str`) – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

```
reset_state()
```

Resets the internal state.

It sets `None` to the `c` and `h` attributes.

```
serialize(serializer: chainer.serializer.AbstractSerializer) → None
```

Serializes the link object.

Parameters **serializer** (`AbstractSerializer`) – Serializer object.

```
set_state(c, h)
```

Sets the internal state.

It sets the `c` and `h` attributes.

Parameters

- **c** (`Variable`) – A new cell states of LSTM units.
- **h** (`Variable`) – A new output at the previous time step.

```
to_chx()
```

Converts parameter variables and persistent values to ChainerX without any copy.

4.3. Link and Chains 603
This method does not handle non-registered attributes. If some of such attributes must be copied to Chain-
erX, the link implementation must override this method to do so.

Returns: self

to_cpu() \rightarrow \text{chainer.device_resident.DeviceResident}
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use \texttt{to_device()} instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override \texttt{device_resident_accept()} to do so.

Returns: self

to_device(device: \text{Union}[\text{backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], Module-
Type, Tuple[ModuleType, int]]]) \rightarrow \text{DeviceResident}
Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

\textbf{device} – Target device specifier. See \texttt{get_device()} for available values.

Returns: self

to_gpu(device: \text{Optional}[\text{Union}[\text{cuda.Device, int, numpy.integer}]] = \text{None}) \rightarrow \text{chainer.device_resident.DeviceResident}
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use \texttt{to_device()} instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override \texttt{device_resident_accept()} to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use \texttt{to_device} to perform inter-GPU transfer.

**Parameters**

\textbf{device} – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64() \rightarrow \text{chainer.device_resident.DeviceResident}
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use \texttt{to_device()} instead.

zerograds() \rightarrow \text{None}

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient \texttt{cleargrads()} instead.
__gt__(value, /)
    Return self>value.
__ge__(value, /)
    Return self>=value.

Attributes

device
    Device instance.

local_link_hooks
    Ordered dictionary of registered link hooks.
    Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions,
    link hooks in this property are specific to this link.

printable_specs
    Generator of printable specs of this link.
    Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword
    and value) that are passed to the __init__(). This pair of key and value is used for
    representing this class or subclass with __str__().

update_enabled
    True if at least one parameter has an update rule enabled.

within_init_scope
    True if the current code is inside of an initialization scope.
    See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.
    Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.StatelessLSTM

class chainer.links.StatelessLSTM(in_size, out_size=None, lateral_init=None, upward_init=None, bias_init=None, forget_bias_init=None)
    Stateless LSTM layer.

    This is a fully-connected LSTM layer as a chain. Unlike the lstm() function, this chain holds upward and
    lateral connections as child links. This link doesn’t keep cell and hidden states.

    Parameters

    • in_size (int or None) – Dimension of input vectors. If None, parameter initializa-
        tion will be deferred until the first forward data pass at which time the size will be deter-
        mined.
    • out_size (int) – Dimensionality of output vectors.

    Variables

    • upward (chainer.links.Linear) – Linear layer of upward connections.
    • lateral (chainer.links.Linear) – Linear layer of lateral connections.
Example

There are several ways to make a StatelessLSTM link.

Let a two-dimensional input array $x$, a cell state array $h$, and the output array of the previous step $\hat{h}$ be:


given in_size and out_size arguments:

```python
>>> x = np.zeros((1, 10), dtype=np.float32)
>>> c = np.zeros((1, 20), dtype=np.float32)
>>> h = np.zeros((1, 20), dtype=np.float32)
```

```python
>>> l = L.StatelessLSTM(10, 20)
>>> c_new, h_new = l(c, h, x)
>>> c_new.shape
(1, 20)
>>> h_new.shape
(1, 20)
```

2. Omit in_size argument or fill it with None:

The below two cases are the same.

```python
>>> l = L.StatelessLSTM(20)
>>> c_new, h_new = l(c, h, x)
>>> c_new.shape
(1, 20)
>>> h_new.shape
(1, 20)
```

```python
>>> l = L.StatelessLSTM(None, 20)
>>> c_new, h_new = l(c, h, x)
>>> c_new.shape
(1, 20)
>>> h_new.shape
(1, 20)
```

Methods

```python
__call__(*args: Any, **kwargs: Any) → Any
```

Call self as a function.

```python
__getitem__(name: str) → Any
```

Equivalent to getattr.

```python
add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
```

Registers a link hook.

Parameters

- hook (:class:`LinkHook`) – Link hook to be registered.

- name (:class:`str`) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self
add_link \( (name: str, link: \text{chainer.link.Link}) \rightarrow \text{None} \)
Registers a child link to this chain.

**Parameters**

- **name** (str) – Name of the child link. This name is also used as the attribute name.
- **link** (Link) – The link object to be registered.

add_param \( (name: str, shape: \text{Optional[Union[int, Sequence[int]]]} = \text{None}, dtype: \text{Any} = \langle \text{class 'numpy.float32'} \rangle, \text{initializer: Optional[Union[\text{chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray}] = None}] \rightarrow \text{None} \)
Registers a parameter to the link.

**Parameters**

- **name** (str) – Name of the parameter. This name is also used as the attribute name.
- **shape** (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer** (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent \( (name: str, value: \text{Any}) \rightarrow \text{None} \)
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- **name** (str) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

addgrads \( (link: \text{chainer.link.Link}) \rightarrow \text{None} \)
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** (Link) – Source link object.

children() \rightarrow \text{Iterator[\text{chainer.link.Link}]}\)
Returns a generator of all child links.

**Returns** A generator object that generates all child links.

cleargrads() \rightarrow \text{None}
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy \( (mode: \text{str} = 'share') \rightarrow \text{chainer.link.Chain} \)
Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

### 4.3. Link and Chains
The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** *(str)* – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters' arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is *share*.

**Returns** Copied link object.

**Return type** `Link`

`copyparams(link: chainer.link.Link, copy_persistent: bool = True) → None`

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an `ndarray`, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** *(Link)* – Source link object.
- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

`count_params() → int`

Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

`delete_hook(name: str) → None`

Unregisters the link hook.

**Parameters**

- **name** *(str)* – The name of the link hook to be unregistered.

`device_resident_accept(visitor)`

Applies the visitor to all the device objects in this instance.

**Parameters**

- **visitor** *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

`disable_update() → None`

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to False.

`enable_update() → None`

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to True.
**forward**\((c, h, x)\)

Returns new cell state and updated output of LSTM.

**Parameters**

- **c** ([Variable]) – Cell states of LSTM units.
- **h** ([Variable]) – Output at the previous time step.
- **x** ([Variable]) – A new batch from the input sequence.

**Returns**

Returns \((c\_new, h\_new)\), where \(c\_new\) represents new cell state, and \(h\_new\) is updated output of LSTM units.

**Return type**

tuple of ~chainer.Variable

**from_chx**()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params**(*args, **kwargs)*

Initialize link with given parameters.

This method initializes the link with given \(N\)-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope**() → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links** (*skipself: bool = False*) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

**Parameters**

- **skipself** (bool) – If True, then the generator skips this link and starts with the first child link.

**Returns**

A generator object that generates all links.

**namedlinks** (*skipself: bool = False*) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters**

- **skipself** (bool) – If True, then the generator skips this link and starts with the first child link.

**Returns**

A generator object that generates all (path, link) pairs.
namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

register_persistent (name: str) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer Sequential block like this:

class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)
    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

• n_repeat (int) – Number of times to repeat.

• mode (str) – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all
elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

```python
serialize(serializer: chainer.serializer.AbstractSerializer) → None
```
Serializes the link object.

**Parameters**

- **serializer** (`AbstractSerializer`) – Serializer object.

```python
to_chx() → chainer.device_resident.DeviceResident
```
Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: `self`

```python
to_cpu() → chainer.device_resident.DeviceResident
```
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: `self`

```python
to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
```
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See `get_device()` for available values.

Returns: `self`

```python
to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
```
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: `self`

```python
to_intel64() → chainer.device_resident.DeviceResident
```
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.
zerograd() \rightarrow None

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

__eq__(value,)

Return self==value.

__ne__(value,)

Return self!=value.

__lt__(value,)

Return self<value.

__le__(value,)

Return self<=value.

__gt__(value,)

Return self>value.

__ge__(value,)

Return self>=value.

Attributes

device

`Device` instance.

local_link_hooks

Ordered dictionary of registered link hooks.

Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs

Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()`. This pair of key and value is used for representing this class or subclass with `__str__()`.

update_enabled

True if at least one parameter has an update rule enabled.

within_init_scope

True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.

xp

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns `numpy, cupy` or `chainerx`. 
4.3.2 Activation/loss/normalization functions with parameters

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.links.BatchNormalization</td>
<td>Batch normalization layer on outputs of linear or convolution functions.</td>
</tr>
<tr>
<td>chainer.links.BatchRenormalization</td>
<td>Batch renormalization layer on outputs of linear or convolution functions.</td>
</tr>
<tr>
<td>chainer.links.DecorrelatedBatchNormalization</td>
<td>Decorrelated batch normalization layer.</td>
</tr>
<tr>
<td>chainer.links.GroupNormalization</td>
<td>Group normalization layer on outputs of convolution functions.</td>
</tr>
<tr>
<td>chainer.links.LayerNormalization</td>
<td>Layer normalization layer on outputs of linear functions.</td>
</tr>
<tr>
<td>chainer.links.BinaryHierarchicalSoftmax</td>
<td>Hierarchical softmax layer over binary tree.</td>
</tr>
<tr>
<td>chainer.links.BlackOut</td>
<td>BlackOut loss layer.</td>
</tr>
<tr>
<td>chainer.links.CRF1d</td>
<td>Linear-chain conditional random field loss layer.</td>
</tr>
<tr>
<td>chainer.links.SimplifiedDropconnect</td>
<td>Fully-connected layer with simplified dropconnect regularization.</td>
</tr>
<tr>
<td>chainer.links.PReLU</td>
<td>Parametric ReLU function as a link.</td>
</tr>
<tr>
<td>chainer.links.Swish</td>
<td>Swish activation function as a link.</td>
</tr>
<tr>
<td>chainer.links.Maxout</td>
<td>Fully-connected maxout layer.</td>
</tr>
<tr>
<td>chainer.links.NegativeSampling</td>
<td>Negative sampling loss layer.</td>
</tr>
</tbody>
</table>

**chainer.links.BatchNormalization**

```python
class chainer.links.BatchNormalization(size=None, decay=0.9, eps=2e-05, dtype=None, use_gamma=True, use_beta=True, initial_gamma=None, initial_beta=None, axis=None, initial_avg_mean=None, initial_avg_var=None)
```

Batch normalization layer on outputs of linear or convolution functions.

This link wraps the `batch_normalization()` and `fixed_batch_normalization()` functions.

It runs in three modes: training mode, fine-tuning mode, and testing mode.

In training mode, it normalizes the input by `batch statistics`. It also maintains approximated population statistics by moving averages, which can be used for instant evaluation in testing mode. Training mode is enabled when `chainer.config.train` is set to `True` and `__call__()` is invoked with `finetune=False` (the default is `False`).

In fine-tuning mode, it accumulates the input to compute `population statistics`. In order to correctly compute the population statistics, a user must use this mode to feed mini-batches running through whole training dataset. Finetuning mode is enabled when `chainer.config.train` is set to `True` and `__call__()` is invoked with `finetune=True`.

In testing mode, it uses pre-computed population statistics to normalize the input variable. The population statistics is approximated if it is computed by training mode, or accurate if it is correctly computed by fine-tuning mode. Testing mode is enabled when `chainer.config.train` is set to `False`.

**Parameters**

- `size` *(int, tuple of ints, or None)* – Size (or shape) of channel dimensions. If `None`, the size will be determined from dimension(s) of the input batch during the first forward pass.
- `decay` *(float)* – Decay rate of moving average. It is used on training.
- `eps` *(float)* – Epsilon value for numerical stability.
• **dtype** *(numpy.dtype)* – Type to use in computing.

• **use_gamma** *(bool)* – If True, use scaling parameter. Otherwise, use unit(1) which makes no effect.

• **use_beta** *(bool)* – If True, use shifting parameter. Otherwise, use unit(0) which makes no effect.

• **axis** *(int or tuple of int)* – Axis over which normalization is performed. When axis is `None`, it is determined from input dimensions. For example, if `x.ndim` is 4, axis becomes (0, 2, 3) and normalization is performed over 0th, 2nd and 3rd axis of input. If it is 2, axis becomes (0) and normalization is performed over 0th axis of input. When a tuple of int is given to this option, numbers in the tuple must be being sorted in ascending order. For example, (0, 2) is OK, but (2, 0) is not.

• **initial_gamma** – Initializer of the scaling parameter. The default value is 1.

• **initial_beta** – Initializer of the shifting parameter. The default value is 0.

• **initial_avg_mean** – Initializer of the moving average of population mean. The default value is 0.

• **initial_avg_var** – Initializer of the moving average of population variance. The default value is 1.

---

**Note:** From v5.0.0, the initial value of the population variance is changed to 1. It does not change the behavior of training, but the resulting model may have a slightly different behavior on inference. To emulate the old behavior, pass `initial_avg_var=0` for training.

---

See: Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift

See also:

`batch_normalization()`, `fixed_batch_normalization()`  

**Variables**

• **gamma** *(Variable)* – Scaling parameter. In mixed16 mode, it is initialized as float32 variable.

• **beta** *(Variable)* – Shifting parameter. In mixed16 mode, it is initialized as float32 variable.

• **avg_mean** *(N-dimensional array)* – Population mean. In mixed16 mode, it is initialized as float32 array.

• **avg_var** *(N-dimensional array)* – Population variance. In mixed16 mode, it is initialized as float32 array.

• **N** *(int)* – Count of batches given for fine-tuning.

• **decay** *(float)* – Decay rate of moving average. It is used on training.

• **eps** *(float)* – Epsilon value for numerical stability. This value is added to the batch variances.

---

**Example**
There are several ways to make a BatchNormalization link. Consider an input of batched 10 images of 32x32 with 3 channels.

```python
>>> x = np.random.randn(10, 3, 32, 32).astype(np.float32)
```

1. Give the parameter size:

   To normalize for each channel, give the number of channels to `size`.

   ```python
   >>> bn = chainer.links.BatchNormalization(3)
   >>> bn.avg_mean.shape
   (3,)
   >>> bn.beta += 2.0
   >>> bn.gamma *= 5.0
   >>> list(sorted(bn.namedparams()))
   [('/beta', variable([2., ..., ])), ('/gamma', variable([5., ..., ]))]
   >>> y = bn(x)
   >>> y.shape
   (10, 3, 32, 32)
   >>> np.testing.assert_allclose(
   ... y.array.mean(axis=(0, 2, 3)), bn.beta.array, atol=1e-6)
   >>> np.testing.assert_allclose(
   ... y.array.std(axis=(0, 2, 3)),
   ... bn.gamma.array, atol=1e-3)
   
   To normalize for each channel for each pixel, `size` should be the tuple of the dimensions.

   ```python
   >>> bn = chainer.links.BatchNormalization((3, 32, 32))
   >>> bn.avg_mean.shape
   (3, 32, 32)
   >>> y = bn(x)
   >>> y.shape
   (10, 3, 32, 32)
   >>> np.testing.assert_allclose(
   ... y.array.mean(axis=(0, 2, 3)), bn.beta.array, atol=1e-6)
   >>> np.testing.assert_allclose(
   ... y.array.std(axis=(0, 2, 3)),
   ... bn.gamma.array, atol=1e-3)
   
   By default, channel axis is (or starts from) the 1st axis of the input shape.
```
2. Give the aggregate axes:

from Chainer v5

With `axis` option, similarly to NumPy, you may specify the aggregate axes, which are treated as the “batch” axes for the batch statistics.

You can omit `size` if `axis` is given. In this case, creation of persistent values `avg_mean`, `avg_var` and parameters `beta`, `gamma` is deferred until first forward propagation.

The examples in 1. corresponds to the following, respectively.

```python
>>> bn = chainer.links.BatchNormalization(axis=(0, 2, 3))
>>> print(bn.avg_mean)
None
>>> y = bn(x)
>>> bn.avg_mean.shape
(3,)

```  
```python
>>> bn = chainer.links.BatchNormalization(axis=0)
>>> print(bn.avg_mean)
None
>>> y = bn(x)
>>> bn.avg_mean.shape
(3, 32, 32)
```

## Methods

### __call__

`__call__(*args: Any, **kwargs: Any) → Any`

Call self as a function.

### add_hook

`add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link`

Registers a link hook.

**Parameters**

- `hook` (*LinkHook*) – Link hook to be registered.

- `name` (*str*) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

**Returns**  
`self`

### add_param

`add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None`

Registers a parameter to the link.

**Parameters**

- `name` (*str*) – Name of the parameter. This name is also used as the attribute name.

- `shape` (*int or tuple of ints*) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

- `dtype` – Data type of the parameter array.

- `initializer` (*initializer*) – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as
a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

**add_persistent** *(name: str, value: Any) → None*

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- **name** *(str)* – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

**addgrads** *(link: chainer.link.Link) → None*

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** *(Link)* – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode: str = 'share') → chainer.link.Link*

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument **mode** below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** *(str)* – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default *mode* is *share*.

**Returns**

Copied link object.

**Return type**

*Link*

**copyparams** *(link: chainer.link.Link, copy_persistent: bool = True) → None*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise,
it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** (`Link`) – Source link object.
- **copy_persistent** (`bool`) – If True, persistent values are also copied. True by default.

**count_params** () → `int`

Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**

The total size of parameters (int)

**delete_hook** (`name: str`) → `None`

Unregisters the link hook.

**Parameters**

- **name** (`str`) – The name of the link hook to be unregistered.

**device_resident_accept** (`visitor`) (method)

Applies the visitor to all the device objects in this instance.

**Parameters**

- **visitor** (`DeviceResidentsVisitor`) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → `None`

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to False.

**enable_update** () → `None`

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to True.

**forward** (`self, x, finetune=False`) (method)

Invokes the forward propagation of BatchNormalization.

In training mode, the BatchNormalization computes moving averages of mean and variance for evaluation during training, and normalizes the input using batch statistics.

**Parameters**

- **x** (`Variable`) – Input variable.
- **finetune** (`bool`) – If it is in the training mode and `finetune` is True, BatchNormalization runs in fine-tuning mode; it accumulates the input array to compute population statistics for normalization, and normalizes the input using batch statistics.

**from_chx** () (method)

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** (*args, **kwargs)** (method)

Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

- some parameters for a specific link.
• constants such as stride width of a convolutional layer.

`init_scope()` → `Iterator[None]`

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

`links` *(skipself: `bool = False`)* → `Iterator[chainer.link.Link]`

Returns a generator of all links under the hierarchy.

**Parameters** `skipself` (*bool*) – If `True`, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all links.

`namedlinks` *(skipself: `bool = False`)* → `Iterator[Tuple[str, chainer.link.Link]]`

Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters** `skipself` (*bool*) – If `True`, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all (path, link) pairs.

`namedparams` *(include_uninit: `bool = True`)* → `Iterator[Tuple[str, chainer.variable.Parameter]]`

Returns a generator of all (path, parameter) pairs under the hierarchy.

**Parameters** `include_uninit` (*bool*) – If `True`, it also generates uninitialized parameters.

**Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

`params` *(include_uninit: `bool = True`)* → `Iterator[chainer.variable.Parameter]`

Returns a generator of all parameters under the link hierarchy.

**Parameters** `include_uninit` (*bool*) – If `True`, it also generates uninitialized parameters.

**Returns** A generator object that generates all parameters.

`register_persistent` *(name: `str`)* → `None`

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters** `name` (*str*) – Name of the attribute to be registered.
**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

---

**Example**

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

---

**Parameters**

- **n_repeat (int)** – Number of times to repeat.
- **mode (str)** – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

Parameters **serializer** (AbstractSerializer) – Serializer object.

**start_finetuning()**

Resets the population count for collecting population statistics.

This method can be skipped if it is the first time to use the fine-tuning mode. Otherwise, this method should be called before starting the fine-tuning mode again.

**to_chx()**

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must overcome this method to do so.
Returns: self

to_cpu() \rightarrow \text{chainer.device_resident.DeviceResident}
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self
to_device(device: \text{Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]} \rightarrow \text{DeviceResident}
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device() for available values.

Returns: self
to_gpu(device: Optional[\text{Union[cuda.Device, int, numpy.integer]}] = \text{None}) \rightarrow \text{chainer.device_resident.DeviceResident}
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64() \rightarrow \text{chainer.device_resident.DeviceResident}
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

to_intel64() \rightarrow \text{None}
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

\_eq\_ (value, /)
Return self==value.

\_ne\_ (value, /)
Return self!=value.

\_lt\_ (value, /)
Return self<value.

\_le\_ (value, /)
Return self<=value.

\_gt\_ (value, /)
Return self>value.
__ge__(value, /)
    Return self>=value.

Attributes

beta = None
device
    Device instance.
gamma = None
local_link_hooks
    Ordered dictionary of registered link hooks.
    Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.
printable_specs
update_enabled
    True if at least one parameter has an update rule enabled.
within_init_scope
    True if the current code is inside of an initialization scope.
    See init_scope() for the details of the initialization scope.
xp
    Array module corresponding to the device.
    Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.BatchRenormalization

class chainer.links.BatchRenormalization(size, rmax=1, dmax=0, decay=0.9, eps=2e-05, dtype=None, use_gamma=True, use_beta=True, initial_gamma=None, initial_beta=None, initial_avg_mean=None, initial_avg_var=None)
Batch renormalization layer on outputs of linear or convolution functions.
This link wraps the batch_renormalization() and fixed_batch_renormalization() functions.
This is an extension of batch normalization, which ensures that the training and inference models generate the same outputs that depend on individual examples rather than the entire minibatch.
See: Batch Renormalization: Towards Reducing Minibatch Dependence in Batch-Normalized Models
See also:
batch_renormalization(), fixed_batch_renormalization()
batch_normalization(),
Methods

__call__("*args: Any, **kwargs: Any) \rightarrow Any
Call self as a function.

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) \rightarrow chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.

• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class ‘numpy.float32’>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) \rightarrow None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.

• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• dtype – Data type of the parameter array.

• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent (name: str, value: Any) \rightarrow None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.

• value – Value to be registered.

addgrads (link: chainer.link.Link) \rightarrow None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters link (Link) – Source link object.

children () \rightarrow Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns A generator object that generates all child links.
cleargrads () → None
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode: str = 'share') → chainer.link.Link
Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the
documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent
chain (even if exists).

Parameters

mode (str) – It should be either init, copy, or share. init means parameter
variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link.
copy means that the link object is deeply copied, so that its parameters are not re-initialized
but are also deeply copied. Thus, all parameters have same initial values but can be changed
independently. share means that the link is shallowly copied, so that its parameters’ arrays
are shared with the original one. Thus, their values are changed synchronously. The default
mode is share.

Returns Copied link object.

Return type Link

copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host
and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of
BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise,
it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be repro-
duced with copy_persistent=False.

Parameters

• link (Link) – Source link object.
• copy_persistent (bool) – If True, persistent values are also copied. True by
default.

count_params () → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link
and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

delete_hook (name: str) → None
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

device_resident_accept (visitor)
Applies the visitor to all the device objects in this instance.

Parameters visitor (DeviceResidentsVisitor) – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update()** → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update()** → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

**forward** *(self, x, finetune=False)*
Invokes the forward propagation of BatchNormalization.

In training mode, the BatchNormalization computes moving averages of mean and variance for evaluation during training, and normalizes the input using batch statistics.

**Parameters**
- **x** *(Variable)* – Input variable.
- **finetune** *(bool)* – If it is in the training mode and finetune is True, BatchNormalization runs in fine-tuning mode; it accumulates the input array to compute population statistics for normalization, and normalizes the input using batch statistics.

**from_chx()**
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** *(args, **kwargs)*
Initialize link with given parameters.

This method initializes the link with given *N*-dimensional arrays. Arguments includes
- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope()** → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the **init_scope** method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))

links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.
Parameters `skipself` *(bool)* – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

**namedlinks** *(skipself: bool = False)* → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters `skipself` *(bool)* – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

**namedparams** *(include_uninit: bool = True)* → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters `include_uninit` *(bool)* – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** *(include_uninit: bool = True)* → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

Parameters `include_uninit` *(bool)* – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

**register_persistent** *(name: str)* → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters `name` *(str)* – Name of the attribute to be registered.

**repeat** *(n_repeat: int, mode: str = 'init')* → chainer.sequential.Sequential

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same
values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** *(int)* – Number of times to repeat.
- **mode** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters**

- **serializer** *(AbstractSerializer)* – Serializer object.

**start_finetuning** ()

Resets the population count for collecting population statistics.

This method can be skipped if it is the first time to use the fine-tuning mode. Otherwise, this method should be called before starting the fine-tuning mode again.

**to_chx** ()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device**() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override **device_resident_accept**() to do so.

Returns: self

**to_device** *(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]] → DeviceResident)*

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See **get_device**() for available values.

Returns: self

**to_gpu** *(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident)*

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use **to_device**() instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters**
- `device` – Target device specifier. If omitted, the current device is used.

  Returns: self

### to_intel64()
- `to_intel64()` → `chainer.device_resident.DeviceResident`
  - Copies parameter variables and persistent values to CPU.
  - Deprecated since version v7.0.0: Use `to_device()` instead.

### zerograds()
- `zerograds()` → `None`
  - Initializes all gradient arrays by zero.
  - Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

- `_eq__(value,/)`
  - Return `self==value`.

- `_ne__(value,/)`
  - Return `self!=value`.

- `_lt__(value,/)`
  - Return `self<value`.

- `_le__(value,/)`
  - Return `self<=value`.

- `_gt__(value,/)`
  - Return `self>value`.

- `_ge__(value,/)`
  - Return `self>=value`.

**Attributes**
- `beta = None`
  - `Device` instance.

- `gamma = None`
  - `Device` instance.

- `local_link_hooks`
  - Ordered dictionary of registered link hooks.
  - Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

- `printable_specs`

- `update_enabled`
  - True if at least one parameter has an update rule enabled.
within_init_scope
True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.

xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.

**chainer.links.DecorrelatedBatchNormalization**

```python
class chainer.links.DecorrelatedBatchNormalization(size, groups=16, decay=0.9, eps=2e-05, dtype=<class 'numpy.float32'>)
```

Decorrelated batch normalization layer.

This link wraps the `decorrelated_batch_normalization()` and `fixed_decorrelated_batch_normalization()` functions. It works on outputs of linear or convolution functions.

It runs in three modes: training mode, fine-tuning mode, and testing mode.

In training mode, it normalizes the input by *batch statistics*. It also maintains approximated population statistics by moving averages, which can be used for instant evaluation in testing mode.

In fine-tuning mode, it accumulates the input to compute *population statistics*. In order to correctly compute the population statistics, a user must use this mode to feed mini-batches running through whole training dataset.

In testing mode, it uses pre-computed population statistics to normalize the input variable. The population statistics is approximated if it is computed by training mode, or accurate if it is correctly computed by fine-tuning mode.

**Parameters**

- **size (int or tuple of ints)** – Size (or shape) of channel dimensions.
- **groups (int)** – Number of groups to use for group whitening.
- **decay (float)** – Decay rate of moving average which is used during training.
- **eps (float)** – Epsilon value for numerical stability.
- **dtype (numpy.dtype)** – Type to use in computing.

See: Decorrelated Batch Normalization

See also:

`decorrelated_batch_normalization()`, `fixed_decorrelated_batch_normalization()`

**Variables**

- **avg_mean (N-dimensional array)** – Population mean.
- **avg_projection (N-dimensional array)** – Population projection.
- **groups (int)** – Number of groups to use for group whitening.
- **N (int)** – Count of batches given for fine-tuning.
- **decay (float)** – Decay rate of moving average which is used during training.
- **eps (float)** – Epsilon value for numerical stability. This value is added to the batch variances.
Methods

__call__ (*args: Any, **kwargs: Any) → Any
Call self as a function.

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.
• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.
• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
• dtype – Data type of the parameter array.
• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent (name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.
• value – Value to be registered.

addgrads (link: chainer.link.Link) → None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters link (Link) – Source link object.

children () → Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns A generator object that generates all child links.
cleargrads() → None
Cleans all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy(mode: str = 'share') → chainer.link.Link
Copies the link hierarchy to a new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters

mode (str) – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link.

COPY means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

Returns Copied link object.

Return type Link

copyparams(link: chainer.link.Link, copy_persistent: bool = True) → None
Copies all parameters from a given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters

• link (Link) – Source link object.

• copy_persistent (bool) – If True, persistent values are also copied. True by default.

count_params() → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

delete_hook(name: str) → None
Unregisters the link hook.

Parameters

name (str) – The name of the link hook to be unregistered.

device_resident_accept(visitor)
Applies the visitor to all the device objects in this instance.

Parameters

visitor (DeviceResidentsVisitor) – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update() → None**
Disables update rules of all parameters under the link hierarchy.
This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

**enable_update() → None**
Enables update rules of all parameters under the link hierarchy.
This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

**forward(self, x, *, finetune=False)**
Invokes the forward propagation of DecorrelatedBatchNormalization.

In training mode, the DecorrelatedBatchNormalization computes moving averages of the mean and projection for evaluation during training, and normalizes the input using batch statistics.

**Parameters**
- `x` *(Variable)* – Input variable.
- `finetune` *(bool)* – If it is in the training mode and `finetune` is `True`, DecorrelatedBatchNormalization runs in fine-tuning mode; it accumulates the input array to compute population statistics for normalization, and normalizes the input using batch statistics.

**from_chx()**
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params(*args, **kwargs)**
Initialize link with given parameters.

This method initializes the link with given *N-dimensional arrays*. Arguments includes
- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope() → Iterator[None]**
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links(skipself: bool = False) → Iterator[chainer.link.Link]**
Returns a generator of all links under the hierarchy.
Parameters `skipself` (bool) – If `True`, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

`namedlinks` (skipself: bool = `False`) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters `skipself` (bool) – If `True`, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

`namedparams` (include_uninit: bool = `True`) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

Parameters `include_uninit` (bool) – If `True`, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

`params` (include_uninit: bool = `True`) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters `include_uninit` (bool) – If `True`, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

`register_persistent` (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters `name` (str) – Name of the attribute to be registered.

`repeat` (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

Example
You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same
values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat (int)** – Number of times to repeat.
- **mode (str)** – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize (serializer)**

Serializes the link object.

**Parameters**

- **serializer (AbstractSerializer)** – Serializer object.

**start_finetuning ()**

Resets the population count for collecting population statistics.

This method can be skipped if it is the first time to use the fine-tuning mode. Otherwise, this method should be called before starting the fine-tuning mode again.

**to_chx ()**

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu () → chainer.device_resident.DeviceResident**

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device () instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept () to do so.

Returns: self

**to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident**

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See get_device () for available values.

Returns: self

**to_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident**

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device () instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters**
- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** () → `chainer.device_resident.DeviceResident`
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

**zerograds** () → `None`
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

**__eq__**(value,/)  
Return `self==value`.

**__ne__**(value,/)  
Return `self!=value`.

**__lt__**(value,/)  
Return `self<value`.

**__le__**(value,/)  
Return `self<=value`.

**__gt__**(value,/)  
Return `self>value`.

**__ge__**(value,/)  
Return `self>=value`.

**Attributes**

- **device**  
  `Device` instance.

- **local_link_hooks**  
  Ordered dictionary of registered link hooks.

  Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

- **printable_specs**  
  Generator of printable specs of this link.

  Yields `specs (tuple of str and object)` – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()` method. This pair of key and value is used for representing this class or subclass with `__str__()`.

- **update_enabled**  
  True if at least one parameter has an update rule enabled.
within_init_scope

True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.

xp

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.

crainer.links.GroupNormalization

class crainer.links.GroupNormalization(groups, size=None, eps=1e-05, initial_gamma=None, initial_beta=None)

Group normalization layer on outputs of convolution functions.

This link implements a “group normalization” which divides the channels into groups and computes within each group the mean and variance, then normalize by these statistics, scales and shifts them. Parameter initialization will be deferred until the first forward data pass at which time the size will be determined.

Parameters

- **groups** (int) – The number of channel groups. This value must be a divisor of the number of channels.
- **size** (int) – Size of input units. If None, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.
- **eps** (float) – Epsilon value for numerical stability of normalization.
- **initial_gamma** (Initializer) – Initializer for scaling parameter. If None, then the vector is filled by 1. If a scalar, the vector is filled by it. If `numpy.ndarray`, the vector is set by it.
- **initial_beta** (Initializer) – Initializer for shifting parameter. If None, then the vector is filled by 0. If a scalar, the vector is filled by it. If `numpy.ndarray`, the vector is set by it.

Variables

- **groups** (int) – The number of channel groups.
- **gamma** (Parameter) – Scaling parameter.
- **beta** (Parameter) – Shifting parameter.
- **eps** (float) – Epsilon value for numerical stability.

See: Group Normalization

Methods

__call__(*args: Any, **kwargs: Any) → Any

Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link

Registers a link hook.

Parameters

- **hook** (LinkHook) – Link hook to be registered.
• **name** (*str*) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

    **Returns** self

    **add_param** (*name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None*) → None

    Registers a parameter to the link.

    **Parameters**

    • **name** (*str*) – Name of the parameter. This name is also used as the attribute name.

    • **shape** (*int or tuple of ints*) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

    • **dtype** – Data type of the parameter array.

    • **initializer** (*initializer*) – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

    **add_persistent** (*name: str, value: Any*) → None

    Registers a persistent value to the link.

    The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

    **Parameters**

    • **name** (*str*) – Name of the persistent value. This name is also used for the attribute name.

    • **value** – Value to be registered.

    **addgrads** (*link: chainer.link.Link*) → None

    Accumulates gradient values from given link.

    This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

    **Parameters** link (*Link*) – Source link object.

    **children** () → Iterator[chainer.link.Link]

    Returns a generator of all child links.

    **Returns** A generator object that generates all child links.

    **cleargrads** () → None

    Clears all gradient arrays.

    This method should be called before the backward computation at every iteration of the optimization.

    **copy** (*mode: str = 'share'*) → chainer.link.Link

    Copies the link hierarchy to new one.

    The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

    The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).
Parameters `mode (str) – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

Returns Copied link object.

Return type `Link`

copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g., the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

Parameters

- `link (Link) – Source link object.
- `copy_persistent (bool) – If True, persistent values are also copied. True by default.`

count_params () → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

delete_hook (name: str) → None
Unregisters the link hook.

Parameters `name (str) – The name of the link hook to be unregistered.`

device_resident_accept (visitor)
Applies the visitor to all the device objects in this instance.

Parameters `visitor (DeviceResidentsVisitor) – Visitor.`

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

disable_update () → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to `False`.

enable_update () → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to `True`.

forward (x)
Apply group normalization to given input.
Parameters $x$ (Variable) – Batch tensors. First dimension of this value must be the size of minibatch and second dimension must be the number of channels. Moreover, this value must have one or more following dimensions, such as height and width.

Returns Output of the group normalization.

Return type Variable

classmethod from_params(*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given $N$-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

init_scope() → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.
Returns: A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

```
params(include_uninit: bool = True) -> Iterator[chainer.variable.Parameter]
```

Returns a generator of all parameters under the link hierarchy.

**Parameters**

- **include_uninit** *(bool)* — If True, it also generates uninitialized parameters.

**Returns**

A generator object that generates all parameters.

```
register_persistent(name: str) -> None
```

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name** *(str)* — Name of the attribute to be registered.

```
repeat(n_repeat: int, mode: str = 'init') -> chainer.sequential.Sequential
```

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** *(int)* — Number of times to repeat.
- **mode** *(str)* — It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial
parameters but can be changed independently. *share* means all the elements which consist the resulting *Sequential* object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

```python
serialize (serializer: chainer.serializer.AbstractSerializer) → None
```

Serializes the link object.

**Parameters**

- **serializer** (*AbstractSerializer*) – Serializer object.

```python
to_chx ()
```

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: `self`

```python
to_cpu () → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: `self`

```python
to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
```

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See `get_device()` for available values.

Returns: `self`

```python
to_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: `self`

```python
to_intel64 () → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

```python
zerograds () → None
```

Initializes all gradient arrays by zero.
Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

```python
__eq__(value,)
    Return self==value.
__ne__(value,)
    Return self!=value.
__lt__(value,)
    Return self<value.
__le__(value,)
    Return self<=value.
__gt__(value,)
    Return self>value.
__ge__(value,)
    Return self>=value.
```

**Attributes**

- `device`
  
  `Device` instance.

- `local_link_hooks`
  
  Ordered dictionary of registered link hooks.

  Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

- `printable_specs`
  
  Generator of printable specs of this link.

  **Yields** specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()` method. This pair of key and value is used for representing this class or subclass with `__str__()`.

- `update_enabled`
  
  True if at least one parameter has an update rule enabled.

- `within_init_scope`
  
  True if the current code is inside of an initialization scope.

  See `init_scope()` for the details of the initialization scope.

- `xp`
  
  Array module corresponding to the device.

  Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`. 
class chainer.links.LayerNormalization(size=None, eps=1e-06, initial_gamma=None, initial_beta=None)
Layer normalization layer on outputs of linear functions.

Warning: This feature is experimental. The interface can change in the future.

This link implements a “layer normalization” layer which normalizes the input units by statistics that are computed along the second axis, scales and shifts them. Parameter initialization will be deferred until the first forward data pass at which time the size will be determined.

Parameters

- size (int) – Size of input units. If None, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.
- eps (float) – Epsilon value for numerical stability of normalization.
- initial_gamma (Initializer) – Initializer for scaling vector. If None, then the vector is filled by 1. If a scalar, the vector is filled by it. If numpy.ndarray, the vector is set by it.
- initial_beta (Initializer) – Initializer for shifting vector. If None, then the vector is filled by 0. If a scalar, the vector is filled by it. If numpy.ndarray, the vector is set by it.

Variables

- gamma (Parameter) – Scaling parameter.
- beta (Parameter) – Shifting parameter.
- eps (float) – Epsilon value for numerical stability.

See: Layer Normalization

Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

- hook (LinkHook) – Link hook to be registered.
- name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters
• **name** (*str*) – Name of the parameter. This name is also used as the attribute name.

• **shape** (*int or tuple of ints*) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• **dtype** – Data type of the parameter array.

• **initializer** (*initializer*) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

### add_persistent

#### Signature

```python
add_persistent(name: str, value: Any) → None
```

#### Description

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

• **name** (*str*) – Name of the persistent value. This name is also used for the attribute name.

• **value** – Value to be registered.

### addgrads

#### Signature

```python
addgrads(link: chainer.link.Link) → None
```

#### Description

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** (*Link*) – Source link object.

### children

#### Signature

```python
children() → Iterator[chainer.link.Link]
```

#### Returns

A generator object that generates all child links.

### cleargrads

#### Signature

```python
cleargrads() → None
```

#### Description

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

### copy

#### Signature

```python
copy(mode: str = 'share') → chainer.link.Link
```

#### Description

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** (*str*) – It should be either `init`, `copy`, or `share`. `init` means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. `copy` means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. `share` means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default `mode` is `share`.

**Returns** 
Copied link object.

**Return type** 
*Link*
**copyparams** *(link: chainer.link.Link, copy_persistent: bool = True) → None*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g., the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** *(Link)* – Source link object.
- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

**count_params** () → int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

**delete_hook** *(name: str) → None*

Unregisters the link hook.

**Parameters** name *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*

Applies the visitor to all the device objects in this instance.

**Parameters** visitor *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update** () → None

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

**forward** *(x)*

Apply layer normalization to given input.

**Parameters** x *(Variable)* – Batch vectors. Shape of this value must be (batch_size, unit_size), e.g., the output of `linear()`.

**Returns** Output of the layer normalization.

**Return type** Variable

**from_chx** ()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.
classmethod from_params(*args, **kwargs)
Initialize link with given parameters.
This method initializes the link with given \(N\)-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

init_scope() \(\rightarrow\) Iterator[None]
Creates an initialization scope.
This method returns a context manager object that enables registration of parameters (and links for \texttt{Chain}) by an assignment. A \texttt{Parameter} object can be automatically registered by assigning it to an attribute under this context manager.

Example
In most cases, the parameter registration is done in the initializer method. Using the \texttt{init_scope} method, we can simply assign a \texttt{Parameter} object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

\texttt{links}(skipself: bool = False) \(\rightarrow\) Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters \texttt{skipself}(bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

\texttt{namedlinks}(skipself: bool = False) \(\rightarrow\) Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters \texttt{skipself}(bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

\texttt{namedparams}(include_uninit: bool = True) \(\rightarrow\) Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, parameter) pairs under the hierarchy.

Parameters \texttt{include_uninit}(bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

\texttt{params}(include_uninit: bool = True) \(\rightarrow\) Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters \texttt{include_uninit}(bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

\texttt{register_persistent}(name: str) \(\rightarrow\) None
Registers an attribute of a given name as a persistent value.
This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name** (*str*) – Name of the attribute to be registered.

- **repeat** (*n_repeat: int, mode: str = 'init'*) – Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)
    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))
net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** (*int*) – Number of times to repeat.
- **mode** (*str*) – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** (*serializer: chainer.serializer.AbstractSerializer*) – Serializes the link object.

**Parameters**

- **serializer** (*AbstractSerializer*) – Serializer object.

**to_chx**()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.
Returns: self

to_cpu() \to \text{chainer.device_resident.DeviceResident}
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

to_device(device: \text{Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]}) \to \text{DeviceResident}
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device() for available values.

Returns: self

to_gpu(device: \text{Optional[Union[cuda.Device, int, numpy.integer]]} = \text{None}) \to \text{chainer.device_resident.DeviceResident}
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64() \to \text{chainer.device_resident.DeviceResident}
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

zerograds() \to \text{None}
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

\_\_eq\_\_(value, /)
Return self==value.

\_\_ne\_\_(value, /)
Return self!=value.

\_\_lt\_\_(value, /)
Return self<value.

\_\_le\_\_(value, /)
Return self<=value.

\_\_gt\_\_(value, /)
Return self>value.
__ge__(value, /)
    Return self>=value.

Attributes

device
    Device instance.

local_link_hooks
    Ordered dictionary of registered link hooks.

    Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions,
link hooks in this property are specific to this link.

printablespecs
    Generator of printable specs of this link.

    Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword
and value) that are passed to the __init__() method. This pair of key and value is used for
representing this class or subclass with __str__().

update_enabled
    True if at least one parameter has an update rule enabled.

within_init_scope
    True if the current code is inside of an initialization scope.

    See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.

    Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.BinaryHierarchicalSoftmax

class chainer.links.BinaryHierarchicalSoftmax (in_size, tree, dtype=None)
    Hierarchical softmax layer over binary tree.

In natural language applications, vocabulary size is too large to use softmax loss. Instead, the hierarchical
softmax uses product of sigmoid functions. It costs only $O(\log(n))$ time where $n$ is the vocabulary size in
average.

At first a user needs to prepare a binary tree whose each leaf is corresponding to a word in a vocabulary. When
a word $x$ is given, exactly one path from the root of the tree to the leaf of the word exists. Let $\text{path}(x) = (e_1, b_1, \ldots, e_m, b_m)$ be the path of $x$, where $e_i$ is an index of $i$-th internal node, and $b_i \in \{-1, 1\}$ indicates
direction to move at $i$-th internal node (-1 is left, and 1 is right). Then, the probability of $x$ is given as below:

$$
P(x) = \prod_{(e_i, b_i) \in \text{path}(x)} P(b_i|e_i)$$

$$
= \prod_{(e_i, b_i) \in \text{path}(x)} \sigma(b_i x^T w_{e_i}),$$

where $\sigma(\cdot)$ is a sigmoid function, and $w$ is a weight matrix.

This function costs $O(\log(n))$ time as an average length of paths is $O(\log(n))$, and $O(n)$ memory as the number
of internal nodes equals $n - 1$.

Parameters
• **in_size** (*int*) – Dimension of input vectors.
• **tree** – A binary tree made with tuples like ((1, 2), 3).
• **dtype** (*numpy.dtype*) – Type to use in computing.

**Variables**

- **W** (*Variable*) – Weight parameter matrix.

See: Hierarchical Probabilistic Neural Network Language Model [Morin+, AISTAT2005].

**Methods**

- **__call__** (**args: Any, **kwargs: Any*) → *Any*

  Call self as a function.

- **add_hook** (*hook: chainer.link_hook.LinkHook, name: Optional[str] = None*) → *chainer.link.Link*

  Registers a link hook.

  **Parameters**

  - **hook** (*LinkHook*) – Link hook to be registered.
  - **name** (*str*) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

  **Returns**

  self

- **add_param** (*name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None*) → *None*

  Registers a parameter to the link.

  **Parameters**

  - **name** (*str*) – Name of the parameter. This name is also used as the attribute name.
  - **shape** (*int or tuple of ints*) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
  - **dtype** – Data type of the parameter array.
  - **initializer** (*initializer*) – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

- **add_persistent** (*name: str, value: Any*) → *None*

  Registers a persistent value to the link.

  The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

  **Parameters**

  - **name** (*str*) – Name of the persistent value. This name is also used for the attribute name.
  - **value** – Value to be registered.

- **addgrads** (*link: chainer.link.Link*) → *None*

  Accumulates gradient values from given link.

  This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.
Parameters link (Link) – Source link object.

cchildren () → Iterator[chainer.link.Link]  
Returns a generator of all child links.

Returns  A generator object that generates all child links.

cleargrads () → None  
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode: str = 'share') → chainer.link.Link  
Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters mode (str) – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

Returns  Copied link object.

Return type  Link

copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None  
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters  
  • link (Link) – Source link object.
  • copy_persistent (bool) – If True, persistent values are also copied. True by default.

count_params () → int  
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns  The total size of parameters (int)

static create_huffman_tree (word_counts)  
Makes a Huffman tree from a dictionary containing word counts.
This method creates a binary Huffman tree, that is required for \texttt{BinaryHierarchicalSoftmax}. For example, \{0: 8, 1: 5, 2: 6, 3: 4\} is converted to \((3, 1), (2, 0)\).

**Parameters** \texttt{word_counts (dict of int key and int or float values)} – Dictionary representing counts of words.

**Returns** Binary Huffman tree with tuples and keys of \texttt{word_counts}.

\texttt{delete\_hook (name: str) \rightarrow None}

Unregisters the link hook.

**Parameters** \texttt{name (str)} – The name of the link hook to be unregistered.

\texttt{device\_resident\_accept (visitor)}

Applies the visitor to all the device objects in this instance.

**Parameters** \texttt{visitor (DeviceResidentsVisitor)} – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

\texttt{disable\_update () \rightarrow None}

Disables update rules of all parameters under the link hierarchy.

This method sets the \texttt{enabled} flag of the update rule of each parameter variable to \texttt{False}.

\texttt{enable\_update () \rightarrow None}

Enables update rules of all parameters under the link hierarchy.

This method sets the \texttt{enabled} flag of the update rule of each parameter variable to \texttt{True}.

\texttt{forward (x, t)}

Computes the loss value for given input and ground truth labels.

**Parameters**

\begin{itemize}
  \item \texttt{x (Variable)} – Input to the classifier at each node.
  \item \texttt{t (Variable)} – Batch of ground truth labels.
\end{itemize}

**Returns** Loss value.

**Return type** \texttt{Variable}

\texttt{from\_chx ()}

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

\texttt{classmethod from\_params (*args, **kwargs)}

Initialize link with given parameters.

This method initializes the link with given \textit{N-dimensional arrays}. Arguments includes

\begin{itemize}
  \item some parameters for a specific link.
  \item constants such as stride width of a convolutional layer.
\end{itemize}

\texttt{init\_scope () \rightarrow Iterator[None]}

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A \texttt{Parameter} object can be automatically registered by assigning it to an attribute under this context manager.

\textbf{Example}
In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

`links` *(skipself: bool = False) → Iterator[chainer.link.Link]*

Returns a generator of all links under the hierarchy.

- **Parameters** `skipself` *(bool)* – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all links.

`namedlinks` *(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]*

Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters** `skipself` *(bool)* – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all (path, link) pairs.

`namedparams` *(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]*

Returns a generator of all (path, parameter) pairs. The paths are relative from this link.

- **Parameters** `include_uninit` *(bool)* – If True, it also generates uninitialized parameters.

- **Returns** A generator object that generates all parameters.

`params` *(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]*

Returns a generator of all parameters under the link hierarchy.

- **Parameters** `include_uninit` *(bool)* – If True, it also generates uninitialized parameters.

- **Returns** A generator object that generates all parameters.

`register_persistent` *(name: str) → None*

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

- **Parameters** `name` *(str)* – Name of the attribute to be registered.

`repeat` *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)
    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat (int)** – Number of times to repeat.
- **mode (str)** – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

serialize (serializer: chainer.serializer.AbstractSerializer) → None

Serializes the link object.

Parameters

- **serializer** (AbstractSerializer) – Serializer object.

to_chx ()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

to_cpu () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident

Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters device** – Target device specifier. See `get_device()` for available values.

Returns: self

```
to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters device** – Target device specifier. If omitted, the current device is used.

Returns: self

```
to_intel64() → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device` instead.

```
zerograds() → None
```

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

```
__eq__(value, /) → Return self==value.
__ne__(value, /) → Return self!=value.
__lt__(value, /) → Return self<value.
__le__(value, /) → Return self<=value.
__gt__(value, /) → Return self>value.
__ge__(value, /) → Return self>=value.
```
Attributes

device

Device instance.

local_link_hooks

Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs

Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__() method. This pair of key and value is used for representing this class or subclass with __str__().

update_enabled

True if at least one parameter has an update rule enabled.

within_init_scope

True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.BlackOut

class chainer.links.BlackOut(in_size, counts, sample_size)

BlackOut loss layer.

See also:

black_out() for more detail.

Parameters

- in_size (int) – Dimension of input vectors.
- counts (int list) – Number of each identifiers.
- sample_size (int) – Number of negative samples.

Variables W (Parameter) – Weight parameter matrix.

Methods

__call__(*args: Any, **kwargs: Any) → Any

Call self as a function.

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link

Registers a link hook.

Parameters

- hook (LinkHook) – Link hook to be registered.
• **name** (*str*) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

**Returns** self

```python
add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
```

Registers a parameter to the link.

**Parameters**

• **name** (*str*) – Name of the parameter. This name is also used as the attribute name.

• **shape** (*int or tuple of ints*) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• **dtype** – Data type of the parameter array.

• **initializer** (*initializer*) – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

```python
add_persistent(name: str, value: Any) → None
```

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

• **name** (*str*) – Name of the persistent value. This name is also used for the attribute name.

• **value** – Value to be registered.

```python
addgrads(link: chainer.link.Link) → None
```

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

• **link** (*Link*) – Source link object.

```python
children() → Iterator[chainer.link.Link]
```

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

```python
cleargrads() → None
```

Cleans all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

```python
copy(mode: str = 'share') → chainer.link.Link
```

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).
Parameters `mode (str)` – It should be either `init`, `copy`, or `share`. `init` means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. `copy` means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. `share` means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is `share`.

Returns Copied link object.

Return type `Link`

`copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None`
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an `ndarray`, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

Parameters

- `link (Link)` – Source link object.
- `copy_persistent (bool)` – If `True`, persistent values are also copied. `True` by default.

`count_params () → int`
Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

`delete_hook (name: str) → None`
Unregisters the link hook.

Parameters `name (str)` – The name of the link hook to be unregistered.

`device_resident_accept (visitor)`
Applies the visitor to all the device objects in this instance.

Parameters `visitor (DeviceResidentsVisitor)` – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

`disable_update () → None`
Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

`enable_update () → None`
Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

`forward (x, t)`
Computes the loss value for given input and ground truth labels.
Parameters

- **x (Variable)** – Input of the weight matrix multiplication.
- **t (Variable)** – Batch of ground truth labels.

Returns Loss value.

Return type **Variable**

**from_chx()**

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params(*args, **kwargs)**

Initialize link with given parameters.

This method initializes the link with given *N*-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope() → Iterator[None]**

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for *Chain*) by an assignment. A *Parameter* object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the *init_scope* method, we can simply assign a *Parameter* object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links (skipself: bool = False) → Iterator[chainer.link.Link]**

Returns a generator of all links under the hierarchy.

Parameters **skipself (bool)** – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

**namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]**

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters **skipself (bool)** – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

**namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]**

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters **include_uninit (bool)** – If True, it also generates uninitialized parameters.
Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** *(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]*

Returns a generator of all parameters under the link hierarchy.

**Parameters** *include_uninit* *(bool) – If True, it also generates uninitialized parameters.*

**Returns** A generator object that generates all parameters.

**register_persistent** *(name: str) → None*

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters** *name* *(str) – Name of the attribute to be registered.*

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)
    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))
net = ConvBNReLU().repeat(16, mode='init')
```

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat**(int) – Number of times to repeat.
- **mode**(str) – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial
parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

```python
serialize(serializer: chainer.serializer.AbstractSerializer) → None
```

Serializes the link object.

**Parameters**

- `serializer` (`AbstractSerializer`) – Serializer object.

```python
to_chx() → chainer.device_resident.DeviceResident
```

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: `self`

```python
to_cpu() → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

**Deprecated since version v7.0.0:** Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: `self`

```python
to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
```

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- `device` – Target device specifier. See `get_device()` for available values.

Returns: `self`

```python
to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to GPU.

**Deprecated since version v7.0.0:** Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters**

- `device` – Target device specifier. If omitted, the current device is used.

Returns: `self`

```python
to_intel64() → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

**Deprecated since version v7.0.0:** Use `to_device()` instead.

```python
zerograds() → None
```

Initializes all gradient arrays by zero.
Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

```python
__eq__(value, /)
    Return self==value.

__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.
```

**Attributes**

- **device**
  - `Device` instance.

- **local_link_hooks**
  - Ordered dictionary of registered link hooks.
    Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

- **printable_specs**
  - Generator of printable specs of this link.
    Yields `specs (tuple of str and object)` – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()`. This pair of key and value is used for representing this class or subclass with `__str__()`.  

- **sample_data = None**

- **update_enabled**
  - `True` if at least one parameter has an update rule enabled.

- **within_init_scope**
  - `True` if the current code is inside of an initialization scope.
    See `init_scope()` for the details of the initialization scope.

- **xp**
  - Array module corresponding to the device.
    Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.  

class chainer.links.CRF1d(n_label, initial_cost=None)
Linear-chain conditional random field loss layer.

This link wraps the `crf1d()` function. It holds a transition cost matrix as a parameter.

Parameters

- `n_label (int)` – Number of labels.
- `initial_cost (initializer)` – Initializer to initialize the transition cost matrix. If this attribute is not specified, the transition cost matrix is initialized with zeros.

See also:

`crf1d()` for more detail.

Variables `cost (Variable)` – Transition cost parameter.

Methods

__call__ (*args: Any, **kwargs: Any) → Any
Call self as a function.

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

- `hook (LinkHook)` – Link hook to be registered.
- `name (str)` – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

Returns self

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = None, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

- `name (str)` – Name of the parameter. This name is also used as the attribute name.
- `shape (int or tuple of ints)` – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- `dtype` – Data type of the parameter array.
- `initializer (initializer)` – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent (name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.
Parameters

- **name (str)** – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

`addgrads (link: chainer.link.Link) → None`

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters

- **link (Link)** – Source link object.

`argmax (xs, transpose=False)`

Computes a state that maximizes a joint probability.

Parameters

- **xs (list of Variable)** – Input vector for each label.
- **transpose (bool)** – If True, input/output sequences
  be sorted in descending order of length. (will) –

Returns A tuple of Variable representing each log-likelihood and a list representing the argmax path.

Return type tuple

See also:

See `crf1d_argmax()` for more detail.

`children () → Iterator[chainer.link.Link]`

Returns a generator of all child links.

Returns A generator object that generates all child links.

`cleargrads () → None`

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

`copy (mode: str = 'share') → chainer.link.Link`

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters

- **mode (str)** – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters' arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

Returns Copied link object.

Return type Link
copyparams (link: chainer.link.Link, copypersistent: bool = True) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

**Parameters**

- **link (Link)** – Source link object.
- **copypersistent (bool)** – If True, persistent values are also copied. True by default.

count_params () → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)
delete_hook (name: str) → None
Unregisters the link hook.

**Parameters**

- **name (str)** – The name of the link hook to be unregistered.

device_resident_accept (visitor)
Applies the visitor to all the device objects in this instance.

**Parameters**

- **visitor (DeviceResidentsVisitor)** – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.
disable_update () → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

enable_update () → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

forward (xs, ys, reduce='mean', transpose=False)
Computes negative log-likelihood of linear-chain CRF

**Parameters**

- **xs (list of Variable)** – Input vector for each label
- **ys (list of Variable)** – Expected output labels.
- **transpose (bool)** – If True, input/output sequences be sorted in descending order of length. (will –

**Returns** A variable holding the average negative log-likelihood of the input sequences.

**Return type** Variable
See also:

See crf1d() for more detail.

from_chx()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(*args, **kwargs)

Initialize link with given parameters.

This method initializes the link with given *N-dimensional arrays*. Arguments includes

• some parameters for a specific link.
• constants such as stride width of a convolutional layer.

init_scope() → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

links (skipself: bool = False) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.
Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example
You can repeat the same link multiple times to create a longer Sequential block like this:

class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

• n_repeat (int) – Number of times to repeat.
• mode (str) – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

serialize (serializer: chainer.serializer.AbstractSerializer) → None
Serializes the link object.

Parameters serializer (AbstractSerializer) – Serializer object.
to_chx()
Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.
Returns: self

to_cpu() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Depreciated since version v7.0.0: Use to_device() instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.
Returns: self

to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.
Parameters device – Target device specifier. See get_device() for available values.
Returns: self

to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.
Depreciated since version v7.0.0: Use to_device() instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.
Returns: self

to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Depreciated since version v7.0.0: Use to_device() instead.

to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Depreciated since version v7.0.0: Use to_device() instead.

zerograds() → None
Initializes all gradient arrays by zero.
Depreciated since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value,)
Return self==value.

__ne__(value,)
Return self!=value.

__lt__(value,)
Return self<value.
__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

device
    Device instance.

local_link_hooks
    Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
    Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
    True if at least one parameter has an update rule enabled.

within_init_scope
    True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

criminator.links.SimplifiedDropconnect

class chainer.links.SimplifiedDropconnect (in_size, out_size, ratio=0.5, nobias=False, initialW=None, initial_bias=None)
    Fully-connected layer with simplified dropconnect regularization.

Notice: This implementation cannot be used for reproduction of the paper. There is a difference between the current implementation and the original one. The original version uses sampling with gaussian distribution before passing activation function, whereas the current implementation averages before activation.

Parameters

• in_size (int) – Dimension of input vectors. If None, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.

• out_size (int) – Dimension of output vectors.

• nobias (bool) – If True, then this link does not use the bias term.

• initialW (initializer) – Initializer to initialize the weight. When it is numpy.ndarray, its ndim should be 3.
• **initial_bias** (*initializer*) – Initializer to initialize the bias. If `None`, the bias will be initialized to zero. When it is `numpy.ndarray`, its `ndim` should be 2.

**Variables**

- `W` (*Variable*) – Weight parameter.
- `b` (*Variable*) – Bias parameter.

**See also:**

`simplified_dropconnect()`

**See also:**


**Methods**

```python
__call__(*args: Any, **kwargs: Any) → Any
```

Call self as a function.

```python
add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
```

Registers a link hook.

**Parameters**

- `hook` (*LinkHook*) – Link hook to be registered.
- `name` (*str*) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

**Returns**

self

```python
add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
```

Registers a parameter to the link.

**Parameters**

- `name` (*str*) – Name of the parameter. This name is also used as the attribute name.
- `shape` (*int or tuple of ints*) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- `dtype` – Data type of the parameter array.
- `initializer` (*initializer*) – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

```python
add_persistent(name: str, value: Any) → None
```

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- `name` (*str*) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

**addgrads**  
(link: chainer.link.Link) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**  
link (Link) – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (mode: str = 'share') → chainer.link.Link

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument **mode** below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**  
mode (str) – It should be either init, copy, or share.  
init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link.  
copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently.  
share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

**Returns** Copied link object.

**Return type** Link

**copyparams** (link: chainer.link.Link, copy_persistent: bool = True) → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

**Parameters**

- **link** (Link) – Source link object.

- **copy_persistent** (bool) – If True, persistent values are also copied. True by default.

**count_params** () → int

Counts the total number of parameters.
This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

```python
delete_hook(name: str) → None
```
Unregisters the link hook.

**Parameters**
- name (str) – The name of the link hook to be unregistered.

```python
device_resident_accept(visitor)
```
Applies the visitor to all the device objects in this instance.

**Parameters**
- visitor (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

```python
disable_update() → None
```
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

```python
enable_update() → None
```
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

```python
forward(x, train=True, mask=None, use_batchwise_mask=True)
```
Applies the simplified dropconnect layer.

**Parameters**
- x (chainer.Variable or N-dimensional array) – Batch of input vectors. Its first dimension \( n \) is assumed to be the minibatch dimension.
- train (bool) – If True, executes simplified dropconnect. Otherwise, simplified dropconnect link works as a linear unit.
- mask (None or chainer.Variable or N-dimensional array) – If None, randomized simplified dropconnect mask is generated. Otherwise, The mask must be \((n, M, N)\) or \((M, N)\) shaped array, and use_batchwise_mask is ignored. Main purpose of this option is debugging. mask array will be used as a dropconnect mask.
- use_batchwise_mask (bool) – If True, dropped connections depend on each sample in mini-batch.

**Returns** Output of the simplified dropconnect layer.

**Return type** `Variable`

```python
from_chx()
```
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

```python
classmethod from_params(*args, **kwargs)
```
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.
**init_scope** () → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links** (skipself: bool = False) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

**Parameters** skipself (bool) – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all links.

**namedlinks** (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters** skipself (bool) – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all (path, link) pairs.

**namedparams** (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

**Parameters** include_uninit (bool) – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

**Parameters** include_uninit (bool) – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all parameters.

**register_persistent** (name: str) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters** name (str) – Name of the attribute to be registered.

**repeat** (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential

Repeats this link multiple times to make a Sequential.
This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- `n_repeat (int)` – Number of times to repeat.
- `mode (str)` – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize**(serializer: chainer.serializer.AbstractSerializer) → None

Serializes the link object.

**Parameters**

- `serializer (AbstractSerializer)` – Serializer object.

**to_chx()**

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu()** → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

*Deprecated since version v7.0.0: Use `to_device()` instead.*

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.
Returns: self

to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

**device** – Target device specifier. See get_device() for available values.

Returns: self
to_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecation: since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

**Parameters**

**device** – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64 () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecation: since version v7.0.0: Use to_device() instead.

zerograds () → None
Initializes all gradient arrays by zero.

Deprecation: since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.
Attributes

device
Device instance.

local_link_hooks
Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.PReLU

class chainer.links.PReLU(shape=(), init=0.25)
Parametric ReLU function as a link.

Parameters

• shape (tuple of ints) – Shape of the parameter array.
• init (float) – Initial parameter value.

See the paper for details: Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification.

To try PReLU instead of ReLU, replace F.relu with individual PReLU links registered to the model. For example, the model defined in the MNIST example can be rewritten as follows.

ReLU version (original):

class MLP(chainer.Chain):
    def __init__(self, n_units, n_out):
        super(MLP, self).__init__()
        with self.init_scope():
            self.l1 = L.Linear(None, n_units)
            self.l2 = L.Linear(None, n_units)
            self.l3 = L.Linear(None, n_out)

    def forward(self, x):
        h1 = F.relu(self.l1(x))

(continues on next page)
PReLU version:

class MLP(chainer.Chain):
    def __init__(self, n_units, n_out):
        super(MLP, self).__init__()
        with self.init_scope():
            self.l1 = L.Linear(None, n_units)
            self.a1 = L.PReLU()
            self.l2 = L.Linear(None, n_units)
            self.a2 = L.PReLU()
            self.l3 = L.Linear(None, n_out)

    def forward(self, x):
        h1 = self.a1(self.l1(x))
        h2 = self.a2(self.l2(h1))
        return self.l3(h2)

See also:

chainer.functions.prelu()

Variables W (Parameter) – Coefficient of parametric ReLU.

Methods

__call__(*args: Any, **kwargs: Any) → Any
    Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
    Registers a link hook.

    Parameters

    • hook (LinkHook) – Link hook to be registered.
    • name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

    Returns

    self

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any =<class 'numpy.float32'>, initializer: Optional[Union[chainer.types(AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray)] = None) → None
    Registers a parameter to the link.

    Parameters

    • name (str) – Name of the parameter. This name is also used as the attribute name.
    • shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
    • dtype – Data type of the parameter array.
• **initializer** *(initializer)* – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

```python
add_persistent (name: str, value: Any) → None
```

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- **name (str)** – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

```python
addgrads (link: chainer.link.Link) → None
```

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** *(Link)* – Source link object.

```python
children () → Iterator[chainer.link.Link]
```

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

```python
cleargrads () → None
```

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

```python
copy (mode: str = 'share') → chainer.link.Link
```

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode (str)** – It should be either `init`, `copy`, or `share`. `init` means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. `copy` means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. `share` means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default `mode` is `share`.

**Returns**

Copied link object.

**Return type**

`Link`

```python
copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None
```

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.
From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- `link (Link)` – Source link object.
- `copy_persistent (bool)` – If True, persistent values are also copied. True by default.

**count_params () → int**

Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**

The total size of parameters (int)

**delete_hook (name: str) → None**

Unregisters the link hook.

**Parameters**

- `name (str)` – The name of the link hook to be unregistered.

**device_resident_accept (visitor)**

Applies the visitor to all the device objects in this instance.

**Parameters**

- `visitor (DeviceResidentsVisitor)` – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update () → None**

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

**enable_update () → None**

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

**forward (x)**

Applies the parametric ReLU activation function.

**Parameters**

- `x (Variable)` – Input variable.

**Returns**

Output of the parametric ReLU function.

**Return type**

`Variable`

**from_chx ()**

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params (*args, **kwargs)**

Initialize link with given parameters.

This method initializes the link with given `N-dimensional arrays`. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

---

4.3. Link and Chains 679
**init_scope()** → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links** (skipself: bool = False) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

**Parameters**

- **skipself** (bool) – If True, then the generator skips this link and starts with the first child link.

**Returns**

A generator object that generates all links.

**namedlinks** (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters**

- **skipself** (bool) – If True, then the generator skips this link and starts with the first child link.

**Returns**

A generator object that generates all (path, link) pairs.

**namedparams** (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, parameter) pairs under the hierarchy.

**Parameters**

- **include_uninit** (bool) – If True, it also generates uninitialized parameters.

**Returns**

A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

**Parameters**

- **include_uninit** (bool) – If True, it also generates uninitialized parameters.

**Returns**

A generator object that generates all parameters.

**register_persistent** (name: str) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name** (str) – Name of the attribute to be registered.

**repeat** (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential

Repeats this link multiple times to make a `Sequential`. 

---
This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))
net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- `n_repeat (int)` – Number of times to repeat.
- `mode (str) – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters** `serializer (AbstractSerializer)` – Serializer object.

**to_chx()**

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu() → chainer.device_resident.DeviceResident**

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.
Returns: self

to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], Module-Type, Tuple[ModuleType, int]] → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the
device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device() for available values.

Returns: self
to_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) →
chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU,
the link implementation must override device_resident_accept() to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use to_device
to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64 () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

zerograds () → None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.
Attributes

device

Device instance.

local_link_hooks

Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs

Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled

True if at least one parameter has an update rule enabled.

within_init_scope

True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.Swish

class chainer.links.Swish(beta_shape, beta_init=1.0)

Swish activation function as a link.

Parameters

• beta_shape (tuple of ints or None) – Shape of the parameter variable \( \beta \). If None, parameter initialization will be deferred until the first forward data pass at which time the shape will be determined.

• beta_init (float) – Initial value of the parameter variable \( \beta \).

See the paper for details: Searching for Activation Functions

To try Swish instead of ReLU, replace F.relu with individual Swish links registered to the model. For example, the model defined in the MNIST example can be rewritten as follows.

ReLU version (original):

class MLP(chainer.Chain):

    def __init__(self, n_units, n_out):
        super(MLP, self).__init__()
        with self.init_scope():
            self.l1 = L.Linear(None, n_units)
            self.l2 = L.Linear(None, n_units)
            self.l3 = L.Linear(None, n_out)

    def forward(self, x):

(continues on next page)
h1 = F.relu(self.l1(x))
h2 = F.relu(self.l2(h1))
return self.l3(h2)

Swish version:

class MLP(chainer.Chain):
    def __init__(self, n_units, n_out):
        super(MLP, self).__init__()
        with self.init_scope():
            self.l1 = L.Linear(None, n_units)
            self.s1 = L.Swish(None)
            self.l2 = L.Linear(None, n_units)
            self.s2 = L.Swish(None)
            self.l3 = L.Linear(None, n_out)

    def forward(self, x):
        h1 = self.s1(self.l1(x))
        h2 = self.s2(self.l2(h1))
        return self.l3(h2)

See also:

See chainer.functions.swish() for the definition of Swish activation function.

Variables beta (Parameter) – Parameter variable \( \beta \).

Methods

__call__(*args: Any, **kwargs: Any) -> Any
Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) -> chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.

• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) -> None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.

• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• dtype – Data type of the parameter array.
• **initializer** *(initializer)* – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

**add_persistent** *(name: str, value: Any) → None*

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

*name (str)* – Name of the persistent value. This name is also used for the attribute name.

*value* – Value to be registered.

**addgrads** *(link: chainer.link.Link) → None*

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

*link (Link)* – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**clearparams** *(link: chainer.link.Link, copy_persistent: bool = True) → None*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.
From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters

- link (Link) – Source link object.
- copy_persistent (bool) – If True, persistent values are also copied. True by default.

count_params() → int
Counts the total number of parameters.
This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.
If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

delete_hook (name: str) → None
Unregisters the link hook.
Parameters name (str) – The name of the link hook to be unregistered.

device_resident_accept (visitor)
Applies the visitor to all the device objects in this instance.
Parameters visitor (DeviceResidentsVisitor) – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

disable_update () → None
Disables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to False.
enable_update () → None
Enables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to True.

forward (x)
Applies the Swish activation function.
Parameters x (Variable) – Input variable.
Returns Output of the Swish activation function.

Return type Variable

from_chx ()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.
classmethod from_params (*args, **kwargs)
Initialize link with given parameters.
This method initializes the link with given N-dimensional arrays. Arguments includes
- some parameters for a specific link.
- constants such as stride width of a convolutional layer.
**init_scope()** → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links**(skipself: bool = False) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

- **Parameters** skipself (bool) – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all links.

**namedlinks**(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters** skipself (bool) – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all (path, link) pairs.

**namedparams**(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

- **Parameters** include_uninit (bool) – If True, it also generates uninitialized parameters.

- **Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params**(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

- **Parameters** include_uninit (bool) – If True, it also generates uninitialized parameters.

- **Returns** A generator object that generates all parameters.

**register_persistent**(name: str) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

- **Parameters** name (str) – Name of the attribute to be registered.

**repeat**(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential

Repeats this link multiple times to make a `Sequential`.
This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

### Example

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

### Parameters

- `n_repeat (int)`: Number of times to repeat.
- `mode (str)`: It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

### serialize

`serialize (serializer: chainer.serializer.AbstractSerializer) → None`

Serializes the link object.

**Parameters**

- `serializer (AbstractSerializer)`: Serializer object.

### to_chx()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

### to_cpu () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.
Returns: self

to_device

```
device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]] ➞ DeviceResident
```
Covers parameters and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See `get_device()` for available values.

Returns: self

to_gpu

```
device: Optional[Union[cuda.Device, int, numpy.integer]] = None ➞ chainer.device_resident.DeviceResident
```
Covers parameter variables and persistent values to GPU.

Deprecates since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64

```
→ chainer.device_resident.DeviceResident
```
Covers parameter variables and persistent values to CPU.

Deprecates since version v7.0.0: Use `to_device()` instead.

zerograds

```
→ None
```
Initializes all gradient arrays by zero.

Deprecates since version v1.15: Use the more efficient `cleargrads()` instead.

__eq__

```
(value, /) ➞ Return self==value.
```

__ne__

```
(value, /) ➞ Return self!=value.
```

__lt__

```
(value, /) ➞ Return self<value.
```

__le__

```
(value, /) ➞ Return self<=value.
```

__gt__

```
(value, /) ➞ Return self>value.
```

__ge__

```
(value, /) ➞ Return self>=value.
```

4.3. Link and Chains
Attributes

*device*

Device instance.

*local_link_hooks*

Ordered dictionary of registered link hooks.

Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

*printable_specs*

Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()` method. This pair of key and value is used for representing this class or subclass with the `__str__()` method.

*update_enabled*

True if at least one parameter has an update rule enabled.

*within_init_scope*

True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.

*xp*

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.

`chainer.links.Maxout`

class `chainer.links.Maxout`(`in_size`, `out_size`, `pool_size`, `initialW=None`, `initial_bias=0`)

Fully-connected maxout layer.

Let $M$, $P$ and $N$ be an input dimension, a pool size, and an output dimension, respectively. For an input vector $x$ of size $M$, it computes

$$Y_i = \max_j (W_{ij}x + b_{ij}).$$

Here $W$ is a weight tensor of shape $(M, P, N)$, $b$ an optional bias vector of shape $(M, P)$ and $W_{ij}$ is a sub-vector extracted from $W$ by fixing first and second dimensions to $i$ and $j$, respectively. Minibatch dimension is omitted in the above equation.

As for the actual implementation, this chain has a Linear link with a $(M \times P, N)$ weight matrix and an optional $(M \times P)$ dimensional bias vector.

Parameters

- `in_size (int)`: Dimension of input vectors.
- `out_size (int)`: Dimension of output vectors.
- `pool_size (int)`: Number of channels.
- `initialW (initializer)`: Initializer to initialize the weight. When it is `numpy.ndarray`, its ndim should be 3.
- `initial_bias (initializer)`: Initializer to initialize the bias. If `None`, the bias is omitted. When it is `numpy.ndarray`, its ndim should be 2.
Variables **linear** *(Link)* – The Linear link that performs affine transformation.

See also:

`maxout()`

See also:


Methods

`__call__(*args: Any, **kwargs: Any) → Any`

Call self as a function.

`__getitem__(name: str) → Any`

Equivalent to `getattr`.

`add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link`

Registers a link hook.

**Parameters**

- `hook` *(LinkHook)* – Link hook to be registered.
- `name` *(str)* – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

**Returns** `self`

`add_link(name: str, link: chainer.link.Link) → None`

Registers a child link to this chain.

**Parameters**

- `name` *(str)* – Name of the child link. This name is also used as the attribute name.
- `link` *(Link)* – The link object to be registered.

`add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None`

Registers a parameter to the link.

**Parameters**

- `name` *(str)* – Name of the parameter. This name is also used as the attribute name.
- `shape` *(int or tuple of ints)* – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- `dtype` – Data type of the parameter array.
- `initializer` *(initializer)* – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

`add_persistent(name: str, value: Any) → None`

Registers a persistent value to the link.

4.3. Link and Chains
The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- **name** (*str*) – Name of the persistent value. This name is also used for the attribute name.

- **value** – Value to be registered.

**addgrads** (*link: chainer.link.Link*) → *None*

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** (*Link*) – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** () → *None*

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode: str = 'share'*) → chainer.link.Chain

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument *mode* below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** (*str*) – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default *mode* is *share*.

**Returns**

Copied link object.

**Return type** *Link*

**copyparams** (*link: chainer.link.Link, copy_persistent: bool = True*) → *None*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using *copy.deepcopy()* . The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

**Parameters**

- **link** (*Link*) – Source link object.
- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

**count_params** () → int
Counts the total number of parameters.
This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

**delete_hook** *(name: str)* → None
Unregisters the link hook.

Parameters name *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*
Applies the visitor to all the device objects in this instance.

Parameters visitor *(DeviceResidentsVisitor)* – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None
Disables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update** () → None
Enables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to True.

**forward** *(x)*
Applies the maxout layer.

Parameters x *(Variable)* – Batch of input vectors.

Returns Output of the maxout layer.

Return type Variable

**from_chx** ()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** (*args, **kwargs*)
Initialize link with given parameters.
This method initializes the link with given N-dimensional arrays. Arguments includes
- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope** () → Iterator[None]
Creates an initialization scope.
This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example
In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

`links (skipself: bool = False) → Iterator[chainer.link.Link]`

Returns a generator of all links under the hierarchy.

- **Parameters** `skipself (bool)` – If `True`, then the generator skips this link and starts with the first child link.
- **Returns** A generator object that generates all links.

`namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]`

Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters** `skipself (bool)` – If `True`, then the generator skips this link and starts with the first child link.
- **Returns** A generator object that generates all (path, link) pairs.

`namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]`

Returns a generator of all (path, parameter) pairs. The paths are relative from this link.

- **Parameters** `include_uninit (bool)` – If `True`, it also generates uninitialized parameters.
- **Returns** A generator object that generates all (path, parameter) pairs.

`params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]`

Returns a generator of all parameters under the link hierarchy.

- **Parameters** `include_uninit (bool)` – If `True`, it also generates uninitialized parameters.
- **Returns** A generator object that generates all parameters.

`register_persistent (name: str) → None`

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

- **Parameters** `name (str)` – Name of the attribute to be registered.

`repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential`

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

• n_repeat (int) – Number of times to repeat.
• mode (str) – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

serialize (serializer: chainer.serializer.AbstractSerializer) → None

Serializes the link object.

Parameters serializer (AbstractSerializer) = Serializer object.

to_chx ()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

to_cpu () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self

to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident

Copies parameter variables and persistent values to the specified device.

4.3. Link and Chains 695
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

device – Target device specifier. See `get_device()` for available values.

Returns: self

```
def to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) -> chainer.device_resident.DeviceResident
    Copies parameter variables and persistent values to GPU.
```

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters**

device – Target device specifier. If omitted, the current device is used.

Returns: self

```
def to_intel64() -> chainer.device_resident.DeviceResident
    Copies parameter variables and persistent values to CPU.
```

Deprecated since version v7.0.0: Use `to_device()` instead.

```
def zerograds() -> None
    Initializes all gradient arrays by zero.
```

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

```
def __eq__(value, /) -> bool
    Return self==value.
```

```
def __ne__(value, /) -> bool
    Return self!=value.
```

```
def __lt__(value, /) -> bool
    Return self<value.
```

```
def __le__(value, /) -> bool
    Return self<=value.
```

```
def __gt__(value, /) -> bool
    Return self>value.
```

```
def __ge__(value, /) -> bool
    Return self>=value.
```
Attributes

device
  Device instance.

local_link_hooks
  Ordered dictionary of registered link hooks.
  Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions,
  link hooks in this property are specific to this link.

printable_specs
  Generator of printable specs of this link.
  Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword
  and value) that are passed to the __init__(). This pair of key and value is used for
  representing this class or subclass with __str__().

update_enabled
  True if at least one parameter has an update rule enabled.

within_init_scope
  True if the current code is inside of an initialization scope.
  See init_scope() for the details of the initialization scope.

xp
  Array module corresponding to the device.
  Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.NegativeSampling

class chainer.links.NegativeSampling(in_size, counts, sample_size, power=0.75, dtype=None)
  Negative sampling loss layer.
  This link wraps the negative_sampling() function. It holds the weight matrix as a parameter. It also
  builds a sampler internally given a list of word counts.

  Parameters
  * in_size (int) – Dimension of input vectors.
  * counts (int list) – Number of each identifiers.
  * sample_size (int) – Number of negative samples.
  * power (float) – Power factor $\alpha$.
  * dtype (numpy.dtype) – Type to use in computing.

  See also:
  negative_sampling() for more detail.

  Variables W (Variable) – Weight parameter matrix.
Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.
• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.
• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
• dtype – Data type of the parameter array.
• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.
• value – Value to be registered.

addgrads(link: chainer.link.Link) → None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters

• link (Link) – Source link object.

children() → Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns A generator object that generates all child links.
cleargrads() → None
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode: str = 'share') → chainer.link.Link
Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters

mode (str) – It should be either init, copy, or share. *init* means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is *share*.

Returns Copied link object.

Return type Link

copyparams(link: chainer.link.Link, copy_persistent: bool = True) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using *copy.deepcopy()* . The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

Parameters

- link (Link) – Source link object.
- copy_persistent (bool) – If True, persistent values are also copied. True by default.

count_params() → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the *Parameters* held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)

delete_hook(name: str) → None
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

device_resident_accept(visitor)
Applies the visitor to all the device objects in this instance.

Parameters visitor (DeviceResidentsVisitor) – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update() → None**

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

**enable_update() → None**

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

**forward(x, t, reduce='sum', *, return_samples=False)**

Computes the loss value for given input and ground truth labels.

**Parameters**

- `x (Variable)` – Input of the weight matrix multiplication.
- `t (Variable)` – Batch of ground truth labels.
- `reduce (str)` – Reduction option. Its value must be either `'sum'` or `'no'`. Otherwise, `ValueError` is raised.
- `return_samples (bool)` – If `True`, the sample array is also returned. The sample array is a (empty) array.

**Returns**

If `return_samples` is `False` (default), loss value is returned.

Otherwise, a tuple of the loss value and the sample array is returned.

**Return type** `Variable` or tuple

**from_chx()**

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params(*args, **kwargs)**

Initialize link with given parameters.

This method initializes the link with given *N*-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope() → Iterator[None]**

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            print("Inside init scope")
```

(continues on next page)
self.W = chainer.Parameter(0, (10, 5))
self.b = chainer.Parameter(0, (5,))

links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example
You can repeat the same link multiple times to create a longer Sequential block like this:

class ConvBNReLU(chainer.Chain):

    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
self.bn = L.BatchNormalization(64)

```python
def forward(self, x):
    return F.relu(self.bn(self.conv(x)))
```

net = ConvBNReLU().repeat(16, mode='init')

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

### Parameters

- **n_repeat** (*int*) – Number of times to repeat.
- **mode** (*str*) – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

### serialize

```python
serialize(serializer: chainer.serializer.AbstractSerializer) \rightarrow None
```

Serializes the link object.

**Parameters**

- **serializer** (*AbstractSerializer*) – Serializer object.

### to_chx

```python
to_chx() \rightarrow None
```

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: `self`

### to_cpu

```python
to_cpu() \rightarrow chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: `self`

### to_device

```python
to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) \rightarrow DeviceResident
```

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See `get_device()` for available values.

Returns: `self`
to_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_resident_accept() to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64 () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

zerograds () → None

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

__eq__ (value, /)

Return self==value.

__ne__ (value, /)

Return self!=value.

__lt__ (value, /)

Return self<value.

__le__ (value, /)

Return self<=value.

__gt__ (value, /)

Return self>value.

__ge__ (value, /)

Return self>=value.

**Attributes**

- **device**

  Device instance.

- **local_link_hooks**

  Ordered dictionary of registered link hooks.

  Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

- **printable_specs**

  Generator of printable specs of this link.

4.3. Link and Chains
Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.
See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.
Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

4.3.3 Machine learning models

chainer.links.Classifier
A simple classifier model.

class chainer.links.Classifier (predictor, lossfun=<function softmax_cross_entropy>, accfun=<function accuracy>, label_key=-1)
A simple classifier model.
This is an example of chain that wraps another chain. It computes the loss and accuracy based on a given input/label pair.

Parameters

• predictor (Link) – Predictor network.
• lossfun (callable) – Loss function. You can specify one of loss functions from built-in loss functions, or your own loss function (see the example below). It should not be an loss functions with parameters (i.e., Link instance). The function must accept two argument (an output from predictor and its ground truth labels), and return a loss. Returned value must be a Variable derived from the input Variable to perform backpropagation on the variable.
• accfun (callable) – Function that computes accuracy. You can specify one of evaluation functions from built-in evaluation functions, or your own evaluation function. The signature of the function is the same as lossfun.
• label_key (int or str) – Key to specify label variable from arguments. When it is int, a variable in positional arguments is used. And when it is str, a variable in keyword arguments is used.

Variables

• predictor (Link) – Predictor network.
• lossfun (callable) – Loss function. See the description in the arguments for details.
• accfun (callable) – Function that computes accuracy. See the description in the arguments for details.
• y (Variable) – Prediction for the last minibatch.
• loss (Variable) – Loss value for the last minibatch.
• **accuracy** (Variable) – Accuracy for the last minibatch.

• **compute_accuracy** (bool) – If True, compute accuracy on the forward computation. The default value is True.

**Note:** This link uses `chainer.softmax_cross_entropy()` with default arguments as a loss function (specified by `lossfun`), if users do not explicitly change it. In particular, the loss function does not support double backpropagation. If you need second or higher order differentiation, you need to turn it on with `enable_double_backprop=True`:

```python
>>> import chainer.functions as F
>>> import chainer.links as L

>>> def lossfun(x, t):
...     return F.softmax_cross_entropy(x, t, enable_double_backprop=True)

>>> predictor = L.Linear(10)
>>> model = L.Classifier(predictor, lossfun=lossfun)
```

### Methods

**__call__** (*args: Any, **kwargs: Any) → Any

Call self as a function.

**__getitem__** (name: str) → Any

Equivalent to getattr.

**add_hook** (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link

Registers a link hook.

**Parameters**

• **hook** (LinkHook) – Link hook to be registered.

• **name** (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

**Returns** self

**add_link** (name: str, link: chainer.link.Link) → None

Registers a child link to this chain.

**Parameters**

• **name** (str) – Name of the child link. This name is also used as the attribute name.

• **link** (Link) – The link object to be registered.

**add_param** (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None

Registers a parameter to the link.

**Parameters**

• **name** (str) – Name of the parameter. This name is also used as the attribute name.
• **shape** (*int* or *tuple of ints*) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• **dtype** – Data type of the parameter array.

• **initializer** (*initializer*) – If it is not *None*, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, *dtype* argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

### add_persistent

(*name: str, value: Any*) → *None*

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

• **name** (*str*) – Name of the persistent value. This name is also used for the attribute name.

• **value** – Value to be registered.

### addgrads

(*link: chainer.link.Link*) → *None*

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

**link** (*Link*) – Source link object.

### children

() → *Iterator[chainer.link.Link]*

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

### cleargrads

() → *None*

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

### copy

(*mode: str = 'share'*) → *chainer.link.Chain*

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument *mode* below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

• **mode** (*str*) – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default *mode* is *share*.

**Returns** Copied link object.

**Return type** *Link*
copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters

• link (Link) – Source link object.
• copy_persistent (bool) – If True, persistent values are also copied. True by default.

count_params () → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)
delete_hook (name: str) → None
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.
device_resident_accept (visitor)
Applies the visitor to all the device objects in this instance.

Parameters visitor (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.
disable_update () → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.
enable_update () → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.
forward (*args, **kwargs)
Computes the loss value for an input and label pair.

It also computes accuracy and stores it to the attribute.

Parameters

• args (list of ~chainer.Variable) – Input minibatch.
• kwargs (dict of ~chainer.Variable) – Input minibatch.

When label_key is int, the corresponding element in args is treated as ground truth labels. And when it is str, the element in kwargs is used. The all elements of args and kwargs except the ground truth labels are features. It feeds features to the predictor and compare the result with ground truth labels.
Note: We set None to the attributes y, loss and accuracy each time before running the predictor, to avoid unnecessary memory consumption. Note that the variables set on those attributes hold the whole computation graph when they are computed. The graph stores interim values on memory required for back-propagation. We need to clear the attributes to free those values.

Returns Loss value.

Return type Variable

from_chx()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

• some parameters for a specific link.
• constants such as stride width of a convolutional layer.

init_scope() → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))

links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[ Tuple[str, chainer.link.Link] ]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.
namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example
You can repeat the same link multiple times to create a longer Sequential block like this:

class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

• n_repeat (int) – Number of times to repeat.
• mode (str) – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all
elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

```
serialize(serializer: chainer.serializer.AbstractSerializer) → None
```

Serializes the link object.

**Parameters**

- **serializer** *(AbstractSerializer)* — Serializer object.

```
to_chx() (chainer.device_resident.DeviceResident)
```

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

```
to_cpu() → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

```
to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
```

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** — Target device specifier. See `get_device()` for available values.

Returns: self

```
to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

**Parameters**

- **device** — Target device specifier. If omitted, the current device is used.

Returns: self

```
to_intel64() → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.
zerograds() → None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value,)
Return self==value.

__ne__(value,)
Return self!=value.

__lt__(value,)
Return self<value.

__le__(value,)
Return self<=value.

__gt__(value,)
Return self>value.

__ge__(value,)
Return self>=value.

Attributes

compute_accuracy = True
device
Device instance.

local_link_hooks
Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions,
link hooks in this property are specific to this link.

printable_specs
Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword
and value) that are passed to the __init__() . This pair of key and value is used for
representing this class or subclass with __str__().

update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.
4.3.4 Pre-trained models

Pre-trained models are mainly used to achieve a good performance with a small dataset, or extract a semantic feature vector. Although `CaffeFunction` automatically loads a pre-trained model released as a caffemodel, the following link models provide an interface for automatically converting caffemodels, and easily extracting semantic feature vectors.

For example, to extract the feature vectors with `VGG16Layers`, which is a common pre-trained model in the field of image recognition, users need to write the following few lines:

```python
from chainer.links import VGG16Layers
from PIL import Image

model = VGG16Layers()
img = Image.open("path/to/image.jpg")
feature = model.extract([img], layers=['fc7'])['fc7']
```

where `fc7` denotes a layer before the last fully-connected layer. Unlike the usual links, these classes automatically load all the parameters from the pre-trained models during initialization.

**VGG Networks**

- `chainer.links.VGG16Layers` - A pre-trained CNN model with 16 layers provided by VGG team.
- `chainer.links.VGG19Layers` - A pre-trained CNN model with 19 layers provided by VGG team.
- `chainer.links.model.vision.vgg.prepare` - Converts the given image to the numpy array for VGG models.

**chainer.links.VGG16Layers**

```python
class chainer.links.VGG16Layers(pretrained_model='auto')
A pre-trained CNN model with 16 layers provided by VGG team.
```

During initialization, this chain model automatically downloads the pre-trained caffemodel, convert to another chain model, stores it on your local directory, and initializes all the parameters with it. This model would be useful when you want to extract a semantic feature vector from a given image, or fine-tune the model on a different dataset. Note that this pre-trained model is released under Creative Commons Attribution License.

If you want to manually convert the pre-trained caffemodel to a chainer model that can be specified in the constructor, please use `convert_caffemodel_to_npz` classmethod instead.


**Parameters**

- `pretrained_model (str)` - the destination of the pre-trained chainer model serialized as a `.npz` file. If this argument is specified as `auto`, it automatically downloads the caffemodel from the internet. Note that in this case the converted chainer model is stored on `SCHAINER_DATASET_ROOT/pfnet/chainer/models` directory, where `SCHAINER_DATASET_ROOT` is set as `HOME/.chainer/dataset` unless you specify another value as an environment variable. The converted chainer model is automatically used from the second time. If the argument is specified as `None`, all the parameters are not initialized by the pre-trained model, but the default initializer used in the original paper, i.e., `chainer.initializers.Normal(scale=0.01)`. 

712 Chapter 4. API Reference
Variables: `available_layers` (list of str) – The list of available layer names used by `forward` and `extract` methods.

Methods

```python
__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.
```

```python
__getitem__(name: str) → Any
Equivalent to `getattr`.
```

```python
add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.
```

Parameters

- `hook` (LinkHook) – Link hook to be registered.
- `name` (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

Returns: self

```python
add_link(name: str, link: chainer.link.Link) → None
Registers a child link to this chain.
```

Parameters

- `name` (str) – Name of the child link. This name is also used as the attribute name.
- `link` (Link) – The link object to be registered.

```python
add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.
```

Parameters

- `name` (str) – Name of the parameter. This name is also used as the attribute name.
- `shape` (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- `dtype` – Data type of the parameter array.
- `initializer` (initializer) – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

```python
add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.
```

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- `name` (str) – Name of the persistent value. This name is also used for the attribute name.
- `value` – Value to be registered.
addgrads (link: chainer.link.Link) → None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters

link (Link) – Source link object.

children () → Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns
A generator object that generates all child links.

cleargrads () → None
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

classmethod convert_caffemodel_to_npz (path_caffemodel, path_npz)
Converts a pre-trained caffemodel to a chainer model.

Parameters

• path_caffemodel (str) – Path of the pre-trained caffemodel.
• path_npz (str) – Path of the converted chainer model.

copy (mode: str = 'share') → chainer.link.Chain
Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters

mode (str) – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

Returns
Copied link object.

Return type
Link

copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters

• link (Link) – Source link object.
- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

    count_params() → int
    Counts the total number of parameters.
    This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.
    If the link contains uninitialized parameters, this method raises a warning.

    Returns The total size of parameters (int)

    delete_hook(name: str) → None
    Unregisters the link hook.

    Parameters name (str) – The name of the link hook to be unregistered.

    device_resident_accept(visitor)
    Applies the visitor to all the device objects in this instance.

    Parameters visitor (DeviceResidentsVisitor) – Visitor.
    This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

    disable_update() → None
    Disables update rules of all parameters under the link hierarchy.
    This method sets the enabled flag of the update rule of each parameter variable to False.

    enable_update() → None
    Enables update rules of all parameters under the link hierarchy.
    This method sets the enabled flag of the update rule of each parameter variable to True.

    extract(self, images, layers=['fc7'], size=(224, 224))
    Extracts all the feature maps of given images.
    The difference of directly executing forward is that it directly accepts images as an input and automatically transforms them to a proper variable. That is, it is also interpreted as a shortcut method that implicitly calls prepare and forward functions.
    Unlike predict method, this method does not override chainer.config.train and chainer.config.enable_backprop configuration. If you want to extract features without updating model parameters, you need to manually set configuration when calling this method as follows:

    ```python
    # model is an instance of VGGLayers (16 or 19 layers)
    with chainer.using_config('train', False):
        with chainer.using_config('enable_backprop', False):
            feature = model.extract([image])
    ```

    Parameters

    - **images** *(iterable of PIL.Image or numpy.ndarray)* – Input images.
    - **layers** *(list of str)* – The list of layer names you want to extract.
    - **size** *(pair of ints)* – The resolution of resized images used as an input of CNN. All the given images are not resized if this argument is None, but the resolutions of all the images should be the same.

    Returns A directory in which the key contains the layer name and the value contains the corresponding feature map variable.

4.3. Link and Chains 715
**Return type** Dictionary of ~chainer.Variable

```python
forward(self, x, layers=['prob'])
```
Computes all the feature maps specified by layers.

**Parameters**
- `x (Variable)` – Input variable. It should be prepared by prepare function.
- `layers (list of str)` – The list of layer names you want to extract. If None, ‘prob’ will be used as layers.

**Returns** A dictionary in which the key contains the layer and the value contains the corresponding feature map variable.

**Return type** Dictionary of ~chainer.Variable

```python
from_chx()
```
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

```python
classmethod from_params(*args, **kwargs)
```
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes
- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

```python
init_scope() → Iterator[None]
```
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

### Example

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

```python
links (skipself: bool = False) → Iterator[chainer.link.Link]
```
Returns a generator of all links under the hierarchy.

**Parameters** `skipself (bool)` – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all links.

```python
namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
```
Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters** `skipself (bool)` – If True, then the generator skips this link and starts with the first child link.
Returns A generator object that generates all (path, link) pairs.

**namedparams** (*include_uninit: bool = True*) → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

**Parameters**

- **include_uninit** (*bool*) – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** (*include_uninit: bool = True*) → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

**Parameters**

- **include_uninit** (*bool*) – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all parameters.

**predict** (*images, oversample=True*)

Computes all the probabilities of given images.

**Parameters**

- **images** (*iterable of PIL.Image or numpy.ndarray*) – Input images. When you specify a color image as a numpy.ndarray, make sure that color order is RGB.

- **oversample** (*bool*) – If True, it averages results across center, corners, and mirrors. Otherwise, it uses only the center.

**Returns** Output that contains the class probabilities of given images.

**Return type** Variable

**register_persistent** (*name: str*) → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name** (*str*) – Name of the attribute to be registered.

**repeat** (*n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):

    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))
```

(continues on next page)
net = ConvBNReLU().repeat(16, mode='init')

The `net` object contains 16 blocks, each of which is ConvBNReLU. And the mode was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat** (*int*) – Number of times to repeat.
- **mode** (*str*) – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

```
serialize(serializer: chainer.serializer.AbstractSerializer) → None
```

Serializes the link object.

Parameters **serializer** (*AbstractSerializer*) – Serializer object.

```
to_chx() → chainer.device_resident.DeviceResident
```

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

```
to_cpu() → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

```
to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
```

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. See `get_device()` for available values.

Returns: self

```
to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
```

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters**

`device` – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

**zerograds** () → None

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

**__eq__**(value, /) →

Return self==value.

**__ne__**(value, /) →

Return self!=value.

**__lt__**(value, /) →

Return self<value.

**__le__**(value, /) →

Return self<=value.

**__gt__**(value, /) →

Return self>value.

**__ge__**(value, /) →

Return self>=value.

**Attributes**

`available_layers`

`device`

`Device` instance.

`functions`

`local_link_hooks`

Ordered dictionary of registered link hooks.

Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

`printable_specs`

Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()`. This pair of key and value is used for representing this class or subclass with `__str__()`. 
update_enabled
True if at least one parameter has an update rule enabled.

within_init_scope
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.VGG19Layers

class chainer.links.VGG19Layers(pretrained_model='auto')
A pre-trained CNN model with 19 layers provided by VGG team.

During initialization, this chain model automatically downloads the pre-trained caffemodel, convert to another chainer model, stores it on your local directory, and initializes all the parameters with it. This model would be useful when you want to extract a semantic feature vector from a given image, or fine-tune the model on a different dataset. Note that this pre-trained model is released under Creative Commons Attribution License.

If you want to manually convert the pre-trained caffemodel to a chainer model that can be specified in the constructor, please use convert_caffemodel_to_npz classmethod instead.

See: K. Simonyan and A. Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition

Parameters
pretrained_model (str) – the destination of the pre-trained chainer model serialized as a .npz file. If this argument is specified as auto, it automatically downloads the caffemodel from the internet. Note that in this case the converted chainer model is stored on $CHAINER_DATASET_ROOT/pfnet/chainer/models directory, where
$CHAINER_DATASET_ROOT is set as $HOME/.chainer/dataset unless you specify another value as an environment variable. The converted chainer model is automatically used from the second time. If the argument is specified as None, all the parameters are not initialized by the pre-trained model, but the default initializer used in the original paper, i.e., chainer.initializers.Normal(scale=0.01).

Variables
available_layers (list of str) – The list of available layer names used by forward and extract methods.

Methods
__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

__getitem__(name: str) → Any
Equivalent to getattr.

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters
• hook (LinkHook) – Link hook to be registered.
• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self
add_link\(\) (name: str, link: chainer.link.Link) → None

Registers a child link to this chain.

Parameters

- **name** (str) – Name of the child link. This name is also used as the attribute name.
- **link** (Link) – The link object to be registered.

add_param\(\) (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None

Registers a parameter to the link.

Parameters

- **name** (str) – Name of the parameter. This name is also used as the attribute name.
- **shape** (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer** (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent\(\) (name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- **name** (str) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

addgrads\(\) (link: chainer.link.Link) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters **link** (Link) – Source link object.

children\(\) () → Iterator[chainer.link.Link]

Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads\(\) () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

classmethod convert_caffemodel_to_npz\(\) (path_caffemodel, path_npz)

Converts a pre-trained caffemodel to a chainer model.

Parameters

- **path_caffemodel** (str) – Path of the pre-trained caffemodel.

4.3. Link and Chains
**path_npz** *(str)* – Path of the converted chainer model.

**copy** *(mode: str = 'share')* → chainer.link.Chain

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument **mode** below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

- **Parameters** **mode** *(str)* – It should be either **init**, **copy**, or **share**. **init** means parameter variables under the returned link object is re-initialized by calling their **initialize()** method, so that all the parameters may have different initial values from the original link. **copy** means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. **share** means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default **mode** is **share**.

- **Returns** Copied link object.

- **Return type** **Link**

**copyparams** *(link: chainer.link.Link, copy_persistent: bool = True)* → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of **BatchNormalization**). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using **copy.deepcopy()**. The old behavior (not copying persistent values) can be reproduced with **copy_persistent=False**.

- **Parameters**
  - **link** *(Link)* – Source link object.
  - **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

**count_params** () → int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the **Parameters** held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

- **Returns** The total size of parameters (int)

**delete_hook** *(name: str)* → None

Unregisters the link hook.

- **Parameters** **name** *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*

Applies the visitor to all the device objects in this instance.

- **Parameters** **visitor** *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.
disable_update() → None
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

enable_update() → None
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

extract(self, images, layers=['fc7'], size=(224, 224))
Extracts all the feature maps of given images.

The difference of directly executing forward is that it directly accepts images as an input and automatically transforms them to a proper variable. That is, it is also interpreted as a shortcut method that implicitly calls prepare and forward functions.

Unlike predict method, this method does not override chainer.config.train and chainer.config.enable_backprop configuration. If you want to extract features without updating model parameters, you need to manually set configuration when calling this method as follows:

```python
# model is an instance of VGGLayers (16 or 19 layers)
with chainer.using_config('train', False):
    with chainer.using_config('enable_backprop', False):
        feature = model.extract([image])
```

Parameters

- **images** (iterable of PIL.Image or numpy.ndarray) – Input images.
- **layers** (list of str) – The list of layer names you want to extract.
- **size** (pair of ints) – The resolution of resized images used as an input of CNN. All the given images are not resized if this argument is None, but the resolutions of all the images should be the same.

Returns A directory in which the key contains the layer name and the value contains the corresponding feature map variable.

Return type Dictionary of ~chainer.Variable

forward(self, x, layers=['prob'])
Computes all the feature maps specified by layers.

Parameters

- **x** (Variable) – Input variable. It should be prepared by prepare function.
- **layers** (list of str) – The list of layer names you want to extract. If None, ‘prob’ will be used as layers.

Returns A dictionary in which the key contains the layer and the value contains the corresponding feature map variable.

Return type Dictionary of ~chainer.Variable

from_chx()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(*args, **kwargs)
Initialize link with given parameters.
This method initializes the link with given \textit{N-dimensional arrays}. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

\texttt{init\_scope()} \rightarrow \texttt{Iterator[None]}

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for \textit{Chain}) by an assignment. A \textit{Parameter} object can be automatically registered by assigning it to an attribute under this context manager.

\textbf{Example}

In most cases, the parameter registration is done in the initializer method. Using the \texttt{init\_scope} method, we can simply assign a \textit{Parameter} object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

\texttt{links} (\texttt{skipself: bool = False}) \rightarrow \texttt{Iterator[chainer.link.Link]}

Returns a generator of all links under the hierarchy.

**Parameters** \texttt{skipself (bool)} – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all links.

\texttt{namedlinks} (\texttt{skipself: bool = False}) \rightarrow \texttt{Iterator[Tuple[str, chainer.link.Link]]}

Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters** \texttt{skipself (bool)} – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all (path, link) pairs.

\texttt{namedparams} (\texttt{include_uninit: bool = True}) \rightarrow \texttt{Iterator[Tuple[str, chainer.variable.Parameter]]}

Returns a generator of all (path, parameter) pairs under the hierarchy.

**Parameters** \texttt{include_uninit (bool)} – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

\texttt{params} (\texttt{include_uninit: bool = True}) \rightarrow \texttt{Iterator[chainer.variable.Parameter]}

Returns a generator of all parameters under the link hierarchy.

**Parameters** \texttt{include_uninit (bool)} – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all parameters.

\texttt{predict (images, oversample=True)}

Computes all the probabilities of given images.

**Parameters**
• **images** *(iterable of PIL.Image or numpy.ndarray)* – Input images. When you specify a color image as a `numpy.ndarray`, make sure that color order is RGB.

• **oversample** *(bool)* – If True, it averages results across center, corners, and mirrors. Otherwise, it uses only the center.

**Returns**  
Output that contains the class probabilities of given images.

**Return type**  
`Variable`

```
register_persistent (name: str) → None
```

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- **name** *(str)* – Name of the attribute to be registered.

```
repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
```

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** *(int)* – Number of times to repeat.

- **mode** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial
parameters but can be changed independently. share means all the elements which con- 
sist the resulting Sequential object are same object because they are shallow-copied, 
so that all parameters of elements are shared with each other.

serialize (serializer: chainer.serializers.AbstractSerializer) → None
Serializes the link object.

Parameters serializer (AbstractSerializer) – Serializer object.

to_chx ()
Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to Chain-
erX, the link implementation must override this method to do so.
Returns: self

to_cpu () → chainer.device.DeviceResident
Copies parameter variables and persistent values to CPU.
Deprecated since version v7.0.0: Use to_device () instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, 
the link implementation should override device_resident_accept () to do so.
Returns: self

to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], Module-
Type, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the 
device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device () for available values.
Returns: self

to_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → 
chainer.device.DeviceResident
Copies parameter variables and persistent values to GPU.
Deprecated since version v7.0.0: Use to_device () instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, 
the link implementation must override device_resident_accept () to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use to_device 
to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.
Returns: self

to_intel64 () → chainer.device.DeviceResident
Copies parameter variables and persistent values to CPU.
Deprecated since version v7.0.0: Use to_device () instead.

degrad () → None
Initializes all gradient arrays by zero.
Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

```
__eq__(value,)
    Return self==value.
__ne__(value,)
    Return self!=value.
__lt__(value,)
    Return self<value.
__le__(value,)
    Return self<=value.
__gt__(value,)
    Return self>value.
__ge__(value,)
    Return self>=value.
```

**Attributes**

**available_layers**

**device**

Device instance.

**functions**

**local_link_hooks**

Ordered dictionary of registered link hooks.

Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

**printable_specs**

Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()` . This pair of key and value is used for representing this class or subclass with `__str__()`.

**update_enabled**

True if at least one parameter has an update rule enabled.

**within_init_scope**

True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.

**xp**

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.

4.3. Link and Chains
**chainer.links.model.vision.vgg.prepare**

`chainer.links.model.vision.vgg.prepare(image, size=224, 224)`

Converts the given image to the numpy array for VGG models.

Note that you have to call this method before `forward` because the pre-trained vgg model requires to resize the given image, covert the RGB to the BGR, subtract the mean, and permute the dimensions before calling.

**Parameters**

- `image` (*PIL.Image or numpy.ndarray*) – Input image. If an input is `numpy.ndarray`, its shape must be `(height, width), (height, width, channels), or (channels, height, width)`, and the order of the channels must be RGB.
- `size` (*pair of ints*) – Size of converted images. If None, the given image is not resized.

**Returns** The converted output array.

**Return type** `numpy.ndarray`

**Note:** ChainerCV contains implementation of VGG networks as well (i.e., `chainercv.links.model.vgg.VGG16`). Unlike the Chainer’s implementation, the ChainerCV’s implementation assumes the color channel of the input image to be ordered in RGB instead of BGR.

---

**GoogLeNet**

`chainer.links.GoogLeNet(pretrained_model='auto')`

A pre-trained GoogLeNet model provided by BVLC.

When you specify the path of the pre-trained chainer model serialized as a `.npz` file in the constructor, this chain model automatically initializes all the parameters with it. This model would be useful when you want to extract a semantic feature vector per image, or fine-tune the model on a different dataset.

If you want to manually convert the pre-trained caffemodel to a chainer model that can be specified in the constructor, please use `convert_caffemodel_to_npz` classmethod instead.

GoogLeNet, which is also called Inception-v1, is an architecture of convolutional neural network proposed in 2014. This model is relatively lightweight and requires small memory footprint during training compared with modern architectures such as ResNet. Therefore, if you fine-tune your network based on a model pre-trained by Imagenet and need to train it with large batch size, GoogLeNet may be useful. On the other hand, if you just want an off-the-shelf classifier, we recommend that you use ResNet50 or other models since they are more accurate than GoogLeNet.

The original model is provided here: https://github.com/BVLC/caffe/tree/master/models/bvlc_googlenet

**Parameters**

- `pretrained_model` (*str*) – the destination of the pre-trained chainer model serialized as a `.npz` file. If this argument is specified as `auto`, it automatically downloads the caffemodel from the internet. Note that in this case the converted chainer model
is stored on $\text{CHAINER}_{-}\text{DATASET\_ROOT}/pfnet/chainer/models directory, where
$\text{CHAINER}_{-}\text{DATASET\_ROOT}$ is set as $\text{HOME}/.chainer/dataset unless you specify
another value as a environment variable. The converted chainer model is automatically used
from the second time. If the argument is specified as None, all the parameters are not ini-
tialized by the pre-trained model, but the default initializer used in BVLC, i.e., chainer.
initializers.LeCunUniform(scale=1.0). Note that, in Caffe, when weight_filler
is specified as “xavier” type without variance_norm parameter, the weights are initialized by
Uniform($-s, s$), where $s = \sqrt{\frac{3}{\text{fan}\_\text{in}}}$ and $\text{fan}\_\text{in}$ is the number of input units. This corresponds to
LeCunUniform in Chainer but not GlorotUniform.

Variables available_layers (list of str) – The list of available layer names used by
forward and extract methods.

Methods

__call__(*args: Any, **kwargs: Any) \rightarrow\ Any
Call self as a function.

__getitem__(name: str) \rightarrow\ Any
Equivalent to getattr.

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[\text{str}] = None) \rightarrow\ chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.

• name (\text{str}) – Name of the link hook. The name must be unique among link hooks
registered to this link. If None, the default name of the link hook is used.

Returns self

add_link (name: \text{str}, link: chainer.link.Link) \rightarrow\ None
Registers a child link to this chain.

Parameters

• name (\text{str}) – Name of the child link. This name is also used as the attribute name.

• link (Link) – The link object to be registered.

add_param (name: \text{str}, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any =
<class '\text{numpy.float32}'>, initializer: Optional[Union[chainer.types.AbstractInitializer,
\text{numpy.generic}, \text{bytes}, \text{str}, \text{memoryview}, \text{numbers.Number}, \text{numpy.\text{ndarray}}]] = None) \rightarrow\ None
Registers a parameter to the link.

Parameters

• name (\text{str}) – Name of the parameter. This name is also used as the attribute name.

• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted,
the parameter variable is left uninitialized.

• dtype – Data type of the parameter array.

• initializer (initializer) – If it is not None, the data is initialized with the given
initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as
a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a
scalar, in which case the data array will be filled by this scalar. Note that float32 is used in
this case.

4.3. Link and Chains 729
add_persistent (name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.

• value – Value to be registered.

addgrads (link: chainer.link.Link) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters link (Link) – Source link object.

children () → Iterator[chainer.link.Link]

Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

classmethod convert_caffemodel_to_npz (path_caffemodel, path_npz)

Converts a pre-trained caffemodel to a chainer model.

Parameters

• path_caffemodel (str) – Path of the pre-trained caffemodel.

• path_npz (str) – Path of the converted chainer model.

copy (mode: str = 'share') → chainer.link.Chain

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters mode (str) – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

Returns Copied link object.

Return type Link

copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None

Copies all parameters from given link.
This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** (`Link`) – Source link object.
- **copy_persistent** (`bool`) – If True, persistent values are also copied. True by default.

**count_params** (`int`) →

Counts the total number of parameters.

This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

**delete_hook** (`name: str`) → None

Unregisters the link hook.

- **Parameters** name (`str`) – The name of the link hook to be unregistered.

**device_resident_accept** (`visitor`) →

Applies the visitor to all the device objects in this instance.

- **Parameters** visitor (`DeviceResidentsVisitor`) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

**enable_update** () → None

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

**extract** (`self`, `images`, `layers=['pool5']`, `size=224, 224`) →

Extracts all the feature maps of given images.

The difference of directly executing `forward` is that it directly accepts images as an input and automatically transforms them to a proper variable. That is, it is also interpreted as a shortcut method that implicitly calls `prepare` and `forward` functions.

Unlike `predict` method, this method does not override `chainer.config.train` and `chainer.config.enable_backprop` configuration. If you want to extract features without updating model parameters, you need to manually set configuration when calling this method as follows:

```python
# model is an instance of `GoogLeNet`
with chainer.using_config('train', False):
    with chainer.using_config('enable_backprop', False):
        feature = model.extract([image])
```

**Parameters**
• **images** (*iterable of PIL.Image or numpy.ndarray*) – Input images.

• **layers** (*list of str*) – The list of layer names you want to extract.

• **size** (*pair of ints*) – The resolution of resized images used as an input of CNN. All the given images are not resized if this argument is `None`, but the resolutions of all the images should be the same.

**Returns** A directory in which the key contains the layer name and the value contains the corresponding feature map variable.

**Return type** Dictionary of `~chainer.Variable`

### `forward(self, x, layers=['prob'])`

Computes all the feature maps specified by `layers`.

**Parameters**

• **x** (*Variable*) – Input variable. It should be prepared by `prepare` function.

• **layers** (*list of str*) – The list of layer names you want to extract.

**Returns** A directory in which the key contains the layer name and the value contains the corresponding feature map variable.

**Return type** Dictionary of `~chainer.Variable`

### `from_chx()`

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

### `classmethod from_params(*args, **kwargs)`

Initialize link with given parameters.

This method initializes the link with given `N-dimensional arrays`. Arguments includes

• some parameters for a specific link.

• constants such as stride width of a convolutional layer.

### `init_scope()` → `Iterator[None]`

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

### `links(skipself: bool = False) → Iterator[chainer.link.Link]`

Returns a generator of all links under the hierarchy.
Parameters **skipself** *(bool)* – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

**namedlinks** *(skipself: bool = False)* → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters **skipself** *(bool)* – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

**namedparams** *(include_uninit: bool = True)* → Iterator[Tuple[str, chainer.variable.Parameter]]

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters **include_uninit** *(bool)* – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** *(include_uninit: bool = True)* → Iterator[chainer.variable.Parameter]

Returns a generator of all parameters under the link hierarchy.

Parameters **include_uninit** *(bool)* – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

**predict** *(images, oversample=True)*

Computes all the probabilities of given images.

Parameters

- **images** *(iterable of PIL.Image or numpy.ndarray)* – Input images. When you specify a color image as a *numpy.ndarray*, make sure that color order is RGB.

- **oversample** *(bool)* – If True, it averages results across center, corners, and mirrors. Otherwise, it uses only the center.

Returns Output that contains the class probabilities of given images.

Return type **Variable**

**register_persistent** *(name: str)* → None

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters **name** *(str)* – Name of the attribute to be registered.

**repeat** *(n_repeat: int, mode: str = 'init')* → chainer.sequential.Sequential

Repeats this link multiple times to make a *Sequential*.

This method returns a *Sequential* object which has the same *Link* multiple times repeatedly. The *mode* argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer *Sequential* block like this:

---

4.3. Link and Chains 733
The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

### Parameters

- **`n_repeat`** (int) – Number of times to repeat.

- **`mode`** (str) – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

### serialize

```python
serialize(serializer: chainer.serializer.AbstractSerializer) → None
```

Serializes the link object.

**Parameters**

- **`serializer`** (AbstractSerializer) – Serializer object.

### to_chx()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

### to_cpu() → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecation since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

### to_device

```python
to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
```

Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters** device – Target device specifier. See `get_device()` for available values.

Returns: self

to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters** device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

**zerograds()** → None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

___eq__(value, /)
Return self==value.

___ne__(value, /)
Return self!=value.

___lt__(value, /)
Return self<value.

___le__(value, /)
Return self<=value.

___gt__(value, /)
Return self>value.

___ge__(value, /)
Return self>=value.
Attributes

available_layers

device
    Device instance.

functions

local_link_hooks
    Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
    Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__(). This pair of key and value is used for representing this class or subclass with __str__().

update_enabled
    True if at least one parameter has an update rule enabled.

within_init_scope
    True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.model.vision.googlenet.prepare

chainer.links.model.vision.googlenet.prepare(image, size=224, 224)

Converts the given image to the numpy array for GoogLeNet.

Note that you have to call this method before forward because the pre-trained GoogLeNet model requires to resize the given image, covert the RGB to the BGR, subtract the mean, and permute the dimensions before calling.

Parameters

- image (PIL.Image or numpy.ndarray) – Input image. If an input is numpy.ndarray, its shape must be (height, width),(height, width, channels), or (channels, height, width), and the order of the channels must be RGB.

- size (pair of ints) – Size of converted images. If None, the given image is not resized.

Returns The converted output array.

Return type numpy.ndarray
Residual Networks

- **chainer.links.model.vision.resnet.ResNetLayers**: A pre-trained CNN model provided by MSRA.
- **chainer.links.ResNet50Layers**: A pre-trained CNN model with 50 layers provided by MSRA.
- **chainer.links.ResNet101Layers**: A pre-trained CNN model with 101 layers provided by MSRA.
- **chainer.links.ResNet152Layers**: A pre-trained CNN model with 152 layers provided by MSRA.
- **chainer.links.model.vision.resnet.prepare**: Converts the given image to a numpy array for ResNet.

**chainer.links.model.vision.resnet.ResNetLayers**

**class** chainer.links.model.vision.resnet.ResNetLayers(*pretrained_model*, *n_layers*, *downsample_fb=False*)

A pre-trained CNN model provided by MSRA.

When you specify the path of the pre-trained chainer model serialized as a .npz file in the constructor, this chain model automatically initializes all the parameters with it. This model would be useful when you want to extract a semantic feature vector per image, or fine-tune the model on a different dataset. Note that unlike VGG16Layers, it does not automatically download a pre-trained caffemodel. This caffemodel can be downloaded at GitHub.

If you want to manually convert the pre-trained caffemodel to a chainer model that can be specified in the constructor, please use convert_caffemodel_to_npz classmethod instead.

See: K. He et. al., Deep Residual Learning for Image Recognition

**Parameters**

- **pretrained_model (str)** – the destination of the pre-trained chainer model serialized as a .npz file. If this argument is specified as auto, it automatically loads and converts the caffemodel from $CHAINER_DATASET_ROOT/pfnet/chainer/models/ResNet-{n-layers}-model.caffemodel, where $CHAINER_DATASET_ROOT is set as $HOME/.chainer/dataset unless you specify another value by modifying the environment variable and {n_layers} is replaced with the specified number of layers given as the first argument to this constructor. Note that in this case the converted chainer model is stored on the same directory and automatically used from the next time. If this argument is specified as None, all the parameters are not initialized by the pre-trained model, but the default initializer used in the original paper, i.e., chainer.initializers.HeNormal(scale=1.0).

- **n_layers (int)** – The number of layers of this model. It should be either 50, 101, or 152.

- **downsample_fb (bool)** – If this argument is specified as False, it performs downsampling by placing stride 2 on the 1x1 convolutional layers (the original MSRA ResNet). If this argument is specified as True, it performs downsampling by placing stride 2 on the 3x3 convolutional layers (Facebook ResNet).

**Variables** available_layers (list of str) – The list of available layer names used by forward and extract methods.
Methods

__call__ (*args: Any, **kwargs: Any) → Any
Call self as a function.

__getitem__ (name: str) → Any
Equivalent to getattr.

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

- **hook** (LinkHook) – Link hook to be registered.
- **name** (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self

add_link (name: str, link: chainer.link.Link) → None
Registers a child link to this chain.

Parameters

- **name** (str) – Name of the child link. This name is also used as the attribute name.
- **link** (Link) – The link object to be registered.

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

- **name** (str) – Name of the parameter. This name is also used as the attribute name.
- **shape** (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left unitialized.
- **dtype** – Data type of the parameter array.
- **initializer** (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent (name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- **name** (str) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

addgrads (link: chainer.link.Link) → None
Accumulates gradient values from given link.
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

*link* (*Link*) – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**classmethod convert_caffemodel_to_npz** (*path_caffemodel*, *path_npz*, *n_layers=50*)

Converts a pre-trained caffemodel to a chainer model.

**Parameters**

- *path_caffemodel* (*str*) – Path of the pre-trained caffemodel.
- *path_npz* (*str*) – Path of the converted chainer model.

**copy** (*mode: str = 'share') → chainer.link.Chain

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument *mode* below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

*mode* (*str*) – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default *mode* is *share*.

**Returns**

Copied link object.

**Return type** *Link*

**copyparams** (*link: chainer.link.Link, copy_persistent: bool = True*) → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using *copy.deepcopy()* The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

**Parameters**

- *link* (*Link*) – Source link object.
- *copy_persistent* (*bool*) – If True, persistent values are also copied. True by default.

4.3. Link and Chains 739
count_params() → int
Counts the total number of parameters.
This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.
If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)
delete_hook(name: str) → None
Unregisters the link hook.
Parameters name (str) – The name of the link hook to be unregistered.
device_resident_accept(visitor)
Applies the visitor to all the device objects in this instance.
Parameters visitor (DeviceResidentsVisitor) – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.
disable_update() → None
Disables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to False.
enable_update() → None
Enables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to True.
extract (self, images, layers=['pool5'], size=224, 224)
Extracts all the feature maps of given images.
The difference of directly executing forward is that it directly accepts images as an input and automatically transforms them to a proper variable. That is, it is also interpreted as a shortcut method that implicitly calls prepare and forward functions.
Unlike predict method, this method does not override chainer.config.train and chainer.config.enable_backprop configuration. If you want to extract features without updating model parameters, you need to manually set configuration when calling this method as follows:

```
# model is an instance of ResNetLayers (50 or 101 or 152 layers)
with chainer.using_config('train', False):
    with chainer.using_config('enable_backprop', False):
        feature = model.extract([image])
```

Parameters
- **images** (iterable of PIL.Image or numpy.ndarray) – Input images.
- **layers** (list of str) – The list of layer names you want to extract.
- **size** (pair of ints) – The resolution of resized images used as an input of CNN. All the given images are not resized if this argument is None, but the resolutions of all the images should be the same.

Returns A directory in which the key contains the layer name and the value contains the corresponding feature map variable.

Return type Dictionary of ~chainer.Variable
forward(self, x, layers=['prob'])
Computes all the feature maps specified by layers.

Parameters

- x (Variable) – Input variable. It should be prepared by prepare function.
- layers (list of str) – The list of layer names you want to extract.

Returns A directory in which the key contains the layer name and the value contains the corresponding feature map variable.

Return type Dictionary of ~chainer.Variable

from_chx()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

init_scope() → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

links(skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.
namedparams (**include_uninit**: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

**Parameters**
**include_uninit** (bool) – If True, it also generates uninitialized parameters.

**Returns**
A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params (**include_uninit**: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

**Parameters**
**include_uninit** (bool) – If True, it also generates uninitialized parameters.

**Returns**
A generator object that generates all parameters.

predict (**images**, **oversample**: bool = True)
Computes all the probabilities of given images.

**Parameters**

- **images** (iterable of PIL.Image or numpy.ndarray) – Input images. When you specify a color image as a numpy.ndarray, make sure that color order is RGB.
- **oversample** (bool) – If True, it averages results across center, corners, and mirrors. Otherwise, it uses only the center.

**Returns**
Output that contains the class probabilities of given images.

**Return type**
Variable

register_persistent (**name**: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**
**name** (str) – Name of the attribute to be registered.

repeat (**n_repeat**: int, **mode**: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

**Example**
You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```
The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- `n_repeat (int)` – Number of times to repeat.
- `mode (str)` – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

`serialize (serializer: chainer.serializer.AbstractSerializer) → None`

Serializes the link object.

**Parameters**

- `serializer (AbstractSerializer)` – Serializer object.

`to_chx ()`

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

`to_cpu () → chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

`to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident`

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- `device` – Target device specifier. See `get_device()` for available values.

Returns: self

`to_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.
Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64 () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Depreciated since version v7.0.0: Use to_device() instead.

zerograds () → None
Initializes all gradient arrays by zero.
Depreciated since version v1.15: Use the more efficient cleargrads() instead.

__eq__ (value, /)
Return self==value.

__ne__ (value, /)
Return self!=value.

__lt__ (value, /)
Return self<value.

__le__ (value, /)
Return self<=value.

__gt__ (value, /)
Return self>value.

__ge__ (value, /)
Return self>=value.

Attributes

available_layers
device
    Device instance.
functions
local_link_hooks
    Ordered dictionary of registered link hooks.
    Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.
printable_specs
    Generator of printable specs of this link.
    Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__() . This pair of key and value is used for representing this class or subclass with __str__().
update_enabled
    True if at least one parameter has an update rule enabled.
Chainer Documentation, Release 7.7.0

within_init_scope
True if the current code is inside of an initialization scope.
See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.
Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.ResNet50Layers

class chainer.links.ResNet50Layers(pretrained_model='auto', downsample_fb=False)
A pre-trained CNN model with 50 layers provided by MSRA.

When you specify the path of the pre-trained chainer model serialized as a .npz file in the constructor, this chain model automatically initializes all the parameters with it. This model would be useful when you want to extract a semantic feature vector per image, or fine-tune the model on a different dataset. Note that unlike VGG16Layers, it does not automatically download a pre-trained caffemodel. This caffemodel can be downloaded at GitHub.

If you want to manually convert the pre-trained caffemodel to a chainer model that can be specified in the constructor, please use convert_caffemodel_to_npz classmethod instead.

ResNet50 has 25,557,096 trainable parameters, and it’s 58% and 43% fewer than ResNet101 and ResNet152, respectively. On the other hand, the top-5 classification accuracy on ImageNet dataset drops only 0.7% and 1.1% from ResNet101 and ResNet152, respectively. Therefore, ResNet50 may have the best balance between the accuracy and the model size. It would be basically just enough for many cases, but some advanced models for object detection or semantic segmentation use deeper ones as their building blocks, so these deeper ResNets are here for making reproduction work easier.

See: K. He et. al., Deep Residual Learning for Image Recognition

Parameters

- **pretrained_model (str)** – the destination of the pre-trained chainer model serialized as a .npz file. If this argument is specified as auto, it automatically loads and converts the caffemodel from $CHAINER_DATASET_ROOT/pfnet/chainer/models/ResNet-50-model.caffemodel, where $CHAINER_DATASET_ROOT is set as $HOME/.chainer/dataset unless you specify another value by modifying the environment variable. Note that in this case the converted chainer model is stored on the same directory and automatically used from the next time. If this argument is specified as None, all the parameters are not initialized by the pre-trained model, but the default initializer used in the original paper, i.e., chainer.initializers.HeNormal(scale=1.0).

- **downsample_fb (bool)** – If this argument is specified as False, it performs downsampling by placing stride 2 on the 1x1 convolutional layers (the original MSRA ResNet). If this argument is specified as True, it performs downsampling by placing stride 2 on the 3x3 convolutional layers (Facebook ResNet).

Variables available_layers (list of str) – The list of available layer names used by forward and extract methods.
Methods

__call__(\*args: Any, **kwargs: Any) \rightarrow Any
Call self as a function.

__getitem__(name: str) \rightarrow Any
Equivalent to getattr.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) \rightarrow chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.

• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self

add_link(name: str, link: chainer.link.Link) \rightarrow None
Registers a child link to this chain.

Parameters

• name (str) – Name of the child link. This name is also used as the attribute name.

• link (Link) – The link object to be registered.

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) \rightarrow None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.

• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• dtype – Data type of the parameter array.

• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) \rightarrow None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.

• value – Value to be registered.

addgrads(link: chainer.link.Link) \rightarrow None
Accumulates gradient values from given link.
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** *(Link)* – Source link object.

**children** → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**classmethod convert_caffemodel_to_npz**(path_caffemodel, path_npz, n_layers=50)

Converts a pre-trained caffemodel to a chainer model.

**Parameters**

- **path_caffemodel** *(str)* – Path of the pre-trained caffemodel.
- **path_npz** *(str)* – Path of the converted chainer model.

**copy**(mode: *str* = 'share') → chainer.link.Chain

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument `mode` below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameter variables under the returned link object is re-initialized by calling their `initialize()` method, so that all the parameters may have different initial values from the original link. `copy` means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. `share` means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is `share`.

**Returns**

Copied link object.

**Return type** **Link**

**copyparams**(link: chainer.link.Link, copy_persistent: *bool* = True) → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

- **link** *(Link)* – Source link object.

- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.
count_params() → int
Counts the total number of parameters.
This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.
If the link contains uninitialized parameters, this method raises a warning.

Returns: The total size of parameters (int)
delete_hook(name: str) → None
Unregisters the link hook.
Parameters: name (str) – The name of the link hook to be unregistered.
device_resident_accept(visitor)
Applies the visitor to all the device objects in this instance.
Parameters: visitor (DeviceResidentsVisitor) – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.
disable_update() → None
Disables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to False.
enable_update() → None
Enables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to True.
extract(self, images, layers=['pool5'], size=224, 224)
Extracts all the feature maps of given images.
The difference of directly executing forward is that it directly accepts images as an input and automatically transforms them to a proper variable. That is, it is also interpreted as a shortcut method that implicitly calls prepare and forward functions.
Unlike predict method, this method does not override chainer.config.train and chainer.config.enable_backprop configuration. If you want to extract features without updating model parameters, you need to manually set configuration when calling this method as follows:

```python
# model is an instance of ResNetLayers (50 or 101 or 152 layers)
with chainer.using_config('train', False):
    with chainer.using_config('enable_backprop', False):
        feature = model.extract([image])
```

Parameters

- images (iterable of PIL.Image or numpy.ndarray) – Input images.
- layers (list of str) – The list of layer names you want to extract.
- size (pair of ints) – The resolution of resized images used as an input of CNN. All the given images are not resized if this argument is None, but the resolutions of all the images should be the same.

Returns: A directory in which the key contains the layer name and the value contains the corresponding feature map variable.

Return type: Dictionary of ~chainer.Variable
forward(self, x, layers=['prob'])
Computes all the feature maps specified by layers.

Parameters
  - x (Variable) – Input variable. It should be prepared by prepare function.
  - layers (list of str) – The list of layer names you want to extract.

Returns A directory in which the key contains the layer name and the value contains the corresponding feature map variable.

Return type Dictionary of ~chainer.Variable

from_chx()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes
  - some parameters for a specific link.
  - constants such as stride width of a convolutional layer.

init_scope() → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example
In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

class MyLink(chainer.Link):
  def __init__(self):
    super().__init__()
    with self.init_scope():
      self.W = chainer.Parameter(0, (10, 5))
      self.b = chainer.Parameter(0, (5,))

links(skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

dependents(skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all dependent links.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all dependent links.

namedlinks(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs under the hierarchy.
namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

predict (images, oversample=True)
Computes all the probabilities of given images.

Parameters

- images (iterable of PIL.Image or numpy.ndarray) – Input images. When you specify a color image as a numpy.ndarray, make sure that color order is RGB.
- oversample (bool) – If True, it averages results across center, corners, and mirrors. Otherwise, it uses only the center.

Returns Output that contains the class probabilities of given images.

Return type Variable

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer Sequential block like this:

class ConvBNReLU(chainer.Chain):

    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the mode was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat** (*int*) - Number of times to repeat.
- **mode** (*str*) - It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** (*serializer: chainer.serializer.AbstractSerializer*) → `None`

Serializes the link object.

**Parameters** serializer (*AbstractSerializer*) - Serializer object.

**to_chx** ()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu** () → `chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

**to_device** (*device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]*) → `DeviceResident`

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters** device - Target device specifier. See `get_device()` for available values.

Returns: self

**to_gpu** (*device: Optional[Union[cuda.Device, int, numpy.integer]] = None*) → `chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.
Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64 () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

zerograds () → None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

__eq__ (value, /)
Return self==value.

__ne__ (value, /)
Return self!=value.

__lt__ (value, /)
Return self<value.

__le__ (value, /)
Return self<=value.

__lt__ (value, /)
Return self>value.

__ge__ (value, /)
Return self>=value.

Attributes

available_layers

device
  Device instance.

functions

local_link_hooks
Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs
Generator of printable specs of this link.

Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the __init__() . This pair of key and value is used for representing this class or subclass with __str__() .

update_enabled
  True if at least one parameter has an update rule enabled.
within_init_scope
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.ResNet101Layers

class chainer.links.ResNet101Layers(pretrained_model='auto', downsample_fb=False)
A pre-trained CNN model with 101 layers provided by MSRA.

When you specify the path of the pre-trained chainer model serialized as a .npz file in the constructor, this chain model automatically initializes all the parameters with it. This model would be useful when you want to extract a semantic feature vector per image, or fine-tune the model on a different dataset. Note that unlike VGG16Layers, it does not automatically download a pre-trained caffemodel. This caffemodel can be downloaded at GitHub.

If you want to manually convert the pre-trained caffemodel to a chainer model that can be specified in the constructor, please use convert_caffemodel_to_npz classmethod instead.

ResNet101 has 44,549,224 trainable parameters, and it’s 43% fewer than ResNet152 model, while the top-5 classification accuracy on ImageNet dataset drops 1.1% from ResNet152. For many cases, ResNet50 may have the best balance between the accuracy and the model size.

See: K. He et. al., Deep Residual Learning for Image Recognition

Parameters

• pretrained_model (str) – the destination of the pre-trained chainer model serialized as a .npz file. If this argument is specified as auto, it automatically loads and converts the caffemodel from $CHAINER_DATASET_ROOT/pfnet/chainer/models/ResNet-101-model.caffemodel, where $CHAINER_DATASET_ROOT is set as $HOME/.chainer/dataset unless you specify another value by modifying the environment variable. Note that in this case the converted chainer model is stored on the same directory and automatically used from the next time. If this argument is specified as None, all the parameters are not initialized by the pre-trained model, but the default initializer used in the original paper, i.e., chainer.initializers.HeNormal(scale=1.0).

• downsample_fb (bool) – If this argument is specified as False, it performs downsampling by placing stride 2 on the 1x1 convolutional layers (the original MSRA ResNet). If this argument is specified as True, it performs downsampling by placing stride 2 on the 3x3 convolutional layers (Facebook ResNet).

Variables available_layers (list of str) – The list of available layer names used by forward and extract methods.
Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

__getitem__(name: str) → Any
Equivalent to getattr.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.
• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns
self

add_link(name: str, link: chainer.link.Link) → None
Registers a child link to this chain.

Parameters

• name (str) – Name of the child link. This name is also used as the attribute name.
• link (Link) – The link object to be registered.

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.
• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
• dtype – Data type of the parameter array.
• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.
• value – Value to be registered.

addgrads(link: chainer.link.Link) → None
Accumulates gradient values from given link.
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters
- **link** *(Link)* – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**classmethod convert_caffemodel_to_npz** *(path_caffemodel, path_npz, n_layers=50)*

Converts a pre-trained caffemodel to a chainer model.

Parameters
- **path_caffemodel** *(str)* – Path of the pre-trained caffemodel.
- **path_npz** *(str)* – Path of the converted chainer model.

**copy**(mode: str = 'share') → chainer.link.Chain

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument **mode** below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters
- **mode** *(str)* – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default **mode** is *share*.

Returns
Copied link object.

Return type **Link**

**copyparams**(link: chainer.link.Link, copy_persistent: bool = True) → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using *copy.deepcopy()*(). The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

Parameters
- **link** *(Link)* – Source link object.
- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.
**count_params** () → int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**
The total size of parameters (int)

**delete_hook** (name: str) → None

Unregisters the link hook.

**Parameters** name (str) – The name of the link hook to be unregistered.

**device_resident_accept** (visitor)

Applies the visitor to all the device objects in this instance.

**Parameters** visitor (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None

Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

**enable_update** () → None

Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

**extract** (self, images, layers=['pool5'], size=224, 224)

Extracts all the feature maps of given images.

The difference of directly executing forward is that it directly accepts images as an input and automatically transforms them to a proper variable. That is, it is also interpreted as a shortcut method that implicitly calls prepare and forward functions.

Unlike predict method, this method does not override chainer.config.train and chainer.config.enable_backprop configuration. If you want to extract features without updating model parameters, you need to manually set configuration when calling this method as follows:

```python
# model is an instance of ResNetLayers (50 or 101 or 152 layers)
with chainer.using_config('train', False):
    with chainer.using_config('enable_backprop', False):
        feature = model.extract([image])
```

**Parameters**

- **images** (iterable of PIL.Image or numpy.ndarray) – Input images.
- **layers** (list of str) – The list of layer names you want to extract.
- **size** (pair of ints) – The resolution of resized images used as an input of CNN.
  All the given images are not resized if this argument is None, but the resolutions of all the images should be the same.

**Returns**
A directory in which the key contains the layer name and the value contains the corresponding feature map variable.

**Return type**
Dictionary of ~chainer.Variable
forward(self, x, layers=['prob'])

Computes all the feature maps specified by layers.

Parameters

• x (Variable) – Input variable. It should be prepared by prepare function.
• layers (list of str) – The list of layer names you want to extract.

Returns A directory in which the key contains the layer name and the value contains the corresponding feature map variable.

Return type Dictionary of ~chainer.Variable

from_chx()

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

classmethod from_params(*args, **kwargs)

Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

• some parameters for a specific link.
• constants such as stride width of a convolutional layer.

init_scope() → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

links(skipself: bool = False) → Iterator[chainer.link.Link]

Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.
**namedparams** *(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]*

Returns a generator of all (path, param) pairs under the hierarchy.

- **Parameters**  
  - include_uninit *(bool) – If True, it also generates uninitialized parameters.*

- **Returns**  
  A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params** *(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]*

Returns a generator of all parameters under the link hierarchy.

- **Parameters**  
  - include_uninit *(bool) – If True, it also generates uninitialized parameters.*

- **Returns**  
  A generator object that generates all parameters.

**predict** *(images, oversample=True)*

Computes all the probabilities of given images.

- **Parameters**
  - images *(iterable of PIL.Image or numpy.ndarray)* – Input images. When you specify a color image as a `numpy.ndarray`, make sure that color order is RGB.
  - oversample *(bool) – If True, it averages results across center, corners, and mirrors. Otherwise, it uses only the center.*

- **Returns**  
  Output that contains the class probabilities of given images.

- **Return type** `Variable`

**register_persistent** *(name: str) → None*

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

- **Parameters**  
  - name *(str)* – Name of the attribute to be registered.

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```
The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- `n_repeat (int)` – Number of times to repeat.
- `mode (str)` – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize**(serializer: chainer.serializer.AbstractSerializer) → None
Serializer the link object.

**Parameters**

- `serializer (AbstractSerializer)` – Serializer object.

**to_chx**()
Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu** () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

**to_device** (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- `device` – Target device specifier. See `get_device()` for available values.

Returns: self

**to_gpu** (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.
### Parameters

**device** – Target device specifier. If omitted, the current device is used.

Returns: self

```python
def to_intel64() -> chainer.device_resident.DeviceResident:
    # Copies parameter variables and persistent values to CPU.
    # Deprecated since version v7.0.0: Use to_device() instead.
```

```python
def zerograd() -> None:
    # Initializes all gradient arrays by zero.
    # Deprecated since version v1.15: Use the more efficient cleargrads() instead.
```

#### Attributes

- **available_layers**
- **device**
  - `Device` instance.
- **functions**
- **local_link_hooks**
  - Ordered dictionary of registered link hooks.
  - Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.
- **printable_specs**
  - Generator of printable specs of this link.

#### Yields

- **specs (tuple of str and object)** – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()`. This pair of key and value is used for representing this class or subclass with `__str__()`.

- **update_enabled**
  - `True` if at least one parameter has an update rule enabled.
within_init_scope
True if the current code is inside of an initialization scope.
See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.
Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.ResNet152Layers

class chainer.links.ResNet152Layers(pretrained_model='auto', downsample_fb=False)
A pre-trained CNN model with 152 layers provided by MSRA.
When you specify the path of the pre-trained chainer model serialized as a .npz file in the constructor, this
chain model automatically initializes all the parameters with it. This model would be useful when you want
to extract a semantic feature vector per image, or fine-tune the model on a different dataset. Note that unlike
VGG16Layers, it does not automatically download a pre-trained caffemodel. This caffemodel can be down-
loaded at GitHub.
If you want to manually convert the pre-trained caffemodel to a chainer model that can be specified in the
constructor, please use convert_caffemodel_to_npz classmethod instead.
ResNet152 has 60,192,872 trainable parameters, and it’s the deepest ResNet model and it achieves the best
result on ImageNet classification task in ILSVRC 2015.
See: K. He et. al., Deep Residual Learning for Image Recognition

Parameters

- pretrained_model (str) – the destination of the pre-trained chainer model serialized
  as a .npz file. If this argument is specified as auto, it automatically loads and con-
  verts the caffemodel from $CHAINER_DATASET_ROOT/pfnet/chainer/models/
  ResNet-152-model.caffemodel, where $CHAINER_DATASET_ROOT is set as
  $HOME/.chainer/dataset unless you specify another value by modifying the envi-
  ronment variable. Note that in this case the converted chainer model is stored on the same
directory and automatically used from the next time. If this argument is specified as None,
all the parameters are not initialized by the pre-trained model, but the default initializer used
in the original paper, i.e., chainer.initializers.HeNormal(scale=1.0).
- downsample_fb (bool) – If this argument is specified as False, it performs downsam-
  pling by placing stride 2 on the 1x1 convolutional layers (the original MSRA ResNet). If
this argument is specified as True, it performs downsampling by placing stride 2 on the
3x3 convolutional layers (Facebook ResNet).

Variables available_layers (list of str) – The list of available layer names used by
forward and extract methods.
Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

__getitem__(name: str) → Any
Equivalent to getattr.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.
• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self

add_link(name: str, link: chainer.link.Link) → None
Registers a child link to this chain.

Parameters

• name (str) – Name of the child link. This name is also used as the attribute name.
• link (Link) – The link object to be registered.

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.
• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
• dtype – Data type of the parameter array.
• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.
• value – Value to be registered.

addgrads(link: chainer.link.Link) → None
Accumulates gradient values from given link.
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

**link** *(Link)* – Source link object.

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**classmethod convert_caffemodel_to_npz**(pathcaffemodel, pathnpz, n_layers=50)

Converts a pre-trained caffemodel to a chainer model.

**Parameters**

- **pathcaffemodel** *(str)* – Path of the pre-trained caffemodel.
- **pathnpz** *(str)* – Path of the converted chainer model.

**copy**(mode: str = 'share') → chainer.link.Chain

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument **mode** below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

**mode** *(str)* – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

**Returns**

Copied link object.

**Return type** *Link*

**copyparams**(link: chainer.link.Link, copy_persistent: bool = True) → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of **BatchNormalization**). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using **copy.deepcopy()**. The old behavior (not copying persistent values) can be reproduced with **copy_persistent=False**.

**Parameters**

- **link** *(Link)* – Source link object.
- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.
count_params () → int
Counts the total number of parameters.
This method counts the total number of scalar values included in all the Parameters held by this link
and its descendants.
If the link contains uninitialized parameters, this method raises a warning.

Returns The total size of parameters (int)
delete_hook (name: str) → None
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.
device_resident_accept (visitor)
Applies the visitor to all the device objects in this instance.

Parameters visitor (DeviceResidentsVisitor) – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.
disable_update () → None
Disables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to False.
enable_update () → None
Enables update rules of all parameters under the link hierarchy.
This method sets the enabled flag of the update rule of each parameter variable to True.
extract (self, images, layers=['pool5'], size=(224, 224))
Extracts all the feature maps of given images.
The difference of directly executing forward is that it directly accepts images as an input and automatically transforms them to a proper variable. That is, it is also interpreted as a shortcut method that implicitly calls prepare and forward functions.
Unlike predict method, this method does not override chainer.config.train and chainer.config.enable_backprop configuration. If you want to extract features without updating model parameters, you need to manually set configuration when calling this method as follows:

```python
# model is an instance of ResNet Layers (50 or 101 or 152 layers)
with chainer.using_config('train', False):
    with chainer.using_config('enable_backprop', False):
        feature = model.extract([image])
```

Parameters

- images (iterable of PIL.Image or numpy.ndarray) – Input images.
- layers (list of str) – The list of layer names you want to extract.
- size (pair of ints) – The resolution of resized images used as an input of CNN.
All the given images are not resized if this argument is None, but the resolutions of all the images should be the same.

Returns A directory in which the key contains the layer name and the value contains the corresponding feature map variable.

Return type Dictionary of ~chainer.Variable
forward(self, x, layers=['prob'])
Computes all the feature maps specified by layers.

Parameters

• x (Variable) – Input variable. It should be prepared by prepare function.
• layers (list of str) – The list of layer names you want to extract.

Returns A directory in which the key contains the layer name and the value contains the corresponding feature map variable.

Return type Dictionary of ~chainer.Variable

classmethod from_params(*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

• some parameters for a specific link.
• constants such as stride width of a convolutional layer.

init_scope() → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

Example

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))

links(skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

classmethod namedlinks(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.
namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.

Parameters

- include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns

A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters

- include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns

A generator object that generates all parameters.

predict (images, oversample=True)
Computes all the probabilities of given images.

Parameters

- images (iterable of PIL.Image or numpy.ndarray) – Input images. When you specify a color image as a numpy.ndarray, make sure that color order is RGB.
- oversample (bool) – If True, it averages results across center, corners, and mirrors. Otherwise, it uses only the center.

Returns

Output that contains the class probabilities of given images.

Return type

Variable

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters

- name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer Sequential block like this:

class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)
    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))
net = ConvBNReLU().repeat(16, mode='init')
The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **`n_repeat`** *(int)* – Number of times to repeat.
- **`mode`** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters**

- **serializer** *(AbstractSerializer)* – Serializer object.

**to_chx** *(self) → chainer.xlink.Xlink*  
  Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: `self`

**to_cpu** *(self) → chainer.device.resident.DeviceResident*  
Copies parameter variables and persistent values to CPU.

Depreciated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: `self`

**to_device** *(device: Union[backend.Device, chainer.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident*  
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See `get_device()` for available values.

Returns: `self`

**to_gpu** *(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device.resident.DeviceResident*  
Copies parameter variables and persistent values to GPU.

Depreciated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.
Warning: This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters** `device` – Target device specifier. If omitted, the current device is used.

Returns: `self`

`to_intel64()` → `chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

`zerograds()` → `None`

Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

`__eq__`(value,)

Return `self==value`.

`__ne__`(value,)

Return `self!=value`.

`__lt__`(value,)

Return `self<value`.

`__le__`(value,)

Return `self<=value`.

`__gt__`(value,)

Return `self>value`.

`__ge__`(value,)

Return `self>=value`.

**Attributes**

`available_layers`

`device`

*Device* instance.

`functions`

`local_link_hooks`

Ordered dictionary of registered link hooks.

Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

`printable_specs`

Generator of printable specs of this link.

Yields `specs (tuple of str and object)` – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()` method. This pair of key and value is used for representing this class or subclass with `__str__()`.

`update_enabled`

`True` if at least one parameter has an update rule enabled.
within_init_scope
True if the current code is inside of an initialization scope.

See init_scope() for the details of the initialization scope.

xp
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.links.model.vision.resnet.prepare
chainer.links.model.vision.resnet.prepare(image, size=224, 224)
Converts the given image to a numpy array for ResNet.

Note that this method must be called before calling forward, because the pre-trained resnet model will resize
the given image, convert from RGB to BGR, subtract the mean, and permute the dimensions before calling.

Parameters

- **image** (PIL.Image or numpy.ndarray) – Input image. If an input is numpy.
  ndarray, its shape must be (height, width), (height, width, channels),
  or (channels, height, width), and the order of the channels must be RGB.

- **size** (pair of ints) – Size of converted images. If None, the given image is not
  resized.

Returns The converted output array.

Return type numpy.ndarray

Note: ChainerCV contains implementation of ResNet as well (i.e., chainercv.links.model.resnet.
ResNet152). Unlike the Chainer’s implementation, the ChainerCV’s implementation assumes the color channel
of the input image to be ordered in RGB instead of BGR.

ChainerCV models

Note: ChainerCV supports implementations of links that are useful for computer vision problems, such as object
detection, semantic segmentation, and instance segmentation. The documentation can be found in chainercv.
links. Here is a subset of models with pre-trained weights supported by ChainerCV:

- **Detection**
  - chainercv.links.model.faster_rcnn.FasterRCNNVGG16
  - chainercv.links.model.ssd.SSD300
  - chainercv.links.model.ssd.SSD512
  - chainercv.links.model.yolo.YOLOv2
  - chainercv.links.model.yolo.YOLOv3

- **Semantic Segmentation**
  - chainercv.links.model.segnet.SegNetBasic
  - chainercv.experimental.links.model.pspnet.PSPNetResNet101
• Instance Segmentation
  - chainercv.experimental.links.model.fcis.FCISResNet101

• Classification
  - chainercv.links.model.resnet.ResNet101
  - chainercv.links.model.resnet.ResNet152
  - chainercv.links.model.resnet.ResNet50
  - chainercv.links.model.senet.SEResNet101
  - chainercv.links.model.senet.SEResNet152
  - chainercv.links.model.senet.SEResNet50
  - chainercv.links.model.senet.SEResNeXt101
  - chainercv.links.model.senet.SEResNeXt50
  - chainercv.links.model.vgg.VGG16

Compatibility with other frameworks

<table>
<thead>
<tr>
<th>chainer.links.TheanoFunction</th>
<th>Theano function wrapper.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.links.caffe.CaffeFunction</td>
<td>Caffe emulator based on the model file of Caffe.</td>
</tr>
</tbody>
</table>

chainer.links.TheanoFunction

class chainer.links.TheanoFunction(inputs, outputs)
  Theano function wrapper.

**Warning:** This feature is experimental. The interface can change in the future.

This function wraps Theano function as a `chainer.Link`. A user needs to make input Theano variables and output Theano variables. This function automatically creates Theano function for forward calculation and backward calculation from inputs and outputs. And then, it sends data in `chainer.Variable` to the function and gets results from Theano.

**Example**

```python
>>> import theano
>>> x = theano.tensor.fvector()
>>> y = theano.tensor.fvector()
>>> z = x + y
>>> w = x - y
>>> f = L.TheanoFunction(inputs=[x, y], outputs=[z, w])
>>> a = chainer.Variable(np.array([1, 2], dtype=np.float32))
>>> b = chainer.Variable(np.array([2, 3], dtype=np.float32))
>>> c, d = f(a, b)
```
array([[3., 5.], dtype=float32)
>>> d.array
array([[-1., -1.], dtype=float32)

Note: The current implementation always copies cupy.ndarray to CPU.

Parameters

- **inputs** (tuple of theano.tensor.TensorVariable) – Input variables of Theano. This function accepts the same number of Variables in forward computation.
- **outputs** (tuple of theano.tensor.TensorVariable) – Output variables of Theano. The function returns the same number of Variables as outputs.

Methods

- **__call__** (*args: Any, **kwargs: Any) → Any
  Call self as a function.
- **add_hook** (hook: chainer.link.hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
  Registers a link hook.
  Parameters
  - **hook** (LinkHook) – Link hook to be registered.
  - **name** (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.
  Returns self
- **add_param** (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
  Registers a parameter to the link.
  Parameters
  - **name** (str) – Name of the parameter. This name is also used as the attribute name.
  - **shape** (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
  - **dtype** – Data type of the parameter array.
  - **initializer** (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.
- **add_persistent** (name: str, value: Any) → None
  Registers a persistent value to the link.
  The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.
  Parameters
• **name** (*str*) – Name of the persistent value. This name is also used for the attribute name.

• **value** – Value to be registered.

**addgrads** (*link: chainer.link.Link*) → *None*

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- **link** (*Link*) – Source link object.

**children** () → *Iterator[chainer.link.Link]*

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** () → *None*

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode: str = 'share'* ) → *chainer.link.Link*

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument *mode* below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- **mode** (*str*) – It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default *mode* is *share*.

**Returns**

Copied link object.

**Return type** *Link*

**copyparams** (*link: chainer.link.Link, copy_persistent: bool = True*) → *None*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

**From v5.0.0:** this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an *ndarray*, the elements are copied. Otherwise, it is copied using *copy.deepcopy()*(). The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

**Parameters**

- **link** (*Link*) – Source link object.

- **copy_persistent** (*bool*) – If True, persistent values are also copied. *True* by default.

**count_params** () → *int*

Counts the total number of parameters.
This method counts the total number of scalar values included in all the `Parameters` held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

```python
def delete_hook(name: str) -> None
```

Unregisters the link hook.

**Parameters**

- `name` (str) – The name of the link hook to be unregistered.

```python
device_resident_accept(visitor)
```

Applies the visitor to all the device objects in this instance.

**Parameters**

- `visitor` (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

```python
def disable_update() -> None
```

Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

```python
def enable_update() -> None
```

Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

```python
forward(*args)
```

```python
from_chx()
```

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

```python
classmethod from_params(*args, **kwargs)
```

Initialize link with given parameters.

This method initializes the link with given `N-dimensional arrays`. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

```python
init_scope() -> Iterator[None]
```

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for `Chain`) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```
links (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters skipself (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, parameter) pairs under the hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

register_persistent (name: str) → None
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters name (str) – Name of the attribute to be registered.

repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example
You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```
The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the mode was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

### Parameters

- **n_repeat** *(int)* – Number of times to repeat.
- **mode** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

### serialize

`serialize(serializer: chainer.serializer.AbstractSerializer) → None`

Serializes the link object.

**Parameters**

- **serializer** *(AbstractSerializer)* – Serializer object.

### to_chx

`to_chx()`

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

### to_cpu

`to_cpu() → chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

Returns: self

### to_device

`to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident`

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. See `get_device()` for available values.

Returns: self

### to_gpu

`to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident`

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.
**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device` to perform inter-GPU transfer.

**Parameters** device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Depreciated since version v7.0.0: Use `to_device()` instead.

zerograds() → None
Initializes all gradient arrays by zero.
Depreciated since version v1.15: Use the more efficient `cleargrads()` instead.

__eq__(value,/)  
Return self==value.

__ne__(value,/)  
Return self!=value.

__lt__(value,/)  
Return self<value.

__le__(value,/)  
Return self<=value.

__gt__(value,/)  
Return self>value.

__ge__(value,/)  
Return self>=value.

**Attributes**

device  
Device instance.

local_link_hooks  
Ordered dictionary of registered link hooks.
Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

printable_specs  
Generator of printable specs of this link.

  Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()` . This pair of key and value is used for representing this class or subclass with `__str__()`.

update_enabled  
True if at least one parameter has an update rule enabled.

within_init_scope  
True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.
Array module corresponding to the device. Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.

**chainer.links.caffe.CaffeFunction**

```python
class chainer.links.caffe.CaffeFunction(model_path)
```

Caffe emulator based on the model file of Caffe.

Given a protocol buffers file of a Caffe model, this class loads and emulates it on `Variable` objects. It supports the official reference models provided by BVLC.

**Note:** CaffeFunction ignores the following layers:
- Layers that CaffeFunction does not support (including data layers)
- Layers that have no top blobs
- Layers whose bottom blobs are incomplete (i.e., some or all of them are not given nor computed)

**Warning:** It does not support full compatibility against Caffe. Some layers and configurations are not implemented in Chainer yet, though the reference models provided by the BVLC team are supported except data layers.

**Example**

Consider we want to extract the (unnormalized) log class probability of given images using BVLC reference CaffeNet. The model can be downloaded from:

http://dl.caffe.berkeleyvision.org/bvlc_reference_caffenet.caffemodel

We want to compute the `fc8` blob from the `data` blob. It is simply written as follows:

```python
# Load the model
func = CaffeFunction('path/to/bvlc_reference_caffenet.caffemodel')

# Minibatch of size 10
x_data = numpy.ndarray((10, 3, 227, 227), dtype=numpy.float32)
...  # (Fill the minibatch here)

# Forward the pre-trained net
x = Variable(x_data)
y, = func(inputs={'data': x}, outputs=['fc8'])
```

The result `y` contains the Variable corresponding to the `fc8` blob. The computational graph is memorized as a usual forward computation in Chainer, so we can run backprop through this pre-trained net.

**Parameters**

- `model_path` *(str)* – Path to the binary-proto model file of Caffe.

**Variables**

- `forwards` *(dict)* – A mapping from layer names to corresponding functions.
## Methods

__call__(*args: Any, **kwargs: Any) → Any

Call self as a function.

__getitem__(name: str) → Any

Equivalent to getattr.

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link

Registers a link hook.

Parameters

- **hook** (LinkHook) – Link hook to be registered.
- **name** (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self

add_link(name: str, link: chainer.link.Link) → None

Registers a child link to this chain.

Parameters

- **name** (str) – Name of the child link. This name is also used as the attribute name.
- **link** (Link) – The link object to be registered.

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None

Registers a parameter to the link.

Parameters

- **name** (str) – Name of the parameter. This name is also used as the attribute name.
- **shape** (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer** (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

- **name** (str) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.

addgrads(link: chainer.link.Link) → None

Accumulates gradient values from given link.
This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- link *(Link)* — Source link object.

**children ()** → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads ()** → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy (mode: str = 'share')** → chainer.link.Chain

Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument *mode* below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

**Parameters**

- *mode* *(str)* — It should be either *init*, *copy*, or *share*. *init* means parameter variables under the returned link object is re-initialized by calling their *initialize()* method, so that all the parameters may have different initial values from the original link. *copy* means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. *share* means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default *mode* is *share*.

**Returns**

Copied link object.

**Return type** *Link*

**copyparams (link: chainer.link.Link, copy_persistent: bool = True)** → None

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of *BatchNormalization*). If the persistent value is an *ndarray*, the elements are copied. Otherwise, it is copied using *copy.deepcopy()* . The old behavior (not copying persistent values) can be reproduced with *copy_persistent=False*.

**Parameters**

- *link* *(Link)* — Source link object.

- *copy_persistent* *(bool)* — If True, persistent values are also copied. True by default.

**count_params ()** → int

Counts the total number of parameters.

This method counts the total number of scalar values included in all the *Parameters* held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**

The total size of parameters (int)
**delete_hook** *(name: str) → None*
Unregisters the link hook.

**Parameters**
- **name** *(str)* – The name of the link hook to be unregistered.

**device_resident_accept** *(visitor)*
Applies the visitor to all the device objects in this instance.

**Parameters**
- **visitor** *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None
Disables update rules of all parameters under the link hierarchy.

This method sets the **enabled** flag of the update rule of each parameter variable to **False**.

**enable_update** () → None
Enables update rules of all parameters under the link hierarchy.

This method sets the **enabled** flag of the update rule of each parameter variable to **True**.

**forward** *(self, inputs, outputs, disable=())*
Executes a sub-network of the network.

This function acts as an interpreter of the network definition for Caffe. On execution, it interprets each layer one by one, and if the bottom blobs are already computed, then emulates the layer and stores output blobs as **Variable** objects.

**Parameters**
- **inputs** *(dict)* – A dictionary whose key-value pairs indicate initial correspondences between blob names and **Variable** objects.
- **outputs** *(Iterable)* – A list of blob names whose corresponding **Variable** objects are returned.
- **disable** *(Iterable)* – A list of layer names that will be ignored during the forward computation.

**Returns**
A tuple of output **Variable** objects corresponding to elements of the **outputs** argument.

**Return type**
**tuple**

**from_chx** ()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** *(args, **kwargs)*
Initialize link with given parameters.

This method initializes the link with given **N-dimensional arrays**. Arguments includes
- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope** () → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for **Chain**) by an assignment. A **Parameter** object can be automatically registered by assigning it to an attribute under this context manager.
Example

In most cases, the parameter registration is done in the initializer method. Using the `init_scope`
method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

`links (skipself: bool = False) → Iterator[chainer.link.Link]`
Returns a generator of all links under the hierarchy.

- Parameters skipself (bool) – If True, then the generator skips this link and starts with the
first child link.
- Returns A generator object that generates all links.

`namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]`
Returns a generator of all (path, link) pairs under the hierarchy.

- Parameters skipself (bool) – If True, then the generator skips this link and starts with the
first child link.
- Returns A generator object that generates all (path, link) pairs.

`namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]`
Returns a generator of all (path, parameter) pairs under the hierarchy.

- Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.
- Returns A generator object that generates all (path, parameter) pairs. The paths are relative from
this link.

`params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]`
Returns a generator of all parameters under the link hierarchy.

- Parameters include_uninit (bool) – If True, it also generates uninitialized parameters.
- Returns A generator object that generates all parameters.

`register_persistent (name: str) → None`
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already
registered as a parameter, this method removes it from the list of parameter names and re-registers it as a
persistent value.

- Parameters name (str) – Name of the attribute to be registered.

`repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential`
Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The
mode argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer Sequential block like this:
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat (int)** – Number of times to repeat.
- **mode (str)** – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

serialize (serializer: chainer.serializer.AbstractSerializer) → None

Serializes the link object.

Parameters **serializer** (AbstractSerializer) – Serializer object.

to_chx() Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self
to_cpu() → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_resident_accept() to do so.

Returns: self
to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident

Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**
- `device` – Target device specifier. See `get_device()` for available values.

Returns: `self`

```python
@dispatch(argtypes=[Optional[Union[cuda.Device, int, numpy.integer]]])
def to_gpu(self, device: Optional[Union[cuda.Device, int, numpy.integer]] = None) -> chainer.device_resident.DeviceResident:
    Copies parameter variables and persistent values to GPU.

    Deprecated since version v7.0.0: Use `to_device()` instead.

    This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.
```

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

**Parameters**
- `device` – Target device specifier. If omitted, the current device is used.

Returns: `self`

```python
@dispatch(argtypes=())
def to_intel64(self) -> chainer.device_resident.DeviceResident:
    Copies parameter variables and persistent values to CPU.

    Deprecated since version v7.0.0: Use `to_device()` instead.

@dispatch(argtypes=())
def zero_grads(self) -> None:
    Initializes all gradient arrays by zero.

    Deprecated since version v1.15: Use the more efficient `clear_grads()` instead.
```

**Special Methods**

```
__eq__(value, /)
    Return self==value.

__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.
```
Attributes

**device**

`Device` instance.

**local_link_hooks**

Ordered dictionary of registered link hooks.

Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

**printable_specs**

Generator of printable specs of this link.

Yields `specs (tuple of str and object)` – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()` function. This pair of key and value is used for representing this class or subclass with `__str__()`.

**update_enabled**

True if at least one parameter has an update rule enabled.

**within_init_scope**

True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.

**xp**

Array module corresponding to the device.

Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.

4.3.5 Link and Chain base classes

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.Link</code></td>
<td>Building block of model definitions.</td>
</tr>
<tr>
<td><code>chainer.Chain</code></td>
<td>Composable link with object-like interface.</td>
</tr>
<tr>
<td><code>chainer.ChainList</code></td>
<td>Composable link with list-like interface.</td>
</tr>
<tr>
<td><code>chainer.Sequential</code></td>
<td>Sequential model which has a single-stream forward pass.</td>
</tr>
</tbody>
</table>

**chainer.Link**

**class** `chainer.Link(**params: Any)`

Building block of model definitions.

Link is a building block of neural network models that support various features like handling parameters, defining network fragments, serialization, etc.

Link is the primitive structure for the model definitions. It supports management of parameter variables and persistent values that should be incorporated to serialization.

Parameter is an instance of `Parameter` registered to a link. A `Parameter` object can be registered as a parameter of the link by assigning it to an attribute within an initialization scope, which is a code surrounded by a `init_scope()` context manager using the `with` statement.

Persistent values are arrays, scalars, or any other serializable values registered via `register_persistent()` or `add_persistent()`.
Note: Whereas arbitrary serializable objects can be registered as persistent values, it is strongly recommended that you just register values that should be treated as results of learning. A typical example of persistent values is ones computed during training and required for testing, e.g. running statistics for batch normalization.

Parameters and persistent values are referred by their names. They can be accessed as attributes of the links. Link class itself manages the lists of names of parameters and persistent values to distinguish parameters and persistent values from other attributes.

Link can be composed into more complex models. This composition feature is supported by child classes like Chain and ChainList. One can create a chain by combining one or more links. See the documents for these classes for details.

As noted above, Link supports the serialization protocol of the Serializer class. Note that only parameters and persistent values are saved and loaded. Other attributes are considered as a part of user program (i.e. a part of network definition). In order to construct a link from saved file, other attributes must be identically reconstructed by user codes.

Example

This is a simple example of custom link definition. Chainer itself also provides many links defined under the links module. They might serve as examples, too.

Consider we want to define a simple primitive link that implements a fully-connected layer based on the linear() function. Note that this function takes input units, a weight variable, and a bias variable as arguments. Then, the fully-connected layer can be defined as follows:

```python
import chainer
import chainer.functions as F
from chainer import initializers
import numpy as np

class LinearLayer(chainer.Link):
    def __init__(self, n_in, n_out):
        super(LinearLayer, self).__init__()
        with self.init_scope():
            self.W = chainer.Parameter(initializers.Normal(), (n_out, n_in))
            self.b = chainer.Parameter(initializers.Zero(), (n_out,))

    def forward(self, x):
        return F.linear(x, self.W, self.b)
```

This example shows that a user can define arbitrary parameters and use them in any methods. Links typically implement the forward operator, although they can also provide other methods to implement the forward propagation.

Parameters params – Names, shapes, and optional dtypes of initial parameters. The keywords are used as the parameter names and the corresponding values consist either of the shape or a tuple of shape and a dtype (shape, dtype). If only the shape is supplied, the default dtype will be used.

Variables name (str) – Name of this link, given by the parent chain (if exists).
Methods

__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.

add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

• hook (LinkHook) – Link hook to be registered.

• name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns self

add_param (name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

• name (str) – Name of the parameter. This name is also used as the attribute name.

• shape (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• dtype – Data type of the parameter array.

• initializer (initializer) – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, dtype argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent (name: str, value: Any) → None
Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

Parameters

• name (str) – Name of the persistent value. This name is also used for the attribute name.

• value – Value to be registered.

addgrads (link: chainer.link.Link) → None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters link (Link) – Source link object.

children () → Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns A generator object that generates all child links.
cleargrads () → None
Cleans all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode: str = 'share') → chainer.link.Link
Copies the link hierarchy to a new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters

- **mode (str)** – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

Returns
Copied link object.

Return type Link

copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters

- **link (Link)** – Source link object.
- **copy_persistent (bool)** – If True, persistent values are also copied. True by default.

count_params () → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

Returns
The total size of parameters (int)

delete_hook (name: str) → None
Unregisters the link hook.

Parameters

- **name (str)** – The name of the link hook to be unregistered.

device_resident_accept (visitor)
Applies the visitor to all the device objects in this instance.

Parameters

- **visitor (DeviceResidentsVisitor)** – Visitor.
This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable_update** () → None
Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `False`.

**enable_update** () → None
Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to `True`.

**from_chx** ()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params** (*args, **kwargs)
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**init_scope** () → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A `Parameter` object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

**links** (skipself: bool = False) → Iterator[chainer.link.Link]
Returns a generator of all links under the hierarchy.

- **Parameters skipself** (bool) – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all links.

**namedlinks** (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters skipself** (bool) – If True, then the generator skips this link and starts with the first child link.

- **Returns** A generator object that generates all (path, link) pairs.

**namedparams** (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
Returns a generator of all (path, param) pairs under the hierarchy.
**Parameters**
`include_uninit (bool) – If True, it also generates uninitialized parameters.

**Returns**
A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

**params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
**
Returns a generator of all parameters under the link hierarchy.

**Parameters**
`include_uninit (bool) – If True, it also generates uninitialized parameters.

**Returns**
A generator object that generates all parameters.

**register_persistent (name: str) → None
**
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**
`name (str) – Name of the attribute to be registered.

**repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
**
Repeats this link multiple times to make a `Sequential`

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

**Example**
You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat (int)** – Number of times to repeat.
- **mode (str)** – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial
parameters but can be changed independently. share means all the elements which con-
sist the resulting Sequential object are same object because they are shallow-copied,
so that all parameters of elements are shared with each other.

**serialize** *(serializer: chainer.serializer.AbstractSerializer) → None*

Serializes the link object.

**Parameters** 

- **serializer** *(AbstractSerializer)* – Serializer object.

**to_chx** (*)

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to Chain-
erX, the link implementation must override this method to do so.

Returns: self

**to_cpu** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device**() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU,
the link implementation should override **device_resident_accept**() to do so.

Returns: self

**to_device** *(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], Module-
Type, Tuple[ModuleType, int]]) → DeviceResident*

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the
device, the link implementation must override this method to do so.

**Parameters** 

- **device** – Target device specifier. See **get_device**() for available values.

Returns: self

**to_gpu** *(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident*

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use **to_device**() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU,
the link implementation must override **device_resident_accept**() to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use **to_device**
to perform inter-GPU transfer.

**Parameters** 

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device**() instead.

**zerograds** () → None

Initializes all gradient arrays by zero.
Deprecated since version v1.15: Use the more efficient `cleargrads()` instead.

```python
__eq__(value,/)  # Return self==value.
__ne__(value,/)  # Return self!=value.
__lt__(value,/)  # Return self<value.
__le__(value,/)  # Return self<=value.
__gt__(value,/)  # Return self>value.
__ge__(value,/)  # Return self>=value.
```

**Attributes**

- `device`  
  `Device` instance.

- `local_link_hooks`  
  Ordered dictionary of registered link hooks.  
  Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

- `printable_specs`  
  Generator of printable specs of this link.  
  **Yields** `specs (tuple of str and object)` – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()`. This pair of key and value is used for representing this class or subclass with `__str__()`.

- `update_enabled`  
  True if at least one parameter has an update rule enabled.

- `within_init_scope`  
  True if the current code is inside of an initialization scope.  
  See `init_scope()` for the details of the initialization scope.

- `xp`  
  Array module corresponding to the device.  
  Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.
**chainer.Chain**

```python
class chainer.Chain(**links: chainer.link.Link)
```

Composable link with object-like interface.

Composability is one of the most important features of neural nets. Neural net models consist of many reusable fragments, and each model itself might be embedded into a larger learnable system. Chain enables us to write a neural net based on composition, without bothering about routine works like collecting parameters, serialization, copying the structure with parameters shared, etc.

This class actually provides a way to compose one or more links into one structure. A chain can contain one or more child links. Child link is a link registered to the chain with its own name. The child link is stored to an attribute of the chain with the name. User can write a whole model or a fragment of neural nets as a child class of Chain.

Each chain itself is also a link. Therefore, one can combine chains into higher-level chains. In this way, links and chains construct a link hierarchy. Link hierarchy forms a tree structure, where each node is identified by the path from the root. The path is represented by a string like a file path in UNIX, consisting of names of nodes on the path, joined by slashes `/`.

A child link can be added just by assigning it to an attribute of the chain within `init_scope()`.

The registered child link is saved and loaded on serialization and deserialization, and involved in the optimization. The registered link is called a child. The child link is accessible via `children()` generator, which returns a generator running through the children in lexical order.

On registration of a child link, its name attribute is also set (or overwritten if the link has already been registered to another chain).

---

**Example**

This is a simple example of custom chain definition. Chainer itself also provides some chains defined under the `links` module. They might serve as examples, too.

Consider we want to define a multi-layer perceptron consisting of two hidden layers with rectifiers as activation functions. We can use the `Linear` link as a building block:

```python
import chainer
import chainer.functions as F
import chainer.links as L

class MultiLayerPerceptron(chainer.Chain):
    def __init__(self, n_in, n_hidden, n_out):
        super(MultiLayerPerceptron, self).__init__()
        with self.init_scope():
            self.layer1 = L.Linear(n_in, n_hidden)
            self.layer2 = L.Linear(n_hidden, n_hidden)
            self.layer3 = L.Linear(n_hidden, n_out)

    def forward(self, x):
        # Forward propagation
        h1 = F.relu(self.layer1(x))
        h2 = F.relu(self.layer2(h1))
        return self.layer3(h2)
```

Child links are registered via the assignment within a `with self.init_scope():` block. The forward propagation is often implemented as the `forward` operator as the above example, though it is not mandatory.
Parameters **links** – Child links. The keywords are used as their names. The names are also set to the links.

Methods

```python
__call__(*args: Any, **kwargs: Any) → Any
Call self as a function.
```

```python
__getitem__(name: str) → Any
Equivalent to getattr.
```

```python
add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.
```

**Parameters**

- **hook** (LinkHook) – Link hook to be registered.
- **name** (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If **None**, the default name of the link hook is used.

**Returns** self

```python
add_link(name: str, link: chainer.link.Link) → None
Registers a child link to this chain.
```

**Parameters**

- **name** (str) – Name of the child link. This name is also used as the attribute name.
- **link** (Link) – The link object to be registered.

```python
add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.
```

**Parameters**

- **name** (str) – Name of the parameter. This name is also used as the attribute name.
- **shape** (int or tuple of ints) – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- **dtype** – Data type of the parameter array.
- **initializer** (initializer) – If it is not **None**, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, **dtype** argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

```python
add_persistent(name: str, value: Any) → None
Registers a persistent value to the link.
```

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- **name** (str) – Name of the persistent value. This name is also used for the attribute name.
- **value** – Value to be registered.
addgrads (link: chainer.link.Link) → None
Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

Parameters
- link (Link) – Source link object.

children () → Iterator[chainer.link.Link]
Returns a generator of all child links.

Returns
- A generator object that generates all child links.

cleargrads () → None
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode: str = 'share') → chainer.link.Chain
Copies the link hierarchy to new one.

The whole hierarchy rooted by this link is copied. There are three modes to perform copy. Please see the documentation for the argument mode below.

The name of the link is reset on the copy, since the copied instance does not belong to the original parent chain (even if exists).

Parameters
- mode (str) – It should be either init, copy, or share. init means parameter variables under the returned link object is re-initialized by calling their initialize() method, so that all the parameters may have different initial values from the original link. copy means that the link object is deeply copied, so that its parameters are not re-initialized but are also deeply copied. Thus, all parameters have same initial values but can be changed independently. share means that the link is shallowly copied, so that its parameters’ arrays are shared with the original one. Thus, their values are changed synchronously. The default mode is share.

Returns
- Copied link object.

Return type
- Link

copyparams (link: chainer.link.Link, copy_persistent: bool = True) → None
Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

From v5.0.0: this method also copies the persistent values (e.g. the moving statistics of BatchNormalization). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using copy.deepcopy(). The old behavior (not copying persistent values) can be reproduced with copy_persistent=False.

Parameters
- link (Link) – Source link object.
- copy_persistent (bool) – If True, persistent values are also copied. True by default.

count_params () → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the Parameters held by this link and its descendants.
If the link contains uninitialized parameters, this method raises a warning.

**Returns**
The total size of parameters (int)

```python
def delete_hook(name: str) -> None
```
Unregisters the link hook.

**Parameters**

- name (str) – The name of the link hook to be unregistered.

```python
def device_resident_accept(visitor)
```
Applies the visitor to all the device objects in this instance.

**Parameters**

- visitor (DeviceResidentsVisitor) – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

```python
def disable_update()
```
Disables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to False.

```python
def enable_update()
```
Enables update rules of all parameters under the link hierarchy.

This method sets the enabled flag of the update rule of each parameter variable to True.

```python
def from_chx()
```
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

```python
@classmethod
def from_params(*args, **kwargs)
```
Initialize link with given parameters.

This method initializes the link with given N-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

```python
def init_scope()
```
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.

**Example**

In most cases, the parameter registration is done in the initializer method. Using the init_scope method, we can simply assign a Parameter object to register it to the link.

```python
class MyLink(chainer.Link):
    
def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

```python
links(skipself: bool = False) -> Iterator[chainer.link.Link]
```
Returns a generator of all links under the hierarchy.

**Parameters**

- skipself (bool) – If True, then the generator skips this link and starts with the first child link.
Returns A generator object that generates all links.

```python
namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]
```

Returns a generator of all (path, link) pairs under the hierarchy.

Parameters `skipself` (bool) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

```python
namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]
```

Returns a generator of all (path, parameter) pairs. The paths are relative from this link.

Parameters `include_uninit` (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

```python
params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]
```

Returns a generator of all parameters under the link hierarchy.

Parameters `include_uninit` (bool) – If True, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

```python
register_persistent (name: str) → None
```

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If name has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

Parameters `name` (str) – Name of the attribute to be registered.

```python
repeat (n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential
```

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to
others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat** (*int*) – Number of times to repeat.
- **mode** (*str*) – It should be either *init*, *copy*, or *share*. *init* means parameters of each repeated element in the returned *Sequential* will be re-initialized, so that all elements have different initial parameters. *copy* means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. *share* means all the elements which consist the resulting *Sequential* object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**serialize** (*serializer: chainer.serializer.AbstractSerializer*) → None

Serializes the link object.

Parameters **serializer** (*AbstractSerializer*) – Serializer object.

**to_chx** ()

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

**to_cpu** () → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use **to_device**() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override **device_resident_accept**() to do so.

Returns: self

**to_device** (*device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]*) → DeviceResident

Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. See **get_device**() for available values.

Returns: self

**to_gpu** (*device: Optional[Union[cuda.Device, int, numpy.integer]] = None*) → chainer.device_resident.DeviceResident

Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use **to_device**() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override **device_resident_accept**() to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use **to_device** to perform inter-GPU transfer.
Parameters `device` – Target device specifier. If omitted, the current device is used.

    Returns: self

`to_intel64` () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecation warning: Since version v7.0.0: Use `to_device()` instead.

`zerograds` () → None
Initializes all gradient arrays by zero.

Deprecation warning: Since version v1.15: Use the more efficient `cleargrads()` instead.

    __eq__(value, /)
    Return self==value.

    __ne__(value, /)
    Return self!=value.

    __lt__(value, /)
    Return self<value.

    __le__(value, /)
    Return self<=value.

    __gt__(value, /)
    Return self>value.

    __ge__(value, /)
    Return self>=value.

Attributes

`device`
Device instance.

`local_link_hooks`
Ordered dictionary of registered link hooks.

Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, link hooks in this property are specific to this link.

`printable_specs`
Generator of printable specs of this link.

Yields `specs (tuple of str and object)` – Basically, it returns the arguments (pair of keyword and value) that are passed to the `__init__()` function. This pair of key and value is used for representing this class or subclass with `__str__()`.

`update_enabled`
True if at least one parameter has an update rule enabled.

`within_init_scope`
True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.

`xp`
Array module corresponding to the device.

Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`.  

798 Chapter 4. API Reference
chainer.ChainList

class chainer.ChainList(*links: chainer.link.Link)
Composable link with list-like interface.

This is another example of compositional link. Unlike Chain, this class can be used like a list of child links. Each child link is indexed by a non-negative integer, and it maintains the current number of registered child links. The add_link() method inserts a new link at the end of the list. It is useful to write a chain with arbitrary number of child links, e.g. an arbitrarily deep multi-layer perceptron.

This class inherits the methods index, count, append, reverse, extend, pop, remove from collections.abc.MutableSequence and can be accessed and assigned by index or slice.

Parameters

- links – Initial child links.

Methods

__call__((*args: Any, **kwargs: Any)) → Any
Call self as a function.

__getitem__(index) → Link
Returns the child at given index.

Parameters

- index (int) – Index of the child in the list.

Returns

The index-th child link.

Return type

Link

__setitem__(index: Union[int, slice], value: Union[chainer.link.Link, Iterable[chainer.link.Link]]) → None
__len__() → int
Returns the number of children.

__iter__() → Iterator[chainer.link.Link]

add_hook(hook: chainer.link_hook.LinkHook, name: Optional[str] = None) → chainer.link.Link
Registers a link hook.

Parameters

- hook (LinkHook) – Link hook to be registered.
- name (str) – Name of the link hook. The name must be unique among link hooks registered to this link. If None, the default name of the link hook is used.

Returns

self

add_link(link: chainer.link.Link) → None
Registers a child link and adds it to the tail of the list.

Parameters

- link (Link) – The link object to be registered.

add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None
Registers a parameter to the link.

Parameters

- name (str) – Name of the parameter. This name is also used as the attribute name.
• **shape** *(int or tuple of ints)* – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

• **dtype** – Data type of the parameter array.

• **initializer** *(initializer)* – If it is not `None`, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

**add_persistent** *(name: str, value: Any) → None*

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

• **name** *(str)* – Name of the persistent value. This name is also used for the attribute name.

• **value** – Value to be registered.

**addgrads** *(link: chainer.link.Link) → None*

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

• **link** *(Link)* – Source link object.

**append** *(value)*

`S.append(value)` – append value to the end of the sequence

**children** () → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**clear** () → None – remove all items from S

**cleargrads** () → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode: str = 'share') → chainer.link.ChainList*

Returns a deep copy of the chainlist.

**copyparams** *(link: chainer.link.Link, copy_persistent: bool = True) → None*

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.

*From v5.0.0:* this method also copies the persistent values (e.g. the moving statistics of `BatchNormalization`). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using `copy.deepcopy()`. The old behavior (not copying persistent values) can be reproduced with `copy_persistent=False`.

**Parameters**

• **link** *(Link)* – Source link object.
• **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

`count` *(value)* → integer – return number of occurrences of value

`count_params` () → int
Counts the total number of parameters.

This method counts the total number of scalar values included in all the *Parameters* held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

`delete_hook` *(name: str)* → None
Unregisters the link hook.

**Parameters** `name` *(str)* – The name of the link hook to be unregistered.

`device_resident_accept` *(visitor)*
Applies the visitor to all the device objects in this instance.

**Parameters** `visitor` *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

`disable_update` () → None
Disables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to False.

`enable_update` () → None
Enables update rules of all parameters under the link hierarchy.

This method sets the `enabled` flag of the update rule of each parameter variable to True.

`extend` *(values)*
S.extend(iterable) – extend sequence by appending elements from the iterable

`from_chx` ()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

`classmethod from_params` *(*args, **kwargs)*
Initialize link with given parameters.

This method initializes the link with given *N-dimensional arrays*. Arguments includes

• some parameters for a specific link.

• constants such as stride width of a convolutional layer.

`index` *(value[, start[, stop]])* → integer – return first index of value.

Raises ValueError if the value is not present.

Supporting start and stop arguments is optional, but recommended.

`init_scope` () → Iterator[None]
Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for *Chain*) by an assignment. A *Parameter* object can be automatically registered by assigning it to an attribute under this context manager.
Example

In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

`insert(index: int, link: chainer.link.Link) → None`
Insert a child link at the given index.

Parameters

- `index (int)`: The position of the list where the new
  `is inserted. (link)`: The link to be inserted.

`links(skipself: bool = False) → Iterator[chainer.link.Link]`
Returns a generator of all links under the hierarchy.

Parameters `skipself (bool)`: If `True`, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

`namedlinks(skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]`
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters `skipself (bool)`: If `True`, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all (path, link) pairs.

`namedparams(include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]`
Returns a generator of all (path, parameter) pairs under the hierarchy.

Parameters `include_uninit (bool)`: If `True`, it also generates uninitialized parameters.

Returns A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

`params(include_uninit: bool = True) → Iterator[chainer.variable.Parameter]`
Returns a generator of all parameters under the link hierarchy.

Parameters `include_uninit (bool)`: If `True`, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

`pop([index]) → item – remove and return item at index (default last).`
Raise IndexError if list is empty or index is out of range.

`register_persistent(name: str) → None`
Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.
Parameters

- **name (str)** – Name of the attribute to be registered.

**remove (value)**

S.remove(value) – remove first occurrence of value. Raise ValueError if the value is not present.

**repeat (n_repeat: int, mode: str = 'init')** → chainer.sequential.Sequential

Repeats this link multiple times to make a Sequential.

This method returns a Sequential object which has the same Link multiple times repeatedly. The mode argument means how to copy this link to repeat.

**Example**

You can repeat the same link multiple times to create a longer Sequential block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The net object contains 16 blocks, each of which is ConvBNReLU. And the mode was init, so each block is re-initialized with different parameters. If you give copy to this argument, each block has same values for its parameters but its object ID is different from others. If it is share, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

**Parameters**

- **n_repeat (int)** – Number of times to repeat.

- **mode (str)** – It should be either init, copy, or share. init means parameters of each repeated element in the returned Sequential will be re-initialized, so that all elements have different initial parameters. copy means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. share means all the elements which consist the resulting Sequential object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**reverse ()**

S.reverse() – reverse IN PLACE

**serialize (serializer: chainer.serializer.AbstractSerializer) → None**

Serializes the link object.

Parameters **serializer (AbstractSerializer)** – Serializer object.

**to_chx ()**

Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

Returns: self

to_cpu() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override device_accept() to do so.

Returns: self

to_device(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device() for available values.

Returns: self

to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use to_device() instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override device_accept() to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

zerograds() → None
Initializes all gradient arrays by zero.

Deprecated since version v1.15: Use the more efficient cleargrads() instead.

__eq__(value, /)  
Return self==value.

__ne__(value, /)  
Return self!=value.

__lt__(value, /)  
Return self<value.

__le__(value, /)  
Return self<=value.
__gt__(value,/)  
    Return self>value.
__ge__(value,/)  
    Return self>=value.

Attributes

device
    Device instance.

local_link_hooks
    Ordered dictionary of registered link hooks.
    Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions, 
    link hooks in this property are specific to this link.

printable_specs
    Generator of printable specs of this link.
    Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword 
    and value) that are passed to the __init__(). This pair of key and value is used for 
    representing this class or subclass with __str__().

update_enabled
    True if at least one parameter has an update rule enabled.

within_init_scope
    True if the current code is inside of an initialization scope.
    See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.
    Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

chainer.Sequential

class chainer.Sequential(*layers)  
    Sequential model which has a single-stream forward pass.

    Warning: This feature is experimental. The interface can change in the future.

This class enables to construct a network which has sequential structure easily. While Chain and ChainList 
can only take Link object as input to their constructor, this Sequential can take arbitrary number of any 
callable objects for the forward pass computation. A Sequential calls the given callable objects sequentially 
inside of the forward() method in the same order as the given arguments. Therefore, you do not need to 
write the forward pass computation explicitly.

Example

The below example code shows how to use this class to construct a simple sequential network:
import chainer
import chainer.functions as F
import chainer.links as L
from chainer import Sequential

# Model definition without writing forward function
model = Sequential(
    L.Linear(n_in, n_hidden),
    F.relu,
    L.Linear(n_hidden, n_hidden),
    F.relu,
    L.Linear(n_hidden, n_out)
)

# Compute the forward pass
y = model(x)

where $x$ denotes a mini-batch of $n_{in}$-dimensional input vectors.

Furthermore, `Sequential` supports built-in APIs, so you can concatenate `Sequential` objects to create a longer `Sequential` model easily with the same ways as Python lists:

```python
>>> from chainer import Sequential
>>> model_A = Sequential(L.Linear(10, 10), F.relu)
>>> model_B = Sequential(L.Linear(10, 10), F.sigmoid)
>>> model_C = model_A + model_B
```

To repeat a `Sequential` object multiple times, you can use `repeat()` method.

```python
>>> model_D = model_A.repeat(3)
```

You can also add your own functions or any callable objects to a `Sequential` object:

```python
from chainer.links.model.vision.vgg import VGG16Layers
model = Sequential()
model.append(L.Linear(n_out, n_hidden))
model.append(F.relu)
model.append(lambda x: F.reshape(x, (1, 3, 224, 224)))
model.append(VGG16Layers())
model.append(lambda x: x['prob'])

y = model(x)
```

The above code example shows how to add some layers to the `model` using `append()` method and then add a large network (`VGG16Layers`) and finally add a lambda function to extract the `prob` output.

You can check the structure of your model briefly using `print` as following:

```python
>>> print(model_C)
Sequential(
    (0): Linear(in_size=10, out_size=10, nobias=False),
    (1): <function relu at 0x...>,
    (2): Linear(in_size=10, out_size=10, nobias=False),
    (3): <function sigmoid at 0x...>,
)
```

**Note:** Note that a `Sequential` link which has at least one lambda function as its member cannot be pickled.
So, please use `partial` method from `functools` package instead:

```python
from functools import partial

# This is not pickable
model = Sequential(
    L.Convolution2D(None, 64, 3, 1, 1),
    lambda x: F.max_pooling_2d(x, 2)
)

# This is pickable
model = Sequential(
    L.Convolution2D(None, 64, 3, 1, 1),
    partial(F.max_pooling_2d, ksize=2)
)
```

**Parameters**

- **layers** – The layers which are called in its order. Each component should be a callable object including `Link` object and functions defined under the `chainer.functions`, e.g., `relu()`, etc.

**Methods**

- `__call__(\*args: Any, **kwargs: Any) \rightarrow Any`
  
  Call self as a function.

- `__getitem__(i)`
  
  Returns the child at given index.

  **Parameters**
  
  - **index** (`int`) – Index of the child in the list.

  **Returns**
  
  The index-th child link.

  **Return type** `Link`

- `__setitem__(i, layer)`

- `__len__()`
  
  Returns the number of children.

- `__iter__()`

- `add_hook (hook: chainer.link_hook.LinkHook, name: Optional[str] = None) \rightarrow chainer.link.Link`
  
  Registers a link hook.

  **Parameters**

  - **hook** (`LinkHook`) – Link hook to be registered.

  - **name** (`str`) – Name of the link hook. The name must be unique among link hooks registered to this link. If `None`, the default name of the link hook is used.

  **Returns**

  `self`

- `add_link (link: chainer.link.Link) \rightarrow None`
  
  Registers a child link and adds it to the tail of the list.

  **Parameters**

  - **link** (`Link`) – The link object to be registered.
add_param(name: str, shape: Optional[Union[int, Sequence[int]]] = None, dtype: Any = <class 'numpy.float32'>, initializer: Optional[Union[chainer.types.AbstractInitializer, numpy.generic, bytes, str, memoryview, numbers.Number, numpy.ndarray]] = None) → None

Registers a parameter to the link.

**Parameters**

- `name (str)` – Name of the parameter. This name is also used as the attribute name.
- `shape (int or tuple of ints)` – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.
- `dtype` – Data type of the parameter array.
- `initializer (initializer)` – If it is not None, the data is initialized with the given initializer. If it is an array, the data is directly initialized by it. If it is callable, it is used as a weight initializer. Note that in these cases, `dtype` argument is ignored. It can also be a scalar, in which case the data array will be filled by this scalar. Note that float32 is used in this case.

add_persistent(name: str, value: Any) → None

Registers a persistent value to the link.

The registered value is saved and loaded on serialization and deserialization. The value is set to an attribute of the link.

**Parameters**

- `name (str)` – Name of the persistent value. This name is also used for the attribute name.
- `value` – Value to be registered.

addgrads(link: chainer.link.Link) → None

Accumulates gradient values from given link.

This method adds each gradient array of the given link to corresponding gradient array of this link. The accumulation is even done across host and different devices.

**Parameters**

- `link (Link)` – Source link object.

append(layer)

S.append(value) – append value to the end of the sequence

children() → Iterator[chainer.link.Link]

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

clear() → None – remove all items from S

cleargrads() → None

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy(mode='share')

Returns a deep copy of the chainlist.

copyparams(link, copy_persistent=True)

Copies all parameters from given link.

This method copies data arrays of all parameters in the hierarchy. The copy is even done across the host and devices. Note that this method does not copy the gradient arrays.
From v5.0.0: this method also copies the persistent values (e.g., the moving statistics of \textit{BatchNormalization}). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using \texttt{copy.deepcopy()}. The old behavior (not copying persistent values) can be reproduced with \texttt{copy_persistent=False}.

**Parameters**

- \texttt{link (Link)} – Source link object.
- \texttt{copy_persistent (bool)} – If \texttt{True}, persistent values are also copied. \texttt{True} by default.

**count\((value)\rightarrow integer\) – return number of occurrences of value**

**count\_by\_layer\_type\((type\_name)\)**

Count the number of layers by layer type.

This method counts the number of layers which have the name given by the argument \texttt{type\_name}. For example, if you want to know the number of Linear layers included in this model, \texttt{type\_name} should be Linear. If you want to know the number of Function classes or user-defined functions which have a specific name, \texttt{type\_name} should be the function name, e.g., relu or reshape, etc.

**Parameters**

- \texttt{type\_name (str)} – The class or function name of a layer you want to enumerate.

**count\_params\() \rightarrow int\)**

Counts the total number of parameters.

This method counts the total number of scalar values included in all the \textit{Parameters} held by this link and its descendants.

If the link contains uninitialized parameters, this method raises a warning.

**Returns**

The total size of parameters (int)

**delete\_hook\((name: str) \rightarrow None\)**

Unregisters the link hook.

**Parameters**

- \texttt{name (str)} – The name of the link hook to be unregistered.

**device\_resident\_accept\((visitor)\)**

Applies the visitor to all the device objects in this instance.

**Parameters**

- \texttt{visitor (DeviceResidentsVisitor)} – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**disable\_update\() \rightarrow None\)**

Disables update rules of all parameters under the link hierarchy.

This method sets the \texttt{enabled} flag of the update rule of each parameter variable to \texttt{False}.

**enable\_update\() \rightarrow None\)**

Enables update rules of all parameters under the link hierarchy.

This method sets the \texttt{enabled} flag of the update rule of each parameter variable to \texttt{True}.

**extend\((sequential)\)**

\texttt{S.extend(iterable)} – extend sequence by appending elements from the iterable

**flatten\()**

Flatten nested \textit{Sequential} links.

This method flattens all the nested \textit{Sequential} links inside this \textit{Sequential} link.

**Returns**

A flattened \textit{Sequential} object.
Example

```python
>>> import chainer
>>> import chainer.functions as F
>>> import chainer.links as L

>>> a = chainer.Sequential(L.Linear(None, 10), F.relu)
>>> b = chainer.Sequential(L.Linear(None, 10), F.relu)

>>> a.append(b)

>>> print(a)  # Without flatten
0  Linear  W(None)  b(10,
1  relu
2  Sequential which has 2 layers

>>> print(a.flatten())  # With flatten
0  Linear  W(None)  b(10,
1  relu
2  Linear  W(None)  b(10,
3  relu
```

**forward(**\(\ast x\))**

Forward pass computation.

This method performs the forward pass computation by giving the input variable \(x\) to the layers registered in the constructor in the same order as the order in which the arguments are given to the constructor.

It should be noted that the input variable is given directly to the first layer and all intermediate outputs generated during the forward pass are also directly fed to the next layer. Therefore, the number of outputs at a layer should be the same as the number of inputs at the next layer.

**Parameters** \(x\) – Input variables.

**Returns** The output of the final layer in the given layers.

**from_chx()**

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**classmethod from_params(**\ast args, **kwargs)**

Initialize link with given parameters.

This method initializes the link with given \(N\)-dimensional arrays. Arguments includes

- some parameters for a specific link.
- constants such as stride width of a convolutional layer.

**index(**\(value, start[, stop])\)** → integer – return first index of value.

Raises ValueError if the value is not present.

Supporting start and stop arguments is optional, but recommended.

**init_scope()** → Iterator[None]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A Parameter object can be automatically registered by assigning it to an attribute under this context manager.
In most cases, the parameter registration is done in the initializer method. Using the `init_scope` method, we can simply assign a `Parameter` object to register it to the link.

```python
class MyLink(chainer.Link):
    def __init__(self):
        super().__init__()
        with self.init_scope():
            self.W = chainer.Parameter(0, (10, 5))
            self.b = chainer.Parameter(0, (5,))
```

`insert(i, layer)`

Insert a child link at the given index.

**Parameters**

- `index (int)` – The position of the list where the new
- `is inserted (link)` –
- `link (Link)` – The link to be inserted.

`links (skipself: bool = False) → Iterator[chainer.link.Link]`

Returns a generator of all links under the hierarchy.

**Parameters**

- `skipself (bool)` – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all links.

`namedlinks (skipself: bool = False) → Iterator[Tuple[str, chainer.link.Link]]`

Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters**

- `skipself (bool)` – If True, then the generator skips this link and starts with the first child link.

**Returns** A generator object that generates all (path, link) pairs.

`namedparams (include_uninit: bool = True) → Iterator[Tuple[str, chainer.variable.Parameter]]`

Returns a generator of all (path, param) pairs under the hierarchy.

**Parameters**

- `include_uninit (bool)` – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all (path, parameter) pairs. The paths are relative from this link.

`params (include_uninit: bool = True) → Iterator[chainer.variable.Parameter]`

Returns a generator of all parameters under the link hierarchy.

**Parameters**

- `include_uninit (bool)` – If True, it also generates uninitialized parameters.

**Returns** A generator object that generates all parameters.

`pop([index]) → item – remove and return item at index (default last).
Raise IndexError if list is empty or index is out of range.

`register_persistent (name: str) → None`

Registers an attribute of a given name as a persistent value.

This is a convenient method to register an existing attribute as a persistent value. If `name` has been already registered as a parameter, this method removes it from the list of parameter names and re-registers it as a persistent value.

**Parameters**

- `name (str)` – Name of the attribute to be registered.
**remove** *(layer)*

S.remove(value) – remove first occurrence of value. Raise ValueError if the value is not present.

**remove_by_layer_type** *(type_name)*

Remove layers by layer type.

This method removes layers from the Sequential object by the layer’s class name or function name. If you want to remove a `Link`, the argument `type_name` should be its class name, e.g., `Linear` or `Convolution2D`, etc. If you want to remove a `Function` class or any other callable objects, `type_name` should be the function name, e.g., `relu` or `reshape`, etc.

Parameters

- **type_name** *(str)* – The name of a layer you want to remove.

**repeat** *(n_repeat: int, mode: str = 'init') → chainer.sequential.Sequential*

Repeats this link multiple times to make a `Sequential`.

This method returns a `Sequential` object which has the same `Link` multiple times repeatedly. The `mode` argument means how to copy this link to repeat.

Example

You can repeat the same link multiple times to create a longer `Sequential` block like this:

```python
class ConvBNReLU(chainer.Chain):
    def __init__(self):
        super(ConvBNReLU, self).__init__()
        with self.init_scope():
            self.conv = L.Convolution2D(
                None, 64, 3, 1, 1, nobias=True)
            self.bn = L.BatchNormalization(64)

    def forward(self, x):
        return F.relu(self.bn(self.conv(x)))

net = ConvBNReLU().repeat(16, mode='init')
```

The `net` object contains 16 blocks, each of which is `ConvBNReLU`. And the `mode` was `init`, so each block is re-initialized with different parameters. If you give `copy` to this argument, each block has same values for its parameters but its object ID is different from others. If it is `share`, each block is same to others in terms of not only parameters but also the object IDs because they are shallow-copied, so that when the parameter of one block is changed, all the parameters in the others also change.

Parameters

- **n_repeat** *(int)* – Number of times to repeat.
- **mode** *(str)* – It should be either `init`, `copy`, or `share`. `init` means parameters of each repeated element in the returned `Sequential` will be re-initialized, so that all elements have different initial parameters. `copy` means that the parameters will not be re-initialized but object itself will be deep-copied, so that all elements have same initial parameters but can be changed independently. `share` means all the elements which consist the resulting `Sequential` object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

**reverse** *

S.reverse() – reverse IN PLACE
serialize (serializer: chainer.serializer.AbstractSerializer) → None
Serialization the link object.

Parameters serializer (AbstractSerializer) – Serializer object.

to_chx ()
Converts parameter variables and persistent values to ChainerX without any copy.
This method does not handle non-registered attributes. If some of such attributes must be copied to Chain-
erX, the link implementation must override this method to do so.
Returns: self

to_cpu () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Deprecation since version v7.0.0: Use to_device() instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU,
the link implementation should override device_resident_accept() to do so.
Returns: self

to_device (device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], Module-
type, Tuple[ModuleType, int]]) → DeviceResident
Copies parameter variables and persistent values to the specified device.
This method does not handle non-registered attributes. If some of such attributes must be copied to the
device, the link implementation must override this method to do so.

Parameters device – Target device specifier. See get_device() for available values.
Returns: self

to_gpu (device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to GPU.
Deprecation since version v7.0.0: Use to_device() instead.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU,
the link implementation must override device_resident_accept() to do so.

Warning: This method does not transfer the parameters if they are already on GPU. Use to_device
to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.
Returns: self

to_intel64 () → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.
Deprecation since version v7.0.0: Use to_device() instead.

zerograds () → None
Initializes all gradient arrays by zero.
Deprecation since version v1.15: Use cleargrads() instead.

eq (value, /)
Return self==value.
__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

__add__(other)

Attributes

device
    Device instance.

local_link_hooks
    Ordered dictionary of registered link hooks.
    Contrary to chainer.thread_local.link_hooks, which registers its elements to all functions,
    link hooks in this property are specific to this link.

printable_specs
    Generator of printable specs of this link.
    Yields specs (tuple of str and object) – Basically, it returns the arguments (pair of keyword
    and value) that are passed to the __init__(). This pair of key and value is used for
    representing this class or subclass with __str__().

update_enabled
    True if at least one parameter has an update rule enabled.

within_init_scope
    True if the current code is inside of an initialization scope.
    See init_scope() for the details of the initialization scope.

xp
    Array module corresponding to the device.
    Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

4.3.6 Link hooks

Chainer provides a link-hook mechanism that enriches the behavior of Link.

<table>
<thead>
<tr>
<th>chainer.link_hooks.</th>
<th>Spectral Normalization link hook implementation.</th>
</tr>
</thead>
<tbody>
<tr>
<td>SpectralNormalization</td>
<td></td>
</tr>
<tr>
<td>chainer.link_hooks.TimerHook</td>
<td>Link hook for measuring elapsed time of Link.</td>
</tr>
<tr>
<td>forward()</td>
<td></td>
</tr>
<tr>
<td>chainer.link_hooks.</td>
<td>Weight Standardization (WS) link hook implementa-</td>
</tr>
<tr>
<td>WeightStandardization</td>
<td>tion.</td>
</tr>
</tbody>
</table>
class chainer.link_hooks.SpectralNormalization(n_power_iteration=1, eps=1e-06, use_gamma=False, factor=None, weight_name='W', name=None)

Spectral Normalization link hook implementation.

This hook normalizes a weight using max singular value and this value is computed via power iteration method. Currently, this hook is supposed to be added to chainer.links.Linear, chainer.links.EmbedID, chainer.links.Convolution2D, chainer.links.ConvolutionND, chainer.links.Deconvolution2D, and chainer.links.DeconvolutionND. However, you can use this to other links like RNNs by specifying weight_name. It is highly recommended to add this hook before optimizer setup because this hook add a scaling parameter gamma if use_gamma is True. Otherwise, the registered gamma will not be updated.

\[ W = \frac{W}{\sigma(W)} \]

, where \( \sigma(W) := \max_{h : h \neq 0} \frac{\|Wh\|_2}{\|h\|_2} = \max_{\|h\|_2 \leq 1} \|Wh\|_2 \)

See: T. Miyato et. al., Spectral Normalization for Generative Adversarial Networks

Parameters

- n_power_iteration (int) – Number of power iteration. The default value is 1.
- eps (float) – Numerical stability in norm calculation. The default value is 1e-6 for the compatibility with mixed precision training. The value used in the author’s implementation is 1e-12.
- use_gamma (bool) – If True, weight scaling parameter gamma which is initialized by initial weight’s max singular value is introduced.
- factor (float, None) – Scaling parameter to divide maximum singular value. The default value is 1.0.
- weight_name (str) – Link’s weight name to apply this hook. The default value is 'W'.
- name (str or None) – Name of this hook. The default value is 'SpectralNormalization'.

Variables

- vector_name (str) – Name of the approximate first left singular vector registered in the target link.
- axis (int) – Axis of weight represents the number of output feature maps or output units (out_channels and out_size, respectively).

Example

There are almost the same but 2 ways to apply spectral normalization (SN) hook to links.

1. Initialize link and SN separately. This makes it easy to handle buffer and parameter of links registered by SN hook.
>>> l = L.Convolution2D(3, 5, 3)
>>> hook = chainer.link_hooks.SpectralNormalization()
>>> _ = l.add_hook(hook)
>>> # Check the shape of the first left singular vector.
>>> getattr(l, hook.vector_name).shape
(5,)
>>> # Delete SN hook from this link.
>>> l.delete_hook(hook.name)

2. Initialize both link and SN hook at one time. This makes it easy to define your original Chain.

>>> # SN hook handles lazy initialization!
>>> layer = L.Convolution2D(...
...   5, 3, stride=1, pad=1).add_hook(...
...   chainer.link_hooks.SpectralNormalization())

Methods

__enter__( )
__exit__( )

added( link )
Callback function invoked when the link hook is registered

Parameters
link ( Link ) – Link object to which the link hook is registered. None if the link
hook is registered globally.

deleted( link )
Callback function invoked when the link hook is unregistered

Parameters
link ( Link ) – Link object to which the link hook is unregistered. None if the
link hook had been registered globally.

forward_postprocess( cb_args )
Callback function invoked after a forward call of a link.

Parameters
args – Callback data. It has the following attributes:

  • link ( Link ) Link object.
  • forward_name ( str ) Name of the forward method.
  • args ( tuple ) Non-keyword arguments given to the forward method.
  • kwargs ( dict ) Keyword arguments given to the forward method.
  • out Return value of the forward method.

forward_preprocess( cb_args )
Callback function invoked before a forward call of a link.

Parameters
args – Callback data. It has the following attributes:

  • link ( Link ) Link object.
  • forward_name ( str ) Name of the forward method.
  • args ( tuple ) Non-keyword arguments given to the forward method.
  • kwargs ( dict ) Keyword arguments given to the forward method.
**normalize_weight** *(link)*

Normalize target weight before every single forward computation.

**reshape_W** *(W)*

Reshape & transpose weight into 2D if necessary.

**__eq__**(value, /)

Return self==value.

**__ne__**(value, /)

Return self!=value.

**__lt__**(value, /)

Return self<value.

**__le__**(value, /)

Return self<=value.

**__gt__**(value, /)

Return self>value.

**__ge__**(value, /)

Return self>=value.

**Attributes**

name = 'SpectralNormalization'

**chainer.link_hooks.TimerHook**

class chainer.link_hooks.TimerHook

Link hook for measuring elapsed time of Link.forward().

**Example**

Code example:

```python
from chainer.link_hooks import TimerHook
hook = TimerHook()
with hook:
    trainer.run()
hook.print_report()
```

Output example:

<table>
<thead>
<tr>
<th>LinkName</th>
<th>ElapsedTime</th>
<th>Occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>41.42sec</td>
<td>2100</td>
</tr>
<tr>
<td>MLP</td>
<td>42.09sec</td>
<td>700</td>
</tr>
<tr>
<td>Classifier</td>
<td>42.39sec</td>
<td>700</td>
</tr>
</tbody>
</table>

where *LinkName* is the name of link that calls the hook, and *ElapsedTime* is the elapsed time the link consumed, and *Occurrence* is the number of calls.

**Warning:** Call graph of links are hierarchical. That means reported elapsed times may be overlapping with each other and the sum may exceed the total time.
Variables **call_history** – List of measurement results. It consists of pairs of the name of the link that calls this hook and the elapsed time the `forward()` method of link consumes.

**Methods**

__enter__ () → chainer.link_hook.LinkHook

__exit__ (*_,)

**added** (`link: Optional[chainer.link.Link]` → `None`)

Callback function invoked when the link hook is registered

**Parameters**

**link (Link)** – Link object to which the link hook is registered. `None` if the link hook is registered globally.

**deleted** (`link: Optional[chainer.link.Link]` → `None`)

Callback function invoked when the link hook is unregistered

**Parameters**

**link (Link)** – Link object to which the link hook is unregistered. `None` if the link hook had been registered globally.

**forward_postprocess** (`args`)

Callback function invoked after a forward call of a link.

**Parameters**

**args** – Callback data. It has the following attributes:

- **link (Link)** Link object.
- **forward_name (str)** Name of the forward method.
- **args (tuple)** Non-keyword arguments given to the forward method.
- **kwargs (dict)** Keyword arguments given to the forward method.
- **out** Return value of the forward method.

**forward_preprocess** (`args`)

Callback function invoked before a forward call of a link.

**Parameters**

**args** – Callback data. It has the following attributes:

- **link (Link)** Link object.
- **forward_name (str)** Name of the forward method.
- **args (tuple)** Non-keyword arguments given to the forward method.
- **kwargs (dict)** Keyword arguments given to the forward method.

**print_report** (`unit='auto', file=<io.TextIOWrapper name='<stdout>' mode='w' encoding='UTF-8'>`)

Prints a summary report of time profiling in links.

**Parameters**

**unit (str)** – Supplementary units used for computational times. `sec`, `ms`, `us`, `ns`, `auto` (default) and `auto_foreach` are supported. If `auto`, units of times are aligned to the largest, and if `auto_foreach`, units of times are adjusted for each element.

**summary** ()

Returns a summary of time profiling in links.

**Returns** A summarized dictionary whose keys are link names and values are dictionaries of `elapsed_time` and `occurrence`.

**total_time** ()

Returns total elapsed time in seconds.
__eq__(value, /)
    Return self==value.

__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

name = 'TimerHook'
table = {'ms': 1000, 'ns': 1000000000, 'sec': 1, 'us': 1000000}

chainer.link_hooks.WeightStandardization

class chainer.link_hooks.WeightStandardization(*, eps=1e-05, weight_name='W', name=None)

Weight Standardization (WS) link hook implementation.

This hook standardizes a weight by weight statistics.

This link hook implements a WS which computes the mean and variance along axis “output channels”, then normalizes by these statistics. WS improves training by reducing the Lipschitz constants of the loss and the gradients like batch normalization (BN) but without relying on large batch sizes during training. Specifically, the performance of WS with group normalization (GN) trained with small-batch is able to match or outperforms that of BN trained with large-batch. WS is originally proposed for 2D convolution layers followed by mainly GN and sometimes BN. Note that this hook is able to handle layers such as N-dimensional convolutional, linear and embedding layers but there is no guarantee that this hook helps training.

See: Siyuan Qiao et. al., Weight Standardization

Parameters

- eps (float) – Numerical stability in standard deviation calculation. The default value is 1e-5.
- weight_name (str) – Link’s weight name to apply this hook. The default value is 'W'.
- name (str or None) – Name of this hook. The default value is 'WeightStandardization'.
Methods

__enter__()  
__exit__()  

added(link)
Callback function invoked when the link hook is registered

Parameters

link (Link) – Link object to which the link hook is registered. None if the link hook is registered globally.

deleted(link: Optional[chainer.link.Link] → None
Callback function invoked when the link hook is unregistered

Parameters

link (Link) – Link object to which the link hook is unregistered. None if the link hook had been registered globally.

forward_postprocess(cb_args)
Callback function invoked after a forward call of a link.

Parameters

args – Callback data. It has the following attributes:

• link (Link) Link object.
• forward_name (str) Name of the forward method.
• args (tuple) Non-keyword arguments given to the forward method.
• kwargs (dict) Keyword arguments given to the forward method.
• out Return value of the forward method.

forward_preprocess(cb_args)
Callback function invoked before a forward call of a link.

Parameters

args – Callback data. It has the following attributes:

• link (Link) Link object.
• forward_name (str) Name of the forward method.
• args (tuple) Non-keyword arguments given to the forward method.
• kwargs (dict) Keyword arguments given to the forward method.

__eq__(value,/)  
Return self==value.

__ne__(value,/)  
Return self!=value.

__lt__(value,/)  
Return self<value.

__le__(value,/)  
Return self<=value.

__gt__(value,/)  
Return self>value.

__ge__(value,/)  
Return self>=value.
Attributes

name = 'WeightStandardization'

You can also implement your own link-hook to inject arbitrary code before/after the forward propagation.

chainer.LinkHook

Base class of hooks for links.

chainer.LinkHook

class chainer.LinkHook

Base class of hooks for links.

LinkHook is a callback object that is registered to a Link. Registered link hooks are invoked before and after calling Link.forward() method of each link.

Link hooks that derive from LinkHook may override the following method:

- added()
- deleted()
- forward_preprocess()
- forward_postprocess()

By default, these methods do nothing.

Specifically, when the __call__() method of some link is invoked, forward_preprocess() (resp. forward_postprocess()) of all link hooks registered to this link are called before (resp. after) Link.forward() method of the link.

There are two ways to register LinkHook objects to Link objects.

The first one is to use with statement. Link hooks hooked in this way are registered to all links within with statement and are unregistered at the end of with statement.

Example

The following code is a simple example in which we measure the elapsed time of a part of forward propagation procedure with TimerHook, which is a subclass of LinkHook.

```python
>>> class Model(chainer.Chain):
...     def __init__(self):
...         super(Model, self).__init__()
...         with self.init_scope():
...             self.l = L.Linear(10, 10)
...     def forward(self, x1):
...         return F.exp(self.l(x1))

>>> model1 = Model()
>>> model2 = Model()
>>> x = chainer.Variable(np.zeros((1, 10), np.float32))
>>> with chainer.link_hooks.TimerHook() as m:
...     _ = model1(x)
...     y = model2(x)
>>> model3 = Model()
>>> z = model3(y)
>>> print('Total time : {}'.format(m.total_time()))
```

(continues on next page)
In this example, we measure the elapsed times for each forward propagation of all functions in `model1` and `model2`. Note that `model3` is not a target measurement as `TimerHook` is unregistered before forward propagation of `model3`.

**Note:** Chainer stores the dictionary of registered link hooks as a thread local object. So, link hooks registered are different depending on threads.

The other one is to register directly to a `Link` object by calling its `add_hook()` method. Link hooks registered in this way can be removed by `delete_hook()` method. Contrary to former registration method, link hooks are registered only to the link which `add_hook()` is called.

**Parameters**

- **name** *(str)* – Name of this link hook.

**Methods**

- **__enter__()** → `chainer.link_hook.LinkHook`
- **__exit__(*)**
- **added**(link: Optional[`chainer.link.Link`]) → None
  Callback function invoked when the link hook is registered

  **Parameters**
  - **link** *(Link)* – Link object to which the link hook is registered. None if the link hook is registered globally.

- **deleted**(link: Optional[`chainer.link.Link`]) → None
  Callback function invoked when the link hook is unregistered

  **Parameters**
  - **link** *(Link)* – Link object to which the link hook is unregistered. None if the link hook had been registered globally.

- **forward_postprocess**(args: `chainer.link_hook._ForwardPostprocessCallbackArgs`) → None
  Callback function invoked after a forward call of a link.

  **Parameters**
  - **args** – Callback data. It has the following attributes:
    - **link** *(Link)* Link object.
    - **forward_name** *(str)* Name of the forward method.
    - **args** *(tuple)* Non-keyword arguments given to the forward method.
    - **kwargs** *(dict)* Keyword arguments given to the forward method.
    - **out** Return value of the forward method.

- **forward_preprocess**(args: `chainer.link_hook._ForwardPreprocessCallbackArgs`) → None
  Callback function invoked before a forward call of a link.

  **Parameters**
  - **args** – Callback data. It has the following attributes:
    - **link** *(Link)* Link object.
    - **forward_name** *(str)* Name of the forward method.
    - **args** *(tuple)* Non-keyword arguments given to the forward method.
**kwargs (dict)  Keyword arguments given to the forward method.

```python
__eq__(value,)
   Return self==value.
__ne__(value,)
   Return self!=value.
__lt__(value,)
   Return self<value.
__le__(value,)
   Return self<=value.
__gt__(value,)
   Return self>value.
__ge__(value,)
   Return self>=value.
```

**Attributes**

```python
name = 'LinkHook'
```

### 4.4 Probability Distributions

Chainer provides many Distribution implementations in the `chainer.distributions` package.

#### 4.4.1 Distributions

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.distributions.Bernoulli</td>
<td>Bernoulli Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.Beta</td>
<td>Beta Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.Categorical</td>
<td>Categorical Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.Cauchy</td>
<td>Cauchy Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.Chisquare</td>
<td>Chi-Square Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.Dirichlet</td>
<td>Dirichlet Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.Exponential</td>
<td>Exponential Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.Gamma</td>
<td>Gamma Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.Independent</td>
<td>Independent distribution.</td>
</tr>
<tr>
<td>chainer.distributions.Laplace</td>
<td>Laplace Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.LogNormal</td>
<td>Logarithm Normal Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.OneHotCategorical</td>
<td>OneHotCategorical Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.Pareto</td>
<td>Pareto Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.Poisson</td>
<td>Poisson Distribution.</td>
</tr>
<tr>
<td>chainer.distributions.Uniform</td>
<td>Uniform Distribution.</td>
</tr>
</tbody>
</table>
class chainer.distributions.Bernoulli(p=None, logit=None, binary_check=False)

Bernoulli Distribution.

The probability mass function of the distribution is expressed as

\[ P(x = 1; p) = p \]
\[ P(x = 0; p) = 1 - p \]

Parameters

- \( p \) (Variable or N-dimensional array) – Parameter of distribution representing \( p \). Either \( p \) or \( \text{logit} \) (not both) must have a value.
- \( \text{logit} \) (Variable or N-dimensional array) – distribution representing \( \log \{ p/(1 - p) \} \). Either \( p \) or \( \text{logit} \) (not both) must have a value.

Methods

cdf(x)
Evaluates the cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Cumulative distribution function value evaluated at \( x \).

Return type Variable

icdf(x)
Evaluates the inverse cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Inverse cumulative distribution function value evaluated at \( x \).

Return type Variable

log_cdf(x)
Evaluates the log of cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of cumulative distribution function value evaluated at \( x \).

Return type Variable

log_prob(x)
Evaluates the logarithm of probability at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of probability evaluated at \( x \).

Return type Variable

log_survival_function(x)
Evaluates the logarithm of survival function at the given points.
Parameters $x$ (Variable or N-dimensional array) – Data points in the domain of the distribution.

Returns Logarithm of survival function value evaluated at $x$.

Return type Variable

**perplexity** ($x$)
Evaluates the perplexity function at the given points.

Parameters $x$ (Variable or N-dimensional array) – Data points in the domain of the distribution.

Returns Perplexity function value evaluated at $x$.

Return type Variable

**prob** ($x$)
Evaluates probability at the given points.

Parameters $x$ (Variable or N-dimensional array) – Data points in the domain of the distribution.

Returns Probability evaluated at $x$.

Return type Variable

**sample** ($sample\_shape=()$)
Samples random points from the distribution.

This function calls `sample_n` and reshapes a result of `sample_n` to \(sample\_shape + batch\_shape + event\_shape\). On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override `sample_n`.

Parameters $sample\_shape$ (tuple of int) – Sampling shape.

Returns Sampled random points.

Return type Variable

**sample_n** ($n$)
Samples $n$ random points from the distribution.

This function returns sampled points whose shape is \((n,) + batch\_shape + event\_shape\). When implementing sampling code in a subclass, it is recommended that you override this method.

Parameters $n$ (int) – Sampling size.

Returns sampled random points.

Return type Variable

**survival_function** ($x$)
Evaluates the survival function at the given points.

Parameters $x$ (Variable or N-dimensional array) – Data points in the domain of the distribution.

Returns Survival function value evaluated at $x$.

Return type Variable

**__eq__**(value, /)
Return self==value.

**__ne__**(value, /)
Return self!=value.
\_\_lt\_\_(value, /)  
    Return self<value.
\_\_le\_\_(value, /)  
    Return self<=value.
\_\_gt\_\_(value, /)  
    Return self>value.
\_\_ge\_\_(value, /)  
    Return self>=value.

**Attributes**

**batch_shape**

**covariance**
    Returns the covariance of the distribution.
    
    **Returns** The covariance of the distribution.
    
    **Return type** *Variable*

**entropy**

**event_shape**

**logit**

**mean**

**mode**
    Returns the mode of the distribution.
    
    **Returns** The mode of the distribution.
    
    **Return type** *Variable*

**p**

**params**

**stddev**

**support**

**variance**

**xp**
    Array module for the distribution.
    
    Depending on which of CPU/GPU this distribution is on, this property returns *numpy* or *cupy*. 
chainer.distributions.Beta

class chainer.distributions.Beta(a, b)

Beta Distribution.

The probability density function of the distribution is expressed as

\[ f(x) = \frac{x^{\alpha - 1}(1 - x)^{\beta - 1}}{B(\alpha, \beta)}, \]

for \(0 < x < 1, \alpha > 0, \beta > 0\).

Parameters

- **a** (*Variable* or *N-dimensional array*) – Parameter of distribution representing \(\alpha\).
- **b** (*Variable* or *N-dimensional array*) – Parameter of distribution representing \(\beta\).

Methods

cdf(x)

Evaluates the cumulative distribution function at the given points.

Parameters **x** (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns Cumulative distribution function value evaluated at \(x\).

Return type *Variable*

icdf(x)

Evaluates the inverse cumulative distribution function at the given points.

Parameters **x** (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns Inverse cumulative distribution function value evaluated at \(x\).

Return type *Variable*

log_cdf(x)

Evaluates the log of cumulative distribution function at the given points.

Parameters **x** (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns Logarithm of cumulative distribution function value evaluated at \(x\).

Return type *Variable*

log_prob(x)

Evaluates the logarithm of probability at the given points.

Parameters **x** (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns Logarithm of probability evaluated at \(x\).

Return type *Variable*

log_survival_function(x)

Evaluates the logarithm of survival function at the given points.
Parameters \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns Logarithm of survival function value evaluated at \( x \).

Return type *Variable*

**perplexity** \( (x) \)
Evaluates the perplexity function at the given points.

Parameters \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns Perplexity function value evaluated at \( x \).

Return type *Variable*

**prob** \( (x) \)
Evaluates probability at the given points.

Parameters \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns Probability evaluated at \( x \).

Return type *Variable*

**sample** \( (\text{sample\_shape}=()) \)
Samples random points from the distribution.

This function calls sample\_n and reshapes a result of sample\_n to sample\_shape + batch\_shape + event\_shape. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override sample\_n.

Parameters **sample\_shape** (*tuple* of *int*) – Sampling shape.

Returns Sampled random points.

Return type *Variable*

**sample\_n** \( (n) \)
Samples \( n \) random points from the distribution.

This function returns sampled points whose shape is \( (n,) + \text{batch\_shape} + \text{event\_shape} \). When implementing sampling code in a subclass, it is recommended that you override this method.

Parameters \( n \) (*int*) – Sampling size.

Returns Sampled random points.

Return type *Variable*

**survival\_function** \( (x) \)
Evaluates the survival function at the given points.

Parameters \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns Survival function value evaluated at \( x \).

Return type *Variable*

**__eq__** \( (\text{value, /}) \)
Return self==value.

**__ne__** \( (\text{value, /}) \)
Return self!=value.
__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

a
b
batch_shape
covariance
    Returns the covariance of the distribution.
    
    Returns  The covariance of the distribution.
    
    Return type  Variable

tf

tf

tf

tf

entropy


event_shape

mean

mode
    Returns the mode of the distribution.
    
    Returns  The mode of the distribution.
    
    Return type  Variable

params

stddev
    Returns the standard deviation of the distribution.
    
    Returns  The standard deviation of the distribution.
    
    Return type  Variable

support

dimension

dimension

dimension

dimension

variance

xp
    Array module for the distribution.
    
    Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.
chainer.distributions.Categorical

class chainer.distributions.Categorical(p=None, **kwargs)
Categorical Distribution.

The probability mass function of the distribution is expressed as

\[ P(x = i; p) = p_i \]

Parameters

- p (Variable or N-dimensional array) – Parameter of distribution.
- logit (Variable or N-dimensional array) – Parameter of distribution representing \( \log\{p\} + C \). Either \( p \) or \( \logit \) (not both) must have a value.

Methods

cdf(x)
Evaluates the cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Cumulative distribution function value evaluated at \( x \).

Return type Variable

icdf(x)
Evaluates the inverse cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Inverse cumulative distribution function value evaluated at \( x \).

Return type Variable

log_cdf(x)
Evaluates the log of cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of cumulative distribution function value evaluated at \( x \).

Return type Variable

log_prob(x)
Evaluates the logarithm of probability at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of probability evaluated at \( x \).

Return type Variable

log_survival_function(x)
Evaluates the logarithm of survival function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution
Returns Logarithm of survival function value evaluated at $x$.

Return type Variable

**perplexity**($x$)
Evaluates the perplexity function at the given points.

Parameters $x$ (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns Perplexity function value evaluated at $x$.

Return type Variable

**prob**($x$)
Evaluates probability at the given points.

Parameters $x$ (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns Probability evaluated at $x$.

Return type Variable

**sample**(*sample_shape=*($()$*))
Samples random points from the distribution.

This function calls *sample_n* and reshapes a result of *sample_n* to *sample_shape + batch_shape + event_shape*. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override *sample_n*.

Parameters *sample_shape*(*tuple of int*) – Sampling shape.

Returns Sampled random points.

Return type Variable

**sample_n**($n$)
Samples $n$ random points from the distribution.

This function returns sampled points whose shape is $(n,) + batch_shape + event_shape$. When implementing sampling code in a subclass, it is recommended that you override this method.

Parameters $n$ (*int*) – Sampling size.

Returns sampled random points.

Return type Variable

**survival_function**($x$)
Evaluates the survival function at the given points.

Parameters $x$ (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns Survival function value evaluated at $x$.

Return type Variable

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.
__le__(value,/)  
    Return self<=value.

__gt__(value,/)  
    Return self>value.

__ge__(value,/)  
    Return self>=value.

**Attributes**

**batch_shape**

**covariance**
    Returns the covariance of the distribution.
    
    **Returns**  The covariance of the distribution.
    
    **Return type**  Variable

**entropy**

**event_shape**

**log_p**

**mean**
    Returns the mean of the distribution.
    
    **Returns**  The mean of the distribution.
    
    **Return type**  Variable

**mode**
    Returns the mode of the distribution.
    
    **Returns**  The mode of the distribution.
    
    **Return type**  Variable

**p**

**params**

**stddev**
    Returns the standard deviation of the distribution.
    
    **Returns**  The standard deviation of the distribution.
    
    **Return type**  Variable

**support**
    Returns the support of the distribution.
    
    **Returns**  String that means support of this distribution.
    
    **Return type**  str

**variance**
    Returns the variance of the distribution.
    
    **Returns**  The variance of the distribution.
    
    **Return type**  Variable
xp
Array module for the distribution.
Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.

chainer.distributions.Cauchy

class chainer.distributions.Cauchy(loc, scale)
Cauchy Distribution.

The probability density function of the distribution is expressed as

\[ p(x; x_0, \gamma) = \frac{1}{\pi} \frac{\gamma}{(x - x_0)^2 + \gamma^2} \]

Parameters

- **loc** *(Variable or N-dimensional array)* – Parameter of distribution representing the location \(x_0\).
- **scale** *(Variable or N-dimensional array)* – Parameter of distribution representing the scale \(\gamma\).

Methods

cdf(x)
Evaluates the cumulative distribution function at the given points.

Parameters **x** *(Variable or N-dimensional array)* – Data points in the domain of the distribution

Returns Cumulative distribution function value evaluated at \(x\).

Return type **Variable**

icdf(x)
Evaluates the inverse cumulative distribution function at the given points.

Parameters **x** *(Variable or N-dimensional array)* – Data points in the domain of the distribution

Returns Inverse cumulative distribution function value evaluated at \(x\).

Return type **Variable**

log_cdf(x)
Evaluates the log of cumulative distribution function at the given points.

Parameters **x** *(Variable or N-dimensional array)* – Data points in the domain of the distribution

Returns Logarithm of cumulative distribution function value evaluated at \(x\).

Return type **Variable**

log_prob(x)
Evaluates the logarithm of probability at the given points.

Parameters **x** *(Variable or N-dimensional array)* – Data points in the domain of the distribution

Returns Logarithm of probability evaluated at \(x\).
Return type  Variable

log_survival_function \( (x) \)
Evaluates the logarithm of survival function at the given points.

Parameters  \( x \) (\textit{Variable} or \textit{N-dimensional array}) – Data points in the domain of the distribution

Returns  Logarithm of survival function value evaluated at \( x \).

Return type  Variable

perplexity \( (x) \)
Evaluates the perplexity function at the given points.

Parameters  \( x \) (\textit{Variable} or \textit{N-dimensional array}) – Data points in the domain of the distribution

Returns  Perplexity function value evaluated at \( x \).

Return type  Variable

prob \( (x) \)
Evaluates probability at the given points.

Parameters  \( x \) (\textit{Variable} or \textit{N-dimensional array}) – Data points in the domain of the distribution

Returns  Probability evaluated at \( x \).

Return type  Variable

sample \( (\text{sample\_shape}=(\)) \)
Samples random points from the distribution.

This function calls \textit{sample\_n} and reshapes a result of \textit{sample\_n} to \textit{sample\_shape} + \textit{batch\_shape} + \textit{event\_shape}. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override \textit{sample\_n}.

Parameters  \text{sample\_shape} (\textit{tuple} of \textit{int}) – Sampling shape.

Returns  Sampled random points.

Return type  Variable

sample\_n \( (n) \)
Samples \( n \) random points from the distribution.

This function returns sampled points whose shape is \( (n,) + \textit{batch\_shape} + \textit{event\_shape} \). When implementing sampling code in a subclass, it is recommended that you override this method.

Parameters  \( n \) (\textit{int}) – Sampling size.

Returns  sampled random points.

Return type  Variable

survival\_function \( (x) \)
Evaluates the survival function at the given points.

Parameters  \( x \) (\textit{Variable} or \textit{N-dimensional array}) – Data points in the domain of the distribution

Returns  Survival function value evaluated at \( x \).

Return type  Variable
__eq__(value, /)
    Return self==value.

__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

**batch_shape**

**covariance**

Returns the covariance of the distribution.

**Returns** The covariance of the distribution.

**Return type** Variable

**entropy**

**event_shape**

**loc**

**mean**

**mode**

Returns the mode of the distribution.

**Returns** The mode of the distribution.

**Return type** Variable

**params**

**scale**

**stddev**

Returns the standard deviation of the distribution.

**Returns** The standard deviation of the distribution.

**Return type** Variable

**support**

**variance**

**xp**

Array module for the distribution.

Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.

4.4. Probability Distributions
chainer.distributions.Chisquare

class chainer.distributions.Chisquare(k)

Chi-Square Distribution.

The probability density function of the distribution is expressed as

\[ p(x; k) = \frac{1}{2^{k/2} \Gamma(k/2)} x^{k/2-1} e^{-x/2} \]

Parameters \( k \) (Variable or N-dimensional array) – Parameter of distribution.

Methods

cdf(x)

Evaluates the cumulative distribution function at the given points.

Parameters \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Cumulative distribution function value evaluated at \( x \).

Return type Variable

icdf(x)

Evaluates the inverse cumulative distribution function at the given points.

Parameters \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Inverse cumulative distribution function value evaluated at \( x \).

Return type Variable

log_cdf(x)

Evaluates the log of cumulative distribution function at the given points.

Parameters \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of cumulative distribution function value evaluated at \( x \).

Return type Variable

log_prob(x)

Evaluates the logarithm of probability at the given points.

Parameters \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of probability evaluated at \( x \).

Return type Variable

log_survival_function(x)

Evaluates the logarithm of survival function at the given points.

Parameters \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of survival function value evaluated at \( x \).

Return type Variable
perplexity \(x\)
Evaluates the perplexity function at the given points.

**Parameters**
- \(x\) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Perplexity function value evaluated at \(x\).

**Return type** *Variable*

prob \(x\)
Evaluates probability at the given points.

**Parameters**
- \(x\) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Probability evaluated at \(x\).

**Return type** *Variable*

sample \(\text{sample\_shape}()\)
Samples random points from the distribution.

This function calls `sample_n` and reshapes a result of `sample_n` to `sample\_shape + batch\_shape + event\_shape`. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override `sample_n`.

**Parameters**
- `sample\_shape` (*tuple of int*) – Sampling shape.

**Returns**
Sampled random points.

**Return type** *Variable*

sample_n \(n\)
Samples \(n\) random points from the distribution.

This function returns sampled points whose shape is \((n,) + batch\_shape + event\_shape\). When implementing sampling code in a subclass, it is recommended that you override this method.

**Parameters**
- \(n\) (*int*) – Sampling size.

**Returns**
sampled random points.

**Return type** *Variable*

survival_function \(x\)
Evaluates the survival function at the given points.

**Parameters**
- \(x\) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Survival function value evaluated at \(x\).

**Return type** *Variable*

__eq__ \(value, /\)
Return `self==value`.

__ne__ \(value, /\)
Return `self!=value`.

__lt__ \(value, /\)
Return `self<value`.

__le__ \(value, /\)
Return `self<=value`.

4.4. Probability Distributions 837
__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

batch_shape

covariance
    Returns the covariance of the distribution.
    
    Returns: The covariance of the distribution.
    
    Return type: Variable

entropy

event_shape

k

mean

mode
    Returns the mode of the distribution.
    
    Returns: The mode of the distribution.
    
    Return type: Variable

params

stddev
    Returns the standard deviation of the distribution.
    
    Returns: The standard deviation of the distribution.
    
    Return type: Variable

support

variance

xp
    Array module for the distribution.
    
    Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.

chainer.distributions.Dirichlet

class chainer.distributions.Dirichlet(alpha)
    Dirichlet Distribution.
    
    The probability density function of the distribution is expressed as
    
    \[ p(x) = \frac{\Gamma\left(\sum_{i=1}^{K} \alpha_i\right)}{\prod_{i=1}^{K} \Gamma(\alpha_i)} \prod_{i=1}^{K} x_i^{\alpha_i-1} \]

    Parameters: alpha (Variable or N-dimensional array) – Parameter of distribution.
Methods

cdf \((x)\)
Evaluates the cumulative distribution function at the given points.

**Parameters** `x` (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns** Cumulative distribution function value evaluated at \(x\).

**Return type** *Variable*

icdf \((x)\)
Evaluates the inverse cumulative distribution function at the given points.

**Parameters** `x` (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns** Inverse cumulative distribution function value evaluated at \(x\).

**Return type** *Variable*

log_cdf \((x)\)
Evaluates the log of cumulative distribution function at the given points.

**Parameters** `x` (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns** Logarithm of cumulative distribution function value evaluated at \(x\).

**Return type** *Variable*

log_prob \((x)\)
Evaluates the logarithm of probability at the given points.

**Parameters** `x` (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns** Logarithm of probability evaluated at \(x\).

**Return type** *Variable*

log_survival_function \((x)\)
Evaluates the logarithm of survival function at the given points.

**Parameters** `x` (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns** Logarithm of survival function value evaluated at \(x\).

**Return type** *Variable*

perplexity \((x)\)
Evaluates the perplexity function at the given points.

**Parameters** `x` (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns** Perplexity function value evaluated at \(x\).

**Return type** *Variable*

prob \((x)\)
Evaluates probability at the given points.
**Parameters** \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns** Probability evaluated at \( x \).

**Return type** *Variable*

\texttt{sample}(*sample\_shape=())

Samples random points from the distribution.

This function calls \texttt{sample\_n} and reshapes a result of \texttt{sample\_n} to \texttt{sample\_shape + batch\_shape + event\_shape}. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override \texttt{sample\_n}.

**Parameters** \texttt{sample\_shape}(*tuple* of *int*) – Sampling shape.

**Returns** Sampled random points.

**Return type** *Variable*

\texttt{sample\_n}(n)

Samples \( n \) random points from the distribution.

This function returns sampled points whose shape is \( (n,) + \text{batch\_shape} + \text{event\_shape} \). When implementing sampling code in a subclass, it is recommended that you override this method.

**Parameters** \texttt{n}(*int*) – Sampling size.

**Returns** sampled random points.

**Return type** *Variable*

\texttt{survival\_function}(x)

Evaluates the survival function at the given points.

**Parameters** \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns** Survival function value evaluated at \( x \).

**Return type** *Variable*

---

**Methods**

- \texttt{__eq__}(value, /)
  
  Return self==value.

- \texttt{__ne__}(value, /)
  
  Return self!=value.

- \texttt{__lt__}(value, /)
  
  Return self<value.

- \texttt{__le__}(value, /)
  
  Return self<=value.

- \texttt{__gt__}(value, /)
  
  Return self>value.

- \texttt{__ge__}(value, /)
  
  Return self>=value.
Attributes

alpha
alpha0
batch_shape
covariance
    Returns the covariance of the distribution.
    Returns  The covariance of the distribution.
    Return type  Variable
terms
entropy
event_shape
mean
mode
    Returns the mode of the distribution.
    Returns  The mode of the distribution.
    Return type  Variable
params
stddev
    Returns the standard deviation of the distribution.
    Returns  The standard deviation of the distribution.
    Return type  Variable
support
variance
xp
    Array module for the distribution.
    Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.

chainer.distributions.Exponential

class  chainer.distributions.Exponential(lam)
    Exponential Distribution.
    The probability density function of the distribution is expressed as
    \[ p(x; \lambda) = \lambda e^{-\lambda x} \]
    Parameters  lam  (Variable or N-dimensional array) – Parameter of distribution \lambda.
Methods

cdf \((x)\)
Evaluates the cumulative distribution function at the given points.

**Parameters**  
\(x\) *(Variable or N-dimensional array)* – Data points in the domain of the distribution

**Returns**  
Cumulative distribution function value evaluated at \(x\).

**Return type**  
Variable

icdf \((x)\)
Evaluates the inverse cumulative distribution function at the given points.

**Parameters**  
\(x\) *(Variable or N-dimensional array)* – Data points in the domain of the distribution

**Returns**  
Inverse cumulative distribution function value evaluated at \(x\).

**Return type**  
Variable

log_cdf \((x)\)
Evaluates the log of cumulative distribution function at the given points.

**Parameters**  
\(x\) *(Variable or N-dimensional array)* – Data points in the domain of the distribution

**Returns**  
Logarithm of cumulative distribution function value evaluated at \(x\).

**Return type**  
Variable

log_prob \((x)\)
Evaluates the logarithm of probability at the given points.

**Parameters**  
\(x\) *(Variable or N-dimensional array)* – Data points in the domain of the distribution

**Returns**  
Logarithm of probability evaluated at \(x\).

**Return type**  
Variable

log_survival_function \((x)\)
Evaluates the logarithm of survival function at the given points.

**Parameters**  
\(x\) *(Variable or N-dimensional array)* – Data points in the domain of the distribution

**Returns**  
Logarithm of survival function value evaluated at \(x\).

**Return type**  
Variable

perplexity \((x)\)
Evaluates the perplexity function at the given points.

**Parameters**  
\(x\) *(Variable or N-dimensional array)* – Data points in the domain of the distribution

**Returns**  
Perplexity function value evaluated at \(x\).

**Return type**  
Variable

prob \((x)\)
Evaluates probability at the given points.
Parameters \( x \) (Variable or \( N \)-dimensional array) – Data points in the domain of the distribution

Returns Probability evaluated at \( x \).

Return type Variable

code

sample(sample_shape=())

Samples random points from the distribution.

This function calls sample_n and reshapes a result of sample_n to sample_shape + batch_shape + event_shape. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override sample_n.

Parameters sample_shape (tuple of int) – Sampling shape.

Returns Sampled random points.

Return type Variable

code

sample_n(n)

Samples \( n \) random points from the distribution.

This function returns sampled points whose shape is \( (n,) + batch_shape + event_shape \). When implementing sampling code in a subclass, it is recommended that you override this method.

Parameters n (int) – Sampling size.

Returns sampled random points.

Return type Variable

code

survival_function(x)

Evaluates the survival function at the given points.

Parameters x (Variable or \( N \)-dimensional array) – Data points in the domain of the distribution.

Returns Survival function value evaluated at \( x \).

Return type Variable

code

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.

__le__(value, /)

Return self<=value.

__gt__(value, /)

Return self>value.

__ge__(value, /)

Return self>=value.
**Attributes**

- **batch_shape**
  Returns the batch shape.

- **covariance**
  Returns the covariance of the distribution.
  - **Returns** The covariance of the distribution.
  - **Return type** `Variable`

- **entropy**

- **event_shape**

- **lam**

- **mean**

- **mode**
  Returns the mode of the distribution.
  - **Returns** The mode of the distribution.
  - **Return type** `Variable`

- **params**

- **stddev**
  Returns the standard deviation of the distribution.
  - **Returns** The standard deviation of the distribution.
  - **Return type** `Variable`

- **support**

- **variance**

- **xp**
  Array module for the distribution.
  Depending on which of CPU/GPU this distribution is on, this property returns `numpy` or `cupy`.

### chainer.distributions.Gamma

**class** `chainer.distributions.Gamma(k, theta)`

Gamma Distribution.

**Parameters**

- **k** (`Variable` or `N-dimensional array`) – Parameter of distribution.
- **theta** (`Variable` or `N-dimensional array`) – Parameter of distribution.
Methods

cdf (x)
Evaluates the cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Cumulative distribution function value evaluated at x.

Return type Variable

icdf (x)
Evaluates the inverse cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Inverse cumulative distribution function value evaluated at x.

Return type Variable

log_cdf (x)
Evaluates the log of cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of cumulative distribution function value evaluated at x.

Return type Variable

log_prob (x)
Evaluates the logarithm of probability at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of probability evaluated at x.

Return type Variable

log_survival_function (x)
Evaluates the logarithm of survival function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of survival function value evaluated at x.

Return type Variable

perplexity (x)
Evaluates the perplexity function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Perplexity function value evaluated at x.

Return type Variable

prob (x)
Evaluates probability at the given points.
Parameters `x` (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns  Probability evaluated at `x`.

Return type *Variable*

**sample** (*sample_shape=()*)

Samples random points from the distribution.

This function calls `sample_n` and reshapes a result of `sample_n` to `sample_shape + batch_shape + event_shape`. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override `sample_n`.

Parameters `sample_shape` (*tuple of int*) – Sampling shape.

Returns  Sampled random points.

Return type *Variable*

**sample_n** (*n*)

Samples `n` random points from the distribution.

This function returns sampled points whose shape is `(n,) + batch_shape + event_shape`. When implementing sampling code in a subclass, it is recommended that you override this method.

Parameters `n` (*int*) – Sampling size.

Returns  sampled random points.

Return type *Variable*

**survival_function** (*x*)

Evaluates the survival function at the given points.

Parameters `x` (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

Returns  Survival function value evaluated at `x`.

Return type *Variable*

**__eq__** (*value,*)

Return `self==value`.

**__ne__** (*value,*)

Return `self!=value`.

**__lt__** (*value,*)

Return `self<value`.

**__le__** (*value,*)

Return `self<=value`.

**__gt__** (*value,*)

Return `self>value`.

**__ge__** (*value,*)

Return `self>=value`.
Attributes

`batch_shape`

Returns the covariance of the distribution.

**Returns** The covariance of the distribution.

**Return type** `Variable`

`covariance`

`entropy`

`event_shape`

`k`

`mean`

`mode`

Returns the mode of the distribution.

**Returns** The mode of the distribution.

**Return type** `Variable`

`params`

`stddev`

Returns the standard deviation of the distribution.

**Returns** The standard deviation of the distribution.

**Return type** `Variable`

`support`

`theta`

`variance`

`xp`

Array module for the distribution.

Depending on which of CPU/GPU this distribution is on, this property returns `numpy` or `cupy`.

**chainer.distributions.Geometric**

```python
class chainer.distributions.Geometric(p)
```

Geometric Distribution.

The probability mass function of the distribution is expressed as

\[ Pr(x = k) = p(1 - p)^{k-1}, \text{for} \ k = 1, 2, 3, \ldots, \]

**Parameters**

- `p (Variable or N-dimensional array)` – Parameter of distribution.

4.4. Probability Distributions
Methods

cdf \(x\)
Evaluates the cumulative distribution function at the given points.

**Parameters**
\(x\) (*Variable or N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Cumulative distribution function value evaluated at \(x\).

**Return type** *Variable*

icdf \(x\)
Evaluates the inverse cumulative distribution function at the given points.

**Parameters**
\(x\) (*Variable or N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Inverse cumulative distribution function value evaluated at \(x\).

**Return type** *Variable*

log_cdf \(x\)
Evaluates the log of cumulative distribution function at the given points.

**Parameters**
\(x\) (*Variable or N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Logarithm of cumulative distribution function value evaluated at \(x\).

**Return type** *Variable*

log_prob \(x\)
Evaluates the logarithm of probability at the given points.

**Parameters**
\(x\) (*Variable or N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Logarithm of probability evaluated at \(x\).

**Return type** *Variable*

log_survival_function \(x\)
Evaluates the logarithm of survival function at the given points.

**Parameters**
\(x\) (*Variable or N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Logarithm of survival function value evaluated at \(x\).

**Return type** *Variable*

perplexity \(x\)
Evaluates the perplexity function at the given points.

**Parameters**
\(x\) (*Variable or N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Perplexity function value evaluated at \(x\).

**Return type** *Variable*

prob \(x\)
Evaluates probability at the given points.
**Parameters**  \( x \) *(Variable or N-dimensional array)* – Data points in the domain of the distribution

**Returns**  Probability evaluated at \( x \).

**Return type**  Variable

**sample** *(sample_shape=())*

Samples random points from the distribution.

This function calls \( \text{sample}_n \) and reshapes a result of \( \text{sample}_n \) to \( \text{sample}_shape + \text{batch}_shape + \text{event}_shape \). On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override \( \text{sample}_n \).

**Parameters**  \( \text{sample}_shape \) *(tuple of int)* – Sampling shape.

**Returns**  Sampled random points.

**Return type**  Variable

**sample_n** *(n)*

Samples \( n \) random points from the distribution.

This function returns sampled points whose shape is \( (n,) + \text{batch}_shape + \text{event}_shape \). When implementing sampling code in a subclass, it is recommended that you override this method.

**Parameters**  \( n \) *(int)* – Sampling size.

**Returns**  sampled random points.

**Return type**  Variable

**survival_function** *(x)*

Evaluates the survival function at the given points.

**Parameters**  \( x \) *(Variable or N-dimensional array)* – Data points in the domain of the distribution

**Returns**  Survival function value evaluated at \( x \).

**Return type**  Variable

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.

__le__(value, /)

Return self<=value.

__gt__(value, /)

Return self>value.

__ge__(value, /)

Return self>=value.
Attributes

**batch_shape**
Returns the covariance of the distribution.

Returns The covariance of the distribution.

Return type Variable

**covariance**
Returns the entropy of the distribution.

Returns The entropy of the distribution.

Return type Variable

**event_shape**

**mean**

**mode**
Returns the mode of the distribution.

Returns The mode of the distribution.

Return type Variable

**p**

**params**

**stddev**
Returns the standard deviation of the distribution.

Returns The standard deviation of the distribution.

Return type Variable

**support**

**variance**

**xp**
Array module for the distribution.

Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.

chainer.distributions.Gumbel
class chainer.distributions.Gumbel(loc, scale)
Gumbel Distribution.

The probability density function of the distribution is expressed as

\[
f(x) = \frac{1}{\eta} \exp \left\{ -\frac{x - \mu}{\eta} \right\} \exp \left[ -\exp \left\{ -\frac{x - \mu}{\eta} \right\} \right].
\]

Parameters

- **loc** (Variable or N-dimensional array) – Parameter of distribution \(\mu\).
- **scale** (Variable or N-dimensional array) – Parameter of distribution \(\eta\).
Methods

cdf \((x)\)
Evaluates the cumulative distribution function at the given points.

Parameters \(x\) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Cumulative distribution function value evaluated at \(x\).

Return type Variable

icdf \((x)\)
Evaluates the inverse cumulative distribution function at the given points.

Parameters \(x\) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Inverse cumulative distribution function value evaluated at \(x\).

Return type Variable

log_cdf \((x)\)
Evaluates the log of cumulative distribution function at the given points.

Parameters \(x\) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of cumulative distribution function value evaluated at \(x\).

Return type Variable

log_prob \((x)\)
Evaluates the logarithm of probability at the given points.

Parameters \(x\) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of probability evaluated at \(x\).

Return type Variable

log_survival_function \((x)\)
Evaluates the logarithm of survival function at the given points.

Parameters \(x\) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of survival function value evaluated at \(x\).

Return type Variable

perplexity \((x)\)
Evaluates the perplexity function at the given points.

Parameters \(x\) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Perplexity function value evaluated at \(x\).

Return type Variable

prob \((x)\)
Evaluates probability at the given points.
Parameters \( x \) (\textit{Variable} or \textit{N-dimensional array}) – Data points in the domain of the distribution

Returns Probability evaluated at \( x \).

Return type \textit{Variable}

\textbf{sample}(\textit{sample_shape}())

Samples random points from the distribution.

This function calls \textit{sample}_n and reshapes a result of \textit{sample}_n to \textit{sample_shape} + \textit{batch_shape} + \textit{event_shape}. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override \textit{sample}_n.

Parameters \textit{sample_shape}(\textit{tuple} of \textit{int}) – Sampling shape.

Returns Sampled random points.

Return type \textit{Variable}

\textbf{sample_n}(\textit{n})

Samples \( n \) random points from the distribution.

This function returns sampled points whose shape is \((n,) + \textit{batch_shape} + \textit{event_shape}\). When implementing sampling code in a subclass, it is recommended that you override this method.

Parameters \textit{n}(\textit{int}) – Sampling size.

Returns sampled random points.

Return type \textit{Variable}

\textbf{survival_function}(x)

Evaluates the survival function at the given points.

Parameters \( x \) (\textit{Variable} or \textit{N-dimensional array}) – Data points in the domain of the distribution

Returns Survival function value evaluated at \( x \).

Return type \textit{Variable}

**__eq__(value,/)**

Return self==value.

**__ne__(value,/)**

Return self!=value.

**__lt__(value,/)**

Return self<value.

**__le__(value,/)**

Return self<=value.

**__gt__(value,/)**

Return self>value.

**__ge__(value,/)**

Return self>=value.
Attributes

batch_shape

covariance

Returns the covariance of the distribution.

Returns

The covariance of the distribution.

Return type Variable

entropy

event_shape

loc

mean

mode

Returns the mode of the distribution.

Returns

The mode of the distribution.

Return type Variable

params

scale

stddev

Returns the standard deviation of the distribution.

Returns

The standard deviation of the distribution.

Return type Variable

support

variance

xp

Array module for the distribution.

Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.

chainer.distributions.Independent

class chainer.distributions.Independent (distribution, interpreted_batch_ndims=None)

Independent distribution.

Parameters

- distribution (Distribution) – The base distribution instance to transform.

- interpreted_batch_ndims (int) – Integer number of rightmost batch dims which will be regarded as event dims. When None all but the first batch axis (batch axis 0) will be transferred to event dimensions.
Methods

cdf \( (x) \)
Evaluates the cumulative distribution function at the given points.

**Parameters** \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

**Returns** Cumulative distribution function value evaluated at \( x \).

**Return type** Variable

icdf \( (x) \)
The inverse cumulative distribution function for multivariate variable.
Cumulative distribution function for multivariate variable is not invertible. This function always raises RuntimeError.

**Parameters** \( x \) (Variable or N-dimensional array) – Data points in the codomain of the distribution

**Raises** RuntimeError –

log_cdf \( (x) \)
Evaluates the log of cumulative distribution function at the given points.

**Parameters** \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

**Returns** Logarithm of cumulative distribution function value evaluated at \( x \).

**Return type** Variable

log_prob \( (x) \)
Evaluates the logarithm of probability at the given points.

**Parameters** \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

**Returns** Logarithm of probability evaluated at \( x \).

**Return type** Variable

log_survival_function \( (x) \)
Evaluates the logarithm of survival function at the given points.

**Parameters** \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

**Returns** Logarithm of survival function value evaluated at \( x \).

**Return type** Variable

perplexity \( (x) \)
Evaluates the perplexity function at the given points.

**Parameters** \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

**Returns** Perplexity function value evaluated at \( x \).

**Return type** Variable

prob \( (x) \)
Evaluates probability at the given points.
**Parameters** \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution.

**Returns** Probability evaluated at \( x \).

**Return type** *Variable*

**sample** (*sample_shape=*\( () \))

Samples random points from the distribution.

This function calls `sample_n` and reshapes a result of `sample_n` to `sample_shape + batch_shape + event_shape`. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override `sample_n`.

**Parameters** `sample_shape` (*tuple* of *int*) – Sampling shape.

**Returns** Sampled random points.

**Return type** *Variable*

**sample_n** (*n*)

Samples \( n \) random points from the distribution.

This function returns sampled points whose shape is \( (n,) + batch_shape + event_shape \). When implementing sampling code in a subclass, it is recommended that you override this method.

**Parameters** `n` (*int*) – Sampling size.

**Returns** sampled random points.

**Return type** *Variable*

**survival_function** (*x*)

Evaluates the survival function at the given points.

**Parameters** \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution.

**Returns** Survival function value evaluated at \( x \).

**Return type** *Variable*

**__eq__** (*value, /*)

Return `self==value`.

**__ne__** (*value, /*)

Return `self!=value`.

**__lt__** (*value, /*)

Return `self<value`.

**__le__** (*value, /*)

Return `self<=value`.

**__gt__** (*value, /*)

Return `self>value`.

**__ge__** (*value, /*)

Return `self>=value`.
Attributes

**batch_shape**

The covariance of the independent distribution.

**covariance**

The covariance of the independent distribution.

By definition, the covariance of the new distribution becomes block diagonal matrix. Let $\Sigma_x$ be the covariance matrix of the original random variable $x \in \mathbb{R}^d$, and $x^{(1)}, x^{(2)}, \ldots, x^{(m)}$ be the $m$ i.i.d. random variables, new covariance matrix $\Sigma_y$ of $y = \begin{bmatrix} x^{(1)}; x^{(2)}; \cdots; x^{(m)} \end{bmatrix} \in \mathbb{R}^{md}$ can be written as

$$
\begin{bmatrix}
\Sigma_x & 0 \\
\vdots & \ddots \\
0 & \Sigma_x^m
\end{bmatrix}.
$$

Note that this relationship holds only if the covariance matrix of the original distribution is given analytically.

**Returns** The covariance of the distribution.

**Return type** `Variable`

class chainer.distributions.Laplace

Laplace Distribution.

The probability density function of the distribution is expressed as

$$p(x; \mu, b) = \frac{1}{2b} \exp\left( -\frac{|x - \mu|}{b} \right)$$

**Parameters**

- **loc** (*Variable* or *N-dimensional array*) – Parameter of distribution representing the location $\mu$.

- **scale** (*Variable* or *N-dimensional array*) – Parameter of distribution representing the scale $b$. 

Methods

cdf \( (x) \)
Evaluates the cumulative distribution function at the given points.

**Parameters** \( x (\textit{Variable or N-dimensional array}) \) – Data points in the domain of the distribution

**Returns** Cumulative distribution function value evaluated at \( x \).

**Return type** \( \textit{Variable} \)

icdf \( (x) \)
Evaluates the inverse cumulative distribution function at the given points.

**Parameters** \( x (\textit{Variable or N-dimensional array}) \) – Data points in the domain of the distribution

**Returns** Inverse cumulative distribution function value evaluated at \( x \).

**Return type** \( \textit{Variable} \)

log_cdf \( (x) \)
Evaluates the log of cumulative distribution function at the given points.

**Parameters** \( x (\textit{Variable or N-dimensional array}) \) – Data points in the domain of the distribution

**Returns** Logarithm of cumulative distribution function value evaluated at \( x \).

**Return type** \( \textit{Variable} \)

log_prob \( (x) \)
Evaluates the logarithm of probability at the given points.

**Parameters** \( x (\textit{Variable or N-dimensional array}) \) – Data points in the domain of the distribution

**Returns** Logarithm of probability evaluated at \( x \).

**Return type** \( \textit{Variable} \)

log_survival_function \( (x) \)
Evaluates the logarithm of survival function at the given points.

**Parameters** \( x (\textit{Variable or N-dimensional array}) \) – Data points in the domain of the distribution

**Returns** Logarithm of survival function value evaluated at \( x \).

**Return type** \( \textit{Variable} \)

perplexity \( (x) \)
Evaluates the perplexity function at the given points.

**Parameters** \( x (\textit{Variable or N-dimensional array}) \) – Data points in the domain of the distribution

**Returns** Perplexity function value evaluated at \( x \).

**Return type** \( \textit{Variable} \)

prob \( (x) \)
Evaluates probability at the given points.
Parameters $x$ (Variable or N-dimensional array) – Data points in the domain of the distribution.

Returns Probability evaluated at $x$.

Return type Variable

sample$(\text{sample\_shape}=())$

Samples random points from the distribution.

This function calls sample_n and reshapes a result of sample_n to sample_shape + batch_shape + event_shape. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override sample_n.

Parameters sample_shape (tuple of int) – Sampling shape.

Returns Sampled random points.

Return type Variable

sample_n$ (n)$

Samples $n$ random points from the distribution.

This function returns sampled points whose shape is $(n,) + \text{batch\_shape} + \text{event\_shape}$. When implementing sampling code in a subclass, it is recommended that you override this method.

Parameters $n$ (int) – Sampling size.

Returns sampled random points.

Return type Variable

survival_function$(x)$

Evaluates the survival function at the given points.

Parameters $x$ (Variable or N-dimensional array) – Data points in the domain of the distribution.

Returns Survival function value evaluated at $x$.

Return type Variable

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.

__le__(value, /)

Return self<=value.

__gt__(value, /)

Return self>value.

__ge__(value, /)

Return self>=value.
Attributes

\texttt{batch\_shape}
\texttt{covariance}
Returns the covariance of the distribution.

\textbf{Returns} \quad \text{The covariance of the distribution.}

\textbf{Return type} \quad \texttt{Variable}

\texttt{entropy}
\texttt{event\_shape}
\texttt{loc}
\texttt{mean}
\texttt{mode}
\texttt{params}
\texttt{scale}
\texttt{stddev}
\texttt{support}
\texttt{variance}
\texttt{xp}
Array module for the distribution.

Depending on which of CPU/GPU this distribution is on, this property returns \texttt{numpy} or \texttt{cupy}.

\texttt{chainer.distributions.LogNormal}

\texttt{class chainer.distributions.LogNormal}(\texttt{mu, sigma})
Logatithm Normal Distribution.

The probability density function of the distribution is expressed as

\[ p(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}x} \exp\left(-\frac{(\log x - \mu)^2}{2\sigma^2}\right) \]

\textbf{Parameters}

\begin{itemize}
  \item \texttt{mu (Variable or N-dimensional array)} – Parameter of distribution \( \mu \).
  \item \texttt{sigma (Variable or N-dimensional array)} – Parameter of distribution \( \sigma \).
\end{itemize}

\textbf{Methods}

\texttt{cdf(x)}
Evaluates the cumulative distribution function at the given points.

\textbf{Parameters} \quad \texttt{x (Variable or N-dimensional array)} – Data points in the domain of the distribution

\textbf{Returns} \quad \text{Cumulative distribution function value evaluated at} \, \texttt{x}.

\textbf{Return type} \quad \texttt{Variable}
icdf$(x)$
Evaluates the inverse cumulative distribution function at the given points.

**Parameters**
- \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Inverse cumulative distribution function value evaluated at \( x \).

**Return type** *Variable*

log_cdf$(x)$
Evaluates the log of cumulative distribution function at the given points.

**Parameters**
- \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Logarithm of cumulative distribution function value evaluated at \( x \).

**Return type** *Variable*

log_prob$(x)$
Evaluates the logarithm of probability at the given points.

**Parameters**
- \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Logarithm of probability evaluated at \( x \).

**Return type** *Variable*

log_survival_function$(x)$
Evaluates the logarithm of survival function at the given points.

**Parameters**
- \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Logarithm of survival function value evaluated at \( x \).

**Return type** *Variable*

perplexity$(x)$
Evaluates the perplexity function at the given points.

**Parameters**
- \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Perplexity function value evaluated at \( x \).

**Return type** *Variable*

prob$(x)$
Evaluates probability at the given points.

**Parameters**
- \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Probability evaluated at \( x \).

**Return type** *Variable*

sample\((sample\_shape=())\)$
Samples random points from the distribution.

This function calls \( \text{sample\_n} \) and reshapes a result of \( \text{sample\_n} \) to \( \text{sample\_shape} + \text{batch\_shape} + \text{event\_shape} \). On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override \( \text{sample\_n} \).
Parameters **sample_shape** *(tuple of int)* – Sampling shape.

Returns Sampled random points.

Return type **Variable**

### sample_n *(n)*

Samples n random points from the distribution.

This function returns sampled points whose shape is \((n,) + \text{batch\_shape} + \text{event\_shape}\). When implementing sampling code in a subclass, it is recommended that you override this method.

Parameters **n** *(int)* – Sampling size.

Returns sampled random points.

Return type **Variable**

### survival_function *(x)*

Evaluates the survival function at the given points.

Parameters **x** *(Variable or N-dimensional array)* – Data points in the domain of the distribution

Returns Survival function value evaluated at \(x\).

Return type **Variable**

---

**Attributes**

**batch_shape**

**covariance**

Returns the covariance of the distribution.

Returns The covariance of the distribution.

Return type **Variable**

**entropy**

**event_shape**

**mean**

**mode**

Returns the mode of the distribution.
Returns
The mode of the distribution.

Return type Variable

mu
params
sigma
stddev
Returns the standard deviation of the distribution.

Returns
The standard deviation of the distribution.

Return type Variable

support
variance
xp
Array module for the distribution.

Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.

chainer.distributions.MultivariateNormal

class chainer.distributions.MultivariateNormal(loc, **kwargs)

MultivariateNormal Distribution.

The probability density function of the distribution is expressed as

\[
p(x; \mu, V) = \frac{1}{\sqrt{\det(2\pi V)}} \exp \left( -\frac{1}{2} (x - \mu)^T V^{-1} (x - \mu) \right)
\]

Parameters

* loc (Variable or N-dimensional array) – Parameter of distribution representing the location \( \mu \).

* scale_tril (Variable or N-dimensional array) – Parameter of distribution representing the scale \( L \) such that \( V = LL^T \).

Methods

__copy__()

cdf (x)

Evaluates the cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Cumulative distribution function value evaluated at \( x \).

Return type Variable

icdf (x)

Evaluates the inverse cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution
Returns Inverse cumulative distribution function value evaluated at $x$.

Return type Variable

$log\_cdf (x)$
Evaluates the log of cumulative distribution function at the given points.

Parameters $x$ (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of cumulative distribution function value evaluated at $x$.

Return type Variable

$log\_prob (x)$
Evaluates the logarithm of probability at the given points.

Parameters $x$ (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of probability evaluated at $x$.

Return type Variable

$log\_survival\_function (x)$
Evaluates the logarithm of survival function at the given points.

Parameters $x$ (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of survival function value evaluated at $x$.

Return type Variable

$perplexity (x)$
Evaluates the perplexity function at the given points.

Parameters $x$ (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Perplexity function value evaluated at $x$.

Return type Variable

$prob (x)$
Evaluates probability at the given points.

Parameters $x$ (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Probability evaluated at $x$.

Return type Variable

$sample (sample\_shape=())$
Samples random points from the distribution.

This function calls $sample\_n$ and reshapes a result of $sample\_n$ to $sample\_shape + batch\_shape + event\_shape$. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override $sample\_n$.

Parameters $sample\_shape$ (tuple of int) – Sampling shape.

Returns Sampled random points.

Return type Variable

4.4. Probability Distributions
sample_n(n)
Samples n random points from the distribution.

This function returns sampled points whose shape is \((n,) + \text{batch\_shape} + \text{event\_shape}\). When implementing sampling code in a subclass, it is recommended that you override this method.

**Parameters**
- n (int) – Sampling size.

**Returns**
sampled random points.

**Return type** Variable

survival_function(x)
Evaluates the survival function at the given points.

**Parameters**
- x (Variable or N-dimensional array) – Data points in the domain of the distribution

**Returns**
survival function value evaluated at \(x\).

**Return type** Variable

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.

**Attributes**

batch_shape
covariance
d
entropy
event_shape
loc
mean
mode

Returns the mode of the distribution.

**Returns**
The mode of the distribution.

**Return type** Variable

params

scale_tril
stddev
Returns the standard deviation of the distribution.

Returns
The standard deviation of the distribution.

Return type
Variable

support

variance
Returns the variance of the distribution.

Returns
The variance of the distribution.

Return type
Variable

xp
Array module for the distribution.

Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.

cgher.distributions.Normal

class chainer.distributions.Normal (loc, scale=None, **kwargs)
Normal Distribution.

The probability density function of the distribution is expressed as

\[ p(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{- (x - \mu)^2}{2\sigma^2}\right) \]

Parameters

• loc (Variable or N-dimensional array) – Parameter of distribution representing the location \(\mu\). This is the mean parameter.

• scale (Variable or N-dimensional array) – Parameter of distribution representing the scale \(\sigma\). Either scale or log_scale (not both) must have a value.

• log_scale (Variable or N-dimensional array) – Parameter of distribution representing the scale \(\log(\sigma)\). Either scale or log_scale (not both) must have a value.

Methods

cdf (x)
Evaluates the cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Cumulative distribution function value evaluated at \(x\).

Return type Variable

icdf (x)
Evaluates the inverse cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Inverse cumulative distribution function value evaluated at \(x\).

Return type Variable
**log_cdf** (x)
Evaluates the log of cumulative distribution function at the given points.

**Parameters**
- **x** (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Logarithm of cumulative distribution function value evaluated at x.

**Return type** *Variable*

**log_prob** (x)
Evaluates the logarithm of probability at the given points.

**Parameters**
- **x** (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Logarithm of probability evaluated at x.

**Return type** *Variable*

**log_survival_function** (x)
Evaluates the logarithm of survival function at the given points.

**Parameters**
- **x** (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Logarithm of survival function value evaluated at x.

**Return type** *Variable*

**perplexity** (x)
Evaluates the perplexity function at the given points.

**Parameters**
- **x** (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Perplexity function value evaluated at x.

**Return type** *Variable*

**prob** (x)
Evaluates probability at the given points.

**Parameters**
- **x** (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns**
Probability evaluated at x.

**Return type** *Variable*

**sample**(sample_shape=())
Samples random points from the distribution.

This function calls **sample_n** and reshapes a result of **sample_n** to **sample_shape + batch_shape + event_shape**. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override **sample_n**.

**Parameters**
- **sample_shape** (*tuple of int*) – Sampling shape.

**Returns**
Sampled random points.

**Return type** *Variable*

**sample_n** (n)
Samples n random points from the distribution.
This function returns sampled points whose shape is \((n,) + \text{batch\_shape} + \text{event\_shape}\). When implementing sampling code in a subclass, it is recommended that you override this method.

**Parameters**

- **n** \((\text{int})\) – Sampling size.

**Returns**

sampled random points.

**Return type** Variable

**survival\_function** \((x)\)

Evaluates the survival function at the given points.

**Parameters**

- **x** \((\text{Variable or N-dimensional array})\) – Data points in the domain of the distribution

**Returns**

Survival function value evaluated at \(x\).

**Return type** Variable

**Attributes**

**batch\_shape**

Returns the batch shape of the distribution.

**covariance**

Returns the covariance of the distribution.

**entropy**

Returns the entropy of the distribution.

**event\_shape**

Returns the event shape of the distribution.

**loc**

Returns the location parameter of the distribution.

**log\_scale**

Returns the log scale parameter of the distribution.

**mean**

Returns the mean of the distribution.

**mode**

Returns the mode of the distribution.

**params**

Returns the parameters of the distribution.

**Return type** Variable

**__eq__** \((value,/)\)

Return self==value.

**__ne__** \((value,/)\)

Return self!=value.

**__lt__** \((value,/)\)

Return self<value.

**__le__** \((value,/)\)

Return self<=value.

**__gt__** \((value,/)\)

Return self>value.

**__ge__** \((value,/)\)

Return self>=value.
scale
stddev
support
variance
xp
Array module for the distribution.
Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.

chainer.distributions.OneHotCategorical

class chainer.distributions.OneHotCategorical(p)
    OneHotCategorical Distribution.

    Parameters p (Variable or N-dimensional array) – Parameter of distribution.

Methods

cdf(x)
    Evaluates the cumulative distribution function at the given points.

    Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

    Returns Cumulative distribution function value evaluated at x.

    Return type Variable

icdf(x)
    Evaluates the inverse cumulative distribution function at the given points.

    Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

    Returns Inverse cumulative distribution function value evaluated at x.

    Return type Variable

log_cdf(x)
    Evaluates the log of cumulative distribution function at the given points.

    Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

    Returns Logarithm of cumulative distribution function value evaluated at x.

    Return type Variable

log_prob(x)
    Evaluates the logarithm of probability at the given points.

    Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

    Returns Logarithm of probability evaluated at x.

    Return type Variable

log_survival_function(x)
    Evaluates the logarithm of survival function at the given points.
Parameters \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns** Logarithm of survival function value evaluated at \( x \).

**Return type** *Variable*

**perplexity** \((x)\)

Evaluates the perplexity function at the given points.

Parameters \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns** Perplexity function value evaluated at \( x \).

**Return type** *Variable*

**prob** \((x)\)

Evaluates probability at the given points.

Parameters \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns** Probability evaluated at \( x \).

**Return type** *Variable*

**sample** \((\text{sample\_shape}=())\)

Samples random points from the distribution.

This function calls \( \text{sample\_n} \) and reshapes a result of \( \text{sample\_n} \) to \( \text{sample\_shape} + \text{batch\_shape} + \text{event\_shape} \). On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override \( \text{sample\_n} \).

Parameters \( \text{sample\_shape} \) (*tuple of int*) – Sampling shape.

**Returns** Sampled random points.

**Return type** *Variable*

**sample\_n** \((n)\)

Samples \( n \) random points from the distribution.

This function returns sampled points whose shape is \( (n,) + \text{batch\_shape} + \text{event\_shape} \). When implementing sampling code in a subclass, it is recommended that you override this method.

Parameters \( n \) (*int*) – Sampling size.

**Returns** Sampled random points.

**Return type** *Variable*

**survival\_function** \((x)\)

Evaluates the survival function at the given points.

Parameters \( x \) (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution

**Returns** Survival function value evaluated at \( x \).

**Return type** *Variable*

\[ \text{__eq__} (value, /) \]

Return \( self==value \).

\[ \text{__ne__} (value, /) \]

Return \( self!=value \).
\_lt\_ (value, \_)
    Return self<value.
\_le\_ (value, \_)
    Return self<=value.
\_gt\_ (value, \_)
    Return self>value.
\_ge\_ (value, \_)
    Return self>=value.

**Attributes**

**batch_shape**

**covariance**

Returns the covariance of the distribution.

Returns The covariance of the distribution.

Return type **Variable**

**entropy**

Returns the entropy of the distribution.

Returns The entropy of the distribution.

Return type **Variable**

**event_shape**

**log_p**

**mean**

**mode**

Returns the mode of the distribution.

Returns The mode of the distribution.

Return type **Variable**

**P**

**params**

**stddev**

Returns the standard deviation of the distribution.

Returns The standard deviation of the distribution.

Return type **Variable**

**support**

Returns the support of the distribution.

Returns String that means support of this distribution.

Return type **str**

**variance**
xp
Array module for the distribution.

Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.

chainer.distributions.Pareto

class chainer.distributions.Pareto(scale, alpha)
Pareto Distribution.

\[ f(x) = \alpha x_m^{\alpha} (x)^{-(\alpha+1)}, \]

Parameters
- scale (Variable or N-dimensional array) – Parameter of distribution \(x_m\).
- alpha (Variable or N-dimensional array) – Parameter of distribution \(\alpha\).

Methods

cdf(x)
Evaluates the cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Cumulative distribution function value evaluated at \(x\).

Return type Variable

icdf(x)
Evaluates the inverse cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Inverse cumulative distribution function value evaluated at \(x\).

Return type Variable

log_cdf(x)
Evaluates the log of cumulative distribution function at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of cumulative distribution function value evaluated at \(x\).

Return type Variable

log_prob(x)
Evaluates the logarithm of probability at the given points.

Parameters x (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of probability evaluated at \(x\).

Return type Variable

log_survival_function(x)
Evaluates the logarithm of survival function at the given points.
Parameters \( x \) (\text{Variable} \text{ or } N\text{-dimensional array}) – Data points in the domain of the distribution.

Returns Logarithm of survival function value evaluated at \( x \).

Return type \text{Variable}

perplexity \((x)\)
Evaluates the perplexity function at the given points.

Parameters \( x \) (\text{Variable} \text{ or } N\text{-dimensional array}) – Data points in the domain of the distribution.

Returns Perplexity function value evaluated at \( x \).

Return type \text{Variable}

prob \((x)\)
Evaluates probability at the given points.

Parameters \( x \) (\text{Variable} \text{ or } N\text{-dimensional array}) – Data points in the domain of the distribution.

Returns Probability evaluated at \( x \).

Return type \text{Variable}

dsampling \(\text{sample}\) \((\text{sample}\_\text{shape}=())\)
Samples random points from the distribution.

This function calls \text{sample}\_\text{n} and reshapes a result of \text{sample}\_\text{n} to \text{sample}\_\text{shape} + \text{batch}\_\text{shape} + \text{event}\_\text{shape}. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override \text{sample}\_\text{n}.

Parameters \text{sample}\_\text{shape} (\text{tuple} of \text{int}) – Sampling shape.

Returns Sampled random points.

Return type \text{Variable}

sampling \(\text{sample}\_\text{n}\) \((n)\)
Samples \(n\) random points from the distribution.

This function returns sampled points whose shape is \((n,) + \text{batch}\_\text{shape} + \text{event}\_\text{shape}\). When implementing sampling code in a subclass, it is recommended that you override this method.

Parameters \( n \) (\text{int}) – Sampling size.

Returns sampled random points.

Return type \text{Variable}

survival\_function \((x)\)
Evaluates the survival function at the given points.

Parameters \( x \) (\text{Variable} \text{ or } N\text{-dimensional array}) – Data points in the domain of the distribution.

Returns Survival function value evaluated at \( x \).

Return type \text{Variable}

\_\_eq\_\_ (\text{value}, /)
Return self==value.

\_\_ne\_\_ (\text{value}, /)
Return self!=value.
\_\_lt\_\_(\text{value,} /) \
\qquad \text{Return } \text{self} < \text{value.}

\_\_le\_\_(\text{value,} /) \
\qquad \text{Return } \text{self} <= \text{value.}

\_\_gt\_\_(\text{value,} /) \
\qquad \text{Return } \text{self} > \text{value.}

\_\_ge\_\_(\text{value,} /) \
\qquad \text{Return } \text{self} >= \text{value.}

**Attributes**

*alpha*

*batch_shape*

*covariance*

\quad \text{Returns the covariance of the distribution.}

\quad \textbf{Returns} \quad \text{The covariance of the distribution.}

\quad \textbf{Return type} \quad \texttt{Variable}

*entropy*

*event_shape*

*mean*

*mode*

\quad \text{Returns the mode of the distribution.}

\quad \textbf{Returns} \quad \text{The mode of the distribution.}

\quad \textbf{Return type} \quad \texttt{Variable}

*params*

*scale*

*stddev*

\quad \text{Returns the standard deviation of the distribution.}

\quad \textbf{Returns} \quad \text{The standard deviation of the distribution.}

\quad \textbf{Return type} \quad \texttt{Variable}

*support*

*variance*

*xp*

\quad \text{Array module for the distribution.}

\quad \text{Depending on which of CPU/GPU this distribution is on, this property returns} \ \texttt{numpy} \ \text{or} \ \texttt{cupy}.
chainer.distributions.Poisson

class chainer.distributions.Poisson(lam)

Poisson Distribution.

The probability mass function of the distribution is expressed as

\[ P(x; \lambda) = \frac{\lambda^x e^{-\lambda}}{x!} \]

Parameters

- **lam** (Variable or N-dimensional array) – Parameter of distribution. \( \lambda \)

Methods

cdf(x)

Evaluates the cumulative distribution function at the given points.

Parameters

- **x** (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns

Cumulative distribution function value evaluated at \( x \).

Return type

Variable

icdf(x)

Evaluates the inverse cumulative distribution function at the given points.

Parameters

- **x** (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns

Inverse cumulative distribution function value evaluated at \( x \).

Return type

Variable

log_cdf(x)

Evaluates the log of cumulative distribution function at the given points.

Parameters

- **x** (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns

Logarithm of cumulative distribution function value evaluated at \( x \).

Return type

Variable

log_prob(x)

Evaluates the logarithm of probability at the given points.

Parameters

- **x** (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns

Logarithm of probability evaluated at \( x \).

Return type

Variable

log_survival_function(x)

Evaluates the logarithm of survival function at the given points.

Parameters

- **x** (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns

Logarithm of survival function value evaluated at \( x \).

Return type

Variable
perplexity \(x\)
Evaluates the perplexity function at the given points.

**Parameters**
- \(x\) *(Variable or N-dimensional array)* – Data points in the domain of the distribution

**Returns**
- Perplexity function value evaluated at \(x\).

**Return type** Variable

prob \(x\)
Evaluates probability at the given points.

**Parameters**
- \(x\) *(Variable or N-dimensional array)* – Data points in the domain of the distribution

**Returns**
- Probability evaluated at \(x\).

**Return type** Variable

sample \((sample\_shape=())\)
Samples random points from the distribution.

This function calls sample_n and reshapes a result of sample_n to sample_shape + batch_shape + event_shape. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override sample_n.

**Parameters**
- \(sample\_shape\) *(tuple of int)* – Sampling shape.

**Returns**
- Sampled random points.

**Return type** Variable

sample_n \((n)\)
Samples \(n\) random points from the distribution.

This function returns sampled points whose shape is \((n,) + batch\_shape + event\_shape\). When implementing sampling code in a subclass, it is recommended that you override this method.

**Parameters**
- \(n\) *(int)* – Sampling size.

**Returns**
- Sampled random points.

**Return type** Variable

survival_function \((x)\)
Evaluates the survival function at the given points.

**Parameters**
- \(x\) *(Variable or N-dimensional array)* – Data points in the domain of the distribution

**Returns**
- Survival function value evaluated at \(x\).

**Return type** Variable

___eq__(value, /)
Return self==value.

___ne__(value, /)
Return self!=value.

___lt__(value, /)
Return self<value.

___le__(value, /)
Return self<=value.
__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

batch_shape

covariance
    Returns the covariance of the distribution.
    
    Returns: The covariance of the distribution.
    
    Return type: Variable

entropy
    Returns the entropy of the distribution.
    
    Returns: The entropy of the distribution.
    
    Return type: Variable

event_shape

lam

mean

mode
    Returns the mode of the distribution.
    
    Returns: The mode of the distribution.
    
    Return type: Variable

params

stddev
    Returns the standard deviation of the distribution.
    
    Returns: The standard deviation of the distribution.
    
    Return type: Variable

support

variance

xp
    Array module for the distribution.
    
    Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.
**chainer.distributions.Uniform**

**class** chainer.distributions.Uniform(**kwargs)

Uniform Distribution.

The probability density function of the distribution is expressed as

\[
p(x; l, h) = \begin{cases} \frac{1}{h-l} & \text{if } l \leq x \leq h \\ 0 & \text{otherwise} \end{cases}
\]

**Parameters**

- **low** (*Variable* or *N-dimensional array*) – Parameter of distribution representing the lower bound \(l\).
- **high** (*Variable* or *N-dimensional array*) – Parameter of distribution representing the higher bound \(h\).

**Methods**

- **cdf**(*x*)
  Evaluates the cumulative distribution function at the given points.
  **Parameters** *x* (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution
  **Returns** Cumulative distribution function value evaluated at *x*.
  **Return type** *Variable*

- **icdf**(*x*)
  Evaluates the inverse cumulative distribution function at the given points.
  **Parameters** *x* (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution
  **Returns** Inverse cumulative distribution function value evaluated at *x*.
  **Return type** *Variable*

- **log_cdf**(*x*)
  Evaluates the log of cumulative distribution function at the given points.
  **Parameters** *x* (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution
  **Returns** Logarithm of cumulative distribution function value evaluated at *x*.
  **Return type** *Variable*

- **log_prob**(*x*)
  Evaluates the logarithm of probability at the given points.
  **Parameters** *x* (*Variable* or *N-dimensional array*) – Data points in the domain of the distribution
  **Returns** Logarithm of probability evaluated at *x*.
  **Return type** *Variable*

- **log_survival_function**(*x*)
  Evaluates the logarithm of survival function at the given points.
Parameters \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Logarithm of survival function value evaluated at \( x \).

Return type Variable

perplexity \((x)\)
Evaluates the perplexity function at the given points.

Parameters \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Perplexity function value evaluated at \( x \).

Return type Variable

prob \((x)\)
Evaluates probability at the given points.

Parameters \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Probability evaluated at \( x \).

Return type Variable

sample \((sample\_shape=())\)
Samples random points from the distribution.

This function calls \( \text{sample\_n} \) and reshapes a result of \( \text{sample\_n} \) to \( \text{sample\_shape} + \text{batch\_shape} + \text{event\_shape} \). On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override \( \text{sample\_n} \).

Parameters \( \text{sample\_shape} \) (tuple of int) – Sampling shape.

Returns Sampled random points.

Return type Variable

sample\_n \((n)\)
Samples \( n \) random points from the distribution.

This function returns sampled points whose shape is \( (n,) + \text{batch\_shape} + \text{event\_shape} \). When implementing sampling code in a subclass, it is recommended that you override this method.

Parameters \( n \) (int) – Sampling size.

Returns sampled random points.

Return type Variable

survival\_function \((x)\)
Evaluates the survival function at the given points.

Parameters \( x \) (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Survival function value evaluated at \( x \).

Return type Variable

__eq\__(value,/)  
Return self==value.

__ne\__(value,/)  
Return self!=value.
_lt__ (value, /)
    Return self<value.

_le__ (value, /)
    Return self<=value.

_gt__ (value, /)
    Return self>value.

_ge__ (value, /)
    Return self>=value.

Attributes

batch_shape

covariance
    Returns the covariance of the distribution.

    Returns  The covariance of the distribution.

    Return type  Variable

entropy

event_shape

high

loc

low

mean

mode
    Returns the mode of the distribution.

    Returns  The mode of the distribution.

    Return type  Variable

params

scale

stddev

support

variance

xp

    Array module for the distribution.

    Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.
### 4.4.2 Functionals of distribution

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.cross_entropy</code></td>
<td>Computes Cross entropy.</td>
</tr>
<tr>
<td><code>chainer.kl_divergence</code></td>
<td>Computes Kullback-Leibler divergence.</td>
</tr>
<tr>
<td><code>chainer.register_kl</code></td>
<td>Decorator to register KL divergence function.</td>
</tr>
</tbody>
</table>

#### chainer.cross_entropy

**Syntax**

```python
chainer.cross_entropy(dist1, dist2)
```

**Description**

Computes Cross entropy.

For two continuous distributions \( p(x) \), \( q(x) \), it is expressed as

\[
H(p, q) = - \int p(x) \log q(x) dx
\]

For two discrete distributions \( p(x) \), \( q(x) \), it is expressed as

\[
H(p, q) = - \sum_x p(x) \log q(x)
\]

This function call `kl_divergence()` and `entropy()` of \( \text{dist1} \). Therefore, it is necessary to register KL divergence function with `register_kl()` decoartor and define `entropy()` in \( \text{dist1} \).

**Parameters**

- **dist1 (Distribution)** – Distribution to calculate cross entropy \( p \). This is the first (left) operand of the cross entropy.
- **dist2 (Distribution)** – Distribution to calculate cross entropy \( q \). This is the second (right) operand of the cross entropy.

**Returns**

Output variable representing cross entropy \( H(p, q) \).

**Return type**

`Variable`

#### chainer.kl_divergence

**Syntax**

```python
chainer.kl_divergence(dist1, dist2)
```

**Description**

Computes Kullback-Leibler divergence.

For two continuous distributions \( p(x) \), \( q(x) \), it is expressed as

\[
D_{KL}(p||q) = \int p(x) \log \frac{p(x)}{q(x)} dx
\]

For two discrete distributions \( p(x) \), \( q(x) \), it is expressed as

\[
D_{KL}(p||q) = \sum_x p(x) \log \frac{p(x)}{q(x)}
\]

**Parameters**

- **dist1 (Distribution)** – Distribution to calculate KL divergence \( p \). This is the first (left) operand of the KL divergence.
- **dist2 (Distribution)** – Distribution to calculate KL divergence \( q \). This is the second (right) operand of the KL divergence.
Returns
Output variable representing kl divergence $D_{KL}(p||q)$.

Return type
Variable

Using `register_kl()`, we can define behavior of `kl_divergence()` for any two distributions.

chainer.register_kl

chainer.register_kl(Dist1, Dist2)

Decorator to register KL divergence function.

This decorator registers a function which computes Kullback-Leibler divergence. This function will be called by `kl_divergence()` based on the argument types.

Parameters

- `Dist1` (type) – type of a class inherit from `Distribution` to calculate KL divergence.
- `Dist2` (type) – type of a class inherit from `Distribution` to calculate KL divergence.

The decorated function takes an instance of `Dist1` and `Dist2` and returns KL divergence value.

Example

This is a simple example to register KL divergence. A function to calculate a KL divergence value between an instance of `Dist1` and an instance of `Dist2` is registered.

```python
from chainer import distributions
@distributions.register_kl(Dist1, Dist2)
def _kl_dist1_dist2(dist1, dist2):
    return KL
```

4.4.3 Base classes

chainer.Distribution

Interface of Distribution

class chainer.Distribution

Interface of Distribution

`Distribution` is a base class for dealing with probability distributions.

This class provides the following capabilities.

1. Sampling random points.
2. Evaluating a probability-related function at a given realization value. (e.g., probability density function, probability mass function)
3. Obtaining properties of distributions. (e.g., mean, variance)

Note that every method and property that computes them from `chainer.Variable` can basically be differentiated.

In this class, sampled random points and realization values given in probability-related function is called `sample`.

4.4. Probability Distributions
Sample consists of *batches*, and each batch consists of independent *events*. Each event consists of values, and each value in an event cannot be sampled independently in general. Each event in a batch is independent while it is not sampled from an identical distribution. And each batch in sample is sampled from an identical distribution.

Each part of the sample-batch-event hierarchy has its own shape, which is called *sample_shape*, *batch_shape*, and *event_shape*, respectively.

On initialization, it takes distribution-specific parameters as inputs. *batch_shape* and *event_shape* is decided by the shape of the parameter when generating an instance of a class.

**Example**

The following code is an example of sample-batch-event hierarchy on using *MultivariateNormal* distribution. This makes 2d normal distributions. *dist* consists of 12(*4 * 3*) independent 2d normal distributions. And on initialization, *batch_shape* and *event_shape* is decided.

```python
>>> import chainer
>>> import chainer.distributions as D
>>> import numpy as np

>>> d = 2
>>> shape = (4, 3)
>>> loc = np.random.normal(...
size=shape + (d,)).astype(np.float32)
>>> cov = np.random.normal(size=shape + (d, d)).astype(np.float32)
>>> cov = np.matmul(cov, np.rollaxis(cov, -1, -2))
>>> l = np.linalg.cholesky(cov)
>>> dist = D.MultivariateNormal(loc, scale_tril=l)

>>> dist.event_shape
(2,)
>>> dist.batch_shape
(4, 3)
>>> sample = dist.sample(sample_shape=(6, 5))
>>> sample.shape
(6, 5, 4, 3, 2)
```

Every probability-related function takes realization value whose shape is the concatenation of *sample_shape*, *batch_shape*, and *event_shape* and returns an evaluated value whose shape is the concatenation of *sample_shape*, and *batch_shape*.

**Methods**

**cdf**(x)

Evaluates the cumulative distribution function at the given points.

**Parameters** x (**Variable** or **N-dimensional array**) – Data points in the domain of the distribution

**Returns** Cumulative distribution function value evaluated at x.

**Return type** Variable

**icdf**(x)

Evaluates the inverse cumulative distribution function at the given points.

**Parameters** x (**Variable** or **N-dimensional array**) – Data points in the domain of the distribution

**Returns** Inverse cumulative distribution function value evaluated at x.
Return type: *Variable*

**log_cdf**(*x*)
Evaluates the log of cumulative distribution function at the given points.

**Parameters**

- *x* (*Variable or N-dimensional array*) – Data points in the domain of the distribution

**Returns**

Logarithm of cumulative distribution function value evaluated at *x*.

Return type: *Variable*

**log_prob**(*x*)
Evaluates the logarithm of probability at the given points.

**Parameters**

- *x* (*Variable or N-dimensional array*) – Data points in the domain of the distribution

**Returns**

Logarithm of probability evaluated at *x*.

Return type: *Variable*

**log_survival_function**(*x*)
Evaluates the logarithm of survival function at the given points.

**Parameters**

- *x* (*Variable or N-dimensional array*) – Data points in the domain of the distribution

**Returns**

Logarithm of survival function value evaluated at *x*.

Return type: *Variable*

**perplexity**(*x*)
Evaluates the perplexity function at the given points.

**Parameters**

- *x* (*Variable or N-dimensional array*) – Data points in the domain of the distribution

**Returns**

Perplexity function value evaluated at *x*.

Return type: *Variable*

**prob**(*x*)
Evaluates probability at the given points.

**Parameters**

- *x* (*Variable or N-dimensional array*) – Data points in the domain of the distribution

**Returns**

Probability evaluated at *x*.

Return type: *Variable*

**sample**(*sample_shape=*)
Samples random points from the distribution.

This function calls *sample_n* and reshapes a result of *sample_n* to *sample_shape + batch_shape + event_shape*. On implementing sampling code in an inherited distribution class, it is not recommended that you override this function. Instead of doing this, it is preferable to override *sample_n*.

**Parameters**

- *sample_shape* (*tuple of int*) – Sampling shape.

**Returns**

Sampled random points.

Return type: *Variable*
sample_n(n)
    Samples n random points from the distribution.
    
    This function returns sampled points whose shape is \((n,) + \text{batch\_shape} + \text{event\_shape}\). When implementing sampling code in a subclass, it is recommended that you override this method.

    Parameters
    
    \(n\) (int) – Sampling size.

    Returns
    sampled random points.

    Return type
    Variable

survival_function(x)
    Evaluates the survival function at the given points.

    Parameters
    
    \(x\) (Variable or N-dimensional array) – Data points in the domain of the distribution

    Returns
    Survival function value evaluated at \(x\).

    Return type
    Variable

__eq__(value, /)
    Return self==value.

__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

batch_shape
    Returns the shape of a batch.

    Returns
    The shape of a sample that is not identical and independent.

    Return type
    tuple

covariance
    Returns the covariance of the distribution.

    Returns
    The covariance of the distribution.

    Return type
    Variable

entropy
    Returns the entropy of the distribution.

    Returns
    The entropy of the distribution.

    Return type
    Variable

event_shape
    Returns the shape of an event.
Returns The shape of a sample that is not identical and independent.

Return type tuple

mean
Returns the mean of the distribution.

Returns The mean of the distribution.

Return type Variable

mode
Returns the mode of the distribution.

Returns The mode of the distribution.

Return type Variable

params
Returns the parameters of the distribution.

Returns The parameters of the distribution.

Return type dict

stddev
Returns the standard deviation of the distribution.

Returns The standard deviation of the distribution.

Return type Variable

support
Returns the support of the distribution.

Returns String that means support of this distribution.

Return type str

variance
Returns the variance of the distribution.

Returns The variance of the distribution.

Return type Variable

xp
Array module for the distribution.

Depending on which of CPU/GPU this distribution is on, this property returns numpy or cupy.

4.5 Optimizers

- `chainer.optimizers.AdaDelta` Zeiler’s ADADELTA.
- `chainer.optimizers.Adam` Adam optimizer.
- `chainer.optimizers.AdamW` AdamW optimizer.
- `chainer.optimizers.AMSGrad` AMSGrad optimizer.
- `chainer.optimizers.AMSBound` AMSBound optimizer.

continues on next page
Chainer Documentation, Release 7.7.0

Table 29 – continued from previous page

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.optimizers.CorrectedMomentumSGD</code></td>
<td>Momentum SGD optimizer.</td>
</tr>
<tr>
<td><code>chainer.optimizers.MomentumSGD</code></td>
<td>Momentum SGD optimizer.</td>
</tr>
<tr>
<td><code>chainer.optimizers.NesterovAG</code></td>
<td>Nesterov’s Accelerated Gradient.</td>
</tr>
<tr>
<td><code>chainer.optimizers.MSVAG</code></td>
<td>M-SVAG optimizer.</td>
</tr>
<tr>
<td><code>chainer.optimizers.RMSprop</code></td>
<td>RMSprop optimizer.</td>
</tr>
<tr>
<td><code>chainer.optimizers.RMSpropGraves</code></td>
<td>Alex Graves’s RMSprop.</td>
</tr>
<tr>
<td><code>chainer.optimizers.SGD</code></td>
<td>Vanilla Stochastic Gradient Descent.</td>
</tr>
<tr>
<td><code>chainer.optimizers.SMORMS3</code></td>
<td>Simon Funk’s SMORMS3.</td>
</tr>
</tbody>
</table>

4.5.1 `chainer.optimizers.AdaDelta`

```python
class chainer.optimizers.AdaDelta(rho=0.95, eps=1e-06)
Zeiler’s ADADELTA.

```

Parameters

- `rho (float)` – Exponential decay rate of the first and second order moments.
- `eps (float)` – Small value for the numerical stability.

Methods

- `add_hook (hook, name=None, timing='auto')`  
  Registers a hook function.

  Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

  Parameters

  - `hook (callable)` – Hook function. If `hook.call_for_each_param` is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.
  - `name (str)` – Name of the registration. If omitted, `hook.name` is used by default.
  - `timing (str)` – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

- `call_hook (hook)`

- `call_hooks (timing='pre')`  
  Invokes hook functions in registration order.

- `check_nan_in_grads ()`  
  Checks if there is NaN in grads when dynamic loss scaling used.

- `create_update_rule ()`  
  Creates a new update rule object.

  This method creates an update rule object. It is called by `setup()` to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.
Returns Update rule object.

Return type UpdateRule

`is_safe_to_update()`

`loss_scaling(interval=1000, scale=None)`

Configures the loss scaling algorithm.

Parameters

- **interval** (int) – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.

- **scale** (float) – Loss scaling factor. If None, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

`new_epoch(auto=False)`

Starts a new epoch.

This method increments the epoch count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

Parameters **auto** (bool) – Should be True if this method is called by an updater. In this case, `use_auto_new_epoch` should be set to True by the updater.

`reallocate_cleared_grads()`

Reallocate gradients cleared by `cleargrad()`.

This method allocates arrays for all gradients which have None. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

`remove_hook(name)`

Removes a hook function.

Parameters **name** (str) – Registered name of the hook function to remove.

`serialize(serializer)`

Serializes or deserializes the optimizer.

It only saves or loads the following things:

- Optimizer states
- Global states (t and epoch)

It does not save nor loads the parameters of the target link. They should be separately saved or loaded.

Parameters **serializer** (AbstractSerializer) – Serializer or deserializer object.

`set_loss_scale(loss_scale)`

Sets loss scaling factor.

`setup(link)`

Sets a target link and initializes the optimizer states.

Given link is set to the target attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

Parameters **link** (Link) – Target link object.

Returns The optimizer instance.
**Note:** As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., `optimizer = SomeOptimizer().setup(link).

```python
update(lossfun=None, *args, **kwds)
```
Updates parameters based on a loss function or computed gradients. This method runs in two ways.
- If `lossfun` is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

```python
update_loss_scale()
```

```python
use_cleargrads(use=True)
```
Enables or disables use of `cleargrads()` in `update`.

**Parameters**

- `use` (bool) – If `True`, this function enables use of `cleargrads`. If `False`, disables use of `cleargrads` (zerograds is used).

Depreciated since version v2.0: Note that `update()` calls `cleargrads()` by default. `cleargrads()` is more efficient than `zerograds()`, so one does not have to call `use_cleargrads()`. This method remains for backward compatibility.

```python
use_fp32_update(flag=True)
```
Enables use of parameter update in fp32.

```python
__eq__(value, /)
```
Return `self==value`.

```python
__ne__(value, /)
```
Return `self!=value`.

```python
__lt__(value, /)
```
Return `self<value`.

```python
__le__(value, /)
```
Return `self<=value`.

```python
__gt__(value, /)
```
Return `self>value`.

```python
__ge__(value, /)
```
Return `self>=value`.

**Attributes**

- `epoch = 0`
- `eps`
  - Alias to `self.hyperparam.eps`
- `rho`
  - Alias to `self.hyperparam.rho`
- `t = 0`
- `target = None`
use_auto_new_epoch = False

4.5.2 chainer.optimizers.AdaGrad

class chainer.optimizers.AdaGrad(lr=0.001, eps=1e-08)
AdaGrad optimizer.
See: http://jmlr.org/papers/v12/duchi11a.html

Parameters
• lr (float) – Learning rate.
• eps (float) – Small value for the numerical stability.

Methods

add_hook (hook, name=None, timing='auto')
Registers a hook function.
Hook function is typically called right after the gradient computation, though the timing depends on the
optimization method, and the timing attribute.

Parameters
• hook (callable) – Hook function. If hook.call_for_each_param is true, this
hook function is called for each parameter by passing the update rule and the parameter.
Otherwise, this hook function is called only once each iteration by passing the optimizer.
• name (str) – Name of the registration. If omitted, hook.name is used by default.
• timing (str) – Specifies when the hook is called. If ‘auto’, the timing property of the
hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’,
the hook will be called after any updates.

call_hook (hook)

call_hooks (timing='pre')
Invokes hook functions in registration order.

check_nan_in_grads ()
Checks if there is NaN in grads when dynamic loss scaling used.

create_update_rule ()
Creates a new update rule object.
This method creates an update rule object. It is called by setup() to set up an update rule of each
parameter. Each implementation of the gradient method should override this method to provide the default
update rule implementation.

Returns Update rule object.

Return type UpdateRule

is_safe_to_update ()

loss_scaling (interval=1000, scale=None)
Configures the loss scaling algorithm.

Parameters

4.5. Optimizers
- **interval** *(int)* – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.
- **scale** *(float)* – Loss scaling factor. If None, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

`new_epoch` *(auto=False)*

Starts a new epoch.

This method increments the *epoch* count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

**Parameters**
- **auto** *(bool)* – Should be True if this method is called by an updater. In this case, `use_auto_new_epoch` should be set to True by the updater.

`reallocate_cleared_grads`()

Reallocate gradients cleared by `cleargrad()`.

This method allocates arrays for all gradients which have None. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

`remove_hook` *(name)*

Removes a hook function.

**Parameters**
- **name** *(str)* – Registered name of the hook function to remove.

`serialize` *(serializer)*

Serializes or deserializes the optimizer.

It only saves or loads the following things:
- Optimizer states
- Global states (*t* and *epoch*)

**It does not saves nor loads the parameters of the target link.** They should be separately saved or loaded.

**Parameters**
- **serializer** *(AbstractSerializer)* – Serializer or deserializer object.

`set_loss_scale` *(loss_scale)*

Sets loss scaling factor.

`setup` *(link)*

Sets a target link and initializes the optimizer states.

Given link is set to the *target* attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

**Parameters**
- **link** *(Link)* – Target link object.

**Returns** The optimizer instance.

**Note:** As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., `optimizer = SomeOptimizer().setup(link)`.

`update` *(lossfun=None, *args, **kwds)*

Updates parameters based on a loss function or computed gradients.

This method runs in two ways.
- If `lossfun` is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.
In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

**update_loss_scale()**

**use_cleargrads**(use=True)  
Enables or disables use of cleargrads() in update.

**Parameters** use (bool) – If True, this function enables use of cleargrads. If False, disables use of cleargrads (zerograd is used).

Deprecated since version v2.0: Note that update() calls cleargrads() by default. cleargrads() is more efficient than zerograd, so one does not have to call use_cleargrads(). This method remains for backward compatibility.

**use_fp32_update**(flag=True)  
Enables use of parameter update in fp32.

**Attributes**

epoch = 0  
eps  
Alias to self.hyperparam.eps  

lr  
Alias to self.hyperparam.lr  
t = 0  
target = None  
use_auto_new_epoch = False
Adam optimizer.

See: Adam: A Method for Stochastic Optimization

Modified for proper weight decay (also called AdamW). AdamW introduces the additional parameters eta and weight_decay_rate, which can be used to properly scale the learning rate, and decouple the weight decay rate from alpha, as shown in the below paper.

Note that with the default values eta = 1 and weight_decay_rate = 0, this implementation is identical to the standard Adam method.

See: Fixing Weight Decay Regularization in Adam

A flag amsgrad to use the AMSGrad variant of Adam from the paper: On the Convergence of Adam and Beyond

A flag adabound to use the AdaBound variant of Adam from the paper: Adaptive Gradient Methods with Dynamic Bound of Learning Rate

If both amsgrad and adabound are True, the optimizer is equivalent to AMSBound proposed in the AdaBound paper.

Parameters

- **alpha (float)** – Coefficient of learning rate.
- **beta1 (float)** – Exponential decay rate of the first order moment.
- **beta2 (float)** – Exponential decay rate of the second order moment.
- **eps (float)** – Small value for the numerical stability.
- **eta (float)** – Schedule multiplier, can be used for warm restarts.
- **weight_decay_rate (float)** – Weight decay rate.
- **amsgrad (bool)** – Whether to use AMSGrad variant of Adam.
- **adabound (bool)** – Whether to use the AdaBound variant of Adam.
- **final_lr (float)** – Final (SGD) learning rate in AdaBound.
- **gamma (float)** – Convergence speed of the bound functions in AdaBound.

Methods

**add_hook (hook, name=None, timing=’auto’)**

Registers a hook function.

Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

Parameters

- **hook (callable)** – Hook function. If hook.call_for_each_param is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.
- **name (str)** – Name of the registration. If omitted, hook.name is used by default.
• **timing** *(str)* – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

```python
call_hook(hook)
```

```python
call_hooks(timing='pre')
```

Invokes hook functions in registration order.

```python
check_nan_in_grads()
```

Checks if there is NaN in grads when dynamic loss scaling used.

```python
create_update_rule()
```

Creates a new update rule object.

This method creates an update rule object. It is called by `setup()` to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

**Returns** Update rule object.

**Return type** *UpdateRule*

```python
is_safe_to_update()
```

```python
loss_scaling(interval=1000, scale=None)
```

Configures the loss scaling algorithm.

**Parameters**

- *interval* *(int)* – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.
- *scale* *(float)* – Loss scaling factor. If `None`, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

```python
new_epoch(auto=False)
```

Starts a new epoch.

This method increments the `epoch` count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

**Parameters** *auto* *(bool)* – Should be `True` if this method is called by an updater. In this case, `use_auto_new_epoch` should be set to `True` by the updater.

```python
reallocate_cleared_grads()
```

Reallocate gradients cleared by `cleargrad()`.

This method allocates arrays for all gradients which have `None`. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

```python
remove_hook(name)
```

Removes a hook function.

**Parameters** *name* *(str)* – Registered name of the hook function to remove.

```python
serialize(serializer)
```

Serializes or deserializes the optimizer.

It only saves or loads the following things:

- Optimizer states
- Global states (`t` and `epoch`)
It does not saves nor loads the parameters of the target link. They should be separately saved or loaded.

**Parameters**

- **serializer** (*AbstractSerializer*) – Serializer or deserializer object.

**set_loss_scale** (*loss_scale*)

Sets loss scaling factor.

**setup** (*link*)

Sets a target link and initializes the optimizer states.

- Given link is set to the `target` attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

**Parameters**

- **link** (*Link*) – Target link object.

**Returns**

The optimizer instance.

---

**Note:** As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., `optimizer = SomeOptimizer().setup(link)`.

**update** (*lossfun=None, *args, **kwds*)

Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

- If `lossfun` is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

**update_loss_scale**()

**use_cleargrads** (*use=True*)

 Enables or disables use of `cleargrads()` in `update`.

**Parameters**

- **use** (*bool*) – If True, this function enables use of cleargrads. If False, disables use of cleargrads (zerograds is used).

  Deprecated since version v2.0: Note that `update()` calls `cleargrads()` by default. `cleargrads()` is more efficient than `zerograds()`, so one does not have to call `use_cleargrads()`. This method remains for backward compatibility.

**use_fp32_update** (*flag=True*)

 Enables use of parameter update in fp32.

---

**__eq__** (*value, /)

Return self==value.

**__ne__** (*value, /)

Return self!=value.

**__lt__** (*value, /)

Return self<value.

**__le__** (*value, /)

Return self<=value.

**__gt__** (*value, /)

Return self>value.

**__ge__** (*value, /)

Return self>=value.
__ge__(value, /)  
    Return self>=value.

Attributes

adabound  
    Alias to self.hyperparam.adabound
alpha  
    Alias to self.hyperparam.alpha
alpha_t  
amsgrad  
    Alias to self.hyperparam.amsgrad
beta1  
    Alias to self.hyperparam.beta1
beta2  
    Alias to self.hyperparam.beta2
epoch = 0
eps  
    Alias to self.hyperparam.eps
eta  
    Alias to self.hyperparam.eta
final_lr  
    Alias to self.hyperparam.final_lr
gamma  
    Alias to self.hyperparam.gamma
lr  
    t = 0
    target = None
use_auto_new_epoch = False
weight_decay_rate  
    Alias to self.hyperparam.weight_decay_rate

4.5.4 chainer.optimizers.AdamW

class chainer.optimizers.AdamW(alpha=0.001, beta1=0.9, beta2=0.999, eps=1e-08, eta=1.0,  
    weight_decay_rate=0)

AdamW optimizer.
This class is a special case of Adam.
See: Fixing Weight Decay Regularization in Adam

Parameters

• alpha (float) – Coefficient of learning rate.
• beta1 (float) – Exponential decay rate of the first order moment.
• **beta2** (*float*) – Exponential decay rate of the second order moment.

• **eps** (*float*) – Small value for the numerical stability.

• **eta** (*float*) – Schedule multiplier, can be used for warm restarts. The default value is 1.0.

• **weight_decay_rate** (*float*) – Weight decay rate. The default value is 0.

### Methods

**add_hook** *(hook, name=None, timing='auto')*

Registers a hook function.

Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

**Parameters**

- **hook** (*callable*) – Hook function. If `hook.call_for_each_param` is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.

- **name** (*str*) – Name of the registration. If omitted, `hook.name` is used by default.

- **timing** (*str*) – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

**call_hook** *(hook)*

**call_hooks** *(timing='pre')*

Invokes hook functions in registration order.

**check_nan_in_grads** ()

Checks if there is NaN in grads when dynamic loss scaling used.

**create_update_rule** ()

Creates a new update rule object.

This method creates an update rule object. It is called by `setup()` to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

**Returns**

Update rule object.

**Return type** `UpdateRule`

**is_safe_to_update** ()

**loss_scaling** *(interval=1000, scale=None)*

Configures the loss scaling algorithm.

**Parameters**

- **interval** (*int*) – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.

- **scale** (*float*) – Loss scaling factor. If `None`, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

**new_epoch** *(auto=False)*

Starts a new epoch.
This method increments the `epoch` count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

**Parameters**

`auto` *(bool)* – Should be `True` if this method is called by an updater. In this case, `use_auto_new_epoch` should be set to `True` by the updater.

`reallocate_cleared_grads()`  
Reallocate gradients cleared by `cleargrad()`.

This method allocates arrays for all gradients which have `None`. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

`remove_hook(name)`  
Removes a hook function.

**Parameters**

`name` *(str)* – Registered name of the hook function to remove.

`serialize(serializer)`  
Serializes or deserializes the optimizer.

It only saves or loads the following things:

- Optimizer states
- Global states (`t` and `epoch`)  

**It does not save nor loads the parameters of the target link.** They should be separately saved or loaded.

**Parameters**

`serializer` *(AbstractSerializer)* – Serializer or deserializer object.

`set_loss_scale(loss_scale)`  
Sets loss scaling factor.

`setup(link)`  
Sets a target link and initializes the optimizer states.

Given link is set to the `target` attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

**Parameters**

`link` *(Link)* – Target link object.

**Returns** The optimizer instance.

**Note:** As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., `optimizer = SomeOptimizer().setup(link)`.

`update(lossfun=None, *args, **kwds)`  
Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

- If `lossfun` is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

`update_loss_scale()`  

`use_cleargrads(use=True)`  
Enables or disables use of `cleargrads()` in `update`.
Parameters `use (bool)` – If `True`, this function enables use of `cleargrads`. If `False`, disables use of `cleargrads` (`zerograds` is used).

Deprecated since version v2.0: Note that `update()` calls `cleargrads()` by default. `cleargrads()` is more efficient than `zerograds()`, so one does not have to call `use_cleargrads()`. This method remains for backward compatibility.

`use_fp32_update (flag=True)`

Enables use of parameter update in fp32.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.

Attributes

`adabound`
Alias to `self.hyperparam.adabound`

`alpha`
Alias to `self.hyperparam.alpha`

`alpha_t`

`amsgrad`
Alias to `self.hyperparam.amsgrad`

`betal`
Alias to `self.hyperparam.betal`

`beta2`
Alias to `self.hyperparam.beta2`

`epoch = 0`

`eps`
Alias to `self.hyperparam.eps`

`eta`
Alias to `self.hyperparam.eta`

`final_lr`
Alias to `self.hyperparam.final_lr`

`gamma`
Alias to `self.hyperparam.gamma`

`lr`
t = 0
target = None
use_auto_new_epoch = False
weight_decay_rate
   Alias to self.hyperparam.weight_decay_rate

4.5.5 chainer.optimizers.AMSGrad

class chainer.optimizers.AMSGrad(alpha=0.001, beta1=0.9, beta2=0.999, eps=1e-08, eta=1.0)
   AMSGrad optimizer.
   This class is a special case of Adam.
   See: On the Convergence of Adam and Beyond

   Parameters
      • alpha (float) – Coefficient of learning rate.
      • beta1 (float) – Exponential decay rate of the first order moment.
      • beta2 (float) – Exponential decay rate of the second order moment.
      • eps (float) – Small value for the numerical stability.
      • eta (float) – Schedule multiplier, can be used for warm restarts.

   Methods

      add_hook (hook, name=None, timing='auto')
      Registers a hook function.

      call_hook (hook)

      call_hooks (timing='pre')
      Invokes hook functions in registration order.

      check_nan_in_grads ()
      Checks if there is NaN in grads when dynamic loss scaling used.

      create_update_rule ()
      Creates a new update rule object.
This method creates an update rule object. It is called by `setup()` to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

**Returns** Update rule object.

**Return type** `UpdateRule`

**is_safe_to_update()**

**loss_scaling(interval=1000, scale=None)**

Configures the loss scaling algorithm.

**Parameters**

- `interval (int)` – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.
- `scale (float)` – Loss scaling factor. If `None`, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

**new_epoch(auto=False)**

Starts a new epoch.

This method increments the `epoch` count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

**Parameters**

- `auto (bool)` – Should be `True` if this method is called by an updaters. In this case, `use_auto_new_epoch` should be set to `True` by the updaters.

**reallocate_cleared_grads()**

Reallocate gradients cleared by `cleargrad()`.

This method allocates arrays for all gradients which have `None`. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

**remove_hook(name)**

Removes a hook function.

**Parameters**

- `name (str)` – Registered name of the hook function to remove.

**serialize(serializer)**

Serializes or deserializes the optimizer.

It only saves or loads the following things:

- Optimizer states
- Global states (`t` and `epoch`)

It does not saves nor loads the parameters of the target link. They should be separately saved or loaded.

**Parameters**

- `serializer (AbstractSerializer)` – Serializer or deserializer object.

**set_loss_scale(loss_scale)**

Sets loss scaling factor.

**setup(link)**

Sets a target link and initializes the optimizer states.

Given link is set to the `target` attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

**Parameters**

- `link (Link)` – Target link object.
Returns The optimizer instance.

Note: As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., `optimizer = SomeOptimizer().setup(link)`.

**update** *(lossfun=None, *args, **kwds)*

Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

- If `lossfun` is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

**update_loss_scale()**

**use_cleargrads**(use=True)

Enables or disables use of `cleargrads()` in `update`.

Parameters use (bool) – If True, this function enables use of `cleargrads`. If False, disables use of `cleargrads` (zerograds is used).

Deprecated since version v2.0: Note that `update()` calls `cleargrads()` by default. `cleargrads()` is more efficient than `zerograds()`, so one does not have to call `use_cleargrads()`. This method remains for backward compatibility.

**use_fp32_update**(flag=True)

Enables use of parameter update in fp32.

___eq__**(value, /)**

Return self==value.

___ne__**(value, /)**

Return self!=value.

___lt__**(value, /)**

Return self<value.

___le__**(value, /)**

Return self<=value.

___gt__**(value, /)**

Return self>value.

___ge__**(value, /)**

Return self>=value.
Attributes

- **adabound**
  Alias to `self.hyperparam.adabound`

- **alpha**
  Alias to `self.hyperparam.alpha`

- **alpha_t**

- **amsgrad**
  Alias to `self.hyperparam.amsgrad`

- **beta1**
  Alias to `self.hyperparam.beta1`

- **beta2**
  Alias to `self.hyperparam.beta2`

- **epoch = 0**

- **eps**
  Alias to `self.hyperparam.eps`

- **eta**
  Alias to `self.hyperparam.eta`

- **final_lr**
  Alias to `self.hyperparam.final_lr`

- **gamma**
  Alias to `self.hyperparam.gamma`

- **lr**

- **t = 0**

- **target = None**

- **use_auto_new_epoch = False**

- **weight_decay_rate**
  Alias to `self.hyperparam.weight_decay_rate`

### 4.5.6 chainer.optimizers.AdaBound

class chainer.optimizers.AdaBound(alpha=0.001, beta1=0.9, beta2=0.999, final_lr=0.1, gamma=0.001, eps=1e-08, eta=1.0)

AdaBound optimizer.

This class is a special case of Adam.

See: Adaptive Gradient Methods with Dynamic Bound of Learning Rate

Parameters

- **alpha** *(float)* – Coefficient of learning rate.
- **beta1** *(float)* – Exponential decay rate of the first order moment.
- **beta2** *(float)* – Exponential decay rate of the second order moment.
- **final_lr** *(float)* – Final (SGD) learning rate in AdaBound.
- **gamma** *(float)* – Convergence speed of the bound functions in AdaBound.
• \texttt{eps (float)} – Small value for the numerical stability.
• \texttt{eta (float)} – Schedule multiplier, can be used for warm restarts.

**Methods**

\texttt{add\_hook} \((\texttt{hook, name=None, timing='auto'})\)

Registers a hook function.

Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

**Parameters**

• \texttt{hook (callable)} – Hook function. If \texttt{hook.call\_for\_each\_param} is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.

• \texttt{name (str)} – Name of the registration. If omitted, \texttt{hook.name} is used by default.

• \texttt{timing (str)} – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

\texttt{call\_hook} \((\texttt{hook})\)

\texttt{call\_hooks} \((\texttt{timing='pre'})\)

Invokes hook functions in registration order.

\texttt{check\_nan\_in\_grads}()

Checks if there is NaN in grads when dynamic loss scaling used.

\texttt{create\_update\_rule}()

Creates a new update rule object.

This method creates an update rule object. It is called by \texttt{setup()} to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

**Returns** Update rule object.

**Return type** \texttt{UpdateRule}

\texttt{is\_safe\_to\_update}()

\texttt{loss\_scaling} \((\texttt{interval=1000, scale=None})\)

Configures the loss scaling.

**Parameters**

• \texttt{interval (int)} – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.

• \texttt{scale (float)} – Loss scaling factor. If \texttt{None}, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

\texttt{new\_epoch} \((\texttt{auto=False})\)

Starts a new epoch.

This method increments the \texttt{epoch} count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

**Parameters** \texttt{auto (bool)} – Should be \texttt{True} if this method is called by an updater. In this case, \texttt{use\_auto\_new\_epoch} should be set to \texttt{True} by the updater.
**reallocate_cleared_grads()**
Reallocate gradients cleared by `cleargrad()`.

This method allocates arrays for all gradients which have `None`. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

**remove_hook(name)**
Removes a hook function.

Parameters **name** *(str)* – Registered name of the hook function to remove.

**serialize(serializer)**
Serializes or deserializes the optimizer.

It only saves or loads the following things:

- Optimizer states
- Global states *(t and epoch)*

It does not save nor loads the parameters of the target link. They should be separately saved or loaded.

Parameters **serializer** *(AbstractSerializer)* – Serializer or deserializer object.

**set_loss_scale(loss_scale)**
Sets loss scaling factor.

**setup(link)**
Sets a target link and initializes the optimizer states.

Given link is set to the `target` attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

Parameters **link** *(Link)* – Target link object.

Returns The optimizer instance.

**Note:** As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., `optimizer = SomeOptimizer().setup(link)`.

**update(lossfun=None, *args, **kwds)**
Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

- If `lossfun` is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

**update_loss_scale()**

**use_cleargrads(use=True)**
Enables or disables use of `cleargrads()` in `update`.

Parameters **use** *(bool)* – If True, this function enables use of `cleargrads`. If False, disables use of `cleargrads` *(zerograds is used)*.

Deprecated since version v2.0: Note that `update()` calls `cleargrads()` by default. `cleargrads()` is more efficient than `zerograds()`, so one does not have to call `use_cleargrads()`. This method remains for backward compatibility.
use_fp32_update (flag=True)
   Enables use of parameter update in fp32.

__eq__(value, /)
   Return self==value.

__ne__(value, /)
   Return self!=value.

__lt__(value, /)
   Return self<value.

__le__(value, /)
   Return self<=value.

__gt__(value, /)
   Return self>value.

__ge__(value, /)
   Return self>=value.

Attributes

adabound
   Alias to self.hyperparam.adabound

alpha
   Alias to self.hyperparam.alpha

alpha_t

amsgrad
   Alias to self.hyperparam.amsgrad

beta1
   Alias to self.hyperparam.beta1

beta2
   Alias to self.hyperparam.beta2

epoch = 0

eps
   Alias to self.hyperparam.eps

eta
   Alias to self.hyperparam.eta

final_lr
   Alias to self.hyperparam.final_lr

gamma
   Alias to self.hyperparam.gamma

lr

t = 0

target = None

use_auto_new_epoch = False

weight_decay_rate
   Alias to self.hyperparam.weight_decay_rate

4.5. Optimizers
4.5.7 chainer.optimizers.AMSBound

class chainer.optimizers.AMSBound(alpha=0.001, beta1=0.9, beta2=0.999, final_lr=0.1, gamma=0.001, eps=1e-08, eta=1.0)

AMSBound optimizer.

This class is a special case of Adam.

See: Adaptive Gradient Methods with Dynamic Bound of Learning Rate

Parameters

• alpha (float) – Coefficient of learning rate.
• beta1 (float) – Exponential decay rate of the first order moment.
• beta2 (float) – Exponential decay rate of the second order moment.
• final_lr (float) – Final (SGD) learning rate in AdaBound.
• gamma (float) – Convergence speed of the bound functions in AdaBound.
• eps (float) – Small value for the numerical stability.
• eta (float) – Schedule multiplier, can be used for warm restarts.

Methods

add_hook (hook, name=None, timing='auto')

Registers a hook function.

Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

Parameters

• hook (callable) – Hook function. If hook.call_for_each_param is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.
• name (str) – Name of the registration. If omitted, hook.name is used by default.
• timing (str) – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

call_hook (hook)

call_hooks (timing='pre')

Invokes hook functions in registration order.

check_nan_in_grads ()

Checks if there is NaN in grads when dynamic loss scaling used.

create_update_rule ()

Creates a new update rule object.

This method creates an update rule object. It is called by setup() to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

Returns Update rule object.

Return type UpdateRule
is_safe_to_update()

loss_scaling(interval=1000, scale=None)
Configures the loss scaling algorithm.

Parameters

• interval (int) – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.

• scale (float) – Loss scaling factor. If None, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

new_epoch(auto=False)
Starts a new epoch.

This method increments the epoch count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

Parameters auto (bool) – Should be True if this method is called by an updater. In this case, use_auto_new_epoch should be set to True by the updater.

reallocate_cleared_grads()
Reallocate gradients cleared by cleargrad().

This method allocates arrays for all gradients which have None. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

remove_hook(name)
Removes a hook function.

Parameters name (str) – Registered name of the hook function to remove.

serialize(serializer)
Serializes or deserializes the optimizer.

It only saves or loads the following things:

• Optimizer states

• Global states (t and epoch)

It does not saves nor loads the parameters of the target link. They should be separately saved or loaded.

Parameters serializer (AbstractSerializer) – Serializer or deserializer object.

set_loss_scale(loss_scale)
Sets loss scaling factor.

setup(link)
Sets a target link and initializes the optimizer states.

Given link is set to the target attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

Parameters link (Link) – Target link object.

Returns The optimizer instance.

Note: As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., optimizer = SomeOptimizer().setup(link).
**update**(lossfun=None, *args, **kwds)

Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

- If `lossfun` is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

**update_loss_scale()**

**use_cleargrads**(use=True)

Enables or disables use of `cleargrads()` in `update`.

**Parameters**

- **use**(bool) – If True, this function enables use of `cleargrads`. If False, disables use of `cleargrads` (zerograds is used).

Deprecated since version v2.0: Note that `update()` calls `cleargrads()` by default. `cleargrads()` is more efficient than `zerograds()`, so one does not have to call `use_cleargrads()`. This method remains for backward compatibility.

**use_fp32_update**(flag=True)

Enables use of parameter update in fp32.

**Attributes**

- **adabound**
  
  Alias to `self.hyperparam.adabound`

- **alpha**
  
  Alias to `self.hyperparam.alpha`

- **alpha_t**

- **amsgrad**
  
  Alias to `self.hyperparam.amsgrad`

- **betal**
  
  Alias to `self.hyperparam.betal`

- **beta2**
  
  Alias to `self.hyperparam.beta2`
epoch = 0
eps
    Alias to self.hyperparam.eps
etta
    Alias to self.hyperparam.eta
final_lr
    Alias to self.hyperparam.final_lr
gamma
    Alias to self.hyperparam.gamma
lr
t = 0
target = None
use_auto_new_epoch = False
weight_decay_rate
    Alias to self.hyperparam.weight_decay_rate

4.5.8 chainer.optimizers.CorrectedMomentumSGD

class chainer.optimizers.CorrectedMomentumSGD (lr=0.01, momentum=0.9)
Momentum SGD optimizer.

This implements momentum correction discussed in the third section of Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour.

MomentumSGD implements the equation (10) of the paper. This optimizer implements the equation (9).

To get better understanding between the two methods, we show the equivalence between the equation (9) and modification of the equation (10) that takes momentum correction into account. First, we set $v_t = \eta_t u_t$. We substitute this relation to the equation (10).

\[
\begin{align*}
v_{t+1} &= m \frac{\eta_{t+1}}{\eta_t} v_t + \eta_{t+1} g_t \\
      &= m \frac{\eta_{t+1}}{\eta_t} \eta_t u_t + \eta_{t+1} g_t \\
      &= \eta_{t+1} (mu_t + g_t)
\end{align*}
\]

From this result, we derive $u_{t+1} = mu_t + g_t$, which is how update tensors are calculated by CorrectedMomentumSGD. Thus, the equivalence is shown.

Parameters

- **lr** (*float*) – Learning rate.
- **momentum** (*float*) – Exponential decay rate of the first order moment.
Methods

add_hook (hook, name=None, timing='auto')
Registers a hook function.

Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

Parameters

• **hook** (callable) – Hook function. If hook.call_for_each_param is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.

• **name** (str) – Name of the registration. If omitted, hook.name is used by default.

• **timing** (str) – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

call_hook (hook)
call_hooks (timing='pre')
Invokes hook functions in registration order.

check_nan_in_grads ()
Checks if there is NaN in grads when dynamic loss scaling used.

create_update_rule ()
Creates a new update rule object.

This method creates an update rule object. It is called by setup() to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

Returns  Update rule object.

Return type  UpdateRule

is_safe_to_update ()

loss_scaling (interval=1000, scale=None)
Configures the loss scaling algorithm.

Parameters

• **interval** (int) – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.

• **scale** (float) – Loss scaling factor. If None, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

new_epoch (auto=False)
Starts a new epoch.

This method increments the epoch count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

Parameters  **auto** (bool) – Should be True if this method is called by an updater. In this case, use_auto_new_epoch should be set to True by the updater.

reallocate_cleared_grads ()
Reallocate gradients cleared by cleargrad().
This method allocates arrays for all gradients which have None. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

```python
remove_hook(name)
```
Removes a hook function.

**Parameters**

name (str) – Registered name of the hook function to remove.

```python
serialize(serializer)
```
Serializes or deserializes the optimizer.

It only saves or loads the following things:

- Optimizer states
- Global states (t and epoch)

It does not saves nor loads the parameters of the target link. They should be separately saved or loaded.

**Parameters**

serializer (AbstractSerializer) – Serializer or deserializer object.

```python
set_loss_scale(loss_scale)
```
Sets loss scaling factor.

```python
setup(link)
```
Sets a target link and initializes the optimizer states.

Given link is set to the target attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

**Parameters**

link (Link) – Target link object.

**Returns**

The optimizer instance.

**Note:** As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., optimizer = SomeOptimizer().setup(link).

```python
update(lossfun=None, *args, **kwds)
```
Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

- If lossfun is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

```python
update_loss_scale()
```

```python
use_cleargrads(use=True)
```
Enables or disables use of cleargrads() in update.

**Parameters**

use (bool) – If True, this function enables use of cleargrads. If False, disables use of cleargrads (zerograd is used).

Deprecated since version v2.0: Note that update() calls cleargrads() by default. cleargrads() is more efficient than zerograd(), so one does not have to call use_cleargrads(). This method remains for backward compatibility.

```python
use_fp32_update(flag=True)
```
Enables use of parameter update in fp32.
__eq__(value,/)  
Return \textit{self}==value.

__ne__(value,/)  
Return \textit{self]!=value.

__lt__(value,/)  
Return \textit{self}<value.

__le__(value,/)  
Return \textit{self}<=value.

__gt__(value,/)  
Return \textit{self}>value.

__ge__(value,/)  
Return \textit{self}>=value.

\textbf{Attributes}

\texttt{epoch = 0}

\texttt{lr}
\hspace{1em}Alias to \texttt{self.hyperparam.lr}

\texttt{momentum}
\hspace{1em}Alias to \texttt{self.hyperparam.momentum}

\texttt{t = 0}

\texttt{target = None}

\texttt{use\_auto\_new\_epoch = False}

\textbf{4.5.9 \texttt{chainer.optimizers.MomentumSGD}}

class \texttt{chainer.optimizers.MomentumSGD}(lr=0.01, momentum=0.9)

Momentum SGD optimizer.

\textbf{Parameters}

\begin{itemize}
\item \texttt{lr (float)} – Learning rate.
\item \texttt{momentum (float)} – Exponential decay rate of the first order moment.
\end{itemize}

\textbf{Methods}

\texttt{add\_hook(hook, name=None, timing='auto')}

Registers a hook function.

Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

\textbf{Parameters}

\begin{itemize}
\item \texttt{hook (callable)} – Hook function. If \texttt{hook.call\_for\_each\_param} is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.
\item \texttt{name (str)} – Name of the registration. If omitted, \texttt{hook.name} is used by default.
\end{itemize}
- **`timing (str)`** – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

```python
call_hook(hook)
call_hooks(timing='pre')
```
Invokes hook functions in registration order.

```python
check_nan_in_grads()
```
Checks if there is NaN in grads when dynamic loss scaling used.

```python
create_update_rule()
```
Creates a new update rule object.

This method creates an update rule object. It is called by `setup()` to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

- **Returns** Update rule object.
- **Return type** `UpdateRule`

```python
is_safe_to_update()
```

```python
loss_scaling(interval=1000, scale=None)
```
Configures the loss scaling algorithm.

- **Parameters**
  - **interval (int)** – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.
  - **scale (float)** – Loss scaling factor. If None, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

```python
new_epoch(auto=False)
```
Starts a new epoch.

This method increments the `epoch` count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

- **Parameters**
  - **auto (bool)** – Should be True if this method is called by an updater. In this case, `use_auto_new_epoch` should be set to True by the updater.

```python
reallocate_cleared_grads()
```
Reallocate gradients cleared by `cleargrad()`.

This method allocates arrays for all gradients which have None. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

```python
remove_hook(name)
```
Removes a hook function.

- **Parameters**
  - **name (str)** – Registered name of the hook function to remove.

```python
serialize(serializer)
```
Serializes or deserializes the optimizer.

It only saves or loads the following things:

- Optimizer states
- Global states (`t` and `epoch`)
It does not saves nor loads the parameters of the target link. They should be separately saved or loaded.

Parameters **serializer** ([AbstractSerializer](#)) – Serializer or deserializer object.

**set_loss_scale** (*loss_scale*)
Sets loss scaling factor.

**setup** (*link*)
Sets a target link and initializes the optimizer states.

Given link is set to the `target` attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

Parameters **link** ([Link](#)) – Target link object.

Returns The optimizer instance.

Note: As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., `optimizer = SomeOptimizer().setup(link)`.

**update** (*lossfun=None, *args, **kwds*)
Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

- If `lossfun` is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

**update_loss_scale** ()

**use_cleargrads** (*use=True*)
Enables or disables use of `cleargrads` in `update`.

Parameters **use** (bool) – If True, this function enables use of `cleargrads`. If False, disables use of `cleargrads` (zerograds is used).

Deprecated since version v2.0: Note that `update()` calls `cleargrads()` by default. `cleargrads()` is more efficient than `zerograds()`, so one does not have to call `use_cleargrads()`. This method remains for backward compatibility.

**use_fp32_update** (*flag=True*)
Enables use of parameter update in fp32.

`__eq__` (*value, /)
Return self==value.

`__ne__` (*value, /)
Return self!=value.

`__lt__` (*value, /)
Return self<value.

`__le__` (*value, /)
Return self<=value.

`__gt__` (*value, /)
Return self>value.

`__ge__` (*value, /)
Return self>=value.
__ge__(value, /)
    Return self>=value.

Attributes

epoch = 0
lr
    Alias to self.hyperparam.lr
momentum
    Alias to self.hyperparam.momentum
t = 0
target = None
use_auto_new_epoch = False

4.5.10 chainer.optimizers.NesterovAG

class chainer.optimizers.NesterovAG(lr=0.01, momentum=0.9)
Nesterov’s Accelerated Gradient.

Parameters

• lr (float) – Learning rate.
• momentum (float) – Exponential decay rate of the first order moment.

Methods

add_hook (hook, name=None, timing=’auto’)
Registers a hook function.
Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

Parameters

• hook (callable) – Hook function. If hook.call_for_each_param is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.
• name (str) – Name of the registration. If omitted, hook.name is used by default.
• timing (str) – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

call_hook (hook)
call_hooks (timing=’pre’)
Invokes hook functions in registration order.

check_nan_in_grads()
Checks if there is NaN in grads when dynamic loss scaling used.
create_update_rule()
Creates a new update rule object.

This method creates an update rule object. It is called by setup() to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

Returns Update rule object.
Return type UpdateRule

is_safe_to_update()
loss_scaling(interval=1000, scale=None)
Configures the loss scaling algorithm.

Parameters

  • interval (int) – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.
  • scale (float) – Loss scaling factor. If None, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

new_epoch( auto=False)
Starts a new epoch.

This method increments the epoch count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

Parameters auto (bool) – Should be True if this method is called by an updater. In this case, use_auto_new_epoch should be set to True by the updater.

reallocate_cleared_grads()
Reallocate gradients cleared by cleargrad().

This method allocates arrays for all gradients which have None. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

remove_hook(name)
Removes a hook function.

Parameters name (str) – Registered name of the hook function to remove.

serialize(serializer)
Serializes or deserializes the optimizer.

It only saves or loads the following things:

  • Optimizer states
  • Global states (t and epoch)

It does not save nor loads the parameters of the target link. They should be separately saved or loaded.

Parameters serializer (AbstractSerializer) – Serializer or deserializer object.

set_loss_scale(loss_scale)
Sets loss scaling factor.

setup(link)
Sets a target link and initializes the optimizer states.

Given link is set to the target attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.
Parameters **link** *(Link)* – Target link object.

**Returns** The optimizer instance.

---

**Note:** As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., `optimizer = SomeOptimizer().setup(link)`.

---

**update** *(lossfun=None, *args, **kwds)*

Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

- If `lossfun` is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

**update_loss_scale** ()

**use_cleargrads** *(use=True)*

Enables or disables use of `cleargrads()` in `update`.

**Parameters** **use** *(bool)* – If True, this function enables use of `cleargrads`. If False, disables use of `cleargrads` (`zerograds` is used).

Deprecated since version v2.0: Note that `update()` calls `cleargrads()` by default. `cleargrads()` is more efficient than `zerograds()`, so one does not have to call `use_cleargrads()`. This method remains for backward compatibility.

**use_fp32_update** *(flag=True)*

Enables use of parameter update in fp32.

---

**__eq__**(value, /)

Return `self==value`.

**__ne__**(value, /)

Return `self!=value`.

**__lt__**(value, /)

Return `self<value`.

**__le__**(value, /)

Return `self<=value`.

**__gt__**(value, /)

Return `self>value`.

**__ge__**(value, /)

Return `self>=value`.
Attributes

epoch = 0
lr
   Alias to self.hyperparam.lr
momentum
   Alias to self.hyperparam.momentum
t = 0
target = None
use_auto_new_epoch = False

4.5.11 chainer.optimizers.MSVAG

class chainer.optimizers.MSVAG(lr=0.1, beta=0.9, eta=1.0, weight_decay_rate=0)
M-SVAG optimizer.

See: Dissecting Adam: The Sign, Magnitude and Variance of Stochastic Gradients
Modified for proper weight decay (also called AdamW). AdamW introduces the additional parameters eta and weight_decay_rate, which can be used to properly scale the learning rate, and decouple the weight decay rate from alpha, as shown in the below paper.

See: Fixing Weight Decay Regularization in Adam

Parameters

• lr (float) – Learning rate.
• beta (float) – Exponential decay rate of the first and second order moment.
• eta (float) – Schedule multiplier, can be used for warm restarts.
• weight_decay_rate (float) – Weight decay rate.

Methods

add_hook (hook, name=None, timing='auto')
Registers a hook function.

Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

Parameters

• hook (callable) – Hook function. If hook.call_for_each_param is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.
• name (str) – Name of the registration. If omitted, hook.name is used by default.
• timing (str) – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

call_hook (hook)
call_hooks \((\text{timing}='pre')\)
Invokes hook functions in registration order.

check_nan_in_grads()
Checks if there is NaN in grads when dynamic loss scaling used.

create_update_rule()
Creates a new update rule object.
This method creates an update rule object. It is called by \text{setup()}\ to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

Returns Update rule object.
Return type \text{UpdateRule}

is_safe_to_update()

loss_scaling \((\text{interval}=1000, \text{scale}=\text{None})\)
Configures the loss scaling algorithm.

Parameters
- \text{interval} (\text{int}) – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.
- \text{scale} (\text{float}) – Loss scaling factor. If \text{None}, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

new_epoch \((\text{auto}=False)\)
Starts a new epoch.
This method increments the \text{epoch} count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

Parameters \text{auto} (\text{bool}) – Should be \text{True} if this method is called by an updater. In this case, \text{use_auto_new_epoch} should be set to \text{True} by the updater.

reallocate_cleared_grads()
Reallocate gradients cleared by \text{cleargrad()}.
This method allocates arrays for all gradients which have \text{None}. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

remove_hook \((\text{name})\)
Removes a hook function.

Parameters \text{name} (\text{str}) – Registered name of the hook function to remove.

serialize \((\text{serializer})\)
Serializes or deserializes the optimizer.
It only saves or loads the following things:
- Optimizer states
- Global states (\(t\) and \text{epoch})

It does not saves nor loads the parameters of the target link. They should be separately saved or loaded.

Parameters \text{serializer} (\text{AbstractSerializer}) – Serializer or deserializer object.

set_loss_scale \((\text{loss_scale})\)
Sets loss scaling factor.
**setup** *(link)*

Sets a target link and initializes the optimizer states.

Given link is set to the `target` attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

**Parameters**

- **link** *(Link)* – Target link object.

**Returns**

The optimizer instance.

**Note:** As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., `optimizer = SomeOptimizer().setup(link)`.

**update** *(lossfun=None, *args, **kwds)*

Updates parameters based on a loss function or computed gradients.

This method runs in two ways:

- If `lossfun` is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

**update_loss_scale** *

**use_cleargrads** *(use=True)*

Enables or disables use of `cleargrads()` in `update`.

**Parameters**

- **use** *(bool)* – If `True`, this function enables use of `cleargrads`. If `False`, disables use of `cleargrads` (`zerograds` is used).

Deprecated since version v2.0: Note that `update()` calls `cleargrads()` by default. `cleargrads()` is more efficient than `zerograds()`, so one does not have to call `use_cleargrads()`. This method remains for backward compatibility.

**use_fp32_update** *(flag=True)*

Enables use of parameter update in fp32.

**__eq__**(value, /)

Return `self==value`.

**__ne__**(value, /)

Return `self!=value`.

**__lt__**(value, /)

Return `self<value`.

**__le__**(value, /)

Return `self<=value`.

**__gt__**(value, /)

Return `self>value`.

**__ge__**(value, /)

Return `self>=value`.
Attributes

beta
   Alias to self.hyperparam.beta

epoch = 0
da
   Alias to self.hyperparam.eta

lr
   Alias to self.hyperparam.lr

t = 0
target = None
use_auto_new_epoch = False

weight_decay_rate
   Alias to self.hyperparam.weight_decay_rate

4.5.12 chainer.optimizers.RMSprop

class chainer.optimizers.RMSprop (lr=0.01, alpha=0.99, eps=1e-08, eps_inside_sqrt=False)
RMSProp optimizer.


Parameters

• lr (float) – Learning rate.
• alpha (float) – Exponential decay rate of the second order moment.
• eps (float) – Small value for the numerical stability.
• eps_inside_sqrt (bool) – When True, gradient will be divided by \( \sqrt{ms + eps} \)
  where \( ms \) is the mean square. When False (default), gradient will be divided by \( \sqrt{ms + eps} \) instead. This option may be convenient for users porting code from other frameworks; see #4754 for details.

Methods

add_hook (hook, name=None, timing='auto')
Registers a hook function.

Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

Parameters

• hook (callable) – Hook function. If hook.call_for_each_param is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.
• name (str) – Name of the registration. If omitted, hook.name is used by default.
• **timing** *(str)* – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

```python
call_hook(hook)
```

```python
call_hooks(timing='pre')
```

Invokes hook functions in registration order.

```python
check_nan_in_grads()
```

Checks if there is NaN in grads when dynamic loss scaling used.

```python
create_update_rule()
```

Creates a new update rule object.

This method creates an update rule object. It is called by `setup()` to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

Returns Update rule object.

Return type `UpdateRule`

```python
is_safe_to_update()
```

```python
loss_scaling(interval=1000, scale=None)
```

Configures the loss scaling algorithm.

Parameters

- • **interval** *(int)* – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.
- • **scale** *(float)* – Loss scaling factor. If `None`, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

```python
new_epoch(auto=False)
```

Starts a new epoch.

This method increments the `epoch` count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

Parameters

- • **auto** *(bool)* – Should be `True` if this method is called by an updater. In this case, `use_auto_new_epoch` should be set to `True` by the updater.

```python
reallocate_cleared_grads()
```

Reallocate gradients cleared by `cleargrad()`.

This method allocates arrays for all gradients which have `None`. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

```python
remove_hook(name)
```

Removes a hook function.

Parameters

- • **name** *(str)* – Registered name of the hook function to remove.

```python
serialize(serializer)
```

Serializes or deserializes the optimizer.

It only saves or loads the following things:

- Optimizer states
- Global states (`t` and `epoch`)
It does not saves nor loads the parameters of the target link. They should be separately saved or loaded.

**Parameters**

- `serializer` *(AbstractSerializer)* – Serializer or deserializer object.

- `set_loss_scale` *(loss_scale)*
  Sets loss scaling factor.

- `setup` *(link)*
  Sets a target link and initializes the optimizer states.

  Given link is set to the `target` attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

  **Parameters**

  - `link` *(Link)* – Target link object.

  **Returns**

  The optimizer instance.

**Note:** As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., `optimizer = SomeOptimizer().setup(link)`.

- `update` *(lossfun=None, *args, **kwds)*
  Updates parameters based on a loss function or computed gradients.

  This method runs in two ways.

  - If `lossfun` is given, then it is used as a loss function to compute gradients.
  - Otherwise, this method assumes that the gradients are already computed.

  In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

- `update_loss_scale` *

- `use_cleargrads` *(use=True)*
  Enables or disables use of `cleargrads()` in `update`.

    **Parameters**

    - `use` *(bool)* – If True, this function enables use of `cleargrads`. If False, disables use of `cleargrads` (`zerograds` is used).

  Deprecated since version v2.0: Note that `update()` calls `cleargrads()` by default. `cleargrads()` is more efficient than `zerograds()`, so one does not have to call `use_cleargrads()`. This method remains for backward compatibility.

- `use_fp32_update` *(flag=True)*
  Enables use of parameter update in fp32.

  __eq__ *(value, /)*
  Return self==value.

  __ne__ *(value, /)*
  Return self!=value.

  __lt__ *(value, /)*
  Return self<value.

  __le__ *(value, /)*
  Return self<=value.

  __gt__ *(value, /)*
  Return self>value.

  __ge__ *(value, /)*
  Return self>=value.
Return self>=value.

Attributes

alpha
   Alias to self.hyperparam.alpha
epoch = 0
eps
   Alias to self.hyperparam.eps
eps_inside_sqrt
   Alias to self.hyperparam.eps_inside_sqrt
lr
   Alias to self.hyperparam.lr
t = 0
target = None
use_auto_new_epoch = False

4.5.13 chainer.optimizers.RMSpropGraves

class chainer.optimizers.RMSpropGraves(lr=0.0001, alpha=0.95, momentum=0.9, eps=0.0001)
Alex Graves’s RMSprop.
See: https://arxiv.org/abs/1308.0850

Parameters

• lr (float) – Learning rate.
• alpha (float) – Exponential decay rate of the first and second order moments of the raw gradient.
• momentum (float) – Exponential decay rate of the first order moment of the adjusted gradient.
• eps (float) – Small value for the numerical stability.

Methods

add_hook (hook, name=None, timing=’auto’)
   Registers a hook function.
   Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

   Parameters

   • hook (callable) – Hook function. If hook.call_for_each_param is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.
   • name (str) – Name of the registration. If omitted, hook.name is used by default.
• **timing** *(str)* – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

```python
call_hook(hook)
call_hooks(timing='pre')
```

Invokes hook functions in registration order.

```python
check_nan_in_grads()
```

Checks if there is NaN in grads when dynamic loss scaling used.

```python
create_update_rule()
```

Creates a new update rule object.

This method creates an update rule object. It is called by `setup()` to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

**Returns** Update rule object.

**Return type** *UpdateRule*

```python
is_safe_to_update()
```

```python
loss_scaling(interval=1000, scale=None)
```

Configures the loss scaling algorithm.

**Parameters**

- **interval** *(int)* – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.

- **scale** *(float)* – Loss scaling factor. If `None`, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

```python
new_epoch(auto=False)
```

Starts a new epoch.

This method increments the `epoch` count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

**Parameters**

- **auto** *(bool)* – Should be `True` if this method is called by an updater. In this case, `use_auto_new_epoch` should be set to `True` by the updater.

```python
reallocate_cleared_grads()
```

Reallocate gradients cleared by `cleargrad()`.

This method allocates arrays for all gradients which have `None`. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

```python
remove_hook(name)
```

Removes a hook function.

**Parameters**

- **name** *(str)* – Registered name of the hook function to remove.

```python
serialize(serializer)
```

Serializes or deserializes the optimizer.

It only saves or loads the following things:

- Optimizer states
- Global states (`t` and `epoch`)

4.5. Optimizers
It does not saves nor loads the parameters of the target link. They should be separately saved or loaded.

Parameters **serializer** (AbstractSerializer) – Serializer or deserializer object.

**set_loss_scale** (*loss_scale*)
Sets loss scaling factor.

**setup** (*link*)
Sets a target link and initializes the optimizer states.

Given link is set to the target attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

Parameters **link** (Link) – Target link object.

Returns The optimizer instance.

---

**update** (*lossfun=None, *args, **kwds*)
Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

- If *lossfun* is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

**update_loss_scale** ()

**use_cleargrads** (*use=True*)
Enables or disables use of cleargrads() in update.

Parameters **use** (bool) – If True, this function enables use of cleargrads. If False, disables use of cleargrads (zerograds is used).

Deprecated since version v2.0: Note that update() calls cleargrads() by default. cleargrads() is more efficient than zerograds(), so one does not have to call use_cleargrads(). This method remains for backward compatibility.

**use_fp32_update** (*flag=True*)
Enables use of parameter update in fp32.

---

__eq__ (*value, /*)
Return self==value.

__ne__ (*value, /*)
Return self!=value.

__lt__ (*value, /*)
Return self<value.

__le__ (*value, /*)
Return self<=value.

__gt__ (*value, /*)
Return self>value.

__ge__ (*value, /*)
Return self>=value.
__ge__(value, /)  
  Return self>=value.

**Attributes**

- **alpha**
  Alias to `self.hyperparam.alpha`  
- **epoch = 0**
- **eps**
  Alias to `self.hyperparam.eps`
- **lr**
  Alias to `self.hyperparam.lr`
- **momentum**
  Alias to `self.hyperparam.momentum`
- **t = 0**
- **target = None**
- **use_auto_new_epoch = False**

### 4.5.14 chainer.optimizers.SGD

```python
class chainer.optimizers.SGD(lr=0.01)
```

*Vanilla Stochastic Gradient Descent.*

**Parameters**

- **lr** (*float*) – Learning rate.

**Methods**

- **add_hook** *(hook, name=None, timing='auto')*
  Registers a hook function.

  Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

  **Parameters**

  - **hook** (*callable*) – Hook function. If `hook.call_for_each_param` is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.
  - **name** (*str*) – Name of the registration. If omitted, `hook.name` is used by default.
  - **timing** (*str*) – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

- **call_hook** *(hook)*

- **call_hooks** *(timing='pre')*
  Invokes hook functions in registration order.

- **check_nan_in_grads** ()
  Checks if there is NaN in grads when dynamic loss scaling used.
create_update_rule()

Creates a new update rule object.

This method creates an update rule object. It is called by setup() to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

Returns Update rule object.

Return type UpdateRule

is_safe_to_update()

loss_scaling(interval=1000, scale=None)

Configures the loss scaling algorithm.

Parameters

- **interval** (int) – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.

- **scale** (float) – Loss scaling factor. If None, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

new_epoch(auto=False)

Starts a new epoch.

This method increments the epoch count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

Parameters auto (bool) – Should be True if this method is called by an updater. In this case, use_auto_new_epoch should be set to True by the updater.

reallocate_cleared_grads()

Reallocate gradients cleared by cleargrad().

This method allocates arrays for all gradients which have None. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

remove_hook(name)

Removes a hook function.

Parameters name (str) – Registered name of the hook function to remove.

serialize(serializer)

Serializes or deserializes the optimizer.

It only saves or loads the following things:

- Optimizer states

- Global states (t and epoch)

It does not saves nor loads the parameters of the target link. They should be separately saved or loaded.

Parameters serializer (AbstractSerializer) – Serializer or deserializer object.

set_loss_scale(loss_scale)

Sets loss scaling factor.

setup(link)

Sets a target link and initializes the optimizer states.

Given link is set to the target attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.
Parameters **link** *(Link)* – Target link object.

**Returns** The optimizer instance.

**Note:** As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., `optimizer = SomeOptimizer().setup(link)`.

**update** *(lossfun=None, *args, **kwds)*

Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

- If `lossfun` is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

**update_loss_scale** *

**use_cleargrads** *(use=True)*

Enables or disables use of `cleargrads()` in `update`.

**Parameters** **use** *(bool)* – If True, this function enables use of `cleargrads`. If False, disables use of `cleargrads` (zerograds is used).

Deprecated since version v2.0: Note that `update()` calls `cleargrads()` by default. `cleargrads()` is more efficient than `zerograds()`, so one does not have to call `use_cleargrads()`. This method remains for backward compatibility.

**use_fp32_update** *(flag=True)*

Enables use of parameter update in fp32.

**__eq__** *(value, /)*

Return `self==value`.

**__ne__** *(value, /)*

Return `self!=value`.

**__lt__** *(value, /)*

Return `self<value`.

**__le__** *(value, /)*

Return `self<=value`.

**__gt__** *(value, /)*

Return `self>value`.

**__ge__** *(value, /)*

Return `self>=value`.

4.5. Optimizers
Attributes

epoch = 0
lr
    Alias to self.hyperparam.lr
t = 0
target = None
use_auto_new_epoch = False

4.5.15 chainer.optimizers.SMORMS3

class chainer.optimizers.SMORMS3(lr=0.001, eps=1e-16)
Simon Funk’s SMORMS3.

Parameters

• lr (float) – Learning rate.
• eps (float) – Small value for the numerical stability.

Methods

add_hook(hook, name=None, timing='auto')
Registers a hook function.
Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

Parameters

• hook (callable) – Hook function. If hook.call_for_each_param is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.
• name (str) – Name of the registration. If omitted, hook.name is used by default.
• timing (str) – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

call_hook(hook)
call_hooks(timing='pre')
Invokes hook functions in registration order.

check_nan_in_grads()
Checks if there is NaN in grads when dynamic loss scaling used.

create_update_rule()
Creates a new update rule object.
This method creates an update rule object. It is called by setup() to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

Returns Update rule object.
Return type *UpdateRule*

**is_safe_to_update**

**loss_scaling** *(interval=1000, scale=None)*

Configures the loss scaling algorithm.

**Parameters**

- **interval** *(int)* – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.
- **scale** *(float)* – Loss scaling factor. If None, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

**new_epoch** *(auto=False)*

Starts a new epoch.

This method increments the *epoch* count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

**Parameters** **auto** *(bool)* – Should be True if this method is called by an updater. In this case, use **auto_new_epoch** should be set to True by the updater.

**reallocate_cleared_grads**

Reallocate gradients cleared by **cleargrad**.

This method allocates arrays for all gradients which have None. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

**remove_hook** *(name)*

Removes a hook function.

**Parameters** **name** *(str)* – Registered name of the hook function to remove.

**serialize** *(serializer)*

Serializes or deserializes the optimizer.

It only saves or loads the following things:

- Optimizer states
- Global states (*t* and *epoch*)

It does not saves nor loads the parameters of the target link. They should be separately saved or loaded.

**Parameters** **serializer** *(AbstractSerializer)* – Serializer or deserializer object.

**set_loss_scale** *(loss_scale)*

Sets loss scaling factor.

**setup** *(link)*

Sets a target link and initializes the optimizer states.

Given link is set to the *target* attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

**Parameters** **link** *(Link)* – Target link object.

**Returns** The optimizer instance.

**Note:** As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., `optimizer = SomeOptimizer().setup(link)`.
**update**(lossfun=None, *args, **kwds)

Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

- If `lossfun` is given, then it is used as a loss function to compute gradients.
- Otherwise, this method assumes that the gradients are already computed.

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

**update_loss_scale()**

**use_cleargrads**(use=True)

Enables or disables use of `cleargrads()` in `update`.

Parameters `use` (bool) – If True, this function enables use of `cleargrads`. If False, disables use of `cleargrads` (zerograd is used).

Deprecated since version v2.0: Note that `update()` calls `cleargrads()` by default. `cleargrads()` is more efficient than `zerograd()`, so one does not have to call `use_cleargrads()`. This method remains for backward compatibility.

**use_fp32_update**(flag=True)

Enables use of parameter update in fp32.

**Attributes**

- `epoch = 0`
- `eps`
  - Alias to `self.hyperparam.eps`
- `lr`
  - Alias to `self.hyperparam.lr`
- `t = 0`
- `target = None`
- `use_auto_new_epoch = False`
4.5.16 Optimizer base classes

<table>
<thead>
<tr>
<th>Class Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.Optimizer</code></td>
<td>Base class of all numerical optimizers.</td>
</tr>
<tr>
<td><code>chainer.UpdateRule</code></td>
<td>Base class of all update rules.</td>
</tr>
<tr>
<td><code>chainer.optimizer.Hyperparameter</code></td>
<td>Set of hyperparameter entries of an optimizer.</td>
</tr>
<tr>
<td><code>chainer.GradientMethod</code></td>
<td>Base class of all single gradient-based optimizers.</td>
</tr>
</tbody>
</table>

**chainer.Optimizer**

class chainer.Optimizer

Base class of all numerical optimizers.

This class provides basic features for all optimization methods. It optimizes parameters of a target link. The target link is registered via the `setup()` method, and then the `update()` method updates its parameters based on a given loss function.

Each optimizer implementation must be defined as a child class of Optimizer. It must override `update()` method.

If the optimizer is based on single gradient computation (like most first-order methods), then it should inherit `GradientMethod`, which adds some features dedicated for the first order methods, including the support of `UpdateRule`.

Optimizer instance also supports hook functions. Hook function is registered by the `add_hook()` method. Each hook function is called in registration order before of after the actual parameter update (configurable). If the hook function has an attribute `call_for_each_param` and its value is `True`, the hook function is used as a hook function of all update rules (i.e., it is invoked for every parameter by passing the corresponding update rule and the parameter).

**Variables**

- **target** – Target link object. It is set by the `setup()` method.
- **t** – Number of update steps. It must be incremented by the `update()` method.
- **epoch** – Current epoch. It is incremented by the `new_epoch()` method.
- **use_auto_new_epoch** – Boolean flag to indicate if `new_epoch()` will be called by the updater. Updater should set this flag to `True` if it automatically calls `new_epoch()`.

**Methods**

- **add_hook** *(hook, name=None, timing='auto')*
  Registers a hook function.

  Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

  **Parameters**

  - **hook** *(callable)* – Hook function. If `hook.call_for_each_param` is `True`, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.
  - **name** *(str)* – Name of the registration. If omitted, `hook.name` is used by default.
• `timing (str)` – Specifies when the hook is called. If ‘auto’, the timing property of the
hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’,
the hook will be called after any updates.

call_hook (hook)
call_hooks (timing='pre')
    Invokes hook functions in registration order.
check_nan_in_grads ()
    Checks if there is NaN in grads when dynamic loss scaling used.

is_safe_to_update ()

loss_scaling (interval=1000, scale=None)
    Configures the loss scaling algorithm.
    Parameters
    • `interval (int)` – Number of iterations until scaling factor gets doubled. This is effec-
tive when “dynamic” loss scaling is used.
    • `scale (float)` – Loss scaling factor. If None, “dynamic” loss scaling is used, otherwise
“static” loss scaling is used.

new_epoch (auto=False)
    Starts a new epoch.
    This method increments the `epoch` count. Note that if the optimizer depends on the epoch count, then
user should call this method appropriately at the beginning of each epoch.
    Parameters auto (bool) – Should be True if this method is called by an updater. In this
case, `use_auto_new_epoch` should be set to True by the updater.

remove_hook (name)
    Removes a hook function.
    Parameters name (str) – Registered name of the hook function to remove.

serialize (serializer)
    Serializes or deserializes the optimizer.
    It only saves or loads the following things:
    • Optimizer states
    • Global states (\(t\) and `epoch`)
    It does not saves nor loads the parameters of the target link. They should be separately saved or loaded.
    Parameters serializer (AbstractSerializer) – Serializer or deserializer object.

set_loss_scale (loss_scale)
    Sets loss scaling factor.

setup (link)
    Sets a target link and initializes the optimizer states.
    Given link is set to the `target` attribute. It also prepares the optimizer state dictionaries corresponding
to all parameters in the link hierarchy. The existing states are discarded.
    Parameters link (Link) – Target link object.
    Returns The optimizer instance.
As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g.,\[\text{optimizer} = \text{SomeOptimizer().setup(link)}.\]

**update** (*lossfun=None, *args, **kwds*)

Updates the parameters.

This method updates the parameters of the target link. The behavior of this method is different for the cases either `lossfun` is given or not.

If `lossfun` is given, this method typically clears the gradients, calls the loss function with given extra arguments, and calls the `backward()` method of its output to compute the gradients. The actual implementation might call `lossfun` more than once.

If `lossfun` is not given, then this method assumes that the gradients of all parameters are already computed. An implementation that requires multiple gradient computations might raise an error on this case.

In both cases, this method invokes the update procedure for all parameters.

**Parameters**

- **lossfun** (*callable*) – Loss function. You can specify one of loss functions from built-in loss functions, or your own loss function. It should not be an loss functions with parameters (i.e., `Link` instance). The function must accept arbitrary arguments and return one `Variable` object that represents the loss (or objective) value. Returned value must be a Variable derived from the input Variable object. `lossfun` can be omitted for single gradient-based methods. In this case, this method assumes gradient arrays computed.

- **kwds** (*args,*) – Arguments for the loss function.

**update_loss_scale**()

- **eq**(value, /)
  Return \(self == value\).

- **ne**(value, /)
  Return \(self != value\).

- **lt**(value, /)
  Return \(self < value\).

- **le**(value, /)
  Return \(self \leq value\).

- **gt**(value, /)
  Return \(self > value\).

- **ge**(value, /)
  Return \(self \geq value\).
Attributes

epoch = 0

\( t = 0 \)

\( \text{target} = \text{None} \)

\( \text{use\_auto\_new\_epoch} = \text{False} \)

chainer.UpdateRule

class chainer.UpdateRule(parent_hyperparam=None)

Base class of all update rules.

Update rule is an object that implements how to update one parameter variable using the gradient of a loss function. This class provides the interface and the common features of any update rules.

An update rule can be set to a Variable object that represents a parameter array of a model. An Optimizer instance defines which parameters to update, and the update rule instance of each parameter defines how to update it.

Hook functions can be set to any update rule instance. The hook function is called just before or after any updates (configurable) in the order of registrations.

An implementation of update rule should override update_core() or its device-dependent variants (i.e., update_core_cpu() and update_core_gpu()).

The state (e.g. a moving average of the gradient) of the update rule is stored into the state dictionary. An implementation of update rule using state should also override init_state() to initialize the state at the first update. The values of the state dictionary are automatically copied to the appropriate device before the update based on the data and grad arrays.

**Parameters**

**parent_hyperparam** *(Hyperparameter)* – Hyperparameter that provides the default values.

**Variables**

- **enabled** *(bool)* – Flag to configure if this update rule is active. If the update rule is not active (i.e., enabled = False), the update() method does not update the parameter.

- **hyperparam** *(Hyperparameter)* – Hyperparameter of the update rule.

- **t** *(int)* – Number of updates made by this update rule.

**Methods**

**add_hook** *(hook, name=None, timing='auto')*

Adds a hook function.

The hook function is called before or after any updates (see the timing attribute).

**Parameters**

- **hook** *(callable)* – Hook function to be added. It takes two arguments: the update rule object and the parameter variable.

- **name** *(str)* – Name of the hook function. The name attribute of the hook function is used by default.
• **timing** *(str)* – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates. If ‘auto’ and the timing property of the hook is not available, timing will default to ‘pre’.

`init_state(param)`
Initializes the state.

Any implementations that use the state should override this method. This method is called at the first update.

**Parameters**
*param* *(Variable)* – Parameter variable. It can be used to extract the shape and the data type of the parameter.

`remove_hook(name)`
Removes the specified hook function.

**Parameters**
*name* *(str)* – Name of the hook function to be removed. The hook function registered with this name will be removed.

`serialize(serializer)`
Serializes the update rule state.

Be careful that this method only saves/loads the state of the update rule. The parameters of the target link is not saved/loaded by this method, and so you need to serialize the target link separately if you want to fully recover the training state including parameters.

**Parameters**
*serializer* *(AbstractSerializer)* – Serializer object.

`update(param)`
Invokes hook functions and updates the parameter.

**Parameters**
*param* *(Variable)* – Variable to be updated.

`update_core(param)`
Updates the parameter.

Implementation of UpdateRule should override this method or both of `update_core_cpu()` and `update_core_gpu()`.

**Parameters**
*param* *(Variable)* – Variable to be updated.

`update_core_chainerx(param)`
Updates the ChainerX parameter.

This method can be overridden to implement custom update logic. The default implementation is to convert the parameter to a memory-shared NumPy/CuPy parameter and call the corresponding update method.

See `update_core()` for details.

**Parameters**
*param* *(Variable)* – Variable to be updated.

`update_core_cpu(param)`
Updates the parameter on CPU.

See `update_core()` for details.

**Parameters**
*param* *(Variable)* – Variable to be updated.

`update_core_gpu(param)`
Updates the parameter on GPU.

See `update_core()` for details.

**Parameters**
*param* *(Variable)* – Variable to be updated.
**use_fp32_update** (*flag=True*)

Enables use of parameter update in fp32.

This method enables use of parameter update in fp32. When it is enabled and data type of original parameter variable is fp16, fp32 copy of parameter variable is automatically created and retained at `self.fp32_param`. And the parameter is update in fp32 in the following way.

1. copies the grad of original parameter variable to the grad of fp32 parameter variable, converting its data type from fp16 to fp32.
2. updates the parameter in fp32.
3. copies the data of fp32 parameter variable to the data of original parameter variable, converting its data type from fp32 to fp16.

See `update()` for details.

```python
__eq__(value, /)
    Return self==value.

__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.
```

**Attributes**

- **is_elementwise = False**
- **state**
  
  State dictionary.

**chainer.optimizer.Hyperparameter**

```python
class chainer.optimizer.Hyperparameter(parent=None)
  Set of hyperparameter entries of an optimizer.

This is a utility class to provide a set of hyperparameter entries for update rules and an optimizer. Each entry can be set as an attribute of a hyperparameter object.

A hyperparameter object can hold a reference to its parent hyperparameter object. When an attribute does not exist in the child hyperparameter, it automatically refers to the parent. We typically set the hyperparameter of the gradient method as the parent of the hyperparameter of each update rule. It enables us to centralize the management of hyperparameters (e.g. we can change the learning rate of all update rules just by modifying the hyperparameter of the central optimizer object), while users can freely customize the hyperparameter of each update rule if needed.

Parameters **parent** *(Hyperparameter)* – Parent hyperparameter.
Methods

get_dict()
Converts the hyperparameter into a dictionary.

Returns Dictionary containing all entries that can be referred by this hyperparameter object.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.

Attributes

parent Parent hyperparameter object.

chainer.GradientMethod

class chainer.GradientMethod
Base class of all single gradient-based optimizers.

This is an extension of the Optimizer class. Typical gradient methods that just require the gradient at the current parameter vector on an update can be implemented as its child class.

This class uses UpdateRule to manage the update rule of each parameter. A child class of GradientMethod should override create_update_rule() to create the default update rule of each parameter.

This class also provides hyperparam, which is the hyperparameter used as the default configuration of each update rule. All built-in gradient method implementations also provide proxy properties that act as aliases to the attributes of hyperparam. It is recommended that you provide such an alias to each attribute. It can be done by only adding one line for each attribute using HyperparameterProxy.

Variables hyperparam (Hyperparameter) – The hyperparameter of the gradient method. It is used as the default configuration of each update rule (i.e., the hyperparameter of each update rule refers this hyperparameter as its parent).
Methods

add_hook (hook, name=None, timing='auto')

Registers a hook function.

Hook function is typically called right after the gradient computation, though the timing depends on the optimization method, and the timing attribute.

Parameters

- **hook** (callable) – Hook function. If hook.call_for_each_param is true, this hook function is called for each parameter by passing the update rule and the parameter. Otherwise, this hook function is called only once each iteration by passing the optimizer.
- **name** (str) – Name of the registration. If omitted, hook.name is used by default.
- **timing** (str) – Specifies when the hook is called. If ‘auto’, the timing property of the hook will decide the timing. If ‘pre’, the hook will be called before any updates. If ‘post’, the hook will be called after any updates.

call_hook (hook)

call_hooks (timing='pre')

Invokes hook functions in registration order.

check_nan_in_grads ()

Checks if there is NaN in grads when dynamic loss scaling used.

create_update_rule ()

Creates a new update rule object.

This method creates an update rule object. It is called by setup() to set up an update rule of each parameter. Each implementation of the gradient method should override this method to provide the default update rule implementation.

Returns Update rule object.

Return type UpdateRule

is_safe_to_update ()

loss_scaling (interval=1000, scale=None)

Configures the loss scaling algorithm.

Parameters

- **interval** (int) – Number of iterations until scaling factor gets doubled. This is effective when “dynamic” loss scaling is used.
- **scale** (float) – Loss scaling factor. If None, “dynamic” loss scaling is used, otherwise “static” loss scaling is used.

new_epoch (auto=False)

Starts a new epoch.

This method increments the epoch count. Note that if the optimizer depends on the epoch count, then user should call this method appropriately at the beginning of each epoch.

Parameters auto (bool) – Should be True if this method is called by an updater. In this case, use_auto_new_epoch should be set to True by the updater.

reallocate_cleared_grads ()

Reallocate gradients cleared by cleargrad().
This method allocates arrays for all gradients which have \texttt{None}. This method is called before and after every optimizer hook. If an inheriting optimizer does not require this allocation, the optimizer can override this method with a blank function.

\textbf{remove\_hook} \texttt{(name)}

Removes a hook function.

\textbf{Parameters} \texttt{name} \texttt{(str)} – Registered name of the hook function to remove.

\textbf{serialize} \texttt{(serializer)}

Serializes or deserializes the optimizer.

It only saves or loads the following things:

\begin{itemize}
  \item Optimizer states
  \item Global states ($t$ and $epoch$)
\end{itemize}

\textbf{It does not saves nor loads the parameters of the target link.} They should be separately saved or loaded.

\textbf{Parameters} \texttt{serializer} \texttt{(AbstractSerializer)} – Serializer or deserializer object.

\textbf{set\_loss\_scale} \texttt{(loss\_scale)}

Sets loss scaling factor.

\textbf{setup} \texttt{(link)}

Sets a target link and initializes the optimizer states.

Given link is set to the \texttt{target} attribute. It also prepares the optimizer state dictionaries corresponding to all parameters in the link hierarchy. The existing states are discarded.

\textbf{Parameters} \texttt{link} \texttt{(Link)} – Target link object.

\textbf{Returns} The optimizer instance.

\textbf{Note:} As of v4.0.0, this function returns the optimizer instance itself so that you can instantiate and setup the optimizer in one line, e.g., \texttt{optimizer = SomeOptimizer().setup(link)}.

\textbf{update} \texttt{(lossfun=None, *args, **kwds)}

Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

\begin{itemize}
  \item If \texttt{lossfun} is given, then it is used as a loss function to compute gradients.
  \item Otherwise, this method assumes that the gradients are already computed.
\end{itemize}

In both cases, the computed gradients are used to update parameters. The actual update routines are defined by the update rule of each parameter.

\textbf{update\_loss\_scale} ()

\textbf{use\_cleargrads} \texttt{(use=True)}

Enables or disables use of \texttt{cleargrads()} in \texttt{update}.

\textbf{Parameters} \texttt{use} \texttt{(bool)} – If True, this function enables use of \texttt{cleargrads}. If False, disables use of \texttt{cleargrads} (\texttt{zerograds} is used).

Deprecated since version v2.0: Note that \texttt{update()} calls \texttt{cleargrads()} by default. \texttt{cleargrads()} is more efficient than \texttt{zerograds()}, so one does not have to call \texttt{use\_cleargrads()}. This method remains for backward compatibility.

\textbf{use\_fp32\_update} \texttt{(flag=True)}

Enables use of parameter update in fp32.
__eq__(value,\/)  
Return self==value.

__ne__(value,\/)  
Return self!=value.

__lt__(value,\/)  
Return self<value.

__le__(value,\/)  
Return self<=value.

__gt__(value,\/)  
Return self>value.

__ge__(value,\/)  
Return self>=value.

Attributes

epoch = 0

t = 0

target = None

use_auto_new_epoch = False

4.5.17 Hook functions

<table>
<thead>
<tr>
<th>chainer.optimizer_hooks.WeightDecay</th>
<th>Optimizer/UpdateRule hook function for weight decay regularization.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.optimizer_hooks.Lasso</td>
<td>Optimizer/UpdateRule hook function for Lasso regularization.</td>
</tr>
<tr>
<td>chainer.optimizer_hooks.GradientClipping</td>
<td>Optimizer hook function for gradient clipping.</td>
</tr>
<tr>
<td>chainer.optimizer_hooks.GradientHardClipping</td>
<td>Optimizer/UpdateRule hook function for gradient clipping.</td>
</tr>
<tr>
<td>chainer.optimizer_hooks.GradientNoise</td>
<td>Optimizer/UpdateRule hook function for adding gradient noise.</td>
</tr>
<tr>
<td>chainer.optimizer_hooks.GradientLARS</td>
<td>Optimizer/UpdateRule hook function for layer wise adaptive rate scaling.</td>
</tr>
</tbody>
</table>

chainer.optimizer_hooks.WeightDecay

class chainer.optimizer_hooks.WeightDecay(rate)  
Optimizer/UpdateRule hook function for weight decay regularization.

This hook function adds a scaled parameter to the corresponding gradient. It can be used as a regularization.

Parameters rate(float) – Coefficient for the weight decay.

Variables

* rate(float) – Coefficient for the weight decay.
• **timing** *(string)* – Specifies when this hook should be called by the Optimizer/UpdateRule. Valid values are ‘pre’ (before any updates) and ‘post’ (after any updates).

• **call_for_each_param** *(bool)* – Specifies if this hook is called for each parameter (True) or only once (False) by an optimizer to which this hook is registered. This function does not expect users to switch the value from default one, which is True.

New in version 4.0.0: The *timing* parameter.

**Methods**

```python
__call__(rule, param)
Call self as a function.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.
```

**Attributes**

```python
call_for_each_param = True
name = 'WeightDecay'
timing = 'pre'
```

**chainer.optimizer_hooks.Lasso**

```python
class chainer.optimizer_hooks.Lasso(rate)
Optimizer/UpdateRule hook function for Lasso regularization.
This hook function adds a scaled parameter to the sign of each weight. It can be used as a regularization.

Parameters **rate** *(float)* – Coefficient for the weight decay.

Variables

• **rate** *(float)* – Coefficient for the weight decay.

• **timing** *(string)* – Specifies when this hook should be called by the Optimizer/UpdateRule. Valid values are ‘pre’ (before any updates) and ‘post’ (after any updates).
• **call_for_each_param** *(bool)* – Specifies if this hook is called for each parameter *(True)* or only once *(False)* by an optimizer to which this hook is registered. This function does not expect users to switch the value from default one, which is *True*.

New in version 4.0.0: The *timing* parameter.

**Methods**

```python
__call__(rule, param)
   Call self as a function.
__eq__(value, /)
   Return self==value.
__ne__(value, /)
   Return self!=value.
__lt__(value, /)
   Return self<value.
__le__(value, /)
   Return self<=value.
__gt__(value, /)
   Return self>value.
__ge__(value, /)
   Return self>=value.
```

**Attributes**

```python
call_for_each_param = True
name = 'Lasso'
timing = 'pre'
```

**chainer.optimizer_hooks.GradientClipping**

```python
class chainer.optimizer_hooks.GradientClipping(threshold)
   Optimizer hook function for gradient clipping.
   This hook function scales all gradient arrays to fit to the defined L2 norm threshold.
   Parameters threshold *(float)* – L2 norm threshold.
   Variables
   • **threshold** *(float)* – L2 norm threshold of gradient norm.
   • **timing** *(string)* – Specifies when this hook should be called by the Optimizer/UpdateRule. Valid values are ‘pre’ (before any updates) and ‘post’ (after any updates).
```

New in version 4.0.0: The *timing* parameter.
Methods

```python
__call__(opt)
Call self as a function.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.
```

Attributes

```python
name = 'GradientClipping'
timing = 'pre'
```

```python
class chainer.optimizer_hooks.GradientHardClipping
Optimizer/UpdateRule hook function for gradient clipping.
This hook function clips all gradient arrays to be within a lower and upper bound.

Parameters

- **lower_bound** *(float)* – The lower bound of the gradient value.
- **upper_bound** *(float)* – The upper bound of the gradient value.

Variables

- **lower_bound** *(float)* – The lower bound of the gradient value.
- **upper_bound** *(float)* – The upper bound of the gradient value.
- **timing** *(string)* – Specifies when this hook should be called by the Optimizer/UpdateRule. Valid values are ‘pre’ (before any updates) and ‘post’ (after any updates).
- **call_for_each_param** *(bool)* – Specifies if this hook is called for each parameter (True) or only once (False) by an optimizer to which this hook is registered. This function does not expect users to switch the value from default one, which is True.

New in version 4.0.0: The **timing** parameter.
Methods

__call__ (rule, param)
Call self as a function.

__eq__ (value, /)
Return self==value.

__ne__ (value, /)
Return self!=value.

__lt__ (value, /)
Return self<value.

__le__ (value, /)
Return self<=value.

__gt__ (value, /)
Return self>value.

__ge__ (value, /)
Return self>=value.

Attributes

call_for_each_param = True
name = 'GradientHardClipping'
timing = 'pre'

chainer.optimizer_hooks.GradientNoise

class chainer.optimizer_hooks.GradientNoise (eta, noise_func=<function exponential_decay_noise>)
Optimizer/UpdateRule hook function for adding gradient noise.
This hook function simply adds noise generated by the noise_func to the gradient. By default it adds time-
dependent annealed Gaussian noise to the gradient at every training step:

\[ g_t \leftarrow g_t + N(0, \sigma_t^2) \]

where

\[ \sigma_t^2 = \frac{\eta}{(1 + t)^\gamma} \]

with \( \eta \) selected from \{0.01, 0.3, 1.0\} and \( \gamma = 0.55 \).

Parameters

• eta (float) – Parameter that defines the scale of the noise. For the default noise function, it is recommended that it be either 0.01, 0.3 or 1.0.

• noise_func (function) – Noise generating function which by default is given by

Adding Gradient Noise Improves Learning for Very Deep Networks.

Variables

• timing (string) – Specifies when this hook should be called by the Optimizer/UpdateRule. Valid values are ‘pre’ (before any updates) and ‘post’ (after any updates).
• **call_for_each_param (bool)** – Specifies if this hook is called for each parameter (True) or only once (False) by an optimizer to which this hook is registered. This function does not expect users to switch the value from default one, which is True.

New in version 4.0.0: The `timing` parameter.

**Methods**

```python
__call__(rule, param)
Call self as a function.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.
```

**Attributes**

```python
call_for_each_param = True
name = 'GradientNoise'
timing = 'pre'
```

**chainer.optimizer_hooks.GradientLARS**

```python
class chainer.optimizer_hooks.GradientLARS (threshold=0.01, weight_decay=0.0, eps=1e-09)
Optimizer/UpdateRule hook function for layer wise adaptive rate scaling.
See: Large Batch Training of Convolutional Networks.
See: Convergence Analysis of Gradient Descent Algorithms with Proportional Updates.
This hook function scales all gradient arrays to fit to the weight norm.
In <https://arxiv.org/abs/1708.03888>,
\[
v_{t+1} = m \ast v_t + \gamma \ast \lambda \ast (\nabla L(w_t) + \beta w_t),
\]
\[
w_{t+1} = w_t - v_{t+1},
\]
where
• \( \gamma \): learning rate
• \( m \): momentum
```
As $l_r$ in chainer.optimizers.SGD or chainer.optimizers.MomentumSGD corresponds to $\gamma \eta$, we define $clip_rate$ as $\frac{\|\nabla L(w_t)\|}{\|\nabla L(w_t)\|+\beta \|w_t\|}$ and reformulate the aforementioned formula as: $v_{t+1} = m * v_t + l_r * clip_rate * (\nabla L(w_t) + \beta w_t)$ and implement in this way. So you do not set lars_coefficient.

**Parameters**

- **threshold (float)** – If weight norm is more than threshold, this function scales all gradient arrays to fit weight norm. (See [https://arxiv.org/abs/1801.03137](https://arxiv.org/abs/1801.03137))
- **weight_decay (float)** – Coefficient for the weight decay.
- **eps (float)** – Small value for the numerical stability. (See [https://arxiv.org/abs/1801.03137](https://arxiv.org/abs/1801.03137))

**Variables**

- **threshold (float)** – If weight norm is more than threshold, this function scales all gradient arrays to fit weight norm. (See [https://arxiv.org/abs/1801.03137](https://arxiv.org/abs/1801.03137))
- **weight_decay (float)** – Coefficient for the weight decay.
- **eps (float)** – Small value for the numerical stability. (See [https://arxiv.org/abs/1801.03137](https://arxiv.org/abs/1801.03137))
- **timing (string)** – Specifies when this hook should be called by the Optimizer/UpdateRule. Valid values are ‘pre’ (before any updates) and ‘post’ (after any updates).
- **call_for_each_param (bool)** – Specifies if this hook is called for each parameter (True) or only once (False) by an optimizer to which this hook is registered. This function does not expect users to switch the value from default one, which is True.

**Methods**

```python
__call__(rule, param)
    Call self as a function.
__eq__(value, /)
    Return self==value.
__ne__(value, /)
    Return self!=value.
__lt__(value, /)
    Return self<value.
__le__(value, /)
    Return self<=value.
__gt__(value, /)
    Return self>value.
__ge__(value, /)
    Return self>=value.
```
4.6 Weight Initializers

Weight initializers are used to initialize arrays. They destructively modify the content of `numpy.ndarray` or `cupy.ndarray`. Typically, weight initializers are passed to `Links` to initialize their weights and biases.

A weight initializer can be any of the following objects.

- `chainer.Initializer` class instance.
- Python or NumPy scalar or `numpy.ndarray`.
- A callable that takes an array (`numpy.ndarray` or `cupy.ndarray`) and feeds the initial data into it.
- `None`, in which case the default initializer is used. Unless explicitly documented, it is `LeCunNormal` with scale value 1.

If an initializer object has the `dtype` attribute, the initializer can assume that the array to feed the data into has that dtype. If the required dtype, depending on the context where the initializer is used, does not match the `dtype` attribute, Chainer will report an error.

4.6.1 Base class

```python
class chainer.Initializer(dtype: Optional[Any] = None)
    Initializes array.
    It initializes the given array.
    
    Variables
dtype – Data type specifier. It is for type check in `__call__` function.

    Methods
    __call__(array: Union[numpy.ndarray, cuda.ndarray, chainerx.ndarray]) → None
    Initializes given array.
    This method destructively changes the value of array. The derived class is required to implement this method. The algorithms used to make the new values depend on the concrete derived classes.
    
    Parameters
    array (N-dimensional array) – An array to be initialized by this initializer.
    __eq__(value, /)
    Return self==value.
    __ne__(value, /)
    Return self!=value.
```
__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

## 4.6.2 Concrete initializers

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.initializers.Identity</td>
<td>Initializes array with the identity matrix.</td>
</tr>
<tr>
<td>chainer.initializers.Constant</td>
<td>Initializes array with constant value.</td>
</tr>
<tr>
<td>chainer.initializers.Zero</td>
<td>Initializes array to all-zero.</td>
</tr>
<tr>
<td>chainer.initializers.One</td>
<td>Initializes array to all-one.</td>
</tr>
<tr>
<td>chainer.initializers.NaN</td>
<td>Initializes array to all-NaN.</td>
</tr>
<tr>
<td>chainer.initializers.Normal</td>
<td>Initializes array with a normal distribution.</td>
</tr>
<tr>
<td>chainer.initializers.LeCunNormal</td>
<td>Initializes array with scaled Gaussian distribution.</td>
</tr>
<tr>
<td>chainer.initializers.GlorotNormal</td>
<td>Initializes array with scaled Gaussian distribution.</td>
</tr>
<tr>
<td>chainer.initializers.HeNormal</td>
<td>Initializes array with scaled Gaussian distribution.</td>
</tr>
<tr>
<td>chainer.initializers.Orthogonal</td>
<td>Initializes array with an orthogonal system.</td>
</tr>
<tr>
<td>chainer.initializers.Uniform</td>
<td>Initializes array with a scaled uniform distribution.</td>
</tr>
<tr>
<td>chainer.initializers.LeCunUniform</td>
<td>Initializes array with a scaled uniform distribution.</td>
</tr>
<tr>
<td>chainer.initializers.GlorotUniform</td>
<td>Initializes array with a scaled uniform distribution.</td>
</tr>
<tr>
<td>chainer.initializers.HeUniform</td>
<td>Initializes array with a scaled uniform distribution.</td>
</tr>
<tr>
<td>chainer.initializers.UpsamplingDeconvFilter</td>
<td>Initializes array with upsampling filter.</td>
</tr>
<tr>
<td>chainer.initializers.DownsamplingConvFilter</td>
<td>Initializes array with downsampling filter.</td>
</tr>
</tbody>
</table>

### chainer.initializers.Identity

```python
class chainer.initializers.Identity (scale=1.0, dtype=None)
```

Initializes array with the identity matrix.

It initializes the given array with the constant multiple of the identity matrix. Note that arrays to be passed must be 2D squared matrices.

**Variables**

- `scale (scalar)`: A constant to be multiplied to identity matrices.
Methods

__call__(array)
Initializes given array.

This method destructively changes the value of array. The derived class is required to implement this
method. The algorithms used to make the new values depend on the concrete derived classes.

Parameters array (N-dimensional array) – An array to be initialized by this initializer.

__eq__(value,)
Return self==value.

__ne__(value,)
Return self!=value.

__lt__(value,)
Return self<value.

__le__(value,)
Return self<=value.

__gt__(value,)
Return self>value.

__ge__(value,)
Return self>=value.

crainer.initializers.Constant

class crainer.initializers.Constant (fill_value, dtype=None)
Initializes array with constant value.

Variables

• fill_value (scalar or N-dimensional array) – A constant to be assigned to the initialized
array. Broadcast is allowed on this assignment.

• dtype – Data type specifier.

Methods

__call__(array)
Initializes given array.

This method destructively changes the value of array. The derived class is required to implement this
method. The algorithms used to make the new values depend on the concrete derived classes.

Parameters array (N-dimensional array) – An array to be initialized by this initializer.

__eq__(value,)
Return self==value.

__ne__(value,)
Return self!=value.

__lt__(value,)
Return self<value.

__le__(value,)
Return self<=value.
Return self>value.

__ge__(value,)
    Return self>=value.

Attributes

fill_value = None

chainer.initializers.Zero

class chainer.initializers.Zero(dtype=None)
    Initializes array to all-zero.

    Variables dtype – Data type specifier.

Methods

__call__(array)
    Initializes given array.

    This method destructively changes the value of array. The derived class is required to implement this
    method. The algorithms used to make the new values depend on the concrete derived classes.

    Parameters array (N-dimensional array) – An array to be initialized by this initializer.

__eq__(value,)
    Return self==value.

__ne__(value,)
    Return self!=value.

__lt__(value,)
    Return self<value.

__le__(value,)
    Return self<=value.

__gt__(value,)
    Return self>value.

__ge__(value,)
    Return self>=value.

Attributes

fill_value = 0.0
chainer.initializers.One

class chainer.initializers.One (dtype=None)
Initializes array to all-one.

Variables dtype – Data type specifier.

Methods

__call__ (array)
Initializes given array.

This method destructively changes the value of array. The derived class is required to implement this method. The algorithms used to make the new values depend on the concrete derived classes.

Parameters array (N-dimensional array) – An array to be initialized by this initializer.

__eq__ (value, /)
Return self==value.

__ne__ (value, /)
Return self!=value.

__lt__ (value, /)
Return self<value.

__le__ (value, /)
Return self<=value.

__gt__ (value, /)
Return self>value.

__ge__ (value, /)
Return self>=value.

Attributes

fill_value = 1.0

chainer.initializers.NaN

class chainer.initializers.NaN (dtype=None)
Initializes array to all-NaN.

Variables dtype – Data type specifier.

Methods

__call__ (array)
Initializes given array.

This method destructively changes the value of array. The derived class is required to implement this method. The algorithms used to make the new values depend on the concrete derived classes.

Parameters array (N-dimensional array) – An array to be initialized by this initializer.

__eq__ (value, /)
Return self==value.
\_
\_ne\_
\_(\text{value},\)\\n\text{Return self}! = \text{value}.
\_
\_lt\_
\_(\text{value},\)\\n\text{Return self} < \text{value}.
\_
\_le\_
\_(\text{value},\)\\n\text{Return self} \leq \text{value}.
\_
\_gt\_
\_(\text{value},\)\\n\text{Return self} > \text{value}.
\_
\_ge\_
\_(\text{value},\)\\n\text{Return self} \geq \text{value}.

\textbf{Attributes}

\texttt{fill\_value} = \texttt{nan}

\texttt{chainer.initializers.Normal}

class \texttt{chainer.initializers.Normal}(\textit{scale}=0.05, \textit{dtype}=\texttt{None}, \*\*\textit{kwargs})
\textit{Initializes array with a normal distribution.}

Each element of the array is initialized by the value drawn independently from Gaussian distribution whose
mean is 0, and standard deviation is \texttt{scale}.

\textbf{Parameters}

\begin{itemize}
  \item \texttt{scale} (\textit{float}) – Standard deviation of Gaussian distribution.
  \item \texttt{dtype} – Data type specifier.
  \item \texttt{rng} (\texttt{xp.random.RandomState}) – Pseudo-random number generator.
\end{itemize}

\textbf{Methods}

\_
\_call\_
\_(\text{array})\\n\textit{Initializes given array.}

This method destructively changes the value of array. The derived class is required to implement this
method. The algorithms used to make the new values depend on the concrete derived classes.

\textbf{Parameters} \texttt{array} (\textit{N-dimensional array}) – An array to be initialized by this initializer.

\_
\_eq\_
\_(\text{value},\)\\n\text{Return self} == \text{value}.
\_
\_ne\_
\_(\text{value},\)\\n\text{Return self}! = \text{value}.
\_
\_lt\_
\_(\text{value},\)\\n\text{Return self} < \text{value}.
\_
\_le\_
\_(\text{value},\)\\n\text{Return self} \leq \text{value}.
\_
\_gt\_
\_(\text{value},\)\\n\text{Return self} > \text{value}.
\_
\_ge\_
\_(\text{value},\)\\n\text{Return self} \geq \text{value}.
class chainer.initializers.LeCunNormal(scale=1.0, dtype=None, **kwargs)
Initializes array with scaled Gaussian distribution.
Each element of the array is initialized by the value drawn independently from Gaussian distribution whose mean is 0, and standard deviation is scale \times \sqrt{\frac{1}{fan_{in}}}, where fan_{in} is the number of input units.

Parameters
- scale (float) – A constant that determines the scale of the standard deviation.
- dtype – Data type specifier.
- rng (xp.random.RandomState) – Pseudo-random number generator.

Methods

__call__(array)
Initializes given array.
This method destructively changes the value of array. The derived class is required to implement this method. The algorithms used to make the new values depend on the concrete derived classes.

Parameters array (N-dimensional array) – An array to be initialized by this initializer.
chainer.initializers.GlorotNormal

class chainer.initializers.GlorotNormal(scale=1.0, dtype=None, **kwargs)

Initializes array with scaled Gaussian distribution.

Each element of the array is initialized by the value drawn independently from Gaussian distribution whose mean is 0, and standard deviation is \( \text{scale} \times \sqrt{\frac{2}{\text{fan_in} + \text{fan_out}}} \), where \( \text{fan_in} \) and \( \text{fan_out} \) are the number of input and output units, respectively.

Reference: Glorot & Bengio, AISTATS 2010

Parameters

- **scale** (float) – A constant that determines the scale of the standard deviation.
- **dtype** – Data type specifier.
- **rng** (xp.random.RandomState) – Pseudo-random number generator.

Methods

- **call**(array)
  
  Initializes given array.

  This method destructively changes the value of array. The derived class is required to implement this method. The algorithms used to make the new values depend on the concrete derived classes.

- **eq**(value, /)
  
  Return self==value.

- **ne**(value, /)
  
  Return self!=value.

- **lt**(value, /)
  
  Return self<value.

- **le**(value, /)
  
  Return self<=value.

- **gt**(value, /)
  
  Return self>value.

- **ge**(value, /)
  
  Return self>=value.

chainer.initializers.HeNormal

class chainer.initializers.HeNormal(scale=1.0, dtype=None, fan_option='fan_in', **kwargs)

Initializes array with scaled Gaussian distribution.

Each element of the array is initialized by the value drawn independently from Gaussian distribution whose mean is 0, and standard deviation is \( \text{scale} \times \sqrt{\frac{2}{\text{fan}}} \). If fan_option == 'fan_in', \( \text{fan} \) is the number of input units. If fan_option == 'fan_out', \( \text{fan} \) is the number of output units.


Parameters

- **scale** (float) – A constant that determines the scale of the standard deviation.
• **dtype** – Data type specifier.

• **fan_option** ({'fan_in', 'fan_out'}) – Decides how to compute the standard deviation. The default value is 'fan_in'.

• **rng** (xp.random.RandomState) – Pseudo-random number generator.

### Methods

**__call__(array)**

Initializes given array.

This method destructively changes the value of array. The derived class is required to implement this method. The algorithms used to make the new values depend on the concrete derived classes.

**Parameters**

- **array** *(N-dimensional array)* – An array to be initialized by this initializer.

**__eq__(value, /)**

Return self==value.

**__ne__(value, /)**

Return self!=value.

**__lt__(value, /)**

Return self<value.

**__le__(value, /)**

Return self<=value.

**__gt__(value, /)**

Return self>value.

**__ge__(value, /)**

Return self>=value.

---

**chainer.initializers.Orthogonal**

**class chainer.initializers.Orthogonal(scale=1.1, dtype=None, mode='auto', **kwargs)**

Initializes array with an orthogonal system.

This initializer first makes a matrix of the same shape as the array to be initialized whose elements are drawn independently from standard Gaussian distribution. Next, it applies QR decomposition to (the transpose of) the matrix. To make the decomposition (almost surely) unique, we require the diagonal of the triangular matrix R to be non-negative (see e.g. Edelman & Rao, [https://web.eecs.umich.edu/~rajnrao/Acta05rmt.pdf](https://web.eecs.umich.edu/~rajnrao/Acta05rmt.pdf)). Then, it initializes the array with the (semi-)orthogonal matrix Q. Finally, the array is multiplied by the constant `scale`.

If the `ndim` of the input array is more than 2, we consider the array to be a matrix by concatenating all axes except the first one.

The number of vectors consisting of the orthogonal system (i.e. first element of the shape of the array) must be equal to or smaller than the dimension of each vector (i.e. second element of the shape of the array).

**Variables**

- **scale** *(float)* – A constant to be multiplied by.

- **dtype** – Data type specifier.

- **mode** *(str)* – Assertion on the initialized shape. 'auto' (default), 'projection' (before v7), 'embedding', or 'basis'.

- **rng** (xp.random.RandomState) – Pseudo-random number generator.
Methods

__call__(array)
Initializes given array.

This method destructively changes the value of array. The derived class is required to implement this method. The algorithms used to make the new values depend on the concrete derived classes.

Parameters array (N-dimensional array) – An array to be initialized by this initializer.

__eq__(value,)
Return self==value.

__ne__(value,)
Return self!=value.

__lt__(value,)
Return self<value.

__le__(value,)
Return self<=value.

__gt__(value,)
Return self>value.

__ge__(value,)
Return self>=value.

chainer.initializers.Uniform

class chainer.initializers.Uniform(scale=0.05, dtype=None, **kwargs)
Initializes array with a scaled uniform distribution.

Each element of the array is initialized by the value drawn independently from uniform distribution \([−scale, scale]\).

Variables

- scale (float) – A constant that determines the scale of the uniform distribution.
- dtype – Data type specifier.
- rng (xp.random.RandomState) – Pseudo-random number generator.

Methods

__call__(array)
Initializes given array.

This method destructively changes the value of array. The derived class is required to implement this method. The algorithms used to make the new values depend on the concrete derived classes.

Parameters array (N-dimensional array) – An array to be initialized by this initializer.

__eq__(value,)
Return self==value.
chainer.initializers.LeCunUniform

class chainer.initializers.LeCunUniform(scale=1.0, dtype=None, **kwargs)

Initializes array with a scaled uniform distribution.

Each element of the array is initialized by the value drawn independently from uniform distribution $[-s, s]$ where $s = scale \times \sqrt{\frac{3}{fan_{in}}}$. Here $fan_{in}$ is the number of input units.


Variables

- `scale (float)` – A constant that determines the scale of the uniform distribution.
- `dtype` – Data type specifier.
- `rng (xp.random.RandomState)` – Pseudo-random number generator.

Methods

__call__(array)

Initializes given array.

This method destructively changes the value of array. The derived class is required to implement this method. The algorithms used to make the new values depend on the concrete derived classes.

Parameters array (N-dimensional array) – An array to be initialized by this initializer.
chainer.initializers.GlorotUniform

class chainer.initializers.GlorotUniform(scale=1.0, dtype=None, **kwargs)
    Initializes array with a scaled uniform distribution.

    Each element of the array is initialized by the value drawn independently from uniform distribution $[-s, s]$ where $s = \text{scale} \times \sqrt{\frac{6}{\text{fan}_{\text{in}} + \text{fan}_{\text{out}}}$. Here, \text{fan}_{\text{in}} and \text{fan}_{\text{out}} are the number of input and output units, respectively.

    Variables
    
    - scale (float) – A constant that determines the scale of the uniform distribution.
    - dtype – Data type specifier.
    - rng (xp.random.RandomState) – Pseudo-random number generator.

Methods

__call__(array)
    Initializes given array.

    This method destructively changes the value of array. The derived class is required to implement this method. The algorithms used to make the new values depend on the concrete derived classes.

Parameters array (N-dimensional array) – An array to be initialized by this initializer.

__eq__(value, /)
    Return self==value.

__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

chainer.initializers.HeUniform

class chainer.initializers.HeUniform(scale=1.0, dtype=None, **kwargs)
    Initializes array with scaled uniform distribution.

    Each element of the array is initialized by the value drawn independently from uniform distribution $[-s, s]$ where $s = \text{scale} \times \sqrt{\frac{6}{\text{fan}_{\text{in}}}$. Here, \text{fan}_{\text{in}} is the number of input units.

    Variables
    
    - scale (float) – A constant that determines the scale of the uniform distribution.
    - dtype – Data type specifier.
    - rng (xp.random.RandomState) – Pseudo-random number generator.
## Methods

__call__(array)

Initializes given array.

This method destructively changes the value of array. The derived class is required to implement this method. The algorithms used to make the new values depend on the concrete derived classes.

**Parameters**

array *(N-dimensional array)* – An array to be initialized by this initializer.

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.

__le__(value, /)

Return self<=value.

__gt__(value, /)

Return self>value.

__ge__(value, /)

Return self>=value.

### chainer.initializers.UpsamplingDeconvFilter

class chainer.initializers.UpsamplingDeconvFilter(interpolation='linear',
                                                   dtype=None)

Initializes array with upsampling filter.

The array is initialized with a standard image upsampling weight. This initializer is often used as initial weight for `DeconvolutionND()`. `DeconvolutionND()` is expected that its stride is equal to 

\((ksize + 1) // 2\).


**Variables**

- `interpolation` *(str)* – Upsampling interpolation method.
- `is 'linear'` *(Default)* –

## Methods

__call__(array)

Initializes given array.

This method destructively changes the value of array. The derived class is required to implement this method. The algorithms used to make the new values depend on the concrete derived classes.

**Parameters**

array *(N-dimensional array)* – An array to be initialized by this initializer.

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.
chainer.initializers.DownsamplingConvFilter

class chainer.initializers.DownsamplingConvFilter (interpolation='linear',
                                                   dtype=None)

Initializes array with downsampling filter.

The array is initialized with a standard image downsampling weight. This initializer is often used as initial
weight for ConvolutionND(). ConvolutionND() is expected that its stride is equal to \((ksize + 1)//2\).


Variables

• **interpolation** *(str)* – Downsampling interpolation method.
• **is 'linear'.*(Default)* –

Methods

__call__(array)

Initializes given array.

This method destructively changes the value of array. The derived class is required to implement this
method. The algorithms used to make the new values depend on the concrete derived classes.

Parameters **array** *(N-dimensional array)* – An array to be initialized by this initializer.

__eq__(value,)

Return self==value.

__ne__(value,)

Return self!=value.

__lt__(value,)

Return self<value.

__le__(value,)

Return self<=value.

__gt__(value,)

Return self>value.

__ge__(value,)

Return self>=value.
### 4.6.3 Helper function

**chainer.initializers.generate_array**

Return initialized array.

The algorithms used to make the new values depend on the concrete derived classes. If the initializer has the `dtype` attribute, it is used to construct the array. Otherwise, `chainer.config.dtype` is used instead. See *Configuring Chainer* for the `dtype` config.

**Parameters**

- **initializer** – A callable object that takes *N-dimensional array* and edits its value.
- **shape** (*int or tuple of int*) – Shape of the initialized array.
- **xp** (*module*) – `cupy`, `numpy`, or `chainerx`.
- **dtype** – Dtype specifier. If omitted, `initializer.dtype` is used.
- **device** – Target device specifier. If omitted, the current device is used for `cupy`, and the default device is used for `chainerx`.

**Returns** An initialized array.

**Return type** *N-dimensional array*

### 4.7 Snapshot Writers

**chainer.training.extensions.snapshot_writers.Writer**

Base class of snapshot writers.

**chainer.training.extensions.snapshot_writers.SimpleWriter**

The most simple snapshot writer.

**chainer.training.extensions.snapshot_writers.ThreadWriter**

Snapshot writer that uses a separate thread.

**chainer.training.extensions.snapshot_writers.ProcessWriter**

Snapshot writer that uses a separate process.

**chainer.training.extensions.snapshot_writers.QueueWriter**

Base class of queue snapshot writers.

**chainer.training.extensions.snapshot_writers.ThreadQueueWriter**

Snapshot writer that uses a thread queue.

**chainer.training.extensions.snapshot_writers.ProcessQueueWriter**

Snapshot writer that uses process queue.
4.7.1 chainer.trainingextensions.snapshot_writers.Writer

class chainer.trainingextensions.snapshot_writers.Writer
Base class of snapshot writers.

Snapshot invokes __call__ of this class every time when taking a snapshot. This class determines how the actual saving function will be invoked.

See also:

• chainer.training.extensions.snapshot()

Methods

__call__(filename, outdir, target)
Invokes the actual snapshot function.

This method is invoked by a Snapshot object every time it takes a snapshot.

Parameters

• filename (str) – Name of the file into which the serialized target is saved. It is a concrete file name, i.e. not a pre-formatted template string.

• outdir (str) – Output directory. Corresponds to Trainer.out.

• target (dict) – Serialized object which will be saved.

finalize()
Finalizes the writer.

Like extensions in Trainer, this method is invoked at the end of the training.

save(filename, outdir, target, savefun, **kwds)

__eq__(value,)
Return self==value.

__ne__(value,)
Return self!=value.

__lt__(value,)
Return self<value.

__le__(value,)
Return self<=value.

__gt__(value,)
Return self>value.

__ge__(value,)
Return self>=value.
4.7.2 chainer.training.extensions.snapshot_writers.SimpleWriter

```python
class chainer.training.extensions.snapshot_writers.SimpleWriter(
    savefun=<function save_npz>, **kwds)
```

The most simple snapshot writer.

This class just passes the arguments to the actual saving function.

**Parameters**

- `savefun` – Callable object. It takes three arguments: the output file path, the serialized dictionary object, and the optional keyword arguments.
- `kwds` – Keyword arguments for the `savefun`.

**See also:**

- `chainer.training.extensions.snapshot()`

**Methods**

- `__call__(filename, outdir, target)`
  
  Invokes the actual snapshot function.
  
  This method is invoked by a `Snapshot` object every time it takes a snapshot.

  **Parameters**

  - `filename` *(str)* – Name of the file into which the serialized target is saved. It is a concrete file name, i.e. not a pre-formatted template string.
  - `outdir` *(str)* – Output directory. Corresponds to `Trainer.out`.
  - `target` *(dict)* – Serialized object which will be saved.

- `finalize()`
  
  Finalizes the writer.
  
  Like extensions in `Trainer`, this method is invoked at the end of the training.

- `save(filename, outdir, target, savefun, **kwds)`

- `__eq__(value, /)`
  
  Return `self==value`.

- `__ne__(value, /)`
  
  Return `self!=value`.

- `__lt__(value, /)`
  
  Return `self<value`.

- `__le__(value, /)`
  
  Return `self<=value`.

- `__gt__(value, /)`
  
  Return `self>value`.

- `__ge__(value, /)`
  
  Return `self>=value`.
4.7.3 chainer.training.extensions.snapshot_writers.ThreadWriter

class chainer.training.extensions.snapshot_writers.ThreadWriter(savefun=<function save_npz>,
**kwds):

Snapshot writer that uses a separate thread.

This class creates a new thread that invokes the actual saving function.

See also:

• chainer.training.extensions.snapshot()

Methods

__call__(filename, outdir, target)
Invokes the actual snapshot function.

This method is invoked by a Snapshot object every time it takes a snapshot.

Parameters

• filename (str) – Name of the file into which the serialized target is saved. It is a
concrete file name, i.e. not a pre-formatted template string.

• outdir (str) – Output directory. Corresponds to Trainer.out.

• target (dict) – Serialized object which will be saved.

create_worker(filename, outdir, target, **kwds)
Creates a worker for the snapshot.

This method creates a thread or a process to take a snapshot. The created worker must have start() and
join() methods.

Parameters

• filename (str) – Name of the file into which the serialized target is saved. It is already
formatted string.

• outdir (str) – Output directory. Passed by trainer.out.

• target (dict) – Serialized object which will be saved.

• kwds – Keyword arguments for the savefun.

finalize()
Finalizes the writer.

Like extensions in Trainer, this method is invoked at the end of the training.

save (filename, outdir, target, savefun, **kwds)

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.
Return self>value.

Return self>=value.

4.7.4 chainer.training.extensions.snapshot_writers.ProcessWriter

```python
class chainer.training.extensions.snapshot_writers.ProcessWriter(savefun=<function save_npz>, **kwds)
```

Snapshot writer that uses a separate process.

This class creates a new process that invokes the actual saving function.

**Note:** Forking a new process from a MPI process might be danger. Consider using `ThreadWriter` instead of `ProcessWriter` if you are using MPI.

**See also:**

- `chainer.training.extensions.snapshot()`

**Methods**

```python
__call__(filename, outdir, target)
```

Invokes the actual snapshot function.

This method is invoked by a `Snapshot` object every time it takes a snapshot.

**Parameters**

- `filename` (**str**): Name of the file into which the serialized target is saved. It is a concrete file name, i.e. not a pre-formatted template string.
- `outdir` (**str**): Output directory. Corresponds to `Trainer.out`.
- `target` (**dict**): Serialized object which will be saved.

```python
create_worker(filename, outdir, target, **kwds)
```

Creates a worker for the snapshot.

This method creates a thread or a process to take a snapshot. The created worker must have `start()` and `join()` methods.

**Parameters**

- `filename` (**str**): Name of the file into which the serialized target is saved. It is already formated string.
- `outdir` (**str**): Output directory. Passed by `trainer.out`.
- `target` (**dict**): Serialized object which will be saved.
- `kwds` – Keyword arguments for the `savefun`.

```python
finalize()
```

Finalizes the writer.

Like extensions in `Trainer`, this method is invoked at the end of the training.
save (filename, outdir, target, savefun, **kwds)

__eq__ (value, /)
    Return self==value.

__ne__ (value, /)
    Return self!=value.

__lt__ (value, /)
    Return self<value.

__le__ (value, /)
    Return self<=value.

__gt__ (value, /)
    Return self>value.

__ge__ (value, /)
    Return self>=value.

4.7.5 chainer.training.extensions.snapshot_writers.QueueWriter

class chainer.training.extensions.snapshot_writers.QueueWriter (savefun=<function save_npz>,
    task=None)

Base class of queue snapshot writers.

This class is a base class of snapshot writers that use a queue. A Queue is created when this class is constructed,
and every time when __call__ is invoked, a snapshot task is put into the queue.

Parameters

• savefun – Callable object which is passed to the create_task() if the task is None. It takes three arguments: the output file path, the serialized dictionary object, and the optional keyword arguments.

• task – Callable object. Its __call__ must have a same interface to Writer. __call__. This object is directly put into the queue.

See also:

• chainer.training.extensions.snapshot_write()  

Methods

__call__ (filename, outdir, target)
    Invokes the actual snapshot function.

This method is invoked by a Snapshot object every time it takes a snapshot.

Parameters

• filename (str) – Name of the file into which the serialized target is saved. It is a concrete file name, i.e. not a pre-formatted template string.

• outdir (str) – Output directory. Corresponds to Trainer.out.

• target (dict) – Serialized object which will be saved.

create_consumer (q)  

consume (q)
**create_queue()**

**create_task**(savefun)

**finalize()**

Finalizes the writer.

Like extensions in Trainer, this method is invoked at the end of the training.

**save**(filename, outdir, target, savefun, **kwds)

**__eq__**(value, /

Return self==value.

**__ne__**(value, /

Return self!=value.

**__lt__**(value, /

Return self<value.

**__le__**(value, /

Return self<=value.

**__gt__**(value, /

Return self>value.

**__ge__**(value, /

Return self>=value.

---

### 4.7.6 chainer.training.extensions.snapshot_writers.ThreadQueueWriter

**class** chainer.training.extensions.snapshot_writers.ThreadQueueWriter(savefun=<function save_npz>, task=None)

Snapshot writer that uses a thread queue.

This class creates a thread and a queue by threading and queue modules respectively. The thread will be a consumer of the queue, and the main thread will be a producer of the queue.

See also:

- chainer.training.extensions.snapshot()

**Methods**

**__call__**(filename, outdir, target)

Invokes the actual snapshot function.

This method is invoked by a Snapshot object every time it takes a snapshot.

**Parameters**

- **filename**(str) – Name of the file into which the serialized target is saved. It is a concrete file name, i.e. not a pre-formatted template string.
- **outdir**(str) – Output directory. Corresponds to Trainer.out.
- **target**(dict) – Serialized object which will be saved.
create_queue()
create_task(savefun)
finalize()
   Finalizes the writer.
   Like extensions in Trainer, this method is invoked at the end of the training.
save (filename, outdir, target, savefun, **kwds)
__eq__(value,)
   Return self==value.
__ne__(value,)
   Return self!=value.
__lt__(value,)
   Return self<value.
__le__(value,)
   Return self<=value.
__gt__(value,)
   Return self>value.
__ge__(value,)
   Return self>=value.

4.7.7 chainer.training.extensions.snapshot_writers.ProcessQueueWriter

class chainer.training.extensions.snapshot_writers.ProcessQueueWriter (savefun=<function
   save_npz>,
   task=None)
   Snapshot writer that uses process queue.
   This class creates a process and a queue by multiprocessing module. The process will be a consumer of
   this queue, and the main process will be a producer of this queue.

   Note: Forking a new process from MPI process might be danger. Consider using ThreadQueueWriter
   instead of ProcessQueueWriter if you are using MPI.

See also:
   • chainer.training.extensions.snapshot_writer()

Methods

__call__ (filename, outdir, target)
   Invokes the actual snapshot function.
   This method is invoked by a Snapshot object every time it takes a snapshot.

   Parameters
      • filename (str) – Name of the file into which the serialized target is saved. It is a
        concrete file name, i.e. not a pre-formatted template string.
      • outdir (str) – Output directory. Corresponds to Trainer.out.
• **target** (*dict*) – Serialized object which will be saved.

```python
consume(q)
create_consumer(q)
create_queue()
create_task(savefun)
```

**finalize()**

Finalizes the writer.

Like extensions in *Trainer*, this method is invoked at the end of the training.

```python
save(filename, outdir, target, savefun, **kwds)
```

```python
__eq__(value,)
    Return self==value.

__ne__(value,)
    Return self!=value.

__lt__(value,)
    Return self<value.

__le__(value,)
    Return self<=value.

__gt__(value,)
    Return self>value.

__ge__(value,)
    Return self>=value.
```

## 4.8 Training Tools

Chainer provides a standard implementation of the training loops under the `chainer.training` module. It is built on top of many other core features of Chainer, including Variable and Function, Link/Chain/ChainList, Optimizer, Dataset, and Reporter/Summary. Compared to the training loop abstraction of other machine learning tool kits, Chainer’s training framework aims at maximal flexibility, while keeps the simplicity for the typical usages. Most components are pluggable, and users can overwrite the definition.

The core of the training loop abstraction is *Trainer*, which implements the training loop itself. The training loop consists of two parts: one is *Updater*, which actually updates the parameters to train, and the other is *Extension* for arbitrary functionalities other than the parameter update.

Updater and some extensions use `chainer.dataset` and *Iterator* to scan the datasets and load mini-batches. The trainer also uses *Reporter* to collect the observed values, and some extensions use *DictSummary* to accumulate them and computes the statistics.

You can find many examples for the usage of this training utilities from the official examples. You can also search the extension implementations from *Extensions*. 

4.8. Training Tools 971
**4.8.1 Trainer**

`chainer.training.Trainer` The standard training loop in Chainer.

```python
class chainer.training.Trainer(updater, stop_trigger=None, out='result', extensions=None)
```

Trainer is an implementation of a training loop. Users can invoke the training by calling the `run()` method.

Each iteration of the training loop proceeds as follows.

- Update of the parameters. It includes the mini-batch loading, forward and backward computations, and an execution of the update formula. These are all done by the update object held by the trainer.
- Invocation of trainer extensions in the descending order of their priorities. A trigger object is attached to each extension, and it decides at each iteration whether the extension should be executed. Trigger objects are callable objects that take the trainer object as the argument and return a boolean value indicating whether the extension should be called or not.

Extensions are callable objects that take the trainer object as the argument. There are three ways to define custom extensions: inheriting the `Extension` class, decorating functions by `make_extension()`, and defining any callable including lambda functions. See `Extension` for more details on custom extensions and how to configure them.

Users can register extensions to the trainer by calling the `extend()` method, where some configurations can be added.

- Trigger object, which is also explained above. In most cases, `IntervalTrigger` is used, in which case users can simply specify a tuple of the interval length and its unit, like `(1000, 'iteration')` or `(1, 'epoch')`.
- The order of execution of extensions is determined by their priorities. Extensions of higher priorities are invoked earlier. There are three standard values for the priorities:
  - PRIORITY_WRITER. This is the priority for extensions that write some records to the observation dictionary. It includes cases that the extension directly adds values to the observation dictionary, or the extension uses the `chainer.report()` function to report values to the observation dictionary.
  - PRIORITY_EDITOR. This is the priority for extensions that edit the observation dictionary based on already reported values.
  - PRIORITY_READER. This is the priority for extensions that only read records from the observation dictionary. This is also suitable for extensions that do not use the observation dictionary at all.

The current state of the trainer object and objects handled by the trainer can be serialized through the standard serialization protocol of Chainer. It enables us to easily suspend and resume the training loop.

```python
>>> serializers.save_npz('my.trainer', trainer) # To suspend and save
>>> serializers.load_npz('my.trainer', trainer) # To load and resume
```

The `snapshot()` method makes regular snapshots of the `Trainer` object during training.

**Note:** The serialization does not recover everything of the training loop. It only recovers the states which change over the training (e.g. parameters, optimizer states, the batch iterator state, extension states, etc.). You
must initialize the objects correctly before deserializing the states.

On the other hand, it means that users can change the settings on deserialization. For example, the exit condition can be changed on the deserialization, so users can train the model for some iterations, suspend it, and then resume it with larger number of total iterations.

During the training, it also creates a `Reporter` object to store observed values on each update. For each iteration, it creates a fresh observation dictionary and stores it in the `observation` attribute.

Links of the target model of each optimizer are registered to the reporter object as observers, where the name of each observer is constructed as the format `<optimizer name><link name>`. The link name is given by the `chainer.Link.namedlink()` method, which represents the path to each link in the hierarchy. Other observers can be registered by accessing the reporter object via the `reporter` attribute.

The default trainer is *plain*, i.e., it does not contain any extensions.

**Parameters**

- `updater` (**Updater**): Updater object. It defines how to update the models.
- `stop_trigger` – Trigger that determines when to stop the training loop. If it is not callable, it is passed to `IntervalTrigger`.
- `out` – Output directory.
- `extensions` – Extensions registered to the trainer.

**Variables**

- `updater` – The updater object for this trainer.
- `stop_trigger` – Trigger that determines when to stop the training loop. The training loop stops at the iteration on which this trigger returns `True`.
- `observation` – Observation of values made at the last update. See the `Reporter` class for details.
- `out` – Output directory.
- `reporter` – Reporter object to report observed values.

**Methods**

- `extend(extension, name=None, trigger=None, priority=None, *, call_before_training=False, **kwargs)`
  Registers an extension to the trainer.

  *Extension* is a callable object which is called after each update unless the corresponding trigger object decides to skip the iteration. The order of execution is determined by priorities: extensions with higher priorities are called earlier in each iteration. Extensions with the same priority are invoked in the order of registrations.

  If two or more extensions with the same name are registered, suffixes are added to the names of the second to last extensions. The suffix is `_N` where N is the ordinal of the extensions.

  See *Extension* for the interface of extensions.

**Parameters**

- `extension` – Extension to register.
• **name** (*str*) – Name of the extension. If it is omitted, the `Extension.name` attribute of the extension is used or the `Extension.default_name` attribute of the extension if `name` is is set to `None` or is undefined. Note that the name would be suffixed by an ordinal in case of duplicated names as explained above.

• **trigger** (*tuple or Trigger*) – Trigger object that determines when to invoke the extension. If it is `None`, `extension.trigger` is used instead. If it is `None` and the extension does not have the trigger attribute, the extension is triggered at every iteration by default. If the trigger is not callable, it is passed to `IntervalTrigger` to build an interval trigger.

• **call_before_training** (*bool*) – Flag to call extension before training. Default is `False`.

• **priority** (*int*) – Invocation priority of the extension. Extensions are invoked in the descending order of priorities in each iteration. If this is `None`, `extension.priority` is used instead.

### get_extension (*name*)
Returns the extension of a given name.

**Parameters**

- **name** (*str*) – Name of the extension.

**Returns**

Extension.

### run (*show_loop_exception_msg=True*)
Executes the training loop.

This method is the core of `Trainer`. It executes the whole loop of training the models.

Note that this method cannot run multiple times for one trainer object.

### serialize (*serializer*)

```
__eq__(value, /)
    Return self==value.

__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.
```
Attributes

**elapsed_time**
Total time used for the training.

The time is in seconds. If the training is resumed from snapshot, it includes the time of all the previous training to get the current state of the trainer.

**is_before_training**
Flag that represents if training has started or not.

True represents ‘before training’ and False represents ‘during/after training’.

This flag is supposed to be used in `Extension.__call__()` (e.g., `PlotReport.__call__()`)
to decide to execute its operation or not. This additional condition is necessary since `Extension._trigger(trainer)` is always False before training and cannot be used.

### 4.8.2 Updaters

<table>
<thead>
<tr>
<th>chainer.training.Updater</th>
<th>Interface of updater objects for trainers.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.training.updaters.StandardUpdater</td>
<td>Standard implementation of Updater.</td>
</tr>
<tr>
<td>chainer.training.updaters.ParallelUpdater</td>
<td>Implementation of a parallel GPU Updater.</td>
</tr>
</tbody>
</table>

**chainer.training.Updater**

```python
class chainer.training.Updater
Interface of updater objects for trainers.

Updater implements a training iteration as `update()`. Typically, the updating iteration proceeds as follows.

- Fetch a minibatch from `dataset` via `Iterator`.
- Run forward and backward process of `Chain`.
- Update parameters according to their `UpdateRule`.

The first line is processed by `Iterator.__next__`. The second and third are processed by `Optimizer.update`. Users can also implement their original updating iteration by overriding `Updater.update`.
```

**Methods**

**connect_trainer**(trainer)
Connects the updater to the trainer that will call it.

The typical usage of this method is to register additional links to the reporter of the trainer. This method is called at the end of the initialization of `Trainer`. The default implementation does nothing.

**Parameters**

- **trainer** *(Trainer)* – Trainer object to which the updater is registered.

**finalize**()
Finalizes the updater object.
This method is called at the end of training loops. It should finalize each dataset iterator used in this updater.

`get_all_optimizers()`

Gets a dictionary of all optimizers for this updater.

**Returns** Dictionary that maps names to optimizers.

**Return type** `dict`

`get_optimizer(name)`

Gets the optimizer of given name.

Updater holds one or more optimizers with names. They can be retrieved by this method.

**Parameters**

- `name (str)` – Name of the optimizer.

**Returns** Optimizer of the name.

**Return type** `Optimizer`

`serialize(serializer)`

Serializes the current state of the updater object.

`update()`

Updates the parameters of the target model.

This method implements an update formula for the training task, including data loading, forward/backward computations, and actual updates of parameters.

This method is called once at each iteration of the training loop.

`__eq__(value, /)`

Return `self==value`.

`__ne__(value, /)`

Return `self!=value`.

`__lt__(value, /)`

Return `self<value`.

`__le__(value, /)`

Return `self<=value`.

`__gt__(value, /)`

Return `self>value`.

`__ge__(value, /)`

Return `self>=value`.

`chainer.training.updaters.StandardUpdater`

**class** `chainer.training.updaters.StandardUpdater(iterator, optimizer, converter=convert.concat_examples, device=None, loss_func=None, loss_scale=None, auto_new_epoch=True, *, input_device=None)`

Standard implementation of Updater.

This is the standard implementation of **Updater**. It accepts one or more training datasets and one or more optimizers. The default update routine assumes that there is only one training dataset and one optimizer. Users can override this update routine by inheriting this class and overriding the `update_core()` method. Each
batch is converted to input arrays by `chainer.dataset.concat_examples()` by default, which can also be manually set by `converter` argument.

**Parameters**

- **iterator** – Dataset iterator for the training dataset. It can also be a dictionary that maps strings to iterators. If this is just an iterator, then the iterator is registered by the name 'main'.

- **optimizer** – Optimizer to update parameters. It can also be a dictionary that maps strings to optimizers. If this is just an optimizer, then the optimizer is registered by the name 'main'.

- **converter** – Converter function to build input arrays. Each batch extracted by the main iterator and the `device` option are passed to this function. `chainer.dataset.concat_examples()` is used by default.

- **device**(device specifier) – Device to which the model is sent. If None, the device of the model will stay unchanged.

- **loss_func** – Loss function. The target link of the main optimizer is used by default.

- **loss_scale**(float) – Loss scaling factor. Loss scaling is a useful technique to mitigate vanishing gradient issue that tends to happen when low precision data type like float16 is used during training. If you set loss scaling factor, gradients of loss values are to be multiplied by the factor before backprop starts. The factor is propagated to whole gradients in a computational graph along the backprop. The gradients of parameters are divided by the factor just before the parameters are to be updated.

- **auto_new_epoch**(bool) – If True, `new_epoch()` of the main optimizer is automatically called when the `is_new_epoch` attribute of the main iterator is True.

- **input_device**(device specifier) – Device to which the training data is sent. If `input_device` is omitted, it will match the `device` argument.

**Variables**

- **converter** – Converter function.

- **loss_func** – Loss function. If it is None, the target link of the main optimizer is used instead.

- **device** – Device to which the model is sent.

- **input_device** – Device to which the training data is sent.

- **iteration** – Current number of completed updates.

- **auto_new_epoch** – If True, `new_epoch()` is automatically called by `update_core()`. In this case, the `use_auto_new_epoch` attribute of each optimizer is also set to True. If `update_core()` is overridden, the implementation should correctly call `new_epoch()` of each optimizer.
Methods

**connect_trainer** *(trainer)*
Connects the updater to the trainer that will call it.

The typical usage of this method is to register additional links to the reporter of the trainer. This method is called at the end of the initialization of Trainer. The default implementation does nothing.

**Parameters**

trainer *(Trainer)* – Trainer object to which the updater is registered.

**finalize()**
Finalizes the updater object.

This method calls the finalize method of each iterator that this updater has. It is called at the end of training loops.

**get_all_optimizers()**
Gets a dictionary of all optimizers for this updater.

**Returns**
Dictionary that maps names to optimizers.

**Return type**
dict

**get_iterator** *(name)*
Gets the dataset iterator of given name.

**Parameters**

name *(str)* – Name of the dataset iterator.

**Returns**
Corresponding dataset iterator.

**Return type**
Iterator

**get_optimizer** *(name)*
Gets the optimizer of given name.

**Parameters**

name *(str)* – Name of the optimizer.

**Returns**
Corresponding optimizer.

**Return type**
Optimizer

**serialize** *(serializer)*
Serializes the current state of the updater object.

**update()**
Updates the parameters of the target model.

This method implements an update formula for the training task, including data loading, forward/backward computations, and actual updates of parameters.

This method is called once at each iteration of the training loop.

**update_core()**

**__eq__(value,/)**
Return self==value.

**__ne__(value,/)**
Return self!=value.

**__lt__(value,/)**
Return self<value.

**__le__(value,/)**
Return self<=value.
__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

device
epoch
epoch_detail
input_device
is_new_epoch
previous_epoch_detail

chainer.training.updaters.ParallelUpdater

class chainer.training.updaters.ParallelUpdater(iterator, optimizer, converter=<chainer.dataset.convert._ArbitraryCallableConverter object>, models=None, devices=None, loss_func=None, loss_scale=None, auto_new_epoch=True)

Implementation of a parallel GPU Updater.

This is an implementation of Updater that uses multiple GPUs. It behaves similarly to StandardUpdater. The update routine is modified to support data-parallel computation on multiple GPUs in one machine. It is based on synchronous parallel SGD: it parallelizes the gradient computation over a mini-batch, and updates the parameters only in the main device.

Parameters

- **iterator** – Dataset iterator for the training dataset. It can also be a dictionary that maps strings to iterators. If this is just an iterator, then the iterator is registered by the name 'main'.

- **optimizer** – Optimizer to update parameters. It can also be a dictionary that maps strings to optimizers. If this is just an optimizer, then the optimizer is registered by the name 'main'.

- **converter** – Converter function to build input arrays. Each batch extracted by the main iterator is split equally between the devices and then passed with corresponding device option to this function. concat_examples() is used by default.

- **models** – Dictionary of models. The main model should be the same model attached to the 'main' optimizer.

- **devices** – Dictionary of devices to which the training data is sent. The devices should be arranged in a dictionary with the same structure as models.

- **loss_func** – Loss function. The model is used as a loss function by default.

- **loss_scale** (float) – Loss scaling factor. Loss scaling is a useful technique to mitigate vanishing gradient issue that tends to happen when low precision data type like float16 is used during training. If you set loss scaling factor, gradients of loss values are to be multiplied by the factor before backprop starts. The factor is propagated to whole gradients
in a computational graph along the backprop. The gradients of parameters are divided by
the factor just before the parameters are to be updated.

• **auto_new_epoch (bool)** – If True, `new_epoch()` of the main optimizer is automat-
ically called when the `is_new_epoch` attribute of the main iterator is True.

### Methods

**connect_trainer (trainer)**
Connects the updater to the trainer that will call it.

The typical usage of this method is to register additional links to the reporter of the trainer. This method is
called at the end of the initialization of `Trainer`. The default implementation does nothing.

**Parameters**

- **trainer (Trainer)** – Trainer object to which the updater is registered.

**finalize ()**
Finalizes the updater object.

This method calls the `finalize` method of each iterator that this updater has. It is called at the end of training
loops.

**get_all_optimizers ()**
Gets a dictionary of all optimizers for this updater.

**Returns**
Dictionary that maps names to optimizers.

**Return type**
`dict`

**get_iterator (name)**
Gets the dataset iterator of given name.

- **Parameters**

  - **name (str)** – Name of the dataset iterator.

  **Returns**
  Corresponding dataset iterator.

  **Return type**
  `Iterator`

**get_optimizer (name)**
Gets the optimizer of given name.

- **Parameters**

  - **name (str)** – Name of the optimizer.

  **Returns**
  Corresponding optimizer.

  **Return type**
  `Optimizer`

**serialize (serializer)**
Serializes the current state of the updater object.

**update ()**
Updates the parameters of the target model.

This method implements an update formula for the training task, including data loading, forward/backward
computations, and actual updates of parameters.

This method is called once at each iteration of the training loop.

**update_core ()**

```python
__eq__ (value, /)
Return self==value.
```

```python
__ne__ (value, /)
Return self!=value.
```
def __lt__(self, value):
    return self < value.

def __le__(self, value):
    return self <= value.

def __gt__(self, value):
    return self > value.

def __ge__(self, value):
    return self >= value.

Attributes

device
epoch
epoch_detail
input_device
is_new_epoch
previous_epoch_detail

chainer.training.updaters.MultiprocessParallelUpdater

class chainer.training.updaters.MultiprocessParallelUpdater(Updater, optimi-
timizer, converter=<chainer.dataset.convert._ArbitraryCallableConverter
object>, devices=None, auto_new_epoch=True):

Implementation of a multiprocess parallel GPU Updater.

This is an implementation of Updater that uses multiple GPUs with multi-process data parallelism. It uses Nvidia NCCL for communication between multiple GPUs.

It behaves similarly to StandardUpdater. The update routine is modified to support data-parallel computation on multiple GPUs in one machine. It is based on synchronous parallel SGD: it parallelizes the gradient computation over a mini-batch, and updates the parameters only in the main device.

It does not transfer the values collected by Reporter in the sub devices to the main device. So you can only see the reported values in the main device.

Parameters

- **iterators** – List of dataset iterator for the training dataset. The number of the iterators must be same to the number of GPUs you use.

- **optimizer** – Optimizer to update parameters. The model should be attached to the optimizer.

- **converter** – Converter function to build input arrays. Each batch extracted by the iterator is split equally between the devices and then passed with corresponding device option to this function. concat_examples() is used by default.

- **devices** – Dictionary or list of devices to which the training data is sent. The master device will be the first one in the list or the value attached to the key 'main'.

4.8. Training Tools 981
• **auto_new_epoch** *(bool)* – If True, **new_epoch()** of the main optimizer is automatically called when the **is_new_epoch** attribute of the main iterator is True.

**Methods**

**static available()**

**connect_trainer** *(trainer)*

Connects the updater to the trainer that will call it.

The typical usage of this method is to register additional links to the reporter of the trainer. This method is called at the end of the initialization of **Trainer**. The default implementation does nothing.

**Parameters**

- **trainer** *(Trainer)* – Trainer object to which the updater is registered.

**finalize()**

Finalizes the updater object.

This method calls the **finalize** method of each iterator that this updater has. It is called at the end of training loops.

**get_all_optimizers()**

Gets a dictionary of all optimizers for this updater.

**Returns**

Dictionary that maps names to optimizers.

**Return type**

dict

**get_iterator** *(name)*

Gets the dataset iterator of given name.

**Parameters**

- **name** *(str)* – Name of the dataset iterator.

**Returns**

Corresponding dataset iterator.

**Return type**

Iterator

**get_optimizer** *(name)*

Gets the optimizer of given name.

**Parameters**

- **name** *(str)* – Name of the optimizer.

**Returns**

Corresponding optimizer.

**Return type**

Optimizer

**serialize** *(serializer)*

Serializes the current state of the updater object.

**setup_workers()**

**update()**

Updates the parameters of the target model.

This method implements an update formula for the training task, including data loading, forward/backward computations, and actual updates of parameters.

This method is called once at each iteration of the training loop.

**update_core()**

**__eq__** *(value, /)*

Return self==value.
__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.

**Attributes**

device
epoch
epoch_detail
input_device
is_new_epoch
previous_epoch_detail

We have two kinds of updaters for multi-gpus training. The pros/cons for the updaters are as follows:

**ParallelUpdater:**

• (+) Can use the same iterator for any number of GPUs
• (-) No parallelism at CPU side
• (-) GPUs used later may be blocked due to the limit of kernel-launch queue size

**MultiprocessParallelUpdater:**

• (+) Parallelism at CPU side
• (+) No degrade due to kernel launch queue size
• (-) Need per-process data iterator
• (-) Reporter cannot collect data except for one of the devices

### 4.8.3 Extensions

An extension is a callable object that can perform arbitrary actions during the training loop. Extensions can be registered to Trainer by using Trainer.extend() method, and they are invoked when the Trigger condition is satisfied.

In addition to the built-in extensions listed below, you can define your own extension by implementing Extension or using the make_extension() decorator. See Trainer Extensions for details.
## chainer.training.Extension

Base class of trainer extensions.

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.training.Extension</code></td>
<td>Base class of trainer extensions.</td>
</tr>
<tr>
<td><code>chainer.training.make_extension</code></td>
<td>Decorator to make given functions into trainer extensions.</td>
</tr>
</tbody>
</table>

### chainer.training.Extension

**Class**: `chainer.training.Extension`

**Base class of trainer extensions.**

Extension of `Trainer` is a callable object that takes the trainer object as the argument. It also provides some default configurations as its attributes, e.g. the default trigger and the default priority. This class provides a set of typical default values for these attributes.

There are three ways to define users’ own extensions: inheriting this class, decorating closures by `make_extension()`, or using any callable including lambda functions as extensions. Decorator can slightly reduce the overhead and is much easier to use, while this class provides more flexibility (for example, it can have methods to configure the behavior). Using a lambda function allows one-line coding for simple purposes, but users have to specify the configurations as arguments to `Trainer.extend()`. For a callable not inheriting this class, the default configurations of this class are used unless the user explicitly specifies them in `Trainer.extend()` method.

#### Variables

- **trigger** – Default value of trigger for this extension. It is set to `(1, 'iteration')` by default.
- **priority** – Default priority of the extension. It is set to `PRIORITY_READER` by default.
- **name** – Name of the extension. It is set to `None` by default. This value will be overwritten when registering an extension to a trainer. See `chainer.training.Trainer.extend()` for details.

#### Methods

- **`__call__(trainer)`**
  Invokes the extension.
  Implementations should override this operator. This method is called at iterations which the corresponding trigger accepts.
  **Parameters**
  - `trainer` (`Trainer`) – Trainer object that calls this operator.

- **`finalize()`**
  Finalizes the extension.
  This method is called at the end of the training loop.

- **`initialize(trainer)`**
  Initializes up the trainer state.
  This method is called before entering the training loop. An extension that modifies the state of `Trainer` can override this method to initialize it.
  When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.
For example, \texttt{ExponentialShift} extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The \texttt{ExponentialShift} extension recovers it in its \texttt{initialize} method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

\texttt{trainer (Trainer)} – Trainer object that runs the training loop.

\texttt{on\_error (trainer, exc, tb)}

Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- \texttt{trainer (Trainer)} – Trainer object that runs the training loop.
- \texttt{exc (Exception)} – arbitrary exception thrown during update loop.
- \texttt{tb (traceback)} – traceback object of the exception

\texttt{serialize (serializer)}

Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

\texttt{\_eq_ (value, /)}

Return \texttt{self==value}.

\texttt{\_ne_ (value, /)}

Return \texttt{self!=value}.

\texttt{\_lt_ (value, /)}

Return \texttt{self<value}.

\texttt{\_le_ (value, /)}

Return \texttt{self<=value}.

\texttt{\_gt_ (value, /)}

Return \texttt{self>value}.

\texttt{\_ge_ (value, /)}

Return \texttt{self>=value}.

**Attributes**

\texttt{default\_name}

Default name of the extension.

It is the name of the class by default. Implementation can override this property, or provide a class attribute to hide it.

\texttt{name = None}

\texttt{priority = 100}

\texttt{trigger = (1, 'iteration')}
chainer.trainings.make_extension

chainer.trainings.make_extension(trigger=None, default_name=None, priority=None, finalizer=None, initializer=None, on_error=None, **kwargs)

Decorator to make given functions into trainer extensions.

This decorator just adds some attributes to a given function. The value of the attributes are given by the arguments of this decorator.

See Extension for details of trainer extensions. Most of the default values of arguments also follow those for this class.

Parameters

- **trigger** – Default trigger of the extension.
- **default_name** – Default name of the extension. The name of a given function is used by default.
- **priority** (int) – Default priority of the extension.
- **finalizer** – Finalizer function of this extension. It is called at the end of the training loop.
- **initializer** – Initializer function of this extension. It is called at the beginning of the training loop.
- **on_error** – Error handler callback function of this extension. It is called after an error is raised during the trainer loop.

Evaluation and Metrics Collection

These extensions provide features to collect additional metrics. The typical use case is to use Evaluator to perform evaluation with a validation dataset to compute validation loss/accuracy.

<table>
<thead>
<tr>
<th>Extension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.trainings.extensionsEvaluator</td>
<td>Trainer extension to evaluate models on a validation set.</td>
</tr>
<tr>
<td>chainer.trainings.extensionsMicroAverage</td>
<td>Calculates micro-average ratio.</td>
</tr>
<tr>
<td>chainer.trainings.extensionsFailOnNonNumber</td>
<td>Trainer extension to raise RuntimeError if parameters contain NaN or Inf.</td>
</tr>
<tr>
<td>chainer.trainings.extensionsParameterStatistics</td>
<td>Trainer extension to report parameter statistics.</td>
</tr>
<tr>
<td>chainer.trainings.extensionsobserve_lr</td>
<td>Returns a trainer extension to record the learning rate.</td>
</tr>
<tr>
<td>chainer.trainings.extensionsobserve_value</td>
<td>Returns a trainer extension to continuously record a value.</td>
</tr>
</tbody>
</table>
chainer.training.extensions.Evaluator

class chainer.training.extensions.Evaluator(self, iterator, target, converter=convert.concat_examples, device=None, eval_hook=None, eval_func=None, *, progress_bar=False)

Trainer extension to evaluate models on a validation set.

This extension evaluates the current models by a given evaluation function. It creates a Reporter object to store values observed in the evaluation function on each iteration. The report for all iterations are aggregated to DictSummary. The collected mean values are further reported to the reporter object of the trainer, where the name of each observation is prefixed by the evaluator name. See Reporter for details in naming rules of the reports.

Evaluator has a structure to customize similar to that of StandardUpdater. The main differences are:

- There are no optimizers in an evaluator. Instead, it holds links to evaluate.
- An evaluation loop function is used instead of an update function.
- Preparation routine can be customized, which is called before each evaluation. It can be used, e.g., to initialize the state of stateful recurrent networks.

There are two ways to modify the evaluation behavior besides setting a custom evaluation function. One is by setting a custom evaluation loop via the eval_func argument. The other is by inheriting this class and overriding the evaluate() method. In latter case, users have to create and handle a reporter object manually. Users also have to copy the iterators before using them, in order to reuse them at the next time of evaluation. In both cases, the functions are called in testing mode (i.e., chainer.config.train is set to False).

This extension is called at the end of each epoch by default.

Parameters

- **iterator** – Dataset iterator for the validation dataset. It can also be a dictionary of iterators. If this is just an iterator, the iterator is registered by the name 'main'.
- **target** – Link object or a dictionary of links to evaluate. If this is just a link object, the link is registered by the name 'main'.
- **converter** – Converter function to build input arrays. concat_examples() is used by default.
- **device** – Device to which the validation data is sent. Negative value indicates the host memory (CPU).
- **eval_hook** – Function to prepare for each evaluation process. It is called at the beginning of the evaluation. The evaluator extension object is passed at each call.
- **eval_func** – Evaluation function called at each iteration. The target link to evaluate as a callable is used by default.
- **progress_bar** – Boolean flag to show a progress bar while training, which is similar to ProgressBar. (default: False)

**Warning:** The argument progress_bar is experimental. The interface can change in the future.

Variables

- **converter** – Converter function.
- **device** – Device to which the validation data is sent.
• **eval_hook** – Function to prepare for each evaluation process.
• **eval_func** – Evaluation function called at each iteration.

**Methods**

__call__ *(trainer=None)*
Executes the evaluator extension.

Unlike usual extensions, this extension can be executed without passing a trainer object. This extension reports the performance on validation dataset using the report() function. Thus, users can use this extension independently from any trainer by manually configuring a Reporter object.

Parameters

- **trainer** *(Trainer)* – Trainer object that invokes this extension. It can be omitted in case of calling this extension manually.

Returns

Result dictionary that contains mean statistics of values reported by the evaluation function.

Return type

dict

**evaluate** *
Evaluates the model and returns a result dictionary.

This method runs the evaluation loop over the validation dataset. It accumulates the reported values to DictSummary and returns a dictionary whose values are means computed by the summary.

Note that this function assumes that the main iterator raises StopIteration or code in the evaluation loop raises an exception. So, if this assumption is not held, the function could be caught in an infinite loop.

Users can override this method to customize the evaluation routine.

---

**Note:** This method encloses eval_func calls with function.no_backprop_mode() context, so all calculations using FunctionNodes inside eval_func do not make computational graphs. It is for reducing the memory consumption.

Returns

Result dictionary. This dictionary is further reported via report() without specifying any observer.

Return type

dict

**finalize** *
Finalizes the evaluator object.

This method calls the finalize method of each iterator that this evaluator has. It is called at the end of training loops.

**get_all_iterators** *
Returns a dictionary of all iterators.

**get_all_targets** *
Returns a dictionary of all target links.

**get_iterator**(name)*
Returns the iterator of the given name.

**get_target**(name)*
Returns the target link of the given name.
**initialize**(*trainer*)

Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of Trainer can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, *ExponentialShift* extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The *ExponentialShift* extension recovers it in its *initialize* method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

- **trainer** (*Trainer*) – Trainer object that runs the training loop.

**on_error**(*trainer, exc, tb*)

Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- **trainer** (*Trainer*) – Trainer object that runs the training loop.
- **exc** (*Exception*) – arbitrary exception thrown during update loop.
- **tb** (*traceback*) – traceback object of the exception

**serialize**(*serializer*)

Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

**__eq__**(*value, /*)

Return self==value.

**__ne__**(*value, /*)

Return self!=value.

**__lt__**(*value, /*)

Return self<value.

**__le__**(*value, /*)

Return self<=value.

**__gt__**(*value, /*)

Return self>value.

**__ge__**(*value, /*)

Return self>=value.
Attributes

- `default_name = 'validation'`
- `name = None`
- `priority = 300`
- `trigger = (1, 'epoch')`

chainer.training.extensions.MicroAverage

class chainer.training.extensions.MicroAverage(numerator_key, denominator_key, result_key, trigger=1, 'epoch')

Calculates micro-average ratio.

Give \(N\) batches and values \(\{n_1, \ldots, n_N\}\) and \(\{d_1, \ldots, d_N\}\), this extension calculates micro-average of these ratio defined as:

\[
\frac{\sum_{i=1}^{N} n_i}{\sum_{i=1}^{N} d_i}
\]

A user usually uses the number of examples which a system correctly predict as \(n_i\) and the number of total examples in \(i\)-th batch as \(d_i\). This value is called macro-average of precision.

Note that macro-average is defined as:

\[
\frac{1}{N} \sum_{i=1}^{N} \frac{n_i}{d_i}
\]

It is same to the micro-average when each mini-batch has the same \(d_i\).

You need to report numerator value (the number of correct examples) and denominator value (the number of examples) in your model.

```python
>>> class MyModel(chainer.Link):
...     def __call__(self, x, y):
...         loss = F.softmax_cross_entropy(x, y)
...         correct = (x.data.argmax(axis=1) == y.data).sum()
...         total = len(y.data)
...         reporter.report({'correct': correct, 'total': total}, self)
...         return loss
```

And then, make an extension with corresponding reporting keys and register it.

```python
>>> ext = extensions.MicroAverage('main/correct', 'main/total', 'main/accuracy')
```

Parameters

- `numerator_key (str)` – Key string of observation storing a numerator value.
- `denominator_key (str)` – Key string of observation storing a denominator value.
- `result_key (str)` – Key string of observation to store a result.
- `trigger` – Trigger that decides when to calculate average. This is distinct from the trigger of this extension itself. If it is a tuple in the form \(<\text{int}>, 'epoch'\) or \(<\text{int}>, 'iteration'\), it is passed to IntervalTrigger.
Methods

__call__(trainer)
Invokes the extension.

Implementations should override this operator. This method is called at iterations which the corresponding
trigger accepts.

Parameters trainer (Trainer) – Trainer object that calls this operator.

finalize()
Finalizes the extension.

This method is called at the end of the training loop.

initialize(trainer)
Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of Trainer
can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the
state of the trainer.

For example, ExponentialShift extension changes the optimizer’s hyperparameter at each invoca-
tion. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension
to recover the hyperparameter. The ExponentialShift extension recovers it in its initialize
method if it has been loaded from a snapshot, or just setting the initial value otherwise.

Parameters trainer (Trainer) – Trainer object that runs the training loop.

on_error (trainer, exc, tb)
Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension
that needs different error handling from finalize, can override this method to handle errors.

Parameters

• trainer (Trainer) – Trainer object that runs the training loop.

• exc (Exception) – arbitrary exception thrown during update loop.

• tb (traceback) – traceback object of the exception

serialize (serializer)
Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.
__ge__(value, /)
    Return self>=value.

Attributes

default_name
    Default name of the extension.
    It is the name of the class by default. Implementation can override this property, or provide a class attribute
to hide it.

name = None
priority = 200
trigger = (1, 'iteration')

chainer.training.extensions.FailOnNonNumber

class chainer.training.extensions.FailOnNonNumber
    Trainer extension to raise RuntimeError if parameters contain NaN or Inf.
    Although parameters including non-number such as NaN and Inf are unnecessary in most cases, Trainer will
continue to compute even if the parameters in a given optimizer diverge. This extension is aimed to reduce
unnecessary computations by throwing RuntimeError if the parameters contain NaN or Inf.

Methods

__call__(trainer)
    Invokes the extension.
    Implementations should override this operator. This method is called at iterations which the corresponding
trigger accepts.

Parameters trainer (Trainer) – Trainer object that calls this operator.

finalize()
    Finalizes the extension.
    This method is called at the end of the training loop.

initialize(trainer)
    Initializes up the trainer state.
    This method is called before entering the training loop. An extension that modifies the state of Trainer
can override this method to initialize it.
    When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the
state of the trainer.
    For example, ExponentialShift extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension
to recover the hyperparameter. The ExponentialShift extension recovers it in its initialize
method if it has been loaded from a snapshot, or just setting the initial value otherwise.

Parameters trainer (Trainer) – Trainer object that runs the training loop.
on_error (trainer, exc, tb)
   Handles the error raised during training before finalization.

   This method is called when an exception is thrown during the training loop, before finalize. An extension
   that needs different error handling from finalize, can override this method to handle errors.

   Parameters
   • trainer (Trainer) – Trainer object that runs the training loop.
   • exc (Exception) – arbitrary exception thrown during update loop.
   • tb (traceback) – traceback object of the exception

serialize (serializer)
   Serializes the extension state.

   It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

   _eq__ (value, /)
       Return self==value.

   _ne__ (value, /)
       Return self!=value.

   _lt__ (value, /)
       Return self<value.

   _le__ (value, /)
       Return self<=value.

   __gt__ (value, /)
       Return self>value.

   __ge__ (value, /)
       Return self>=value.

Attributes

default_name
   Default name of the extension.

   It is the name of the class by default. Implementation can override this property, or provide a class attribute
   to hide it.

   name = None
   priority = 100
   trigger = (1, 'iteration')

chainer.training.extensions.ParameterStatistics

class chainer.training.extensions.ParameterStatistics (links, statistics='default',
   report_params=True, report_grads=True, prefix=None, trigger=1, 'epoch',
   skip_nan_params=False)

   Trainer extension to report parameter statistics.
Statistics are collected and reported for a given Link or an iterable of Links. If a link contains child links, the statistics are reported separately for each child.

Any function that takes a one-dimensional numpy.ndarray or a cupy.ndarray and outputs a single or multiple real numbers can be registered to handle the collection of statistics, e.g. numpy.ndarray.mean().

The keys of reported statistics follow the convention of link name followed by parameter name, attribute name and function name, e.g. VGG16Layers/conv1_1/W/data/mean. They are prepended with an optional prefix and appended with integer indices if the statistics generating function return multiple values.

**Parameters**

- **links** (Link or iterable of ~chainer.Link) – Link(s) containing the parameters to observe. The link is expected to have a name attribute which is used as a part of the report key.

- **statistics** (dict or 'default') – Dictionary with function name to function mappings. The name is a string and is used as a part of the report key. The function is responsible for generating the statistics. If the special value 'default' is specified, the default statistics functions will be used.

- **report_params** (bool) – If True, report statistics for parameter values such as weights and biases.

- **report_grads** (bool) – If True, report statistics for parameter gradients.

- **prefix** (str) – Optional prefix to prepend to the report keys.

- **trigger** – Trigger that decides when to aggregate the results and report the values.

- **skip_nan_params** (bool) – If True, statistics are not computed for parameters including NaNs and a single NaN value is immediately reported instead. Otherwise, this extension will simply try to compute the statistics without performing any checks for NaNs.

**Note:** The default statistic functions are as follows:

- 'mean'(xp.mean(x))
- 'std'(xp.std(x))
- 'min'(xp.min(x))
- 'max'(xp.max(x))
- 'zeros'(xp.count_nonzero(x == 0))
- 'percentile'(xp.percentile(x, (0.13, 2.28, 15.87, 50, 84.13, 97.72, 99.87)))

**Methods**

__call__(trainer)
Execute the statistics extension.

Collect statistics for the current state of parameters.

Note that this method will merely update its statistic summary, unless the internal trigger is fired. If the trigger is fired, the summary will also be reported and then reset for the next accumulation.

**Parameters**

trainer (Trainer) – Associated trainer that invoked this extension.
**finalize()**

Finalizes the extension.

This method is called at the end of the training loop.

**initialize(trainer)**

Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of Trainer can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, `ExponentialShift` extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The `ExponentialShift` extension recovers it in its initialize method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

- `trainer (Trainer)` – Trainer object that runs the training loop.

**on_error(trainer, exc, tb)**

Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- `trainer (Trainer)` – Trainer object that runs the training loop.
- `exc (Exception)` – arbitrary exception thrown during update loop.
- `tb (traceback)` – traceback object of the exception

**register_statistics(name, function)**

Register a function to compute a certain statistic.

The registered function will be called each time the extension runs and the results will be included in the report.

**Parameters**

- `name (str)` – Name of the statistic.
- `function` – Function to generate the statistic. Any function that takes a one-dimensional `numpy.ndarray` or a `cupy.ndarray` and outputs a single or multiple real numbers is allowed.

**serialize(serializer)**

Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

**eq(value, /)**

Return `self == value`.

**ne(value, /)**

Return `self != value`.

**lt(value, /)**

Return `self < value`.

**le(value, /)**

Return `self <= value`.

**4.8. Training Tools 995**
__gt__(value,/)  
Return self>value.

__ge__(value,/)  
Return self>=value.

Attributes

default_name = 'parameter_statistics'
default_statistics = {'max': <function <lambda>>, 'mean': <function <lambda>>, 'min': <function <lambda>>}
name = None
priority = 300
report_key_template = '{prefix}{link_name}{param_name}/{attr_name}/{function_name}'
trigger = (1, 'iteration')

chainer.training.extensions.observe_lr

c harasser.traing.extensions.observe_lr( optimizer_name='main', observation_key='lr' )
Returns a trainer extension to record the learning rate.

Parameters

• optimizer_name (str) – Name of optimizer whose learning rate is recorded.
• observation_key (str) – Key of observation to record.

Returns  The extension function.
This extension is triggered each epoch by default. To change this, use the trigger argument with the
 Trainer.extend() method.

chainer.training.extensions.observe_value

c harasser.traing.extensions.observe_value( observation_key, target_func )
Returns a trainer extension to continuously record a value.

Parameters

• observation_key (str) – Key of observation to record.
• target_func (function) – Function that returns the value to record. It must take one

Returns  The extension function.
This extension is triggered each epoch by default. To change this, use the trigger argument with the
 Trainer.extend() method.
Optimizer Behavior Control

These extensions provide features to adjust optimizer behavior. The typical use case is to change the learning rate of the optimizer over time.

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>ExponentialShift</code></td>
<td>Trainer extension to exponentially shift an optimizer attribute.</td>
</tr>
<tr>
<td><code>InverseShift</code></td>
<td>Trainer extension to shift an optimizer attribute.</td>
</tr>
<tr>
<td><code>LinearShift</code></td>
<td>Trainer extension to change an optimizer attribute linearly.</td>
</tr>
<tr>
<td><code>MultistepShift</code></td>
<td>Trainer extension to shift an optimizer attribute in several steps.</td>
</tr>
<tr>
<td><code>PolynomialShift</code></td>
<td>Trainer extension to polynomially shift an optimizer attribute.</td>
</tr>
<tr>
<td><code>WarmupShift</code></td>
<td>Trainer extension to gradually initialize an optimizer attribute.</td>
</tr>
<tr>
<td><code>StepShift</code></td>
<td>Trainer extension to shift an optimizer attribute in “steps”.</td>
</tr>
</tbody>
</table>

**chainer.training.extensions.ExponentialShift**

```python
class chainer.training.extensions.ExponentialShift(attr, rate, init=None, target=None, optimizer=None)
```

Trainer extension to exponentially shift an optimizer attribute.

This extension exponentially increases or decreases the specified attribute of the optimizer. The typical use case is an exponential decay of the learning rate.

This extension is also called before the training loop starts by default.

**Parameters**

- `attr (str)` – Name of the attribute to shift.
- `rate (float)` – Rate of the exponential shift. This value is multiplied to the attribute at each call.
- `init (float)` – Initial value of the attribute. If it is `None`, the extension extracts the attribute at the first call and uses it as the initial value.
- `target (float)` – Target value of the attribute. If the attribute reaches this value, the shift stops.
- `optimizer (Optimizer)` – Target optimizer to adjust the attribute. If it is `None`, the main optimizer of the updater is used.
Methods

__call__ (trainer)
Invokes the extension.

Implementations should override this operator. This method is called at iterations which the corresponding
trigger accepts.

**Parameters**

trainer (Trainer) – Trainer object that calls this operator.

finalize ()
Finalizes the extension.

This method is called at the end of the training loop.

initialize (trainer)
Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of Trainer
can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the
state of the trainer.

For example, ExponentialShift extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension
to recover the hyperparameter. The ExponentialShift extension recovers it in its initialize
method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

trainer (Trainer) – Trainer object that runs the training loop.

on_error (trainer, exc, tb)
Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension
that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- trainer (Trainer) – Trainer object that runs the training loop.
- exc (Exception) – arbitrary exception thrown during update loop.
- tb (traceback) – traceback object of the exception

serialize (serializer)
Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

__eq__ (value, /)
Return self==value.

__ne__ (value, /)
Return self!=value.

__lt__ (value, /)
Return self<value.

__le__ (value, /)
Return self<=value.

__gt__ (value, /)
Return self>value.
Return self>=value.

Attributes

default_name
Default name of the extension.
It is the name of the class by default. Implementation can override this property, or provide a class attribute
to hide it.

name = None
priority = 100
trigger = (1, 'iteration')

chainer.training.extensions.InverseShift

class chainer.training.extensions.InverseShift(attr, gamma, power, init=None, target=None, optimizer=None)
Trainer extension to shift an optimizer attribute.
The new value is computed according to the formula below: new_attr = init_attr * (1 + gamma * iter) ** (- power),
which is compatible to the inv learning rate policy in Caffe.
The typical use is to decrease the learning rate during the training.
This extension is also called before the training loop starts by default.

Parameters

• attr (str) – Name of the attribute to shift.
• gamma (float) – Parameter used to compute the new value. Refer to the fomula above.
  Note that gamma is assumed to be nonnegative.
• power (float) – Parameter used to compute the new value. Refer to the fomula above.
• init (float) – Initial value of the attribute. If it is None, the extension extracts the
  attribute at the first call and uses it as the initial value.
• target (float) – Target value of the attribute. If the attribute reaches this value, the shift
  stops.
• optimizer (Optimizer) – Target optimizer to adjust the attribute. If it is None, the
  main optimizer of the updater is used.

Methods

__call__(trainer)
Invokes the extension.
Implementations should override this operator. This method is called at iterations which the corresponding
trigger accepts.

Parameters trainer (Trainer) – Trainer object that calls this operator.
**finalize**

Finalizes the extension.

This method is called at the end of the training loop.

**initialize**(trainer)

Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of Trainer can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, ExponentialShift extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The ExponentialShift extension recovers it in its initialize method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

trainer (Trainer) – Trainer object that runs the training loop.

**on_error**(trainer, exc, tb)

Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- trainer (Trainer) – Trainer object that runs the training loop.
- exc (Exception) – arbitrary exception thrown during update loop.
- tb (traceback) – traceback object of the exception

**serialize**(serializer)

Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

**Special Methods**

- **__eq__**(value, /)
  
  Return self==value.

- **__ne__**(value, /)
  
  Return self!=value.

- **__lt__**(value, /)
  
  Return self<value.

- **__le__**(value, /)
  
  Return self<=value.

- **__gt__**(value, /)
  
  Return self>value.

- **__ge__**(value, /)
  
  Return self>=value.
Attributes

**default_name**
Default name of the extension.

It is the name of the class by default. Implementation can override this property, or provide a class attribute to hide it.

```python
name = None
priority = 100
trigger = (1, 'iteration')
```

### chainer.training.extensions.LinearShift

**class** chainer.training.extensions.LinearShift(*attr, value_range, time_range, optimizer=None*)

Trainer extension to change an optimizer attribute linearly.

This extension changes an optimizer attribute from the first value to the last value linearly within a specified duration. The typical use case is warming up of the momentum coefficient.

For example, suppose that this extension is called at every iteration, and `value_range == (x, y)` and `time_range == (i, j)`. Then, this extension keeps the attribute to be `x` up to the `i`-th iteration, linearly shifts the value to `y` by the `j`-th iteration, and then keeps the value to be `y` after the `j`-th iteration.

This extension is also called before the training loop starts by default.

**Parameters**

- **attr** (*str*) – Name of the optimizer attribute to adjust.
- **value_range** (*tuple of float*) – The first and the last values of the attribute.
- **time_range** (*tuple of ints*) – The first and last counts of calls in which the attribute is adjusted.
- **optimizer** (*Optimizer*) – Target optimizer object. If it is None, the main optimizer of the trainer is used.

**Methods**

**__call__**(*trainer*)
Invokes the extension.

Implementations should override this operator. This method is called at iterations which the corresponding trigger accepts.

**Parameters**

- **trainer** (*Trainer*) – Trainer object that calls this operator.

**finalize**()
Finalizes the extension.

This method is called at the end of the training loop.

**initialize**(*trainer*)
Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of `Trainer` can override this method to initialize it.
When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, `ExponentialShift` extension changes the optimizer's hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The `ExponentialShift` extension recovers it in its `initialize` method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

trainer (Trainer) – Trainer object that runs the training loop.

**on_error** (trainer, exc, tb)

Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- trainer (Trainer) – Trainer object that runs the training loop.
- exc (Exception) – arbitrary exception thrown during update loop.
- tb (traceback) – traceback object of the exception

**serialize** (serializer)

Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

**Attributes**

- default_name
  Default name of the extension.
  It is the name of the class by default. Implementation can override this property, or provide a class attribute to hide it.

  name = None

  priority = 100

  trigger = (1, 'iteration')
chainer.training.extensions.MultistepShift

class chainer.training.extensions.MultistepShift(attr, gamma, step_value, init, optimizer=None)

Trainer extension to shift an optimizer attribute in several steps.

This extension changes an optimizer attribute in several steps, every step the attribute will multiply a factor gamma.

For example, suppose that this extension is called at every iteration, and init = x, gamma = y, step_value = [s1, s2, s3]. Then during the iterations from 0 to (s1 - 1), the attr will be x. During the iterations from s1 to (s2 - 1), the attr will be x * y. During the iterations from s2 to (s3 - 1), the attr will be x * y * y. During the iterations after s3, the attr will be x * y * y * y.

This extension is also called before the training loop starts by default.

Parameters

- **attr** (str) – Name of the attribute to shift.
- **init** (float) – Initial value of the attribute. If it is None, the extension extracts the attribute at the first call and uses it as the initial value.
- **gamma** (float) – The factor which the attr will multiply at the beginning of each step.
- **step_value** (tuple) – The first iterations of each step.
- **optimizer** (Optimizer) – Target optimizer to adjust the attribute. If it is None, the main optimizer of the updater is used.

Methods

__call__(trainer)

Invokes the extension.

Implementations should override this operator. This method is called at iterations which the corresponding trigger accepts.

Parameters

- **trainer** (Trainer) – Trainer object that calls this operator.

finalize()

Finalizes the extension.

This method is called at the end of the training loop.

initialize(trainer)

Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of Trainer can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, ExponentialShift extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The ExponentialShift extension recovers it in its initialize method if it has been loaded from a snapshot, or just setting the initial value otherwise.

Parameters

- **trainer** (Trainer) – Trainer object that runs the training loop.
### on_error

\(\text{on}\_\text{error}(\text{trainer, exc, tb})\)

Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- **trainer** (Trainer) – Trainer object that runs the training loop.
- **exc** (Exception) – arbitrary exception thrown during update loop.
- **tb** (traceback) – traceback object of the exception

### serialize

\(\text{serialize} (\text{serializer})\)

Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

- `__eq__(value,/)`
  - Return `self==value`.
- `__ne__(value,/)`
  - Return `self!=value`.
- `__lt__(value,/)`
  - Return `self<value`.
- `__le__(value,/)`
  - Return `self<=value`.
- `__gt__(value,/)`
  - Return `self>value`.
- `__ge__(value,/)`
  - Return `self>=value`.

### Attributes

- **default_name**
  - Default name of the extension.
  - It is the name of the class by default. Implementation can override this property, or provide a class attribute to hide it.

  ```python
  name = None
  priority = 100
  trigger = (1, 'iteration')
  ```

### chainer.training.extensions.PolynomialShift

**class** chainer.training.extensions.PolynomialShift

Trainer extension to polynomially shift an optimizer attribute.

This extension polynomially decreases the specified attribute of the optimizer. The typical use case is a polynomial decay of the learning rate at each iteration.
For example, suppose that this extension is invoke at every iteration. Then this extension will set the corresponding attribute to $init\_value \times (1 - i / max\_iter)^{rate}$ at the $i$-th iteration, where the $max\_iter$ is the number of iterations to be running.

This extension is also called before the training loop starts by default.

**Parameters**

- **attr** *(str)* – Name of the attribute to shift.
- **rate** *(float)* – Exponent of polynomial shift.
- **max_count** *(int)* – Number of this extension to be invoked.
- **init** *(float)* – Initial value of the attribute. If it is None, the extension extracts the attribute at the first call and uses it as the initial value.
- **target** *(float)* – Target value of the attribute. If the attribute reaches this value, the shift stops.
- **optimizer** *(Optimizer)* – Target optimizer to adjust the attribute. If it is None, the main optimizer of the updater is used.

**Methods**

**__call__(trainer)**
Invokes the extension.

Implementations should override this operator. This method is called at iterations which the corresponding trigger accepts.

**Parameters**

- **trainer** *(Trainer)* – Trainer object that calls this operator.

**finalize()**
Finalizes the extension.

This method is called at the end of the training loop.

**initialize(trainer)**
Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of Trainer can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, ExponentialShift extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The ExponentialShift extension recovers it in its initialize method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

- **trainer** *(Trainer)* – Trainer object that runs the training loop.

**on_error(trainer, exc, tb)**
Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- **trainer** *(Trainer)* – Trainer object that runs the training loop.
• **exc** (**Exception**) – arbitrary exception thrown during update loop.
• **tb** (**traceback**) – traceback object of the exception

**serialize** (**serializer**)
Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

```python
__eq__(value,)
Return self==value.

__ne__(value,)
Return self!=value.

__lt__(value,)
Return self<value.

__le__(value,)
Return self<=value.

__gt__(value,)
Return self>value.

__ge__(value,)
Return self>=value.
```

**Attributes**

**default_name**
Default name of the extension.

It is the name of the class by default. Implementation can override this property, or provide a class attribute to hide it.

```python
invoke_before_training = True
name = None
priority = 100
trigger = (1, 'iteration')
```

**chainer.training.extensions.WarmupShift**

```python
class chainer.training.extensions.WarmupShift (attr, warmup_start, warmup_iter, init, optimizer=None)
```

Trainer extension to gradually initialize an optimizer attribute.

This extension changes an optimizer attribute evenly at the beginning of one training.

For example, suppose that this extension is called at every iteration, and warmup_start = x , init = y, warmup_iter = t. Then this extension will set the corresponding attribute to from x to y evenly in first t iterations.

This extension is also called before the training loop starts by default.

**Parameters**

• **attr** (**str**) – Name of the optimizer attribute to adjust.
• **warmup_start** (**float**) – the value of the attr at the beginning of one training.
• **init** (**float**) – the value of the attr after warm up iterations.
• **warmup_iter** (*int*) – the number of the iterations in which the attr changes from `warmup_start` to `init`.

• **optimizer** (*Optimizer*) – Target optimizer object. If it is None, the main optimizer of the trainer is used.

**Methods**

__call__ (*trainer*)

Invokes the extension.

Implementations should override this operator. This method is called at iterations which the corresponding trigger accepts.

**Parameters**

- **trainer** (*Trainer*) – Trainer object that calls this operator.

finalize ()

Finalizes the extension.

This method is called at the end of the training loop.

initialize (*trainer*)

Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of `Trainer` can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, `ExponentialShift` extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The `ExponentialShift` extension recovers it in its `initialize` method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

- **trainer** (*Trainer*) – Trainer object that runs the training loop.

on_error (*trainer, exc, tb*)

Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- **trainer** (*Trainer*) – Trainer object that runs the training loop.
- **exc** (*Exception*) – arbitrary exception thrown during update loop.
- **tb** (*traceback*) – traceback object of the exception

serialize (*serializer*)

Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

__eq__ (*value, /*)

Return self==value.

__ne__ (*value, /*)

Return self!=value.

__lt__ (*value, /*)

Return self<value.
__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

default_name
    Default name of the extension.
    It is the name of the class by default. Implementation can override this property, or provide a class attribute
to hide it.

    name = None
    priority = 100
    trigger = (1, 'iteration')

chainer.training.extensions.StepShift

class chainer.training.extensions.StepShift (attr, gamma, step, init=None, target=None, optimizer=None)
    Trainer extension to shift an optimizer attribute in “steps”.
    This extension multiplies the specified attribute of the optimizer in “steps”. The typical use case is to scale the
    attribute at every kth iteration.
    For example, suppose that this extension is invoked at every iteration, then given k, a multiplier gamma and
    an initial value init, the optimizer attribute is set to init * gamma ^ (floor(i / k)), where i
    represents the index of the current iteration.
    This extension is also called before the training loop starts by default.

Parameters

* attr (str) – Name of the optimizer attribute to adjust.
* gamma (float) – The multiplier.
* step (int) – The interval for the multiplication, i.e., k.
* init (float) – Initial value of the attribute. If it is None, the extension extracts the
    attribute at the first call and uses it as the initial value.
* target (float) – Target value of the attribute. If the attribute reaches this value, the shift
    stops.
* optimizer (Optimizer) – Target optimizer object. If it is None, the main optimizer of
    the trainer is used.
Methods

`__call__`(trainer)
Invokes the extension.

Implementations should override this operator. This method is called at iterations which the corresponding trigger accepts.

**Parameters**

- `trainer (Trainer)` – Trainer object that calls this operator.

`finalize()`
Finalizes the extension.

This method is called at the end of the training loop.

`initialize`(trainer)
Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of `Trainer` can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, `ExponentialShift` extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The `ExponentialShift` extension recovers it in its `initialize` method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

- `trainer (Trainer)` – Trainer object that runs the training loop.

`on_error`(trainer, exc, tb)
Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- `trainer (Trainer)` – Trainer object that runs the training loop.
- `exc (Exception)` – arbitrary exception thrown during update loop.
- `tb (traceback)` – traceback object of the exception

`serialize`(serializer)
Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

`__eq__`(value, /)
Return self==value.

`__ne__`(value, /)
Return self!=value.

`__lt__`(value, /)
Return self<value.

`__le__`(value, /)
Return self<=value.

`__gt__`(value, /)
Return self>value.

`__ge__`(value, /)
Return self>=value.
__ge__(value, /)
    Return self>=value.

Attributes

default_name
    Default name of the extension.
    It is the name of the class by default. Implementation can override this property, or provide a class attribute
to hide it.

name = None
priority = 100
trigger = (1, 'iteration')

Reporting

These extensions provide features to perform reporting of metrics and various statistics to the console or files.

<table>
<thead>
<tr>
<th>Extension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.training.extensions.PrintReport</td>
<td>Trainer extension to print the accumulated results.</td>
</tr>
<tr>
<td>chainer.training.extensions.ProgressBar</td>
<td>Trainer extension to print a progress bar and recent training status.</td>
</tr>
<tr>
<td>chainer.training.extensions.LogReport</td>
<td>Trainer extension to output the accumulated results to a log file.</td>
</tr>
<tr>
<td>chainer.training.extensions.PlotReport</td>
<td>Trainer extension to output plots.</td>
</tr>
<tr>
<td>chainer.training.extensions.DumpGraph</td>
<td>Trainer extension to dump a computational graph.</td>
</tr>
</tbody>
</table>

chainer.training.extensions.PrintReport

class chainer.training.extensions.PrintReport(entries, log_report='LogReport',
    out=<io.TextIOWrapper name='<stdout>' mode='w',
    encoding='UTF-8'>)

Trainer extension to print the accumulated results.

This extension uses the log accumulated by a LogReport extension to print specified entries of the log in a human-readable format.

Parameters

- **entries (list of str)** – List of keys of observations to print.
- **log_report (str or LogReport)** – Log report to accumulate the observations. This is either the name of a LogReport extensions registered to the trainer, or a LogReport instance to use internally.
- **out** – Stream to print the bar. Standard output is used by default.
Methods

__call__(trainer)
Invokes the extension.

Implementations should override this operator. This method is called at iterations which the corresponding trigger accepts.

Parameters trainer (Trainer) – Trainer object that calls this operator.

finalize()
Finalizes the extension.

This method is called at the end of the training loop.

initialize(trainer)
Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of Trainer can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, ExponentialShift extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The ExponentialShift extension recovers it in its initialize method if it has been loaded from a snapshot, or just setting the initial value otherwise.

Parameters trainer (Trainer) – Trainer object that runs the training loop.

on_error (trainer, exc, tb)
Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

Parameters

• trainer (Trainer) – Trainer object that runs the training loop.

• exc (Exception) – arbitrary exception thrown during update loop.

• tb (traceback) – traceback object of the exception

serialize (serializer)
Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.
__ge__(value,/)  
Return self>=value.

Attributes

default_name
Default name of the extension.
It is the name of the class by default. Implementation can override this property, or provide a class attribute
to hide it.

name = None
priority = 100
trigger = (1, 'iteration')

chainer.training.extensions.ProgressBar

class chainer.training.extensions.ProgressBar(training_length=None, update_interval=100, bar_length=50, out=<_io.TextIOWrapper name='<stdout>' mode='w' encoding='UTF-8'>)

Trainer extension to print a progress bar and recent training status.

This extension prints a progress bar at every call. It watches the current iteration and epoch to print the bar.

Parameters

• training_length (tuple) – Length of whole training. It consists of an integer and
either 'epoch' or 'iteration'. If this value is omitted and the stop trigger of the
trainer is IntervalTrigger, this extension uses its attributes to determine the length of
the training.

• update_interval (int) – Number of iterations to skip printing the progress bar.

• bar_length (int) – Length of the progress bar in characters.

• out – Stream to print the bar. Standard output is used by default.

Methods

__call__(trainer)
Invokes the extension.
Implementations should override this operator. This method is called at iterations which the corresponding
trigger accepts.

Parameters trainer (Trainer) – Trainer object that calls this operator.

finalize ()
Finalizes the extension.
This method is called at the end of the training loop.

initialize (trainer)
Initializes up the trainer state.
This method is called before entering the training loop. An extension that modifies the state of Trainer can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, ExponentialShift extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The ExponentialShift extension recovers it in its initialize method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

trainer (Trainer) – Trainer object that runs the training loop.

**on_error** (trainer, exc, tb)

Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- trainer (Trainer) – Trainer object that runs the training loop.
- exc (Exception) – arbitrary exception thrown during update loop.
- tb (traceback) – traceback object of the exception

**serialize** (serializer)

Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

```
__eq__.__doc__
Return self==value.

__ne__.__doc__
Return self!=value.

__lt__.__doc__
Return self<value.

__le__.__doc__
Return self<=value.

__gt__.__doc__
Return self>value.

__ge__.__doc__
Return self>=value.
```

**Attributes**

**default_name**

Default name of the extension.

It is the name of the class by default. Implementation can override this property, or provide a class attribute to hide it.

```
name = None
```

```
priority = 100
```

```
trigger = (1, 'iteration')
```
chainer.training.extensions.LogReport

class chainer.training.extensions.LogReport(keys=None, trigger=1, 'epoch', postprocess=None, filename='log')

Trainer extension to output the accumulated results to a log file.

This extension accumulates the observations of the trainer to DictSummary at a regular interval specified by a supplied trigger, and writes them into a log file in JSON format.

There are two triggers to handle this extension. One is the trigger to invoke this extension, which is used to handle the timing of accumulating the results. It is set to 1, 'iteration' by default. The other is the trigger to determine when to emit the result. When this trigger returns True, this extension appends the summary of accumulated values to the list of past summaries, and writes the list to the log file. Then, this extension makes a new fresh summary object which is used until the next time that the trigger fires.

It also adds some entries to each result dictionary.

• 'epoch' and 'iteration' are the epoch and iteration counts at the output, respectively.
• 'elapsed_time' is the elapsed time in seconds since the training begins. The value is taken from Trainer.elapsed_time.

Parameters

• keys (iterable of strs) – Keys of values to accumulate. If this is None, all the values are accumulated and output to the log file.

• trigger – Trigger that decides when to aggregate the result and output the values. This is distinct from the trigger of this extension itself. If it is a tuple in the form <int>, 'epoch' or <int>, 'iteration', it is passed to IntervalTrigger.

• postprocess – Callback to postprocess the result dictionaries. Each result dictionary is passed to this callback on the output. This callback can modify the result dictionaries, which are used to output to the log file.

• filename (str) – Name of the log file under the output directory. It can be a format string: the last result dictionary is passed for the formatting. For example, users can use '{iteration}' to separate the log files for different iterations. If the log name is None, it does not output the log to any file. For historical reasons log_name is also accepted as an alias of this argument.

Methods

__call__(trainer)

Invokes the extension.

Implementations should override this operator. This method is called at iterations which the corresponding trigger accepts.

Parameters trainer (Trainer) – Trainer object that calls this operator.

finalize ()

Finalizes the extension.

This method is called at the end of the training loop.

initialize (trainer)

Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of Trainer can override this method to initialize it.
When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, `ExponentialShift` extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The `ExponentialShift` extension recovers it in its `initialize` method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

`trainer` (Trainer) – Trainer object that runs the training loop.

**on_error** (trainer, exc, tb)

Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- `trainer` (Trainer) – Trainer object that runs the training loop.
- `exc` (Exception) – arbitrary exception thrown during update loop.
- `tb` (traceback) – traceback object of the exception

**serialize** (serializer)

Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

**Attributes**

**default_name**

Default name of the extension.

It is the name of the class by default. Implementation can override this property, or provide a class attribute to hide it.

**log**

The current list of observation dictionaries.

**name** = None

**priority** = 100

**trigger** = (1, 'iteration')
Trainer extension to output plots.

This extension accumulates the observations of the trainer to `DictSummary` at a regular interval specified by a supplied trigger, and plot a graph with using them.

There are two triggers to handle this extension. One is the trigger to invoke this extension, which is used to handle the timing of accumulating the results. It is set to 1, 'iteration' by default. The other is the trigger to determine when to emit the result. When this trigger returns True, this extension appends the summary of accumulated values to the list of past summaries, and writes the list to the log file. Then, this extension makes a new fresh summary object which is used until the next time that the trigger fires.

It also adds 'epoch' and 'iteration' entries to each result dictionary, which are the epoch and iteration counts at the output.

**Warning:** If your environment needs to specify a backend of matplotlib explicitly, please call `matplotlib.use` before calling `trainer.run`. For example:

```python
import matplotlib
matplotlib.use('Agg')

trainer.extend(
    extensions.PlotReport(['main/loss', 'validation/main/loss'],
                          'epoch', filename='loss.png'))
trainer.run()
```

Then, once one of instances of this extension is called, `matplotlib.use` will have no effect.

For the details, please see here: [https://matplotlib.org/faq/usage_faq.html#what-is-a-backend](https://matplotlib.org/faq/usage_faq.html#what-is-a-backend)

**Parameters**

- **y_keys** *(iterable of strs)* – Keys of values regarded as y. If this is None, nothing is output to the graph.
- **x_key** *(str)* – Keys of values regarded as x. The default value is ‘iteration’.
- **trigger** – Trigger that decides when to aggregate the result and output the values. This is distinct from the trigger of this extension itself. If it is a tuple in the form <int>, 'epoch' or <int>, 'iteration', it is passed to IntervalTrigger.
- **postprocess** – Callback to postprocess the result dictionaries. Figure object, Axes object, and all plot data are passed to this callback in this order. This callback can modify the figure.
- **filename** *(str)* – Name of the figure file under the output directory. It can be a format string. For historical reasons `file_name` is also accepted as an alias of this argument.
- **marker** *(str)* – The marker used to plot the graph. Default is ‘x’. If None is given, it draws with no markers.
- **grid** *(bool)* – If True, set the axis grid on. The default value is True.
Methods

__call__(trainer)
Invokes the extension.

Implementations should override this operator. This method is called at iterations which the corresponding trigger accepts.

Parameters
trainer (Trainer) – Trainer object that calls this operator.

static available()

finalize()
Finalizes the extension.

This method is called at the end of the training loop.

initialize(trainer)
Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of Trainer can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, ExponentialShift extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The ExponentialShift extension recovers it in its initialize method if it has been loaded from a snapshot, or just setting the initial value otherwise.

Parameters
trainer (Trainer) – Trainer object that runs the training loop.

on_error (trainer, exc, tb)
Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

Parameters

• trainer (Trainer) – Trainer object that runs the training loop.
• exc (Exception) – arbitrary exception thrown during update loop.
• tb (traceback) – traceback object of the exception

serialize (serializer)
Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.
__gt__ (value, /)
    Return self>value.
__ge__ (value, /)
    Return self>=value.

Attributes

default_name
    Default name of the extension.
    It is the name of the class by default. Implementation can override this property, or provide a class attribute
to hide it.

    name = None
    priority = 100
    trigger = (1, 'iteration')

chainer.training.extensions.VariableStatisticsPlot

class chainer.training.extensions.VariableStatisticsPlot (targets,
    max_sample_size=1000,
    report_data=True,
    report_grad=True,
    plot_mean=True,
    plot_std=True,
    per-
    centile_sigmas=0, 0.13, 2.28, 15.87, 50, 84.13, 97.72, 99.87, 100,
    trigger=1, 'epoch', file-
    name='statistics.png',
    figsize=None,
    marker=None,
    grid=True)

Trainer extension to plot statistics for Variables.

This extension collects statistics for a single Variable, a list of Variables or similarly a single or a list of
Links containing one or more Variables. In case multiple Variables are found, the means are computed.
The collected statistics are plotted and saved as an image in the directory specified by the Trainer.

Statistics include mean, standard deviation and percentiles.

This extension uses reservoir sampling to preserve memory, using a fixed size running sample. This means that
collected items in the sample are discarded uniformly at random when the number of items becomes larger than
the maximum sample size, but each item is expected to occur in the sample with equal probability.

Parameters

    • targets (Variable, Link or list of either) – Parameters for which statistics are col-
      lected.

    • max_sample_size (int) – Maximum number of running samples.

    • report_data (bool) – If True, data (e.g. weights) statistics are plotted. If False,
      they are neither computed nor plotted.
• **report_grad**(bool) – If True, gradient statistics are plotted. If False, they are neither computed nor plotted.

• **plot_mean**(bool) – If True, means are plotted. If False, they are neither computed nor plotted.

• **plot_std**(bool) – If True, standard deviations are plotted. If False, they are neither computed nor plotted.

• **percentile_sigmas**(float or tuple of floats) – Percentiles to plot in the range [0, 100].

• **trigger** – Trigger that decides when to save the plots as an image. This is distinct from the trigger of this extension itself. If it is a tuple in the form '<int>', 'epoch' or '<int>', 'iteration', it is passed to IntervalTrigger.

• **filename**(str) – Name of the output image file under the output directory. For historical reasons file_name is also accepted as an alias of this argument.

• **figsize**(tuple of int) – Matplotlib figsize argument that specifies the size of the output image.

• **marker**(str) – Matplotlib marker argument that specified the marker style of the plots.

• **grid**(bool) – Matplotlib grid argument that specifies whether grids are rendered in in the plots or not.

### Methods

**__call__**(trainer)

Invokes the extension.

Implementations should override this operator. This method is called at iterations which the corresponding trigger accepts.

**Parameters**

- **trainer**(Trainer) – Trainer object that calls this operator.

**static available()**

**finalize()**

Finalizes the extension.

This method is called at the end of the training loop.

**initialize**(trainer)

Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of Trainer can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, ExponentialShift extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The ExponentialShift extension recovers it in its initialize method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

- **trainer**(Trainer) – Trainer object that runs the training loop.

**on_error**(trainer, exc, tb)

Handles the error raised during training before finalization.
This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- `trainer` *(Trainer)* – Trainer object that runs the training loop.
- `exc` *(Exception)* – arbitrary exception thrown during update loop.
- `tb` *(traceback)* – traceback object of the exception

**save_plot_using_module** *(file_path, plt)*

**serialize** *(serializer)*

Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

**Attributes**

- `default_name`
  
  Default name of the extension.

  It is the name of the class by default. Implementation can override this property, or provide a class attribute to hide it.

  name = None

  priority = 100

  trigger = (1, 'iteration')

**chainer.training.extensions.DumpGraph**

**class chainer.training.extensions.DumpGraph** *(root_name, filename='cg.dot', variable_style=None, function_style=None)*

Trainer extension to dump a computational graph.

This extension dumps a computational graph. The graph is output in DOT language. If graphviz is available, this also renders and saves the image of the computational graph.

It only dumps a graph at the first invocation.
Note: The computational graph is not kept by default. This extension changes this behavior until the first
 invocation. **It is strongly recommended that you use it with the default trigger setting.**

The detailed behavior of this extension is as follows.

1. In its initializer, it turns on the `chainer.config.keep_graph_on_report` flag.
2. At the first iteration, it dumps the graph using the graph held by the reported variable.
3. After dumping the graph, it turns off the flag (if it was originally turned off) so that any variable reported
   afterward does not hold a computational graph.

When the `keep_graph_on_report` flag is turned on, the computational graph created by the updater is
 kept during the invocation of extensions. It will cause an unnecessarily large memory consumption when an
 extension also uses a large amount of memory, e.g. `Evaluator`.

With the default setting, the `DumpGraph` extension is called at the first iteration. Since `Evaluator` is not
called at the first iteration in most cases, it does not cause any memory problem.

**Parameters**

- `root_name (str)` – Name of the root of the computational graph. The root variable is
  retrieved by this name from the observation dictionary of the trainer.
- `filename (str)` – Output file name. For historical reasons `out_name` is also accepted
  as an alias of this argument.
- `variable_style (dict)` – Dot node style for variables. Each variable is rendered by
  an octagon by default.
- `function_style (dict)` – Dot node style for functions. Each function is rendered by a
  rectangular by default.

**See also:**

See `build_computational_graph()` for the `variable_style` and `function_style` arguments.

**Methods**

- `__call__ (trainer)`
  Invokes the extension.
  Implementations should override this operator. This method is called at iterations which the corresponding
  trigger accepts.

  Parameters `trainer (Trainer)` – Trainer object that calls this operator.

- `finalize ()`
  Finalizes the extension.

- `initialize (trainer)`
  Initializes up the trainer state.

  This method is called before entering the training loop. An extension that modifies the state of `Trainer`
  can override this method to initialize it.

  When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the
  state of the trainer.
For example, *ExponentialShift* extension changes the optimizer’s hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The *ExponentialShift* extension recovers it in its *initialize* method if it has been loaded from a snapshot, or just setting the initial value otherwise.

**Parameters**

- `trainer (Trainer)` – Trainer object that runs the training loop.

**on_error** *(trainer, exc, tb)*

Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

**Parameters**

- `trainer (Trainer)` – Trainer object that runs the training loop.
- `exc (Exception)` – arbitrary exception thrown during update loop.
- `tb (traceback)` – traceback object of the exception

**serialize** *(serializer)*

Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

**trigger** *(trainer)*

- `tuple() -> empty tuple`  
- `tuple(iterable) -> tuple initialized from iterable’s items`

If the argument is a tuple, the return value is the same object.

**Attributes**

- `default_name = 'dump_graph'`
- `name = None`
- `priority = 100`
**Snapshot**

These extensions provide features to take snapshots of models.

<table>
<thead>
<tr>
<th>chainer.training.extensions.snapshot</th>
<th>Returns a trainer extension to take snapshots of the trainer.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.training.extensions.snapshot_object</td>
<td>Returns a trainer extension to take snapshots of a given object.</td>
</tr>
</tbody>
</table>

**chainer.training.extensions.snapshot**

```python
counter = chainer.training.extensions.snapshot(savefun=chainer.serializers.save_npz, 
   filename='snapshot_iter_{.updater.iteration}', 
   target=None, condition=None)
```

Returns a trainer extension to take snapshots of the trainer.

This extension serializes the trainer object and saves it to the output directory. It is used to support resuming the training loop from the saved state.

This extension is called once per epoch by default. To take a snapshot at a different interval, a trigger object specifying the required interval can be passed along with this extension to the `extend()` method of the trainer.

The default priority is -100, which is lower than that of most built-in extensions.

**Note:** This extension first writes the serialized object to a temporary file and then rename it to the target file name. Thus, if the program stops right before the renaming, the temporary file might be left in the output directory.

**Parameters**

- **savefun** – Function to save the trainer. It takes two arguments: the output file path and the trainer object. It is `chainer.serializers.save_npz()` by default. If `writer` is specified, this argument must be `None`.

- **filename (str)** – Name of the file into which the trainer is serialized. It can be a format string, where the trainer object is passed to the `str.format()` method.

- **target** – Object to serialize. If it is not specified, it will be the trainer object.

- **condition** – Condition object. It must be a callable object that returns boolean without any arguments. If it returns `True`, the snapshot will be done. If not, it will be skipped. The default is a function that always returns `True`.

- **writer** – Writer object. It must be a callable object. See below for the list of built-in writers. If `savefun` is other than `None`, this argument must be `None`. In that case, a `SimpleWriter` object instantiated with specified `savefun` argument will be used.

- **snapshot_on_error (bool)** – Whether to take a snapshot in case trainer loop has been failed.

- **n_retains (int)** – Number of snapshot files to retain through the cleanup. Must be a positive integer for any cleanup to take place. Automatic deletion of old snapshots only works when the filename is string.

- **num_retains (int)** – Same as `n_retains` (deprecated).
• **autoload** *(bool)* – With this enabled, the extension automatically finds the latest snapshot and loads the data to the target. Automatic loading only works when the filename is a string. It is assumed that snapshots are generated by `chainer.serializers.save_npz()`.

**Returns**  
Snapshot extension object.

### Using asynchronous writers

By specifying `writer` argument, writing operations can be made asynchronous, hiding I/O overhead of snapshots.

```python
>>> from chainer.training import extensions
>>> writer = extensions.snapshot_writers.ProcessWriter()
>>> trainer.extend(extensions.snapshot(writer=writer), trigger=(1, 'epoch'))
```

To change the format, such as npz or hdf5, you can pass a saving function as `savefun` argument of the writer.

```python
>>> from chainer.training import extensions
>>> from chainer import serializers

>>> writer = extensions.snapshot_writers.ProcessWriter(
...     savefun=serializers.save_npz)

>>> trainer.extend(extensions.snapshot(writer=writer), trigger=(1, 'epoch'))
```

This is the list of built-in snapshot writers.

- `chainer.training.extensions.snapshot_writers.SimpleWriter`
- `chainer.training.extensions.snapshot_writers.ThreadWriter`
- `chainer.training.extensions.snapshot_writers.ProcessWriter`
- `chainer.training.extensions.snapshot_writers.ThreadQueueWriter`
- `chainer.training.extensions.snapshot_writers.ProcessQueueWriter`

**See also:**

- `chainer.training.extensions.snapshot_object()`

### `chainer.training.extensions.snapshot_object`

`chainer.training.extensions.snapshot_object` *(target, filename, savefun=None, *, condition=None, writer=None, snapshot_on_error=False, n_retains=-1, autoload=False)*

Returns a trainer extension to take snapshots of a given object.

This extension serializes the given object and saves it to the output directory.

This extension is called once per epoch by default. To take a snapshot at a different interval, a trigger object specifying the required interval can be passed along with this extension to the `extend()` method of the trainer.

The default priority is -100, which is lower than that of most built-in extensions.

**Parameters**

- **target** – Object to serialize.
• **filename** (*str*) – Name of the file into which the object is serialized. It can be a format string, where the trainer object is passed to the `str.format()` method. For example, `'snapshot_{.updater.iteration}'` is converted to `'snapshot_10000'` at the 10,000th iteration.

• **savefun** – Function to save the object. It takes two arguments: the output file path and the object to serialize.

• **condition** – Condition object. It must be a callable object that returns boolean without any arguments. If it returns `True`, the snapshot will be done. If not, it will be skipped. The default is a function that always returns `True`.

• **writer** – Writer object. It must be a callable object. See below for the list of built-in writers. If `savefun` is other than `None`, this argument must be `None`. In that case, a `SimpleWriter` object instantiated with specified `savefun` argument will be used.

• **snapshot_on_error** (*bool*) – Whether to take a snapshot in case trainer loop has been failed.

• **n_retains** (*int*) – Number of snapshot files to retain through the cleanup. Must be a positive integer for any cleanup to take place. Automatic deletion of old snapshots only works when the filename is string.

• **num_retain** (*int*) – Same as `n_retains` (deprecated).

• **autoload** (*bool*) – With this enabled, the extension automatically finds the latest snapshot and loads the data to the target. Automatic loading only works when the filename is a string.

**Returns** Snapshot extension object.

**See also:**

• `chainer.training.extensions.snapshot()`

### Memory Release

These extensions provide features to release memories.

<table>
<thead>
<tr>
<th><code>chainer.training.extensions.unchain_variables</code></th>
<th>Trainer extension to unchain all computational graphs.</th>
</tr>
</thead>
</table>

**class** `chainer.training.extensions.unchain_variables`

Trainer extension to unchain all computational graphs.

This extension unchains all computational graphs after all extensions are run to release memory and to avoid memory leak. This extension can be used as a last resort when there is an extension that use a variable graph and cannot release the graph in itself. It observes the previous `chainer.config.keep_graph_on_report` flag. The extension is triggered when the flag is turned on.
Methods

__call__(trainer)

Invokes the extension.

Implementations should override this operator. This method is called at iterations which the corresponding trigger accepts.

Parameters

- **trainer** (Trainer) – Trainer object that calls this operator.

finalize()

Finalizes the extension.

This method is called at the end of the training loop.

initialize()

Initializes up the trainer state.

This method is called before entering the training loop. An extension that modifies the state of `Trainer` can override this method to initialize it.

When the trainer has been restored from a snapshot, this method has to recover an appropriate part of the state of the trainer.

For example, `ExponentialShift` extension changes the optimizer's hyperparameter at each invocation. Note that the hyperparameter is not saved to the snapshot; it is the responsibility of the extension to recover the hyperparameter. The `ExponentialShift` extension recovers it in its `initialize` method if it has been loaded from a snapshot, or just setting the initial value otherwise.

Parameters

- **trainer** (Trainer) – Trainer object that runs the training loop.

on_error(trainer, exc, tb)

Handles the error raised during training before finalization.

This method is called when an exception is thrown during the training loop, before finalize. An extension that needs different error handling from finalize, can override this method to handle errors.

Parameters

- **trainer** (Trainer) – Trainer object that runs the training loop.
- **exc** (Exception) – arbitrary exception thrown during update loop.
- **tb** (traceback) – traceback object of the exception

serialize(serializer)

Serializes the extension state.

It is called when a trainer that owns this extension is serialized. It serializes nothing by default.

trigger(

tuple() -> empty tuple
tuple(iterable) -> tuple initialized from iterable’s items

If the argument is a tuple, the return value is the same object.

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.
\_\_le\_\_(value,/)  
Return self<=value.

\_\_gt\_\_(value,/)  
Return self>value.

\_\_ge\_\_(value,/)  
Return self>=value.

**Attributes**

**default_name**  
Default name of the extension.

It is the name of the class by default. Implementation can override this property, or provide a class attribute to hide it.

\_\_name = None

\_\_priority = 0

### 4.8.4 Triggers

A trigger is a callable object to decide when to process some specific event within the training loop. It takes a Trainer object as the argument, and returns True if some event should be fired.

It is mainly used to determine when to call an extension. It is also used to determine when to quit the training loop.

<table>
<thead>
<tr>
<th>chainer.training.get_trigger</th>
<th>Gets a trigger object.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.training.triggers.BestValueTrigger</td>
<td>Trigger invoked when specific value becomes best.</td>
</tr>
<tr>
<td>chainer.training.triggers.EarlyStoppingTrigger</td>
<td>Trigger for Early Stopping</td>
</tr>
<tr>
<td>chainer.training.triggers.IntervalTrigger</td>
<td>Trigger based on a fixed interval.</td>
</tr>
<tr>
<td>chainer.training.triggers.ManualScheduleTrigger</td>
<td>Trigger invoked at specified point(s) of iterations or epochs.</td>
</tr>
<tr>
<td>chainer.training.triggers.MaxValueTrigger</td>
<td>Trigger invoked when specific value becomes maximum.</td>
</tr>
<tr>
<td>chainer.training.triggers.MinValueTrigger</td>
<td>Trigger invoked when specific value becomes minimum.</td>
</tr>
<tr>
<td>chainer.training.triggers.OnceTrigger</td>
<td>Trigger based on the starting point of the iteration.</td>
</tr>
<tr>
<td>chainer.training.triggers.TimeTrigger</td>
<td>Trigger based on a fixed time interval.</td>
</tr>
</tbody>
</table>
chainer.training.get_trigger

**chainer.training.get_trigger**(trigger)

Gets a trigger object.

Trigger object is a callable that accepts a *Trainer* object as an argument and returns a boolean value. When it returns True, various kinds of events can occur depending on the context in which the trigger is used. For example, if the trigger is passed to the *Trainer* as the *stop trigger*, the training loop breaks when the trigger returns True. If the trigger is passed to the *extend()* method of a trainer, then the registered extension is invoked only when the trigger returns True.

This function returns a trigger object based on the argument. If *trigger* is already a callable, it just returns the trigger. If *trigger* is None, it returns a trigger that never fires. Otherwise, it passes the value to *IntervalTrigger*.

**Parameters**

- **trigger** – Trigger object. It can be either an already built trigger object (i.e., a callable object that accepts a trainer object and returns a bool value), or a tuple. In latter case, the tuple is passed to *IntervalTrigger*.

**Returns**

- trigger if it is a callable, otherwise a *IntervalTrigger* object made from trigger.

chainer.training.triggers.BestValueTrigger

**class** chainer.training.triggers.BestValueTrigger *(key, compare, trigger=1, 'epoch')*

Trigger invoked when specific value becomes best.

**Parameters**

- **key** *(str)* – Key of value.
- **compare** *(callable)* – Compare function which takes current best value and new value and returns whether new value is better than current best.
- **trigger** – Trigger that decides the comparison interval between current best value and new value. This must be a tuple in the form of *(int), 'epoch'* or *(int), 'iteration'* which is passed to *IntervalTrigger*.

**Methods**

- **__call__**(trainer)
  Decides whether the extension should be called on this iteration.

  **Parameters**

  - **trainer** *(Trainer)* – Trainer object that this trigger is associated with. The observation of this trainer is used to determine if the trigger should fire.

  **Returns**

  - True if the corresponding extension should be invoked in this iteration.

  **Return type**

  - bool

- **serialize**(serializer)

- **__eq__**(value, )
  Return self==value.

- **__ne__**(value, )
  Return self!=value.

- **__lt__**(value, )
  Return self<value.
\texttt{\_\_le\_\_}(value, \slash)
\hspace{1em} \text{Return self}\leq\text{value.}

\texttt{\_\_gt\_\_}(value, \slash)
\hspace{1em} \text{Return self}>\text{value.}

\texttt{\_\_ge\_\_}(value, \slash)
\hspace{1em} \text{Return self}\geq\text{value.}

\textbf{chainer.training.triggers.EarlyStoppingTrigger}

\textbf{class} chainer.training.triggers.EarlyStoppingTrigger (self, check_trigger=1, 'epoch', monitor='main/loss', patience=3, mode='auto', verbose=False, max_trigger=100, 'epoch')

Trigger for Early Stopping

It can be used as a stop trigger of \texttt{Trainer} to realize early stopping technique.

This trigger works as follows. Within each check interval defined by the check_trigger argument, it mon-
itors and accumulates the reported value at each iteration. At the end of each interval, it computes the mean of
the accumulated values and compares it to the previous ones to maintain the best value. When it finds that the
best value is not updated for some periods (defined by patience), this trigger fires.

\textbf{Parameters}

- \textbf{monitor (str)} – The metric you want to monitor
- \textbf{check_trigger} – Trigger that decides the comparison interval between current best
value and new value. This must be a tuple in the form of \texttt{<int>, 'epoch'} or \texttt{<int>,
'iteration'} which is passed to \texttt{IntervalTrigger}.
- \textbf{patience (int)} – Counts to let the trigger be patient. The trigger will not fire until the
condition is met for successive patience checks.
- \textbf{mode (str)} – \texttt{'max'}, \texttt{'min'}, or \texttt{'auto'}. It is used to determine how to compare the
monitored values.
- \textbf{verbose (bool)} – Enable verbose output. If verbose is true, you can get more information
- \textbf{max_trigger} – Upper bound of the number of training loops

\textbf{Note:} patience is also available as an alias of patience for historical reason.

\textbf{Methods}

\textbf{\_\_call\_\_}(trainer)
\hspace{1em} Decides whether the training loop should be stopped.

\textbf{Parameters} \texttt{trainer (Trainer)} – Trainer object that this trigger is associated with. The
observation of this trainer is used to determine if the trigger should fire.

\textbf{Returns} True if the training loop should be stopped.

\textbf{Return type} bool

\textbf{get\_training\_length}()
__eq__(value,/)  
Return self==value.

__ne__(value,/)  
Return self!=value.

__lt__(value,/)  
Return self<value.

__le__(value,/)  
Return self<=value.

__gt__(value,/)  
Return self>value.

__ge__(value,/)  
Return self>=value.

chainer.training.triggers.IntervalTrigger

class chainer.training.triggers.IntervalTrigger(period, unit)
  Trigger based on a fixed interval.
  This trigger accepts iterations divided by a given interval. There are two ways to specify the interval: per iterations and epochs. Iteration means the number of updates, while epoch means the number of sweeps over the training dataset. Fractional values are allowed if the interval is a number of epochs; the trigger uses the iteration and epoch_detail attributes defined by the updater.
  For the description of triggers, see get_trigger().

Parameters

  • period (int or float) – Length of the interval. Must be an integer if unit is 'iteration'.
  • unit (str) – Unit of the length specified by period. It must be either 'iteration' or 'epoch'.

Methods

__call__(trainer)
  Decides whether the extension should be called on this iteration.

  Parameters trainer (Trainer) – Trainer object that this trigger is associated with. The updater associated with this trainer is used to determine if the trigger should fire.

  Returns True if the corresponding extension should be invoked in this iteration.

   Return type bool

get_training_length()

serialize (serializer)

__eq__(value,/)  
Return self==value.

__ne__(value,/)  
Return self!=value.

__lt__(value,/)  
Return self<value.

__ge__(value,/)  
Return self>=value.
__le__ (value, /)
    Return self<=value.

__gt__ (value, /)
    Return self>value.

__ge__ (value, /)
    Return self>=value.

chainer.training.triggers.ManualScheduleTrigger

class chainer.training.triggers.ManualScheduleTrigger (points, unit)
    Trigger invoked at specified point(s) of iterations or epochs.
    This trigger accepts iterations or epochs indicated by given point(s). There are two ways to specify the point(s): iteration and epoch. iteration means the number of updates, while epoch means the number of sweeps over the training dataset. Fractional values are allowed if the point is a number of epochs; the trigger uses the iteration and epoch_detail attributes defined by the updater.

Parameters

• points (int, float, or list of int or float) – time of the trigger. Must be an integer or list of integer if unit is 'iteration'.

• unit (str) – Unit of the time specified by points. It must be either 'iteration' or 'epoch'.

Variables

• finished (bool) – Flag that indicates whether or not this trigger will
  in the future. This flag is used to determine if the
  extension (fire) –

• be initialized after resume. (should) –

Methods

__call__ (trainer)
    Decides whether the extension should be called on this iteration.

Parameters trainer (Trainer) – Trainer object that this trigger is associated with. The updater associated with this trainer is used to determine if the trigger should fire.

Returns True if the corresponding extension should be invoked in this iteration.

Return type bool

serialize (serializer)

__eq__ (value, /)
    Return self==value.

__ne__ (value, /)
    Return self!=value.

__lt__ (value, /)
    Return self<value.

__le__ (value, /)
    Return self<=value.
class chainer.training.triggers.MaxValueTrigger(key, trigger=1, 'epoch')

Trigger invoked when specific value becomes maximum.

For example you can use this trigger to take snapshot on the epoch the validation accuracy is maximum.

Parameters

- **key** (str) – Key of value. The trigger fires when the value associated with this key becomes maximum.

- **trigger** – Trigger that decides the comparison interval between current best value and new value. This must be a tuple in the form of <int>, 'epoch' or <int>, 'iteration' which is passed to IntervalTrigger.

Methods

__call__(trainer)

Decides whether the extension should be called on this iteration.

Parameters

- **trainer** (Trainer) – Trainer object that this trigger is associated with. The observation of this trainer is used to determine if the trigger should fire.

Returns

True if the corresponding extension should be invoked in this iteration.

Return type

bool

serialize(serializer)

eq__(value, /)

Return self==value.

ne__(value, /)

Return self!=value.

lt__(value, /)

Return self<value.

le__(value, /)

Return self<=value.

gt__(value, /)

Return self>value.

ge__(value, /)

Return self>=value.
chainer.training.triggers.MinValueTrigger

class chainer.training.triggers.MinValueTrigger(key, trigger=(1, 'epoch'))
Trigger invoked when specific value becomes minimum.
For example you can use this trigger to take snapshot on the epoch the validation loss is minimum.

Parameters

- **key** (str) – Key of value. The trigger fires when the value associated with this key becomes minimum.

- **trigger** – Trigger that decides the comparison interval between current best value and new value. This must be a tuple in the form of <int>, 'epoch' or <int>, 'iteration' which is passed to IntervalTrigger.

Methods

__call__(trainer)
Decides whether the extension should be called on this iteration.

Parameters

- **trainer** (Trainer) – Trainer object that this trigger is associated with. The observation of this trainer is used to determine if the trigger should fire.

Returns

- **True** if the corresponding extension should be invoked in this iteration.

Return type

bool

serialize(serializer)

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.

chainer.training.triggers.OnceTrigger

class chainer.training.triggers.OnceTrigger(call_on_resume=False)
Trigger based on the starting point of the iteration.
This trigger accepts only once at starting point of the iteration. There are two ways to specify the starting point: only starting point in whole iteration or called again when training resumed.

Parameters

- **call_on_resume** (bool) – Whether the extension is called again or not when restored from a snapshot. It is set to False by default.

Variables
• **finished** *(bool)* – Flag that indicates whether or not this trigger will
  * in the future. This flag is used to determine if the
  extension *(fire)* –
  • be initialized after resume. *(should)* –

**Methods**

```python
__call__(trainer)
  Call self as a function.

serialize (serializer)

__eq__(value, /)
  Return self==value.

__ne__(value, /)
  Return self!=value.

__lt__(value, /)
  Return self<value.

__le__(value, /)
  Return self<=value.

__gt__(value, /)
  Return self>value.

__ge__(value, /)
  Return self>=value.
```

**Attributes**

- **finished**

**chainer.training.triggers.TimeTrigger**

```python
class chainer.training.triggers.TimeTrigger *(period)*
Trigger based on a fixed time interval.

This trigger accepts iterations with a given interval time.

Parameters **period** *(float)* – Interval time. It is given in seconds.
```

**Methods**

```python
__call__(trainer)
  Call self as a function.

serialize (serializer)

__eq__(value, /)
  Return self==value.

__ne__(value, /)
  Return self!=value.
```
__lt__(value, /)
    Return self<value.
__le__(value, /)
    Return self<=value.
__gt__(value, /)
    Return self>value.
__ge__(value, /)
    Return self>=value.

4.9 Datasets

4.9.1 Dataset Abstraction (chainer.dataset)

Chainer supports a common interface for training and validation of datasets. The dataset support consists of three components: datasets, iterators, and batch conversion functions.

Dataset represents a set of examples. The interface is only determined by combination with iterators you want to use on it. The built-in iterators of Chainer require the dataset to support __getitem__ and __len__ methods. In particular, the __getitem__ method should support indexing by both an integer and a slice. We can easily support slice indexing by inheriting DatasetMixin, in which case users only have to implement get_example() method for indexing. Basically, datasets are considered as stateless objects, so that we do not need to save the dataset as a checkpoint of the training procedure.

Iterator iterates over the dataset, and at each iteration, it yields a mini-batch of examples as a list. Iterators should support the Iterator interface, which includes the standard iterator protocol of Python. Iterators manage where to read next, which means they are stateful.

Batch conversion function converts the mini-batch into arrays to feed to the neural nets. They are also responsible to send each array to an appropriate device. Chainer currently provides two implementations:

- concat_examples() is a plain implementation which is used as the default choice.
- ConcatWithAsyncTransfer is a variant which is basically same as concat_examples() except that it overlaps other GPU computations and data transfer for the next iteration.

These components are all customizable, and designed to have a minimum interface to restrict the types of datasets and ways to handle them. In most cases, though, implementations provided by Chainer itself are enough to cover the usages.

Chainer also has a light system to download, manage, and cache concrete examples of datasets. All datasets managed through the system are saved under the dataset root directory, which is determined by the CHAINER_DATASET_ROOT environment variable, and can also be set by the set_dataset_root() function.

Dataset Representation

See Dataset Examples (chainer.datasets) for dataset implementations.

chainer.dataset.DatasetMixin

Default implementation of dataset indexing.
chainer.dataset.DatasetMixin

class chainer.dataset.DatasetMixin
    Default implementation of dataset indexing.

    DatasetMixin provides the __getitem__() operator. The default implementation uses get_example() to extract each example, and combines the results into a list. This mixin makes it easy to implement a new dataset that does not support efficient slicing.

    Dataset implementation using DatasetMixin still has to provide the __len__() operator explicitly.

Methods

__getitem__(index)
Returns an example or a sequence of examples.

    It implements the standard Python indexing and one-dimensional integer array indexing. It uses the get_example() method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

    Parameters index (int, slice, list or numpy.ndarray) – An index of an example or indexes of examples.

    Returns If index is int, returns an example created by get_example. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by get_example.

Example

```python
>>> import numpy
>>> from chainer import dataset
>>> class SimpleDataset(dataset.DatasetMixin):
...     def __init__(self, values):
...         self.values = values
...     def __len__(self):
...         return len(self.values)
...     def get_example(self, i):
...         return self.values[i]
...
>>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]  # Access by int
1
>>> ds[1:3]  # Access by slice
[1, 2]
>>> ds[[4, 0]]  # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)
>>> ds[index]  # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]
```

__len__()
Returns the number of data points.

get_example(i)
Returns the i-th example.

    Implementations should override it. It should raise IndexError if the index is invalid.
Parameters $i$ (int) – The index of the example.

Returns The $i$-th example.

---

**__eq__**(value)
Return self==value.

**__ne__**(value)
Return self!=value.

**__lt__**(value)
Return self<value.

**__le__**(value)
Return self<=value.

**__gt__**(value)
Return self>value.

**__ge__**(value)
Return self>=value.

---

### Tabular Dataset Representation

**chainer.dataset.TabularDataset**
An abstract class that represents tabular dataset.

**chainer.dataset.TabularDataset**
An abstract class that represents tabular dataset.

This class represents a tabular dataset. In a tabular dataset, all examples have the same number of elements. For example, all examples of the dataset below have three elements ($a[i], b[i], c[i]$).

```
<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>a[0]</td>
<td>b[0]</td>
<td>c[0]</td>
</tr>
</tbody>
</table>
```

Since an example can be represented by both tuple and dict ($\{(a[i], b[i], c[i])\}$ and {'$a$: $a[i]$, 'b': $b[i]$, 'c': $c[i]$}), this class uses `mode` to indicate which representation will be used. If there is only one column, an example also can be represented by a value ($a[i]$). In this case, `mode` is `None`.

An inheritance should implement **__len__**( ), **keys**, **mode** and **get_examples**( ).

```python
>>> import numpy as np
>>> from chainer import dataset
>>> class MyDataset(dataset.TabularDataset):
...     def __len__(self):
...         return 4
...```
Methods

__getitem__(index)
Returns an example or a sequence of examples.

It implements the standard Python indexing and one-dimensional integer array indexing. It uses the get_example() method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

Parameters index (int, slice, list or numpy.ndarray) – An index of an example or indexes of examples.

Returns If index is int, returns an example created by get_example. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by get_example.
```python
>>> class SimpleDataset(dataset.DatasetMixin):
...    def __init__(self, values):
...        self.values = values
...    def __len__(self):
...        return len(self.values)
...    def get_example(self, i):
...        return self.values[i]
...
>>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]  # Access by int
1
>>> ds[1:3]  # Access by slice
[1, 2]
>>> ds[[4, 0]]  # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)
>>> ds[index]  # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]
```

__len__

Returns the number of data points.

__iter__

asdict

Return a view with dict mode.

    Returns A view whose mode is dict.

astuple

Return a view with tuple mode.

    Returns A view whose mode is tuple.

concat (*datasets)

Stack datasets along rows.

    Parameters datasets (iterable of TabularDataset) – Datasets to be concatenated. All datasets must have the same keys.

    Returns A concatenated dataset.

convert (data)

Convert fetched data.

This method takes data fetched by fetch() and pre-process them before passing them to models. The default behaviour is converting each column into an ndarray. This behaviour can be overridden by with_converter(). If the dataset is constructed by concat() or join(), the converter of the first dataset is used.

    Parameters data (tuple or dict) – Data from fetch().

    Returns A tuple or dict. Each value is an ndarray.

fetch()

Fetch data.

This method fetches all data of the dataset/view. Note that this method returns a column-major data (i.e. \{(a[0], ..., a[3]), ..., (c[0], ... c[3])\}, \{'a': [a[0], ..., a[3]], .., 'c': [c[0], ... c[3]]\}.or [a[0], ..., a[3]], ...

4.9. Datasets
```
Returns  If mode is tuple, this method returns a tuple of lists/arrays. If mode is dict, this method returns a dict of lists/arrays.

get_example(i)
Returns the i-th example.
Implementations should override it. It should raise IndexError if the index is invalid.

Parameters  i (int) – The index of the example.

Returns  The i-th example.

get_examples(indices, key_indices)
Return a part of data.

Parameters
• indices (list of ints or slice) – Indices of requested rows. If this argument is None, it indicates all rows.
• key_indices (tuple of ints) – Indices of requested columns. If this argument is None, it indicates all columns.

Returns  tuple of lists/arrays

join(*datasets)
Stack datasets along columns.

Parameters  datasets (iterable of TabularDataset) – Datasets to be concatenated. All datasets must have the same length

Returns  A joined dataset.

transform(keys, transform)
Apply a transform to each example.

Parameters
• keys (tuple of strs) – The keys of transformed examples.
• transform (callable) – A callable that takes an example and returns transformed example. mode of transformed dataset is determined by the transformed examples.

Returns  A transfromed dataset.

transform_batch(keys, transform_batch)
Apply a transform to examples.

Parameters
• keys (tuple of strs) – The keys of transformed examples.
• transform_batch (callable) – A callable that takes examples and returns transformed examples. mode of transformed dataset is determined by the transformed examples.

Returns  A transfromed dataset.

with_converter(converter)
Override the behaviour of convert().

This method overrides convert().

Parameters  converter (callable) – A new converter.

Returns  A dataset with the new converter.
__eq__(value,/)  
    Return self==value.

__ne__(value,/)  
    Return self!=value.

__lt__(value,/)  
    Return self<value.

__le__(value,/)  
    Return self<=value.

__gt__(value,/)  
    Return self>value.

__ge__(value,/)  
    Return self>=value.

**Attributes**

**keys**

Names of columns.

A tuple of strings that indicate the names of columns.

**mode**

Mode of representation.

This indicates the type of value returned by `fetch()` and `__getitem__()`. `tuple`, `dict`, and `None` are supported.

**slice**

Get a slice of dataset.

**Parameters**

- **indices** *(list/array of ints/bools or slice)* – Requested rows.
- **keys** *(tuple of ints/strs or int or str)* – Requested columns.

**Returns** A view of specified range.

**Tabular Dataset Helpers**

<table>
<thead>
<tr>
<th>chainer.dataset.tabular.DelegateDataset</th>
<th>A helper class to implement a TabularDataset.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.dataset.tabular.from_data</td>
<td>Create a TabularDataset from lists/arrays/callables.</td>
</tr>
</tbody>
</table>
### chainer.dataset.tabular.DelegateDataset

**class** `chainer.dataset.tabular.DelegateDataset(dataset)`

A helper class to implement a TabularDataset.

This class wraps an instance of `TabularDataset` and provides methods of `TabularDataset`. This class is useful to create a custom dataset class by inheriting it.

```python
>>> import numpy as np
>>> from chainer.dataset import tabular
>>> class MyDataset/tabular.DelegateDataset):
...     def __init__(self):
...         super().__init__(tabular.from_data((
...             ('a', np.arange(10)),
...             ('b', self.get_b),
...             ('c', [3, 1, 4, 5, 9, 2, 6, 8, 7, 0]),
...             (('d', 'e'), self.get_de))))
...
...     def get_b(self, i):
...         return 'b[{i}].format(i)
...     def get_de(self, i):
...         return {'d': 'd[{i}].format(i)', 'e': 'e[{i}].format(i)'}
...
>>> dataset = MyDataset()
>>> len(dataset)
10
>>> dataset.keys
('a', 'b', 'c', 'd', 'e')
>>> dataset[0]
(0, 'b[0]', 3, 'd[0]', 'e[0]')
```

**Parameters**

- **dataset** *(chainer.dataset.TabularDataset)* — An underlying dataset.

**Methods**

- **__getitem__(index)**

  Returns an example or a sequence of examples.

  It implements the standard Python indexing and one-dimensional integer array indexing. It uses the `get_example()` method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

  **Parameters**

  - **index** *(int, slice, list or numpy.ndarray)* — An index of an example or indexes of examples.

  **Returns**

  If index is int, returns an example created by `get_example`. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by `get_example`.
>>> class SimpleDataset(dataset.DatasetMixin):
...     def __init__(self, values):
...         self.values = values
...     def __len__(self):
...         return len(self.values)
...     def get_example(self, i):
...         return self.values[i]
...
>>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]  # Access by int
1
>>> ds[1:3]  # Access by slice
[1, 2]
>>> ds[[4, 0]]  # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)
>>> ds[index]  # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]

__len__()

Returns the number of data points.

__iter__()

asdict()

Return a view with dict mode.

Returns A view whose mode is dict.

astuple()

Return a view with tuple mode.

Returns A view whose mode is tuple.

concat(*datasets)

Stack datasets along rows.

Parameters datasets (iterable of TabularDataset) – Datasets to be concatenated. All datasets must have the same keys.

Returns A concatenated dataset.

convert(data)

Convert fetched data.

This method takes data fetched by `fetch()` and pre-process them before passing them to models. The default behaviour is converting each column into an ndarray. This behaviour can be overridden by `with_converter()`. If the dataset is constructed by `concat()` or `join()`, the converter of the first dataset is used.

Parameters data (tuple or dict) – Data from `fetch()`.

Returns A tuple or dict. Each value is an ndarray.

fetch()

Fetch data.

This method fetches all data of the dataset/view. Note that this method returns a column-major data (i.e. `{a: [a[0], ..., a[3]], ..., [c: [c[0], ... c[3]]}, {"a": [a[0], ..., a[3]], .., "c": [c[0], ..., c[3]]}, or [a[0], ..., a[3]]).
Returns If `mode` is `tuple`, this method returns a tuple of lists/arrays. If `mode` is `dict`, this method returns a dict of lists/arrays.

get_example (i)
Returns the i-th example.

Implementations should override it. It should raise `IndexError` if the index is invalid.

Parameters
- **i** (*int*) – The index of the example.

Returns The i-th example.

get_examples (indices, key_indices)
Return a part of data.

Parameters
- **indices** (*list of ints or slice*) – Indices of requested rows. If this argument is `None`, it indicates all rows.
- **key_indices** (*tuple of ints*) – Indices of requested columns. If this argument is `None`, it indicates all columns.

Returns tuple of lists/arrays

join (*datasets*)
Stack datasets along columns.

Parameters
- **datasets** (*iterable of TabularDataset*) – Datasets to be concatenated. All datasets must have the same length.

Returns A joined dataset.

transform (keys, transform)
Apply a transform to each example.

Parameters
- **keys** (*tuple of strs*) – The keys of transformed examples.
- **transform** (*callable*) – A callable that takes an example and returns transformed example. `mode` of transformed dataset is determined by the transformed examples.

Returns A transformed dataset.

transform_batch (keys, transform_batch)
Apply a transform to examples.

Parameters
- **keys** (*tuple of strs*) – The keys of transformed examples.
- **transform_batch** (*callable*) – A callable that takes examples and returns transformed examples. `mode` of transformed dataset is determined by the transformed examples.

Returns A transformed dataset.

with_converter (converter)
Override the behaviour of `convert()`.

This method overrides `convert()`.

Parameters
- **converter** (*callable*) – A new converter.

Returns A dataset with the new converter.
__eq__(value, /)
    Return self==value.

__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.

Attributes

keys
mode
slice
    Get a slice of dataset.

Parameters

• indices(list/array of ints/bools or slice) – Requested rows.
• keys(tuple of ints/strs or int or str) – Requested columns.

Returns
    A view of specified range.

chainer.dataset.tabular.from_data

chainer.dataset.tabular.from_data(data, *, size=None)
Create a TabularDataset from lists/arrays/callables.

```python
>>> from chainer.dataset import tabular
>>> dataset = tabular.from_data([0, 1, 2])
>>> dataset[0]
0
>>> dataset = tabular.from_data([[0, 1, 2], [3, 4, 5]])
>>> dataset[0]
(0, 3)
>>> dataset = tabular.from_data((["a", [0, 1, 2]], ["b", [3, 4, 5]]))
>>> dataset.keys
(['a', 'b'])
>>> dataset[0]
(0, 3)
>>> dataset = tabular.from_data({"a": [0, 1, 2], 'b': [3, 4, 5]})
>>> sorted(dataset[0].items())
[('a', 0), ('b', 3)]
>>> dataset = tabular.from_data({"a": lambda i: i * i}, size=10)
>>> dataset[5]
25
```
Parameters

- **data** *(list, array, tuple, or dict)* – Data in following format.
  - list/array
  - (str, list/array/callable)
  - (str, ...), callable)
  - ((list/array)/(str, list/array/callable)/(key, ...), callable), ...)
  - {str: (list/array/callable)/(str, ...): callable, ...}

- **size** *(int)* – The length of the dataset. This argument is required when no lists/arrays exist in data.

Returns A TabularDataset.

**Iterator Interface**

See *Iterator* for dataset iterator implementations.

```
chainer.dataset.Iterator
```

**chainer.dataset.Iterator**

class chainer.dataset.Iterator

Base class of all dataset iterators.

Iterator iterates over the dataset, yielding a minibatch at each iteration. Minibatch is a list of examples. Each implementation should implement an iterator protocol (e.g., the __next__() method).

Note that, even if the iterator supports setting the batch size, it does not guarantee that each batch always contains the same number of examples. For example, if you let the iterator to stop at the end of the sweep, the last batch may contain a fewer number of examples.

The interface between the iterator and the underlying dataset is not fixed, and up to the implementation.

Each implementation should provide the following attributes (not needed to be writable).

- **batch_size**: Number of examples within each minibatch.
- **epoch**: Number of completed sweeps over the dataset.
- **epoch_detail**: Floating point number version of the epoch. For example, if the iterator is at the middle of the dataset at the third epoch, then this value is 2.5.
- **previous_epoch_detail**: The value of epoch_detail at the previous iteration. This value is None before the first iteration.
- **is_new_epoch**: True if the epoch count was incremented at the last update.

Each implementation should also support serialization to resume/suspend the iteration.
Methods

__enter__()  

__exit__(exc_type, exc_value, traceback)  

__next__()  
  Returns the next batch.
  
  This is a part of the iterator protocol of Python. It may raise the StopIteration exception when it stops the iteration.

__iter__()  
  Returns self.

finalize()  
  Finalizes the iterator and possibly releases the resources.
  
  This method does nothing by default. Implementation may override it to better handle the internal resources.
  
  This method can be called multiple times.

next()  
  Python2 alternative of __next__.
  
  It calls __next__() by default.

serialize(serializer)  
  Serializes the internal state of the iterator.
  
  This is a method to support the serializer protocol of Chainer.

  Note: It should only serialize the internal state that changes over the iteration. It should not serialize what is set manually by users such as the batch size.

__eq__(value,/)  
  Return self==value.

__ne__(value,/)  
  Return self!=value.

__lt__(value,/)  
  Return self<value.

__le__(value,/)  
  Return self<=value.

__gt__(value,/)  
  Return self>value.

__ge__(value,/)  
  Return self>=value.
Batch Conversion Function

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.dataset.Converter</td>
<td>Base class of converters.</td>
</tr>
<tr>
<td>chainer.dataset.converter</td>
<td>Decorator to make a converter.</td>
</tr>
<tr>
<td>chainer.dataset.concat_examples</td>
<td>Converter to wrap a callable with arbitrary arguments.</td>
</tr>
<tr>
<td>chainer.dataset.ConcatWithAsyncTransfer</td>
<td>Interface to concatenate data and transfer them to GPU asynchronously.</td>
</tr>
<tr>
<td>chainer.dataset.to_device</td>
<td>Send an array to a given device.</td>
</tr>
</tbody>
</table>

**chainer.dataset.Converter**

class chainer.dataset.Converter

Base class of converters.

Converters receive batched data retrieved from iterators and perform arbitrary transforms as well as device transfer.

Implementation should override the __call__ method.

See also:

chainer.dataset.converter() — a decorator to turn a converter function into a Converter instance.

**Methods**

__call__(batch, device)

Performs conversion.

Parameters:

- **batch** — A batch. The type and value are arbitrary, depending on usage.
- **device** (Device) — Device to which the converter is expected to send the batch.

Returns: A converted batch.

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.

__le__(value, /)

Return self<=value.

__gt__(value, /)

Return self>value.

__ge__(value, /)

Return self>=value.
chainer.dataset.converter

chainer.dataset.converter()

Decorator to make a converter.

This decorator turns a converter function into a chainer.dataset.Converter class instance, which also is a callable. This is required to use the converter function from an old module that does not support chainer.backend.Device instances (See the Device argument conversion section below).

Requirements of the target function

The target converter function must accept two positional arguments: a batch and a device, and return a converted batch.

The type of the device argument is chainer.backend.Device.

The types and values of the batches (the first argument and the return value) are not specified: they depend on how the converter is used (e.g. by updaters).

Example

```python
>>> @chainer.dataset.converter()
... def custom_converter(batch, device):
...    assert isinstance(device, chainer.backend.Device)
...    # do something with batch...
...    return device.send(batch)
```

Device argument conversion

For backward compatibility, the decorator wraps the function so that if the converter is called with the device argument with int type, it is converted to a chainer.backend.Device instance before calling the original function. The int value indicates the CUDA device of the cupy backend.

Without the decorator, the converter cannot support ChainerX devices. If the batch were requested to be converted to ChainerX with such converters, RuntimeError will be raised.

Note: Converters using this decorator can't be pickled causing chainer.training.updaters.MultiprocessParallelUpdater to fail when the multiprocessing start mode is set to 'spawn' or 'forkserver'. Should you need to use such feature, please rely on class style converters.

chainer.dataset.concat_examples

chainer.dataset.concat_examples = <chainer.dataset.convert._ArbitraryCallableConverter object>

Converter to wrap a callable with arbitrary arguments.

This class accepts arbitrary arguments and pass-through to the underlying callable, with device argument replaced.
chainer.dataset.ConcatWithAsyncTransfer

class chainer.dataset.ConcatWithAsyncTransfer(stream=None, compute_stream=None)

Interface to concatenate data and transfer them to GPU asynchronously.

It enables to transfer next batch of input data to GPU while GPU is running kernels for training using current
batch of input data.

An instance of this class is mainly intended to be used as a converter function of an updater like below.

```python
from chainer.dataset import convert
...
updater = chainer.training.updaters.StandardUpdater(...,
    converter=convert.ConcatWithAsyncTransfer(),
    ...)
```

**Parameters**

- `stream` (*cupy.cuda.Stream*) – CUDA stream. If `None`, a stream is automatically cre-
  ated on the first call. Data transfer operation is launched asynchronously using the stream.

- `compute_stream` (*cupy.cuda.Stream*) – CUDA stream used for compute kernels. If not `None`, CUDA events are created/used to avoid global synchronization and overlap execution of compute kernels and data transfers as much as possible. If `None`, global syn-
  chronization is used instead.

**Methods**

- `__call__(batch, device=None, padding=None)`

  Concatenate data and transfer them to GPU asynchronously.

  See also `chainer.dataset.concat_examples()`.

  **Parameters**

  - `batch` (*list*) – A list of examples.
  - `device` (*int*) – Device ID to which each array is sent.
  - `padding` – Scalar value for extra elements.

  **Returns** Array, a tuple of arrays, or a dictionary of arrays. The type depends on the type of each
  example in the batch.

- `__eq__(value, /)`

  Return `self==value`.

- `__ne__(value, /)`

  Return `self!=value`.

- `__lt__(value, /)`

  Return `self<value`.

- `__le__(value, /)`

  Return `self<=value`.

- `__gt__(value, /)`

  Return `self>value`.

- `__ge__(value, /)`

  Return `self>=value`.
__ge__(value, /)
    Return self>=value.

**chainer.dataset.to_device**

chainer.dataset.to_device(device, x)
Send an array to a given device.

This method sends a given array to a given device. This method is used in `concat_examples()`.
You can also use this method in a custom converter method used in `Updater` and `Extension` such as `StandardUpdater` and `Evaluator`.

See also `chainer.dataset.concat_examples()`.

**Parameters**

- **device** *(None or int or device specifier)* – A device to which an array is sent. If it is a negative integer, an array is sent to CPU. If it is a positive integer, an array is sent to GPU with the given ID. If it is ”None”, an array is left in the original device. Also, any of device specifiers described at `DeviceId` is accepted.

- **x** *(N-dimensional array)* – An array to send.

**Returns** Converted array.

**Dataset Management**

<table>
<thead>
<tr>
<th>chainer.dataset.get_dataset_root</th>
<th>Gets the path to the root directory to download and cache datasets.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.dataset.set_dataset_root</td>
<td>Sets the root directory to download and cache datasets.</td>
</tr>
<tr>
<td>chainer.dataset.cached_download</td>
<td>Downloads a file and caches it.</td>
</tr>
<tr>
<td>chainer.dataset.cache_or_load_file</td>
<td>Caches a file if it does not exist, or loads it otherwise.</td>
</tr>
</tbody>
</table>

**chainer.dataset.get_dataset_root**

chainer.dataset.get_dataset_root()
Gets the path to the root directory to download and cache datasets.

**Returns** The path to the dataset root directory.

**Return type** str

**chainer.dataset.set_dataset_root**

chainer.dataset.set_dataset_root(path)
Sets the root directory to download and cache datasets.

There are two ways to set the dataset root directory. One is by setting the environment variable `CHAINER_DATASET_ROOT` . The other is by using this function. If both are specified, one specified via this function is used. The default dataset root is $HOME/.chainer/dataset.

**Parameters** path *(str)* – Path to the new dataset root directory.
**chainer.dataset.cached_download**

**chainer.dataset.cached_download(url)**

Downloads a file and caches it.

It downloads a file from the URL if there is no corresponding cache. After the download, this function stores a cache to the directory under the dataset root (see `set_dataset_root()`). If there is already a cache for the given URL, it just returns the path to the cache without downloading the same file.

**Note:** This function raises `OSError` when it fails to create the cache directory. In older version, it raised `RuntimeError`.

**Parameters**
- `url (str)` – URL to download from.

**Returns**
- Path to the downloaded file.

**Return type**
- `str`

**chainer.dataset.cache_or_load_file**

**chainer.dataset.cache_or_load_file(path, creator, loader)**

Caches a file if it does not exist, or loads it otherwise.

This is a utility function used in dataset loading routines. The `creator` creates the file to given path, and returns the content. If the file already exists, the `loader` is called instead, and it loads the file and returns the content.

Note that the path passed to the creator is temporary one, and not same as the path given to this function. This function safely renames the file created by the creator to a given path, even if this function is called simultaneously by multiple threads or processes.

**Parameters**
- `path (str)` – Path to save the cached file.
- `creator` – Function to create the file and returns the content. It takes a path to temporary place as the argument. Before calling the creator, there is no file at the temporary path.
- `loader` – Function to load the cached file and returns the content.

**Returns**
- It returns the returned values by the creator or the loader.

### 4.9.2 Dataset Examples (chainer.datasets)

The most basic `dataset` implementation is an array. Both NumPy and CuPy arrays can be used directly as datasets.

In many cases, though, the simple arrays are not enough to write the training procedure. In order to cover most of such cases, Chainer provides many built-in implementations of datasets.

These built-in datasets are divided into two groups. One is a group of general datasets. Most of them are wrapper of other datasets to introduce some structures (e.g., tuple or dict) to each data point. The other one is a group of concrete, popular datasets. These concrete examples use the downloading utilities in the `chainer.dataset` module to cache downloaded and converted datasets.
4.9.3 General Datasets

General datasets are further divided into four types.

The first one is `DictDataset` and `TupleDataset`, both of which combine other datasets and introduce some structures on them.

The second one is `ConcatenatedDataset` and `SubDataset`. `ConcatenatedDataset` represents a concatenation of existing datasets. It can be used to merge datasets and make a larger dataset. `SubDataset` represents a subset of an existing dataset. It can be used to separate a dataset for hold-out validation or cross validation. Convenient functions to make random splits are also provided.

The third one is `TransformDataset`, which wraps around a dataset by applying a function to data indexed from the underlying dataset. It can be used to modify behavior of a dataset that is already prepared.

The last one is a group of domain-specific datasets. Currently, implementations for datasets of images (`ImageDataset`, `LabeledImageDataset`, etc.) and text (`TextDataset`) are provided.

**DictDataset**

chainer.datasets.DictDataset

Dataset of a dictionary of datasets.

class chainer.datasets.DictDataset(**datasets)

Dataset of a dictionary of datasets.

It combines multiple datasets into one dataset. Each example is represented by a dictionary mapping a key to an example of the corresponding dataset.

**Parameters**

- `datasets` – Underlying datasets. The keys are used as the keys of each example. All datasets must have the same length.

**Methods**

- **getitem**(index)
- **len**()
- **eq**(value, /)
  - Return self==value.
- **ne**(value, /)
  - Return self!=value.
- **lt**(value, /)
  - Return self<value.
- **le**(value, /)
  - Return self<=value.
- **gt**(value, /)
  - Return self>value.
- **ge**(value, /)
  - Return self>=value.
TupleDataset

chainer.datasets.TupleDataset

class chainer.datasets.TupleDataset(*datasets)

Dataset of tuples from multiple equal-length datasets.

A TupleDataset combines multiple equal-length datasets into a single dataset of tuples. The i-th tuple contains the i-th example from each of the argument datasets, in the same order that they were supplied.

Recall that in Chainer, a dataset is defined as an iterable that supports both \_\_getitem\_\_ and \_\_len\_. The \_\_getitem\_\_ method should support indexing by both an integer and a slice.

As an example, consider creating a TupleDataset from two argument datasets d1 = [8, 0, 5, 1] and d2 = [3, 1, 7, 4] as tuple_dataset = TupleDataset(d1, d2). The tuple_dataset will then contain the examples (8, 3), (0, 1), (5, 7), (1, 4). Note that this behavior is similar to that of the built-in \texttt{zip()} function.

Parameters datasets

- Underlying datasets that will be aggregated. Each dataset must be an iterable that implements \_\_getitem\_\_ and \_\_len\_. The j-th dataset will be used for the j-th item of each example tuple. All datasets must have the same length.

Methods

\_\_getitem\_\_(index)

\_\_len\_()

\_\_eq\_(value, /)

Return self==value.

\_\_ne\_(value, /)

Return self!=value.

\_\_lt\_(value, /)

Return self<value.

\_\_le\_(value, /)

Return self<=value.

\_\_gt\_(value, /)

Return self>value.

\_\_ge\_(value, /)

Return self>=value.
ConcatenatedDataset

Dataset which concatenates some base datasets.

```python
chainer.datasets.ConcatenatedDataset
```

class chainer.datasets.ConcatenatedDataset(*datasets)

Dataset which concatenates some base datasets.

This dataset wraps some base datasets and works as a concatenated dataset. For example, if a base dataset with 10 samples and another base dataset with 20 samples are given, this dataset works as a dataset which has 30 samples.

**Parameters**

- **datasets** – The underlying datasets. Each dataset has to support `__len__()` and `__getitem__()`.

**Methods**

- **__getitem__(index)**

  Returns an example or a sequence of examples.

  It implements the standard Python indexing and one-dimensional integer array indexing. It uses the `get_example()` method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

  **Parameters**

  - **index** (int, slice, list or numpy.ndarray) – An index of an example or indexes of examples.

  **Returns**

  If index is int, returns an example created by `get_example`. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by `get_example`.

**Example**

```python
>>> import numpy
>>> from chainer import dataset
>>> class SimpleDataset(dataset.DatasetMixin):
...     def __init__(self, values):
...         self.values = values
...     def __len__(self):
...         return len(self.values)
...     def get_example(self, i):
...         return self.values[i]
...
>>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]  # Access by int
1
>>> ds[1:3]  # Access by slice
[1, 2]
>>> ds[[4, 0]]  # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)
>>> ds[index]  # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]
```
__len__

Returns the number of data points.

get_example(i)

Returns the i-th example.

Implementations should override it. It should raise IndexError if the index is invalid.

Parameters

i (int) – The index of the example.

Returns

The i-th example.

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.

__le__(value, /)

Return self<=value.

__gt__(value, /)

Return self>value.

__ge__(value, /)

Return self>=value.

SubDataset

chainer.datasets.SubDataset

Subset of a base dataset.

chainer.datasets.split_dataset

Splits a dataset into two subsets.

chainer.datasets.split_dataset_random

Splits a dataset into two subsets randomly.

chainer.datasets.get_cross_validation_datasets

Creates a set of training/test splits for cross validation.

chainer.datasets.get_cross_validation_datasets_random

Creates a set of training/test splits for cross validation randomly.

chainer.datasets.SubDataset

class chainer.datasets.SubDataset (dataset, start, finish, order=None)

Subset of a base dataset.

SubDataset defines a subset of a given base dataset. The subset is defined as an interval of indexes, optionally with a given permutation.

If order is given, then the i-th example of this dataset is the order[start + i]-th example of the base dataset, where i is a non-negative integer. If order is not given, then the i-th example of this dataset is the start + i-th example of the base dataset. Negative indexing is also allowed: in this case, the term start + i is replaced by finish + i.

SubDataset is often used to split a dataset into training and validation subsets. The training set is used for training, while the validation set is used to track the generalization performance, i.e. how the learned model works well on unseen data. We can tune hyperparameters (e.g. number of hidden units, weight initializers, learning rate, etc.) by comparing the validation performance. Note that we often use another set called test set
to measure the quality of the tuned hyperparameter, which can be made by nesting multiple SubDatasets.

There are two ways to make training-validation splits. One is a single split, where the dataset is split just into two subsets. It can be done by `split_dataset()` or `split_dataset_random()`. The other one is a $k$-fold cross validation, in which the dataset is divided into $k$ subsets, and $k$ different splits are generated using each of the $k$ subsets as a validation set and the rest as a training set. It can be done by `get_cross_validation_datasets()`.

**Parameters**

- **dataset** – Base dataset.
- **start** *(int)* – The first index in the interval.
- **finish** *(int)* – The next-to-the-last index in the interval.
- **order** *(sequence of ints)* – Permutation of indexes in the base dataset. If this is None, then the ascending order of indexes is used.

**Methods**

__getitem__(index)

Returns an example or a sequence of examples.

It implements the standard Python indexing and one-dimensional integer array indexing. It uses the `get_example()` method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

**Parameters**

index *(int, slice, list or numpy.ndarray)* – An index of an example or indexes of examples.

**Returns**

If index is int, returns an example created by `get_example`. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by `get_example`.

**Example**

```python
>>> import numpy
>>> from chainer import dataset
>>> class SimpleDataset(dataset.DatasetMixin):
...     def __init__(self, values):
...         self.values = values
...     def __len__(self):
...         return len(self.values)
...     def get_example(self, i):
...         return self.values[i]
...
>>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]  # Access by int
1
>>> ds[1:3]  # Access by slice
[1, 2]
>>> ds[[4, 0]]  # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)
>>> ds[index]  # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]
```
__len__ ()
   Returns the number of data points.

get_example (i)
   Returns the i-th example.
   Implementations should override it. It should raise IndexError if the index is invalid.

Parameters
   i (int) – The index of the example.

Returns
   The i-th example.

__eq__ (value, /)
   Return self==value.

__ne__ (value, /)
   Return self!=value.

__lt__ (value, /)
   Return self<value.

__le__ (value, /)
   Return self<=value.

__gt__ (value, /)
   Return self>value.

__ge__ (value, /)
   Return self>=value.

chainer.datasets.split_dataset

chainer.datasets.split_dataset (dataset, split_at, order=None)
   Splits a dataset into two subsets.
   This function creates two instances of SubDataset. These instances do not share any examples, and they
together cover all examples of the original dataset.

Parameters
   • dataset – Dataset to split.
   • split_at (int) – Position at which the base dataset is split.
   • order (sequence of ints) – Permutation of indexes in the base dataset. See the
documentation of SubDataset for details.

Returns
   Two SubDataset objects. The first subset represents the examples of indexes order[:split_at] while the second subset represents the examples of indexes order[split_at:].

Return type
   tuple
**chainer.datasets.split_dataset_random**

*chainer.datasets.split_dataset_random*(dataset, first_size, seed=None)

Splits a dataset into two subsets randomly.

This function creates two instances of SubDataset. These instances do not share any examples, and they together cover all examples of the original dataset. The split is automatically done randomly.

**Parameters**

- **dataset** – Dataset to split.
- **first_size** *(int)* – Size of the first subset.
- **seed** *(int)* – Seed the generator used for the permutation of indexes. If an integer being convertible to 32 bit unsigned integers is specified, it is guaranteed that each sample in the given dataset always belongs to a specific subset. If None, the permutation is changed randomly.

**Returns** Two SubDataset objects. The first subset contains first_size examples randomly chosen from the dataset without replacement, and the second subset contains the rest of the dataset.

**Return type** tuple

**chainer.datasets.get_cross_validation_datasets**

*chainer.datasets.get_cross_validation_datasets*(dataset, n_folds=None, order=None, **kwargs)

Creates a set of training/test splits for cross validation.

This function generates n_folds splits of the given dataset. The first part of each split corresponds to the training dataset, while the second part to the test dataset. No pairs of test datasets share any examples, and all test datasets together cover the whole base dataset. Each test dataset contains almost same number of examples (the numbers may differ up to 1).

**Parameters**

- **dataset** – Dataset to split.
- **n_folds** *(int)* – Number of splits for cross validation.
- **order** *(sequence of ints)* – Order of indexes with which each split is determined. If it is None, then no permutation is used.

**Returns** List of dataset splits.

**Return type** list of tuples
chainer.datasets.get_cross_validation_datasets_random

chainer.datasets.get_cross_validation_datasets_random(dataset, n_folds, seed=None, **kwargs)

Creates a set of training/test splits for cross validation randomly.

This function acts almost same as get_cross_validation_dataset(), except automatically generating random permutation.

Parameters

- **dataset** – Dataset to split.
- **n_fold** (int) – (deprecated) n_fold is now deprecated for consistency of naming choice. Please use n_folds instead.
- **n_folds** (int) – Number of splits for cross validation.
- **seed** (int) – Seed the generator used for the permutation of indexes. If an integer beging convertible to 32 bit unsigned integers is specified, it is guaranteed that each sample in the given dataset always belongs to a specific subset. If None, the permutation is changed randomly.

Returns List of dataset splits.

Return type list of tuples

TransformDataset

chainer.datasets.TransformDataset

Dataset that indexes the base dataset and transforms the data.

This dataset wraps the base dataset by modifying the behavior of the base dataset’s __getitem__(). Arrays returned by __getitem__() of the base dataset with an integer as an argument are transformed by the given function transform. Also, __len__() returns the integer returned by the base dataset’s __len__().

The function transform takes, as an argument, in_data, which is the output of the base dataset’s __getitem__(), and returns the transformed arrays as output. Please see the following example. Since in_data directly refers to the item in the dataset, take care that transform not modify it. For example, note that the line img = img - 0.5 bellow is correct since it makes a copy of img. However, it would be incorrect to use img -= 0.5 since that would update the contents of the item in the dataset in place, corrupting it.

```python
>>> from chainer.datasets import get_mnist
>>> from chainer.datasets import TransformDataset

>>> dataset, _ = get_mnist()
>>> def transform(in_data):
...     img, label = in_data
...     img = img - 0.5  # scale to [-0.5, 0.5]
...     return img, label
>>> dataset = TransformDataset(dataset, transform)
```
Parameters

- **dataset** – The underlying dataset. The index of this dataset corresponds to the index of the base dataset. This object needs to support functions `__getitem__()` and `__len__()` as described above.

- **transform** (**callable**) – A function that is called to transform values returned by the underlying dataset’s `__getitem__()`.

Methods

**__getitem__(index)**

Returns an example or a sequence of examples.

It implements the standard Python indexing and one-dimensional integer array indexing. It uses the `get_example()` method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

Parameters **index** (**int, slice, list or numpy.ndarray**) – An index of an example or indexes of examples.

Returns If index is int, returns an example created by `get_example`. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by `get_example`.

Example

```python
>>> import numpy
>>> from chainer import dataset
>>> class SimpleDataset(dataset.DatasetMixin):
...     def __init__(self, values):
...         self.values = values
...     def __len__(self):
...         return len(self.values)
...     def get_example(self, i):
...         return self.values[i]
... >>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]  # Access by int
1
>>> ds[1:3]  # Access by slice
[1, 2]
>>> ds[[4, 0]]  # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)
>>> ds[index]  # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]
```

**__len__()**

Returns the number of data points.

**get_example(i)**

Returns the i-th example.

Implementations should override it. It should raise `IndexError` if the index is invalid.

Parameters **i** (**int**) – The index of the example.

Returns The i-th example.
__eq__(value, /)
    Return self==value.
__ne__(value, /)
    Return self!=value.
__lt__(value, /)
    Return self<value.
__le__(value, /)
    Return self<=value.
__gt__(value, /)
    Return self>value.
__ge__(value, /)
    Return self>=value.

ImageDataset

Dataset of images built from a list of paths to image files.

chainer.datasets.ImageDataset

chainer.datasets.ZippedImageDataset

chainer.datasets.MultiZippedImageDataset

chainer.datasets.ImageDataset

class chainer.datasets.ImageDataset(paths, root='.', dtype=None)

Dataset of images built from a list of paths to image files.

This dataset reads an external image file on every call of the __getitem__() operator. The paths to the image to retrieve is given as either a list of strings or a text file that contains paths in distinct lines.

Each image is automatically converted to arrays of shape channels, height, width, where channels represents the number of channels in each pixel (e.g., 1 for grey-scale images, and 3 for RGB-color images).

Note: This dataset requires the Pillow package being installed. In order to use this dataset, install Pillow (e.g. by using the command pip install Pillow). Be careful to prepare appropriate libraries for image formats you want to use (e.g. libpng for PNG images, and libjpeg for JPG images).

Warning: You are responsible for preprocessing the images before feeding them to a model. For example, if your dataset contains both RGB and grayscale images, make sure that you convert them to the same format. Otherwise you will get errors because the input dimensions are different for RGB and grayscale images.

Parameters

- paths (str or list of str)—If it is a string, it is a path to a text file that contains paths to images in distinct lines. If it is a list of paths, the i-th element represents the path to the i-th image. In both cases, each path is a relative one from the root path given by another argument.
• **root** (**str**) – Root directory to retrieve images from.

• **dtype** – Data type of resulting image arrays. `chainer.config.dtype` is used by default (see Configuring Chainer).

### Methods

__getitem__ (index)

Returns an example or a sequence of examples.

It implements the standard Python indexing and one-dimensional integer array indexing. It uses the `get_example()` method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

**Parameters**

index (**int, slice, list or numpy.ndarray**) – An index of an example or indexes of examples.

**Returns**

If index is int, returns an example created by `get_example`. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by `get_example`.

#### Example

```python
>>> import numpy
>>> from chainer import dataset
>>> class SimpleDataset(dataset.DatasetMixin):
...   def __init__(self, values):
...     self.values = values
...   def __len__(self):
...     return len(self.values)
...   def get_example(self, i):
...     return self.values[i]
...
>>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]  # Access by int
1
>>> ds[1:3]  # Access by slice
[1, 2]
>>> ds[[4, 0]]  # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)
>>> ds[index]  # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]
```

__len__ ()

Returns the number of data points.

get_example (i)

Returns the i-th example.

Implementations should override it. It should raise `IndexError` if the index is invalid.

**Parameters**

i (**int**) – The index of the example.

**Returns**

The i-th example.

__eq__ (value, /)

Return self==value.
\_\_\text{ne\_}\_\text{__(value, /)\n}\n\hspace{1em} \text{return} self!=value.
\_\_\text{lt\_}\_\text{__(value, /)\n}\n\hspace{1em} \text{return} self<value.
\_\_\text{le\_}\_\text{__(value, /)\n}\n\hspace{1em} \text{return} self<=value.
\_\_\text{gt\_}\_\text{__(value, /)\n}\n\hspace{1em} \text{return} self>value.
\_\_\text{ge\_}\_\text{__(value, /)\n}\n\hspace{1em} \text{return} self>=value.

\text{chainer.datasets.ZippedImageDataset}

class chainer.datasets.ZippedImageDataset (zipfilename, dtype=None)
Dataset of images built from a zip file.

This dataset reads an external image file in the given zipfile. The zipfile shall contain only image files. This shall be able to replace ImageDataset and works better on NFS and other networked file systems. If zipfile becomes too large you may consider \text{MultiZippedImageDataset} as a handy alternative.

Known issue: pickle and unpickle on same process may cause race condition on ZipFile. Pickle of this class is expected to be sent to different processes via ChainerMN.

Parameters

\begin{itemize}
\item \text{zipfilename (str)} – a string to point zipfile path
\item \text{dtype} – Data type of resulting image arrays. chainer.config.dtype is used by default (see \text{Configuring Chainer}).
\end{itemize}

Methods

\_\_\text{getitem\_}\_\text{__(index)\n}\n\hspace{1em} \text{return} an example or a sequence of examples.

It implements the standard Python indexing and one-dimensional integer array indexing. It uses the \text{get_example()} method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

Parameters index (int, slice, list or \text{numpy.ndarray}) – An index of an example or indexes of examples.

Returns If index is int, returns an example created by \text{get_example}. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by \text{get_example}.

Example

\begin{verbatim}
>>> import numpy
>>> from chainer import dataset
>>> class SimpleDataset(dataset.DatasetMixin):
...     def _init__ (self, values):
...         self.values = values
...     def _len__ (self):
...         return len(self.values)
\end{verbatim}
... def get_example(self, i):
...     return self.values[i]
...
>>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]  # Access by int
1
>>> ds[1:3]  # Access by slice
[1, 2]
>>> ds[[4, 0]]  # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)
>>> ds[index]  # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]

__len__

Returns the number of data points.

get_example(i_or_filename)

Returns the i-th example.

Implementations should override it. It should raise IndexError if the index is invalid.

Parameters

i (int) – The index of the example.

Returns

The i-th example.

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.

__le__(value, /)

Return self<=value.

__gt__(value, /)

Return self>value.

__ge__(value, /)

Return self>=value.

chainer.datasets.MultiZippedImageDataset

class chainer.datasets.MultiZippedImageDataset(zipfilenames, dtype=None)

Dataset of images built from a list of paths to zip files.

This dataset reads an external image file in given zipfiles. The zipfiles shall contain only image files. This shall be able to replace ImageDataset and works better on NFS and other networked file systems. The user shall find good balance between zipfile size and number of zipfiles (e.g. granularity)

Parameters

• zipfilenames (list of strings) – List of zipped archive filename.

• dtype – Data type of resulting image arrays. chainer.config.dtype is used by default (see Configuring Chainer).
Methods

__getitem__(index)
Returns an example or a sequence of examples.

It implements the standard Python indexing and one-dimensional integer array indexing. It uses the get_example() method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

Parameters index (int, slice, list or numpy.ndarray) – An index of an example or indexes of examples.

Returns If index is int, returns an example created by get_example. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by get_example.

Example

```python
>>> import numpy
>>> from chainer import dataset
>>> class SimpleDataset(dataset.DatasetMixin):
...     def __init__(self, values):
...         self.values = values
...     def __len__(self):
...         return len(self.values)
...     def get_example(self, i):
...         return self.values[i]
...
>>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]  # Access by int
1
>>> ds[1:3]  # Access by slice
[1, 2]
>>> ds[[4, 0]]  # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)
>>> ds[index]  # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]
```

__len__()
Returns the number of data points.

get_example (i)
Returns the i-th example.

Implementations should override it. It should raise IndexError if the index is invalid.

Parameters i (int) – The index of the example.

Returns The i-th example.

eq (value,)
Return self==value.

eq (value,)
Return self!=value.

lt (value,)
Return self<value.
__le__ (value, /)
Return self<=value.

gt__ (value, /)
Return self>=value.

gt__ (value, /)
Return self>=value.

**LabeledImageDataset**

<table>
<thead>
<tr>
<th>chainer.datasets.LabeledImageDataset</th>
<th>Dataset of image and label pairs built from a list of paths and labels.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.datasets.LabeledZippedImageDataset</td>
<td>Dataset of zipped image and label pairs.</td>
</tr>
</tbody>
</table>

**chainer.datasets.LabeledImageDataset**

```python
class chainer.datasets.LabeledImageDataset(pairs, root='.', dtype=None, label_dtype=numpy.int32):
```

Dataset of image and label pairs built from a list of paths and labels.

This dataset reads an external image file like `ImageData`. The difference from `ImageData` is that this dataset also returns a label integer. The paths and labels are given as either a list of pairs or a text file contains paths/labels pairs in distinct lines. In the latter case, each path and corresponding label are separated by white spaces. This format is same as one used in Caffe.

**Note:** This dataset requires the Pillow package being installed. In order to use this dataset, install Pillow (e.g. by using the command `pip install Pillow`). Be careful to prepare appropriate libraries for image formats you want to use (e.g. libpng for PNG images, and libjpeg for JPG images).

**Warning:** You are responsible for preprocessing the images before feeding them to a model. For example, if your dataset contains both RGB and grayscale images, make sure that you convert them to the same format. Otherwise you will get errors because the input dimensions are different for RGB and grayscale images.

**Parameters**

- **pairs** (*str or list of tuples*)  - If it is a string, it is a path to a text file that contains paths to images in distinct lines. If it is a list of pairs, the i-th element represents a pair of the path to the i-th image and the corresponding label. In both cases, each path is a relative one from the root path given by another argument.

- **root** (*str*)  - Root directory to retrieve images from.

- **dtype**  - Data type of resulting image arrays. `chainer.config.dtype` is used by default (see Configuring Chainer).

- **label_dtypes**  - Data type of the labels.
Methods

__getitem__(index)
Returns an example or a sequence of examples.

It implements the standard Python indexing and one-dimensional integer array indexing. It uses the
get_example() method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

Parameters  

index (int, slice, list or numpy.ndarray) – An index of an example or indexes of examples.

Returns  

If index is int, returns an example created by get_example. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by get_example.

Example

```python
>>> import numpy
>>> from chainer import dataset
>>> class SimpleDataset(dataset.DatasetMixin):
...     def __init__(self, values):
...         self.values = values
...     def __len__(self):
...         return len(self.values)
...     def get_example(self, i):
...         return self.values[i]
...
>>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]  # Access by int
1
>>> ds[1:3]  # Access by slice
[1, 2]
>>> ds[[4, 0]]  # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)
>>> ds[index]  # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]
```

__len__()
Returns the number of data points.

get_example(i)
Returns the i-th example.

Implementations should override it. It should raise IndexError if the index is invalid.

Parameters  
i (int) – The index of the example.

Returns  
The i-th example.

__eq__(value,)
Return self==value.

__ne__(value,)
Return self!=value.

__lt__(value,)
Return self<value.
__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.

chainer.datasets.LabeledZippedImageDataset

class chainer.datasets.LabeledZippedImageDataset(zipfilename, labelfilename, dtype=None, label_dtype=<class 'numpy.int32'>)

Dataset of zipped image and label pairs.

This dataset is zip version of LabeledImageDataset. It takes a zipfile like ZippedImageDataset. The label file shall contain lines like text file used in LabeledImageDataset, but a filename in each line of the label file shall match with a file in the zip archive.

Parameters

- zipfilename (str) – Path to a zipfile with images
- labelfilename (str) – Path to a label file. i-th line shall contain a filename and an integer label that corresponds to the i-th sample. A filename in the label file shall match with a filename in the zip file given with zipfilename.
- dtype – Data type of resulting image arrays. chainer.config.dtype is used by default (see Configuring Chainer).
- label_dtype – Data type of the labels.

Methods

__getitem__(index)
Returns an example or a sequence of examples.

It implements the standard Python indexing and one-dimensional integer array indexing. It uses the get_example() method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

Parameters index (int, slice, list or numpy.ndarray) – An index of an example or indexes of examples.

Returns If index is int, returns an example created by get_example. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by get_example.

Example

```python
>>> import numpy
>>> from chainer import dataset
>>> class SimpleDataset(dataset.DatasetMixin):
...     def __init__(self, values):
...         self.values = values
...     def __len__(self):
...         return len(self.values)
```
... def get_example(self, i):
...     return self.values[i]
...
>>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]   # Access by int
1
>>> ds[1:3] # Access by slice
[1, 2]
>>> ds[[4, 0]] # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)
>>> ds[index] # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]

__len__()
Returns the number of data points.

get_example(i)
Returns the i-th example.

Implementations should override it. It should raise IndexError if the index is invalid.

Parameters
i (int) – The index of the example.

Returns
The i-th example.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=(value.

TextDataset

chainer.datasets.TextDataset

class chainer.datasets.TextDataset(paths, encoding=None, errors=None, newline=None, filter_func=None)

Dataset of a line-oriented text file.

This dataset reads each line of text file(s) on every call of the __getitem__() operator. Positions of line boundaries are cached so that you can quickly random access the text file by the line number.

Note: Cache will be built in the constructor. You can pickle and unpickle the dataset to reuse the cache, but in that case you are responsible to guarantee that files are not modified after the cache has built.

Parameters

- **paths (str or list of str)** – Path to the text file(s). If it is a string, this dataset reads a line from the text file and emits it as str. If it is a list of string, this dataset reads lines from each text file and emits it as a tuple of str. In this case, number of lines in all files must be the same.

- **encoding (str or list of str)** – Name of the encoding used to decode the file. See the description in open() for the supported options and how it works. When reading from multiple text files, you can also pass a list of str to use different encoding for each file.

- **errors (str or list of str)** – String that specifies how decoding errors are to be handled. See the description in open() for the supported options and how it works. When reading from multiple text files, you can also pass a list of str to use different error handling policy for each file.

- **newline (str or list of str)** – Controls how universal newlines mode works. See the description in open() for the supported options and how it works. When reading from multiple text files, you can also pass a list of str to use different mode for each file.

- **filter_func (callable)** – Function to filter each line of the text file. It should be a function that takes number of arguments equals to the number of files. Arguments are lines loaded from each file. The filter function must return True to accept the line, or return False to skip the line.

Methods

__getitem__(index)

Returns an example or a sequence of examples.

It implements the standard Python indexing and one-dimensional integer array indexing. It uses the get_example() method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

Parameters index (int, slice, list or numpy.ndarray) – An index of an example or indexes of examples.

Returns If index is int, returns an example created by get_example. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by get_example.

Example
>>> import numpy
>>> from chainer import dataset
>>> class SimpleDataset(dataset.DatasetMixin):
...     def __init__(self, values):
...         self.values = values
...     def __len__(self):
...         return len(self.values)
...     def get_example(self, i):
...         return self.values[i]

>>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]  # Access by int
1
>>> ds[1:3]  # Access by slice
[1, 2]
>>> ds[[4, 0]]  # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)
>>> ds[index]  # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]

`__len__()`

Returns the number of data points.

`close()`

Manually closes all text files.

In most cases, you do not have to call this method, because files will automatically be closed after Text- Dataset instance goes out of scope.

`get_example(idx)`

Returns the i-th example.

Implementations should override it. It should raise `IndexError` if the index is invalid.

**Parameters**

`i` *(int)* – The index of the example.

**Returns**

The i-th example.

`__eq__(value, /)`

Return self==value.

`__ne__(value, /)`

Return self!=value.

`__lt__(value, /)`

Return self<value.

`__le__(value, /)`

Return self<=value.

`__gt__(value, /)`

Return self>value.

`__ge__(value, /)`

Return self>=value.
PickleDataset

chainer.datasets.PickleDataset

Dataset stored in a storage using pickle.

chainer.datasets.PickleDatasetWriter

Writer class that makes PickleDataset.

chainer.datasets.open_pickle_dataset

Opens a dataset stored in a given path.

open_pickle_dataset_writer

Opens a writer to make a PickleDataset.

chainer.datasets.PickleDataset

```
class chainer.datasets.PickleDataset(reader):
    Dataset stored in a storage using pickle.

    pickle is the default serialization library of Python. This dataset stores any objects in a storage using pickle. Even when a user wants to use a large dataset, this dataset can stores all data in a large storage like HDD and each data can be randomly accessible.

>>> with chainer.datasets.open_pickle_dataset_writer(path_to_data) as w:
...     w.write((1, 2.0, 'hello'))
...     w.write((2, 3.0, 'good-bye'))
... >>> with chainer.datasets.open_pickle_dataset(path_to_data) as dataset:
...     print(dataset[1])
... (2, 3.0, 'good-bye')
```

**Parameters**

- **reader** – File like object. *reader* must support random access.

**Methods**

- __enter__()
- __exit__(exc_type, exc_value, traceback)
- __getitem__(index)

  Returns an example or a sequence of examples.

  It implements the standard Python indexing and one-dimensional integer array indexing. It uses the `get_example()` method by default, but it may be overridden by the implementation to, for example, improve the slicing performance.

  **Parameters**

  - **index** *(int, slice, list or numpy.ndarray)* – An index of an example or indexes of examples.

  **Returns**

  If index is int, returns an example created by `get_example`. If index is either slice or one-dimensional list or numpy.ndarray, returns a list of examples created by `get_example`.

**Example**

```python
>>> import numpy
>>> from chainer import dataset
>>> class SimpleDataset(dataset.DatasetMixin):
...     def __init__(self, values):
...         self.values = values
... >>> dataset = SimpleDataset([1, 2.0, 'hello', 2, 3.0, 'good-bye'])
>>> print(dataset[1])
(2, 3.0, 'good-bye')
```
...     def __len__(self):
...         return len(self.values)
...     def get_example(self, i):
...         return self.values[i]

>>> ds = SimpleDataset([0, 1, 2, 3, 4, 5])
>>> ds[1]  # Access by int
1
>>> ds[1:3]  # Access by slice
[1, 2]
>>> ds[[4, 0]]  # Access by one-dimensional integer list
[4, 0]
>>> index = numpy.arange(3)

>>> ds[index]  # Access by one-dimensional integer numpy.ndarray
[0, 1, 2]

__len__()
Returns the number of data points.

close()
Closes a file reader.

After a user calls this method, the dataset will no longer be accessible..

get_example(index)
Returns the i-th example.

Implementations should override it. It should raise IndexError if the index is invalid.

Parameters  i  (int) – The index of the example.

Returns  The i-th example.

__eq__(value,)
Return self==value.

__ne__(value,)
Return self!=value.

__lt__(value,)
Return self<value.

__le__(value,)
Return self<=value.

__gt__(value,)
Return self>value.

__ge__(value,)
Return self>=value.
**Chainer Documentation, Release 7.7.0**

---

**chainer.datasets.PickleDatasetWriter**

```python
class chainer.datasets.PickleDatasetWriter(writer, protocol=4)

Writer class that makes PickleDataset.

To make PickleDataset, a user needs to prepare data using PickleDatasetWriter.

**Parameters**

- **writer** – File like object that supports write and tell methods.
- **protocol** (*int*) – Valid protocol for pickle.
```

**Methods**

```python
__enter__()
__exit__(exc_type, exc_value, traceback)
close()
flush()
write(x)
__eq__(value,)
    Return self==value.
__ne__(value,)
    Return self!=value.
__lt__(value,)
    Return self<value.
__le__(value,)
    Return self<=value.
__gt__(value,)
    Return self>value.
__ge__(value,)
    Return self>=value.
```

---

**chainer.datasets.open_pickle_dataset**

```python
chainer.datasets.open_pickle_dataset(path)

Opens a dataset stored in a given path.

This is a helper function to open PickleDataset. It opens a given file in binary mode, and creates a PickleDataset instance.

This method does not close the opened file. A user needs to call PickleDataset.close() or use with:
```
```python
with chainer.datasets.open_pickle_dataset('path') as dataset:
    pass  # use dataset
```

**Parameters**

- **path** (*str*) – Path to a dataset.

**Returns**

Opened dataset.

**Return type**

chainer.datasets.PickleDataset

---

4.9. Datasets 1075
chainer.datasets.open_pickle_dataset_writer

chainer.datasets.open_pickle_dataset_writer(path, protocol=4)
Opens a writer to make a PickleDataset.

This is a helper function to open PickleDatasetWriter. It opens a given file in binary mode and creates a PickleDatasetWriter instance.

This method does not close the opened file. A user needs to call PickleDatasetWriter.close() or use with:

```python
with chainer.datasets.open_pickle_dataset_writer('path') as writer:
    pass  # use writer
```

Parameters

- **path (str)** – Path to a dataset.
- **protocol (int)** – Valid protocol for pickle.

Returns

Opened writer.

Return type chainer.datasets.PickleDatasetWriter

4.9.4 Concrete Datasets

<table>
<thead>
<tr>
<th>chainer.datasets.get_mnist</th>
<th>Gets the MNIST dataset.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.datasets.get_kuzushiji_mnist</td>
<td>Gets the Kuzushiji-MNIST dataset.</td>
</tr>
<tr>
<td>chainer.datasets.get_kuzushiji_mnist_labels</td>
<td>Provides a list of labels for the Kuzushiji-MNIST dataset.</td>
</tr>
<tr>
<td>chainer.datasets.get_fashion_mnist_labels</td>
<td>Provide a list of the string value names of the labels.</td>
</tr>
<tr>
<td>chainer.datasets.get_fashion_mnist</td>
<td>Gets the Fashion-MNIST dataset.</td>
</tr>
<tr>
<td>chainer.datasets.get_cifar10</td>
<td>Gets the CIFAR-10 dataset.</td>
</tr>
<tr>
<td>chainer.datasets.get_cifar100</td>
<td>Gets the CIFAR-100 dataset.</td>
</tr>
<tr>
<td>chainer.datasets.get_ptb_words</td>
<td>Gets the Penn Tree Bank dataset as long word sequences.</td>
</tr>
<tr>
<td>chainer.datasets.get_ptb_words_vocabulary</td>
<td>Gets the Penn Tree Bank word vocabulary.</td>
</tr>
<tr>
<td>chainer.datasets.get_svhn</td>
<td>Gets the SVHN dataset.</td>
</tr>
</tbody>
</table>

chainer.datasets.get_mnist

chainer.datasets.get_mnist(withlabel=True, ndim=1, scale=1.0, dtype=None, label_dtype=<class 'numpy.int32'>, rgb_format=False)

Gets the MNIST dataset.

MNIST is a set of hand-written digits represented by grey-scale 28x28 images. In the original images, each pixel is represented by one-byte unsigned integer. This function scales the pixels to floating point values in the interval [0, scale].

This function returns the training set and the test set of the official MNIST dataset. If withlabel is True, each dataset consists of tuples of images and labels, otherwise it only consists of images.

Parameters
• **withlabel** (*bool*) – If True, it returns datasets with labels. In this case, each example is a tuple of an image and a label. Otherwise, the datasets only contain images.

• **ndim** (*int*) – Number of dimensions of each image. The shape of each image is determined depending on ndim as follows:
  - ndim == 1: the shape is (784,)
  - ndim == 2: the shape is (28, 28)
  - ndim == 3: the shape is (1, 28, 28)

• **scale** (*float*) – Pixel value scale. If it is 1 (default), pixels are scaled to the interval [0, 1].

• **dtype** – Data type of resulting image arrays. chainer.config.dtype is used by default (see *Configuring Chainer*).

• **label_dtype** – Data type of the labels.

• **rgb_format** (*bool*) – if ndim == 3 and rgb_format is True, the image will be converted to rgb format by duplicating the channels so the image shape is (3, 28, 28). Default is False.

**Returns** A tuple of two datasets. If withlabel is True, both datasets are TupleDataset instances. Otherwise, both datasets are arrays of images.

### chainer.datasets.get_kuzushiji_mnist

chainer.datasets.get_kuzushiji_mnist (*withlabel=True, ndim=1, scale=1.0, dtype=None, label_dtype=<class 'numpy.int32'>, rgb_format=False)

Gets the Kuzushiji-MNIST dataset.

**Kuzushiji-MNIST (KMNST)** is a set of hand-written Japanese characters represented by grey-scale 28x28 images. In the original images, each pixel is represented by one-byte unsigned integer. This function scales the pixels to floating point values in the interval [0, scale].

This function returns the training set and the test set of the official KMNST dataset. If withlabel is True, each dataset consists of tuples of images and labels, otherwise it only consists of images.

**Parameters**

• **withlabel** (*bool*) – If True, it returns datasets with labels. In this case, each example is a tuple of an image and a label. Otherwise, the datasets only contain images.

• **ndim** (*int*) – Number of dimensions of each image. The shape of each image is determined depending on ndim as follows:
  - ndim == 1: the shape is (784,)
  - ndim == 2: the shape is (28, 28)
  - ndim == 3: the shape is (1, 28, 28)

• **scale** (*float*) – Pixel value scale. If it is 1 (default), pixels are scaled to the interval [0, 1].

• **dtype** – Data type of resulting image arrays. chainer.config.dtype is used by default (see *Configuring Chainer*).

• **label_dtype** – Data type of the labels.
• **rgb_format (bool)** – If `ndim == 3` and `rgb_format` is True, the image will be converted to rgb format by duplicating the channels so the image shape is `(3, 28, 28)`. Default is `False`.

**Returns** A tuple of two datasets. If `withlabel` is `True`, both datasets are `TupleDataset` instances. Otherwise, both datasets are arrays of images.

### chainer.datasets.get_kuzushiji_mnist_labels

**chainer.datasets.get_kuzushiji_mnist_labels()**  
Provides a list of labels for the Kuzushiji-MNIST dataset.

**Returns** List of labels in the form of tuples. Each tuple contains the character name in romaji as a string value and the unicode codepoint for the character.

### chainer.datasets.get_fashion_mnist_labels

**chainer.datasets.get_fashion_mnist_labels()**  
Provide a list of the string value names of the labels.

**Returns** List of string values of the image labels.

### chainer.datasets.get_fashion_mnist

**chainer.datasets.get_fashion_mnist(withlabel=True, ndim=1, scale=1.0, dtype=None, label_dtype=<class 'numpy.int32'>, rgb_format=False)**  
Gets the Fashion-MNIST dataset.

Fashion-MNIST is a set of fashion articles represented by grey-scale 28x28 images. In the original images, each pixel is represented by one-byte unsigned integer. This function scales the pixels to floating point values in the interval `[0, scale]`.

This function returns the training set and the test set of the official Fashion-MNIST dataset. If `withlabel` is `True`, each dataset consists of tuples of images and labels, otherwise it only consists of images.

**Parameters**

• **withlabel (bool)** – If True, it returns datasets with labels. In this case, each example is a tuple of an image and a label. Otherwise, the datasets only contain images.

• **ndim (int)** – Number of dimensions of each image. The shape of each image is determined depending on `ndim` as follows:
  – `ndim == 1`: the shape is `(784,)`
  – `ndim == 2`: the shape is `(28, 28)`
  – `ndim == 3`: the shape is `(1, 28, 28)`

• **scale (float)** – Pixel value scale. If it is 1 (default), pixels are scaled to the interval `[0, 1]`.

• **dtype** – Data type of resulting image arrays. `chainer.config.dtype` is used by default (see Configuring Chainer).

• **label_dtype** – Data type of the labels.

• **rgb_format (bool)** – If `ndim == 3` and `rgb_format` is True, the image will be converted to rgb format by duplicating the channels so the image shape is `(3, 28, 28)`. Default is `False`. 
Returns A tuple of two datasets. If `withlabel` is `True`, both datasets are `TupleDataset` instances. Otherwise, both datasets are arrays of images.

chainer.datasets.get_cifar10

chainer.datasets.get_cifar10(withlabel=True, ndim=3, scale=1.0, dtype=None)

Gets the CIFAR-10 dataset.

CIFAR-10 is a set of small natural images. Each example is an RGB color image of size 32x32, classified into 10 groups. In the original images, each component of pixels is represented by one-byte unsigned integer. This function scales the components to floating point values in the interval \([0, \text{scale}]\).

This function returns the training set and the test set of the official CIFAR-10 dataset. If `withlabel` is `True`, each dataset consists of tuples of images and labels, otherwise it only consists of images.

Parameters

- `withlabel` (bool) – If `True`, it returns datasets with labels. In this case, each example is a tuple of an image and a label. Otherwise, the datasets only contain images.
- `ndim` (int) – Number of dimensions of each image. The shape of each image is determined depending on `ndim` as follows:
  - `ndim == 1`: the shape is \((3072,)\)
  - `ndim == 3`: the shape is \((3, 32, 32)\)
- `scale` (float) – Pixel value scale. If it is 1 (default), pixels are scaled to the interval \([0, 1]\).
- `dtype` – Data type of resulting image arrays. `chainer.config.dtype` is used by default (see `Configuring Chainer`).

Returns A tuple of two datasets. If `withlabel` is `True`, both datasets are `TupleDataset` instances. Otherwise, both datasets are arrays of images.

chainer.datasets.get_cifar100

chainer.datasets.get_cifar100(withlabel=True, ndim=3, scale=1.0, dtype=None)

Gets the CIFAR-100 dataset.

CIFAR-100 is a set of small natural images. Each example is an RGB color image of size 32x32, classified into 100 groups. In the original images, each component pixels is represented by one-byte unsigned integer. This function scales the components to floating point values in the interval \([0, \text{scale}]\).

This function returns the training set and the test set of the official CIFAR-100 dataset. If `withlabel` is `True`, each dataset consists of tuples of images and labels, otherwise it only consists of images.

Parameters

- `withlabel` (bool) – If `True`, it returns datasets with labels. In this case, each example is a tuple of an image and a label. Otherwise, the datasets only contain images.
- `ndim` (int) – Number of dimensions of each image. The shape of each image is determined depending on `ndim` as follows:
  - `ndim == 1`: the shape is \((3072,)\)
  - `ndim == 3`: the shape is \((3, 32, 32)\)
- `scale` (float) – Pixel value scale. If it is 1 (default), pixels are scaled to the interval \([0, 1]\).
• **dtype** – Data type of resulting image arrays. `chainer.config.dtype` is used by default (see Configuring Chainer).

Returns A tuple of two datasets. If `withlabel` is True, both are `TupleDataset` instances. Otherwise, both datasets are arrays of images.

### `chainer.datasets.get_ptb_words`

**chainer.datasets.get_ptb_words()**  
Gets the Penn Tree Bank dataset as long word sequences.

**Penn Tree Bank** is originally a corpus of English sentences with linguistic structure annotations. This function uses a variant distributed at [https://github.com/wojzaremba/lstm](https://github.com/wojzaremba/lstm), which omits the annotation and splits the dataset into three parts: training, validation, and test.

This function returns the training, validation, and test sets, each of which is represented as a long array of word IDs. All sentences in the dataset are concatenated by End-of-Sentence mark ‘<eos>’, which is treated as one of the vocabulary.

**Returns** Int32 vectors of word IDs.  
**Return type** tuple of `numpy.ndarray`

See also:  
Use `get_ptb_words_vocabulary()` to get the mapping between the words and word IDs.

### `chainer.datasets.get_ptb_words_vocabulary`

**chainer.datasets.get_ptb_words_vocabulary()**  
Gets the Penn Tree Bank word vocabulary.

**Returns** Dictionary that maps words to corresponding word IDs. The IDs are used in the Penn Tree Bank long sequence datasets.

**Return type** dict

See also:  
See `get_ptb_words()` for the actual datasets.

### `chainer.datasets.get_svhn`

**chainer.datasets.get_svhn(withlabel=True, scale=1.0, dtype=None, label_dtype=<class 'numpy.int32'>, add_extra=False)**  
Gets the SVHN dataset.

The Street View House Numbers (SVHN) dataset is a dataset similar to MNIST but composed of cropped images of house numbers. The functionality of this function is identical to the counterpart for the MNIST dataset (`get_mnist()`), with the exception that there is no `ndim` argument.

**Note:** SciPy is required to use this feature.

**Parameters**

- **withlabel (bool)** – If True, it returns datasets with labels. In this case, each example is a tuple of an image and a label. Otherwise, the datasets only contain images.
• **scale**(float) – Pixel value scale. If it is 1 (default), pixels are scaled to the interval \([0, 1]\).

• **dtype** – Data type of resulting image arrays. `chainer.config.dtype` is used by default (see Configuring Chainer).

• **label_dtype** – Data type of the labels.

• **add_extra** – Use extra training set.

**Returns** If `add_extra` is False, a tuple of two datasets (train and test). Otherwise, a tuple of three datasets (train, test, and extra). If `withlabel` is True, all datasets are `TupleDataset` instances. Otherwise, both datasets are arrays of images.

**Note:** ChainerCV supports implementations of datasets that are useful for computer vision problems, which can be found in `chainercv.datasets`. Here is a subset of data loaders supported by ChainerCV:

- **Bounding Box Datasets**
  - `chainercv.datasets.VOCBboxDataset`
  - `chainercv.datasets.COCOBboxDataset`

- **Semantic Segmentation Datasets**
  - `chainercv.datasets.ADE20KSemanticSegmentationDataset`
  - `chainercv.datasets.CamVidDataset`
  - `chainercv.datasets.CityscapesSemanticSegmentationDataset`
  - `chainercv.datasets.VOCSemanticSegmentationDataset`

- **Instance Segmentation Datasets**
  - `chainercv.datasets.COCOInstanceSegmentationDataset`
  - `chainercv.datasets.VOCInstanceSegmentationDataset`

- **Classification Datasets**
  - `chainercv.datasets.CUBLabelDataset`
  - `chainercv.datasets.OnlineProductsDataset`

### 4.10 Iterator

Chainer provides some iterators that implement typical strategies to create mini-batches by iterating over datasets. `SerialIterator` is the simplest one, which extracts mini-batches in the main thread. `MultiprocessIterator` and `MultithreadIterator` are parallelized versions of `SerialIterator`. They maintain worker subprocesses and subthreads, respectively, to load the next mini-batch in parallel.

<table>
<thead>
<tr>
<th><code>chainer.iterators.SerialIterator</code></th>
<th>Dataset iterator that serially reads the examples.</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.iterators.MultiprocessIterator</code></td>
<td>Dataset iterator that loads examples in parallel.</td>
</tr>
<tr>
<td><code>chainer.iterators.MultithreadIterator</code></td>
<td>Dataset iterator that loads examples in parallel.</td>
</tr>
<tr>
<td><code>chainer.iterators.DaliIterator</code></td>
<td>(Experimental) Iterator for DALI pipeline.</td>
</tr>
</tbody>
</table>
4.10.1 chainer.iterators.SerialIterator

```python
class chainer.iterators.SerialIterator(dataset, batch_size, repeat=True, shuffle=None, order_sampler=None)
```

Dataset iterator that serially reads the examples.

This is a simple implementation of `Iterator` that just visits each example in either the order of indexes or a shuffled order.

To avoid unintentional performance degradation, the `shuffle` option is set to `True` by default. For validation, it is better to set it to `False` when the underlying dataset supports fast slicing. If the order of examples has an important meaning and the updater depends on the original order, this option should be set to `False`.

This iterator saves -1 instead of `None` in snapshots since some serializers do not support `None`.

**Parameters**

- **dataset** – Dataset to iterate.
- **batch_size** (`int`) – Number of examples within each batch.
- **repeat** (`bool`) – If `True`, it infinitely loops over the dataset. Otherwise, it stops iteration at the end of the first epoch.
- **shuffle** (`bool`) – If `True`, the order of examples is shuffled at the beginning of each epoch. Otherwise, examples are extracted in the order of indexes. If `None` and no `order_sampler` is given, the behavior is the same as the case with `shuffle=True`.
- **order_sampler** (`callable`) – A callable that generates the order of the indices to sample in the next epoch when a epoch finishes. This function should take two arguments: the current order and the current position of the iterator. This should return the next order. The size of the order should remain constant. This option cannot be used when `shuffle` is not `None`.

**Methods**

- **__enter__()**
- **__exit__(exc_type, exc_value, traceback)**
- **__next__()**
  Returns the next batch.
  This is a part of the iterator protocol of Python. It may raise the `StopIteration` exception when it stops the iteration.
- **__iter__()**
  Returns self.
- **finalize()**
  Finalizes the iterator and possibly releases the resources.
  This method does nothing by default. Implementation may override it to better handle the internal resources.
  This method can be called multiple times.
- **next ()**
  Returns the next batch.
  This is a part of the iterator protocol of Python. It may raise the `StopIteration` exception when it stops the iteration.
reset()

serialize(serializer)

Serializes the internal state of the iterator.

This is a method to support the serializer protocol of Chainer.

**Note:** It should only serialize the internal state that changes over the iteration. It should not serialize what
is set manually by users such as the batch size.

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.

__le__(value, /)

Return self<=value.

__gt__(value, /)

Return self>value.

__ge__(value, /)

Return self>=value.

Attributes

current_position

epoch

epoch_detail

is_new_epoch

previous_epoch_detail

repeat

4.10.2 chainer.iterators.MultiprocessIterator

class chainer.iterators.MultiprocessIterator (dataset, batch_size, repeat=True, shuffle=None, n_processes=None, n_prefetch=1, shared_mem=None, order_sampler=None, dataset_timeout=30.0, maxtasksperchild=None)

Dataset iterator that loads examples in parallel.

This is an implementation of Iterator that loads examples with worker processes. It uses the standard
multiprocessing module to parallelize the loading. The dataset is sent to the worker processes in the
standard way using pickle.

Note that this iterator effectively prefetches the examples for the next batch asynchronously after the current
batch is returned.

This iterator saves -1 instead of None in snapshots since some serializers do not support None.
Note: When you are using OpenCV somewhere in your code and the `MultiprocessIterator` is used in the training code, the training loop may get stuck at some point. In such situation, there are several workarounds to prevent the process got stuck.

1. Set the environment variable as follows: `OMP_NUM_THREADS=1`
2. Add `cv2.setNumThreads(0)` right after `import cv2` in your training script.
3. Use `MultithreadIterator` instead of `MultiprocessIterator`.

Parameters

- `dataset (Dataset)` – Dataset to iterate.
- `batch_size (int)` – Number of examples within each batch.
- `repeat (bool)` – If True, it infinitely loops over the dataset. Otherwise, it stops iteration at the end of the first epoch.
- `shuffle (bool)` – If True, the order of examples is shuffled at the beginning of each epoch. Otherwise, examples are extracted in the order of indexes. If None and no `order_sampler` is given, the behavior is the same as the case with `shuffle=True`.
- `n_processes (int)` – Number of worker processes. The number of CPUs is used by default.
- `n_prefetch (int)` – Number of prefetch batches.
- `shared_mem (int)` – The size of using shared memory per data. If None, size is adjusted automatically.
- `dataset_timeout (float)` – `MultiprocessIterator.TimeoutWarning` will be issued after this time in seconds elapsed in each dataset realization. None to disable the warning. You can turn this warning into an error by using `warnings.simplefilter()`:

```python
warnings.simplefilter('error',
                     chainer.iterators.MultiprocessIterator.TimeoutWarning)
```

- `order_sampler (callable)` – A callable that generates the order of the indices to sample in the next epoch when a epoch finishes. This function should take two arguments: the current order and the current position of the iterator. This should return the next order. The size of the order should remain constant. This option cannot be used when `shuffle` is not None.
- `maxtasksperchild (int)` – Number of tasks a worker of prefetch process can complete before it will exit and be replaced with a fresh worker process, to enable unused resources to be freed. If None, worker processes will live as long as the pool.
Methods

__enter__()  
__exit__(exc_type, exc_value, traceback)

__next__()  
    Returns the next batch.
    This is a part of the iterator protocol of Python. It may raise the StopIteration exception when it stops the iteration.

__iter__()  
    Returns self.
__copy__()

finalize()  
    Finalizes the iterator and possibly releases the resources.
    This method does nothing by default. Implementation may override it to better handle the internal resources.
    This method can be called multiple times.

next()  
    Returns the next batch.
    This is a part of the iterator protocol of Python. It may raise the StopIteration exception when it stops the iteration.

reset()  

serialize(serializer)  
    Serializes the internal state of the iterator.
    This is a method to support the serializer protocol of Chainer.

    Note: It should only serialize the internal state that changes over the iteration. It should not serialize what is set manually by users such as the batch size.

__eq__(value, /)  
    Return self==value.
__ne__(value, /)  
    Return self!=value.
__lt__(value, /)  
    Return self<value.
__le__(value, /)  
    Return self<=value.
__gt__(value, /)  
    Return self>value.
__ge__(value, /)  
    Return self>=value.
Attributes

current_position
epoch
epoch_detail
is_new_epoch
previous_epoch_detail

4.10.3 chainer.iterators.MultithreadIterator

class chainer.iterators.MultithreadIterator (dataset, batch_size, repeat=True,
shuffle=None, n_threads=1, order_sampler=None)

Dataset iterator that loads examples in parallel.

This is an implementation of Iterator that loads examples with worker threads. It uses the standard
threading module to parallelize the loading.

Note that this iterator effectively prefetches the examples for the next batch asynchronously after the current
batch is returned.

This iterator saves -1 instead of None in snapshots since some serializers do not support None.

Parameters

• dataset (Dataset) – Dataset to iterate.
• batch_size (int) – Number of examples within each batch.
• repeat (bool) – If True, it infinitely loops over the dataset. Otherwise, it stops iteration
at the end of the first epoch.
• shuffle (bool) – If True, the order of examples is shuffled at the beginning of each
epoch. Otherwise, examples are extracted in the order of indexes. If None and no
order_sampler is given, the behavior is the same as the case with shuffle=True.
• n_threads (int) – Number of worker threads.
• order_sampler (callable) – A callable that generates the order of the indices to
sample in the next epoch when a epoch finishes. This function should take two arguments:
the current order and the current position of the iterator. This should return the next order.
The size of the order should remain constant. This option cannot be used when shuffle
is not None.

Methods

__enter__ ()

__exit__ (exc_type, exc_value, traceback)

__next__ ()

Returns the next batch.

This is a part of the iterator protocol of Python. It may raise the StopIteration exception when it
stops the iteration.

__iter__ ()

Returns self.
finalize()
Finalizes the iterator and possibly releases the resources.

This method does nothing by default. Implementation may override it to better handle the internal resources.

This method can be called multiple times.

next()
Returns the next batch.

This is a part of the iterator protocol of Python. It may raise the StopIteration exception when it stops the iteration.

reset()
serialize(serializer)
Serializes the internal state of the iterator.

This is a method to support the serializer protocol of Chainer.

Note: It should only serialize the internal state that changes over the iteration. It should not serialize what is set manually by users such as the batch size.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.

Attributes

current_position
epoch
epoch_detail
is_new_epoch
previous_epoch_detail
repeat
4.10.4 chainer.iterators.DaliIterator

class chainer.iterators.DaliIterator (pipeline, repeat=True)

(Experimental) Iterator for DALI pipeline.

Parameters

- pipeline – DALI pipeline.
- repeat (bool) – If True, it infinitely loops over the dataset. Otherwise, it stops iteration at the end of the first epoch.

Methods

__enter__ ()
__exit__ (exc_type, exc_value, traceback)
__next__ ()
  Returns the next batch.
  This is a part of the iterator protocol of Python. It may raise the StopIteration exception when it stops the iteration.
__iter__ ()
  Returns self.
finalize ()
  Finalizes the iterator and possibly releases the resources.
  This method does nothing by default. Implementation may override it to better handle the internal resources.
  This method can be called multiple times.
next ()
  Returns the next batch.
  This is a part of the iterator protocol of Python. It may raise the StopIteration exception when it stops the iteration.
reset ()
serialize (serializer)
  Serializes the internal state of the iterator.
  This is a method to support the serializer protocol of Chainer.

Note: It should only serialize the internal state that changes over the iteration. It should not serialize what is set manually by users such as the batch size.

__eq__ (value, /)
  Return self==value.
__ne__ (value, /)
  Return self!=value.
__lt__ (value, /)
  Return self<value.
__le__(value, /)
    Return self<=value.
__gt__(value, /)
    Return self>value.
__ge__(value, /)
    Return self>=value.

Attributes

batch_size
epoch_detail
previous_epoch_detail
repeat

4.10.5 Order sampler examples

An Iterator iterates over a dataset according to an order represented by a 1-D array of indices. Order samplers are callables that are used by those iterators to generate this array.

<table>
<thead>
<tr>
<th>chainer.iterators.OrderSampler</th>
<th>Base class of all order samplers.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.iterators.</td>
<td>Sampler that generates random orders.</td>
</tr>
<tr>
<td>ShuffleOrderSampler</td>
<td></td>
</tr>
</tbody>
</table>

chainer.iterators.OrderSampler

class chainer.iterators.OrderSampler
    Base class of all order samplers.

    Every order sampler subclass has to provide a method __call__(). This method is called by an iterator before a new epoch, and it should return a new index order for the next epoch.

Methods

__call__(current_order, current_position)
    Sample the next order.

    Parameters
    • current_order (numpy.ndarray) – 1-D array of indices. The length should be the same as the dataset to sample data from.
    • current_position (int) – The current position of an iterator.

    Returns 1-D array of indices. This is the order in which examples are sampled from a dataset in the next epoch.

    Return type numpy.ndarray

__eq__(value, /)
    Return self==value.
class chainer.iterators.ShuffleOrderSampler(random_state=None)

Sampler that generates random orders.

This is expected to be used together with Chainer’s iterators. An order sampler is called by an iterator every epoch.

The two initializations below create basically the same objects.

```python
>>> dataset = [(1, 2), (3, 4)]
>>> it = chainer.iterators.MultiprocessIterator(dataset, 1, shuffle=True)
>>> it = chainer.iterators.MultiprocessIterator(...
...    dataset, 1, order_sampler=chainer.iterators.ShuffleOrderSampler())
```

**Parameters**

*random_state (numpy.random.RandomState)* – Pseudo-random number generator.

**Methods**

___call__ (current_order, current_position)

Sample the next order.

**Parameters**

- **current_order (numpy.ndarray)** – 1-D array of indices. The length should be the same as the dataset to sample data from.

- **current_position (int)** – The current position of an iterator.

**Returns**

1-D array of indices. This is the order in which examples are sampled from a dataset in the next epoch.

**Return type**

numpy.ndarray

___eq__ (value, /)

Return self==value.

___ne__ (value, /)

Return self!=value.

___lt__ (value, /)

Return self<value.

___le__ (value, /)

Return self<=value.

___gt__ (value, /)

Return self>value.

___ge__ (value, /)

Return self>=value.
```python
__le__(value,)
    Return self<=value.
__gt__(value,)
    Return self>value.
__ge__(value,)
    Return self>=value.
```

## 4.11 Serializers

### 4.11.1 Serialization in NumPy NPZ format

NumPy serializers can be used in arbitrary environments that Chainer runs with. It consists of asymmetric serializer/deserializer due to the fact that `numpy.savez()` does not support online serialization. Therefore, serialization requires two-step manipulation: first packing the objects into a flat dictionary, and then serializing it into npz format.

<table>
<thead>
<tr>
<th>Serializer</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.serializers.</td>
<td>Serializer for dictionary.</td>
</tr>
<tr>
<td>DictionarySerializer</td>
<td></td>
</tr>
<tr>
<td>chainer.serializers.NpzDeserializer</td>
<td>Deserializer for NPZ format.</td>
</tr>
<tr>
<td>chainer.serializers.save_npz</td>
<td>Saves an object to the file in NPZ format.</td>
</tr>
<tr>
<td>chainer.serializers.load_npz</td>
<td>Loads an object from the file in NPZ format.</td>
</tr>
</tbody>
</table>

**chainer.serializers.DictionarySerializer**

```python
class chainer.serializers.DictionarySerializer (target=None, path='')
    Serializer for dictionary.
```

This is the standard serializer in Chainer. The hierarchy of objects are simply mapped to a flat dictionary with keys representing the paths to objects in the hierarchy.

**Note:** Despite of its name, this serializer DOES NOT serialize the object into external files. It just build a flat dictionary of arrays that can be fed into `numpy.savez()` and `numpy.savez_compressed()`. If you want to use this serializer directly, you have to manually send a resulting dictionary to one of these functions.

**Parameters**

- **target (dict)** – The dictionary that this serializer saves the objects to. If target is `None`, then a new dictionary is created.
- **path (str)** – The base path in the hierarchy that this serializer indicates.

**Variables**

- **target (dict)** – The target dictionary. Once the serialization completes, this dictionary can be fed into `numpy.savez()` or `numpy.savez_compressed()` to serialize it in the NPZ format.
Methods

__call__(key, value)
Serializes or deserializes a value by given name.

This operator saves or loads a value by given name.

If this is a serializer, then the value is simply saved at the key. Note that some type information might be missed depending on the implementation (and the target file format).

If this is a deserializer, then the value is loaded by the key. The deserialization differently works on scalars and arrays. For scalars, the value argument is used just for determining the type of restored value to be converted, and the converted value is returned. For arrays, the restored elements are directly copied into the value argument. String values are treated like scalars.

Note: Serializers and deserializers are required to correctly handle the None value. When value is None, serializers save it in format-dependent ways, and deserializers just return the loaded value. When the saved None value is loaded by a deserializer, it should quietly return the None value without modifying the value object.

Parameters
- key (str) – Name of the serialization entry.
- value (scalar, numpy.ndarray, cupy.ndarray, None, or str) – Object to be (de)serialized. None is only supported by deserializers.

Returns Serialized or deserialized value.

__getitem__(key)
Gets a child serializer.

This operator creates a _child_ serializer represented by the given key.

Parameters key (str) – Name of the child serializer.

save (obj)
Saves an object by this serializer.

This is equivalent to obj.serialize(self).

Parameters obj – Target object to be serialized.

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.
chainer.serializers.NpzDeserializer

class chainer.serializers.NpzDeserializer (npz, path='', strict=True, ignore_names=None)
Deserialization for NPZ format.

This is the standard deserializer in Chainer. This deserializer can be used to read an object serialized by save_npz().

Parameters
• npz – npz file object.
• path – The base path that the deserialization starts from.
• strict (bool) – If True, the deserializer raises an error when an expected value is not found in the given NPZ file. Otherwise, it ignores the value and skip deserialization.
• ignore_names (string, callable or list of them) – If callable, it is a function that takes a name of a parameter and a persistent and returns True when it needs to be skipped. If string, this is a name of a parameter or persistent that are going to be skipped. This can also be a list of callables and strings that behave as described above.

Methods
__call__ (key, value)
Serializes or deserializes a value by given name.

This operator saves or loads a value by given name.

If this is a serializer, then the value is simply saved at the key. Note that some type information might be missed depending on the implementation (and the target file format).

If this is a deserializer, then the value is loaded by the key. The deserialization differently works on scalars and arrays. For scalars, the value argument is used just for determining the type of restored value to be converted, and the converted value is returned. For arrays, the restored elements are directly copied into the value argument. String values are treated like scalars.

Note: Serializers and deserializers are required to correctly handle the None value. When value is None, serializers save it in format-dependent ways, and deserializers just return the loaded value. When the saved None value is loaded by a deserializer, it should quietly return the None value without modifying the value object.

Parameters
• key (str) – Name of the serialization entry.
• value (scalar, numpy.ndarray, cupy.ndarray, None, or str) – Object to be (de)serialized. None is only supported by deserializers.

Returns Serialized or deserialized value.

__getitem__ (key)
Gets a child serializer.

This operator creates a _child_ serializer represented by the given key.

Parameters key (str) – Name of the child serializer.
load(obj)
    Loads an object from this deserializer.

    This is equivalent to obj.serialize(self).

    Parameters obj – Target object to be serialized.

    __eq__(value,)
        Return self==value.

    __ne__(value,)
        Return self!=value.

    __lt__(value,)
        Return self<value.

    __le__(value,)
        Return self<=value.

    __gt__(value,)
        Return self>value.

    __ge__(value,)
        Return self>=value.

chainer.serializers.save_npz

chainer.serializers.save_npz(file, obj, compression=True)
    Saves an object to the file in NPZ format.

    This is a short-cut function to save only one object into an NPZ file.

    Parameters

        • file(str or file-like) – Target file to write to.
        • obj – Object to be serialized. It must support serialization protocol. If it is a dictionary object, the serialization will be skipped.
        • compression(bool) – If True, compression in the resulting zip file is enabled.

    See also:

        chainer.serializers.load_npz()

chainer.serializers.load_npz

chainer.serializers.load_npz(file, obj, path='', strict=True, ignore_names=None)
    Loads an object from the file in NPZ format.

    This is a short-cut function to load from an .npz file that contains only one object.

    Parameters

        • file(str or file-like) – File to be loaded.
        • obj – Object to be deserialized. It must support serialization protocol.
        • path(str) – The path in the hierarchy of the serialized data under which the data is to be loaded. The default behavior (blank) will load all data under the root path.
        • strict(bool) – If True, the deserializer raises an error when an expected value is not found in the given NPZ file. Otherwise, it ignores the value and skip deserialization.
• **ignore_names** *(string, callable or list of them)* – If callable, it is a function that takes a name of a parameter and a persistent and returns `True` when it needs to be skipped. If string, this is a name of a parameter or persistent that are going to be skipped. This can also be a list of callables and strings that behave as described above.

See also:

```
chainer.serializers.save_npz()
```

### 4.11.2 Serialization in HDF5 format

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.serializers.HDF5Serializer</code></td>
<td>Serializer for HDF5 format.</td>
</tr>
<tr>
<td><code>chainer.serializers.HDF5Deserializer</code></td>
<td>Deserializer for HDF5 format.</td>
</tr>
<tr>
<td><code>chainer.serializers.save_hdf5</code></td>
<td>Saves an object to the file in HDF5 format.</td>
</tr>
<tr>
<td><code>chainer.serializers.load_hdf5</code></td>
<td>Loads an object from the file in HDF5 format.</td>
</tr>
</tbody>
</table>

#### `chainer.serializers.HDF5Serializer`

**class** `chainer.serializers.HDF5Serializer` *(group, compression=4)*

Serializer for HDF5 format.

This is the standard serializer in Chainer. The chain hierarchy is simply mapped to HDF5 hierarchical groups.

**Parameters**

- **group** *(h5py.Group)* – The group that this serializer represents.
- **compression** *(int)* – Gzip compression level.

**Methods**

```
__call__(key, value)
```

Serializes or deserializes a value by given name.

This operator saves or loads a value by given name.

If this is a serializer, then the value is simply saved at the key. Note that some type information might be missed depending on the implementation (and the target file format).

If this is a deserializer, then the value is loaded by the key. The deserialization differently works on scalars and arrays. For scalars, the `value` argument is used just for determining the type of restored value to be converted, and the converted value is returned. For arrays, the restored elements are directly copied into the `value` argument. String values are treated like scalars.

**Note:** Serializers and deserializers are required to correctly handle the `None` value. When `value` is `None`, serializers save it in format-dependent ways, and deserializers just return the loaded value. When the saved `None` value is loaded by a deserializer, it should quietly return the `None` value without modifying the `value` object.

**Parameters**

- **key** *(str)* – Name of the serialization entry.
• value (scalar, numpy.ndarray, cupy.ndarray, None, or str) – Object to be (de)serialized. None is only supported by deserializers.

Returns Serialized or deserialized value.

__getitem__(key)

Gets a child serializer.

This operator creates a _child_ serializer represented by the given key.

Parameters key (str) – Name of the child serializer.

save(obj)

Saves an object by this serializer.

This is equivalent to obj.serialize(self).

Parameters obj – Target object to be serialized.

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.

__le__(value, /)

Return self<=value.

__gt__(value, /)

Return self>value.

__ge__(value, /)

Return self>=value.

chainer.serializers.HDF5Deserializer
class chainer.serializers.HDF5Deserializer(group, strict=True)

Deserializer for HDF5 format.

This is the standard deserializer in Chainer. This deserializer can be used to read an object serialized by HDF5Serializer.

Parameters

• group (h5py.Group) – The group that the deserialization starts from.

• strict (bool) – If True, the deserializer raises an error when an expected value is not found in the given HDF5 file. Otherwise, it ignores the value and skip deserialization.
Methods

__call__(key, value)  
Serializes or deserializes a value by given name.

This operator saves or loads a value by given name.

If this is a serializer, then the value is simply saved at the key. Note that some type information might be missed depending on the implementation (and the target file format).

If this is a deserializer, then the value is loaded by the key. The deserialization differently works on scalars and arrays. For scalars, the value argument is used just for determining the type of restored value to be converted, and the converted value is returned. For arrays, the restored elements are directly copied into the value argument. String values are treated like scalars.

**Note:** Serializers and deserializers are required to correctly handle the None value. When value is None, serializers save it in format-dependent ways, and deserializers just return the loaded value. When the saved None value is loaded by a deserializer, it should quietly return the None value without modifying the value object.

**Parameters**

- **key** (str) – Name of the serialization entry.
- **value** (scalar, numpy.ndarray, cupy.ndarray, None, or str) – Object to be (de)serialized. None is only supported by deserializers.

**Returns**  Serialized or deserialized value.

__getitem__(key)  
Gets a child serializer.

This operator creates a _child_ serializer represented by the given key.

**Parameters**  key (str) – Name of the child serializer.

load(obj)  
Loads an object from this deserializer.

This is equivalent to obj.serialize(self).

**Parameters**  obj – Target object to be serialized.

__eq__(value, /)  
Return self==value.

__ne__(value, /)  
Return self!=value.

__lt__(value, /)  
Return self<value.

__le__(value, /)  
Return self<=value.

__gt__(value, /)  
Return self>value.

__ge__(value, /)  
Return self>=value.
chainer.serializers.save_hdf5

chainer.serializers.save_hdf5(filename, obj, compression=4)
Saves an object to the file in HDF5 format.

This is a short-cut function to save only one object into an HDF5 file. If you want to save multiple objects to one HDF5 file, use HDF5Serializer directly by passing appropriate h5py.Group objects.

Parameters

- **filename** (str) – Target file name.
- **obj** – Object to be serialized. It must support serialization protocol. If it is a dictionary object, the serialization will be skipped.
- **compression** (int) – Gzip compression level.

**Note:** Currently save_hdf5() only supports writing to an actual file on file system due to a limitation of HD5F library. See h5py/h5py#687 for details.

See also:

chainer.serializers.load_hdf5()

chainer.serializers.load_hdf5

chainer.serializers.load_hdf5(filename, obj)
Loads an object from the file in HDF5 format.

This is a short-cut function to load from an HDF5 file that contains only one object. If you want to load multiple objects from one HDF5 file, use HDF5Deserializer directly by passing appropriate h5py.Group objects.

Parameters

- **filename** (str) – Name of the file to be loaded.
- **obj** – Object to be deserialized. It must support serialization protocol.

**Note:** Currently load_hdf5() only supports loading an actual file on file system due to a limitation of HD5F library. See h5py/h5py#687 for details.

See also:

chainer.serializers.save_hdf5()

### 4.11.3 Serializers base classes

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.Serializer</td>
<td>Base class of all serializers.</td>
</tr>
<tr>
<td>chainer.AbstractSerializer</td>
<td>Abstract base class of all serializers and deserializers.</td>
</tr>
<tr>
<td>chainer.Deserializer</td>
<td>Base class of all deserializers.</td>
</tr>
</tbody>
</table>
chainer.Serializer

class chainer.Serializer
   Base class of all serializers.

Methods

__call__ (key, value)
   Serializes or deserializes a value by given name.
   This operator saves or loads a value by given name.
   If this is a serializer, then the value is simply saved at the key. Note that some type information might be
   missed depending on the implementation (and the target file format).
   If this is a deserializer, then the value is loaded by the key. The deserialization differently works on scalars
   and arrays. For scalars, the value argument is used just for determining the type of restored value to be
   converted, and the converted value is returned. For arrays, the restored elements are directly copied into
   the value argument. String values are treated like scalars.

   Parameters
   • key (str) – Name of the serialization entry.
   • value (scalar, numpy.ndarray, cupy.ndarray, None, or str) – Object to be (de)serialized. None is only supported by deserializers.

   Returns Serialized or deserialized value.

__getitem__ (key)
   Gets a child serializer.
   This operator creates a _child_ serializer represented by the given key.

   Parameters key (str) – Name of the child serializer.

save (obj)
   Saves an object by this serializer.
   This is equivalent to obj.serialize(self).

   Parameters obj – Target object to be serialized.

__eq__ (value, /)
   Return self==value.

__ne__ (value, /)
   Return self!=value.

__lt__ (value, /)
   Return self<value.

__le__ (value, /)
   Return self<=value.
__gt__ (value, /)
    Return self>value.
__ge__ (value, /)
    Return self>=value.

chainer.AbstractSerializer

class chainer.AbstractSerializer
    Abstract base class of all serializers and deserializers.

Methods

__call__ (key, value)
    Serializes or deserializes a value by given name.
    This operator saves or loads a value by given name.
    If this is a serializer, then the value is simply saved at the key. Note that some type information might be
    missed depending on the implementation (and the target file format).
    If this is a deserializer, then the value is loaded by the key. The deserialization differently works on scalars
    and arrays. For scalars, the value argument is used just for determining the type of restored value to be
    converted, and the converted value is returned. For arrays, the restored elements are directly copied into
    the value argument. String values are treated like scalars.

    Parameters
        • key (str) – Name of the serialization entry.
        • value (scalar, numpy.ndarray, cupy.ndarray, None, or str) –
            Object to be (de)serialized. None is only supported by deserializers.

    Returns
        Serialized or deserialized value.

__getitem__ (key)
    Gets a child serializer.
    This operator creates a _child_ serializer represented by the given key.

    Parameters
        key (str) – Name of the child serializer.

__eq__ (value, /)
    Return self==value.
__ne__ (value, /)
    Return self!=value.
__lt__ (value, /)
    Return self<value.
__le__ (value, /)
    Return self<=value.
chainer.Deserializer

class chainer.Deserializer
    Base class of all deserializers.

Methods

__call__(key, value)
    Serializes or deserializes a value by given name.
    This operator saves or loads a value by given name.
    If this is a serializer, then the value is simply saved at the key. Note that some type information might be
    missed depending on the implementation (and the target file format).
    If this is a deserializer, then the value is loaded by the key. The deserialization differently works on scalars
    and arrays. For scalars, the value argument is used just for determining the type of restored value to be
    converted, and the converted value is returned. For arrays, the restored elements are directly copied into
    the value argument. String values are treated like scalars.

    Parameters
    • key (str) – Name of the serialization entry.
    • value (scalar, numpy.ndarray, cupy.ndarray, None, or str) – Object to be (de)serialized. None is only supported by deserializers.

    Returns
    Serialized or deserialized value.

__getitem__(key)
    Gets a child serializer.
    This operator creates a _child_serializer represented by the given key.

    Parameters
    key (str) – Name of the child serializer.

load(obj)
    Loads an object from this deserializer.
    This is equivalent to obj.serialize(self).

    Parameters
    obj – Target object to be serialized.

__eq__(value,)
    Return self==value.
__ne__(value,)
    Return self!=value.
__lt__(value,)
    Return self<value.
__le__(value,)
    Return self<=value.
__gt__(value,)
    Return self>value.
__ge__(value,)
    Return self>=value.

4.12 Backends and Devices

4.12.1 Common Classes and Utilities

<table>
<thead>
<tr>
<th>Module</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.backend.Device</td>
<td>A base class of unified devices.</td>
</tr>
<tr>
<td>chainer.get_device</td>
<td>Returns a device object.</td>
</tr>
<tr>
<td>chainer.using_device</td>
<td>Context manager to apply the thread-local device state.</td>
</tr>
<tr>
<td>chainer.backend.</td>
<td></td>
</tr>
<tr>
<td>get_device_from_array</td>
<td>Gets the device from arrays.</td>
</tr>
<tr>
<td>chainer.backend.get_array_module</td>
<td>Gets an appropriate NumPy-compatible module to process arguments</td>
</tr>
<tr>
<td>chainer.DeviceResident</td>
<td>A base class of objects with multi-device hierarchy.</td>
</tr>
<tr>
<td>chainer.device_resident. DeviceResidentsVisitor</td>
<td>Base class of visitors that visits device resident objects recursively.</td>
</tr>
<tr>
<td>chainer.backend.copyto</td>
<td>Copies the elements of an ndarray to those of another one.</td>
</tr>
</tbody>
</table>

class chainer.backend.Device

A base class of unified devices.

Chainer has the following concrete implementations:

- chainer.backend.CpuDevice
- chainer.backend.GpuDevice
- chainer.backend.Intel64Device
- chainer.backend.ChainerxDevice
Methods

__enter__()
A dummy definition that simply raises RuntimeError.

    chainer.using_device() should be used instead.

__exit__(exc_type, exc_value, traceback)
A dummy definition that should never be called.

create_context()
Returns a context manager in which the device is made current.

    See also:
    chainer.using_device() calls this method internally.

is_array_supported(array)
Returns if the specified array is compatible with the device. :param array: An array to be checked :type array: N-dimensional array

    Returns True if the array is compatible with the device. Otherwise False is returned.

send(arrays)
Transfers given arrays to the device.

    Parameters arrays -- Array or arrays of NumPy, CuPy, or ChainerX.

    Returns Transferred arrays.

use()
Makes the device current in the current thread.

__eq__(other)
Return self==value.

__ne__(other)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.

Attributes

name
A unique name of the device.

supported_array_types
Array types supported by the device.

    Returns tuple of array types which the device’s module functions can handle.

xp
Array module corresponding to the device.
chainer.get_device

chainer.get_device(device_spec: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]]) \rightarrow chainer.backends.Device

Returns a device object.

Parameters device_spec (object) – Device specifier. If a chainer.backends.Device instance is given, it is returned intact. Otherwise the following values are supported:

- ChainerX devices
  - A string representing a device. (ex. 'native:0', 'native')
  - A chainerx.Device object.
- CuPy
  - A string starts with '@cupy:'. (ex. '@cupy:0')
  - A cupy.cuda.Device object.
- NumPy
  - The string '@numpy'.
- NumPy with Intel Architecture
  - The string '@intel64'.

chainer.using_device

chainer.using_device(device_spec)

Context manager to apply the thread-local device state.

Parameters device_spec (object) – Device specifier. See chainer.get_device() for details.

Example

```python
with chainer.using_device('@cupy:1'):
    a = cupy.empty((3, 2))

assert a.device.id == 1
```

chainer.backend.get_device_from_array

chainer.backend.get_device_from_array(*arrays)

Gets the device from arrays.

The device on which the given array reside is returned.

Note: Unlike get_array_module(), this method does not recognize Variable objects. If you need to get device from the Variable instance v, you need to use get_device_from_array(v.array).
**Parameters** **arrays** *(array or list of arrays)* – Arrays to determine the device. If multiple arrays are given, the device corresponding to the first array which is not NumPy array is returned.

**Returns** Device instance.

**Return type** *chainer.backend.Device*

**chainer.backend.get_array_module**

**chainer.backend.get_array_module** (*args*)

Gets an appropriate NumPy-compatible module to process arguments

This function will return their data arrays’ array module for `Variable` arguments.

**Parameters** **args** – Values to determine whether NumPy, CuPy, or ChainerX should be used.

**Returns** `numpy`, `cupy`, or `chainerx` is returned based on the types of the arguments.

**Return type** *module*

**chainer.DeviceResident**

**class** *chainer.DeviceResident*

A base class of objects with multi-device hierarchy.

**Methods**

**device_resident_accept** *(visitor)*

Applies the visitor to all the device objects in this instance.

**Parameters** **visitor** *(DeviceResidentsVisitor)* – Visitor.

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**from_chx** *

Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**to_chx** *

Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to ChainerX, the link implementation must override this method to do so.

**Returns**: self

**to_cpu** *

Copies parameter variables and persistent values to CPU.

**Deprecated since version v7.0.0**: Use **to_device()** instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override **device_resident_accept()** to do so.

**Returns**: self

**to_device** *(device: Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], ModuleType, Tuple[ModuleType, int]])* → DeviceResident

Copies parameter variables and persistent values to the specified device.

4.12. Backends and Devices 1105
This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**
- **device** – Target device specifier. See `get_device()` for available values.

Returns: self

```python
to_gpu(device: Optional[Union[cuda.Device, int, numpy.integer]] = None) → chainer.device_resident.DeviceResident
```
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.

**Warning:** This method does not transfer the parameters if they are already on GPU. Use `to_device()` to perform inter-GPU transfer.

**Parameters**
- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

```python
to_intel64() → chainer.device_resident.DeviceResident
```
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

```python
__eq__(value, /)
```
Return `self==value`.

```python
__ne__(value, /)
```
Return `self!=value`.

```python
__lt__(value, /)
```
Return `self<value`.

```python
__le__(value, /)
```
Return `self<=value`.

```python
__gt__(value, /)
```
Return `self>value`.

```python
__ge__(value, /)
```
Return `self>=value`.

**Attributes**

- **device**
  - `Device` instance.

- **xp**
  - Array module corresponding to the device.

  Depending on the device in which this object resides, this property returns `numpy`, `cupy` or `chainerx`. 
class chainer.device_resident.DeviceResidentsVisitor

Base class of visitors that visits device resident objects recursively.

See also:

chainer.DeviceResident

Methods

visit_array(arr)

Processes an array and returns a new one.

If the visitor does not create a new array, it can simply return the original array.

visit_device_resident(device_resident)

Processes a DeviceResident instance.

visit_variable(param)

Processes a Variable or a Parameter.

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.

__le__(value, /)

Return self<=value.

__gt__(value, /)

Return self>value.

__ge__(value, /)

Return self>=value.

chainer.backend.copyto

crainer.backend.copyto(dst, src)

Copies the elements of an ndarray to those of another one.

This function can copy the CPU/GPU arrays to the destination arrays on another device.

Parameters

- `dst` (numpy.ndarray, cupy.ndarray, ideep4py.mdarray or chainerx.ndarray) – Destination array.

- `src` (numpy.ndarray, cupy.ndarray, ideep4py.mdarray or chainerx.ndarray) – Source array.
4.12.2 Concrete Device Classes

- **chainer.backend.CpuDevice**: Device for CPU (NumPy) backend
- **chainer.backend.GpuDevice**: Device for GPU (CuPy) backend
- **chainer.backend.Intel64Device**: Device for Intel64 (Intel Architecture) backend with iDeep
- **chainer.backend.ChainerxDevice**: Device for ChainerX backend

### chainer.backend.CpuDevice

*Class chainer.backend.CpuDevice*

Device for CPU (NumPy) backend

#### Methods

- **__enter__()**: A dummy definition that simply raises RuntimeError. `chainer.using_device()` should be used instead.
- **__exit__(exc_type, exc_value, traceback)**: A dummy definition that should never be called.
- **create_context()**: Returns a context manager in which the device is made current. See also: `chainer.using_device()` calls this method internally.
- **static from_array(array)**
- **is_array_supported(array)**: Returns if the specified array is compatible with the device. :param array: An array to be checked :type array: N-dimensional array
  
  Returns True if the array is compatible with the device. Otherwise False is returned.
- **send(arrays)**: Transfers given arrays to the device.
  
  Parameters arrays – Array or arrays of NumPy, CuPy, or ChainerX.
  
  Returns Transferred arrays.
- **send_array(array)**
- **use()**: Makes the device current in the current thread.
- **__eq__(other)**: Return self==value.
- **__ne__(other)**: Return self!=value.
- **__lt__(value,/)**: Return self<value.
__le__(value, /)  
Return self<=value.

__gt__(value, /)  
Return self>value.

__ge__(value, /)  
Return self>==value.

Attributes

name = '@numpy'
supported_array_types = (<class 'numpy.ndarray'>,)

chainer.backend.GpuDevice

class chainer.backend.GpuDevice(device)
    Device for GPU (CuPy) backend

Methods

__enter__()  
A dummy definition that simply raises RuntimeError.

chainer.using_device() should be used instead.

__exit__(exc_type, exc_value, traceback)  
A dummy definition that should never be called.

create_context()  
Returns a context manager in which the device is made current.

See also:

chainer.using_device() calls this method internally.

static from_array(array)  
static from_device_id(device_id)  
Returns a GpuDevice corresponding to the CUDA device ID.

is_array_supported(array)  
Returns if the specified array is compatible with the device. 
:param array: An array to be checked
:type array: N-dimensional array

Returns True if the array is compatible with the device. Otherwise False is returned.

send(arrays)  
Transfers given arrays to the device.

Parameters arrays – Array or arrays of NumPy, CuPy, or ChainerX.

Returns Transferred arrays.

send_array(array)  
use()  
Makes the device current in the current thread.

4.12. Backends and Devices
__eq__(other)
   Return self==value.

__ne__(other)
   Return self!=value.

__lt__(value, /)
   Return self<value.

__le__(value, /)
   Return self<=value.

__gt__(value, /)
   Return self>value.

__ge__(value, /)
   Return self>=value.

Attributes

name

 supported_array_types = (<class 'chainer.backends.cuda.ndarray'>,)
 xp = <object object>

chainer.backend.Intel64Device

class chainer.backend.Intel64Device
   Device for Intel64 (Intel Architecture) backend with iDeep

Methods

__enter__()  
   A dummy definition that simply raises RuntimeError.
   chainer.using_device() should be used instead.

__exit__(exc_type, exc_value, traceback)
   A dummy definition that should never be called.

create_context()
   Returns a context manager in which the device is made current.
   See also:
   chainer.using_device() calls this method internally.

static from_array(array)

is_array_supported(array)
   Returns if the specified array is compatible with the device. :param array: An array to be checked :type array: N-dimensional array
   
   Returns: True if the array is compatible with the device. Otherwise False is returned.

send(arrays)
   Transfers given arrays to the device.

   Parameters arrays – Array or arrays of NumPy, CuPy, or ChainerX.
**Returns** Transferred arrays.

```python
send_array(array)
```

**use()**  
Makes the device current in the current thread.

```python
__eq__(other)
Return self==value.
```

```python
__ne__(other)
Return self!=value.
```

```python
__lt__(value,)
Return self<value.
```

```python
__le__(value,)
Return self<=value.
```

```python
__gt__(value,)
Return self>value.
```

```python
__ge__(value,)
Return self>=value.
```

**Attributes**

```python
name = '@intel64'
supported_array_types = (numpy.ndarray, chainer.backends.intel64.mdarray)
```

### chainer.backend.ChainerxDevice

**class chainer.backend.ChainerxDevice(device: chainerx.Device)**  
Device for ChainerX backend

**Methods**

```python
__enter__()  
A dummy definition that simply raises RuntimeError.
```

```python
chainer.using_device() should be used instead.
```

```python
__exit__(exc_type, exc_value, traceback)
A dummy definition that should never be called.
```

**create_context()**  
Returns a context manager in which the device is made current.

**See also:**

```python
chainer.using_device() calls this method internally.
```

**static from_array(array)**

**static from_fallback_device(device)**  
Returns a ChainerxDevice corresponding to the fallback device.

**See also:**

```python
fallback_device
```

### 4.12. Backends and Devices

1111
**is_array_supported** *(array)*

Returns if the specified array is compatible with the device.  
:param array: An array to be checked  
:type array: *N-dimensional array*

Returns `True` if the array is compatible with the device. Otherwise `False` is returned.

**send** *(arrays)*

Transfers given arrays to the device.

**Parameters**

- **arrays** – Array or arrays of NumPy, CuPy, or ChainerX.

**Returns**

Transferred arrays.

**send_array** *(array)*

**use** ()

Makes the device current in the current thread.

**__eq__** *(other)*

Return `self==value`.

**__ne__** *(other)*

Return `self!=value`.

**__lt__** *(value, /)*

Return `self<value`.

**__le__** *(value, /)*

Return `self<=value`.

**__gt__** *(value, /)*

Return `self>value`.

**__ge__** *(value, /)*

Return `self>=value`.

**Attributes**

**fallback_device**

Fallback device.

A fallback device is either a `CpuDevice` or a `GpuDevice` which shares the same physical device with the original ChainerX device.

For example, the fallback device of `native:0` ChainerX device is `CpuDevice`. The fallback device of `cuda:1` ChainerX device is `GpuDevice` with device ID 1.

**name**

**supported_array_types** = (`<class 'chainerx.ndarray'>`, )
4.12.3 GPU (CuPy)

Device, context and memory management on CuPy.

**Note:** The package `chainer.cuda` has been renamed to `chainer.backends.cuda` as of v4.0.0, but the previous module path `chainer.cuda` is also available.

Chainer uses CuPy (with very thin wrapper) to exploit the speed of GPU computation. Following modules and classes defined in CuPy are imported to `chainer.backends.cuda` module for convenience (refer to this table when reading chainer’s source codes).

<table>
<thead>
<tr>
<th>imported name</th>
<th>original name</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.backends.cuda.cupy</code></td>
<td><code>cupy</code></td>
</tr>
<tr>
<td><code>chainer.backends.cuda.cupyx</code></td>
<td><code>cupyx</code></td>
</tr>
<tr>
<td><code>chainer.backends.cuda.ndarray</code></td>
<td><code>cupy.ndarray</code></td>
</tr>
<tr>
<td><code>chainer.backends.cuda.cupy.cuda</code></td>
<td><code>cupy.cuda</code></td>
</tr>
<tr>
<td><code>chainer.backends.cuda.cupy.Device</code></td>
<td><code>cupy.cuda.Device</code></td>
</tr>
<tr>
<td><code>chainer.backends.cuda.cupy.Event</code></td>
<td><code>cupy.cuda.Event</code></td>
</tr>
<tr>
<td><code>chainer.backends.cuda.cupy.Stream</code></td>
<td><code>cupy.cuda.Stream</code></td>
</tr>
</tbody>
</table>

Chainer replaces the default allocator of CuPy by its memory pool implementation. It enables us to reuse the device memory over multiple forward/backward computations, and temporary arrays for consecutive elementwise operations.

**Devices**

<table>
<thead>
<tr>
<th><code>chainer.backends.cuda.get_device</code></th>
<th>Gets the device from a device object, an ID integer or an array object.</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.backends.cuda.get_device_from_id</code></td>
<td>Gets the device from an ID integer.</td>
</tr>
<tr>
<td><code>chainer.backends.cuda.get_device_from_array</code></td>
<td>Gets the device from a list of CuPy array or a single CuPy array.</td>
</tr>
</tbody>
</table>

**chainer.backends.cuda.get_device**

`chainer.backends.cuda.get_device(*args)`

Gets the device from a device object, an ID integer or an array object.

**Note:** This API is deprecated since v3.0.0. Please use `get_device_from_id()` or `get_device_from_array()` instead.

This is a convenient utility to select a correct device if the type of `arg` is unknown (i.e., one can use this function on arrays that may be on CPU or GPU). The returned device object supports the context management protocol of Python for the `with` statement.

**Parameters**

- `args` – Values to specify a GPU device. The first device object, integer or `cupy.ndarray` object is used to select a device. If it is a device object, it is returned. If it is an integer, the corresponding device is returned. If it is a CuPy array, the device on which this array reside is returned. If any arguments are neither integers nor CuPy arrays, a dummy device object representing CPU is returned.
Returns  Device object specified by given args.

See also:
See `cupy.cuda.Device` for the device selection not by arrays.

```python
chainer.backends.cuda.get_device_from_id
```

```python
chainer.backends.cuda.get_device_from_id(device_id: Optional[int]) → chainer.backends.cuda.Device
```

Gets the device from an ID integer.

**Parameters**

- **device_id** (*int or None*) – The ID of the device which this function returns.

```python
chainer.backends.cuda.get_device_from_array
```

```python
chainer.backends.cuda.get_device_from_array(*arrays: chainer.backends.cuda.ndarray) → chainer.backends.cuda.Device
```

Gets the device from a list of CuPy array or a single CuPy array.

Deprecated since version v6.0.0: This API is deprecated. Please use `chainer.backend.get_device_from_array()` instead.

The device on which the given CuPy array reside is returned.

**Note:** This method only recognizes `cupy.ndarray` in arguments. Especially note that, unlike `get_array_module()`, this method does not recognize `Variable` objects. If you need to get device from the `Variable` instance `v`, you need to use `get_device_from_array(v.array)`.

**Parameters**

- **arrays** (*`cupy.ndarray` or list of `cupy.ndarray* ) – A CuPy array which this function returns the device corresponding to. If a list of `cupy.ndarray`s are given, it returns the first device object of an array in the list.

**CuPy array allocation and copy**

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.backends.cuda.copy</code></td>
<td>Copies a <code>cupy.ndarray</code> object using the default stream.</td>
</tr>
<tr>
<td><code>chainer.backends.cuda.to_cpu</code></td>
<td>Copies the given GPU array to host CPU.</td>
</tr>
<tr>
<td><code>chainer.backends.cuda.to_gpu</code></td>
<td>Copies the given CPU array to the specified device.</td>
</tr>
</tbody>
</table>

```python
chainer.backends.cuda.copy
```

```python
chainer.backends.cuda.copy(array, out=None, out_device=None, stream=None)
```

Copies a `cupy.ndarray` object using the default stream.

This function can copy the device array to the destination array on another device.

**Parameters**

- **array** (`cupy.ndarray`) – Array to be copied.
- **out** (`cupy.ndarray`) – Destination array. If it is not None, then out_device argument is ignored.
• **out_device** – Destination device specifier. Actual device object is obtained by passing this value to `get_device()`.

• **stream** (`cupy.cuda.Stream`) – CUDA stream.

**Returns**

Copied array.

If `out` is not specified, then the array is allocated on the device specified by `out_device` argument.

**Return type** `cupy.ndarray`

---

### `chainer.backends.cuda.to_cpu`

**Function**

`chainer.backends.cuda.to_cpu(array, stream=None)`

Copies the given GPU array to host CPU.

**Parameters**

- **array** (`array`, `None`, `list` or `tuple`) – Array or arrays to be sent to CPU.

- **stream** (`cupy.cuda.Stream`) – CUDA stream.

**Returns**

Array on CPU.

If some of the arrays are already on CPU, then this function just returns those arrays without performing any copy.

If input arrays include `None`, it is returned as `None` as is.

**Return type** `numpy.ndarray`, `list` or `tuple`

---

### `chainer.backends.cuda.to_gpu`

**Function**

`chainer.backends.cuda.to_gpu(array, device=None, stream=None)`

Copies the given CPU array to the specified device.

**Parameters**

- **array** (`array`, `None`, `list` or `tuple`) – Array or arrays to be sent to GPU.

- **device** – CUDA device specifier. If `None` or `cuda.DummyDevice`, the arrays will be copied to the current CUDA device.

- **stream** (`Stream`) – *(deprecated since v3.0.0)* CUDA stream. If not `None`, the copy runs asynchronously.

**Returns**

Array or arrays on GPU.

If some of the arrays are already on GPU, then this function just returns those arrays without performing any copy.

If input arrays include `None`, it is returned as `None` as is.

**Return type** `cupy.ndarray`, `list` or `tuple`
## Kernel definition utilities

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.backends.cuda.memoize</code></td>
<td>Makes a function memoizing the result for each argument and device.</td>
</tr>
<tr>
<td><code>chainer.backends.cuda.clear_memo</code></td>
<td>Clears the memoized results for all functions decorated by memoize.</td>
</tr>
<tr>
<td><code>chainer.backends.cuda.elementwise</code></td>
<td>Creates an elementwise kernel function.</td>
</tr>
<tr>
<td><code>chainer.backends.cuda.raw</code></td>
<td>Creates a raw kernel function.</td>
</tr>
<tr>
<td><code>chainer.backends.cuda.reduce</code></td>
<td>Creates a global reduction kernel function.</td>
</tr>
</tbody>
</table>

### chainer.backends.cuda.memoize

**chainer.backends.cuda.memoize**(for_each_device=False)

 Makes a function memoizing the result for each argument and device.

This is a similar version of `cupy.memoize()`. The difference is that this function can be used in the global scope even if CUDA is not available. In such a case, this function does nothing.

**Note:** This decorator acts as a dummy if CUDA is not available. It cannot be used for general purpose memoization even if for_each_device is set to False.

### chainer.backends.cuda.clear_memo

**chainer.backends.cuda.clear_memo()**

Clears the memoized results for all functions decorated by memoize.

This function works like `cupy.clear_memo()` as a counterpart for `chainer.backends.cuda.memoize()`. It can be used even if CUDA is not available. In such a case, this function does nothing.

### chainer.backends.cuda.elementwise

**chainer.backends.cuda.elementwise**(in_params, out_params, operation, name, **kwargs)

Creates an elementwise kernel function.

This function uses `memoize()` to cache the kernel object, i.e. the resulting kernel object is cached for each argument combination and CUDA device.

The arguments are the same as those for `cupy.ElementwiseKernel`, except that the name argument is mandatory.
chainer.backends.cuda.raw

chainer.backends.cuda.raw(`code`, `name`, *args, **kwargs)
    Creates a raw kernel function.
    This function uses memoize() to cache the resulting kernel object, i.e. the resulting kernel object is cached for each argument combination and CUDA device.
    The arguments are the same as those for cupy.RawKernel.

chainer.backends.cuda.reduce

chainer.backends.cuda.reduce(`in_params`, `out_params`, `map_expr`, `reduce_expr`, `post_map_expr`, `identity`, `name`, **kwargs)
    Creates a global reduction kernel function.
    This function uses memoize() to cache the resulting kernel object, i.e. the resulting kernel object is cached for each argument combination and CUDA device.
    The arguments are the same as those for cupy.ReductionKernel, except that the name argument is mandatory.

CPU/GPU generic code support

chainer.backends.cuda.get_array_module
    Gets an appropriate one from numpy or cupy.
    This is almost equivalent to cupy.get_array_module(). The differences are that this function can be used even if CUDA is not available and that it will return their data arrays’ array module for Variable arguments.
    Deprecated since version v5.0.0: This API is deprecated. Please use get_array_module() instead.

Parameters
    `args` – Values to determine whether NumPy or CuPy should be used.

Returns
    cupy or numpy is returned based on the types of the arguments.

Return type
    module

cuDNN support

chainer.backends.cuda.set_max_workspace_size
    Sets the workspace size for cuDNN.

chainer.backends.cuda.get_max_workspace_size
    Gets the workspace size for cuDNN.
chainer.backends.cuda.set_max_workspace_size

chainer.backends.cuda.set_max_workspace_size(size)
Sets the workspace size for cuDNN.

Parameters size – The workspace size for cuDNN.

chainer.backends.cuda.get_max_workspace_size

chainer.backends.cuda.get_max_workspace_size()
Gets the workspace size for cuDNN.

4.12.4 Intel64 (iDeep)

iDeep is a module that provides NumPy-like API and DNN acceleration using MKL-DNN for Intel CPUs. See Tips and FAQs and Performance Best Practices for details.

chainer.backends.intel64.is_ideep_available

chainer.backends.intel64.is_ideep_available()
Returns if iDeep is available.

Returns True if the supported version of iDeep is installed.

Return type bool

4.12.5 ChainerX

chainer.backend.from_chx

Converts an array or arrays from ChainerX to NumPy or CuPy ones.

chainer.backend.to_chx

Converts an array or arrays to ChainerX.
chainer.backend.from_chx

chainer.backend.from_chx(array)
Converting an array or arrays from ChainerX to NumPy or CuPy ones.
Destination array types are chosen such that no copies occur.

chainer.backend.to_chx

chainer.backend.to_chx(array)
Converting an array or arrays to ChainerX.
Destination ChainerX devices are chosen according to the types of input arrays.

4.13 Utilities

4.13.1 Convolution/Deconvolution utilities

<table>
<thead>
<tr>
<th>chainer.utils.get_conv_outsize</th>
<th>Calculates output size of convolution.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.utils.get_deconv_outsize</td>
<td>Calculates output size of deconvolution.</td>
</tr>
</tbody>
</table>

chainer.utils.get_conv_outsize

chainer.utils.get_conv_outsize(size, k, s, p, cover_all=False, d=1)
Calculates output size of convolution.
This function takes the size of input feature map, kernel, stride, and pooling of one particular dimension, then calculates the output feature map size of that dimension.

See also:
generate_deconv_outsize()

Parameters
- **size (int)** – The size of input feature map. It usually is the length of a side of feature map.
- **k (int)** – The size of convolution kernel.
- **s (int)** – The size of stride.
- **p (int)** – The size of padding.
- **cover_all (bool)** – Use cover_all option or not.
- **d (int)** – The size of dilation.

Returns The expected output size of the convolution operation.

Return type int
chainer.utils.get_deconv_outsize

chainer.utils.get_deconv_outsize(size, k, s, p, cover_all=False, d=1)
Calculates output size of deconvolution.

This function takes the size of input feature map, kernel, stride, and pooling of one particular dimension, then calculates the output feature map size of that dimension.

See also:
get_conv_outsize()

Parameters

- **size** (*int*) – The size of input feature map. It usually is the length of a side of feature map.
- **k** (*int*) – The size of deconvolution kernel.
- **s** (*int*) – The size of stride.
- **p** (*int*) – The size of padding.
- **cover_all** (*bool*) – Use cover_all option or not.
- **d** (*int*) – The size of dilation.

Returns The expected output size of the deconvolution operation.

Return type int

4.13.2 Common algorithms

chainer.utils.WalkerAlias

class chainer.utils.WalkerAlias(probs)
Implementation of Walker’s alias method.

This method generates a random sample from given probabilities \(p_1, \ldots, p_n\) in \(O(1)\) time. It is more efficient than choice(). This class works on both CPU and GPU.

Parameters **probs** (*float list*) – Probabilities of entries. They are normalized with sum(probs).

See: Wikipedia article
Methods

**device_resident_accept**(visitor)
Applies the visitor to all the device objects in this instance.

**Parameters**

**visitor** *(DeviceResidentsVisitor) – Visitor.*

This method should be overridden if the concrete class has custom sub-hierarchy of device resident objects.

**from_chx**()
Converts parameter variables and persistent values from ChainerX to NumPy/CuPy devices without any copy.

**sample**(shape)
Generates a random sample based on given probabilities.

**Parameters**

**shape** *(tuple of int) – Shape of a return value.*

**Returns**
Returns a generated array with the given shape. If a sampler is in CPU mode the return value is a `numpy.ndarray` object, and if it is in GPU mode the return value is a `cupy.ndarray` object.

**sample_gpu**(shape)

**sample_xp**(xp, shape)

**to_chx**()
Converts parameter variables and persistent values to ChainerX without any copy.

This method does not handle non-registered attributes. If some of such attributes must be copied to Chain-
erX, the link implementation must override this method to do so.

**Returns:** self

**to_cpu**()
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation should override `device_resident_accept()` to do so.

**Returns:** self

**to_device**(device: `Union[backend.Device, chainerx.Device, cuda.Device, str, Tuple[str, int], Module- Type, Tuple[ModuleType, int]]`) → DeviceResident
Copies parameter variables and persistent values to the specified device.

This method does not handle non-registered attributes. If some of such attributes must be copied to the device, the link implementation must override this method to do so.

**Parameters**

**device** – Target device specifier. See `get_device()` for available values.

**Returns:** self

**to_gpu**(device: `Optional[Union[cuda.Device, int, numpy.integer]] = None`) → DeviceResident
Copies parameter variables and persistent values to GPU.

Deprecated since version v7.0.0: Use `to_device()` instead.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override `device_resident_accept()` to do so.
Warning: This method does not transfer the parameters if they are already on GPU. Use to_device to perform inter-GPU transfer.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64() → chainer.device_resident.DeviceResident
Copies parameter variables and persistent values to CPU.

Deprecated since version v7.0.0: Use to_device() instead.

__eq__(value, /)  
Return self==value.

__ne__(value, /)   
Return self!=value.

__lt__(value, /)   
Return self<value.

__le__(value, /)    
Return self<=value.

__gt__(value, /)    
Return self>value.

__ge__(value, /)    
Return self>=value.

Attributes

device
Device instance.

use_gpu
xp
Array module corresponding to the device.
Depending on the device in which this object resides, this property returns numpy, cupy or chainerx.

4.13.3 Common utilities

chainer.print_runtime_info  Shows Chainer runtime information.
chainer.print_runtime_info

chainer.print_runtime_info(out=None)
    Shows Chainer runtime information.

    Runtime information includes:
    • OS platform
    • Chainer version
    • ChainerX version
    • NumPy version
    • CuPy version
      – CUDA information
      – cuDNN information
      – NCCL information
    • iDeep version

    Parameters out – Output destination. If it is None, runtime information will be shown in sys.stdout.

4.13.4 Reporter

<table>
<thead>
<tr>
<th>chainer.Reporter</th>
<th>Object to which observed values are reported.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.get_current_reporter</td>
<td>Returns the current reporter object.</td>
</tr>
<tr>
<td>chainer.report</td>
<td>Reports observed values with the current reporter object.</td>
</tr>
<tr>
<td>chainer.report_scope</td>
<td>Returns a report scope with the current reporter.</td>
</tr>
</tbody>
</table>

chainer.Reporter

class chainer.Reporter
    Object to which observed values are reported.

    Reporter is used to collect values that users want to watch. The reporter object holds a mapping from value names to the actually observed values. We call this mapping observations.

    When a value is passed to the reporter, an object called observer can be optionally attached. In this case, the name of the observer is added as the prefix of the value name. The observer name should be registered beforehand.

    See the following example:

    >>> from chainer import Reporter, report, report_scope
    >>> reporter = Reporter()
    >>> observer = object()  # it can be an arbitrary (reference) object
    >>> reporter.add_observer('my_observer', observer)
    >>> observation = {}
    >>> with reporter.scope(observation):
    ...    reporter.report({'x': 1}, observer)

(continues on next page)
There are also a global API to add values:

```python
>>> reporter = Reporter()
>>> observation = {}
>>> with reporter:
...     with report_scope(observation):
...         report({'x': 1})
...
>>> observation
{'x': 1}
```

The most important application of Reporter is to report observed values from each link or chain in the training and validation procedures. `Trainer` and some extensions prepare their own Reporter object with the hierarchy of the target link registered as observers. We can use `report()` function inside any links and chains to report the observed values (e.g., training loss, accuracy, activation statistics, etc.).

**Variables**

- **observation** – Dictionary of observed values.

**Methods**

- **__enter__()**
  Makes this reporter object current.

- **__exit__(exc_type, exc_value, traceback)**
  Recovers the previous reporter object to the current.

- **add_observer(name, observer)**
  Registers an observer of values.

  Observer defines a scope of names for observed values. Values observed with the observer are registered with names prefixed by the observer name.

  **Parameters**

  - **name (str)** – Name of the observer.
  - **observer** – The observer object. Note that the reporter distinguishes the observers by their object ids (i.e., `id(owner)`), rather than the object equality.

- **add_observers(prefix, observers)**
  Registers multiple observers at once.

  This is a convenient method to register multiple objects at once.

  **Parameters**

  - **prefix (str)** – Prefix of each name of observers.
  - **observers** – Iterator of name and observer pairs.

- **report(values, observer=None)**
  Reports observed values.

  The values are written with the key, prefixed by the name of the observer object if given.
Note: If a value is of type Variable, the variable is copied without preserving the computational graph and the new variable object purged from the graph is stored to the observer. This behavior can be changed by setting chainer.config.keep_graph_on_report to True.

Parameters

• values (dict) – Dictionary of observed values.

• observer – Observer object. Its object ID is used to retrieve the observer name, which is used as the prefix of the registration name of the observed value.

scope (observation)

Creates a scope to report observed values to observation.

This is a context manager to be passed to with statements. In this scope, the observation dictionary is changed to the given one.

It also makes this reporter object current.

Parameters observation (dict) – Observation dictionary. All observations reported inside of the with statement are written to this dictionary.

__eq__ (value, /)

Return self==value.

__ne__ (value, /)

Return self!=value.

__lt__ (value, /)

Return self<value.

__le__ (value, /)

Return self<=value.

__gt__ (value, /)

Return self>value.

__ge__ (value, /)

Return self>=value.

chainer.get_current_reporter

chainer.get_current_reporter ()

Returns the current reporter object.

chainer.report

chainer.report (values, observer=None)

Reports observed values with the current reporter object.

Any reporter object can be set current by the with statement. This function calls the Reporter.report () method of the current reporter. If no reporter object is current, this function does nothing.
The most typical example is a use within links and chains. Suppose that a link is registered to the current reporter as an observer (for example, the target link of the optimizer is automatically registered to the reporter of the Trainer). We can report some values from the link as follows:

```python
class MyRegressor(chainer.Chain):
    def __init__(self, predictor):
        super(MyRegressor, self).__init__(predictor=predictor)

    def __call__(self, x, y):
        # This chain just computes the mean absolute and squared errors between the prediction and y.
        pred = self.predictor(x)
        abs_error = F.sum(abs(pred - y)) / len(x)
        loss = F.mean_squared_error(pred, y)

        # Report the mean absolute and squared errors.
        chainer.report({'abs_error': abs_error, 'squared_error': loss}, self)

        return loss
```

If the link is named 'main' in the hierarchy (which is the default name of the target link in the StandardUpdater), these reported values are named 'main/abs_error' and 'main/squared_error'. If these values are reported inside the Evaluator extension, 'validation/' is added at the head of the link name, thus the item names are changed to 'validation/main/abs_error' and 'validation/main/squared_error' ('validation' is the default name of the Evaluator extension).

**Parameters**

- **values (dict)** – Dictionary of observed values.
- **observer** – Observer object. Its object ID is used to retrieve the observer name, which is used as the prefix of the registration name of the observed value.

**chainer.report_scope**

`chainer.report_scope(observation)`

Returns a report scope with the current reporter.

This is equivalent to `get_current_reporter().scope(observation)`, except that it does not make the reporter current redundantly.
4.13.5 Summary and DictSummary

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.Summary</td>
<td>Online summarization of a sequence of scalars.</td>
</tr>
<tr>
<td>chainer.DictSummary</td>
<td>Online summarization of a sequence of dictionaries.</td>
</tr>
</tbody>
</table>

**chainer.Summary**

**class chainer.Summary**

Online summarization of a sequence of scalars.

Summary computes the statistics of given scalars online.

**Methods**

**add**(value, weight=1)

Adds a scalar value.

**Parameters**

- **value** – Scalar value to accumulate. It is either a NumPy scalar or a zero-dimensional array (on CPU or GPU).
- **weight** – An optional weight for the value. It is a NumPy scalar or a zero-dimensional array (on CPU or GPU). Default is 1 (integer).

**compute_mean**()

Computes the mean.

**make_statistics**()

Computes and returns the mean and standard deviation values.

**Returns** Mean and standard deviation values.

**Return type** tuple

**serialize**(serializer)

**eq**(value, /)

Return self==value.

**ne**(value, /)

Return self!=value.

**lt**(value, /)

Return self<value.

**le**(value, /)

Return self<=value.

**gt**(value, /)

Return self>value.

**ge**(value, /)

Return self>=value.
class chainer.DictSummary

Online summarization of a sequence of dictionaries.

DictSummary computes the statistics of a given set of scalars online. It only computes the statistics for scalar values and variables of scalar values in the dictionaries.

Methods

add(d)

Adds a dictionary of scalars.

Parameters

- **d** *(dict)* — Dictionary of scalars to accumulate. Only elements of scalars, zero-dimensional arrays, and variables of zero-dimensional arrays are accumulated. When the value is a tuple, the second element is interpreted as a weight.

compute_mean()

Creates a dictionary of mean values.

It returns a single dictionary that holds a mean value for each entry added to the summary.

Returns

Dictionary of mean values.

Return type

**dict**

make_statistics()

Creates a dictionary of statistics.

It returns a single dictionary that holds mean and standard deviation values for every entry added to the summary. For an entry of name 'key', these values are added to the dictionary by names 'key' and 'key.std', respectively.

Returns

Dictionary of statistics of all entries.

Return type

**dict**

serialize(serializer)

__eq__(value, /)

Return self==value.

__ne__(value, /)

Return self!=value.

__lt__(value, /)

Return self<value.

__le__(value, /)

Return self<=value.

__gt__(value, /)

Return self>value.

__ge__(value, /)

Return self>=value.
4.13.6 Sparse utilities

A `chainer.Variable` can be converted into a sparse matrix in e.g. COO (Coordinate list) format. A sparse matrix stores the same data as the original object but with a different internal representation, optimized for efficient operations on sparse data, i.e. data with many zero elements.

Following are a list of supported sparse matrix formats and utilities for converting between a `chainer.Variable` and these representations.

**Note:** Please be aware that only certain functions accept sparse matrices as inputs, such as `chainer.functions.sparse_matmul()`.

<table>
<thead>
<tr>
<th>Class/Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.utils.CooMatrix</code></td>
<td>A sparse matrix in COO format.</td>
</tr>
<tr>
<td><code>chainer.utils.to_coo</code></td>
<td>Returns a single or a batch of matrices in COO format.</td>
</tr>
</tbody>
</table>

### chainer.utils.CooMatrix

**class** chainer.utils.CooMatrix(data, row, col, shape=None, order=None, requires_grad=False)

A sparse matrix in COO format.

**Parameters**

- **data** (*N-dimensional array*) – The entries of the matrix. The entries are usually non-zero-elements in the matrix.
- **row** (*N-dimensional array*) – The row indices of the matrix entries.
- **col** (*N-dimensional array*) – The column indices of the matrix entries.
- **shape** (*tuple of int*) – The shape of the matrix in dense format.
- **order** (‘C’, ‘F’, ‘other’ or None) – If ‘C’, the matrix is assumed that its row indices are sorted. If ‘F’, the matrix is assumed that its column indices are sorted. If ‘other’, the matrix is assumed as neither ‘C’ order nor ‘F’ order. If None (this is the default), the matrix is automatically checked if it is ‘C’ order, ‘F’ order or another. This information will be used by some functions like `sparse_matmul()` as a hint to improve performance.
- **requires_grad** (bool) – If True, gradient of this sparse matrix will be computed in back-propagation.

**See also:**

See `to_coo()` for how to construct a COO matrix from an array.

**Methods**

- **to_dense()**
  
  Returns a dense matrix format of this sparse matrix.

- **__eq__(value,/)**
  
  Return self==value.

- **__ne__(value,/)**
  
  Return self!=value.
chainer.utils.to_coo

chainer.utils.to_coo(x, ldnz=None, requires_grad=False)
Returns a single or a batch of matrices in COO format.

Parameters

- x (N-dimensional array) – Input dense matrix. The ndim of x must be two or three. If ndim
  is two, it is treated as a single matrix. If three, it is treated as batched matrices.

- ldnz (int) – Size of arrays for data, row index and column index to be created. The Actual
  size becomes max(nnz, ldnz) where nnz is number of non-zero elements in a input dense
  matrix.

- requires_grad (bool) – If True, gradient of sparse matrix will be computed in back-
  propagation.

Returns A sparse matrix or batched sparse matrices in COO format of a given dense matrix or
batched dense matrices.

Return type CooMatrix

Example
Create a CooMatrix from an array with 2 non-zero elements and 4 zeros and access its attributes. No batch
dimension is involved.

```python
>>> data = np.array([[0, 2, 0], [-1, 0, 0]], np.float32)
>>> x = chainer.utils.to_coo(data)
>>> x.data
variable([2., -1.])
>>> x.row
array([0, 1], dtype=int32)
>>> x.col
array([1, 0], dtype=int32)
>>> x.shape
(2, 3)
```
4.13.7 Experimental feature annotation

**chainer.utils.experimental**

Declares that user is using an experimental feature.

```python
from chainer import utils

def f(x):
    utils.experimental('chainer.foo.bar.f')
    # concrete implementation of f follows
f(1)
```

... FutureWarning: chainer.foo.bar.f is experimental. The interface can change in the future. ...

We can also make a whole class experimental. In that case, we should call this function in its `__init__` method.

```python
class C():
    def __init__(self):
        utils.experimental('chainer.foo.C')
C()
```

... FutureWarning: chainer.foo.C is experimental. The interface can change in the future. ...

If we want to mark `__init__` method only, rather than class itself, it is recommended that we explicitly feed its API name.

```python
class D():
    def __init__(self):
        utils.experimental('D.__init__')
D()
```

... FutureWarning: D.__init__ is experimental. The interface can change in the future. ...

Currently, we do not have any sophisticated way to mark some usage of non-experimental function as experimental. But we can support such usage by explicitly branching it.
def g(x, experimental_arg=None):
    if experimental_arg is not None:
        utils.experimental('experimental_arg of chainer.foo.g')

Parameters `api_name (str)` – The name of an API marked as experimental.

## 4.14 Configuring Chainer

Chainer provides some global settings that affect the behavior of some functionalities. Such settings can be configured using the unified configuration system. The system provides a transparent way to manage the configuration for each process and for each thread.

The configuration is managed by two global objects: `chainer.global_config` and `chainer.config`.

- The `global_config` object maintains the configuration shared in the Python process. This is an instance of the `GlobalConfig` class. It can be used just as a plain object, and users can freely set any attributes on it.

- The `config` object, on the other hand, maintains the configuration for the current thread. This is an instance of the `LocalConfig` class. It behaves like a thread-local object, and any attribute modifications are only visible to the current thread.

If no value is set to `config` for a given key, `global_config` is transparently referred. Thanks to this transparent lookup, users can always use `config` to read any configuration so that the thread-local configuration is used if available and otherwise the default global setting is used.

The following entries of the configuration are currently provided by Chainer. Some entries support environment variables to set the default values. Note that the default values are set in the global config.

### 4.14.1 Configuration Keys

- **cudnn_deterministic (default: False)** Flag to configure deterministic computations in cuDNN APIs.
  
  If it is True, convolution functions that use cuDNN use the deterministic mode (i.e., the computation is reproducible). Otherwise, the results of convolution functions using cuDNN may be non-deterministic in exchange for better performance.

- **debug (default: False)** Debug mode flag.
  
  If it is True, Chainer runs in debug mode. Enabling debug mode may introduce some performance overhead. See Debug Mode for more information of the debug mode.

  You can change the default value to True by setting CHAINER_DEBUG environment variable to 1.

- **dtype (default: numpy.float32)** Default floating point data type.
  
  Chainer uses this dtype to construct arrays when the dtype is not specified (e.g. initializers).

  You can change the default value by setting CHAINER_DTYPE environment variable to mixed16, float16, float32, float64.

  **Note:** If you want to use float16 for better performance, it is recommended that you use mixed16 instead of float16.

- **enable_backprop (default: True)** Flag to enable backpropagation support.
If it is `True`, computational graphs are created during forward passes by `FunctionNode`, allowing backpropagation to start from any `Variable` in the graph. Otherwise, computational graphs are not created but memory consumptions are reduced. So calling `backward()` on the results of a function will not compute any gradients of any input.

- **keep_graph_on_report (default: False)** Flag to configure whether or not to let `report()` keep the computational graph.

  If it is `False`, `report()` does not keep the computational graph when a `Variable` object is reported. It means that `report()` stores a copy of the `Variable` object which is purged from the computational graph. If it is `True`, `report()` just stores the `Variable` object as is with the computational graph left attached.

  You can change the default value to `True` by setting `CHAINER_KEEP_GRAPH_ON_REPORT` environment variable to `1`.

- **warn_nondeterministic (default: False)** Flag to give warning when a non-deterministic function is used. This function is experimental.

  If it is `true`, then functions that use non-deterministic functions and cannot be given a seed, such as `atomicAdd`, will give a warning when executed. For functions that can take a seed argument, such as `split_dataset_random()`, setting the seed should be done when the function is called and will not be flagged by this setting.

  Note that this feature is provided as best-effort. It cannot assure that every nondeterministic function can be detected. For example, SSE computations in CPU mode may cause non-deterministic behavior that would not raise a warning.

  Also, deterministic outputs may still result, even if this flag produces a non-deterministic warning. For example, reduction on 1-dim axis should always be deterministic, but it may raise a warning.

- **train (default: True)** Training mode flag.

  If it is `True`, Chainer runs in training mode. Otherwise, it runs in the testing (evaluation) mode.

  This configuration is used by Functions and Links that need to behave differently between training phase and evaluation (inference) phase. One example is `chainer.links.BatchNormalization` updates statistics using input data only when `train` is set to `True`. The other example is `chainer.functions.dropout()`, which does nothing when `train` is set to `False`.

  Generally, you are responsible to change the configuration to `False` during evaluation. If you are using `Trainer` with `Evaluator` extension, `train` configuration will automatically be switched to `False` during evaluation in the training loop.

  Note that this parameter does not reduce memory consumption or affect the creation of computational graphs required in order to compute gradients.

- **type_check (default: True)** Type checking mode flag.

  If it is `True`, Chainer checks the types (data types and shapes) of inputs on `Function` applications. Otherwise, it skips type checking.

  You can change the default value to `False` by setting `CHAINER_TYPE_CHECK` environment variable to `0`.

- **use_cudnn (default: 'auto')** Flag to configure whether or not to use cuDNN.

  This is a ternary flag with 'always', 'auto', and 'never' as its allowed values. The meaning of each flag is as follows.

  - If it is 'always', Chainer will try to use cuDNN everywhere if possible.
If it is `auto`, Chainer will use cuDNN only if it is known that the usage does not degrade the performance.

- If it is `never`, Chainer will never use cuDNN anywhere.

You can change the default value by setting `CHAINER_USE_CUDNN` environment variable to any of `always`, `auto` or `never`.

**use_ideep (default: `never`)** Flag to configure whether or not to use iDeep.

This is a ternary flag with `always`, `auto`, and `never` as its allowed values. The meaning of each flag is as follows.

- If it is `always`, Chainer will try to use iDeep everywhere if possible.
- If it is `auto`, Chainer will use iDeep only if it is known that the usage does not degrade the performance.
- If it is `never`, Chainer will never use iDeep anywhere.

You can change the default value by setting `CHAINER_USE_IDEEP` environment variable to any of `always`, `auto` or `never`.

Note that in spite of the configuration, optimizers will use iDeep if and only if the link is converted manually to iDeep (e.g., `model.to_intel64()`).

**lazy_grad_sum (default: False)** Flag to control the behavior of gradient accumulation.

If it is True, gradients are accumulated in batch for performance. Otherwise gradients are accumulated one by one.

You can change the default value to True by setting `CHAINER_LAZY_GRAD_SUM` environment variable to 1.

**use_cudnn_tensor_core (default: `auto`)** Flag to configure whether or not to enable Tensor Core operations in cuDNN.

This is a ternary flag with `always`, `auto`, and `never` as its allowed values. The meaning of each flag is as follows.

- If it is `always`, Chainer uses cuDNN’s Tensor Core operations.
- If it is `never`, Chainer does not use cuDNN’s Tensor Core operations.
- If it is `auto`, Chainer checks cuDNN version, the data type of input, the compute capability of the GPU used, and configures whether or not to use cuDNN’s Tensor Core operations.

**autotune (default: False)** Autotune for convolutional networks flag.

If it is True, Chainer uses the cuDNN autotune feature to find the fastest calculation process for `chainer.links.Convolution2D`, `ConvolutionND`, `Deconvolution2D`, or `DeconvolutionND` links.

**cudnn_fast_batch_normalization (default: False)** Flag to configure whether or not to enable use of fast implementation for batch normalization in cuDNN.

If True, Chainer will try to use the fast implementation for batch normalization in cuDNN by setting cuDNN’s batch normalization mode to `CUDNN_BATCHNORM_SPATIAL_PERSISTENT`. You can change the default value to True by setting `CHAINER_CUDNN_FAST_BATCH_NORMALIZATION` environment variable to 1.

**in_recomputing (default: False)** This flag is automatically set by `chainer.functions.forget()` and not intended to be changed by users. You can use this flag when implementing
your own Link to avoid updating the internal states during recomputation done by \texttt{chainer.functions.forget()}. See the documentation of \texttt{chainer.functions.forget()} for details.

- **use\_static\_graph** (default: \texttt{True}) Flag to configure whether or not to use the static subgraph optimization feature. Where the static subgraph optimization decorator is used, we generally assume that the feature should be used and the default value is thus \texttt{True}. However, if you would want to run the same code without the feature, you can simply set the flag to \texttt{False} instead of removing the decorators. This is useful when for instance running your model with ChainerX, since ChainerX is not supported by the static subgraph optimization feature.

### 4.14.2 User-defined Keys

Users can also define their own configurations. There are two ways:

1. Use Chainer’s configuration objects. In this case, \textit{it is strongly recommended that the name be prefixed by “user_”} to avoid name conflicts with configurations introduced to Chainer in the future.

2. Use your own configuration objects. Users can define their own configuration objects using \texttt{chainer.configuration.GlobalConfig} and \texttt{chainer.configuration.LocalConfig}. In this case, there is no need to take care of the name conflicts.

### 4.14.3 Changing Configuration

If you want to share a setting within the process, set an attribute to the global configuration. This value is automatically extracted by referring to the local config.

```python
>>> chainer.global_config.train
True
>>> chainer.config.train
True

>>> chainer.global_config.train = False

>>> chainer.global_config.train
False
>>> chainer.config.train
False
```

If you set an attribute to the local configuration, the value is only visible to the current thread.

```python
>>> chainer.global_config.train
True
>>> chainer.config.train
True

>>> chainer.config.train = False

>>> chainer.global_config.train
True
>>> chainer.config.train
False
```

If you want to temporarily modify the configuration for the specific scope, you can use \texttt{using_config()}. For example, if you only want to enable debug mode in a fragment of code, write as follows.

```python
>>> using_config(train=False):

>>> chainer.global_config.train
True
>>> chainer.config.train
False
```

4.14. Configuring Chainer 1135
>>> with chainer.using_config('debug', True):
...   pass  # code running in debug mode

If you want to switch to the test mode for an evaluation, you can do that in the same way.

>>> # Do training here
>>> with chainer.using_config('train', False):
...   pass  # Perform evaluation here

Note that Evaluator automatically switches to the test mode, and thus you do not need to manually switch in the loss function for the evaluation.

You can also make your own code behave differently in training and test modes as follows.

```python
if chainer.config.train:
  pass  # code only running in the training mode
else:
  pass  # code only running in the test mode
```

<table>
<thead>
<tr>
<th>chainer.global_config</th>
<th>Thread-local configuration of Chainer.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.config</td>
<td>Context manager to temporarily change the thread-local configuration.</td>
</tr>
<tr>
<td>chainer.using_config</td>
<td>Thread-local configuration of Chainer.</td>
</tr>
<tr>
<td>chainer.configuration.GlobalConfig</td>
<td></td>
</tr>
<tr>
<td>chainer.configuration.LocalConfig</td>
<td></td>
</tr>
</tbody>
</table>

**chainer.global_config**

chainer.global_config = <chainer.configuration.GlobalConfig object>

**chainer.config**

chainer.config = <chainer.configuration.LocalConfig object>

Thread-local configuration of Chainer.

This class implements the local configuration. When a value is set to this object, the configuration is only updated in the current thread. When a user tries to access an attribute and there is no local value, it automatically retrieves a value from the global configuration.

**chainer.using_config**

chainer.using_config(name, value, config=chainer.config)

Context manager to temporarily change the thread-local configuration.

**Parameters**

- **name (str)** – Name of the configuration to change.
- **value** – Temporary value of the configuration entry.
- **config (LocalConfig)** – Configuration object. Chainer’s thread-local configuration is used by default.
See also:

*Configuring Chainer*

chainer.configuration.GlobalConfig

class chainer.configuration.GlobalConfig

**Methods**

*show* *(file=sys.stdout)*

Prints the global config entries.

The entries are sorted in the lexicographical order of the entry name.

**Parameters**

- **file** – Output file-like object.

___eq__ *(value, /)

Return self==value.

___ne__ *(value, /)

Return self!=value.

___lt__ *(value, /)

Return self<value.

___le__ *(value, /)

Return self<=value.

___gt__ *(value, /)

Return self>value.

___ge__ *(value, /)

Return self>=value.

**Attributes**

- **autotune** = None

- **compute_mode** = None

  The plain object that represents the global configuration of Chainer.

- **cudnn_deterministic** = None

- **cudnn_fast_batch_normalization** = None

- **debug** = None

- **dtype** = None

- **enable_backprop** = None

- **in_recomputing** = None

- **keep_graph_on_report** = None

- **lazy_grad_sum** = None

- **schedule_func** = None

- **train** = None

type_check = None
use_cudnn = None
use_cudnn_tensor_core = None
use_ideep = None
use_static_graph = None
warn_nondeterministic = None

chainer.configuration.LocalConfig

class chainer.configuration.LocalConfig(global_config)
    Thread-local configuration of Chainer.

    This class implements the local configuration. When a value is set to this object, the configuration is only
    updated in the current thread. When a user tries to access an attribute and there is no local value, it automatically
    retrieves a value from the global configuration.

Methods

show(file=sys.stdout)
    Prints the config entries.

    The entries are sorted in the lexicographical order of the entry names.

    Parameters file – Output file-like object.

Example

You can easily print the list of configurations used in the current thread.

```python
>>> chainer.config.show()
deprecated False
deprecated_signal False
deprecated_error False
debug False
enable_backprop True
train True
type_check True
```

__eq__(value, /)
    Return self==value.

__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.
Related functions

<table>
<thead>
<tr>
<th>chainer.get_dtype</th>
<th>Resolves Chainer’s default dtype.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.mixed16</td>
<td>Dtype-like object that represents 16/32 bits mixed precision float.</td>
</tr>
</tbody>
</table>

**chainer.get_dtype**

chainer.get_dtype (dtype=None, map_mixed16=None)

Resolves Chainer’s default dtype.

**Parameters**

- **dtype** – Dtype specifier. If this value is specified (not None), this function returns the dtype object corresponding to it.
- **map_mixed16** – Dtype specifier. When chainer.config.dtype is mixed16, this option is used. If this value is None, float16 is used.

**Returns**

If dtype is not None, it returns the dtype normalized by numpy.dtype(). Otherwise, it returns chainer.config.dtype (see Configuring Chainer) normalized as well. When chainer.config.dtype is mixed16 and map_mixed16 is specified, it returns the normalized version of map_mixed16.

**chainer.mixed16**

chainer.mixed16 = dtype('mixed16')

Dtype-like object that represents 16/32 bits mixed precision float.

### 4.14.4 Environment Variables

Here are the environment variables Chainer uses.
CHAINER_SEED | Default seed value of random number generators for CUDA. If it is not set, the seed value is generated from Python random module. Set an integer value in decimal format.
---|---
CHAINER_DATASET_ROOT | Default directory path to store the downloaded datasets. See Datasets for details.
---|---
CHAINER_CUDNN | Set 0 to completely disable cuDNN in Chainer. In this case, cuDNN will not be used regardless of CHAINER_USE_CUDNN and chainer.config.use_cudnn configuration. Otherwise cuDNN is enabled automatically.
---|---
CHAINER_USE_CUDNN | Used as the default value for chainer.config.use_cudnn configuration. The value must be any of 'always', 'auto' or 'never'. If CHAINER_CUDNN is set to 0, this environment variable has no effect. See Configuring Chainer for details.
---|---
CHAINER_CUDNN_FAST_BATCH_NORMALIZATION | Used as the default value for chainer.config.cudnn_fast_batch_normalization configuration. Set 1 to enable use of fast implementation for batch normalization in cuDNN. See Configuring Chainer for details.
---|---
CHAINER_USE_IDEEP | Used as the default value for chainer.config.use_ideep configuration. The value must be any of 'always', 'auto' or 'never'. See Configuring Chainer for details.
---|---
CHAINER_LAZY_GRAD_SUM | Used as the default value for chainer.config.lazy_grad_sum configuration. Set 1 to enable batch accumulation of gradients. See Configuring Chainer for details.
---|---
CHAINER_DTYPE | Used as the default value for chainer.config.dtype configuration. The value must be any of 'mixed16', 'float16', 'float32' or 'float64'. See Configuring Chainer for details.
---|---
CHAINER_TYPE_CHECK | Used as the default value for chainer.config.type_check configuration. Set 0 to disable type checking. Otherwise type checking is enabled automatically. See Configuring Chainer and Type checking utilities for details.
---|---
CHAINER_DEBUG | Used as the default value for chainer.config.debug configuration. Set 1 to enable debug mode. It is disabled by default. In debug mode, Chainer performs various runtime checks that can help debug user's code at the cost of some overhead. See Configuring Chainer and Debug Mode for details.
---|---
CHAINER_KEEP_GRAPH_ON_REPORT | Used as the default value for chainer.config.keep_graph_on_report configuration. Set 1 to let report() keep the computational graph. See Configuring Chainer for details.
---|---
CHAINER_PYTHON_350_FORCE | Set 1 to force using Chainer with Python 3.5.0. Note that Chainer does not work with Python 3.5.0. Use Python 3.5.2+ or other supported versions (see Installation).
---|---

The following environment variables are only effective when running unit tests.

---|---
CHAINER_TEST_GPU | Number of GPUs available for unit tests. When running unit test, test cases that require more GPUs than the specified value will be skipped. Set 0 to skip all test cases that require GPU. See Unit Testing for details.
---|---
CHAINER_TEST_RANDOM_NONDETERMINISTIC | Set 1 to use non-fixed seed for random number generators, even for test cases annotated with fix_random.

### 4.15 Debug Mode

In debug mode, Chainer checks values of variables on runtime and shows more detailed error messages. It helps you to debug your programs. However, it requires some additional overhead time.

If you want to enable debug mode for the entire code, you can set CHAINER_DEBUG environment variable to 1.

You can also enable or disable debug mode for the specific scope of code with chainer.using_config() or by changing chainer.config.debug configuration.
with chainer.using_config('debug', True):
...

See Configuring Chainer for the details of Chainer’s configuration mechanism.

In debug mode, Chainer checks all results of forward and backward computation, and if it finds a NaN value, it raises a RuntimeError. Some functions and links also check validity of input values more strictly.

You can check if debug mode is enabled with chainer.is_debug() function.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.is_debug</td>
<td>Returns if the debug mode is enabled or not in the current thread.</td>
</tr>
<tr>
<td>chainer.set_debug</td>
<td>Enables or disables the debug mode in the current thread.</td>
</tr>
</tbody>
</table>

### 4.15.1 chainer.is_debug

chainer.is_debug()

Returns if the debug mode is enabled or not in the current thread.

Returns True if the debug mode is enabled.

Return type bool

### 4.15.2 chainer.set_debug

chainer.set_debug(debug)

Enables or disables the debug mode in the current thread.

**Note:** chainer.set_debug(value) is equivalent to chainer.config.debug = value.

Parameters debug (bool) – New debug mode.

### 4.16 Visualization of Computational Graph

As neural networks get larger and complicated, it gets much harder to confirm if their architectures are constructed properly. Chainer supports visualization of computational graphs. Users can generate computational graphs by invoking build_computational_graph(). Generated computational graphs are dumped to specified format (Currently Dot Language is supported).

Basic usage is as follows:

```python
import chainer.computational_graph as c
... g = c.build_computational_graph(vs)
with open('path/to/output/file', 'w') as o:
    o.write(g.dump())
```

where vs is list of Variable instances and g is an instance of ComputationalGraph. This code generates the computational graph that are backward-reachable (i.e. reachable by repetition of steps backward) from at least one of vs.
Here is an example of (a part of) the generated graph (inception(3a) in GoogLeNet). This example is from example/imagenet.

**chainer.computational_graph.build_computational_graph**

Builds a graph of functions and variables backward-reachable from outputs.

**chainer.computational_graph.ComputationalGraph**

Class that represents computational graph.

### 4.16.1 chainer.computational_graph.build_computational_graph

`chainer.computational_graph.build_computational_graph(outputs, remove_split=True, variable_style='default', function_style='default', rankdir='TB', remove_variable=False, show_name=True)`

Builds a graph of functions and variables backward-reachable from outputs.

**Parameters**

- **outputs** (`Variable, VariableNode, FunctionNode, or list`) – node(s) from which the graph is constructed. Each element of outputs must be either `Variable` object, `VariableNode` object, or `FunctionNode` object.

- **remove_split** (`bool`) – It must be `True`. This argument is left for backward compatibility.

- **variable_style** (`dict or 'default'`) – Dot node style for variable. Possible keys are 'shape', 'color', 'fillcolor', 'style' etc. If the special value 'default' is specified, the default configuration will be used.

- **function_style** (`dict or 'default'`) – Dot node style for function. Possible keys are 'shape', 'color', 'fillcolor', 'style' etc. If the special value 'default' is specified, the default configuration will be used.

- **rankdir** (`str`) – Direction of the graph that must be TB (top to bottom), BT (bottom to top), LR (left to right) or RL (right to left).

- **remove_variable** (`bool`) – If True, VariableNodes are removed from the resulting computational graph. Only FunctionNodes are shown in the output.
• **show_name (bool)** – If True, the name attribute of each node is added to the label of the node. Default is True.

**Returns**

A graph consisting of nodes and edges that are backward-reachable from at least one of outputs.

If `unchain_backward` was called in some variable in the computational graph before this function, backward step is stopped at this variable.

For example, suppose that computational graph is as follows:

```
    |--> f ---> y
   x --+      
  |--> g ---> z
```

Let `outputs = [y, z]`. Then the full graph is emitted.

Next, let `outputs = [y]`. Note that `z` and `g` are not backward-reachable from `y`. The resulting graph would be following:

```
x ---> f ---> y
```

See `TestGraphBuilder` for details.

**Return type** `ComputationalGraph`

---

**Note:** The default configuration for `variable_style` is `{'shape': 'octagon', 'fillcolor': '#E0E0E0', 'style': 'filled'}` and the default configuration for `function_style` is `{'shape': 'record', 'fillcolor': '#6495ED', 'style': 'filled'}`.

---

**Note:** The default behavior of `ComputationalGraph` has been changed from v1.23.0, so that it outputs the richest representation of a graph as default, namely, styles are set and names of functions and variables are shown. To reproduce the same result as previous versions (<= v1.22.0), please specify `variable_style=None`, `function_style=None`, and `show_name=False` explicitly.

### 4.16.2 chainer.computational_graph.ComputationalGraph

```python
class chainer.computational_graph.ComputationalGraph(nodes, edges, variable_style='default', function_style='default', rankdir='TB', remove_variable=False, show_name=True)
```

Class that represents computational graph.

**Note:** We assume that the computational graph is directed and acyclic.

**Parameters**

- **nodes** (`list`) – List of nodes. Each node is either `VariableNode` object or `FunctionNode` object.
• **edges** *(list)* – List of edges. Each edge consists of pair of nodes.

• **variable_style** *(dict or 'default')* – Dot node style for variable. If the special value 'default' is specified, the default configuration will be used.

• **function_style** *(dict or 'default')* – Dot node style for function. If the special value 'default' is specified, the default configuration will be used.

• **rankdir** *(str)* – Direction of the graph that must be TB (top to bottom), BT (bottom to top), LR (left to right) or RL (right to left).

• **remove_variable** *(bool)* – If True, VariableNodes are removed from the resulting computational graph. Only FunctionNodes are shown in the output.

• **show_name** *(bool)* – If True, the name attribute of each node is added to the label of the node. Default is True.

**Note:** The default configuration for variable_style is {'shape': 'octagon', 'fillcolor': '#E0E0E0', 'style': 'filled'} and the default configuration for function_style is {'shape': 'record', 'fillcolor': '#6495ED', 'style': 'filled'}.

**Note:** The default behavior of ComputationalGraph has been changed from v1.23.0, so that it outputs the richest representation of a graph as default, namely, styles are set and names of functions and variables are shown. To reproduce the same result as previous versions (<= v1.22.0), please specify variable_style=None, function_style=None, and show_name=False explicitly.

**Methods**

**dump** *(format='dot')*  
Dumps graph as a text.

**Parameters**

• **format** *(str)* – The graph language name of the output.

  • **it must be 'dot'** *(Currently,)* –

**Returns**  
The graph in specified format.

**Return type**  
str

**__eq__** *(value, /)*  
Return self==value.

**__ne__** *(value, /)*  
Return self!=value.

**__lt__** *(value, /)*  
Return self<value.

**__le__** *(value, /)*  
Return self<=value.

**__gt__** *(value, /)*  
Return self>value.

**__ge__** *(value, /)*  
Return self>=value.
4.17 Static Subgraph Optimizations: Usage

**Note:** This is an experimental feature and so the API might change in the future as it is developed.

This feature intends to improve runtime performance by optimizing the execution of the static subgraphs in a model. When this feature is enabled, the first iteration runs as normal except that an execution trace is also collected. The trace is then used to generate optimized code that is will be called instead of the define-by-run code starting from the second iteration.

```python
chainer.static_graph
```

Decorator to mark a Chain's `__call__` as a static sub-graph.

### 4.17.1 chainer.static_graph

```python
chainer.static_graph(*args, **kwargs)
```

Decorator to mark a Chain's `__call__` as a static sub-graph.

This decorator marks the define-by-run code inside the `__call__()` method of a Chain instance as corresponding to a static computation graph or sub-graph. Such a chain will be referred to as a ‘static chain’. This allows various “static graph” optimizations to be performed, which can result in significant speedups for some models.

When this decorator is used, the chain’s define-by-run code executes during the first iteration as usual. However, while the define-by-run code is executing, a trace is also performed to incrementally create a corresponding static schedule. This static schedule will only contain the subset of the computations inside the define-by-run code that actually needs to run every iteration. Specifically, this will contain the code inside any functions called that were annotated with the `@static_code` decorator, which will include all Chainer built-in functions, as well as any user-defined functions that use `@static_code`. Then, starting from the second iteration, when the static chain is called, its static schedule code will be executed instead of its define-by-run code.

However, the user must also be careful of the following: - The user is responsible for applying this decorator correctly. The framework does not check that the define-by-run code corresponds to a static graph. The graph can be different between training and evaluation mode (such as when dropout and/or batch normalization are used), but should otherwise be static. - When `chainer.config.enable_backprop` is enabled, if a backward pass is not performed each iteration, then the user code must call a method `chain.schedule_manager.end_forward()` on the static chain each iteration. - Static graphs allow tradeoffs between computation and memory usage. For example, the `minimize_cache_size` argument will typically result in higher memory usage when set to `False` because all cached schedules are retained. - When this feature is enabled, only the Chainer function and/or link calls inside the chain’s `__call__()` method will be included in the static schedule by default. An other code that the user puts in `__call__()`, such as a print statement or code to increment a counter for example, will not automatically get added. We will refer to such code other than Chainer function/link calls as “side-effect” code. Since side-effect code does not get included in the static schedule by default, this means that it will only every execute once, during the first iteration. There is a way to force side-effect code to be included in the static schedule, however: the user can wrap such code inside a function that is decorated with `@static_code` to ensure that it gets added to the static schedule. For an example of this, refer to the documentation. - This feature is experimental and advanced optimizations such as kernel fusion and various memory optimizations are not implemented yet.

**Usage:**

This decorator should only be applied to define-by-run code that actually corresponds to a static subgraph. Refer to the documentation for additional details and examples of correct usage. This decorator should be applied to each of the largest static subgraphs in the model; it can also be applied to a static subgraph that is not the largest subgraph, but that could result in reduced performance. It is not currently allowed to mark a chain as static if...
it is contained within another chain that is also marked as being static. For example, suppose a static graph \( A \) contains a static sub-graph \( B \). Then, only the chain corresponding to \( A \) should be marked as static and the chain corresponding to \( B \) should not be marked as static.

The behavior of a static chain depends on the training mode flag, `chainer.config.train`. If it is `True`, then a static chain that is called multiple times will try to use a distinct static schedule object (that is, call a distinct instance of a FunctionNode that implements that static schedule) on each call. The same schedule instance cannot be reused until the forward pass has completed, which is signaled by performing a backward pass through the model. It is therefore important that the backward pass be performed after each forward pass during training. Since this is usually the case, most usages of static chain will not required any modifications to existing code other than applying this decorator. However, if you would like to perform multiple forward passes during training before performing a backward pass, then you must call `chain.schedule_manager.end_forward()` after the end of each forward pass.

If test mode is active (`chainer.config.train` is `False`) then it is not necessary to inform the chain at the end of each forward pass because in test mode, a static chain always attempts to reuse existing static schedule objects. The same static schedule can be reused during a single forward pass, because it is not necessary to compute gradients. It is also possible to disable static optimizations while in test mode by setting the decorator argument `force_test_define_by_run=True`.

Note: If either `chainer.config.enable_backprop` or `chainer.config.train` is set to `False`, then cached static schedules will be reused when possible to reduce memory usage.

**Double-backprop:** Double-backpropagation is not enabled by default. It can be enabled by supplying the keyword argument `enable_double_backprop=True` to this decorator. Note: this feature has not been tested yet.

**Restrictions on input arguments and return values of a static chain:** Recall that unlike a function, there is no restrictions on the arguments to a chain. However, there currently are some restrictions when a static chain is used. Specifically, the arguments to a static chain must consist of a variable, list or tuple. In the case of a list or tuple, the elements are required to be an instance of variable, list, or tuple. There can be an arbitrary number of nested lists/ tuples. No other object types are allowed. In addition, keyword arguments are not allowed. The return value of a static chain must be a variable, list, or tuple in which each element of the list or tuple is also a variable, list, or tuple.

This decorator can be supplied with the following optional keyword arguments. This is an experimental feature, and the API and arguments might change.

**Parameters**

- **force_test_define_by_run** (`bool`) – If `True`, disable static graph optimizations during test mode (that is, when `chainer.config.train` is `False`). This may be needed in order for some existing RNN links such as LSTM to work correctly, since some existing links do not correspond to a static graph in some cases. The default is `False`.

- **minimize_cache_size** (`bool`) – If `True`, minimize the number of cached static schedules in order to reduce memory usage. For example, if the mini-batch size changes or the training mode changes, the schedules will need to be recomputed, but memory is also saved by not retaining all cached schedules. The default value is `True`.

- **verbosity_level** (`int`) – Depending on the value, print additional information: 0: Warnings only. (the default value) 1: Show only information that is collected during the first iteration and when a new static schedule is created. 2: Detailed debugging information, possibly showing new information every iteration.

- **enable_double_backprop** (`bool`) – If `True`, enable double-backprop. The default value is `False` (not enabled).

**Returns** Wrapped `__call__()` method with static chain support.
4.17.2 Basic usage

To enable static graph optimizations, it is only necessary to add the `chainer.static_graph()` decorator to a chain’s `__call__()` method. We will now show how the Chainer MNIST example can be modified to use this feature. The modified version with static subgraph optimizations is located at `examples/static_graph_optimizations/mnist`.

The first step is to import the necessary packages:

```python
from chainer import static_code
from chainer import static_graph
```

Since the neural network model MLP corresponds to a static graph, we can annotate it as a static graph by using the `chainer.static_graph()` decorator on the chain’s `__call__()` method. This lets the framework know that the define-by-run code of the chain always creates the same graph (that is, it always performs the same sequence of computations) each time it is called. We will refer to such a chain as a static chain in the documentation.

```python
# Network definition
class MLP(chainer.Chain):
    
    """A fully-connected neural network for digit classification.
    """

    def __init__(self, n_units, n_out):
        super(MLP, self).__init__()
        with self.init_scope():
            # the size of the inputs to each layer will be inferred
            self.l1 = L.Linear(None, n_units)  # n_in -> n_units
            self.l2 = L.Linear(None, n_units)  # n_units -> n_units
            self.l3 = L.Linear(None, n_out)   # n_units -> n_out

    @static_graph
    def __call__(self, x):
        h1 = F.relu(self.l1(x))
        h2 = F.relu(self.l2(h1))
        return self.l3(h2)
```

Note: If your model’s define-by-run code has any control flow operations that could cause it to potentially call different Chainer functions/links each time it is called, then you cannot use this decorator.

Note: There are currently some restrictions on how variables can be passed into a static chain’s `__call__()` method. Refer to the documentation of `chainer.static_graph()` for details.

Recall that the define-by-run code of a static chain’s `__call__()` method only actually runs during the first iteration and is then replaced by optimized static schedule code. The current implementation only knows how to do this auto-replacement for calls to Chainer functions and links. Any other code that the user puts in `__call__()` (which we refer to as “side-effect code”) will only ever get called once by default, since the define-by-run code is only executed during the first iteration. In order to make sure such “side effect” code actually gets called each iteration, we need to put it inside a function or method decorated by `static_code()`.

4.17. Static Subgraph Optimizations: Usage
of the static graph MNIST example.

In this example, we only need to use `chainer.static_graph()` on the model chain, since the whole model is static. However, in more general dynamic models, each of the largest static subgraphs (which should each be written as a chain) should also use `chainer.static_graph()`.

**Note:** Nested application of `chainer.static_graph()` is not allowed. That is, if a `chainer.static_graph()`-decorated chain calls another chains, only the outermost chain should use the decorator.

### 4.17.3 Calling a static chain multiple times in the same iteration

In a general dynamic graph network, it is not possible to know in advance how many times a static chain will be called in any particular iteration. Note that during training, it is necessary to maintain separate internal state (such as intermediate activations) for each of these calls so that the gradients can be computed in the backward pass. So, although the layer functions of the static schedule will be identical each time the same static chain is called, any internal state must be distinct. It is also possible that a static chain could be called multiple times with inputs of different shapes and/or types during the same iteration. To avoid confusion, “static schedule” will refer to both the functions and any corresponding internal state such as activations.

If backpropagation mode is disabled (`chainer.config.enable_backprop` is `False`), it is safe for the implementation to simply compute a static schedule for the first call and reuse it for subsequent calls, provided that the cached schedule is compatible with the input shapes/types. However, during training, it is necessary to maintain distinct internal state for each call in order to compute the gradients for the backward pass, which prevents us from reusing the same static schedule for each of the multiple calls of a static chain in an iteration.

The current implementation handles this issues as follows. A cache of static schedules, which is initially empty, is associated with each static chain. The size of this cache will be equal to the maximum number of times that the static chain has been called in any previous iteration, and the cache is reset whenever certain chain configuration flags change, such as training mode and backpropagation model. At the start of a given iteration, all cached schedules are available for use and the number of available schedules is decremented each time the static chain is called. If the chain is called when the cache is size zero, then its define-by-run code will execute to create a new schedule cache.

In order for such an implementation to work, each static chain must be notified when the forward pass has ended (or when the forward pass is started) so that all cached schedules can be made available for use again. In the current implementation, this is accomplished by calling the `backward()` method on a loss variable in the model. This is expected to handle the typical use cases. However, in some models it may be necessary to perform multiple forward passes before calling `backward()`. In such a case, to signal to a static chain that the forward pass (and the iteration) has ended, call `my_chain.schedule_manager.end_forward()`. The `schedule_manager` attribute of a static chain is an instance of a class called `StaticScheduleFunction` that will be available after the chain has been called.

### 4.17.4 Effects on model debugging

Note that since the code in the static chain’s `__call__()` only runs during the first iteration, you will only be able to debug this code as define-by-run during the first iteration. It is assumed that if the chain is actually is static, any problems in its define-by-run code should be apparent during the first iteration and it should not be (as) necessary to debug this code in later iterations. However, this feature does provide some functionality to help with debugging. For example, it is possible to obtain and inspect the current static schedules. It is also possible to directly step through the code of the static schedule if you wish (by debugging the `forward()` method of `StaticScheduleFunction` in `static_graph`).

1148 Chapter 4. API Reference
4.17.5 Disabling the static subgraph optimization

It is possible to turn off the static subgraph optimization feature by setting the \texttt{chainer.config.use\_static\_graph} to \texttt{False}. If set to \texttt{False}, the \texttt{chainer.static\_graph()} decorator will simply call the wrapped function without any further side effects.

4.17.6 Limitations and future work

- Optimization switches to let the user select the trade-off between runtime performance and memory usage: The current implementation achieves its speedups mainly by reducing the amount of Python code that needs to run, but does not yet implement advanced optimizations for memory usage or runtime performance. Ideally, the user should be able to adjust performance tuning parameters to control the trade-off between memory consumption and runtime performance.

- Incompatibility with GRU and LSTM links: This feature requires that all input variables to a chain need to explicitly appear in the arguments to the chain’s \texttt{\_call\_()} method. However, the GRU and LSTM links with state maintain variable attributes of the chain for the RNN state variables. Design changes to support such links and/or modifications to these links are being considered. These links may still be used with the current implementation, as long as the corresponding RNN is unrolled inside of a static chain. For an example of this, see the modified ptb example at \texttt{examples/static\_graph\_optimizations/ptb}

- Memory usage: The current implementation caches all static schedules which can lead to high memory usage in some cases. For example, separate schedules are created when the training mode or mini-batch size changes.

- Advanced graph optimizations: Advanced optimizations such as fusion of operations is not yet implemented.

- Constraints on arguments to a static chain: The current version requires that all input variables used inside \texttt{\_call\_()} of a static chain must either appear in the arguments of this method or be defined in the define-by-run code. Furthermore, any variables that appear in the arguments list must appear by themselves or be contained inside a list or tuple. Arbitrary levels of nesting are allowed.

- Model export: In the case where the complete computation graph for the model is static, it should be possible in principle to export the static schedule in a format that can be run on other platforms and languages. One of the other original motivations for this feature was to support exporting static Chainer models to run on C/C++ and/or optimize the static schedule execution code in Cython/C/C++. However, it seems that ONNX is now fulfilling this purpose and there is a separate ONNX exporter already in development for Chainer. Perhaps these two features can be merged at some point in the future.

- Double-backward support: This feature was designed to support double-backward (gradient of gradient) but it has not been tested.

- ChainerX is not supported. If you have code written using this feature but would like to run the model with ChainerX, please set the \texttt{chainer.config.use\_static\_graph} configuration to \texttt{False}. The code should then work without any additional changes.

4.17.7 Examples

For additional examples that use this feature, refer to the examples in \texttt{examples/static\_graph\_optimizations}.
4.18 Static Subgraph Optimizations: Design Notes

This documentation is intended provide information on the architecture and design of the static subgraph optimizations feature for those who are interested in contributing to its development. This documentation also describes how existing Chainer functions can be modified to run more efficiently when static subgraph optimizations are enabled.

4.18.1 Overview of dynamic and static graph frameworks

Existing deep learning frameworks can roughly be classified as either a “static graph” or “dynamic graph” framework. In a static graph framework, which we also call “define-and-run”, the computation graph is defined before the model is run. This implies that the same neural network model will be used each iteration without modifications, hence the name “static.” This allows various graph optimizations to potentially be performed to improve the runtime performance and/or reduce memory usage. The optimized code for the computation graph is then used when the model is run.

However, in a “dynamic graph” (also called “define-by-run”) framework such as Chainer, the computation graph is not defined before the model is run. Rather, it is constructed incrementally and automatically by the framework as the computations of the forward pass are executed. In Chainer, the user writes code to perform the computations of the forward pass in terms of Chainer functions, which have an API similar to an array library like NumPy. As these functions execute, the computation graph is incrementally built so that it will be available after the last function in the forward pass has been called. This has some advantages, such as allowing easier debugging compared to a static graph framework, since the user can step through the computations of the forward pass in a debugger. Define-by-run also provides the flexibility to include control flow operations so that a modified or even completely different graph can be constructed each iteration. Unfortunately, this flexibility also tends to make dynamic graph frameworks slower than static graph frameworks. For example, in Chainer there is a performance penalty involved in dynamically constructing the graph each iteration, since it involves creating many objects; each function call creates a new FunctionNode object as well as creating new VariableNode and array memory allocation for each output of the function. There are also various dynamic type checks and graph traversal that need to be performed, adding to the runtime overhead. Further, we cannot perform some optimizations such as function/kernel fusion and in-place operations.

4.18.2 Static subgraph optimizations feature

This feature is motivated by the observation that typical deep neural networks correspond to a static computation graph and that even those that correspond to a dynamic graph are typically mostly static. By “mostly static”, we mean that the largest static subgraphs each tend to contain many function nodes (that is, layers) so that the total number of function nodes in the graph tends to be much larger than the total number of largest static subgraphs. If the graph is at least mostly static, then a naive implementation of define-by-run will result in a large amount of redundant operations being performed each iteration to rebuild exactly the same subgraphs, perform the same dynamic type-checking operations, etc., which can sometimes be slow in Python; it will also result in lost opportunities to perform potential graph optimizations. A key assumption motivating this feature is that the main performance bottlenecks tend to occur inside the largest static subgraphs. So, if we can optimize these static subgraphs, it might be fine for any remaining framework code to remain implemented in pure Python. Although such Python code would be slow, it could have negligible runtime overhead.

The solution proposed by this feature is to retain the existing define-by-run style for specifying the model, but to also optionally allow the user to annotate the largest static subgraphs in a model. These “static graph” annotations will then allow the framework to automatically replace the define-by-run code of the static subgraphs with more performance-optimized code. The define-by-run code will still execute during the first iteration, to retain ease of debugging. However, as this code executes, a trace of the needed computations is also collected so that optimized static schedules can be generated for the annotated static subgraphs. Then, starting from the second iteration, this optimized code will automatically be run in place of the original define-by-run code. Note that in the common case in which the whole model is static, the user only needs to add a single “static graph” annotation and their code will then run with the performance of a static graph framework, while still supporting the define-by-run coding style.
The benefit of annotating the static subgraphs in the model is that it allows the define-by-run code to be replaced with an optimized static schedule, which can then potentially support a user-controllable trade-off between runtime performance and memory usage. This is possible because having the full computation graph available enables various optimizations that cannot safely or automatically be performed in define-by-run. Examples (which we have not yet implemented; contributions from the open source community are welcomed) include sub-linear memory usage [1], exploiting graph parallelism, operator fusion, and in-place optimizations.

The current implementation achieves its speedup by retaining only the code that is actually needed to compute the forward pass, backward pass, and so on. This allows us to remove most of the Python interpreter overhead because the Python code that performs dynamic operations such as allocating `FunctionNode` and `Variable` objects, checking types, and traversing the backward graph is not included in the optimized static schedule code.

### 4.18.3 Adding support to existing functions

Most functions and links will not need to be modified at all in order to support this feature, since the framework code will attempt to auto-wrap them inside a `@static_code`-decorated function. However, some functions might see a performance benefit if static graph support is added manually, since it may result in less redundant code being included in the static schedule. For example, any dynamic checking code that will return the same result every iteration does not need to be included in the static schedule.

An existing function (that is, a subclass of `FunctionNode`) can be modified to support static graph optimizations as follows. The basic idea is to wrap any code that needs to be called each iteration inside a method that is decorated with `@static_code`. Note that code that should only run once, such as initializing parameters, should not be wrapped.

It is also necessary to set the `_supports_static_optimizations = True` class attribute. Note that this attribute is `False` by default in `FunctionNode`.

Since the function is part of a static graph, any parameters and output arrays should ideally be statically allocated during the first iteration (while the define-by-run code is executing) and then reused starting from the second iteration. The `@static_code`-decorated functions that are called each iteration will perform the various deep learning computations, writing results in-place into these static arrays. Since the results are written in-place, there is no need for an `@static_code`-decorated function to explicitly return a result. Rather, any results arrays should be passed as inputs along with any other input arguments to the function. However, it also is allowed to return dynamically allocated arrays so that existing Chainer functions can be easily supported. The following code shows the typical pattern for performing the forward computations in a `FunctionNode`:

```python
@static_code
def static_forward(self, inputs, outputs):
    # This function will get included in the static
    # schedule and called each iteration.
    # Any input arrays must be passed in a list
    # to the `inputs` keyword argument.
    x = inputs[0]
    # Any output arrays must be passed in a list
    # to the `outputs` keyword argument, and must
    # have already been initialized to the required
    # shape. Results are written in-place into output
    # arrays.
    y = outputs[0]
    # Read from x, write results into y in-place.
    # Don't forget to zero y if necessary.
    y[:] = 0.0  # (if necessary)
    y[:] = 3.0*x  # for example
```

(continues on next page)
def forward(self, inputs):
    # Initialization/type checking code.
    # (only gets called once, during first iteration)
    type_check_blah(inputs)

    # Allocate output array. Note that since this line
    # is not wrapped using @static_code, it
    # will only ever get called once, during the first
    # iteration.
    y = xp.empty(y_shape).astype(x.dtype)

    # Call static function
    # (it will get called every iteration from optimized schedule)
    self.static_forward(inputs=[x], outputs=[y])
    return y,

It should not be necessary to modify the \texttt{backward()} implementation. As of Chainer v3 when double-backward (i.e., grad of grad) support was added, the \texttt{backward()} method of \texttt{FunctionNode} actually calls the \texttt{forward()} method of other \texttt{FunctionNode}'s, and so it is only necessary that the \texttt{'forward()} functions be wrapped.

For an example of how to add support to an existing function, see the \texttt{Linear} function.

### 4.18.4 Adding support to existing links

Most existing links will work as-is and do not need to be modified. However, if a link needs to perform computations each iteration that are performed in code other than calling chainer functions, this code will need to be manually placed in a \texttt{@static_code}-decorated function or method of the link.

If a link performs different computations depending on the training mode but is otherwise static, then it does not need to be modified.

### 4.18.5 Reference

[1] Training deep nets with sublinear memory cost

### 4.19 Caffe Model Support

Caffe is a popular framework maintained by BVLC at UC Berkeley. It is widely used by computer vision communities, and aims at fast computation and easy usage without any programming. The BVLC team provides trained reference models in their Model Zoo, which can reduce training time required for a new task.

#### 4.19.1 Import

Chainer can import the reference models and emulate the network by \texttt{Link} implementations. This functionality is provided by the \texttt{chainer.links.caffe.CaffeFunction} class.

\texttt{chainer.links.caffe.CaffeFunction} \hspace{1cm} Caffe emulator based on the model file of Caffe.
Chainer Documentation, Release 7.7.0

4.19.2 Export

Chainer can export a model from Link.

\[
\text{chainer.exporters.caffe.export}
\]

(Experimental) Export a computational graph as Caffe format.

\[
\text{chainer.exporters.caffe.export}(\text{model}, \text{args}, \text{directory}=\text{None}, \text{export_params}=\text{True}, \text{graph_name}=\text{'Graph'})
\]

(Experimental) Export a computational graph as Caffe format.

**Parameters**

- **model** (Chain) – The model object you want to export in Caffe format. It should have \_\_call\_\_() method because the second argument \text{args} is directly given to the model by the () accessor.
- **args** (list of ~chainer.Variable) – The arguments which are given to the model directly.
- **directory** (str) – The directory used for saving the resulting Caffe model. If None, nothing is saved to the disk.
- **export_params** (bool) – If True, this function exports all the parameters included in the given model at the same time. If False, the exported Caffe model doesn’t include any parameter values.
- **graph_name** (str) – A string to be used for the name field of the graph in the exported Caffe model.

**Note:** Currently, this function supports networks that created by following layer functions.

- **linear()**
- **convolution_2d()**
- **deconvolution_2d()**
- **max_pooling_2d()**
- **average_pooling_2d()**
- **batch_normalization()**
- **local_response_normalization()**
- **relu()**
- **leaky_relu()**
- **concat()**
- **softmax()**
- **reshape()**
- **add()**

This function can export at least following networks.

- GoogLeNet
• ResNet
• VGG
And, this function use testing (evaluation) mode.

Example

```python
>>> from chainer.exporters import caffe
>>> 
>>> class Model(chainer.Chain):
...     def __init__(self):
...         super(Model, self).__init__()
...         with self.init_scope():
...             self.l1 = L.Convolution2D(None, 1, 1, 1, 0)
...             self.b2 = L.BatchNormalization(1)
...             self.l3 = L.Linear(None, 1)
...
...     def __call__(self, x):
...         h = F.relu(self.l1(x))
...         h = self.b2(h)
...         return self.l3(h)
...
>>> x = chainer.Variable(np.zeros((1, 10, 10, 10), np.float32))
>>> caffe.export(Model(), [x], None, True, 'test')
```

4.20 Assertion and Testing

Chainer provides some facilities to make debugging easy.

4.20.1 Type checking utilities

`FunctionNode` uses a systematic type checking of the `chainer.utils.type_check` module. It enables users to easily find bugs of forward and backward implementations. You can find examples of type checking in some function implementations.

```
chainer.utils.type_check.Expr    Abstract syntax tree of an expression.
chainer.utils.type_check.eval    Evaluates and tests all given expressions.
chainer.utils.type_check.TypeInfo
chainer.utils.type_check.TypeInfoTuple
chainer.utils.type_check.Variable
```
Chainer Documentation, Release 7.7.0

chainer.utils.type_check.Expr
class chainer.utils.type_check.Expr(priority)
Abstract syntax tree of an expression.
It represents an abstract syntax tree, and isn’t a value. You can get its actual value with eval() function, and
get syntax representation with the __str__() method. Each comparison operator (e.g. ==) generates a new
Expr object which represents the result of comparison between two expressions.
Example
Let x and y be instances of Expr, then
>>> x = Variable(1, 'x')
>>> y = Variable(1, 'y')
>>> c = (x == y)

is also an instance of Expr. To evaluate and get its value, call eval() method:
>>> c.eval()
True

Call str function to get a representation of the original equation:
>>> str(c)
'x == y'

You can actually compare an expression with a value:
>>> (x == 1).eval()
True

Note that you can’t use boolean operators such as and, as they try to cast expressions to boolean values:
>>> z = Variable(1, 'z')
>>> x == y and y == z # raises an error
Traceback (most recent call last):
RuntimeError: Don't convert Expr to bool. Please call Expr.eval method to
˓→evaluate expression.

Methods
__call__(*args)
Call self as a function.
__getitem__(key)
eval()
Evaluates the tree to get actual value.
Behavior of this function depends on an implementation class. For example, a binary operator + calls the
__add__ function with the two results of eval() function.
__eq__(y)
Return self==value.

4.20. Assertion and Testing

1155


Chainer Documentation, Release 7.7.0

```python
    __ne__(y)
    Return self!=value.

    __lt__(y)
    Return self<value.

    __le__(y)
    Return self<=value.

    __gt__(y)
    Return self>value.

    __ge__(y)
    Return self>=value.

    __nonzero__()  
    __bool__()  
    __neg__()  
    __add__(y)  
    __radd__(y)  
    __sub__(y)  
    __rsub__(y)  
    __mul__(y)  
    __rmul__(y)  
    __truediv__(y)  
    __rtruediv__(y)  
    __floordiv__(y)  
    __rfloordiv__(y)  
    __pow__(y)
```

**chainer.utils.type_check.eval**

```python
chainer.utils.type_check.eval(exp)
```

**chainer.utils.type_check.expect**

```python
chainer.utils.type_check.expect(*bool_exprs)
    Evaluates and tests all given expressions.
```

This function evaluates given boolean expressions in order. When at least one expression is evaluated as `False`, that means the given condition is not satisfied. You can check conditions with this function.

**Parameters**

- `bool_exprs` *(tuple of Bool expressions)* – Bool expressions you want to evaluate.

1156  Chapter 4. API Reference
chainer.utils.type_check.TypeInfo

class chainer.utils.type_check.TypeInfo(shape, dtype)
Type information of an input/gradient array.

It contains type information of an array, such as the shape of array and the number of dimensions. This information is independent of CPU or GPU array.

Methods

__eq__(value)  
Return self==value.

__ne__(value)  
Return self!=value.

__lt__(value)  
Return self<value.

__le__(value)  
Return self<=value.

__gt__(value)  
Return self>value.

__ge__(value)  
Return self>=value.

Attributes

size

chainer.utils.type_check.TypeInfoTuple

class chainer.utils.type_check.TypeInfoTuple
Type information of input/gradient tuples.

It is a sub-class of tuple containing TypeInfo. The i-th element of this object contains type information of the i-th input/gradient data. As each element is Expr, you can easily check its validity.

Methods

__getitem__(key)  
Return self[key].

__len__()  
Return len(self).

__iter__()  
Implement iter(self).

count (value) → integer – return number of occurrences of value

index (value[, start[, stop ]]) → integer – return first index of value.
  Raises ValueError if the value is not present.
size()  
Returns an expression representing its length.

Returns: An expression object representing length of the tuple.

Return type: Expr

__eq__(value, /)
Return self==value.

__ne__(value, /)
Return self!=value.

__lt__(value, /)
Return self<value.

__le__(value, /)
Return self<=value.

__gt__(value, /)
Return self>value.

__ge__(value, /)
Return self>=value.

__add__(value, /)
Return self+value.

__mul__(value, /)
Return self*value.

__rmul__(value, /)
Return value*self.

chainer.utils.type_check.Variable

class chainer.utils.type_check.Variable(value, name)

Methods

__call__(*args)
Call self as a function.

__getitem__(key)

eval()
Evaluates the tree to get actual value.

Behavior of this function depends on an implementation class. For example, a binary operator + calls the
__add__ function with the two results of eval() function.

__eq__(y)
Return self==value.

__ne__(y)
Return self!=value.

__lt__(y)
Return self<value.

__le__(y)
Return self<=value.
__gt__(y)
    Return self>value.

__ge__(y)
    Return self>=value.

__nonzero__()
__bool__()

__neg__()

__add__(y)
__radd__(y)

__sub__(y)
__rsub__(y)

__mul__(y)
__rmul__(y)

__truediv__(y)
__rtruediv__(y)

__floordiv__(y)
__rfloordiv__(y)

__pow__(y)


4.20.2 Gradient checking utilities

Most function implementations are numerically tested by gradient checking. This method computes numerical gradients of forward routines and compares their results with the corresponding backward routines. It enables us to make the source of issues clear when we hit an error of gradient computations. The chainer.gradient_check module makes it easy to implement the gradient checking.

<table>
<thead>
<tr>
<th>chainer.gradient_check.check_backward</th>
<th>Test backward procedure of a given function.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.gradient_check.check_double_backward</td>
<td>Test twice differentiation of a given procedure.</td>
</tr>
<tr>
<td>chainer.gradient_check.numerical_grad</td>
<td>Computes numerical gradient by finite differences.</td>
</tr>
</tbody>
</table>

chainer.gradient_check.check_backward

chainer.gradient_check.check_backward(func, x_data, y_grad, params=(), eps=0.001, atol=1e-05, rtol=0.0001, no_grads=None, dtype=None, detect_nondifferentiable=False)

Test backward procedure of a given function.

This function automatically checks the backward-process of a given function to ensure that the computed gradients are approximately correct. For example, assuming you’ve defined a FunctionNode class MyFunc, that takes two arguments and returns one value, you can wrap it in a ordinary function and check its gradient computations as follows:
def func(xs):
    y, = MyFunc().apply(xs)
    return y

x1_data = xp.array(...)  # Example input data
x2_data = xp.array(...)  # Example input data
gy_data = xp.array(...)  # Example input data
check_backward(func, (x1_data, x2_data), gy_data)

This function creates Variable objects with x_data and calls func with the Variables to get its result as Variable. Then, it sets y_grad array to grad attribute of the result and calls backward method to get gradients of the inputs. To check correctness of the gradients, the function calls numerical_grad() to calculate numerically the gradients and compares the types of gradients with chainer.testing.assert_allclose().

To reduce computational time, it uses directional derivative along a random vector. A function \( g : \mathbb{R} \rightarrow \mathbb{R}^n \) is defined as \( g(\delta) = f(x + \delta r) \), where \( \delta \in \mathbb{R}, r \in \mathbb{R}^n \) is a random vector and \( f \) is a function which you want to test. Its gradient is

\[
g'(\delta) = f'(x + \delta r) \cdot r.
\]

Therefore, \( g'(0) = f'(x) \cdot r \). So we can check the correctness of back propagation of \( f \) indirectly by comparing this equation with the gradient of \( g \) numerically calculated and that of \( f \) computed by backprop. If \( r \) is chosen from uniform distribution, we can conclude with high probability that the gradient of \( f \) itself is correct.

If the function is non-differentiable with respect to some input objects, we can check its backprop to such objects by no_grads argument. gradient_check computes numerical backward to inputs that correspond to False in no_grads. It also asserts that the backprop leaves gradients None for inputs that correspond to True in no_grads. The default of no_grads argument is the tuple of truth values whether input objects (x1_data or/and x2_data in this example) represent integer variables.

You can simplify a test when MyFunc gets only one argument:

check_backward(func, x1_data, gy_data)

If MyFunc is a loss function which returns a zero-dimensional array, pass None to gy_data. In this case, it sets 1 to grad attribute of the result:

check_backward(my_loss_func, (x1_data, x2_data), None)

If MyFunc returns multiple outputs, pass all gradients for outputs as a tuple:

gy1_data = xp.array(...)  # Gradient of output 1
gy2_data = xp.array(...)  # Gradient of output 2
check_backward(func, x1_data, (gy1_data, gy2_data))

You can also test a Link. To check gradients of parameters of the link, set a tuple of the parameters to params arguments:

check_backward(my_link, (x1_data, x2_data), gy_data, (my_link.W, my_link.b))

Note that params are not ndarrays, but Variables.

Function objects are acceptable as func argument:
check_backward(lambda x1, x2: f(x1, x2), (x1_data, x2_data), gy_data)

Note: func is called many times to get numerical gradients for all inputs. This function doesn’t work correctly when func behaves randomly as it gets different gradients.

Parameters

- **func** *(callable)* – A function which gets Variables and returns Variables. func must returns a tuple of Variables or one Variable. You can use a Function, FunctionNode or a Link object or any other function satisfying the condition.
- **x_data** *(ndarray or tuple of ndarrays)* – A set of ndarrays to be passed to func. If x_data is one ndarray object, it is treated as (x_data,).
- **y_grad** *(ndarray or tuple of ndarrays or None)* – A set of ndarrays representing gradients of return-values of func. If y_grad is one ndarray object, it is treated as (y_grad,). If func is a loss-function, y_grad should be set to None.
- **params** *(Variable or tuple of ~chainder.Variable)* – A set of Variables whose gradients are checked. When func is a Link object, set its parameters as params. If params is one Variable object, it is treated as (params,).
- **eps** *(float)* – Epsilon value to be passed to numerical_grad().
- **atol** *(float)* – Absolute tolerance to be passed to chainer.testing.assert_allclose().
- **rtol** *(float)* – Relative tolerance to be passed to chainer.testing.assert_allclose().
- **no_grads** *(list of bool)* – Flag to skip variable for gradient assertion. It should be same length as x_data.
- **dtype** *(dtype)* – x_data, y_grad and params are casted to this dtype when calculating numerical gradients. Only float types and None are allowed.
- **detect_nondifferentiable** *(bool)* – If True, check for non-differentiable inputs is enabled. If func is non-differentiable at x_data, check_backward raises NondifferentiableError.

See also:

numerical_grad()

chainer.gradient_check.check_double_backward

chainer.gradient_check.check_double_backward(func, x_data, y_grad, x_grad_grad, params=(), params_grad_grad=(), eps=0.001, atol=0.0001, rtol=0.001, no_grads=None, dtype=None, detect_nondifferentiable=False)

Test twice differentiation of a given procedure.

This function automatically checks if the backward procedure of func is correctly implemented for further differentiation. It first computes the gradient of func w.r.t. its inputs in the same way as check_backward(). This function then further invokes the backward procedure against the gradient variables, starting from the initial
gradient given by \( x_{\text{grad\_grad}} \). It also computes the second gradient using \texttt{numerical\_grad()}\). The resulting gradients are compared to confirm if the second-order gradients are approximately correct.

Note that this function \textbf{DOES NOT} check if the first-order differentiation is correct; the numerical gradient assumes that the first-order gradient given by the usual \texttt{chainer.Variable.backward()} is correct. The implementation of each differentiable function should be tested by \texttt{check\_backward()} first, and then should be tested by this function if necessary.

For the details of the arguments, see \texttt{check\_backward()}. The additional arguments \textit{x\_grad\_grad} and \textit{params\_grad\_grad} are (tuples of) \texttt{Variable(s)} that include the initial gradient corresponding to the first-order gradient of each input and parameter. Note that the default error tolerance \texttt{atol} and \texttt{rtol} are slightly larger than those of \texttt{check\_backward()} because the numerical gradients of the second order differentiation are less accurate than those of the first order gradients.

\texttt{chainer.gradient\_check.numerical\_grad}

\texttt{chainer.gradient\_check.numerical\_grad(f, inputs, grad\_outputs, eps=0.001, detect\_nondifferentiable=False, diff\_atol=0, diff\_rtol=0.01, center\_outputs=None)}

Computes numerical gradient by finite differences.

This function is used to implement gradient check. For usage example, see unit tests of \texttt{chainer.functions}.

By default, \texttt{numerical\_grad} computes the gradient to the first order of \( \epsilon \).

**Parameters**

- \texttt{f (callable)} – Python function with no arguments that runs forward computation and returns the result.
- \texttt{inputs (tuple of arrays)} – Tuple of arrays that should be treated as inputs. Each element of them is slightly modified to realize numerical gradient by finite differences.
- \texttt{grad\_outputs (tuple of arrays or scalars)} – Tuple of arrays or scalars that are treated as output gradients.
- \texttt{eps (float)} – Epsilon value of finite differences.
- \texttt{detect\_nondifferentiable (bool)} – \texttt{False} by default. If \texttt{True}, \texttt{numerical\_grad} checks whether \( f \) is differentiable at \texttt{inputs}. It requires evaluation of \( f \) at 5 points instead of 2. As a side effect, the accuracy of numerical gradient will be increased to the third order of \( \epsilon \). If it turns out that \( f \) is non-differentiable at \texttt{input}, \texttt{numerical\_grad} raises \texttt{NondifferentiableError}.
- \texttt{diff\_atol (float)} – Absolute tolerance of fitting error of non-differentiable point detection.
- \texttt{diff\_rtol (float)} – Tolerance of fitting error of non-differentiable point detection relative to the output values of \( f \).
- \texttt{center\_outputs (tuple of arrays or None)} – Only used if \texttt{detect\_nondifferentiable} is \texttt{True}. If specified, these arrays are used as the outputs of \( f \) at \texttt{inputs}. Otherwise, it is calculated. It can be used to reduce the computation if these arrays are already calculated before calling \texttt{numerical\_grad}.

**Returns** Numerical gradient arrays corresponding to \texttt{inputs}.

**Return type** \texttt{tuple}
4.20.3 Standard Assertions

The assertions have same names as NumPy's ones. The difference from NumPy is that they can accept both `numpy.ndarray` and `cupy.ndarray`.

- `chainer.testing.assert_allclose` Asserts if some corresponding element of x and y differs too much.

- `chainer.testing.assert_warns` This function can handle both CPU and GPU arrays simultaneously.

#### Parameters

- **x** – Left-hand-side array.
- **y** – Right-hand-side array.
- **atol** (`float`) – Absolute tolerance.
- **rtol** (`float`) – Relative tolerance.
- **verbose** (`bool`) – If True, it outputs verbose messages on error.

4.20.4 Function testing utilities

Utilities for testing functions.

- `chainer.testing.FunctionTestCase` A base class for function test cases.
- `chainer.testing.unary_math_function_unittest` Decorator for testing unary mathematical Chainer functions.

### chainer.testing.FunctionTestCase

```python
class chainer.testing.FunctionTestCase(*args, **kwargs)
    A base class for function test cases.
```

Function test cases can inherit from this class to define a set of function tests.
### Required methods

Each concrete class must at least override the following three methods.

- **forward**(self, inputs, device) Implements the target forward function. inputs is a tuple of Variables. This method is expected to return the output Variables with the same array types as the inputs. device is the device corresponding to the input arrays.

- **forward_expected**(self, inputs) Implements the expectation of the target forward function. inputs is a tuple of numpy.ndarrays. This method is expected to return the output numpy.ndarrays.

- **generate_inputs**(self) Returns a tuple of input arrays of type numpy.ndarray.

### Optional methods

Additionally the concrete class can override the following methods.

- **before_test**(self, test_name) A callback method called before each test. Typically a skip logic is implemented by conditionally raising unittest.SkipTest. test_name is one of 'test_forward', 'test_backward', and 'test_double_backward'.

- **generate_grad_outputs**(self, outputs_template) Returns a tuple of output gradient arrays of type numpy.ndarray or None for omitted the gradients. outputs_template is a tuple of template arrays. The returned arrays are expected to have the same shapes and dtypes as the template arrays.

- **generate_grad_grad_inputs**(self, input_template) Returns a tuple of the second order input gradient arrays of type numpy.ndarray or None for omitted gradients. input_template is a tuple of template arrays. The returned arrays are expected to have the same shapes and dtypes as the template arrays.

- **check_forward_outputs**(self, outputs, expected_outputs) Implements check logic of forward outputs. Typically additional check can be done after calling super(). outputs and expected_outputs are tuples of arrays. In case the check fails, FunctionTestError should be raised.

### Configurable attributes

The concrete class can override the following attributes to control the behavior of the tests.

- **skip_forward_test**(bool): Whether to skip forward computation test. False by default.

- **skip_backward_test**(bool): Whether to skip backward computation test. False by default.

- **skip_double_backward_test**(bool): Whether to skip double-backward computation test. False by default.

- **dodge_nondifferentiable**(bool): Enable non-differentiable point detection in numerical gradient calculation. If the inputs returned by generate_inputs turns out to be a non-differentiable point, the test will repeatedly resample inputs until a differentiable point will be finally sampled. False by default.

- **numerical_grad_dtype**(dtype): Input arrays are casted to this dtype when calculating the numerical gradients. It is float64 by default, no matter what the original input dtypes were, to maximize precision.

- **contiguous**(None or ‘C’): Specifies the contiguousness of incoming arrays (i.e. inputs, output gradients, and the second order input gradients). If None, the arrays will be non-contiguous as long as possible. If ‘C’, the arrays will be C-contiguous. None by default.
Passive attributes

These attributes are automatically set.

**test_name** *(str):* The name of the test being run. It is one of 'test_forward', 'test_backward', and 'test_double_backward'.

**backend_config** *(BackendConfig):* The backend configuration.

**Note:** This class assumes `chainer.testing.inject_backend_tests()` is used together. See the example below.

### Example

```python
@chainer.testing.inject_backend_tests(
    None,
    [  
        {},   # CPU
        {'use_cuda': True},   # GPU
    ])
class TestReLU(chainer.testing.FunctionTestCase):

    # ReLU function has a non-differentiable point around zero, so
    # dodge_nondifferentiable should be set to True.
    dodge_nondifferentiable = True

    def generate_inputs(self):
        x = numpy.random.uniform(-1, 1, (2, 3)).astype(numpy.float32)
        return x,

    def forward(self, inputs, device):
        x, = inputs
        return F.relu(x),

    def forward_expected(self, inputs):
        x, = inputs
        expected = x.copy()
        expected[expected < 0] = 0
        return expected,
```

See also:

*LinkTestCase*

### Methods

**__call__** (*args, **kwds*)

Call self as a function.

**addCleanup** *(function, *args, **kwargs)*

Add a function, with arguments, to be called when the test is completed. Functions added are called on a LIFO basis and are called after tearDown on test failure or success.

Cleanup items are called even if setUp fails (unlike tearDown).
addTypeEqualityFunc (typeobj, function)
Add a type specific assertEqual style function to compare a type.

This method is for use by TestCase subclasses that need to register their own type equality functions to provide nicer error messages.

Parameters
• typeobj – The data type to call this function on when both values are of the same type in assertEqual().
• function – The callable taking two arguments and an optional msg= argument that raises self.failureException with a useful error message when the two arguments are not equal.

assertAlmostEqual (first, second, places=None, msg=None, delta=None)
Fail if the two objects are unequal as determined by their difference rounded to the given number of decimal places (default 7) and comparing to zero, or by comparing that the difference between the two objects is more than the given delta.

Note that decimal places (from zero) are usually not the same as significant digits (measured from the most significant digit).

If the two objects compare equal then they will automatically compare almost equal.

assertAlmostEquals (**kwargs)

assertCountEqual (first, second, msg=None)
An unordered sequence comparison asserting that the same elements, regardless of order. If the same element occurs more than once, it verifies that the elements occur the same number of times.

    self.assertEqual(Counter(list(first)), Counter(list(second)))

Example:
• [0, 1, 1] and [1, 0, 1] compare equal.
• [0, 0, 1] and [0, 1] compare unequal.

assertDictContainsSubset (subset, dictionary, msg=None)
Checks whether dictionary is a superset of subset.

assertDictEqual (d1, d2, msg=None)

assertEqual (first, second, msg=None)
Fail if the two objects are unequal as determined by the ‘==’ operator.

assertEquals (**kwargs)

assertFalse (expr, msg=None)
Check that the expression is false.

assertGreater (a, b, msg=None)
Just like self.assertTrue(a > b), but with a nicer default message.

assertGreaterEqual (a, b, msg=None)
Just like self.assertTrue(a >= b), but with a nicer default message.

assertIn (member, container, msg=None)
Just like self.assertTrue(a in b), but with a nicer default message.

assertIs (expr1, expr2, msg=None)
Just like self.assertTrue(a is b), but with a nicer default message.
assertIsInstance (obj, cls, msg=None)
    Same as self.assertTrue(isinstance(obj, cls)), with a nicer default message.

assertIsNone (obj, msg=None)
    Same as self.assertTrue(obj is None), with a nicer default message.

assertIsNot (expr1, expr2, msg=None)
    Just like self.assertTrue(a is not b), but with a nicer default message.

assertIsNotNone (obj, msg=None)
    Included for symmetry with assertIsNone.

assertLess (a, b, msg=None)
    Just like self.assertTrue(a < b), but with a nicer default message.

assertLessEqual (a, b, msg=None)
    Just like self.assertTrue(a <= b), but with a nicer default message.

assertListEqual (list1, list2, msg=None)
    A list-specific equality assertion.

    Parameters
    • list1 – The first list to compare.
    • list2 – The second list to compare.
    • msg – Optional message to use on failure instead of a list of differences.

assertLogs (logger=None, level=None)
    Fail unless a log message of level level or higher is emitted on logger_name or its children. If omitted, level defaults to INFO and logger defaults to the root logger.

    This method must be used as a context manager, and will yield a recording object with two attributes: output and records. At the end of the context manager, the output attribute will be a list of the matching formatted log messages and the records attribute will be a list of the corresponding LogRecord objects.

    Example:

    ```python
    with self.assertLogs('foo', level='INFO') as cm:
        logging.getLogger('foo').info('first message')
        logging.getLogger('foo.bar').error('second message')
        self.assertEqual(cm.output, ['INFO:foo:first message', 'ERROR:foo.bar:second message'])
    ```

assertMultiLineEqual (first, second, msg=None)
    Assert that two multi-line strings are equal.

assertNotAlmostEqual (first, second, places=None, msg=None, delta=None)
    Fail if the two objects are equal as determined by their difference rounded to the given number of decimal places (default 7) and comparing to zero, or by comparing that the difference between the two objects is less than the given delta.

    Note that decimal places (from zero) are usually not the same as significant digits (measured from the most significant digit).

assertNotAlmostEquals (**kwargs)

assertNotEqual (first, second, msg=None)
    Fail if the two objects are equal as determined by the ‘!’ operator.

assertNotEquals (**kwargs)
assertNotIn (member, container, msg=None)
    Just like self.assertTrue(a not in b), but with a nicer default message.

assertNotIsInstance (obj, cls, msg=None)
    Included for symmetry with assertIsInstance.

assertNotRegex (text, unexpected_regex, msg=None)
    Fail the test if the text matches the regular expression.

assertNotRegexpMatches (**kwargs)

assertRaises (expected_exception, *args, **kwargs)
    Fail unless an exception of class expected_exception is raised by the callable when invoked with specified positional and keyword arguments. If a different type of exception is raised, it will not be caught, and the test case will be deemed to have suffered an error, exactly as for an unexpected exception.

    If called with the callable and arguments omitted, will return a context object used like this:

    ```python
    with self.assertRaises(SomeException):
        do_something()
    ```

    An optional keyword argument ‘msg’ can be provided when assertRaises is used as a context object.

    The context manager keeps a reference to the exception as the ‘exception’ attribute. This allows you to inspect the exception after the assertion:

    ```python
    with self.assertRaises(SomeException) as cm:
        do_something()
    the_exception = cm.exception
    self.assertEqual(the_exception.error_code, 3)
    ```

assertRaisesRegex (expected_exception, expected_regex, *args, **kwargs)
    Asserts that the message in a raised exception matches a regex.

Parameters
    • expected_exception – Exception class expected to be raised.
    • expected_regex – Regex (re pattern object or string) expected to be found in error message.
    • args – Function to be called and extra positional args.
    • kwargs – Extra kwargs.
    • msg – Optional message used in case of failure. Can only be used when assertRaisesRegex is used as a context manager.

assertRaisesRegexp (**kwargs)

assertRegex (text, expected_regex, msg=None)
    Fail the test unless the text matches the regular expression.

assertRegexpMatches (**kwargs)

assertSequenceEqual (seq1, seq2, msg=None, seq_type=None)
    An equality assertion for ordered sequences (like lists and tuples).

    For the purposes of this function, a valid ordered sequence type is one which can be indexed, has a length, and has an equality operator.

Parameters
    • seq1 – The first sequence to compare.
- seq2 – The second sequence to compare.

- seq_type – The expected datatype of the sequences, or None if no datatype should be enforced.

- msg – Optional message to use on failure instead of a list of differences.

assertSetEqual (set1, set2, msg=None)

A set-specific equality assertion.

Parameters

- set1 – The first set to compare.

- set2 – The second set to compare.

- msg – Optional message to use on failure instead of a list of differences.

assertSetEqual uses ducktyping to support different types of sets, and is optimized for sets specifically (parameters must support a difference method).

assertTrue (expr, msg=None)

Check that the expression is true.

assertTupleEqual (tuple1, tuple2, msg=None)

A tuple-specific equality assertion.

Parameters

- tuple1 – The first tuple to compare.

- tuple2 – The second tuple to compare.

- msg – Optional message to use on failure instead of a list of differences.

assertWarns (expected_warning, *args, **kwargs)

Fail unless a warning of class warnClass is triggered by the callable when invoked with specified positional and keyword arguments. If a different type of warning is triggered, it will not be handled: depending on the other warning filtering rules in effect, it might be silenced, printed out, or raised as an exception.

If called with the callable and arguments omitted, will return a context object used like this:

```python
with self.assertWarns(SomeWarning):
    do_something()
```

An optional keyword argument ‘msg’ can be provided when assertWarns is used as a context object.

The context manager keeps a reference to the first matching warning as the ‘warning’ attribute; similarly, the ‘filename’ and ‘lineno’ attributes give you information about the line of Python code from which the warning was triggered. This allows you to inspect the warning after the assertion:

```python
with self.assertWarns(SomeWarning) as cm:
    do_something()
the_warning = cm.warning
self.assertEqual(the_warning.some_attribute, 147)
```

assertWarnsRegex (expected_warning, expected_regex, *args, **kwargs)

Asserts that the message in a triggered warning matches a regexp. Basic functioning is similar to assertWarns() with the addition that only warnings whose messages also match the regular expression are considered successful matches.

Parameters

- expected_warning – Warning class expected to be triggered.
• **expected_regex** – Regex (re pattern object or string) expected to be found in error message.

• **args** – Function to be called and extra positional args.

• **kwargs** – Extra kwargs.

• **msg** – Optional message used in case of failure. Can only be used when assertWarnsRegex is used as a context manager.

```python
assert_ (**kwargs)
```

```python
before_test (test_name)
```

```python
check_forward_outputs (outputs, expected_outputs)
```

```python
countTestCases ()
```

def debug ()

Run the test without collecting errors in a TestResult

defaultTestResult ()

doCleanups ()

Execute all cleanup functions. Normally called for you after tearDown.

```python
fail (msg=None)
```

Fail immediately, with the given message.

```python
failIf (**kwargs)
```

```python
failIfAlmostEqual (**kwargs)
```

```python
failIfEqual (**kwargs)
```

```python
failUnless (**kwargs)
```

```python
failUnlessAlmostEqual (**kwargs)
```

```python
failUnlessEqual (**kwargs)
```

```python
failUnlessRaises (**kwargs)
```

```python
forward (inputs, device)
```

```python
forward_expected (inputs)
```

```python
generate_grad_grad_inputs (inputs_template)
```

```python
generate_grad_outputs (outputs_template)
```

```python
generate_inputs ()
```

```python
id ()
```

```python
run (result=None)
```

```python
run_test_backward (backend_config)
```

```python
run_test_double_backward (backend_config)
```

```python
run_test_forward (backend_config)
```

```python
setUp ()
```

Hook method for setting up the test fixture before exercising it.

```python
classmethod setUpClass ()
```

Hook method for setting up class fixture before running tests in the class.
shortDescription()
   Returns a one-line description of the test, or None if no description has been provided.
   The default implementation of this method returns the first line of the specified test method’s docstring.

skipTest(reason)
   Skip this test.

subTest(msg=<object object>, **params)
   Return a context manager that will return the enclosed block of code in a subtest identified by the optional message and keyword parameters. A failure in the subtest marks the test case as failed but resumes execution at the end of the enclosed block, allowing further test code to be executed.

tearDown()
   Hook method for deconstructing the test fixture after testing it.

classmethod tearDownClass()
   Hook method for deconstructing the class fixture after running all tests in the class.

test_backward(backend_config)
   Tests backward computation.

test_double_backward(backend_config)
   Tests double-backward computation.

test_forward(backend_config)
   Tests forward computation.

__eq__(other)
   Return self==value.

__ne__(value, /)
   Return self!=value.

__lt__(value, /)
   Return self<value.

__le__(value, /)
   Return self<=value.

__gt__(value, /)
   Return self>value.

__ge__(value, /)
   Return self>=value.

Attributes

backend_config = None
check_backward_options = None
check_double_backward_options = None
check_forward_options = None
contiguous = None
dodge_nondifferentiable = False
longMessage = True
maxDiff = 640
skip_backward_test = False
skip_double_backward_test = False
skip_forward_test = False

chainer.testing.unary_math_function_unittest

chainer.testing.unary_math_function_unittest(func, func_expected=None, label_expected=None, make_data=None, is_linear=None, forward_options=None, backward_options=None, double_backward_options=None)

Decorator for testing unary mathematical Chainer functions.

This decorator makes test classes test unary mathematical Chainer functions. Tested are forward and backward, including double backward, computations on CPU and GPU across parameterized shape and dtype.

Parameters

- **func** *(function or Function)* – Chainer function to be tested by the decorated test class. Taking Function is for backward compatibility.

- **func_expected** – Function used to provide expected values for testing forward computation. If not given, a corresponding numpy function for func is implicitly picked up by its name.

- **label_expected** *(string)* – String used to test labels of Chainer functions. If not given, the name of func is implicitly used.

- **make_data** – Function to customize input and gradient data used in the tests. It takes shape and dtype as its arguments, and returns a tuple of input, gradient and double gradient data. By default, uniform distribution ranged [-1, 1] is used for all of them.

- **is_linear** – Tells the decorator that func is a linear function so that it wraps func as a non-linear function to perform double backward test. This argument is left for backward compatibility. Linear functions can be tested by default without specifying is_linear in Chainer v5 or later.

- **forward_options** *(dict)* – Options to be specified as an argument of chainer.testing.assert_allclose() function. If not given, preset tolerance values are automatically selected.

- **backward_options** *(dict)* – Options to be specified as an argument of chainer.gradient_check.check_backward() function. If not given, preset tolerance values are automatically selected depending on dtype.

- **double_backward_options** *(dict)* – Options to be specified as an argument of chainer.gradient_check.check_double_backward() function. If not given, preset tolerance values are automatically selected depending on dtype.

The decorated test class tests forward, backward and double backward computations on CPU and GPU across the following parameterized parameters:

- **shape**: rank of zero, and rank of more than zero

- **dtype**: numpy.float16, numpy.float32 and numpy.float64

Additionally, it tests the label of the Chainer function.

Chainer functions tested by the test class decorated with the decorator should have the following properties:
• Unary, taking one parameter and returning one value
• dtype of input and output are the same
• Elementwise operation for the supplied ndarray

Example

The following code defines a test class that tests \texttt{sin()} Chainer function, which takes a parameter with dtype of float and returns a value with the same dtype.

```python
>>> import unittest
>>> from chainer import testing
>>> from chainer import functions as F

>>> @testing.unary_math_function_unittest(F.sin)
... class TestSin(unittest.TestCase):
...     pass
```

Because the test methods are implicitly injected to \texttt{TestSin} class by the decorator, it is enough to place \texttt{pass} in the class definition.

To customize test data, \texttt{make_data} optional parameter can be used. The following is an example of testing \texttt{sqrt} Chainer function, which is tested in positive value domain here instead of the default input.

```python
>>> import numpy

>>> def make_data(shape, dtype):
...     x = numpy.random.uniform(0.1, 1, shape).astype(dtype)
...     gy = numpy.random.uniform(-1, 1, shape).astype(dtype)
...     ggx = numpy.random.uniform(-1, 1, shape).astype(dtype)
...     return x, gy, ggx

>>> @testing.unary_math_function_unittest(F.sqrt,
... make_data=make_data)
... class TestSqrt(unittest.TestCase):
...     pass
```

\texttt{make_data} function which returns input, gradient and double gradient data generated in proper value domains with given shape and dtype parameters is defined, then passed to the decorator’s \texttt{make_data} parameter.

4.20.5 Link testing utilities

Utilities for testing links.

| chainer.testing. LinkInitializersTestCase | A base class for link parameter initializer test cases. |
| chainer.testing. LinkTestCase | A base class for link forward and backward test cases. |

4.20. Assertion and Testing
A base class for link parameter initializer test cases.

Link test cases can inherit from this class to define a set of link tests for parameter initialization.

**Required methods**

Each concrete class must at least override the following methods.

**generate_params(self)** Returns a tuple of initializers-likes. The tuple should contain an initializer-like for each initializer-like argument, i.e. the parameters to the link constructor. These will be passed to create_link.

**create_link(self, initializers)** Returns a link. The link should be initialized with the given initializer-likes initializers. initializers is a tuple of same length as the number of parameters.

**generate_inputs(self)** Returns a tuple of input arrays of type `numpy.ndarray`.

**forward(self, link, inputs, device)** Implements the target forward function. link is a link created by create_link and inputs is a tuple of Variables. This method is expected to return the output Variables with the same array types as the inputs. device is the device corresponding to the input arrays. A default implementation is provided for links that only takes the inputs defined in generate_inputs (wrapped in Variables) and returns nothing but output Variables in its forward computation.

**get_initializers(self)** Returns a tuple with the same length as the number of initializers that the constructor of the link accepts. Each element in the tuple is a container itself, listing all initializers-likes that should be tested. Each initializer-like in the tuple is tested one at a time by being passed to create_link. When the length of the tuple is greater than one (i.e. if the link accepts multiple initializers), the ones not being tested are replaced by the ones returned by generate_params. Initializer-likes returned here should be deterministic since test will invoke them multiple times to test the correctness.

For testing initializer arguments that can be non-initializer values such as None, one can use the InitializerArgument, defining a pair of the link constructor argument and actual initializer-like used by the link. This method must be implemented if `skip_initializers_test` is False in which case the initializers test is executed.

**Optional methods**

Each concrete class may override the following methods.

**before_test(self, test_name)** A callback method called before each test. Typically a skip logic is implemented by conditionally raising unittest.SkipTest. test_name is always of 'test_initializers'.
Attributes

The concrete class can override the following attributes to control the behavior of the tests.

**param_names (list of str):** A list of strings with all the names of the parameters that should be tested. E.g. `['gamma', 'beta']` for the batch normalization link. [] by default.

**contiguous (None or ‘C’):** Specifies the contiguousness of incoming arrays (i.e. inputs, parameters and gradients. If None, the arrays will be non-contiguous as long as possible. If 'C', the arrays will be C-contiguous. None by default.

**Note:** This class assumes `chainer.testing.inject_backend_tests()` is used together. See the example below.

**Note:** When implementing `LinkTestCase` and `LinkInitializersTestCase` to test both forward/backward and initializers, it is often convenient to refactor out common logic in a separate class.

Example

```python
@chainer.testing.inject_backend_tests
    (None, [
        {}, # CPU
        {'use_cuda': True}, # GPU
    ])  
class TestLinear(chainer.testing.LinkInitializersTestCase):
    param_names = ['W', 'b']

    def generate_params(self):
        initialW = numpy.random.uniform(-1, 1, (3, 2)).astype(numpy.float32)
        initial_bias = numpy.random.uniform(-1, 1, (3,)).astype(numpy.float32)
        return initialW, initial_bias

    def generate_inputs(self):
        x = numpy.random.uniform(-1, 1, (1, 2)).astype(numpy.float32)
        return x,

    def create_link(self, initializers):
        initialW, initial_bias = initializers
        link = chainer.links.Linear(2, 3, initialW=initialW, initial_bias=initial_bias)
        return link

    def forward(self, link, inputs, device):
        x, = inputs
        return link(x),

    def get_initializers(self):
        initialW = [initializers.Constant(1), 2]
        initial_bias = [initializers.Constant(2), 3,
```

(continues on next page)
See also:

`LinkTestCase` `FunctionTestCase`

Methods

__call__(\*args, **kwds)

Call self as a function.

addCleanup(function, \*args, **kwargs)

Add a function, with arguments, to be called when the test is completed. Functions added are called on a LIFO basis and are called after tearDown on test failure or success.

Cleanup items are called even if setUp fails (unlike tearDown).

addTypeEqualityFunc(typeobj, function)

Add a type specific assertEqual style function to compare a type.

This method is for use by TestCase subclasses that need to register their own type equality functions to provide nicer error messages.

Parameters

- **typeobj** – The data type to call this function on when both values are of the same type in assertEqual().
- **function** – The callable taking two arguments and an optional msg= argument that raises self.failureException with a useful error message when the two arguments are not equal.

assertAlmostEqual(first, second, places=None, msg=None, delta=None)

Fail if the two objects are unequal as determined by their difference rounded to the given number of decimal places (default 7) and comparing to zero, or by comparing that the difference between the two objects is more than the given delta.

Note that decimal places (from zero) are usually not the same as significant digits (measured from the most significant digit).

If the two objects compare equal then they will automatically compare almost equal.

assertAlmostEquals(**kwargs)

assertCountEqual(first, second, msg=None)

An unordered sequence comparison asserting that the same elements, regardless of order. If the same element occurs more than once, it verifies that the elements occur the same number of times.

```python
self.assertEqual(Counter(list(first)), Counter(list(second)))
```

Example:

- [0, 1, 1] and [1, 0, 1] compare equal.
- [0, 0, 1] and [0, 1] compare unequal.

assertDictContainsSubset(subset, dictionary, msg=None)

Checks whether dictionary is a superset of subset.
Chainer Documentation, Release 7.7.0

assertDictEqual (d1, d2, msg=None)
assertEqual (first, second, msg=None)
Fail if the two objects are unequal as determined by the ‘==' operator.
assertEquals (**kwargs)
assertFalse (expr, msg=None)
Check that the expression is false.
assertGreater (a, b, msg=None)
Just like self.assertTrue(a > b), but with a nicer default message.
assertGreaterEqual (a, b, msg=None)
Just like self.assertTrue(a >= b), but with a nicer default message.
assertIn (member, container, msg=None)
Just like self.assertTrue(a in b), but with a nicer default message.
assertIs (expr1, expr2, msg=None)
Just like self.assertTrue(a is b), but with a nicer default message.
assertIsInstance (obj, cls, msg=None)
Same as self.assertTrue(isinstance(obj, cls)), with a nicer default message.
assertIsNone (obj, msg=None)
Same as self.assertTrue(obj is None), with a nicer default message.
assertIsNot (expr1, expr2, msg=None)
Just like self.assertTrue(a is not b), but with a nicer default message.
assertIsNotNone (obj, msg=None)
Included for symmetry with assertIsNone.
assertLess (a, b, msg=None)
Just like self.assertTrue(a < b), but with a nicer default message.
assertLessEqual (a, b, msg=None)
Just like self.assertTrue(a <= b), but with a nicer default message.
assertListEqual (list1, list2, msg=None)
A list-specific equality assertion.

Parameters
- list1 – The first list to compare.
- list2 – The second list to compare.
- msg – Optional message to use on failure instead of a list of differences.

assertLogs (logger=None, level=None)
Fail unless a log message of level level or higher is emitted on logger_name or its children. If omitted, level defaults to INFO and logger defaults to the root logger.

This method must be used as a context manager, and will yield a recording object with two attributes: output and records. At the end of the context manager, the output attribute will be a list of the matching formatted log messages and the records attribute will be a list of the corresponding LogRecord objects.

Example:

```python
with self.assertLogs('foo', level='INFO') as cm:
    logging.getLogger('foo').info('first message')
    logging.getLogger('foo.bar').error('second message')
```

(continues on next page)
assertEqual(cm.output, ['INFO:foo:first message', 'ERROR:foo.bar:second message'])

assertMultiLineEqual(first, second, msg=None)
Assert that two multi-line strings are equal.

assertNotAlmostEqual(first, second, places=None, msg=None, delta=None)
Fail if the two objects are equal as determined by their difference rounded to the given number of decimal places (default 7) and comparing to zero, or by comparing that the difference between the two objects is less than the given delta.

Note that decimal places (from zero) are usually not the same as significant digits (measured from the most significant digit).

Objects that are equal automatically fail.

assertNotAlmostEquals(**kwargs)

assertNotEqual(first, second, msg=None)
Fail if the two objects are equal as determined by the ‘!=' operator.

assertNotEquals(**kwargs)

assertNotIn(member, container, msg=None)
Just like self.assertTrue(a not in b), but with a nicer default message.

assertNotIsInstance(obj, cls, msg=None)
Included for symmetry with assertIsInstance.

assertNotRegex(text, unexpected_regex, msg=None)
Fail the test if the text matches the regular expression.

assertNotRegexpMatches(**kwargs)

assertRaises(expected_exception, *args, **kwargs)
Fail unless an exception of class expected_exception is raised by the callable when invoked with specified positional and keyword arguments. If a different type of exception is raised, it will not be caught, and the test case will be deemed to have suffered an error, exactly as for an unexpected exception.

If called with the callable and arguments omitted, will return a context object used like this:

```python
with self.assertRaises(SomeException):
    do_something()
```

An optional keyword argument ‘msg’ can be provided when assertRaises is used as a context object.

The context manager keeps a reference to the exception as the ‘exception’ attribute. This allows you to inspect the exception after the assertion:

```python
with self.assertRaises(SomeException) as cm:
    do_something()
the_exception = cm.exception
self.assertEqual(the_exception.error_code, 3)
```

assertRaisesRegex(expected_exception, expected_regex, *args, **kwargs)
Asserts that the message in a raised exception matches a regex.

Parameters

- expected_exception – Exception class expected to be raised.
• **expected_regex** – Regex (re pattern object or string) expected to be found in error message.

• **args** – Function to be called and extra positional args.

• **kwargs** – Extra kwargs.

• **msg** – Optional message used in case of failure. Can only be used when `assertRaisesRegex` is used as a context manager.

`assertRaisesRegex (**kwargs)`

`assertRegex (text, expected_regex, msg=None)`

Fail the test unless the text matches the regular expression.

`assertRegexpMatches (**kwargs)`

`assertSequenceEqual (seq1, seq2, msg=None, seq_type=None)`

An equality assertion for ordered sequences (like lists and tuples).

For the purposes of this function, a valid ordered sequence type is one which can be indexed, has a length, and has an equality operator.

Parameters

• **seq1** – The first sequence to compare.

• **seq2** – The second sequence to compare.

• **seq_type** – The expected datatype of the sequences, or None if no datatype should be enforced.

• **msg** – Optional message to use on failure instead of a list of differences.

`assertSetEqual (set1, set2, msg=None)`

A set-specific equality assertion.

Parameters

• **set1** – The first set to compare.

• **set2** – The second set to compare.

• **msg** – Optional message to use on failure instead of a list of differences.

`assertTupleEqual (tuple1, tuple2, msg=None)`

A tuple-specific equality assertion.

Parameters

• **tuple1** – The first tuple to compare.

• **tuple2** – The second tuple to compare.

• **msg** – Optional message to use on failure instead of a list of differences.

`assertWarns (expected_warning, *args, **kwargs)`

Fail unless a warning of class `warnClass` is triggered by the callable when invoked with specified positional and keyword arguments. If a different type of warning is triggered, it will not be handled: depending on the other warning filtering rules in effect, it might be silenced, printed out, or raised as an exception.

4.20. Assertion and Testing 1179
If called with the callable and arguments omitted, will return a context object used like this:

```python
with self.assertWarns(SomeWarning):
    do_something()
```

An optional keyword argument ‘msg’ can be provided when assertWarns is used as a context object.

The context manager keeps a reference to the first matching warning as the ‘warning’ attribute; similarly, the ‘filename’ and ‘lineno’ attributes give you information about the line of Python code from which the warning was triggered. This allows you to inspect the warning after the assertion:

```python
with self.assertWarns(SomeWarning) as cm:
    do_something()
    the_warning = cm.warning
    self.assertEqual(the_warning.some_attribute, 147)
```

**assertWarnsRegex** *(expected_warning, expected_regex, *args, **kwargs)*

Asserts that the message in a triggered warning matches a reexp. Basic functioning is similar to assertWarns() with the addition that only warnings whose messages also match the regular expression are considered successful matches.

**Parameters**

- **expected_warning** – Warning class expected to be triggered.
- **expected_regex** – Regex (re pattern object or string) expected to be found in error message.
- **args** – Function to be called and extra positional args.
- **kwargs** – Extra kwargs.
- **msg** – Optional message used in case of failure. Can only be used when assertWarnsRegex is used as a context manager.

**assert_**(**kwargs)**

**before_test** *(test_name)*

**check_forward_outputs** *(outputs, expected_outputs)*

**countTestCases** *

**create_link** *(initializers)*

**debug** *

Run the test without collecting errors in a TestResult

**defaultTestResult** *

**doCleanups** *

Execute all cleanup functions. Normally called for you after tearDown.

**fail** *(msg=None)*

Fail immediately, with the given message.

**failIf** (**kwargs)**

**failIfAlmostEqual** (**kwargs)**

**failIfEqual** (**kwargs)**

**failUnless** (**kwargs)**

**failUnlessAlmostEqual** (**kwargs)**

**failUnlessEqual** (**kwargs)**

**failUnlessAlmostEqual** (**kwargs)**
failUnlessEqual (**kwargs)
failUnlessRaises (**kwargs)
forward (link, inputs, device)
generate_inputs ()
generate_params ()
get_initializers ()
id ()
run (result=None)

setUp ()
Hook method for setting up the test fixture before exercising it.

classmethod setUpClass ()
Hook method for setting up class fixture before running tests in the class.

shortDescription ()
Returns a one-line description of the test, or None if no description has been provided.

The default implementation of this method returns the first line of the specified test method’s docstring.

skipTest (reason)
Skip this test.

subTest (msg=<object object>, **params)
Return a context manager that will return the enclosed block of code in a subtest identified by the optional message and keyword parameters. A failure in the subtest marks the test case as failed but resumes execution at the end of the enclosed block, allowing further test code to be executed.

tearDown ()
Hook method for deconstructing the test fixture after testing it.

classmethod tearDownClass ()
Hook method for deconstructing the class fixture after running all tests in the class.

test_initializers (backend_config)
Tests that the parameters of a links are correctly initialized.

__eq__ (other)
Return self==value.

__ne__ (value, /)
Return self!=value.

__lt__ (value, /)
Return self<value.

__le__ (value, /)
Return self<=value.

__gt__ (value, /)
Return self>value.

__ge__ (value, /)
Return self>=value.

4.20. Assertion and Testing 1181
Attributes

backend_config = None
check_initializers_options = None
contiguous = None
longMessage = True
maxDiff = 640
param_names = ()

chainer.testing.LinkTestCase

class chainer.testing.LinkTestCase(*args, **kwargs)
A base class for link forward and backward test cases.

Link test cases can inherit from this class to define a set of link tests for forward and backward computations.

Required methods

Each concrete class must at least override the following methods.

generate_params(self) Returns a tuple of initializers-likes. The tuple should contain an initializer-like for each initializer-like argument, i.e. the parameters to the link constructor. These will be passed to create_link.

create_link(self, initializers) Returns a link. The link should be initialized with the given initializer-likes initializers. initializers is a tuple of same length as the number of parameters.

generate_inputs(self) Returns a tuple of input arrays of type numpy.ndarray.

forward(self, link, inputs, device) Implements the target forward function. link is a link created by create_link and inputs is a tuple of Variables. This method is expected to return the output Variables with the same array types as the inputs. device is the device corresponding to the input arrays. A default implementation is provided for links that only takes the inputs defined in generate_inputs (wrapped in Variables) and returns nothing but output Variables in its forward computation.

Optional methods

Each concrete class may override the following methods depending on the skip flags skip_forward_test and skip_backward_test.

before_test(self, test_name) A callback method called before each test. Typically a skip logic is implemented by conditionally raising unittest.SkipTest. test_name is one of 'test_forward' and 'test_backward'.

forward_expected(self, link, inputs) Implements the expectation of the target forward function. link is the initialized link that was used to compute the actual forward which the results of this method will be compared against. The link is guaranteed to reside on the CPU. inputs is a tuple of numpy.ndarrays. This method is expected to return the output numpy.ndarrays. This method must be implemented if either skip_forward_test or skip_backward_test is False in which case forward or backward tests are executed.
generate_grad_outputs(self, outputs_template)  Returns a tuple of output gradient arrays of type numpy.ndarray. outputs_template is a tuple of template arrays. The returned arrays are expected to have the same shapes and dtypes as the template arrays.

check_forward_outputs(self, outputs, expected_outputs)  Implements check logic of forward outputs. Typically additional check can be done after calling super(). outputs and expected_outputs are tuples of arrays. In case the check fails, LinkTestError should be raised.

Attributes

The concrete class can override the following attributes to control the behavior of the tests.

param_names (tuple of str):  A tuple of strings with all the names of the parameters that should be tested. E.g. ('gamma', 'beta') for the batch normalization link. () by default.

skip_forward_test (bool):  Whether to skip forward computation test. False by default.

skip_backward_test (bool):  Whether to skip backward computation test. False by default.

dodge_nondifferentiable (bool):  Enable non-differentiable point detection in numerical gradient calculation. If the data returned by generate_params, create_link and generate_inputs turns out to be a non-differentiable point, the test will repeatedly resample those until a differentiable point will be finally sampled. False by default.

numerical_grad_dtype (dtype):  Input arrays are casted to this dtype when calculating the numerical gradients. It is float64 by default, no matter what the original input dtypes were, to maximize precision.

contiguous (None or 'C'):  Specifies the contiguousness of incoming arrays (i.e. inputs, parameters and gradients. If None, the arrays will be non-contiguous as long as possible. If 'C', the arrays will be C-contiguous. None by default.

Note:  This class assumes chainer.testing.inject_backend_tests() is used together. See the example below.

Note:  When implementing LinkTestCase and LinkInitializersTestCase to test both forward/backward and initializers, it is often convenient to refactor out common logic in a separate class.

Example

```python
@chainer.testing.inject_backend_tests
    None,
    [  
        {},  # CPU
        {'use_cuda': True},  # GPU
    ]
class TestLinear(chainer.testing.LinkTestCase):
    param_names = ('W', 'b')

    def generate_params(self):
        initialW = numpy.random.uniform(-1, 1, (3, 2)).astype(numpy.float32)
        initial_bias = numpy.random.uniform(  
```
-1, 1, (3,)).astype(numpy.float32)
    return initialW, initial_bias

def generate_inputs(self):
    x = numpy.random.uniform(-1, 1, (1, 2)).astype(numpy.float32)
    return x,

def create_link(self, initializers):
    initialW, initial_bias = initializers
    link = chainer.links.Linear(2, 3, initialW=initialW, initial_bias=initial_bias)
    return link

def forward(self, link, inputs, device):
    x, = inputs
    return link(x),

def forward_expected(self, link, inputs):
    W = link.W.array
    b = link.b.array
    x, = inputs
    expected = x.dot(W.T) + b
    return expected,

See also:

LinkInitializersTestCase FunctionTestCase

Methods

__call__(*args, **kwds)
Call self as a function.

addCleanup (function, *args, **kwargs)
Add a function, with arguments, to be called when the test is completed. Functions added are called on a
LIFO basis and are called after tearDown on test failure or success.

Cleanup items are called even if setUp fails (unlike tearDown).

addTypeEqualityFunc (typeobj, function)
Add a type specific assertEqual style function to compare a type.

This method is for use by TestCase subclasses that need to register their own type equality functions to
provide nicer error messages.

Parameters

- typeobj – The data type to call this function on when both values are of the same type
  in assertEqual().
- function – The callable taking two arguments and an optional msg= argument that
  raises self.failureException with a useful error message when the two arguments are not
  equal.

assertAlmostEqual (first, second, places=None, msg=None, delta=None)
Fail if the two objects are unequal as determined by their difference rounded to the given number of decimal
places (default 7) and comparing to zero, or by comparing that the difference between the two objects is more than the given delta.

Note that decimal places (from zero) are usually not the same as significant digits (measured from the most significant digit).

If the two objects compare equal then they will automatically compare almost equal.

**assertAlmostEquals(**kwargs**)

**assertCountEqual**(first, second, msg=None)

An unordered sequence comparison asserting that the same elements, regardless of order. If the same element occurs more than once, it verifies that the elements occur the same number of times.

```
self.assertEqual(Counter(list(first)), Counter(list(second)))
```

Example:

- \([0, 1, 1]\) and \([1, 0, 1]\) compare equal.
- \([0, 0, 1]\) and \([0, 1]\) compare unequal.

**assertDictContainsSubset**(subset, dictionary, msg=None)

Checks whether dictionary is a superset of subset.

**assertDictEqual**(d1, d2, msg=None)

Fail if the two objects are unequal as determined by the `==` operator.

**assertEqual**(first, second, msg=None)

**assertEquals**(**kwargs**)

**assertFalse**(expr, msg=None)

Check that the expression is false.

**assertGreater**(a, b, msg=None)

Just like `self.assertTrue(a > b)`, but with a nicer default message.

**assertGreaterEqual**(a, b, msg=None)

Just like `self.assertTrue(a >= b)`, but with a nicer default message.

**assertIn**(member, container, msg=None)

Just like `self.assertTrue(a in b)`, but with a nicer default message.

**assertIs**(expr1, expr2, msg=None)

Just like `self.assertTrue(a is b)`, but with a nicer default message.

**assertIsInstance**(obj, cls, msg=None)

Same as `self.assertTrue(isinstance(obj, cls))`, with a nicer default message.

**assertIsNone**(obj, msg=None)

Same as `self.assertTrue(obj is None)`, with a nicer default message.

**assertIsNot**(expr1, expr2, msg=None)

Just like `self.assertTrue(a is not b)`, but with a nicer default message.

**assertIsNotNone**(obj, msg=None)

Included for symmetry with `assertIsNone`.

**assertLess**(a, b, msg=None)

Just like `self.assertTrue(a < b)`, but with a nicer default message.

**assertLessEqual**(a, b, msg=None)

Just like `self.assertTrue(a <= b)`, but with a nicer default message.
**assertListEqual** *(list1, list2, msg=None)*

A list-specific equality assertion.

**Parameters**

- **list1** – The first list to compare.
- **list2** – The second list to compare.
- **msg** – Optional message to use on failure instead of a list of differences.

**assertLogso**(logger=None, level=None)

Fail unless a log message of level *level* or higher is emitted on *logger_name* or its children. If omitted, *level* defaults to INFO and *logger* defaults to the root logger.

This method must be used as a context manager, and will yield a recording object with two attributes: *output* and *records*. At the end of the context manager, the *output* attribute will be a list of the matching formatted log messages and the *records* attribute will be a list of the corresponding LogRecord objects.

Example:

```python
with self.assertLogs('foo', level='INFO') as cm:
    logging.getLogger('foo').info('first message')
    logging.getLogger('foo.bar').error('second message')
self.assertEqual(cm.output, ['INFO:foo:first message', 'ERROR:foo.bar:second message'])
```

**assertMultiLineEqual** *(first, second, msg=None)*

Assert that two multi-line strings are equal.

**assertNotAlmostEqual** *(first, second, places=None, msg=None, delta=None)*

Fail if the two objects are equal as determined by their difference rounded to the given number of decimal places (default 7) and comparing to zero, or by comparing that the difference between the two objects is less than the given delta.

Note that decimal places (from zero) are usually not the same as significant digits (measured from the most significant digit).

Objects that are equal automatically fail.

**assertNotAlmostEquals** (**kwargs**)

**assertNotEqual** *(first, second, msg=None)*

Fail if the two objects are equal as determined by the ‘!=$ operator.

**assertNotEquals** (**kwargs**)

**assertNotIn** *(member, container, msg=None)*

Just like self.assertTrue(a not in b), but with a nicer default message.

**assertNotIsInstance** *(obj, cls, msg=None)*

Included for symmetry with assertIsInstance.

**assertNotRegex** *(text, unexpected_regex, msg=None)*

Fail the test if the text matches the regular expression.

**assertNotRegexpMatches** (**kwargs**)

**assertRaises** *(expected_exception, *args, **kwargs)*

Fail unless an exception of class *expected_exception* is raised by the callable when invoked with specified positional and keyword arguments. If a different type of exception is raised, it will not be caught, and the test case will be deemed to have suffered an error, exactly as for an unexpected exception.

If called with the callable and arguments omitted, will return a context object used like this:
An optional keyword argument ‘msg’ can be provided when assertRaises is used as a context object.

The context manager keeps a reference to the exception as the ‘exception’ attribute. This allows you to inspect the exception after the assertion:

```python
with self.assertRaises(SomeException) as cm:
    do_something()
the_exception = cm.exception
self.assertEqual(the_exception.error_code, 3)
```

### assertRaisesRegex

```python
assertRaisesRegex(expected_exception, expected_regex, *args, **kwargs)
```

Asserts that the message in a raised exception matches a regex.

**Parameters**

- `expected_exception` – Exception class expected to be raised.
- `expected_regex` – Regex (re pattern object or string) expected to be found in error message.
- `args` – Function to be called and extra positional args.
- `kwargs` – Extra kwargs.
- `msg` – Optional message used in case of failure. Can only be used when assertRaisesRegex is used as a context manager.

### assertRaisesRegexp

```python
assertRaisesRegexp(**kwargs)
```

### assertRegex

```python
assertRegex(text, expected_regex, msg=None)
```

Fail the test unless the text matches the regular expression.

### assertRegexpMatches

```python
assertRegexpMatches(**kwargs)
```

### assertSequenceEqual

```python
assertSequenceEqual(seq1, seq2, msg=None, seq_type=None)
```

An equality assertion for ordered sequences (like lists and tuples).

For the purposes of this function, a valid ordered sequence type is one which can be indexed, has a length, and has an equality operator.

**Parameters**

- `seq1` – The first sequence to compare.
- `seq2` – The second sequence to compare.
- `seq_type` – The expected datatype of the sequences, or None if no datatype should be enforced.
- `msg` – Optional message to use on failure instead of a list of differences.

### assertSetEqual

```python
assertSetEqual(set1, set2, msg=None)
```

A set-specific equality assertion.

**Parameters**

- `set1` – The first set to compare.
- `set2` – The second set to compare.
- `msg` – Optional message to use on failure instead of a list of differences.
assertSetEqual uses ducktyping to support different types of sets, and is optimized for sets specifically (parameters must support a difference method).

**assertTrue** *(expr, msg=None)*

Check that the expression is true.

**assertTupleEqual** *(tuple1, tuple2, msg=None)*

A tuple-specific equality assertion.

**Parameters**

- **tuple1** – The first tuple to compare.
- **tuple2** – The second tuple to compare.
- **msg** – Optional message to use on failure instead of a list of differences.

**assertWarns** *(expected_warning, *args, **kwargs)*

Fail unless a warning of class warnClass is triggered by the callable when invoked with specified positional and keyword arguments. If a different type of warning is triggered, it will not be handled: depending on the other warning filtering rules in effect, it might be silenced, printed out, or raised as an exception.

If called with the callable and arguments omitted, will return a context object used like this:

```python
with self_ASSERT_WARN_TUPLE_EQUAL:
    do_something()
```

An optional keyword argument ‘msg’ can be provided when assertWarns is used as a context object.

The context manager keeps a reference to the first matching warning as the ‘warning’ attribute; similarly, the ‘filename’ and ‘lineno’ attributes give you information about the line of Python code from which the warning was triggered. This allows you to inspect the warning after the assertion:

```python
with self_ASSERT_WARN_TUPLE_EQUAL as cm:
    do_something()
the_warning = cm.warning
self.assertEqual(the_warning.some_attribute, 147)
```

**assertWarnsRegex** *(expected_warning, expected_regex, *args, **kwargs)*

Asserts that the message in a triggered warning matches a regexp. Basic functioning is similar to assertWarns() with the addition that only warnings whose messages also match the regular expression are considered successful matches.

**Parameters**

- **expected_warning** – Warning class expected to be triggered.
- **expected_regex** – Regex (re pattern object or string) expected to be found in error message.
- **args** – Function to be called and extra positional args.
- **kwargs** – Extra kwargs.
- **msg** – Optional message used in case of failure. Can only be used when assertWarnsRegex is used as a context manager.

**assert_** *(**kwargs)*

**before_test** *(test_name)*

**check_forward_outputs** *(outputs, expected_outputs)*

**countTestCases** ()
create_link (initializers)

debug ()
    Run the test without collecting errors in a TestResult

defaultTestResult ()

doCleanups ()
    Execute all cleanup functions. Normally called for you after tearDown.

fail (msg=None)
    Fail immediately, with the given message.

failIf (**kwargs)

failIfAlmostEqual (**kwargs)

failIfEqual (**kwargs)

failUnless (**kwargs)

failUnlessAlmostEqual (**kwargs)

failUnlessEqual (**kwargs)

failUnlessRaises (**kwargs)

forward (link, inputs, device)

forward_expected (link, inputs)

generate_grad_outputs (outputs_template)

generate_inputs ()

generate_params ()

id ()

run (result=None)

setUp ()
    Hook method for setting up the test fixture before exercising it.

classmethod setUpClass ()
    Hook method for setting up class fixture before running tests in the class.

shortDescription ()
    Returns a one-line description of the test, or None if no description has been provided.

    The default implementation of this method returns the first line of the specified test method’s docstring.

skipTest (reason)
    Skip this test.

subTest (msg=<object object>, **params)
    Return a context manager that will return the enclosed block of code in a subtest identified by the optional message and keyword parameters. A failure in the subtest marks the test case as failed but resumes execution at the end of the enclosed block, allowing further test code to be executed.

tearDown ()
    Hook method for deconstructing the test fixture after testing it.

classmethod tearDownClass ()
    Hook method for deconstructing the class fixture after running all tests in the class.
**test_backward** *(backend_config)*
Tests backward computation.

**test_forward** *(backend_config)*
Tests forward computation.

___eq___ *(other)*
Return self==value.

___ne___ *(value,+)/
Return self!=value.

___lt___ *(value,+)/
Return self<value.

___le___ *(value,+)/
Return self<=value.

___gt___ *(value,+)/
Return self>value.

___ge___ *(value,+)/
Return self>=value.

**Attributes**

```
backend_config = None
check_backward_options = None
check_forward_options = None
contiguous = None
dodge_nondifferentiable = False
longMessage = True
maxDiff = 640
param_names = ()
skip_backward_test = False
skip_forward_test = False
```

### 4.20.6 Serialization testing utilities

Utilities for testing serializable objects.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.testing.save_and_load</code></td>
<td>Saves src and loads it to dst using a de/serializer.</td>
</tr>
<tr>
<td><code>chainer.testing.save_and_load_hdf5</code></td>
<td>Saves src to an HDF5 file and loads it to dst.</td>
</tr>
<tr>
<td><code>chainer.testing.save_and_load_npz</code></td>
<td>Saves src to an NPZ file and loads it to dst.</td>
</tr>
</tbody>
</table>
chainer.testing.save_and_load

chainer.testing.save_and_load(src, dst, filename, saver, loader)
Saves src and loads it to dst using a de/serializer.

This function simply runs a serialization and deserialization to check if the serialization code is correctly implemented. The save and load are done within a temporary directory.

Parameters

- **src** – An object to save from.
- **dst** – An object to load into.
- **filename** (str) – File name used during the save/load.
- **saver** (callable) – Function that saves the source object.
- **loader** (callable) – Function that loads the file into the destination object.

chainer.testing.save_and_load_hdf5

chainer.testing.save_and_load_hdf5(src, dst)
Saves src to an HDF5 file and loads it to dst.

This is a short cut of `save_and_load()` using HDF5 de/serializers.

Parameters

- **src** – An object to save.
- **dst** – An object to load to.

chainer.testing.save_and_load_npz

chainer.testing.save_and_load_npz(src, dst)
Saves src to an NPZ file and loads it to dst.

This is a short cut of `save_and_load()` using NPZ de/serializers.

Parameters

- **src** – An object to save.
- **dst** – An object to load to.

4.20.7 Trainer Extension Testing Utilities

Utilities for testing trainer extensions.

chainer.testing.get_trainer_with_mock_updater

Returns a Trainer object with mock updater.
chainer.testing.get_trainer_with_mock_updater

chainer.testing.get_trainer_with_mock_updater
\[\text{stop_trigger}=10, \quad \text{'iteration'}, \quad \text{iter_per_epoch}=10, \quad \text{extensions}=\text{None}\]

Returns a Trainer object with mock updater.

The returned trainer can be used for testing the trainer itself and the extensions. A mock object is used as its updater. The update function set to the mock correctly increments the iteration counts (updater.iteration), and thus you can write a test relying on it.

Parameters

- **stop_trigger** – Stop trigger of the trainer.
- **iter_per_epoch** – The number of iterations per epoch.
- **extensions** – Extensions registered to the trainer.

Returns Trainer object with a mock updater.

4.20.8 Repeat decorators

These decorators have a decorated test run multiple times in a single invocation. Criteria of passing / failing of the test changes according to the type of decorators. See the documentation of each decorator for details.

4.20.9 Unit test annotation

Decorators for annotating unit tests.

<table>
<thead>
<tr>
<th>Decorator</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.testing.attr.gpu</td>
<td>Decorator to indicate that GPU is required to run the test.</td>
</tr>
<tr>
<td>chainer.testing.attr.multi_gpu</td>
<td>Decorator to indicate number of GPUs required to run the test.</td>
</tr>
<tr>
<td>chainer.testing.withRequires</td>
<td>Run a test case only when given requirements are satisfied.</td>
</tr>
<tr>
<td>chainer.testing.fix_random</td>
<td>Decorator that fixes random numbers in a test.</td>
</tr>
</tbody>
</table>

chainer.testing.attr.gpu

chainer.testing.attr.gpu\(f\)

Decorator to indicate that GPU is required to run the test.

Tests can be annotated with this decorator (e.g., @gpu) to declare that one GPU is required to run.
chainer.testing.attr.multi_gpu

chainer.testing.attr.multi_gpu(gpu_num)
Decorator to indicate number of GPUs required to run the test.

Tests can be annotated with this decorator (e.g., @multi_gpu(2)) to declare number of GPUs required to run. When running tests, if CHAINER_TEST_GPU_LIMIT environment variable is set to value greater than or equals to 0, test cases that require GPUs more than the limit will be skipped.

chainer.testing.with_requires

chainer.testing.with_requires(*requirements)
Run a test case only when given requirements are satisfied.

Example

This test case runs only when numpy>=1.10 is installed.

```python
>>> import unittest
>>> from chainer import testing
>>> class Test(unittest.TestCase):
...     @testing.with_requires('numpy>=1.10')
...     def test_for_numpy_1_10(self):
...         pass
```

Parameters requirements – A list of string representing requirement condition to run a given test case.

chainer.testing.fix_random

chainer.testing.fix_random(*, setup_method='setUp', teardown_method='tearDown')
Decorator that fixes random numbers in a test.

This decorator can be applied to either a test case class or a test method. It should not be applied within condition.retry or condition.repeat.

4.20.10 Parameterized test

Decorators for making a unit test parameterized.

chainer.testing.parameterize
chainer.testing.product
chainer.testing.product_dict
chainer.testing.inject_backend_tests
chainer.testing.parameterize

chainer.testing.parameterize(*params)

chainer.testing.product

chainer.testing.product(product)

chainer.testing.product_dict

chainer.testing.product_dict(*parameters)

chainer.testing.inject_backend_tests

chainer.testing.inject_backend_tests(method_names, params)
CHAPTER FIVE

INSTALLATION

5.1 Recommended Environments

We recommend the following Linux distributions.

- **Ubuntu** 14.04 / 16.04 LTS (64-bit)
- **CentOS** 7 (64-bit)

**Note:** We are automatically testing Chainer on all the recommended environments above. We cannot guarantee that Chainer works on other environments including Windows and macOS (especially with CUDA support), even if Chainer may seem to be running correctly.

5.2 Requirements

You need to have the following components to use Chainer.

- **Python**
  - Supported Versions: 3.5.2+, 3.6.0+, 3.7.0+ and 3.8.0+.
- **NumPy**
  - Supported Versions: 1.9, 1.10, 1.11, 1.12, 1.13, 1.14, 1.15, 1.16 and 1.17.
  - NumPy will be installed automatically during the installation of Chainer.

Before installing Chainer, we recommend that you upgrade *setuptools* and *pip*:

```
$ pip install -U setuptools pip
```

**Note:** Python 2 is not supported in Chainer v7.x releases. Please consider migrating Python 3 or use Chainer v6.x, which is the last version that supports Python 2.
5.2.1 Hardware Acceleration Support

You can accelerate performance of Chainer by installing the following optional components.

- NVIDIA CUDA / cuDNN
  - CuPy 5.0+
  - See CuPy Installation Guide for instructions.
- Intel CPU (experimental)
  - iDeep 2.0.0.post3+
  - See Tips and FAQs for instructions.

5.2.2 Optional Features

The following packages are optional dependencies. Chainer can be installed without them, in which case the corresponding features are not available.

- Image dataset support
  - pillow 2.3+
  - Run `pip install pillow` to install.
- HDF5 serialization support
  - h5py 2.5+
  - Run `pip install h5py` to install.
- Distributed Deep Learning using ChainerMN
  - CUDA-aware MPI
  - mpi4py
  - See ChainerMN installation guide for installation instructions.

5.3 Install Chainer

5.3.1 Using pip

We recommend to install Chainer via pip:

```
$ pip install chainer
```

Note: Any optional dependencies (including CuPy) can be added after installing Chainer. Chainer automatically detects the available packages and enables/disables the optional features appropriately.
5.3.2 Using Tarball

The tarball of the source tree is available via `pip download chainer` or from the release notes page. You can install Chainer from the tarball:

```
$ pip install chainer-x.x.x.tar.gz
```

You can also install the development version of Chainer from a cloned Git repository:

```
$ git clone https://github.com/chainer/chainer.git
$ cd chainer
$ pip install .
```

5.3.3 Enable CUDA/cuDNN support

In order to enable CUDA support, you have to install CuPy manually. If you also want to use cuDNN, you have to install CuPy with cuDNN support. See CuPy’s installation guide to install CuPy. Once CuPy is correctly set up, Chainer will automatically enable CUDA support.

You can refer to the following flags to confirm if CUDA/cuDNN support is actually available.

`chainer.backends.cuda.available` `True` if Chainer successfully imports `cupy`.

`chainer.backends.cuda.cudnn_enabled` `True` if cuDNN support is available.

5.3.4 Google Colaboratory

You can install Chainer and CuPy using the following snippet on Google Colaboratory:

```
!curl https://colab.chainer.org/install | sh -
```

See `chainer/google-colaboratory` for more details and examples.

5.4 Uninstall Chainer

Use `pip` to uninstall Chainer:

```
$ pip uninstall chainer
```

**Note:** When you upgrade Chainer, `pip` sometimes install the new version without removing the old one in `site-packages`. In this case, `pip uninstall` only removes the latest one. To ensure that Chainer is completely removed, run the above command repeatedly until `pip` returns an error.
5.5 Upgrade Chainer

Just use `pip` with `-U` option:

```
$ pip install -U chainer
```

5.6 Reinstall Chainer

If you want to reinstall Chainer, please uninstall Chainer and then install it. We recommend to use `--no-cache-dir` option as `pip` sometimes uses cache:

```
$ pip uninstall chainer
$ pip install chainer --no-cache-dir
```

5.7 Run Chainer with Docker

We are providing the official Docker image. Use `nvidia-docker` command to run Chainer image with GPU. You can login to the environment with `bash`, and run the Python interpreter:

```
$ nvidia-docker run -it chainer/chainer /bin/bash
```

Or run the interpreter directly:

```
$ nvidia-docker run -it chainer/chainer /usr/bin/python
```

5.8 FAQ

5.8.1 Warning message “cuDNN is not enabled” appears

You failed to build CuPy with cuDNN. If you don’t need cuDNN, ignore this message. Otherwise, retry to install CuPy with cuDNN. `pip install -vvvv` option helps you. There is no need of re-installing Chainer itself. See CuPy’s installation guide for more details.

5.8.2 CuPy always raises `cupy.cuda.compiler.CompileException`

See FAQ section of CuPy’s installation guide for details.
5.8.3 h5py installation failed

If the installation failed with error saying `hdf5.h is not found`, you need to install `libhdf5` first. The way to install it depends on your environment:

```
# Ubuntu 14.04/16.04
$ apt-get install libhdf5-dev

# CentOS 7
$ yum -y install epel-release
$ yum install hdf5-devel
```

Note that `h5py` is not required unless you need HDF5 serialization support.
Warning: This feature is still in the earliest stage of its development. The behavior and interface are subject to change.

ChainerX is an ndarray implementation with Define-by-Run automatic differentiation capability. It roughly corresponds to “NumPy/CuPy + Chainer Variable”, while some additional features follow:

- **Speed**: The whole ndarray and autograd implementation is written in C++, with a thin Python binding. It lowers the overhead existing in the pure Python implementation of Chainer.
- **Extensibility**: The backend is pluggable so that it is much easier to add a support of new devices.

The speed is best achieved by directly using ChainerX APIs, while it also provides a compatibility layer through the conventional `chainer.Variable` interface for easier adoption of ChainerX in existing projects. See ChainerX Tutorial for more details.

### 6.1 Installation

ChainerX, or chainerx, can be installed as a top level Python package along with Chainer by configuring the environment variables below.

**Note**: Chainer must currently be installed from source in order to include ChainerX, but this is expected to change in the near future.

#### 6.1.1 Installing from source

The following environment variables are available for building ChainerX from source.
Environment variable | Description
--- | ---
CHAINER_BUILD_CHAINERX | 1 to build the chainerx package along with chainer. 0 to skip. Default is 0.
CHAINERX_BUILD_CUDA | 1 to build chainerx with CUDA support. 0 to skip. Default is 0. See also CUDA support section below.
CHAINERX_ENABLE_BLAS | 1 to enable BLAS, 0 to disable it. Default is 1. If BLAS is enabled, it is searched for and used if found. If not found, ChainerX will behave as if BLAS was disabled and use a basic implementation instead.
CHAINERX_ENABLE_LAPACK | 1 to enable LAPACK, 0 to disable it. Default is 1. If LAPACK is enabled, it is searched for and used if found. If not found, ChainerX will behave as if LAPACK was disabled and may cause runtime errors.

Simply run `pip install chainer` after configuring the above environment variables. See Examples below.

### 6.1.2 CUDA support

When installing with the CUDA support, you also need to specify the cuDNN installation path.

You can specify either of the following environment variables to specify where to look for cuDNN installation.

<table>
<thead>
<tr>
<th>Environment variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CUDNN_ROOT_DIR</td>
<td>Path to your cuDNN installation.</td>
</tr>
<tr>
<td>CHAINERX_CUDNN_USE_CUPY</td>
<td>1 to search for cuDNN library and include files in existing CuPy installation. Only applicable for CuPy installed via wheel (binary) distribution. Other variables related to cuDNN paths (such as CUDNN_ROOT_DIR) are ignored. Be warned that the resulting executable will be invalidated if CuPy is uninstalled, moved or replaced.</td>
</tr>
</tbody>
</table>

To support the NumPy/CuPy fallback mechanism, currently ChainerX with the CUDA support requires CuPy to be installed together.

See also:

CuPy installation guide

### 6.1.3 Examples

Install ChainerX without CUDA support:

```bash
$ export CHAINER_BUILD_CHAINERX=1
$ export MAKEFLAGS=-j8   # Using 8 parallel jobs.
$ pip install chainer
```

Install ChainerX depending on CuPy wheel distribution:

```bash
$ pip install cupy_cuda101   # Note: Choose the proper CUDA SDK version number.
$ export CHAINER_BUILD_CHAINERX=1
$ export CHAINERX_BUILD_CUDA=1
$ export CHAINERX_CUDNN_USE_CUPY=1
$ export MAKEFLAGS=-j8       # Using 8 parallel jobs.
$ pip install chainer
```
Install ChainerX with CuPy built from source:

```
$ export CHAINER_BUILD_CHAINERX=1
$ export CHAINERX_BUILD_CUDA=1
$ export CUDNN_ROOT_DIR=path/to/cudnn
$ export MAKEFLAGS=-j8   # Using 8 parallel jobs.
$ pip install cupy
$ pip install chainer
```

### 6.2 ChainerX Tutorial

ChainerX, or `chainerx`, is meant to be a drop-in replacement for NumPy and CuPy, with additional operations specific to neural networks. As its core is implemented in C++, you can reduce the Python overhead for both the forward and backward passes compared to Chainer, speeding up your training and inference. This section will guide you through the essential APIs of Chainer to utilize ChainerX, but also how to use ChainerX on its own.

#### 6.2.1 Introduction to ChainerX

The module `chainerx` aims to support a NumPy compatible interface with additional operations specific to neural networks. It for instance provides `chainerx.conv()` for N-dimensional convolutions and `chainerx.batch_norm()` for batch normalization. Additionally, and most importantly, the array in ChainerX `chainerx.ndarray` distinguishes itself from NumPy and CuPy arrays in the following two aspects.

**Automatic differentiation**  Graph construction and backpropagation is built into the array, meaning that any function, including the NumPy-like functions, can be backpropagated through. In Chainer terms, it is a NumPy/CuPy array with `chainer.Variable` properties.

**Device agnostic**  Arrays can be allocated on any device belonging to any backend, in contrast to NumPy/CuPy arrays which are implemented for specific computing platforms (i.e. CPUs/GPUs respectively).

These differences are explained more in details by the sections further down.

**The array `chainerx.ndarray`**

The following example demonstrates how you can create an array and access its most basic attributes. Note that the APIs are identical to that of NumPy and CuPy. Other array creation routines including `chainerx.ones()`, `chainerx.ones_like()` and `chainerx.random.normal()` are all listed [here](#).

```python
import chainerx as chx

x = chx.array([[0, 1, 2], [3, 4, 5]], dtype=chx.float32)

x.shape # (2, 3)
x.dtype # dtype('float32')
x.size # 6
x.ndim # 2
```
Backends and devices

Chainer distinguishes between CPU and GPU arrays using NumPy and CuPy but ChainerX arrays may be allocated on any device on any backend. You can specify the device during instantiation or transfer the array to a different device after it has been created.

```python
x = chx.array([1, 2, 3])
x.device  # native:0
x = chx.array([1, 2, 3], device='cuda:0')
x.device  # cuda:0
x = x.to_device('cuda:1')
x.device  # cuda:1
```

The left-hand-side of the colon shows the name of the backend to which the device belongs. `native` in this case refers to the CPU and `cuda` to CUDA GPUs. The integer on the right-hand-side shows the device index. Together, they uniquely identify a physical device on which an array is allocated.

If you do not want to specify the device each time you create an array, it is possible to change the default device with `chainerx.using_device()`.

```python
with chx.using_device('cuda:0')
    x = chx.array([1, 2, 3])
x.device  # cuda:0
```

**Note:** Currently, two backends are built into ChainerX.

1. The `native` backend, which is built by default.
2. The `cuda` backend which is optional (See installation).

This backend abstraction allows developers to implement their own backends and plug them into ChainerX to perform computations on basically any other platform.

Array operations and backpropagation

Arrays support basic arithmetics and can be passed to functions just as you would expect. By marking an array to require gradients with `chainerx.ndarray.require_grad()`, further computations involving that array will construct a computational graph allowing backpropagation directly from the array. The following code shows how you could implement an affine transformation and backpropagate through it to compute the gradient of the output w.r.t. the input weight and bias.

```python
x = chx.ones(784, dtype=chx.float32)
W = chx.random.normal(size=(784, 1000)).astype(chx.float32).require_grad()
b = chx.random.normal(size=(1000)).astype(chx.float32).require_grad()
y = x.dot(W) + b
y.grad = chx.ones_like(y)  # Initial upstream gradients, i.e. 'grad_outputs'.
y.backward()

assert type(W.grad) is chx.ndarray
assert type(b.grad) is chx.ndarray
```
Note: The code above is device agnostic, meaning that you can execute it on any backend by simply wrapping the code with a `chainerx.using_device()`.

### 6.2.2 Relation to Chainer

A `chainerx.ndarray` can be wrapped in a `chainer.Variable` and passed to any existing Chainer code.

```python
var = ch.Variable(x)  # x is a chainerx.ndarray.
# Your Chainer code...
```

When further applying functions to the `var`, the computational graph is recorded in the underlying ndarray in C++ implementation, not in the `chainer.Variable` or the `chainer.FunctionNode`, as in the conventional Chainer. This eliminates the heavy Python overhead of the graph construction. Similarly, calling `chainer.Variable.backward()` on any resulting variable will delegate the work to C++ by calling `chainerx.ndarray.backward()` spending no time in the Python world.

#### NumPy/CuPy fallback

As the features above require ChainerX to provide an implementation corresponding to every `chainer.FunctionNode` implementation in Chainer, ChainerX utilizes a fallback mechanism while gradually extending the support. This approach is taken because the integration with Chainer takes time and we do not want existing Chainer users to have to make severe changes to their code bases in order to try ChainerX. The fallback logic simply casts the `chainerx.ndarray`s inside the `chainer.Variable` to `numpy.ndarray`s or `cupy.ndarray`s (without copy) and calls the forward and backward methods respectively.

#### Run your Chainer code with ChainerX

In order to utilize `chainerx`, you first need to transfer your model to a ChainerX device using `chainer.Link.to_device()`. This is a new method that has been introduced to replace `chainer.Link.to_cpu()` and `chainer.Link.to_gpu()`, extending device transfer to arbitrary devices. Similarly, you have to transfer the data (`chainer.Variables`) to the same device before feeding them to the model.

#### Will my FunctionNode work with ChainerX?

Our expectation is that it should work because of the fallback mechanism explained above, but in practice you may need some occasional fixes, depending on how the function was implemented. Also, you will not see any performance improvements from the fallback (but most likely a degradation because of the additional conversions).

To support ChainerX with your `chainer.FunctionNode`, you need to implement `chainer.FunctionNode.forward_chainerx()` with the same signature as `chainer.FunctionNode.forward()`, but where given inputs are of type `chainerx.ndarray`. It is expected to return a tuple just like `chainer.FunctionNode.forward()`.

The example below shows how `chainer.functions.matmul()` is extended to support ChainerX. Note that `chainer.Fallback` can be returned in case the function cannot be implemented using ChainerX functions. This is also the default behavior in case the method is not implemented at all.
class MatMul(function_node.FunctionNode):

    def forward_chainerx(self, x):
        a, b = x
        if self.transa or self.transb or self.transc:
            return chainer.Fallback
        if a.dtype != b.dtype:
            return chainer.Fallback
        if a.ndim != 2 or b.ndim != 2:
            return chainer.Fallback
        if self.dtype is not None and self.dtype != a.dtype:
            return chainer.Fallback
        return chainerx.dot(a, b),  # Fast C++ implementation

6.3 Limitations

There are some non-obvious limitations in ChainerX:

• ChainerX only supports a limited set of dtypes: bool_ int8 int16 int32 int64 uint8 float32 float64.

• Operations with mixed dtypes are not supported. You need to explicitly convert dtypes using either chainerx.astype() or F.cast().

• True division of Python, where 2/3 returns .66 rather than 0, is not supported yet. Given an ndarray a of the dtype int32, a / a does not return an array of float64, but returns an array of int32.

• Only a limited set of Chainer functions are well tested with the ChainerX integration.

• ChainerX CUDA backend requires cuDNN. See installation for details.

• As ChainerX arrays have a computational graph in their own, some operations are prohibited for safety:
  – Unless an array is free from the computational graph, in-place modification of its data is prohibited.

    a = chainerx.zeros((2,), chainerx.float32)
    a.require_grad()  # install the computational graph on `a`.
    a += 1  # ! error

    The reason of this limitation is that, as backward operations may depend on the value of a, the backward gradients might be unexpectedly affected if it would be altered.

    You may circumvent this limitation by making a disconnected view:

    # A memory-shared view of `a` which is disconnected from the computational graph of `a`.
    b = a.as_grad_stopped()
    b += 1

    Note however that this operation is inherently dangerous. You should be super careful to ensure that that does not affect backward computations.

    Note also that we may restrict further in the future so that even in-place modification on a disconnected view is only allowed if it is actually safe.

  – If an array is wrapped with a Variable with requires_grad=True (which is default), you won’t be able to re-assign the array:
$$a = \text{chainerx.zeros}((2,), \text{chainerx.float32})$$
$$b = \text{chainerx.zeros}((2,), \text{chainerx.float32})$$
$$\text{var} = \text{chainer.Variable}(a)$$
$$\text{var.array} = b \quad \# \text{! error}$$

You may circumvent this by using in-place assignment on var.array:

$$\text{var.array[:] = b}$$

This workaround may also be dangerous just as in the previous limitation.

## 6.4 Reference

### 6.4.1 Multi-Dimensional Array (ndarray)

<table>
<thead>
<tr>
<th>chainerx.ndarray</th>
<th>Multi-dimensional array, the central data structure of ChainerX.</th>
</tr>
</thead>
</table>

**chainerx.ndarray**

**class** chainerx.ndarray(*shape*, *dtype*, *device=None*)

Multi-dimensional array, the central data structure of ChainerX.

This class, along with other APIs in the chainerx module, provides a subset of NumPy APIs. This class works similar to numpy.ndarray, except for some differences including the following noticeable points:

- **chainerx.ndarray** has a *device* attribute. It indicates on which device the array is allocated.
- **chainerx.ndarray** supports Define-by-Run backpropagation. Once you call *require_grad()*, the array starts recording the operations applied to it recursively. Gradient of the result with respect to the original array can be computed then with the *backward()* method or the *chainerx.backward()* function.

**Parameters**

- **shape** (*tuple of ints*) – Shape of the new array.
- **dtype** – Data type.
- **device** (*Device*) – Device on which the array is allocated. If omitted, *the default device* is chosen.

**See also:**

numpy.ndarray
Methods

__getitem__(key)
__getitem__(self, key) Returns self[key].

Note: Currently, only basic indexing is supported not advanced indexing.

__setitem__(key, value)

__len__() Returns the length of the first axis.

all()

any()

argmax(axis=None)
Returns the indices of the maximum elements along a given axis.

See chainerx.argmax() for the full documentation.

argmin(axis=None)
Returns the indices of the minimum elements along a given axis.

See chainerx.argmin() for the full documentation.

as_grad_stopped(copy=False)
Creates a view or a copy of the array that stops gradient propagation.

This method behaves similar to view() and copy(), except that the gradient is not propagated through this operation (internally, this method creates a copy or view of the array without connecting the computational graph for backprop).

Parameters copy (bool) – If True, it copies the array. Otherwise, it returns a view of the original array.

Returns A view or a copy of the array without propagating the gradient on backprop.

Return type ndarray

astype(dtype, copy=True)
Casts each element to the specified data type.

Parameters

• dtype – Data type of the new array.

• copy (bool) – If True, this method always copies the data. Otherwise, it creates a view of the array if possible.

Returns An array with the specified dtype.

Return type ndarray

backward(backprop_id=None, enable_double_backprop=False)
Performs backpropagation starting from this array.

This method is equivalent to chainerx.backward([self], *args). See chainerx.backward() for the full documentation.

cleargrad()
Clears the gradient held by this array.
clip \((a_{\text{min}}, a_{\text{max}})\)
Returns an array with values limited to \([a_{\text{min}}, a_{\text{max}}]\).

See also:
chainerx.clip() for full documentation, numpy.ndarray.clip()

copy()
Creates an array and copies all the elements to it.
The copied array is allocated on the same device as self.
See also:
chainerx.copy()
dot \((b)\)
Returns the dot product with a given array.
See chainerx.dot() for the full documentation.

fill \((value)\)
Fills the array with a scalar value in place.

Parameters value – Scalar value with which the array will be filled.

flatten()

get_grad()
Returns the gradient held by the array.
If the gradient is not available, it returns None.

is_backprop_required()
Returns True if gradient propagates through this array on backprop.
See the note on require_grad() for details.

is_grad_required()
Returns True if the gradient will be set after backprop.
See the note on require_grad() for details.

item()
Copies an element of an array to a standard Python scalar and returns it.

Returns A copy of the specified element of the array as a suitable Python scalar.

Return type z

See also:
numpy.item()

max \((axis=None, keepdims=False)\)
Returns the maximum along a given axis.
See chainerx.amax() for the full documentation.

mean()

min \((axis=None, keepdims=False)\)
Returns the minimum along a given axis.
See chainerx.amin() for the full documentation.

ravel()
repeat (repeats, axis=None)
Constructs an array by repeating a given array.
See chainerx.repeats() for the full documentation.

require_grad()
Declares that a gradient for this array will be made available after backprop.
Once calling this method, any operations applied to this array are recorded for later backprop. After backprop, the grad attribute holds the gradient array.

Note: ChainerX distinguishes gradient requirements and backprop requirements strictly. They are strongly related, but different concepts as follows.

- Gradient requirement indicates that the gradient array should be made available after backprop. This attribute is not propagated through any operations. It implicates the backprop requirement.
- Backprop requirement indicates that the gradient should be propagated through the array during backprop. This attribute is propagated through differentiable operations.

require_grad() sets the gradient requirement flag. If you need to extract the gradient after backprop, you have to call require_grad() on the array even if the array is an intermediate result of differentiable computations.

Returns self
Return type ndarray

reshape (newshape)
Creates an array with a new shape and the same data.
See chainerx.reshape() for the full documentation.

set_grad (grad)
Sets a gradient to the array.
This method overwrites the gradient with a given array.
Parameters grad (ndarray) – New gradient array.

squeeze (axis=None)
Removes size-one axes from an array.
See chainerx.squeeze() for the full documentation.

sum (axis=None, keepdims=False)
Returns the sum of an array along given axes.
See chainerx.sum() for the full documentation.

swapaxes (axis1, axis2)
Interchange two axes of an array.
See chainerx.swapaxes() for the full documentation.

take (indices, axis)
Takes elements from the array along an axis.
See chainerx.take() for the full documentation.

to_device (device, index=None)
Transfers the array to the specified device.
Parameters

- **device** *(Device or str)* – Device to which the array is transferred, or a backend name. If it is a backend name, **index** should also be specified.

- **index** *(int)* – Index of the device for the backend specified by **device**.

**Returns** An array on the target device. If the original array is already on the device, it is a view of that. Otherwise, it is a copy of the array on the target device.

**Return type** *ndarray*

tolist()

transpose(*axes=None*)

Creates a view of an array with permutated axes.

See [chainerx.transpose()](https://docs.chainerx.io/en/latest/) for the full documentation.

var()

view()

Returns a view of the array.

The returned array shares the underlying buffer, though it has a different identity as a Python object.

__eq__(other)

Computes \( x = y \) elementwise.

__ne__(other)

Computes \( x \neq y \) elementwise.

__lt__(other)

Computes \( x < y \) elementwise.

__le__(other)

Computes \( x \leq y \) elementwise.

__gt__(other)

Computes \( x > y \) elementwise.

__ge__(other)

Computes \( x \geq y \) elementwise.

__bool__()

Casts a size-one array into a bool value.

__neg__()

Computes \(-x\) elementwise.

__abs__()

__add__(other)

Computes \( x + y \) elementwise.

__radd__(other)

Computes \( y + x \) elementwise.

__sub__(other)

Computes \( x - y \) elementwise.

__rsub__(other)

Computes \( y - x \) elementwise.

__mul__(other)

Computes \( x \ast y \) elementwise.
__rmul__(other)
Computes \( y \times x \) elementwise.

__truediv__(other)
Computes \( x / y \) elementwise.

__rtruediv__()

__floordiv__()

__rfloordiv__()

__pow__()

__rpow__()

Attributes

\( T \)
Shape-reversed view of the array.
New array is created at every access to this property. \( x.T \) is just a shorthand of \( x.transpose() \).

Type ndarray
data_ptr
Address of the underlying memory allocation.
The meaning of the address is device-dependent.
Type int
data_size
Total size of the underlying memory allocation.
Type int
device
Device on which the data exists.
Type Device
dtype
Data type of the array.

grad
Gradient held by the array.
It is None if the gradient is not available. Setter of this property overwrites the gradient.

Type ndarray

is_contiguous
True iff the array is stored in the C-contiguous order.

Type bool

itemsize
Size of each element in bytes.

Type int

nbytes
Total size of all elements in bytes.
It does not count skips between elements.
Type int

\textbf{ndim}
Number of dimensions.
Type int

\textbf{offset}
Offset of the first element from the memory allocation in bytes.
Type int

\textbf{shape}
Lengths of axes.

\textbf{Note:} Currently, this property does not support setter.

Type tuple of int

\textbf{size}
Number of elements in the array.
Type int

\textbf{strides}
Strides of axes in bytes.
Type tuple of int

\textbf{Utility functions}

\texttt{\texttt{chainerx.to_numpy}} Converts a ChainerX array to NumPy

\texttt{chainerx.to}\texttt{\_}\texttt{numpy}

\texttt{chainerx.to\_numpy} \texttt{(array, copy=True)}
Converts a ChainerX array to NumPy

\textbf{Parameters}

- \texttt{array (ndarray)} – ChainerX array.
- \texttt{copy (bool)} – If \texttt{True}, a copy is always made. Otherwise, the resulting array may be aliased with the input array.

\textbf{Returns} NumPy array.

\textbf{Return type} \texttt{numpy.ndarray}
### 6.4.2 Array Operations

**Array creation routines**

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainerx.empty</code></td>
<td>Returns an array without initializing the elements.</td>
</tr>
<tr>
<td><code>chainerx.empty_like</code></td>
<td>Returns a new array with same shape and dtype of a given array.</td>
</tr>
<tr>
<td><code>chainerx.eye</code></td>
<td>Returns a 2-D array with ones on the diagonals and zeros elsewhere.</td>
</tr>
<tr>
<td><code>chainerx.identity</code></td>
<td>Returns a 2-D identity array.</td>
</tr>
<tr>
<td><code>chainerx.ones</code></td>
<td>Returns a new array of given shape and dtype, filled with ones.</td>
</tr>
<tr>
<td><code>chainerx.ones_like</code></td>
<td>Returns an array of ones with same shape and dtype as a given array.</td>
</tr>
<tr>
<td><code>chainerx.zeros</code></td>
<td>Returns a new array of given shape and dtype, filled with zeros.</td>
</tr>
<tr>
<td><code>chainerx.zeros_like</code></td>
<td>Returns an array of zeros with same shape and dtype as a given array.</td>
</tr>
<tr>
<td><code>chainerx.full</code></td>
<td>Returns a new array of given shape and dtype, filled with a given value.</td>
</tr>
<tr>
<td><code>chainerx.full_like</code></td>
<td>Returns a full array with same shape and dtype as a given array.</td>
</tr>
<tr>
<td><code>chainerx.array</code></td>
<td>Creates an array.</td>
</tr>
<tr>
<td><code>chainerx.asarray</code></td>
<td>Converts an object to an array.</td>
</tr>
<tr>
<td><code>chainerx.asanyarray</code></td>
<td>Converts an object to an array.</td>
</tr>
<tr>
<td><code>chainerx.ascontiguousarray</code></td>
<td>Returns a C-contiguous array.</td>
</tr>
<tr>
<td><code>chainerx.copy</code></td>
<td>Creates a copy of a given array.</td>
</tr>
<tr>
<td><code>chainerx.frombuffer</code></td>
<td>Returns a 1-D array interpretation of a buffer.</td>
</tr>
<tr>
<td><code>chainerx.fromfile</code></td>
<td>Constructs an array from data in a text or binary file.</td>
</tr>
<tr>
<td><code>chainerx.fromfunction</code></td>
<td>Constructs an array by executing a function over each coordinate.</td>
</tr>
<tr>
<td><code>chainerx.fromiter</code></td>
<td>Constructs a new 1-D array from an iterable object.</td>
</tr>
<tr>
<td><code>chainerx.fromstring</code></td>
<td>Constructs a new 1-D array initialized from text data in a string.</td>
</tr>
<tr>
<td><code>chainerx.loadtxt</code></td>
<td>Constructs an array by loading data from a text file.</td>
</tr>
<tr>
<td><code>chainerx.arange</code></td>
<td>Returns an array with evenly spaced values within a given interval.</td>
</tr>
<tr>
<td><code>chainerx.linspace</code></td>
<td>Returns an array with evenly spaced numbers over a specified interval.</td>
</tr>
<tr>
<td><code>chainerx.diag</code></td>
<td>Returns a diagonal or a diagonal array.</td>
</tr>
<tr>
<td><code>chainerx.diagflat</code></td>
<td>Creates a diagonal array from the flattened input.</td>
</tr>
<tr>
<td><code>chainerx.meshgrid</code></td>
<td>Returns coordinate matrices from coordinate vectors.</td>
</tr>
<tr>
<td><code>chainerx.tri</code></td>
<td>Returns a 2-D array with ones at and below the given diagonal and zeros elsewhere.</td>
</tr>
<tr>
<td><code>chainerx.tril</code></td>
<td>Lower triangle of an array.</td>
</tr>
<tr>
<td><code>chainerx.triu</code></td>
<td>Upper triangle of an array.</td>
</tr>
</tbody>
</table>
**chainerx.empty**

chainerx.empty(shape, dtype, device=None)

Returns an array without initializing the elements.

**Parameters**

- **shape** (tuple of ints) – Shape of the array.
- **dtype** – Data type of the array.
- **device** (Device) – Device on which the array is allocated. If omitted, the default device is chosen.

**Returns**

New array with elements not initialized.

**Return type** ndarray

See also:

numpy.empty()

**chainerx.empty_like**

chainerx.empty_like(a, device=None)

Returns a new array with same shape and dtype of a given array.

**Parameters**

- **a** (ndarray) – Prototype array.
- **device** (Device) – Device on which the array is allocated. If omitted, the default device is chosen.

**Returns**

New array with same shape and dtype as a with elements not initialized.

**Return type** ndarray

**Warning:** If device argument is omitted, the new array is created on the default device, not the device of the prototype array.

See also:

numpy.empty_like()

**chainerx.eye**

chainerx.eye(N, M=None, k=0, dtype=float64, device=None)

Returns a 2-D array with ones on the diagonals and zeros elsewhere.

**Parameters**

- **N** (int) – Number of rows.
- **M** (int) – Number of columns. M == N by default.
- **k** (int) – Index of the diagonal. Zero indicates the main diagonal, a positive index an upper diagonal, and a negative index a lower diagonal.
- **dtype** – Data type.
• **device** (Device) – Device on which the array is allocated. If omitted, the default device is chosen.

**Returns**  A 2-D array with given diagonals filled with ones and zeros elsewhere.

**Return type**  ndarray

See also:

numpy.eye()

---

**chainerx.identity**

chainerx.identity(n, dtype=None, device=None)

Returns a 2-D identity array.

It is equivalent to eye(n, n, dtype).

**Parameters**

• **n** (int) – Number of rows and columns.

• **dtype** – Data type.

• **device** (Device) – Device on which the array is allocated. If omitted, the default device is chosen.

**Returns**  A 2-D identity array.

**Return type**  ndarray

See also:

numpy.identity()

---

**chainerx.ones**

chainerx.ones(shape, dtype=None, device=None)

Returns a new array of given shape and dtype, filled with ones.

**Parameters**

• **shape** (tuple of ints) – Shape of the array.

• **dtype** – Data type.

• **device** (Device) – Device on which the array is allocated. If omitted, the default device is chosen.

**Returns**  New array.

**Return type**  ndarray

See also:

numpy.ones()
**chainerx.ones_like**

`chainerx.ones_like(a, device=None)`

Returns an array of ones with same shape and dtype as a given array.

- **Parameters**
  - `a (ndarray)` – Prototype array.
  - `device (Device)` – Device on which the array is allocated. If omitted, *the default device* is chosen.

- **Returns**
  New array.

- **Return type** `ndarray`

**Warning:** If `device` argument is omitted, the new array is created on the default device, not the device of the prototype array.

**See also:**
- `numpy.ones_like()`

**chainerx.zeros**

`chainerx.zeros(shape, dtype, device=None)`

Returns a new array of given shape and dtype, filled with zeros.

- **Parameters**
  - `shape (tuple of ints)` – Shape of the array.
  - `dtype` – Data type.
  - `device (Device)` – Device on which the array is allocated. If omitted, *the default device* is chosen.

- **Returns**
  New array.

- **Return type** `ndarray`

**See also:**
- `numpy.zeros()`

**chainerx.zeros_like**

`chainerx.zeros_like(a, device=None)`

Returns an array of zeros with same shape and dtype as a given array.

- **Parameters**
  - `a (ndarray)` – Prototype array.
  - `device (Device)` – Device on which the array is allocated. If omitted, *the default device* is chosen.

- **Returns**
  New array.

- **Return type** `ndarray`
Warning: If `device` argument is omitted, the new array is created on the default device, not the device of the prototype array.

See also:

`numpy.zeros_like()`

**chainerx.full**

chainerx.full(`shape`, `fill_value`, `dtype`, `device=None`)  
Returns a new array of given shape and `dtype`, filled with a given value.

Parameters

- `shape` (tuple of ints) – Shape of the array.  
- `dtype` – Data type.  
- `device` (Device) – Device on which the array is allocated. If omitted, *the default device* is chosen.

Returns  New array.

Return type  ndarray

See also:

`numpy.full()`

**chainerx.full_like**

chainerx.full_like(`a`, `fill_value`, `dtype=None`, `device=None`)  
Returns a full array with same shape and `dtype` as a given array.

Parameters

- `a` (ndarray) – Prototype array.  
- `dtype` – Data type.  
- `device` (Device) – Device on which the array is allocated. If omitted, *the default device* is chosen.

Returns  New array.

Return type  ndarray

Warning: If `device` argument is omitted, the new array is created on the default device, not the device of the prototype array.

See also:

`numpy.full_like()`
chainerx.array

`chainerx.array(object, dtype=None, copy=True, device=None)`

Creates an array.

Parameters

- **object** – A `ndarray` object or any other object that can be passed to `numpy.array()`.
- **dtype** – Data type. If omitted, it’s inferred from the input.
- **copy** (bool) – If True, the object is always copied. Otherwise, a copy will only be made if it is needed to satisfy any of the other requirements (dtype, device, etc.).
- **device** (Device) – Device on which the array is allocated. If omitted, the default device is chosen.

Returns New array.

Return type `ndarray`

Warning: If `device` argument is omitted, the new array is created on the default device, not the device of the input array.

See also:

- `numpy.array()`

chainerx.asarray

`chainerx.asarray(a, dtype=None, device=None)`

Converts an object to an array.

Parameters

- **a** – The source object.
- **dtype** – Data type. If omitted, it’s inferred from the input.
- **device** (Device) – Device on which the array is allocated. If omitted, the default device is chosen.

Returns Array interpretation of a. If a is already an ndarray on the given device with matching dtype, no copy is performed.

Return type `ndarray`

Warning: If `device` argument is omitted, the new array is created on the default device, not the device of the input array.

See also:

- `numpy.asarray()`
**chainerx.asanyarray**

`chainerx.asanyarray(a, dtype=None, device=None)`  
Converts an object to an array.

This is currently equivalent to `asarray()`, since there are no subclasses of `ndarray` in ChainerX. Note that the original `numpy.asanyarray()` returns the input array as is, if it is an instance of a subtype of `numpy.ndarray`.

**See also:**

`chainerx.asarray()`, `numpy.asanyarray()`

**chainerx.ascontiguousarray**

`chainerx.ascontiguousarray(a, dtype=None, device=None)`  
Returns a C-contiguous array.

**Parameters**

- `a (ndarray)` – Source array.
- `dtype` – Data type.
- `device (Device)` – Device on which the array is allocated. If omitted, the default device is chosen.

**Returns** C-contiguous array. A copy will be made only if needed.

**Return type** `ndarray`

**Warning:** If `device` argument is omitted, the new array is created on the default device, not the device of the input array.

**See also:**

`numpy.ascontiguousarray()`

**chainerx.copy**

`chainerx.copy(a)`  
Creates a copy of a given array.

**Parameters** `a (ndarray)` – Source array.

**Returns** A copy array on the same device as `a`.

**Return type** `ndarray`

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array `a`.

**See also:**

`numpy.copy()`
chainerx.frombuffer

chainerx.frombuffer(buffer, dtype=float, count=-1, offset=0, device=None)

Returns a 1-D array interpretation of a buffer.

The given buffer memory must be usable on the given device, otherwise, an error is raised.

**Note:** The native backend requires a buffer of main memory, and the cuda backend requires a buffer of CUDA memory. No copy is performed.

**Parameters**

- **buffer** – An object that exposes the buffer interface.
- **dtype** – Data type of the returned array.
- **count** (int) – Number of items to read. -1 means all data in the buffer.
- **offset** (int) – Start reading the buffer from this offset (in bytes).
- **device** (Device) – Device of the returned array. If omitted, the default device is chosen.

**Returns** 1-D array interpretation of `buffer`.

**Return type** ndarray

See also:

numpy.frombuffer()

chainerx.fromfile

chainerx.fromfile(file, dtype=<class ‘float’>, count=-1, sep='', device=None)

Constructs an array from data in a text or binary file.

This is currently equivalent to numpy.fromfile() wrapped by chainerx.array(), given the device argument.

**See also:**

numpy.fromfile()

chainerx.fromfunction

chainerx.fromfunction(function, shape, **kwargs)

Constructs an array by executing a function over each coordinate.

This is currently equivalent to numpy.fromfunction() wrapped by chainerx.array(), given the device argument.

**Note:** Keywords other than dtype and device are passed to `function`.

**See also:**

numpy.fromfunction()
chainerx.fromiter

chainerx.fromiter( *iterable, dtype, count=-1, device=None)

Constructs a new 1-D array from an iterable object.

This is currently equivalent to numpy.fromiter() wrapped by chainerx.array(), given the device argument.

See also:

numpy.fromiter()

chainerx.fromstring

chainerx.fromstring(*string, dtype=<class 'float'>, count=-1, sep='', device=None)

Constructs a new 1-D array initialized from text data in a string.

This is currently equivalent to numpy.fromstring() wrapped by chainerx.array(), given the device argument.

See also:

numpy.fromstring()

chainerx.loadtxt

chainerx.loadtxt(*fname, dtype=<class 'float'>, comments='#', delimiter=None, converters=None, skiprows=0, usecols=None, unpack=False, ndmin=0, encoding='bytes', device=None)

Constructs an array by loading data from a text file.

This is currently equivalent to numpy.loadtxt() wrapped by chainerx.array(), given the device argument.

See also:

numpy.loadtxt()

chainerx.arange

chainerx.arange(*[start=0], stop[, step=1], dtype=None, device=None)

Returns an array with evenly spaced values within a given interval.

Values are generated within the half-open interval [start, stop). The first three arguments are mapped like the range built-in function, i.e. start and step are optional.

Parameters

• **start** – Start of the interval.
• **stop** – End of the interval.
• **step** – Step width between each pair of consecutive values.
• **dtype** – Data type specifier. It is inferred from other arguments by default.
• **device** (Device) – Device on which the array is allocated. If omitted, the default device is chosen.
**Returns**  The 1-D array of range values.

**Return type**  *ndarray*

**See also:**

* numpy.arange()  

**chainerx.linspace**

**chainerx.linspace**(*start*, *stop*, *num=50*, *endpoint=True*, *dtype=None*, *device=None*)

Returns an array with evenly spaced numbers over a specified interval.

Instead of specifying the step width like *chainerx.arange()*, this function requires the total number of elements specified.

**Parameters**

- *start* – Start of the interval.
- *stop* – End of the interval.
- *num* – Number of elements.
- *endpoint* (*bool*) – If True, the stop value is included as the last element. Otherwise, the stop value is omitted.
- *dtype* – Data type specifier. It is inferred from the start and stop arguments by default.
- *device* (*Device*) – Device on which the array is allocated. If omitted, the default device is chosen.

**Returns**  The 1-D array of ranged values.

**Return type**  *ndarray*

**See also:**

* numpy.linspace()  

**chainerx.diag**

**chainerx.diag**(*v*, *k=0*, *device=None*)

Returns a diagonal or a diagonal array.

**Parameters**

- *k* (*int*) – Index of diagonals. Zero indicates the main diagonal, a positive value an upper diagonal, and a negative value a lower diagonal.
- *device* (*Device*) – Device on which the array is allocated. If omitted, the default device is chosen.

**Returns**  If *v* is a 1-D array, then it returns a 2-D array with the specified diagonal filled by *v*. If *v* is a 2-D array, then it returns the specified diagonal of *v*. In latter case, if *v* is a *chainerx.ndarray* object, then its view is returned.

**Return type**  *ndarray*
chainerx.diagflat

chainerx.diagflat(v, k=0, device=None)

Creates a diagonal array from the flattened input.

Parameters

- v (ndarray) – Array object.
- k (int) – Index of diagonals. See chainerx.diag().
- device (Device) – Device on which the array is allocated. If omitted, the default device is chosen.

Returns

A 2-D diagonal array with the diagonal copied from v.

Return type

ndarray

Note: The argument v does not support array-like objects yet.

See also:

numpy.diagflat()

chainerx.meshgrid

chainerx.meshgrid(xi, indexing='xy')

Returns coordinate matrices from coordinate vectors.

Make N-D coordinate arrays for vectorized evaluations of N-D scalar/vector fields over N-D grids, given one-dimensional coordinate arrays x1, x2, ..., xn.

Parameters

- xi (sequence of ndarrays) – 1-D arrays representing the coordinates of a grid.
- indexing (str) – {'xy', 'ij'}, optional Cartesian ('xy', default) or matrix ('ij') indexing of output.

Returns

For vectors x1, x2, ..., 'xn' with lengths Ni=len(xi), return (N1, N2, N3,...Nn) shaped arrays if indexing='ij' or (N2, N1, N3,...Nn) shaped arrays if indexing='xy' with the elements of xi repeated to fill the matrix along the first dimension for x1, the second for x2 and so on.

Return type

list of ndarrays

See also:

numpy.meshgrid()
chainerx.tri

chainerx.tri(N, M=None, k=0, dtype=float32, device=None)

Returns a 2-D array with ones at and below the given diagonal and zeros elsewhere.

Parameters

- N (int) – Number of rows.
- M (int) – Number of columns. M == N by default.
- k (int) – Index of the diagonal. Zero indicates the main diagonal, a positive index an upper diagonal, and a negative index a lower diagonal.
- dtype – Data type.
- device (Device) – Device on which the array is allocated. If omitted, the default device is chosen.

Returns A 2-D array with given diagonals filled ones at and below the given diagonal and zeros elsewhere.

Return type ndarray

See also:
numpy.tri()

chainerx.tril

chainerx.tril(m, k=0)

Lower triangle of an array.

Returns a copy of an array with elements above the k-th diagonal zeroed.

Parameters

- m (ndarray) – Input array.
- k (int) – Index of the diagonal. Zero indicates the main diagonal, a positive index an upper diagonal, and a negative index a lower diagonal.

Returns Lower triangle of m.

Return type ndarray

See also:
numpy.tril()

chainerx.triu

chainerx.triu(m, k=0)

Upper triangle of an array.

Returns a copy of an array with elements below the k-th diagonal zeroed.

Parameters

- m (ndarray) – Input array.
- k (int) – Index of the diagonal. Zero indicates the main diagonal, a positive index an upper diagonal, and a negative index a lower diagonal.
Returns Upper triangle of \( m \).

Return type \texttt{ndarray}

See also:

\texttt{numpy.triu()}

### Activation functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>\texttt{chainerx.log_softmax}</td>
<td>The log of the softmax of input array.</td>
</tr>
<tr>
<td>\texttt{chainerx.tanh}</td>
<td>Element-wise hyperbolic tangent function.</td>
</tr>
<tr>
<td>\texttt{chainerx.relu}</td>
<td>Rectified Linear Unit function.</td>
</tr>
<tr>
<td>\texttt{chainerx.sigmoid}</td>
<td>Element-wise sigmoid logistic function.</td>
</tr>
<tr>
<td>\texttt{chainerx.slstm}</td>
<td>S-LSTM units as an activation function.</td>
</tr>
<tr>
<td>\texttt{chainerx.tree_lstm}</td>
<td>TreeLSTM unit as an activation function.</td>
</tr>
</tbody>
</table>

#### chainerx.log_softmax

\texttt{chainerx.log_softmax}(x, axis=None)

The log of the softmax of input array.

**Parameters**

- \( x \) (\texttt{ndarray}) – Input array.
- \( \text{axis} \) (\texttt{None or int or tuple of ints}) – Axis or axes along which a sum is performed. The flattened array is used by default.

**Returns** The log of the softmax of input elements over a given axis.

**Return type** \texttt{ndarray}

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

#### chainerx.tanh

\texttt{chainerx.tanh}(x)

Element-wise hyperbolic tangent function.

**Parameters** \( x \) (\texttt{ndarray}) – Input array.

**Returns** Returned array: \( y = \tanh x \).

**Return type** \texttt{ndarray}

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

See also:

\texttt{numpy.tanh}
chainerx.relu

chainerx.relu()
Rectified Linear Unit function.

:param x: Input array.
:type x: chainerx.ndarray

Returns
Returned array: \( y = \max(0, x) \).

Return type
ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

chainerx.sigmoid

chainerx.sigmoid(x)
Element-wise sigmoid logistic function.

Parameters
x (ndarray) – Input array.

Returns
Returned array: \( f(x) = (1 + \exp(-x))^{-1} \).

Return type
ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

See also:
chainer.functions.sigmoid()

chainerx.slstm

chainerx.slstm(c_prev1, c_prev2, x1, x2)
S-LSTM units as an activation function.

This function implements S-LSTM unit. It is an extension of LSTM unit applied to tree structures. The function is applied to binary trees. Each node has two child nodes. It gets four arguments, previous cell states \( c_{\text{prev1}} \) and \( c_{\text{prev2}} \), and input arrays \( x_1 \) and \( x_2 \). First both input arrays \( x_1 \) and \( x_2 \) are split into eight arrays \( a_1, i_1, f_1, o_1, a_2, i_2, f_2, o_2 \). They have the same shape along the second axis. It means that \( x_1 \) and \( x_2 \) ‘s second axis must have 4 times the length of \( c_{\text{prev1}} \) and \( c_{\text{prev2}} \). The split input arrays are corresponding to

- \( a_i \): sources of cell input
- \( i_i \): sources of input gate
- \( f_i \): sources of forget gate
- \( o_i \): sources of output gate

It computes the updated cell state \( c \) and the outgoing signal \( h \) as:

\[
c = \tanh(a_1 + a_2)\sigma(i_1 + i_2) + c_{\text{prev1}}\sigma(f_1) + c_{\text{prev2}}\sigma(f_2),
\]

\[
h = \tanh(c)\sigma(o_1 + o_2),
\]

where \( \sigma \) is the elementwise sigmoid function. The function returns \( c \) and \( h \) as a tuple.
• \texttt{c\_prev1 (array)} – Variable that holds the previous cell state of the first child node. The cell state should be a zero array or the output of the previous call of LSTM.

• \texttt{c\_prev2 (array)} – Variable that holds the previous cell state of the second child node.

• \texttt{x1 (array)} – Variable that holds the sources of cell input, input gate, forget gate and output gate from the first child node. It must have the second dimension whose size is four times of that of the cell state.

• \texttt{x2 (array)} – Variable that holds the input sources from the second child node.

\textbf{Returns} Two \texttt{array} objects \(c\) and \(h\). \(c\) is the cell state. \(h\) indicates the outgoing signal.

\textbf{Return type} tuple

See detail in paper: Long Short-Term Memory Over Tree Structures.

\textbf{Example}

Assuming \(c_1, c_2\) is the previous cell state of children, and \(h_1, h_2\) is the previous outgoing signal from children. Each of \(c_1, c_2, h_1\) and \(h_2\) has \texttt{n\_units} channels. Most typical preparation of \(x_1, x_2\) is:

\begin{verbatim}
>>> n_units = 100
>>> c1 = chainerx.ones((1, n_units), np.float32)
>>> c2 = chainerx.ones((1, n_units), np.float32)
>>> x1 = chainerx.ones((1, 4 \times n_units), chainerx.float32)
>>> x2 = chainerx.ones((1, 4 \times n_units), chainerx.float32)
>>> c, h = chainerx.slstm(c1, c2, x1, x2)
\end{verbatim}

\texttt{chainerx.tree\_lstm}

\texttt{chainerx.tree\_lstm(*inputs)}

TreeLSTM unit as an activation function.

This function implements TreeLSTM units both for N-ary TreeLSTM and Child-Sum TreeLSTM. Let the children cell states \(c_1, c_2, \ldots, c_N\), and the incoming signal \(x\). First, the incoming signal \(x\) is split into \((3 + N)\) arrays \(a, i, o, f_1, f_2, \ldots, f_N\) of the same shapes along the second axis. It means that \(x\) ’s second axis must have \((3 + N)\) times of the length of each \(c_n\). The splitted input signals are corresponding to

• \textbf{a} : sources of cell input
• \textbf{i} : sources of input gate
• \textbf{o} : sources of output gate
• \textbf{f} \textsubscript{n} : sources of forget gate for n-th ary

Second, it computes outputs as

\[
c = \tanh(a)\text{sigmoid}(i) + c_1\text{sigmoid}(f_1) + c_2\text{sigmoid}(f_2) + \ldots + c_N\text{sigmoid}(f_N),
\]

\[
h = \tanh(c)\text{sigmoid}(o).
\]

These are returned as a tuple of \((N + 1)\) variables.
Parameters **inputs** (list of `array`) – Variable arguments which include all cell vectors from child-nodes, and an input vector. Each of the cell vectors and the input vector is `array`. The input vector must have the second dimension whose size is \( (N + 3) \) times of that of each cell, where \( N \) denotes the total number of cells.

Returns Two `array` objects \( c \) and \( h \). \( c \) is the updated cell state. \( h \) indicates the outgoing signal.

Return type `tuple`

See the papers for details: Improved Semantic Representations From Tree-Structured Long Short-Term Memory Networks and A Fast Unified Model for Parsing and Sentence Understanding. Tai et al.’s N-Ary TreeLSTM is little extended in Bowman et al., and this link is based on the variant by Bowman et al. Specifically, eq. 10 in Tai et al. only has one \( W \) matrix to be applied to \( x \), consistently for all children. On the other hand, Bowman et al.’s model has multiple matrices, each of which affects the forget gate for each child’s cell individually.

Example

Assuming \( y \) is the current input signal, \( c \) is the previous cell state, and \( h \) is the previous output signal from a `tree_lstm()` function. Each of \( y, c \) and \( h \) has \( n\_units \) channels. Using 2-ary (binary) TreeLSTM, most typical preparation of \( x \) is

```python
>>> c1 = chainerx.ones((4, 10), dtype = chainerx.float32)
>>> c2 = chainerx.ones((4, 10), dtype = chainerx.float32)
>>> x = chainerx.ones((4, 50), dtype = chainerx.float32)
>>> c, h = chainerx.tree_lstm(c1, c2, x)
```

---

**Array manipulation routines**

- `chainerx.reshape` Returns a reshaped array.
- `chainerx.ravel` Returns a flattened array.
- `chainerx.transpose` Permutes the dimensions of an array.
- `chainerx.broadcast_to` Broadcasts an array to a given shape.
- `chainerx.squeeze` Removes size-one axes from the shape of an array.
- `chainerx.asarray` Converts an object to an array.
- `chainerx.ascontiguousarray` Returns a C-contiguous array.
- `chainerx.concatenate` Joins arrays along an axis.
- `chainerx.stack` Stacks arrays along a new axis.
- `chainerx.hstack` Stack arrays in sequence horizontally (column wise).
- `chainerx.vstack` Stack arrays in sequence vertically (row wise).
- `chainerx.dstack` Stack arrays in sequence depth wise (along third axis).
- `chainerx.atleast_2d` View inputs as arrays with at least two dimensions.
- `chainerx.atleast_3d` View inputs as arrays with at least three dimensions.
- `chainerx.split` Splits an array into multiple sub arrays along a given axis.
- `chainerx.dsplits` Split array into multiple sub-arrays along the 3rd axis (depth).
- `chainerx.vsplit` Splits an array into multiple sub-arrays vertically (row wise).
- `chainerx.hsplit` Split an array into multiple sub-arrays horizontally (column-wise).
- `chainerx.swapaxes` Interchange two axes of an array.

continues on next page
### Table 5 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainerx.repeat</code></td>
<td>Constructs an array by repeating a given array.</td>
</tr>
<tr>
<td><code>chainerx.expand_dims</code></td>
<td>Expand the shape of an array.</td>
</tr>
<tr>
<td><code>chainerx.flip</code></td>
<td>Reverse the order of elements in an array along the given axis.</td>
</tr>
<tr>
<td><code>chainerx.fliplr</code></td>
<td>Flip array in the left/right direction.</td>
</tr>
<tr>
<td><code>chainerx.flipud</code></td>
<td>Flip array in the up/down direction.</td>
</tr>
<tr>
<td><code>chainerx.moveaxis</code></td>
<td>Move axes of an array to new positions.</td>
</tr>
</tbody>
</table>

#### `chainerx.reshape`

**Function**: `chainerx.reshape(a, newshape)`  
Returns a reshaped array.

**Parameters**

- `a (ndarray)` – Array to be reshaped.
- `newshape (int or tuple of ints)` – The new shape of the array to return. If it is an integer, then it is treated as a tuple of length one. It should be compatible with `a.size`. One of the elements can be `-1`, which is automatically replaced with the appropriate value to make the shape compatible with `a.size`.

**Returns** A reshaped view of `a` if possible, otherwise a copy.

**Return type** `ndarray`

**Note**: During backpropagation, this function propagates the gradient of the output array to the input array `a`.

**See also**:  
`numpy.reshape()`  

#### `chainerx.ravel`

**Function**: `chainerx.ravel(a)`  
Returns a flattened array.

**Parameters** `a (ndarray)` – Array to be flattened.

**Returns** A flattened view of `a` if possible, otherwise a copy.

**Return type** `ndarray`

**Note**: During backpropagation, this function propagates the gradient of the output array to the input array `a`.

**See also**:  
`numpy.ravel()`
chainerx.transpose

chainerx.transpose(a, axes=None)
Permutates the dimensions of an array.

Parameters
- `a (ndarray)` – Array to permute the dimensions.
- `axes (tuple of ints)` – Permutation of the dimensions. This function reverses the shape by default.

Returns A view of `a` with the dimensions permuted.

Return type `ndarray`

Note: During backpropagation, this function propagates the gradient of the output array to the input array `a`.

See also:
- `numpy.transpose()`

chainerx.broadcast_to

chainerx.broadcast_to(array, shape)
Broadcasts an array to a given shape.

Parameters
- `array (ndarray)` – Array to broadcast.
- `shape (tuple of ints)` – The shape of the desired array.

Returns Broadcasted view.

Return type `ndarray`

Note: During backpropagation, this function propagates the gradient of the output array to the input array `array`.

See also:
- `numpy.broadcast_to()`

chainerx.squeeze

chainerx.squeeze(a, axis=None)
Removes size-one axes from the shape of an array.

Parameters
- `a (ndarray)` – Array to be reshaped.
- `axis (int or tuple of ints)` – Axes to be removed. This function removes all size-one axes by default. If one of the specified axes is not of size one, an exception is raised.

Returns An array without (specified) size-one axes.
Return type  ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array a.

See also:

numpy.squeeze()

chainerx.concatenate

chainerx.concatenate(arrays, axis=0)
Joins arrays along an axis.

Parameters

• arrays (sequence of ndarrays) – Arrays to be joined. All of these should have the same dimensionalities except the specified axis.

• axis (int) – The axis to join arrays along.

Returns  Joined array.

Return type  ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input arrays in arrays.

See also:

numpy.concatenate()

chainerx.stack

chainerx.stack(arrays, axis=0)
Stacks arrays along a new axis.

Parameters

• arrays (sequence of ndarrays) – Arrays to be stacked.

• axis (int) – Axis along which the arrays are stacked.

Returns  Stacked array.

Return type  ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input arrays in arrays.

See also:

numpy.stack()
**chainerx.hstack**

**chainerx.hstack** *(arrays)*
- Stack arrays in sequence horizontally (column wise).

  **Parameters**
  - **arrays** *(sequence of ndarrays)* – Arrays to be stacked.

  **Returns**
  - Stacked array.

  **Return type**
  - ndarray

  **Note:** During backpropagation, this function propagates the gradient of the output array to the input arrays in arrays.

  **See also:**
  - numpy.hstack()

**chainerx.vstack**

**chainerx.vstack** *(arrays)*
- Stack arrays in sequence vertically (row wise).

  **Parameters**
  - **arrays** *(sequence of ndarrays)* – Arrays to be stacked.

  **Returns**
  - Stacked array.

  **Return type**
  - ndarray

  **Note:** During backpropagation, this function propagates the gradient of the output array to the input arrays in arrays.

  **See also:**
  - numpy.vstack()

**chainerx.dstack**

**chainerx.dstack** *(arrays)*
- Stack arrays in sequence depth wise (along third axis).

  **Parameters**
  - **arrays** *(sequence of ndarrays)* – Arrays to be stacked.

  **Returns**
  - Stacked array.

  **Return type**
  - ndarray

  **Note:** During backpropagation, this function propagates the gradient of the output array to the input arrays in arrays.

  **See also:**
  - numpy.dstack()
chainerx.atleast_2d

chainerx.atleast_2d(a)
View inputs as arrays with at least two dimensions.

Parameters  a (ndarray) – Array.

Returns  An array with a.ndim >= 2. Copies are avoided where possible, and views with two or more dimensions are returned.

Return type  ndarray

Note:
• Arrays that already have two or more dimensions are preserved.
• During backpropagation, this function propagates the gradient of the output array to the input arrays in a.

See also:
numpy.atleast_2d()

chainerx.atleast_3d

chainerx.atleast_3d(a)
View inputs as arrays with at least three dimensions.

Parameters  a (ndarray) – Array.

Returns  An array with a.ndim >= 3. Copies are avoided where possible, and views with three or more dimensions are returned.

Return type  ndarray

Note:
• Arrays that already have three or more dimensions are preserved.
• During backpropagation, this function propagates the gradient of the output array to the input arrays in a.

See also:
numpy.atleast_3d()

chainerx.split

chainerx.split(ary, indices_or_sections, axis=0)
Splits an array into multiple sub arrays along a given axis.

Parameters
• ary (ndarray) – Array to split.
• indices_or_sections (int or sequence of ints) – A value indicating how to divide the axis. If it is an integer, then is treated as the number of sections, and the axis is evenly divided. Otherwise, the integers indicate indices to split at. Note that a sequence on the device memory is not allowed.
• **axis** (*int*) – Axis along which the array is split.

Returns A list of sub arrays. Each array is a partial view of the input array.

Return type list of *ndarrays*

**Note:** During backpropagation, this function propagates the gradients of the output arrays to the input array.

See also:

numpy.split()

**chainerx.dsplit**

[chainerx.dsplit](ary, indices_or_sections)

Split array into multiple sub-arrays along the 3rd axis (depth).

Parameters

• **ary** (*ndarray*) – Array to split.

• **indices_or_sections** (*int or sequence of ints*) – A value indicating how to divide the axis. If it is an integer, then is treated as the number of sections, and the axis is evenly divided. Otherwise, the integers indicate indices to split at. Note that a sequence on the device memory is not allowed.

Returns A list of sub arrays. Each array is a partial view of the input array.

Return type list of *ndarrays*

**Note:** During backpropagation, this function propagates the gradients of the output arrays to the input array.

See also:

numpy.dsplit()

**chainerx.vsplit**

[chainerx.vsplit](ary, indices_or_sections)

Splits an array into multiple sub-arrays vertically (row-wise).

Parameters

• **ary** (*ndarray*) – Array to split.

• **indices_or_sections** (*int or sequence of ints*) – A value indicating how to divide the axis. If it is an integer, then is treated as the number of sections, and the axis is evenly divided. Otherwise, the integers indicate indices to split at. Note that a sequence on the device memory is not allowed.

Returns A list of sub arrays. Each array is a partial view of the input array.

Return type list of *ndarrays*
Note: During backpropagation, this function propagates the gradients of the output arrays to the input array ary.

See also:

numpy.vsplit()

chainerx.hsplit

chainerx.hsplit (ary, indices_or_sections)
Split an array into multiple sub-arrays horizontally (column-wise).

Parameters

• ary (ndarray) – Array to split.
• indices_or_sections (int or sequence of ints) – A value indicating how to divide the axis. If it is an integer, then is treated as the number of sections, and the axis is evenly divided. Otherwise, the integers indicate indices to split at. Note that a sequence on the device memory is not allowed.

Returns A list of sub arrays. Each array is a partial view of the input array.

Return type list of ndarrays

Note: During backpropagation, this function propagates the gradients of the output arrays to the input array ary.

See also:

numpy.hsplit()

chainerx.swapaxes

chainerx.swapaxes (a, axis1, axis2)
Interchange two axes of an array.

Parameters

• a (ndarray) – Array to swapaxes.
• axis1 (int) – First Axis
• axis2 (int) – Second Axis

Returns Swaped array.

Return type ndarray

Note:

• Output array is a view of the input array.
• During backpropagation, this function propagates the gradients of the output arrays to the input array a.
See also:

numpy.swapaxes()

**chainerx.repeat**

**chainerx.repeat** *(a, repeats, axis=None)*  
Constructs an array by repeating a given array.

**Parameters**

- *a* *(ndarray)* – Array to repeat.
- *repeats* *(int or tuple of ints)* – The number of times which each element of a is repeated.
- *axis* *(int)* – The axis along which to repeat values.

**Returns**
The repeated output array.

**Return type** *ndarray*

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array *a*.

**See also:**

numpy.repeat()

**chainerx.expand_dims**

**chainerx.expand_dims** *(a, axis)*  
Expand the shape of an array.

**Parameters**

- *a* *(ndarray)* – Input Array.
- *axis* *(int)* – Position in the expanded axes where the new axis is placed.

**Returns**

Output array.

**Return type** *ndarray*

**Note:**  
- Output array may or may not be a view of the input array.
- During backpropagation, this function propagates the gradients of the output arrays to the input array *a*.

**See also:**

numpy.expand_dims()
chainerx.flip

chainerx.flip(m, axis)
Reverse the order of elements in an array along the given axis.

Parameters
- m (ndarray) – Input Array.
- axis (int or tuple of ints) – Axis or axes along which to flip over.

Returns A view of m with the entries of axis reversed. Since a view is returned, this operation is done in constant time.

Return type ndarray

Note:
- Output array is a view of the input array.
- During backpropagation, this function propagates the gradients of the output arrays to the input array m.

See also:
numpy.flip()

chainerx.fliplr

chainerx.fliplr(m)
Flip array in the left/right direction.

Parameters m (ndarray) – Input Array.

Returns A view of m with the columns reversed. Since a view is returned, this operation is done in constant time.

Return type ndarray

Note:
- Output array is a view of the input array.
- During backpropagation, this function propagates the gradients of the output arrays to the input array m.

See also:
numpy.fliplr()
chainerx.flipud

chainerx.flipud(m)
Flip array in the up/down direction.

Parameters m(ndarray) – Input Array.

Returns A view of m with the rows reversed. Since a view is returned, this operation is done in constant time.

Return type ndarray

Note:
• Output array is a view of the input array.
• During backpropagation, this function propagates the gradients of the output arrays to the input array m.

See also:
numpy.flipud()

chainerx.moveaxis

chainerx.moveaxis(a, source, destination)
Move axes of an array to new positions.
Other axes remain in their original order.

Parameters
• a(ndarray) – Input Array.
• source(int or tuple of ints) – Original positions of the axes to move.
• must be unique. (These)–
• destination(int or tuple of ints) – Destination positions for each of original axes. These must also be unique. (the)–

Returns Array with moved axes. This array is a view of the input array.

Return type ndarray

Note:
• During backpropagation, this function propagates the gradients of the output arrays to the input array a.

See also:
numpy.moveaxis()
Evaluation routines

**chainerx.accuracy**

*Computes multiclass classification accuracy of the minibatch.*

```python
chainerx.accuracy(y, t, ignore_label=None)
```

**Parameters**

- `y` *(ndarray)* — Array whose (i, j, k, . . . )-th element indicates the score of the class j at the (i, k, . . . )-th sample. The prediction label \( \hat{t} \) is calculated by the formula \( \hat{t}(i, k, . . . ) = \arg\max_j y(i, j, k, . . . ) \).
- `t` *(ndarray)* — Array of ground truth labels.
- `ignore_label` *(int or None)* — Skip calculating accuracy if the true label is `ignore_label`.

**Returns** A variable holding a scalar array of the accuracy.

**Return type** *ndarray()

**Note:** This function is non-differentiable.

**See also:**

*chainer.functions.accuracy()*

**Example**

We show the most common case, when `y` is the two dimensional array.

```python
>>> y = chainerx.array([[0.1, 0.7, 0.2],  # prediction label is 1
...                      [8.0, 1.0, 2.0],  # prediction label is 0
...                      [-8.0, 1.0, 2.0],  # prediction label is 2
...                      [-8.0, -1.0, -2.0]])  # prediction label is 1
>>> t = chainerx.array([1, 0, 2, 1], chainerx.int32)
>>> chainerx.accuracy(y, t)  # 100% accuracy because all samples are correct
array(1., shape=(), dtype=float64, device='native:0')
>>> t = chainerx.array([1, 0, 0, 0], chainerx.int32)
>>> chainerx.accuracy(y, t)  # 50% accuracy because 1st and 2nd samples are correct
array(0.5, shape=(), dtype=float64, device='native:0')
>>> chainerx.accuracy(y, t, ignore_label=0)  # 100% accuracy because of ignoring the 2nd, 3rd and 4th samples.
array(1., shape=(), dtype=float64, device='native:0')
```
Indexing routines

<table>
<thead>
<tr>
<th>chainerx.take</th>
<th>Takes elements from an array along an axis.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainerx.where</td>
<td>Return elements chosen from ( x ) or ( y ) depending on condition.</td>
</tr>
<tr>
<td>chainerx.nonzero</td>
<td>Return the indices of the elements that are non-zero.</td>
</tr>
</tbody>
</table>

**chainerx.take**

chainerx.take \((a, indices, axis)\)

Takes elements from an array along an axis.

**Parameters**

- \( a \) (ndarray) – Source array.
- \( indices \) (ndarray) – The indices of the values to extract. When indices are out of bounds, they are wrapped around.
- \( axis \) (int) – The axis over which to select values.
- \( mode \) (str) – Specifies how out-of-bounds indices will behave. ‘raise’ - raise an error ‘wrap’ - wrap around ‘clip’ - clip to the range

**Returns** Output array.

**Return type** ndarray()

**Note:** This function currently does not support \( axis=None \)

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array \( a \).

**Note:** The default mode for the native backend is ‘raise’, while for the cuda backend is ‘wrap’ in order to prevent device synchronization. ‘raise’ mode is currently not supported in the CUDA backend.

**See also:**

numpy.take()

**chainerx.where**

chainerx.where \((condition, x, y)\)

Return elements chosen from \( x \) or \( y \) depending on condition.

**Parameters**

- \( condition \) (ndarray) – Where True, yield \( x \), otherwise
- \( y \) (yield)
- \( x \) (ndarray) – Values from which to choose.
- \( y \) (ndarray) – Values from which to choose.
Returns

An array with elements from \( x \) where condition is True, and elements from \( y \) elsewhere.

Return type \( \text{ndarray()} \)

Note: During backpropagation, this function propagates the gradient of the output array to the input array \( x \) and \( y \).

See also:

numpy.where()

chainerx.nonzero

chainerx.nonzero(a)

Return the indices of the elements that are non-zero.

Parameters a (ndarray) – Input array.

Returns Indices of elements that are non-zero.

Return type tuple of ndarray()

Note: During backpropagation, this function does not propagate gradients.

See also:

numpy.nonzero()

Linear algebra

| chainerx.dot | Returns a dot product of two arrays. |
| chainerx.linalg.cholesky | Computes the Cholesky decomposition of a matrix. |
| chainerx.linalg.qr | Compute the qr factorization of a matrix. |
| chainerx.linalg.svd | Compute the eigenvalues and eigenvectors of a real symmetric matrix. |
| chainerx.linalg.eigh | Compute the eigenvalues of a real symmetric matrix. |
| chainerx.linalg.solve | Solves a linear matrix equation, or system of linear scalar equations. |
| chainerx.linalg.inv | Computes the inverse of a matrix. |
| chainerx.linalg.pinv | Compute the (Moore-Penrose) pseudo-inverse of a matrix. |
chainerx.dot

chainerx.dot(a, b)
Returns a dot product of two arrays.

For arrays with more than one axis, it computes the dot product along the last axis of a and the second-to-last axis of b. This is just a matrix product if the both arrays are 2-D. For 1-D arrays, it uses their unique axis as an axis to take dot product over.

Parameters

- a (ndarray) – The left argument.
- b (ndarray) – The right argument.

Returns Output array.
Return type ndarray

Note: This function currently does not support N > 2 dimensional arrays.

Note: During backpropagation, this function propagates the gradient of the output array to input arrays a and b.

See also:

numpy.dot()

chainerx.linalg.cholesky

chainerx.linalg.cholesky(a)
Computes the Cholesky decomposition of a matrix.

Returns the Cholesky decomposition, \( A = LL^T \), for the square matrix a.

Parameters a (ndarray) – Symmetric positive-definite input matrix.

Return type ndarray

Note: The forward computation does not necessarily check if the input matrix is symmetric (e.g. the native backend relying on LAPACK does not). However, both the forward and the backward computations assume that it is and their results are unspecified otherwise. The computed gradient is always a symmetric matrix. More specifically, the gradient is computed as if the function is restricted to a Riemannian submanifold of \( \mathbb{R}^{n \times n} \) consisting just of positive-definite symmetric matrices and is faithful to the mathematical definition of the Cholesky decomposition.

Note:

- GPU implementation of the Cholesky decomposition routine is based on cuSOLVER library. Older versions (<10.1) of it might not raise an error for some non positive-definite matrices.
- The dtype must be float32 or float64 (float16 is not supported yet.)
chainerx.linalg.qr

chainerx.linalg.qr (a, mode='reduced')

Compute the qr factorization of a matrix.

Factor the matrix a as qr, where q is orthonormal and r is upper-triangular.

Parameters
• a (ndarray) – Matrix to be factored.
• mode (str) – The mode of decomposition. ‘reduced’ : returns q, r with dimensions (M, K), (K, N) (default) ‘complete’ : returns q, r with dimensions (M, M), (M, N) ‘r’ : returns r only with dimensions (K, N) ‘raw’ : returns h, tau with dimensions (N, M), (K,), where (M, N) is the shape of the input matrix and K = min(M, N)

Returns A matrix with orthonormal columns. r (~chainerx.ndarray): The upper-triangular matrix.

Return type q (ndarray)

Note:
• The dtype must be float32 or float64 (float16 is not supported yet.)
• Backpropagation is not implemented for non-square output matrix r.
• Backpropagation is not implemented for ‘r’ or ‘raw’ modes.

See also:
numpy.linalg.qr()

chainerx.linalg.svd

chainerx.linalg.svd (a, full_matrices=True, compute_uv=True)

Singular Value Decomposition.

Factorizes the matrix a into two unitary matrices U and Vt, and a 1-D array s of singular values such that a == U * S * Vt, where S is a suitably shaped matrix of zeros with main diagonal s and * represents a dot product.

Parameters
• a (ndarray) – The input matrix with dimension (M, N).
• full_matrices (bool) – If True, it returns u and v with dimensions (M, M) and (N, N). Otherwise, the dimensions of u and v are respectively (M, K) and (K, N), where K = min(M, N).
• compute_uv (bool) – If False, only singular values are computed.

Returns A tuple of (U, s, Vt) such that a = U * diag(s) * Vt. When compute_uv is False only singular values s are returned.
Return type  tuple of `chainerx.ndarray`

Note:

- The dtype must be `float32` or `float64` (float16 is not supported yet.)
- The SVD is commonly written as $a = U \cdot \text{diag}(s) \cdot V^T$. The $Vt$ returned by this function is $V^T$.
- During backpropagation, this function requires $U$ and $Vt$ computed, therefore differentiation does not work for `compute_uv=False`.
- Backpropagation is not implemented for `full_matrices=True`.

See also:

`numpy.linalg.svd()`

`chainerx.linalg.eigh`

`chainerx.linalg.eigh(a, UPLO='L')`

Compute the eigenvalues and eigenvectors of a real symmetric matrix.

Parameters

- `a` (ndarray) – Real symmetric matrix whose eigenvalues and eigenvectors are to be computed.
- `UPLO` (str) – Specifies whether the calculation is done with the lower triangular part of a (`'L'`, default) or the upper triangular part (`'U'`).

Returns

Returns a tuple $(w, v)$.

- $w$ contains eigenvalues and $v$ contains eigenvectors.
- $v[:, i]$ is an eigenvector corresponding to an eigenvalue $w[i]$.

Return type  tuple of `ndarray`

Note:  Although `UPLO` can be specified to ignore either the strictly lower or upper part of the input matrix, the backward computation assumes that the inputs is symmetric and the computed gradient is always a symmetric matrix with respect to `UPLO`. More specifically, the gradient is computed as if the function is restricted to a Riemannian submanifold of $\mathbb{R}^{n \times n}$ consisting just of symmetric matrices and is faithful to the mathematical definition of the eigenvalue decomposition of symmetric matrices.

See also:

`numpy.linalg.eigh()`

Note:  The dtype must be `float32` or `float64` (float16 is not supported yet.)
chainerx.linalg.eigvalsh

chainerx.linalg.eigvalsh(a, UPLO='L')

Compute the eigenvalues of a real symmetric matrix.
Main difference from eigh: the eigenvectors are not computed.

Parameters

- **a** (ndarray) – Real symmetric matrix whose eigenvalues and eigenvectors are to be computed.
- **UPLO** (str) – Specifies whether the calculation is done with the lower triangular part of a ('L', default) or the upper triangular part ('U'). (optional).

Returns Returns eigenvalues as a vector.

Return type ndarray

Note:

- The dtype must be float32 or float64 (float16 is not supported yet.)
- Backpropagation requires eigenvectors and, therefore, is not implemented for this function. linalg.eigh should be used instead.

See also:

numpy.linalg.eigvalsh()

chainerx.linalg.solve

chainerx.linalg.solve(a, b)

Solves a linear matrix equation, or system of linear scalar equations.
It computes the exact solution of \( x \) in \( ax = b \), where \( a \) is a square and full rank matrix, \( b \) can be a vector, or a rectangular matrix. When \( b \) is matrix, its columns are treated as separate vectors representing multiple right-hand sides.

Parameters

- **a** (ndarray) – Coefficient matrix.
- **b** (ndarray) – “dependent variable” values.

Returns Solution to the system \( ax = b \). Shape is identical to \( b \).

Return type ndarray

Note: The dtype must be float32 or float64 (float16 is not supported yet.)

See also:

numpy.linalg.solve()
chainerx.linalg.inv

chainerx.linalg.inv(a)

Computes the inverse of a matrix.

This function computes matrix \( a^{-1} \) from square matrix \( a \) such that \( \text{dot}(a, a^{-1}) = \text{dot}(a^{-1}, a) = \text{eye}(a\text{.shape}[0]) \).

**Parameters**

- **a** (*ndarray*) – The matrix to be inverted.

**Returns**

The inverse of a matrix.

**Return type**

*ndarray*

**Note:** The `dtype` must be `float32` or `float64` (float16 is not supported yet.)

**See also:**

numpy.linalg.inv()

chainerx.linalg.pinv

chainerx.linalg.pinv(a, rcond=1e-15)

Compute the (Moore-Penrose) pseudo-inverse of a matrix.

Calculate the generalized inverse of a matrix using its singular-value decomposition (SVD) and including all large singular values.

**Parameters**

- **a** (*ndarray*) – The input matrix to be pseudo-inverted.
- **rcond** (*float*) – Cutoff for small singular values.

**Returns**

The pseudo-inverse of \( a \).

**Return type**

*ndarray*

**Note:** The `dtype` must be `float32` or `float64` (float16 is not supported yet.)

**See also:**

numpy.linalg.pinv()

**Logic functions**

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainerx.all</td>
<td>Test whether all array elements along a given axis evaluate to True.</td>
</tr>
<tr>
<td>chainerx.any</td>
<td>Test whether any array element along a given axis evaluate to True.</td>
</tr>
<tr>
<td>chainerx.isinf</td>
<td>Test element-wise for positive or negative infinity.</td>
</tr>
<tr>
<td>chainerx.isnan</td>
<td>Test element-wise for NaN and return result as a boolean array.</td>
</tr>
<tr>
<td>chainerx.logical_and</td>
<td>Returns an array of x1 AND x2 element-wise.</td>
</tr>
</tbody>
</table>

continues on next page
Table 9 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainerx.logical_or</code></td>
<td>Returns an array of x1 OR x2 element-wise.</td>
</tr>
<tr>
<td><code>chainerx.logical_xor</code></td>
<td>Returns an array of x1 XOR x2 element-wise.</td>
</tr>
<tr>
<td><code>chainerx.logical_not</code></td>
<td>Returns an array of NOT x element-wise.</td>
</tr>
<tr>
<td><code>chainerx.greater</code></td>
<td>Returns an array of (x1 &gt; x2) element-wise.</td>
</tr>
<tr>
<td><code>chainerx.greater_equal</code></td>
<td>Returns an array of (x1 &gt;= x2) element-wise.</td>
</tr>
<tr>
<td><code>chainerx.less</code></td>
<td>Returns an array of (x1 &lt; x2) element-wise.</td>
</tr>
<tr>
<td><code>chainerx.less_equal</code></td>
<td>Returns an array of (x1 &lt;= x2) element-wise.</td>
</tr>
<tr>
<td><code>chainerx.equal</code></td>
<td>Returns an array of (x1 == x2) element-wise.</td>
</tr>
<tr>
<td><code>chainerx.not_equal</code></td>
<td>Returns an array of (x1 != x2) element-wise.</td>
</tr>
</tbody>
</table>

**chainerx.all**

`chainerx.all(x)`

Test whether all array elements along a given axis evaluate to True.

**Parameters**

- `x (ndarray)` – Input array.
- `axis (None or int or tuple of ints)` – Axis or axes along which AND reduction is performed. The flattened array is used by default.
- `keepdims (bool)` – If this is set to True, the reduced axes are left in the result as dimensions with size one.

**Returns** Output array of type bool.

**Return type** `ndarray`

**Note:** During backpropagation, this function does not propagate gradients.

**See also:**

`numpy.all`

**chainerx.any**

`chainerx.any(x)`

Test whether any array element along a given axis evaluate to True.

**Parameters**

- `x (ndarray)` – Input array.
- `axis (None or int or tuple of ints)` – Axis or axes along which OR reduction is performed. The flattened array is used by default.
- `keepdims (bool)` – If this is set to True, the reduced axes are left in the result as dimensions with size one.

**Returns** Output array of type bool.

**Return type** `ndarray`
Note: During backpropagation, this function does not propagate gradients.

See also:
numpy.any

chainerx.isinf

chainerx.isinf(x)
Test element-wise for positive or negative infinity.

Parameters  
\(x\) (ndarray) – Input array.

Returns  
True where \(x\) is positive or negative infinity, false otherwise.

Return type  
ndarray

Note: During backpropagation, this function does not propagate gradients.

See also:
numpy.isinf

chainerx.isnan

chainerx.isnan(x)
Test element-wise for NaN and return result as a boolean array.

Parameters  
\(x\) (ndarray) – Input array.

Returns  
True where \(x\) is NaN, false otherwise.

Return type  
ndarray

Note: During backpropagation, this function does not propagate gradients.

See also:
numpy.isnan

chainerx.logical_and

chainerx.logical_and(x1, x2)
Returns an array of x1 AND x2 element-wise.

Parameters
• \(x1\) (ndarray) – Input array.
• \(x2\) (ndarray) – Input array.

Returns  
Output array of type bool.

Return type  
ndarray

6.4. Reference
Note: During backpropagation, this function does not propagate gradients.

See also:
numpy.logical_and

chainerx.logical_or

chainerx.logical_or(x1, x2)
Returns an array of x1 OR x2 element-wise.

Parameters
- x1 (ndarray) – Input array.
- x2 (ndarray) – Input array.

Returns Output array of type bool.

Return type ndarray

Note: During backpropagation, this function does not propagate gradients.

See also:
numpy.logical_or

chainerx.logical_xor

chainerx.logical_xor(x1, x2)
Returns an array of x1 XOR x2 element-wise.

Parameters
- x1 (ndarray) – Input array.
- x2 (ndarray) – Input array.

Returns Output array of type bool.

Return type ndarray

Note: During backpropagation, this function does not propagate gradients.

See also:
numpy.logical_xor
chainerx.logical_not

chainerx.logical_not(x)
Returns an array of NOT x element-wise.

Parameters x (ndarray) – Input array.
Returns Output array of type bool.
Return type ndarray

Note: During backpropagation, this function does not propagate gradients.

See also:
numpy.logical_not

chainerx.greater

chainerx.greater(x1, x2)
Returns an array of (x1 > x2) element-wise.

Parameters
• x1 (ndarray) – Input array.
• x2 (ndarray) – Input array.
Returns Output array of type bool.
Return type ndarray

Note: During backpropagation, this function does not propagate gradients.

See also:
numpy.greater

chainerx.greater_equal

chainerx.greater_equal(x1, x2)
Returns an array of (x1 >= x2) element-wise.

Parameters
• x1 (ndarray) – Input array.
• x2 (ndarray) – Input array.
Returns Output array of type bool.
Return type ndarray

Note: During backpropagation, this function does not propagate gradients.

See also:
numpy.greater_equal

chainerx.less

chainerx.less(x1, x2)
  Returns an array of (x1 < x2) element-wise.
  
  Parameters
  - x1 (ndarray) – Input array.
  - x2 (ndarray) – Input array.
  
  Returns Output array of type bool.
  
  Return type ndarray

  Note: During backpropagation, this function does not propagate gradients.

  See also:
  numpy.less

chainerx.less_equal

chainerx.less_equal(x1, x2)
  Returns an array of (x1 <= x2) element-wise.
  
  Parameters
  - x1 (ndarray) – Input array.
  - x2 (ndarray) – Input array.
  
  Returns Output array of type bool.
  
  Return type ndarray

  Note: During backpropagation, this function does not propagate gradients.

  See also:
  numpy.less_equal

chainerx.equal

chainerx.equal(x1, x2)
  Returns an array of (x1 == x2) element-wise.
  
  Parameters
  - x1 (ndarray) – Input array.
  - x2 (ndarray) – Input array.
  
  Returns Output array of type bool.
Return type `ndarray`

**Note:** During backpropagation, this function does not propagate gradients.

**See also:**

`numpy.equal`

### chainerx.not_equal

**chainerx.not_equal**(x₁, x₂)

Returns an array of `(x₁ ≠ x₂)` element-wise.

**Parameters**

- **x₁ (ndarray)** – Input array.
- **x₂ (ndarray)** – Input array.

**Returns**

Output array of type bool.

**Return type** `ndarray`

**Note:** During backpropagation, this function does not propagate gradients.

**See also:**

`numpy.not_equal`

---

**Loss functions**

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainerx.absolute_error</code></td>
<td>Element-wise absolute error function.</td>
</tr>
<tr>
<td><code>chainerx.squared_error</code></td>
<td>Element-wise squared error function.</td>
</tr>
<tr>
<td><code>chainerx.huber_loss</code></td>
<td>Element-wise Huber loss.</td>
</tr>
<tr>
<td><code>chainerx.gaussian_kl_divergence</code></td>
<td>Element-wise KL-divergence of Gaussian variables from the standard one.</td>
</tr>
<tr>
<td><code>chainerx.sigmoid_cross_entropy</code></td>
<td>Element-wise cross entropy loss for pre-sigmoid activations.</td>
</tr>
<tr>
<td><code>chainerx.softmax_cross_entropy</code></td>
<td>Element-wise cross entropy loss for pre-softmax activations.</td>
</tr>
</tbody>
</table>

---

### chainerx.absolute_error

**chainerx.absolute_error()**

Element-wise absolute error function.

Computes the element-wise absolute error `L` between two inputs `x₁` and `x₂` defined as follows.

\[ L = |x₁ - x₂| \]

**Parameters**

- **x₁ (ndarray)** – Input variable.

Returns

A variable holding an array representing the absolute error of two inputs.

Return type

ndarray

See also:

chainer.functions.absolute_error()

chainerx.squared_error

chainerx.squared_error()

Element-wise squared error function.

Computes the element-wise squared error :math:`L` between two inputs \( x_1 \) and \( x_2 \) defined as follows.

\[
L = (x_1 - x_2)^2
\]

Can be used to compute mean squared error by just calling :meth:`mean()` on the output array.

Parameters

- :math:`x0` (ndarray) – Input variable.

Returns

A variable holding an array representing the squared error of two inputs.

Return type

ndarray

See also:

chainer.functions.squared_error()

chainerx.huber_loss

chainerx.huber_loss()

Element-wise Huber loss.

The Huber loss is similar to the squared error but is less sensitive to outliers in the data. It is defined as

\[
L_{\delta}(a) = \begin{cases} 
\frac{1}{2}a^2 & \text{if } |a| \leq \delta \\
\delta(|a| - \frac{1}{2}\delta) & \text{otherwise,}
\end{cases}
\]

where \( a = x - t \) is the difference between the input \( x \) and the target \( t \).

See: Huber loss - Wikipedia.

Parameters

- \( x \) (ndarray) – Input variable.
- \( t \) (ndarray) – Target variable for regression.
- \( \text{delta} \) (float) – Constant variable for Huber loss function as used in definition.

Returns

A variable object holding an array representing the Huber loss :math:`L_{\delta}` of the two inputs.

Return type

ndarray

See also:

chainer.functions.huber_loss()
chainerx.gaussian_kl_divergence

chainerx.gaussian_kl_divergence()
Element-wise KL-divergence of Gaussian variables from the standard one.

Given two variable mean representing \( \mu \) and ln_var representing \( \log(\sigma^2) \), this function calculates the element-wise KL-divergence between the given multi-dimensional Gaussian \( N(\mu, S) \) and the standard Gaussian \( N(0, I) \)

\[
D_{KL}(N(\mu, S)\|N(0, I)),
\]

where \( S \) is a diagonal matrix such that \( S_{ii} = \sigma_i^2 \) and \( I \) is an identity matrix.

Parameters

- mean (ndarray) – A variable representing mean of given gaussian distribution, \( \mu \).
- ln_var (ndarray) – A variable representing logarithm of variance of given gaussian distribution, \( \log(\sigma^2) \).

Returns A variable representing KL-divergence between given gaussian distribution and the standard gaussian.

Return type ndarray

See also:
chainer.functions.gaussian_kl_divergence()

chainerx.sigmoid_cross_entropy

chainerx.sigmoid_cross_entropy(x1, x2)
Element-wise cross entropy loss for pre-sigmoid activations.

Parameters

- x1 (ndarray) – An array whose \((i, j)\)-th element indicates the unnormalized log probability of the \( j \)-th unit at the \( i \)-th example.
- x2 (ndarray) – An array whose \((i, j)\)-th element indicates a signed integer vector of ground truth labels 0 or 1. If \( x2[i, j] == -1 \), corresponding \( x1[i, j] \) is ignored. Loss is zero if all ground truth labels are -1.

Returns An array of the cross entropy.

Return type ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \( x1 \) only.
chainerx.softmax_cross_entropy

chainerx.softmax_cross_entropy(x1, x2)
Element-wise cross entropy loss for pre-softmax activations.

Parameters

- **x1** (ndarray) – An array whose element indicates unnormalized log probability: the first axis of the array represents the number of samples, and the second axis represents the number of classes.
- **x2** (ndarray) – A signed integer vector of ground truth labels. If \(x2[i] == -1\), corresponding \(x1[i]\) is ignored.

Returns
An array of the cross entropy.

Return type
ndarray

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array \(x1\) only.

Mathematical functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainerx.negative</td>
<td>Numerical negative, element-wise.</td>
</tr>
<tr>
<td>chainerx.add</td>
<td>Add arguments, element-wise.</td>
</tr>
<tr>
<td>chainerx.subtract</td>
<td>Subtract arguments, element-wise.</td>
</tr>
<tr>
<td>chainerx.multiply</td>
<td>Multiply arguments, element-wise.</td>
</tr>
<tr>
<td>chainerx.divide</td>
<td>Divide arguments, element-wise.</td>
</tr>
<tr>
<td>chainerx.mod</td>
<td>remainder(x1, x2) Return element-wise remainder of division.</td>
</tr>
<tr>
<td>chainerx.remainder</td>
<td>Return element-wise remainder of division.</td>
</tr>
<tr>
<td>chainerx.sum</td>
<td>Sum of array elements over a given axis.</td>
</tr>
<tr>
<td>chainerx.maximum</td>
<td>Maximum arguments, element-wise.</td>
</tr>
<tr>
<td>chainerx.minimum</td>
<td>Minimum arguments, element-wise.</td>
</tr>
<tr>
<td>chainerx.exp</td>
<td>Numerical exponential, element-wise.</td>
</tr>
<tr>
<td>chainerx.log</td>
<td>Natural logarithm, element-wise.</td>
</tr>
<tr>
<td>chainerx.log10</td>
<td>Base 10 logarithm, element-wise.</td>
</tr>
<tr>
<td>chainerx.log2</td>
<td>Base 2 logarithm, element-wise.</td>
</tr>
<tr>
<td>chainerx.log1p</td>
<td>Natural logarithm of one plus the input, element-wise.</td>
</tr>
<tr>
<td>chainerx.logsumexp</td>
<td>The log of the sum of exponentials of input array.</td>
</tr>
<tr>
<td>chainerx.logsoftmax</td>
<td>The log of the softmax of input array.</td>
</tr>
<tr>
<td>chainerx.sqrt</td>
<td>Non-negative square-root, element-wise</td>
</tr>
<tr>
<td>chainerx.sin</td>
<td>Sine, element-wise</td>
</tr>
<tr>
<td>chainerx.cos</td>
<td>Cosine, element-wise</td>
</tr>
<tr>
<td>chainerx.tan</td>
<td>Tangent, element-wise</td>
</tr>
<tr>
<td>chainerx.arcsin</td>
<td>Inverse sine, element-wise</td>
</tr>
<tr>
<td>chainerx.arccos</td>
<td>Trigonometric inverse cosine, element-wise</td>
</tr>
<tr>
<td>chainerx.arctan</td>
<td>Trigonometric inverse tangent, element-wise</td>
</tr>
<tr>
<td>chainerx.arctan2</td>
<td>Element-wise arc tangent of (\frac{\pi}{2}), choosing the quadrant correctly.</td>
</tr>
<tr>
<td>chainerx.sinh</td>
<td>Hyperbolic Sine, element-wise</td>
</tr>
</tbody>
</table>
Table 11 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainerx.cosh</code></td>
<td>Hyperbolic Cosine, element-wise</td>
</tr>
<tr>
<td><code>chainerx.tanh</code></td>
<td>Element-wise hyperbolic tangent function.</td>
</tr>
<tr>
<td><code>chainerx.arcsinh</code></td>
<td>Inverse hyperbolic sine, element-wise</td>
</tr>
<tr>
<td><code>chainerx.arccosh</code></td>
<td>Inverse hyperbolic inverse cosine, element-wise</td>
</tr>
<tr>
<td><code>chainerx.square</code></td>
<td>Returns the element-wise square of the input.</td>
</tr>
<tr>
<td><code>chainerx.clip</code></td>
<td>Clips the values of an array to a given interval.</td>
</tr>
<tr>
<td><code>chainerx.fabs</code></td>
<td>Compute the absolute values element-wise.</td>
</tr>
<tr>
<td><code>chainerx.sign</code></td>
<td>Returns an element-wise indication of the sign of a number.</td>
</tr>
<tr>
<td><code>chainerx.ceil</code></td>
<td>Return the ceiling of the input, element-wise.</td>
</tr>
<tr>
<td><code>chainerx.floor</code></td>
<td>Return the floor of the input, element-wise.</td>
</tr>
<tr>
<td><code>chainerx.bitwise_and</code></td>
<td>Compute the bit-wise AND of two arrays element-wise.</td>
</tr>
<tr>
<td><code>chainerx.bitwise_or</code></td>
<td>Compute the bit-wise OR of two arrays element-wise.</td>
</tr>
<tr>
<td><code>chainerx.bitwise_xor</code></td>
<td>Compute the bit-wise XOR of two arrays element-wise.</td>
</tr>
<tr>
<td><code>chainerx.left_shift</code></td>
<td>Shift the bits of an integer to the left.</td>
</tr>
<tr>
<td><code>chainerx.right_shift</code></td>
<td>Shift the bits of an integer to the right.</td>
</tr>
</tbody>
</table>

**chainerx.negative**

`chainerx.negative(x)`

Numerical negative, element-wise.

- **Parameters** `x (ndarray)` – Input array.
- **Returns** Returned array: $y = -x$.
- **Return type** `ndarray`

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array $x$.

**See also:**

`numpy.negative`

**chainerx.add**

`chainerx.add(x1, x2)`

Add arguments, element-wise.

- **Parameters**
  - `x1 (ndarray or scalar)` – Input array.
  - `x2 (ndarray or scalar)` – Input array.
- **Returns** Returned array: $y = x_1 + x_2$.
- **Return type** `ndarray`

**Note:** During backpropagation, this function propagates the gradient of the output array to the input arrays $x_1$ and $x_2$.

**See also:**

6.4. Reference
numpy.add

chainerx.subtract

chainerx.subtract(x1, x2)
Subtract arguments, element-wise.

Parameters

• x1 (ndarray or scalar) – Input array.
• x2 (ndarray or scalar) – Input array.

Returns Returned array: $y = x_1 - x_2$.

Return type ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input arrays $x_1$ and $x_2$.

See also:

numpy.subtract

chainerx.multiply

chainerx.multiply(x1, x2)
Multiply arguments, element-wise.

Parameters

• x1 (ndarray or scalar) – Input array.
• x2 (ndarray or scalar) – Input array.

Returns Returned array: $y = x_1 \times x_2$.

Return type ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input arrays $x_1$ and $x_2$.

See also:

numpy.multiply
chainerx.divide

chainerx.divide(x1, x2)
Divide arguments, element-wise.

Parameters

• x1 (ndarray or scalar) – Input array.
• x2 (ndarray or scalar) – Input array.

Returns
Returned array: \( y = \frac{x_1}{x_2} \).

Return type ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input arrays x1 and x2.

See also:

numpy.divide

chainerx.mod

chainerx.mod()
remainder(x1, x2) Return element-wise remainder of division.

Parameters

• x1 (ndarray or scalar) – Input array.
• x2 (ndarray or scalar) – Input array.

Returns
Returned array: The element-wise remainder of the quotient floor_divide(x1, x2).

Return type ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input arrays x1 and x2.

See also:

numpy.remainder

chainerx.remainder

chainerx.remainder(x1, x2)
Return element-wise remainder of division.

Parameters

• x1 (ndarray or scalar) – Input array.
• x2 (ndarray or scalar) – Input array.

Returns
Returned array: The element-wise remainder of the quotient floor_divide(x1, x2).

Return type ndarray
Note: During backpropagation, this function propagates the gradient of the output array to the input arrays \(x_1\) and \(x_2\).

See also:

`numpy.remainder`

**chainerx.sum**

`chainerx.sum(a, axis=None, keepdims=False)`

Sum of array elements over a given axis.

**Parameters**

- \(a\) (ndarray) – Input array.
- \(axis\) (`None` or int or tuple of ints) – Axis or axes along which a sum is performed. The flattened array is used by default.
- \(keepdims\) (bool) – If this is set to `True`, the reduced axes are left in the result as dimensions with size one.

**Returns**
The sum of input elements over a given axis.

**Return type** `ndarray`

Note: During backpropagation, this function propagates the gradient of the output array to the input array \(a\).

See also:

`numpy.sum()`

**chainerx.maximum**

`chainerx.maximum(x1, x2)`

Maximum arguments, element-wise.

**Parameters**

- \(x1\) (ndarray or scalar) – Input array.
- \(x2\) (ndarray or scalar) – Input array.

**Returns**
Returned array: \(y = \max\{x_1, x_2\}\).

**Return type** `ndarray`

Note: During backpropagation, this function propagates the gradient of the output array to the input arrays \(x_1\) and \(x_2\).

See also:

`numpy.maximum`
chainerx.minimum

chainerx.\texttt{minimum}(x1, x2)
Minimum arguments, element-wise.

Parameters
- \(x1\) (ndarray or scalar) – Input array.
- \(x2\) (ndarray or scalar) – Input array.

Returns
Returned array: \(y = \min\{x_1, x_2\}\).

Return type
ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input arrays \(x1\) and \(x2\).

See also:
numpy.minimum

chainerx.exp

chainerx.\texttt{exp}(x)
Numerical exponential, element-wise.

Parameters \(x\) (ndarray) – Input array.

Returns
Returned array: \(y = \exp x\).

Return type
ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \(x\).

See also:
numpy.exp

chainerx.log

chainerx.\texttt{log}(x)
Natural logarithm, element-wise.

Parameters \(x\) (ndarray) – Input array.

Returns
Returned array: \(y = \ln x\).

Return type
ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \(x\).

See also:
numpy.log
chainerx.log10

chainerx.log10(x)
Base 10 logarithm, element-wise.

Parameters
- x (ndarray): Input array.

Returns
- Returned array: $y = \log_{10} x$.

Return type: ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array $x$.

See also:
- numpy.log10

chainerx.log2

chainerx.log2(x)
Base 2 logarithm, element-wise.

Parameters
- x (ndarray): Input array.

Returns
- Returned array: $y = \log_{2} x$.

Return type: ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array $x$.

See also:
- numpy.log2

chainerx.log1p

chainerx.log1p(x)
Natural logarithm of one plus the input, element-wise.

Parameters
- x (ndarray): Input array.

Returns
- Returned array: $y = \log(1 + x)$.

Return type: ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array $x$.

See also:
- numpy.log1p
chainerx.logsumexp

\texttt{chainerx.logsumexp}(x, axis=None, keepdims=False)

The log of the sum of exponentials of input array.

**Parameters**
- \texttt{x (ndarray)} – Input array.
- \texttt{axis (None or int or tuple of ints)} – Axis or axes along which a sum is performed. The flattened array is used by default.
- \texttt{keepdims (bool)} – If this is set to \texttt{True}, the reduced axes are left in the result as dimensions with size one.

**Returns** The log of the sum of exponentials of input elements over a given axis.

**Return type** \texttt{ndarray}

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

chainerx.sqrt

\texttt{chainerx.sqrt}(x)

Non-negative square-root, element-wise

**Parameters** \texttt{x (ndarray)} – Input array.

**Returns** Returned array: \( y = \sqrt{x} \).

**Return type** \texttt{ndarray}

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

See also:
\texttt{numpy.sqrt}

chainerx.sin

\texttt{chainerx.sin}(x)

Sine, element-wise

**Parameters** \texttt{x (ndarray)} – Input array.

**Returns** Returned array: \( y = \sin x \).

**Return type** \texttt{ndarray}

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

See also:
\texttt{numpy.sin}
**chainerx.cos**

chainerx.cos(x)

Cosine, element-wise

Parameters  
  x (ndarray) – Input array.

Returns  
  Returned array: \( y = \cos x \).

Return type  
  ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

See also:

numpy.cos

**chainerx.tan**

chainerx.tan(x)

Tangent, element-wise

Parameters  
  x (ndarray) – Input array.

Returns  
  Returned array: \( y = \tan x \).

Return type  
  ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

See also:

numpy.tan

**chainerx.arcsin**

chainerx.arcsin(x)

Inverse sine, element-wise

Parameters  
  x (ndarray) – Input array.

Returns  
  Returned array: \( y = \arcsin x \).

Return type  
  ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

See also:

numpy.arcsin
chainerx.arccos

chainerx.arccos(x)
Trigonometric inverse cosine, element-wise

Parameters x (ndarray) – Input array.
Returns Returned array: \( y = \arccos x \).
Return type ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

See also:
numpy.arccos

chainerx.arctan

chainerx.arctan(x)
Trigonometric inverse tangent, element-wise

Parameters x (ndarray) – Input array.
Returns Returned array: \( y = \arctan x \).
Return type ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

See also:
numpy.arctan

chainerx.arctan2

chainerx.arctan2(x1, x2)
Element-wise arc tangent of \( \frac{x_1}{x_2} \) choosing the quadrant correctly.

Parameters
- x1 (ndarray) – Input array.
- x2 (ndarray) – Input array.

Returns Returns an array where each element represents \( \theta \) in the range \([-\pi, \pi]\), such that \( x_1 = r \sin(\theta) \) and \( x_2 = r \cos(\theta) \) for some \( r > 0 \).
Return type ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \( x_1 \) and/or \( x_2 \).

See also:
numpy.arctan2
chainerx.sinh

**chainerx.sinh**(*x*)

Hyperbolic Sine, element-wise

**Parameters**
- *x* *(ndarray)* – Input array.

**Returns**
- Returned array: \( y = \sinh x \).

**Return type** *ndarray*

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array *x*.

**See also:**
- numpy.sinh

chainerx.cosh

**chainerx.cosh**(*x*)

Hyperbolic Cosine, element-wise

**Parameters**
- *x* *(ndarray)* – Input array.

**Returns**
- Returned array: \( y = \cosh x \).

**Return type** *ndarray*

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array *x*.

**See also:**
- numpy.cosh

chainerx.arcsinh

**chainerx.arcsinh**(*x*)

Inverse hyperbolic sine, element-wise

**Parameters**
- *x* *(ndarray)* – Input array.

**Returns**
- Returned array: \( y = x \).

**Return type** *ndarray*

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array *x*.

**See also:**
- numpy.arcsinh
chainerx.arccosh

chainerx.arccosh(x)
Inverse hyperbolic inverse cosine, element-wise

Parameters
x (ndarray) – Input array.

Returns
Returned array: \( y = x \).

Return type
ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

See also:
numpy.arccosh

chainerx.square

chainerx.square(x)
Returns the element-wise square of the input.

Parameters
x (ndarray or scalar) – Input data

Returns
Returned array: \( y = x \times x \). A scalar is returned if \( x \) is a scalar.

Return type
ndarray

Note: During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

See also:
numpy.square

chainerx.clip

chainerx.clip(a, a_min, a_max)
Clips the values of an array to a given interval.

Given an interval, values outside the interval are clipped to the interval edges. For example, if an interval of [0, 1] is specified, values smaller than 0 become 0, and values larger than 1 become 1.

Parameters

• a (ndarray) – Array containing elements to clip.

• a_min (scalar) – Minimum value.

• a_max (scalar) – Minimum value.

Returns
An array with the elements of \( a \), but where values \(< a_{min} \) are replaced with \( a_{min} \), and those \( > a_{max} \) with \( a_{max} \).

Return type
ndarray
Note: The `ndarray` typed `a_min` and `a_max` are not supported yet.

Note: During backpropagation, this function propagates the gradient of the output array to the input array `a`.

See also:

`numpy.clip()`

**chainerx.fabs**

`chainerx.fabs(x)`

Compute the absolute values element-wise. :param x: Input array. :type x: ~chainerx.ndarray

Returns The absolute values of `x`, the returned values are always floats.

Return type `ndarray`

See also:

`numpy.fabs`

**chainerx.sign**

`chainerx.sign(x)`

Returns an element-wise indication of the sign of a number. The sign function returns \(-1\) if \(x < 0\), 0 if \(x == 0\), 1 if \(x > 0\). `nan` is returned for `nan` inputs. :param x: Input array. :type x: ~chainerx.ndarray

Returns The sign of `x`.

Return type `ndarray`

See also:

`numpy.sign`

**chainerx.ceil**

`chainerx.ceil(x)`

Return the ceiling of the input, element-wise.

Parameters `x` (ndarray) – Input array.

Returns The ceiling of each element in array.

Return type `ndarray`

See also:

`numpy.ceil`
chainerx.floor

chainerx.floor(x)
Return the floor of the input, element-wise. :

:param x: Input array. :
type x: ~chainerx.ndarray

Returns  The floor of each element in array.

Return type  ndarray

See also:  
numpy.floor

chainerx.bitwise_and

chainerx.bitwise_and(x1, x2)
Compute the bit-wise AND of two arrays element-wise.

Parameters

- x1 (ndarray or scalar) – Input array of integers.
- x2 (ndarray or scalar) – Input array of integers.

Returns  Returned array: \( y = x_1 \& x_2 \)

Return type  ndarray

Note:  During backpropagation, this function does not propagate gradients.

See also:  
numpy.bitwise_and

chainerx.bitwise_or

chainerx.bitwise_or(x1, x2)
Compute the bit-wise OR of two arrays element-wise.

Parameters

- x1 (ndarray or scalar) – Input array of integers.
- x2 (ndarray or scalar) – Input array of integers.

Returns  Returned array: \( y = x_1 | x_2 \)

Return type  ndarray

Note:  During backpropagation, this function does not propagate gradients.

See also:  
numpy.bitwise_or
chainerx.bitwise_xor

chainerx.bitwise_xor(x1, x2)
Compute the bit-wise XOR of two arrays element-wise.

Parameters
• x1 (ndarray or scalar) – Input array of integers.
• x2 (ndarray or scalar) – Input array of integers.

Returns
Returned array: \( y = x_1 \oplus x_2 \)

Return type ndarray

Note: During backpropagation, this function does not propagate gradients.

See also:
numpy.bitwise_xor

chainerx.left_shift

chainerx.left_shift(x1, x2)
Shift the bits of an integer to the left.

Parameters
• x1 (ndarray or scalar) – Input array of integers.
• x2 (ndarray or scalar) – Input array of integers.

Returns
Return x1 with bits shifted x2 times to the left.

Return type ndarray

Note: During backpropagation, this function does not propagate gradients.

See also:
numpy.left_shift

chainerx.right_shift

chainerx.right_shift(x1, x2)
Shift the bits of an integer to the right.

Parameters
• x1 (ndarray or scalar) – Input array of integers.
• x2 (ndarray or scalar) – Input array of integers.

Returns
Return x1 with bits shifted x2 times to the right.

Return type ndarray
Note: During backpropagation, this function does not propagate gradients.

See also:
numpy.right_shift

Random sampling

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainerx.random.normal</td>
<td>Draws random samples from a normal (Gaussian) distribution.</td>
</tr>
<tr>
<td>chainerx.random.uniform</td>
<td>Draws samples from a uniform distribution.</td>
</tr>
</tbody>
</table>

chainerx.random.normal

chainerx.random.normal(*args, **kwargs, device=None)

Draws random samples from a normal (Gaussian) distribution.

This is currently equivalent to numpy.random.normal() wrapped by chainerx.array(), given the device argument.

See also:
numpy.random.normal()

chainerx.random.uniform

chainerx.random.uniform(*args, **kwargs, device=None)

Draws samples from a uniform distribution.

This is currently equivalent to numpy.random.normal() wrapped by chainerx.array(), given the device argument.

See also:
numpy.random.uniform()

Sorting, searching, and counting

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainerx.argmax</td>
<td>Returns the indices of the maximum along an axis.</td>
</tr>
<tr>
<td>chainerx.argmin</td>
<td>Returns the indices of the minimum along an axis.</td>
</tr>
</tbody>
</table>
**chainerx.argmax**

**chainerx.argmax**(\(a, axis=None\))

Returns the indices of the maximum along an axis.

**Parameters**

- \(a\) (ndarray) – Array to take the indices of the maximum of.
- \(axis\) (None or int) – Along which axis to compute the maximum. The flattened array is used by default.

**Returns**

The indices of the maximum of \(a\), along the axis if specified.

**Return type**

ndarray

**See also:**

numpy.argmax()

**chainerx.argmin**

**chainerx.argmin**(\(a, axis=None\))

Returns the indices of the minimum along an axis.

**Parameters**

- \(a\) (ndarray) – Array to take the indices of the minimum of.
- \(axis\) (None or int) – Along which axis to compute the minimum. The flattened array is used by default.

**Returns**

The indices of the minimum of \(a\), along the axis if specified.

**Return type**

ndarray

**See also:**

numpy.argmin()

**Statistics**

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>chainerx.amax</strong></td>
<td>Returns the maximum of an array or the maximum along an axis.</td>
</tr>
<tr>
<td><strong>chainerx.mean</strong></td>
<td>Compute the arithmetic mean along the specified axis.</td>
</tr>
<tr>
<td><strong>chainerx.var</strong></td>
<td>Compute the arithmetic var along the specified axis.</td>
</tr>
</tbody>
</table>

**chainerx.amax**

**chainerx.amax**(\(a, axis=None, keepdims=False\))

Returns the maximum of an array or the maximum along an axis.

**Note:** When at least one element is NaN, the corresponding max value will be NaN.

**Parameters**
**amax**

- **a** (*ndarray*) – Array to take the maximum.
- **axis** (*None or int or tuple of ints*) – Along which axis to take the maximum. The flattened array is used by default. If this is a tuple of ints, the maximum is selected over multiple axes, instead of a single axis or all the axes.
- **keepdims** (*bool*) – If True, the axis is remained as an axis of size one.

**Returns** The maximum of a, along the axis if specified.

**Return type** *ndarray*

---

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array a.

**See also:**

numpy.amax()

### chainerx.mean

**chainerx.mean** (*a*, **axis**=*None*, **keepdims**=*False*)

Compute the arithmetic mean along the specified axis.

Returns the average of the array elements. The average is taken over the flattened array by default, otherwise over the specified axis.

**Parameters**

- **a** (*ndarray*) – Array to take the mean of.
- **axis** (*None or int or tuple of ints*) – Along which axis or axes to compute mean. The flattened array is used by default.
- **keepdims** (*bool*) – If this is set to True, the axes which are reduced are in the result as dimensions with size one. With this option, the result will broadcast correctly against the input array.

**Returns** The mean of a, along the axis or axes if specified.

**Return type** *ndarray*

**See also:**

numpy.mean()
chainerx.var

chainerx.var\( (a, \text{axis}\!=\!\text{None}, \text{keepdims}\!=\!\text{False}) \)
Compute the arithmetic var along the specified axis.

Returns the var of the array elements. The var is taken over the flattened array by default, otherwise over the specified axis.

Parameters

- \( a \) (ndarray) – Array to take the var of.
- \( \text{axis} \) (None or int or tuple of ints) – Along which axis or axes to compute var. The flattened array is used by default. (the)
- \( \text{keepdims} \) (bool) – If this is set to True, the axes which are reduced are in the result as dimensions with size one. With this option, the result will broadcast correctly against the input array. (the)

Returns The var of \( a \), along the axis or axes if specified.

Return type ndarray

See also: numpy.var()

Connection

<table>
<thead>
<tr>
<th>chainerx.conv</th>
<th>N-dimensional convolution.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainerx.conv_transpose</td>
<td>N-dimensional transposed convolution.</td>
</tr>
<tr>
<td>chainerx.linear</td>
<td>Linear function, or affine transformation.</td>
</tr>
<tr>
<td>chainerx.lstm</td>
<td>Long Short-Term Memory units as an activation function.</td>
</tr>
</tbody>
</table>

chainerx.conv

chainerx.conv\( (x, w, b\!=\!\text{None}, \text{stride}\!=\!1, \text{pad}\!=\!0, \text{cover_all}\!=\!\text{False}) \)
N-dimensional convolution.

This is an implementation of N-dimensional convolution which is generalized two-dimensional convolution in ConvNets. It takes three arrays: the input \( x \), the filter weight \( w \) and the bias vector \( b \).

Notation: here is a notation for dimensionalities.

- \( N \) is the number of spatial dimensions.
- \( n \) is the batch size.
- \( c_I \) and \( c_O \) are the number of the input and output channels, respectively.
- \( d_1, d_2, ..., d_N \) are the size of each axis of the input’s spatial dimensions, respectively.
- \( k_1, k_2, ..., k_N \) are the size of each axis of the filters, respectively.
- \( l_1, l_2, ..., l_N \) are the size of each axis of the output’s spatial dimensions, respectively.
**p_1, p_2, ..., p_N** are the size of each axis of the spatial padding size, respectively.

Then the **conv** function computes correlations between filters and patches of size \((k_1, k_2, ..., k_N)\) in \(x\). Note that correlation here is equivalent to the inner product between expanded tensors. Patches are extracted at positions shifted by multiples of **stride** from the first position \((-p_1, -p_2, ..., -p_N)\) for each spatial axis.

Let \((s_1, s_2, ..., s_N)\) be the stride of filter application. Then, the output size \((l_1, l_2, ..., l_N)\) is determined by the following equations:

\[
l_n = \frac{(d_n + 2p_n - k_n)}{s_n} + 1 \quad (n = 1, ..., N)
\]

If **cover_all** option is True, the filter will cover the all spatial locations. So, if the last stride of filter does not cover the end of spatial locations, an additional stride will be applied to the end part of spatial locations. In this case, the output size is determined by the following equations:

\[
l_n = \frac{(d_n + 2p_n - k_n + s_n - 1)}{s_n} + 1 \quad (n = 1, ..., N)
\]

**Parameters**

- **x** *(ndarray)* – Input array of shape \((n, c_I, d_1, d_2, ..., d_N)\).
- **w** *(ndarray)* – Weight array of shape \((c_O, c_I, k_1, k_2, ..., k_N)\).
- **b** *(None or ndarray)* – One-dimensional bias array with length \(c_O\) (optional).
- **stride** *(int or tuple of int)* – Stride of filter applications \((s_1, s_2, ..., s_N)\). **stride**=s is equivalent to \((s, s, ..., s)\).
- **pad** *(int or tuple of int)* – Spatial padding width for input arrays \((p_1, p_2, ..., p_N)\). **pad**=p is equivalent to \((p, p, ..., p)\).
- **cover_all** *(bool)* – If True, all spatial locations are convoluted into some output pixels. It may make the output size larger. **cover_all** needs to be False if you want to use cuda backend.

**Returns** Output array of shape \((n, c_O, l_1, l_2, ..., l_N)\).

**Return type** *ndarray*

**Note:** In cuda backend, this function uses cuDNN implementation for its forward and backward computation.

**Note:** In cuda backend, this function has following limitations yet:

- The **cover_all**=True option is not supported yet.
- The dtype must be float32 or float64 (float16 is not supported yet.)

**Note:** During backpropagation, this function propagates the gradient of the output array to input arrays \(x\), \(w\), and \(b\).

**See also:**

```
chainer.functions.convolution_nd()
```

**Example**
```python
>>> n = 10
>>> c_i, c_o = 3, 1
>>> d1, d2, d3 = 30, 40, 50
>>> k1, k2, k3 = 10, 10, 10
>>> p1, p2, p3 = 5, 5, 5
>>> x = chainerx.random.uniform(0, 1, (n, c_i, d1, d2, d3)).astype(np.float32)
>>> x.shape
(10, 3, 30, 40, 50)
>>> w = chainerx.random.uniform(0, 1, (c_o, c_i, k1, k2, k3)).astype(np.float32)
>>> w.shape
(1, 3, 10, 10, 10)
>>> b = chainerx.random.uniform(0, 1, (c_o)).astype(np.float32)
>>> b.shape
(1,)
>>> s1, s2, s3 = 2, 4, 6
>>> y = chainerx.conv(x, w, b, stride=(s1, s2, s3), pad=(p1, p2, p3))
>>> y.shape
(10, 1, 16, 11, 9)
```

```
chainerx.conv_transpose

chainerx.conv_transpose(x, w=b=None, stride=1, pad=0, outsize=None)
N-dimensional transposed convolution.

This is an implementation of N-dimensional transposed convolution, which is previously known as deconvolution in Chainer.

It takes three arrays: the input x, the filter weight w, and the bias vector b.

Notation: here is a notation for dimensionalities.

- \( N \) is the number of spatial dimensions.
- \( n \) is the batch size.
- \( c_I \) and \( c_O \) are the number of the input and output channels, respectively.
- \( d_1, d_2, \ldots, d_N \) are the size of each axis of the input’s spatial dimensions, respectively.
- \( k_1, k_2, \ldots, k_N \) are the size of each axis of the filters, respectively.
- \( p_1, p_2, \ldots, p_N \) are the size of each axis of the spatial padding size, respectively.
- \( s_1, s_2, \ldots, s_N \) are the stride of each axis of filter application, respectively.

If the `outsize` option is `None`, the output size \((l_1, l_2, \ldots, l_N)\) is determined by the following equations with the items in the above list:

\[
l_n = s_n (d_n - 1) + k_n - 2p_n \quad (n = 1, \ldots, N)
\]
If `outsize` option is given, the output size is determined by `outsize`. In this case, the `outsize` 
\((l_1, l_2, ..., l_N)\) must satisfy the following equations:

\[
d_n = \left\lfloor \frac{(l_n + 2p_n - k_n)}{s_n} \right\rfloor + 1 \quad (n = 1, ..., N)
\]

Parameters

- `x` (*ndarray*) — Input array of shape \((n, c_I, d_1, d_2, ..., d_N)\).
- `w` (*ndarray*) — Weight array of shape \((c_I, c_O, k_1, k_2, ..., k_N)\).
- `b` (None or *ndarray*) — One-dimensional bias array with length \(c_O\) (optional).
- `stride` (int or tuple of int) — Stride of filter applications \((s_1, s_2, ..., s_N)\).
  `stride=s` is equivalent to \((s, s, ..., s)\).
- `pad` (int or tuple of int) — Spatial padding width for input arrays \((p_1, p_2, ..., p_N)\).
  `pad=p` is equivalent to \((p, p, ..., p)\).
- `outsize` (None or tuple of int) — Expected output size of deconvolutional operation.
  It should be a tuple of ints \((l_1, l_2, ..., l_N)\). Default value is None and the `outsize` is estimated
  by input size, stride and pad.

Returns

Output array of shape \((n, c_O, l_1, l_2, ..., l_N)\).

Return type *ndarray*

Note: During backpropagation, this function propagates the gradient of the output array to input arrays `x`, `w`, and `b`.

See also:

`chainer.functions.deconvolution_nd()`

Example

**Example1**: the case when `outsize` is not given.

```python
>>> n = 10
>>> c_i, c_o = 3, 1
>>> d1, d2, d3 = 5, 10, 15
>>> k1, k2, k3 = 10, 10, 10
>>> p1, p2, p3 = 5, 5, 5
>>> x = chainerx.random.uniform(0, 1, (n, c_i, d1, d2, d3)).astype(np.float32)
>>> x.shape
(10, 3, 5, 10, 15)
>>> w = chainerx.random.uniform(0, 1, (c_i, c_o, k1, k2, k3)).astype(np.float32)
>>> w.shape
(3, 10, 10, 10)
>>> b = chainerx.random.uniform(0, 1, (c_o)).astype(np.float32)
>>> b.shape
(10,)
>>> s1, s2, s3 = 2, 4, 6
>>> y = chainerx.conv_transpose(x, w, b, stride=(s1, s2, s3), pad=(p1, p2, p3))
>>> y.shape
(10, 1, 8, 36, 84)
>>> l1 = s1 * (d1 - 1) + k1 - 2 * p1
>>> l2 = s2 * (d2 - 1) + k2 - 2 * p2
>>> l3 = s3 * (d3 - 1) + k3 - 2 * p3
(continues on next page)```
Example2: the case when `outsize` is given.

```python
>>> n = 10
>>> c_i, c_o = 3, 1
>>> d1, d2, d3 = 5, 10, 15
>>> k1, k2, k3 = 10, 10, 10
>>> p1, p2, p3 = 5, 5, 5
>>> x = chainerx.array(np.random.uniform(0, 1, (n, c_i, d1, d2, d3)).astype(np.float32))
>>> x.shape
(10, 3, 5, 10, 15)
>>> w = chainerx.array(np.random.uniform(0, 1, (c_i, c_o, k1, k2, k3)).astype(np.float32))
>>> w.shape
(3, 1, 10, 10, 10)
>>> b = chainerx.array(np.random.uniform(0, 1, (c_o))).astype(np.float32)
>>> b.shape
(1,)
>>> s1, s2, s3 = 2, 4, 6
>>> l1, l2, l3 = 9, 38, 87
>>> d1 == int((l1 + 2 * p1 - k1) / s1) + 1
True
>>> d2 == int((l2 + 2 * p2 - k2) / s2) + 1
True
>>> d3 == int((l3 + 2 * p3 - k3) / s3) + 1
True
>>> y = chainerx.conv_transpose(x, w, b, stride=(s1, s2, s3), pad=(p1, p2, p3), outsize=(l1, l2, l3))
>>> y.shape
(10, 1, 9, 38, 87)
>>> y.shape == (n, c_o, l1, l2, l3)
True
```

**chainerx.linear**

chainerx.linear(x, W, b=None, n_batch_axis=1)

Linear function, or affine transformation.

It accepts two or three arguments: an input minibatch `x`, a weight matrix `W`, and optionally a bias vector `b`. It computes

\[ Y = xW^T + b. \]

**Parameters**

- **x (ndarray)** – Input array, which is a \((s_1, s_2, \ldots, s_n)\)-shaped array.
- **W (ndarray)** – Weight variable of shape \((M, N)\), where \((N = s_{n\_batch\_axes} \times \cdots \times s_n)\).
- **b (ndarray)** – Bias variable (optional) of shape \((M,)\).
- **n_batch_axes (int)** – The number of batch axes. The default is 1. The input variable is reshaped into \((n\_batch\_axes + 1)\)-dimensional tensor. This should be greater than 0.
Returns
Output array with shape of \((s_1, ..., s_{n_{\text{batch axes}}}, M)\).

Return type \(\text{ndarray}\)

Note: During backpropagation, this function propagates the gradient of the output array to input arrays \(x\), \(w\) and \(b\).

cchainex.lstm

\texttt{chainerx.lstm}(c\_prev, x)

Long Short-Term Memory units as an activation function.

This function implements LSTM units with forget gates. Let the previous cell state \(c_{\text{prev}}\) and the input array \(x\). First, the input array \(x\) is split into four arrays \(a, i, f, o\) of the same shapes along the second axis. It means that \(x\) ’s second axis must have 4 times the \(c_{\text{prev}}\)’s second axis. The split input arrays are corresponding to:

- \(a\): sources of cell input
- \(i\): sources of input gate
- \(f\): sources of forget gate
- \(o\): sources of output gate

Second, it computes the updated cell state \(c\) and the outgoing signal \(h\) as

\[
\begin{align*}
c &= \tanh(a)\sigma(i) + c_{\text{prev}}\sigma(f), \\
h &= \tanh(c)\sigma(o),
\end{align*}
\]

where \(\sigma\) is the elementwise sigmoid function. These are returned as a tuple of two variables. This function supports variable length inputs. The mini-batch size of the current input must be equal to or smaller than that of the previous one. When mini-batch size of \(x\) is smaller than that of \(c\), this function only updates \(c[0:len(x)]\) and doesn’t change the rest of \(c, c[len(x):]\). So, please sort input sequences in descending order of lengths before applying the function.

Parameters

- \(c_{\text{prev}}\) (\text{array}) – Variable that holds the previous cell state. The cell state should be a zero array or the output of the previous call of LSTM.
- \(x\) (\text{array}) – Variable that holds the sources of cell input, input gate, forget gate and output gate. It must have the second dimension whose size is four times of that of the cell state.

Returns
Two \texttt{array} objects \(c\) and \(h\). \(c\) is the updated cell state. \(h\) indicates the outgoing signal.

Return type \texttt{tuple}

See the original paper proposing LSTM with forget gates: Long Short-Term Memory in Recurrent Neural Networks.

Example

Assuming \(y\) is the current incoming signal, \(c\) is the previous cell state, and \(h\) is the previous outgoing signal from an \texttt{lstm} function. Each of \(y, c\) and \(h\) has \texttt{n\_units} channels. Most typical preparation of \(x\) is

```python
>>> n_units = 100
>>> c_prev = chainerx.zeros((1, n_units), chainerx.float32)
>>> x = chainerx.zeros((1, 4 * n_units), chainerx.float32)
>>> c, h = chainerx.lstm(c_prev, x)
```
It corresponds to calculate the input array $x$, or the input sources $a, i, f, o$, from the current incoming signal $y$ and the previous outgoing signal $h$. Different parameters are used for different kind of input sources.

### Normalization

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainerx.batch_norm</code></td>
<td>Batch normalization function.</td>
</tr>
<tr>
<td><code>chainerx.fixed_batch_norm</code></td>
<td>Batch normalization function with fixed statistics.</td>
</tr>
</tbody>
</table>

#### `chainerx.batch_norm` function

`chainerx.batch_norm(x, gamma, beta, running_mean, running_var, eps=2e-05, decay=0.9, axis=None)`

Batch normalization function.

It takes the input array $x$ and two parameter arrays $gamma$ and $beta$. The parameter arrays must both have the same size.

**Parameters**

- $x$ (ndarray) – Input array.
- $gamma$ (ndarray) – Scaling parameter of normalized data.
- $beta$ (ndarray) – Shifting parameter of scaled normalized data.
- $running_mean$ (ndarray) – Running average of the mean. This is a running average of the mean over several mini-batches using the decay parameter. The function takes a previous running average, and updates the array in-place by the new running average.
- $running_var$ (ndarray) – Running average of the variance. This is a running average of the variance over several mini-batches using the decay parameter. The function takes a previous running average, and updates the array in-place by the new running average.
- $eps$ (float) – Epsilon value for numerical stability.
- $decay$ (float) – Decay rate of moving average. It is used during training.
- $axis$ (int, tuple of int or None) – Axis over which normalization is performed. When axis is None, the first axis is treated as the batch axis and will be reduced during normalization.

**Note:** During backpropagation, this function propagates the gradient of the output array to the input arrays $x$, $gamma$ and $beta$.

See: Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift
**chainerx.fixed_batch_norm**

**chainerx.fixed_batch_norm**(x, gamma, beta, mean, var, eps=2e-05, axis=None)

Batch normalization function with fixed statistics.

This is a variant of `batch_norm()`, where the mean and array statistics are given by the caller as fixed variables.

**Parameters**

- **x** (ndarray) – Input array.
- **gamma** (ndarray) – Scaling parameter of normalized data.
- **beta** (ndarray) – Shifting parameter of scaled normalized data.
- **mean** (ndarray) – Shifting parameter of input.
- **var** (ndarray) – Square of scaling parameter of input.
- **eps** (float) – Epsilon value for numerical stability.
- **axis** (int, tuple of int or None) – Axis over which normalization is performed. When axis is None, the first axis is treated as the batch axis and will be reduced during normalization.

**Note:** During backpropagation, this function does not propagate gradients.

---

**Pooling**

- **chainerx.max_pool**
  Spatial max pooling function.

- **chainerx.average_pool**
  Spatial average pooling function.

**chainerx.max_pool**

**chainerx.max_pool**(x, ksize, stride=None, pad=0, cover_all=False)

Spatial max pooling function.

This acts similarly to `conv()`, but it computes the maximum of input spatial patch for each channel without any parameter instead of computing the inner products.

**Parameters**

- **x** (ndarray) – Input array.
- **ksize** (int or tuple of ints) – Size of pooling window. ksize=k and ksize=(k, k, ..., k) are equivalent.
- **stride** (int or tuple of ints or None) – Stride of pooling applications. stride=s and stride=(s, s, ..., s) are equivalent. If None is specified, then it uses same stride as the pooling window size.
- **pad** (int or tuple of ints) – Spatial padding width for the input array. pad=p and pad=(p, p, ..., p) are equivalent.
- **cover_all** (bool) – If True, all spatial locations are pooled into some output pixels. It may make the output size larger.
Returns Output array.
Return type `ndarray`

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array \( x \). This function is only differentiable up to the second order.

**Note:** In `cuda` backend, only 2 and 3 dim arrays are supported as \( x \) because cuDNN pooling supports 2 and 3 spatial dimensions.

### `chainerx.average_pool`

```python
chainerx.average_pool(x, ksize, stride=None, pad=0, pad_mode='ignore')
```

Spatial average pooling function.

This acts similarly to `conv()`, but it computes the average of input spatial patch for each channel without any parameter instead of computing the inner products.

**Parameters**

- \( x \) (`ndarray`) – Input array.
- `ksize` (`int` or `tuple of ints`) – Size of pooling window. \( ksize=k \) and \( ksize=(k, k, ..., k) \) are equivalent.
- `stride` (`int` or `tuple of ints` or `None`) – Stride of pooling applications. \( stride=s \) and \( stride=(s, s, ..., s) \) are equivalent. If `None` is specified, then it uses same stride as the pooling window size.
- `pad` (`int` or `tuple of ints`) – Spatial padding width for the input array. \( pad=p \) and \( pad=(p, p, ..., p) \) are equivalent.
- `pad_mode` (`{'zero', 'ignore'}`) – Specifies how padded region is treated.
  - 'zero' – the values in the padded region are treated as 0
  - 'ignore' – padded region is ignored (default)

Returns Output array.
Return type `ndarray`

**Note:** During backpropagation, this function propagates the gradient of the output array to the input array \( x \).

**Note:** In `cuda` backend, only 2 and 3 dim arrays are supported as \( x \) because cuDNN pooling supports 2 and 3 spatial dimensions.
RNN

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainerx.n_step_lstm</code></td>
<td>Stacked Uni-directional Long Short-Term Memory function.</td>
</tr>
<tr>
<td><code>chainerx.n_step_bilstm</code></td>
<td>Stacked Bi-directional Long Short-Term Memory function.</td>
</tr>
<tr>
<td><code>chainerx.n_step_gru</code></td>
<td>Stacked Uni-directional Gated Recurrent Unit function.</td>
</tr>
<tr>
<td><code>chainerx.n_step_bigru</code></td>
<td>Stacked Bi-directional Gated Recurrent Unit function.</td>
</tr>
<tr>
<td><code>chainerx.n_step_rnn</code></td>
<td>Stacked Uni-directional RNN function for sequence inputs.</td>
</tr>
<tr>
<td><code>chainerx.n_step_birnn</code></td>
<td>Stacked Bi-directional RNN function for sequence inputs.</td>
</tr>
</tbody>
</table>

**`chainerx.n_step_lstm`**

```python
chainerx.n_step_lstm(n_layers, hx, cx, ws, bs, xs)
```

Stacked Uni-directional Long Short-Term Memory function.

This function calculates stacked Uni-directional LSTM with sequences. This function gets an initial hidden state \( h_0 \), an initial cell state \( c_0 \), an input sequence \( x \), weight matrices \( W \), and bias vectors \( b \). This function calculates hidden states \( h_t \) and \( c_t \) for each time \( t \) from input \( x_t \).

\[
egin{align*}
    i_t &= \sigma(W_0 x_t + W_4 h_{t-1} + b_0 + b_4) \\
    f_t &= \sigma(W_1 x_t + W_5 h_{t-1} + b_1 + b_5) \\
    o_t &= \sigma(W_2 x_t + W_6 h_{t-1} + b_2 + b_6) \\
    a_t &= \tanh(W_3 x_t + W_7 h_{t-1} + b_3 + b_7) \\
    c_t &= f_t \cdot c_{t-1} + i_t \cdot a_t \\
    h_t &= o_t \cdot \tanh(c_t)
\end{align*}
\]

As the function accepts a sequence, it calculates \( h_t \) for all \( t \) with one call. Eight weight matrices and eight bias vectors are required for each layer. So, when \( S \) layers exist, you need to prepare \( 8\times S \) weight matrices and \( 8\times S \) bias vectors. If the number of layers \( n\_layers \) is greater than 1, the input of the \( k \)-th layer is the hidden state \( h_{k-1} \) of the \( k-1 \)-th layer. Note that all input variables except the first layer may have different shape from the first layer.

**Parameters**

- **n_layers** (*int*) – The number of layers.
- **hx** (*array*) – Variable holding stacked hidden states. Its shape is \((S, B, N)\) where \( S \) is the number of layers and is equal to \( n\_layers \), \( B \) is the mini-batch size, and \( N \) is the dimension of the hidden units.
- **cx** (*array*) – Variable holding stacked cell states. It has the same shape as \( hx \).
- **ws** (list of list of *array*) – Weight matrices. \( ws[i] \) represents the weights for the \( i \)-th layer. Each \( ws[i] \) is a list containing eight matrices. \( ws[i][j] \) corresponds to \( W_j \) in the equation. Only \( ws[0][j] \) where \( 0 \leq j < 4 \) are \((N, I)\)-shaped as they are multiplied with input variables, where \( I \) is the size of the input and \( N \) is the dimension of the hidden units. All other matrices are \((N, N)\)-shaped.
- **bs** (list of list of *array*) – Bias vectors. \( bs[i] \) represents the biases for the \( i \)-th layer. Each \( bs[i] \) is a list containing eight vectors. \( bs[i][j] \) corresponds to \( b_j \) in the equation. The shape of each matrix is \((N,)\) where \( N \) is the dimension of the hidden units.
• **xs** (list of array) – A list of array holding input values. Each element xs[t] holds input value for time t. Its shape is (B_t, I), where B_t is the mini-batch size for time t. When sequences have different lengths, they must be sorted in descending order of their lengths. So xs needs to satisfy xs[t].shape[0] >= xs[t + 1].shape[0].

**Returns**

This function returns a tuple containing three elements, hy, cy and ys.

• hy is an updated hidden states whose shape is the same as hx.

• cy is an updated cell states whose shape is the same as cx.

• ys is a list of array. Each element ys[t] holds hidden states of the last layer corresponding to an input xs[t]. Its shape is (B_t, N) where B_t is the mini-batch size for time t, and N is size of hidden units. Note that B_t is the same value as xs[t].

**Return type** tuple

**Note:** The dimension of hidden units is limited to only one size N. If you want to use variable dimension of hidden units, please use chainerx.lstm.

**See also:**

chainerx.lstm()

**Example**

```python
>>> import chainerx as chx
>>> batches = [3, 2, 1]  # support variable length sequences
>>> in_size, out_size, n_layers = 3, 2, 2
>>> xs = [chx.ones((b, in_size)).astype(chx.float32) for b in batches]
>>> [x.shape for x in xs]
[(3, 3), (2, 3), (1, 3)]
>>> h_shape = (n_layers, batches[0], out_size)
>>> hx = chx.ones(h_shape).astype(chx.float32)
>>> cx = chx.ones(h_shape).astype(chx.float32)
>>> w_in = lambda i, j: in_size if i == 0 and j < 4 else out_size
>>> ws = []
>>> bs = []
>>> for n in range(n_layers):
...     ws.append([chx.ones((out_size, w_in(n, i))).astype(np.float32) for i in range(8)])
...     bs.append([chx.ones((out_size,)).astype(chx.float32) for _ in range(8)])
...     w_shape = chx.n_step_lstm(...
...         n_layers, hx, cx, ws, bs, xs)
>>> hy.shape
(2, 3)
>>> cy.shape
(2,)
>>> [hy, cy, ys = chx.n_step_lstm(...
...         n_layers, hx, cx, ws, bs, xs)
>>> hy.shape
(2, 3)
>>> cy.shape
(2,)
```

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chainerx.n_step_bilstm

Stacked Bi-directional Long Short-Term Memory function. This function calculates stacked Bi-directional LSTM with sequences. This function gets an initial hidden state $h_0$, an initial cell state $c_0$, an input sequence $x$, weight matrices $W$, and bias vectors $b$. This function calculates hidden states $h_t$ and $c_t$ for each time $t$ from input $x_t$.

\[
\begin{align*}
i^f_t &= \sigma(W^f_0 x_t + W^f_4 h_{t-1} + b^f_0 + b^f_4), \\
f^f_t &= \sigma(W^f_1 x_t + W^f_5 h_{t-1} + b^f_1 + b^f_5), \\
o^f_t &= \sigma(W^f_2 x_t + W^f_6 h_{t-1} + b^f_2 + b^f_6), \\
a^f_t &= \tanh(W^f_3 x_t + W^f_7 h_{t-1} + b^f_3 + b^f_7), \\
c^f_t &= f^f_t \cdot c^f_{t-1} + i^f_t \cdot a^f_t, \\
h^f_t &= o^f_t \cdot \tanh(c^f_t), \\
i^b_t &= \sigma(W^b_0 x_t + W^b_4 h_{t-1} + b^b_0 + b^b_4), \\
f^b_t &= \sigma(W^b_1 x_t + W^b_5 h_{t-1} + b^b_1 + b^b_5), \\
o^b_t &= \sigma(W^b_2 x_t + W^b_6 h_{t-1} + b^b_2 + b^b_6), \\
a^b_t &= \tanh(W^b_3 x_t + W^b_7 h_{t-1} + b^b_3 + b^b_7), \\
c^b_t &= f^b_t \cdot c^b_{t-1} + i^b_t \cdot a^b_t, \\
h^b_t &= o^b_t \cdot \tanh(c^b_t), \\
[h^f_t; h^b_t]
\end{align*}
\]

where $W^f$ is the weight matrices for forward-LSTM, $W^b$ is weight matrices for backward-LSTM. As the function accepts a sequence, it calculates $h_t$ for all $t$ with one call. Eight weight matrices and eight bias vectors are required for each layer of each direction. So, when $S$ layers exist, you need to prepare $16S$ weight matrices.
and 16.5 bias vectors. If the number of layers `n_layers` is greater than 1, the input of the k-th layer is the hidden state $h_t$ of the k-1-th layer. Note that all input variables except the first layer may have different shape from the first layer.

**Parameters**

- `n_layers` (int) – The number of layers.
- `hx` (array) – Variable holding stacked hidden states. Its shape is $(2S, B, N)$ where $S$ is the number of layers and is equal to `n_layers`, $B$ is the mini-batch size, and $N$ is the dimension of the hidden units. Because of bi-direction, the first dimension length is $2S$.
- `cx` (array) – Variable holding stacked cell states. It has the same shape as `hx`.
- `ws` (list of list of array) – Weight matrices. $ws[2 * l + m]$ represents the weights for the l-th layer of the m-th direction. ($m == 0$ means the forward direction and $m == 1$ means the backward direction.) Each $ws[i]$ is a list containing eight matrices. $ws[i][j]$ corresponds to $W_{ij}$ in the equation. $ws[0][j]$ and $ws[1][j]$ where $0 <= j < 4$ are $(N, I)$-shaped because they are multiplied with input variables, where $I$ is the size of the input. $ws[i][j]$ where $2 <= i$ and $0 <= j < 4$ are $(N, 2N)$-shaped because they are multiplied with two hidden layers $h_t = [h_t^f; h_t^b]$. All other matrices are $(N, N)$-shaped.
- `bs` (list of list of array) – Bias vectors. $bs[2 * l + m]$ represents the weights for the l-th layer of m-th direction. ($m == 0$ means the forward direction and $m == 1$ means the backward direction.) Each $bs[i]$ is a list containing eight vectors. $bs[i][j]$ corresponds to $b_{ij}$ in the equation. The shape of each matrix is $(N,)$.
- `xs` (list of array) – A list of array holding input values. Each element $xs[t]$ holds input value for time $t$. Its shape is $(B_t, I)$, where $B_t$ is the mini-batch size for time $t$. When sequences has different lengths, they must be sorted in descending order of their lengths. So $xs$ needs to satisfy $xs[t].shape[0] >= xs[t + 1].shape[0]$.

**Returns**

This function returns a tuple containing three elements, $hy$, $cy$ and $ys$.

- $hy$ is an updated hidden states whose shape is the same as `hx`.
- $cy$ is an updated cell states whose shape is the same as `cx`.
- $ys$ is a list of array. Each element $ys[t]$ holds hidden states of the last layer corresponding to an input $xs[t]$. Its shape is $(B_t, 2N)$ where $B_t$ is the mini-batch size for time $t$, and $N$ is size of hidden units. Note that $B_t$ is the same value as $xs[t]$.

**Return type** tuple

**Example**

```python
>>> import chainerx as chx
>>> batches = [3, 2, 1] # support variable length sequences
>>> in_size, out_size, n_layers = 3, 2, 2
>>> dropout_ratio = 0.0
>>> xs = [chx.ones((b, in_size)).astype(chx.float32) for b in batches]
>>> [x.shape for x in xs]
[(3, 3), (2, 3), (1, 3)]
>>> h_shape = (n_layers * 2, batches[0], out_size)
>>> hx = chx.ones(h_shape).astype(chx.float32)
>>> cx = chx.ones(h_shape).astype(chx.float32)
>>> def w_in(i, j):
...     if i == 0 and j < 4:
```

(continues on next page)
... return in_size
... elif i > 0 and j < 4:
... return out_size * 2
... else:
... return out_size
...

ws = []
bs = []

for n in range(n_layers):
    for direction in (0, 1):
        ws.append([chx.ones((out_size, w_in(n, i))).astype(np.float32) for i in range(8)])
        bs.append([chx.ones((out_size,)).astype(chx.float32) for _ in range(8)])

ws[0][0].shape  # ws[0:2][:4].shape are (out_size, in_size)
(2, 3)

ws[2][0].shape  # ws[2:][:4].shape are (out_size, 2 * out_size)
(2, 4)

ws[0][4].shape  # others are (out_size, out_size)
(2, 2)

bs[0][0].shape
(2,)

hy, cy, ys = chx.n_step_bilstm(
    n_layers, hx, cx, ws, bs, xs)

hy.shape
(4, 3, 2)

cy.shape
(4, 3, 2)

[y.shape for y in ys]
[(3, 4), (2, 4), (1, 4)]

chainerx.n_step_gru

chainerx.n_step_gru(n_layers, hx, ws, bs, xs)

Stacked Uni-directional Gated Recurrent Unit function. This function calculates stacked Uni-directional GRU with sequences. This function gets an initial hidden state $h_0$, an input sequence $x$, weight matrices $W$, and bias vectors $b$. This function calculates hidden states $h_t$ for each time $t$ from input $x_t$.

$$
r_t = \sigma(W_0 x_t + W_3 h_{t-1} + b_0 + b_3)$$
$$z_t = \sigma(W_1 x_t + W_4 h_{t-1} + b_1 + b_4)$$
$$h'_t = \tanh(W_2 x_t + b_2 + r_t \cdot (W_5 h_{t-1} + b_5))$$
$$h_t = (1 - z_t) \cdot h'_t + z_t \cdot h_{t-1}$$

As the function accepts a sequence, it calculates $h_t$ for all $t$ with one call. Six weight matrices and six bias vectors are required for each layers. So, when $S$ layers exists, you need to prepare $6S$ weight matrices and $6S$ bias vectors. If the number of layers n_layers is greater than 1, input of $k$-th layer is hidden state $h_t$ of $k-1$-th layer. Note that all input variables except first layer may have different shape from the first layer.

Parameters

- **n_layers (int)** – Number of layers.
- **hx (array)** – Variable holding stacked hidden states. Its shape is $(S, B, N)$ where $S$
is number of layers and is equal to n\_layers, B is mini-batch size, and N is dimension of hidden units.

- **ws** (list of list of array) – Weight matrices. ws[i] represents weights for i-th layer. Each ws[i] is a list containing six matrices. ws[i][j] is corresponding with w\_j\_i in the equation. Only ws[0][j] where 0 <= j < 3 is \((N, I)\) shape as they are multiplied with input variables. All other matrices has \((N, N)\) shape.

- **bs** (list of list of array) – Bias vectors. bs[i] represents biases for i-th layer. Each bs[i] is a list containing six vectors. bs[i][j] is corresponding with b\_j\_i in the equation. Shape of each matrix is \((N, I)\) where N is dimension of hidden units.

- **xs** (list of array) – A list of array holding input values. Each element xs[t] holds input value for time t. Its shape is \((B_t, I)\), where B\_t is mini-batch size for time t, and I is size of input units. Note that this function supports variable length sequences. When sequences has different lengths, sort sequences in descending order by length. So xs needs to satisfy xs[t].shape[0] >= xs[t + 1].shape[0].

Returns

This function returns a tuple containing two elements, hy and ys.

- **hy** is an updated hidden states whose shape is same as hx.
- **ys** is a list of array. Each element ys[t] holds hidden states of the last layer corresponding to an input xs[t]. Its shape is \((B_t, N)\) where B\_t is mini-batch size for time t, and N is size of hidden units. Note that B\_t is the same value as xs[t]

Return type *tuple*

**chainerx.n_step_bigru**

chainerx.n_step_bigru (n\_layers, hx, ws, bs, xs)

Stacked Bi-directional Gated Recurrent Unit function. This function calculates stacked Bi-directional GRU with sequences. This function gets an initial hidden state h\_0, an input sequence x, weight matrices W, and bias vectors b. This function calculates hidden states h\_t for each time t from input x\_t.

\[
\begin{align*}
r^f_t &= \sigma(W^f_0 x_t + W^f_3 h_{t-1} + b^f_0 + b^f_3) \\
z^f_t &= \sigma(W^f_1 x_t + W^f_4 h_{t-1} + b^f_1 + b^f_4) \\
h^f_t &= \tanh(W^f_2 x_t + b^f_2 + r^f_t \cdot (W^f_5 h_{t-1} + b^f_5)) \\
h^f_t &= (1 - z^f_t) \cdot h^f_{t-1} + z^f_t \cdot h_{t-1} \\
r^b_t &= \sigma(W^b_0 x_t + W^b_3 h_{t-1} + b^b_0 + b^b_3) \\
z^b_t &= \sigma(W^b_1 x_t + W^b_4 h_{t-1} + b^b_1 + b^b_4) \\
h^b_t &= \tanh(W^b_2 x_t + b^b_2 + r^b_t \cdot (W^b_5 h_{t-1} + b^b_5)) \\
h^b_t &= (1 - z^b_t) \cdot h^b_{t-1} + z^b_t \cdot h_{t-1} \\
h_t &= [h^f_t; h^b_t]
\end{align*}
\]

where \(W^f\) is weight matrices for forward-GRU, \(W^b\) is weight matrices for backward-GRU. As the function accepts a sequence, it calculates h\_t for all t with one call. Six weight matrices and six bias vectors are required for each layers. So, when S layers exists, you need to prepare 6*S weight matrices and 6*S bias vectors. If the number of layers n\_layers is greater than 1, input of k-th layer is hidden state h\_t of k-1-th layer. Note that all input variables except first layer may have different shape from the first layer.

Parameters
• **n_layers** *(int)* – Number of layers.

• **hx** *(array)* – Variable holding stacked hidden states. Its shape is \((2S, B, N)\) where \(S\) is number of layers and is equal to \(n\_layers\), \(B\) is mini-batch size, and \(N\) is dimension of hidden units.

• **ws** *(list of list of array)* – Weight matrices. \(ws[i]\) represents weights for \(i\)-th layer. Each \(ws[i]\) is a list containing six matrices. \(ws[i][j]\) is corresponding with \(W_j\) in the equation. Only \(ws[0][j]\) where \(0 <= j < 3\) is \((N, I)\) shape as they are multiplied with input variables. All other matrices has \((N, N)\) shape.

• **bs** *(list of list of array)* – Bias vectors. \(bs[i]\) represents biases for \(i\)-th layer. Each \(bs[i]\) is a list containing six vectors. \(bs[i][j]\) is corresponding with \(b_j\) in the equation. Shape of each matrix is \((N,)\) where \(N\) is dimension of hidden units.

• **xs** *(list of array)* – A list of array holding input values. Each element \(xs[t]\) holds input value for time \(t\). Its shape is \((B_t, I)\), where \(B_t\) is mini-batch size for time \(t\), and \(I\) is size of input units. Note that this function supports variable length sequences. When sequences has different lengths, sort sequences in descending order by length. So \(xs\) needs to satisfy \(xs[t].shape[0] >= xs[t + 1].shape[0]\).

**Returns**

This function returns a tuple containing two elements, \(hy\) and \(ys\).

• **hy** is an updated hidden states whose shape is same as \(hx\).

• **ys** is a list of array. Each element \(ys[t]\) holds hidden states of the last layer corresponding to an input \(xs[t]\). Its shape is \((B_t, N)\) where \(B_t\) is mini-batch size for time \(t\), and \(N\) is size of hidden units. Note that \(B_t\) is the same value as \(xs[t]\).

**Return type**  tuple

**chainerx.n_step_rnn**

chainerx.n_step_rnn(*n_layers*, *hx*, *ws*, *bs*, *xs*, **activation**='tanh')

Stacked Uni-directional RNN function for sequence inputs. This function calculates stacked Uni-directional RNN with sequences. This function gets an initial hidden state \(h_0\), an initial cell state \(c_0\), an input sequence \(x\), weight matrices \(W\), and bias vectors \(b\). This function calculates hidden states \(h_t\) and \(c_t\) for each time \(t\) from input \(x_t\).

\[
h_t = f(W_0x_t + W_1h_{t-1} + b_0 + b_1)
\]

where \(f\) is an activation function. Weight matrices \(W\) contains two matrices \(W_0\) and \(W_1\). \(W_0\) is a parameter for an input sequence. \(W_1\) is a parameter for a hidden state. Bias matrices \(b\) contains two matrices \(b_0\) and \(b_1\). \(b_0\) is a parameter for an input sequence. \(b_1\) is a parameter for a hidden state. As the function accepts a sequence, it calculates \(h_t\) for all \(t\) with one call. Two weight matrices and two bias vectors are required for each layer. So, when \(S\) layers exist, you need to prepare \(2S\) weight matrices and \(2S\) bias vectors. If the number of layers \(n\_layers\) is greater than 1, input of \(k\)-th layer is hidden state \(h_{t-k}\) of \(k-1\)-th layer. Note that all input variables except first layer may have different shape from the first layer.

**Parameters**

• **n_layers** *(int)* – Number of layers.

• **hx** *(array)* – Variable holding stacked hidden states. Its shape is \((S, B, N)\) where \(S\) is number of layers and is equal to \(n\_layers\), \(B\) is mini-batch size, and \(N\) is dimension of hidden units.
ChainerX Documentation, Release 7.7.0

- **ws** (list of list of *array*) – Weight matrices. *ws[i]* represents weights for i-th layer. Each *ws[i]* is a list containing two matrices. *ws[i][j]* is corresponding with *W_j* in the equation. Only *ws[0][j]* where 0 <= j < 1 is (N, I) shape as they are multiplied with input variables. All other matrices has (N, N) shape.
- **bs** (list of list of *array*) – Bias vectors. *bs[i]* represents biases for i-th layer. Each *bs[i]* is a list containing two vectors. *bs[i][j]* is corresponding with *b_j* in the equation. Shape of each matrix is (N, N) where N is dimension of hidden units.
- **xs** (list of *array*) – A list of *array* holding input values. Each element *xs[t]* holds input value for time *t*. Its shape is (B_t, I), where B_t is mini-batch size for time *t*, and I is size of input units. Note that this function supports variable length sequences. When sequences has different lengths, sort sequences in descending order by length. So *xs* needs to satisfy *xs[t].shape[0] >= xs[t + 1].shape[0]*.
- **activation** (*str*) – Activation function name. Please select *tanh* or *relu*.

**Returns**

This function returns a tuple containing two elements, *hy* and *ys*.

- *hy* is an updated hidden states whose shape is same as *hx*.
- *ys* is a list of *array*. Each element *ys[t]* holds hidden states of the last layer corresponding to an input *xs[t]*. Its shape is (B_t, N) where B_t is mini-batch size for time *t*, and N is size of hidden units. Note that B_t is the same value as *xs[t]*.

**Return type**  *tuple*

### chainerx.n_step_birnn

**chainerx.n_step_birnn** (*n_layers, hx, ws, bs, xs, activation='tanh')

Stacked Bi-directional RNN function for sequence inputs. This function calculates stacked Bi-directional RNN with sequences. This function gets an initial hidden state *h_0*, an initial cell state *c_0*, an input sequence *x*, weight matrices *W*, and bias vectors *b*. This function calculates hidden states *h_t* and *c_t* for each time *t* from input *x_t*.

\[
\begin{align*}
    h_t^f &= f(W_0^f x_t + W_1^f h_{t-1} + b_0^f + b_1^f), \\
    h_t^b &= f(W_0^b x_t + W_1^b h_{t-1} + b_0^b + b_1^b), \\
    h_t &= [h_t^f; h_t^b],
\end{align*}
\]

where *f* is an activation function. Weight matrices *W* contains two matrices *W_f* and *W_b*. *W_f* is weight matrices for forward directional RNN. *W_b* is weight matrices for backward directional RNN. *W_f* contains *W_0^f* for an input sequence and *W_1^f* for a hidden state. *W_b* contains *W_0^b* for an input sequence and *W_1^b* for a hidden state. Bias matrices *b* contains two matrices *b_f* and *b_b*. *b_f* contains *b_0^f* for an input sequence and *b_1^f* for a hidden state. *b_b* contains *b_0^b* for an input sequence and *b_1^b* for a hidden state. As the function accepts a sequence, it calculates *h_t* for all *t* with one call. Two weight matrices and two bias vectors are required for each layer. So, when *S* layers exist, you need to prepare 2*S* weight matrices and 2*S* bias vectors. If the number of layers *n_layers* is greater than 1, input of *k*-th layer is hidden state *h_{t-1}^k* of *k-1*-th layer. Note that all input variables except first layer may have different shape from the first layer.

**Parameters**

- **n_layers** (*int*) – Number of layers.
• **hx** (*array*) – Variable holding stacked hidden states. Its shape is \((2S, B, N)\) where \(S\) is number of layers and is equal to \(n\_layers\), \(B\) is mini-batch size, and \(N\) is dimension of hidden units. Because of bi-direction, the first dimension length is \(2S\).

• **ws** (list of list of *array*) – Weight matrices. \(ws[i + di]\) represents weights for \(i\)-th layer. Note that \(di = 0\) for forward-RNN and \(di = 1\) for backward-RNN. Each \(ws[i + di]\) is a list containing two matrices. \(ws[i + di][j]\) is corresponding with \(W^f\) if \(di = 0\) and corresponding with \(W^b\) if \(di = 1\) in the equation. Only \(ws[0][j]\) and \(ws[1][j]\) where \(0 \leq j < 1\) are \((I, N)\) shape as they are multiplied with input variables. All other matrices has \((N, N)\) shape.

• **bs** (list of list of *array*) – Bias vectors. \(bs[i + di]\) represents biases for \(i\)-th layer. Note that \(di = 0\) for forward-RNN and \(di = 1\) for backward-RNN. Each \(bs[i + di]\) is a list containing two vectors. \(bs[i + di][j]\) is corresponding with \(b^f\) if \(di = 0\) and corresponding with \(b^b\) if \(di = 1\) in the equation. Shape of each matrix is \((N,)\) where \(N\) is dimension of hidden units.

• **xs** (list of *array*) – A list of *array* holding input values. Each element \(xs[t]\) holds input value for time \(t\). Its shape is \((B_t, I)\), where \(B_t\) is mini-batch size for time \(t\), and \(I\) is size of input units. Note that this function supports variable length sequences. When sequences has different lengths, sort sequences in descending order by length. So \(xs\) needs to satisfy \(xs[t].shape[0] >= xs[t + 1].shape[0]\).

• **activation** (*str*) – Activation function name. Please select *tanh* or *relu*.

**Returns**

This function returns a tuple containing two elements, \(hy\) and \(ys\).

• \(hy\) is an updated hidden states whose shape is same as \(hx\).

• \(ys\) is a list of *array*. Each element \(ys[t]\) holds hidden states of the last layer corresponding to an input \(xs[t]\). Its shape is \((B_t, N)\) where \(B_t\) is mini-batch size for time \(t\), and \(N\) is size of hidden units. Note that \(B_t\) is the same value as \(xs[t]\).

**Return type**  tuple

### 6.4.3 Context

**chainerx.Context**

An isolated execution environment of ChainerX.

**chainerx.Context**

**class chainerx.Context**

An isolated execution environment of ChainerX.

In Python binding, a single context is automatically created and set as the global default context on import. Only advanced users will have to care about contexts.
Methods

get_backend()
get_device()
make_backprop_id()
release_backprop_id()

__eq__(value,)
    Return self==value.

__ne__(value,)
    Return self!=value.

__lt__(value,)
    Return self<value.

__le__(value,)
    Return self<=value.

__gt__(value,)
    Return self>value.

__ge__(value,)
    Return self>=value.

6.4.4 Backend and Device

ChainerX adds a level of abstraction between the higher level array operations and the lower level computations and resource management. This abstraction is managed by the Backend and the Device classes. Native (CPU) and CUDA backends are two concrete implementations currently provided by ChainerX but the abstraction allows you to plug any backend into the framework.

Backend

<table>
<thead>
<tr>
<th>chainerx.Backend</th>
<th>Pluggable entity that abstracts various computing platforms.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainerx.get_backend</td>
<td>Returns a backend specified by the name.</td>
</tr>
</tbody>
</table>

chainerx.Backend

class chainerx.Backend
    Pluggable entity that abstracts various computing platforms.

    A backend holds one or more Devices, each of which represents a physical computing unit.
Methods

**get_device** *(index)*

Returns a device specified by the given index.

**Parameters**

- **index** *(int)* – Device index.

**Returns**

Device object.

**Return type**

*Device*

**get_device_count** *

Returns the number of devices available in this backend.

**Returns**

Number of devices.

**Return type**

*int*

**__eq__** *(value, /)*

Return self==value.

**__ne__** *(value, /)*

Return self!=value.

**__lt__** *(value, /)*

Return self<value.

**__le__** *(value, /)*

Return self<=value.

**__gt__** *(value, /)*

Return self>value.

**__ge__** *(value, /)*

Return self>=value.

Attributes

**context**

Context to which this backend belongs.

**Returns**

Context object.

**Return type**

*Context*

**name**

Backend name.

**Returns**

Backend name.

**Return type**

*str*
chainerx.get_backend

chainerx.get_backend(backend_name)
Returns a backend specified by the name.

   Parameters backend_name (str) – Backend name.
   Returns Backend object.
   Return type Backend

Device

chainerx.Device	 Represents a physical computing unit.
chainerx.get_device	 Returns a device specified by the arguments.
chainerx.get_default_device	 Returns the default device associated with the current thread.
chainerx.set_default_device	 Sets the given device as the default device of the current thread.
chainerx.using_device	 Creates a context manager to temporarily set the default device.

class chainerx.Device
Represents a physical computing unit.

Methods

synchronize()
Synchronizes the device.

__eq__(value, /)
    Return self==value.

__ne__(value, /)
    Return self!=value.

__lt__(value, /)
    Return self<value.

__le__(value, /)
    Return self<=value.

__gt__(value, /)
    Return self>value.

__ge__(value, /)
    Return self>=value.
Attributes

**backend**
Backend to which this device belongs.

**Returns** Backend object.

**Return type** Backend

**context**
Context to which this device belongs.

**Returns** Context object.

**Return type** Context

**index**
Index of this device.

**Returns** Index of this device.

**Return type** int

**name**
Device name.

It is the backend name and the device index concatenated with a colon, e.g. `native:0`.

**Returns** Device name.

**Return type** str

**chainerx.get_device**

`chainerx.get_device(*device)`

Returns a device specified by the arguments.

If the argument is a single `Device` instance, it’s simply returned.

Otherwise, there are three ways to specify a device:

```python
# Specify a backend name and a device index separately.
chainerx.get_device('native', 0)

# Specify a backend name and a device index in a single string.
chainerx.get_device('native:0')

# Specify only a backend name. In this case device index 0 is chosen.
chainerx.get_device('native')
```

**Returns** Device object.

**Return type** Device
**chainerx.get_default_device**

`chainerx.get_default_device()`

Returns the default device associated with the current thread.

- **Returns** The default device.
- **Return type** `Device`

**See also:**
- `chainerx.set_default_device()`
- `chainerx.using_device()`

**chainerx.set_default_device**

`chainerx.set_default_device(device)`

Sets the given device as the default device of the current thread.

- **Parameters** `device` *(Device or str)* – Device object or device name to set as the default device.

**See also:**
- `chainerx.get_default_device()`
- `chainerx.using_device()`

**chainerx.using_device**

`chainerx.using_device(device)`

Creates a context manager to temporarily set the default device.

- **Parameters** `device` *(Device or str)* – Device object or device name to set as the default device during the context. See `chainerx.Device.name` for the specification of device names.

**See also:**
- `chainerx.get_default_device()`
- `chainerx.set_default_device()`

### 6.4.5 Utilities for Backpropagation

<table>
<thead>
<tr>
<th>chainerx.backward</th>
<th>Runs backpropagation.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainerx.no_backprop_mode</td>
<td>Creates a context manager which temporarily disables backpropagation.</td>
</tr>
<tr>
<td>chainerx.force_backprop_mode</td>
<td>Creates a context manager which temporarily enables backpropagation.</td>
</tr>
<tr>
<td>chainerx.is_backprop_required</td>
<td>Returns whether the backpropagation is enabled in the current thread.</td>
</tr>
</tbody>
</table>
**chainerx.backward**

chainerx.backward(outputs, *, enable_double_backprop=False)

Runs backpropagation.

On backpropagation (a.k.a. backprop), the computational graph is traversed backward starting from the output arrays, up until the root arrays on which ndarray.require_grad() have been called.

Backpropagation uses ndarray.grad held by the output arrays as the initial gradients. You can manually assign them before calling this function. Otherwise, they are assumed to be 1.

To enable higher order differentiation, pass enable_double_backprop=True so that you can further run backpropagation from the resulting gradient arrays. Note that enabling it results in larger memory consumption needed to store the gradients w.r.t intermediate arrays that are required for the second gradient computation.

**Note:** The whole process of backpropagation is executed in C++, except those operations whose backward computation falls back to the corresponding Python implementation. Currently this function does not release the GIL at all.

**Parameters**

- **outputs** *(ndarray or list of ndarrays)* – Output arrays from which backpropagation starts.
- **enable_double_backprop** *(bool)* – If True, a computational trace of the whole backpropagation procedure is recorded to the computational graph so that one can further do backpropagation from the resulting gradients.

**See also:**

- chainerx.ndarray.backward()

**chainerx.no_backprop_mode**

chainerx.no_backprop_mode()

Creates a context manager which temporarily disables backpropagation.

Within this context, no computational graph will be formed unless force_backprop_mode() is used.

Arrays resulting from operations enclosed with this context will be disconnected from the computational graph. Trying to perform backpropagation from such arrays would result in an error.

```python
x = chainerx.array([4, 3], numpy.float32)
x.require_grad()

with chainerx.no_backprop_mode():
    y = 2 * x + 1

y.backward()  # ! error
```

Benefits of no_backprop_mode include reduced CPU overhead of building computational graphs, and reduced consumption of device memory that would be otherwise retained for backward propagation.

**See also:**

- chainerx.force_backprop_mode()
chainerx.force_backprop_mode

chainerx.force_backprop_mode()

Creates a context manager which temporarily enables backpropagation.

This context re-enables backpropagation that is disabled by any surrounding no_backprop_mode() context.

```python
x = chainerx.array([4, 3], numpy.float32)
x.require_grad()

with chainerx.no_backprop_mode():
    with chainerx.force_backprop_mode():
        y = 2 * x + 1

y.backward()
x.grad
# array([2., 2.], shape=(2,), dtype=float32, device='native:0')
```

See also:

- chainerx.no_backprop_mode()
- chainerx.is_backprop_required()
- chainer.force_backprop_mode()

chainerx.is_backprop_required

chainerx.is_backprop_required()

Returns whether the backpropagation is enabled in the current thread.

The result is affect by chainerx.no_backprop_mode() and chainerx.force_backprop_mode().

See also:

- chainerx.no_backprop_mode()
- chainerx.force_backprop_mode()

### 6.5 Contribution Guide

This is a guide aimed towards contributors of ChainerX which is mostly implemented in C++. It describes how to build the project and how to run the test suite so that you can get started contributing.

**Note:** Please refer to the Chainer Contribution Guide for the more general contribution guideline that is not specific to ChainerX. E.g. how to download the source code, manage git branches, send pull requests or contribute to Chainer’s Python code base.
Note: There is a public ChainerX Product Backlog.

### 6.5.1 Building the shared library

You can build the C++ ChainerX project to generate a shared library similar to any other cmake project. Run the following command from the root of the project to generate `chainerx_cc/build/chainerx/libchainerx.so`.

```
$ mkdir chainerx_cc/build
$ cd chainerx_cc/build
$ cmake ..
$ make
```

The CUDA support is enabled by, either setting `CHAINERX_BUILD_CUDA=1` as an environment variable or specifying `-DCHAINERX_BUILD_CUDA=1` in cmake. When building with the CUDA support, either the `CUDNN_ROOT_DIR` environment variable or `-DCUDNN_ROOT_DIR` is required to locate the cuDNN installation path.

Note: CUDA without cuDNN is currently not supported.

Then, to install the headers and the library, run:

```
$ make install
```

You can specify the installation path using the prefix `-DCMAKE_INSTALL_PREFIX=<...>` in cmake.

### 6.5.2 Running the test suite

The test suite can be built by passing `-DCHAINERX_BUILD_TEST=ON` to cmake. It is not built by default. Once built, run the suite with the following command from within the build directory.

```
$ cd chainerx_cc/build
$ ctest -V
```

### 6.5.3 Coding standards

The ChainerX C++ coding standard is mostly based on the Google C++ Style Guide and principles.

**Formatting**

ChainerX is formatted using `clang-format`. To fix the formatting in-place, run the following command from `chainerx_cc` directory:

```
$ cd chainerx_cc
$ scripts/run-clang-format.sh --in-place
```
**Chainer Documentation, Release 7.7.0**

### Lint checking

ChainerX uses the `cpplint` and `clang-tidy` for lint checking. Note that clang-tidy requires that you’ve finished running `cmake`. To run `cpplint`, run `scripts/run-cpplint.sh` from `chainerx_cc` directory:

```shell
$ cd chainerx_cc
$ scripts/run-cpplint.sh
```

To run `clang-tidy`, run `make clang-tidy` from the build directory:

```shell
$ cd chainerx_cc/build
$ make clang-tidy
```

### 6.5.4 Thread sanitizer

The thread sanitizer can be used to detect thread-related bugs, such as data races. To enable the thread sanitizer, pass `DCHAINERX_ENABLE_THREAD_SANITIZER=ON` to `cmake`.

You can run the test with `ctest -V` as usual and you will get warnings if the thread sanitizer detects any issues.

CUDA runtime is known to cause a thread leak error as a false alarm. In such case, disable the thread leak detection using environment variable `TSAN_OPTIONS='report_thread_leaks=0'`.

### 6.5.5 Python contributions and unit tests

To test the Python binding, run the following command at the repository root:

```shell
$ pytest
```

The above command runs all the tests in the repository, including Chainer and ChainerMN. To run only ChainerX tests, specify the test directory:

```shell
$ pytest tests/chainerx_tests
```

Run tests with coverage:

```shell
$ pytest --cov --no-cov-on-fail --cov-fail-under=80 tests/chainerx_tests
```

Run tests without CUDA GPU:

```shell
$ pytest -m 'not cuda' tests/chainerx_tests
```

### 6.6 Tips and FAQs

#### 6.6.1 Can I use ChainerX without Chainer?

Yes, it is possible. See the code samples below:

- Train an MLP with MNIST dataset (`chainerx_cc/examples/mnist_py`)
- Train a CNN with ImageNet dataset (`chainerx_cc/examples/imagenet_py`)
6.6.2 What does the C++ interface look like?

It is almost identical to the Python interface with a 1-to-1 mapping. The interface is still subject to change, but there is
an example code:

- Train an MLP with MNIST dataset in C++ (chainerx_cc/examples/mnist)

6.6.3 GPU memory consumption is too high when used with CuPy

Both ChainerX and CuPy use their own GPU memory pools, meaning that GPU memory is not efficiently utilized
(unused memory is kept without being freed by both ChainerX and CuPy). You can run your script after setting the
environment variable CHAINERX_CUDA_CUPY_SHARE_ALLOCATOR to 1 to use the experimental feature which
makes sure that both ChainerX and CuPy share the same memory pool, hence reducing your peak GPU memory-usage.
You may also invoke chainerx._cuda.cupy_share_allocator instead of setting the environment variable
for the same effect. In this case, it is recommended that you call the function prior to any GPU memory allocation.
DISTRIBUTED DEEP LEARNING WITH CHAINERMN

ChainerMN enables multi-node distributed deep learning with the following features:

- **Scalable** — it makes full use of the latest technologies such as NVIDIA NCCL and CUDA-Aware MPI,
- **Flexible** — even dynamic neural networks can be trained in parallel thanks to Chainer’s flexibility, and
- **Easy** — minimal changes to existing user code are required.

This blog post provides our benchmark results using up to 128 GPUs.

ChainerMN can be used for both inner-node (i.e., multiple GPUs inside a node) and inter-node settings. For inter-node settings, we highly recommend to use high-speed interconnects such as InfiniBand.

ChainerMN examples are available on GitHub. These examples are based on the examples of Chainer and the differences are highlighted.

### 7.1 Installation

#### 7.1.1 Installation Guide

**Requirements**

ChainerMN depends on the following software libraries: CUDA-Aware MPI, NVIDIA NCCL, and a few Python packages including CuPy and MPI4py.

**Note:** In Chainer v5, ChainerMN became a part of Chainer package. Installing Chainer (`pip install chainer`) automatically makes ChainerMN available. Note that you still need to separately install requirements described below to actually run code using ChainerMN.

Before upgrading from Chainer v4 to v5 or later, make sure to remove existing `chainermn` package (`pip uninstall chainermn`).

CUDA-Aware MPI

ChainerMN relies on MPI. In particular, for efficient communication between GPUs, it uses CUDA-aware MPI. For details about CUDA-aware MPI, see this introduction article. (If you use only the CPU mode, MPI does not need to be CUDA-Aware. See Installation on Non-GPU Environments for more details.)

The CUDA-aware features depend on several MPI packages, which need to be configured and built properly. The following are examples of Open MPI and MVAPICH.

Open MPI (for details, see Open MPI’s official instructions):

```
$ ./configure --with-cuda
$ make -j4
$ sudo make install
```

MVAPICH (for details, see Mvapich’s official instructions):

```
$ ./configure --enable-cuda
$ make -j4
$ sudo make install
$ export MV2_USE_CUDA=1  # Should be set all the time when using ChainerMN
```

NCCL

Note: If you are installing CuPy using wheels (i.e., `pip install cupy-cudaXX` where `XX` is the CUDA version), you don’t have to install NCCL manually. The latest NCCL 2.x library is bundled with CuPy wheels.

See CuPy Installation Guide for the detailed steps to install CuPy.

To enable efficient intra- and inter-node GPU-to-GPU communication, we use NVIDIA Collective Communications Library (NCCL). See NCCL’s official instructions for installation.

ChainerMN requires NCCL even if you have only one GPU per node. The only exception is when you run ChainerMN on CPU-only environments. See Installation on Non-GPU Environments for more details.

Note: We recommend NCCL 2 but NCCL 1 can be used. However, for NCCL 1, PureNcclCommunicator is not supported in ChainerMN. If you use NCCL 1, please properly configure environment variables to expose NCCL both when you install and use ChainerMN. Typical configurations should look like the following:

```
export NCCL_ROOT=<path to NCCL directory>
export CPATH=$NCCL_ROOT/include:$CPATH
export LD_LIBRARY_PATH=$NCCL_ROOT/lib/:$LD_LIBRARY_PATH
export LIBRARY_PATH=$NCCL_ROOT/lib/:$LIBRARY_PATH
```

If you change the version of NCCL installed, you have to reinstall CuPy. Because, current ChainerMN applies CuPy to use NCCL. See CuPy official instructions for reinstalltion.
MPI4py

You can install MPI4py by:

```bash
$ pip install mpi4py
```

Please make sure to properly configure environment variables so that MPI is available at installation time, because MPI4py links to MPI library at installation time. In particular, if you have multiple MPI implementations installed in your environment, please expose the implementation that you want to use both when you install and use ChainerMN.

As of writing, MPI4py does not support Open MPI 4.x. Please use versions from the Tested Environments section below.

CuPy

Chainer and ChainerMN rely on CuPy to use GPUs. Please refer to CuPy Installation Guide for the detailed steps to install CuPy.

In most cases it is recommended that you install CuPy using wheel distribution (precompiled binary) rather than source distribution. If you are installing from source, NCCL library must be installed before installing CuPy to enable NCCL feature in CuPy. Refer to NCCL for the installation steps of NCCL library. See Check if NCCL is enabled in CuPy, if you want to check whether NCCL is enabled in your CuPy.

Chainer and ChainerMN can be installed without CuPy, in which case the corresponding features are not available. See Installation on Non-GPU Environments for more details.

Tested Environments

We tested ChainerMN on all the following environments.

- **OS**
  - Ubuntu 14.04 LTS 64bit
  - Ubuntu 16.04 LTS 64bit
- **Python** 2.7.13, 3.5.2, 3.6.1
- **MPI**
  - Open MPI 2.1.6, 3.0.4, 3.1.4
- **MPI4py** 3.0.0
- **NCCL** 2.3.2 2.4.2

**Note:** Note that the following versions of Open MPI have some bugs that might cause ChainerMN programs to hang: 3.0.[0-2] and 3.1.[0-2]. For more details, see Open MPI Issue #3972 and Chainer Issue #5740.

Also, mpi4py does not support Open MPI 4.0.x.
Installation on Non-GPU Environments

Users who want to try ChainerMN in CPU-only environment may skip installation of CuPy. Non-GPU setup may not be performant as GPU-enabled setup, but would be useful for testing or debugging training program in non-GPU environment such as laptops or CI jobs.

In this case, the MPI does not have to be CUDA-aware. Only naive communicator works with the CPU mode.

7.1.2 Step-by-Step Troubleshooting

This section is a step-by-step troubleshooting guide for ChainerMN. Please follow these steps to identify and fix your problem.

We assume that you are using Linux or another Unix-like environment.

Single-node environment

Basic MPI installation

Although ChainerMN stands for “Chainer MultiNode,” it is good to start from single-node execution. First of all, you need MPI. If MPI is correctly installed, you will see the `mpicc` and `mpiexec` commands in your PATH.

Below is an example of the output from Mvapich on Linux:

```bash
$ which mpicc
/usr/local/bin/mpicc

$ mpicc -show
gcc -I/usr/local/include ...(snip)... -lmpi

$ which mpiexec
/usr/local/bin/mpiexec

$ mpiexec --version
HYDRA build details:
Version: 3.1.4
Release Date: Wed Sep 7 14:33:43 EDT 2016
CC: gcc
CXX: g++
F77: 
F90: 
Configure options: (snip)
Process Manager: pmi
Launchers available: ssh rsh fork slurm ll lsf sge manual persist
Topology libraries available: hwloc
Resource management kernels available: user slurm ll lsf sge pbs cobalt
Checkpointing libraries available: 
Demux engines available: poll select
```

If you see any error in above commands, please go back to the CUDA-Aware MPI and check your MPI installation.
Check what MPI you are using

In CUDA-Aware MPI, we mention both of Open MPI and Mvapich. If the MPI is provided by the system administrator and you are not really sure which MPI you are using, check the output of `mpiexec --version`.

- If the output contains HYDRA, then it’s MVAPICH (or possibly MPICH).
- If the output contains OpenRTE, then it’s Open MPI.

However, in such a case, you should make sure that the MPI is CUDA-aware, as mentioned below. We recommend to build your own MPI.

Check if MPI is CUDA-aware

Your MPI must be configured as CUDA-aware. You can use the following C program to check it.

```c
/* check_cuda_aware.c */
#include <assert.h>
#include <stdio.h>
#include <mpi.h>
#include <cuda_runtime.h>

#define CUDA_CALL(expr) do { 
  cudaError_t err; 
  err = expr; 
  assert(err == cudaSuccess); 
} while(0)

int main(int argc, char **argv) {
  int rank, size;

  MPI_Init(&argc, &argv);
  MPI_Comm_rank(MPI_COMM_WORLD, &rank);
  MPI_Comm_size(MPI_COMM_WORLD, &size);

  int *sendbuf_d = NULL;
  int *recvbuf_d = NULL;

  CUDA_CALL(cudaMalloc((void**)&sendbuf_d, sizeof(int)));
  CUDA_CALL(cudaMalloc((void**)&recvbuf_d, sizeof(int)));
  CUDA_CALL(cudaMemcpy(sendbuf_d, &rank, sizeof(int), cudaMemcpyDefault));

  MPI_Reduce(sendbuf_d, recvbuf_d, 1, MPI_INT, MPI_SUM, 0, MPI_COMM_WORLD);

  if (rank == 0) {
    int sum = -1;
    CUDA_CALL(cudaMemcpy(&sum, recvbuf_d, sizeof(int), cudaMemcpyDefault));
    if (sum == (size-1) * size / 2) {
      printf("OK.\n");
    } else {
      printf("Error.\n");
    }
  }

  cudaFree(sendbuf_d);
  cudaFree(recvbuf_d);
}
```

(continues on next page)
Save the code to a file named `check_cuda_aware.c`. You can compile and run it with the following command:

```bash
$ export MPICH_CC=nvcc # if you use Mvapich
$ export OMPI_CC=nvcc # if you use Open MPI
$ $(mpicc -show check_cuda_aware.c -arch sm_53 | sed -e 's/-Wl,/"Xlinker /g' | sed -e 's/-pthread/-Xcompiler -pthread/')
$ ./a.out
OK.
```

If the program prints `OK.`, your MPI is correctly configured.

### Check mpi4py

Next, let’s check that mpi4py is correctly installed. You can use the following script to check it:

```python
# coding: utf-8
import os
from mpi4py import MPI

comm = MPI.COMM_WORLD
size = comm.Get_size()
rank = comm.Get_rank()

for i in range(size):
    if i == rank:
        print("{} {}".format(os.uname()[1], i))

comm.Barrier()
```

Save the script into a file named `check_mpi4py.py` and run it. The output from the script should look like this:

```
$ mpiexec -np 4 python check_mpi4py.py
host00 0
dhost00 1
dhost00 2
dhost00 3
```

The script prints hostnames and ranks (process id in MPI) from each MPI process in a sequential manner. `host00` is the host name of the machine your are running the process. If you get an output like below, it indicates something is wrong with your installation:

```
# Wrong output!
$ mpiexec -n 4 python check_mpi4py.py
host00 0
host00 0
host00 0
host00 0
```

A common problem is that the `mpicc` used to build mpi4py and `mpiexec` used to run the script are from different MPI installations.

Finally, run `pytest` to check the single-node configuration is ready:
$ git clone git@github.com:chainer/chainer.git
Cloning into 'chainer'...
remote: Enumerating objects: 7, done.
remote: Counting objects: 100% (7/7), done.
remote: Compressing objects: 100% (7/7), done.
remote: Total 168242 (delta 1), reused 2 (delta 0), pack-reused 168235
Receiving objects: 100% (168242/168242), 41.15 MiB | 1.65 MiB/s, done.
Resolving deltas: 100% (123696/123696), done.
Checking connectivity... done.
$ cd chainer/
$ pytest tests/chainermn_tests/
......S.S...S.S...S.S...S.S........SS
---------------------------------------------------------------
Ran 38 tests in 63.083s

OK (SKIP=10)

Check if NCCL is enabled in CuPy

CuPy requires NCCL to be enabled. You can check it with the following command.:

$ python -c 'from cupy.cuda import nccl'

If you get an output like below, NCCL is not enabled in CuPy. Please check the installation guide of CuPy.:

Traceback (most recent call last):
  File "<string>"", line 1, in <module>
ImportError: cannot import name 'nccl'

Multi-node environment

Check SSH connection and environment variables

To use ChainerMN on multiple hosts, you need to connect to computing hosts, including the one you are currently logged into, via ssh without password authentication (and preferably without username).:

$ ssh host00 'hostname'
host00  # without hitting the password

$ ssh host01 'hostname'
host01  # without hitting the password

You may get a message like this:

The authenticity of host 'host01 (xxx.xxx.xxx.xxx)' can't be established.
ECDSA key fingerprint is SHA256:haGUMcCeC5A81Gh11pjpwL5dF4xCg12Arhhxxxxxxxxx.
Are you sure you want to continue connecting (yes/no)?

This message appears when you log in a host for the first time. Just type yes and the message won’t appear again. You need to repeat this process on all computing hosts.

7.1. Installation 1309
Also, you need to pay attention to the environment variables on remote hosts. The MPI runtime connects to the remote hosts in *non-interactive* mode, and environment variables may differ from your interactive login sessions:

```
$ ssh host00 'env' | grep LD_LIBRARY_PATH
# Check the values and compare it to the local value.

$ ssh host01 'env' | grep LD_LIBRARY_PATH
# Check the values and compare it to the local value.
```

In particular, check the following variables, which are critical to executing MPI programs:

- PATH
- LD_LIBRARY_PATH
- MV2_USE_CUDA (if you use MVAPICH)
- MV2_SMP_USE_CMA (if you use MVAPICH)

Besides, you need to make sure the same `mpiexec` binary is used to run MPI programs:

```
$ ssh host00 'which mpiexec'
/usr/local/bin/mpiexec

$ ssh host01 'which mpiexec'
/usr/local/bin/mpiexec
```

All the commands should give the same `mpiexec` binary path.

### Program files and data

When you run MPI programs, all hosts must have the same Python binary and script files in the same path. First, check that the python binary and version are identical among hosts. Be careful if you are using *pyenv* or *Anaconda*:

```
$ ssh host00 'which python; python --version'
/home/username/.pyenv/shims/python
Python 3.6.0 :: Anaconda 4.3.1 (64-bit)

$ ssh host01 'which python'
/home/username/.pyenv/shims/python
Python 3.6.0 :: Anaconda 4.3.1 (64-bit)
```

Also, the script file (and possibly data files) must be in the same path on each host.

```
$ ls yourscript.py  # in the current directory
yourscript.py

$ ssh host00 "ls $PWD/yourscript.py"
/home/username/your/dir/yourscript.py

$ ssh host01 "ls $PWD/yourscript.py"
/home/username/your/dir/yourscript.py
```

...
If you are using NFS, everything should be okay. If not, you need to transfer all the necessary files manually.

In particular, when you run the ImageNet example in ChainerMN repository, all data files must be available on all computing hosts.

### hostfile

The next step is to create a hostfile. A hostfile is a list of hosts on which MPI processes run.: 

```
$ vi hostfile
$ cat hostfile
host00
host01
host02
host03
```

Then, you can run your MPI program using the hostfile. To check if the MPI processes run over multiple hosts, save the following script to a file and run it via `mpiexec`:

```
# print_rank.py
import os

from mpi4py import MPI

comm = MPI.COMM_WORLD
size = comm.Get_size()
rank = comm.Get_rank()

for i in range(size):
    if i == rank:
        print("{} {}".format(os.uname()[1], i))
    comm.Barrier()
```

If you get an output like below, it is working correctly.: 

```
$ mpiexec -n 4 --hostfile hostfile python print_rank.py
host00 0
host01 1
host02 2
host03 3
```

If you have multiple GPUs, you may want to run multiple processes on each host. You can modify hostfile and specify the number of processes to run on each host.: 

```
# If you are using Mvapich:
$ cat hostfile
host00:4
host01:4
host02:4
host03:4

# If you are using Open MPI
$ cat hostfile
host00 cpu=4
host01 cpu=4
host02 cpu=4
host03 cpu=4
```
With this hostfile, try running mpiexec again:

```
$ mpiexec -n 8 --hostfile hostfile python print_rank.py
host00 0
host00 1
host00 2
host00 3
host01 4
host01 5
host01 6
host01 7
```

You will find that the first 4 processes run on host00 and the latter 4 on host01.

You can also specify computing hosts and resource mapping/binding using command line options of mpiexec. Please refer to the MPI manual for the more advanced use of mpiexec command.

**If you get runtime error:**

If you get the following error messages, please check the specified section of the troubleshooting or installation guide.

```
[hostxxx:mpi_rank_0][MPIDI_CH3I_SMP_init] CMA is not available. Set MV2_SMP_USE_CMA=0 to disable CMA.
[cli_0]: aborting job:
Fatal error in PMPI_Init_thread:
Other MPI error, error stack:
MPIR_Init_thread(514)....:
MPID_Init(365)............: channel initialization failed
MPIDI_CH3_Init(404).......:
MPIDI_CH3I_SMP_Init(2132): process_vm_readv: Operation not permitted

= BAD TERMINATION OF ONE OF YOUR APPLICATION PROCESSES
= PID 20327 RUNNING AT hostxxx
= EXIT CODE: 1
= CLEANING UP REMAINING PROCESSES
= YOU CAN IGNORE THE BELOW CLEANUP MESSAGES
```

-> Check the value of MV2_SMP_USE_CMA (see CUDA-Aware MPI and Check SSH connection and environment variables).

```
[hostxx:mpi_rank_0][error_sighandler] Caught error: Segmentation fault (signal 11)

= BAD TERMINATION OF ONE OF YOUR APPLICATION PROCESSES
= PID 20643 RUNNING AT hostxx
= EXIT CODE: 11
= CLEANING UP REMAINING PROCESSES
= YOU CAN IGNORE THE BELOW CLEANUP MESSAGES
```

YOUR APPLICATION TERMINATED WITH THE EXIT STRING: Segmentation fault (signal 11)
This typically refers to a problem with your application.
Please see the FAQ page for debugging suggestions
-> Check the value of `MV2_USE_CUDA` (see CUDA-Aware MPI and Check SSH connection and environment variables)

## 7.2 Tutorial

### 7.2.1 Overview

**Data Parallelism**

ChainerMN employs the data parallel approach for distributed training. In the data parallel approach, each worker has a model copy, and computes a gradient against a batch. Then, the workers collaborate to update the model using the gradients of all workers.

**Training Iterations**

What ChainerMN does for distributed training is actually quite simple. Let us look at what we do in each iteration. The following figure illustrates an iteration of standard training using Chainer (without ChainerMN). It consists of three steps: forward, backward and optimize.

When using ChainerMN, an additional step all-reduce is inserted after the backward step. In this step, workers communicate to obtain the averaged gradient over gradients of all workers. Then, the aggregated gradient is used to improve the model in the optimization step.
ChainerMN is built on MPI. MPI invokes our training script in the SPMD (single program, multiple data) way. ChainerMN is designed to create a process on each GPU. For example, let us suppose you have two nodes with four GPUs each, and want to run `train_imagenet.py`. Then, you will invoke eight Python processes running `train_imagenet.py` by using `mpiexec` or `mpirun`.

### 7.2.2 Step 1: Communicators and Optimizers

In the following, we explain how to modify your code using Chainer to enable distributed training with ChainerMN. We take Chainer's MNIST example and modify it in a step-by-step manner to see the standard way of using ChainerMN.

**Creating a Communicator**

We first need to create a *communicator*. A communicator is in charge of communication between workers. A communicator can be created as follows:

```python
comm = chainermn.create_communicator()
```

Workers in a node have to use different GPUs. For this purpose, `intra_rank` property of communicators is useful. Each worker in a node is assigned a unique `intra_rank` starting from zero. Therefore, it is often convenient to use the `intra_rank`-th GPU.

The following line of code is found in the original MNIST example:

```python
chainer.cuda.get_device_from_id(args.gpu).use()
```

which we modify as follows:

```python
device = comm.intra_rank
chainer.cuda.get_device_from_id(device).use()
```
Creating a Multi-Node Optimizer

This is the most important step. We need to insert the communication right after backprop and right before optimization. In ChainerMN, it is done by creating a multi-node optimizer.

Method create_multi_node_optimizer receives a standard Chainer optimizer, and it returns a new optimizer. The returned optimizer is called multi-node optimizer. It behaves exactly same as the supplied original standard optimizer (e.g., you can add hooks such as WeightDecay), except that it communicates model parameters and gradients properly in a multi-node setting.

The following is the code line found in the original MNIST example:

```python
optimizer = chainer.optimizers.Adam()
```

To obtain a multi-node optimizer, we modify that part as follows:

```python
optimizer = chainermn.create_multi_node_optimizer(
    chainer.optimizers.Adam(), comm)
```

Run

With the above two changes, your script is ready for distributed training. Invoke your script with mpiexec or mpirun (see your MPI’s manual for details). The following is an example of executing the training with four processes at localhost:

```
$ mpiexec -n 4 python train_mnist.py
```

In the non-GPU mode, you may see a warning like shown below, but this message is harmless, and you can ignore it for now

```
Warning: using naive communicator because only naive supports CPU-only execution
```

If you have multiple GPUs on the localhost, 4 for example, you may also want to try:

```
$ mpiexec -n 4 python train_mnist.py --gpu
```

Multi-node execution

If you can successfully run the multi-process version of the MNIST example, you are almost ready for multi-node execution. The simplest way is to specify the --host argument to the mpiexec command. Let’s suppose you have two GPU-equipped computing nodes: host00 and host01, each of which has 4 GPUs, and so you have 8 GPUs in total:

```
$ mpiexec -n 8 -host host00,host01 python train_mnist.py
```

The script should print similar results to the previous intra-node execution.
Copying datasets

In the MNIST example, the rank 0 process reads the entire portion of the dataset and scatters it to other processes. In some applications, such as the ImageNet ChainerMN example, however, only the pathes to each data file are scattered and each process reads the actual data files. In such cases, all datasets must be readable on all computing nodes in the same location. You don’t need to worry about this if you use NFS (Network File System) or any other similar data synchronizing system. Otherwise, you need to manually copy data files between nodes using `scp` or `rsync`.

If you have trouble

If you have any trouble running the sample programs in your environment, go to the Step-by-Step Troubleshooting page and follow the steps to check your environment and configuration.

Next Steps

With only the above two changes distributed training is already performed. Thus, the model parameters are updated by using gradients that are aggregated over all the workers. However, this MNIST example still has a few areas in need of improvement. In the next page, we will see how to address the following problems:

- Training period is wrong; ‘one epoch’ is not one epoch.
- Evaluation is not parallelized.
- Status outputs to stdout are repeated and annoying.

7.2.3 Step 2: Datasets and Evaluators

Following from the previous step, we continue to explain general steps to modify your code for ChainerMN through the MNIST example. All of the steps below are optional, although useful for many cases.

Scattering Datasets

If you want to keep the definition of ‘one epoch’ correct, we need to scatter the dataset to all workers.

For this purpose, ChainerMN provides a method `scatter_dataset`. It scatters the dataset of the specified root worker (by default, the worker whose `comm.rank` is 0) to all workers. The given dataset of other workers are ignored. The dataset is split into sub datasets of equal sizes, by duplicating some elements if necessary, and scattered to the workers. To create a sub dataset, `chainer.datasets.SubDataset` is used.

The following line of code from the original MNIST example loads the dataset:

```python
train, test = chainer.datasets.get_mnist()
```

We modify it as follows. Only worker 0 loads the dataset, and then it is scattered to all the workers:

```python
if comm.rank == 0:
    train, test = chainer.datasets.get_mnist()
else:
    train, test = None, None

train = chainermn.scatter_dataset(train, comm)
test = chainermn.scatter_dataset(test, comm)
```
Creating A Multi-Node Evaluator

This step is also an optional step, but useful when validation is taking a considerable amount of time. In this case, you can also parallelize the validation by using multi-node evaluators.

Similarly to multi-node optimizers, you can create a multi-node evaluator from a standard evaluator by using method create_multi_node_evaluator. It behaves exactly the same as the given original evaluator except that it reports the average of results over all workers.

The following line from the original MNIST example adds an evaluator extension to the trainer::

```python
trainer.extend(extensions.Evaluator(test_iter, model, device=args.gpu))
```

To create and use a multi-node evaluator, we modify that part as follows:

```python
evaluator = extensions.Evaluator(test_iter, model, device=device)
evaluator = chainermn.create_multi_node_evaluator(evaluator, comm)
trainer.extend(evaluator)
```

Suppressing Unnecessary Extensions

Some of extensions should be invoked only by one of the workers. For example, if the PrintReport extension is invoked by all of the workers, many redundant lines will appear in your console. Therefore, it is convenient to register these extensions only at workers of rank zero as follows:

```python
if comm.rank == 0:
    trainer.extend(extensions.DumpGraph('main/loss'))
    trainer.extend(extensions.LogReport())
    trainer.extend(extensions.PrintReport(
        ['epoch', 'main/loss', 'validation/main/loss',
        'main/accuracy', 'validation/main/accuracy', 'elapsed_time']))
    trainer.extend(extensions.ProgressBar())
```

7.2.4 Tips and FAQs

Using MultiprocessIterator

If you are using MultiprocessIterator and communication goes through InfiniBand, you would probably face crashing problems. This is because MultiprocessIterator creates child processes by the fork system call, which has incompatibilities with the design of MPI and InfiniBand. To cope with this issue, use multiprocessing.set_start_method to start child processes, with a process explicitly forked right after, before communicator is created as follows:

```python
multiprocessing.set_start_method('forkserver')
p = multiprocessing.Process()
p.start()
p.join()
communicator = chainermn.create_communicator(...)
```

Either forkserver mode or spawn mode should work. See our ImageNet example script for working sample code of MultiprocessIterator and forkserver. Unfortunately, multiprocessing.set_start_method is only available in Python 3.4+.
Using Your Own Evaluator

Method `create_multi_node_evaluator` can also be used for customized evaluator classes that inherit from `chainer.training.extensions.Evaluator`. Specifically, it wraps the `evaluate` method and returns the averaged values over all workers. Please also refer to our ImageNet example, where a customized evaluator is used.

Using MPI4py Communicator

ChainerMN is based on MPI4py. For advanced users (e.g., those who want to parallelize preprocessing, create custom extension, etc.), we encourage you to make use of MPI4py communicators. Let `comm` be a ChainerMN communicator, then you can obtain MPI4py communicator by `comm.mpi_comm`. Please refer to MPI4py API reference.

Using FP16

FP16 (16-bit half precision floating point values) is supported in `pure_nccl` of a ChainerMN communicator.

MPI process hangs after an unhandled Python exception.

An MPI runtime is expected to kill all of its child processes if one of them exits abnormally or without calling `MPI_Finalize()`. However, when a Python program runs on `mpi4py`, the MPI runtime often fails to detect the process failure, and the rest of the processes hang infinitely. It is especially problematic when you run your ChainerMN program on a cloud environment, in which you are charged on time basis.

This tiny program demonstrates the issue (note that it is not specific to ChainerMN).

```python
# test.py
import mpi4py.MPI
mpi_comm = mpi4py.MPI.COMM_WORLD
if mpi_comm.rank == 0:
    raise ValueError('failure!')

mpi4py.MPI.COMM_WORLD.Barrier()

if __name__ == '__main__':
    func()
```

`mpi4py` offers a solution to force all processes to abort if an uncaught exception occurs.

```bash
$ mpiexec -n 2 python -m mpi4py yourscript.py ...
```

This also works well with ChainerMN. See [here](#) for more details.

If you cannot apply the solution (i.e. you don’t have a control of how Python interpreter is invoked), you can inject the following code snippet into your script file

```python
import sys

# === begin code snippet
__old_hook = sys.excepthook

# Global error handler
```

(continues on next page)
def global_except_hook(exctype, value, traceback):
    try:
        import mpi4py.MPI
    except ImportError:
        pass

$ mpiexec -n 2 -x CHAINERMN_FORCE_ABORT_ON_EXCEPTION=1 python yourscript.py ...

Alternatively, you can explicitly call chainermn.global_except_hook.add_hook() from your code:

    import chainermn
    chainermn.global_except_hook.add_hook()

The handler hooks uncaught exceptions and call MPI_Abort() to ensure that all process are terminated.

You can choose any of these solutions depending on your environment and restrictions.

NOTE: These techniques are effective only for unhandled Python exceptions. If your program crashes due to lower-level issues such as SIGSEGV, the MPI process may still hang.

## 7.3 Model Parallel

### 7.3.1 Overview

#### Model Parallelism

Even though ChainerMN mainly supports the data parallel approach for distributed training, it also has experimental APIs for the model parallel approach. The model parallel approach splits a given model into subcomponents loaded on several processes. This approach is useful in cases where

- large mini-batch or high-resolution is needed.
- the model is too huge to run on a single process.
- the mixture of experts are trained.

#### Philosophy

ChainerMN takes the following three approaches to realize the model parallelism.

1. Communication as Function

ChainerMN provides several special functions for communications such as chainermn.functions.bcast and chainermn.functions.alltoall, which wraps raw MPI communications. Users define communications between processes as Chainer function calls in the model definitions. This enables highly flexible communication patterns. Moreover, parameter updates in backward propagation are automatically invoked through backward defined in those functions for communications.
2. Synchronous Model Parallel

ChainerMN restricts itself to synchronous SGD. Though the asynchronous counterpart seems to be more computationally efficient, asynchronous SGD often suffer from the stale gradients problem and results in difficulty while debugging. ChainerMN’s synchronous communication model makes SGD simpler.

3. Single-Program-Multiple-Data (SPMD)

In principle, ChainerMN supports single-program-multiple-data (SPMD), which means the same program is invoked and different data are used on each process.

References

- More Effective Distributed ML via a Stale Synchronous Parallel Parameter Server
- Outrageously Large Neural Networks: The Sparsely-Gated Mixture-of-Experts Layer
- AMPNet: Asynchronous Model-Parallel Training for Dynamic Neural Networks
- Deep Mixture of Experts via Shallow Embedding
- Mesh-TensorFlow: Deep Learning for Supercomputers
- GPipe: Efficient Training of Giant Neural Networks using Pipeline Parallelism

7.3.2 Model Parallel on ChainerMN

Step 1: Communicators

To perform multi-node communications, a communicator is needed. Basic usages are the same with the case of the data parallel, see *Step 1: Communicators and Optimizers*:

```
comm = chainermn.create_communicator()
```
If you want to define collective communications among limited number of processes later, it is useful to split the communicator:

```python
subcomm = comm.split(comm.rank % 2, comm.rank)
```

For further detail about the communicator split, please refer to MPI tutorial.

**Step 2: Datasets and Iterators**

In model parallel training, all processes belong to at least one of the following dataset input patterns.

1. model inputs come from datasets, and each process takes different mini-batches
2. model inputs come from datasets, and several processes share the same mini-batches
3. model inputs come from other processes

**1. scatter_dataset**

For the first case, you may use `scatter_dataset` as is introduced in *Step 2: Datasets and Evaluators*. 
2. multi node iterator

For the second case, iterator need to be modified, where `create_multi_node_iterator` is useful:

```python
train, test = chainer.datasets.get_mnist()
train_iter = chainermn.iterators.create_multi_node_iterator(
    chainer.iterators.SerialIterator(train, batchsize), comm)
test_iter = chainermn.iterators.create_multi_node_iterator(
    chainer.iterators.SerialIterator(test, batchsize), comm)
```

The resulting iterators return the same mini-batches among processes specified by the communicator.
3. empty dataset

For the last case, you may use `create_empty_dataset`, which returns a dataset with the same number of empty tuples as the original dataset:

```python
train, test = chainer.datasets.get_mnist()
train = chainermn.datasets.create_empty_dataset(train)
test = chainermn.datasets.create_empty_dataset(test)
```

This input pattern appears in the subsequent examples such as *Example 1: Simple MLP*. Note that datasets are required in Chainer’s updater API. The empty dataset can be used as a dummy dataset.

---

**Step 3: Define Communications**

ChainerMN supports most of the MPI communications as Chainer functions, including point-to-point and collective communications. To know usages of each communication, please refer to API Reference.

**Example 1: Point-to-point Communication**

This is an example to use point-to-point communications:

```python
def __call__(self, x):
    h = f(x)
    h = chainermn.functions.send(x, comm, rank=1)
    return h
```
The communication target is specified by rank parameter. Note that the return value of send is often not negligible. Please refer to *Note: Define-by-Run and Model Parallelism*.

**Example 2: Collective Communication**

Here is another example to use collective communications:

```python
def __call__(self, x):
    h = f(x)
    h = chainermn.functions.allgather(comm, h)
    h = F.stack(h, axis=0)
    h = F.average(h, axis=0)
    return h
```

This pattern often appears in the averaging ensemble training.

**Note: Define-by-Run and Model Parallelism**

In model-parallel training, a model on each process may become non-connected computational graph. Let’s take a look at an example.

Naive implementation of a model on process #0 could be:

```python
class Model_0(chainer.Chain):
    def __call__(self, x):
        # first component
        z = f(x)
        chainermn.functions.send(z, comm, rank=1)

        # second component
        z = chainermn.functions.recv(comm, rank=1)
        y = h(z)

        return y
```

One may notice that there is no connection between the first and second components of computational graph. As we rely on defined-by-run framework, we cannot build a backward path from the second component to the first component. In order to build the backward path, a dummy variable, which we call delegate_variable, is needed.

The variable \(\phi\) in the above figure is delegate_variable, which is a return value of send and passed to an argument of recv:

```python
class Model_0(chainer.Chain):
    def __call__(self, x):
        # first component
        z = f(x)
        phi = chainermn.functions.send(z, comm, rank=1)

        # second component
        z = chainermn.functions.recv(comm, rank=1, delegate_variable=phi)
        y = h(z)

        return y
```

```python
class Model_1(chainer.Chain):
    def __call__(self, _):
        # (continues on next page)
```

7.3. Model Parallel
Model_1 also need to return a delegate variable $\phi$ to backtrack its computational graph to compute gradients. Thus, the backward computation is guaranteed. Otherwise, backward computation will cause deadlock.

**Note: Delegate Variable and Pseudo Connect**

As we just see above, delegate variables must be appropriately handled to avoid potential deadlock. However, there are still some pathological cases. Let’s consider to send variables twice.

```python
class Model_0(chainer.Chain):
    def __call__(self, x):
        z1, z2 = f(x)
        phi1 = chainermn.functions.send(z1, comm, rank=1)
        phi2 = chainermn.functions.send(z2, comm, rank=1)
        psi = chainermn.functions.pseudo_connect(phi1, phi2)
        return psi
```

Here, we must guarantee that backward tracking can find two send, but we can only return one delegate variable from each model. pseudo_connect is a special function to combine one delegate variable to another variable.

In the above case, the returned variable $\psi$ from pseudo_connect behaves as if it is $\phi_2$, while its backward backtracks both $\phi_1$ and $\phi_2$:
class Model_1(chainer.Chain):
    def __call__(self, _):
        z1 = chainermn.functions.recv(comm, rank=0)
        z2 = chainermn.functions.recv(comm, rank=0)
        y = g(z1, z2)
        return y

7.3.3 Example 1: Simple MLP

Here is the first example of model parallel, a simple MLP separated on two processes.

First, let’s create a ChainerMN communicator:

```python
if args.gpu:
    comm = chainermn.create_communicator('pure_nccl')
    device = comm.intra_rank
else:
    comm = chainermn.create_communicator('naive')
    device = -1
```

As we saw in *Model Parallel on ChainerMN*, one naive implementation would be to use the point-to-point communication such as `send` and `recv`:
class MLP0(chainer.Chain):
    def __init__(self, comm, n_out):
        super(MLP0SubA, self).__init__(
            l1=L.Linear(784, n_out))
    def __call__(self, x):
        h0 = F.relu(self.l1(x))
        phi = chainermn.functions.send(h0, self.comm, rank=1)
        # Note: do not forget to pass delegate variable
        y = chainermn.functions.recv(self.comm, rank=1, delegate_variable=phi)
        return y

class MLP1(chainer.Chain):
    def __init__(self, n_units, n_out):
        super(MLP1Sub, self).__init__(
            l2=L.Linear(None, n_units),
            l3=L.Linear(None, n_out))
    def __call__(self, _):
        h0 = chainermn.functions.recv(self.comm, rank=0)
        h1 = F.relu(self.l2(h0))
        return chainermn.functions.send(self.l3(h1), self.comm, rank=0)

One should note that

- MLP0: delegate variable is indispensable which is passed from send to recv.
- MLP1: the return value from send must be returned in __call__, which is used to track back the computational graph.

On each process, different models are trained:

```python
if comm.rank == 0:
    model = L.Classifier(MLP0(comm, 100))
elif comm.rank == 1:
    model = MLP1(comm, 100, 10)
```

Since MLP1 receives its inputs from MLP0 over the point-to-point communication, let’s use `empty_dataset` instead of the usual dataset:

```python
# Iterate dataset only on worker 0.
train, test = chainer.datasets.get_mnist()
if comm.rank == 1:
    train = chainermn.datasets.create_empty_dataset(train)
    test = chainermn.datasets.create_empty_dataset(test)
```

Now we can run a model parallel architecture.

There is an alternative API to define the same model without explicitly defining communication paths:

```python
class MLP0SubA(chainer.Chain):
    def __init__(self, comm, n_out):
        super(MLP0SubA, self).__init__(
            l1=L.Linear(784, n_out))
    def __call__(self, x):
        return F.relu(self.l1(x))
```

(continues on next page)
MultiNodeChainList enables to define a multi model architecture, by adding non-connected component with add_link. Two arguments rank_in and rank_out specifies from which process the added link receives their inputs, and to which process it sends their outputs.

Although it may seems that there is no necessity to parallelize MLP with this size, it can be useful to train a MLP with many layers and parameters so that the entire model cannot be loaded on a single GPU. The entire training code is available here.

### 7.3.4 Example 2: seq2seq

This example shows how to parallelize models that involves RNN.

Above figure depicts a typical encoder-decoder model, where the model is split up to encoder and decoder, both running respectively in two processes. When f or g are large models that consume huge memory such as CNN, model parallelism like this would be useful. In the forward computation, the encoder invokes send function to send its context vectors, and the decoder invokes recv to receive them. The backward computation must be built by pseudo_connect. As this communication pattern is very popular in RNNs, MultiNodeNStepRNN is a ready-made utility link for this pattern. It can replace this complicated communication pattern.

MultiNodeNStepRNN can be created by create_multi_node_n_step_rnn:

```python
rnn = chainermn.links.create_multi_node_n_step_rnn(
    L.NStepLSTM(n_layers, n_units, n_units, 0.1),
    comm, rank_in=None, rank_out=1)
```

where `comm` is a ChainerMN communicator (see Step 1: Communicators).
7.3. Model Parallel
The overall model definition can be written as follows:

```python
class Encoder(chainer.Chain):
    def __init__(self, comm, n_layers, n_units):
        super(Encoder, self).__init__(
            # Corresponding decoder LSTM will be invoked on process 1.
            mn_encoder=chainermn.links.create_multi_node_n_step_rnn(
                L.NStepLSTM(n_layers, n_units, n_units, 0.1),
                comm, rank_in=None, rank_out=1
            ),
        )
        self.comm = comm
        self.n_layers = n_layers
        self.n_units = n_units

def __call__(self, *xs):
    exs = f(xs)
    c, h, _, phi = self.mn_encoder(exs)
    return phi

class Decoder(chainer.Chain):
    def __init__(self, comm, n_layers, n_units):
        super(Decoder, self).__init__(
            # Corresponding encoder LSTM will be invoked on process 0.
            mn_decoder=chainermn.links.create_multi_node_n_step_rnn(
                L.NStepLSTM(n_layers, n_units, n_units, 0.1),
                comm, rank_in=0, rank_out=None
            ),
        )
        self.comm = comm
        self.n_layers = n_layers
        self.n_units = n_units

def __call__(self, *ys):
    c, h, os, _ = self.mn_decoder(ys)
    # compute loss (omitted)
```

An example code with a training script is available [here](#).

### 7.3.5 Example 3: Channel-wise Parallel Convolution

This is an example to parallelize CNN in channel-wise manner. This parallelization is useful with large batch size, or with high resolution images.

The basic strategy is

1. to pick channels that each process is responsible for
2. to apply convolution, and
3. to use `allgather` to combine outputs of all channels into a single tensor

on each process. Parallel convolution model implementation could be like this:

```python
class ParallelConvolution2D(chainer.links.Convolution2D):
    def __init__(self, comm, in_channels, out_channels, *args, **kwargs):
        self.comm = comm
```

(continues on next page)
self.in_channels = in_channels
self.out_channels = out_channels
super(ParallelConvolution2D, self).__init__(
    self._in_channel_size, self._out_channel_size, *args, **kwargs)

def __call__(self, x):
x = x[:, self._channel_indices, :, :]
y = super(ParallelConvolution2D, self).__call__(x)
ys = chainermn.functions.allgather(self.comm, y)
return F.concat(ys, axis=1)

def _channel_size(self, n_channel):
    # Return the size of the corresponding channels.
    n_proc = self.comm.size
    i_proc = self.comm.rank
    return n_channel // n_proc + (1 if i_proc < n_channel % n_proc else 0)

@property
def _in_channel_size(self):
    return self._channel_size(self.in_channels)

@property
def _out_channel_size(self):
    return self._channel_size(self.out_channels)

@property
def _channel_indices(self):
    # Return the indices of the corresponding channel.
indices = np.arange(self.in_channels)
indices = indices[indices % self.comm.size == 0] + self.comm.rank
return [i for i in indices if i < self.in_channels]

where `comm` is a ChainerMN communicator (see Step 1: Communicators).

`ParallelConvolution2D` can simply replace with the original `Convolution2D`. For the first convolution layer, all processes must input the same images to the model. `MultiNodeIterator` distributes the same batches to all processes every iteration:

```python
if comm.rank != 0:
    train = chainermn.datasets.create_empty_dataset(train)
    test = chainermn.datasets.create_empty_dataset(test)

train_iter = chainermn.iterators.create_multi_node_iterator(
    chainer.iterators.SerialIterator(train, args.batchsize), comm)

test_iter = chainermn.iterators.create_multi_node_iterator(
    chainer.iterators.SerialIterator(test, args.batchsize, repeat=False, shuffle=False),
    comm)
```

An example code with a training script for VGG16 parallelization is available here.

### 7.3.6 Example 4: Ensemble

Ensemble is a training technique to obtain better classification performance by combining multiple base classifiers. Averaging ensemble is one of the simplest examples of ensemble, which takes average of all classifier outputs in the test phase. Model parallelism and collective communications can effectively help to implement it.

The following wrapper makes model parallel averaging ensemble easier:

```python
class Averaging(chainer.Chain):
    def __init__(self, comm, block):
        super(Averaging, self).__init__()
        self.comm = comm
        with self.init_scope():
            self.block = block

    def __call__(self, x):
        y = self.block(x)

        if not chainer.config.train:
            y = chainermn.functions.allgather(self.comm, y)
            y = F.stack(y, axis=0)
            y = F.average(y, axis=0)

        return y
```

Then, any links wrapped by `Averaging` are ready to be parallelized and averaged:

```python
class Model(chainer.Chain):
    def __init__(self, comm):
        super(Model, self).__init__()
        self.comm = comm
        with self.init_scope():
            self.l1 = L.Linear(d0, d1)
```

(continues on next page)
From the perspective of model inputs/outputs, the averaged model is compatible with the original model. Thus, we only need to replace the last layer with the averaged layer.

In averaging ensemble, each base classifier is trained independently and ensembled in the test phase. This can be implemented by using `MultiNodeIterator` only for the test iterator:

```python
# train = (training dataset)
# test = (test dataset)

if comm.rank != 0:
    train = chainermn.datasets.create_empty_dataset(train)
    test = chainermn.datasets.create_empty_dataset(test)

train_iter = chainer.iterators.SerialIterator(train, batchsize)

if comm.rank != 0:
    test_iter = chainermn.iterators.create_multi_node_iterator(
        chainer.iterators.SerialIterator(test, batchsize, repeat=False, shuffle=False),
        comm)
```

7.3. Model Parallel

---

```python
self.l2 = L.Linear(d1, d2)
self.l3 = Averaging(self.comm, L.Linear(d2, d3))

def __call__(self, x):
    h = F.relu(self.l1(x))
    h = F.relu(self.l2(h))
    y = F.relu(self.l3(h))
    return y
```
7.4 API Reference

7.4.1 Communicators

```
c imprisonmn.create_communicator(communicator_name='pure_nccl', mpi_comm=None, **kwargs)
```

Create a ChainerMN communicator.

Different communicators provide different approaches of communication, so they have different performance characteristics. The default communicator `pure_nccl` is expected to generally perform well on a variety of environments, so one need not to change communicators in most cases. However, you may need to choose other communicators depending on your computing platform and the availability of NCCL library. The following communicators are available.

<table>
<thead>
<tr>
<th>Name</th>
<th>CPU</th>
<th>GPU</th>
<th>NCCL</th>
<th>Recommended Use Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>pure_nccl</td>
<td>OK</td>
<td>Required (&gt;= v2)</td>
<td>pure_nccl is recommended when NCCL2 is available in the environment.</td>
<td></td>
</tr>
<tr>
<td>flat</td>
<td>OK</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>naive</td>
<td>OK</td>
<td></td>
<td></td>
<td>Testing on CPU mode</td>
</tr>
</tbody>
</table>

`pure_nccl` communicator supports multiple data types, FP32 and FP16, in gradient exchange. The communication data type is determined based on `chainer.global_config.dtype` and `allreduce_grad_dtype`. When `allreduce_grad_dtype` is the default value `None`, FP32 is used when `chainer.global_config.dtype` is `numpy.float32` and FP16 otherwise. `allreduce_grad_dtype` parameter, which is either `numpy.float16` or `numpy.float32`, overwrites the `chainer.global_config.dtype`.

The table below summarizes the data type selection in gradient exchange.

<table>
<thead>
<tr>
<th>allreduce_grad_dtype</th>
<th>chainer.mixed16</th>
<th>numpy.float16</th>
<th>numpy.float32</th>
</tr>
</thead>
<tbody>
<tr>
<td>global_config.dtype</td>
<td>None</td>
<td>numpy.float16</td>
<td>numpy.float32</td>
</tr>
<tr>
<td>FP16</td>
<td>FP16</td>
<td>FP16</td>
<td>FP32</td>
</tr>
<tr>
<td>FP16</td>
<td>FP16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FP32</td>
<td>FFP</td>
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<tr>
<td>FP32</td>
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</tr>
<tr>
<td>FP32</td>
<td>FFP</td>
<td>FFP</td>
<td>FFP</td>
</tr>
</tbody>
</table>

Other communicators, namely `flat` and `naive`, support only float32 communication, no matter what the model is. This is due to MPI’s limited support of float16.

**Parameters**

- `communicator_name` — The name of communicator (naive, flat, or pure_nccl)
- `mpi_comm` — MPI4py communicator
- `allreduce_grad_dtype` — Data type of gradient used in All-Reduce. If `None`, the dtype of a model is used.

**Returns** ChainerMN communicator that implements methods defined in `chainermn. CommunicatorBase`

`class chainermn. CommunicatorBase`

Interface definition of all communicators.

All communicators that have compatible set of methods with this class is supposed to work in ChainerMN’s parallel computation implementation. The methods are named after MPI functions, such as `bcast()` came from `MPI_Bcast()`.

There are two types of methods: one that treats Python objects have _obj suffix. The other has methods without any suffix and it handles ndarray and arrays filled with scalar values. So the number of methods would be
(with single exception alltoall, multi_node_mean_grad, split and bcast_data so far). Also methods are supposed to be written in this order. All those methods must be implemented in its implementation class, or otherwise it cannot be instantiated in runtime.

**Note:** As most implementation of _obj-sufficed methods involves Python object pickling and unpickling, there is an implicit size limit.

TODO(kuenishi): as of now no implementation class actually has allreduce method.

**abstract allgather**(x)
A primitive of inter-process all-gather communication.

This method tries to invoke all-gather communication within the communicator. All processes in the communicator are expected to invoke allgather(). This method relies on mpi4py fast communication optimized for numpy arrays, as well as send() and recv().

Note that this method can only handle the same shapes of data over all processes, and cannot handle tuple data.

**Parameters**
x (numpy/cupy array) – Array to be gathered.

**Returns**
Received arrays.

**Return type**
ys (tuple of numpy/cupy array)

**abstract allreduce**(data)
Allreduce operation among processes

Processes one of several aggregation operations using all data from all processes and returns the result of the aggregation to all processes.

TODO(kuenishi): add op argument once we find a use case for operations other than ‘SUM’.

**Parameters**
data (ndarray) – the data to aggregate among all nodes.

**Returns**
Sum of all data from all processes.

**allreduce_grad**(model, zero_fill=False)
mean Chainer model gradients.

Deprecated since version v7.0.0: This API is deprecated. Please use multi_node_mean_grad() instead.

**Parameters**

- **link** (Link) – Link object.

- **zero_fill** – A knob to control whether to fill gradients of initialized and unused Link (which is None internally) with zero-valued array, because the all gradients must be an array among processes for performing all-reduce, which might be an array or None after backward computation. Gradients of uninitialized Link are skipped. If it is False, gradients of unused Link are just skipped.

**abstract allreduce_obj**(obj)
Apply a reduce operation to all objects and spread the result.

For example of integers and summation, equivalent local code is:
>>> from functools import reduce
>>> reduce(lambda x, y: x + y, [1, 2, 3, 4, 5])
15

The only operation currently supported is summation.

TODO(kuenishi): support other operations such as ‘MAX’, ‘MIN’ and ‘PROD’ with op argument once we need any of them.

Parameters

- obj (arbitrary object) – An arbitrary object to apply reduce operation. Must have corresponding operation method e.g. __plus__().

Returns

The result of the operation applied to all objects.

abstract alltoall(xs)

All-to-all implementation for ndarray

Parameters

- xs (tuple of numpy/cupy array) –

Returns

Received arrays. The length of tuple equals to the communicator size.

Return type

ys (tuple of numpy/cupy array)

abstract bcast(data, max_buf_len=None, root=0)

Broadcasts an ndarray from root process to all processes

Parameters

- data (numpy/cupy array) – for root process, the data to broadcast. For non-root processes, this argument is ignored.
- max_buf_len (int) – Length of send buffer.
- root (int) – the process who has the data to broadcast.

Returns

The data sent from root process

Return type

ys (numpy/cupy array)

abstract bcast_data(model)

Broadcast Chainer model parameter data

abstract bcast_obj(obj, max_buf_len=None, root=0)

Broadcasts an arbitrary object from root to all non-root processes.

Parameters

- obj (arbitrary object) – arbitrary object to broadcast to all other non-root processes. Will be ignored at all non-root processes.
- max_buf_len (int) – max length of the send buffer
- root (int) – rank of the root processes who sends an object

Returns

an object sent from the root process.

finalize()

Finalizes and cleans up internal resource.

The communicator SHALL NOT be used after calling this finalize(). The behaviour is undefined when calling finalize on the same communicator multiple times.

abstract gather(data, root=0)

Gathers an ndarray from all processes to root process

Parameters
• **data** (*ndarray, or scaler*) – for root process this is ignored. For non-root processes, the data to send to root process.

• **root** (*int*) – rank of the process who receives the data.

**Returns** For root process, the ndarray sent from non-root processes. For non-root processes, what?

### abstract `gather_obj(obj, root=0)`
Gathers arbitrary objects from all non-root processes to the root.

**Parameters**

- **obj** – arbitrary object to send to root process. Root process will receive this argument included in returned list.

- **root** (*int*) – rank of the root node who receives all objects.

**Returns** A list of objects sent from all processes.

TODO(kuenishi): make sure the ordering of objects in the returned list.

### get_config(name=None)
Get configuration value(s)

**Parameters**

- **name** (*str*) – Name of the configuration to get. If it is `None`, all config names and values are returned.

**Returns** Actual value of the configuration if it is on. `None` if it is off. If `None` is given as `name`, `None` or dictionary of names and configuration values is returned.

**property inter_rank**
The rank of this node in the cluster.

**property inter_size**
Number of nodes that participates the cluster.

**property intra_rank**
Intra rank (process id in the machine) of this process.

### abstract `multi_node_mean_grad(model, zero_fill=False)`
mean Chainer model gradients.

**Parameters**

- **link** (*Link*) – Link object.

- **zero_fill** – A knob to control whether to fill gradients of initialized and unused Link (which is None internally) with zero-valued array, because the all gradients must be an array among processes for performing all-reduce, which might be an array or None after backward computation. Gradients of uninitialized Link are skipped. If it is False, gradients of unused Link are just skipped.

**property rank**
Rank (process id in the cluster) of this process in integer.

### abstract `recv(source, tag)`
Receives an ndarray from source.

To receive the message, sender must send the data.

**Parameters**

- **source** (*int*) – Rank of the source process

- **tag** (*int*) – The tag to specifically receive the message
Returns: The data sent from source process

**abstract recv_obj** (source, tag)
Receives an arbitrary Python object from source process with a tag.

Parameters:
- **source** (int) – Rank number of sender process, to selectively receive the object.
- **tag** – tag to identify the message.

Returns: an object sent from the source by `send_obj`.

**abstract scatter** (xs, root=0)
A primitive of inter-process scatter communication.

This method tries to invoke scatter communication within the communicator. All processes in the communicator are expected to invoke `scatter()`.

Parameters:
- **xs** (tuple of numpy/cupy array) – Arrays to be scattered.
- **root** (int) – Rank of root process.

Returns: Received arrays.

Return type: ys (numpy/cupy array)

**abstract send** (data, dest, tag)
Sends an ndarray to destination

Receiver must invoke `recv()` to wait for the message.

Parameters:
- **data** – data to be sent (tuple, list or raw numpy/cupy array)
- **dest** (int) – Rank of the destination process
- **tag** (int) – The tag to identify the message

**abstract send_obj** (obj, dest, tag)
Sends an arbitrary Python object to destination with a tag.

Parameters:
- **obj** – Arbitrary object to send to receiver.
- **dest** (int) – Rank number of receiver process (destination).
- **tag** – tag to identify the message.

**set_config** (name, **kwargs)
Set configurations(s) on/off

The usage of configurations depends on each communicator. See `create_communicator()` for available configurations.

Parameters:
- **name** (str) – Name of configuration to set.
- **value** – Give arbitrary object to set.
- **kwargs** – Arbitrary arguments depending on each configuration.

**property size**
Number of processes of the cluster.
abstract split (color, key)
A function analogous to MPI_Comm_Split.
This method splits the inter MPI communicator and return a wrapped ChainerMN communicator.

Parameters

- **color (int)** – Index of new group. The process with the same color will be assigned to the same group.
- **key (int)** – Control of rank assignment. The process will be assigned a rank in the new group ordered by the value of key. If you do not care of the rank, you can just simply specify the original rank.

Returns CommunicatorBase

7.4.2 Optimizers and Evaluators

chainermn.create_multi_node_optimizer (actual_optimizer, communicator, double_buffering=False, zero_fill=True)
Create a multi node optimizer from a Chainer optimizer.

Parameters

- **actual_optimizer** – Chainer optimizer (e.g., chainer.optimizers.Adam).
- **communicator** – ChainerMN communicator.
- **double_buffering** – If True, all-reduce and other processing (such as forward and backward) are overlapped using double buffering. There are cases where accuracy is affected because the gradients of the previous iteration are used for update. This flag is supported by PureNcclCommunicator only.
- **zero_fill** – A knob to control whether to fill gradients of initialized and unused Link (which is None internally) with zero-valued array, because the all gradients must be an array among processes for performing all-reduce, which might be an array or None after backward computation. Gradients of uninitialized Link are skipped. If it is False, gradients of unused Link are just skipped.

Returns The multi node optimizer based on actual_optimizer.

chainermn.create_multi_node_evaluator (actual_evaluator, communicator)
Create a multi node evaluator from a normal evaluator.

Actually this method patches the evaluator to work in multi node environment. This method adds several hidden attributes starting with _mn_ prefix.

Parameters

- **actual_evaluator** – evaluator to be patched (e.g., chainer.training.extensions.Evaluator)
- **communicator** – ChainerMN communicator

Returns The multi-node patched actual_evaluator.

**Note:** After patched, original evaluator does not work correctly in non-MPI environment.
Generic multi-node evaluator for non-allreducable evaluation.

This is to evaluate a Dataset that cannot evenly divided across all processes in the communicator, for evaluation calculation that is not applicable to a simple add-and-devide style averaging among processes.

Users are recommended to implement its own local calculation `calc_local()` (e.g. at each distributed GPU) and aggregation `aggregate()` of its results. Although it has built-in implementation of those two methods.

It has several drawbacks; 1) Additional implementation of aggregation required to users, and 2) no compatibility with `Evaluator`.

**Note:** No automatic support of Reporter is provided; Set it up at `initialize()` method

### Parameters

- **comm** – ChainerMN communicator object
- **iterator** – An iterator for test dataset. Must be non-repeated.
- **target** (callable) – A model to evaluate with test dataset
- **device** (int or chainer.backend.Device) – A device indicator to send data with converter. Not used when the converter is not using any devices.
- **converter** (callable) – A converter. Default value is `chainer.dataset.concat_examples()`.
- **root** (int) – Rank number of root process to run bcast and gather with.
- **progress_hook** (callable) – A callable that receives single argument for indicators. The callable is only called at root process.

### aggregate(results)

A generic aggregation method.

Override this method for original aggregation calculation. By default, it just does nothing but returns the input. This method is called once and only once across the cluster, at root process. Reporting can be run here.

**Parameters**

- **results** (list) – List of return value of `calc_local()` obtained from all nodes.

### calc_local(*args, **kwargs)

A generic method for local calculation.

Override this method to run its local calculation. Otherwise, results are calculated with original target and test dataset.

**Parameters**

- **args** – Result of converter when it is tuple.
- **kwargs** – Result of converter when it is dict.

**Returns**
Arbitrary value may be returned, but must not be `None`.
7.4.3 Dataset Utilities

**chainermn.scatter_dataset**(dataset, comm, root=0, shuffle=False, seed=None, max_buf_len=268435456, *, force_equal_length=True)

Scatter the given dataset to the workers in the communicator.

The dataset of worker root (i.e., the worker whose comm.rank is root) is scattered to all workers. The given dataset of other workers are ignored. The dataset is split to sub datasets of almost equal sizes and scattered to workers. To create a sub dataset, chainer.datasets.SubDataset is used.

**Note:** Make sure force_equal_length flag is not off for multi-node evaluator or multi-node updaters, which assume that the iterator has the same lengths among processes to work correctly.

**Parameters**

- **dataset** – A dataset (e.g., list, numpy.ndarray, chainer.datasets.TupleDataset,...).
- **comm** – ChainerMN communicator or MPI4py communicator.
- **shuffle** *(bool)* – If True, the order of examples is shuffled before being scattered.
- **root** *(int)* – The root process of the scatter operation.
- **seed** *(int)* – Seed the generator used for the permutation of indexes. If an integer being convertible to 32 bit unsigned integers is specified, it is guaranteed that each sample in the given dataset always belongs to a specific subset. If None, the permutation is changed randomly.
- **max_buf_len** *(int)* – Max buffer size to be used at broadcasting binaries. Must not be larger than 2147483647.
- **force_equal_length** *(bool)* – Force the scattered fragments of the dataset have equal length. If True, number of scattered examples is guaranteed to be equal among processes and scattered datasets may have duplication among processes. Otherwise, number of scattered examples may not be equal among processes, but scattered examples are guaranteed to have no duplication among processes, intended for strict evaluation of test dataset to avoid duplicated examples.

**Returns** Scattered dataset.

**chainermn.scatter_index**(n_total_samples, comm, root=0, *, force_equal_length=True)

Scatters only index to avoid heavy dataset broadcast

This is core functionality of scatter_dataset, which is almost equal to following code snippet:

```python
(b, e) = scatter_index(len(dataset), comm)
order = None
if shuffle:
    order = numpy.random.RandomState(seed).permutation(n_total_samples)
    order = comm.bcast_obj(order)
dataset = SubDataset(dataset, b, e, order)
```

**Note:** Make sure force_equal_length flag is not off for multi-node evaluator or multi-node updaters, which assume that the iterator has the same lengths among processes to work correctly.

**Parameters**

- **n_total_samples** *(int)* – number of total samples to scatter
• **comm** – ChainerMN communicator object
• **root (int)** – root rank to coordinate the operation
• **force_equal_length (bool)** – Force the scattered fragments of the index have equal length. If True, number of scattered indices is guaranteed to be equal among processes and scattered datasets may have duplication among processes. Otherwise, number of scattered indices may not be equal among processes, but scattered indices are guaranteed to have no duplication among processes, intended for strict evaluation of test dataset to avoid duplicated examples.

**Returns** Tuple of two integers, that stands for beginning and ending offsets of the assigned sub part of samples. The ending offset is not border inclusive.

chainermn.datasets.create_empty_dataset(dataset)
Creates an empty dataset for models with no inputs and outputs.

This function generates an empty dataset, i.e., `__getitem__()` only returns `None`. Its dataset is compatible with the original one. Such datasets used for models which do not take any inputs, neither return any outputs. We expect models, e.g., whose `forward()` is starting with `chainermn.functions.recv()` and ending with `chainermn.functions.send()`.

**Parameters**
- **dataset** – Dataset to convert.

**Returns** Dataset consists of only patterns in the original one.

**Return type** `TransformDataset`

### 7.4.4 Links

**class** chainermn.MultiNodeChainList(comm)
Combining multiple non-connected components of computational graph.

This class combines each `chainer.Chain`, which represents one of the non-connected component in computational graph. In `__call__()`, the returned object of `chainer.Chain` (which represents pointer) are passed to the next `chainer.Chain`, in order to retain the computational graph connected and make backprop work properly.

Users add each `chainer.Chain` by `add_link()` method. Each chain is invoked in forward computation according to the order they are added, and in backward computation according to the reversed order.

**Example (basic usage)**

This is a simple example of the model which sends its outputs to rank=1 machine:

```python
import chainer
import chainer.functions as F
import chainermn

class SimpleModelSub(chainer.Chain):
    def __init__(self, n_in, n_hidden, n_out):
        super(SimpleModelSub, self).__init__(
            11=L.Linear(n_in, n_hidden),
            12=L.Linear(n_hidden, n_out))

    def __call__(self, x):
```

(continues on next page)
class SimpleModel(chainermn.MultiNodeChainList):
    def __init__(self, comm, n_in, n_hidden, n_out):
        super(SimpleModel, self).__init__(comm)
        self.add_link(
            SimpleModelSub(n_in, n_hidden, n_out),
            rank_in=None,
            rank_out=1)

Example (split MLP on 2 processes)
This is the other example of two models interacting each other:

```python
import chainer
import chainer.functions as F
import chainermn

class MLP(chainer.Chain):
    def __init__(self, n_in, n_hidden, n_out):
        super(MLP, self).__init__(
            l1=L.Linear(n_in, n_hidden),
            l2=L.Linear(n_hidden, n_hidden),
            l3=L.Linear(n_hidden, n_out))
    def __call__(self, x):
        h1 = F.relu(self.l1(x))
        h2 = F.relu(self.l2(h1))
        return self.l3(h2)

class Model0(chainermn.MultiNodeChainList):
    def __init__(self, comm):
        super(Model0, self).__init__(comm)
        self.add_link(MLP(10000, 5000, 2000), rank_in=None, rank_out=1)
        self.add_link(MLP(100, 50, 10), rank_in=1, rank_out=None)

class Model1(chainermn.MultiNodeChainList):
    def __init__(self, comm):
        super(Model1, self).__init__(comm)
        self.add_link(MLP(2000, 500, 100), rank_in=0, rank_out=0)
```
Model0 is expected to be on rank=0, and Model1 is expected to be on rank=1. The first MLP in Model0 will send its outputs to Model1, then MLP in Model1 will receive it and send its outputs to the second MLP in Model0.

Example (sending tuples)

This is the example for sending a tuple:

```python
import chainer
import chainer.functions as F
import chainermn

class NN0(chainer.Chain):
    def __call__(self, x):
        y0 = some_calculation_nn0_0(x)
        y1 = some_calculation_nn1_1(x)
        return y0, y1

class NN1(chainer.Chain):
    def __call__(self, y):
        y0, y1 = y  # unpack tuple from NN0
        return some_calculation_nn1(y0, y1)

class Model_on_Process_0(chainermn.MultiNodeChainList):
    def __init__(self, comm):
        super(Model_on_Process_0, self).__init__(comm=comm)
        self.add_link(NN0(), rank_in=None, rank_out=1)

class Model_on_Process_1(chainermn.MultiNodeChainList):
    def __init__(self, comm):
        super(Model_on_Process_1, self).__init__(comm=comm)
        self.add_link(NN1(), rank_in=0, rank_out=None)
```

In this example, Model_on_Process_0 sends two elemental tuple (y0, y1) (returned by NN0. __call__) to Model_on_Process_1, which can be unpacked as shown in NN1.__call__.

**Parameters**

- `comm` (*chainermn.communicators._base.CommunicatorBase*) – ChainerMN communicator.

- `add_link` (*link, rank_in=None, rank_out=None*)
  Register one connected link with its inout rank.

  **Parameters**

  - `link` (*chainer.Link*) – The link object to be registered.
  - `rank_in` (*int, list, or None*) – Ranks from which it receives data. If None is specified, the model does not receive from any machines.
  - `rank_out` (*int, list, or None*) – Ranks to which it sends data. If None is specified, the model will not send to any machine.
Batch normalization layer that can use the whole batch stats.

When using chainer.link.BatchNormalization, batch mean and std are computed independently for the local batch in each worker. When local batch size is too small, training is unstable due to unreliable batch stats.

In contrast, when using this MultiNodeBatchNormalization, workers communicate to conduct ‘correct’ batch normalization (e.g., obtaining mean and std for the whole global batch).

This link works only with Chainer >= 2.0.0.

Parameters

- **size** (int or tuple of ints) – Size (or shape) of channel dimensions.
- **comm** (ChainerMN communicator) – Communicator to share the batch stats.
- **decay** (float) – Decay rate of moving average. It is used on training.
- **eps** (float) – Epsilon value for numerical stability.
- **dtype** (numpy.dtype) – Type to use in computing.
- **use_gamma** (bool) – If True, use scaling parameter. Otherwise, use unit(1) which makes no effect.
- **use_beta** (bool) – If True, use shifting parameter. Otherwise, use unit(0) which makes no effect.
- **communication_backend** (str) – mpi, nccl or auto. It is used to determine communication backend. If auto, use the best communication backend for each communicator.

Create a link object with MultiNodeBatchNormalization.

Returns a copy of link, where BatchNormalization is replaced by MultiNodeBatchNormalization.

Parameters

- **link** – Link object
- **comm** – ChainerMN communicator
- **communication_backend** (str) – mpi, nccl or auto. It is used to determine communication backend of MultiNodeBatchNormalization. If auto, use the best communication backend for each communicator.

Returns Link object where BatchNormalization is replaced by MultiNodeBatchNormalization.
7.4.5 Functions

chainermn.functions.send(x, communicator, rank, tag=0)
Send elements to target process.

This function returns a dummy variable only holding the computational graph. If backward() is invoked by this dummy variable, it will try to receive gradients from the target process and send them back to the parent nodes.

Parameters

- **x (Variable)** – Variable holding a matrix which you would like to send.
- **communicator (chainer.communicators.CommunicatorBase)** – ChainerMN communicator.
- **rank (int)** – Target process specifier.
- **tag (int)** – Optional message ID (MPI feature).

Returns A dummy variable with no actual data, only holding the computational graph. Please refer chainermn.functions.pseudo_connect for detail.

Return type **Variable**

chainermn.functions.recv(communicator, rank, delegate_variable=None, tag=0, force_tuple=False)
Receive elements from target process.

This function returns data received from target process. If backward() is invoked, it will try to send gradients to the target process. The received array will be on the current CUDA device if the corresponding send() is invoked with arrays on GPU. Please be aware that the current CUDA device is intended one. (https://docs-cupy.chainer.org/en/stable/tutorial/basic.html#current-device)

**Note:** If you define non-connected computational graph on one process, you have to use delegate_variable to specify the output of previous computational graph component. Otherwise backward() does not work well. Please refer chainermn.functions.pseudo_connect for detail.

Parameters

- **communicator (chainer.communicators.CommunicatorBase)** – ChainerMN communicator.
- **rank (int)** – Target process specifier.
- **delegate_variable (chainer.Variable)** – Pointer to the other non-connected component.
- **tag (int)** – Optional message ID (MPI feature).
- **force_tuple (bool)** – If False (the default) a Variable will be returned when the number of outputs is one. Otherwise, this method returns a tuple even when the number of outputs is one.

Returns Data received from target process. If backward() is invoked by this variable, it will send gradients to the target process.

Return type **Variable**
chainermn.functions.pseudo_connect (delegate_variable, *actual_variables)

Connect independent connected graph component.

This function is implemented to return received arguments directly, except the first delegate_variable. In backward computation, it returns received gradients directly, adding a zero grad corresponding to delegate_variable. The detail of delegate_variable is described in the following notes.

**Note:** In model-parallel framework, models on each process might have many non-connected components. Here we call a given graph non-connected when multiple inter-process communications are needed for its computation. For example, consider the following example:

```python
class ConnectedGraph(chainermn.MultiNodeChainList):
    def __init__(self, comm):
        super(ConnectedGraph, self).__init__(comm)
        self.add_link(ConnectedGraphSub(), rank_in=3, rank_out=1)
```

This model receives inputs from rank=3 process and sends its outputs to rank=1 process. The entire graph can be seen as one connected component ConnectedGraphSub. Please refer the documentation of MultiNodeChainList for detail.

On the other hand, see the next example:

```python
class NonConnectedGraph(chainermn.MultiNodeChainList):
    def __init__(self, comm):
        super(NonConnectedGraph, self).__init__(comm)
        self.add_link(NonConnectedGraphSubA(), rank_in=3, rank_out=1)
        self.add_link(NonConnectedGraphSubB(), rank_in=1, rank_out=2)
```

This model consists of two components: at first, NonConnectedGraphSubA receives inputs from rank=3 process and sends its outputs to rank=1 process, and then NonConnectedGraphSubB receives inputs from rank=1 process and sends its outputs to rank=2 process. Here multiple inter-process communications are invoked between NonConnectedGraphSubA and NonConnectedGraphSubB, so it is regarded as non-connected.

Such kind of non-connected models can be problematic in backward computation. Chainer traces back the computational graph from the output variable, however naive implementation of chainermn.functions.recv does not take any inputs rather receives inputs by MPI_Recv, where backward path vanishes.

To prevent this, dummy variables what we call delegate_variable are used. In principle, chainermn.functions.send does not return any outputs because it sends data to the other process by MPI_Send. However, chainermn.functions.send returns a dummy/empty variable in our implementation, which is called delegate_variable. This variable does not hold any data, just used for retaining backward computation path. We can guarantee the backward computation just by putting delegate_variable to the next chainermn.functions.recv (chainermn.functions.recv has an optional argument to receive delegate_variable).

**Note:** In some cases the intermediate graph component returns model outputs. See the next example:

```python
class NonConnectedGraph2(chainermn.MultiNodeChainList):
    def __init__(self, comm):
        super(NonConnectedGraph2, self).__init__(comm)
        self.add_link(NonConnectedGraphSubA(), rank_in=1, rank_out=None)
        self.add_link(NonConnectedGraphSubB(), rank_in=None, rank_out=1)
```

7.4. API Reference 1351
This model first receives inputs from rank=1 process and make model outputs (specified by `rank_out=None`) in `NonConnectedGraphSubA`. Then using model inputs (specified by `rank_in=None`), `NonConnectedGraphSubB` sends its outputs to rank=1 process. Since `MultiNodeChainList.__call__` returns outputs of the last component (in this case, outputs of `NonConnectedGraphSubB`), naive implementation cannot output the returned value of `NonConnectedGraphSubA` as the model outputs. In this case, `pseudo_connect` should be used.

`pseudo_connect` takes two arguments. The first one `delegate_variable` is what we explained in above note. In this case, returned value of `NonConnectedGraphSubB` corresponds to `delegate_variable`. The second one `actual_variables` is “what we want `delegate_variable` to imitate”. In `NonConnectedGraph2`, we obtain returned value of `NonConnectedGraphSubB` as the model outputs, but what we actually want is returned value of `NonConnectedGraphSubA`. At the same time we want to trace back this resulted variable in backward computation. Using `pseudo_connect`, we can make a variable whose data is the same as the returned value of `NonConnectedGraphSubA`, and which traces back `NonConnectedGraphSubB` first.

`pseudo_connect` should also be used in some pathological cases, for example, where multiple `chainermn.functions.send` occurs sequentially.

**Parameters**

- `delegate_variable (chainer.Variable)` – Pointer to the previous non-connected graph component.
- `actual_variables (tuple of chainer.Variable)` – Actual values which `delegate_variable` imitate.

**Returns** A variable with the given values combined with delegating variable.

**Return type** tuple of chainer.Variable

`chainermn.functions.bcast (comm, x, root=0)`

Differentiable broadcast communication between workers.

This function invokes broadcast communications among processes specified by the communicator. Backward will be invoked as well as the ordinary chainer functions, where gradients are gathered to the root process and summed up.

The received array will be on the current CUDA device if `x` on the invoking process is on GPU. Please be aware that the current CUDA device is intended one. ([https://docs-cupy.chainer.org/en/stable/tutorial/basic.html#current-device](https://docs-cupy.chainer.org/en/stable/tutorial/basic.html#current-device))

**Parameters**

- `comm` – ChainerMN communicator.
- `x (chainer.Variable)` – Variable to be sent.

**Returns** Broadcasted variable.

**Return type** `y (chainer.Variable)`

`chainermn.functions.gather (comm, x, root=0)`

Differentiable gather communication between workers.

This function invokes gather communications among processes specified by the communicator. Backward will be invoked as well as the ordinary chainer functions, where gradients are scattered from the root process to each slave.
The received array will be on the current CUDA device if \( x \) on the root process is on GPU. Please be aware that the current CUDA device is intended one. (https://docs-cupy.chainer.org/en/stable/tutorial/basic.html#current-device)

**Parameters**

- \( \text{comm} \) – ChainerMN communicator.
- \( x \) (chainer.Variable) – Variable to be sent.

**Returns** Gathered variables. None for slaves.

**Return type** \( y \) (chainer.Variable)

```python
chainermn.functions.scatter(comm, xs, root=0)
```

Differentiable scatter communication between workers.

This function invokes scatter communications among processes specified by the communicator. Backward will be invoked as well as the ordinary chainer functions, where gradients are gathered to the root process.

The received array will be on the current CUDA device if \( xs \) on the root process is on GPU. Please be aware that the current CUDA device is intended one. (https://docs-cupy.chainer.org/en/stable/tutorial/basic.html#current-device)

**Parameters**

- \( \text{comm} \) – ChainerMN communicator.
- \( xs \) (list of chainer.Variable) – Variables to be scattered for master process.
  
  None for slave process.

**Returns** Scattered variable.

**Return type** \( y \) (chainer.Variable)

```python
chainermn.functions.alltoall(comm, xs)
```

Differentiable all-to-all communication between workers.

This function invokes all-to-all communications among processes specified by the communicator. Backward will be invoked as well as the ordinary chainer functions, just passing input gradients back. Unlike point-to-point communication such as `chainermn.functions.send` and `chainermn.functions.recv`, users need not to care about delegate variables, since `backward()` will not be invoked until all gradients from output direction arrive. Please refer to `chainermn.functions.pseudo_connect` about the detail of delegate variables.

The received array will be on the current CUDA device on the invoking process if \( xs \) is on GPU. Please be aware that the current CUDA device is intended one. (https://docs-cupy.chainer.org/en/stable/tutorial/basic.html#current-device)

**Parameters**

- \( \text{comm} \) – ChainerMN communicator.
- \( xs \) (list of chainer.Variables) – Variables to send.

**Returns** Received variables.

**Return type** \( ys \) (list of chainer.Variables)

```python
chainermn.functions.allgather(comm, x)
```

Differentiable all-gather communication between workers.

This function invokes gather communications among processes specified by the communicator. Backward will be invoked as well as the ordinary chainer functions, where gradients are reduced to each process.
The received array will be on the current CUDA device on the invoking process if x is on GPU. Please be aware that the current CUDA device is intended one. (https://docs-cupy.chainer.org/en/stable/tutorial/basic.html#current-device)

Parameters

- **comm** – ChainerMN communicator.
- **x** (chainer.Variables) – Variables to send.

Returns Received variables.

Return type ys (list of chainer.Variables)

7.4.6 Iterators

chainermn.iterators.create_multi_node_iterator(actual_iterator, communicator, rank_master=0)

Create a multi node iterator from a Chainer iterator.

This iterator shares the same batches on multiple processes, simply broadcasting batches from master process to slave processes in each iteration. Master process obtains batches from actual_iterator, which you can specify any Chainer iterator (e.g. chainer.iterators.SerialIterator).

Here is an example situation. When we train a sequence-to-sequence model, where the encoder and the decoder is located on two different processes, we want to share the same batches on each process, thus inputs for the encoder and output teacher signals for the decoder become consistent.

In order to use the multi node iterator, first create the iterator from Chainer iterator and ChainerMN communicator:

```python
iterator = chainermn.iterators.create_multi_node_iterator(
    chainer.iterators.SerialIterator(
        dataset, batch_size, shuffle=True),
    communicator)
```

Then you can use it as the ordinary Chainer iterator:

```python
updater = chainer.training.StandardUpdater(iterator, optimizer)
trainer = training.Trainer(updater)
trainer.run()
```

Since this iterator shares batches through network in each iteration, communication might be large. If you train your model-parallel network on extremely large dataset, you can also consider to use chainermn.iterators.create_synchronized_iterator.

Current multi node iterator supports numpy.float32 or tuple of numpy.float32 as the data type of the batch element.

**Note:** create_multi_node_iterator and serialize of created iterators must be called at the same time by master and slaves, unless it falls into deadlock because they synchronize internal states of iterators.

Parameters

- **actual_iterator** – Chainer iterator (chainer.iterators.SerialIterator and chainer.iterators.MultiprocessIterator are supported).
- **communicator** – ChainerMN communicator.
• `rank_master` – process rank to be master.

**Returns** The master-slave iterator based on `actual_iterator`.

```python
chainermn.iterators.create_synchronized_iterator(actual_iterator, communicator)
```

Create a synchronized iterator from a Chainer iterator.

This iterator shares the same batches on multiple processes, using the same random number generators to maintain the order of batch shuffling same.

Here is an example situation. When we train a sequence-to-sequence model, where the encoder and the decoder is located on two different processes, we want to share the same batches on each process, thus inputs for the encoder and output teacher signals for the decoder become consistent.

In order to use the synchronized iterator, first create the iterator from Chainer iterator and ChainerMN communicator:

```python
iterator = chainermn.iterators.create_synchronized_iterator(
    chainer.iterators.SerialIterator(
        dataset, batch_size, shuffle=True),
    communicator)
```

Then you can use it as the ordinary Chainer iterator:

```python
updater = chainer.training.StandardUpdater(iterator, optimizer)
trainer = training.Trainer(updater)
trainer.run()
```

The resulting iterator shares the same shuffling order among processes in the specified communicator.

**Parameters**

- `actual_iterator` – Chainer iterator (e.g., `chainer.iterators.SerialIterator`).
- `communicator` – ChainerMN communicator.

**Returns** The synchronized iterator based on `actual_iterator`.

### 7.4.7 Trainer extensions

**class** `chainermn.extensions.AllreducePersistent(model, comm)`

Chainer extension to averagize persistent variables over workers.

When called, this extension invokes all-reduce communication among workers to compute averages of persistent variables in the model. Persistent variables are updated to the averages. Currently, we ignore integer persistent variables, and only float persistent variables are handled.

This extension is mainly to improve the running mean and variance of BatchNormalization by increasing the effective number of examples. We do not need to call this frequently; call just before storing or evaluating the model.

**Parameters**

- `model` (`chainer.link.Link`) – Target link object.
- `comm` (ChainerMN communicator) – communicator to compute averages.

**class** `chainermn.extensions.multi_node_snapshot(comm, snapshot, replica_sets)`

Create trainer extension for multi-node snapshots.
Provides generis multi-node snapshot saving and auto-load feature at multi-node environment, leveraging power of single-node snapshot.

In many cases snapshot target may differ, e.g. only trainer of rank 0 process often has extensions such as LogReport and so on, to not confuse terminal output. Just loading at one process and broadcasting it to other processes does not work in that case.

This wrapper addresses that issue by defining sets of replicas where within the set the target object is replicated and supposed to be same among processes. For example, a trainer example, only the trainer at rank 0 has special extensions and others doesn’t:

```python
trainer = Trainer(updater)
if comm.rank == 0:
    trainer.extend(extensions.DumpGraph('main/loss'))
    trainer.extend(extensions.LogReport())
    trainer.extend(extensions.ProgressBar())
```

This case can be described with two replica sets, where each set can be represented as single integer that indicates rank number, or iterable set/list/generator of integers like this:

```python
replica_sets = [[0], range(1, comm.size)]
```

Here the first replica set is described as [0], or simply in short just 0, and the second replica set is `range(1, comm.size)`, representing rest of processes other than 0. The remaining list can be omitted. Thus in that case, it can be simplified more:

```python
replica_sets = [0,]
```

In this case, the snapshot will be saved at rank 0 process and at rank 1 process. The latter represents the replica set of `range(1, comm.size)`. In this case autoloading at initialization of snapshot extension works after the restart cleanly, even though the size of the communicator differs.

Once the replica sets are defined, it can be easily extended:

```python
replica_sets = [0,]
snapshot = multi_node_snapshot(comm, extensions.snapshot(),
    replica_sets)
trainer.extend(snapshot, trigger=(1, 'epoch'))
```

More example tuples of replica set representation follows:

<table>
<thead>
<tr>
<th>code</th>
<th>nproc</th>
<th>actual sets</th>
</tr>
</thead>
<tbody>
<tr>
<td>[0]</td>
<td>4</td>
<td>[{0}, {1, 2, 3}]</td>
</tr>
<tr>
<td>[0, 1]</td>
<td>4</td>
<td>[[0], {1}, {2, 3}]</td>
</tr>
<tr>
<td>[0, 1], [2, 3]</td>
<td>4</td>
<td>[{0, 1}, {2, 3}]</td>
</tr>
<tr>
<td>[]</td>
<td>4</td>
<td>[{0, 1, 2, 3}]</td>
</tr>
</tbody>
</table>
| [range(0, 8, 2)] | 8 | [set(range(0, 8, 2)), set(range(1, 8, 2))]

**Parameters**

- `comm (ChainerMN communicator)` – communicator object
- `snapshot` – Snapshot extension object obtained via `snapshot()`.
• **replica_sets** – list of replica set definition, where a replica set can be defined by single integer as rank number, or iterable integers.

**Returns**  Trainer extension that wraps snapshot and properly controls number of snapshots.

```python
c chainermn.create_multi_node_checkpointer(name, comm, cp_interval=5, gc_interval=5, path=None)
```

Create multi-node checkpointer object

Generational snapshot extension to allow fault tolerance; It keeps several old snapshots to rollback synchronized snapshot at each MPI process. Snapshot files are identified as `<name>.<rank>.<iteration>`.

- `<name>` … identifier of the run where snapshot is kept for
- `<rank>` … which process owned the model
- `<iteration>` … number of iteration.

This extension keeps several files for each execution and allows users to resume the whole job at the latest snapshots of each MPI process, and the iteration where all snapshots agree.

As this object is a usual Chainer extension, users can just create this object and pass to the trainer as an extension:

```python
checkpointer = create_multi_node_checkpointer(name=run_id, comm=comm)
trainer.extend(checkpointer, trigger=(25, 'iteration'))
```

To run recovery at startup, before first iteration, run

```python
checkpointer.maybe_load(trainer, optimizer)
```

before `trainer.run()` . If nothing is recovered (i.e. no snapshot found), `trainer.updater.iteration` will remain 0 . Otherwise it will have the value of snapshot and the training will resume from that iteration. `optimizer` is optional but this will let multi node optimizer avoid initial broadcast when all snapshot data among nodes are all in sync.

**Note:** Make sure that `checkpointer.maybe_load` is called after all extensions with states, such as `ExponentialShift`, set to the trainer.

**Note:** The checkpointer is deprecated. Please use `chainermn.extensions.multi_node_snapshot()` instead.

After training finished without errors all those temporary checkpoints will be cleaned up at all nodes.

Another example to use checkpointer without trainer would be:

```python
checkpointer = create_multi_node_checkpointer(name=run_id, comm=comm)
checkpointer.maybe_load(obj_you_want_to_snap, optimizer)

while True:  # Training loop
    ...  
    updater.update()
    ...  
    checkpoint.save(obj_you_want_to_snap)  # Make a checkpoint
```

**Parameters**

- **name** *(str)* – unique id of the run
• **comm** – communicator in ChainerMN
• **cp_interval** *(int)* – minimum number of checkpoints to preserve
• **gc_interval** *(int)* – interval to collect non-preserved checkpoints

### 7.4.8 Configurations

#### Environmental Variables

**CHAINERMN_FORCE_ABORT_ON_EXCEPTIONS** If this variable is set to a non-empty value, ChainerMN installs a global hook to Python’s `sys.excepthook` to call `MPI_Abort()` when an unhandled exception occurs. See *MPI process hangs after an unhandled Python exception.*

ChainerMN issue #236 may also help to understand the problem.

#### Execution Control

```python
chainermn.global_except_hook.add_hook()
```

Add a global hook function that captures all unhandled exceptions.

The function calls `MPI_Abort()` to force all processes abort. It is useful when you run your training script on a cloud platform.
8.1 Introduction
ONNX-Chainer converts Chainer model to ONNX format, export it.

8.1.1 Installation
Install dependencies using pip via PyPI:

```
$ pip install 'onnx<1.7.0'
```

8.1.2 Quick Start
First, install ChainerCV to get the pre-trained models.

```
import numpy as np
import chainer
import chainercv.links as C
import onnx_chainer

model = C.VGG16(pretrained_model='imagenet')

# Pseudo input
x = np.zeros((1, 3, 224, 224), dtype=np.float32)

onnx_chainer.export(model, x, filename='vgg16.onnx')
```

vgg16.onnx file will be exported.

Other export examples are put on onnx_chainer/examples. Please check them.
8.1.3 Supported Functions

Currently 82 Chainer Functions are supported to export in ONNX format.

**Activation**
- ClippedReLU
- ELU
- HardSigmoid
- LeakyReLU
- LogSoftmax
- PReLUFunction
- ReLU
- Sigmoid
- Softmax
- Softplus
- Tanh

**Array**
- Cast
- Concat
- Copy
- Depth2Space
- Dstack
- ExpandDims
- GetItem
- Hstack
- Pad\(^1\)
- Permute
- Repeat
- Reshape
- ResizeImages
- Separate
- Shape\(^5\)
- Space2Depth
- SplitAxis
- Squeeze
- Stack

---

\(^1\) mode should be either ‘constant’, ‘reflect’, or ‘edge’

\(^2\) ONNX doesn’t support multiple constant values for Pad operation

\(^5\) Chainer doesn’t support Shape function
• Swapaxes
• Tile
• Transpose
• Vstack
• Where

Connection
• Convolution2DFunction
• ConvolutionND
• Deconvolution2DFunction
• DeconvolutionND
• EmbedIDFunction
• LinearFunction

Loss
• SoftmaxCrossEntropy

Math
• Absolute
• Add
• AddConstant
• ArgMax
• ArgMin
• BroadcastTo
• Clip
• Div
• DivFromConstant
• Exp
• Identity
• LinearInterpolate
• LogSumExp
• MatMul
• Max
• Maximum
• Mean
• Min
• Minimum
• Mul

3 Current ONNX doesn’t support ignore_label for EmbedID
• MulConstant
• Neg
• PowConstVar
• PowVarConst
• PowVarVar
• Prod
• RsqrtGPU
• Sqrt
• Square
• Sub
• SubFromConstant
• Sum

Noise
• Dropout\(^4\)

Normalization
• BatchNormalization
• FixedBatchNormalization
• LocalResponseNormalization
• NormalizeL2

Pooling
• AveragePooling2D
• AveragePoolingND
• MaxPooling2D
• MaxPoolingND
• ROI Pooling2D
• Unpooling2D

### 8.1.4 Tested Environments

- **OS**
  - Ubuntu 16.04, 18.04
  - Windows 10
- **Python** 3.5.5, 3.6.7, 3.7.2
- **ONNX** 1.4.1, 1.5.0, 1.6.0
  - opset version 7, 8, 9, 10, 11
- **ONNX-Runtime** 0.5.0

\(^4\) In test mode, all dropout layers aren’t included in the exported file
8.1.5 Run Test

1. Install test modules

First, test modules for testing:

```
$ pip install -e .[test]
$ pip install onnxruntime
```

Test on GPU environment requires CuPy:

```
$ pip install cupy  # or cupy-cudaXX is useful
```

2. Run tests

Next, run pytest:

```
$ pytest -m "not gpu" tests/onnx_chainer_tests
```

on GPU environment:

```
$ pytest tests/onnx_chainer_tests
```

8.1.6 Contribution

Any contribution to ONNX-Chainer is welcome!

- Python codes follow Chainer Coding Guidelines

8.2 Module Reference

8.2.1 Export

ONNX-Chainer exports Chainer model to ONNX graph with various options.

<table>
<thead>
<tr>
<th><code>onnx_chainer.export</code></th>
<th>Export function for chainer.Chain in ONNX format.</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>onnx_chainer.export_testcase</code></td>
<td>Export model and I/O tensors of the model in protobuf format.</td>
</tr>
</tbody>
</table>

```
onnx_chainer.export

`onnx_chainer.export` (model, args, filename=None, export_params=True, graph_name='Graph', save_text=False, opset_version=None, input_names=None, output_names=None, train=False, return_named_inout=False, external_converters=None, external_opset_imports=None, input_shapes=None, no_testcase=False)
onnx_chainer.export
```

Export function for chainer.Chain in ONNX format.

This function performs a forward computation of the given Chainer model, by passing the given arguments `args` directly. It means, the output `Variable` object `y` to make the computational graph will be created by:
\[ y = \text{model}(*\text{args}) \]

`external_converters` and `external_opset_imports` are for external custom operator. When some `~\text{chainer}.\text{FunctionNode}` are expected to convert to own customized operator, set converter function with `~\text{chainer}.\text{FunctionNode}` name.

```python
>>> \text{import} \text{onnx}
>>> \text{def} \ \text{custom_converter}(\text{param}):
... \ \text{return} \ \text{onnx}.\text{helper}.\text{make_node}(
... \ \quad \ 'CustomizedRelu', \ \text{param}.\text{input_names}, \ \text{param}.\text{output_names},
... \ \quad \ \text{domain}='\text{chainer}')
>>> \text{external_converters} = \{'\text{ReLU}': \text{custom_converter}\}
>>> \text{external_imports} = \{\text{chainer}': 0\}
>>> \text{model} = \text{chainer}.\text{Sequential}(\text{F.relu}) \quad \# \text{set the target model}
>>> \text{args} = \text{chainer}.\text{Variable}(\text{np.random.rand}(1,10)) \quad \# \text{set dummy input}
>>> \text{onnx_graph} = \text{onnx_chainer}.\text{export}(\text{model}, \text{args},
... \quad \text{model}, \ \text{args},
... \quad \text{external_converters}=\text{external_converters},
... \quad \text{external_opset_imports}=\text{external_imports})
```

Returned model has `CustomizedRelu` node.

**Parameters**

- **model** (`Chain`) – The model object you want to export in ONNX format. It should have `__call__()` method because the second argument `args` is directly given to the model by the `[]` accessor.
- **args** (`list` or `dict`) – The arguments which are given to the model directly.
- **filename** (`str` or `file-like object`) – The filename used for saving the resulting ONNX model. If None, nothing is saved to the disk.
- **export_params** (`bool`) – If True, this function exports all the parameters included in the given model at the same time. If False, the exported ONNX model doesn’t include any parameter values.
- **graph_name** (`str`) – A string to be used for the `name` field of the graph in the exported ONNX model.
- **save_text** (`bool`) – If True, the text format of the output ONNX model is also saved with `.txt` extension.
- **opset_version** (`int`) – The operator set version of ONNX. If not specified or `None` is given, the latest opset version of the `onnx` module is used. If an integer is given, it will be ensured that all the operator version in the exported ONNX file is less than this value.
- **input_names** (`str`, `list` or `dict`) – Customize input names of the graph. Number of `input_names` must be same as number of `args`. When set dict type, keys must be same as `args`'s keys.
- **output_names** (`str`, `list` or `dict`) – Customize output name of the graph. Number of `output_names` must be same as actual outputs from `model`. When set dict type, keys must be same as the key of `model` output.
- **train** (`bool`) – If True, output computational graph with train mode.
- **return_named_inout** (`bool`) – If set True, return ONNX model with named inputs, and named outputs.
• **external_converters** *(dict)* – Add-on converter. Convert functions keyed by ~chainer.FunctionNode name.

• **external_opset_imports** *(dict)* – Import external opset. opset version number keyed by domain name.

• **input_shapes** *(tuple, list, dict)* – Input shape of output graph follows the customized shapes if set. When input are collection type, set list or dict. Tuple of tuple is not allowed.

**Returns** When `return_named_inout` is `False`, return ModelProto as an ONNX model. Otherwise return the tuple of ModelProto, named inputs and outputs, both inputs and outputs are list of ~chainer.Variable.

**Return type** ModelProto or tuple

**onnx_chainer.export_testcase**

```python
onnx_chainer.export_testcase(model, args, out_dir, output_grad=False, **kwargs)
```

Export model and I/O tensors of the model in protobuf format.

Similar to the `export` function, this function first performs a forward computation to a given input for obtaining an output. Then, this function saves the pair of input and output in Protobuf format, which is a defacto-standard format in ONNX.

This function also saves the model with the name “model.onnx”.

**Parameters**

• **model** *(Chain)* – The model object.

• **args** *(list)* – The arguments which are given to the model directly. Unlike `export` function, only `list` type is accepted.

• **out_dir** *(str)* – The directory name used for saving the input and output.

• **output_grad** *(bool)* – If True, this function will output model’s gradient with names ‘gradient_%d.pb’.

• ****kwargs** *(dict)* – keyword arguments for `onnx_chainer.export`.

### 8.2.2 Export Utilities

ONNX-Chainer provides some utility functions to help exporting.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>onnx_chainer.replace_func.fake_as_funcnode</code></td>
<td>The target function fakes FunctionNode</td>
</tr>
<tr>
<td><code>onnx_chainer.replace_func.as_funcnode</code></td>
<td>The target function fakes FunctionNode</td>
</tr>
</tbody>
</table>

---

8.2. Module Reference 1365
The target function fakes FunctionNode

The target function is replaced to the alternative function to connect variable node by acting function node.

The alternative function must satisfy the following restrictions.

1. Inputs includes one or more `chainer.Variable` to trace variables.
2. Output consists nothing but `ndarray` or `chainer.Variable`

Even if `alt_func` returns `ndarray`, the value forced to be converted to `chainer.Variable`. A caller of the target function have to care both cases, returning `ndarray` and `chainer.Variable`.

When `alt_func` returns `list` of variable, the wrapped function will also returns multiple variables as `tuple`. However `dict` cannot be return, the wrapped function breaks down the returned values as `tuple` of values, keys will be ignored.

Arguments of `alt_func` except for `chainer.Variable` are set as function attributes. Attribute names are set `argN` (N is index number) or keyword on default.

Example

```python
>>> def func(x, a, b, c=1, d=2): pass
>>> # x is variable
>>> func = onnx_chainer.replace_func.fake_as_funcnode(func, 'CustomNode', rename_attributes=[(1, 'value'), ('c', 'y')])
```

Then `func` will be operated as a function node named “CustomNode”, and 'value', 'b', 'y', 'd' are set as function’s attributes. See tests/test_replace_func.py more details.

Parameters

- `alt_func (func)` – actual called function. There are some constrains, see the above documentation.
- `name (str)` – function name. This name is used for what ONNX operator to be assigned.
- `rename_attributes (list or tuple)` – rename attribute name, set list of `tuple(index_of_args, new_name)` or `tuple(kwargs_name, new_name)`.
- `experimental_warning` – this function is experimental utility, if set `False`, run without experimental warning.

Returns wrapped function, called on exporting.

Return type `func`
onnx_chainer.replace_func.as_funcnode

onnx_chainer.replace_func.as_funcnode(name, rename_attributes=None)

The target function fakes FunctionNode

The target function is overwrapped to connect variable node by acting function node. Expected to be used as decorator. More detail, see fake_as_funcnode documentation.

Example

```python
>>> @onnx_chainer.replace_func.as_funcnode(
    ... 'CustomNode', rename_attributes=[(1, 'value'), ('c', 'y')])
    ... def func(x, a, b, c=1, d=2): pass
```

Parameters

- **name (str)** – function name. This name is used for what ONNX operator to be assigned.
- **rename_attributes (list or tuple)** – rename attribute name, set list of `tuple(index_of_args, new_name)` or `tuple(kwargs_name, new_name)`

### 8.2.3 Convert Utilities

These utilities helps converting from Chainer model to ONNX format, mainly used them internally.

### 8.2.4 Testing Utilities

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>onnx_chainer.testing.input_generator.increasing</code></td>
<td>Returns a monotonically increasing ndarray for test inputs.</td>
</tr>
<tr>
<td><code>onnx_chainer.testing.input_generator.nonzero_increasing</code></td>
<td>Returns a monotonically increasing ndarray for test inputs.</td>
</tr>
<tr>
<td><code>onnx_chainer.testing.input_generator.positive_increasing</code></td>
<td>Returns a monotonically increasing ndarray for test inputs.</td>
</tr>
</tbody>
</table>

**onnx_chainer.testing.input_generator.increasing**

```python
onnx_chainer.testing.input_generator.increasing(*shape, dtype=<class 'numpy.float32'>)

Returns a monotonically increasing ndarray for test inputs.

The output will contain both zero, negative numbers, and non integer numbers for float dtypes. A test writer is supposed to consider this function first.

Example:

```python
>>> onnx_chainer.testing.input_generator.increasing(3, 4)
array([[-3., -2.5, -2., -1.5],
       [-2.5, -2., -1.5, -1.],
       [-2., -1.5, -1., -0.5]])
```
```
Parameters

- **shape** (*tuple of int*) – The shape of the output array.
- **dtype** (*numpy.dtype*) – The dtype of the output array.

Returns `numpy.ndarray`

**onnx_chainer.testing.input_generator.nonzero_increasing**

`onnx_chainer.testing.input_generator.nonzero_increasing(*shape, dtype=<class 'numpy.float32'>, bias=1e-07)`

Returns a monotonically increasing ndarray for test inputs.

Similar to `increasing` but contains no zeros. Expected to be used for divisors.

Example:

```python
>>> onnx_chainer.testing.input_generator.nonzero_increasing(3, 4)
array([[-3.0000000e+00, -2.5000000e+00, -1.9999999e+00, -1.4999999e+00],
       [-9.9999988e-01, -4.9999991e-01, 1.0000000e-07, 5.0000012e-01],
       [ 1.0000001e+00, 1.5000001e+00, 2.0000000e+00, 2.5000000e+00]],
dtype=float32)
```

Parameters

- **shape** (*tuple of int*) – The shape of the output array.
- **dtype** (*numpy.dtype*) – The dtype of the output array.
- **bias** (*float*) – The bias to avoid zero.

Returns `numpy.ndarray`

**onnx_chainer.testing.input_generator.positive_increasing**

`onnx_chainer.testing.input_generator.positive_increasing(*shape, dtype=<class 'numpy.float32'>, bias=1e-07)`

Returns a monotonically increasing ndarray for test inputs.

Similar to `increasing` but contains only positive numbers. Expected to be used for `math.log`, `math.sqrt`, etc.

Example:

```python
>>> onnx_chainer.testing.input_generator.positive_increasing(3, 4)
array([[1.0000000e-07, 5.0000012e-01, 1.0000001e+00, 1.5000001e+00],
       [2.0000000e+00, 2.5000000e+00, 3.0000000e+00, 3.5000000e+00],
       [4.0000000e+00, 4.5000000e+00, 5.0000000e+00, 5.5000000e+00]],
dtype=float32)
```

Parameters

- **shape** (*tuple of int*) – The shape of the output array.
• **dtype** (*numpy.dtype*) – The dtype of the output array.
• **bias** (*float*) – The bias to avoid zero.

**Returns** numpy.ndarray

### 8.3 Indices and tables

- genindex
- search
CHAPTER NINE

API COMPATIBILITY POLICY

This documentation explains the design policy on compatibilities of Chainer APIs. Development team should follow this policy on deciding to add, extend, and change APIs and their behaviors.

This documentation is written for both users and developers. Users can decide the level of dependencies on Chainer’s implementations in their codes based on this document. Developers should read through this documentation before creating pull requests that contain changes on the interface. Note that this documentation may contain ambiguities on the level of supported compatibilities.

9.1 Versioning and Backward Compatibility

The versioning of Chainer follows the PEP 440 and a part of Semantic versioning. See Contribution Guide for details of versioning.

The backward compatibility is kept for revision updates and minor updates, which are applied to the stable version. A major update from the latest release candidate basically keeps the backward compatibility, although it is not guaranteed. Any pre-releases may break the backward compatibility.

9.2 Breaking the Compatibility

We sometimes need to break the backward compatibility to improve the framework design and to support new kinds of machine learning methods. Such a change is only made into pre-releases (alpha, beta, and release candidate) and sometimes into the major update.

A change that breaks the compatibility affects user codes. We try to lower the cost of adapting your code to the newer version. The following list shows an example of what we can do to reduce the cost (Note: this is not a promise; what kind of actions we can take depends on the situation).

• When an argument is removed from an existing API, passing the argument to the updated API will emit an error with a special error message. The error message tells you how to fix your code.

• When a function or a class is removed, we make the current stable version emit a deprecation warning. Note that the deprecation warning is not printed by default in Python. You have to manually turn on the deprecation warning by warnings.simplefilter('always', DeprecationWarning).

• When a definition of a link is changed, we try to enable it to deserialize a model dumped with an older version of Chainer. In most cases, we cannot guarantee that a model serialized with a newer version of Chainer is loadable by an older version of Chainer.
9.3 Experimental APIs

Thanks to many contributors, we have introduced many new features to Chainer. However, we have sometimes released new features only to later notice that their APIs are not appropriate. In particular, we sometimes know that the API is likely to be modified in the near future because we do not have enough knowledge about how well the current design fits to the real usages. The objective of experimental APIs is to declare that the APIs are likely to be updated in the near future so that users can decide if they can(not) use them.

Any newly added API can be marked as experimental. Any API that is not experimental is called stable in this document.

Note: Undocumented behaviors are not considered as APIs, so they can be changed at any time (even in a revision update). The treatment of undocumented behaviors are described in Undocumented behaviors section.

When users use experimental APIs for the first time, warnings are raised once for each experimental API, unless users explicitly disable the emission of the warnings in advance.

See the documentation of chainer.utils.experimental() to know how developers mark APIs as experimental and how users enable or disable the warnings practically.

Note: It is up to developers if APIs should be annotated as experimental or not. We recommend to make the APIs experimental if they implement large modules or make a decision from several design choices.

9.4 Supported Backward Compatibility

This section defines backward compatibilities that revision updates must maintain.

9.4.1 Documented Interface

Chainer has the official API documentation. Many applications can be written based on the documented features. We support backward compatibilities of documented features. In other words, codes only based on the documented features run correctly with revision-updated versions.

Developers are encouraged to use apparent names for objects of implementation details. For example, attributes outside of the documented APIs should have one or more underscores at the prefix of their names.

Note: Although it is not stated as a rule, we also try to keep the compatibility for any interface that looks like a stable feature. For example, if the name of a symbol (function, class, method, attribute, etc.) is not prefixed by an underscore and the API is not experimental, the API should be kept over revision updates even if it is not documented.
9.4.2 Undocumented behaviors

Behaviors of Chainer implementation not stated in the documentation are undefined. Undocumented behaviors are not guaranteed to be stable between different revision versions.

Even revision updates may contain changes to undefined behaviors. One of the typical examples is a bug fix. Another example is an improvement on implementation, which may change the internal object structures not shown in the documentation. As a consequence, even revision updates do not support compatibility of pickling, unless the full layout of pickled objects is clearly documented.

9.4.3 Documentation Error

Compatibility is basically determined based on the documentation, although it sometimes contains errors. It may make the APIs confusing to assume the documentation always stronger than the implementations. We therefore may fix the documentation errors in any updates that may break the compatibility in regard to the documentation.

Note: Developers should not fix the documentation and implementation of the same functionality at the same time in revision updates as a “bug fix” unless the bug is so critical that no users are expected to be using the old version correctly.

9.4.4 Object Attributes and Properties

Object attributes and properties are sometimes replaced by each other. It does not break the user codes, except the codes depend on how the attributes and properties are implemented.

9.4.5 Functions and Methods

Methods may be replaced by callable attributes keeping the compatibility of parameters and return values. It does not break the user codes, except the codes depend on how the methods and callable attributes are implemented.

9.4.6 Exceptions and Warnings

The specifications of raising exceptions are considered as a part of standard backward compatibilities. No exception is raised in the future revision versions with correct usages that the documentation allows.

On the other hand, warnings may be added at any revision updates for any APIs. It means revision updates do not keep backward compatibility of warnings.

9.5 Model Format Compatibility

Links and chains serialized by official serializers that Chainer provides are correctly loaded with the future versions. They might not be correctly loaded with Chainer of the lower versions.

Note: Current serialization APIs do not support versioning. It prevents us from introducing changes in the layout of objects that support serialization. We are discussing versioning in serialization APIs.
9.6 Installation Compatibility

The installation process is another concern of compatibilities.

Any changes on the set of dependent libraries that force modifications on the existing environments should be done in pre-releases and major updates. Such changes include following cases:

- dropping supported versions of dependent libraries (e.g. dropping cuDNN v2)
- adding new mandatory dependencies (e.g. adding h5py to setup_requires)

Note: We sometimes have to narrow the supported versions due to bugs in the specific versions of libraries. In such a case, we may drop the support of those versions even in revision updates unless a workaround is found for the issue.
Chainer is an open source software hosted on GitHub and welcomes contributors to take part in the development of the framework. This is a document aimed towards such contributors. Anyone who for instance would like to file an issue or send a pull request (PR) is encouraged to go through it.

Note: As announced, Chainer is under the maintenance phase and further development will be limited to bug-fixes and maintenance only. Pull-requests for new features, enhancements, or backward-compatibility breaking changes will not be accepted.

10.1 Issues and Pull Requests

First steps in contributing to Chainer often involve filing an issue or creating a PR. This section describes how to do so.

10.1.1 How to File an Issue

To file an issue on GitHub, you often only need to follow instructions given by the template. Write precise explanations on how you want Chainer to behave or include necessary and sufficient conditions to reproduce the bugs. Feature requests should include what you want to do and preferably why. You may additionally suggest how.

Warning: If you have a question regarding the usage of Chainer, it is recommended that you send a post to StackOverflow or the Chainer User Group instead of the issue tracker. The issue tracker is not a place to share knowledge on practices.

10.1.2 How to Send a Pull Request

If you can write code to fix an issue, it is encouraged to send a PR.

In that case, confirm the following points before starting to write any code.

- Read Coding Guidelines and Unit Testing.

- Check the appropriate branch to which you should send a PR, following Git Branches. If you are unsure about which branch to target, choose the master branch. The current source tree of the chosen branch is the starting point of your change.
After writing your code (including unit tests and hopefully documentations!), send a PR on GitHub. You have to write a precise explanation of what and how in the description; this is the first documentation of your code and an important part of your PR.

However, even if your code is not complete, you can send a PR as a work-in-progress (WIP) PR by prefixing the PR title with [WIP]. If you just describe the PR, the core team and other contributors can join the discussion about how to proceed with it. WIP PRs may occasionally be useful for discussing based on concrete code.

When a PR is created (or updated), it is automatically tested in one of our CI environments, namely Travis CI. There are other CI environments as well often manually triggered by the reviewer. The various CIs are required to test for instance different platforms or CUDA environments. Once the tests in all CI environments pass and/or the PR is approved by the reviewer, the PR will be merged.

**Note:** If you are planning to add a new feature or modify existing APIs, it is recommended that you open an issue and discuss the design first. Following the consequences of the discussions, you can send a PR that is smoothly reviewed in a shorter time.

### 10.1.3 Issue/Pull Request Labels

Issues and PRs are labeled on GitHub so that they can be grouped, filtered and better maintained. For instance, a label can indicate that a ticket needs response from the PR author, or that an issue needs immediate action in case of a critical bug. Please refer to the list of labels on GitHub.

### 10.2 Coding Guidelines

We follow PEP 8 and partially OpenStack Style Guidelines as basic style guidelines. Any contributions in terms of code are expected to follow these guidelines.

You can use the autotest and the flake8 commands to check whether or not your code follows the guidelines. In order to avoid confusion from using different tool versions, we pin the versions of those tools. Install them with the following command (from within the top directory of the Chainer repository):

```
$ pip install -e '.[stylecheck]'
```

And check your code with:

```
$ autotest path/to/your/code.py
$ flake8 path/to/your/code.py
```

autotest can automatically correct Python code to conform to the PEP 8 style guide:

```
$ autotest --in-place path/to/your/code.py
```

The flake8 command lets you know parts of your code that are not following the style guidelines.

Note that flake8 command is not perfect. It does not check some of the style guidelines. Here is a (not-exhaustive) list of the rules that flake8 cannot check:

- Relative imports are prohibited. [H304]
- Importing non-module symbols is prohibited.
- Import statements must be organized into three parts: standard libraries, third-party libraries, and internal imports. [H306]
In addition, we restrict the usage of *shortcut aliases* in any global-scope code. In particular, you cannot use shortcut aliases to designate a parent class in global-scope class definitions. When you want to make a class inheriting another class defined in another module, you have to spell out the full module name instead of importing a module that provides an alias.

For example, the following code is not allowed.

```python
import chainer

class MyLink(chainer.Link): ...
```

Instead, import `chainer.link` and use that.

```python
import chainer.link

class MyLink(chainer.link.Link): ...
```

If you feel the code too verbose, you can also use `from import` or `import as`.

```python
from chainer import link

class MyLink(link.Link): ...
```

**Note:** From v3.0, we allow shortcut aliases used inside of functions and methods that are not called from any global scope code. For example, you can write `chainer.Variable` instead of `chainer.variable.Variable` inside of functions and methods. Use of such aliases was prohibited in the past for avoiding confusing errors related to cyclic dependencies; we relaxed the rule so that the library code looks similar to user code.

When you use such shortcut aliases, please be careful of cyclic imports. One of the typical pitfalls is a way to import `chainer.functions`. An import like `import chainer.functions as F` within modules under `chainer.functions` does not work. An import like `from chainer import functions` works well with Python 3, but does not with Python 2. We recommend that you use `import chainer.functions` and spell out like `chainer.functions.foo` in your methods.

### 10.3 Unit Testing

Testing is one of the most important aspects of your PR. You should write test cases and verify your implementation by following the testing guide above. If you modify code related to existing unit tests, you must run appropriate commands and confirm that the tests still pass.

Note that we are using `pytest` and the `mock` package for testing. They are not included in Chainer and need to be installed as follows:
$ pip install pytest mock

### 10.3.1 How to Run Tests

You can run all unit tests with the following command from the root directory of the Chainer:

```
$ python -m pytest
```

Or specify a test script that you want to run:

```
$ python -m pytest path/to/your/test.py
```

You can also run all unit tests under a specific directory:

```
$ python -m pytest tests/chainer_tests/<directory name>
```

Some tests require CUDA and cuDNN by default. In order to run unit tests that do not require CUDA and cuDNN, set an environment variable and filter using test marks as follows:

```
$ export CHAINER_TEST_GPU_LIMIT=0
$ python -m pytest path/to/your/test.py -m='not cudnn'
```

Some GPU tests involve multiple GPUs. If you want to run GPU tests with insufficient number of GPUs, specify the number of available GPUs to `CHAINER_TEST_GPU_LIMIT`. For example, if you only have a single GPU, launch `pytest` with the following command to skip multi-GPU tests:

```
$ export CHAINER_TEST_GPU_LIMIT=1
$ python -m pytest path/to/gpu/test.py
```

Some tests spend too much time. If you want to skip such tests, pass `-m='not slow'` option to the command:

```
$ python -m pytest path/to/your/test.py -m='not slow'
```

### 10.3.2 Test File and Directory Naming Conventions

Tests are found in the `tests/chainer_tests` directory. In order to enable the test runner to find test scripts correctly, we are using a special naming convention for the test subdirectories and the test scripts.

- The name of each subdirectory of `tests` must end with the `_tests` suffix.
- The name of each test script must start with the `test_` prefix.

When we write a test for a module, we use the appropriate path and file name for the test script whose correspondence to the tested module is clear. For example, if you want to write a test for a module `chainer.x.y.z`, the test script must be located at `tests/chainer_tests/x_tests/y_tests/test_z.py`. 
10.3.3 How to Write Tests

There are many examples of unit tests under the tests directory, so reading some of them is a good and recommended way to learn how to write tests for Chainer. They use the unittest package of the standard library, while some tests are additionally using utilities from chainer.testing.

In addition to the Coding Guidelines mentioned above, the following rules apply to the test code:

- All test classes must inherit from unittest.TestCase.
- Use unittest features to write tests, except for the following cases:
  - Use assert statement instead of self.assert* methods (e.g., write assert x == 1 instead of self.assertEqual(x, 1)).
  - Use with pytest.raises(...) instead of with self.assertRaises(...):

Note: We are incrementally applying the above style. Some existing tests may be using the old style (self.assertRaises, etc.), but all newly written tests should follow the above style.

Even if your patch includes GPU-related code, your tests should not fail without GPU capability. Test functions that require CUDA must be tagged with the chainer.testing.attr.gpu decorator:

```python
import unittest
from chainer.testing import attr
class TestMyFunc(unittest.TestCase):
    ...
    @attr.gpu
    def test_my_gpu_func(self):
        ...
```

The functions tagged with the gpu decorator are skipped if CHAINER_TEST_GPU_LIMIT=0 environment variable is set. We also have the chainer.testing.attr.cudnn decorator to let pytest know that the test depends on cuDNN. The test functions decorated with cudnn are skipped if -m='not cudnn' is given.

The test functions decorated with gpu must not depend on multiple GPUs. In order to write tests for multiple GPUs, use the chainer.testing.attr.multi_gpu() decorator instead:

```python
import unittest
from chainer.testing import attr
class TestMyFunc(unittest.TestCase):
    ...
    @attr.multi_gpu(2)  # specify the number of required GPUs here
    def test_my_two_gpu_func(self):
        ...
```

If your test requires too much time, add the chainer.testing.attr.slow decorator. The test functions decorated with slow are skipped if -m='not slow' is given:

```python
import unittest
from chainer.testing import attr
class TestMyFunc(unittest.TestCase):
    ...
```
@attr.slow
def test_my_slow_func(self):
...

Note: If you want to specify more than two attributes, use `and` operator like `-m='not cudnn and not slow'`. See detail in the documentation of pytest.

10.4 Documentation

When adding a new feature to the framework, you should also document it in the reference so that other users can find it in the official documentation. For example, if you are adding a new function under `chainer.functions`, `Functions` should be updated.

The documentation source is stored under `docs` directory and written in `reStructuredText` format.

To build the documentation, you need to install `Sphinx`:

```
$ pip install sphinx sphinx_rtd_theme
```

Note: Docstrings (documentation comments in the source code) are collected from the installed Chainer module. If you have edited docstrings in checked-out source files and want to see those changes reflected in the generated html, Chainer must be installed in develop mode to see those changes reflected in the generated documentation. To do this use `pip install -e` from the the top of the Chainer directory.

Then you can build the documentation in HTML format locally:

```
$ cd docs
$ make html
```

HTML files are generated under `build/html` directory. Open `index.html` with the browser and see if it is rendered as expected.

Note: If you are unsure about how to write the documentation or failed to build it locally, you can submit a PR without documentation. Reviewers will help you with it.

10.5 Other Forms of Contribution

There are several other ways in which you can contribute to Chainer without directly working with the code base. Following are such contributions.

- Sending a question/reply to StackOverflow (with `chainer` tag) or Chainer User Group
- Open-sourcing an external example
- Writing a post about Chainer
10.6 Development Cycle

This section explains the development process of Chainer.

10.6.1 Versioning

The versioning of Chainer follows PEP 440 and a part of Semantic versioning. The version number consists of three or four parts: \( X.Y.Zw \) where \( X \) denotes the major version, \( Y \) denotes the minor version, \( Z \) denotes the revision number, and the optional \( w \) denotes the pre-release suffix. While the major, minor, and revision numbers follow the rule of semantic versioning, the pre-release suffix follows PEP 440, the Python community standards.

Note that a major update basically does not contain compatibility-breaking changes from the last release candidate (RC). This is not a strict rule, though; if there is a critical bug in the API that need to be fixed for the major version, breaking changes may be introduced.

For more on backward compatibility, please refer to the API Compatibility Policy.

10.6.2 Release Cycle

A milestone for each upcoming release is published on GitHub. The GitHub milestones are used to group issues and PRs belonging to a release.

10.6.3 Git Branches

master branch is used for Chainer v7.x development.
11.1 It takes too long time to compile a computational graph. Can I skip it?

Chainer does not compile computational graphs, so you cannot skip it, or, I mean, you have already skipped it :).

It seems you have actually seen on-the-fly compilations of CUDA kernels. CuPy compiles kernels on demand to make kernels optimized to the number of dimensions and element types of input arguments. Pre-compilation is not available, because we have to compile an exponential number of kernels to support all CuPy functionalities. This restriction is unavoidable because Python cannot call CUDA/C++ template functions in generic way. Note that every framework using CUDA require compilation at some point; the difference between other statically-compiled frameworks (such as cutorch) and Chainer is whether a kernel is compiled at installation or at the first use.

These compilations should run only at the first use of the kernels. The compiled binaries are cached to the `${HOME}/.cupy/kernel_cache` directory by default. If you see that compilations run every time you run the same script, then the caching is failed. Please check that the directory is kept as is between multiple executions of the script. If your home directory is not suited to caching the kernels (e.g. in case that it uses NFS), change the kernel caching directory by setting the `CUPY_CACHE_DIR` environment variable to an appropriate path. See CuPy Overview for more details.

11.2 MNIST example does not converge in CPU mode on Mac OS X

**Note:** Mac OS X is not an officially supported OS.

Many users have reported that MNIST example does not work correctly when using vecLib as NumPy backend on Mac OS X. vecLib is the default BLAS library installed on Mac OS X.

We recommend using other BLAS libraries such as OpenBLAS.

To use an alternative BLAS library, it is necessary to reinstall NumPy. Here are instructions to install NumPy with OpenBLAS using Conda.

```
$ conda install -c conda-forge numpy
```

Otherwise, to install NumPy without Conda, you may need to install NumPy from source.

Use Homebrew to install OpenBLAS.

```
$ brew install openblas
```

Uninstall existing NumPy installation
$ pip uninstall numpy

You’ll to create a file called `.numpy-site.cfg` in your home (~/) directory with the following:

```ini
[openblas]
libraries = openblas
library_dirs = /usr/local/opt/openblas/lib
include_dirs = /usr/local/opt/openblas/include
```

Install NumPy from the source code

```bash
pip install --no-binary :all: numpy
```

Confirm NumPy has been installed with OpenBLAS by running this command:

```bash
$ python -c "import numpy; print(numpy.show_config())"
```

You should see the following information:

```python
blas_mkl_info:
   NOT AVAILABLE
blis_info:
   NOT AVAILABLE
openblas_info:
   libraries = ['openblas', 'openblas']
   library_dirs = ['/usr/local/opt/openblas/lib']
   language = c
   define_macros = [('HAVE_CBLAS', None)]
   runtime_library_dirs = ['/usr/local/opt/openblas/lib']
```

Once this is done, you should be able to `import chainer` without OpenBLAS errors.

For details of this problem, see issue #704.

### 11.3 How do I fix InvalidType error?

Chainer raises an InvalidType exception when invalid inputs are given to `Functions`. If you got InvalidType, generally you need to check if `dtype` and/or `shape` of inputs are valid for the function.

Here are some examples of InvalidType errors:

```python
import chainer.functions as F
import numpy as np

arr = np.arange(10) - 5
F.relu(arr)
```

```
Traceback (most recent call last):
  ...
chainer.utils.type_check.InvalidType:
  Invalid operation is performed in: ReLU (Forward)

  Expect: x.dtype.kind == f
  Actual: i != f
```

```
In this case, \texttt{kind} of \texttt{x} (the first argument of the function \texttt{relu()}) is expected to be \texttt{f} (floating-point), whereas the input was \texttt{i} (signed integer). You need to cast the input appropriately before passing to the function (e.g., \texttt{x.astype(np.float32)}).

```python
import chainer.functions as F
import numpy as np
x = np.ones((4, 4))
y = np.ones((3, 3))
F.concat([x, y])
```

Traceback (most recent call last):
...
chainer.utils.type_check.InvalidType:
Invalid operation is performed in: Concat (Forward)
Expect: in_types[0].shape[0] == in_types[1].shape[0]
Actual: 4 != 3

In this case, the function expects that \texttt{x.shape[0]} is equal to \texttt{y.shape[0]}, but actually it was 4 and 3, respectively.

See \textit{Type Checks} for the detailed behavior of type checking system in Chainer.

### 11.4 How do I accelerate my model using Chainer Backend for Intel Architecture?

Follow these steps to utilize Chainer Backend for Intel Architecture in your model.

#### 11.4.1 Install Chainer Backend for Intel Architecture

The following environments are recommended by Chainer Backend for Intel Architecture.

- Ubuntu 14.04 / 16.04 LTS (64-bit) and CentOS 7 (64-bit)
- Python 2.7.6+, 3.5.2+, and 3.6.0+

On recommended systems, you can install Chainer Backend for Intel Architecture wheel (binary distribution) by:

```bash
$ pip install 'ideep4py<2.1'
```

Note: \texttt{ideep4py} v1.0.x is incompatible with v2.0.x, and is not supported in Chainer v5.0 or later.
11.4.2 Enable Chainer Backend for Intel Architecture Configuration

Currently, Chainer Backend for Intel Architecture is disabled by default because it is an experimental feature. You need to manually enable it by changing `chainer.config.use_ideep` configuration to 'auto'. See Configuring Chainer for details.

The easiest way to change the configuration is to set environment variable as follows:

```bash
export CHAINER_USE_IDEEP="auto"
```

You can also use `chainer.using_config()` to change the configuration.

```python
x = np.ones((3, 3), dtype='f')
with chainer.using_config('use_ideep', 'auto'):
    y = chainer.functions.relu(x)
print(type(y.data))
```

```
<class 'ideep4py.mdarray'>
```

11.4.3 Convert Your Model to Chainer Backend for Intel Architecture

You need to call `model.to_intel64()` (in the same way you call `model.to_gpu()` to transfer your link to GPU) to convert the link to Chainer Backend for Intel Architecture.

11.4.4 Run Your Model

Now your model is accelerated by Chainer Backend for Intel Architecture!

Please note that not all functions and optimizers support Chainer Backend for Intel Architecture acceleration. Also note that Chainer Backend for Intel Architecture will not be used depending on the shape and data type of the input data.

11.5 My training process gets stuck when using MultiprocessIterator

When you are using OpenCV somewhere in your code and the `MultiprocessIterator` is used in the training code, the training loop may get stuck at some point. In such situation, there are several workarounds to prevent the process got stuck.

1. Set the environment variable as follows: `OMP_NUM_THREADS=1`

2. Add `cv2.setNumThreads(0)` right after `import cv2` in your training script.

3. Use `MultithreadIterator` instead of `MultiprocessIterator`.

This problem is originally reported here: A training loop got stuck in a certain condition with multi-processing updater and opencv for Chainer and the discussion on related problems is still going here: OpenCV + Python multiprocessing breaks on OSX.
PERFORMANCE BEST PRACTICES

This guide explains some tips and advice for maximizing the performance of Chainer.

12.1 Use the Latest Version

It is generally recommended that you use the latest version of Chainer and its dependent libraries (CUDA, cuDNN, iDeep, etc.). Some of the new features and performance optimizations introduced in newer versions of dependent libraries may not be available in older versions of Chainer. Also, Chainer itself is incrementally being improved to provide better performance.

If you are using Chainer v4 or later, you can check the version configuration by:

```
chainer.print_runtime_info()
```

Chainer: 4.0.0
NumPy: 1.14.3
CuPy:
  CuPy Version : 4.0.0
  CUDA Root     : /usr/local/cuda
  CUDA Build Version : 9000
  CUDA Driver Version : 9000
  CUDA Runtime Version : 9000
  cuDNN Build Version : 7100
  cuDNN Version : 7100
  NCCL Build Version : 2102

Generally, the Chainer team is maintaining the API between minor updates (e.g., v4.0 to v4.1) so that users can upgrade Chainer without modifying their code (see API Compatibility Policy for our policy). As for major updates, please refer to the Upgrade Guide to understand what should be done for migration.

12.2 Enable Hardware Accelerations

12.2.1 Using GPU

In most cases, running on GPU will give you better performance than on CPU. When using GPU, also make sure to install cuDNN, which is a library to accelerate deep neural network computations.

Note: You don’t have to manually install cuDNN if you are using CuPy wheels, which includes the latest version of cuDNN. Check the output of `chainer.print_runtime_info()`; if you see the cuDNN version number, it is
installed properly and will be used by Chainer automatically.

Note: If you wish, you can manually disable use of cuDNN using `chainer.config.use_cudnn` configuration option. See *Configuring Chainer* for details.

### 12.2.2 Using CPU

If you are running Chainer on CPU, you can use iDeep to utilize vector instructions of CPU. See *Tips and FAQs* for steps to run your model with iDeep.

You can also improve performance by building NumPy linked to Intel MKL. See *Numpy/Scipy with Intel® MKL and Intel® Compilers* for the detailed instructions.

Note: If you installed `numpy` package using Anaconda, you may already have MKL-linked NumPy. Check the output of `numpy.show_config()` to see what linear algebra library is linked.

Note: Use of iDeep and MKL-linked NumPy are orthogonal. You can use both of them at once to maximize the performance.

### 12.3 Migrate Data Preprocessing Code from NumPy to CuPy

If you are preprocessing your dataset or running data augmentation using NumPy, you may be able to use CuPy as a substitution to improve performance.

Note: It is not always efficient to use CuPy instead of NumPy, especially when the computation is not very heavy, or it cannot be done in batch.

### 12.4 Avoid Data Transfer

If you are using GPU, be aware of data transfer between CPU and GPU. For example, printing `chainer.Variable` on GPU (e.g., for debugging) will cause memory transfer from GPU to CPU, which will incur synchronization overhead.

You can use *NVIDIA Visual Profiler* to diagnose this kind of issue.
12.5 Optimize cuDNN Convolution

12.5.1 Workspace Size

Some convolution algorithms in cuDNN use additional GPU memory as a temporary buffer. This is called “workspace,” and users can adjust the upper limit of its size. By increasing the limit of workspace size, cuDNN may be able to use better (i.e., memory consuming but faster) algorithm.

The default size (in bytes) is:

```python
>>> chainer.backends.cuda.get_max_workspace_size()
8388608
```

and can be adjusted using `chainer.backends.cuda.set_max_workspace_size()`.

Maximum required workspace size may vary depending on various conditions such as GPU hardware and batch size of inputs.

12.5.2 Auto-Tuner

Some convolution algorithms in cuDNN support the auto-tuner feature that finds the fastest convolution algorithm for given inputs. You can turn on this feature by setting `autotune` configuration to `True`.

See Configuring Chainer for detailed descriptions.

**Note:** Auto-tuner tries to find the best algorithm for every first observation of the input shape combination. Therefore, the first batch will become slower when auto-tuner is enabled. The result of auto-tuner is cached on memory so that it can be reused for data with the same input shape combination. In other words, algorithm selected in the first batch will be reused for the second and later batches, as long as the input shape combination is the same.

If you set `autotune` configuration to `False`, the default convolution algorithm will always be selected, regardless of the previous auto-tuner results.

**Note:** Auto-tuner always use the maximum workspace size.

12.6 Fine-Tune Configuration

There are some Chainer configuration values that affect performance. Although the default values work well in most cases, you can adjust the following configurations for better performance.

- `enable_backprop`
  
  If you are running your model for inference (i.e., you don’t have to use back propagation because you are not training the model), you can set this configuration to `False` to improve performance and reduce memory consumption.

- `type_check`
  
  By default, Chainer checks the integrity between input data and functions. This makes possible to display friendly message when, for example, data with invalid dtype or shape is given to a function. By setting this configuration to `False`, you can let Chainer skip such check to improve performance. It is recommended that you turn off the check only for well-tested code and input data.
See Configuring Chainer for detailed descriptions.

## 12.7 Load Datasets Concurrently

If loading process of your dataset is I/O-bound or CPU-bound, consider using chainer.iterators.MultithreadIterator or chainer.iterators.MultiprocessIterator to load dataset concurrently using multiple threads or processes, instead of chainer.iterators.SerialIterator which works in a single thread in a single process.

## 12.8 Use Multiple GPUs

You can utilize multiple GPUs to make the training process faster.

For data parallelism, you can use chainer.training.updaters.ParallelUpdater or chainer.training.updaters.MultiprocessParallelUpdater instead of chainer.training.updaters.StandardUpdater. For model parallelism, you need to manually transfer each chainer.Link in your model to each device.

See Using GPU(s) in Chainer for the working examples of each case.

## 12.9 Use Multiple Nodes

You can scale-out the training process of your Chainer model to multiple-node cluster by using ChainerMN module which enables distributed deep learning.
This is a list of changes introduced in each release that users should be aware of when migrating from older versions. Most changes are carefully designed not to break existing code; however changes that may possibly break them are highlighted with a box.

13.1 Chainer v7

13.1.1 Dropping Support of Python 2.7

In Chainer v7, Python 2.7 is no longer supported as it reaches its end-of-life (EOL) in January 2020. Python 3.5.2 is the minimum Python version supported by Chainer v7. Please upgrade the Python version if you are using Python 2.7 to any later versions listed under Installation.

13.1.2 CuPy v7

Chainer v7 requires CuPy v7 if you need GPU support. Please see the Upgrade Guide for CuPy v7 for details.

13.2 Chainer v6

13.2.1 Dropping Support of Python 3.4

In Chainer v6, Python 3.4 is no longer supported as it reaches its end-of-life (EOL) in March 2019. Python 3.5.1 is the minimum Python 3 version supported by Chainer v6. Please upgrade the Python version if you are using Python 3.4 to any later versions listed under Installation.

13.2.2 CuPy Needs To Be Manually Updated

Prior to Chainer v6, CuPy is automatically updated to the appropriate version when updating Chainer (i.e., pip install -U chainer updates CuPy package). In Chainer v6, Chainer does not perform this automatic update. You need to manually update CuPy package when updating Chainer package.

This is because the automatic update made users difficult to switch between CuPy packages (e.g. cupy-cuda90 and cupy-cuda92 etc). See #5425 for details.
13.2.3 Deprecation Notice on Communicators and Old NCCL versions

Chainer v6 only supports NCCL 2.3 and newer versions. Old NCCL versions are to be deprecated and will be removed in future versions. As of old NCCL deprecation, several communicators built for them are to be deprecated as well:

- hierarchical
- two_dimensional
- single_node

They will be removed in future versions. Also, default communicator changed to pure_nccl from hierarchical.

13.2.4 CuPy v6

Chainer v6 requires CuPy v6 if you need GPU support. Please see the Upgrade Guide for CuPy v6 for details.

13.3 Chainer v5

13.3.1 ChainerMN Became Part of Chainer

ChainerMN, which enables multi-node distributed deep learning using Chainer, has been merged to Chainer v5.

Prior to Chainer v4, ChainerMN was provided as a separate chainermn package. In Chainer v5, ChainerMN now became a part of Chainer; ChainerMN will be installed just by installing chainer package. If you are using chainermn package, make sure to remove it by pip uninstall chainermn before upgrading to Chainer v5 or later.

For documentation of ChainerMN, see Distributed Deep Learning with ChainerMN.

13.3.2 Use forward Instead of __call__ in Links

Prior to Chainer v5, __call__ method is used to define the behavior of Link. In Chainer v5, forward method has been introduced, and is now recommended that you use it instead of __call__. The base class (Link) provides __call__ method implementation that invokes forward method defined in the subclass; the only thing you need to do is to rename the method name (replace def __call__(...) with def forward(...)).

For backward compatibility, you can still use __call__ to define your own link. However, new features introduced in Chainer v5 (e.g., LinkHook) may not be available for such links.

13.3.3 FunctionNode Classes are Hidden from chainer.functions

Prior to Chainer v5, FunctionNode classes (e.g., chainer.functions.MaxPooling2D) are exposed under chainer.functions. In Chainer v5, these classes are hidden from chainer.functions. Use the equivalent wrapper functions listed in Functions (e.g., chainer.functions.max_pooling_2d()) instead.

Some wrapper functions now provide options to access internal states to avoid directly using FunctionNode classes.

- chainer.functions.max_pooling_2d(): return_indices
- chainer.functions.max_pooling_nd(): return_indices
- chainer.functions.dropout(): mask, return_mask
- chainer.functions.gaussian(): eps, return_eps
For example, suppose your existing code needs to access `MaxPooling2D.indexes` to later perform upsampling:

```python
p = F.MaxPooling2D(2, 2)
h = p.apply((x,))[0]
...
y = F.upsampling_2d(h, p.indexes, ksize=2)
```

The above code may raise this error in Chainer v5:

```python
AttributeError: module 'chainer.functions' has no attribute 'MaxPooling2D'
```

You can rewrite the above code using `return_indices` option of `chainer.functions.max_pooling_2d`:

```python
h, indices = F.max_pooling_2d(x, 2, 2, return_indices=True)
...
y = F.upsampling_2d(h, indices, ksize=2)
```

### 13.3.4 Persistent Values are Copied in `Link.copyparams`

`chainer.Link.copyparams()` is a method to copy all parameters of the link to another link. This method can be used, for example, to copy parameters between two chains that partially share the same network structure to reuse pretrained weights.

Prior to Chainer v5, only parameters are copied between links. In Chainer v5, in addition to parameters, persistent values (see Serializers – saving and loading for details) are also copied between links. This is especially beneficial when copying parameters of `BatchNormalization`, as it uses persistent values to record running statistics.

You can skip copying persistent values by passing newly introduced `copy_persistent=False` option to `copyparams()` so that it behaves as in Chainer v4.

### 13.3.5 Updaters Automatically Call Optimizer. `new_epoch`

This change should affect only a minority of users (who call `new_epoch()` while using a trainer, or who implement their own `Updater` class).

Optimizers provide `new_epoch()` method, which can be used to change the behavior of optimizers depending on the current epoch number. Prior to Chainer v5, this method was expected to be called by users. In Chainer v5, updaters have been changed to call `new_epoch()` automatically. If you have been calling `new_epoch()` method manually while using a trainer (or an updater), you may need any of the following fixes:

- Pass `auto_new_epoch=False` to the constructor of the updater (e.g., `StandardUpdater`) to stop `new_epoch()` from being called automatically by the updater.
- Avoid calling `new_epoch()` method manually.

If you implement your own `Updater` class, you may need to update your code to automatically call `new_epoch()` (you can refer to the changes introduced in #4608 to understand how to fix your updater).
13.3.6 Extending the Backend Namespace

In addition to chainer.backends, we introduced chainer.backend. This subpackage contains utility functions that span several backends. For instance, it includes chainer.backend.get_array_module() which used to be defined in chainer.backends.cuda.get_array_module(). Both can be used but the latter will be deprecated.

13.3.7 get_device_from_array Returns Actual Device for Empty Arrays

Prior to Chainer v5, chainer.backends.cuda.get_device_from_array() returned chainer.backends.cuda.DummyDeviceType if the array is empty. In Chainer v5, it has been changed to return the actual cupy.cuda.Device object:

```python
>>> x = cupy.array([])
>>> chainer.backends.cuda.get_device_from_array(x)
<CUDA Device 0>
```

13.3.8 Update of Docker Images

Chainer official Docker images (see Installation for details) are now updated to use CUDA 9.2 and cuDNN 7. To use these images, you may need to upgrade the NVIDIA driver on your host. See Requirements of nvidia-docker for details.

13.3.9 CuPy v5

Chainer v5 requires CuPy v5 if you need GPU support. Please see the Upgrade Guide for CuPy v5 for details.

13.4 Chainer v4

13.4.1 Introduction of Backend Namespace

We introduced chainer.backends subpackage for future support of various backend libraries other than NumPy and CuPy. By this change, chainer.cuda module is now moved to chainer.backends.cuda. This does not break the existing code; you can safely continue to use chainer.cuda (e.g., from chainer import cuda) but it is now encouraged to use from chainer.backends import cuda instead.

13.4.2 Namespace Changes for Updaters

chainer.training.StandardUpdater and chainer.training.ParallelUpdater are now moved to chainer.training.updaters.StandardUpdater and chainer.training.updaters.ParallelUpdater respectively, to align with the namespace convention of other subpackages. See the discussion in #2982 for more details.

This change does not break the existing code; you can safely continue to use updater classes directly under chainer.training but it is now encouraged to use chainer.training.updaters instead.
13.4.3 Namespace Changes for Optimizer Hooks

*Optimizer hook functions* are moved from `chainer.optimizer.*` to `chainer.optimizer_hooks.*`. For example, `chainer.optimizer.WeightDecay` is now located `chainer.optimizer_hooks.WeightDecay`.

If the existing code is using hooks directly under `chainer.optimizer`, `DeprecationWarning` will be shown. You are now encouraged to use `chainer.optimizer_hooks` instead.

13.4.4 Prohibition of Mixed Use of Arrays on Different Devices in Function Arguments

Argument validation of functions is now strictened to check device consistency of argument variables to provide better error messages to users. Suppose the following code:

```python
v1 = chainer.Variable(np.arange(10, dtype=np.float32))  # CPU
v2 = chainer.Variable(cupy.arange(10, dtype=cupy.float32))  # GPU
# The line below raises an exception, because arguments are on different device.
F.maximum(v1, v2)
```

Prior to v4, the above code raises an exception like `ValueError: object __array__ method not producing an array`, which was difficult to understand. In v4, the error message would become `TypeError: incompatible array types are mixed in the forward input (Maximum)`. This kind of error usually occurs by mistake (for example, not performing `to_gpu` for some variables).

**Attention:** As the argument validation is strictened, call of functions intentionally mixing NumPy/CuPy arrays in arguments will not work in Chainer v4. Please transfer all arrays to the same device before calling functions.

13.4.5 References to Function Nodes Not Retained in TimerHook and CupyMemoryProfilerHook

To reduce memory consumption, references to the function nodes will no longer be retained in the `chainer.function_hooks.CupyMemoryProfileHook` and `chainer.function_hooks.TimerHook`. See the discussion in #4300 for more details.

**Attention:** The existing code using function nodes retained in `call_history` attribute of these hooks will not work. The first element of `call_history` became the name of the function, instead of the function node instance itself. You can define your own function hook if you need to access the function node instances.
13.4.6 Update of Docker Images

Chainer official Docker images (see Installation for details) are now updated to use CUDA 8.0 and cuDNN 6.0. This change was introduced because CUDA 7.5 does not support NVIDIA Pascal GPUs.

To use these images, you may need to upgrade the NVIDIA driver on your host. See Requirements of nvidia-docker for details.

13.4.7 CuPy v4

Chainer v4 requires CuPy v4 if you need GPU support. Please see the Upgrade Guide for CuPy v4 for details.

13.5 Chainer v3

13.5.1 Introduction of New-style Functions

This release introduces new-style functions (classes inheriting from FunctionNode) that support double backward (gradient of gradient). See the Release Note for v3.0.0 for the usage of this feature.

Many of Functions are already migrated to new-style, although some of functions are still old-style (classes inheriting from Function). We are going to migrate more old-style functions to new-style in upcoming minor releases.

This does not break the existing code. Old-style functions (classes inheriting from Function) are still supported in v3 and future versions of Chainer.

If you are going to write new functions, it is encouraged to use FunctionNode to support double backward.

**Attention:** Users relying on undocumented function APIs (directly instantiating old-style classes) may experience an error like TypeError: 'SomeFunction' object is not callable after upgrading to v3. Please use the function APIs documented in Functions.

13.5.2 Changed Behavior of matmul Function

The behavior of chainer.functions.matmul() has been changed to behave like the corresponding NumPy function (numpy.matmul()). See the discussion in #2426 for more details.

**Attention:** The existing code using chainer.functions.matmul() may require modification to work with Chainer v3.

Also note that chainer.functions.batch_matmul() is now depreciated by this change. You can rewrite it using chainer.functions.matmul().
13.5.3 Removed use_cudnn Argument in spatial_transformer_grid and spatial_transformer_sampler Functions

use_cudnn argument has been removed from `chainer.functions.spatial_transformer_grid()` and `chainer.functions.spatial_transformer_sampler()`. See the discussion in #2955 for more details.

**Attention:** The existing code using use_cudnn argument of `chainer.functions.spatial_transformer_grid()` and `chainer.functions.spatial_transformer_sampler()` require modification to work with Chainer v3. Please use the configuration context (e.g., with `chainer.using_config('use_cudnn', 'auto'):`) to enable or disable use of cuDNN. See Configuring Chainer for details.

13.5.4 CuPy v2

Chainer v3 requires CuPy v2 if you need GPU support. Please see the Upgrade Guide for CuPy v2 for details.

13.6 Chainer v2

See Upgrade Guide from v1 to v2 for the changes introduced in Chainer v2.

13.6.1 Upgrade Guide from v1 to v2

This documentation provides detailed information of differences between Chainer v1 and v2. You will know by reading it which part of your code is required (or recommended) to be fixed when you upgrade Chainer from v1 to v2.

- **CuPy**
  - CuPy has been separated from Chainer into a separate package
- **Global configurations**
  - Training mode is configured by a thread-local flag
  - Configurations are added and replace some of existing global flags
- **Variable**
  - Volatile flag is removed
  - Variable is not a part of a computational graph anymore
  - Parameter has to be an instance of Parameter class
  - Small changes to Variable
- **Function**
  - The force_tuple option of split_axis is True by default
  - Type check APIs are updated to enable lazy building of the error messages
  - Methods to release unneeded arrays are added
- **Link/Chain/ChainList**
– wscale option is removed from links
– bias option is removed from links
– The bias vector is enabled by default in N-dimensional convolution links
– init_weight function is removed
– The order of arguments of GRU is changed
– The default value of the forget bias for LSTM and StatelessLSTM is changed to 1
– The interfaces of GRU and LSTM are aligned
– Aliases of links in chainer.functions are removed
– Parameter link is removed
– New-style parameter registration APIs are added to Link
– New-style child link registration APIs are added to Chain
– The input-size placeholder of links are made optional

• Optimizer
  – Deprecated methods of Optimizer are removed
  – GradientMethod uses Link.cleargrads instead of Link.zerograds by default
  – GradientMethod is redesigned to allow parameter-specific update rules

• Serializer
  – None is serializable

• Trainer and Extension
  – Updater and Evaluator pass raw data arrays to the loss function
  – trigger option is removed from snapshot and snapshot_object
  – Extension.invoke_before_training is removed
  – The dump_graph extension dumps the valid graph only at its first invocation

• Reporter
  – When a variable is reported, the variable is copied with the graph purged

• Other utilities
  – Some obsolete classes and functions are removed

CuPy

**CuPy has been separated from Chainer into a separate package**

CuPy, which was originally a part of Chainer, has been separated into a different Python package since Chainer v2. It changes the way to set up Chainer with CUDA support. In particular, you have to separately install cupy package to enable CUDA support. See Installation for the recommended installation steps.

Fortunately, there is no need of updating your source code to catch up with this change.
Global configurations

Training mode is configured by a thread-local flag

In Chainer v2, the concept of *training mode* is added. It is represented by a thread-local flag `chainer.config.train`, which is a part of the unified configuration. When `chainer.config.train` is True, functions of Chainer run in the training mode, and otherwise they run in the test mode. For example, `BatchNormalization` and `dropout()` behave differently in each mode.

In Chainer v1, such a behavior was configured by the `train` or `test` argument of each function. **This train/test argument has been removed in Chainer v2.** If your code is using the `train` or `test` argument, you have to update it. In most cases, what you have to do is just removing the `train/test` argument from any function calls.

**Example**

Consider the following model definition and the code to call it in test mode written for Chainer v1.

```python
# Chainer v1
import chainer.functions as F

class MyModel(chainer.Link):
    ...

    def __call__(self, x, train=True):
        return f(F.dropout(x, train=train))

m = MyModel(...)
y = m(x, train=False)
```

In Chainer v2, it should be updated into the following code:

```python
# Chainer v2
import chainer.functions as F

class MyModel(chainer.Link):
    ...

    def __call__(self, x):
        return f(F.dropout(x))

m = MyModel(...)
with chainer.using_config('train', False):
    y = m(x)
```

**Configurations are added and replace some of existing global flags**

There are many global settings moved to the unified configuration other than the training mode. Following is the complete list of the configuration entries that have corresponding features in Chainer v1.

`chainer.config.cudnn_deterministic` It is corresponding to the `deterministic` argument of some convolution functions in Chainer v1. **This argument has been removed since Chainer v2.** If you are using this argument, you have to use the `chainer.config.cudnn_deterministic` flag to change the behavior of the convolution functions.
chainer.config.debug It is corresponding to the debug mode in Chainer v1, which was configured by set_debug() and extracted by is_debug(). These functions are also available in Chainer v2, so you basically do not need to update the code related to the debug mode.

chainer.config.enable_backprop It is corresponding to the backprop mode in Chainer v1. The functions no_backprop_mode() and force_backprop_mode() are still available in Chainer v2, which automatically turns on/off the enable_backprop flag. One important difference from Chainer v1 is that the volatile flag is removed from Variable. Therefore, there are more situations that you need to modify the enable_backprop flag.

chainer.config.keep_graph_on_report This flag configures whether or not to keep the computational graph alive for a reported variable. In Chainer v2, when a Variable object is reported by report(), a copy of the variable isolated from the computational graph is created and stored by default. Setting True to this flag, you can change this behavior and then the original Variable object is stored as is. See When a variable is reported, the variable is copied with the graph purged for the details.

chainer.config.train It is corresponding to the train or test argument of some functions in Chainer v1. This argument has been removed since Chainer v2. If you are using this argument, you have to use the chainer.config.train flag instead. See Training mode is configured by a thread-local flag for more details.

chainer.config.type_check It is corresponding to the Function.type_check_enable flag. If your code touches this flag, you have to use chainer.config.type_check instead. Note that the environment variable CHAINER_TYPE_CHECK is still available in Chainer v2, so if you are only using the environment variable, there is no need of updating your code.

chainer.config.use_cudnn It is corresponding to the use_cudnn argument of many functions that have cuDNN implementations. This argument has been removed since Chainer v2. If you are using this argument, you have to use the chainer.config.use_cudnn flag instead. Note that this flag is ternary, not binary. See Configuring Chainer for more details.

These configurations can be modified in two ways.

- Simply substituting a new value to an entry, like chainer.config.train = False.
- Using the chainer.using_config context manager. It can be used with the with statement of Python as follows:

```python
with chainer.using_config('train', False):
    do something  # this code runs with chainer.config.train == False
```

It recovers the original configuration after quitting the with block.

The chainer.config manages the thread-local configuration. You can also set the global configuration by modifying chainer.global_config. Note that the global configuration is used only if the entry of the thread-local configuration is not explicitly set up.

**Variable**

**Volatile flag is removed**

The Variable.volatile flag has been removed since Chainer v2.

Instead, the configuration chainer.config.enable_backprop can be used to enable/disable the automatic differentiation feature. If it is True, Chainer always creates a computational graph on the forward propagation, which corresponds to passing non-volatile variables in Chainer v1. Otherwise, Chainer does not create a graph, which corresponds to passing volatile variables in Chainer v1. The biggest difference is that enable_backprop is a thread-local flag, whereas volatile was a flag local to each Variable object. Note that enable_backprop
flag has already existed in Chainer v1, which took effect only if all the inputs to the function have `volatile == 'auto'`.

The `chainer.config.enable_backprop` flag can be modified directly or by using `using_config()`. See *Configuring Chainer* for details. There is also a convenience function, `no_backprop_mode()`, to turn off the flag.

If you are using the `Variable.volatile` flag, you have to stop setting this flag (it will not take effect), and set the `enable_backprop` flag instead.

---

### Example

Let `model` be your model, and consider the following code that calls it in volatile mode.

```python
# Chainer v1
x_data = ...  # ndarray
x = chainer.Variable(x_data, volatile=True)
y = model(x)
```

In Chainer v2, it should be updated as follows.

```python
# Chainer v2
x_data = ...  # ndarray
x = chainer.Variable(x_data)
with chainer.no_backprop_mode():
    y = model(x)
```

---

### Variable is not a part of a computational graph anymore

The `Variable` class has been separated into two distinct classes, the `Variable` class and the `VariableNode` class, since Chainer v2. Every `Variable` object owns its own `VariableNode` object. A computational graph consists of `Function` objects and `VariableNode` objects. When one applies a `Function` to a `Variable`, the `VariableNode` object of the variable is extracted and set to one of the inputs of the function.

Note that the underlying data array of the variable is still held by the `Variable` object. It allows each `Function` implementation to release unneeded arrays from the computational graph, resulting in greatly reduced memory consumption.

**This change does not affect most users’ code.** If you are directly traversing the computational graph by yourself or modifying the graph ad-hoc, you may have to update your code. In most cases, it is enough to just change `Variable` into `VariableNode` in the code traversing the computational graph.

---

### Parameter has to be an instance of Parameter class

Chainer v2 has a subclass of `Variable` called `Parameter`. This class has an interface convenient on setting up a parameter variable registered to `Link`.

You basically do not need to update your code because `Link.add_param()` creates a `Parameter` object in Chainer v2. There is a new recommended way of registering parameters to a link in Chainer v2, though. See here for the recommended way of parameter registration.
Small changes to Variable

There are some changes on the interface and specification of methods.

- `len(variable)` returns the length of the first axis of the underlying array in Chainer v2. This is equivalent to `len(variable.data)`. It is different from the behavior of Chainer v1, in which `len` returned the total number of elements in the underlying array.

- `repr(variable)` returns a NumPy-like text representation of the underlying array in Chainer v2. In Chainer v1, it just returns a string that shows the name of the variable.

Function

The force_tuple option of split_axis is True by default

In Chainer v2, the `force_tuple` argument of `functions.split_axis()` is set to `True` by default. Therefore, it always returns a tuple regardless of the number of sections made after the split. It was `False` by default in Chainer v1.

Type check APIs are updated to enable lazy building of the error messages

In Chainer v2, the type check APIs are updated so that the overhead of checking types is greatly reduced. In order to achieve the overhead reduction, some APIs are changed.

If you have custom Function implementations that do type checking, you have to update your code. The following list shows which part has to be updated.

- Use `utils.type_check.eval()` instead of `Expr.eval`.
- Use `utils.type_check.make_variable()` to create a `utils.type_check.Variable` object instead of directly constructing it by yourself.
- Stop using `.name` attribute of any expression.

Background of this change: In Chainer v1, the type checking APIs build an abstract syntax tree (AST) based on each expression that tests some condition. The AST is used to emit a kind error message. However, building an AST requires constructions of many Python objects, which adds large Python overheads. In Chainer v2, the `Function.type_check_forward()` method is called once or twice. At the first call, the type checking APIs run in lightweight mode, where it does not build an AST and just checks the condition. The second call is made only if there is a test that fails, where it builds an AST. This change makes the ordinary path of running the type checking much faster, while keeping the kind error messages.

Methods to release unneeded arrays are added

As is written above, Chainer v2 introduced a new mechanism to reduce the memory consumption of each Function implementation. In many cases, a Function implementation does not need some input arrays in its backward computation. A new method called `Function.retain_inputs()` can be used to specify which input arrays are actually needed. This method must not be called from the outside of `Function.forward()`.

Example

For example, consider the following simple addition function.
class AddFunction(chainer.Function):
    def forward(self, inputs):
        return inputs[0] + inputs[1],
    
    def backward(self, inputs, grad_outputs):
        return grad_outputs[0], grad_outputs[0]

It can be seen that the backward computation of this function does not use any of the inputs. Then, specifying an empty tuple of indexes to retain_inputs() will reduce the memory overhead.

class AddFunction(chainer.Function):
    def forward(self, inputs):
        self.retain_inputs(())
        # does not retain both inputs
        return inputs[0] + inputs[1],
    
    def backward(self, inputs, grad_outputs):
        return grad_outputs[0], grad_outputs[0]

In some cases, the function can (or have to) use the output arrays instead of the inputs in its backward computation. In Chainer v1, we have written code that store the output arrays to attributes of the Function object and reuse them in the backward() method. In Chainer v2, it is recommended that you use Function.retain_outputs() to declare which outputs are required in the backward computation. The retained output arrays can be accessed via Function.output_data.

Note: The existing Function implementations that store the output arrays to its attributes will run correctly in Chainer v2. There is no any memory overhead right now. It is recommended that you use retain_outputs(), though, so that we can incorporate more memory optimization in the future.

Example

For example, consider the following simple implementation of the tanh function.

class TanhFunction(chainer.Function):
    def forward(self, inputs):
        xp = chainer.cuda.get_array_module(inputs[0])
        self.y = xp.tanh(inputs[0])
        return self.y,
    
    def backward(self, inputs, grad_outputs):
        one = self.y.dtype.type(1)
        # avoid type promotion
        return grad_outputs[0] * (one - self.y * self.y),

We can use retain_outputs() instead of preserving the output array by ourselves as follows.

class TanhFunction(chainer.Function):
    def forward(self, inputs):
        self.retain_outputs((0,))
        xp = chainer.cuda.get_array_module(inputs[0])
        return xp.tanh(inputs[0]),
    
    def backward(self, inputs, grad_outputs):
        y = self.output_data[0]
        one = y.dtype.type(1)
        # avoid type promotion
        return grad_outputs[0] * (one - y * y)
Link/Chain/ChainList

wscale option is removed from links

The `wscale` option has been removed from links since Chainer v2. **If you are using wscale option, you have to update your code.** The recommended way is to explicitly set the initializer.

Example

Consider the case of adding a `Linear` link with the weight initialized by 0.5x of the default initialization.

```python
# Chainer v1
linear = chainer.links.Linear(10, 5, wscale=0.5)
```

Note that the default initializer of the weight matrix of `Linear` is a normal distribution of the standard deviation $\frac{1}{\sqrt{\text{fanin}}}$. Therefore, it can be fixed as follows.

```python
# Chainer v2
linear = chainer.links.Linear(10, 5, initialW=chainer.initializers.Normal(0.5 / math.sqrt(10)))
```

Or, by using the fact that `initializers.HeNormal` provides the initialization with a normal distribution of the standard deviation $\text{scale} \times \sqrt{\frac{2}{\text{fanin}}}$, the following code is also equivalent to the original.

```python
# Chainer v2, using HeNormal
linear = chainer.links.Linear(10, 5, initialW=chainer.initializers.HeNormal(0.5 / math.sqrt(2)))
```

bias option is removed from links

In Chainer v2, the `bias` option is removed from the following links: `Linear`, `Convolution2D`, `Deconvolution2D`, and `DilatedConvolution2D`. The effect of this argument was duplicated with the `initial_bias` option. Use `initial_bias` instead.

**The bias vector is enabled by default in N-dimensional convolution links**

In Chainer v2, the bias parameter is enabled by default in `ConvolutionND` and `DeconvolutionND`. It was unintentionally disabled by default in Chainer v1.

**If you are using ConvolutionND or DeconvolutionND without specifying the initial_bias argument, you have to fix your code.** If you want to keep the old behavior (i.e., no bias vector is created by the link), pass `nobias=True` to the link at the construction. Otherwise it will automatically create a bias vector.
**init_weight function is removed**

The `chainer.initializers.init_weight` function that was used on weight initialization has been removed since Chainer v2.

**You have to update your code if you are using** `init_weight`. In most cases, the update is simple: pass an initializer to `Parameter`.

**Example**

Consider the following code that initializes a weight matrix randomly and a bias vector by zero.

```python
# Chainer v1
class MyLink(chainer.Link):
    def __init__(self):
        super(MyLink, self).__init__(
            W=(10, 5),
            b=(5,),
        )
        chainer.initializers.init_weight(self.W, chainer.initializers.Normal(0.05))
        self.b.data.fill(0)
...
```

This code should be fixed as follows (see the next topic for the use of `Parameter`).

```python
# Chainer v2
class MyLink(chainer.Link):
    def __init__(self):
        super(MyLink, self).__init__()
        self.W = chainer.Parameter(chainer.initializers.Normal(0.05), (10, 5))
        self.b = chainer.Parameter(0, (5,))
...
```

**The order of arguments of GRU is changed**

In Chainer v2, the first two arguments of `GRU` is the input size and the output size. It was reversed in Chainer v1, causing an inconsistent interface compared to other links including `LSTM`. **If you are using GRU, you have to update your code.** The update is done by simply flipping the first two arguments.

**Example**

Consider the following code that creates a `GRU` link.

```python
# Chainer v1
gru = chainer.links.GRU(20, 10)
```

It should be fixed into the following code.

```python
# Chainer v2
gru = chainer.links.GRU(10, 20)
```

Note that if you were omitting the output size, the code works as is because `GRU` supports **the omitted input size**.
# Chainer v1/v2

```python
# Chainer v1/v2
gru = chainer.links.GRU(20)
```

## The default value of the forget bias for LSTM and StatelessLSTM is changed to 1

In Chainer v2, the default forget bias value of LSTM and StatelessLSTM links is changed to 1. This change is based on the paper reporting that using a large forget bias improves the training performance. The new behavior is also consistent with the implementation of BasicLSTMCell in TensorFlow.

It will improve the most use cases of LSTMs, although this change would break the reproducibility of the existing experiments. **If you want to keep the same initialization procedure, you have to update your code.** The change is simple: pass `forget_bias_init=0` to LSTM and StatelessLSTM.

## The interfaces of GRU and LSTM are aligned

In Chainer v1, GRU was stateless, as opposed to the current implementation. To align with the naming convention of LSTM links, we have changed the naming convention from Chainer v2 so that the shorthand name points the stateful links. **If you are using StatelessGRU for stateless version, whose implementation is identical to chainer.linksGRU in v1.**

## Aliases of links in chainer.functions are removed

For the compatibility reason, there were some links that have aliases in the `chainer.functions` module. These aliases are removed in Chainer v2. Use `chainer.links` instead.

## Parameter link is removed

The `chainer.links.Parameter` link is removed in Chainer v2. This link existed in Chainer v1 only for the backward compatibility. Use `chainer.Parameter` instead (for the new `Parameter` class, see **Parameter has to be an instance of Parameter class**).

## New-style parameter registration APIs are added to Link

In Chainer v2, `Link.init_scope()` method returns a context manager that automatically registers a `Parameter` object to the link at setting it to an attribute. If you are using IDE like PyCharm, it is recommended that you use this new-style parameter registration so that IDEs can easily detect the existence of the parameter as an attribute. It is also a good practice to use the new-style API even if you are not using IDEs, if you are planning to make the code public.

**Note:** The existing code that uses the conventional way of registering parameters are still valid.

## Example

For example, the following link initialization code

```python
```
is recommended to be updated as follows.

### Chainer v2

class MyLink(chainer.Link):
    def __init__(self):
        super(MyLink, self).__init__()
        with self.init_scope():
            self.W = chainer.Parameter(chainer.initializers.Normal(0.05), (10, 5))
            self.b = chainer.Parameter(0, (5,))  # initialize by zero
...

**Note:** To keep a Parameter object as an attribute without registration, you can set the attribute without using the with self.init_scope(): block.

### New-style child link registration APIs are added to Chain

Like Parameter, a Link object is also automatically registered to a Chain object by substitution to an attribute within a init_scope() scope. If you are using IDE like PyCharm, it is recommended that you use the new-style child link registration so that IDEs can easily detect the existence of the child link as an attribute. It is also a good practice to use the new-style API even if you are not using IDEs, if you are planning to make the code public.

**Note:** The existing code that uses the conventional way of registering child links are still valid.

### Example

For example, the following chain initialization code

```python
# Chainer v1
class MyMLP(chainer.Chain):
    def __init__(self):
        super(MyMLP, self).__init__()
        layer1=L.Linear(None, 20),
        layer2=L.Linear(None, 30),
    ...
```

is recommended to be updated as follows.
# Chainer v2

```python
class MyMLP(chainer.Chain):
    def __init__(self):
        super(MyMLP, self).__init__()
        with self.init_scope():
            self.layer1 = L.Linear(20)
            self.layer2 = L.Linear(30)
```

Note that this example also demonstrates the use of new APIs with the omitted input size, explained below.

**Note:** To keep a `Link` object as an attribute without registration, you can set the attribute without using the `with self.init_scope():` block.

### The input-size placeholder of links are made optional

In Chainer v2, the input size of many links, including `Linear` and `Convolution2D`, is made optional. In Chainer v1, we had to use `None` as the placeholder to specify that the input size should be determined at the first iteration. The placeholder can also be used in Chainer v2, although it is easier to just omit the input size.

See the previous item for the example of omitting the input size of `Linear`. The following links currently support the omitted input size.

- `Convolution2D`
- `Deconvolution2D`
- `DilatedConvolution2D`
- `Linear`
- `LSTM`
- `MLPConvolution2D`
- `StatelessLSTM`

### Optimizer

**Deprecated methods of Optimizer are removed**

The following methods are removed from `Optimizer`. These methods have been already deprecated in the past versions. **If you are using these methods, you have to update your code.**

- `zero_grads`: use `Link.zerograds()` instead.
- `compute_grads_norm`: you can compute the gradient norm by iterating the list of parameters by `Link.params()`.
- `clip_grads`: use `GradientClipping` instead.
- `weight_decay`: use `WeightDecay` instead.
- `accumulate_grads`: use `Link.addgrads()` instead.
GradientMethod uses Link.cleargrads instead of Link.zerograds by default

In Chainer v2, GradientMethod clears the gradient before running backprop by Link.cleargrads(). It means that the gradient of each parameter is initialized by None instead of a zero array. Note that all the optimizer implementations provided by Chainer are subclasses of GradientMethod, and therefore this change affects all of them.

In most cases, you do not need to update your code. If your code relies on the zeroing initialization, you have to fix your code to explicitly initialize the gradient by zero, or to pass False to GradientMethod.use_cleargrads().

GradientMethod is redesigned to allow parameter-specific update rules

In Chainer v2, the new class UpdateRule is used to define an update rule specific to each Parameter object. The UpdateRule is set to each Parameter object, and is used at each update step. This object implements an update formula using the data and gradient arrays.

Each UpdateRule object has enabled flag, which configures if the update rule should be applied to that parameter on update. By setting the flag to False, you can freeze the parameter. There is also a convenient method Link.enable_update() and Link.disable_update(), which configure the flag of each parameter under the link hierarchy. In other frameworks, a similar feature is called layer freezing. In Chainer v2, this is officially supported by these methods.

Each UpdateRule object can also hold its own hook functions similar to Optimizer. The built-in hook functions except for GradientClipping can also be used as a hook function of UpdateRule.

In most cases, you do not have to update your code because each optimizer automatically sets up an appropriate Updaterule object to each parameter.

If you are using a custom gradient-based optimizer implementation, you need to update the implementation. The following list shows what you have to do.

- Write a subclass of UpdateRule that implements the update rule.
- Rewrite your GradientMethod implementation. The new implementation only has to set up the update rule for each parameter in the target link.

You can see live examples in the optimizer implementations provided by Chainer.

Serializer

None is serializable

In Chainer v2, all serializers start supporting None value to be serialized and deserialized. Users’ code can rely on this feature, i.e., it can serialize and deserialize None value with any given serializer. This change only affects your code if it provides its own serializer implementations.
Trainer and Extension

Updater and Evaluator pass raw data arrays to the loss function

In Chainer v2, Updater and Evaluator pass raw data arrays to the loss function without wrapping them with Variable. You might need to update your code so that the loss function (in most cases, the model's `__call__`) accepts raw arrays.

Note that raw arrays can be directly passed to any Function; they are automatically wrapped by Variable. For example, if the input is directly passed to a Function object (or any function under chainer.functions), you do not need to update the code.

Example

Consider the following code that obtains the shape of the input via Variable.data.

```python
# Chainer v1
class MyLink(chainer.Link):
    def __call__(self, x):
        shape = x.data.shape  # valid if x is Variable, invalid if x is ndarray
        ...
```

It should be updated so that the link also accepts a raw array as the input. In this case, we have `Variable.shape` which is equivalent to `data.shape`, so you can simply write as follows.

```python
# Chainer v2
class MyLink(chainer.Link):
    def __call__(self, x):
        shape = x.shape  # valid regardless of x being Variable or ndarray
        ...
```

trigger option is removed from snapshot and snapshot_object

In Chainer v2, the trigger option is removed from the snapshot() and snapshot_object() extensions. The effect of the option was duplicated with the trigger option of Trainer.extend. If you are passing the trigger argument to these extensions, you have to update your code. The update can be done by passing the value to the corresponding Trainer.extend.

Example

Assume that trainer is an instance of Trainer, and consider that you were adding a snapshot() extension as follows.

```python
# Chainer v1
trainer.extend(chainer.training.extensions.snapshot(trigger=(1000, 'iteration'))
```

It should be updated as follows (note that this code also works with Chainer v1).

```python
# Chainer v1/v2
trainer.extend(chainer.training.extensions.snapshot(), trigger=(1000, 'iteration'))
```
Extension.invoke_before_training is removed

In Chainer v2, the attribute invoke_before_training of Extension is removed. Instead, the Extension.initialize method is added. This method is called by Trainer.run before entering the training loop.

In Chainer v1, the extension is just called before entering the training loop when invoke_before_training is True. If you have a custom extension that has invoke_before_training=True, you have to update the code. What you have to do is to remove the invoke_before_training flag and override initialize() method. If you are using the make_extension() decorator, you can set the initialize function by passing the initializer argument to make_extension().

The dump_graph extension dumps the valid graph only at its first invocation

In Chainer v2, the dump_graph() extension dumps the valid computational graph only at its first invocation. If you want to dump the graph more than once, you have to fix the code. The easiest fix is setting the chainer.config.keep_graph_on_report flag to True. Note that this fix will cancel the improvement on the memory consumption made in Chainer v2. More memory-efficient fix is to dump the graph without using an extension, e.g. by customizing the loss function or the updater.

Here is the background of this change. In Chainer v2, the Reporter copies reported variables with purging the computational graph by default. On the other hand, the dump_graph() extension requires the computational graph reachable from the reported variable. In order to make the graph available, the dump_graph() extension turns on the chainer.config.keep_graph_on_report flag at its initializer (i.e., it turns on the graph before entering the training loop). Since we also wanted to achieve the memory efficiency, the dump_graph() extension turns off the flag after dumping the graph at its first invocation (strictly speaking, it recovers the original value). As a result, the computational graph is not available from the second invocation.

Since the dump_graph() recovers the original flag value at its invocation, you can keep the graph dumped more than once by changing the original flag value.

Reporter

When a variable is reported, the variable is copied with the graph purged

In Chainer v2, when a Variable object is reported using report() function (or directly using Reporter), a copy of the variable is made without preserving the computational graph. If your code depends on the reachability of the computational graph from the reported variable, you have to update your code. The easiest way to update your code is setting chainer.config.keep_graph_on_report to True, then Chainer will keep the computational graph reachable from the reported variable.

The possible examples that are affected by this change are as follows (not exhaustive).

- A custom extension that runs backprop from a reported variable. It is definitely an example of assuming the reachability of the computational graph from the reported variable.

- An extension that visualizes the computational graph from a reported variable. If you are writing such an extension by yourself, you have to turn on the keep_graph_on_report flag. The dump_graph() extension is another example, for which see the above item for the details.

This change is made for the memory performance reason; with this change, the memory used by the computational graph for training is immediately released before invoking extensions. Therefore, changing the behavior by overwriting chainer.config.keep_graph_on_report may increase the memory consumption. It may cause an out-of-memory error if the computational graph of the loss function consumes almost all the memory available in your environment and there is an extension that uses a certain amount of memory (e.g. Evaluator).
Other utilities

Some obsolete classes and functions are removed

The following classes and functions are removed in Chainer v2.

- `chainer.Flag`
- `chainer.FunctionSet` (Use `Chain` or `ChainList` instead)
- `chainer.cuda.init` (It did nothing except for calling `check_cuda_available()`)
- `chainer.cuda.empty` (Use `cupy.empty()`)
- `chainer.cuda.empty_like` (Use `cupy.empty_like()`)
- `chainer.cuda.full` (Use `cupy.full()`)
- `chainer.cuda.full_like` (Use `cupy.full_like()`)
- `chainer.cuda.ones` (Use `cupy.ones()`)
- `chainer.cuda.ones_like` (Use `cupy.ones_like()`)
- `chainer.cuda.zeros` (Use `cupy.zeros()`)
- `chainer.cuda.zeros_like` (Use `cupy.zeros_like()`)
CHAPTER
FOURTEEN

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CHAPTER
FIFTEEN

INDICES AND TABLES

• genindex
• modindex
• search


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C
chainer, 1098
chainer.backend, 1102
chainer.backends.cuda, 1113
chainer.backends.intel64, 1118
chainer.computational_graph, 1141
chainer.dataset, 1035
chainer.datasets, 1052
chainer.distributions, 823
chainer.exporters, 1153
chainer.function_hooks, 311
chainer.functions, 154
chainer.gradient_check, 1159
chainer.initializers, 950
chainer.iterators, 1081
chainer.link_hooks, 814
chainer.links, 322
chainer.links.caffe, 1152
chainer.optimizers, 885
chainer.serializers, 1091
chainer.testing, 1163
chainer.training, 963
chainer.training.extensions.snapshot_writers, 963
chainer.utils, 1371
chainer.utils.type_check, 1154
chainermn, 1313
chainerx, 1214

O
onnx_chainer, 1363
INDEX

Symbols

__abs__() (chainer.Parameter method), 148
__abs__() (chainer.Variable method), 138
__abs__() (chainerx.ndarray method), 1211
__add__() (chainer.Parameter method), 148
__add__() (chainer.Sequential method), 814
__add__() (chainer.Variable method), 138
__add__() (chainer.utils.type_check.Expr method), 1156
__add__() (chainer.utils.type_check.TypeInfoTuple method), 1158
__add__() (chainer.utils.type_check.Variable method), 1159
__add__() (chainerx.ndarray method), 1211
__bool__() (chainer.Parameter method), 147
__bool__() (chainer.Variable method), 138
__bool__() (chainer.utils.type_check.Expr method), 1156
__bool__() (chainer.utils.type_check.Variable method), 1159
__call__() (chainer.AbstractSerializer method), 1100
__call__() (chainer.Chain method), 793
__call__() (chainer.ChainList method), 799
__call__() (chainer.Deserializer method), 1101
__call__() (chainer.Function method), 294
__call__() (chainer.FunctionAdapter method), 298
__call__() (chainer.FunctionNode method), 304
__call__() (chainer.Initializer method), 949
__call__() (chainer.Link method), 786
__call__() (chainer.Sequential method), 807
__call__() (chainer.Serializer method), 1099
__call__() (chainer.dataset.ConcatWithAsyncTransfer method), 1050
__call__() (chainer.dataset.Converter method), 1048
__call__() (chainer.iterators.OrderSampler method), 1089
__call__() (chainer.iterators.OrderSampler method), 1090
__call__() (chainer.iterators.ShuffleOrderSampler method), 1092
__call__() (chainer.links.BatchNormalization method), 616
__call__() (chainer.links.BatchRenormalization method), 623
__call__() (chainer.links.Bias method), 323
__call__() (chainer.links.Bilinear method), 330
__call__() (chainer.links.BinaryHierarchicalSoftmax method), 650
__call__() (chainer.links.BlackOut method), 656
__call__() (chainer.links.CRF1d method), 663
__call__() (chainer.links.CRF1d method), 664
__call__() (chainer.links.Classifier method), 705
__call__() (chainer.links.Convolution1D method), 343
__call__() (chainer.links.Convolution2D method), 351
__call__() (chainer.links.Convolution3D method), 362
__enter__()  (chainer.iterators.DaliIterator method), 1088
__enter__()  (chainer.iterators.MultiprocessIterator method), 1085
__enter__()  (chainer.iterators.MultithreadIterator method), 1086
__enter__()  (chainer.iterators.SerialIterator method), 1082
__enter__()  (chainer.link_hooks.SpectralNormalization method), 816
__enter__()  (chainer.link_hooks.TimerHook method), 818
__enter__()  (chainer.link_hooks.WeightStandardization method), 820
__eq__()  (chainer.AbstractSerializer method), 1100
__eq__()  (chainer.Chain method), 798
__eq__()  (chainer.ChainList method), 804
__eq__()  (chainer.DeviceResident method), 1101
__eq__()  (chainer.DictSummary method), 1106
__eq__()  (chainer.Distribution method), 884
__eq__()  (chainer.DistributionAdapter method), 302
__eq__()  (chainer.DistributionFunctionHook method), 321
__eq__()  (chainer.DistributionNode method), 308
__eq__()  (chainer.GradientMethod method), 941
__eq__()  (chainer.Initializer method), 949
__eq__()  (chainer.Link method), 791
__eq__()  (chainer.LinkHook method), 823
__eq__()  (chainer.Optimizer method), 935
__eq__()  (chainer.Parameter method), 147
__eq__()  (chainer.Reporter method), 1125
__eq__()  (chainer.Sequential method), 813
__eq__()  (chainer.SerializedObject method), 1099
__eq__()  (chainer.Summary method), 1127
__eq__()  (chainer.UpdateRule method), 938
__eq__()  (chainer.Variable method), 137
__eq__()  (chainer.backend.ChainerxDevice method), 1112
__eq__()  (chainer.backend.CpuDevice method), 1108
__eq__()  (chainer.backend.Device method), 1103
__eq__()  (chainer.backend.GpuDevice method), 1109
__eq__()  (chainer.backend.Intel64Device method), 1111
__eq__()  (chainer.computational_graph.ComputationalGraph method), 1144
__eq__()  (chainer.configuration.GlobalConfig method), 1137
__eq__()  (chainer.configuration.LocalConfig method), 1138
__eq__()  (chainer.dataset.ConcatWithAsyncTransfer method), 1050
__eq__()  (chainer.dataset.Converter method), 1048
__eq__()  (chainer.dataset.DatasetMixin method), 1037
__eq__()  (chainer.dataset.DatasetMixIn method), 1037
__eq__()  (chainer.dataset.DatasetIterator method), 1047
__eq__()  (chainer.dataset.TabularDataset method), 1040
__eq__()  (chainer.dataset.tabular.DelegateDataset method), 1044
__eq__()  (chainer.datasets.ConcatenatedDataset method), 1056
__eq__()  (chainer.datasets.DictDataset method), 1053
__eq__()  (chainer.datasets.ImageDataset method), 1063
__eq__()  (chainer.datasets.LabeledImageDataset method), 1068
__eq__()  (chainer.datasets.LabeledZippedImageDataset method), 1070
__eq__()  (chainer.datasets.MultiZippedImageDataset method), 1066
__eq__()  (chainer.datasets.PickleDataset method), 1074
__eq__()  (chainer.datasets.PickleDatasetWriter method), 1075
__eq__()  (chainer.datasets.SubDataset method), 1058
__eq__()  (chainer.datasets.TextDataset method), 1072
__eq__()  (chainer.datasets.TransformDataset method), 1061
__eq__()  (chainer.datasets.TupleDataset method), 1054
__eq__()  (chainer.datasets.ZippedImageDataset method), 1065
__eq__()  (chainer.device_resident.DeviceResidentsVisitor method), 1107
__eq__()  (chainer.distributions.Bernoulli method), 825
__eq__()  (chainer.distributions.Beta method), 828
__eq__()  (chainer.distributions.Categorical method), 831
__eq__()  (chainer.distributions.Cauchy method), 834
__eq__()  (chainer.distributions.Chisquare method), 837
__eq__()  (chainer.distributions.Dirichlet method), 840
__eq__()  (chainer.distributions.Distribution method), 843
__eq__()  (chainer.distributions.Exponential method), 846
__eq__()  (chainer.distributions.Gamma method), 849
__eq__()  (chainer.distributions.Geometric method), 852
__eq__()  (chainer.distributions.Gumbel method), 855
__eq__()  (chainer.distributions.Laplace method), 858
__eq__()  (chainer.distributions.LogNormal method), 861
__eq__()  (chainer.distributions.MultivariateNormal method), 864
Index
Index
Index
__gt__ (chainer.links.BatchRenormalization method), 628
__gt__ (chainer.links.Bias method), 328
__gt__ (chainer.links.Bilinear method), 335
__gt__ (chainer.links.BinaryHierarchicalSoftmax method), 655
__gt__ (chainer.links.BlackOut method), 662
__gt__ (chainer.links.CRF1d method), 669
__gt__ (chainer.links.ChildSumTreeLSTM method), 342
__gt__ (chainer.links.Classifier method), 711
__gt__ (chainer.links.Convolution1D method), 349
__gt__ (chainer.links.Convolution2D method), 357
__gt__ (chainer.links.Convolution3D method), 363
__gt__ (chainer.links.ConvolutionND method), 371
__gt__ (chainer.links.Deconvolution1D method), 378
__gt__ (chainer.links.Deconvolution2D method), 386
__gt__ (chainer.links.Deconvolution3D method), 392
__gt__ (chainer.links.DecorrelatedBatchNormalization method), 635
__gt__ (chainer.links.DeformableConvolution2D method), 407
__gt__ (chainer.links.DepthwiseConvolution2D method), 414
__gt__ (chainer.links.DilatedConvolution2D method), 421
__gt__ (chainer.links.EmbedID method), 428
__gt__ (chainer.links.GRU method), 435
__gt__ (chainer.links.GoogLeNet method), 735
__gt__ (chainer.links.GroupNormalization method), 642
__gt__ (chainer.links.Highway method), 441
__gt__ (chainer.links.Inception method), 448
__gt__ (chainer.links.InceptionBN method), 455
__gt__ (chainer.links.LSTM method), 477
__gt__ (chainer.links.LayerNormalization method), 648
__gt__ (chainer.links.Linear method), 462
__gt__ (chainer.links.LocalConvolution2D method), 469
__gt__ (chainer.links.MLPConvolution2D method), 484
__gt__ (chainer.links.Maxout method), 696
__gt__ (chainer.links.NStepBiGRU method), 498
__gt__ (chainer.links.NStepBiLSTM method), 506
__gt__ (chainer.links.NStepBiRNReLU method), 513
__gt__ (chainer.links.NStepBiRNNTanH method), 521
__gt__ (chainer.links.NStepGRU method), 528
__gt__ (chainer.links.NStepLSTM method), 536
__gt__ (chainer.links.NStepRNNReLU method), 544
__gt__ (chainer.links.NStepRNNTanH method), 551
__gt__ (chainer.links.NaryTreeLSTM method), 491
__gt__ (chainer.links.NegativeSampling method), 703
__gt__ (chainer.links.PReLU method), 682
__gt__ (chainer.links.Parameter method), 557
__gt__ (chainer.links.ResNet101Layers method), 760
__gt__ (chainer.links.ResNet152Layers method), 768
__gt__ (chainer.links.ResNet50Layers method), 752
__gt__ (chainer.links.Scale method), 564
__gt__ (chainer.links.SimplifiedDropconnect method), 675
__gt__ (chainer.links.StatefulGRU method), 571
__gt__ (chainer.links.StatefulMGU method), 585
__gt__ (chainer.links.StatefulPeepholeLSTM method), 598
__gt__ (chainer.links.StatefulZoneoutLSTM method), 604
__gt__ (chainer.links.StatelessGRU method), 579
__gt__ (chainer.links.StatelessLSTM method), 612
__gt__ (chainer.links.StatelessMGU method), 591
__gt__ (chainer.links.Swish method), 689
__gt__ (chainer.links.TheanoFunction method), 776
__gt__ (chainer.links.VGG16Layers method), 719
__gt__ (chainer.links.VGG19Layers method), 727
__gt__ (chainer.links.caffe.CaffeFunction method), 783
__gt__ (chainer.model.vision.resnet.ResNetLayers method), 744
__gt__ (chainer.optimizer.Hyperparameter method), 939
__gt__ (chainer.optimizer_hooks.GradientClipping method), 945
__gt__ (chainer.optimizer_hooks.GradientHardClipping method), 946
__gt__ (chainer.optimizer_hooks.GradientLARS method), 948
__gt__ (chainer.optimizer_hooks.GradientNoise method), 947
__gt__ (chainer.optimizer_hooks.Lasso method), 944
__gt__ (chainer.optimizer_hooks.WeightDecay method), 943
__gt__ (chainer.optimizers.AMBSBound method), 908
__gt__ (chainer.optimizers.ADMGrad method), 901
__gt__ (chainer.optimizers.AdaBound method), 905
__gt__ (chainer.optimizers.AdaDelta method), 888
__gt__ (chainer.optimizers.AdaGrad method), 891
Index 1435

... (chainer.optimizers.Adam method), 894
__gt__ () (chainer.optimizers.AdamW method), 898
__gt__ () (chainer.optimizers.CorrectedMomentumSGD method), 912
__gt__ () (chainer.optimizers.MSVAG method), 920
__gt__ () (chainer.optimizers.MomentumSGD method), 914
__gt__ () (chainer.optimizers.NesterovAG method), 917
__gt__ () (chainer.optimizers.RMSprop method), 923
__gt__ () (chainer.optimizers.RMSpropGraves method), 926
__gt__ () (chainer.optimizers.SGD method), 929
__gt__ () (chainer.optimizers.SMORMS3 method), 932
__gt__ () (chainer.serializers.DictionarySerializer method), 1092
__gt__ () (chainer.serializers.HDF5Deserializer method), 1097
__gt__ () (chainer.serializers.HDF5Serializer method), 1096
__gt__ () (chainer.serializers.NpzDeserializer method), 1094
__gt__ () (chainer.testing.FunctionTestCase method), 1171
__gt__ () (chainer.testing.LinkInitializersTestCase method), 1181
__gt__ () (chainer.testing.LinkTestCase method), 1190
__gt__ () (chainer.training.Extension method), 985
__gt__ () (chainer.training.Trainer method), 974
__gt__ () (chainer.training.Updater method), 976
__gt__ () (chainer.training.extensions.DumpGraph method), 1022
__gt__ () (chainer.training.extensions.Evaluator method), 989
__gt__ () (chainer.training.extensions.ExponentialShift method), 998
__gt__ () (chainer.training.extensions.FailOnNonNumber method), 993
__gt__ () (chainer.training.extensions.InverseShift method), 1000
__gt__ () (chainer.training.extensions.LinearShift method), 1002
__gt__ () (chainer.training.extensions.LogReport method), 1015
__gt__ () (chainer.training.extensions.MicroAverage method), 991
__gt__ () (chainer.training.extensions.MultistepShift method), 1004
__gt__ () (chainer.training.extensions.ParameterStatistics method), 995
__gt__ () (chainer.training.extensions.PlotReport method), 1017
__gt__ () (chainer.training.extensions.PolynomialShift method), 1006
__gt__ () (chainer.training.extensions.PrintReport method), 1011
__gt__ () (chainer.training.extensions.ProgressBar method), 1013
__gt__ () (chainer.training.extensions.StepShift method), 1009
__gt__ () (chainer.training.extensions.VariableStatisticsPlot method), 1020
__gt__ () (chainer.training.extensions.WarmupShift method), 1008
__gt__ () (chainer.training.extensions.snapshot_writers.ProcessQueueWriter method), 971
__gt__ () (chainer.training.extensions.snapshot_writers.ProcessWriter method), 968
__gt__ () (chainer.training.extensions.snapshot_writers.QueueWriter method), 969
__gt__ () (chainer.training.extensions.snapshot_writers.SimpleWriter method), 965
__gt__ () (chainer.training.extensions.snapshot_writers.ThreadQueueWriter method), 970
__gt__ () (chainer.training.extensions.snapshot_writers.ThreadWriter method), 966
__gt__ () (chainer.training.extensions.snapshot_writers.Writer method), 964
__gt__ () (chainer.training.extensions.unchain_variables method), 1027
__gt__ () (chainer.training.triggers.BestValueTrigger method), 1029
__gt__ () (chainer.training.triggers.EarlyStoppingTrigger method), 1030
__gt__ () (chainer.training.triggers.IntervalTrigger method), 1031
__gt__ () (chainer.training.triggers.ManualScheduleTrigger method), 1031
__gt__ () (chainer.training.triggers.MaxValueTrigger method), 1032
__gt__ () (chainer.training.triggers.MinValueTrigger method), 1033
__gt__ () (chainer.training.triggers.OnceTrigger method), 1034
__gt__ () (chainer.training.triggers.TimeTrigger method), 1035
__gt__ () (chainer.training.updaters.MultiprocessParallelUpdater method), 983
__gt__ () (chainer.training.updaters.StandardUpdater method), 981
__gt__ () (chainer.training.updaters.StandardUpdater method), 978
__gt__ () (chainer.utils.CooMatrix method), 1130
__gt__ () (chainer.utils.WalkerAlias method), 1122
__gt__ () (chainer.utils.type_check.Expr method), 1156
__gt__ () (chainer.utils.type_check.TypeInfo method), 1157
__le__ (chainer.links.DecorrelatedBatchNormalization method), 635
__le__ (chainer.links.DeformableConvolution2D method), 407
__le__ (chainer.links.DepthwiseConvolution2D method), 414
__le__ (chainer.links.DilatedConvolution2D method), 421
__le__ (chainer.links.EmbedID method), 428
__le__ (chainer.links.GRU method), 435
__le__ (chainer.links.GoogLeNet method), 735
__le__ (chainer.links.GroupNormalization method), 642
__le__ (chainer.links.Highway method), 441
__le__ (chainer.links.Inception method), 448
__le__ (chainer.links.InceptionBN method), 455
__le__ (chainer.links.LSTM method), 477
__le__ (chainer.links.LayerNormalization method), 648
__le__ (chainer.links.Linear method), 462
__le__ (chainer.links.LocalConvolution2D method), 469
__le__ (chainer.links.MLPConvolution2D method), 484
__le__ (chainer.links.Maxout method), 696
__le__ (chainer.links.NStepBiGRU method), 498
__le__ (chainer.links.NStepBiLSTM method), 506
__le__ (chainer.links.NStepBiRNNReLU method), 513
__le__ (chainer.links.NStepBiRNNTanh method), 521
__le__ (chainer.links.NStepGRU method), 528
__le__ (chainer.links.NStepLSTM method), 536
__le__ (chainer.links.NStepRNNReLU method), 544
__le__ (chainer.links.NStepRNNTanh method), 551
__le__ (chainer.links.NaryTreeLSTM method), 491
__le__ (chainer.links.NegativeSampling method), 703
__le__ (chainer.links.PReLU method), 682
__le__ (chainer.links.Parameter method), 557
__le__ (chainer.links.ResNet101Layers method), 760
__le__ (chainer.links.ResNet152Layers method), 768
__le__ (chainer.links.ResNet50Layers method), 752
__le__ (chainer.links.Scale method), 564
__le__ (chainer.links.SimplifiedDropconnect method), 675
__le__ (chainer.links.StatefulGRU method), 571
__le__ (chainer.links.StatefulMGU method), 585
__le__ (chainer.links.StatefulPeepholeLSTM method), 598
__le__ (chainer.links.StatefulZoneoutLSTM method), 604
__le__ (chainer.links.StatelessGRU method), 579
__le__ (chainer.links.StatelessLSTM method), 612
__le__ (chainer.links.StatelessMGU method), 591
__le__ (chainer.links.Swish method), 689
__le__ (chainer.links.TheanoFunction method), 776
__le__ (chainer.links.VGG16Layers method), 719
__le__ (chainer.links.VGG19Layers method), 727
__le__ (chainer.links.caFe.CaffeFunction method), 783
__le__ (chainer.links.model.vision.resnet.ResNetLayers method), 744
__le__ (chainer.optimizer.Hyperparameter method), 939
__le__ (chainer.optimizer_hooks.GradientClipping method), 945
__le__ (chainer.optimizer_hooks.GradientHardClipping method), 946
__le__ (chainer.optimizer_hooks.GradientLARS method), 948
__le__ (chainer.optimizer_hooks.GradientNoise method), 947
__le__ (chainer.optimizer_hooks.Lasso method), 944
__le__ (chainer.optimizer_hooks.WeightDecay method), 943
__le__ (chainer.optimizers.AMSBound method), 908
__le__ (chainer.optimizers.AMSGrad method), 901
__le__ (chainer.optimizers.AdamBound method), 905
__le__ (chainer.optimizers.AdamDelta method), 888
__le__ (chainer.optimizers.Adagrad method), 891
__le__ (chainer.optimizers.Adam method), 894
__le__ (chainer.optimizers.AdamW method), 898
__le__ (chainer.optimizers.Adadelta method), 890
__le__ (chainer.optimizers.MomentumSGD method), 914
__le__ (chainer.optimizers.NesterovAG method), 917
__le__ (chainer.optimizers.RMSprop method), 923
__le__ (chainer.optimizers.RMSpropGraves method), 926
__le__ (chainer.optimizers.SGD method), 929
__le__ (chainer.optimizers.SMORMS3 method), 932
__le__ (chainer.serializers.DictionarySerializer method), 1092
__le__ (chainer.serializers.HDF5Deserializer method), 1097
__le__ (chainer.serializers.HDF5Deserializer method), 1096
__le__ (chainer.serializers.NpzDeserializer method), 1094
__le__ (chainer.testing.FunctionTestCase method), 1171
825  \text{(chainer.distributions.Beta method), 828}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Categorical method), 831}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Cauchy method), 835}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Chisquare method), 837}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Dirichlet method), 840}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Exponential method), 843}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Gamma method), 846}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Gumbel method), 849}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Gumbel method), 852}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Independent method), 855}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Laplace method), 858}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.LogNormal method), 861}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.MultivariateNormal method), 864}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Normal method), 867}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.OneHotCategorical method), 869}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Pareto method), 872}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Poisson method), 875}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.distributions.Uniform method), 878}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.function_hooks.CUDAPROFilingHook method), 312}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.function_hooks.CupyMemoryProfileHook method), 314}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.function_hooks.PrintHook method), 316}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.function_hooks.TimerHook method), 318}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.Constant method), 951}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.DownsamplingConvFilter method), 962}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.GlorotNormal method), 956}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.GlorotUniform method), 960}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.HeNormal method), 957}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.HeUniform method), 961}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.Identity method), 951}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.LeCunNormal method), 955}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.LeCunUniform method), 959}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.NaN method), 954}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.Normal method), 954}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.One method), 953}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.Orthogonal method), 952}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.UpsamplingDeconvFilter method), 961}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.initializers.Zero method), 952}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.DaliIterator method), 1088}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.MultiprocessIterator method), 1085}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.MultithreadIterator method), 1087}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.OrderSampler method), 1090}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.SerialSampler method), 1093}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.SerialSampler method), 1093}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.TimerHook method), 1096}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.TimerHook method), 1096}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.WeightStandardization method), 820}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.BatchNormalization method), 621}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.BatchRenormalization method), 628}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.Bias method), 328}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.Bilinear method), 335}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.Binomial method), 335}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.Categorical method), 655}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.Classifier method), 711}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.Convolution1D method), 348}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.Convolution2D method), 357}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.ConvolutionND method), 371}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.Deconvolution1D method), 378}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.Deconvolution2D method), 386}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.Deconvolution3D method), 392}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.DeconvolutionND method), 400}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.DecorrelatedBatchNormalization method), 635}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.DeformableConvolution1D method), 407}  \text{\textasciicircum lt\textasciicircum}()  \text{(chainer.iterators.DeformableConvolution2D method), 414}
Index 1443

Chainer Documentation, Release 7.7.0

__lt__() (chainer.training.extensions.DumpGraph method), 1022
__lt__() (chainer.training.extensions.Evaluator method), 989
__lt__() (chainer.training.extensions.ExponentialShift method), 998
__lt__() (chainer.training.extensions.FailOnNonNumber method), 993
__lt__() (chainer.training.extensions.InverseShift method), 1000
__lt__() (chainer.training.extensions.LinearShift method), 1002
__lt__() (chainer.training.extensions.LogReport method), 1015
__lt__() (chainer.training.extensions.MicroAverage method), 991
__lt__() (chainer.training.extensions.MultistepShift method), 1004
__lt__() (chainer.training.extensions.ParameterStatistics method), 995
__lt__() (chainer.training.extensions.PlotReport method), 1017
__lt__() (chainer.training.extensions.PolynomialShift method), 1006
__lt__() (chainer.training.extensions.PrintReport method), 1011
__lt__() (chainer.training.extensions.ProgressBar method), 1013
__lt__() (chainer.training.extensions.StepShift method), 1009
__lt__() (chainer.training.extensions.VariableStatisticsPlot method), 1020
__lt__() (chainer.training.extensions.WarmupShift method), 1007
__lt__() (chainer.training.snapshot_writers.QueueWriter method), 149
__matmul__() (chainer.Parameter method), 139
__mul__() (chainer.Variable method), 138
__mul__() (chainer.extensions.split_backward method), 151
__mul__() (chainerx.ndarray method), 148
__mul__() (chainer.Function method), 297
__mul__() (chainer.Chain method), 798
__mul__() (chainer.ChainList method), 804
__mul__() (chainer.Function method), 297
__mul__() (chainer.Device method), 1294
__mul__() (chainer.dev.method), 138
__mul__() (chainerx.Backend method), 1293
__mul__() (chainerx.Context method), 1292
__mul__() (chainerx.Device method), 1294
__mul__() (chainerx.ndarray method), 1211
__mul__() (chainer.Variable method), 139
__mul__() (chainer.utilities.aliased method), 1106
__mul__() (chainerx.utils.aliased method), 1211
__mul__() (chainerx.ndarray method), 148
__ne__() (chainer.AbstractSerializer method), 1100
__ne__() (chainer.Chain method), 798
__ne__() (chainer.ChainList method), 804
__ne__() (chainer.Deserializer method), 1101
__ne__() (chainer.DeviceResident method), 1106
__ne__() (chainer.DictSummary method), 1122
__ne__() (chainer.Distribution method), 884
__ne__() (chainer.earlystopping.BaseEarlyStopping method), 1028
__ne__() (chainer.earlystopping.EarlyStopping method), 1030

Index 1443
...


__rtruediv__() (chainerx.ndarray method), 1211
__rtruediv__() (chainer.Parameter method), 149
__rtruediv__() (chainer.Variable method), 139
__rtruediv__() (chainer.utils.type_check.Expr method), 1156
__rtruediv__() (chainer.utils.type_check.Variable method), 1159
__rtruediv__() (chainer.n.ndarray method), 1212
__getitem__() (chainer.ChainList method), 799
__getitem__() (chainer.Sequential method), 807
__getitem__() (chainer.links.MLPConvolution2D method), 478
__getitem__() (chainer.links.NStepBiGRU method), 492
__getitem__() (chainer.links.NStepBiLSTM method), 500
__getitem__() (chainer.links.NStepBiRNNReLU method), 507
__getitem__() (chainer.links.NStepBiRNNReLU method), 515
__getitem__() (chainer.links.NStepGRU method), 522
__getitem__() (chainer.links.NStepLSTM method), 530
__getitem__() (chainer.links.NStepRNReLu method), 538
__getitem__() (chainer.links.NStepRNNReLU method), 545
__getitem__() (chainer.links.NStepRNNReLU method), 545
__getitem__() (chainer.n.ndarray method), 1208
__getitem__() (chainer.Parameter method), 148
__getitem__() (chainer.Variable method), 138
__getitem__() (chainer.utils.type_check.Expr method), 1156
__getitem__() (chainer.utils.type_check.Variable method), 1159
__getitem__() (chainer.n.ndarray method), 1211
__truediv__() (chainer.Parameter method), 148
__truediv__() (chainer.Variable method), 139
__truediv__() (chainer.utils.type_check.Expr method), 1156
__truediv__() (chainer.utils.type_check.Variable method), 1159
__truediv__() (chainer.n.ndarray method), 1212

A

a (chainer.distributions.Beta attribute), 829
absolute() (in module chainer.functions), 250
absolute_error() (in module chainer.functions), 230
absolute_error() (in module chainerx), 1253
AbstractSerializer (class in chainer), 1100
accuracy() (in module chainer.functions), 226
accuracy() (in module chainerx), 1240
add() (chainer.DictSummary method), 1128
add() (chainer.Summary method), 1127
add() (in module chainer.functions), 155
add() (in module chainerx), 1257
add_hook() (chainer.Chain method), 793
add_hook() (chainer.ChainList method), 799
add_hook() (chainer.Function method), 294
add_hook() (chainer.FunctionAdapter method), 298
add_hook() (chainer.FunctionNode method), 304
add_hook() (chainer.GradientMethod method), 940
add_hook() (chainer.Link method), 786
add_hook() (chainer.links.BatchNormalization method), 616
add_hook() (chainer.links.BatchNormalization method), 623
add_hook() (chainer.links.Bias method), 323
add_hook() (chainer.links.Bilinear method), 330
add_hook() (chainer.links.BinaryHierarchicalSoftmax method), 650
add_hook() (chainer.links.BlackOut method), 656
add_hook() (chainer.links.caffe.CaffeFunction method), 778
add_hook() (chainer.links.ChildSumTreeLSTM method), 337
add_hook() (chainer.links.Classifier method), 705
add_hook() (chainer.links.Convolution1D method), 343
add_hook() (chainer.links.Convolution2D method), 351
add_hook() (chainer.links.Convolution3D method), 358
add_hook() (chainer.links.ConvolutionND method), 366
add_hook() (chainer.links.CRF1d method), 663
add_hook() (chainer.links.Deconvolution1D method), 373
add_hook() (chainer.links.Deconvolution2D method), 381
add_hook() (chainer.links.Deconvolution3D method), 387
add_hook() (chainer.links.DeconvolutionND method), 395
adabound (chainer.optimizers.Adam attribute), 905
adabound (chainer.optimizers.AdamW attribute), 908
adabound (chainer.optimizers.AMSGrad attribute), 902
AdaBound (class in chainer.optimizers), 902
AdaDelta (class in chainer.optimizers), 886
AdaGrad (class in chainer.optimizers), 889
Adam (class in chainer.optimizers), 892
AdamW (class in chainer.optimizers), 895
add() (chainer.DictSummary method), 1128
add() (chainer.Summary method), 1127
add() (in module chainer.functions), 155
add() (in module chainerx), 1257
add_hook() (chainer.Chain method), 793
add_hook() (chainer.ChainList method), 799
add_hook() (chainer.Function method), 294
add_hook() (chainer.FunctionAdapter method), 298
add_hook() (chainer.FunctionNode method), 304
add_hook() (chainer.GradientMethod method), 940
add_hook() (chainer.Link method), 786
add_hook() (chainer.links.BatchNormalization method), 616
add_hook() (chainer.links.BatchNormalization method), 623
add_hook() (chainer.links.Bias method), 323
add_hook() (chainer.links.Bilinear method), 330
add_hook() (chainer.links.BinaryHierarchicalSoftmax method), 650
add_hook() (chainer.links.BlackOut method), 656
add_hook() (chainer.links.caffe.CaffeFunction method), 778
add_hook() (chainer.links.ChildSumTreeLSTM method), 337
add_hook() (chainer.links.Classifier method), 705
add_hook() (chainer.links.Convolution1D method), 343
add_hook() (chainer.links.Convolution2D method), 351
add_hook() (chainer.links.Convolution3D method), 358
add_hook() (chainer.links.ConvolutionND method), 366
add_hook() (chainer.links.CRF1d method), 663
add_hook() (chainer.links.Deconvolution1D method), 373
add_hook() (chainer.links.Deconvolution2D method), 381
add_hook() (chainer.links.Deconvolution3D method), 387
add_hook() (chainer.links.DeconvolutionND method), 395

1448 Index
add_hook(chainer.links.DecorrelatedBatchNormalization method), 630
add_hook(chainer.links.DeformableConvolution2D method), 402
add_hook(chainer.links.DepthwiseConvolution2D method), 409
add_hook(chainer.links.DilatedConvolution2D method), 416
add_hook(chainer.links.EmbedID method), 423
add_hook(chainer.links.GoogLeNet method), 729
add_hook(chainer.links.GroupNormalization method), 636
add_hook(chainer.links.GRU method), 429
add_hook(chainer.links.Highway method), 436
add_hook(chainer.links.Inception method), 443
add_hook(chainer.links.InceptionBN method), 450
add_hook(chainer.links.LayerNormalization method), 643
add_hook(chainer.links.Linear method), 457
add_hook(chainer.links.LocalConvolution2D method), 464
add_hook(chainer.links.LSTM method), 471
add_hook(chainer.links.Maxout method), 691
add_hook(chainer.links.MLPConvolution2D method), 479
add_hook(chainer.links.model.vision.resnet.ResNetLayers method), 738
add_hook(chainer.links.NaryTreeLSTM method), 486
add_hook(chainer.links.NegativeSampling method), 698
add_hook(chainer.links.NStepBiGRU method), 493
add_hook(chainer.links.NStepBiLSTM method), 500
add_hook(chainer.links.NStepBiRNNReLU method), 507
add_hook(chainer.links.NStepBiRNNTanh method), 515
add_hook(chainer.links.NStepGRU method), 522
add_hook(chainer.links.NStepLSTM method), 530
add_hook(chainer.links.NStepRNNReLU method), 538
add_hook(chainer.links.NStepRNNTanh method), 545
add_hook(chainer.links.Parameter method), 552
add_hook(chainer.links.PReLU method), 677
add_hook(chainer.links.ResNet101Layers method), 754
add_hook(chainer.links.ResNet152Layers method), 762
add_hook(chainer.links.ResNet50Layers method), 746
add_hook(chainer.links.Scale method), 559
add_hook(chainer.links.SimplifiedDropconnect method), 670
add_hook(chainer.links.StatefulGRU method), 566
add_hook(chainer.links.StatefulMGU method), 580
add_hook(chainer.links.StatefulPeepholeLSTM method), 593
add_hook(chainer.links.StatefulZoneoutLSTM method), 599
add_hook(chainer.links.StatelessGRU method), 573
add_hook(chainer.links.StatelessLSTM method), 606
add_hook(chainer.links.StatelessMGU method), 586
add_hook(chainer.links.Swish method), 684
add_hook(chainer.links.TheanoFunction method), 771
add_hook(chainer.links.VGG16Layers method), 713
add_hook(chainer.links.VGG19Layers method), 720
add_hook(chainer.optimizers.Adam method), 896
add_hook(chainer.optimizers.AdaDelta method), 886
add_hook(chainer.optimizers.AdamW method), 889
add_hook(chainer.optimizers.AdaGrad method), 892
add_hook(chainer.optimizers.AdaBound method), 899
add_hook(chainer.optimizers.AdaGradW method), 910
add_hook(chainer.optimizers.AdaGradGraves method), 912
add_hook(chainer.optimizers.AdaGradGraves method), 918
add_hook(chainer.optimizers.NesterovAG method), 915
add_hook(chainer.optimizers.RMSprop method), 921
add_hook(chainer.optimizers.RMSpropGraves method), 924
add_hook(chainer.optimizers.SGD method), 927
add_hook(chainer.optimizers.SMORMS3 method), 930
add_hook(chainer.optimizers.SMORMS3 method), 936
add_hook(chainer.Sequential method), 807
add_hook(chainer.UpdateRule method), 936
add_hook(ermn.global_except_hook), 1358
add_link(chainer.Chain method), 793
add_link(chainer.ChainList method), 799
add_link(chainer.links.caffe.CaffeFunction method), 778
<table>
<thead>
<tr>
<th>Add Link Method</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.ChildSumTreeLSTM method)</td>
<td>337</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.Classifier method)</td>
<td>705</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.DeformableConvolution2D method)</td>
<td>402</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.GoogLeNet method)</td>
<td>729</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.GRU method)</td>
<td>429</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.Highway method)</td>
<td>436</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.Inception method)</td>
<td>443</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.InceptionBN method)</td>
<td>450</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.LSTM method)</td>
<td>471</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.Maxout method)</td>
<td>691</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.MLPConvolution2D method)</td>
<td>479</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.model.vision.resnet.ResNetLayers method)</td>
<td>738</td>
</tr>
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<td><code>add_link()</code></td>
<td>(chainer.links.NaryTreeLSTM method)</td>
<td>486</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.NStepBiGRU method)</td>
<td>493</td>
</tr>
<tr>
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<td>(chainer.links.NStepBiLSTM method)</td>
<td>500</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.NStepBiRNNReLU method)</td>
<td>507</td>
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<td><code>add_link()</code></td>
<td>(chainer.links.NStepBiRNNTanH method)</td>
<td>515</td>
</tr>
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<td>(chainer.links.NStepGRU method)</td>
<td>522</td>
</tr>
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<td>(chainer.links.NStepLSTM method)</td>
<td>530</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.NStepRNNReLU method)</td>
<td>538</td>
</tr>
<tr>
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<td>(chainer.links.NStepRNNTanH method)</td>
<td>545</td>
</tr>
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<td><code>add_link()</code></td>
<td>(chainer.links.ResNet101Layers method)</td>
<td>754</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.ResNet152Layers method)</td>
<td>762</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.ResNet50Layers method)</td>
<td>746</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.Scale method)</td>
<td>559</td>
</tr>
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<td><code>add_link()</code></td>
<td>(chainer.links.StatefulGRU method)</td>
<td>566</td>
</tr>
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<td><code>add_link()</code></td>
<td>(chainer.links.StatefulMGU method)</td>
<td>580</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.StatefulPeepholeLSTM method)</td>
<td>593</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.StatefulZoneoutLSTM method)</td>
<td>599</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.StatelessGRU method)</td>
<td>606</td>
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<td>(chainer.links.StatelessLSTM method)</td>
<td>606</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.VGG16Layers method)</td>
<td>713</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.links.VGG19Layers method)</td>
<td>720</td>
</tr>
<tr>
<td><code>add_link()</code></td>
<td>(chainer.Sequential method)</td>
<td>807</td>
</tr>
</tbody>
</table>

**Add Observer Method**

<table>
<thead>
<tr>
<th>Add Observer Method</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>add_observer()</code></td>
<td>(chainer.Reporter method)</td>
<td>1124</td>
</tr>
<tr>
<td><code>add_observers()</code></td>
<td>(chainer.Reporter method)</td>
<td>1124</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.Chain method)</td>
<td>793</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.ChainList method)</td>
<td>799</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.Link method)</td>
<td>786</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.BatchNormalization method)</td>
<td>616</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.BatchRenormalization method)</td>
<td>623</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.Bias method)</td>
<td>323</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.Bilinear method)</td>
<td>330</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.BinaryHierarchicalSoftmax method)</td>
<td>650</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.BlackOut method)</td>
<td>657</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.caffe.CaffeFunction method)</td>
<td>778</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.ChildSumTreeLSTM method)</td>
<td>337</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.Classifier method)</td>
<td>705</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.Convolution1D method)</td>
<td>343</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.Convolution2D method)</td>
<td>351</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.Convolution3D method)</td>
<td>358</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.ConvolutionND method)</td>
<td>366</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.CRF1d method)</td>
<td>663</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.Deconvolution1D method)</td>
<td>373</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.Deconvolution2D method)</td>
<td>381</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.Deconvolution3D method)</td>
<td>387</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.DeconvolutionND method)</td>
<td>395</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.DecorrelatedBatchNormalization method)</td>
<td>630</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.DeformableConvolution2D method)</td>
<td>402</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.DepthwiseConvolution2D method)</td>
<td>409</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.DilatedConvolution2D method)</td>
<td>416</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.EmbedID method)</td>
<td>423</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.GoogLeNet method)</td>
<td>729</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.GroupNormalization method)</td>
<td>637</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.GRU method)</td>
<td>430</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.Highway method)</td>
<td>436</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.Inception method)</td>
<td>443</td>
</tr>
<tr>
<td><code>add_param()</code></td>
<td>(chainer.links.InceptionBN method)</td>
<td>450</td>
</tr>
<tr>
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<td>(chainermn.MultiNodeChainList method)</td>
<td>1348</td>
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<td>(chainer.Reporter method)</td>
<td>1124</td>
</tr>
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<td>1124</td>
</tr>
<tr>
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<td>(chainer.Chain method)</td>
<td>793</td>
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<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.ChainList method)</td>
<td>799</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.Link method)</td>
<td>786</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.BatchNormalization method)</td>
<td>616</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.BatchRenormalization method)</td>
<td>623</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.Bias method)</td>
<td>323</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.Bilinear method)</td>
<td>330</td>
</tr>
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<td><code>add_stateful()</code></td>
<td>(chainer.links.BinaryHierarchicalSoftmax method)</td>
<td>650</td>
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<td><code>add_stateful()</code></td>
<td>(chainer.links.BlackOut method)</td>
<td>657</td>
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<td><code>add_stateful()</code></td>
<td>(chainer.links.caffe.CaffeFunction method)</td>
<td>778</td>
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<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.ChildSumTreeLSTM method)</td>
<td>337</td>
</tr>
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<td>(chainer.links.Classifier method)</td>
<td>705</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.Convolution1D method)</td>
<td>343</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.Convolution2D method)</td>
<td>351</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.Convolution3D method)</td>
<td>358</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.ConvolutionND method)</td>
<td>366</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.CRF1d method)</td>
<td>663</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.Deconvolution1D method)</td>
<td>373</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.Deconvolution2D method)</td>
<td>381</td>
</tr>
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<td><code>add_stateful()</code></td>
<td>(chainer.links.Deconvolution3D method)</td>
<td>387</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.DeconvolutionND method)</td>
<td>395</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.DecorrelatedBatchNormalization method)</td>
<td>630</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.DeformableConvolution2D method)</td>
<td>402</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.DepthwiseConvolution2D method)</td>
<td>409</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.DilatedConvolution2D method)</td>
<td>416</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.EmbedID method)</td>
<td>423</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.GoogLeNet method)</td>
<td>729</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.GroupNormalization method)</td>
<td>637</td>
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<td>(chainer.links.GRU method)</td>
<td>430</td>
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<td>(chainer.links.Highway method)</td>
<td>436</td>
</tr>
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<td><code>add_stateful()</code></td>
<td>(chainer.links.Inception method)</td>
<td>443</td>
</tr>
<tr>
<td><code>add_stateful()</code></td>
<td>(chainer.links.InceptionBN method)</td>
<td>450</td>
</tr>
</tbody>
</table>

**Index**
<table>
<thead>
<tr>
<th>Method</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>add_param()</code> (chainer.links.LayerNormalization method)</td>
<td>643</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.Linear method)</td>
<td>457</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.LocalConvolution2D method)</td>
<td>464</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.LSTM method)</td>
<td>471</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.Maxout method)</td>
<td>691</td>
</tr>
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<td><code>add_param()</code> (chainer.links.MLPConvolution2D method)</td>
<td>479</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.model.vision.resnet.ResNetLayers method)</td>
<td>738</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.NaryTreeLSTM method)</td>
<td>486</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.NegativeSampling method)</td>
<td>698</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.NStepBiGRU method)</td>
<td>493</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.NStepBiLSTM method)</td>
<td>500</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.NStepBiRNNReLU method)</td>
<td>508</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.NStepBiRNNTanh method)</td>
<td>515</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.NStepGRU method)</td>
<td>522</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.NStepLSTM method)</td>
<td>531</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.NStepRNNReLU method)</td>
<td>538</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.NStepRNNTanh method)</td>
<td>545</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.Parameter method)</td>
<td>552</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.PReLU method)</td>
<td>677</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.ResNet101Layers method)</td>
<td>754</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.ResNet152Layers method)</td>
<td>762</td>
</tr>
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<td>746</td>
</tr>
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<td><code>add_param()</code> (chainer.links.Scale method)</td>
<td>559</td>
</tr>
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<td><code>add_param()</code> (chainer.links.SimplifiedDropconnect method)</td>
<td>670</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.StatefulGRU method)</td>
<td>566</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.StatefulMGU method)</td>
<td>580</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.StatefulPeepholeLSTM method)</td>
<td>593</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.StatefulZoneoutLSTM method)</td>
<td>599</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.StatelessGRU method)</td>
<td>574</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.StatelessLSTM method)</td>
<td>607</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.StatelessMGU method)</td>
<td>586</td>
</tr>
<tr>
<td><code>add_param()</code> (chainer.links.Swish method)</td>
<td>684</td>
</tr>
</tbody>
</table>
addgrads() (chainer.Linked method), 786
addgrads() (chainer.Linked.BatchNormalization method), 617
addgrads() (chainer.Linked.BatchRenormalization method), 623
addgrads() (chainer.Linked.Bias method), 324
addgrads() (chainer.Linked.Bilinear method), 331
addgrads() (chainer.Linked.BinaryHierarchicalSoftmax method), 650
addgrads() (chainer.Linked.BlackOut method), 657
addgrads() (chainer.Linked.Caffe.CaffeFunction method), 778
addgrads() (chainer.Linked.ChildSumTreeLSTM method), 337
addgrads() (chainer.Linked.Classifier method), 706
addgrads() (chainer.Linked.Convolution1D method), 344
addgrads() (chainer.Linked.Convolution2D method), 352
addgrads() (chainer.Linked.Convolution3D method), 358
addgrads() (chainer.Linked.ConvolutionND method), 367
addgrads() (chainer.Linked.CRF1d method), 664
addgrads() (chainer.Linked.Deconvolution1D method), 373
addgrads() (chainer.Linked.Deconvolution2D method), 381
addgrads() (chainer.Linked.Deconvolution3D method), 387
addgrads() (chainer.Linked.DeconvolutionND method), 395
addgrads() (chainer.Linked.DecorrelatedBatchNormalization method), 630
addgrads() (chainer.Linked.DeformableConvolution2D method), 402
addgrads() (chainer.Linked.DepthwiseConvolution2D method), 409
addgrads() (chainer.Linked.DilatedConvolution2D method), 417
addgrads() (chainer.Linked.EmbedID method), 424
addgrads() (chainer.Linked.GoogLeNet method), 730
addgrads() (chainer.Linked.GroupNormalization method), 637
addgrads() (chainer.Linked.GRU method), 430
addgrads() (chainer.Linked.Highway method), 437
addgrads() (chainer.Linked.Inception method), 444
addgrads() (chainer.Linked.InceptionBN method), 450
addgrads() (chainer.Linked.LayerNormalization method), 644
addgrads() (chainer.Linked.Linear method), 458
addgrads() (chainer.Linked.LocalConvolution2D method), 464
addgrads() (chainer.Linked.LSTM method), 472
addgrads() (chainer.Linked.Maxout method), 692
addgrads() (chainer.Linked.MLPConvolution2D method), 479
addgrads() (chainer.Linked.NaryTreeLSTM method), 486
addgrads() (chainer.Linked.NegativeSampling method), 698
addgrads() (chainer.Linked.NStepBiGRU method), 493
addgrads() (chainer.Linked.NStepBiLSTM method), 501
addgrads() (chainer.Linked.NStepBiRNNReLU method), 508
addgrads() (chainer.Linked.NStepBiRNNTanh method), 516
addgrads() (chainer.Linked.NStepGRU method), 523
addgrads() (chainer.Linked.NStepLSTM method), 531
addgrads() (chainer.Linked.NStepRNNReLU method), 539
addgrads() (chainer.Linked.NStepRNNTanh method), 546
addgrads() (chainer.Linked.Parameter method), 553
addgrads() (chainer.Linked.PReLU method), 559
addgrads() (chainer.Linked.ResNet101Layers method), 678
addgrads() (chainer.Linked.ResNet152Layers method), 754
addgrads() (chainer.Linked.ResNet152Layers method), 762
addgrads() (chainer.Linked.ResNet50Layers method), 746
addgrads() (chainer.Linked.Scale method), 559
addgrads() (chainer.Linked.SimplifiedDropconnect method), 671
addgrads() (chainer.Linked.StatefulGRU method), 567
addgrads() (chainer.Linked.StatefulMGU method), 580
addgrads() (chainer.Linked.StatefulPeepholeLSTM method), 593
addgrads() (chainer.Linked.StatefulZoneoutLSTM method), 600
addgrads() (chainer.Linked.StatelessGRU method), 574
addgrads() (chainer.Linked.StatelessLSTM method), 607
addgrads() (chainer.Linked.StatelessMGU method), 587
addgrads() (chainer.Linked.Swish method), 685
addgrads() (chainer.Linked.TheanoFunction method), 772
addgrads() (chainer.Linked.VGG16Layers method), 713
addgrads() (chainer.Linked.VGG19Layers method), 721
addgrads() (chainer.Linked.Sequential method), 808
addgrads() (chainer.testing.FunctionTestCase method), 815
assert_()
    (chainer.testing.LinkInitializersTestCase
        method), 1180
assert_()
    (chainer.testing.LinkTestCase
        method), 1188
assert_allclose()
    (in module chainer.testing), 1163
assert_warns()
    (in module chainer.testing), 1163
assertAlmostEqual()
    (chainer.testing.FunctionTestCase
        method), 1166
assertAlmostEqual()
    (chainer.testing.LinkInitializersTestCase
        method), 1176
assertAlmostEqual()
    (chainer.testing.LinkTestCase
        method), 1185
assertAlmostEqual()
    (chainer.testing.LinkInitializersTestCase
        method), 1176
assertAlmostEqual()
    (chainer.testing.LinkTestCase
        method), 1185
assertCountEqual()
    (chainer.testing.FunctionTestCase
        method), 1166
assertCountEqual()
    (chainer.testing.LinkInitializersTestCase
        method), 1176
assertCountEqual()
    (chainer.testing.LinkTestCase
        method), 1185
assertDictContainsSubset()
    (chainer.testing.FunctionTestCase
        method), 1166
assertDictContainsSubset()
    (chainer.testing.LinkInitializersTestCase
        method), 1176
assertDictContainsSubset()
    (chainer.testing.LinkTestCase
        method), 1185
assertDictEqual()
    (chainer.testing.FunctionTestCase
        method), 1166
assertDictEqual()
    (chainer.testing.LinkInitializersTestCase
        method), 1176
assertDictEqual()
    (chainer.testing.LinkTestCase
        method), 1185
assertEquals()
    (chainer.testing.FunctionTestCase
        method), 1166
assertEquals()
    (chainer.testing.LinkInitializersTestCase
        method), 1176
assertEquals()
    (chainer.testing.LinkTestCase
        method), 1185
assertFalse()
    (chainer.testing.FunctionTestCase
        method), 1166
assertFalse()
    (chainer.testing.LinkInitializersTestCase
        method), 1176
assertFalse()
    (chainer.testing.LinkTestCase
        method), 1185
assertGreater()
    (chainer.testing.FunctionTestCase
        method), 1166
assertGreater()
    (chainer.testing.LinkInitializersTestCase
        method), 1176
assertGreater()
    (chainer.testing.LinkTestCase
        method), 1185
assertGreaterEqual()
    (chainer.testing.FunctionTestCase
        method), 1166
assertGreaterEqual()
    (chainer.testing.LinkInitializersTestCase
        method), 1176
assertGreaterEqual()
    (chainer.testing.LinkTestCase
        method), 1185
assertIn()
    (chainer.testing.FunctionTestCase
        method), 1166
assertIn()
    (chainer.testing.LinkInitializersTestCase
        method), 1176
assertIn()
    (chainer.testing.LinkTestCase
        method), 1185
assertIs()
    (chainer.testing.FunctionTestCase
        method), 1166
assertIs()
    (chainer.testing.LinkInitializersTestCase
        method), 1176
assertIs()
    (chainer.testing.LinkTestCase
        method), 1185
assertIsInstance()
    (chainer.testing.FunctionTestCase
        method), 1166
assertIsInstance()
    (chainer.testing.LinkInitializersTestCase
        method), 1177
assertIsInstance()
    (chainer.testing.LinkTestCase
        method), 1185
assertIsNone()
    (chainer.testing.FunctionTestCase
        method), 1167
assertIsNone()
    (chainer.testing.LinkInitializersTestCase
        method), 1177
assertIsNone()
    (chainer.testing.LinkTestCase
        method), 1185
assertIsNot()
    (chainer.testing.FunctionTestCase
        method), 1167
assertIsNot()
    (chainer.testing.LinkInitializersTestCase
        method), 1177
assertIsNot()
    (chainer.testing.LinkTestCase
        method), 1185
assertEquals()
    (chainer.testing.FunctionTestCase
        method), 1166
assertEquals()
    (chainer.testing.LinkInitializersTestCase
        method), 1177
assertEquals()
    (chainer.testing.LinkTestCase
        method), 1185
assertGreater()
    (chainer.testing.FunctionTestCase
        method), 1165
assertGreater()
    (chainer.testing.LinkInitializersTestCase
        method), 1177
assertGreater()
    (chainer.testing.LinkTestCase
        method), 1185
assertGreaterEqual()
    (chainer.testing.FunctionTestCase
        method), 1166
assertGreaterEqual()
    (chainer.testing.LinkInitializersTestCase
        method), 1177
assertGreaterEqual()
    (chainer.testing.LinkTestCase
        method), 1185
assertIn()
    (chainer.testing.FunctionTestCase
        method), 1165
assertIn()
    (chainer.testing.LinkInitializersTestCase
        method), 1177
assertIn()
    (chainer.testing.LinkTestCase
        method), 1185
assertIs()
    (chainer.testing.FunctionTestCase
        method), 1165
assertIs()
    (chainer.testing.LinkInitializersTestCase
        method), 1177
assertIs()
    (chainer.testing.LinkTestCase
        method), 1185
assertIsInstance()
    (chainer.testing.FunctionTestCase
        method), 1166
assertIsInstance()
    (chainer.testing.LinkInitializersTestCase
        method), 1177
assertIsInstance()
    (chainer.testing.LinkTestCase
        method), 1185
assertIsNone()
    (chainer.testing.FunctionTestCase
        method), 1167
assertIsNone()
    (chainer.testing.LinkInitializersTestCase
        method), 1177
assertIsNone()
    (chainer.testing.LinkTestCase
        method), 1185
assertIsNot()
    (chainer.testing.FunctionTestCase
        method), 1167
assertIsNot()
    (chainer.testing.LinkInitializersTestCase
        method), 1177
assertIsNot()
    (chainer.testing.LinkTestCase
        method), 1185
assertIsNot() (chainer.testing.LinkTestCase method), 1177
assertIsNotNone() (chainer.testing.FunctionTestCase method), 1167
assertIsNotNone() (chainer.testing.LinkInitializersTestCase method), 1177
assertIsNotNone() (chainer.testing.LinkTestCase method), 1185
assertIsNot() (chainer.testing.FunctionTestCase method), 1177
assertIsNotNone() (chainer.testing.FunctionTestCase method), 1167
assertIsNotNone() (chainer.testing.LinkInitializersTestCase method), 1178
assertIsNotNone() (chainer.testing.LinkTestCase method), 1186
assertNotAlmostEqual() (chainer.testing.LinkTestCase method), 1186
assertNotAlmostEqual() (chainer.testing.FunctionTestCase method), 1167
assertNotAlmostEqual() (chainer.testing.LinkInitializersTestCase method), 1178
assertNotAlmostEqual() (chainer.testing.LinkTestCase method), 1186
assertNotAlmostEquals() (chainer.testing.FunctionTestCase method), 1167
assertNotAlmostEquals() (chainer.testing.LinkInitializersTestCase method), 1178
assertNotAlmostEquals() (chainer.testing.LinkTestCase method), 1186
assertNotEqual() (chainer.testing.FunctionTestCase method), 1167
assertNotEqual() (chainer.testing.LinkInitializersTestCase method), 1178
assertNotEqual() (chainer.testing.LinkTestCase method), 1186
assertNotEquals() (chainer.testing.FunctionTestCase method), 1167
assertNotEquals() (chainer.testing.LinkInitializersTestCase method), 1178
assertNotEquals() (chainer.testing.LinkTestCase method), 1186
assertNotIn() (chainer.testing.FunctionTestCase method), 1167
assertNotIn() (chainer.testing.LinkInitializersTestCase method), 1178
assertNotIn() (chainer.testing.LinkTestCase method), 1186
assertNotIsInstance() (chainer.testing.FunctionTestCase method), 1168
assertNotIsInstance() (chainer.testing.LinkInitializersTestCase method), 1178
assertNotIsInstance() (chainer.testing.LinkTestCase method), 1186
assertNotRegex() (chainer.testing.FunctionTestCase method), 1168
assertNotRegex() (chainer.testing.LinkInitializersTestCase method), 1178
assertNotRegex() (chainer.testing.LinkTestCase method), 1186
assertNotRegexpMatches() (chainer.testing.FunctionTestCase method), 1168
assertNotRegexpMatches() (chainer.testing.LinkInitializersTestCase method), 1178
assertNotRegexpMatches() (chainer.testing.LinkTestCase method), 1186
assertRaises() (chainer.testing.FunctionTestCase method), 1168
assertRaises() (chainer.testing.LinkInitializersTestCase method), 1178
assertRaises() (chainer.testing.LinkTestCase method), 1186
Chainer Documentation, Release 7.7.0

Index 1457
average_pooling_2d() (in module chainer.functions), 282
average_pooling_3d() (in module chainer.functions), 283
average_pooling_nd() (in module chainer.functions), 283

B
b (chainer.distributions.Beta attribute), 829
backend (chainerx.Device attribute), 1295
Backend (class in chainerx), 1292
backend_config (chainer.testing.FunctionTestCase attribute), 1171
backend_config (chainer.testing.LinkInitializersTestCase attribute), 1182
backend_config (chainer.testing.LinkTestCase attribute), 1190
backward() (chainer.Function method), 294
backward() (chainer.FunctionAdapter method), 299
backward() (chainer.FunctionNode method), 304
backward() (chainer.Parameter method), 144
backward() (chainer.Variable method), 135
backward() (chainerx.ndarray method), 1208
backward() (in module chainer), 142
backward() (in module chainerx), 1297
backward_accumulate() (chainer.FunctionAdapter method), 299
backward_accumulate() (chainer.FunctionNode method), 305
backward_cpu() (chainer.Function method), 295
backward_gpu() (chainer.Function method), 295
backward_postprocess() (chainer.function_hooks.CUDAProfileHook method), 311
backward_postprocess() (chainer.function_hooks.CupyMemoryProfileHook method), 313
backward_postprocess() (chainer.function_hooks.PrintHook method), 315
backward_postprocess() (chainer.function_hooks.TimerHook method), 317
backward_postprocess() (chainer.FunctionHook method), 320
backward_preprocess() (chainer.function_hooks.CUDAProfileHook method), 311
backward_preprocess() (chainer.function_hooks.CupyMemoryProfileHook method), 313
backward_preprocess() (chainer.function_hooks.PrintHook method), 316

backward_preprocess() (chainer.function_hooks.TimerHook method), 317
backward_preprocess() (chainer.FunctionHook method), 321
batch_det() (in module chainer.functions), 256
batch_inv() (in module chainer.functions), 252
batch_l2_norm_squared() (in module chainer.functions), 252
batch_matmul() (in module chainer.functions), 253
batch_norm() (in module chainerx), 1280
batch_normalization() (in module chainer.functions), 276
batch_renormalization() (in module chainer.functions), 277
batch_shape (chainer.Distribution attribute), 884
batch_shape (chainer.distributions.Bernoulli attribute), 826
batch_shape (chainer.distributions.Beta attribute), 829
batch_shape (chainer.distributions.Categorical attribute), 832
batch_shape (chainer.distributions.Cauchy attribute), 835
batch_shape (chainer.distributions.Chisquare attribute), 838
batch_shape (chainer.distributions.Dirichlet attribute), 841
batch_shape (chainer.distributions.Exponential attribute), 844
batch_shape (chainer.distributions.Gamma attribute), 847
batch_shape (chainer.distributions.Geometric attribute), 850
batch_shape (chainer.distributions.Gumbel attribute), 853
batch_shape (chainer.distributions.Independent attribute), 856
batch_shape (chainer.distributions.Laplace attribute), 859
batch_shape (chainer.distributions.LogNormal attribute), 861
batch_shape (chainer.distributions.MultivariateNormal attribute), 864
batch_shape (chainer.distributions.Normal attribute), 867
batch_shape (chainer.distributions.OneHotCategorical attribute), 870
batch_shape (chainer.distributions.Pareto attribute), 873
batch_shape (chainer.distributions.Poisson attribute), 876
batch_shape (chainer.distributions.Uniform attribute), 879
batch_size (chainer.iterators.DaliIterator attribute), 1089
BatchNormalization (class in chainer.links), 613
BatchRenormalization (class in chainer.links), 622
bcast() (chainermn.CommunicatorBase method), 1340
bcast() (in module chainermn.functions), 1352
bcast_data() (chainermn.CommunicatorBase method), 1340
bcast_obj() (chainermn.CommunicatorBase method), 1340
before_test() (chainer.testing.FunctionTestCase method), 1170
before_test() (chainer.testing.LinkInitializersTestCase method), 1180
before_test() (chainer.testing.LinkTestCase method), 1188
Bernoulli (class in chainer.distributions), 824
bernoulli_nll() (in module chainer.functions), 230
BestValueTrigger (class in chainer.training.triggers), 1028
beta (chainer.links.BatchNormalization attribute), 622
beta (chainer.links.BatchRenormalization attribute), 628
beta (chainer.optimizers.MSVAG attribute), 921
Beta (class in chainer.distributions), 827
beta1 (chainer.optimizers.AdaBound attribute), 905
beta1 (chainer.optimizers.Adam attribute), 895
beta1 (chainer.optimizers.AdamW attribute), 898
beta1 (chainer.optimizers.AMSBound attribute), 908
beta1 (chainer.optimizers.AMSGrad attribute), 902
beta2 (chainer.optimizers.AdaBound attribute), 905
beta2 (chainer.optimizers.Adam attribute), 895
beta2 (chainer.optimizers.AdamW attribute), 898
beta2 (chainer.optimizers.AMSBound attribute), 908
beta2 (chainer.optimizers.AMSGrad attribute), 902
Bias (class in chainer.links), 323
bias() (in module chainer.functions), 253
Bilinear (class in chainer.links), 329
bilinear() (in module chainer.functions), 201
binary_accuracy () (in module chainer.functions), 227
BinaryHierarchicalSoftmax (class in chainer.links), 649
bitwise_and() (in module chainerx), 1269
bitwise_or() (in module chainerx), 1269
bitwise_xor() (in module chainerx), 1270
black_out() (in module chainer.functions), 231
BlackOut (class in chainer.links), 656
broadcast() (in module chainer.functions), 173
broadcast_to() (in module chainer.functions), 173
broadcast_to() (in module chainerx), 1231
build_computational_graph() (in module chainer.computational_graph), 1142
C

cache_or_load_file() (in module chainer.dataset), 1052
cached_download() (in module chainer.dataset), 1052
CaffeFunction (class in chainer.links.caffe), 777
calc_local() (chainermn.extensions.GenericMultiNodeEvaluator method), 1344
call_for_each_param (chainer.optimizer_hooks.GradientHardClipping attribute), 946
call_for_each_param (chainer.optimizer_hooks.GradientLARS attribute), 949
call_for_each_param (chainer.optimizer_hooks.GradientNoise attribute), 947
call_for_each_param (chainer.optimizer_hooks.Lasso attribute), 944

call_for_each_param (chainer.optimizer_hooks.WeightDecay attribute), 943
call_hook() (chainer.GradientMethod method), 940
call_hook() (chainer.Optimizer method), 934
call_hook() (chainer.optimizers.AdaBound method), 903
call_hook() (chainer.optimizers.AdaDelta method), 886
call_hook() (chainer.optimizers.AdaGrad method), 889
call_hook() (chainer.optimizers.Adam method), 893
call_hook() (chainer.optimizers.AdamW method), 896
call_hook() (chainer.optimizers.AMSSBound method), 906
call_hook() (chainer.optimizers.AMSGrad method), 899
call_hook() (chainer.optimizers.CorrectedMomentumSGD method), 910
call_hook() (chainer.optimizers.MomentumSGD method), 913
call_hook() (chainer.optimizers.MSVAG method), 918
call_hook() (chainer.optimizers.NesterovAG method), 915
call_hook() (chainer.optimizers.RMSprop method), 922
call_hook() (chainer.optimizers.RMSpropGraves method), 925
| children() | (chainer.links.ChildSumTreeLSTM method), 338 |
| children() | (chainer.links.Classifier method), 706 |
| children() | (chainer.links.Convolution1D method), 344 |
| children() | (chainer.links.Convolution2D method), 352 |
| children() | (chainer.links.Convolution3D method), 358 |
| children() | (chainer.links.ConvolutionND method), 367 |
| children() | (chainer.links.CRF1d method), 664 |
| children() | (chainer.links.Deconvolution1D method), 373 |
| children() | (chainer.links.Deconvolution2D method), 381 |
| children() | (chainer.links.Deconvolution3D method), 388 |
| children() | (chainer.links.DeconvolutionND method), 395 |
| children() | (chainer.links.DecorrelatedBatchNormalization method), 630 |
| children() | (chainer.links.DeformableConvolution2D method), 403 |
| children() | (chainer.links.DepthwiseConvolution2D method), 409 |
| children() | (chainer.links.DilatedConvolution2D method), 417 |
| children() | (chainer.links.EmbedID method), 424 |
| children() | (chainer.links.GoogLeNet method), 730 |
| children() | (chainer.links.GroupNormalization method), 637 |
| children() | (chainer.links.GRU method), 430 |
| children() | (chainer.links.Highway method), 437 |
| children() | (chainer.links.Inception method), 444 |
| children() | (chainer.links.InceptionBN method), 451 |
| children() | (chainer.links.LayerNormalization method), 644 |
| children() | (chainer.links.Linear method), 458 |
| children() | (chainer.links.LocalConvolution2D method), 465 |
| children() | (chainer.links.LSTM method), 472 |
| children() | (chainer.links.Maxout method), 692 |
| children() | (chainer.links.MLPConvolution2D method), 480 |
| children() | (chainer.links.model.vision.resnet.ResNetLayers method), 739 |
| children() | (chainer.links.NaryTreeLSTM method), 487 |
| children() | (chainer.links.NegativeSampling method), 698 |
| children() | (chainer.links.NStepBiGRU method), 493 |
| children() | (chainer.links.NStepBiLSTM method), 501 |
| children() | (chainer.links.NStepBiRNNReLU method), 508 |
| children() | (chainer.links.NStepBiRNNNTanh method), 516 |
| children() | (chainer.links.NStepGRU method), 523 |
| children() | (chainer.links.NStepLSTM method), 531 |
| children() | (chainer.links.NStepGRUChainer parameter), 539 |
| children() | (chainer.links.NStepRNNTanh method), 546 |
| children() | (chainer.links.Parameter method), 553 |
| children() | (chainer.links.PReLU method), 678 |
| children() | (chainer.links.ResNet152Layers method), 763 |
| children() | (chainer.links.ResNet50Layers method), 747 |
| children() | (chainer.links.Scale method), 560 |
| children() | (chainer.links.SimplifiedDropconnect method), 671 |
| children() | (chainer.links.StatefulGRU method), 567 |
| children() | (chainer.links.StatefulMGU method), 581 |
| children() | (chainer.links.StatefulPeepholeLSTM method), 594 |
| children() | (chainer.links.StatefulZoneoutLSTM method), 600 |
| children() | (chainer.links.StatelessGRU method), 574 |
| children() | (chainer.links.StatelessLSTM method), 607 |
| children() | (chainer.links.StatelessMGU method), 587 |
| children() | (chainer.links.Swish method), 685 |
| children() | (chainer.links.TheanoFunction method), 772 |
| children() | (chainer.links.VGG16Layers method), 714 |
| children() | (chainer.links.VGG19Layers method), 721 |
| children() | (chainer.Sequential method), 808 |
| children() | (ChildSumTreeLSTM class in chainer), 336 |
| children() | (Chisquare class in chainer.distributions), 836 |
| children() | (cholesky () in module chainer.functions), 254 |
| children() | (cholesky () in module chainerx.linalg), 1243 |
| children() | (chx_array chainer.Parameter attribute), 149 |
| children() | (chx_array chainer.Variable attribute), 140 |
| children() | (classification_summary() in module chainer.functions), 228 |
| children() | (Classifier class in chainer), 704 |
| clear() | (chainer.ChainList method), 800 |
| clear() | (chainer.links.MLPConvolution2D method), 480 |
| clear() | (chainer.links.NStepBiGRU method), 494 |
| clear() | (chainer.links.NStepBiLSTM method), 501 |
clear() (chainer.links.NStepBiRNNReLU method), 508
clear() (chainer.links.NStepBiRNNNTanh method), 516
clear() (chainer.links.NStepGRU method), 523
clear() (chainer.links.NStepLSTM method), 531
clear() (chainer.links.NStepRNNReLU method), 539
clear() (chainer-links.NStepRNNNTanh method), 546
clear() (chainer.Sequential method), 808
clear_memo() (in module chainer.backends.cuda), 1116
cleargrad() (chainer.Parameter method), 145
cleargrad() (chainer.Variable method), 136
cleargrads() (chainerx.ndarray method), 1208
cleargrads() (chainer.Chain method), 794
cleargrads() (chainer.ChainList method), 800
cleargrads() (chainer.Link method), 786

cleargrads() (chainer.links.BatchNormalization method), 617
cleargrads() (chainer.links.BatchRenormalization method), 623

cleargrads() (chainer.links.Bias method), 324
cleargrads() (chainer.links.Bilinear method), 331

cleargrads() (chainer.links.BinaryHierarchicalSoftmax method), 651
cleargrads() (chainer.links.BlackOut method), 657

cleargrads() (chainer.links.caffe.CaffeFunction method), 779

cleargrads() (chainer.links.CaffeFunction method), 779

cleargrads() (chainer.links.ChiLD method), 220
cleargrads() (chainer.links.ChiLD method), 220

cleargrads() (chainer.links.Classifier method), 706

cleargrads() (chainer.links.Convolution1D method), 344

cleargrads() (chainer.links.Convolution2D method), 352

cleargrads() (chainer(links.Convolution3D method), 358

cleargrads() (chainer.links.ConvolutionND method), 367

cleargrads() (chainer.links.CRF1d method), 664

cleargrads() (chainer.links.Convolution1D method), 373

cleargrads() (chainer.links.Convolution2D method), 381

cleargrads() (chainer.links.Convolution3D method), 388

cleargrads() (chainer.links.ConvolutionND method), 395

cleargrads() (chainer.links.DecorrelatedBatchNormalization method), 630

cleargrads() (chainer.links.DeformableConvolution2D method), 403

cleargrads() (chainer.links.DepthwiseConvolution2D method), 409

cleargrads() (chainer.links.DilatedConvolution2D method), 567

cleargrads() (chainer.links.EmbedID method), 424

cleargrads() (chainer.links.GoogLeNet method), 430

cleargrads() (chainer-links.GroupNormalization method), 637

cleargrads() (chainer.links.GRU method), 430

cleargrads() (chainer.links.Highway method), 444

cleargrads() (chainer.links.Inception method), 444

cleargrads() (chainer.links.InceptionBN method), 451

cleargrads() (chainer.links.Linear method), 458

cleargrads() (chainer.links.LocalConvolution2D method), 465

cleargrads() (chainer.links.LSTM method), 472

cleargrads() (chainer.links.Maxout method), 692

cleargrads() (chainer.links.MLPConvolution2D method), 480

cleargrads() (chainer.links.Model.vision.resnet.ResNetLayers method), 739

cleargrads() (chainer.links.NaryTreeLSTM method), 659

cleargrads() (chainer.links.NegativeSampling method), 698

cleargrads() (chainer.links.NStepBiGRU method), 494

cleargrads() (chainer links.NStepBiLSTM method), 501

cleargrads() (chainer.links.NStepBiRNNReLU method), 508

cleargrads() (chainer.links.NStepBiRNNNTanh method), 516

cleargrads() (chainer.links.NStepGRU method), 523

cleargrads() (chainer.links.NStepLSTM method), 531

cleargrads() (chainer.links.NStepRNNReLU method), 539

cleargrads() (chainerlinks.NStepRNNNTanh method), 546

cleargrads() (chainer.links.PerLU method), 763

cleargrads() (chainerlinks. PerLU method), 763

cleargrads() (chainer.links.Parameter method), 553

cleargrads() (chainerlinks.PReLU method), 678


cleargrads() (chainer.links.ResNet152Layers method), 763

cleargrads() (chainerlinks.ResNet50Layers method), 747

cleargrads() (chainer.links.Scale method), 560

cleargrads() (chainer.links.SimplifiedDropconnect method), 671

cleargrads() (chainer.links.StatefulGRU method), 671

Index 1463
| copyparams() (chainer.links.Convolution2D method), 374 | copyparams() (chainer.links.Convolution3D method), 382 | copyparams() (chainer.links.ConvolutionND method), 396 | copyparams() (chainer.links.CRF1d method), 374 |
| copyparams() (chainer.links.DeformableConvolution2D method), 432 | copyparams() (chainer.links.DEGRU method), 438 | copyparams() (chainer.links.DEGRU method), 444 | copyparams() (chainer.links.DEGRU method), 450 |
| copyparams() (chainer.links.DEGRU method), 456 | copyparams() (chainer.links.DEGRU method), 462 | copyparams() (chainer.links.DEGRU method), 468 | copyparams() (chainer.links.DEGRU method), 474 |
| copyparams() (chainer.links.DEGRU method), 480 | copyparams() (chainer.links.DEGRU method), 486 | copyparams() (chainer.links.DEGRU method), 492 | copyparams() (chainer.links.DEGRU method), 498 |
| copyparams() (chainer.links.DEGRU method), 504 | copyparams() (chainer.links.DEGRU method), 510 | copyparams() (chainer.links.DEGRU method), 516 | copyparams() (chainer.links.DEGRU method), 522 |
| copyparams() (chainer.links.DEGRU method), 528 | copyparams() (chainer.links.DEGRU method), 534 | copyparams() (chainer.links.DEGRU method), 540 | copyparams() (chainer.links.DEGRU method), 546 |
| copyparams() (chainer.links.DEGRU method), 552 | copyparams() (chainer.links.DEGRU method), 558 | copyparams() (chainer.links.DEGRU method), 564 | copyparams() (chainer.links.DEGRU method), 570 |
| copyparams() (chainer.links.DEGRU method), 576 | copyparams() (chainer.links.DEGRU method), 582 | copyparams() (chainer.links.DEGRU method), 588 | copyparams() (chainer.links.DEGRU method), 594 |
| copyparams() (chainer.links.DEGRU method), 590 | copyparams() (chainer.links.DEGRU method), 596 | copyparams() (chainer.links.DEGRU method), 602 | copyparams() (chainer.links.DEGRU method), 608 |
| copyparams() (chainer.links.DEGRU method), 614 | copyparams() (chainer.links.DEGRU method), 620 | copyparams() (chainer.links.DEGRU method), 626 | copyparams() (chainer.links.DEGRU method), 632 |
| copyparams() (chainer.links.DEGRU method), 638 | copyparams() (chainer.links.DEGRU method), 644 | copyparams() (chainer.links.DEGRU method), 650 | copyparams() (chainer.links.DEGRU method), 656 |
| copyparams() (chainer.links.DEGRU method), 662 | copyparams() (chainer.links.DEGRU method), 668 | copyparams() (chainer.links.DEGRU method), 674 | copyparams() (chainer.links.DEGRU method), 680 |
| copyparams() (chainer.links.DEGRU method), 686 | copyparams() (chainer.links.DEGRU method), 692 | copyparams() (chainer.links.DEGRU method), 698 | copyparams() (chainer.links.DEGRU method), 704 |
| copyparams() (chainer.links.DEGRU method), 710 | copyparams() (chainer.links.DEGRU method), 716 | copyparams() (chainer.links.DEGRU method), 722 | copyparams() (chainer.links.DEGRU method), 728 |
| copyparams() (chainer.links.DEGRU method), 734 | copyparams() (chainer.links.DEGRU method), 740 | copyparams() (chainer.links.DEGRU method), 746 | copyparams() (chainer.links.DEGRU method), 752 |
| copyparams() (chainer.links.DEGRU method), 758 | copyparams() (chainer.links.DEGRU method), 764 | copyparams() (chainer.links.DEGRU method), 770 | copyparams() (chainer.links.DEGRU method), 776 |
| copyparams() (chainer.links.DEGRU method), 782 | copyparams() (chainer.links.DEGRU method), 788 | copyparams() (chainer.links.DEGRU method), 794 | copyparams() (chainer.links.DEGRU method), 800 |
| copyparams() (chainer.links.DEGRU method), 806 | copyparams() (chainer.links.DEGRU method), 812 | copyparams() (chainer.links.DEGRU method), 818 | copyparams() (chainer.links.DEGRU method), 824 |
| copyparams() (chainer.links.DEGRU method), 830 | copyparams() (chainer.links.DEGRU method), 836 | copyparams() (chainer.links.DEGRU method), 842 | copyparams() (chainer.links.DEGRU method), 848 |
| copyparams() (chainer.links.DEGRU method), 854 | copyparams() (chainer.links.DEGRU method), 860 | copyparams() (chainer.links.DEGRU method), 866 | copyparams() (chainer.links.DEGRU method), 872 |
| copyparams() (chainer.links.DEGRU method), 878 | copyparams() (chainer.links.DEGRU method), 884 | copyparams() (chainer.links.DEGRU method), 890 | copyparams() (chainer.links.DEGRU method), 896 |
| copyparams() (chainer.links.DEGRU method), 902 | copyparams() (chainer.links.DEGRU method), 908 | copyparams() (chainer.links.DEGRU method), 914 | copyparams() (chainer.links.DEGRU method), 920 |
copyto() (in module chainer.backend), 1107
CorrectedMomentumSGD (class in chainer.optimizers), 909
cos() (in module chainer.functions), 254
cos() (in module chainerx), 1264
cosh() (in module chainer.functions), 255
cosh() (in module chainerx), 1266
count() (chainer.ChainList method), 801
count() (chainer.links.MLPConvolution2D method), 480
count() (chainer.links.NStepBiGRU method), 494
count() (chainer.links.NStepBiLSTM method), 501
count() (chainer.links.NStepBiRNNTanh method), 509
count() (chainer.links.NStepBiGRU method), 516
count() (chainer.links.NStepBiLSTM method), 524
count() (chainer.links.NStepLSTM method), 532
count() (chainer.links.NStepRNNTanh method), 547
count() (chainer.Sequential method), 809
count() (chainer.utils.type_check.TypeInfoTuple), 1157
count_by_layer_type() (chainer.Sequential method), 809
count_params() (chainer.Chain method), 794
count_params() (chainer.ChainList method), 801
count_params() (chainer.Link method), 787
count_params() (chainer.links.BatchNormalization method), 618
count_params() (chainer.links.BatchRenormalization method), 624
count_params() (chainer.links.Bias method), 325
count_params() (chainer.links.Bilinear method), 331
count_params() (chainer.links.BinaryHierarchicalSoftmax method), 651
count_params() (chainer.links.BlackOut method), 658
count_params() (chainer.links.caffe.CaffeFunction method), 779
count_params() (chainer.links.ChildSumTreeLSTM method), 338
count_params() (chainer.links.Classifier method), 707
count_params() (chainer.links.Convolution1D method), 345
count_params() (chainer.links.Convolution2D method), 353
count_params() (chainer.links.Convolution3D method), 359
count_params() (chainer.links.ConvolutionND method), 367
count_params() (chainer.links.CRF1d method), 665
count_params() (chainer.links.Deconvolution1D method), 374
count_params() (chainer.links.Deconvolution2D method), 382
count_params() (chainer.links.Deconvolution3D method), 388
count_params() (chainer.links.DecorrelatedBatchNormalization method), 631
count_params() (chainer.links.DeformableConvolution2D method), 403
count_params() (chainer.links.DepthwiseConvolution2D method), 410
count_params() (chainer.links.DilatedConvolution2D method), 418
count_params() (chainer.links.EmbedID method), 425
count_params() (chainer.links.GoogLeNet method), 731
count_params() (chainer.links.GroupNormalization method), 638
count_params() (chainer.links.GRU method), 431
count_params() (chainer.links.Highway method), 438
count_params() (chainer.links.Inception method), 444
count_params() (chainer.links.InceptionBN method), 451
count_params() (chainer.links.LayerNormalization method), 645
count_params() (chainer.links.Linear method), 458
count_params() (chainer.links.LocalConvolution2D method), 465
count_params() (chainer.links.LSTM method), 473
count_params() (chainer.links.Maxout method), 693
count_params() (chainer.links.MLPConvolution2D method), 480
count_params() (chainer.links.model.vision.resnet.ResNetLayers method), 739
count_params() (chainer.links.NaryTreeLSTM method), 487
count_params() (chainer.links.NegativeSampling method), 699
count_params() (chainer.links.NStepBiGRU method), 494
count_params() (chainer.links.NStepBiLSTM method), 501
count_params() (chainer.links.NStepBiRNNTanh method), 509
count_params() (chainer.links.NStepBiGRU method), 516
count_params() (chainer.links.NStepBiLSTM method), 524
count_params() (chainer.links.NStepLSTM method), 532
count_params() (chainer.links.NStepRNNTanh method), 547
count_params() (chainer.Sequential method), 809
count_params() (chainer.utils.type_check.TypeInfoTuple), 1157
count_by_layer_type() (chainer.Sequential method), 809
count_params() (chainer.Chain method), 794
count_params() (chainer.ChainList method), 801
count_params() (chainer.Link method), 787
count_params() (chainer.links.BatchNormalization method), 618
count_params() (chainer.links.BatchRenormalization method), 624
count_params() (chainer.links.Bias method), 325
count_params() (chainer.links.Bilinear method), 331
count_params() (chainer.links.BinaryHierarchicalSoftmax method), 651
count_params() (chainer.links.BlackOut method), 658
count_params() (chainer.links.caffe.CaffeFunction method), 779
count_params() (chainer.links.ChildSumTreeLSTM method), 338
count_params() (chainer.links.Classifier method), 707
count_params() (chainer.links.Convolution1D method), 345
count_params() (chainer.links.Convolution2D method), 353
count_params() (chainer.links.Convolution3D method), 359
count_params() (chainer.links.ConvolutionND method), 367
count_params() (chainer.links.CRF1d method), 665
covariance (chainer.distributions.Categorical attribute), 832
covariance (chainer.distributions.Chisquare attribute), 838
covariance (chainer.distributions.Dirichlet attribute), 841
covariance (chainer.distributions.Exponential attribute), 844
covariance (chainer.distributions.Gamma attribute), 847
covariance (chainer.distributions.Geometric attribute), 850
covariance (chainer.distributions.Gumbel attribute), 853
covariance (chainer.distributions.Independent attribute), 856
covariance (chainer.distributions.Laplace attribute), 859
covariance (chainer.distributions.LogNormal attribute), 861
covariance (chainer.distributions.MultivariateNormal attribute), 864
covariance (chainer.distributions.Normal attribute), 867
covariance (chainer.distributions.OneHotCategorical attribute), 870
covariance (chainer.distributions.Pareto attribute), 873
covariance (chainer.distributions.Poisson attribute), 876
covariance (chainer.distributions.Uniform attribute), 879
CpuDevice (class in chainer.backend), 1108
create_communicator() (in module chainermn), 1338
create_consumer() (chainer.training.extensions.snapshot_writers.ProcessQueueWriter method), 971
create_consumer() (chainer.training.extensions.snapshot_writers.QueueWriter method), 968
create_consumer() (chainer.training.extensions.snapshot_writers.ThreadQueueWriter method), 969
distribution (chainer.distributions.Independent attribute), 856
Distribution (class in chainer), 881
divide() (in module chainerx), 1259
doCleanups() (chainer.testing.FunctionTestCase method), 1170
doCleanups() (chainer.testing.LinkInitializersTestCase method), 1180
doCleanups() (chainer.testing.LinkTestCase method), 1189
dodge_nondifferentiable (chainer.testing.FunctionTestCase attribute), 1171
dodge_nondifferentiable (chainer.testing.LinkTestCase attribute), 1190
dot() (chainerx.ndarray method), 1209
dot() (in module chainerx), 1243
downsamplingConvFilter (class in chainer.initializers), 962
dropout() (in module chainer.functions), 272
dsplit() (in module chainerx), 1235
dstack() (in module chainer.functions), 177
dstack() (in module chainerx), 1233
dtype (chainer.configuration.GlobalConfig attribute), 1137
dtype (chainer.Parameter attribute), 150
dtype (chainer.Variable attribute), 141
dtype (chainer.variable.VariableNode attribute), 153
dtype (chainerx.ndarray attribute), 1212
dump() (chainer.computational_graph.ComputationalGraph method), 1144
DumpGraph (class in chainer.training.extensions), 1020
DumpGraph(), 62

E
EarlyStoppingTrigger (class in chainer.training.triggers), 1029
eigh() (in module chainerx.linalg), 1245
eigvalsh() (in module chainerx.linalg), 1246
einsum() (in module chainer.functions), 256
elapsed_time (chainer.training.Trainer attribute), 975
elementwise() (in module chainer.backends.cuda), 1116
elu() (in module chainer.functions), 157
embed_id() (in module chainer.functions), 214
EmbedID (class in chainer.links), 422
empty() (in module chainerx), 1215
empty_like() (in module chainerx), 1215
enable_backprop (chainer.configuration.GlobalConfig attribute), 1137
enable_update() (chainer.chain method), 795
enable_update() (chainer.ChainList method), 801
enable_update() (chainer.Link method), 788
enable_update() (chainer.links.BatchNormalization method), 618
enable_update() (chainer.links.BatchRenormalization method), 625
enable_update() (chainer.links.Bias method), 325
enable_update() (chainer.links.Bilinear method), 332
enable_update() (chainer.links.BinaryHierarchicalSoftmax method), 652
enable_update() (chainer.links.BlackOut method), 658
enable_update() (chainer.links.CaffeFunction method), 780
enable_update() (chainer.links.ChildSumTreeLSTM method), 339
enable_update() (chainer.links.Classifier method), 707
enable_update() (chainer.links.Convolution1D method), 345
enable_update() (chainer.links.Convolution2D method), 353
enable_update() (chainer.links.Convolution3D method), 360
enable_update() (chainer.links.ConvolutionND method), 368
enable_update() (chainer.links.CRF1d method), 665
enable_update() (chainer.links.Deconvolution1D method), 375
enable_update() (chainer.links.Deconvolution2D method), 383
enable_update() (chainer.links.Deconvolution3D method), 389
enable_update() (chainer.links.DeconvolutionND method), 397
enable_update() (chainer.links.DecorrelatedBatchNormalization method), 632
enable_update() (chainer.links.DeformableConvolution2D method), 404
enable_update() (chainer.links.DepthwiseConvolution2D method), 411
enable_update() (chainer.links.DilatedConvolution2D method), 418
enable_update() (chainer.links.EmbedID method), 425
enable_update() (chainer.links.GoogLeNet method), 731
enable_update() (chainer.links.GroupNormalization method), 638
enable_update() (chainer.links.GRU method), 431
enable_update() (chainer.links.Highway method), 438
enable_update() (chainer.links.Inception method), 780
epoch (chainer.iterators.SerialIterator attribute), 1083
epoch (chainer.Optimizer attribute), 936
epoch (chainer.optimizers.AdaBound attribute), 905
epoch (chainer.optimizers.AdaDelta attribute), 888
epoch (chainer.optimizers.Adam attribute), 891
epoch (chainer.optimizers.Adam attribute), 895
eval() (chainer.utils.type_check.Expr method), 1155
eval() (chainer.utils.type_check.Variable method), 1158
eval() (in module chainer.utils.type_check), 1156
evaluate() (chainer.training.extensions.Evaluator method), 988
Evaluator, 62
Evaluator (class in chainer.training.extensions), 987
event_shape (chainer.Distribution attribute), 884
event_shape (chainer.distributions.Bernoulli attribute), 829
event_shape (chainer.distributions.Beta attribute), 829
event_shape (chainer.distributions.Categorical attribute), 832
event_shape (chainer.distributions.Cauchy attribute), 835
event_shape (chainer.distributions.Chisquare attribute), 838
event_shape (chainer.distributions.Dirichlet attribute), 841
event_shape (chainer.distributions.Exponential attribute), 844
event_shape (chainer.distributions.Gamma attribute), 850
event_shape (chainer.distributions.Geometric attribute), 850
event_shape (chainer.distributions.Gumbel attribute), 853
event_shape (chainer.distributions.Independent attribute), 856
event_shape (chainer.distributions.Laplace attribute), 859
event_shape (chainer.distributions.LogNormal attribute), 861
event_shape (chainer.distributions.MultivariateNormal attribute), 864
event_shape (chainer.distributions.Normal attribute), 867
event_shape (chainer.distributions.OneHotCategorical attribute), 870
event_shape (chainer.distributions.Pareto attribute), 873
event_shape (chainer.distributions.Poisson attribute), 873
flipud() (in module chainerx), 1239
floor() (in module chainer.functions), 259
floor() (in module chainerx), 1269
flush() (chainer.datasets.PickleDatasetWriter method), 1075
fmod() (in module chainer.functions), 259
force_backprop_mode() (in module chainer), 309
force_backprop_mode() (in module chainerx), 1298
forget() (in module chainer.functions), 292
forward() (chainer.Function method), 296
forward() (chainer.FunctionAdapter method), 300
forward() (chainer.FunctionNode method), 306
forward() (chainer.links.BatchNormalization method), 618
forward() (chainer.links.BatchRenormalization method), 625
forward() (chainer.links.Bias method), 325
forward() (chainer.links.Bilinear method), 332
forward() (chainer.links.BinaryHierarchicalSoftmax method), 652
forward() (chainer.links.BlackOut method), 658
forward() (chainer.links.caffe.CaffeFunction method), 780
forward() (chainer.links.ChildSumTreeLSTM method), 339
forward() (chainer.links.Classifier method), 707
forward() (chainer.links.Convolution1D method), 345
forward() (chainer.links.Convolution2D method), 353
forward() (chainer.links.Convolution3D method), 360
forward() (chainer.links.ConvolutionND method), 368
forward() (chainer.links.CRF1d method), 665
forward() (chainer.links.Deconvolution1D method), 375
forward() (chainer.links.Deconvolution2D method), 383
forward() (chainer.links.Deconvolution3D method), 389
forward() (chainer.links.DeconvolutionND method), 397
forward() (chainer.links.DecorrelatedBatchNormalization method), 632
forward() (chainer.links.DeformableConvolution2D method), 404
forward() (chainer.links.DepthwiseConvolution2D method), 411
forward() (chainer.links.DilatedConvolution2D method), 418
forward() (chainer.links.EmbedID method), 425
forward() (chainer.links.GoogLeNet method), 732
forward() (chainer.links.GroupNormalization method), 638
forward() (chainer.links.GRU method), 431
forward() (chainer.links.Highway method), 438
forward() (chainer.links.Inception method), 445
forward() (chainer.links.InceptionBN method), 452
forward() (chainer.links.LayerNormalization method), 645
forward() (chainer.links.Linear method), 459
forward() (chainer.links.LocalConvolution2D method), 466
forward() (chainerlinks.LSTM method), 473
forward() (chainer.links.Maxout method), 693
forward() (chainerlinks.MLPConvolution2D method), 481
forward() (chainerlinks.model.vision.resnet.ResNetLayers method), 740
forward() (chainerlinks.NaryTreeLSTM method), 488
forward() (chainer.links.NegativeSampling method), 700
forward() (chainer.links.NStepBiGRU method), 494
forward() (chainer.links.NStepBiLSTM method), 502
forward() (chainer.links.NStepBiRNNReLU method), 509
forward() (chainerlinks.NStepBiRNNTanH method), 517
forward() (chainerlinks.NStepGRU method), 524
forward() (chainerlinks.NStepLSTM method), 532
forward() (chainerlinks.NStepRNNReLU method), 540
forward() (chainerlinks.NStepRNNTanH method), 547
forward() (chainer.links.Parameter method), 554
forward() (chainer.links.PReLU method), 679
forward() (chainerlinks.ResNet101Layers method), 756
forward() (chainerlinks.ResNet152Layers method), 764
forward() (chainerlinks.ResNet50Layers method), 748
forward() (chainer.links.Scale method), 561
forward() (chainer.links.SimplifiedDropconnect method), 672
forward() (chainerlinks.StatefulGRU method), 568
forward() (chainerlinks.StatefulMGU method), 582
forward() (chainerlinks.StatefulPeepholeLSTM method), 595
forward() (chainerlinks.StatefulZoneoutLSTM method), 601
forward() (chainerlinks.StatelessGRU method), 576
forward() (chainerlinks.StatelessLSTM method), 608
forward() (chainerlinks.StatelessMGU method), 588
forward() (chainer.links.Swish method), 686
forward() (chainerlinks.TheanoFunction method), 773
forward() (chainerlinks.VGG16Layers method), 716
forward() (chainerlinks.VGG19Layers method), 723
forward() (chainer.Sequential method), 810
forward() (chainer.testing.FunctionTestCase method),
<table>
<thead>
<tr>
<th>Line</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>375</td>
<td><code>from_chx()</code> (chainer.links.DecorrelatedBatchNormalization method),</td>
</tr>
<tr>
<td>383</td>
<td><code>from_chx()</code> (chainer.links.Deconvolution2D method),</td>
</tr>
<tr>
<td>389</td>
<td><code>from_chx()</code> (chainer.links.Deconvolution3D method),</td>
</tr>
<tr>
<td>397</td>
<td><code>from_chx()</code> (chainer.links.DeconvolutionND method),</td>
</tr>
<tr>
<td>404</td>
<td><code>from_chx()</code> (chainer.links.DeformableConvolution2D method),</td>
</tr>
<tr>
<td>411</td>
<td><code>from_chx()</code> (chainer.links.DepthwiseConvolution2D method),</td>
</tr>
<tr>
<td>418</td>
<td><code>from_chx()</code> (chainer.links.DilatedConvolution2D method),</td>
</tr>
<tr>
<td>425</td>
<td><code>from_chx()</code> (chainer.links.EmbedID method),</td>
</tr>
<tr>
<td>432</td>
<td><code>from_chx()</code> (chainer.links.GRU method),</td>
</tr>
<tr>
<td>438</td>
<td><code>from_chx()</code> (chainer.links.Highway method),</td>
</tr>
<tr>
<td>445</td>
<td><code>from_chx()</code> (chainer.links.Inception method),</td>
</tr>
<tr>
<td>451</td>
<td><code>from_chx()</code> (chainer.links.InceptionBN method),</td>
</tr>
<tr>
<td>459</td>
<td><code>from_chx()</code> (chainer.links.Linear method),</td>
</tr>
<tr>
<td>466</td>
<td><code>from_chx()</code> (chainer.links.LocalConvolution2D method),</td>
</tr>
<tr>
<td>473</td>
<td><code>from_chx()</code> (chainer.links.LSTM method),</td>
</tr>
<tr>
<td>481</td>
<td><code>from_chx()</code> (chainer.links.MLPConvolution2D method),</td>
</tr>
<tr>
<td>495</td>
<td><code>from_chx()</code> (chainer.links.NStepBiGRU method),</td>
</tr>
<tr>
<td>502</td>
<td><code>from_chx()</code> (chainer.links.NStepBiLSTM method),</td>
</tr>
<tr>
<td>510</td>
<td><code>from_chx()</code> (chainer.links.NStepBiRNNReLU method),</td>
</tr>
<tr>
<td>517</td>
<td><code>from_chx()</code> (chainer.links.NStepBiRNNTanh method),</td>
</tr>
<tr>
<td>525</td>
<td><code>from_chx()</code> (chainer.links.NStepGRU method),</td>
</tr>
<tr>
<td>533</td>
<td><code>from_chx()</code> (chainer.links.NStepLSTM method),</td>
</tr>
<tr>
<td>540</td>
<td><code>from_chx()</code> (chainer.links.NStepRNNReLU method),</td>
</tr>
<tr>
<td>548</td>
<td><code>from_chx()</code> (chainer.links.NStepRNNTanh method),</td>
</tr>
<tr>
<td>554</td>
<td><code>from_chx()</code> (chainer.links.Parameter method),</td>
</tr>
<tr>
<td>557</td>
<td><code>from_chx()</code> (chainer.links.ResNet101Layers method),</td>
</tr>
<tr>
<td>561</td>
<td><code>from_chx()</code> (chainer.links.Scale method),</td>
</tr>
<tr>
<td>568</td>
<td><code>from_chx()</code> (chainer.links.StatefulGRU method),</td>
</tr>
<tr>
<td>576</td>
<td><code>from_chx()</code> (chainer.links.StatelessGRU method),</td>
</tr>
<tr>
<td>588</td>
<td><code>from_chx()</code> (chainer.links.StatelessMGU method),</td>
</tr>
<tr>
<td>609</td>
<td><code>from_chx()</code> (chainer.links.StatelessLSTM method),</td>
</tr>
<tr>
<td>618</td>
<td><code>from_chx()</code> (chainer.links.VGG16Layers method),</td>
</tr>
<tr>
<td>639</td>
<td><code>from_chx()</code> (chainer.links.GroupNormalization method),</td>
</tr>
<tr>
<td>652</td>
<td><code>from_chx()</code> (chainer.links.Softmax method),</td>
</tr>
<tr>
<td>659</td>
<td><code>from_chx()</code> (chainer.links.ResNet152Layers method),</td>
</tr>
<tr>
<td>662</td>
<td><code>from_chx()</code> (chainer.links.ResNet152Layers method),</td>
</tr>
<tr>
<td>672</td>
<td><code>from_chx()</code> (chainer.links.ResNet50Layers method),</td>
</tr>
<tr>
<td>686</td>
<td><code>from_chx()</code> (chainer.links.Swish method),</td>
</tr>
<tr>
<td>693</td>
<td><code>from_chx()</code> (chainer.links.Maxout method),</td>
</tr>
<tr>
<td>700</td>
<td><code>from_chx()</code> (chainer.links.NegativeSampling method),</td>
</tr>
<tr>
<td>709</td>
<td><code>from_chx()</code> (chainer.links.BinaryHierarchicalSoftmax method),</td>
</tr>
<tr>
<td>716</td>
<td><code>from_chx()</code> (chainer.links.NStepBiGRU method),</td>
</tr>
<tr>
<td>723</td>
<td><code>from_chx()</code> (chainer.links.VGG19Layers method),</td>
</tr>
<tr>
<td>732</td>
<td><code>from_chx()</code> (chainer.links.GoogLeNet method),</td>
</tr>
<tr>
<td>741</td>
<td><code>from_chx()</code> (chainer.links.model.vision.resnet.ResNetLayers method),</td>
</tr>
<tr>
<td>749</td>
<td><code>from_chx()</code> (chainer.links.ResNet50Layers method),</td>
</tr>
<tr>
<td>757</td>
<td><code>from_chx()</code> (chainer.links.ResNet152Layers method),</td>
</tr>
<tr>
<td>765</td>
<td><code>from_chx()</code> (chainer.links.Scale method),</td>
</tr>
<tr>
<td>773</td>
<td><code>from_chx()</code> (chainer.links.TheanoFunction method),</td>
</tr>
<tr>
<td>801</td>
<td><code>from_params()</code> (chainer.Chain class method),</td>
</tr>
<tr>
<td>804</td>
<td><code>from_params()</code> (chainer.ChainList class method),</td>
</tr>
<tr>
<td>810</td>
<td><code>from_chx()</code> (chainer.Sequential method),</td>
</tr>
<tr>
<td>819</td>
<td><code>from_chx()</code> (chainer.utils.WalkerAlias method),</td>
</tr>
<tr>
<td>824</td>
<td><code>from_chx()</code> (chainer.Variable method),</td>
</tr>
<tr>
<td>828</td>
<td><code>from_chx()</code> (chainer.NaryTreeLSTM method),</td>
</tr>
<tr>
<td>840</td>
<td><code>from_chx()</code> (chainer.backend.ChainerxDevice static method),</td>
</tr>
<tr>
<td>847</td>
<td><code>from_chx()</code> (chainer.backend.GpuDevice static method),</td>
</tr>
<tr>
<td>854</td>
<td><code>from_params()</code> (chainer.Chain class method),</td>
</tr>
<tr>
<td>857</td>
<td><code>from_params()</code> (chainer.ChainList class method),</td>
</tr>
<tr>
<td>864</td>
<td><code>from_chx()</code> (chainer.backend.GpuDevice static method),</td>
</tr>
<tr>
<td>867</td>
<td><code>from_params()</code> (chainer.Chain class method),</td>
</tr>
<tr>
<td>870</td>
<td><code>from_params()</code> (chainer.ChainList class method),</td>
</tr>
<tr>
<td>873</td>
<td><code>from_chx()</code> (chainershortcode.BatchNormalization class method),</td>
</tr>
<tr>
<td>876</td>
<td><code>from_params()</code> (chainer shortcode.BatchNormalization class method),</td>
</tr>
<tr>
<td>879</td>
<td><code>from_params()</code> (chainer shortcode.BatchNormalization class method),</td>
</tr>
<tr>
<td>882</td>
<td><code>from_chx()</code> (chainer_shortcode.BatchNormalization class method),</td>
</tr>
<tr>
<td>885</td>
<td><code>from_params()</code> (chainer_shortcode.BatchNormalization class method),</td>
</tr>
<tr>
<td>888</td>
<td><code>from_chx()</code> (chainer_shortcode.BatchNormalization class method),</td>
</tr>
<tr>
<td>891</td>
<td><code>from_params()</code> (chainer_shortcode.BatchNormalization class method),</td>
</tr>
<tr>
<td>894</td>
<td><code>from_chx()</code> (chainer_shortcode.BatchNormalization class method),</td>
</tr>
<tr>
<td>897</td>
<td><code>from_params()</code> (chainer_shortcode.BatchNormalization class method),</td>
</tr>
</tbody>
</table>

Index | 1483
from_params() (chainer.links.Swish class method), 686
from_params() (chainer.links.TheanoFunction class method), 773
from_params() (chainer.links.VGG16Layers class method), 716
from_params() (chainer.links.VGG19Layers class method), 723
from_params() (chainer.Sequential class method), 810
frombuffer() (in module chainerx), 1221
fromfile() (in module chainerx), 1221
fromfunction() (in module chainerx), 1221
domiter() (in module chainerx), 1222
domstring() (in module chainerx), 1222
full() (in module chainerx), 1218
full_like() (in module chainerx), 1218
function (chainer.FunctionAdapter attribute), 302
Function (class in chainer), 294
FunctionAdapter (class in chainer), 298
FunctionHook (class in chainer), 319
FunctionNode (class in chainer), 303
functions (chainer.links.GoogLeNet attribute), 736
functions (chainer.links.model.vision.resnet.ResNetLayers attribute), 744
functions (chainer.links.ResNet101Layers attribute), 760
functions (chainer.links.ResNet152Layers attribute), 768
functions (chainer.links.ResNet50Layers attribute), 752
functions (chainer.links.VGG16Layers attribute), 719
functions (chainer.links.VGG19Layers attribute), 727
FunctionTestCase (class in chainer.testing), 1163

gamma (chainer.links.BatchNormalization attribute), 622
gamma (chainer.links.BatchRenormalization attribute), 628
gamma (chainer.optimizers.Adam attribute), 905
gamma (chainer.optimizers.AdamW attribute), 909
gamma (chainer.optimizers.AMSGrad attribute), 902
class in chainer.distributions), 844
gather() (chainermn.CommunicatorBase method), 1340
gather() (in module chainermn.functions), 1352
gather_obj() (chainermn.CommunicatorBase method), 1341
gaussian() (in module chainer.functions), 273
gaussian_kl_divergence() (in module chainer.functions), 238
gaussian() (in module chainer.functions), 273
get_all_optimizers() (in module chainer.optimizers), 963
get_all_grad_grad_inputs() (in module chainer.extensions, 1170
get_all_outputs() (in module chainer.testing.FunctionTestCase method), 1170
get_all_outputs() (in module chainer.testing.LinkTestCase method), 1189
get_all_inputs() (in module chainer.testing.FunctionTestCase method), 1170
get_all_inputs() (in module chainer.testing.LinkInitializersTestCase method), 1181
get_all_inputs() (in module chainer.testing.LinkTestCase method), 1189
get_all_grad_grad_inputs() (in module chainer.extensions, 1170
get_all_optimizers() (in module chainer.training.update.updaters.ParallelUpdater method), 982
get_all_optimizers() (in module chainer.training.update.updaters.ParallelUpdater method), 980
get_all_optimizers() (in module chainer.training.update.updaters.ParallelUpdater method), 980
get_all_optimizers() (in module chainer.training.update.updaters.MultiprocessParallelUpdater method), 982
get_all_optimizers() (in module chainer.training.update.updaters.MultiprocessParallelUpdater method), 988
get_all_optimizers() (in module chainer.training.update.updaters.MultiprocessParallelUpdater method), 988
get_all_optimizers() (in module chainer.backends.cuda), 1117
get_backend() (chainerx.Context method), 1292
get_backend() (in module chainer), 1294
get_cifar10() (in module chainer.datasets), 1079
get_cifar100() (in module chainer.datasets), 1079
get_config() (chainermn.CommunicatorBase method), 1341
get_conv_outsize() (in module chainer.datasets), 1119
get_cross_validation_datasets() (in module chainer.datasets), 1059
get_cross_validation_datasets_random() (in module chainer.datasets), 1060
get_current_reporter() (in module chainer), 1125
get_dataset_root() (in module chainer.datasets), 1051
get_deconv_outsize() (in module chainer.datasets), 1120
get_default_device() (in module chainerx), 1296
get_device() (chainerx.Backend method), 1299
get_device() (chainer.Context method), 1292
get_device() (in module chainer), 1104
get_device() (in module chainer.backends.cuda), 1113
get_device() (in module chainerx), 1295
get_device_count() (chainerx.Backend method), 1293
get_device_from_array() (in module chainer.backends), 1104
get_device_from_array() (in module chainer.backends.cuda), 1114
get_device_from_id() (in module chainer.backends.cuda), 1114
get_dict() (chainer.optimizer.Hyperparameter method), 939
get_dtype() (in module chainer.datasets), 1061
get_example() (chainer.datasets.TransformDataset method), 1064
get_example() (chainer.datasets.ZippedImageDataset method), 1065
get_examples() (chainer.dataset.tabular.DelegateDataset method), 1044
get_examples() (chainer.dataset.TabularDataset method), 1040
get_extension() (chainer.training.Trainer method), 974
get_fashion_mnist() (in module chainer.datasets), 1078
get_fashion_mnist_labels() (in module chainer.datasets), 1078
get_grad() (chainerx.ndarray method), 1209
get_initializers() (chainer.testing.LinkInitializersTestCase method), 1181
get_item() (in module chainer.functions), 180
get_iterator() (chainer.training.extensions.Evaluator method), 988
get_iterator() (chainer.training.updaters.MultiprocessParallelUpdater method), 982
get_iterator() (chainer.training.updaters.ParallelUpdater method), 980
get_iterator() (chainer.training.updaters.StandardUpdater method), 978
get_kuzushiji_mnist() (in module chainer.datasets), 1077
get_kuzushiji_mnist_labels() (in module chainer.datasets), 1078
get_max_workspace_size() (in module chainer.backends.cuda), 1118
get_mnist() (in module chainer.datasets), 1076
get_optimizer() (chainer.training.Updater method), 764
get_optimizer() (chainer.training.updaters.MultiprocessParallelUpdater method), 982
get_optimizer() (chainer.training.updaters.ParallelUpdater method), 980
get_optimizer() (chainer.training.updaters.StandardUpdater method), 978
get_ptb_words() (in module chainer.datasets), 1080
get_ptb_words_vocabulary() (in module chainer.datasets), 1080
get_retained_inputs() (chainer.FunctionAdapter method), 301
get_retained_inputs() (chainer.FunctionNode method), 307
get_retained_outputs() (chainer.FunctionAdapter method), 301
get_retained_outputs() (chainer.FunctionNode method), 307
get_svhn() (in module chainer.datasets), 1080
get_target() (chainer.training.extensions.Evaluator method), 988
get_trainer_with_mock_updater() (in module chainer.testing), 1192
get_training_length()
(chainer.training.triggers.EarlyStoppingTrigger method), 1029
get_training_length()
(chainer.training.triggers.IntervalTrigger method), 1030
get_trigger() (in module chainer.training), 1028
get_variable() (chainer.variable.VariableNode method), 152
get_variable_or_none()
(chainer.variable.VariableNode method), 152
global_config (in module chainer), 1136
GlobalConfig (class in chainer.configuration), 1137
GlorotNormal (class in chainer.initializers), 956
GlorotUniform (class in chainer.initializers), 960
GoogleNet (class in chainer.links), 728
gpu() (in module chainer.testing.attr), 1192
GpuDevice (class in chainer.backend), 1109
grad (chainer.Parameter attribute), 150
grad (chainer.Variable attribute), 141
grad (chainer.variable.VariableNode attribute), 153
gradient_clipping (class in chainer.optimizer_hooks), 944
GradientHardClipping (class in chainer.optimizer_hooks), 945
GradientLARS (class in chainer.optimizer_hooks), 947
GradientMethod (class in chainer), 939
GradientNoise (class in chainer.optimizer_hooks), 946
greater() (in module chainerx), 1251
greater_equal() (in module chainerx), 1251
group_normalization() (in module chainer.functions), 279
GroupNormalization (class in chainer.links), 636
GRU (class in chainer.links), 429
Gumbel (class in chainer.distributions), 850
gumbel_softmax() (in module chainer.functions), 274
H
hard_sigmoid() (in module chainer.functions), 158
HDF5Deserializer (class in chainer.serializers), 1096
HDF5Serializer (class in chainer.serializers), 1095
HeNormal (class in chainer.initializers), 956
HeUniform (class in chainer.initializers), 960
high (chainer.distributions.Uniform attribute), 879
Highway (class in chainer.links), 435
hinge() (in module chainer.functions), 239
hsplit() (in module chainerx), 1236
hstack() (in module chainer.functions), 181
hstack() (in module chainerx), 1233
huber_loss() (in module chainer.functions), 240
huber_loss() (in module chainerx), 1254
Hyperparameter (class in chainer.optimizer), 938

icdf() (chainer.Distribution method), 882
icdf() (chainer.distributions.Bernoulli method), 824
icdf() (chainer.distributions.Beta method), 827
icdf() (chainer.distributions.Categorical method), 830
icdf() (chainer.distributions.Cauchy method), 833
icdf() (chainer.distributions.Chisquare method), 836
icdf() (chainer.distributions.Dirichlet method), 839
icdf() (chainer.distributions.Exponential method), 842
icdf() (chainer.distributions.Gamma method), 845
icdf() (chainer.distributions.Geometric method), 848
icdf() (chainer.distributions.Gumbel method), 851
icdf() (chainer.distributions.Independent method), 854
icdf() (chainer.distributions.Laplace method), 857
icdf() (chainer.distributions.LogNormal method), 859
icdf() (chainer.distributions.MultivariateNormal method), 862
icdf() (chainer.distributions.Normal method), 865
icdf() (chainer.distributions.OneHotCategorical method), 868
icdf() (chainer.distributions.Pareto method), 871
icdf() (chainer.distributions.Poisson method), 874
icdf() (chainer.distributions.Uniform method), 877
id() (chainer.testing.FunctionTestCase method), 1170
id() (chainer.testing.LinkInitializersTestCase method), 1181
id() (chainer.testing.LinkTestCase method), 1189
Identity (class in chainer.initializers), 950
identity() (in module chainer.functions), 260
identity() (in module chainerx), 1216
ifft() (in module chainer.functions), 260
ignore_label (chainer.links.EmbedID attribute), 429
imos() (in module chainer.functions), 182
ImageDataset (class in chainer.datasets), 1062
in_recomputing (chainer.configuration.GlobalConfig attribute), 1137
Inception (class in chainer.links), 442
InceptionBN (class in chainer.links), 449
increasing() (in module onnx_chainer.testing.input_generator), 1367
Independent (class in chainer.distributions), 853
inter_size() (chainermn.CommunicatorBase property), 1341
IntervalTrigger (class in chainer.training.triggers), 1030
intra_rank() (chainermn.CommunicatorBase property), 1341
inv() (in module chainer.functions), 260
inv() (in module chainerx.linalg), 1247
InverseShift (class in chainer.training.extensions), 999
invoke_before_training (chainer.training.extensions.PolynomialShift attribute), 1006
is_array_supported() (chainer.backend.ChainerxDevice method), 1111
is_array_supported() (chainer.backend.CpuDevice method), 1108
is_array_supported() (chainer.backend.Device method), 1103
is_array_supported() (chainer.backend.Intel64Device method), 1110
is_backprop_required() (chainerx.ndarray method), 1209
is_backprop_required() (in module chainerx), 1298
is_before_training (chainer.training.Trainer attribute), 975
is_contiguous (chainerx.ndarray attribute), 1212
is_debug() (in module chainer), 1141
is_elementwise (chainer.FunctionAdapter attribute), 302
is_elementwise (chainer.FunctionNode attribute), 308
is_elementwise (chainer.UpdateRule attribute), 938
is_grad_required() (chainerx.ndarray method), 1209
is_ideep_available() (in module chainer.backends.intel64), 1118
is_initialized (chainer.Parameter attribute), 150
is_new_epoch (chainer.iterators.MultiprocessIterator attribute), 1086
is_new_epoch (chainer.iterators.MultithreadIterator attribute), 1087
is_new_epoch (chainer.iterators.SerialIterator attribute), 1083
is_new_epoch (chainer.training.updaters.MultiprocessParallelUpdater attribute), 983
is_new_epoch (chainer.training.updaters.ParallelUpdater attribute), 981
is_new_epoch (chainer.training.updaters.StandardUpdater attribute), 979
is_safe_to_update() (chainer.GradientMethod method), 940
is_safe_to_update() (chainer.Optimizer method), 934
is_safe_to_update() (chainer.optimizers.AdaBound method), 903
is_safe_to_update() (chainer.optimizers.AdaDelta method), 887
is_safe_to_update() (chainer.optimizers.AdaGrad method), 889
is_safe_to_update() (chainer.optimizers.Adam method), 893
is_safe_to_update() (chainer.optimizers.AdamW method), 896
is_safe_to_update() (chainer.optimizers.AMSBound method), 906
is_safe_to_update() (chainer.optimizers.AMSGrad method), 900
is_safe_to_update() (chainer.optimizers.CorrectedMomentumSGD method), 910
is_safe_to_update() (chainer.optimizers.MomentumSGD method), 913
is_safe_to_update() (chainer.optimizers.MSVAG method), 919
is_safe_to_update() (chainer.optimizers.NesterovAG method), 916
is_safe_to_update() (chainer.optimizers.RMSprop method), 922
is_safe_to_update() (chainer.optimizers.RMSpropGraves method), 925
is_safe_to_update() (chainer.optimizers.SGD method), 928
is_safe_to_update() (chainer.optimizers.SMORMS3 method), 931
isinf() (in module chainerx), 1249
isnan() (in module chainerx), 1249
item() (chainer.Parameter method), 146
item() (chainer.Variable method), 136
item() (chainerx.ndarray method), 1209
itemsize (chainerx.ndarray attribute), 1212
Iterator (class in chainer.dataset), 1046
J
join() (chainer.dataset.tabular.DelegateDataset method), 1044
join() (chainer.dataset.TabularDataset method), 1040
LabeledZippedImageDataset (class in chainer.datasets), 1067
LabeledImageDataset (class in chainer.datasets), 1067
LabeledZippedImageDataset (class in chainer.datasets), 1069
lambda (chainer.distributions.Exponential attribute), 844
lambda (chainer.distributions.Poisson attribute), 876
Laplace (class in chainer.distributions), 856
Lasso (class in chainer.optimizer_hooks), 943
layer_normalization() (in module chainer.functions), 280
LayerNormalization (class in chainer.links), 643
layout (chainer.Parameter attribute), 150
layout (chainer.Variable attribute), 141
lazy_grad_sum (chainer.configuration.GlobalConfig attribute), 1137
lazy_grad_sum (chainer.FunctionAdapter attribute), 302
lazy_grad_sum (chainer.FunctionNode attribute), 308
LD_LIBRARY_PATH, 1310
leaky_relu() (in module chainer.functions), 158
LeCunNormal (class in chainer.initializers), 955
LeCunUniform (class in chainer.initializers), 959
left_shift() (in module chainer), 1270
less() (in module chainer), 1252
less_equal() (in module chainer), 1252
lgamma() (in module chainer.functions), 260
Linear (class in chainer.links), 456
linear() (in module chainer.functions), 215
linear() (in module chainer), 1278
linear_interpolate() (in module chainer.functions), 261
LinearShift (class in chainer.training.extensions), 1001
Link (class in chainer), 784
LinkHook (class in chainer), 821
LinkInitializersTestCase (class in chainer.testing), 1174
links() (chainer.Chain method), 795
links() (chainer.ChainList method), 802
links() (chainer.Link method), 788
links() (chainer.links.BatchNormalization method), 619
links() (chainer.links.BatchRenormalization method), 625
links() (chainer.links.Bias method), 326
links() (chainer.links.Bilinear method), 333
links() (chainer.links.BinaryHierarchicalSoftmax method), 653
links() (chainer.links.BlackOut method), 659
links() (chainer.links.caffe.CaffeFunction method), 781
links() (chainer.links.ChildSumTreeLSTM method), 340
links() (chainer.links.Classifier method), 708
links() (chainer.links.Convolution1D method), 346
links() (chainer.links.Convolution2D method), 354
links() (chainer.links.Convolution3D method), 361
links() (chainer.links.ConvolutionND method), 369
links() (chainer.links.CRF1d method), 666
links() (chainer.links.Deconvolution1D method), 375
links() (chainer.links.Deconvolution2D method), 383
links() (chainer.links.Deconvolution3D method), 389
links() (chainer.links.DeconvolutionND method), 397
links() (chainer.links.DecimalBatchNormalization method), 632
links() (chainer.links.DeformableConvolution2D method), 404
links() (chainer.links.DepthwiseConvolution2D method), 411
links() (chainer.links.DilatedConvolution2D method), 419
links() (chainer.links.EmbedID method), 426
links() (chainer.links.GoogLeNet method), 732
links() (chainer.links.GroupNormalization method), 639
links() (chainer.links.GRU method), 432
links() (chainer.links.Highway method), 439
links() (chainer.links.Inception method), 446
links() (chainer.links.InceptionBN method), 452
links() (chainer.links.LayerNormalization method), 646
links() (chainer.links.Linear method), 460
links() (chainer.links.LocalConvolution2D method), 466
links() (chainer.links.LSTM method), 474
links() (chainer.links.Maxout method), 694
links() (chainer.links.MLPConvolution2D method), 482
Chainer Documentation, Release 7.7.0

local_convolution_2d() (chainer.functions), 215

local_function_hooks (chainer.Function attribute), 297

local_function_hooks (chainer.FunctionAdapter attribute), 302

local_function_hooks (chainer.FunctionNode attribute), 308

local_link_hooks (chainer.Chain attribute), 791

local_link_hooks (chainer.ChainList attribute), 805

local_link_hooks (chainer.Link attribute), 791

local_link_hooks (chainer.links.BatchNormalization attribute), 622

local_link_hooks (chainer.links.BatchRenormalization attribute), 628

local_link_hooks (chainer.links.Bias attribute), 329

local_link_hooks (chainer.links.Bilinear attribute), 335

local_link_hooks (chainer.links.BinaryHierarchicalSoftmax attribute), 656

local_link_hooks (chainer.links.BlackOut attribute), 662

local_link_hooks (chainer.links.caffe.CaffeFunction attribute), 784

local_link_hooks (chainer.links.CRF1d attribute), 342

local_link_hooks (chainer.links.Classifier attribute), 711

local_link_hooks (chainer.links.Convolution1D attribute), 349

local_link_hooks (chainer.links.Convolution2D attribute), 357

local_link_hooks (chainer.links.Convolution3D attribute), 364

local_link_hooks (chainer.links.ConvolutionND attribute), 372

local_link_hooks (chainer.links.CRF1d attribute), 669

local_link_hooks (chainer.links.Deconvolution1D attribute), 378

local_link_hooks (chainer.links.Deconvolution2D attribute), 386

local_link_hooks (chainer.links.Deconvolution3D attribute), 392

local_link_hooks (chainer.links.DeconvolutionND attribute), 400

local_link_hooks (chainer.links.DecorrelatedBatchNormalization attribute), 635

local_link_hooks (chainer.links.DeformableConvolution2D attribute), 407

local_link_hooks (chainer.links.DepthwiseConvolution2D attribute), 414

local_link_hooks (chainer.links.DilatedConvolution2D attribute), 422
<table>
<thead>
<tr>
<th>Local Link Hooks</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.EmbedID attribute), 429</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.GoogLeNet attribute), 736</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.GroupNormalization attribute), 642</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.GRU attribute), 435</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.Highway attribute), 442</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.Inception attribute), 448</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.InceptionBN attribute), 455</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.LayerNormalization attribute), 649</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.Linear attribute), 463</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.LocalConvolution2D attribute), 469</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.LSTM attribute), 477</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.Maxout attribute), 697</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.MLPConvolution2D attribute), 484</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.model.vision.resnet.ResNetLayers attribute), 744</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.NaryTreeLSTM attribute), 491</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.NegativeSampling method), 703</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.NStepBiGRU attribute), 499</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.NStepBiLSTM attribute), 506</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.NStepBiRNNReLUTanh attribute), 514</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.NStepBiRNNTanhd attribute), 521</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.NStepGRU attribute), 528</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.NStepLSTM attribute), 537</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.NStepRNNReLU attribute), 544</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.NStepRNNNTanh attribute), 551</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.Parameter attribute), 558</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.PReLU attribute), 683</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.ResNet101Layers attribute), 760</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.ResNet152Layers attribute), 768</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.ResNet50Layers attribute), 752</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.StatefulLSTM attribute), 585</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.StatefulPeepholeLSTM attribute), 598</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.StatefulZoneoutLSTM attribute), 605</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.StatelessGRU attribute), 579</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.StatelessLSTM attribute), 612</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.StatelessMGU attribute), 591</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.Swish attribute), 690</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.TheanoFunction attribute), 776</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.VGG16Layers attribute), 719</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.links.VGG19Layers attribute), 727</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.Sequential attribute), 814</td>
</tr>
<tr>
<td>local_link_hooks</td>
<td>(chainer.training.extensions.LogReport attribute), 1015</td>
</tr>
</tbody>
</table>

Chainer Documentation, Release 7.7.0
log_cdf() (chainer.distributions.Dirichlet method)
836
log_cdf() (chainer.distributions.Exponential method)
839
log_cdf() (chainer.distributions.Gamma method)
842
log_cdf() (chainer.distributions.Geometric method)
845
log_cdf() (chainer.distributions.Gumbel method)
848
log_cdf() (chainer.distributions.Independent method)
851
log_cdf() (chainer.distributions.Laplace method)
854
log_cdf() (chainer.distributions.LogNormal method)
857
log_cdf() (chainer.distributions.MultivariateNormal method)
860
log_cdf() (chainer.distributions.Normal method)
863
log_cdf() (chainer.distributions.OneHotCategorical method)
866
log_cdf() (chainer.distributions.Pareto method)
869
log_cdf() (chainer.distributions.Poisson method)
872
log_cdf() (chainer.distributions.Uniform method)
875
log_prob() (chainer.distributions.Bernoulli method)
878
log_prob() (chainer.distributions.Beta method)
881
log_prob() (chainer.distributions.Categorical method)
884
log_prob() (chainer.distributions.Cauchy method)
887
log_prob() (chainer.distributions.Chisquare method)
870
log_prob() (chainer.distributions.Dirichlet method)
873
log_prob() (chainer.distributions.Exponential method)
876
log_prob() (chainer.distributions.Gamma method)
879
log_prob() (chainer.distributions.Geometric method)
882
log_prob() (chainer.distributions.Gumbel method)
885
log_prob() (chainer.distributions.Independent method)
888
log_prob() (chainer.distributions.Laplace method)
891
log_prob() (chainer.distributions.LogNormal method)
894
log_prob() (chainer.distributions.MultivariateNormal method)
897
log_prob() (chainer.distributions.Normal method)
900
log_prob() (chainer.distributions.OneHotCategorical method)
903
log_prob() (chainer.distributions.Pareto method)
906
log_prob() (chainer.distributions.Poisson method)
909
log_prob() (chainer.distributions.Uniform method)
912
log_prob() (chainer.distributions.Categorical attribute)
915
log_prob() (chainer.distributions.OneHotCategorical attribute)
918
log_softmax() (in module chainer.functions)
921
log_softmax() (in module chainerx)
924
log_survival_function() (chainer.Distribution method)
927
log_survival_function() (chainer.distributions.Bernoulli method)
930
log_survival_function() (chainer.distributions.Beta method)
933
log_survival_function() (chainer.distributions.Categorical method)
936
log_survival_function() (chainer.distributions.Cauchy method)
939
log_survival_function() (chainer.distributions.Chisquare method)
942
log_survival_function() (chainer.distributions.Dirichlet method)
945
log_survival_function() (chainer.distributions.Exponential method)
948
log_survival_function() (chainer.distributions.Gamma method)
951
log_survival_function() (chainer.distributions.Geometric method)
954
log_survival_function() (chainer.distributions.Gumbel method)
957
log_survival_function() (chainer.distributions.Independent method)
960
log_survival_function() (chainer.distributions.Laplace method)
963
log_survival_function() (chainer.distributions.LogNormal method)
966
log_survival_function() (chainer.distributions.MultivariateNormal method)
969
log_survival_function() (chainer.distributions.Normal method)
972
log_survival_function() (chainer.distributions.OneHotCategorical method)
975
log_survival_function() (chainer.distributions.Pareto method)
978
log_survival_function() (chainer.distributions.Poisson method)
981
log_survival_function() (chainer.distributions.Uniform method)
984
log_scale (chainer.distributions.Normal attribute)
987
log_pdf() (in module chainer.functions)
990
log_pdf() (in module chainerx)
993
log_survival_function() (chainer.distributions.Bernoulli method)
996
log_survival_function() (chainer.distributions.Beta method)
999
log_survival_function() (chainer.distributions.Categorical method)
1002
log_survival_function() (chainer.distributions.Cauchy method)
1005
log_survival_function() (chainer.distributions.Chisquare method)
1008
log_survival_function() (chainer.distributions.Dirichlet method)
1011
log_survival_function() (chainer.distributions.Exponential method)
1014
log_survival_function() (chainer.distributions.Gamma method)
1017
log_survival_function() (chainer.distributions.Geometric method)
1020
log_survival_function() (chainer.distributions.Gumbel method)
1023
log_survival_function() (chainer.distributions.Independent method)
1026
log_survival_function() (chainer.distributions.Laplace method)
1029
log_survival_function() (chainer.distributions.LogNormal method)
1032
log_survival_function() (chainer.distributions.MultivariateNormal method)
1035
log_survival_function() (chainer.distributions.Normal method)
1038
log_survival_function() (chainer.distributions.OneHotCategorical method)
1041
log_survival_function() (chainer.distributions.Pareto method)
1044
log_survival_function() (chainer.distributions.Poisson method)
1047
log_survival_function() (chainer.distributions.Uniform method)
1050
log_pdf() (chainer.distributions.Bernoulli method)
1053
log_pdf() (chainer.distributions.Beta method)
1056
log_pdf() (chainer.distributions.Categorical method)
1059
log_pdf() (chainer.distributions.Cauchy method)
1062
log_pdf() (chainer.distributions.Chisquare method)
1065
log_pdf() (chainer.distributions.Dirichlet method)
1068
log_pdf() (chainer.distributions.Exponential method)
1071
log_pdf() (chainer.distributions.Gamma method)
1074
log_pdf() (chainer.distributions.Geometric method)
1077
log_pdf() (chainer.distributions.Gumbel method)
1080
log_pdf() (chainer.distributions.Independent method)
1083
log_pdf() (chainer.distributions.Laplace method)
1086
log_pdf() (chainer.distributions.LogNormal method)
1089
log_pdf() (chainer.distributions.MultivariateNormal method)
1092
log_pdf() (chainer.distributions.Normal method)
1095
log_pdf() (chainer.distributions.OneHotCategorical method)
1098
log_pdf() (chainer.distributions.Pareto method)
1101
log_pdf() (chainer.distributions.Poisson method)
1104
log_pdf() (chainer.distributions.Uniform method)
1107
log_survival_function()
  (chainer.distributions.MultivariateNormal
   method, 863)
log_survival_function()
  (chainer.distributions.Normal method, 866)
log_survival_function()
  (chainer.distributions.OneHotCategorical
   method, 868)
log_survival_function()
  (chainer.distributions.Pareto method, 871)
log_survival_function()
  (chainer.distributions.Poisson method, 874)
log_survival_function()
  (chainer.distributions.Uniform
   method, 877)
logical_and() (in module chainerx), 1249
logical_not() (in module chainerx), 1251
logical_or() (in module chainerx), 1250
logical_xor() (in module chainerx), 1250
logit (chainer.distributions.Bernoulli
   attribute), 826
LogNormal (class in chainer.distributions), 859
LogReport, 61
LogReport (class in chainer.training
   extensions), 1014
logsumexp() (in module chainer
   functions), 262
logsumexp() (in module chainerx), 1263
longMessage (chainer.testing.FunctionTestCase
   attribute), 1171
longMessage (chainer.testing.LinkInitializersTest
   Case attribute), 1182
longMessage (chainer.testing.LinkTestCase
   attribute), 1190
loss_scaling() (chainer.GradientMethod
   method), 940
loss_scaling() (chainer.Optimizer
   method), 934
loss_scaling() (chainer.optimizers.Adabelta
   method), 903
loss_scaling() (chainer.optimizers.Adadelta
   method), 887
loss_scaling() (chainer.optimizers.Adagrad
   method), 889
loss_scaling() (chainer.optimizers.Adam
   method), 893
loss_scaling() (chainer.optimizers.Adamw
   method), 896
loss_scaling() (chainer.optimizers.Amsbound
   method), 907
loss_scaling() (chainer.optimizers.Amsgrad
   method), 900
loss_scaling() (chainer.optimizers.CorrectedMomentumSGD
   method), 910
loss_scaling() (chainer.optimizers.MomentumSGD
   method), 913
loss_scaling() (chainer.optimizers.Msvag
   method), 919
loss_scaling() (chainer.optimizers.NesterovAG
   method), 916
loss_scaling() (chainer.optimizers.RMSprop
   method), 922
loss_scaling() (chainer.optimizers.RMSpropGraves
   method), 925
loss_scaling() (chainer.optimizers.SGD
   method), 928
loss_scaling() (chainer.optimizers.SMORMS3
   method), 931
low (chainer.distributions.Uniform
   attribute), 879
lr (chainer.optimizers.Adabelta
   attribute), 905
lr (chainer.optimizers.Adadelta
   attribute), 911
lr (chainer.optimizers.Adam
   attribute), 915
lr (chainer.optimizers.AdamW
   attribute), 919
lr (chainer.optimizers.Amsbound
   attribute), 927
lr (chainer.optimizers.Amsgrad
   attribute), 930
lr (chainer.optimizers.SMORMS3
   attribute), 932
LSTM (class in chainer
   links), 470
lstm() (in module
   chainer.functions), 160
lstm() (in module chainerx), 1279

M
make_backprop_id() (chainerx.
   Context method), 1292
make_extension() (in module chainer
   training), 986
make_statistics() (chainer.
   DictSummary method), 1128
make_statistics() (chainer.
   Summary method), 1127
ManualScheduleTrigger (class
   in chainer.
   training
   triggers), 1031
matmul() (in module
   chainer.functions), 263
max() (chainer.
   ndarray
   method), 1209
max() (in module
   chainer.functions), 263
max_pool() (in module chainerx), 284
max_pooling_1d() (in module
   chainer.functions), 284
max_pooling_2d() (in module
   chainer.functions), 284
max_pooling_3d() (in module
   chainer.functions), 285
max_pooling_nd() (in module
   chainer.functions), 285
max_diff (chainer.
   testing.
   Function
   TestCase
   attribute), 1171
maxDiff (chainer.testing.LinkInitializersTestCase attribute), 1182
maxDiff (chainer.testing.LinkTestCase attribute), 1190
maximum() (in module chainer.functions), 264
maximum() (in module chainerx), 1260
Maxout (class in chainer.links), 690
maxout() (in module chainer.functions), 161
MaxValueTrigger (class in chainer.training.triggers), 1032
mean (chainer.Distribution attribute), 885
mean (chainer.distributions.Bernoulli attribute), 826
mean (chainer.distributions.Categorical attribute), 832
mean (chainer.distributions.Cauchy attribute), 835
mean (chainer.distributions.Chisquare attribute), 838
mean (chainer.distributions.Dirichlet attribute), 841
mean (chainer.distributions.Exponential attribute), 844
mean (chainer.distributions.Gamma attribute), 847
mean (chainer.distributions.Geometric attribute), 850
mean (chainer.distributions.Gumbel attribute), 853
mean (chainer.distributions.Laplace attribute), 859
mean (chainer.distributions.LogNormal attribute), 861
mean (chainer.distributions.MultivariateNormal attribute), 864
mean (chainer.distributions.Normal attribute), 867
mean (chainer.distributions.OneHotCategorical attribute), 870
mean (chainer.distributions.Pareto attribute), 873
mean (chainer.distributions.Poisson attribute), 876
mean (chainer.distributions.Uniform attribute), 879
mean() (chainer.Parameter method), 146
mean() (chainer.Variable method), 136
mean() (chainerx.ndarray method), 1209
mean() (in module chainer.functions), 264
mean() (in module chainerx), 1273
mean_absolute_error() (in module chainer.functions), 241
mean_squared_error() (in module chainer.functions), 242
memoize() (in module chainer.backends.cuda), 1116
meshgrid() (in module chainerx), 1224
MicroAverage (class in chainer.training.extensions), 990
min() (chainerx.ndarray method), 1209
min() (in module chainer.functions), 265
minimum() (in module chainer.functions), 265
minimum() (in module chainerx), 1261
MinValueTrigger (class in chainer.training.triggers), 1033
mixed16 (in module chainerx), 1139
MLPConvolution2D (class in chainer.links), 478
mod() (in module chainerx), 1259
mode (chainer.dataset.tabular.DelegateDataset attribute), 1045
mode (chainer.dataset.TabularDataset attribute), 1041
mode (chainer.Distribution attribute), 885
mode (chainer.distributions.Bernoulli attribute), 826
mode (chainer.distributions.Categorical attribute), 832
mode (chainer.distributions.Cauchy attribute), 835
mode (chainer.distributions.Chisquare attribute), 838
mode (chainer.distributions.Dirichlet attribute), 841
mode (chainer.distributions.Exponential attribute), 844
mode (chainer.distributions.Gamma attribute), 847
mode (chainer.distributions.Geometric attribute), 850
mode (chainer.distributions.Gumbel attribute), 853
mode (chainer.distributions.Independent attribute), 856
mode (chainer.distributions.Laplace attribute), 859
mode (chainer.distributions.LogNormal attribute), 861
mode (chainer.distributions.MultivariateNormal attribute), 864
mode (chainer.distributions.Normal attribute), 867
mode (chainer.distributions.Pareto attribute), 873
mode (chainer.distributions.Poisson attribute), 876
mode (chainer.distributions.Uniform attribute), 879
module
chainer, 133, 784, 1098
chainer.backend, 1102
chainer.backends.cuda, 1113
chainer.backends.intel64, 1118
chainer.computational_graph, 1141
chainer.dataset, 1035
chainer.datasets, 1052
chainer.distributions, 823
chainer.exporters, 1153
chainer.function_hooks, 311
chainer.functions, 154
chainer.gradient_check, 1159
chainer.initializers, 950
chainer.iterators, 1081
chainer.link_hooks, 814
chainer.links, 322
chainer.models.caffe, 1152
chainer.optimizers, 885
chainer.serializers, 1091
chainer.testing, 1163
chainer.training, 963
chainer.training.extensions.snapshot_writers, 963
chainer.utils, 1371
chainer.utils.type_check, 1154
chainermn, 1303, 1313, 1319, 1337
chainerx, 1207, 1214, 1292, 1296
onnx_chainer, 1363

1496 Index
momentum(chainer.optimizers.MomentumSGD attribute), 912
momentum (chainer.optimizers.MomentumSGD attribute), 915
momentum (chainer.optimizers.NesterovAG attribute), 918
momentum (chainer.optimizers.RMSpropGraves attribute), 927
MomentumSGD(class in chainer.optimizers), 912
moveaxis() (in module chainer.functions), 183
moveaxis() (in module chainerx), 1239
MSVA (class in chainer.optimizers), 918
mu (chainer.distributions.LogNormal attribute), 862
multi_gpu() (in module chainerx.testing.attr), 1193
multi_node_mean_grad() (chainermn.CommunicatorBase method), 1341
multi_node_snapshot() (in module chainermn.extensions), 1355
MultiNodeBatchNormalization (class in chainermn.links), 1348
MultiNodeChainList (class in chainermn), 1346
multiply() (in module chainerx), 1258
MultiprocessParallelUpdater (class in chainer.training.updaters), 981
MultistepShift (class in chainer.training.extensions), 1003
MultithreadIterator (class in chainer.iterators), 1086
MultivariateNormal (class in chainer.distributions), 862
MultiZippedImageDataset (class in chainer.datasets), 1065
MV2_SMP_USE_CMA, 1310, 1312
MV2_USE_CUDA, 1310, 1313

N
n_cells (chainer.links.NStepBiGRU attribute), 499
n_cells (chainer.links.NStepBiLSTM attribute), 506
n_cells (chainer.links.NStepBiRNNReLU attribute), 514
n_cells (chainer.links.NStepBiRNNTanh attribute), 521
n_cells (chainer.links.NStepGRU attribute), 528
n_cells (chainer.links.NStepLSTM attribute), 537
n_cells (chainer.links.NStepRNNReLU attribute), 544
n_cells (chainer.links.NStepRNNReLU attribute), 551
n_step_bigru() (in module chainer.functions), 216
n_step_bigru() (in module chainerx), 1288
n_step_bilstm() (in module chainer.functions), 218
n_step_bilstm() (in module chainerx), 1285
n_step_birnn() (in module chainer.functions), 220
n_step_birnn() (in module chainerx), 1290
n_step_gru() (in module chainer.functions), 222
n_step_gru() (in module chainerx), 1287
n_step_lstm() (in module chainer.functions), 223
n_step_lstm() (in module chainerx), 1283
n_step_rnn() (in module chainer.functions), 225
n_step_rnn() (in module chainerx), 1289
n_weights (chainer.links.NStepBiGRU attribute), 499
n_weights (chainer.links.NStepBiLSTM attribute), 506
n_weights (chainer.links.NStepBiRNNReLU attribute), 514
n_weights (chainer.links.NStepBiRNNTanh attribute), 521
n_weights (chainer.links.NStepGRU attribute), 528
n_weights (chainer.links.NStepLSTM attribute), 537
n_weights (chainer.links.NStepRNNReLU attribute), 544
n_weights (chainer.links.NStepRNNTanh attribute), 551
name (chainer.backend.CuDevice attribute), 1112
name (chainer.backend.CpuDevice attribute), 1109
name (chainer.backend.Device attribute), 1103
name (chainer.backend.GpuDevice attribute), 1110
name (chainer.backend.Intel64Device attribute), 1111
name (chainer.function_hooks.CUDAProfileHook attribute), 312
name (chainer.function_hooks.CupAMemoryProfileHook attribute), 314
name (chainer.function_hooks.PrintMemoryProfileHook attribute), 317
name (chainer.function_hooks.TimerHook attribute), 319
name (chainer.link_hooks.GradientClipping attribute), 322
name (chainer.link_hooks.GradientHardClipping attribute), 817
name (chainer.link_hooks.WeightNormalization attribute), 819
name (chainer.link_hooks.WeightStandardization attribute), 821
name (chainer.LinkHook attribute), 823
name (chainer.optimizer_hooks.GradientClipping attribute), 945
name (chainer.optimizer_hooks.GradientHardClipping attribute), 946
name (chainer.optimizer_hooks.GradientLARS attribute), 949
name (chainer.optimizer_hooks.GradientNoise attribute), 947
name (chainer.optimizer_hooks.Lasso attribute), 944
name (chainer.optimizer_hooks.WeightDecay attribute), 943
name (chainer.Parameter attribute), 150
name (chainer.training.Evaluator attribute), 985
name (chainer.training.extensions.DumpGraph attribute), 1022
name (chainer.training.extensions.Evaluator attribute), 990

Index 1497
name (chainer.training.extensions.ExponentialShift attribute), 999
name (chainer.training.extensions.FailOnNonNumber attribute), 993
name (chainer.training.extensions.InverseShift attribute), 1001
name (chainer.training.extensions.LinearShift attribute), 1002
name (chainer.training.extensions.LogReport attribute), 1015
name (chainer.training.extensions.MicroAverage attribute), 992
name (chainer.training.extensions.MultistepShift attribute), 1004
name (chainer.training.extensions.ParameterStatistics attribute), 996
name (chainer.training.extensions.PlotReport attribute), 1018
name (chainer.training.extensions.PrintReport attribute), 1012
name (chainer.training.extensions.ProgressBar attribute), 1013
name (chainer.training.extensions.StepShift attribute), 1010
name (chainer.training.extensions.unchain_variables attribute), 1027
name (chainer.training.extensions.VariableStatisticsPlot attribute), 1020
name (chainer.training.extensions.WarmupShift attribute), 1008
name (chainer.Variable attribute), 141
name (chainerx.Backend attribute), 1293
name (chainerx.Device attribute), 1295
namedlinks() (chainer.Chain method), 796
namedlinks() (chainer.ChainList method), 802
namedlinks() (chainer.Link method), 788
namedlinks() (chainer.links.BatchNormalization method), 619
namedlinks() (chainer.links.BatchRenormalization method), 626
namedlinks() (chainer.links.Bias method), 326
namedlinks() (chainer.links.Bilinear method), 333
namedlinks() (chainer.links.BinaryHierarchicalSoftmax method), 653
namedlinks() (chainer.links.BlackOut method), 659
namedlinks() (chainer.links.caffe.CaffeFunction method), 781
namedlinks() (chainer.links.ChildSumTreeLSTM method), 340
namedlinks() (chainer.links.Classifier method), 708
namedlinks() (chainer.links.Convolution3D method), 361
namedlinks() (chainer.links.ConvolutionND method), 369
namedlinks() (chainer.links.CRF1d method), 666
namedlinks() (chainer.links.Deconvolution3D method), 411
namedlinks() (chainer.links.DeformableConvolution2D method), 405
namedlinks() (chainer.links.DepthwiseConvolution2D method), 419
namedlinks() (chainer.links.EmbedID method), 426
namedlinks() (chainer.links.GoogLeNet method), 733
namedlinks() (chainer.links.GroupNormalization method), 639
namedlinks() (chainer.links.GRU method), 432
namedlinks() (chainer.links.Highway method), 439
namedlinks() (chainer.links.Inception method), 446
namedlinks() (chainer.links.InceptionBN method), 453
namedlinks() (chainer.links.LayerNormalization method), 646
namedlinks() (chainer.links.Linear method), 460
namedlinks() (chainer.links.LocalConvolution2D method), 467
namedlinks() (chainer.links.LSTM method), 474
namedlinks() (chainer.links.Maxout method), 694
namedlinks() (chainer.links.MLPConvolution2D method), 482
namedlinks() (chainer.links.model.vision.resnet.ResNetLayers method), 741
namedlinks() (chainer.links.NaryTreeLSTM method), 489
namedlinks() (chainer.links.NegativeSampling method), 701
namedlinks() (chainer.links.NStepBiGRU method), 496
namedlinks() (chainer links.NStepBiLSTM method), 503
namedlinks() (chainer.links.NStepBiRNNReLU method), 511
<table>
<thead>
<tr>
<th>Function Name</th>
<th>Chainer Documentation, Release 7.7.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>namedlinks()</td>
<td>chainer.links.NStepBiRNNTanh method, 518</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.NStepGRU method, 526</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.NStepLSTM method, 534</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.NStepRNNReLU method, 541</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.NStepRNNTanh method, 549</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.Parameter method, 555</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.PReLU method, 569</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.ResNet101Layers method, 757</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.ResNet152Layers method, 765</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.ResNet50Layers method, 749</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.Scale method, 680</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.SimplifiedDropconnect method, 673</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.StatefulGRU method, 569</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.StatefulMGU method, 583</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.StatefulPeepholeLSTM method, 596</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.StatefulZoneoutLSTM method, 602</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.StatelessGRU method, 576</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.StatelessLSTM method, 609</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.StatelessMGU method, 589</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.Swish method, 687</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.TheanoFunction method, 774</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.VGG16Layers method, 716</td>
</tr>
<tr>
<td>namedlinks()</td>
<td>chainer.links.VGG19Layers method, 724</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.CaffeFunction method, 781</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.ChildSumTreeLSTM method, 340</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.Classifier method, 708</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.Convolution1D method, 346</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.Convolution2D method, 354</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.Convolution3D method, 361</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.ConvolutionND method, 369</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.CRF1d method, 666</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.DecorrelatedBatchNormalization method, 633</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.DeformableConvolution2D method, 405</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.DepthwiseConvolution2D method, 412</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.DilatedConvolution2D method, 419</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.EmbedID method, 426</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.GoogLeNet method, 375</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.Deconvolution1D method, 397</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.Deconvolution2D method, 408</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.Deconvolution3D method, 419</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.GroupNormalization method, 639</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.GRU method, 432</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.Highway method, 439</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.Inception method, 446</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.InceptionBN method, 453</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.LayerNormalization method, 646</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.Linear method, 460</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.LocalConvolution2D method, 467</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.LSTM method, 474</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.Maxout method, 694</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.MLPConvolution2D method, 482</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.model.vision.resnet.ResNetLayers method, 741</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.MLPConvolution2D method, 489</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.NaryTreeLSTM method, 489</td>
</tr>
<tr>
<td>namedparams()</td>
<td>chainer.links.NegativeSampling method, 659</td>
</tr>
</tbody>
</table>
Parameter (class in chainer.links, 552)
parameterize() (in module chainer.testing), 1194
ParameterStatistics (class in chainer.training.extensions), 993
params (chainer.Distribution attribute), 885
params (chainer.distributions.Bernoulli attribute), 826
params (chainer.distributions.Beta attribute), 829
params (chainer.distributions.Categorical attribute), 832
params (chainer.distributions.Cauchy attribute), 835
params (chainer.distributions.Chisquare attribute), 838
params (chainer.distributions/dirichlet attribute), 841
params (chainer.distributions.Exponential attribute), 844
params (chainer.distributions.Gamma attribute), 847
params (chainer.distributions.Geometric attribute), 850
params (chainer.distributions.Gumbel attribute), 853
params (chainer.distributions.Independent attribute), 856
params (chainer.distributions.Laplace attribute), 859
params (chainer.distributions.LogNormal attribute), 862
params (chainer.distributions.MultivariateNormal attribute), 864
params (chainer.distributions.Normal attribute), 867
params (chainer.distributions.OneHotCategorical attribute), 870
params (chainer.distributions.Pareto attribute), 873
params (chainer.distributions.Poisson attribute), 876
params (chainer.distributions.Uniform attribute), 879
params () (chainer.Chain method), 796
params () (chainer.ChainList method), 802
params () (chainer.Link method), 789
params () (chainer.links.BatchNormalization method), 619
params () (chainer.links.BatchRenormalization method), 626
params () (chainer.links.Bias method), 326
params () (chainer.links.Bilinear method), 333
params () (chainer.links.BinaryHierarchicalSoftmax method), 653
params () (chainer.links.BlackOut method), 660
params () (chainer.links.caffe.CaffeFunction method), 781
params () (chainer.links.ChildSumTreeLSTM method), 794
params () (chainer.links.Classifier method), 709
params () (chainer.links.Convolution1D method), 346
params () (chainer.links.Convolution2D method), 354
params () (chainer.links.Convolution3D method), 361
params () (chainer.links.ConvolutionND method), 369
params () (chainer.links.CRF1d method), 666
params () (chainer.links.Deconvolution1D method), 376
params () (chainer.links.Deconvolution2D method), 384
params () (chainer.links.Deconvolution3D method), 390
params () (chainer.links.DeconvolutionND method), 398
params () (chainer.links.DeformableConvolution2D method), 405
params () (chainer.links.DepthwiseConvolution2D method), 412
params () (chainer.links.DilatedConvolution2D method), 419
params () (chainer.links.EmbedID method), 426
params () (chainer.links.GoogLeNet method), 733
params () (chainer.links.GroupNormalization method), 640
params () (chainer.links.GRU method), 432
params () (chainer.links.Highway method), 439
params () (chainer.links.Inception method), 446
params () (chainer.links.InceptionBN method), 453
params () (chainer.links.LayerNormalization method), 646
params () (chainer.links.Linear method), 460
params () (chainer.links.LocalConvolution2D method), 467
params () (chainer.links.LSTM method), 474
params () (chainer.links.Maxout method), 694
params () (chainer.links.MLPConvolution2D method), 482
params () (chainer.links.model.vision.resnet.ResNetLayers), 742
params () (chainer.links.NaryTreeLSTM method), 489
params () (chainer.links.NegativeSampling method), 701
params () (chainer.links.NStepBiGRU method), 496
params () (chainer.links.NStepBiLSTM method), 504
params () (chainer.links.NStepBiRNNReLU method), 511
params () (chainer.links.NStepBiRNNTanH method), 518
params () (chainer.links.NStepGRU method), 526
params () (chainer.links.NStepLSTM method), 534
params () (chainer.links.NStepRNNReLU method), 541
params () (chainer.links.NStepRNNTanH method), 549
params () (chainer.links.Parameter method), 555
params () (chainer.links.PReLU method), 680
params () (chainer.links.ResNet101Layers method), 758
params () (chainer.links.ResNet152Layers method), 766
params () (chainer.links.ResNet50Layers method), 750
params () (chainer.links.Scale method), 562
null
(chainer.links.SimplifiedDropconnect method), 673
remove() (chainer.links.StatefulGRU method), 569
remove_persistent() (chainer.links.StatefulMGU method), 583
remove_persistent() (chainer.links.StatefulPeepholeLSTM method), 596
remove_persistent() (chainer.links.StatefulZoneoutLSTM method), 602
remove_persistent() (chainer.links.StatelessGRU method), 577
remove_persistent() (chainer.links.VGG16Layers method), 717
remove_persistent() (chainer.links.VGG19Layers method), 725
remove_persistent() (chainer.Sequential method), 811
remove_statistics() (chainer.training.extensions.ParameterStatistics method), 995
reinterpreted_batch_ndims (chainer.distributions.Independent attribute), 856
release_backprop_id() (chainerx.Context method), 1292
relu() (in module chainer.functions), 164
relu() (in module chainerx), 1227
relu6() (in module chainer.functions), 164
remainder() (in module chainerx), 1259
remove() (chainer.ChainList method), 803
remove() (chainer.links.MLPConvolution2D method), 482
remove() (chainer.links.NStepBiGRU method), 496
remove() (chainer.links.NStepBiLSTM method), 504
remove() (chainer.links.NStepBiRNNReLU method), 511
remove() (chainer.links.NStepBiRNNTanh method), 519
remove() (chainer.links.NStepGRU method), 526
remove() (chainer.links.NStepLSTM method), 534
remove() (chainer.links.NStepRNNReLU method), 542
remove() (chainer.links.NStepRNNTanh method), 549
remove() (chainer.Sequential method), 811
remove_by_layer_type() (chainer.Sequential method), 812
remove_hook() (chainer.GradientMethod method), 941
remove_hook() (chainer.optimizers.Adam method), 893
remove_hook() (chainer.optimizers.AdamW method), 897
remove_hook() (chainer.optimizers.AMSBound method), 907
remove_hook() (chainer.optimizers.AMSSGrad method), 900
remove_hook() (chainer.optimizers.CorrectedMomentumSGD method), 911
remove_hook() (chainer.optimizers.MomentumSGD method), 913
remove_hook() (chainer.optimizers.MSVAG method), 919
remove_hook() (chainer.optimizers.NesterovAG method), 916
remove_hook() (chainer.optimizers.RMSprop method), 922
remove_hook() (chainer.optimizers.RMSpropGraves method), 925
remove_hook() (chainer.optimizers.SGD method), 928
remove_hook() (chainer.optimizers.SMORMS3 method), 931
remove_hook() (chainer.iterators.DaliIterator attribute), 1089
remove_hook() (chainer.iterators.SerialIterator attribute), 1087
remove_hook() (chainer.iterators.MulithreadIterator attribute), 1087
remove_hook() (chainer.iterators.SerialIterator attribute), 1083
remove() (chainer.Chain method), 796
remove() (chainer.ChainList method), 803
remove() (chainer.Link method), 789
remove() (chainer.links.BatchNormalization method), 619
remove() (chainer.links.BatchNormalizat method), 626
remove() (chainer.links.Bias method), 327
remove() (chainer.links.Bilinear method), 333
remove() (chainer.links.BinaryHierarchicalSoftmax method), 653
remove() (chainer.links.BlackOut method), 660
remove() (chainer.links.caffe.CaffeFunction method),
reset_state() (chainer.links.StatefulStatefulMGU method), 584
reset_state() (chainer.links.StatefulPeepholeLSTM method), 597
reset_state() (chainer.links.StatefulZoneoutLSTM method), 603
reshape() (chainer.Parameter method), 146
reshape() (chainer.Variable method), 136
reshape() (chainerx.ndarray method), 1210
reshape() (in module chainer.functions), 186
reshape() (in module chainerx), 1230
reshape_W() (chainer.link_hooks.SpectralNormalization method), 817
resize_images() (in module chainer.functions), 187
ResNet101Layers (class in chainer.links), 753
ResNet152Layers (class in chainer.links), 761
ResNet50Layers (class in chainer.links), 745
ResNetLayers (class in chainer.links.model.vision.resnet), 737
retain_data() (chainer.Parameter method), 146
retain_data() (chainer.Variable method), 136
retain_data() (chainer.variable.VariableNode method), 152
retain_inputs() (chainer.Function method), 296
retain_inputs() (chainer.FunctionAdapter method), 301
retain_inputs() (chainer.FunctionNode method), 307
retain_outputs() (chainer.Function method), 296
retain_outputs() (chainer.FunctionAdapter method), 301
retain_outputs() (chainer.FunctionNode method), 307
reverse() (chainer.ChainList method), 803
reverse() (chainer.links.MLPConvolution2D method), 483
reverse() (chainer.links.NStepBiGRU method), 497
reverse() (chainer.links.NStepBiLSTM method), 505
reverse() (chainer.links.NStepBiRNNReLU method), 512
reverse() (chainer.links.NStepBiRNNTanh method), 519
reverse() (chainer.links.NStepGRU method), 527
reverse() (chainer.links.NStepLSTM method), 535
reverse() (chainer.links.NStepRNNReLU method), 542
reverse() (chainer.links.NStepRNNTanh method), 550
rnn() (chainerlinks.NStepBiRNNReLU method), 512
rnn() (chainerlinks.NStepBiRNNTanh method), 519
rnn() (chainerlinks.NStepGRU method), 527
rnn() (chainerlinks.NStepLSTM method), 535
rnn() (chainerlinks.NStepRNNReLU method), 542
rnn() (chainerlinks.NStepRNNTanh method), 550
roi_average_align_2d() (in module chainer.functions), 286
roi_average_pooling_2d() (in module chainer.functions), 286
roi_max_align_2d() (in module chainer.functions), 287
roi_max_pooling_2d() (in module chainer.functions), 287
roi_pooling_2d() (in module chainer.functions), 288
rollaxis() (in module chainer.functions), 188
rrelu() (in module chainer.functions), 163
rsqrt() (in module chainer.functions), 266
run() (chainer.testing.FunctionTestCase method), 1170
run() (chainer.testing.LinkInitializersTestCase method), 1181
run() (chainer.testing.LinkTestCase method), 1189
run() (chainer.training.Trainer method), 974
run_test_backward() (chainer.testing.FunctionTestCase method), 1170
run_test_double_backward() (chainer.testing.FunctionTestCase method), 1170
run_test_forward() (chainer.testing.FunctionTestCase method), 1170
S
sample() (chainer.distributions.Distribution method), 883
sample() (chainer.distributions.Bernoulli method), 825
sample() (chainer.distributions.Beta method), 828
sample() (chainer.distributions.Categorical method), 831
sample() (chainer.distributions.Cauchy method), 834
sample() (chainer.distributions.Chisquare method), 837
sample() (chainer.distributions.Dirichlet method), 840
sample() (chainer.distributions.Exponential method), 843
sample() (chainer.distributions.Gamma method), 846
sample() (chainer.distributions.Geometric method), 849
sample() (chainer.distributions.Gumbel method), 852
sample() (chainer.distributions.Independent method), 855
sample() (chainer.distributions.Laplace method), 858
send() (chainer.backend.GpuDevice method), 1109
send() (chainer.backend.Intel64Device method), 1110
send() (chainermn.CommunicatorBase method), 1342
send() (in module chainer.functions), 1350
send_array() (chainermn.ChainerxDevice method), 1112
send_array() (chainer.backend.CpuDevice method), 1108
send_array() (chainer.backend.GpuDevice method), 1109
send_array() (chainer.backend.Intel64Device method), 1111
send_obj() (chainermn.CommunicatorBase method), 1342
separate() (in module chainer.functions), 189
SerialIterator (class in chainer.iterators), 1082
serialize() (chainer.Chain method), 797
serialize() (chainer.ChainList method), 803
serialize() (chainer.dataset.Iterator method), 1047
serialize() (chainer.DictSummary method), 1128
serialize() (chainer.GradientMethod method), 941
serialize() (chainer.iterators.DaliIterator method), 1088
serialize() (chainer.iterators.MultiprocessIterator method), 1085
serialize() (chainer.iterators.MultithreadIterator method), 1087
serialize() (chainer.iterators.SerialIterator method), 1083
serialize() (chainer.Link method), 790
serialize() (chainer.links.BatchNormalization method), 620
serialize() (chainer.links.BatchRenormalization method), 627
serialize() (chainer.links.Bias method), 327
serialize() (chainer.links.Bilinear method), 334
serialize() (chainer.links.BinaryHierarchicalSoftmax method), 654
serialize() (chainer.links.BlackOut method), 661
serialize() (chainer.links.caffe.CaffeFunction method), 782
serialize() (chainer.links.ChildSumTreeLSTM method), 341
serialize() (chainer.links.Classifier method), 710
serialize() (chainer.links.Convolution1D method), 347
serialize() (chainer.links.Convolution2D method), 355
serialize() (chainer.links.Convolution3D method), 362
serialize() (chainer.links.ConvolutionND method), 370
serialize() (chainer.links.CRF1d method), 667
serialize() (chainer.links.Deconvolution1D method), 377
serialize() (chainer.links.Deconvolution2D method), 385
serialize() (chainer.links.Deconvolution3D method), 391
serialize() (chainer.links.DeconvolutionND method), 399
serialize() (chainer.links.DecorrelatedBatchNormalization method), 634
serialize() (chainer.links.DeformableConvolution2D method), 406
serialize() (chainer.links.DepthwiseConvolution2D method), 413
serialize() (chainer.links.DilatedConvolution2D method), 420
serialize() (chainer.links.EmbedID method), 427
serialize() (chainer.links.GoogLeNet method), 734
serialize() (chainer.links.GroupNormalization method), 641
serialize() (chainer.links.GRU method), 433
serialize() (chainer.links.Highway method), 440
serialize() (chainer.links.Inception method), 447
serialize() (chainer.links.InceptionBN method), 454
serialize() (chainer.links.LayerNormalization method), 467
serialize() (chainer.links.Linear method), 461
serialize() (chainer.links.LocalConvolution2D method), 468
serialize() (chainer.links.LSTM method), 475
serialize() (chainer.links.Maxout method), 695
serialize() (chainer.links.MLPConvolution2D method), 483
serialize() (chainer.links.model.vision.resnet.ResNetLayers method), 743
serialize() (chainer.links.NaryTreeLSTM method), 490
serialize() (chainer.links.NegativeSampling method), 702
serialize() (chainer.links.NStepBiGRU method), 497
serialize() (chainer.links.NStepBiLSTM method), 505
serialize() (chainer.links.NStepBiRNNReLU method), 512
serialize() (chainer.links.NStepBiRNNTanh method), 520
serialize() (chainer.links.NStepGRU method), 527
serialize() (chainer.links.NStepLSTM method), 535
serialize() (chainer.links.NStepRNNReLU method), 543
serialize() (chainer.links.NStepRNNTanh method), 550
serialize() (chainer.links.Parameter method), 556
serialize() (chainer.links.PReLU method), 681
serialize() (chainer.links.ResNet101Layers method), 759
serialize() (chainer.links.ResNet152Layers method), 767
serialize() (chainer.links.ResNet50Layers method), 751
serialize() (chainer.links.Scale method), 563
serialize() (chainer.links.SimplifiedDropconnect method), 674
serialize() (chainer.links.StatefulGRU method), 570
serialize() (chainer.links.StatefulMGU method), 584
serialize() (chainer.links.StatefulPeepholeLSTM method), 597
serialize() (chainer.links.StatefulZoneoutLSTM method), 603
serialize() (chainer.links.StatelessGRU method), 577
serialize() (chainer.links.StatelessLSTM method), 611
serialize() (chainer.links.StatelessMGU method), 590
serialize() (chainer.links.Swish method), 688
serialize() (chainer.links.TheanoFunction method), 775
serialize() (chainer.links.VGG16Layers method), 718
serialize() (chainer.links.VGG19Layers method), 726
serialize() (chainer.Optimizer method), 934
serialize() (chainer.optimizers.Adam method), 893
serialize() (chainer.optimizers.AdamW method), 897
serialize() (chainer.optimizers.AMSBound method), 907
serialize() (chainer.optimizers.AMSGrad method), 900
serialize() (chainer.optimizers.CorrectedMomentumSGD method), 911
serialize() (chainer.optimizers.MomentumSGD method), 913
serialize() (chainer.optimizers.MSVAG method), 919
serialize() (chainer.optimizers.NesterovAG method), 916
serialize() (chainer.optimizers.RMSprop method), 922
serialize() (chainer.optimizers.RMSpropGraves method), 925
serialize() (chainer.optimizers.SGD method), 928
serialize() (chainer.optimizers.SMORMS3 method), 931
serialize() (chainer.Sequential method), 812
serialize() (chainer.Summary method), 1127
serialize() (chainer.training.Extension method), 985
serialize() (chainer.training.extensions.DumpGraph method), 1022
serialize() (chainer.training.extensions.Evaluator method), 989
serialize() (chainer.training.extensions.ExponentialShift method), 998
serialize() (chainer.training.extensions.FailOnNonNumber method), 993
serialize() (chainer.training.extensions.InverseShift method), 1000
serialize() (chainer.training.extensions.LinearShift method), 1002
serialize() (chainer.training.extensions.LogReport method), 1015
serialize() (chainer.training.extensions.MultistepShift method), 1004
serialize() (chainer.training.extensions.ParameterStatistics method), 995
serialize() (chainer.training.extensions.PlotReport method), 1017
serialize() (chainer.training.extensions.PolynomialShift method), 1006
serialize() (chainer.training.extensions.PrintReport method), 1011
serialize() (chainer.training.extensions.ProgressBar method), 1013
serialize() (chainer.training.extensions.StepShift method), 1009
serialize() (chainer.training.extensions.unchain_variables method), 1026
serialize() (chainer.training.extensions.VariableStatisticsPlot method), 1020
serialize() (chainer.training.extensions.WarmupShift method), 1007
serialize() (chainer.training.Trainer method), 974
serialize() (chainer.training.triggers.BestValueTrigger method), 1028
serialize() (chainer.training.triggers.IntervalTrigger method), 1030
serialize() (chainer.training.triggers.ManualScheduleTrigger method), 1031
serialize() (chainer.training.triggers.MaxValueTrigger method), 1032
squared_error() (in module chainer.functions), 246
squared_error() (in module chainerx), 1254
squeeze() (chainerx.ndarray method), 1210
squeeze() (in module chainer.functions), 193
squeeze() (in module chainerx), 1231
stack (chainer.Function attribute), 298
stack (chainer.FunctionAdapter attribute), 302
stack (chainer.FunctionNode attribute), 308
stack() (in module chainer.functions), 194
stack() (in module chainerx), 1232
StandardUpdater (class in chainer.training.updaters), 976
start_finetuning() (chainer.links.BatchNormNormalization method), 620
start_finetuning() (chainer.links.BatchNormRenormalization method), 627
start_finetuning() (chainer.links.DecorrelatedBatchNormalization method), 634
state (chainer.UpdateRule attribute), 938
StatefulGRU (class in chainer.links), 565
StatefulMGU (class in chainer.links), 579
StatefulPeepholeLSTM (class in chainer.links), 592
StatefulZoneoutLSTM (class in chainer.links), 599
StatelessGRU (class in chainer.links), 572
StatelessLSTM (class in chainer.links), 605
StatelessMGU (class in chainer.links), 586
static_graph() (in module chainer), 1145
stddev (chainer.Distribution attribute), 885
stddev (chainer.distributions.Bernoulli attribute), 826
stddev (chainer.distributions.Beta attribute), 829
stddev (chainer.distributions.Categorical attribute), 832
stddev (chainer.distributions.Cauchy attribute), 835
stddev (chainer.distributions.Gamma attribute), 847
stddev (chainer.distributions.Geometric attribute), 850
stddev (chainer.distributions.Gumbel attribute), 853
stddev (chainer.distributions.Independent attribute), 856
stddev (chainer.distributions.Laplace attribute), 859
stddev (chainer.distributions.LogNormal attribute), 862
stddev (chainer.distributions.MultivariateNormal attribute), 864
stddev (chainer.distributions.Normal attribute), 868
stddev (chainer.distributions.OneHotCategorical attribute), 870
stddev (chainer.distributions.Pareto attribute), 873
stddev (chainer.distributions.Poisson attribute), 876
stddev (chainer.distributions.Uniform attribute), 879
StepShift (class in chainer.training.extensions), 1008
strides (chainerx.ndarray attribute), 1213
SubDataset (class in chainer.datasets), 1056
subTest() (chainer.testing.FunctionTestCase method), 1171
subTest() (chainer.testing.LinkInitializersTestCase method), 1181
subTest() (chainer.testing.LinkTestCase method), 1189
subtract() (in module chainerx), 1258
sum() (chainerx.ndarray method), 1210
sum() (in module chainer.functions), 270
sum() (in module chainerx), 1260
sum_to() (in module chainer.functions), 270
Summary (class in chainer), 1127
summary() (chainer.function_hooks.CupyMemoryProfileHook method), 314
summary() (chainer.function_hooks.TimerHook method), 318
summary() (chainer.link_hooks.TimerHook method), 818
summary() (chainer.Parameter method), 146
summary() (chainer.Variable method), 137
support (chainer.Distribution attribute), 885
support (chainer.distributions.Bernoulli attribute), 826
support (chainer.distributions.Beta attribute), 829
support (chainer.distributions.Categorical attribute), 832
support (chainer.distributions.Cauchy attribute), 835
support (chainer.distributions.Chisquare attribute), 838
support (chainer.distributions.Dirichlet attribute), 841
support (chainer.distributions.Exponential attribute), 844
support (chainer.distributions.Gamma attribute), 847
support (chainer.distributions.Geometric attribute), 850
support (chainer.distributions.Gumbel attribute), 853
support (chainer.distributions.Independent attribute), 856
support (chainer.distributions.Laplace attribute), 859
support (chainer.distributions.LogNormal attribute), 862
support (chainer.distributions.MultivariateNormal attribute), 865
support (chainer.distributions.Normal attribute), 868
support (chainer.distributions.OneHotCategorical attribute), 870
support (chainer.distributions.Pareto attribute), 873
support (chainer.distributions.Poisson attribute), 876
support (chainer.distributions.Uniform attribute), 879
supported_array_types
 supported_array_types (chainer.backend.CpuDevice attribute), 1109
 supported_array_types (chainer.backend.Device attribute), 1103
 supported_array_types (chainer.backend.GpuDevice attribute), 1110
 supported_array_types (chainer.backend.Intel64Device attribute), 1111
 survival_function() (chainer.Distribution method), 884
 survival_function() (chainer.distributions.Bernoulli method), 825
 survival_function() (chainer.distributions.Beta method), 828
 survival_function() (chainer.distributions.Categorical method), 831
 survival_function() (chainer.distributions.Cauchy method), 834
 survival_function() (chainer.distributions.Chisquare method), 837
 survival_function() (chainer.distributions.Dirichlet method), 840
 survival_function() (chainer.distributions.Exponential method), 843
 survival_function() (chainer.distributions.Gamma method), 846
 survival_function() (chainer.distributions.Geometric method), 849
 survival_function() (chainer.distributions.Gumbel method), 852
 survival_function() (chainer.distributions.Independent method), 855
 survival_function() (chainer.distributions.Laplace method), 858
 survival_function() (chainer.distributions.LogNormal method), 861
 survival_function() (chainer.distributions.MultivariateNormal method), 864
 survival_function() (chainer.distributions.Normal method), 867
 survival_function() (chainer.distributions.OneHotCategorical method), 869
 survival_function() (chainer.distributions.Pareto method), 872
 survival_function() (chainer.distributions.Poisson method), 875
 survival_function() (chainer.distributions.Uniform method), 878
 svd() (in module chainerx.linalg), 1244
 swapaxes() (chainerx.ndarray method), 1210
 swapaxes() (in module chainer.functions), 195
 swapaxes() (in module chainerx), 1236
 Swish (class in chainer.links), 683
 swish() (in module chainer.functions), 168
 synchronize() (chainerx.Device method), 1294

T
 t (chainer.GradientMethod attribute), 942
 t (chainer.Optimizer attribute), 936
 t (chainer.optimizers.AdaBound attribute), 905
 t (chainer.optimizers.AdaDelta attribute), 888
 t (chainer.optimizers.AdaGrad attribute), 891
 t (chainer.optimizers.Adam attribute), 895
 t (chainer.optimizers.AdamW attribute), 898
 t (chainer.optimizers.AMSBound attribute), 909
 t (chainer.optimizers.AMSGrad attribute), 902
 t (chainer.optimizers.CorrectedMomentumSGD attribute), 912
 t (chainer.optimizers.MomentumSGD attribute), 915
 t (chainer.optimizers.MSAG attribute), 921
 t (chainer.optimizers.NesterovAG attribute), 918
 t (chainer.optimizers.RMSprop attribute), 924
 t (chainer.optimizers.RMSpropGraves attribute), 927
 t (chainer.optimizers.SGD attribute), 930
 t (chainer.optimizers.SMORMS3 attribute), 932
 T (chainer.Parameter attribute), 149
 T (chainer.Variable attribute), 140
 T (chainerx.ndarray attribute), 1212
 table (chainer.function_hooks.TimerHook attribute), 319
 table (chainer.link_hooks.TimerHook attribute), 819
 TabularDataset (class in chainer.dataset), 1037
 take() (chainerx.ndarray method), 1210
 take() (in module chainerx), 1241
 tan() (in module chainer.functions), 271
 tan() (in module chainerx), 1264
 tanh() (in module chainer.functions), 169
 tanh() (in module chainerx), 1226
 target (chainer.GradientMethod attribute), 942
 target (chainer.Optimizer attribute), 936
 target (chainer.optimizers.AdaBound attribute), 905
 target (chainer.optimizers.AdaDelta attribute), 888
 target (chainer.optimizers.AdaGrad attribute), 891
Chainer Documentation, Release 7.7.0

| to_chx() (chainer.links.GRU method), 434 | to_chx() (chainer.utils.WalkerAlias method), 1121 |
| to_chx() (chainer.links.Highway method), 440 | to_chx() (chainer.Variable method), 137 |
| to_chx() (chainer.links.Inception method), 447 | to_chx() (in module chainer.backend), 1119 |
| to_chx() (chainer.links.InceptionBN method), 454 | to_chx() (in module chainer.utils), 1130 |
| to_chx() (chainer.links.LayerNormalization method), 467 | to_cpu() (chainer.Chain method), 797 |
| to_chx() (chainer.links.Linear method), 461 | to_cpu() (chainer.ChainList method), 804 |
| to_chx() (chainer.links.LocalConvolution2D method), 468 | to_cpu() (chainer.DeviceResident method), 1105 |
| to_chx() (chainer.links.LSTM method), 476 | to_cpu() (chainer.Link method), 790 |
| to_chx() (chainer.links.MLPConvolution2D method), 483 | to_cpu() (chainer.links.BatchNormalization method), 621 |
| to_chx() (chainer.links.NaryTreeLSTM method), 490 | to_cpu() (chainer.links.Bias method), 328 |
| to_chx() (chainer.links.NegativeSampling method), 702 | to_cpu() (chainer.links.Bilinear method), 334 |
| to_chx() (chainer.links.NStepBiGRU method), 497 | to_cpu() (chainer.links.BatchNorm method), 641 |
| to_chx() (chainer.links.NStepBiLSTM method), 505 | to_cpu() (chainer.links.CallableFunction method), 654 |
| to_chx() (chainer.links.NStepBiRNNReLU method), 512 | to_cpu() (chainer.links.CaffeFunction method), 782 |
| to_chx() (chainer.links.NStepBiRNNTanh method), 520 | to_cpu() (chainer.links.Classifier method), 710 |
| to_chx() (chainer.links.NStepGRU method), 527 | to_cpu() (chainer.links.Convolution1D method), 348 |
| to_chx() (chainer.links.NStepLSTM method), 535 | to_cpu() (chainer.links.Convolution2D method), 356 |
| to_chx() (chainer.links.NStepRNNReLU method), 543 | to_cpu() (chainer.links.Convolution3D method), 362 |
| to_chx() (chainer.links.NStepRNNReLUs method), 550 | to_cpu() (chainer.links.ConvolutionND method), 371 |
| to_chx() (chainer.links.Parameter method), 556 | to_cpu() (chainer.links.CRF1d method), 668 |
| to_chx() (chainer.links.PReLU method), 681 | to_cpu() (chainer.links.Convolution2D method), 377 |
| to_chx() (chainer.links.ResNet152Layers method), 767 | to_cpu() (chainer.links.ConvolutionND method), 391 |
| to_chx() (chainer.links.ResNet50Layers method), 751 | to_cpu() (chainer.links.DecorrelatedBatchNormalization method), 399 |
| to_chx() (chainer.links.Scale method), 563 | to_cpu() (chainer.links.DeformableConvolution2D method), 634 |
| to_chx() (chainer.links.SimplifiedDropconnect method), 674 | to_cpu() (chainer.links.DeformableConvolution2D method), 406 |
| to_chx() (chainer.links.StatefulGRU method), 570 | to_cpu() (chainer.links.DepthwiseConvolution2D method), 413 |
| to_chx() (chainer.links.StatefulMGU method), 584 | to_cpu() (chainer.links.DilatedConvolution2D method), 421 |
| to_chx() (chainer.links.StatefulPeepholeLSTM method), 597 | to_cpu() (chainer.links.EmbedID method), 427 |
| to_chx() (chainer.links.StatefulZoneoutLSTM method), 603 | to_cpu() (chainer.links.GoogLeNet method), 734 |
| to_chx() (chainer.links.StatelessGRU method), 578 | to_cpu() (chainer.links.GroupNormalization method), 641 |
| to_chx() (chainer.links.StatelessLSTM method), 611 | to_cpu() (chainer.links.GRU method), 434 |
| to_chx() (chainer.links.StatelessMGU method), 590 | to_cpu() (chainer.links.Highway method), 440 |
| to_chx() (chainer.links.Swish method), 688 | to_cpu() (chainer.links.Inception method), 447 |
| to_chx() (chainer.links.TheanoFunction method), 775 | to_cpu() (chainer.links.InceptionBN method), 454 |
| to_chx() (chainer.links.VGG16Layers method), 718 | to_cpu() (chainer.links.LayerNormalization method), 648 |
| to_chx() (chainer.links.VGG19Layers method), 726 | to_cpu() (chainer.links.Linear method), 461 |
to_device() (chainer.links.MLPConvolution2D method), 483
to_device() (chainer.links.model.vision.resnet.ResNetLayers method), 743
to_device() (chainer.links.NaryTreeLSTM method), 490
to_device() (chainer.links.NegativeSampling method), 702
to_device() (chainer.links.NStepBiGRU method), 498
to_device() (chainer.links.NStepBiLSTM method), 505
to_device() (chainer.links.NStepBiRNNTanh method), 512
to_device() (chainer.links.NStepBiRNReLU method), 520
to_device() (chainer.links.NStepGRU method), 527
to_device() (chainer.links.NStepLSTM method), 536
to_device() (chainer.links.NStepRNNTanh method), 543
to_device() (chainer.links.NStepRNReLU method), 550
to_device() (chainer.links.Parameter method), 557
to_device() (chainer.links.PReLU method), 682
to_device() (chainer.links.ResNet101Layers method), 759
to_device() (chainer.links.ResNet152Layers method), 767
to_device() (chainer.links.ResNet50Layers method), 751
to_device() (chainer.links.Scale method), 563
to_device() (chainer.links.SimplifiedDropconnect method), 675
to_device() (chainer.links.StatefulGRU method), 571
to_device() (chainer.links.StatefulMGU method), 584
to_device() (chainer.links.StatefulPeepholeLSTM method), 597
to_device() (chainer.links.StatefulZoneoutLSTM method), 604
to_device() (chainer.links.StatelessGRU method), 578
to_device() (chainer.links.StatelessLSTM method), 611
to_device() (chainer.links.StatelessMGU method), 590
to_device() (chainer.links.Swish method), 689
to_device() (chainer.links.TheanoFunction method), 775
to_device() (chainer.links.VGG16Layers method), 718
to_device() (chainer.links.VGG19Layers method), 726

to_device() (chainer.Sequential method), 813
to_device() (chainer.rnnt.WalkerAlias method), 1121
to_device() (chainer.Variable method), 137
to_device() (chainer.randnarray method), 1210
to_device() (in module chainer.dataset), 1051
to_gpu() (chainer.Chain method), 797
to_gpu() (chainer.ChainList method), 804
to_gpu() (chainer.DeviceResident method), 1106
to_gpu() (chainer.Link method), 790
to_gpu() (chainer.links.BatchNorm normalization method), 621

Index 1521
Index

648
to_gpu() (chainer.links.Linear method), 462
to_gpu() (chainer.links.LocalConvolution2D method), 468
to_gpu() (chainer.links.LSTM method), 476
to_gpu() (chainer.links.Maxout method), 696
to_gpu() (chainer.links.MLPConvolution2D method), 484
to_gpu() (chainer.links.model.vision.resnet.ResNetLayers method), 743
to_gpu() (chainer.links.NStepBiGRU method), 498
to_gpu() (chainer.links.NStepBiLSTM method), 505
to_gpu() (chainer.links.NStepBiRNNReLU method), 513
to_gpu() (chainer.links.NStepBiRNNTanhn method), 520
to_gpu() (chainer.links.NStepGRU method), 528
to_gpu() (chainer.links.NStepLSTM method), 536
to_gpu() (chainer.links.NStepRNNReLU method), 543
to_gpu() (chainer.links.NStepRNNTanhn method), 551
to_gpu() (chainer.links.Parameter method), 557
to_gpu() (chainer.links.PReLU method), 682
to_gpu() (chainer.links.ResNet101Layers method), 759
to_gpu() (chainer.links.ResNet152Layers method), 767
to_gpu() (chainer.links.Scale method), 563
to_gpu() (chainer.links.SimplifiedDropconnect method), 675
to_gpu() (chainer.links.StatefulGRU method), 571
to_gpu() (chainer.links.StatefulMGU method), 584
to_gpu() (chainer.links.StatefulPeepholeLSTM method), 597
to_gpu() (chainer.links.StatefulZoneoutLSTM method), 604
to_gpu() (chainer.links.StatelessGRU method), 578
to_gpu() (chainer.links.StatelessLSTM method), 611
to_gpu() (chainer.links.StatelessMGU method), 590
to_gpu() (chainer.links.Swish method), 689
to_gpu() (chainer.links.TheanoFunction method), 775
to_gpu() (chainer.links.VGG16Layers method), 718
to_gpu() (chainer.links.VGG19Layers method), 726
to_gpu() (chainer.Parameter method), 146
to_gpu() (chainer.Sequential method), 813
to_gpu() (chainer.utils.WalkerAlias method), 1121
to_gpu() (chainer.Variable method), 137
(to in module chainer.backends.cuda), 1115
to_intel64() (chainer.Chain method), 798
to_intel64() (chainer.ChainList method), 804
to_intel64() (chainer.DeviceResident method), 1106
to_intel64() (chainer.Link method), 790
to_intel64() (chainer.links.BatchNormalization method), 621
to_intel64() (chainer.links.BatchRenormalization method), 628
to_intel64() (chainer.links.Bias method), 328
to_intel64() (chainer.links.BinaryHierarchicalSoftmax method), 655
to_intel64() (chainer.links.BlackOut method), 661
to_intel64() (chainer.links.caffe.CaffeFunction method), 783
to_intel64() (chainer.links.ChildSumTreeLSTM method), 342
to_intel64() (chainer.links.Classifier method), 710
to_intel64() (chainer.links.Convolution1D method), 348
to_intel64() (chainer.links.Convolution2D method), 356
to_intel64() (chainer.links.Convolution3D method), 363
to_intel64() (chainer.links.ConvolutionND method), 371
to_intel64() (chainer.links.CRF1d method), 668
to_intel64() (chainer.links.Deconvolution1D method), 377
to_intel64() (chainer.links.Deconvolution2D method), 385
to_intel64() (chainer.links.Deconvolution3D method), 392
to_intel64() (chainer.links.DeconvolutionND method), 399
to_intel64() (chainer.links.DecorrelatedBatchNormalization method), 635
to_intel64() (chainer.links.DeformableConvolution2D method), 407
to_intel64() (chainer.links.DepthwiseConvolution2D method), 413
to_intel64() (chainer.links.DilatedConvolution2D method), 421
to_intel64() (chainer.links.EmbedID method), 428
to_intel64() (chainer.links.GoogLeNet method), 735
to_intel64() (chainer.links.GroupNormalization method), 641
to_intel64() (chainer.links.GRU method), 434
to_intel64() (chainer.links.Highway method), 441
to_intel64() (chainer.links.Inception method), 448
to_intel64() (chainer.links.InceptionBN method), 454
to_intel64() (chainer.links.LayerNormalization method), 648
trigger (chainer.training.extensions.InverseShift attribute), 1001
trigger (chainer.training.extensions.LinearShift attribute), 1002
trigger (chainer.training.extensions.LogReport attribute), 1015
trigger (chainer.training.extensions.MicroAverage attribute), 992
trigger (chainer.training.extensions.MultistepShift attribute), 1004
trigger (chainer.training.extensions.ParameterStatistics attribute), 996
trigger (chainer.training.extensions.PlotReport attribute), 1018
trigger (chainer.training.extensions.PolynomialShift attribute), 1006
trigger (chainer.training.extensions.PrintReport attribute), 1012
trigger (chainer.training.extensions.ProgressBar attribute), 1013
trigger (chainer.training.extensions.StepShift attribute), 1010
trigger (chainer.training.extensions.VariableStatisticsPlot update) (chainer.optimizers.MSAGMethod), 920
update () (chainer.optimizers.NesterovAG method), 917
update () (chainer.optimizers.RMSprop method), 923
update () (chainer.optimizers.RMSpropGraves method), 926
update () (chainer.optimizers.SGD method), 929
update () (chainer.optimizers.SMORMS3 method), 931
update () (chainer.optimizers.Parameter method), 147
update () (chainer.training.Updater method), 976
update () (chainer.training.updaters.ParallelUpdater method), 982
update () (chainer.training.updaters.ParallelUpdater method), 980
update () (chainer.training.updaters.StandardUpdater method), 978
update () (chainer.UpdateRule method), 937
update_core () (chainer.training.updaters.MultiprocessParallelUpdater method), 982
update_core () (chainer.training.updaters.ParallelUpdater method), 980
update_core () (chainer.training.updaters.StandardUpdater method), 978
update_core () (chainer.UpdateRule method), 937
update_core_chainerx() (chainer.UpdateRule method), 937
update_core_cpu() (chainer.UpdateRule method), 937
update_core_gpu() (chainer.UpdateRule method), 937
update_enabled (chainer.Chain attribute), 798
update_enabled (chainer.ChainList attribute), 805

uniform (class in chainer.distributions), 877
uniform () (in module chainerx.random), 1271
unpooling_1d() (in module chainer.functions), 289
unpooling_2d() (in module chainer.functions), 289
unpooling_3d() (in module chainer.functions), 290
unpooling_nd() (in module chainer.functions), 290
update () (chainer.GradientMethod method), 941
update () (chainer.Optimizer method), 935
update () (chainer.optimizers.Adam method), 894
update () (chainer.optimizers.AdamGrad method), 890
update () (chainer.optimizers.AMSBound method), 907
update () (chainer.optimizers.AMSGrad method), 901
update () (chainer.optimizers.AdaBound method), 904
update () (chainer.optimizers.AdaGrad method), 888
update () (chainer.optimizers.AdaDelta method), 893
update () (chainer.optimizers.Adagrad method), 888
update () (chainer.optimizers.Adam method), 877
update () (chainer.optimizers.MomentumSGD method), 911
update () (chainer.optimizers.MomentumSGD method), 914
update () (chainer.optimizers.MSAGMethod), 920
update () (chainer.optimizers.NesterovAG method), 917
update () (chainer.optimizers.RMSprop method), 923
update () (chainer.optimizers.RMSpropGraves method), 926
update () (chainer.optimizers.SGD method), 929
update () (chainer.optimizers.SMORMS3 method), 931
update () (chainer.optimizers.Parameter method), 147
update () (chainer.training.Updater method), 976
update () (chainertraining.updaters.ParallelUpdater method), 982
update () (chainertraining.updaters.ParallelUpdater method), 980
update () (chainertraining.updaters.StandardUpdater method), 978
update () (chainer.UpdateRule method), 937
update_core () (chainertraining.updaters.MultiprocessParallelUpdater method), 982
update_core () (chainertraining.updaters.ParallelUpdater method), 980
update_core () (chainertraining.updaters.StandardUpdater method), 978
update_core () (chainer.UpdateRule method), 937
update_core_chainerx() (chainer.UpdateRule method), 937
update_core_cpu() (chainer.UpdateRule method), 937
update_core_gpu() (chainer.UpdateRule method), 937
update_enabled (chainer.Chain attribute), 798
update_enabled (chainer.ChainList attribute), 805

U
unary_math_function_unittest() (in module chainer.testing), 1172
unchain() (chainer.Function method), 297
unchain() (chainer.FunctionAdapter method), 302
unchain() (chainer.FunctionNode method), 308
unchain() (chainer.Parameter method), 147
unchain() (chainer.Variable method), 137
unchain() (chainer.variable.VariableNode method), 152
unchain_backward() (chainer.Parameter method), 147
unchain_backward() (chainer.Variable method), 137
unchain_variables (class in chainer.training.extensions), 1025
update_enabled (chainer.Link attribute), 791
update_enabled (chainer.links.BatchNormalization attribute), 622
update_enabled (chainer.links.BatchRenormalization attribute), 628
update_enabled (chainer.links.Bias attribute), 329
update_enabled (chainer.links.Bilinear attribute), 336
update_enabled (chainer.links.BinaryHierarchicalSoftmax attribute), 656
update_enabled (chainer.links.BlackOut attribute), 662
update_enabled (chainer.links.caffe.CaffeFunction attribute), 784
update_enabled (chainer.links.ChildSumTreeLSTM attribute), 342
update_enabled (chainer.links.Classifier attribute), 711
update_enabled (chainer.links.Convolution attribute), 349
update_enabled (chainer.links.Convolution1D attribute), 357
update_enabled (chainer.links.Convolution2D attribute), 364
update_enabled (chainer.links.ConvolutionND attribute), 372
update_enabled (chainer.links.CRF1d attribute), 669
update_enabled (chainer.links.Deconvolution1D attribute), 378
update_enabled (chainer.links.Deconvolution2D attribute), 386
update_enabled (chainer.links.Deconvolution3D attribute), 392
update_enabled (chainer.links.DeconvolutionND attribute), 400
update_enabled (chainer.links.DecorrelatedBatchNormalization attribute), 635
update_enabled (chainer.links.DeformableConvolution2D attribute), 407
update_enabled (chainer.links.DepthwiseConvolution2D attribute), 414
update_enabled (chainer.links.DilatedConvolution2D attribute), 422
update_enabled (chainer.links.EmbedID attribute), 429
update_enabled (chainer.links.GoogLeNet attribute), 736
update_enabled (chainer.links.GroupNormalization attribute), 642
update_enabled (chainer.links.GRU attribute), 435
update_enabled (chainer.links.Highway attribute), 442
update_enabled (chainer.links.Inception attribute), 449
update_enabled (chainer.links.InceptionBN attribute), 455
update_enabled (chainer.links.LayerNormalization attribute), 459
update_enabled (chainer.links.Linear attribute), 463
update_enabled (chainer.links.LocalConvolution2D attribute), 469
update_enabled (chainer.links.LSTM attribute), 477
update_enabled (chainer.links.Maxout attribute), 697
update_enabled (chainer.links.MLPConvolution2D attribute), 485
update_enabled (chainer.links.model.vision.resnet.ResNetLayers attribute), 744
update_enabled (chainer.links.NaryTreeLSTM attribute), 492
update_enabled (chainer.links.NegativeSampling attribute), 704
update_enabled (chainer.links.NStepBiGRU attribute), 499
update_enabled (chainer.links.NStepBiLSTM attribute), 506
update_enabled (chainer.links.NStepBiRNNReLU attribute), 514
update_enabled (chainer.links.NStepBiRNNTanh attribute), 521
update_enabled (chainer.links.NStepGRU attribute), 529
update_enabled (chainer.links.NStepLSTM attribute), 537
update_enabled (chainer.links.NStepRNNReLU attribute), 544
update_enabled (chainer.links.NStepRNNTanh attribute), 552
update_enabled (chainer.links.Parameter attribute), 558
update_enabled (chainer.links.PReLU attribute), 683
update_enabled (chainer.links.ResNet101Layers attribute), 760
update_enabled (chainer.links.ResNet152Layers attribute), 768
update_enabled (chainer.links.ResNet50Layers attribute), 752
update_enabled (chainer.links.Scale attribute), 564
update_enabled (chainer.links.SimplifiedDropconnect attribute), 676
update_enabled (chainer.links.StatefulGRU attribute), 572
update_enabled (chainer.links.StatefulMGU attribute), 585
update_enabled (chainer.links.StatefulPeepholeLSTM attribute), 598
update_enabled (chainer.links.StatefulZoneoutLSTM attribute), 605
update_enabled (chainer.links.StatelessGRU attribute), 579
update_enabled (chainer.links.StatelessLSTM attribute), 612
update_enabled (chainer.links.StatelessMGU attribute), 591
update_enabled (chainer.links.Swish attribute), 690
update_enabled (chainer.links.TheanoFunction attribute), 776
update_enabled (chainer.links.VGG16Layers attribute), 719
update_enabled (chainer.links.VGG19Layers attribute), 727
update_enabled (chainer.Sequential attribute), 814
update_loss_scale () (chainer.GradientMethod method), 941
update_loss_scale () (chainer.Optimizer method), 935
update_loss_scale () (chainer.optimizers.AdaBound method), 904
update_loss_scale () (chainer.optimizers.AdaDelta method), 888
update_loss_scale () (chainer.optimizers.AdaGrad method), 891
update_loss_scale () (chainer.optimizers.Adam method), 894
update_loss_scale () (chainer.optimizers.AdamW method), 897
update_loss_scale () (chainer.optimizers.AMSBound method), 908
update_loss_scale () (chainer.optimizers.AMSGrad method), 901
update_loss_scale () (chainer.optimizers.CorrectedMomentumSGD method), 911
update_loss_scale () (chainer.optimizers.MomentumSGD method), 914
update_loss_scale () (chainer.optimizers.MSVAG method), 920
update_loss_scale () (chainer.optimizers.NesterovAG method), 917
update_loss_scale () (chainer.optimizers.RMSprop method), 923
update_loss_scale () (chainer.optimizers.RMSpropGraves method), 926
update_loss_scale () (chainer.optimizers.SGD method), 929
update_loss_scale () (chainer.optimizers.SMORMS3 method), 932
Updater (class in chainer.training), 975
UpdateRule (class in chainer), 936
upsampling_2d () (in module chainer.functions), 291
UpsamplingDeconvFilter (class in chainer.initializers), 961
use () (chainer.backend.ChainerxDevice method), 1112
use () (chainer.backend.CpuDevice method), 1108
use () (chainer.backend.Device method), 1103
use () (chainer.backend.GpuDevice method), 1109
use () (chainer.backend.Intel64Device method), 1111
use_auto_new_epoch (chainer.GradientMethod attribute), 942
use_auto_new_epoch (chainer.Optimizer attribute), 936
use_auto_new_epoch (chainer.optimizers.AdaBound attribute), 905
use_auto_new_epoch (chainer.optimizers.AdaDelta attribute), 888
use_auto_new_epoch (chainer.optimizers.AdaGrad attribute), 891
use_auto_new_epoch (chainer.optimizers.Adam attribute), 895
use_auto_new_epoch (chainer.optimizers.AdamW attribute), 899
use_auto_new_epoch (chainer.optimizers.AMSBound attribute), 909
use_auto_new_epoch (chainer.optimizers.AMSGrad attribute), 902
use_auto_new_epoch (chainer.optimizers.CorrectedMomentumSGD attribute), 912
use_auto_new_epoch (chainer.optimizers.MomentumSGD attribute), 915
use_auto_new_epoch (chainer.optimizers.MSVAG attribute), 921
use_auto_new_epoch (chainer.optimizers.NesterovAG attribute), 918
use_auto_new_epoch (chainer.optimizers.RMSprop attribute), 924
use_auto_new_epoch (chainer.optimizers.RMSpropGraves attribute), 927
use_auto_new_epoch (chainer.optimizers.SGD attribute), 930
use_auto_new_epoch (chainer.optimizers.SMORMS3 attribute), 932

1526 Index
weight_decay_rate (chainer.optimizers.Adam attribute), 895
weight_decay_rate (chainer.optimizers.AdamW attribute), 899
weight_decay_rate (chainer.optimizers.AMSBound attribute), 909
weight_decay_rate (chainer.optimizers.AMSGrad attribute), 902
weight_decay_rate (chainer.optimizers.MSVAG attribute), 921
WeightDecay (class in chainer.optimizer_hooks), 942
WeightStandardization (class in chainer.link_hooks), 819
where() (in module chainer.functions), 199
where() (in module chainerx), 1241
with_converter() (chainer.dataset.tabular.DelegateDataset method), 1044
with_converter() (chainer.dataset.TabularDataset method), 1040
with_requires() (in module chainer.testing), 1193
within_init_scope (chainer.Chain attribute), 798
within_init_scope (chainer.ChainList attribute), 805
within_init_scope (chainer.Link attribute), 791
within_init_scope (chainer.links.BatchNormalization attribute), 622
within_init_scope (chainer.links.BatchRenormalization attribute), 628
within_init_scope (chainer.links.Bias attribute), 329
within_init_scope (chainer.links.Bilinear attribute), 336
within_init_scope (chainer.links.BinaryHierarchicalSoftmax attribute), 656
within_init_scope (chainer.links.BlackOut attribute), 662
within_init_scope (chainer.links.caffe.CaffeFunction attribute), 784
within_init_scope (chainer.links.ChildSumTreeLSTM attribute), 342
within_init_scope (chainer.links.Classifier attribute), 711
within_init_scope (chainer.links.Convolution1D attribute), 349
within_init_scope (chainer.links.Convolution2D attribute), 357
within_init_scope (chainer.links.Convolution3D attribute), 364
within_init_scope (chainer.links.ConvolutionND...
xp (chainer.links.Scale attribute), 564
xp (chainer.links.SimplifiedDropconnect attribute), 676
xp (chainer.links.StatefulGRU attribute), 572
xp (chainer.links.StatefulMGU attribute), 585
xp (chainer.links.StatefulPeepholeLSTM attribute), 599
xp (chainer.links.StatefulZoneoutLSTM attribute), 605
xp (chainer.links.StatelessGRU attribute), 579
xp (chainer.links.StatelessMGU attribute), 612
xp (chainer.links.StatelessLSTM attribute), 591
xp (chainer.links.Swish attribute), 690
xp (chainer.links.TheanoFunction attribute), 776
xp (chainer.links.VGG16Layers attribute), 720
xp (chainer.links.VGG19Layers attribute), 727
xp (chainer.Parameter attribute), 151
xp (chainer.Sequential attribute), 814
xp (chainer.utils.WalkerAlias attribute), 1122
xp (chainer.Variable attribute), 141

Z
Zero (class in chainer.initializers), 952
zero_grads() (chainer.links.Bilinear method), 335
zero_grad() (chainer.Parameter method), 147
zero_grads() (chainer.Variable method), 137
zero_grads() (chainer.Chain method), 798
zero_grads() (chainer.ChainList method), 804
zero_grads() (chainer.Link method), 790
zero_grads() (chainer.links.BatchNormalization method), 621
zero_grads() (chainer.links.BatchRenormalization method), 628
zero_grads() (chainer.links.Bias method), 328
zero_grads() (chainer.links.Bilinear method), 335
zero_grads() (chainer.links.BinaryHierarchicalSoftmax method), 655
zero_grads() (chainer.links.BlackOut method), 661
zero_grads() (chainer.links.caffe.CaffeFunction method), 783
zero_grads() (chainer.links.ChildSumTreeLSTM method), 342
zero_grads() (chainer.links.Classifier method), 710
zero_grads() (chainer.links.Convolution1D method), 348
zero_grads() (chainer.links.Convolution2D method), 356
zero_grads() (chainer.links.Convolution3D method), 363
zero_grads() (chainer.links.ConvolutionND method), 371
zero_grads() (chainer.links.CRF1d method), 668
zero_grads() (chainer.links.Convolution1D method), 377
zero_grads() (chainer.links.Convolution2D method), 385
zero_grads() (chainer.links.Deconvolution3D method), 392
zero_grads() (chainer.links.DeconvolutionND method), 399
zero_grads() (chainer.links.DecorrelatedBatchNormalization method), 635
zero_grads() (chainer.links.DeformableConvolution2D method), 407
zero_grads() (chainer.links.DepthwiseConvolution2D method), 414
zero_grads() (chainer.links.DilatedConvolution2D method), 421
zero_grads() (chainer.links.EmbedID method), 428
zero_grads() (chainer.links.GoogLeNet method), 735
zero_grads() (chainer.links.GroupNormalization method), 641
zero_grads() (chainer.links.GRU method), 434
zero_grads() (chainer.links.Highway method), 441
zero_grads() (chainer.links.Inception method), 448
zero_grads() (chainer.links.InceptionBN method), 455
zero_grads() (chainer.links.LayerNormalization method), 648
zero_grads() (chainer.links.Linear method), 462
zero_grads() (chainer.links.LocalConvolution2D method), 469
zero_grads() (chainer.links.LSTM method), 476
zero_grads() (chainer.links.Maxout method), 696
zero_grads() (chainer.links.MLPConvolution2D method), 484
zero_grads() (chainer.links.model.vision.resnet.ResNetLayers method), 744
zero_grads() (chainer.links.NaryTreeLSTM method), 491
zero_grads() (chainer.links.NegativeSampling method), 703
zero_grads() (chainer.links.NStepBiGRU method), 498
zero_grads() (chainer.links.NStepBiLSTM method), 506
zero_grads() (chainer.links.NStepBiRNNReLU method), 513
zero_grads() (chainer.links.NStepBiRNNTanh method), 520
zero_grads() (chainer.links.NStepGRU method), 528
zero_grads() (chainer.links.NStepLSTM method), 536
zero_grads() (chainer.links.NStepRNNReLU method), 543
zero_grads() (chainer.links.NStepRNNTanh method), 551
zero_grads() (chainer.links.Parameter method), 557
zero_grads() (chainer.links.PReLU method), 682
zero_grads() (chainer.links.ResNet101Layers method), 760
zero_grads() (chainer.links.ResNet152Layers method), 764

Index
zerograds() (chainer.links.Swish method), 689
zerograds() (chainer.links.StatelessGRU method), 578
zerograds() (chainer.links.StatelessLSTM method), 611
zerograds() (chainer.links.StatelessMGU method), 591
zerograds() (chainer.links.Swish method), 689
zerograds() (chainer.links.StatefulPeepholeLSTM method), 598
zerograds() (chainer.links.StatefulZoneoutLSTM method), 604
zerograds() (chainer.links.StatefulGRU method), 571
zerograds() (chainer.links.StatefulMGU method), 585
zerograds() (chainer.links.StatefulGRU method), 768
zerograds() (chainer.links.ResNet50Layers method), 752
zerograds() (chainer.links.Scale method), 564
zerograds() (chainer.links.SimplifiedDropconnect method), 675
zerograds() (chainer.links.StatefulGRU method), 571
zerograds() (chainer.links.StatefulMGU method), 585
zerograds() (chainer.links.StatefulPeepholeLSTM method), 598
zerograds() (chainer.links.StatefulZoneoutLSTM method), 604
zerograds() (chainer.links.StatelessGRU method), 578
zerograds() (chainer.links.StatelessLSTM method), 611
zerograds() (chainer.links.StatelessMGU method), 591
zerograds() (chainer.links.Swish method), 689
zerograds() (chainer.links.TheanoFunction method), 776
zerograds() (chainer.links.VGG16Layers method), 719
zerograds() (chainer.links.VGG19Layers method), 726
zerograds() (chainer.Sequential method), 813
zeros() (in module chainerx), 1217
zeros_like() (in module chainerx), 1217
zeta() (in module chainer.functions), 272
ZippedImageDataset (class in chainer.datasets), 1064
zoneout() (in module chainer.functions), 275