# Tutorials

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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 backpropagation. It makes code intuitive and easy to debug.
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 deathly?

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](https://www.kaggle.com/uciml/mushroom), 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. \texttt{chainer.links} contain trainable parameters and \texttt{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
from chainer.training import extensions
import numpy as np
```

We'll use Matplotlib for the graphs to show training progress.

```python
import matplotlib
matplotlib.use('Agg')
```

1.2.2 Trainer Structure

A \texttt{trainer} is used to set up our neural network and data for training. The components of the \texttt{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 \texttt{extensions}, which are added after the \texttt{trainer} is defined.
1.2.3 Dataset

```
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))
```

Our first step is to format the *dataset*. From the raw mushrooms.csv, we format the data into a Chainer *TupleDataset*.

1.2.4 Iterator

```
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))
```

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 (\texttt{relu()}).

Using the \texttt{Sequential} allows us to define the neural network model in a compact format.

```python
# Network definition
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 \texttt{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)
```

1.2.6 Optimizer

Pick an \texttt{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, and then 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)
```

Set up the updater to be called after the training batches and set the number of batches per epoch to 100. The learning rate per epoch will be output to the directory result.

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

1.2.8 Extensions

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
# Evaluate the model with the test dataset for each epoch
trainer.extend(extensions.Evaluator(test_iter, model, device=-1))
```
# Dump a computational graph from 'loss' variable at the first iteration
# The "main" refers to the target link of the "main" optimizer.
trainer.extend(extensions.dump_graph('main/loss'))

Take a snapshot of the \texttt{trainer} object every 20 epochs.
trainer.extend(extensions.snapshot(), trigger=(20, 'epoch'))

Write a log of evaluation statistics for each epoch.
trainer.extend(extensions.LogReport())

Save two plot images to the result directory.
if extensions.PlotReport.available():
    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.
    'main/accuracy', 'validation/main/accuracy', 'elapsed_time']))

Run the training.
trainer.run()

1.2.9 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]).data
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:

<table>
<thead>
<tr>
<th>epoch</th>
<th>main/loss</th>
<th>validation/main/loss</th>
<th>main/accuracy</th>
<th>validation/main/accuracy</th>
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(continues on next page)
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<th>Actual Edible</th>
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</table>

Our prediction was correct. Success!

The loss function:
And the accuracy
CHAPTER 2

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
```
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 to 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:
>>> 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 linearm(), 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)
>>> f.b.array
array([0., 0.], 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 $W$ will be a $2 \times M$ matrix. Note that its parameters are initialized in a lazy manner at the first mini-batch. Therefore, $f$ 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()
```

**Note:** cleargrads() is introduced in v1.15 to replace zerograds() for efficiency. zerograds() is left only for backward compatibility.
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 import backends
from chainer.backends import cuda
from chainer import Function, 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.

First, suppose we want to define an elementwise function \( f(x, y, z) = x \ast y + z \). While it is possible to implement this equation using a combination of the \( \ast \) 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 \( \text{MulAdd} \).

Let's start with defining MulAdd working on the CPU. Any function 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 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

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

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 methods. You can easily predict that the methods we have to write are named forward_gpu() and backward_gpu():

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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.

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 is used as follows:

```
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:

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

(continues on next page)
2.4.2 Unified forward/backward methods with NumPy/CuPy functions

CuPy also 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 $\text{ExpAdd}$ 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):
        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 `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
### 2.4.3 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 and backward 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 reduces the memory consumption.

Most functions only require elementwise operations like MulAdd. CuPy provides a useful tool to define elementwise kernels, the `cupy.elementwise.ElementwiseKernel` class, and Chainer wraps it by `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 = cupy.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
```

(continues on next page)
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 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):
        ...

    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 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 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:

```python
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.

2.4.5 Links that wrap functions

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). Here we

2.4. Define your own function
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 forward(self, x):
        return self.W * x
```

For another example, assume we want to define a simple linear layer. It is already defined as `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(Function):
    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()(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 forward(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 to 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 Testing Function

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:

```python
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.

```python
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()

        def f():
            return F.relu(x).array,
        gx, = gradient_check.numerical_grad(f, (x,), (y.grad,))

testing.assert_allclose(gx, x.grad)
```

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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.

## 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 import backends
from chainer.backends import cuda
from chainer import Function, 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
```

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:
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.

**Note:** In Chainer v1, we could also register the trainable layers (i.e., `Link` s) to the model by putting them to the `__init__()` of `Chain` or registering them via `add_link()`. But as these ways are deprecated in Chainer v2, users are recommended to use the way explained above.

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.backends import cuda
from chainer import Function, 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()
```
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(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 `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, 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 1. 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 which takes a Trainer object as an argument 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:

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

The learning rate will be dropped according to the curve below with power = 0.5:

```
class PolynomialShift(trainer.Extension):
```

(continues on next page)
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[1] + ' 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):
    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, 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:** From v2.0.0, CuPy is turned into a separate package and repository. 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:

2.9. Using GPU(s) in Chainer
cuda.get_device_from_id(1).use()
x_gpu1 = cupy.empty((4, 3), dtype=cupy.float32)

with cuda.get_device_from_id(1):
    x_gpu1 = cupy.empty((4, 3), dtype=cupy.float32)

with cuda.get_device_from_array(x_gpu1):
    y_gpu1 = x_gpu1 + 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:

```python
# Stable implementation of log(1 + exp(x))
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')
```

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]])
```

(continues on next page)
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 --> l1 --> l2 --> l3 --> l4 --> l5 --> l6 --> output
|     |     |     |
(GPU1) +--> l1 --> l2 --> l3 --> l4 --> l5 --> l6 +
```

We can use the above MLP chain as following diagram:

```
(GPU0) input --> mlp1 --> mlp2 --> output
|     |     |
(GPU1) +--> mlp1 --> mlp2 +
```

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):
        z0 = self.mlp1_gpu0(x)
        z1 = F.copy(z0, 1)
        h0 = F.relu(z0 + z1)
        h1 = F.relu(z1 + z0)
        y0 = self.mlp2_gpu0(h0)
        y1 = self.mlp2_gpu1(h1)

        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:

```python
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.

```python
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.

```python
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.

```python
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:

```python
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:

```python
batchsize = 100
data_size = len(x_train)
for epoch in range(20):
    print('epoch %d' % epoch)
    indexes = np.random.permutation(data_size)
    for i in range(0, data_size, batchsize):
        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`:

```python
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

```python
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:

```python
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)`. `type_check.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:

```python
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:

```python
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:

```python
x_type.shape[0] == utils.type_check.Variable(self.in_size, "in_size")
```

This code can check the equivalent condition below:

```python
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:

```
chainer.utils.type_check.InvalidType: 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:

```
chainer.utils.type_check.InvalidType: 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.InvalidType: 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 \texttt{Expr} and get its result value with \texttt{eval()} method. Then check the condition and show warning message by hand:

\begin{verbatim}
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.InvalidType(expect_msg, actual_msg)
\end{verbatim}

Please write a readable error message. This code generates the following error message:

\begin{verbatim}
Traceback (most recent call last):
...  
chainer.utils.type_check.InvalidType: Expect: Shape is expected to be ...
Actual: Shape is ...
\end{verbatim}

2.10.7 Typical type check example

We show a typical type check for a function.

First check the number of arguments:

\begin{verbatim}
utils.type_check.expect(in_types.size() == 2)
\end{verbatim}

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

And then, get each type:

\begin{verbatim}
x_type, y_type = in_types
\end{verbatim}

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

\begin{verbatim}
utils.type_check.expect(
    in_types.size() == 2,
    in_types[0].ndim == 3,
)
\end{verbatim}

After that, check each type:

\begin{verbatim}
utils.type_check.expect(
    x_type.dtype == np.float32,
    x_type.ndim == 3,
    x_type.shape[1] == 2,
)
\end{verbatim}

The above example works correctly even when \texttt{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:

Assuming we have defined a model:

```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:

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

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.

```python
>>> 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:

```python
>>> 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)
```

(continues on next page)
... 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 val-
ues 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.11 = L.Linear(None, n_units) # n_in -> n_units
...             self.12 = L.Linear(None, n_units) # n_units -> n_units
...             self.13 = L.Linear(None, n_out) # n_units -> n_out
...     def forward(self, x):
...         h1 = F.relu(self.11(x))
...         h2 = F.relu(self.12(h1))
...         y = self.13(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()
```
```python
>>> 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.backends import cuda
from chainer import Function, 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.
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’s recommended to 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.

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.

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.

---

**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.

### 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.

```python
# 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.

### 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)
• Save the model architecture as a Graphviz’s dot file (`dump_graph()`)

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.PrintReport(['epoch', 'main/loss', 'main/accuracy', ...
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.dump_graph('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()** `snapshot()` 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.
dump_graph()  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 an 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 `dump_graph()` 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 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](image)

```
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.
import math
import numpy as np
import chainer
from chainer import backend
from chainer import backends
cuda
import chainer.functions as F
import chainer.models as M
import chainer.models as L
from chainer.training import iterators, optimizers, serializers
import chainer.optimizers as O
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')
print('label:', t)

label: 5

The saved image 5.png will look like:

![5.png](image)

### 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.
from chainer import iterators

# Choose the minibatch size.
batchsize = 128

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

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

train = [(x1, t1), (x2, t2), ...]  # A list of tuples
train_iter = iterators.SerialIterator(train, batchsize)

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

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.array, or cupy.array as its inputs and calculates the forward pass using them.

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()

gpu_id = 0  # Set to -1 if you use CPU
if gpu_id >= 0:
    model.to_gpu(gpu_id)

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.

```
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 ---------------------
```

(continues on next page)
# 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 = []
while True:
    test_batch = test_iter.next()
    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)

    if test_iter.is_new_epoch:
        test_iter.epoch = 0
        test_iter.current_position = 0
        test_iter.is_new_epoch = False
        test_iter._pushed_position = None
        break

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

Output

epoch:01 train_loss:0.8072 val_loss:0.7592 val_accuracy:0.8289
epoch:02 train_loss:0.5021 val_loss:0.4467 val_accuracy:0.8841
epoch:03 train_loss:0.3539 val_loss:0.3673 val_accuracy:0.9007
epoch:04 train_loss:0.2524 val_loss:0.3307 val_accuracy:0.9067
epoch:05 train_loss:0.4232 val_loss:0.3076 val_accuracy:0.9136
epoch:06 train_loss:0.3033 val_loss:0.2910 val_accuracy:0.9167
epoch:07 train_loss:0.2004 val_loss:0.2773 val_accuracy:0.9222
epoch:08 train_loss:0.2885 val_loss:0.2679 val_accuracy:0.9239
epoch:09 train_loss:0.2818 val_loss:0.2579 val_accuracy:0.9266
epoch:10 train_loss:0.2403 val_loss:0.2484 val_accuracy:0.9307

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.

3.2. MNIST with a Manual Training Loop
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)

# 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 .array attribute.
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 `Chain`,
- 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.
import math
import numpy as np
import chainer
from chainer import backend
from chainer import backends
cudarom chainer import Function, 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:

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)
            self.conv2 = L.Convolution2D(
                in_channels=6, out_channels=16, ksize=5, stride=1)
            self.conv3 = L.Convolution2D(
                in_channels=16, out_channels=120, ksize=4, stride=1)
            self.fc4 = L.Linear(None, 84)
            self.fc5 = L.Linear(84, 10)

    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 FunctionNodes and Links (actually a Link calls a corresponding FunctionNode inside of it), so that you don’t need to 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()`.

Note: In Chainer v1, if a function or link behaved differently in training and other modes, it was common that it held an attribute that represented its running mode or was provided with the mode from outside as an argument. In Chainer v2, it is recommended to 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 += [('sigmoid1', F.sigmoid)]
        net += [('mpool1', partial(F.max_pooling_2d, ksize=2, stride=2))]
        net += [('conv2', L.Convolution2D(6, 16, 5, 1))]
        net += [('sigmoid2', F.sigmoid)]
        net += [('mpool2', partial(F.max_pooling_2d, ksize=2, stride=2))]
        net += [('conv3', L.Convolution2D(16, 120, 4, 1))]
        net += [('sigmoid3', F.sigmoid)]
        net += [('mpool3', partial(F.max_pooling_2d, ksize=2, stride=2))]
        net += [('fc4', L.Linear(None, 84))]
        net += [('sigmoid4', F.sigmoid)]
        net += [('fc5', L.Linear(84, 10))]
        net += [('sigmoid5', F.sigmoid)]
        with self.init_scope():
            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, there 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:

```python
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),
        )

(continues on next page)
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
    def forward(self, x):
        h = F.relu(self.conv1(x))
        h = F.relu(self.conv2(h))
        if self.n_convs == 3:
            h = F.relu(self.conv3(h))
        h = F.max_pooling_2d(h, 2, 2)
        if self.fc:
            h = F.dropout(F.relu(self.fc4(h)))
            h = F.dropout(F.relu(self.fc5(h)))
            h = self.fc6(h)
        return h

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:
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)

class ResBlock(chainer.ChainList):
    def __init__(self, n_layers, n_in, n_mid, n_out, stride=2):
        super(ResBlock, self).__init__()
        self.add_link(BottleNeck(n_in, n_mid, n_out, stride, True))
        for _ in range(n_layers - 1):
            self.add_link(BottleNeck(n_out, n_mid, n_out))

    def forward(self, x):
        for f in self.children():
            x = f(x)
        return x

class BottleNeck(chainer.Chain):
    def __init__(self, n_in, n_mid, n_out, stride=1, proj=False):
        w = chainer.initializers.HeNormal()
        super(BottleNeck, self).__init__()
        with self.init_scope():
            self.conv1x1a = L.Convolution2D(  
                n_in, n_mid, 1, stride, 0, initialW=w, nobias=True)
            self.conv3x3b = L.Convolution2D(  
                n_mid, n_mid, 3, 1, 1, initialW=w, nobias=True)
            self.conv1x1c = L.Convolution2D(  
                n_mid, n_out, 1, 1, 0, initialW=w, nobias=True)
            self.bn_a = L.BatchNormalization(n_mid)
            self.bn_b = L.BatchNormalization(n_mid)
            self.bn_c = L.BatchNormalization(n_out)
            if proj:
                self.conv1x1r = L.Convolution2D(  
                    n_in, n_out, 1, stride, 0, initialW=w, nobias=True)
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):
OSError: 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`.

---

3.3. Convolutional Network for Visual Recognition Tasks 71
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. Generative 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:

![Fig. 1: cited from [1]](image_url)
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 $G : z \mapsto s$. 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 [2] 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:

$$D(s) = \frac{p(s)}{p(s) + p_{\text{model}}(s)}$$

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].

The $D_{JS}$ of $p_{\text{model}}(s)$ and $p(s)$ can be written as follows by using $D(s)$:

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

$$\mathbb{E}_{p(s)} \log \frac{2p(s)}{p(s) + p_{\text{model}}(s)} + \mathbb{E}_{p_{\text{model}}(s)} \log \frac{2p_{\text{model}}(s)}{p(s) + p_{\text{model}}(s)}$$

$$= \mathbb{E}_{p(s)} \log D(s) + \mathbb{E}_{p_{\text{model}}(s)} \log(1 - D(s)) + \log 4$$

$$= \mathbb{E}_{p(s)} \log D(s) + \mathbb{E}_{p_{\text{model}}(s)} \log(1 - D(G(z))) + \log 4$$

where $\bar{p}(s) = \frac{p(s) + p_{\text{model}}(s)}{2}$. The $D_{JS}$ will be minimized 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 $p(s)$.

$$\min_G \max_D \mathbb{E}_{p(s)} \log D(s) + \mathbb{E}_{p_{\text{model}}(s)} \log(1 - D(G(z)))$$

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:

### 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.

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
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 $p_{data}(x)$.
    • Update the discriminator by ascending its stochastic gradient:
      \[
      \nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[ \log D(x^{(i)}) + \log \left(1 - D(G(z^{(i)}))\right) \right].
      \]
  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:
    \[
    \nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log \left(1 - D(G(z^{(i)}))\right).
    \]
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]

Fig. 3: cited from [5]
2.1 Define the generator model

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

Listing 1: train_dcgan.py

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():
            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):
        return numpy.random.uniform(-1, 1, (batchsize, self.n_hidden, 1, 1))
        .astype(numpy.float32)

    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, 3, 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):
        h = add_noise(x)
        h = F.leaky_relu(add_noise(self.c0_0(h)))
        h = F.leaky_relu(add_noise(self.bn0_1(self.c0_1(h))))
        h = F.leaky_relu(add_noise(self.bn1_0(self.c1_0(h))))
        h = F.leaky_relu(add_noise(self.bn1_1(self.c1_1(h))))
        h = F.leaky_relu(add_noise(self.bn2_0(self.c2_0(h))))
        h = F.leaky_relu(add_noise(self.bn2_1(self.c2_1(h))))
        h = F.leaky_relu(add_noise(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(h, sigma=0.2):
    xp = backend.get_array_module(h.data)
    if chainer.config.train:
        h = h + xp.random.normal(0, sigma, h.shape)
    return h
```

(continues on next page)
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()
```

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, 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 6: train_dcgan.py

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()
        x_real = Variable(self.converter(batch, self.device)) / 255.
        xp = chainer.backend.get_array_module(x_real.data)
        gen, dis = self.gen, self.dis
        batchsize = len(batch)
        y_real = dis(x_real)
        z = Variable(xp.asarray(gen.make_hidden(batchsize)))
        x_fake = gen(z)
        y_fake = dis(x_fake)

        dis_optimizer.update(self.loss_dis, dis, y_fake, y_real)
        gen_optimizer.update(self.loss_gen, gen, y_fake)

In the intilizer `__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_optimizer('gen')` and `self.get_optimizer('dis')`.

3.4. DCGAN: Generate images with Deep Convolutional GAN
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.backends.cuda.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=args.gpu)
```

---

**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', 'gen, dis', '10, 10, args.seed, args.out]), 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**

```python
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
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, 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 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:
>>> 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__()
        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

rnn = RNN()
model = L.Classifier(rnn)
optimizer = optimizers.SGD()
optimizer.setup(model)
```

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:
Suppose we have a list of word variables \( x_{\text{list}} \).
\[
\begin{align*}
\text{rnn}.\text{reset}_\text{state}() \\
\text{model}.\text{cleargrads}() \\
\text{loss} &= \text{compute}_\text{loss}(x_{\text{list}}) \\
\text{loss}.\text{backward}() \\
\text{optimizer}.\text{update}() 
\end{align*}
\]

Or equivalently we can use the `compute_loss` as a loss function:
\[
\begin{align*}
\text{rnn}.\text{reset}_\text{state}() \\
\text{optimizer}.\text{update}(\text{compute}_\text{loss}, x_{\text{list}}) 
\end{align*}
\]

### 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:
\[
\begin{align*}
\text{loss} &= 0 \\
\text{count} &= 0 \\
\text{seqlen} &= \text{len}(x_{\text{list}}[1:]) \\
\text{rnn}.\text{reset}_\text{state}() \\
\text{for} \ \text{cur}_\text{word}, \ \text{next}_\text{word} \ \text{in} \ \text{zip}(x_{\text{list}}, x_{\text{list}}[1:]):
\begin{align*}
&\text{loss} += \text{model}(\text{cur}_\text{word}, \text{next}_\text{word}) \\
&\text{count} += 1 \\
&\text{if} \ \text{count} \ % \ 30 == 0 \ \text{or} \ \text{count} == \text{seqlen}:
\begin{align*}
&\text{model}.\text{cleargrads}() \\
&\text{loss}.\text{backward}() \\
&\text{loss}.\text{unchain}_\text{backward}() \\
&\text{optimizer}.\text{update}() 
\end{align*}
\end{align*}
\]

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

    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.

```python
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
```

(continues on next page)
# The core part of the update routine can be customized by overriding.

```python

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

updater = BPTTUpdater(train_iter, optimizer, bprop_len)  # instantiation
```

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 RNN Language Models

### 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>$h_t^{(i)}$</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>

![Diagram of RNNLM](image-url)
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:

\[
\log_b |\mathcal{V}| \sum_{n=1}^{|D|} \sum_{t=1}^{T^{(n)}} \log_b P_{\text{model}}(x_t^{(n)}, x_{[a,t-1]}^{(n)})
\]

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: \texttt{examples/ptb}
2.1 Model Overview

![Diagram of RNNLM](image)

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>
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<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>

**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
import chainer
import chainer.functions as F
import chainer.links as L
from chainer import training
from chainer.training import extensions
```
2.2.2 Define Training Settings

Define all training settings here.

Listing 12: train_ptb.py

```python
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.data[...] = np.random.uniform(-0.1, 0.1, param.data.shape)

    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))
```

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

```python
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.data[...] = np.random.uniform(-0.1, 0.1, param.data.shape)

            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 $|\mathcal{V}|$-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):
        self.dataset = dataset
        self.batch_size = batch_size  # batch size
        # 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
        self.repeat = repeat
        length = len(dataset)
        # Offsets maintain the position of each sequence in the mini-batch.
```

(continues on next page)
self.offsets = [i * length // batch_size for i in range(batch_size)]
# 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
    # forward the "current" position.
    length = len(self.dataset)
    if not self.repeat and self.iteration * self.batch_size >= length:
        # If not self.repeat, this iterator stops at the end of the first
        # epoch (i.e., when all words are visited once).
        raise StopIteration
    cur_words = self.get_words()
    self._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 + \
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 optimizing 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:

$$
\mathcal{L} = - \sum_{t=0}^{T} \sum_{n=1}^{[|W|]} \hat{P}(x_{t+1}^{(n)}) \log P_{\text{model}}(x_{t+1}^{(n)} | x_{t}^{(n)})
$$

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

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):
                # 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
                x, t = self.converter(batch, self.device)

                # 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
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))
```
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, args.gpu)
trgainer = 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=args.gpu,
    # Reset the RNN state at the beginning of each evaluation
    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:
    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.

Listing 22: train_ptb.py

```python
print('test')
eval_rnn.reset_state()
evaluator = extensions.Evaluator(test_iter, eval_model, device=args.gpu)
result = evaluator()
print('test perplexity: {}'.format(np.exp(float(result['main/loss']))))
```

2.3 Run Example

2.3.1 Training the model

You can train the model with the script: examples/ptb/train_ptb.py
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

```
$ 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.

![Diagram]

: Center Word

: Context Word

c=0 The cute cat jumps over the lazy dog.
c=1 The cute cat jumps over the lazy dog.
c=2 The cute cat jumps over the lazy dog.

### 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>$</td>
<td>V</td>
</tr>
<tr>
<td>$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, ${v_{t+c}}_{c=-C}^{C}\setminus v_t$</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>

**Note:** Using **negative sampling** or **hierarchical softmax** for the loss function is very common, however, in this tutorial, we will use the **softmax over all words** and skip the other variants for the sake of simplicity.

### 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: $l_H = W_H v_t$
2. Calculate an output vector of the embedding vector: $l_O = W_O l_H$
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: $l_H = \frac{1}{2C} \sum_{V_{t\pm C}} W_H v_{t+c}$
2. Calculate an output vector of the embedding vector: $l_O = W_O l_H$
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:

$$L(v_t | V_{t\pm C}; W_H, W_O) = - \log (p(v_t | V_{t\pm C}))$$

$$= - \log (v_t^T \hat{v}_t)$$

### 3.7.4 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 $|V|$ 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 $[0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0]$ 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 $l_O$. 

3.7. Word2Vec: Obtain word embeddings 99
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 numpy as np
import six

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
```

(continues on next page)
from chainer import training
from chainer.training import extensions

4.2 Define a Skip-gram model

Next, let’s define a network for Skip-gram.

Listing 24: train_word2vec.py

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

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 s.t. 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.

3.7 Word2Vec: Obtain word embeddings 101
First, we obtain the embedding vectors of contexts by $e = \text{self.embed}(\text{contexts})$. Then $\text{F.broadcast_to}(x[:, \text{None}], (\text{batch_size}, n_{\text{context}}))$ performs broadcasting of $x$ (its shape is $(\text{batch_size},))$ to $(\text{batch_size}, n_{\text{context}})$ by copying the same value $n_{\text{context}}$ time to fill the second axis, and then the broadcasted $x$ is reshaped into 1-D vector $(\text{batchsize} \times n_{\text{context}},)$ while $e$ is reshaped to $(\text{batchsize} \times n_{\text{context}}, n_{\text{units}})$. 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 $(\text{batchsize} \times n_{\text{context}})$ center word predictions by applying $\text{self.out}$ 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.

```python
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:

```python
>>> train
array([ 0,  1,  2, ..., 39, 26, 24], dtype=int32)
>>> val
array([2211, 396, 1129, ..., 108, 27, 24], dtype=int32)
```

Listing 26: train_word2vec.py

```python
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, ..., 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."
        return
```

(continues on next page)
Each item indicates a different position in the original sequence.

```python
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)

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

3.7. Word2Vec: Obtain word embeddings
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=args.gpu)
```

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=args.gpu))
trainer.extend(extensions.LogReport())
trainer.extend(extensions.PrintReport(
    ['epoch', 'main/loss', 'validation/main/loss']))
trainer.extend(extensions.ProgressBar())
trainer.run()
```

4.5 Start training

```bash
$ 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
```

(continues on next page)
<table>
<thead>
<tr>
<th></th>
<th>4231.94</th>
<th>1247.66</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>5642.04</td>
<td>2495.3</td>
</tr>
<tr>
<td>7</td>
<td>5640.82</td>
<td>4990.64</td>
</tr>
<tr>
<td>8</td>
<td>5639.31</td>
<td>2495.28</td>
</tr>
<tr>
<td>9</td>
<td>2817.89</td>
<td>4990.62</td>
</tr>
<tr>
<td>10</td>
<td>1408.03</td>
<td>3742.94</td>
</tr>
<tr>
<td>11</td>
<td>5633.11</td>
<td>1247.62</td>
</tr>
<tr>
<td>12</td>
<td>4221.71</td>
<td>2495.21</td>
</tr>
<tr>
<td>13</td>
<td>4219.3</td>
<td>4990.56</td>
</tr>
<tr>
<td>14</td>
<td>4216.57</td>
<td>2495.16</td>
</tr>
<tr>
<td>15</td>
<td>4213.52</td>
<td>2495.12</td>
</tr>
<tr>
<td>16</td>
<td>5616.03</td>
<td>1247.55</td>
</tr>
<tr>
<td>17</td>
<td>5611.34</td>
<td>3742.78</td>
</tr>
<tr>
<td>18</td>
<td>2800.31</td>
<td>3742.74</td>
</tr>
<tr>
<td>19</td>
<td>1397.79</td>
<td>2494.95</td>
</tr>
<tr>
<td>20</td>
<td>2794.1</td>
<td>3742.66</td>
</tr>
</tbody>
</table>

4.5 Search the similar words

```
$ 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 $\mathcal{V}(s)$ and $\mathcal{V}(t)$, all the elements $x_i$ and $y_j$s satisfy $x_i \in \mathbb{R}^{\left|\mathcal{V}(s)\right|}$ and $y_i \in \mathbb{R}^{\left|\mathcal{V}(t)\right|}$. 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 $\text{BOS}$, which is the virtual word representing the beginning of the sentence, and $y_{J+1}$ is that of $\text{EOS}$, which is the virtual word representing the end of the sentence.

**The Notations of Conditional Probability $P(Y|X)$**

Next, let’s think about the conditional probability $P(Y|X)$ generating the output sequence $Y$ when the input sequence $X$ is given. The purpose of seq2seq model is modeling the probability $P(Y|X)$. However, the seq2seq model does not model the probability $P(Y|X)$ directly. Actually, it models the probability $P(y_j|Y_{<j}, X)$, 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 $P_\theta(Y|X)$ with the product of $P_\theta(y_j|Y_{<j}, X)$:

$$P_\theta(Y|X) = \prod_{j=1}^{J+1} P_\theta(y_j|Y_{<j}, X)$$

**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 $P_\theta(y_j|Y_{<j}, X)$ is actually calculated by $P_\theta(y_j|Y_{<j}, z)$. 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:

\[
P_\theta(y_j|Y_{<j}, X) = \Upsilon(h_j^{(t)}, y_j)
\]

\[
h_j^{(t)} = \Psi(h_{j-1}^{(t)}, y_{j-1})
\]

\( \Psi \) 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:

<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>

### 1.2.1 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.

### 1.2.3 Decoder Embedding Layer

The decoder embedding layer converts the 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 \( h^{(t)}_j \) : 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 \( \psi^{(t)} \):

\[
\begin{align*}
h^{(t)}_j &= \psi^{(t)}(\bar{y}_j, h^{(t)}_{j-1}) \\
&= \tanh \left( W^{(t)} \begin{bmatrix} h^{(t)}_{j-1} \\ \bar{y}_j \end{bmatrix} + b^{(t)} \right)
\end{align*}
\]

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:

\[
h^{(t)}_0 = z = h^{(s)}_f
\]

### 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 \( h^{(t)}_j \) : 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

\[
\begin{align*}
p_j &= P_\theta(y_j | Y_{<j}) = \text{softmax}(o_j) \cdot y_j \\
&= \text{softmax}(W^{(o)} h^{(t)}_j + b^{(o)}) \cdot y_j
\end{align*}
\]

**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`
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
import numpy
import progressbar
import six
import chainer
from chainer.backends import cuda
```

(continues on next page)
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('--gpu', '-g', type=int, default=-1,
    help='GPU ID (negative value indicates CPU)')
parser.add_argument('--resume', '-r', default='',
    help='resume the training from snapshot')
parser.add_argument('--save', '-s', default='',
    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('--out', '-o', default='result',
    help='directory to output the result')
```

2.2.3 Define Network Structure

The Chainer implementation of seq2seq is shown below. It implements the model depicted in the above figure.

3.8. Write a Sequence to Sequence (seq2seq) Model
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.data}, self)
        n_words = concat_ys_out.shape[0]
        perp = self.xp.exp(loss.data * batch / n_words)
        chainer.report({'perp': perp}, self)
        return loss

    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)

                # (continues on next page)
cys = F.concat(ys, axis=0)
wy = self.W(cys)
ys = self.xp.argmax(wy.data, axis=1).astype(numpy.int32)
result.append(ys)

# Using `xp.concatenate(...)` instead of `xp.stack(result)` here to
# support NumPy 1.9.
result = cuda.to_cpu(
    self.xp.concatenate([self.xp.expand_dims(x, 0) 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)
yes_in = [F.concat([eos, y], axis=0) for y in ys]
yes_out = [F.concat([y, eos], axis=0) for y in ys]
```

(continues on next page)
# 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.data}, self)
n_words = concat_ys_out.shape[0]
perp = self.xp.exp(loss.data * batch / n_words)
chainer.report({'perp': perp}, self)
return

• 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 \( h^{(t)}_{[1:L]} \) 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 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] for x in xs].

Listing 37: seq2seq.py

```python
def translate(self, xs, max_length=100):
    batch = len(xs)
```

(continues on next page)
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.data, axis=1).astype(numpy.int32)
        result.append(ys)
    result = cuda.to_cpu(self.xp.concatenate([self.xp.expand_dims(x, 0) for x in result]).T)
    result = result[:, :max_length]
    # Using `xp.concatenate(...)` instead of `xp.stack(result)` here to
    # support NumPy 1.9.
    result = cuda.to_cpu(result)
    result = result[:, :max_length]
    result = cuda.to_cpu(result)

    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('[{}]

print('[{}]
```

(continues on next page)
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: %.2f%%' %
          (train_source_unknown * 100))
    print('Train target unknown ratio: %.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
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.

class CalculateBleu(chainer.training.Extension):
    trigger = 1, 'epoch'
    priority = chainer.training.PRIORITY_WRITER

    def __init__(self, model, test_data, key, batch=100, device=-1, 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):
        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 = [chainer.dataset.to_device(self.device, x) for x in sources]
                ys = [y.tolist() for y in self.model.translate(sources, self.max_length)]

                (continues on next page)
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.

Listing 45: seq2seq.py

optimizer = chainer.optimizers.Adam()
optimizer.setup(model)

2.2.9 Setup and Run Trainer

Let’s make a trainer object.

Listing 46: seq2seq.py

updater = training.updaters.StandardUpdater(
    train_iter, optimizer, converter=convert, device=args.gpu)
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'))
Setup the trainer’s extension to see the BLEU score on the test data.

Listing 47: seq2seq.py

```python
test_source = load_data(source_ids, args.validation_source)
test_target = load_data(target_ids, args.validation_target)
assert len(test_source) == len(test_target)
test_data = list(six.moves.zip(test_source, test_target))

assert 0 < len(s) and 0 < len(t)
for s, t in test_data:
    test_source_unknown = calculate_unknown_ratio(s)
    test_target_unknown = calculate_unknown_ratio(t)

print('Validation data: %d' % len(test_data))
print('Validation source unknown ratio: %.2f%%' % (test_source_unknown * 100))
print('Validation target unknown ratio: %.2f%%' % (test_target_unknown * 100))

@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=args.gpu),
              trigger=(args.validation_interval, 'iteration'))
```

Let’s start the training!

Listing 48: seq2seq.py

```python
if args.resume:
    # Resume from a snapshot
    chainer.serializers.load_npz(args.resume, trainer)

trainer.run()

if args.save:
    # Save a snapshot
    chainer.serializers.save_npz(args.save, trainer)
```

**2.3 Run Example**

3.8. Write a Sequence to Sequence (seq2seq) Model
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
```

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:

```
... 
# 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</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>
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#### 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]`  
  ```python
  __getitem__()  
  ```

- Addition: `a + b`  
  ```python
  __add__(), __radd__()  
  ```
• Subtraction: \( a - b \) (`\_\_sub\_\_`, `\_\_rsub\_\_`)  
• Multiplication: \( a \times b \) (`\_\_mul\_\_`, `\_\_rmul\_\_`)  
• Division: \( a / b \) (`\_\_div\_\_`, `\_\_rdiv\_\_`, `\_\_truediv\_\_`, `\_\_rtruediv\_\_`)  
• Floor Division: \( a // b \) (`\_\_floordiv\_\_`, `\_\_rfloordiv\_\_`)  
• Exponentiation: \( a ** b \) (`\_\_pow\_\_`, `\_\_rpow\_\_`)  
• Matrix Multiplication: \( a @ b \) (`\_\_matmul\_\_`, `\_\_rmatmul\_\_`)  
• Negation (Arithmetic): \(- a\) (`\_\_neg\_\_`)  
• Absolute value: \( \text{abs}(a) \) (`\_\_abs\_\_`)  

---

**Warning:** volatile argument is not supported anymore since v2. Instead, use `chainer.no_backprop_mode()`.

### 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 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 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))
```

```python
array(
    [[[ 0, 1, 2],
      [ 3, 4, 5]],
     [[ 6, 7, 8],
      [ 9, 10, 11]]])
```

```python
>>> F.get_item(x, 0)
variable([[0, 1, 2],
         [3, 4, 5]])
```

```python
>>> F.get_item(x, (0, 0, slice(0, 2, 1)))  # equals x[0, 0, 0:2:1]
variable([0, 1])
```

```python
>>> F.get_item(x, (Ellipsis, 2))  # equals x[…, 2]
variable([[ 2, 5],
         [ 8, 11]])
```

```python
>>> 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__()`

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.

### `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 to set this flag `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.

```python
    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

    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_cpu()
    Copies the data and gradient arrays to CPU.

    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.

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.

Deprecation warning: since version v1.15: Use cleargrad() instead.

__eq__(other)  
This operator is not defined for Variable.

__ne__(other)  
This operator is not defined for Variable.

__lt__(other)  
This operator is not defined for Variable.

__le__(other)  
This operator is not defined for Variable.

__gt__(other)  
This operator is not defined for Variable.

__ge__(other)  
This operator is not defined for Variable.

__nonzero__()  
This operator is not defined for Variable.

__bool__()  
This operator is not defined for Variable.

__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.
__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 uninitialized state.
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`.

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.

grad_var
Gradient variable.

label
Short text that represents the variable.

name

ndim

node

rank

requires_grad
It indicates that `grad` will be set in backward calculation.

shape

size

xp
Array module for this variable.
Depending on which of CPU/GPU this variable is on, this property returns `numpy` or `cupy`.
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.Parameter

class chainer.Parameter(initializer=None, shape=None, name=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.

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 to set this flag 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

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.

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_cpu()
Copies the data and gradient arrays to CPU.

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 **cleargrad()** instead.

**__eq__(other)**
This operator is not defined for Variable.

**__ne__(other)**
This operator is not defined for Variable.

**__lt__(other)**
This operator is not defined for Variable.

**__le__(other)**
This operator is not defined for Variable.

**__gt__(other)**
This operator is not defined for Variable.

**__ge__(other)**
This operator is not defined for Variable.

**__nonzero__()**
This operator is not defined for Variable.

**__bool__()**
This operator is not defined for Variable.

**__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.
__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 in an uninitialized state.

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`.

**dtype**
Gradient array of this variable.

**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.

**grad_var**
Gradient variable.

**initializer = None**

**label**
Short text that represents the variable.

**name**

**ndim**

**node**

**rank**

**requires_grad**
It indicates that `grad` will be set in backward calculation.

**shape**

**size**

**xp**
Array module for this variable.

Depending on which of CPU/GPU this variable is on, this property returns `numpy` or `cupy`.

### chainer.variable.VariableNode

**class** `chainer.variable.VariableNode(variable, name, **kwargs)`

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`.

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:

```
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.

```
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`.

`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`. 

---

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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`

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`.

Note: As of v1.5, the concept of parameterized functions are gone, and they are replaced by corresponding `Link` implementations. They are found in the `chainer.links` namespace.

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.

**chainer.functions.add**

`chainer.functions.add(*xs)`

Element-wise addition.

**Returns** Output variable.

**Return type** Variable

### 4.2.2 Activation functions

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**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.data < 0)
False
>>> np.any(y.data > 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.


**Parameters**

- x (**Variable** or **N-dimensional array**): Input variable. A \((s_1, s_2, \ldots, s_N)\)-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 \((s_1, s_2 \times 2, \ldots, s_N)\)-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.data
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.data
array([[-0.63212055,  0.  ],
       [ 2.        , -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 $[0, 1]$. 
>>> x = np.array([-2.6, -1, 0, 1, 2.6])
>>> x
array([-2.6, -1. , 0. , 1. , 2.6])
>>> F.hard_sigmoid(x).data
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.],
        [-2.,  1.]],
       dtype=float32)
>>> F.leaky_relu(x, slope=0.2).data
array([[[-0.2, 0. ],
        [ 2. , -0.6],
        [-0.4, 1. ]],
       dtype=float32)
```

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 \(c = (c_1, c_2, ..., c_D)\) 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. $\log\_\text{softmax}$ method is more stable.

Parameters

- $x$ (Variable or N-dimensional array) – Input variable. A $n$-dimensional ($n \geq 2$) float array.
- $\text{axis}$ (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).data
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
```

chainer.functions.lstm

chainer.functions.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 $c\_prev$ 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**

- \( c_{\text{prev}} \) (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 of 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 \( n_{\text{units}} \) channels. Most typical preparation of \( x \) is:

```python
def example():
    >>> n_units = 100
    >>> y = chainer.Variable(np.zeros((1, n_units), dtype=np.float32))
    >>> h = chainer.Variable(np.zeros((1, n_units), dtype=np.float32))
    >>> c = chainer.Variable(np.zeros((1, n_units), dtype=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 * 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 ≥ 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 * pool_size.

Returns Output variable. The shape of the output is same as x except that axis dimension is transformed from M * 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.

```python
>>> 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)).data
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.data
```
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 \( PReLU(x) = \max(x, W \ast x) \), where \( \ast \) is an elementwise multiplication for each sample in the batch.

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.

Parameters
- x (Variable or N-dimensional array) – Input variable. Its first argument is assumed to be the minibatch dimension.
- W (Variable or N-dimensional array) – Weight variable.

Returns Output variable
Return type Variable

See also:
PReLU

chainer.functions.rrelu

chainer.functions.rrelu (x, l=1. / 8, u=1. / 3, *, r=None, return_r=False)
Randomized Leaky Rectified Liner Unit function.

This function is expressed as

\[ f(x) = \max(x, ax), \]

where \( a \) is a random number sampled from a uniform distribution \( U(l, u) \).


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, a r will be generated randomly according to the given l and u. If r is specified, l and u will be ignored.
- 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 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]], 'f')
>>> x
array([[-1., 0.],
       [ 2., -3.],
       [-2., 1.]], dtype=float32)
```

```python
>>> F.relu(x).data  # doctest: +SKIP
array([[-0.24850948, 0.],
       [ 2.00000000, -0.50844127],
       [-0.59853500, 1.00000000]], 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.data < 0)
False
>>> y.shape
(3, 2)
```

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

\[
f(x) = \lambda \left\{ \begin{array}{ll}
  x & \text{if } x \geq 0 \\
  \alpha(\exp(x) - 1) & \text{if } x < 0,
\end{array} \right.
\]

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.

• \(\text{alpha}\) (float) – Parameter \(\alpha\).

• \(\text{scale}\) (float) – Parameter \(\lambda\).

Returns Output variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.

Return type Variable

**chainer.functions.sigmoid**

\texttt{chainer.functions.sigmoid}(x)

Element-wise sigmoid logistic function.

\[ f(x) = \frac{1}{1 + \exp(-x)}. \]

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**

It maps the input values into the range of \([0, 1]\).

```python
>>> x = np.arange(-2, 3, 2).astype(np.float32)
>>> x
array([-2., 0., 2.], dtype=float32)
>>> F.sigmoid(x)
variable([0.11920291, 0.5 , 0.8807971 ])
```

**chainer.functions.slstm**

\texttt{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 \(a_1, i_1, f_1, o_1, a_2, i_2, f_2, o_2\). They have the same shape along the second axis. It means that \(x1\) and \(x2\)’s second axis must have 4 times the length of \(c_{prev1}\) and \(c_{prev2}\).

The split input arrays are corresponding to:

• \(a_i\) : 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:

\[
c = \tanh(a_1 + a_2)\sigma(i_1 + i_2) + c_{prev1}\sigma(f_1) + c_{prev2}\sigma(f_2),
\]

\[
h = \tanh(c)\sigma(o_1 + o_2),
\]

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 \(n\_units\) 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.
- \( \text{axis} \) (*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.data
array([[0.09003057, 0.24472848, 0.66524094],
       [0.01587624, 0.11731043, 0.86681336]], dtype=float32)
>>> F.sum(y, axis=1).data
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 \((s_1, s_2, \ldots, s_N)\)-shaped float array.
- \( \text{beta} \) (*float*) – Parameter \( \beta \).

**Returns**

Output variable. A \((s_1, s_2, \ldots, s_N)\)-shaped float array.

**Return type** *Variable*

**Example**

```python
```
```python
>>> x = np.arange(-2, 3, 2).astype(np.float32)
array([-2.,  0.,  2.], dtype=float32)
```
```python
>>> x = np.arange(-1, 4, 2).astype(np.float32)
>>> x
array([-1., 1., 3.], dtype=float32)
>>> F.tanh(x).data
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 \(c_1, c_2, \ldots, c_N\), 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:
- \(a\) : 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:

\[
c = \tanh(a)\text{sigmoid}(i) \\
\quad + c_1\text{sigmoid}(f_1), \\
\quad + c_2\text{sigmoid}(f_2), \\
\quad + ..., \\
\quad + c_N\text{sigmoid}(f_N), \\
\]

\[
h = \tanh(c)\text{sigmoid}(o).
\]

These are returned as a tuple of \((N + 1)\) variables.

**Parameters inputs** (list of 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 \texttt{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 $h1$ and $h2$. Different parameters are used for different kind of input sources.

### 4.2.3 Array manipulations

- **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.expand_dims**: Concatenates variables along third axis (depth wise).
- **chainer.functions.flatten**: Expands dimensions of an input variable without copy.
- **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.reshape**: Reshapes 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.

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**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 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.data)
True
>>> z = np.random.uniform(0, 1, (3, 2)).astype(np.float32)
>>> y, w = F.broadcast(x, z)
>>> np.all(x == y.data) & np.all(z == w.data)
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 be broadcasted. A \((s_1, s_2, ..., s_N)\)-shaped float array.
- `shape` (tuple) – Tuple of int of the shape of the output variable.

4.2. Functions
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.data
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, ..., s_N)*-shaped float 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)
>>> z.data
array([[ 0,  1,  2,  3,  0],
       [ 4,  5,  6,  7,  1],
       [ 8,  9, 10, 11,  2]])
```

---

**chainer.functions.copy**

chainer.functions.\texttt{copy}(x, dst)

Copies the input variable onto the specified device.

This function copies the array of input variable onto the device specified by dst. When dst == -1, it copies the array onto 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** (*int*) -- Target device specifier.

**Returns** Output variable.

**Return type** *Variable*

**Example**

```python
>>> import chainer.backends.cuda as cuda

>>> x = np.random.uniform(-1, 1, (5, 10))
>>> cuda.get_device_from_array(x).id
-1

>>> y = F.copy(x, 0)  # from host to device0
>>> cuda.get_device_from_array(y.data).id
0

>>> z = F.copy(y, -1)  # from device0 to host
>>> cuda.get_device_from_array(z.data).id
-1
```
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).

**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)
>>> y = F.depth2space(X, 2)
>>> y.shape
(1, 1, 4, 6)
>>> y.data
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

• \textbf{x} (Variable or N-dimensional array) – A variable to be sliced.

• \textbf{offset} (int) – Offset from the principal diagonal. An upper diagonal matrix can have nonzero diagonals with nonnegative offsets.

• \textbf{axis1} (int) – First axis (that has row indices) of matrix

• \textbf{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.])
```

\textbf{chainer.functions.dstack}

\textbf{chainer.functions.dstack} (xs)

Concatenate variables along third axis (depth wise).

Parameters \textbf{xs} (list of Variable or N-dimensional array) – Input variables to be concatenated.

The variables must have the same \textit{ndim}. When the variables have the third axis (i.e. \textit{ndim} \geq 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. \textit{ndim} < 3), the variables must have the same shape.

Returns Output variable. When the input variables have the third axis (i.e. \textit{ndim} \geq 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 \(\text{\textit{N1, N2}}\) (i.e. \textit{ndim} = 2),
the shape of output is \(\text{\textit{N1, N2, 2}}\). When the shape of variables are \(\text{\textit{N1, N2, 2}}\) (i.e. \textit{ndim} = 1),
the shape of output is \(\text{\textit{1, N1, 2}}\). When the shape of variables are \(\text{}\) (i.e. \textit{ndim} = 0), the
shape of output is \(\text{\textit{1, 1, 2}}\).

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.data
```

(continues on next page)
array([[1, 2],
       [2, 3],
       [3, 4]])

>>> 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.data
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.data
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 
$-\text{ndim} - 1 \leq \text{axis} \leq \text{ndim}$. (ndim is the dimension of input variables). When 
axis < 0, the result is the same with ndim + 1 − |axis|.

Returns Variable that holds a expanded input. The ndim of output is one grater 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.data
array([[1, 2, 3]])
>>> y = F.expand_dims(x, axis=1)
>>> y.shape
(3, 1)
>>> y.data
array([[1],
       [2],
       [3]])
>>> y = F.expand_dims(x, axis=-2)
>>> y.shape
(1, 3)
>>> y.data
array([[1, 2, 3]])
```

chainer.functions.flatten

chainer.functions.flatten(x)

Flatten a given array into one dimension.

Parameters x (Variable or N-dimensional array) – Input variable.

Returns Output variable flatten 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,)
```
Chainer Documentation, Release 5.3.0

>>> y.data
array([1, 2, 3, 4])

>>> x = np.arange(8).reshape(2, 2, 2)
>>> x.shape
(2, 2, 2)
>>> y = F.flatten(x)
>>> y.shape
(8,)
>>> y.data
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
• \texttt{x} \textit{(Variable or N-dimensional array)} – A variable to be sliced.
• \texttt{slices} \textit{(int, slice, Ellipsis, None, integer array-like, boolean array-like or tuple of them)} – An object to specify the selection of elements.

Returns A \texttt{Variable} object which contains sliced array of \texttt{x}.

\textbf{Note:} It only supports types that are supported by CUDA’s atomicAdd when an integer array is included in \texttt{slices}. The supported types are \texttt{numpy.float32}, \texttt{numpy.int32}, \texttt{numpy.uint32}, \texttt{numpy.uint64} and \texttt{numpy.ulonglong}.

\textbf{Note:} It does not support \texttt{slices} that contains multiple boolean arrays.

\textbf{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])
```

\texttt{chainer.functions.hstack}

\texttt{chainer.functions.hstack(xs)}

Concatenate variables horizontally (column wise).

\textbf{Parameters} \texttt{xs} \textit{(list of Variable or N-dimensional array)} – Input variables to be concatenated. The variables must have the same \texttt{ndim}. When the variables have the second axis (i.e. \texttt{ndim} \geq 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. \texttt{ndim} < 2), the variables need not to have the same shape.

\textbf{Returns} Output variable. When the input variables have the second axis (i.e. \texttt{ndim} \geq 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. \texttt{ndim} < 2), the shape of output is \((N, )\) \((N\) is the sum of the input variables’ size).
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.hstack((x1, x2))
>>> y.shape
(6,)
>>> y.data
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, 18).reshape(3, 2)
>>> x2.shape
(3, 2)
>>> x2
array([[12, 13],
       [14, 15],
       [16, 17]])
>>> y = F.hstack([x1, x2])
>>> y.shape
(3, 6)
>>> y.data
array([[ 0,  1,  2,  3, 12, 13],
       [ 4,  5,  6,  7, 14, 15],
       [ 8,  9, 10, 11, 16, 17]])
```

---

**chainer.functions.im2col**

chainer.functions.im2col(x, ksize, stride=1, pad=0, cover_all=False, dilate=1)

Extract patches from an image based on the filter.

This function rearranges patches of an image and puts them in the channel dimension of the output.

Patches are extracted 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.

Notation: here is a notation.

- $n$ is the batch size.
- $c$ is the number of the input channels.
- $h$ 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.
- $s_Y$ and $s_X$ are the strides of the filter.
• $p_H$ and $p_W$ are the spatial padding sizes.
• $d_Y$ and $d_X$ are the dilation factors of filter application.

The output size $(h_O, w_O)$ is determined by the following equations when $\text{cover\_all} = \text{False}$:

$$h_O = (h + 2p_H - k_H - (k_H - 1) * (d_Y - 1))/s_Y + 1,$$
$$w_O = (w + 2p_W - k_W - (k_W - 1) * (d_X - 1))/s_X + 1.$$

When $\text{cover\_all} = \text{True}$, the output size is determined by the following equations:

$$h_O = (h + 2p_H - k_H - (k_H - 1) * (d_Y - 1) + s_Y - 1)/s_Y + 1,$$
$$w_O = (w + 2p_W - k_W - (k_W - 1) * (d_X - 1) + s_X - 1)/s_X + 1.$$

**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.
- $\text{cover\_all}$ (*bool*) – If 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** ($x$, $source$, $destination$)

Move the source axes to the destination.

This function transpose the input $x$ by moving the axes $source$ to the axes $destination$. 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**
>>> 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 permute *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.data
array([[4., 5.],
       [0., 1.],
       [2., 3.]], dtype=float32)
>>> y = F.permutate(x, indices, inv=True)
>>> y.data
array([[2., 3.],
       [4., 5.],
       [0., 1.]], dtype=float32)
>>> indices = np.array([1, 0], np.int32)
>>> y = F.permutate(x, indices, axis=1)
>>> y.data
array([[1., 0.],
       [3., 2.],
       [5., 4.]], dtype=float32)
```

chainer.functions.repeat

[chainer.functions.repeat](functions.repeat)

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.data
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.data
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.data
array([[1, 2],
       [3, 4],
       [3, 4]])
```

chainer.functions.reshape

chainer.functions.reshape(x, shape)

Reshapes an input variable without copy.

Parameters

- **x** *(Variable or N-dimensional array)* – Input variable.
- **shape** *(tuple of int s)* – Expected shape of the output array. The number of elements which the array of shape contains must be equal to that of input array. One shape dimension can be -1. In this case, the value is inferred from the length of the array and remaining dimensions.

Returns Variable that holds a reshaped version of the input variable.

Return type Variable

See also:
numpy.reshape(), cupy.reshape()
array([1, 2, 3, 4, 5, 6, 7, 8])
>>> y = F.reshape(x, (4, -1)) # the shape of output is inferred
>>> y.shape
(4, 2)
>>> y.data
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)
<BLANKLINE>
Expect: prod(in_types[0].shape) == prod((4, 3))
Actual: 8 != 12

chainer.functions.resize_images

chainer.functions.resize_images(x, output_shape)

Resize images to the given shape.

This function resizes 2D data to output_shape. Currently, only bilinear interpolation is supported as the sampling method.

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.

Returns

Resized image whose shape is $(n, c_I, h_O, w_O)$.

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.data
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 (s1, s2, ..., sN) - 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
>>> 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].data
array([0., 1., 2.], dtype=float32)
>>> y = F.separate(x, axis=1)
>>> len(y)
3
>>> y[0].shape
(2,)
```
chainer.functions.space2depth

chainer.functions.space2depth(X, r)
Computes the space2depth transformation for subpixel calculations.

Parameters
• X (Variable or N-dimensional array) – Variable holding a 4d array of shape (batch,
channel, dim1 * r, dim2 * r).
• r (int) – the downscaling factor.

Returns A variable holding the downscaled layer array from subpixel array sampling. The shape is
(batch, channel * r * r, dim1, dim2).

Return type Variable

Note: This can be used to compute inverse super-resolution transformations. See https://arxiv.org/abs/1609.05158 for details.

See also: depth2space()

Example

```python
>>> X = np.arange(24).reshape(1, 1, 4, 6).astype(np.float32)
>>> X.shape
(1, 1, 4, 6)
>>> 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)
>>> y = F.space2depth(X, 2)
>>> y.shape
(1, 4, 2, 3)
>>> y.data
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**

```python
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 \((x^w_t, y^w_t)\), the point sampled from the source image \((x^s_i, y^s_i)\) are calculated by the following equation.

\[
\begin{pmatrix}
  x^s_i \\
  y^s_i
\end{pmatrix}
= \begin{pmatrix}
  \theta_{11} & \theta_{12} & \theta_{13} \\
  \theta_{21} & \theta_{22} & \theta_{23}
\end{pmatrix}
\begin{pmatrix}
  x^w_t \\
  y^w_t \\
  1
\end{pmatrix}
\]

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**

```python
chainer.functions.spatial_transformer_sampler(x, grid, **kwargs)
```

2D Spatial Transformer sampler.

This is a differentiable image sampler. With a set of sampling points \(grid\) 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 \(grid\) 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 \((x, \text{indices\_or\_sections, axis, force\_tuple=\text{True}})\)

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.
- \( \text{force\_tuple} \) (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 \((x, \text{axis=\text{None}})\)

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.data
array([[0., 1., 2.],
       [3., 4., 5.]], dtype=float32)
>>> y = F.squeeze(x, axis=1)
>>> y.shape
(2, 1, 3)
>>> y.data
array([[0., 1., 2.],
       [3., 4., 5.]], dtype=float32)
>>> y = F.squeeze(x, axis=(1, 2))
>>> y.shape
(2, 3)
>>> y.data
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 \(x_1, x_2, \ldots, x_n\) 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**  

---

**4.2. Functions**
```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.data
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.data
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=2)
>>> y.shape
(3, 4, 2)
>>> y.data
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

\texttt{chainer.functions.swapaxes}(x, axis1, axis2)

Swap two axes of a variable.

**Parameters**

- \texttt{x} (\texttt{Variable} or \texttt{N-dimensional array}) – Input variable. A \((s_1, s_2, ..., s_N)\)-shaped float array.
- \texttt{axis1} (\texttt{int}) – The first axis to swap.
- \texttt{axis2} (\texttt{int}) – The second axis to swap.

**Returns** Variable whose axes are swapped.

**Return type** \texttt{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.data
array([[0., 1., 2.],
       [3., 4., 5.]], dtype=float32)
```

chainer.functions.tile

\texttt{chainer.functions.tile}(x, reps)

Construct an array by tiling a given array.

**Parameters**

- \texttt{x} (\texttt{Variable} or \texttt{N-dimensional array}) – Input variable. Let the length of \texttt{reps} be \(d\). If \texttt{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 \texttt{x.ndim} > \(d\), \texttt{reps} is treated as \texttt{x.ndim}-dimensional by pre-pending 1’s. For example, when the shape of \(x\) is \((2, 3, 2, 3)\), the 2-dim \texttt{reps} of \((2, 2)\) is treated as \((1, 1, 2, 2)\).
- \texttt{reps} (\texttt{int} or \texttt{tuple} of \texttt{int} s) – The number of times which \(x\) is replicated along each axis.

**Returns** The tiled output Variable. Let the length of \texttt{reps} be \(d\), the output has the dimension of \(\max(d, x.ndim)\).

**Return type** \texttt{Variable}

**Example**

```python
```
```python
>>> x = np.array([0, 1, 2])
>>> x.shape
(3,)
>>> y = F.tile(x, 2)
>>> y.shape
(6,)
>>> y.data
array([0, 1, 2, 0, 1, 2])
>>> y = F.tile(x, (2, 2))
>>> y.shape
(2, 6)
>>> y.data
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.data
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.data
array([[1, 2, 1, 2],
       [3, 4, 3, 4]])
>>> y = F.tile(x, (2, 2))
>>> y.shape
(4, 4)
>>> y.data
array([[1, 2, 1, 2],
       [3, 4, 3, 4],
       [1, 2, 1, 2],
       [3, 4, 3, 4]])
>>> y = F.tile(x, (2, 1, 2))
>>> y.shape
(2, 2, 4)
>>> y.data
array([[[1, 2, 1, 2],
         [3, 4, 3, 4]],
        [[1, 2, 1, 2],
         [3, 4, 3, 4]]])
```

**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 \(s_1, s_2, \ldots, s_N\)-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
>>> x = np.array([[[0, 1, 2], [3, 4, 5]]], np.float32)
>>> x.shape
(1, 2, 3)
>>> y = F.transpose(x)  # reverse the dimensions
>>> y.shape
(3, 2, 1)
>>> y.data
array([[[0.,
    [3.],
    ...
    [2.,
    [5.]]],
    dtype=float32
>>> y = F.transpose(x, axes=(1, 0, 2))  # swap 1st and 2nd axis
>>> y.shape
(2, 1, 3)
>>> y.data
array([[[0., 1., 2.],
    [3., 4., 5.]],
    dtype=float32)
```

---

**chainer.functions.transpose_sequence**

**chainer.functions.transpose_sequence**(xs)

Transpose 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]))]
```

(continues on next page)
[variable([1, 1, 1]), variable([2, 2]), variable([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. \( ndim \geq 2 \)), 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. \( ndim \geq 2 \)), 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

>>> 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.data
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.data
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11],
       [12, 13, 14, 15],
       [16, 17, 18, 19]])

(continues on next page)
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 `(s_1, s_2, ..., s_N)`-shaped boolean array. Only boolean array is permitted.
- `x` (*Variable* or *N-dimensional array*) – Input variable chosen when `condition` is True. A `(s_1, s_2, ..., s_N)`-shaped float array.
- `y` (*Variable* or *N-dimensional array*) – Input variable chosen when `condition` is False. A `(s_1, s_2, ..., s_N)`-shaped float array.

**Returns** Variable containing chosen values.

**Return type** *Variable*

**Example**

```python
>>> cond = np.array([[1, 0], [0, 1]], dtype=np.bool)
>>> cond
array([[ True, False],
       [False,  True]])
>>> x = np.array([[1, 2], [3, 4]], np.float32)
>>> y = np.zeros((2, 2), np.float32)
>>> F.where(cond, x, y).data
array([[1., 0.],
       [0., 4.]], dtype=float32)
```

### 4.2.4 Neural network connections

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**chainer.functions.bilinear**

**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].

### chainer.functions.convolution_1d

```python
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

```python
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:

\[
\begin{align*}
  h_O &= (h_I + 2h_P - h_K)/s_Y + 1, \\
  w_O &= (w_I + 2w_P - w_K)/s_X + 1.
\end{align*}
\]
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:

\[
\begin{align*}
h_O &= (h_I + 2h_P - h_K + s_Y - 1)/s_Y + 1, \\
w_O &= (w_I + 2w_P - w_K + s_X - 1)/s_X + 1.
\end{align*}
\]

If the bias vector is given, then it is added to all spatial locations of the output of convolution.

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.

---

**Warning:** deterministic argument is not supported anymore since v2. Instead, use `chainer.using_config('cudnn_deterministic', value)` (value is either True or False). See `chainer.using_config()`.

**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. `stride=s` and `stride=(s, s)` are equivalent.
- **pad** *(int or pair of int s)* – Spatial padding width for input arrays. `pad=p` and `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. `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. 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`

**Example**
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.
- \( c_1 \) and \( c_0 \) 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.
• $k_1, k_2, ..., k_N$ 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 $stride$ 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 `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:

$$l_n = (d_n + 2p_n - k_n + s_n - 1) / s_n + 1 \quad (n = 1, ..., N)$$

The N-dimensional convolution function is defined as follows.

**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) – 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 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.

**Returns** Output variable of shape $(n, c_O, l_1, l_2, ..., l_N)$.

**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 ≥ 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, 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
(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)
>>> 11 = int((d1 + 2 * p1 - k1) / s1 + 1)
>>> 12 = int((d2 + 2 * p2 - k2) / s2 + 1)
>>> 13 = int((d3 + 2 * p3 - k3) / s3 + 1)
>>> y.shape == (n, c_o, 11, 12, 13)
True
>>> y = F.convolution_nd(x, W, b, stride=(s1, s2, s3), pad=(p1, p2, p3), cover_all=True)
>>> y.shape == (n, c_o, 11, 12, 13 + 1)
True
```

`chainer.functions.deconvolution_1d`

`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()`.
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:

\[
  h_O = s_Y(h_I - 1) + h_K - 2h_P, \\
  w_O = s_X(w_I - 1) + w_K - 2w_P.
\]

The output of this function can be non-deterministic when it uses cuDNN. If \( \text{chainer.config.deterministic} \) is \( \text{True} \) 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 \( \text{chainer.using_config('autotune', True)} \).

---

**Warning:** deterministic argument is not supported anymore since v2. Instead, use \( \text{chainer.using_config('cudnn_deterministic', value)} \) (value is either True or False). See \( \text{chainer.using_config()} \).

---

**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).
- \( \text{stride} \) (int or pair of int s) – Stride of filter applications. \( \text{stride}=s \) and \( \text{stride}=(s, s) \) are equivalent.
- \( \text{pad} \) (int or pair of int s) – Spatial padding width for input arrays. \( \text{pad}=p \) and \( \text{pad}=(p, p) \) are equivalent.
- \( \text{outsize} \) (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.
- \( \text{dilate} \) (int or pair of int s) – Dilation factor of filter applications. \( \text{dilate}=d \) and \( \text{dilate}=(d, d) \) are equivalent.
• \textbf{groups} \texttt{(int)} – The number of groups to use grouped deconvolution. The default is one, where grouped deconvolution is not used.

\textbf{Returns} Output variable of shape \((n, c_O, h_O, w_O)\).

\textbf{Return type} \texttt{Variable}

\textbf{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)
>>> y.shape == (n, c_o, h_o, w_o)
True
```

\texttt{chainer.functions.deconvolution\_3d}

\texttt{chainer.functions.deconvolution\_3d}(\texttt{x, W, b=None, stride=1, pad=0, outsize=None, dilate=1, groups=1})

3-dimensional deconvolution function.

\textbf{Note:} This function calls \texttt{deconvolution\_nd()} internally, so see the details of the behavior in the documentation of \texttt{deconvolution\_nd()}.

\texttt{chainer.functions.deconvolution\_nd}

\texttt{chainer.functions.deconvolution\_nd}(\texttt{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 \texttt{transposed convolution}. But because of historical reasons (e.g. paper by Ziller Deconvolutional Networks) and backward compatibility, this function is called \texttt{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.
- \(d_1, d_2, \ldots, d_N\) 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 \(\text{outsize}\) option is \(\text{None}\), 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 \(\text{outsize}\) option is given, the output size is determined by \(\text{outsize}\). In this case, the \(\text{outsize}\) \((l_1, l_2, \ldots, l_N)\) must satisfy the following equations:

\[
d_n = \lfloor (l_n + 2p_n - k_n)/s_n \rfloor + 1 \quad (n = 1, \ldots, N)
\]

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**

- \(x\) (\(\text{Variable or N-dimensional array}\)) – Input variable of shape \((n, c_I, d_1, d_2, \ldots, d_N)\).
- \(W\) (\(\text{Variable or N-dimensional array}\)) – Weight variable of shape \((c_I, c_O, k_1, k_2, \ldots, k_N)\).
- \(b\) (\(\text{None or Variable or N-dimensional array}\)) – One-dimensional bias variable with length \(c_O\) (optional).
- \(\text{stride}\) (\(\text{int or tuple of int s}\)) – Stride of filter applications \((s_1, s_2, \ldots, s_N)\). \(\text{stride=s}\) is equivalent to \((s, s, \ldots, s)\).
- \(\text{pad}\) (\(\text{int or tuple of int s}\)) – Spatial padding width for input arrays \((p_1, p_2, \ldots, p_N)\). \(\text{pad=p}\) is equivalent to \((p, p, \ldots, p)\).
- \(\text{outsize}\) (\(\text{None or tuple of int s}\)) – Expected output size of deconvolutional operation. It should be a tuple of ints \((l_1, l_2, \ldots, l_N)\). Default value is \(\text{None}\) and the \(\text{outsize}\) is estimated by input size, stride and \(\text{pad}\).
- \(\text{dilate}\) (\(\text{int or tuple of int s}\)) – Dilation factor of filter applications. \(\text{dilate=d}\) and \(\text{dilate=(d, d, \ldots, d)}\) are equivalent.
- \(\text{groups}\) (\(\text{int}\)) – 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`

**See also:**

`links.DeconvolutionND`, `deconvolution_2d()`
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 = s1 * (d1 - 1) + k1 - 2 * p1
>>> l2 = s2 * (d2 - 1) + k2 - 2 * p2
>>> l3 = s3 * (d3 - 1) + k3 - 2 * p3
>>> 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
```
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 \( c_M * c_I \) (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 \((n, c_I * c_M, h_O, w_O)\).

Return type Variable

Like \texttt{Convolution2D}, \texttt{DepthwiseConvolution2D} function computes correlations between filters and patches of size \((k_H, k_W)\) in \( x \). But unlike \texttt{Convolution2D}, \texttt{DepthwiseConvolution2D} does not add up input channels of filters but concatenates them. For that reason, the shape of outputs of depthwise convolution are \((n, c_I * c_M, h_O, w_O)\), \( c_M \) is called channel multiplier.

\((h_O,w_O)\) is determined by the equivalent equation of \texttt{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:

\texttt{DepthwiseConvolution2D}

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)
```
Two-dimensional deformable convolution function using computed offset.

This is an implementation of two-dimensional deformable convolution from Deformable Convolutional Networks.

It takes four variables: the input image \( x \), the offset image \( \text{offset} \), the filter weight \( W \), and the bias vector \( b \).

Notation: here is the notation for the 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.
- \( s_Y \) and \( s_X \) are the strides of the filter.
- \( p_H \) and \( p_W \) are the spatial padding sizes.

The output size \((h_O, w_O)\) is determined by the following equations:

\[
\begin{align*}
    h_O &= (h + 2p_H - k_H)/s_Y + 1, \\
    w_O &= (w + 2p_W - k_W)/s_X + 1.
\end{align*}
\]

**Parameters**

- \( x \) (Variable or N-dimensional array) – Input variable of shape \((n, c_I, h, w)\).
- \( \text{offset} \) (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).
- \( \text{stride} \) (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.

**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

**Example**
Chainer Documentation, Release 5.3.0

```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_2dSampler(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 column is the \(x[i]\)-th column 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 column of return value is filled with 0.

**Returns** Output variable.

**Return type** *Variable*

**See also:** *EmbedID*

**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).data
array([[2., 2., 2.],
        [1., 1., 1.]], dtype=float32)
>>> F.embed_id(x, W, ignore_label=1).data
array([[2., 2., 2.],
        [0., 0., 0.]], dtype=float32)
```
Chainer Documentation, Release 5.3.0

chainer.functions.linear

chainer.functions.linear(x, W=None, 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

\[ y_i = W x_i + b. \]

Parameters

- **x** (*Variable* or *N-dimensional array*) – Input variable, which is a \((s_1, s_2, ..., s_n)\)-shaped float array. Its first \(n_{\text{batch}}\) dimensions are handled as *minibatch dimensions*. The other dimensions are handled as concatenated one dimension whose size must be \((s_{n_{\text{batch}}}, ... \times s_n = N)\).
- **W** (*Variable* or *N-dimensional array*) – Weight variable of shape \((M, N)\), where \(N = s_{n_{\text{batch}}}, ... \times s_n\).
- **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 \((n_{\text{batch}} + 1)\)-dimensional tensor. This should be greater than 0.

Returns

Output variable. A float array with shape of \((s_1, ..., s_{n_{\text{batch}}}, M)\).

Return type

*Variable*

See also:

*Linear*

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=None, 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 $(n, c_I * c_O, h_O, w_O)$.

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

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 $x_t$.

\[
\begin{align*}
    r_t^f &= \sigma(W_0^f x_t + W_1^f h_{t-1} + b_0^f + b_1^f) \\
    z_t^f &= \sigma(W_0^f x_t + W_1^f h_{t-1} + b_0^f + b_1^f) \\
    h_t^{f'} &= \tanh(W_2^f x_t + b_2^f + r_t^f \cdot (W_3^f h_{t-1} + b_3^f)) \\
    h_t^f &= (1 - z_t^f) \cdot h_t^{f'} + z_t^f \cdot h_{t-1} \\
\end{align*}
\]

\[
\begin{align*}
    r_t^b &= \sigma(W_0^b x_t + W_1^b h_{t-1} + b_0^b + b_1^b) \\
    z_t^b &= \sigma(W_0^b x_t + W_1^b h_{t-1} + b_0^b + b_1^b) \\
    h_t^{b'} &= \tanh(W_2^b x_t + b_2^b + r_t^b \cdot (W_3^b h_{t-1} + b_3^b)) \\
    h_t^b &= (1 - z_t^b) \cdot h_t^{b'} + z_t^b \cdot h_{t-1} \\
    h_t &= [h_t^f; h_t^b]
\end{align*}
\]

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 $6S$ 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.

**Warning:** train and use_cudnn arguments are not supported anymore since v2. Instead, use chainer.using_config('train', train) and chainer.using_config('use_cudnn', use_cudnn) respectively. See chainer.using_config().

**Parameters**

- **n_layers** (`int`) – Number of layers.
- **dropout_ratio** (`float`) – Dropout ratio.
- **hx** (`chainer.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 chainer.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 $(I, N)$ shape as they are multiplied with input variables. All other matrices has $(N, N)$ shape.
- **bs** (`list of list of chainer.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 chainer.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 $xs[t].shape[0] \geq xs[t + 1].shape[0]$.  
- **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 \( \text{Variable} \). 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_bilstm

\[
\text{chainer.functions.n_step_bilstm}(n\_layers, \text{dropout\_ratio}, hx, cx, ws, bs, xs)
\]

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 $x_t$.

\[ i_t^f = \sigma(W_f^f x_t + W_{f-1} h_{t-1} + b_f^f + b_{f}^l), \]

\[ f_t^f = \sigma(W_f^f x_t + W_{f-1} h_{t-1} + b_f^f + b_{f}^b), \]

\[ o_t^f = \sigma(W_f^f x_t + W_{f-1} h_{t-1} + b_f^f + b_{f}^b), \]

\[ a_t^f = \tanh(W_f^f x_t + W_{f-1} h_{t-1} + b_f^f + b_{f}^b), \]

\[ c_t^f = f_t^f \cdot c_{t-1}^f + i_t^f \cdot o_t^f, \]

\[ h_t^f = o_t^f \cdot \tanh(c_t^f), \]

\[ i_t^b = \sigma(W_b^b x_t + W_{b-1} h_{t-1} + b_b^b + b_{b}^l), \]

\[ f_t^b = \sigma(W_b^b x_t + W_{b-1} h_{t-1} + b_b^b + b_{b}^b), \]

\[ o_t^b = \sigma(W_b^b x_t + W_{b-1} h_{t-1} + b_b^b + b_{b}^b), \]

\[ a_t^b = \tanh(W_b^b x_t + W_{b-1} h_{t-1} + b_b^b + b_{b}^b), \]

\[ c_t^b = f_t^b \cdot c_{t-1}^b + i_t^b \cdot o_t^b, \]

\[ h_t^b = o_t^b \cdot \tanh(c_t^b), \]

\[ h_t = [h_t^f; h_t^b] \]

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 $h_{k-1}$ of the $k-1$-th layer. Note that all input variables except the first layer may have different shape from the first layer.

**Warning:** `train` and `use_cudnn` arguments are not supported anymore since v2. Instead, use `chainer.using_config('train', train)` and `chainer.using_config('use_cudnn', use_cudnn)` respectively. See `chainer.using_config()`.

**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 \((1, N)\)-shaped because they are multiplied with input variables, where \(i\) is the size of the input. \(ws[1][j]\) where \(2 <= i < 4\) 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 have 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**

```
>>> 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)
>>> 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:
...
(continues on next page)
```
... 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  # others are (out_size, out_size)
(2, 2)

>>> hy, cy, ys = F.n_step_bilstm(  
...     n_layers, dropout_ratio, hx, cx, ws, bs, xs)

>>> hy.shape  # hy, cy, ys = F.n_step_bilstm(  
...     n_layers, dropout_ratio, hx, cx, ws, bs, xs)
(4, 3, 2)

>>> cy.shape  # hy, cy, ys = F.n_step_bilstm(  
...     n_layers, dropout_ratio, hx, cx, ws, bs, xs)
(4, 3, 2)

>>> [y.shape for y in ys]  # hy, cy, ys = F.n_step_bilstm(  
...     n_layers, dropout_ratio, hx, cx, ws, bs, xs)
[(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 \( W_0^f \) 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 $2S$ 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.

```
Warning: train and use_cudnn arguments are not supported anymore since v2. Instead, use chainer.using_config('train', train) and chainer.using_config('use_cudnn', use_cudnn) respectively. See chainer.using_config().
```

**Parameters**

- `n_layers` (*int*) – Number of layers.

- `dropout_ratio` (*float*) – Dropout ratio.

- `hx` (*chainer.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 chainer.Variable*) – 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 $W^{f}_j$ if $di = 0$ and corresponding with $W^{b}_j$ if $di = 1$ in the equation. Only $ws[0][j]$ and $ws[1][j]$ where $0 <= j < 1$ are $(I, N)$ shape as they are multiplied with input variables. All other matrices has $(N, N)$ shape.

- `bs` (*list of list of chainer.Variable*) – 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 $b^{f}_j$ if $di = 0$ and corresponding with $b^{b}_j$ if $di = 1$ in the equation. Shape of each matrix is $(N,)$ where $N$ is dimension of hidden units.

- `xs` (*list of chainer.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.

**Warning:** train and use_cudnn arguments are not supported anymore since v2. Instead, use chainer.using_config('train', train) and chainer.using_config('use_cudnn', use_cudnn) respectively. See chainer.using_config().

### Parameters

- **n_layers** (*int*) – Number of layers.
- **dropout_ratio** (*float*) – Dropout ratio.
- **hx** (*chainer.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 chainer.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 $0 <= j < 3$ is $(I, N)$ shape as they are multiplied with input variables. All other matrices has $(N, N)$ shape.
- **bs** (*list of list of chainer.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 chainer.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 $xs[t].shape[0] >= xs[t + 1].shape[0]$.

### Returns

This function returns a tuple containing three elements, $hy$ and $ys$.

- **$hy$** is an updated hidden states whose shape is same as $hx$. 

---

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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 ℎ₀, an initial cell state 𝑐₀, an input sequence 𝑥, weight matrices 𝑊, and bias vectors 𝑏. This function calculates hidden states ℎₜ and ℎₜ for each time 𝑡 from input 𝑥ₜ.

\[
\begin{align*}
iₜ &= \sigma(W₀xₜ + W₃hₜ₋₁ + b₀ + b₄) \\
fₜ &= \sigma(W₁xₜ + W₅hₜ₋₁ + b₁ + b₅) \\
oₜ &= \sigma(W₂xₜ + W₆hₜ₋₁ + b₂ + b₆) \\
aₜ &= \tanh(W₇xₜ + W₈hₜ₋₁ + b₃ + b₇) \\
cₜ &= fₜ \cdot cₜ₋₁ + iₜ \cdot aₜ \\
hₜ &= oₜ \cdot \tanh(cₜ)
\end{align*}
\]

As the function accepts a sequence, it calculates ℎₜ 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 ℎₜₙ of the 𝑘−1-th layer. Note that all input variables except the first layer may have different shape from the first layer.

Warning: train and use_cudnn arguments are not supported anymore since v2. Instead, use chainer.using_config('train', train) and chainer.using_config('use_cudnn', use_cudnn) respectively. See chainer.using_config().

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 𝑊ᵢ in the equation. Only ws[0][j] where 0 <= j < 4 are (I, N)-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 𝑏ᵢ in the equation. The shape of each matrix is (N,) where N is the dimension of the hidden units.
• \(\mathbf{xs}\) (list of \texttt{Variable}) – A list of \texttt{Variable} holding input values. Each element \(\mathbf{xs}[t]\) 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. \texttt{transpose_sequence()} can be used to transpose a list of \texttt{Variables} each representing a sequence. When sequences has different lengths, they must be sorted in descending order of their lengths before transposing. So \(\mathbf{xs}\) needs to satisfy \(\mathbf{xs}[t].shape[0] \geq \mathbf{xs}[t + 1].shape[0]\).

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 \texttt{Variable}. Each element \(\mathbf{ys}[t]\) holds hidden states of the last layer corresponding to an input \(\mathbf{xs}[t]\). 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 \(\mathbf{xs}[t]\).

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 \texttt{chainer.functions.lstm}.

See also:

\texttt{chainer.functions.lstm()}

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, batches[0], out_size)
>>> hx = np.ones(h_shape).astype(np.float32)
>>> cx = np.ones(h_shape).astype(np.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([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][:4].shape are (out_size, in_size)
(2, 3)
>>> ws[1][0].shape  # others are (out_size, out_size)
(2, 2)
>>> bs[0][0].shape
(2,)
>>> hy, cy, ys = F.n_step_lstm(...  # n_layers, dropout_ratio, hx, cx, ws, bs, xs)
>>> 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, 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 \( n\_layers \) 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.

**Warning:** `train` and `use_cudnn` arguments are not supported anymore since v2. Instead, use `chainer.using_config('train', train)` and `chainer.using_config('use_cudnn', use_cudnn)` respectively. See `chainer.using_config()`.

**Parameters**

- **n_layers** *(int)* – Number of layers.
- **dropout_ratio** *(float)* – Dropout ratio.
- **hx** *(chainer.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 chainer.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 \( 0 <= j < 1 \) is \((I, N)\) shape as they are multiplied with input variables. All other matrices has \((N, N)\) shape.
- **bs** *(list of list of chainer.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.

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- **xs** (*list of chainer.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 have different lengths, sort sequences in descending order by length, and transpose the sorted sequence. `transpose_sequence()` transposes a list of Variable() holding sequence. So \(xs\) needs to satisfy \(xs[t].shape[0] \geq xs[t + 1].shape[0]\).

- **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.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

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### 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, ...) 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** *(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],  # 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 = np.array([1, 0, 2, 1], np.int32)
>>> F.accuracy(y, t).data  # 100% accuracy because all samples are correct
array(1.)
>>> t = np.array([1, 0, 0, 0], np.int32)
>>> F.accuracy(y, t).data  # 50% accuracy because 1st and 2nd samples are correct.
array(0.5)
>>> F.accuracy(y, t, ignore_label=0).data  # 100% accuracy because of ignoring the -> 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([[-2.0, 0.0], ...
# prediction labels are [0, 1]
... [3.0, -5.0]]) # prediction labels are [1, 0]
>>> t = np.array([[0, 1], ...
# [0, 1], np.int32])
>>> y = np.array([[0, 1], ...
[1, 0], np.int32])
>>> F.binary_accuracy(y, t).data # 100% accuracy because all samples are correct.
array(1.)
>>> t = np.array([[0, 0], ...
[1, 1], np.int32])
>>> F.binary_accuracy(y, t).data # 50% accuracy because y[0][0] and y[1][0] are correct.
array(0.5)
>>> t = np.array([[0, -1], ...
[1, -1], np.int32])
>>> F.binary_accuracy(y, t).data # 100% accuracy because of ignoring y[0][1] and y[1][1].
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:** \( \frac{tp}{tp+tn} \)
- **F beta Score:** The weighted harmonic average of Precision and Recall.
- **Support:** The number of instances of each ground truth label.

Here, \( tp, fp, \) and \( tn \) stand for the number of true positives, false positives, and true negative, 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**

```python
chainer.functions.f1_score(y, t, label_num=None, ignore_label=-1)
```

**chainer.functions.precision**

```python
chainer.functions.precision(y, t, label_num=None, ignore_label=-1)
```

**chainer.functions.r2_score**

```python
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**

```python
chainer.functions.recall(y, t, label_num=None, ignore_label=-1)
```

**4.2.6 Loss functions**

**chainer.functions.absolute_error**  
Element-wise absolute error function.

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### `chainer.functions.absolute_error`

`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`

`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', loss values are summed up.

**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.
- \( \text{reduce} \) (*str*) – Reduction option. Its value must be either 'sum' 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', the output variable holds a scalar value.

**Return type** *Variable*

### chainer.functions.black_out

```python
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

\[p(y) = \frac{\exp(W_y^T x)}{\sum_{s \in \text{samples}} \exp(W_s^T x)}.\]

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

See: BlackOut: Speeding up Recurrent Neural Network Language Models With Very Large Vocabularies
See also: BlackOut.

chainer.functions.connectionist_temporal_classification

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 $x$.

**Note:** This function supports (batch, sequence, 1-dimensional input)-data.

```python
chainer.functions.contrastive
```

**chainer.functions.contrastive**($x_0$, $x_1$, $y$, 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 $d_n = \|x_{0n} - x_{1n}\|_2$, $x_{0n}$ and $x_{1n}$ 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**

4.2. Functions
```python
>>> 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')
>>> z.shape
(2,)
>>> z.data
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 $t$, $x_t$ 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

$$L = -\left( \sum_{i=1}^{l} x_{i} y_{i} + \sum_{i=1}^{l-1} c_{y_{i} y_{i+1}} - \log(Z) \right),$$

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)
```

```python
>>> a = [a1, a2, a3, a4]
>>> b = [b1, b2, b3]
>>> c = [c1, c2]
```

where `a1` 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:
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].
chainer.functions.cross_covariance

```
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 covariancet 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*

---

chainer.functions.decov

```
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:* This cost can be used to disentangle variables. See [https://arxiv.org/abs/1412.6583v3](https://arxiv.org/abs/1412.6583v3) for details.

**chainer.functions.discriminative_margin_based_clustering_loss**

This is the implementation of the following paper: [https://arxiv.org/abs/1708.02551](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**

This 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 $N(0, I)$

$$D_{\text{KL}}(N(\mu, S)\|N(0, I)),$$

where $S$ is a diagonal matrix such that $S_{ii} = \sigma^2_i$ 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`, loss values are summed up.

**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` 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`, the output variable holds a scalar value.

**Return type** *Variable*

**chainer.functions.gaussian_nll**

```python
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 $S_{ii} = \sigma^2_i$.

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`, loss values are summed up.

**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` 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`, 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 \(l(x, \delta)\) be \([\max(0, 1 - \delta x)]^p\). 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.

```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([1, 0]).astype(np.int32)
>>> t
array([1, 0], dtype=int32)
>>> F.hinge(x, t)
variable(2.5)
```
F.hinge(x, t, reduce='no')
variable([[0., 0., 1.5],
         [0., 3., 0.5]])
F.hinge(x, t, norm='L2')
variable(5.75)

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 \((N, K)\).
- \( t \) (Variable or N-dimensional array) – Target variable for regression. The shape of \( t \) should be \((N, K)\).
- \( \delta \) (float) – Constant variable for Huber loss function as used in definition.
- \( \text{reduce} \) (str) – Reduction option. Its value must be either 'sum_along_second_axis' or 'no'. Otherwise, \( \text{ValueError} \) is raised.

Returns A variable object holding a scalar array of the Huber loss \( L_{\delta} \). If \( \text{reduce} \) 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 \( t \).

>>> 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')
Example with reduction along the second axis.

```python
>>> 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.mean_absolute_error(x0, x1)`

Mean absolute error function.

This function computes mean absolute error between two variables. The mean is taken over the minibatch.

**Parameters**


**Returns** A variable holding an array representing the mean absolute error of two inputs.

**Return type** [Variable](https://pytorch.org/docs/stable/torch.html#torch.Variable)

**chainer.functions.mean_squared_error**

`chainer.functions.mean_squared_error(x0, x1)`

Mean squared error function.

This function computes mean squared error between two variables. The mean is taken over the minibatch. Note that the error is not scaled by 1/2.

**Parameters**


**Returns** A variable holding an array representing the mean squared error of two inputs.

**Return type** [Variable](https://pytorch.org/docs/stable/torch.html#torch.Variable)

**chainer.functions.negative_sampling**

`chainer.functions.negative_sampling(x, t, W, sampler, sample_size, reduce='sum')`

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.

\[
f(x, p) = -\log \sigma(x^\top w_p) - k \sum_{i \sim P(i)} \log \sigma(-x^\top w_i)\]

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 *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, *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 ’sum’, the output variable holds a scalar value.

**Return type** *Variable*

See: Distributed Representations of Words and Phrases and their Compositionality

See also: *NegativeSampling*.

**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 '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.data
array([[ 0.126928 , 0.04858735, 0.974077 ],
       [ 0.00671535, 0.126928 , -0. ]], dtype=float32)
```

**chainer.functions.softmax_cross_entropy**

chainer.functions.**softmax_cross_entropy**(x, t, normalize=True, cache_score=True, class_weight=None, ignore_label=-1, reduce='mean', enable_double_backprop=False)

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] == ignore_label, corresponding x[i] is ignored.

- **normalize (bool)** – If True, this function normalizes the cross entropy loss across all instances. If False, it only normalizes along a batch size.
• **cache_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 `enable_double_backprop` option is True, this option is forcibly turned off and the function does not cache the intermediate value.

• **class_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.shape[1],)`. If this is not None, each class weight `class_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.

• **ignore_label** *(int)* – Label value you want to ignore. Its default value is `-1`. See description of the argument `t`.

• **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.

• **enable_double_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.

**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** *(x0, x1)*

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**

- **x0** (*Variable* or *N-dimensional array*) – Input variable.
- **x1** (*Variable* or *N-dimensional array*) – Input variable.

**Returns** A variable holding an array representing the squared error of two inputs.

**Return type** *Variable*

### 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 $(N, K)$.

$$L(a, p, n) = \frac{1}{N} \left( \sum_{i=1}^{N} \max\{d(a_i, p_i) - d(a_i, n_i) + \text{margin}, 0\} \right)$$

where $d(x_i, y_i) = \|x_i - y_i\|_2^2$.

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.
>> 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.data
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

- **chainer.functions.absolute**: Element-wise absolute.
- **chainer.functions.arccos**: Elementwise arccosine function.
- **chainer.functions.arcsin**: Elementwise arcsine function.
- **chainer.functions.arctan**: Elementwise arctangent function.
- **chainer.functions.arctan2**: Elementwise arctangent function with two arguments.
- **chainer.functions.argmax**: Returns index which holds maximum of array elements over a given axis.
- **chainer.functions.argmin**: Returns index which holds minimum of array elements over a given axis.
- **chainer.functions.average**: Calculate weighted average of array elements over a given axis.
- **chainer.functions.batch_inv**: Computes the inverse of a batch of square matrices.
- **chainer.functions.batch_l2_norm_squared**: L2 norm (a.k.a. Euclidean norm) squared.
- **chainer.functions.batch_matmul**: Computes the batch matrix multiplications of two sets of arrays.
- **chainer.functions.bias**: Elementwise summation with broadcasting.
- **chainer.functions.ceil**: Elementwise ceil function.
- **chainer.functions.clip**: Clips (limits) elements of input variable.
- **chainer.functions.cos**: Elementwise cos function.
- **chainer.functions.cosh**: Elementwise hyperbolic cosine function.
- **chainer.functions.cumprod**: Cumulative prod of array elements over a given axis.
- **chainer.functions.cumsum**: Cumulative sum of array elements over a given axis.
- **chainer.functions.det**: Computes the determinant of a single square matrix.
- **chainer.functions.batch_det**: Computes the determinant of a batch of square matrices.
- **chainer.functions.digamma**: Digamma function.
- **chainer.functions.einsum**: Einstein summation
- **chainer.functions.erf**: Elementwise error function.
- **chainer.functions.erfc**: Elementwise complementary error function.
- **chainer.functions.erfcinv**: Elementwise inverse function of complementary error function.
- **chainer.functions.erfcx**: Elementwise scaled complementary error function.
- **chainer.functions.erfinv**: Elementwise inverse function of error function.
- **chainer.functions.exp**: Elementwise exponential function.

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<td>Element-wise maximum of input variables.</td>
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chainer.functions.absolute

chainer.functions.absolute(self)

Element-wise absolute.

Returns  Output variable.

Return type  Variable

chainer.functions.arccos

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

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

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.
- \( x_2 \) (Variable or N-dimensional array) – X-coordinates.

**Returns** Angles in radians, in the range \([-\pi, \pi]\).

**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. \(axis\) 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:

\[
\begin{align*}
x & : 100 \times 3 \times 40 \times 5 \times 6 \\
y & : 3 \times 40 \\
axis & : 1
\end{align*}
\]

is equivalent to the following numpy broadcasting:

\[
\begin{align*}
x & : 100 \times 3 \times 40 \times 5 \times 6 \\
y & : (1 \times) 3 \times 40 \times 1 \times 1
\end{align*}
\]

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 summed.
- \(y\) (*Variable* or *N-dimensional array*) – Input variable to sum, broadcasted.
- \(axis\) (*int*) – The first axis of \(x\) along which \(y\) is applied.

**Returns** Output variable.

**Return type** *Variable*

### chainer.functions.ceil

\[
\text{chainer.functions.}\text{ceil}(x)
\]

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.clip

\[
\text{chainer.functions.}\text{clip}(x, x_{\text{min}}, x_{\text{max}})
\]

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.

**Parameters**

- \(x\) (*Variable* or *N-dimensional array*) – Input variable to be clipped.
- \(x_{\text{min}}\) (*float*) – Minimum value.
- \(x_{\text{max}}\) (*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

chainer.functions.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

chainer.functions.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', 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)
>>> 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 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.erfcx

chainer.functions.erfcx(x)
Elementwise scaled 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.erfinv

chainer.functions.erfinv(x)
Elementwise inverse function of error 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.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.

   \[ y_i = x_i \mod\ divisor \]

   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.

**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**

```python
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**

```python
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**

```python
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**

```python
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).data
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.

- **x2** (*Variable* or *N-dimensional array*) – Input variables to be compared.

Returns   Output variable.

Return type   *Variable*
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 can not 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  \textit{Variable}

\textbf{chainer.functions.rsqrt}

\texttt{chainer.functions.rsqrt}(x)

Computes elementwise reciprocal of square root of input $x_i$.

$$y_i = \frac{1}{\sqrt{x_i}}.$$  

\textbf{Parameters}  \textit{x} (\textit{Variable} or \textit{N-dimensional array}) – Input variable.

\textbf{Returns}  Output variable.

\textbf{Return type}  \textit{Variable}

See also:  \texttt{sqrt()}

\textbf{chainer.functions.scale}

\texttt{chainer.functions.scale}(x, y, \textit{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. \textit{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{verbatim}
  x : 100 x 3 x 40 x 5 x 6
  y : 3 x 40
  axis : 1
\end{verbatim}

is equivalent to the following numpy broadcasting:

\begin{verbatim}
  x : 100 x 3 x 40 x 5 x 6
  y : (1 x) 3 x 40 x 1 x 1
\end{verbatim}

Note that the axis of \textit{x} to which we apply \textit{y} is specified by the argument \textit{axis}, whose meaning is different from numpy's \textit{axis}.

\textbf{Parameters}

\begin{itemize}
  \item \textit{x} (\textit{Variable} or \textit{N-dimensional array}) – Input variable to be scaled.
  \item \textit{y} (\textit{Variable} or \textit{N-dimensional array}) – Input variable to scale, broadcasted.
  \item \textit{axis} (\textit{int}) – The first axis of \textit{x} along which \textit{y} is applied.
\end{itemize}

\textbf{Returns}  Output variable.

\textbf{Return type}  \textit{Variable}

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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.

   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.
• \texttt{b} (\texttt{Variable} or \texttt{CooMatrix}) – The right operand of matrix multiplication.
• \texttt{transa} (\texttt{bool}) – If \texttt{True}, each matrix in \texttt{a} will be transposed.
• \texttt{transb} (\texttt{bool}) – If \texttt{True}, each matrix in \texttt{b} will be transposed.

\textbf{Returns} Result of batched mat-mul.

\textbf{Return type} \texttt{Variable}

\textbf{See also:}
See \texttt{to_coo()} for how to construct a COO matrix from an array.

\textbf{Note:} Performance of this function on GPU can be improved by using the \texttt{order} argument of \texttt{CooMatrix} when the sparse matrix is created.

\textbf{chainer.functions.sqrt}

\texttt{chainer.functions.sqrt}(\texttt{x})

Elementwise square root function.

$$y_i = \sqrt{x_i}.$$  

If the value of \(x_i\) is negative, it returns \texttt{Nan} for \(y_i\) respect to underlying numpy and cupy specification.

\textbf{Parameters} \texttt{x} (\texttt{Variable} or \texttt{N-dimensional array}) – Input variable.

\textbf{Returns} Output variable.

\textbf{Return type} \texttt{Variable}

\textbf{chainer.functions.square}

\texttt{chainer.functions.square}(\texttt{x})

Elementwise square function.

$$y_i = x_i^2.$$  

\textbf{Parameters} \texttt{x} (\texttt{Variable} or \texttt{N-dimensional array}) – Input variable.

\textbf{Returns} Output variable.

\textbf{Return type} \texttt{Variable}

\textbf{chainer.functions.squared_difference}

\texttt{chainer.functions.squared_difference}(\texttt{x1}, \texttt{x2})

Squared difference of input variables.

\textbf{Parameters}
• \texttt{x1} (\texttt{Variable} or \texttt{N-dimensional array}) – Input variables to be compared.
• \texttt{x2} (\texttt{Variable} or \texttt{N-dimensional array}) – Input variables to be compared.

\textbf{Returns} \((x1 - x2) ** 2\) element-wise.

\textbf{Return type} \texttt{Variable}
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 \((s_1, s_2, ..., s_N)\) -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
()  
>>> y.data
array(15., dtype=float32)
>>> y = F.sum(x, axis=1)
>>> y.shape
(2,)
>>> y.data
array([ 3., 12.], dtype=float32)
>>> y = F.sum(x, keepdims=True)
>>> y.shape
(1, 1)
>>> y.data
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
```
```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**

```python
>>> 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:
4.2.8 Noise injections

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**chainer.functions.dropout**

`chainer.functions.dropout(x, ratio=.5, *, mask=None, return_mask=False)`

Drops elements of input variable randomly.

This function drops input elements randomly with probability `ratio` and scales the remaining elements by factor \( 1 / (1 - \text{ratio}) \). In testing mode (i.e., `chainer.config.train` is set to `False`), it does nothing and just returns `x`.

**Warning:** train argument is not supported anymore since v2. Instead, use `chainer.using_config('train', boolean)`. See `chainer.using_config()`.

**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 <= \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.
```python
>>> x = np.array([[-1, 0], [2, -3], [-2, 1]], np.float32)
>>> with chainer.using_config('train', True):
...     y = F.dropout(x)
>>> y.data
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.data).all()
True
>>> with chainer.using_config('train', False):
...     y = F.dropout(x)  # dropout in test mode returns original input
>>> (x == y.data).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 \( \text{Gumbel}(0, 1) \).

See Categorical Reparameterization with Gumbel-Softmax.

**Parameters**

- \( \log \pi \) (\text{Variable or N-dimensional array}) – Input variable representing pre-normalized log-probability \( \log \pi \).

- \( \tau \) (float or \text{Variable or N-dimensional array}) – Input variable representing temperature \( \tau \).

**Returns** Output variable.

**Return type** \text{Variable}

### chainer.functions.simplified_dropconnect

```python
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 \( \text{ratio} \) 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 \( Y = x W^\top + b \).

In testing mode, zero will be used as simplified dropconnect ratio instead of \( \text{ratio} \).

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**

- \( x \) (\text{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 \( N \).

- \( W \) (\text{Variable or N-dimensional array}) – Weight variable of shape \( (M, N) \).

- \( b \) (\text{Variable or N-dimensional array}) – Bias variable (optional) of shape \( (M,) \).

- \( \text{ratio} \) (float) – Dropconnect ratio.

- \( \text{train} \) (bool) – If \text{True}, executes simplified dropconnect. Otherwise, simplified dropconnect function works as a linear function.

- \( \text{mask} \) (None or \text{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 \text{use_batchwise_mask} is ignored. Main purpose of this option is debugging. \text{mask} array will be used as a dropconnect mask.

- \( \text{use_batchwise_mask} \) (bool) – If \text{True}, dropped connections depend on each sample in mini-batch.

**Returns** Output variable.

**Return type** \text{Variable}

See also:

Dropconnect

See also:
chainer.functions.zoneout

chainer.functions.zoneout(h, x, ratio=.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 \( x \).

**Warning:** train argument is not supported anymore since v2. Instead, use chainer.
using_config('train', train). See chainer.using_config().

**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

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chainer.functions.batch_normalization

chainer.functions.batch_normalization(x, gamma, beta, eps=2e-5, 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.

**Warning:** `train` argument is not supported anymore since v2. Instead, use `chainer.using_config('train', train)`. See `chainer.using_config()`.

**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`

`chainer.functions.batch_renormalization`

**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.

See: [Batch Renormalization: Towards Reducing Minibatch Dependence in Batch-Normalized Models](#).

See also: `BatchRenormalization`

### chainer.functions.fixed_batch_normalization

```python
caller.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

```python
caller.functions.fixed_batch_renormalization(x, gamma, beta, mean, var, eps=2e-05)
```

### chainer.functions.group_normalization

```python
caller.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

**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 \( \text{linear}() \).
- **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

**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:

\[
y_i = \frac{x_i}{\left(k + \alpha \sum_{j=\max(1,i-n/2)}^{\min(N,i+n/2)} x_j^2 \right)^{\beta}}.
\]

**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

chainer.functions.normalize(x, eps=1e-05, axis=1)
L2 norm squared (a.k.a. Euclidean norm).

This function implements L2 normalization on a vector along the given axis. No reduction is done along the normalization axis.

In the case when 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:

\[ y_i = \frac{x_i}{\|x_i\|_2 + \epsilon} \]

eps is used to avoid division by zero when norm of x along the given axis is zero.

The default value of axis is determined for backward compatibility.

Parameters
• x (Variable or N-dimensional array) – Two dimensional output variable. The first dimension is assumed to be the mini-batch dimension.
• eps (float) – Epsilon value for numerical stability.
• 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

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Spatial pyramid pooling function.

chainer.functions.unpooling_1d

Inverse operation of 1-dimensional spatial pooling.

chainer.functions.unpooling_2d

Inverse operation of pooling for 2d array.

chainer.functions.unpooling_3d

Inverse operation of 3-dimensional spatial pooling.

chainer.functions.unpooling_nd

Inverse operation of N-dimensional spatial pooling.

chainer.functions.upsampling_2d

Upsampling using pooling indices.

chainer.functions.average_pooling_1d

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

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()`.

```python
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 False, 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

```python
chainer.functions.roi_average_align_2d
```

chainer.functions.roi_average_align_2d(x, rois, roi_indices, outsize, spatial_scale, sampling_ratio=None)

Spatial Region of Interest (ROI) average align function.

This function acts similarly to `roi_pooling_2d()`, but it computes average 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_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:

\[
\begin{align*}
k_h^{(i)} &= \lceil b_h / 2^i \rceil, \\
k_w^{(i)} &= \lceil b_w / 2^i \rceil, \\
p_h^{(i)} &= (2^i k_h^{(i)} - b_h) / 2, \\
p_w^{(i)} &= (2^i k_w^{(i)} - b_w) / 2,
\end{align*}
\]

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.


Parameters

- **x** *(Variable)* – Input variable. The shape of $x$ should be $(\text{batchsize}, \# \text{ of channels}, \text{height}, \text{width})$.
- **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 $(\text{batchsize}, c \sum_{h=0}^{H-1} 2^h, 1, 1)$, 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**

```
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**

```
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 \((p_1, p_2, ..., p_N)\). pad=p is equivalent to \((p, p, ..., p)\).

• **outsize** (*None or pair of ints*) – Expected output size of unpooling operation \((out_1, out_2, ..., out_N)\). 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 is False.

**Returns** Output variable.

**Return type** *Variable*

### chainer.functions.upsampling_2d

chainer.functions.upsampling_2d(x, indexes, ksize=None, stride=None, pad=0, outsize=None, cover_all=True)

Upsampling using pooling indices.

This function produces an upscaled 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)
>>> pooled_x.array
array([[[ 8., 10., 12.],
        [20., 22., 24.],
        [32., 34., 36.]]], dtype=float32)
>>> 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:]
...)
>>> upsampled_x.shape
(1, 1, 6, 6)
>>> upsampled_x.data
array([[[ 0.,  0.,  0.,  0.,  0.,  0.],
        [ 0.,  8.,  0., 10.,  0., 12.],
        [ 0.,  0.,  0.,  0.,  0.,  0.],
        [ 0., 20.,  0., 22.,  0., 24.],
```

(continues on next page)
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. `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 (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

**chainer.functions.forget**

Calls a function without storing intermediate results.

**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 computational graph as they are required on backward propagation. Sometimes these results consume too much memory. `F.forget` forgets such intermediate results on forward propagation, and still supports backpropagation with recalculation.

On a forward propagation, `F.forget` calls a given function with given variables without creating a computational 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:** F.forget does not support functions which behave differently in multiple calls with the same inputs, such as `F.dropout()` and `F.negative_sampling()`.

**Note:** In case input argument variables are of N-dimensional array objects, arguments will automatically be converted to Variables. This conversion takes place to ensure that this function is included in the computational graph to enable backward computations.

**Note:** F.forget does not support double backpropagation.

**Note:** If you want to use 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 `chainer.config.in_recomputing` flag to check if the forward computation is the first call in an iteration. Please see the implementation of `BatchNormalization` for detail.

**Parameters**

- `func` (callable) – A function to call. It needs to be called with Variable object(s) and to return a Variable object or a tuple of Variable objects.
- `xs` (tuple of Variable or N-dimensional array) – Argument variables of the function.

**Returns** A variable `func` returns. If it returns a tuple, the method returns a tuple too.

**Return type** Variable

### 4.2.12 Function base

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**chainer.Function**

**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 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, 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.

**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)
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 own-
ership 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 attribute of input variables exist on a GPU device, that device is made current before
calling forward(), so implementors 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_indexes)` 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*.
Check 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 the function hook.

Parameters:

- `name` (str) – The name of the function hook to be unregistered.

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.

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.

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 re-
quired 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.

Attributes

function
The Function object that this adapter is wrapping.
inputs = None

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.

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()`.

**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 attribute of input variables exist on a GPU device, that device is made current before calling forward(), so implementors 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 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 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_indexes) 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_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_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.

**Attributes**

`inputs = None`

`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.

`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)
```

See also:
See `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
```

See also:
See `force_backprop_mode()` for details on how to override this context.

**chainer.grad**

`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 back-
  prop 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 Nones.

- **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
  Nones.

- **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 back-
  propagation.

- **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钩子名称</th>
<th>功能描述</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.function_hooks.CUDAProfileHook</td>
<td>函数钩子，用于测量函数在cupy内存池中的内存使用情况。</td>
</tr>
<tr>
<td>chainer.function_hooks.CupyMemoryProfileHook</td>
<td>函数钩子，用于打印调试信息。</td>
</tr>
<tr>
<td>chainer.function_hooks.TimerHook</td>
<td>函数钩子，用于测量函数的耗时。</td>
</tr>
</tbody>
</table>

### 4.2. Functions

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**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.
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:

```
<table>
<thead>
<tr>
<th>FunctionName</th>
<th>UsedBytes</th>
<th>AcquiredBytes</th>
<th>Occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>LinearFunction</td>
<td>5.16GB</td>
<td>179.98MB</td>
<td>3900</td>
</tr>
<tr>
<td>ReLU</td>
<td>991.82MB</td>
<td>458.97MB</td>
<td>2600</td>
</tr>
<tr>
<td>SoftmaxCrossEntropy</td>
<td>7.71MB</td>
<td>5.08MB</td>
<td>1300</td>
</tr>
<tr>
<td>Accuracy</td>
<td>617.97KB</td>
<td>351.00KB</td>
<td>700</td>
</tr>
</tbody>
</table>
```

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

__enter__(self)
__exit__(self, *args)

added (function=None)

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=None)
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 (file=<_io.TextIOWrapper name='<stdout>' mode='w' encoding='UTF-8'>)
Prints a summary report of memory profiling in functions.

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.

Attributes

name = 'CupyMemoryProfileHook'
Chainer Documentation, Release 5.3.0

chainer.function_hooks.PrintHook

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() # doctest:+SKIP
```

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

__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.

4.2. Functions
• **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.

**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>593.05ms</td>
<td>2600</td>
</tr>
<tr>
<td>SoftmaxCrossEntropy</td>
<td>824.11ms</td>
<td>1300</td>
</tr>
<tr>
<td>Accuracy</td>
<td>176.54ms</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**

```python
__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** *(file=<_io.TextIOWrapper name='<stdout>' mode='w' encoding='UTF-8'>)*
Prints a summary report of time profiling in functions.

**summary** ()
Returns a summary of time profiling in functions.

**total_time** ()
Returns total elapsed time in seconds.

**Attributes**

**name = 'TimerHook'**
You can also implement your own function-hook to inject arbitrary code before/after the forward/backward propagation.

**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 \( \text{backward}() \) of some \( \text{Variable} \) is invoked, \( \text{backward\_preprocess}() \) (resp. \( \text{backward\_postprocess}() \)) of all function hooks registered to the function which holds this variable as a gradient are called before (resp. after) backward propagation.

\( \text{added}() \) and \( \text{deleted}() \) are called when the hook is registered or unregistered, respectively.

There are two ways to register \( \text{FunctionHook} \) objects to \( \text{FunctionNode} \) objects.

The first one is to use \texttt{with} statement. Function hooks hooked in this way are registered to all functions within \texttt{with} statement and are unregistered at the end of \texttt{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 \( \text{TimerHook} \), which is a subclass of \( \text{FunctionHook} \).

```python
>>> class Model(chainer.Chain):
...     def __init__(self):
...         super(Model, self).__init__()
...         with self.init_scope():
...             self.l = L.Linear(10, 10)
...         def __call__(self, x1):
...             return F.exp(self.l(x1))

>>> model1 = Model()
>>> model2 = Model()
>>> x = chainer.Variable(np.zeros((1, 10), np.float32))
>>> with chainer.function_hooks.TimerHook() as m:
...     _ = model1(x)
...     y = model2(x)
>>> model3 = Model()
>>> z = model3(y)
>>> print('Total time : {:.3f}'.format(m.total_time()))
... # doctest:+ELLIPSIS
Total time : ...
```

In this example, we measure the elapsed times for each forward propagation of all functions in \texttt{model1} and \texttt{model2}. Note that \texttt{model3} is not a target of measurement as \( \text{TimerHook} \) is unregistered before forward propagation of \texttt{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 \( \text{FunctionNode} \) object by calling its \texttt{add\_hook()} method. Function hooks registered in this way can be removed by \texttt{delete\_hook()} method. Contrary to the former registration method, function hooks are registered only to the function whose \texttt{add\_hook()} method is called.

If the hook is registered globally using \texttt{with} statement, \texttt{None} is passed as the \texttt{function} argument of \texttt{added()} and \texttt{deleted()}.

If the hook is registered in a specific function using \texttt{add\_hook()}, the \( \text{FunctionNode} \) instance is passed as the \texttt{function} argument of \texttt{added()} and \texttt{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.

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 to use them via the `chainer.links` package.

## 4.3.1 Learnable connections

<table>
<thead>
<tr>
<th>Link Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.links.Bias</code></td>
<td>Broadcasted elementwise summation with learnable parameters.</td>
</tr>
<tr>
<td><code>chainer.links.Bilinear</code></td>
<td>Bilinear layer that performs tensor multiplication.</td>
</tr>
<tr>
<td><code>chainer.links.ChildSumTreeLSTM</code></td>
<td>Child-Sum TreeLSTM unit.</td>
</tr>
<tr>
<td><code>chainer.links.Convolution1D</code></td>
<td>1-dimensional convolution layer.</td>
</tr>
<tr>
<td><code>chainer.links.Convolution2D</code></td>
<td>Two-dimensional convolutional layer.</td>
</tr>
<tr>
<td><code>chainer.links.Convolution3D</code></td>
<td>3-dimensional convolution layer.</td>
</tr>
<tr>
<td><code>chainer.links.ConvolutionND</code></td>
<td>N-dimensional convolution layer.</td>
</tr>
<tr>
<td><code>chainer.links.Deconvolution1D</code></td>
<td>1-dimensional deconvolution layer.</td>
</tr>
<tr>
<td><code>chainer.links.Deconvolution2D</code></td>
<td>Two dimensional deconvolution function.</td>
</tr>
<tr>
<td><code>chainer.links.Deconvolution3D</code></td>
<td>3-dimensional deconvolution layer.</td>
</tr>
<tr>
<td><code>chainer.links.DeconvolutionND</code></td>
<td>N-dimensional deconvolution function.</td>
</tr>
<tr>
<td><code>chainer.links.DeformableConvolution2D</code></td>
<td>Two-dimensional deformable convolutional layer.</td>
</tr>
<tr>
<td><code>chainer.links.DepthwiseConvolution2D</code></td>
<td>Two-dimensional depthwise convolutional layer.</td>
</tr>
<tr>
<td><code>chainer.links.DilatedConvolution2D</code></td>
<td>Two-dimensional dilated convolutional layer.</td>
</tr>
<tr>
<td><code>chainer.links.EmbedID</code></td>
<td>Efficient linear layer for one-hot input.</td>
</tr>
<tr>
<td><code>chainer.links.GRU</code></td>
<td>Stateful Gated Recurrent Unit function (GRU)</td>
</tr>
<tr>
<td><code>chainer.links.Highway</code></td>
<td>Highway module.</td>
</tr>
<tr>
<td><code>chainer.links.Inception</code></td>
<td>Inception module of GoogLeNet.</td>
</tr>
<tr>
<td><code>chainer.links.InceptionBN</code></td>
<td>Inception module of the new GoogLeNet with Batch-Normalization.</td>
</tr>
<tr>
<td><code>chainer.links.Linear</code></td>
<td>Linear layer (a.k.a. fully-connected layer).</td>
</tr>
<tr>
<td><code>chainer.links.LocalConvolution2D</code></td>
<td>Two-dimensional local convolutional layer.</td>
</tr>
<tr>
<td><code>chainer.links.LSTM</code></td>
<td>Fully-connected LSTM layer.</td>
</tr>
<tr>
<td><code>chainer.links.MLPConvolution2D</code></td>
<td>Two-dimensional MLP convolution layer of Network in Network.</td>
</tr>
<tr>
<td><code>chainer.links.NaryTreeLSTM</code></td>
<td>N-ary TreeLSTM unit.</td>
</tr>
<tr>
<td><code>chainer.links.NStepBiGRU</code></td>
<td>Stacked Bi-directional GRU for sequences.</td>
</tr>
<tr>
<td><code>chainer.links.NStepBiLSTM</code></td>
<td>Stacked Bi-directional LSTM for sequences.</td>
</tr>
<tr>
<td><code>chainer.links.NStepBiRNNReLU</code></td>
<td>Stacked Bi-directional RNN for sequences.</td>
</tr>
<tr>
<td><code>chainer.links.NStepBiRNNNTanh</code></td>
<td>Stacked Bi-directional RNN for sequences.</td>
</tr>
<tr>
<td><code>chainer.links.NStepGRU</code></td>
<td>Stacked Uni-directional GRU for sequences.</td>
</tr>
<tr>
<td><code>chainer.links.NStepLSTM</code></td>
<td>Stacked Uni-directional LSTM for sequences.</td>
</tr>
<tr>
<td><code>chainer.links.NStepRNNReLU</code></td>
<td>Stacked Uni-directional RNN for sequences.</td>
</tr>
<tr>
<td><code>chainer.links.NStepRNNTanh</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>
</tbody>
</table>

Continued on next page
Table 16 – continued from previous page

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<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></td>
</tr>
<tr>
<td><code>chainer.links.StatelessLSTM</code></td>
<td>Stateless LSTM layer.</td>
</tr>
</tbody>
</table>

**chainer.links.Bias**

```python
class chainer.links.Bias(axis=1, shape=None)
```

Class to broadcast an elementwise summation with learnable parameters.

Broadcasts an 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.

**Methods**

- `__call__(*args, **kwargs)`
  Call self as a function.
- `add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent**(name, value)
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)
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**()
Returns a generator of all child links.

**Returns**
A generator object that generates all child links.

**cleargrads**()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy**(mode='share')
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, 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 `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 True, persistent values are also copied. True by default.

**count_params()**

Counts the total number of parameters.

This method counts the total number of scalar values included in all the \texttt{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)**

Unregisters the link hook.

**Parameters** \texttt{name (str)} – The name of the link hook to be unregistered.

**disable\_update()**

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()**

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}.

**forward(*xs)**

Applies broadcasted elementwise summation.

**Parameters** \texttt{xs (list of Variables)} – Input variables whose length should be one if the link has a learnable bias parameter, otherwise should be two.

**init\_scope()**

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,))
```

**links (skipself=False)**

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=False)`

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=True)`

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=True)`

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)`

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, mode='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)
        self.conv = L.Convolution2D(None, 64, 3, 1, 1, nobias=True)
        self.bn = L.BatchNormalization(64)
        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.

**to_cpu**

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu**(device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

*device* – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64**

Copies parameter variables and persistent values to CPU.

**zerograds**

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

**Attributes**

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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 e1 (J)
• right_size (int) – Dimension of input vector e2 (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 are numpy.ndarray. If None, V1 and V2 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.
• V1 (Variable) – Linear weight parameter for the first argument.
• V2 (Variable) – Linear weight parameter for the second argument.
• b (Variable) – Bias parameter.

Methods
__call__(*args, **kwargs)
Call self as a function.

add_hook(hook, name=None)
Registers a link hook.

Parameters
• hook (LinkHook) – Link hook to be registered.
**add_param** *(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent** *(name, value)*

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)*

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** *

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads** *

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode='share')*

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

---

**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
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, 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 `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()`
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)`
Unregisters the link hook.

**Parameters** `name (str)` – The name of the link hook to be unregistered.

`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`.

`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`.

`forward(e1, e2)`
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`
**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,))
```

**links** *(skipself=False)*

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=False)*

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=True)*

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=True)*

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)*

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, mode='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)**

Serializes the link object.

**Parameters** `serializer` (`AbstractSerializer`) – Serializer object.

**to_cpu()**

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu (device=None)**

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters** `device` – Target device specifier. If omitted, the current device is used.

4.3. Link and Chains
Returns: self
to_intel64()
Copies parameter variables and persistent values to CPU.
zero_grads()
zero.grads()
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for
backward compatibility.
Deprecated since version v1.15: Use cleargrads() instead.

Attributes

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.

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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, **kwargs)

Call self as a function.

___getitem___(name)

Equivalent to getattr.

add_hook(hook, name=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(name, link)

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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

add_persistent(name, value)

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*)

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**()

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads**()

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode*='*share*')

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 it 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*, *copy_persistent*=*False*)

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**()

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)
```

Unregisters the link hook.

**Parameters** `name` (str) – The name of the link hook to be unregistered.

```python
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
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
forward(*cshsx)
```

Returns new cell state and output of Child-Sum TreeLSTM.

**Parameters** `cshsx` (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

```python
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=False)
```

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=False)
```

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=True)*

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=True)*

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)*

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, mode='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.
• **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.

`to_cpu` ()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

`to_gpu` *(device=None)*

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

* device – Target device specifier. If omitted, the current device is used.

Returns: self

`to_intel64` ()

Copies parameter variables and persistent values to CPU.

`zerograds` ()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

• **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.

• **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 for this link.

Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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, **kwargs)

Call self as a function.

add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add.persistent(name, value)

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)
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 ()
Returns a generator of all child links.

Returns
A generator object that generates all child links.

cleargrads ()
Clears all gradient arrays.
This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')
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, 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
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 ()
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)
```
Unregisters the link hook.

**Parameters** `name` (str) – The name of the link hook to be unregistered.

```python
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
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
forward(x)
```
Applies N-dimensional convolution layer.

**Parameters** `x` (Variable) – Input image.

**Returns** Output of convolution.

**Return type** Variable

```python
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=False)
```
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=False)
```
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=True)
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=True)
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)
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, mode='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:

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.

**to_cpu**

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu** *(device=None)*

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64**

Copies parameter variables and persistent values to CPU.

**zerograds**

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

**Attributes**

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.
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)

Warning: deterministic argument is not supported anymore since v2. Instead, use chainer.using_config('cudnn_deterministic', value (value is either True or False). See chainer.using_config().

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

4.3. Link and Chains
• \texttt{W (Variable)} – Weight parameter.
• \texttt{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 \texttt{in_channels} or fill it with \texttt{None}:

The below two cases are the same.

```python
>>> l = L.Convolution2D(7, 5)
>>> y = l(x)
>>> y.shape
(1, 7, 6, 6)
```

```python
>>> l = L.Convolution2D(\texttt{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 \texttt{stride} as keyword arguments. So the below two cases are the same.

```python
>>> l = L.Convolution2D(7, 5, \texttt{stride=1, pad=0})
>>> y = l(x)
>>> y.shape
(1, 7, 6, 6)
```

```python
>>> l = L.Convolution2D(\texttt{None}, 7, 5, 1, 0)
>>> y = l(x)
>>> y.shape
(1, 7, 6, 6)
```

Methods

```python
__call__(\*args, **kwargs)
Call self as a function.
add_hook(hook, name=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_param** *(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent** *(name, value)*

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)*

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** *

Returns a generator of all child links.

Returns A generator object that generates all child links.

**cleargrads** *

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode='share')*

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, 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 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 ()
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)
Unregisters the link hook.

Parameters **name** (str) – The name of the link hook to be unregistered.

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.

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.

forward (x)
Applies the convolution layer.

Parameters **x** (Variable) – Input image.

Returns Output of the convolution.

Return type Variable

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,))
```

links (skipself=False)

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=False)

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=True)

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=True)

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)

 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, mode='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)**

Serializes the link object.

Parameters **serializer** (AbstractSerializer) – Serializer object.

**to_cpu ()**

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu (device=None)**

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64()  
Copies parameter variables and persistent values to CPU.

zerograds()  
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

Attributes

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.

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 for this link.

Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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, **kwargs)  
Call self as a function.

add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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()
Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy(mode='share')
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 \textit{Link}

\texttt{copyparams}(\textit{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.

\textit{From v5.0.0:} this method also copies the persistent values (e.g. the moving statistics of \texttt{BatchNormalization}). If the persistent value is an \texttt{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}.

\textbf{Parameters}

\begin{itemize}
  \item \texttt{link (Link)} – Source link object.
  \item \texttt{copy\_persistent (bool)} – If True, persistent values are also copied. True by default.
\end{itemize}

\texttt{count\_params()}

Counts the total number of parameters.

This method counts the total number of scalar values included in all the \texttt{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)

\texttt{delete\_hook(name)}

Unregisters the link hook.

\textbf{Parameters} \texttt{name (str)} – The name of the link hook to be unregistered.

\texttt{disable\_update()}

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()}

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)}

Applies N-dimensional convolution layer.

\textbf{Parameters} \texttt{x (Variable)} – Input image.

\textbf{Returns} Output of convolution.

\textbf{Return type} \textit{Variable}

\texttt{init\_scope()}

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 \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 \texttt{init\_scope} method, we can simply assign a \texttt{Parameter} object to register it to the link.

4.3. Link and Chains 325
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=False)
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=False)
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=True)
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=True)
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)
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, mode='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:

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.

to_cpu()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

to_gpu(device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64()

Copies parameter variables and persistent values to CPU.

zerograds()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

4.3. Link and Chains
Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

`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.

`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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

### 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`.  

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• **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='f').reshape(1, 2, 5, 5, 5)
```

1. Give the first four arguments explicitly:

```python
>>> l = L.ConvolutionND(3, 2, 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(3, 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 auguments. 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, **kwargs)
Call self as a function.

add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

add_persistent(name, value)
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)
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()
Returns a generator of all child links.
Returns  A generator object that generates all child links.

cleargrads ()
Clears all gradient arrays.
This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')
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, 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 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 ()
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)
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

disable_update ()
Disables update rules of all parameters under the link hierarchy.

4.3. Link and Chains
This method sets the enabled flag of the update rule of each parameter variable to False.

**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.

**forward(x)**

Applies N-dimensional convolution layer.

- **Parameters** `x` (Variable) – Input image.
- **Returns** Output of convolution.
- **Return type** Variable

**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,))
```

**links**(skipself=False)

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=False)

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=True)

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=True)

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)

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, mode='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)

Serializes the link object.

Parameters

serializer (AbstractSerializer) – Serializer object.
to_cpu()
Copies parameter variables and persistent values to CPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.
Returns: self
to_gpu(device=None)
Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.
Parameters
device – Target device specifier. If omitted, the current device is used.
Returns: self
to_intel64()
Copies parameter variables and persistent values to CPU.
zerograds()
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
Deprecated since version v1.15: Use cleargrads() instead.

Attributes
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.
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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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, **kwargs)
Call self as a function.

add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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()
Returns a generator of all child links.

Returns
A generator object that generates all child links.

cleargrads()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy(mode='share')
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, 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 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 ()
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)
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

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.

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.

forward (x)
**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,))
```

**links** *(skipself=False)*

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=False)*

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=True)*

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=True)*

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)*

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, mode='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)

Serializes the link object.

Parameters `serializer` (AbstractSerializer) – Serializer object.

**to_cpu**()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu** (device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters `device` – Target device specifier. If omitted, the current device is used.
Returns: self

to_intel64()
Copies parameter variables and persistent values to CPU.

zerograds()
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for
backward compatibility.
Deprecated since version v1.15: Use cleargrads() instead.

Attributes

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.

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

chainer.links.Deconvolution2D

class chainer.links.Deconvolution2D(self, in_channels, out_channels, ksize=None, stride=1, pad=0, nobias=False, outsize=None, initialW=None, initial_bias=None, *, 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 algo-
rithm for images of fixed-size, can provide a significant performance boost for fixed neural nets. To enable, set
chainer.using_config('autotune', True)

Warning: deterministic argument is not supported anymore since v2. Instead, use chainer.using_config('cudnn_deterministic', value) (value is either True or False). See chainer.using_config().

Parameters

• in_channels (int or None) – Number of channels of input arrays. If None, param-
eter 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.

• **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:
See chainer.links.Convolution2D() for the examples of ways to give arguments to this link.

Example
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
   >>> 1 = L.Deconvolution2D(3, 7, 4)
   >>> y = 1(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, **kwargs)**

Call self as a function.

**add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.
add_persistent (name, value)
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)
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 ()
Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads ()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')
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, 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 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()**
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)
Unregisters the link hook.

**Parameters** name *(str)* – The name of the link hook to be unregistered.

**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.

**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.

**forward**(x)

**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,))
```

**links**(skipself=False)
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=False)
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=True*)

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=True*)

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*)

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*, **mode='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.
• **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)
```

Serializes the link object.

**Parameters**

- **serializer** (*AbstractSerializer*) – Serializer object.

```python
to_cpu()
```

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

**Returns:** self

```python
to_gaps(device=None)
```

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

**Returns:** self

```python
to_intel64()
```

Copies parameter variables and persistent values to CPU.

```python
zerograds()
```

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

### 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.

### 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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

chainer.links.Deconvolution3D

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, **kwargs)
Call self as a function.

add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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.

tochildren()
Returns a generator of all child links.

Returns
A generator object that generates all child links.
cleargrads()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.
copy (mode='share')
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, 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 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()
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)
    Unregisters the link hook.

    Parameters name (str) -- The name of the link hook to be unregistered.
```

```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 forward(x)
```

```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,))
```

**links (skipself=False)**

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=False)**

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=True)**

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=True)*

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)*

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, mode='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

Serializes the link object.

**Parameters**

*serializer* ([AbstractSerializer](#abstractserializer)) – Serializer object.

to_cpu

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

to_gpu (*device=None*)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

*device* – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64

Copies parameter variables and persistent values to CPU.

zerograds

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

**Attributes**

**local_link_hooks**

Ordered dictionary of registered link hooks.

Contrary to [chainer.thread_local.link_hooks](#linkhooks), which registers its elements to all functions, link hooks in this property are specific to this link.

**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()](#initscope) for the details of the initialization scope.

**xp**

Array module for this link.

Depending on which of CPU/GPU this link is on, this property returns [numpy](#numpy) or [cupy](#cupy).

**chainer.links.DeconvolutionND**

**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 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.

**See also:**

`deconvolution_nd()`

**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 DeconvolutionND link.

Let an input vector `x` be:

```python
>>> x = np.arange(2 * 5 * 5 * 5, dtype='f').reshape(1, 2, 5, 5, 5)
```

1. Give the first four arguments explicitly:
2. Omit \texttt{in\_channels} or fill it with \texttt{None}:

The below two cases are the same.

\begin{verbatim}
>>> l = L.DeconvolutionND(3, 7, 4)
>>> y = l(x)
>>> y.shape
(1, 7, 8, 8, 8)
\end{verbatim}

\begin{verbatim}
>>> l = L.DeconvolutionND(3, None, 7, 4)
>>> y = l(x)
>>> y.shape
(1, 7, 8, 8, 8)
\end{verbatim}

When you omit the second argument, you need to specify the other subsequent arguments from \texttt{stride} as keyword arguments. So the below two cases are the same.

\begin{verbatim}
>>> l = L.DeconvolutionND(3, 7, 4, stride=2, pad=1)
>>> y = l(x)
>>> y.shape
(1, 7, 10, 10, 10)
\end{verbatim}

\begin{verbatim}
>>> l = L.DeconvolutionND(3, None, 7, 4, 2, 1)
>>> y = l(x)
>>> y.shape
(1, 7, 10, 10, 10)
\end{verbatim}

---

**Methods**

\texttt{\_\_call\_\_}(\*\texttt{args}, **\texttt{kwargs})

Call self as a function.

\texttt{add\_hook}(\texttt{hook}, \texttt{name}=\texttt{None})

Registers a link hook.

**Parameters**

- \texttt{hook} (\texttt{LinkHook}) – Link hook to be registered.
- \texttt{name} (\texttt{str}) – Name of the link hook. The name must be unique among link hooks registered to this link. If \texttt{None}, the default name of the link hook is used.

**Returns** self

\texttt{add\_param}(\texttt{name}=\texttt{None}, \texttt{shape}=\texttt{None}, \texttt{dtype}=\texttt{numpy.float32}, \texttt{initializer}=\texttt{None})

Registers a parameter to the link.

**Parameters**

- \texttt{name} (\texttt{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** – 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.

### add_persistent *(name, value)*

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)*

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 *

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

### cleargrads *

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

### copy *(mode='share')*

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, 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 `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()**

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)**

Unregisters the link hook.

**Parameters**
- `name` ([`str`]) – The name of the link hook to be unregistered.

**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`.

**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`.

**forward(x)**

**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,))```
`links` *(skipself=False)*

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=False)*

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=True)*

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=True)*

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)*

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, mode='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)*  
Serializes the link object.

**to_cpu** *(None)*  
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu** *(device=None)*  
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters** device – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** *(None)*  
Copies parameter variables and persistent values to CPU.

**zerograds** *(None)*  
Initializes all gradient arrays by zero.

This method can be used for the same purpose of `cleargrads`, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

**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.
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 for this link.

Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

chainer.links.DeformableConvolution2D

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.

- **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.

- **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, **kwargs)
Call self as a function.

__getitem__(name)
Equivalent to getattr.

add_hook(hook, name=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(name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

add_persistent(name, value)
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)
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()
Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')
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, 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 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()
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.

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If the link contains uninitialized parameters, this method raises a warning.

**Returns** The total size of parameters (int)

**delete_hook**(name)
Unregisters the link hook.

**Parameters** name (str) – The name of the link hook to be unregistered.

**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.

**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.

**forward**(x)
Applies the deformable convolution.

**Parameters** x (Variable) – Input image.

**Returns** Output of the deformable convolution.

**Return type** Variable

**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,))
```

**links**(skipself=False)
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=False)
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=True*)

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=True*)

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*)

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*, *mode='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)*

Serializes the link object.

**Parameters**

- **serializer** *(AbstractSerializer)* – Serializer object.

**to_cpu** ()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu** *(device=None)*

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** ()

Copies parameter variables and persistent values to CPU.

**zerograds** ()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

**Attributes**

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.
chainer.links.DepthwiseConvolution2D

```python
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, **kwargs)**

  Call self as a function.

- **add_hook** (`hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)

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)

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()

Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads()

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy(mode='share')

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, 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 *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**()
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*)
Unregisters the link hook.

**Parameters**  
name (*str*) – The name of the link hook to be unregistered.

**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.

**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.

**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**

**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,))

links (skipself=False)
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=False)
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=True)
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=True)
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)
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, mode='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:
```
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.

to_cpu()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

to_gpu(device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64()

Copies parameter variables and persistent values to CPU.

zerograds()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
Deprecation since version v1.15: Use `cleargrads()` instead.

### Attributes

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

---

**chainer.links.DilatedConvolution2D**

```python
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.

**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.

---

**Note:** You can also define a dilated convolutional layer by passing `dilate` argument to `chainer.links.Convolution2D`. The functionality is the same.
• **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:

```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.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)
```

```python
>>> 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)
```

```python
>>> l = L.DilatedConvolution2D(7, 5, stride=1, pad=0, dilate=2)
>>> y = l(x)
>>> y.shape
(1, 7, 2, 2)
```
Methods

__call__ (*args, **kwargs)
Call self as a function.

add_hook(hook, name=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

add_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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()
Returns a generator of all child links.

Returns

A generator object that generates all child links.

cleargrads()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.
copy (mode='share')
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.

Returns Link

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
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 ()
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)
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

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.

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.
**forward**(*x*)

Applies the convolution layer.

- **Parameters**: *x*(Variable) – Input image.
- **Returns**: Output of the convolution.
- **Return type**: Variable

**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,))
```

**links**(skipself=False)

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=False)

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=True)

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=True)

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)

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**

\textbf{name} (\texttt{str}) -- Name of the attribute to be registered.

\textbf{repeat} (\texttt{n\_repeat, mode='init'})

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.

**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():
            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 \textit{mode} was \textit{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**

- \textbf{n\_repeat} (\texttt{int}) -- Number of times to repeat.
- \textbf{mode} (\texttt{str}) -- It should be either \textit{init}, \textit{copy}, or \textit{share}. \textit{init} means parameters of each repeated element in the returned \textit{Sequential} will be re-initialized, so that all elements have different initial parameters. \textit{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. \textit{share} means all the elements which consist the resulting \textit{Sequential} object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

\textbf{serialize} (\texttt{serializer})

Serializes the link object.

**Parameters**

- \textbf{serializer} (\texttt{AbstractSerializer}) -- Serializer object.

\textbf{to\_cpu}()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.
Returns: self

to_gpu (device=None)
Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64()
Copies parameter variables and persistent values to CPU.
zerograds()
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
Depreciated since version v1.15: Use cleargrads() instead.

Attributes

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.

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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 column 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)
>>> y = l(x)
>>> y.array
array([[2., 2., 2.],
       [1., 1., 1.]], dtype=float32)
```

---

**Methods**

**__call__(*)**

Call self as a function.

**add_hook** (*hook, name=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_param** (*name=None, shape=None, dtype=<class 'numpy.float32'>, initializer=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` – 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.
add_persistent (name, value)

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)

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 ()

Returns a generator of all child links.

Returns

A generator object that generates all child links.

cleargrads ()

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')

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, 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 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**()
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*)
Unregisters the link hook.

**Parameters** *name* (*str*) – The name of the link hook to be unregistered.

**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.

**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.

**forward** (*x*)
Extracts the word embedding of given IDs.

**Parameters** *x* (*Variable*) – Batch vectors of IDs.

**Returns** Batch of corresponding embeddings.

**Return type** *Variable*

**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,))
```

**links** (*skipself=False*)
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.

dnamedlinks (skipself=False)

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=True)

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.

dparams (include_uninit=True)

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.

dregister_persistent (name)

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.

derepeat (n_repeat, mode='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:

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.BatchNorm(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.

**to_cpu** ()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu** (*device=None*)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** ()

Copies parameter variables and persistent values to CPU.

**zerograds** ()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use *cleargrads()* instead.

**Attributes**

- **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.

- **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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

### 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`.

**Warning:** In Chainer v1, GRU was *stateless*, as opposed to the current implementation. To align with LSTM links, we have changed the naming convention from Chainer v2 so that the shorthand name points the stateful links. You can use `StatelessGRU` for stateless version, whose implementation is identical to GRU in v1.

See issue #2537 for details.

#### Methods

```python
__call__(*args, **kwargs)
Call self as a function.

__getitem__(name)
Equivalent to getattr.

add_hook(hook, name=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(name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent** (*name, value*)

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*)

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** (*)

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads** (*)

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode='share'* *)

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, 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 `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()**

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)*

Unregisters the link hook.

**Parameters** `name` *(str)* – The name of the link hook to be unregistered.

**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`.

**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`.

**forward** *(self, x)*

Does forward propagation.

**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,))
```
links (skipself=False)
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=False)
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=True)
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=True)
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)
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, mode='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:

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()`

Serializes the link object.

Parameters `serializer (AbstractSerializer)` – Serializer object.

`serialize (serializer)`

`set_state (h)`

`to_cpu ()`

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

`to_gpu (device=None)`

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters `device` – Target device specifier. If omitted, the current device is used.

Returns: self

`to_intel64 ()`

Copies parameter variables and persistent values to CPU.

`zerograds ()`

Initializes all gradient arrays by zero.

This method can be used for the same purpose of `cleargrads`, but less efficient. This method is left for backward compatibility.

Deprecation since version v1.15: Use `cleargrads()` instead.

Attributes

`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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

**chainer.links.Highway**

```python
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, ...).

See: Highway Networks.

**Methods**

- **__call__(**args, **kwargs)**
  Call self as a function.

- **__getitem__(**name)**
  Equivalent to getattr.
add_hook (hook, name=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 (name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent (name, value)
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)
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 ()
Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads ()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.
copy (mode='share')
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, 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
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 ()
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)
Unregisters the link hook.

Parameters

- **name** *(str)* – The name of the link hook to be unregistered.

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.

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.
**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*

**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,))
```

**links** (*skipself=False*)
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=False*)
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=True*)
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=True*)
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*)
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, mode='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)
```

Serializes the link object.

**Parameters**

- **`serializer (AbstractSerializer)`** – Serializer object.

```
to_cpu()
```

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.
Returns: self

to_gpu (device=None)
Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64 ()
Copies parameter variables and persistent values to CPU.
zerograds ()
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
Deprecated since version v1.15: Use cleargrads() instead.

**Attributes**

- **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.

- **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 for this link.
  Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

**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, **kwargs*)
Call self as a function.

__getitem__ (name)
Equivalent to getattr.

add_hook (hook, name=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 (name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.
add_persistent (name, value)
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)
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 ()
Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads ()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')
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, 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 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()**
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*)
Unregisters the link hook.

**Parameters** *name* (*str*) – The name of the link hook to be unregistered.

**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.

**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.

**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 \( \text{out1 + out3 + out5 + proj\_pool} \).

**Return type** *Variable*

**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,))
```

**links** (*skipself=False*)
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=False)
```

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=True)
```

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=True)
```

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)
```

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, mode='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)

Serializes the link object.

Parameters **serializer**(AbstractSerializer) – Serializer object.

**to_cpu**()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu**(device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64**()

Copies parameter variables and persistent values to CPU.

**zerograds**()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

**Attributes**

**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.

**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 for this link.
   Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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

Methods
__call__(*args, **kwargs)
   Call self as a function.
__getitem__(name)
   Equivalent to getattr.
add_hook(hook, name=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** (*name*, *link*)

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*, *shape=None*, *dtype=*<class 'numpy.float32'>*, *initializer=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** – 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.

**add_persistent** (*name*, *value*)

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*)

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** ()

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads** ()

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode='share'*)

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, 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 `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** *

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)*

Unregisters the link hook.

**Parameters**

- **name** *(str)* – The name of the link hook to be unregistered.

**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`.

**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`.

**forward** *(x)*

**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,))
```

links (skipself=False)
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=False)
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=True)
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=True)
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)
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, mode='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)`

Serializes the link object.

Parameters `serializer (AbstractSerializer)` – Serializer object.

`to_cpu ()`  
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

`to_gpu (device=None)`  
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters `device` – Target device specifier. If omitted, the current device is used.

Returns: self
**to_intel64()**
Copies parameter variables and persistent values to CPU.

**zerograds()**
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

**chainer.links.Linear**

**class** `chainer.links.Linear` *(in_size: int or None, out_size: int, nobias: bool, initialW: Initializer, initial_bias: int or None)*

Linear layer (a.k.a. fully-connected layer).

This is a link that 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.

```python
>>> 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, **kwargs)
Call self as a function.

`add_hook` (hook, name=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_param** *(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent** *(name, value)*  
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)*  
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** *

Returns a generator of all child links.

**Returns**  
A generator object that generates all child links.

**cleargrads** *

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode='share')*

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, 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 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** *

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)*

Unregisters the link hook.

**Parameters** name *(str)* – The name of the link hook to be unregistered.

**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.

**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.

**forward** *(x, n_batch_axes=1)*

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

**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,))
```

- **links** *(skipself=False)*
  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=False)*
  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=True)*
  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=True)*
  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)*
  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, mode='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)`

Serializes the link object.

Parameters **serializer** (*AbstractSerializer*) – Serializer object.

`to_cpu()`

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

`to_gpu (device=None)`

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64()
Copies parameter variables and persistent values to CPU.

zerograds()
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
Deprecated since version v1.15: Use cleargrads() instead.

Attributes

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.

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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**

```python
__call__(*args, **kwargs)
```
Call self as a function.

```python
add_hook(hook, name=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

```python
add_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

```python
add_persistent(name, value)
```
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)
```
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** ()  
Returns a generator of all child links.

**Returns**  
A generator object that generates all child links.

**cleargrads** ()  
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode*='share')  
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*, *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 *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** ()  
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)*
Unregisters the link hook.

**Parameters** name *(str)* – The name of the link hook to be unregistered.

**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.

**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.

**forward(x)**
Applies the local convolution layer.

**Parameters** x *(Variable)* – Input image.

**Returns** Output of the convolution.

**Return type** Variable

**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,))
```

**links** *(skipself=False)*
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=False)*
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=True)*
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=True)
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)
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, mode='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 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)
```
Serializes the link object.

**Parameters** `serializer` ([AbstractSerializer](#)) – Serializer object.

to_cpu()
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, 
the link implementation must override this method to do so.

Returns: self

to_gpu(device=None)
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, 
the link implementation must override this method to do so.

**Parameters** `device` – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64()
Copies parameter variables and persistent values to CPU.

zerograds()
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for 
backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

```
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.

```
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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.
chainer.links.LSTM

class 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 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

- **in_size (int)** – Dimension of input vectors. 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_size (int)** – Dimensionality of output vectors.
- **lateral_init** – A callable that takes \( N \)-dimensional array and edits its value. It is used for initialization of the lateral connections. May be None to use default initialization.
- **upward_init** – A callable that takes \( N \)-dimensional array and edits its value. It is used for initialization of the upward connections. May be None to use default initialization.
- **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 None, the cell-input bias is initialized to zero.
- **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 None, the forget bias is initialized to one.

Variables

- **upward (Linear)** – Linear layer of upward connections.
- **lateral (Linear)** – Linear layer of lateral connections.
- **c (Variable)** – Cell states of LSTM units.
- **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:

```
>>> x = np.zeros((1, 10), dtype=np.float32)
```

1. Give both **in_size** and **out_size** arguments:
>>> 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)

>>> l = L.LSTM(None, 20)
>>> h_new = l(x)
>>> h_new.shape
(1, 20)
```

Methods

___call___(*args, **kwargs)
Call self as a function.

___getitem____(name)
Equivalent to getattr.

add_hook(hook, name=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(name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent**(name, value)

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)

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**

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads**

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy**(mode='share')

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, 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 5.0.0:* 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()**

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)**

Unregisters the link hook.

**Parameters** name (*str*) – The name of the link hook to be unregistered.

**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.

**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.

**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

**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,))
```
links \(\text{skipself=}False\)  
Returns a generator of all links under the hierarchy.

- **Parameters**  
  **skipself** \(\text{bool}\) – If True, then the generator skips this link and starts with the first child link.

- **Returns**  
  A generator object that generates all links.

namedlinks \(\text{skipself=}False\)  
Returns a generator of all (path, link) pairs under the hierarchy.

- **Parameters**  
  **skipself** \(\text{bool}\) – 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 \(\text{include_uninit=}True\)  
Returns a generator of all (path, param) pairs under the hierarchy.

- **Parameters**  
  **include_uninit** \(\text{bool}\) – 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 \(\text{include_uninit=}True\)  
Returns a generator of all parameters under the link hierarchy.

- **Parameters**  
  **include_uninit** \(\text{bool}\) – If True, it also generates uninitialized parameters.

- **Returns**  
  A generator object that generates all parameters.

register_persistent \(\text{name}\)  
Registers an attribute of a given name as a persistent value.

- **Parameters**  
  **name** \(\text{str}\) – Name of the attribute to be registered.

repeat \(n\_repeat, \text{mode=}\text{init}'\)  
Repeats this link multiple times to make a `Sequential`.

- **Returns**  
  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
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 (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)}
Serializes the link object.

**Parameters**

- \texttt{serializer (AbstractSerializer)} – Serializer object.

\texttt{set\_state (c, h)}
Sets the internal state.
It sets the \texttt{c} and \texttt{h} attributes.

**Parameters**

- \texttt{c (Variable)} – A new cell states of LSTM units.
- \texttt{h (Variable)} – A new output at the previous time step.

\texttt{to\_cpu ()}
Copies parameter variables and persistent values to CPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

\texttt{to\_gpu (device=None)}
Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

- \texttt{device} – Target device specifier. If omitted, the current device is used.

Returns: self

\texttt{to\_intel64 ()}
Copies parameter variables and persistent values to CPU.

\texttt{zerograds ()}
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

---

**chainer.links.MLPConvolution2D**

```python
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, **kwargs)**
  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, value)**

- **__len__()**

- **__iter__()**

- **add_hook(hook, name=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)**
  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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent** *(name, value)*

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)*

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** *()*

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**clear()** → None – remove all items from S

**cleargrads()**

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 `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()**

Counts the total number of parameters.
This method counts the total number of scalar values included in all the \texttt{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)

\texttt{delete\_hook (name)}

Unregisters the link hook.

**Parameters** \texttt{name (str)} – The name of the link hook to be unregistered.

\texttt{disable\_update ()}

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 ()}

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{extend (values)}

\texttt{S.extend(iterable)} – extend sequence by appending elements from the iterable

\texttt{forward (x)}

Computes the output of the mlpconv layer.

**Parameters** \texttt{x (Variable)} – Input image.

**Returns** Output of the mlpconv layer.

**Return type** \texttt{Variable}

\texttt{index (value, start [, stop ])} \rightarrow \text{integer} – return first index of value.

Raises \texttt{ValueError} if the value is not present.

Supporting \texttt{start} and \texttt{stop} arguments is optional, but recommended.

\texttt{init\_scope ()}

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{insert (index, link)}

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=False)*
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=False)*
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=True)*
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=True)*
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)*
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, mode='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:
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.

to_cpu()
    Copies parameter variables and persistent values to CPU.
    This method does not handle non-registered attributes. If some of such attributes must be copied to CPU,
    the link implementation must override this method to do so.
    Returns: self

to_gpu(*device=None*)
    Copies parameter variables and persistent values to GPU.
    This method does not handle non-registered attributes. If some of such attributes must be copied to GPU,
    the link implementation must override this method to do so.

    Parameters **device** – Target device specifier. If omitted, the current device is used.
    Returns: self
to_intel64()
Copies parameter variables and persistent values to CPU.

zerograds()
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
Depreciated since version v1.15: Use cleargrads() instead.

Attributes

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.

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

chainer.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 \((a, i, o, f)\) 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, **kwargs)
Call self as a function.

__getitem__(name)
Equivalent to getattr.

add_hook(hook, name=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(name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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*)
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**
Returns a generator of all child links.

**Returns**
A generator object that generates all child links.

**cleargrads**
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode='share'*)
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*, *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 *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**
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)
```
Unregisters the link hook.

**Parameters**
- `name` (str) – The name of the link hook to be unregistered.

```python
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
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
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 \( n_{\text{ary}} \times 2 + 1 \).

**Returns**
- Returns \((c_{\text{new}}, h_{\text{new}})\), where \(c_{\text{new}}\) represents new cell state vector, and \(h_{\text{new}}\) is new output vector.

**Return type**
tuple of ~chainer.Variable

```python
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=False)
```
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=False)
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=True)
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=True)
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)
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, mode='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:

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.

**to_cpu ()**

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu (device=None)**

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64 ()**

Copies parameter variables and persistent values to CPU.

**zerograds ()**

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use **cleargrads ()** instead.

Attributes

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

chainer.links.NStepBiGRU

class chainer.links.NStepBiGRU

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.

**Warning:** `use_cudnn` argument is not supported anymore since v2. Instead, use `chainer.using_config('use_cudnn', use_cudnn)`. See `chainer.using_config()`.

**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, **kwargs*)
  
  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, value*)

- **__len__**()
  
  Returns the number of children.

- **__iter__**()

- **add_hook**(*hook, name=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*)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent** (*name, value*)
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*)
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** ()
Returns a generator of all child links.

**Returns**  
A generator object that generates all child links.

**clear** () → `None` – remove all items from `S`

**cleargrads** ()
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 `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**()
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*)
Unregisters the link hook.

**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.

**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.

**extend** (*values*)
`S.extend(iterable)` – extend sequence by appending elements from the iterable

**forward** (*self*, *hx*, *xs*)
Calculate all hidden states and cell states.

**Warning:** train argument is not supported anymore since v2. Instead, use chainer.using_config('train', train). See chainer.using_config().

**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 ~chainer.Variable*) – List of input sequences. Each element xs[i] is a chainer.Variable holding a sequence. Its shape is \((L_i, I)\), where \(L_t\) is the length of a sequence for batch \(i\), and \(I\) is the size of the input and is equal to \(\text{in\_size}\).

**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 \(ys[i]\) 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 \(L_t\) is the length of a sequence for batch \(i\), and \(N\) is size of hidden units.

**Return type** tuple

\[\text{index}(\text{value}, \text{start}, \text{stop}) \rightarrow \text{integer} \]

– return first index of value.

Supporting start and stop arguments is optional, but recommended.

**init_hx(xs)**

**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,))
```

**insert(index, link)**

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=False)**

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=False)
   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=True)
   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=True)
   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)
   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, mode='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:

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)**

Serializes the link object.

- **Parameters** `serializer` (`AbstractSerializer`) – Serializer object.

**to_cpu()**

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu(device=None)**

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

- **Parameters** `device` (`None`) – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64()**

Copies parameter variables and persistent values to CPU.

**zerograds()**

Initializes all gradient arrays by zero.

This method can be used for the same purpose of `cleargrads`, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.
Attributes

**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**
Returns the number of cells.
This function must be implemented in a child class.

**n_weights = 6**

**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 for this link.
Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

### chainer.links.NStepBiLSTM

**class** `chainer.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 `chainer.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 `chainer.Variable` holding sequences.

| Warning: use_cudnn argument is not supported anymore since v2. Instead, use `chainer.using_config('use_cudnn', use_cudnn)` | **See** `chainer.using_config()` |

**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__(*args, **kwargs)
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, value)

__len__()
Returns the number of children.

__iter__()

add_hook(hook, name=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)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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 ()
Returns a generator of all child links.

Returns
A generator object that generates all child links.

clear () → None – remove all items from S

cleargrads ()
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 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 ()
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)
Unregisters the link hook.

Parameters

name (str) – The name of the link hook to be unregistered.

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.
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.

extend(values)
S.extend(iterable) – extend sequence by appending elements from the iterable

forward(self, hx, cx, xs)
Calculate all hidden states and cell states.

Warning: train argument is not supported anymore since v2. Instead, use chainer.
using_config('train', train). See chainer.using_config().

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 LSTM and (2S, B, N) for bi-directional LSTM 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 or None) – Initial cell states. If None is specified zero-vector is used. It has the same shape as hx.

- **xs** (list of ~chainer.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

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()

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 \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{insert(index, link)}
Insert a child link at the given index.

Parameters
- \texttt{index(int)} – The position of the list where the new
- \texttt{is inserted.(link)} –
- \texttt{link(Link)} – The link to be inserted.

\texttt{links(skipself=False)}
Returns a generator of all links under the hierarchy.

Parameters \texttt{skipself(bool)} – If \texttt{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=False)}
Returns a generator of all (path, link) pairs under the hierarchy.

Parameters \texttt{skipself(bool)} – If \texttt{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=True)}
Returns a generator of all (path, param) pairs under the hierarchy.

Parameters \texttt{include_uninit(bool)} – If \texttt{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=True)}
Returns a generator of all parameters under the link hierarchy.

Parameters \texttt{include_uninit(bool)} – If \texttt{True}, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

\texttt{pop([index]) \rightarrow item} \texttt{– remove and return item at index (default last).}
Raise IndexError if list is empty or index is out of range.

\texttt{register\_persistent(name)}
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(str)} – Name of the attribute to be registered.
remove \( (\text{value}) \)

\( \text{S.remove(value)} \) – remove first occurrence of value. Raise ValueError if the value is not present.

repeat \( (n\_repeat, \text{mode}=\text{'init'}) \)

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.

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():
            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 \textit{mode} was \textit{init}, so each block is re-initialized with different parameters. If you give \textit{copy} to this argument, each block has same values for its parameters but its object ID is different from others. If it is \textit{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

- \textbf{\texttt{n\_repeat (int)}} – Number of times to repeat.
- \textbf{\texttt{mode (str)}} – It should be either \textit{init}, \textit{copy}, or \textit{share}. \textit{init} means parameters of each repeated element in the returned \textit{Sequential} will be re-initialized, so that all elements have different initial parameters. \textit{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. \textit{share} means all the elements which consist the resulting \textit{Sequential} object are same object because they are shallow-copied, so that all parameters of elements are shared with each other.

reverse()

\( \text{S.reverse()} \) – reverse \textit{IN PLACE}

rnn(*\textit{args})

Calls RNN function.

This function must be implemented in a child class.

serialize(\textit{serializer})

Serializes the link object.

- \textbf{\textit{Parameters serializer (AbstractSerializer)}} – Serializer object.
to_cpu()
    Copies parameter variables and persistent values to CPU.
    This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.
    Returns: self

to_gpu(device=None)
    Copies parameter variables and persistent values to GPU.
    This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

    Parameters
    device – Target device specifier. If omitted, the current device is used.
    Returns: self

to_intel64()
    Copies parameter variables and persistent values to CPU.

zerograds()
    Initializes all gradient arrays by zero.
    This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

    Deprecated since version v1.15: Use cleargrads() instead.

Attributes

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
    Returns the number of cells.

    This function must be implemented in a child class.

n_weights = 8

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 for this link.
    Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.
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.

Warning: use_cudnn argument is not supported anymore since v2. Instead, use chainer.using_config('use_cudnn', use_cudnn). See chainer.using_config().

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, **kwargs)

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, value)

__len__()

Returns the number of children.

__iter__()

add_hook(hook, name=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)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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()
Returns a generator of all child links.

Returns A generator object that generates all child links.

clear() → None – remove all items from S

cleargrads()
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 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 ()
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)
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

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.

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.

extend (values)
S.extend(iterable) – extend sequence by appending elements from the iterable

forward (self, hx, xs)
Calculate all hidden states and cell states.

Warning: train argument is not supported anymore since v2. Instead, use chainer.using_config('train', train). See chainer.using_config().

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 ~chainer.Variable) – List of input sequences. Each element xs[i] is a chainer.Variable holding a sequence. Its shape is (L_i, I), where L_t 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, \( h_y \) and \( y_s \).

- \( h_y \) is an updated hidden states whose shape is same as \( h_x \).
- \( y_s \) is a list of \texttt{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

\[ \text{index} \left( \text{value, start[, stop]} \right) \rightarrow \text{integer} \]  

\( \text{index} \) – return first index of value.  

Raises ValueError if the value is not present.

\text{init}_x(\text{x})

\text{init}_s()  

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 \text{init}_s\text{cope} 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,))

\text{insert}(\text{index, link})

Insert a child link at the given index.

Parameters

- \text{index} \texttt{(int)} – The position of the list where the new
- \text{is inserted} \texttt{(link)} –
- \text{link} \texttt{(Link)} – The link to be inserted.

\text{links}(\text{skipself=False})

Returns a generator of all links under the hierarchy.

Parameters \text{skipself} \texttt{(bool)} – If \texttt{True}, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

\text{namedlinks}(\text{skipself=False})

Returns a generator of all \((\text{path, link})\) 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=True)`
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=True)`
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)`
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, mode='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.

reverse()

S.reverse() – reverse IN PLACE

rnn(*args)

Calls RNN function.

serialize(*serializer*)

Serializes the link object.

Parameters *serializer*(*AbstractSerializer*) – Serializer object.

to_cpu()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

to_gpu(*device=None*)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters *device* – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64()

Copies parameter variables and persistent values to CPU.

zerograds()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

**Attributes**

- **local_link_hooks**

  Ordered dictionary of registered link hooks.
Contrary to :class:`chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

```python
n_cells
```

Returns the number of cells.

This function must be implemented in a child class.

```python
n_weights = 2
```

```python
update_enabled
```

True if at least one parameter has an update rule enabled.

```python
use_bi_direction = True
```

```python
within_init_scope
```

True if the current code is inside of an initialization scope.

See :func:`init_scope()` for the details of the initialization scope.

```python
xp
```

Array module for this link.

Depending on which of CPU/GPU this link is on, this property returns :mod:`numpy` or :mod:`cupy`.

.. autoclass:: chainer.links.NStepBiRNNTanh
   :noindex:

.. code:: python

    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 :math:`\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 :func:`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 :class:`chainer.Variable` holding sequences.

    .. warning::
        use_cudnn argument is not supported anymore since v2. Instead, use

        Parameters

        * n_layers (:class:`int`) – Number of layers.
        * in_size (:class:`int`) – Dimensionality of input vectors.
        * out_size (:class:`int`) – Dimensionality of hidden states and output vectors.
        * dropout (:class:`float`) – Dropout ratio.

        See also:

        :func:`chainer.functions.n_step_birnn()`

        Methods

        :func:`__call__`(*args, **kwargs)
        
        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, value)

_add_link(link)
Registers a child link and adds it to the tail of the list.

Parameters

link (Link) – The link object to be registered.

add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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**

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**clear** () → None – remove all items from S

**cleargrads** ()

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 `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** ()

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)*

Unregisters the link hook.

**Parameters** **name**(str) – The name of the link hook to be unregistered.

**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`.

**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`. 
extend(values)
S.extend(iterable) – extend sequence by appending elements from the iterable

forward(self, hx, xs)
Calculate all hidden states and cell states.

Warning: train argument is not supported anymore since v2. Instead, use chainer.
using_config('train', train). See chainer.using_config().

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 ~chainer.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 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

index(value[, start[, stop ]]) → integer – return first index of value.

Raises ValueError if the value is not present.

init_hx(xs)

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.

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, link)*
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=False)*
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=False)*
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=True)*
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=True)*
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)*
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, mode='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.

**reverse()**

S.reverse() – reverse IN PLACE

**rnn(**args**)**

Calls RNN function.

This function must be implemented in a child class.

**serialize**(serializer)

Serializes the link object.

Parameters **serializer** (AbstractSerializer) – Serializer object.

**to_cpu()**

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu**(device=None)

Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

- `device` – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64()  
Copies parameter variables and persistent values to CPU.

zerograds()  
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

**Attributes**

- `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`  
  Returns the number of cells.

  This function must be implemented in a child class.

- `n_weights = 2`

- `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 for this link.

  Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

**chainer.links.NStepGRU**

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.
Warning: use_cudnn argument is not supported anymore since v2. Instead, use chainer.using_config('use_cudnn', use_cudnn). See chainer.using_config().

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_gru()

Methods

__call__(*args, **kwargs)

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, value)

__len__()

__iter__()

add_hook (hook, name=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)

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, shape=None, dtype=<class 'numpy.float32'>, initializer=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` – 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.

`add_persistent (name, value)`
 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)`
 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 ()`
 Returns a generator of all child links.

**Returns**
 A generator object that generates all child links.

`clear ()` → None – remove all items from S

`cleargrads ()`
 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 `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()
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)
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

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.

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.

extend(values)
S.extend(iterable) – extend sequence by appending elements from the iterable

forward(self, hx, xs)
Calculate all hidden states and cell states.

Warning: train argument is not supported anymore since v2. Instead, use chainer.
using_config('train', train). See chainer.using_config().

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 ~chainer.Variable) – List of input sequences. Each element xs[i] is a chainer.Variable holding a sequence. Its shape is (L_i, I), where L_t 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 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_t is the length of a sequence for batch i, and N is size of hidden units.

Return type: tuple

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()
```

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, link)
```

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=False)
```

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=False)
```

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=True)
```

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=True)
```

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)
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, mode='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 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.
reverse()
S.reverse() – reverse IN PLACE

rnn(*args)
Calls RNN function.
This function must be implemented in a child class.

serialize(serializer)
Serializes the link object.

Parameters

serializer (AbstractSerializer) – Serializer object.

to_cpu()
Copies parameter variables and persistent values to CPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU,
the link implementation must override this method to do so.
Returns: self

to_gpu(device=None)
Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU,
the link implementation must override this method to do so.

Parameters
device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64()
Copies parameter variables and persistent values to CPU.

zerograds()
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for
backward compatibility.
Deprecrated since version v1.15: Use cleargrads() instead.

Attributes

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
Returns the number of cells.
This function must be implemented in a child class.

n_weights = 6

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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.

Warning: use_cudnn argument is not supported anymore since v2. Instead, use chainer.
using_config('use_cudnn', use_cudnn). See chainer.using_config().

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()

Methods
__call__(*args, **kwargs)
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, value)

__len__()
Returns the number of children.

__iter__()}
add_hook (hook, name=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)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent (name, value)
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)
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 ()
Returns a generator of all child links.

Returns A generator object that generates all child links.

clear () → None – remove all items from S

cleargrads ()
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 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 ()
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)
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.
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.
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.
extend (values)
S.extend(iterable) – extend sequence by appending elements from the iterable
forward (self, hx, cx, xs)
Calculate all hidden states and cell states.

Warning: train argument is not supported anymore since v2. Instead, use chainer.
using_config('train', train). See chainer.using_config().

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 LSTM and (2S, B, N) for bi-
directional LSTM where $S$ is the number of layers and is equal to $n_{\text{layers}}$, $B$ 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 $h_x$.

- **xs** *(list of ~chainer.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 $in_{\text{size}}$.

**Returns**

This function returns a tuple containing three elements, $h_y$, $c_y$ and $y$s.

- $h_y$ is an updated hidden states whose shape is the same as $h_x$.

- $c_y$ is an updated cell states whose shape is the same as $cx$.

- $y$s is a list of Variable. Each element $y$s[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

**index** *(value[, start[, stop]])* $\rightarrow$ integer – return first index of value.

   Raises ValueError if the value is not present.

**init_hx** *(xs)*

**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,))
```

**insert** *(index, link)*

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=False)*

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=False)*

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=True)*

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=True)*

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)*

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, mode='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)
```

(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

**rnn(*args)**
Calls RNN function.

This function must be implemented in a child class.

**serialize(serializer)**
Serializes the link object.

**Parameters** serializer *(AbstractSerializer)* – Serializer object.

**to_cpu()**
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu(device=None)**
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters** device – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64()**
Copies parameter variables and persistent values to CPU.
zerograds()
   Initializes all gradient arrays by zero.

   This method can be used for the same purpose of cleargrads, but less efficient. This method is left for
   backward compatibility.

   Deprecated since version v1.15: Use cleargrads() instead.

Attributes

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
   Returns the number of cells.

   This function must be implemented in a child class.

n_weights = 8

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 for this link.

   Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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.

   Warning: use_cudnn argument is not supported anymore since v2. Instead, use chainer.
   using_config('use_cudnn', use_cudnn). See chainer.using_config().

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, **kwargs)`

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, value)`

`__len__()`

Returns the number of children.

`__iter__()`

`add_hook(hook, name=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)`

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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

`add_persistent(name, value)`

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*)
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** ()
Returns a generator of all child links.

Returns A generator object that generates all child links.

**clear** () → None – remove all items from S

**cleargrads** ()
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 *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** ()
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*)
Unregisters the link hook.

Parameters **name** (*str*) – The name of the link hook to be unregistered.
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.

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.

extend(values)
S.extend(iterable) – extend sequence by appending elements from the iterable

forward(self, hx, xs)
Calculate all hidden states and cell states.

---

**Warning:** train argument is not supported anymore since v2. Instead, use chainer.
using_config('train', train). See chainer.using_config().

**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 ~chainer.Variable)* – List of input sequences. Each element \(xs[i]\) is a chainer.Variable holding a sequence. Its shape is \((L_i, I)\), where \(L_t\) 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 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 \((L_t, N)\) for uni-directional RNN and \((L_t, 2N)\) for bi-directional RNN where \(L_t\) is the length of a sequence for batch \(i\), and \(N\) is size of hidden units.

**Return type** tuple

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()
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, link)*
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=False)*
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=False)*
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=True)*
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=True)*
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)*
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 \((n\_repeat, mode='init')\)

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.

reverse()

\(S.reverse()\) – reverse \(IN\ \text{PLACE}\)

rnn(*args)

Calls RNN function.

This function must be implemented in a child class.

serialize \((serializer)\)

Serializes the link object.

Parameters \(serializer\) (AbstractSerializer) – Serializer object.
to_cpu()
Copies parameter variables and persistent values to CPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.
Returns: self

to_gpu(device=None)
Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters
device – Target device specifier. If omitted, the current device is used.
Returns: self

to_intel64()
Copies parameter variables and persistent values to CPU.

zerograds()
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
Deprecated since version v1.15: Use cleargrads() instead.

Attributes

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
Returns the number of cells.
This function must be implemented in a child class.

n_weights = 2

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.
**chainer.links.NStepRNNTanh**

```python
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 \texttt{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 \texttt{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 \texttt{chainer.Variable} holding sequences.

    Warning: \texttt{use_cudnn} argument is not supported anymore since v2. Instead, use \texttt{chainer.using_config('use_cudnn', use_cudnn)}. See \texttt{chainer.using_config()}.
```

**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:**

- \texttt{chainer.functions.n_step_rnn()}

**Methods**

- **\_call\_** (*args, **kwargs*)
  Call self as a function.
- **\_getitem\_** (*index*)
  Returns the child at given index.
    - **Parameters** \texttt{index} (*int*) – Index of the child in the list.
    - **Returns** The \texttt{index}-th child link.
    - **Return type** \texttt{Link}
- **\_setitem\_** (*index, value*)
- **\_len\_**()
  Returns the number of children.
- **\_iter\_**()
- **add\_hook** (*hook, name=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 \texttt{None}, the default name of the link hook is used.
    - **Returns** self
add_link(link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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()
Returns a generator of all child links.

Returns

A generator object that generates all child links.

clear()
→ None – remove all items from S

cleargrads()
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 \texttt{BatchNormalization}). If the persistent value is an \texttt{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 (\texttt{Link})} – Source link object.
- \texttt{copy_persistent (\texttt{bool})} – If True, persistent values are also copied. True by default.

**count (value) \rightarrow integer** – return 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 \texttt{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)**

Unregisters the link hook.

**Parameters** \texttt{name (\texttt{str})} – The name of the link hook to be unregistered.

**disable_update ()**

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 ()**

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 (values)**

\texttt{S.extend(iterable)} – extend sequence by appending elements from the iterable

**forward (self, hx, xs)**

Calculate all hidden states and cell states.

**Warning:** train argument is not supported anymore since v2. Instead, use \texttt{chainer.using_config('train', train)}. See \texttt{chainer.using_config()}.**

**Parameters**

- \texttt{hx (\texttt{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 \texttt{n_layers}, \(B\) is the mini-batch size, and \(N\) is the dimension of the hidden units.

- \texttt{xs (list of \texttt{~chainer.Variable})} – List of input sequences. Each element \texttt{xs[i]} is a \texttt{chainer.Variable} holding a sequence. Its shape is \((L_i, I)\), where \(L_{-t}\) is the length of a sequence for batch \(i\), and \(I\) is the size of the input and is equal to \texttt{in_size}. **478 Chapter 4. API Reference**
Returns

This function returns a tuple containing three elements, \( \text{hy} \) and \( \text{ys} \).

- \( \text{hy} \) is an updated hidden states whose shape is same as \( \text{hx} \).
- \( \text{ys} \) is a list of \text{Variable}. Each element \( \text{ys}[i] \) holds hidden states of the last layer corresponding to an input \( \text{xs}[i] \). Its shape is \((L_i, N)\) for uni-directional RNN and \((L_i, 2N)\) for bi-directional RNN where \( L_t \) is the length of a sequence for batch \( i \), and \( N \) is size of hidden units.

Return type: tuple

\[ \text{index} \ (\text{value}, \text{start}, \text{stop}) \rightarrow \text{integer} \]

Returns first index of value. Raises ValueError if the value is not present.

\[ \text{init_hx} \ (\text{xs}) \]

\[ \text{init_scope} () \]

Creates an initialization scope.

This method returns a context manager object that enables registration of parameters (and links for Chain) by an assignment. A \text{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_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,))
```

\[ \text{insert} \ (\text{index}, \text{link}) \]

Insert a child link at the given index.

Parameters

- \( \text{index} \ (\text{int}) \) – The position of the list where the new
- \( \text{is inserted} \ (\text{link}) \) –
- \( \text{link} \ (\text{Link}) \) – The link to be inserted.

\[ \text{links} \ (\text{skipself}=\text{False}) \]

Returns a generator of all links under the hierarchy.

Parameters \text{skipself} (\text{bool}) – If True, then the generator skips this link and starts with the first child link.

Returns A generator object that generates all links.

\[ \text{namedlinks} \ (\text{skipself}=\text{False}) \]

Returns a generator of all (path, link) pairs under the hierarchy.
Parameters \texttt{skipself} (\texttt{bool}) – If \texttt{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=True})

Returns a generator of all (path, param) pairs under the hierarchy.

Parameters \texttt{include\_uninit} (\texttt{bool}) – If \texttt{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=True})

Returns a generator of all parameters under the link hierarchy.

Parameters \texttt{include\_uninit} (\texttt{bool}) – If \texttt{True}, it also generates uninitialized parameters.

Returns A generator object that generates all parameters.

\texttt{pop} ([\texttt{index}]) \rightarrow \texttt{item} – remove and return item at index (default last).

Raise IndexError if list is empty or index is out of range.

\texttt{register\_persistent} (\texttt{name})

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} (\texttt{str}) – Name of the attribute to be registered.

\texttt{remove} (\texttt{value})

\texttt{S.remove(value)} – remove first occurrence of value. Raise ValueError if the value is not present.

\texttt{repeat} (\texttt{n\_repeat}, \texttt{mode='init'})

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(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

- **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.
```

```python
serialize(serializer)
    Serializes the link object.
```

Parameters **serializer** *(AbstractSerializer)* – Serializer object.

```python
to_cpu()
    Copies parameter variables and persistent values to CPU.
```

```
    This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.
```

```
    Returns: self
```

```python
to_gpu(device=None)
    Copies parameter variables and persistent values to GPU.
```

```
    This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.
```

```
    Parameters **device** – Target device specifier. If omitted, the current device is used.
```

```
    Returns: self
```

```python
to_intel64()
    Copies parameter variables and persistent values to CPU.
```

```python
zerograds()
    Initializes all gradient arrays by zero.
```

```
    This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
```

```
    Deprecated since version v1.15: Use cleargrads() instead.
```

Attributes

- **local_link_hooks**
  Ordered dictionary of registered link hooks.

4.3. Link and Chains
Contrary to `chainer.thread_local.link_hooks`, which registers its elements to all functions, link hooks in this property are specific to this link.

\texttt{n\_cells}

Returns the number of cells.

This function must be implemented in a child class.

\texttt{n\_weights} = 2

\texttt{update\_enabled}

True if at least one parameter has an update rule enabled.

\texttt{use\_bi\_direction} = False

\texttt{within\_init\_scope}

True if the current code is inside of an initialization scope.

See `init\_scope()` for the details of the initialization scope.

\texttt{xp}

Array module for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

\texttt{chainer.links.Parameter}

\texttt{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 as of v1.5. Use them directly instead.

\textbf{Parameters}

- \texttt{array} – Initial parameter array.

\textbf{Variables}

- \texttt{W (Variable)} – Parameter variable.

\textbf{Methods}

\texttt{__call__ (*args, **kwargs)}

Call self as a function.

\texttt{add\_hook (hook, name=None)}

Registers a link hook.

\textbf{Parameters}

- \texttt{hook (LinkHook)} – Link hook to be registered.

- \texttt{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.

\textbf{Returns}

self

\texttt{add\_param (name, shape=None, dtype=<class 'numpy.float32'>, initializer=None)}

Registers a parameter to the link.

\textbf{Parameters}

- \texttt{name (str)} – Name of the parameter. This name is also used as the attribute name.

- \texttt{shape (int or tuple of ints)} – Shape of the parameter array. If it is omitted, the parameter variable is left uninitialized.

- \texttt{dtype} – Data type of the parameter array.
• **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.

**add_persistent**( `name`, `value`)  
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`)  
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**( )  
Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads**( )  
Clears all gradient arrays.  
This method should be called before the backward computation at every iteration of the optimization.

**copy**( `mode='share'`)  
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`, `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 `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()**

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)**

Unregisters the link hook.

**Parameters**

- `name (str)` – The name of the link hook to be unregistered.

**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.

**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.

**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`

**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,))
```
**links** *(skipself=False)*  
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=False)*  
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=True)*  
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=True)*  
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)*  
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, mode='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')
```

---

**4.3. Link and Chains**
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.

**to_cpu**()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu**(device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64**()

Copies parameter variables and persistent values to CPU.

**zerograds**()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

Attributes

**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.
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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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, **kwargs)
Call self as a function.

__getitem__(name)
Equivalent to getattr.

add_hook(hook, name=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** (*name, link*)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent** (*name, value*)
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*)
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** ()
Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads** ()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode='share'*)
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*, *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 `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**()

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)*

Unregisters the link hook.

**Parameters**

- **name** *(str)* – The name of the link hook to be unregistered.

**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`.

**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`.

**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.
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.

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=False)

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=False)

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=True)

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=True)

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)

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, mode='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)

Serializes the link object.

Parameters `serializer` (`AbstractSerializer`) – Serializer object.

to_cpu()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

to_gpu (device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters `device` – Target device specifier. If omitted, the current device is used.
Returns: self
to_intel64()
Copies parameter variables and persistent values to CPU.
zerograd()
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for
backward compatibility.
Deprecated since version v1.15: Use cleargrads() instead.

Attributes

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.

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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

- **in_size** (*int*) – Dimension of input vector \( x \).
- **out_size** (*int*) – Dimension of hidden vector \( h \).
- **init** – Initializer for GRU’s input units \( W \). It is a callable that takes \( N \)-dimensional array and edits its value. If it is None, the default initializer is used.
- **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 None, the default initializer is used.
- **bias_init** – Bias initializer. It is a callable that takes \( N \)-dimensional array and edits its value. If None, the bias is set to zero.

Variables

- **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:

```
>>> in_size = 10
>>> out_size = 20
>>> x = np.zeros((1, in_size), dtype=np.float32)
```

1. Give only in_size and out_size arguments:

```
>>> l = L.StatefulGRU(in_size, out_size)
>>> h_new = l(x)
>>> h_new.shape
(1, 20)
```

2. Give all optional arguments:

```
>>> 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, **kwargs)***
  Call self as a function.

- **__getitem__(**name)***
  Equivalent to getattr.
add_hook (hook, name=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 (name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

add_persistent (name, value)
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)
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 ()
Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads ()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.
copy (mode='share')
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, 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 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 ()
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)
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

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.

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.
forward(x)

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.

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=False)

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=False)

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=True)

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=True)

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)

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*, *mode='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.

**reset_state**()

**serialize**(serializer)

Serializes the link object.

**Parameters**

- **serializer (AbstractSerializer)** – Serializer object.

**set_state**(*h*)

**to_cpu**()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self
to_gpu (device=None)
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters
device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64 ()
Copies parameter variables and persistent values to CPU.
zerograds ()
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

Attributes
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.

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 for this link.

Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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

\[ r = \sigma(W_r x + U_r h), \]
\[ z = \sigma(W_z x + U_z h), \]
\[ \tilde{h} = \tanh(W x + U(r \odot h)), \]
\[ h' = (1 - z) \odot h + z \odot \tilde{h}, \]

where \( \sigma \) is the sigmoid function, and \( \odot \) is the element-wise product.

As the name indicates, \texttt{StatelessGRU} is stateless, meaning that it does not hold the value of hidden vector \( h \). For a stateful GRU, use \texttt{StatefulGRU}.

**Parameters**

- \texttt{in\_size (int)} – Dimension of input vector \( x \). If \texttt{None}, parameter initialization will be deferred until the first forward data pass at which time the size will be determined.
- \texttt{out\_size (int)} – Dimension of hidden vector \( h, \tilde{h} \) and \( h' \).

**See:**

- On the Properties of Neural Machine Translation: Encoder-Decoder Approaches \cite{Cho+SSST2014}.
- Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling \cite{Chung+NIPS2014DLWorkshop}.

**See also:**

\texttt{StatefulGRU}

**Example**

There are several ways to make a \texttt{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 \texttt{in\_size} and \texttt{out\_size} arguments:

```python
>>> l = L.StatelessGRU(in_size, out_size)
>>> h_new = l(h, x)
>>> h_new.shape
(1, 20)
```  
2. Omit \texttt{in\_size} argument or fill it with \texttt{None}:

```python
>>> l = L.StatelessGRU(None, out_size)
>>> h_new = l(h, x)
>>> h_new.shape
(1, 20)
```
Methods

__call__(*args, **kwargs)
Call self as a function.

__getitem__(name)
Equivalent to getattr.

add_hook(hook, name=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(name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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()
Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads()
Clears all gradient arrays.
This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')
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, 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 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 ()
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)
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.
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.

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.

forward(h, x)

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.

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=False)
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=False)
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=True)
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=True)
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 \((name)\)
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 \((n\_repeat, mode='init')\)
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** \((serializer)\)
Serializes the link object.

**Parameters**

- **serializer** \((AbstractSerializer)\) – Serializer object.

**to_cpu**()
Copies parameter variables and persistent values to CPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

to_gpu (device=None)
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters

device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64 ()
Copies parameter variables and persistent values to CPU.

zerograds ()
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads () instead.

Attributes

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.

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 for this link.

Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

chainer.links.StatefulMGU

class chainer.links.StatefulMGU (in_size, out_size)

Methods

__call__ (*args, **kwargs)
Call self as a function.

__getitem__ (name)
Equivalent to getattr.
add_hook (hook, name=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 (name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent (name, value)
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)
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 ()
Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads ()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.
copy (mode='share')
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, 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
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 ()
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)
Unregisters the link hook.

Parameters  
name (str) – The name of the link hook to be unregistered.

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.

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.
forward($x$)

`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,))
```

**links**

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**

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=True)*

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=True)*

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)*

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, mode='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.

**reset_state** ()

**serialize** *(serializer)*

Serializes the link object.

**Parameters**

- **serializer** *(AbstractSerializer)* – Serializer object.

**set_state** *(h)*

**to_cpu** ()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self
to_gpu (device=None)
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**
- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64 ()
Copies parameter variables and persistent values to CPU.

zero_grads ()
Initializes all gradient arrays by zero.

This method can be used for the same purpose of clear_grads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use clear_grads () instead.

**Attributes**

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.

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 for this link.

Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

chainer.links.StatelessMGU

class chainer.links.StatelessMGU (n_inputs, n_units)

**Methods**

__call__ (*args, **kwargs)
Call self as a function.

__getitem__ (name)
Equivalent to getattr.

add_hook (hook, name=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** *(name, link)*

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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent** *(name, value)*

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)*

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** ()

Returns a generator of all child links.

Returns A generator object that generates all child links.

**cleargrads** ()

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode='share')*

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, 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 `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 ()**
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)**
Unregisters the link hook.

**Parameters**

- **name (str)** – The name of the link hook to be unregistered.

**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`.

**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`.

**forward (h, x)**

**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,))
```

**links** (skipself=False)
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=False)
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=True)
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=True)
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)
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, mode='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)`

Serializes the link object.

Parameters `serializer (AbstractSerializer)` – Serializer object.

`to_cpu ()` 
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

`to_gpu (device=None)` 
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters `device` – Target device specifier. If omitted, the current device is used.

Returns: self

4.3. Link and Chains 513
**to_intel64**
Copies parameter variables and persistent values to CPU.

**zerograds**
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
Deprecated since version v1.15: Use *cleargrads()* instead.

**Attributes**

**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.

**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 for this link.
Depending on which of CPU/GPU this link is on, this property returns *numpy* or *cupy*.

**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

\[
\begin{align*}
a &= \tanh(upwardx + lateralth), \\
i &= \sigma(upwardx + lateralth + peep_i c), \\
f &= \sigma(upwardx + lateralth + peep_f c), \\
c' &= a \odot i + f \odot c, \\
o &= \sigma(upwardx + lateralth + peep_o c'), \\
h' &= o \tanh(c'),
\end{align*}
\]
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, **kwargs)`
  Call self as a function.

- `__getitem__ (name)`
  Equivalent to `getattr`.

- `add_hook (hook, name=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 (name, link)`
  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=None, shape=None, dtype=<class 'numpy.float32'>, initializer=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 uninitialzied.
  - `dtype` – Data type of the parameter array.
• **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.

**add_persistent** *(name, value)*  
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)*  
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** *()*  
Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads** *()*  
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode='share')*

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, 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 `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}.

\textbf{Parameters}

- \textit{link} (\texttt{Link}) – Source link object.
- \textit{copy_persistent} (\texttt{bool}) – If True, persistent values are also copied. \texttt{True} by default.

\texttt{count_params()}

Counts the total number of parameters.

This method counts the total number of scalar values included in all the \texttt{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)

\texttt{delete_hook(name)}

Unregisters the link hook.

\textbf{Parameters} \texttt{name} (\texttt{str}) – The name of the link hook to be unregistered.

\texttt{disable_update()}

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()}

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)}

Updates the internal state and returns the LSTM outputs.

\textbf{Parameters} \texttt{x} (\texttt{Variable}) – A new batch from the input sequence.

\textbf{Returns} Outputs of updated LSTM units.

\textbf{Return type} \texttt{Variable}

\texttt{init_scope()}

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.

\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 \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,))
```
links\(\text{skipself=False}\)
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\(\text{skipself=False}\)
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\(\text{include_uninit=True}\)
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\(\text{include_uninit=True}\)
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\(name\)
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\(n\_repeat, mode='init'\)
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.

**reset_state ()**

Resets the internal states.

It sets `None` to the `c` and `h` attributes.

**serialize (serializer)**

Serializes the link object.

Parameters `serializer (AbstractSerializer) – Serializer object.`

**to_cpu ()**

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: `self`

**to_gpu (device=None)**

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters `device` – Target device specifier. If omitted, the current device is used.

Returns: `self`

**to_intel64 ()**

Copies parameter variables and persistent values to CPU.

**zerograds ()**

Initializes all gradient arrays by zero.

This method can be used for the same purpose of `cleargrads`, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads ()` instead.
Attributes

**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.

**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 for this link.
Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

### chainer.links.StatefulZoneoutLSTM

class chainer.links.StatefulZoneoutLSTM(in_size, out_size, c_ratio=0.5, h_ratio=0.5, **kwargs)

Methods

**__call__**(args, **kwargs)
Call self as a function.

**__getitem__**(name)
Equivalent to getattr.

**add_hook**(hook, name=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**(name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent** *(name, value)*

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)*

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** *

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads** *

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode='share')*

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, 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 `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**()

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*)

Unregisters the link hook.

**Parameters**

- `name` ([str](#)) – The name of the link hook to be unregistered.

**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.

**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.

**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](#)

**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,))
```

**links** *(skipself=False)*

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=False)*

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=True)*

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=True)*

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)*

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, mode='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__()
```

(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.

reset_state()

Resets the internal state.

It sets None to the c and h attributes.

serialize(serializer)

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_cpu()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

to_gpu(device=None)

Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

**to_intel64**

Copies parameter variables and persistent values to CPU.

**zerograds**

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

- **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.

- **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 for this link.
  Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

**chainer.links.StatelessLSTM**

```python
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 initialization will be deferred until the first forward data pass at which time the size will be determined.

- **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 $h$ be:

```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)
```

1. Give both `in_size` and `out_size` arguments:

```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

___call___(*args, **kwargs)

Call self as a function.

___getitem___(name)

Equivalent to getattr.

add_hook (hook, name=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 (name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent (name, value)
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)
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 ()
Returns a generator of all child links.

Returns
A generator object that generates all child links.

cleargrads ()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')
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, 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 *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using *copy.deepcopy()*.

**Parameters**

- **link** *(Link)* – Source link object.
- **copy_persistent** *(bool)* – If True, persistent values are also copied. True by default.

**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**(name)

Unregisters the link hook.

**Parameters** name *(str)* – The name of the link hook to be unregistered.

**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.

**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.

**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 \((c_{\text{new}}, h_{\text{new}})\), where \(c_{\text{new}}\) represents new cell state, and \(h_{\text{new}}\) is updated output of LSTM units.

Return type
tuple of \(-\text{chainer.Variable}\)

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,))
```

links \((\text{skipself}=\text{False})\)

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 \((\text{skipself}=\text{False})\)

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 \((\text{include_uninit}=\text{True})\)

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 \((\text{include_uninit}=\text{True})\)

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 \((\text{name})\)

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, mode='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.

**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.

**to_cpu** ()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu** *(device=None)*

Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

**device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64()**
Copies parameter variables and persistent values to CPU.

**zerograds()**
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

### 4.3.2 Activation/loss/normalization functions with parameters

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<th>Link</th>
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<td><code>chainer.links.BatchNormalization</code></td>
<td>Batch normalization layer on outputs of linear or convolution functions.</td>
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<th>Module</th>
<th>Description</th>
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<tbody>
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<td><code>chainer.links.Maxout</code></td>
<td>Fully-connected maxout layer.</td>
</tr>
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<td><code>chainer.links.NegativeSampling</code></td>
<td>Negative sampling loss layer.</td>
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</table>

`chainer.links.BatchNormalization`

class `chainer.links.BatchNormalization`:

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.
- **beta** *(Variable)* – Shifting parameter.
- **avg_mean** *(N-dimensional array)* – Population mean.
- **avg_var** *(N-dimensional array)* – Population variance.
- **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**

```python
>>> x = np.arange(12).reshape(4, 3).astype(np.float32) ** 2
>>> x
array([[ 0.,  1.,  4.],
       [ 9., 16., 25.],
       [36., 49., 64.],
       [81., 100., 121.]], dtype=float32)
>>> bn = chainer.links.BatchNormalization(3)
>>> bn(x)
variable([[ 1.5714285,  1.5404074,  1.5160886 ],
         [ 0.14285715,  0.19748813,  0.23583598],
         [-0.71428573, -0.6714596 , -0.6401263 ]])
>>> (x - x.mean(axis=0)) / np.sqrt(x.var(axis=0) + 2e-5)
array([[ 1.5714285,  1.5404074,  1.5160886 ],
       [ 0.14285715,  0.19748813,  0.23583598],
       [-0.71428573, -0.6714596 , -0.6401263 ]])
```

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`. 4.3. Link and Chains 533
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)
>>> bn.avg_mean.shape
(3,)
>>> bn = chainer.links.BatchNormalization(axis=(0, 2, 3))
>>> print(bn.avg_mean)
None
>>> y = bn(x)
>>> bn.avg_mean.shape
(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,)
>>> bn = chainer.links.BatchNormalization(axis=0)
>>> print(bn.avg_mean)
None
>>> y = bn(x)
>>> bn.avg_mean.shape
(3, 32, 32)
```
Methods

__call__(*args, **kwargs)
Call self as a function.

add_hook (hook, name=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_param (name, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent (name, value)
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)
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 ()
Returns a generator of all child links.

Returns

- A generator object that generates all child links.

cleargrads ()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')
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, 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 `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 ()**

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)**

Unregisters the link hook.

**Parameters**

- `name (str)` – The name of the link hook to be unregistered.

**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`.

**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`.

**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.

**Warning:** test argument is not supported anymore since v2. Instead, use chainer.using_config('train', False). See chainer.using_config().

**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.

**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,))
```

**links (skipself=False)**

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=False)**

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=True)**

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=True)
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)
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, mode='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)
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_cpu()
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

to_gpu(device=None)
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters

device – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64()
Copies parameter variables and persistent values to CPU.

zerograds()
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

Attributes

avg_mean = None
avg_var = None
beta = None
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.

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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, **kwargs)
Call self as a function.

add_hook (hook, name=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_param (name, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.
**add_persistent** *(name, value)*

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)*

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** *()*

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads** *()*

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode='share')*

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, 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 *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()
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)
Unregisters the link hook.

*Parameters name* *(str)* – The name of the link hook to be unregistered.

### 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.

### 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.

### 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.

**Warning:** test argument is not supported anymore since v2. Instead, use chainer. using_config('train', False). See chainer.using_config().

*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.

### 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,))
```

**links** *(skipself=False)*

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=False)*

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=True)*

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=True)*

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)*

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, mode='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__()
```

(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.

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_cpu()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

to_gpu *(device=None)*

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64()

Copies parameter variables and persistent values to CPU.
zerograds()
   Initializes all gradient arrays by zero.

   This method can be used for the same purpose of cleargrads, but less efficient. This method is left for
   backward compatibility.

   Deprecated since version v1.15: Use cleargrads() instead.

Attributes

avg_mean = None
avg_var = None
beta = None
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.

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 for this link.

   Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

chainer.links.GroupNormalization

class chainer.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__(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*

add_hook (hook, name=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_param (name, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

add_persistent (name, value)

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)

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**()

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads**()

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy**(mode='share')

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, 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 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**()

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)
Unregisters the link hook.

**Parameters**

name (str) – The name of the link hook to be unregistered.

**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.

**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.

**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,))
```

**links**(skipself=False)
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=False)
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=True)
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=True)*

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)*

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, mode='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.

```python
serialize(serializer)
```
Serializes the link object.

**Parameters**

`serializer` *(AbstractSerializer)* – Serializer object.

```python
to_cpu()
```
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: `self`

```python
to_gpu(device=None)
```
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

`device` – Target device specifier. If omitted, the current device is used.

Returns: `self`

```python
to_intel64()
```
Copies parameter variables and persistent values to CPU.

```python
zerograds()
```
Initializes all gradient arrays by zero.

This method can be used for the same purpose of `cleargrads`, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

```python
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.

```python
update_enabled
```
True if at least one parameter has an update rule enabled.

```python
within_init_scope
```
True if the current code is inside of an initialization scope.

See `init_scope()` for the details of the initialization scope.

```python
xp
```
Array module for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.  

---

**Chainer Documentation, Release 5.3.0**

Chapter 4. API Reference
chainer.links.LayerNormalization

```python
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**

```python
__call__(*args, **kwargs)
    Call self as a function.

add_hook(hook, name=None)
    Registers a link hook.

    Parameters
    ----------
    hook : LinkHook
        Link hook to be registered.
    name : str, optional
        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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

```python
add_persistent (name, value)
```

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)
```

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 ()
```

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

```python
cleargrads ()
```

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

```python
copy (mode='share')
```

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, 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 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()**

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)**

Unregisters the link hook.

**Parameters** **name** (str) – The name of the link hook to be unregistered.

**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.

**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.

**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

**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.
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=False)
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=False)
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=True)
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=True)
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)
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, mode='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:

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.

**serialize** *(serializer)*

Serializes the link object.

- **Parameters** **serializer** *(AbstractSerializer)—Serializer object.*

**to_cpu** *

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu**(device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

- **Parameters** **device** —Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** *

Copies parameter variables and persistent values to CPU.

**zerograd** *

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

`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.

`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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

**chainer.links.BinaryHierarchicalSoftmax**

```python
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:

$$
P(x) = \prod_{(e_i, b_i) \in \text{path}(x)} P(b_i | e_i) 
= \prod_{(e_i, b_i) \in \text{path}(x)} \sigma(b_i x^\top w_{e_i}),
$$

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, **kwargs)
Call self as a function.
```

```
add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.
```

```
add_persistent(name, value)
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)
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()
Returns a generator of all child links.

Returns
A generator object that generates all child links.
```

```
cleargrads()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.
```

```
copy(mode='share')
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, 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 `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

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

`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 `BinaryHierarchicalSoftmax`. For example, `{0: 8, 1: 5, 2: 6, 3: 4}` is converted to `((3, 1), (2, 0))`.

**Parameters**

- **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 `word_counts`.

### delete_hook

`delete_hook(name)`

Unregisters the link hook.

**Parameters**

- **name** (`str`) – The name of the link hook to be unregistered.
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.

disable_update()

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.

enable_update()

forward($x, t$)  
Computes the loss value for given input and ground truth labels.

Parameters

- $x$ (Variable) – Input to the classifier at each node.
- $t$ (Variable) – Batch of ground truth labels.

Returns Loss value.

Return type Variable

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.

init_scope()

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($skipself=False$)  
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($skipself=False$)  
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($include_uninit=True$)  
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=True)
Returns a generator of all parameters under the link hierarchy.

Parameters include_uninit (bool) – If True, it also generates unitialized parameters.

Returns A generator object that generates all parameters.

register_persistent (name)
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, mode='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:

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.

**to_cpu**
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

**Returns**: self

**to_gpu** *(device=None)*
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

**Returns**: self

**to_intel64**
Copies parameter variables and persistent values to CPU.

**zerograd**
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use *cleargrads()* instead.

**Attributes**

- **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.

- **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 for this link.

  Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

4.3. Link and Chains
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, **kwargs)
Call self as a function.

add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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 ()
Returns a generator of all child links.

Returns

A generator object that generates all child links.

cleargrads ()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')
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, 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 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 ()
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)

Unregisters the link hook.

**Parameters**

- **name**(str) – The name of the link hook to be unregistered.

### 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.

### 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.

### 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

### 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,))
```

### links(skipself=False)

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=False)

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=True)*

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=True)*

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)*

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, mode='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.
• **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.

**to_cpu** ()

    Copies parameter variables and persistent values to CPU.

    This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

    Returns: self

**to_gpu** (*device=None*)

    Copies parameter variables and persistent values to GPU.

    This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

    **Parameters**

    *device* – Target device specifier. If omitted, the current device is used.

    Returns: self

**to_intel64** ()

    Copies parameter variables and persistent values to CPU.

**zerograds** ()

    Initializes all gradient arrays by zero.

    This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

    Deprecated since version v1.15: Use *cleargrads()* instead.

**Attributes**

**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.

**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.
Array module for this link.

Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

```
chainer.links.CRF1d
```

### 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, **kwargs)`
  Call self as a function.

- `add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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` – 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.

- `add_persistent(name, value)`
  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*)

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*)

Computes a state that maximizes a joint probability.

Parameters **xs** (*list of Variable*) – Input vector for each label.

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**

Returns a generator of all child links.

Returns A generator object that generates all child links.

**cleargrads**

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** (*mode='share'*)

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, 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 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()
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)
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

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.

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.

forward (xs, ys, reduce='mean')

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.

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=False)
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=False`)  
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=True`)  
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=True`)  
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`)  
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`, `mode='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)

Serializes the link object.

Parameters **serializer** (AbstractSerializer) – Serializer object.

**to_cpu** ()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu** (device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64** ()

Copies parameter variables and persistent values to CPU.

**zerograds** ()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

**Attributes**

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

chainer.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

__call__(*args, **kwargs)
Call self as a function.

add_hook (hook, name=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_param**(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent**(name, value)

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)

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**()

Returns a generator of all child links.

  **Returns** A generator object that generates all child links.

**cleargrads**()

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy**(mode='share')

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, 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 *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()`

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)`

Unregisters the link hook.

**Parameters**

- **name** (*str*) – The name of the link hook to be unregistered.

`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*.

`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*.

`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

### 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,))
```

### links (skipself=False)

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=False)

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=True)

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=True)

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)

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, mode='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)

Serializes the link object.

Parameters serializer (AbstractSerializer) – Serializer object.

to_cpu ()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.
Returns: self

to_gpu(device=None)
Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU,
the link implementation must override this method to do so.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64()
Copies parameter variables and persistent values to CPU.

zerograd()    
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for
backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

Attributes

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.

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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.

See also:

chainer.functions.prelu()

Variables W (Parameter) – Coefficient of parametric ReLU.
Methods

__call__(*args, **kwargs)
Call self as a function.

add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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()
Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads()
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy(mode='share')
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, 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
`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 ()`
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)`
Unregisters the link hook.

**Parameters** `name (str)` – The name of the link hook to be unregistered.

`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`.

`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`.

`forward (x)`
Applies the parametric ReLU activation function.
Parameters $x$ (Variable) – Input variable.

Returns Output of the parametric ReLU function.

Return type Variable

def __init__(self):
    super().__init__()

    with self.init_scope():
        self.W = chainer.Parameter(0, (10, 5))
        self.b = chainer.Parameter(0, (5,))

Links (skipself=False)

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=False)

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=True)

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=True)

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.

RegisterPersistent (name)

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, mode='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)`
Serializes the link object.

Parameters `serializer (AbstractSerializer)` – Serializer object.

`to_cpu ()`
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

`to_gpu (device=None)`
Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

**Returns**

- `self`

**to_intel64()**

Copies parameter variables and persistent values to CPU.

**zerograds()**

Initializes all gradient arrays by zero.

This method can be used for the same purpose of `cleargrads()`, but less efficient. This method is left for backward compatibility.

Deprecates since version v1.15: Use `cleargrads()` instead.

**Attributes**

- **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.

- **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 for this link.

  Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

---

### 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):

```python
...```
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))
        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, **kwargs)
    Call self as a function.

add_hook (hook, name=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_param (name, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

### add_persistent(name, value)

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)

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()

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

### cleargrads()

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

### copy(mode='share')

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*, *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 *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** ()

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*)

Unregisters the link hook.

**Parameters** *name* (*str*) – The name of the link hook to be unregistered.

**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.

**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.

**forward** (*x*)

Applies the Swish activation function.

**Parameters** *x* (*Variable*) – Input variable.

**Returns** Output of the Swish activation function.

**Return type** *Variable*

**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.
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=False)
    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=False)
    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=True)
    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=True)
    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)
    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, mode='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)

Serializes the link object.

Parameters `serializer` (AbstractSerializer) – Serializer object.

to_cpu ()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

to_gpu (device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters `device` – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64 ()

Copies parameter variables and persistent values to CPU.

zerograds ()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
Deprecation since version v1.15: Use `cleargrads()` instead.

Attributes

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

**chainer.links.Maxout**

```python
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()`
Methods

__call__(*args, **kwargs)
Call self as a function.

__getitem__(name)
Equivalent to getattr.

add_hook(hook, name=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(name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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()**
Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads()**
Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy**(mode='share')
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, 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 **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()**
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)
Unregisters the link hook.
Parameters

**name** (*str*) – The name of the link hook to be unregistered.

**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`.

**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`.

**forward**(*x*)

Applies the maxout layer.

**Parameters**

**x** (*Variable*) – Batch of input vectors.

**Returns**

Output of the maxout layer.

**Return type** *Variable*

**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,))
```

**links** (*skipself=False*)

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=False*)

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=True*)

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=True)
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)
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, mode='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:

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.

**to_cpu**  
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

**Returns**: self

**to_gpu** *(device=None)*  
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**  
**device**  
Target device specifier. If omitted, the current device is used.

**Returns**: self

**to_intel64**  
Copies parameter variables and persistent values to CPU.

**zerograd**  
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

**Deprecation**: Since version v1.15: Use **cleargrads()** instead.

**Attributes**

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns **numpy** or **cupy**.

**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, **kwargs)

Call self as a function.

add_hook(hook, name=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_param(name, shape=None, dtype=<class 'numpy.float32'>, initializer=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` – 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.

add_persistent(name, value)

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)
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()
Returns a generator of all child links.

Returns

A generator object that generates all child links.

cleargrads()
Cleans all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')
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, 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 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()
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)
Unregisters the link hook.

**Parameters**

name (`str`) – The name of the link hook to be unregistered.

### 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`.

### 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`.

### forward (x, t, reduce='sum')
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.

**Returns** Loss value.

**Return type** `Variable`

### 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,))
```

### links (skipself=False)
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=False)
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=True)
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=True)
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)
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, mode='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:

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.

```
to_cpu ()
```

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

```
to_gpu (device=None)
```

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self

```
to_intel64 ()
```

Copies parameter variables and persistent values to CPU.

```
zerograds ()
```

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

Attributes

```
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.

```
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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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:

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```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, **kwargs)
Call self as a function.

#### `__getitem__`(name)
Equivalent to getattr.

#### `add_hook`(hook, name=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`(name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

#### `add_persistent`(name, value)
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)`

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 ()`

Returns a generator of all child links.

Returns A generator object that generates all child links.

`cleargrads ()`

Cleans all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

`copy (mode='share')`

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, 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 `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()
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)
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

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.

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.

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

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.
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=False)
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=False)
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=True)
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=True)
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)
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, mode='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:

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.

to_cpu()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

to_gpu(device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64()

Copies parameter variables and persistent values to CPU.

zerograds()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

- `compute_accuracy = True`
- `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.
- `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 for this link.
  Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

### 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

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td><code>chainer.links.VGG16Layers</code></td>
<td>A pre-trained CNN model with 16 layers provided by VGG team.</td>
</tr>
<tr>
<td><code>chainer.links.VGG19Layers</code></td>
<td>A pre-trained CNN model with 19 layers provided by VGG team.</td>
</tr>
<tr>
<td><code>chainer.links.model.vision.vgg.prepare</code></td>
<td>Converts the given image to the numpy array for VGG models.</td>
</tr>
</tbody>
</table>
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 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 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 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, **kwargs)**
  Call self as a function.

- **__getitem__(name)**
  Equivalent to getattr.

- **add_hook (hook, name=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 (name, link)**
  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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

### add_persistent (**name**, **value**)

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**)

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 ()

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

### cleargrads ()

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**=`'share'`)

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

copypararams (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 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 ()
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 containst uninitialed parameters, this method raises a warning.

Returns The total size of parameters (int)

delete_hook (name)
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.

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.

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.

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):
```

(continues on next page)
with chainer.using_config('enable_backprop', False):
    feature = model.extract([image])

**Warning:** `test` and `volatile` arguments are not supported anymore since v2. Instead, users should configure training and volatile modes with `train` and `enable_backprop`, respectively.

Note that default behavior of this method is different between v1 and later versions. Specifically, the default values of `test` in v1 were `True` (test mode). But that of `chainer.config.train` is also `True` (train mode). Therefore, users need to explicitly switch `train` to `False` to run the code in test mode and `enable_backprop` to `False` to turn off computational graph construction.

See the upgrade guide.

**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`.

**Warning:** `test` argument is not supported anymore since v2. Instead, use `chainer.using_config('train', False)` to run in test mode. See `chainer.using_config()`.

**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

**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**

4.3. Link and Chains

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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=False``)
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=False``)
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=True``)
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=True``)
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``)
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, mode='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**)  
Serializes the link object.

**Parameters**  
**serializer** (**AbstractSerializer**) – Serializer object.

**to_cpu** ()
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: `self`

**to_gpu** (**device=None**)  
Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**
- **device** – Target device specifier. If omitted, the current device is used.

**Returns**: self

to_intel64()
Copies parameter variables and persistent values to CPU.

zerograds()
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

**available_layers**

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

### 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 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 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, **kwargs)
Call self as a function.

__getitem__(name)
Equivalent to getattr.

add_hook (hook, name=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 (name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

add_persistent (name, value)
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*)

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**()

Returns a generator of all child links.

**Returns**

A generator object that generates all child links.

**cleargrads**()

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*='share')

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*, *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 *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 ()**
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)**
Unregisters the link hook.

**Parameters** name (str) – The name of the link hook to be unregistered.

**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.

**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.

**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])
```

**Warning:** test and volatile arguments are not supported anymore since v2. Instead, users should configure training and volatile modes with train and enable_backprop, respectively.

Note that default behavior of this method is different between v1 and later versions. Specifically, the default values of test in v1 were True (test mode). But that of chainer.config.train is also True (train mode). Therefore, users need to explicitly switch train to False to run the code in test mode and enable_backprop to False to turn off computational graph construction.

See the upgrade guide.

**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*.

**Warning:** *test* argument is not supported anymore since v2. Instead, use `chainer.using_config('train', False)` to run in test mode. See `chainer.using_config()`.

**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`

**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,))
```

**links** *(skipself=False)*
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=False)*
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=True)`

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=True)`

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)`

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, mode='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)
```

(continues on next page)
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.

to_cpu()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

to_gpu (device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters **device** – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64()

Copies parameter variables and persistent values to CPU.

zerograds()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.
Attributes

available_layers

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.

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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
A pre-trained GoogLeNet model provided by BVLC.

chainer.links.model.vision.googlenet.prepare
Converts the given image to the numpy array for GoogLeNet.

4.3. Link and Chains
chainer.links.GoogLeNet

class 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 you to 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 $CHAINER_DATASET_ROOT/pfnet/chainer/models directory, where $CHAINER_DATASET_ROOT is set as $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 initialized 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 $s = \sqrt{\frac{3}{fanin}}$ and $fanin$ 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, **kwargs)
  Call self as a function.

- __getitem__(name)
  Equivalent to getattr.

- add_hook(hook, name=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(name, link)
  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*, *shape=None*, *dtype=<class 'numpy.float32'>*, *initializer=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** – 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.

**add_persistent** (*name*, *value*)

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*)

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**()

Returns a generator of all child links.

Returns A generator object that generates all child links.

**cleargrads**()

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='share'*)

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, 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 *BatchNormalization*). If the persistent value is an ndarray, the elements are copied. Otherwise, it is copied using *copy.deepcopy()*.

**Parameters**

- *link* *(Link)*—Source link object.
- *copy_persistent* *(bool)*—If True, persistent values are also copied. True by default.

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 *(name)*
Unregisters the link hook.

**Parameters** *name* *(str)*—The name of the link hook to be unregistered.

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.

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.

event *(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])
```

**Warning:** `train` and `volatile` arguments are not supported anymore since v2. Instead, users should configure training and volatile modes with `train` and `enable_backprop`, respectively.

Note that default behavior of this method is different between v1 and later versions. Specifically, the default values of `train` arguments in v1 were `False` and `OFF`, while that of `chainer.config.train` are `True`. Therefore, users need to explicitly switch `train` to `False` to run the code in test mode to turn off computational graph construction.

See the upgrade guide.

**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`.

**Warning:** `train` argument is not supported anymore since v2. Instead, use `chainer.using_config('train', train)`. See `chainer.using_config()`.

**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`

**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,))
```

**links (skipself=False)**
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=False)**
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=True)**
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=True)**
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)*

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, mode='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)*

Serializes the link object.

**Parameters**

- **serializer** *(AbstractSerializer)* – Serializer object.

**to_cpu** *

Copies parameter variables and persistent values to CPU.

---

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This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self
to_gpu (device=None)
Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters

device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64 ()
Copies parameter variables and persistent values to CPU.

zerograds ()
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

Attributes

available_layers
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.

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

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

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**chainer.links.model.vision.resnet.ResNetLayers**

```python
class chainer.links.model.vision.resnet.ResNetLayers(pretrained_model, n_layers, downsampel_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, **kwargs)
Call self as a function.

___getitem___(name)
Equivalent to `getattr`.

add_hook(hook, name=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(name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

add_persistent(name, value)
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)
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()
Returns a generator of all child links.

Returns
A generator object that generates all child links.

cleargrads()
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='share')
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, 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
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.

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copy_persistent \((bool)\) – If True, persistent values are also copied. True by default.

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 \((\text{int})\)

delete_hook \((name)\)
Unregisters the link hook.

Parameters name \((str)\) – The name of the link hook to be unregistered.

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.

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.

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])
```

Warning: test and volatile arguments are not supported anymore since v2. Instead, users should configure training and volatile modes with train and enable_backprop, respectively.

Note that default behavior of this method is different between v1 and later versions. Specifically, the default values of test in v1 were True (test mode). But that of chainer.config.train is also True (train mode). Therefore, users need to explicitly switch train to False to run the code in test mode and enable_backprop to False to turn off computational graph construction.

See the upgrade guide.

Parameters

- images \((\text{iterable of PIL.Image or numpy.ndarray})\) – Input images.
- layers \((\text{list of str})\) – 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

```python
def forward(self, x, layers=['prob'])
```

Computes all the feature maps specified by `layers`.

---

**Warning:** test argument is not supported anymore since v2. Instead, use chainer.using_config('train', train). See chainer.using_config().

**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

### init_scope

```python
def __init__(self):
    super().__init__()
    with self.init_scope():
        self.W = chainer.Parameter(0, (10, 5))
        self.b = chainer.Parameter(0, (5,))
```

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

```python
def links(self, skipself=False)
```

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

```python
def namedlinks(self, skipself=False)
```

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=True)*
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=True)*
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)*
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, mode='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)))
```

(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)*

Serializes the link object.

**Parameters** serializer *(AbstractSerializer)* – Serializer object.

**to_cpu()**

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu**(device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters** device – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64()**

Copies parameter variables and persistent values to CPU.

**zerograds()**

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

**available_layers**
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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

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**

```python
__call__(*args, **kwargs)
Call self as a function.
```

```python
__getitem__(name)
Equivalent to getattr.
```

```python
add_hook(hook, name=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
```

```python
add_link(name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.
```

```python
add_persistent(name, value)
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)
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 ()
Returns a generator of all child links.

Returns
A generator object that generates all child links.

cleargrads ()
Cleans 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='share')
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, 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
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**()

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*)

Unregisters the link hook.

**Parameters**  
*name* (*str*) – The name of the link hook to be unregistered.

**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.

**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.

**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])
```

**Warning:**  
*test* and *volatile* arguments are not supported anymore since v2. Instead, users should configure training and volatile modes with *train* and *enable_backprop*, respectively.

Note that default behavior of this method is different between v1 and later versions. Specifically, the default values of *test* in v1 were True (test mode). But that of *chainer.config.train* is also True (train mode). Therefore, users need to explicitly switch *train* to False to run the code in test mode and *enable_backprop* to False to turn off computational graph construction.

See the upgrade guide.

**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

`forward(self, x, layers=['prob'])`

Computes all the feature maps specified by `layers`.

**Warning:** `test` argument is not supported anymore since v2. Instead, use `chainer.using_config('train', train)`. See `chainer.using_config()`.

**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

#### 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,))
```

#### links

`links(skip_self=False)`

Returns a generator of all links under the hierarchy.

**Parameters** `skip_self` *(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(skip_self=False)`

Returns a generator of all (path, link) pairs under the hierarchy.

**Parameters** `skip_self` *(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=True)*
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=True)*
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)*
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, mode='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)))
```

(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

Serializes the link object.

**Parameters**

- **serializer** (`AbstractSerializer`) – Serializer object.

### to_cpu

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

### to_gpu (device=None)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

### to_intel64

Copies parameter variables and persistent values to CPU.

### zerograd

Initializes all gradient arrays by zero.

This method can be used for the same purpose of `cleargrads`, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

### Attributes

- **available_layers**
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.

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 for this link.

Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

chainer.links.ResNet101Layers

class chainer.links.ResNet101Layers
(pretrained_model='auto', downsampling=True)

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).

• downsampling (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.

4.3. Link and Chains
Methods

__call__(*args, **kwargs)
Call self as a function.

__getitem__(name)
Equivalent to getattr.

add_hook(hook, name=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(name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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()

Returns a generator of all child links.

Returns A generator object that generates all child links.

cleargrads()

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='share')

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, 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 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()

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** *(str)* – The name of the link hook to be unregistered.

### 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`.

### 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`.

### extract

Extracts all the feature maps of given images.

The difference of directly executing the `forward` method 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 the `prepare` and `forward` functions.

Unlike the `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])
```

**Warning:**  `test` and `volatile` arguments are not supported anymore since v2. Instead, users should configure training and volatile modes with `train` and `enable_backprop`, respectively.

Note that default behavior of this method is different between v1 and later versions. Specifically, the default values of `test` in v1 were `True` (test mode). But that of `chainer.config.train` is also `True` (train mode). Therefore, users need to explicitly switch `train` to `False` to run the code in test mode and enable backprop to `False` to turn off computational graph construction.

See the upgrade guide.

**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.

**Warning:** test argument is not supported anymore since v2. Instead, use chainer.
using_config('train', train). See chainer.using_config().

**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

**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,))
```

**links** (skipself=False)

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=False)

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=True)

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=True)*

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)*

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, mode='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*)

Serializes the link object.

**Parameters**

*serializer* (*AbstractSerializer*) – Serializer object.

**to_cpu**()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu**(*device=None*)

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

*device* – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64**()

Copies parameter variables and persistent values to CPU.

**zerograds**()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use **cleargrads()** instead.

**Attributes**

**available_layers**

**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.

**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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

counterparts
.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-
  pleting 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, **kwargs)
Call self as a function.

__getitem__(name)
Equivalent to getattr.

add_hook(hook, name=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 (name, link)`

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, shape=None, dtype=<class 'numpy.float32'>, initializer=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` – 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.

`add_persistent (name, value)`

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)`

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 ()`

Returns a generator of all child links.

Returns: A generator object that generates all child links.

`cleargrads ()`

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='share')*

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, 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 `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** ()

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)*

Unregisters the link hook.

**Parameters** **name** *(str)* – The name of the link hook to be unregistered.

**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`. 
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.

eextract (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])
```

**Warning:** test and volatile arguments are not supported anymore since v2. Instead, users should configure training and volatile modes with train and enable_backprop, respectively.

Note that default behavior of this method is different between v1 and later versions. Specifically, the default values of test in v1 were True (test mode). But that of chainer.config.train is also True (train mode). Therefore, users need to explicitly switch train to False to run the code in test mode and enable_backprop to False to turn off computational graph construction.

See the upgrade guide.

**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.

**Warning:** test argument is not supported anymore since v2. Instead, use chainer.using_config('train', train). See chainer.using_config().

**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

`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,))
```

`links(skipself=False)` 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=False)` 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=True)` 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=True)` 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`)
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`, `mode='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)
```

Serializes the link object.

**Parameters** *serializer* (*AbstractSerializer*) – Serializer object.

```
to_cpu ()
```

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

```
to_gpu (device=None)
```

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters** *device* – Target device specifier. If omitted, the current device is used.

Returns: self

```
to_intel64 ()
```

Copies parameter variables and persistent values to CPU.

```
zerograds ()
```

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use *cleargrads()* instead.

**Attributes**

```
available_layers
```

```
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.

```
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 for this link.

Depending on which of CPU/GPU this link is on, this property returns *numpy* or *cupy*.  

---
**chainer.links.model.vision.resnet.prepare**

chainer.links.model.vision.resnet.

`prepare(image, size=(224, 224))`

Converts the given image to the numpy array for ResNets.

Note that you have to call this method before `forward` because the pre-trained resnet 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 ResNet as well (i.e., `chainercv.links.model.resnet.ResNet50`, `chainercv.links.model.resnet.ResNet101`, `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

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<td>chainer.links.TheanoFunction</td>
<td>Theano function wrapper.</td>
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<td>chainer.links.caffe.CaffeFunction</td>
<td>Caffe emulator based on the model file of Caffe.</td>
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**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)
>>> c.array
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, **kwargs*)
Call self as a function.

**add_hook** (hook, name=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_param** (name, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent** (name, value)
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)
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** ()
Returns a generator of all child links.

**Returns**
A generator object that generates all child links.
**cleargrads()**
Clears all gradient arrays.
This method should be called before the backward computation at every iteration of the optimization.

**copy**(mode='share')
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, 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 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()**
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)
Unregisters the link hook.

**Parameters**

**name**(str) — The name of the link hook to be unregistered.

**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.
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.

forward(*args)

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.

```
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=False)
  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=False)
  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=True)
  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=True)
  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.

registerPersistent (name)
  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, mode='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)*

Serializes the link object.

**Parameters**

- `serializer` *(AbstractSerializer)* – Serializer object.

**to_cpu** ()

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.
Returns: self
to_gpu(device=None)
Copies parameter variables and persistent values to GPU.
This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters device – Target device specifier. If omitted, the current device is used.

Returns: self
to_intel64()
Copies parameter variables and persistent values to CPU.
zerograd()
Initializes all gradient arrays by zero.
This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.
Depreciated since version v1.15: Use cleargrads() instead.

Attributes

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.

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 for this link.
Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

chainer.links.caffe.CaffeFunction

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 binaryPROTO model file of Caffe.
- `forwards` (dict) – A mapping from layer names to corresponding functions.

Methods
- `__call__(args, **kwargs)`
  Call self as a function.
- `__getitem__(name)`
  Equivalent to `getattr`.
- `add_hook(hook, name=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(name, link)`
  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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

**add_persistent** *(name, value)*

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)*

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** *

Returns a generator of all child links.

**Returns** A generator object that generates all child links.

**cleargrads** *

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

**copy** *(mode='share')*

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, 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
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 ()
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)
Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.
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.
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.
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.

Warning: train argument is not supported anymore since v2. Instead, use chainer.
using_config('train', train). See chainer.using_config().

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

### 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,))
```

### links (skipself=False)
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=False)
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=True)
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=True)
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)
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, mode='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:

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.
**to_cpu()**
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu**(device=None)
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

Parameters

- **device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64()**
Copies parameter variables and persistent values to CPU.

**zerograds()**
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use cleargrads() instead.

**Attributes**

- **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.

- **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 for this link.

  Depending on which of CPU/GPU this link is on, this property returns numpy or cupy.

### 4.3.5 Link and Chain base classes

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.Link</td>
<td>Building block of model definitions.</td>
</tr>
<tr>
<td>chainer.Chain</td>
<td>Composable link with object-like interface.</td>
</tr>
<tr>
<td>chainer.ChainList</td>
<td>Composable link with list-like interface.</td>
</tr>
<tr>
<td>chainer.Sequential</td>
<td>Sequential model which has a single-stream forward pass.</td>
</tr>
</tbody>
</table>
class chainer.Link(**params)
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 to 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()
```
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.

```python
initializers.Zero(), (n_out,))

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

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, **kwargs)
Call self as a function.

`add_hook` (hook, name=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_param` (name, shape=None, dtype=<class 'numpy.float32'>, initializer=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` – 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.

`add_persistent` (name, value)
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)
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()
Returns a generator of all child links.

Returns
- A generator object that generates all child links.

cleargrads()
Clears all gradient arrays.
This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')
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, 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 **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()
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)**

Unregisters the link hook.

**Parameters**

- **name (str)** – The name of the link hook to be unregistered.

**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.

**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.

**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,))
```

**links (skipself=False)**

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=False)**

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=True)**

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=True*)

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*)

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*, *mode='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

Serializes the link object.

**Parameters**

<table>
<thead>
<tr>
<th>Name</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>serializer</td>
<td>AbstractSerializer</td>
<td>- Serializer object.</td>
</tr>
</tbody>
</table>

**to_cpu**

Copies parameter variables and persistent values to CPU.

- This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu**(device=None)

Copies parameter variables and persistent values to GPU.

- This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters**

<table>
<thead>
<tr>
<th>Name</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>device</td>
<td>None</td>
<td>- Target device specifier. If omitted, the current device is used.</td>
</tr>
</tbody>
</table>

Returns: self

**to_intel64**

Copies parameter variables and persistent values to CPU.

**zerograds**

Initializes all gradient arrays by zero.

- This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

**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.

**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 for this link.

- Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

**chainer.Chain**

**class chainer.Chain(**links**)

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 \textit{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 \texttt{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 \textit{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 \texttt{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 \texttt{children()} generator, which returns a generator running through the children in lexical order.

On registration of a child link, its \texttt{name} attribute is also set (or overwritten if the link has already been registered to another chain).

\section*{Example}

This is a simple example of custom chain definition. Chainer itself also provides some chains defined under the \texttt{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 \texttt{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 \texttt{with self.init\_scope():} block. The forward propagation is often implemented as the \texttt{forward} operator as the above example, though it is not mandatory.

\textbf{Parameters} \texttt{links} – Child links. The keywords are used as their names. The names are also set to the links.
Methods

__call__(*args, **kwargs)
Call self as a function.

__getitem__(name)
Equivalent to getattr.

add_hook(hook, name=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(name, link)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 – 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.

add_persistent(name, value)
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)
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()

Returns a generator of all child links.

Returns  A generator object that generates all child links.

cleargrads()

Clears all gradient arrays.

This method should be called before the backward computation at every iteration of the optimization.

copy (mode='share')

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, 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 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 ()

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)

Unregisters the link hook.

Parameters name (str) – The name of the link hook to be unregistered.
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.

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.

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.

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=False)  
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=False)  
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=True)  
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=True)  
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)  
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*, *mode='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*)

Serializes the link object.

**Parameters**

- **serializer** (*AbstractSerializer*) – Serializer object.

**to_cpu()**

Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.
Returns: self

**to_gpu** *(device=None)*

Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU,
the link implementation must override this method to do so.

**Parameters**

**device** – Target device specifier. If omitted, the current device is used.

Returns: self

to_intel64()

Copies parameter variables and persistent values to CPU.

zerograds()

Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for
backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

**chainer.ChainList**

**class** `chainer.ChainList (*links)`

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, **kwargs)
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, value)
__len__()

__iter__()

add_hook(hook, name=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)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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 -- 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.

add_persistent(name, value)
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)
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 ()
Returns a generator of all child links.

Returns
A generator object that generates all child links.
clear ()
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 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 ()
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)
Unregisters the link hook.

Parameters
- name (str) – The name of the link hook to be unregistered.
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.
**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`.

**extend(values)**
S.extend(iterable) – extend sequence by appending elements from the iterable

**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()**
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, link)**
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=False)**
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=False)**
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=True)**
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=True)*
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)*
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, mode='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.

    `reverse()`  
    S.reverse() – reverse **IN PLACE**

    `serialize(serializer)`  
    Serializes the link object.
    
    **Parameters** `serializer` *(AbstractSerializer)* – Serializer object.

    `to_cpu()`  
    Copies parameter variables and persistent values to CPU.
    
    This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.
    
    Returns: self

    `to_gpu(device=None)`  
    Copies parameter variables and persistent values to GPU.
    
    This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.
    
    **Parameters** `device` – Target device specifier. If omitted, the current device is used.
    
    Returns: self

    `to_intel64()`  
    Copies parameter variables and persistent values to CPU.

    `zerograds()`  
    Initializes all gradient arrays by zero.
    
    This method can be used for the same purpose of `cleargrads()`, but less efficient. This method is left for backward compatibility.
    
    Deprecated since version v1.15: Use `cleargrads()` instead.

**Attributes**

    `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.

    `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 for this link.

Depending on which of CPU/GPU this link is on, this property returns \texttt{numpy} or \texttt{cupy}.

\texttt{chainer.Sequential}

\texttt{class chainer.Sequential(*layers)}
Sequential model which has a single-stream forward pass.

\textbf{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 \texttt{Chain} and \texttt{ChainList} can only take \texttt{Link} object as input to their constructor, this \texttt{Sequential} can take arbitrary number of any callable objects for the forward pass computation. A \texttt{Sequential} calls the given callable objects sequentially inside of the \texttt{forward()} method in the same order as the given arguments. Therefore, you do not need to write the forward pass computation explicitly.

\textbf{Example}
The below example code shows how to use this class to construct a simple sequential network:

\begin{verbatim}
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)
\end{verbatim}

where \texttt{x} denotes a mini-batch of \texttt{n_in}-dimensional input vectors.

Furthermore, \texttt{Sequential} supports built-in list APIs, so you can concatenate \texttt{Sequential} objects to create a longer \texttt{Sequential} model easily with the same ways as Python lists:

\begin{verbatim}
>>> 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
\end{verbatim}

To repeat a \texttt{Sequential} object multiple times, you can use \texttt{repeat()} method.

\begin{verbatim}
>>> model_D = model_A.repeat(3)
\end{verbatim}

You can also add your own functions or any callable objects to a \texttt{Sequential} object:
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)  # doctest: +NORMALIZE_WHITESPACE
0    Linear  W(10, 10)  b(10,)
    relu
2    Linear  W(10, 10)  b(10,)
    sigmoid
```

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, **kwargs)
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, name=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)
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, shape=None, dtype=<class 'numpy.float32'>, initializer=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** – 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.

add_persistent (name, value)
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)
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 ()
Returns a generator of all child links.
Returns A generator object that generates all child links.

`clear()` → None – remove all items from S

`cleargrads()`
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 `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_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 `type_name`. For example, if you want to know the number of `Linear` layers included in this model, `type_name` should be `Linear`. If you want to know the number of `Function` classes or user-defined functions which have a specific name, `type_name` should be the function name, e.g., `relu` or `reshape`, etc.

Parameters `type_name (str)` – The class or function name of a layer you want to enumerate.

`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(name)`
Unregisters the link hook.

Parameters `name (str)` – The name of the link hook to be unregistered.

`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`.

`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`. 

**extend** *(sequential)*

S.extend(iterable) – extend sequence by appending elements from the iterable

**flatten()**

Flatten nested *Sequential* links.

This method flattens all the nested *Sequential* links inside this *Sequential* link.

**Returns** A flattened *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**(\*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.

**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()**

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** (*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=False*)
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=False*)
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=True*)
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=True*)
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*)
Remove and return item at index (default last).
Raise IndexError if list is empty or index is out of range.

**register_persistent** (*name*)
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** (*name*)
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*, *mode='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.

**reverse**()

S.reverse() – reverse IN PLACE

**serialize**(*serializer*)

Serializes the link object.
Parameters **serializer** (*AbstractSerializer*) – Serializer object.

**to_cpu**
Copies parameter variables and persistent values to CPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to CPU, the link implementation must override this method to do so.

Returns: self

**to_gpu** (*device=None*)
Copies parameter variables and persistent values to GPU.

This method does not handle non-registered attributes. If some of such attributes must be copied to GPU, the link implementation must override this method to do so.

**Parameters device** – Target device specifier. If omitted, the current device is used.

Returns: self

**to_intel64**
Copies parameter variables and persistent values to CPU.

**zerograds**
Initializes all gradient arrays by zero.

This method can be used for the same purpose of cleargrads, but less efficient. This method is left for backward compatibility.

Deprecated since version v1.15: Use `cleargrads()` instead.

**__add__** (*other*)

**Attributes**

**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.

**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 for this link.

Depending on which of CPU/GPU this link is on, this property returns `numpy` or `cupy`.

### 4.3.6 Link hooks

Chainer provides a link-hook mechanism that enriches the behavior of `Link`.

**`chainer.link_hooks.TimerHook`** Link hook for measuring elapsed time of `forward()`.
**chainer.link_hooks.TimerHook**

```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__()`
- `__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(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** *(file=<_io.TextIOWrapper name='<stdout>' mode='w' encoding='UTF-8'>)*

Prints a summary report of time profiling in links.

**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**
- **occurrence**

**total_time()**

Returns total elapsed time in seconds.

**Attributes**

```
name = 'TimerHook'
```

You can also implement your own link-hook to inject arbitrary code before/after the forward propagation.

```python
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 __call__(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()))
... # doctest:+ELLIPSIS
Total time : ...
```

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__()`  
- `__exit__(*args)`  
- `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**(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.

**Attributes**

name = 'LinkHook'

### 4.4 Probability Distributions

Chainer provides many `Distribution` implementations in the `chainer.distributions` package.

#### 4.4.1 Distributions


### chainer.distributions.Bernoulli

**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 \( \log\left\{ p/(1 - p) \right\} \). 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 to 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 to 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
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.
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 \( x \) \((\text{Variable or N-dimensional array})\) – Data points in the domain of the distribution

Returns Logarithm of survival function value evaluated at \( x \).

Return type \( \text{Variable} \)

\textsf{perplexity}(x)

Evaluates the perplexity function at the given points.

Parameters \( x \) \((\text{Variable or N-dimensional array})\) – Data points in the domain of the distribution

Returns Perplexity function value evaluated at \( x \).

Return type \( \text{Variable} \)

\textsf{prob}(x)

Evaluates probability at the given points.

Parameters \( x \) \((\text{Variable or N-dimensional array})\) – Data points in the domain of the distribution

Returns Probability evaluated at \( x \).

Return type \( \text{Variable} \)

\textsf{sample}(\text{sample_shape}=())

Samples random points from the distribution.

This function calls \textsf{sample_n} and reshapes a result of \textsf{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 to override this function. Instead of doing this, it is preferable to override \textsf{sample_n}.

Parameters \( \text{sample_shape} \) \((\text{tuple of int})\) – Sampling shape.

Returns Sampled random points.

Return type \( \text{Variable} \)

\textsf{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 to override this method.

Parameters \( n \) \((\text{int})\) – Sampling size.

Returns Sampled random points.

Return type \( \text{Variable} \)

\textsf{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 \( \text{Variable} \)
Attributes

a
b

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.

### 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 to 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 to 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**

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

**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

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.

chainer.distributions.Dirichlet
class chainer.distributions.Dirichlet(alpha)
Dirichlet Distribution.

The probability density function of the distribution is expressed as

\[ p(x) = \frac{\Gamma(\sum_{i=1}^{K} \alpha_i)}{\prod_{i=1}^{K} \Gamma(\alpha_i)} \prod_{i=1}^{K} x_i^{\alpha_i-1} \]

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**
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**
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**
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**
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 to 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 to override this method.

Parameters

- **n** *(int)* – Sampling size.

Returns sampled random points.

Return type *Variable*

**survival_function**
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

alpha
alpha0

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.
support
Returns the support of the distribution.

\textbf{Returns} String that means support of this distribution.

\textbf{Return type} \textit{str}

\textbf{variance}
Returns the variance of the distribution.

\textbf{Returns} The variance of the distribution.

\textbf{Return type} \textit{Variable}

\textbf{xp}
Array module for the distribution.

Depending on which of CPU/GPU this distribution is on, this property returns \texttt{numpy} or \texttt{cupy}.

c\textbf{hainer.distributions.Laplace}

c\texttt{lass} \texttt{hainer.distributions.Laplace(loc, scale)}
Laplace Distribution.

The probability density function of the distribution is expressed as

\[ p(x; \mu, b) = \frac{1}{2b} \exp \left( -\frac{|x - \mu|}{b} \right) \]

\textbf{Parameters}

\begin{itemize}
  \item \texttt{loc} \textit{(Variable or N-dimensional array)} – Parameter of distribution representing the location \(\mu\).
  \item \texttt{scale} \textit{(Variable or N-dimensional array)} – Parameter of distribution representing the scale \(b\).
\end{itemize}

\textbf{Methods}

c\texttt{df(x)}
Evaluates the cumulative distribution function at the given points.

\textbf{Parameters} \textbf{\texttt{x}} \textit{(Variable or N-dimensional array)} – Data points in the domain of the distribution.

\textbf{Returns} Cumulative distribution function value evaluated at \(x\).

\textbf{Return type} \textit{Variable}

ic\texttt{df(x)}
Evaluates the inverse cumulative distribution function at the given points.

\textbf{Parameters} \textbf{\texttt{x}} \textit{(Variable or N-dimensional array)} – Data points in the domain of the distribution.

\textbf{Returns} Inverse cumulative distribution function value evaluated at \(x\).

\textbf{Return type} \textit{Variable}

log\_\texttt{df(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 to 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 to override this method.

**Parameters** $n$ (*int*) – Sampling size.
<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>sample()</code></td>
<td>Returns sampled random points.</td>
</tr>
<tr>
<td><code>survival_function(x)</code></td>
<td>Evaluates the survival function at the given points.</td>
</tr>
<tr>
<td><code>Parameters x</code></td>
<td>Data points in the domain of the distribution.</td>
</tr>
<tr>
<td><code>Returns</code></td>
<td>Survival function value evaluated at x.</td>
</tr>
</tbody>
</table>

### Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>batch_shape</code></td>
<td>Returns the shape of a batch.</td>
</tr>
<tr>
<td><code>Returns</code></td>
<td>The shape of a sample that is not identical and independent.</td>
</tr>
<tr>
<td><code>Return type</code></td>
<td>tuple</td>
</tr>
<tr>
<td><code>covariance</code></td>
<td>Returns the covariance of the distribution.</td>
</tr>
<tr>
<td><code>Returns</code></td>
<td>The covariance of the distribution.</td>
</tr>
<tr>
<td><code>Return type</code></td>
<td>Variable</td>
</tr>
<tr>
<td><code>entropy</code></td>
<td>Returns the entropy of the distribution.</td>
</tr>
<tr>
<td><code>Returns</code></td>
<td>The entropy of the distribution.</td>
</tr>
<tr>
<td><code>Return type</code></td>
<td>Variable</td>
</tr>
<tr>
<td><code>event_shape</code></td>
<td>Returns the shape of an event.</td>
</tr>
<tr>
<td><code>Returns</code></td>
<td>The shape of a sample that is not identical and independent.</td>
</tr>
<tr>
<td><code>Return type</code></td>
<td>tuple</td>
</tr>
<tr>
<td><code>mean</code></td>
<td>Returns the mean of the distribution.</td>
</tr>
<tr>
<td><code>Returns</code></td>
<td>The mean of the distribution.</td>
</tr>
<tr>
<td><code>Return type</code></td>
<td>Variable</td>
</tr>
<tr>
<td><code>mode</code></td>
<td>Returns the mode of the distribution.</td>
</tr>
<tr>
<td><code>Returns</code></td>
<td>The mode of the distribution.</td>
</tr>
<tr>
<td><code>Return type</code></td>
<td>Variable</td>
</tr>
<tr>
<td><code>params</code></td>
<td>Returns the parameters of the distribution.</td>
</tr>
<tr>
<td><code>Returns</code></td>
<td>The parameters of the distribution.</td>
</tr>
<tr>
<td><code>Return type</code></td>
<td>dict</td>
</tr>
</tbody>
</table>
**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.LogNormal**

**class** chainer.distributions.LogNormal(mu, sigma)
Logatithm Normal Distribution.

The probability density function of the distribution is expressed as

\[
p(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left(-\frac{(\log(x) - \mu)^2}{2\sigma^2}\right)
\]

**Parameters**
- **mu** (Variable or N-dimensional array) – Parameter of distribution \(\mu\).
- **sigma** (Variable or N-dimensional array) – Parameter of distribution \(\sigma\).

**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 to 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 to 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**
  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

- **mu**
**params**
Returns the parameters of the distribution.

Returns The parameters of the distribution.

Return type dict

**sigma**
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.MultivariateNormal**

**class** chainer.distributions.MultivariateNormal(loc, **kwargs)
MultivariateNormal Distribution.

The probability density function of the distribution is expressed as

\[ p(x; \mu, V) = \frac{1}{\sqrt{\det(2\pi V)}} \exp \left( -\frac{1}{2} (x - \mu)V^{-1}(x - \mu) \right) \]

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

---

4.4. Probability Distributions
Returns Cumulative distribution function value evaluated at $x$.

Return type Variable

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 to 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 to 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**

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`.

---

**chainer.distributions.Normal**

```python
class chainer.distributions.Normal(loc, scale=\text{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

\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 \( \text{sample\_shape} + \text{batch\_shape} + \text{event\_shape} \). On implementing sampling code in an inherited distribution class, it is not recommended to 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 to 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 \texttt{x} (Variable or N-dimensional array) – Data points in the domain of the distribution

Returns Survival function value evaluated at \( x \).

Return type Variable

\textbf{Attributes}

\texttt{batch\_shape}

Returns the shape of a batch.

Returns The shape of a sample that is not identical and independent.

Return type tuple

\texttt{covariance}

Returns the covariance of the distribution.

Returns The covariance of the distribution.

Return type Variable

\texttt{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

**log_scale**

**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

**scale**

**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.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 *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 to 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 to 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**

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

high
c loc
def
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

scale
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.

4.4.2 Functionals of distribution

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<th>Function</th>
<th>Description</th>
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<td>Computes Cross entropy.</td>
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<tr>
<td>chainer.kl_divergence</td>
<td>Computes Kullback-Leibler divergence.</td>
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<tr>
<td>chainer.register_kl</td>
<td>Decorator to register KL divergence function.</td>
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**chainer.cross_entropy**

**chainer.cross_entropy** *(dist1, dist2)*
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 calls **kl_divergence()** and **entropy()** of dist1. Therefore, it is necessary to register KL divergence function with **register_kl()** decorator and define **entropy()** in 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**

**chainer.kl_divergence** *(dist1, dist2)*
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**

`chainer.Distribution`

`chainer.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`. 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 to 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 to 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

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

deparams
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

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<td>Zeiler’s ADADELTA.</td>
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<td>Adam optimizer.</td>
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<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_hooks** (*timing='pre'*)

Invokes hook functions in registration order.

**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*

**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.

**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**

- **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_hooks (timing='pre')
        Invokes hook functions in registration order.

    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

    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 \(\text{epoch}\))

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.

```
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.

```python
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

### 4.5.3 `chainer.optimizers.Adam`

```python
class chainer.optimizers.Adam(alpha=0.001, beta1=0.9, beta2=0.999, eps=1e-08, eta=1.0, weight_decay_rate=0, amsgrad=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

**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.
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_hooks (timing='pre')
Invokes hook functions in registration order.

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

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.

`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**

- `alpha`
  Alias to `self.hyperparam.alpha`

- `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

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.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.

```python
call_hooks(timing='pre')
```
Invokes hook functions in registration order.

```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
ew_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
toggle_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.
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.

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

- **epoch** = 0
- **lr**
  
  Alias to self.hyperparam.lr

  momentum
  
  Alias to self.hyperparam.momentum

- **t** = 0

- **target** = None

- **use_auto_new_epoch** = False

4.5.5 chainer.optimizers.MomentumSGD

class chainer.optimizers.MomentumSGD(lr=0.01, momentum=0.9)

Momentum SGD optimizer.

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_hooks (timing='pre')
Invokes hook functions in registration order.

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

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.

**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

**lr**
Alias to `self.hyperparam.lr`

**momentum**
Alias to `self.hyperparam.momentum`

**t** = 0

**target** = None

**use_auto_new_epoch** = False
4.5.6 chainer.optimizers.NesterovAG

class chainer.optimizers.NesterovAG(lr=0.01, momentum=0.9)
Nesterov’s Accelerated Gradient.


Parameters

• \( \text{lr} \) (float) – Learning rate.

• \( \text{momentum} \) (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 \( \text{hook.call_for_each_param} \) 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, \( \text{hook.name} \) 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_hooks (timing='pre')
Invokes hook functions in registration order.

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

new_epoch (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 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 ()
Realloacte 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.

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
lr
    Alias to self.hyperparam.lr

momentum
    Alias to self.hyperparam.momentum

t = 0

target = None

use_auto_new_epoch = False

4.5.7 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.

- **call_hooks** (timing='pre')
    Invokes hook functions in registration order.

- **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}

\textbf{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.

\textbf{reallocate\_cleared\_grads ()}

Reallocate gradients cleared by \texttt{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 (name)}

Removes a hook function.

**Parameters** \texttt{name (str)} – Registered name of the hook function to remove.

\textbf{serialize (serializer)}

Serializes or deserializes the optimizer.

It only saves or loads the following things:

- Optimizer states
- Global states (\texttt{t} and \texttt{epoch})

It does not save nor loads the parameters of the target link. They should be separately saved or loaded.

**Parameters** \texttt{serializer (AbstractSerializer)} – Serializer or deserializer object.

\textbf{set\_loss\_scale (loss\_scale)}

Sets loss scaling factor.

\textbf{setup (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.

**Parameters** \texttt{link (Link)} – Target link object.

**Returns** The optimizer instance.

\textbf{update (lossfun=None, *args, **kwds)}

Updates parameters based on a loss function or computed gradients.

This method runs in two ways.

- If \texttt{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.

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

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

4.5.8 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.

**call_hooks** *(timing='pre')*

Invokes hook functions in registration order.

**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

**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.

**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**

**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

### 4.5.9 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_hooks (timing='pre')`
  Invokes hook functions in registration order.

- `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`

- `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.

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

epoch = 0

lr
Alias to self.hyperparam.lr
4.5.10 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_hooks(timing='pre')
Invokes hook functions in registration order.

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

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.

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

epoch = 0
eps
  Alias to self.hyperparam.eps
lr
  Alias to self.hyperparam.lr
t = 0
target = None
use_auto_new_epoch = False

4.5.11 Optimizer base classes

<table>
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<tr>
<th>Class</th>
<th>Description</th>
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<td>Base class of all numerical optimizers.</td>
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<tr>
<td>chainer.UpdateRule</td>
<td>Base class of all update rules.</td>
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<td>chainer.optimizer.Hyperparameter</td>
<td>Set of hyperparameter entries of an optimizer.</td>
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<td>chainer.GradientMethod</td>
<td>Base class of all single gradient-based optimizers.</td>
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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_hooks** *(timing='pre')*

Invokes hook functions in registration order.

**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 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.
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.

Attributes

epoch = 0
t = 0
target = None
use_auto_new_epoch = 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_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 `meth: update` for details.

**Attributes**

- **state**

  State dictionary.

**chainer.optimizer.Hyperparameter**

**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.

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 to 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_hooks(timing='pre')
Invokes hook functions in registration order.

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.

\textbf{Returns} Update rule object.

\textbf{Return type} \texttt{UpdateRule}

\textbf{new\_epoch (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.

\textbf{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.

\textbf{reallocate\_cleared\_grads ()}

Reallocate gradients cleared by \texttt{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 (name)}

Removes a hook function.

\textbf{Parameters} \texttt{name (str)} – Registered name of the hook function to remove.

\textbf{serialize (serializer)}

Serializes or deserializes the optimizer.

It only saves or loads the following things:

\begin{itemize}
  \item Optimizer states
  \item Global states (\texttt{t} and \texttt{epoch})
\end{itemize}

\textbf{It does not save nor loads the parameters of the target link.} They should be separately saved or loaded.

\textbf{Parameters} \texttt{serializer (AbstractSerializer)} – Serializer or deserializer object.

\textbf{set\_loss\_scale (loss\_scale)}

Sets loss scaling factor.

\textbf{setup (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 (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 (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.
\end{itemize}
• 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.

`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**
- `epoch = 0`
- `t = 0`
- `target = None`
- `use_auto_new_epoch = False`

### 4.5.12 Hook functions

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<th>Class/Function</th>
<th>Description</th>
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<td>Optimizer/UpdateRule hook function for weight decay regularization.</td>
</tr>
<tr>
<td><code>chainer.optimizer_hooks.Lasso</code></td>
<td>Optimizer/UpdateRule hook function for Lasso regularization.</td>
</tr>
<tr>
<td><code>chainer.optimizer_hooks.GradientClipping</code></td>
<td>Optimizer hook function for gradient clipping.</td>
</tr>
<tr>
<td><code>chainer.optimizer_hooks.GradientHardClipping</code></td>
<td>Optimizer/UpdateRule hook function for gradient clipping.</td>
</tr>
<tr>
<td><code>chainer.optimizer_hooks.GradientNoise</code></td>
<td>Optimizer/UpdateRule hook function for adding gradient noise.</td>
</tr>
<tr>
<td><code>chainer.optimizer_hooks.GradientLARS</code></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 Opti-
mizer/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.
```

**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.
```

**Attributes**

```python
call_for_each_param = True
name = 'Lasso'
timing = 'pre'
```
chainer.optimizer_hooks.GradientClipping

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
__call__(opt)
Call self as a function.

Attributes
- name = 'GradientClipping'
- timing = 'pre'

chainer.optimizer_hooks.GradientHardClipping

class chainer.optimizer_hooks.GradientHardClipping(lower_bound, upper_bound)
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.

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:

\[ g_t \leftarrow g_t + N(0, \sigma^2_t) \]

where

\[ \sigma^2_t = \eta \frac{1}{(1 + t)^\gamma} \]

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, which for the default noise function is recommended to 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

__call__(rule, param)
Call self as a function.
Attributes

call_for_each_param = True
name = 'GradientNoise'
timing = 'pre'

chainer.optimizer_hooks.GradientLARS

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>,
\[ v_{t+1} = m \cdot v_t + \gamma \cdot \lambda \cdot (\nabla L(w_t) + \beta w_t), \]
\[ w_{t+1} = w_t - v_{t+1}, \]

where

• \( \gamma \): learning_rate
• \( m \): momentum
• \( \beta \): weight_decay
• \( \eta \): lars_coefecient
• \( \lambda \): local_lr = \( \eta \cdot \frac{\|w_t\|}{\|\nabla L(w_t)\| + \beta \cdot \|w_t\|} \).

As \( lr \) in chainer.optimizers.SGD or chainer.optimizers.MomentumSGD corresponds to \( \gamma \cdot \eta \), we define \( clip\_rate \) as \( \frac{\|w_t\|}{\|\nabla L(w_t)\| + \beta \cdot \|w_t\|} \) and reformulate the aforementioned formula as: \( v_{t+1} = m \cdot v_t + lr \cdot clip\_rate \cdot (\nabla L(w_t) + \beta w_t) \) and implement in this way. So you do not set lars_coefecient.

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>)

• weight_decay (float) – Coefficient for the weight decay.

• eps (float) – Small value for the numerical stability. (See <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>)

• weight_decay (float) – Coefficient for the weight decay.

• eps (float) – Small value for the numerical stability. (See <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.
```

**Attributes**

```python
call_for_each_param = True
name = 'GradientLARS'
timing = 'pre'
```

## 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 specified, 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
chainer.Initializer
Initializes array.
```

**chainer.Initializer**

```python
class chainer.Initializer(*dtype=None*)
Initializes array.
```

It initializes the given array.

**Variables**

- **dtype** – Data type specifier. It is for type check in __call__ function.
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.

### 4.6.2 Concrete initializers

<table>
<thead>
<tr>
<th>Class Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.initializers.Identity</code></td>
<td>Initializes array with the identity matrix.</td>
</tr>
<tr>
<td><code>chainer.initializers.Constant</code></td>
<td>Initializes array with constant value.</td>
</tr>
<tr>
<td><code>chainer.initializers.Zero</code></td>
<td>Initializes array to all-zero.</td>
</tr>
<tr>
<td><code>chainer.initializers.One</code></td>
<td>Initializes array to all-one.</td>
</tr>
<tr>
<td><code>chainer.initializers.NaN</code></td>
<td>Initializes array to all-NaN.</td>
</tr>
<tr>
<td><code>chainer.initializers.Normal</code></td>
<td>Initializes array with a normal distribution.</td>
</tr>
<tr>
<td><code>chainer.initializers.LeCunNormal</code></td>
<td>Initializes array with scaled Gaussian distribution.</td>
</tr>
<tr>
<td><code>chainer.initializers.GlorotNormal</code></td>
<td>Initializes array with scaled Gaussian distribution.</td>
</tr>
<tr>
<td><code>chainer.initializers.HeNormal</code></td>
<td>Initializes array with scaled Gaussian distribution.</td>
</tr>
<tr>
<td><code>chainer.initializers.Orthogonal</code></td>
<td>Initializes array with an orthogonal system.</td>
</tr>
<tr>
<td><code>chainer.initializers.Uniform</code></td>
<td>Initializes array with a scaled uniform distribution.</td>
</tr>
<tr>
<td><code>chainer.initializers.LeCunUniform</code></td>
<td>Initializes array with a scaled uniform distribution.</td>
</tr>
<tr>
<td><code>chainer.initializers.GlorotUniform</code></td>
<td>Initializes array with a scaled uniform distribution.</td>
</tr>
<tr>
<td><code>chainer.initializers.HeUniform</code></td>
<td>Initializes array with a scaled uniform distribution.</td>
</tr>
</tbody>
</table>

### chainer.initializers.Identity

**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.

### chainer.initializers.Constant

**class** `chainer.initializers.Constant`(fill_value, dtype=None)

Initializes array with constant value.

**Variables** fill_value

### 4.6. Weight Initializers
• **fill_value** (scalar or \textit{N-dimensional array}) – A constant to be assigned to the initialized array. Broadcast is allowed on this assignment.

• **dtype** – Data type specifier.

**Methods**

```python
__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** \textit{(N-dimensional array)} – An array to be initialized by this initializer.

**Attributes**

- **fill_value** = \texttt{None}

**chainer.initializers.Zero**

```python
class chainer.initializers.Zero(dtype=None)
```
Initializes array to all-zero.

**Variables**

- **dtype** – Data type specifier.

**Methods**

```python
__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** \textit{(N-dimensional array)} – An array to be initialized by this initializer.

**Attributes**

- **fill_value** = \texttt{0.0}

**chainer.initializers.One**

```python
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.

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.

Attributes

fill_value = nan

chainer.initializers.Normal

class chainer.initializers.Normal(scale=0.05, dtype=None)
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 scale.

Parameters

• scale (float) – Standard deviation of Gaussian distribution.
• dtype – Data type specifier.
Methods

```python
__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.LeCunNormal**

```python
class chainer.initializers.LeCunNormal(scale=1.0, dtype=None)
```

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.

---

**Methods**

```python
__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**

```python
class chainer.initializers.GlorotNormal(scale=1.0, dtype=None)
```

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 $scale \times \sqrt{\frac{2}{fan_{in} + fan_{out}}}$, where $fan_{in}$ and $fan_{out}$ 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.
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.HeNormal
class chainer.initializers.HeNormal(scale=1.0, dtype=None, fan_option='fan_in')

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 $scale \times \sqrt{\frac{2}{fan}}$. If $fan_option == 'fan_in'$, $fan$ is the number of input units. If $fan_option == 'fan_out'$, $fan$ 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'.

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.Orthogonal
class chainer.initializers.Orthogonal(scale=1.1, dtype=None)

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 Singular Value Decomposition (SVD) to the matrix. Then, it initializes the array with either side of resultant orthogonal matrices, depending on the shape of the input array. 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.


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.Uniform`

class `chainer.initializers.Uniform(scale=0.05, dtype=None)`

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.

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.LeCunUniform`

class `chainer.initializers.LeCunUniform(scale=1.0, dtype=None)`

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.
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)
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 
\[
s = \text{scale} \times \sqrt{\frac{6}{\text{fan}_{	ext{in}} + \text{fan}_{	ext{out}}}}. \\
\]
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.

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.HeUniform

class chainer.initializers.HeUniform(scale=1.0, dtype=None)
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.

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.
4.6.3 Helper function

chainer.initializers.generate_array
Return initialized array.

counter

chainer.initializers.generate_array (initializer, shape, xp, dtype=None)
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 (tuple) – Shape of a return array.
- xp (module) – cupy or numpy.
- dtype – Dtype specifier. If omitted, initializer.dtype is used.

Returns An initialized array.
Return type N-dimensional array

4.7 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, Optim-
izer, 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 accu-
mulate 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.

4.7.1 Trainer

chainer.training.Trainer
The standard training loop in Chainer.

class chainer.training.Trainer (updater, stop_trigger=None, out=’result’, extensions=None)
The standard training loop in Chainer.
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

```python
extend(extension, name=None, trigger=None, priority=None, **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.
- **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)

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.

4.7.2 Updaters

<table>
<thead>
<tr>
<th>chainer.training.Updater</th>
<th>Interface of updater objects for trainers.</th>
</tr>
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<td>Implementation of a multiprocess parallel GPU Updater.</td>
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</table>

chainer.training.Updater

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.

`chainer.training.updaters.StandardUpdater`

class `chainer.training.updaters.StandardUpdater(iterator, optimizer, converter=<function concat_examples>, device=None, loss_func=None, loss_scale=None, auto_new_epoch=True)`

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 to which the training data is sent. Negative value indicates the host memory (CPU).

• **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.

**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 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 ()

Attributes

epoch
epoch_detail
is_new_epoch
previous_epoch_detail

chainer.training.updaters.ParallelUpdater

class chainer.training.updaters.ParallelUpdater (iterator, optimizer, converter=<function concat_examples>, 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 automatically 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()

Attributes

epoch
epoch_detail
is_new_epoch
previous_epoch_detail

chainer.training.updaters.MultiprocessParallelUpdater

class chainer.training.updaters.MultiprocessParallelUpdater(iterators, optimizer, converter=concat_examples(), 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 compu-
tation 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 opti-
mizer.
- 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'.
- auto_new_epoch (bool) – If True, new_epoch() of the main optimizer is automati-
cally 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()  

Attributes

effect

effect_detail

is_new_epoch
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

### 4.7.3 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.

#### Common

<table>
<thead>
<tr>
<th>Module</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>
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#### 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 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.

**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.make_extension**

`chainer.training.make_extension(trigger=None, default_name=None, priority=None, finalizer=None, initializer=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.

### 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>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.training.extensions.Evaluator</code></td>
<td>Trainer extension to evaluate models on a validation set.</td>
</tr>
<tr>
<td><code>chainer.training.extensions.MicroAverage</code></td>
<td>Calculates micro-average ratio.</td>
</tr>
<tr>
<td><code>chainer.training.extensions.FailOnNonNumber</code></td>
<td>Trainer extension to raise RuntimeError if parameters contain NaN or Inf.</td>
</tr>
<tr>
<td><code>chainer.training.extensions.observe_lr</code></td>
<td>Returns a trainer extension to record the learning rate.</td>
</tr>
<tr>
<td><code>chainer.training.extensions.observe_value</code></td>
<td>Returns a trainer extension to continuously record a value.</td>
</tr>
</tbody>
</table>

**chainer.training.extensions.Evaluator**

```python
class chainer.training.extensions.Evaluator(iterator, target, converter=<function concat_examples>, device=None, eval_hook=None, eval_func=None)
```

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.

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 `FunctionNode.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.

`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 = '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 <int>, 'epoch' or <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 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.

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 = 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.

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')
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) – 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.
- **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.

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.

**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.

**Attributes**

- **default_name** = 'parameter_statistics'
- **default_statistics** = {'max': <function ParameterStatistics.<lambda>>, 'mean': <function Pipeline.<lambda>>}, 'std': <function ParameterStatistics.<lambda>>, 'zeros': <function ParameterStatistics.<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

chainer.training.extensions.observe_lr(\texttt{optimizer\_name}='main', \texttt{observation\_key}='lr')

Returns a trainer extension to record the learning rate.

Parameters

- \texttt{optimizer\_name} (\texttt{str}) – Name of optimizer whose learning rate is recorded.
- \texttt{observation\_key} (\texttt{str}) – Key of observation to record.

Returns The extension function.

chainer.training.extensions.observe_value

chainer.training.extensions.observe_value(\texttt{observation\_key}, \texttt{target\_func})

Returns a trainer extension to continuously record a value.

Parameters

- \texttt{observation\_key} (\texttt{str}) – Key of observation to record.
- \texttt{target\_func} (function) – Function that returns the value to record. It must take one argument: \texttt{class:~chainer.training.Trainer} object.

Returns The extension function.

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.

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chainer.training.extensions.ExponentialShift

class chainer.training.extensions.ExponentialShift(\texttt{attr}, \texttt{rate}, \texttt{init}=None, \texttt{target}=None, \texttt{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 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.

- **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.InverseShift

class chainer.training.extensions.InverseShift

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 formula above. Note that gamma is assumed to be nonnegative.
- **power** (float) – Parameter used to compute the new value. Refer to the formula 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.

`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` isthe 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`

```python
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**(train)**er)
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.

**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.

`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')`
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 $init_value \times (1 - \frac{i}{max_iter})^rate$ 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.
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.

invoke_before_training = True

name = None

priority = 100

trigger = (1, 'iteration')

chainer.training.extensions.WarmupShift

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.

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.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 \(k\)th iteration.

For example, suppose that this extension is invoked at every iteration, then given \(k\), a multiplier \(\gamma\) and an initial value \(\text{init}\), the optimizer attribute is set to \(\text{init} \times \gamma^{\left\lfloor \frac{i}{k} \right\rfloor}\), 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.

#### 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')
**Reporting**

These extensions provide features to perform reporting of metrics and various statistics to the console or files.

- **chainer.training.extensions.PrintReport**: Trainer extension to print the accumulated results.
- **chainer.training.extensions.ProgressBar**: Trainer extension to print a progress bar and recent training status.
- **chainer.training.extensions.LogReport**: Trainer extension to output the accumulated results to a log file.
- **chainer.training.extensions.PlotReport**: Trainer extension to output plots.
- **chainer.training.extensions.VariableStatisticsPlot**: Trainer extension to plot statistics for Variables.
- **chainer.training.extensions.dump_graph**: Alias of `chainer.training.extensions.computational_graph.DumpGraph`

**class chainer.training.extensions.PrintReport**

```python
```

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**

```python
__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.

```python
finalize()
```

Finalizes the extension.

This method is called at the end of the training loop.

```python
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.
- **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.ProgressBar

**class** chainer.training.extensions.ProgressBar (training_length=None, update_interval=100, bar_length=50, out=<\_io.TextIOWrapper \nname='\<stdout\>' \nmode='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 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.

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.LogReport

class chainer.training.extensions.LogReport(keys=None, trigger=(1, 'epoch'), postpro-
cess=None, log_name='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

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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.
- **log_name** (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.

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.
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')

chainer.training.extensions.PlotReport

class chainer.training.extensions.PlotReport(y_keys, x_key='iteration', trigger=(1, 'epoch'), postprocess=None, file_name='plot.png', marker='x', grid=True)

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', file_name='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
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.
- `file_name` (str) – Name of the figure file under the output directory. It can be a format string.
- `marker` (str) – The marker used to plot the graph. Default is ‘x’. If None is given, it draws with no markers.
- `grid` (bool) – Set the axis grid on if True. Default 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.

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.

```python
name = None
```

```python
priority = 100
```

```python
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, percentile_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 collected.

- **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`.

• **file_name** (`str`) – Name of the output image file under the output directory.

• **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.

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.

```python
name = None
priority = 100
trigger = (1, 'iteration')
```

**chainer.training.extensions.dump_graph**

```python
chainer.training.extensions.dump_graph
```

alias of `chainer.training.extensions.computational_graph.DumpGraph`

**Snapshot**

These extensions provide features to take snapshots of models.

<table>
<thead>
<tr>
<th>Extension</th>
<th>Description</th>
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<tbody>
<tr>
<td><code>chainer.training.extensions.snapshot</code></td>
<td>Returns a trainer extension to take snapshots of the trainer.</td>
</tr>
<tr>
<td><code>chainer.training.extensions.snapshot_object</code></td>
<td>Returns a trainer extension to take snapshots of a given object.</td>
</tr>
</tbody>
</table>

**chainer.training.extensions.snapshot**

```python
chainer.training.extensions.snapshot
```

`savelfun=<function save_npz>,
filename='snapshot_iter_{.updater.iteration}''
```

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**

- `savelfun` – Function to save the trainer. It takes two arguments: the output file path and the trainer object.
- `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.
chainer.training.extensions.snapshot_object

chainer.training.extensions.snapshot_object(target, filename, savefun=<function save_npz>)

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 for-
  mat 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.

Returns An extension function.

4.7.4 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.

chainer.training.get_trigger

chainer.training.triggers.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

### chainer.training.triggers.EarlyStoppingTrigger

**class** chainer.training.triggers.EarlyStoppingTrigger(check_trigger=(1, 'epoch'), monitor='main/loss', patients=3, mode='auto', verbose=False, max_trigger=(100, 'epoch'))

Trigger for Early Stopping

It can be used as a stop trigger of Trainer to realize early stopping technique.

This trigger works as follows. Within each check interval defined by the check_trigger argument, it monitors 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 patients), this trigger fires.

Parameters

- **monitor** (str) – The metric you want to monitor
- **check_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.
- **patients** (int) – Counts to let the trigger be patient. The trigger will not fire until the condition is met for successive patient checks.
- **mode** (str) – 'max', 'min', or 'auto'. It is used to determine how to compare the monitored values.
- **verbose** (bool) – Enable verbose output. If verbose is true, you can get more information
- **max_trigger** – Upper bound of the number of training loops

Methods

___call___(trainer)

Decides whether the training loop should be stopped.

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 training loop should be stopped.

Return type bool

get_training_length()
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*)

class chainer.training.triggers.ManualScheduleTrigger

**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'.

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*)

class chainer.training.triggers.MaxValueTrigger

**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

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 be-
comes 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

chainer.training.triggers.TimeTrigger

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

__call__(trainer)
Call self as a function.

serialize (serializer)
4.8 Datasets

4.8.1 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.

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<thead>
<tr>
<th>chainer.dataset.DatasetMixin</th>
<th>Default implementation of dataset indexing.</th>
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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.

Iterator Interface

See Iterator for dataset iterator implementations.

chainer.dataset.Iterator Base class of all dataset iterators.
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__()**
  With statement context manager method
  
  This method does nothing by default. Implementation may override it to better handle the internal resources by with statement.

- **__exit__(exc_type, exc_value, traceback)**
  With statement context manager method
  
  This method does nothing by default. Implementation may override it to better handle the internal resources by with statement.

- **__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.

- **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 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.

### Batch Conversion Function

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
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<td>Chainer.dataset.concat_examples</td>
<td>Concatenates a list of examples into array(s).</td>
</tr>
<tr>
<td>Chainer.dataset.ConcatWithAsyncTransfer</td>
<td>Interface to concatenate data and transfer them to GPU asynchronously.</td>
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<td>Chainer.dataset.to_device</td>
<td>Send an array to a given device.</td>
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**Chainer.dataset.concat_examples**

Chainer.dataset.concat_examples *(batch, device=None, padding=None)*

Concatenates a list of examples into array(s).

This function converts an “array of tuples” into a “tuple of arrays”. Specifically, given a list of examples each of which consists of a list of elements, this function first makes an array by taking the element in the same position from each example and concatenates them along the newly-inserted first axis (called batch dimension) into one array. It repeats this for all positions and returns the resulting arrays.

The output type depends on the type of examples in batch. For instance, consider each example consists of two arrays *(x, y)*. Then, this function concatenates x’s into one array, and y’s into another array, and returns a tuple of these two arrays. Another example: consider each example is a dictionary of two entries whose keys are ‘x’ and ‘y’, respectively, and values are arrays. Then, this function concatenates x’s into one array, and y’s into another array, and returns a dictionary with two entries x and y whose values are the concatenated arrays.

When the arrays to concatenate have different shapes, the behavior depends on the padding value. If padding is None (default), it raises an error. Otherwise, it builds an array of the minimum shape that the contents of all arrays can be substituted to. The padding value is then used to the extra elements of the resulting arrays.

**Example**

```python
>>> import numpy as np
>>> from chainer import dataset
>>> x = [(array([1, 2]), 1),
...      (array([3, 4], 2),
...      (array([5, 6], 3))
>>> dataset.concat_examples(x)
(array([1, 2],
      [3, 4],
      [5, 6]), array([1, 2, 3]))
>>> y = [(np.array([1, 2]), 0),
...      (np.array([3], 1),
...      (np.array([4], 2))
>>> dataset.concat_examples(y, padding=100)
```

(continues on next page)
(array([[ 1,  2],
        [ 3, 100],
        [100, 100]]), array([[0,  1,  2]]))

>>> z = [(np.array([1, 2]), np.array([0])),
      (np.array([3]), np.array([])),
      (np.array([]), np.array([2]))]

>>> dataset.concat_examples(z, padding=(100, 200))
(array([[ 1,  2],
        [ 3, 100],
        [100, 100]]), array([[ 0],
        [200],
        [ 2]]))

>>> w = [{'feature': np.array([1, 2]), 'label': 0},
       {'feature': np.array([3, 4]), 'label': 1},
       {'feature': np.array([5, 6]), 'label': 2}]

>>> dataset.concat_examples(w)  # doctest: +SKIP
{'feature': array([[1, 2],
                   [3, 4],
                   [5, 6]]), 'label': array([0, 1, 2])}

Parameters

- **batch** (list) – A list of examples. This is typically given by a dataset iterator.
- **device** (int) – Device ID to which each array is sent. Negative value indicates the host memory (CPU). If it is omitted, all arrays are left in the original device.
- **padding** – Scalar value for extra elements. If this is None (default), an error is raised on shape mismatch. Otherwise, an array of minimum dimensionalities that can accommodate all arrays is created, and elements outside of the examples are padded by this value.

Returns

Array, a tuple of arrays, or a dictionary of arrays. The type depends on the type of each example in the batch.

**chainer.dataset.ConcatWithAsyncTransfer**

**class chainer.dataset.ConcatWithAsyncTransfer**

*stream=*, *compute_stream=* 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 created 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 synchronization is used instead.

**Methods**

```python
__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.

**chainer.dataset.to_device**

```python
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` (*int or None*) – Device ID to which an array is sent. If it is negative value, an array is sent to CPU. If it is positive, an array is sent to GPU with the given ID. If it is `None`, an array is left in the original device.
- `x` (*N-dimensional array*) – An array to send.

**Returns** Converted array.

**Dataset Management**

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**chainer.dataset.get_dataset_root**

```python
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.
4.8.2 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.

4.8.3 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__()
**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 `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__()`

**ConcatenatedDataset**

**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.

SubDataset

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<td>Creates a set of training/test splits for cross validation randomly.</td>
</tr>
</tbody>
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**chainer.datasets.SubDataset**

```python
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

```py
>>> 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]
...```

(continues on next page)
>>> 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.

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_fold*, *order=None*)

Creates a set of training/test splits for cross validation.

This function generates *n_fold* 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_fold** (*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_fold*, *seed=None*)

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*) – Number of splits for cross validation.

• **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** List of dataset splits.

**Return type** list of tuples
**TransformDataset**

chainer.datasets.TransformDataset

Dataset that indexes the base dataset and transforms the data.

chainer.datasets.TransformDataset

class chainer.datasets.TransformDataset (dataset, transform)

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__()` method. 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` below 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.

**ImageDataset**

<table>
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<tr>
<th>chainer.datasets.ImageDataset</th>
<th>Dataset of images built from a list of paths to image files.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.datasets.MultiZippedImageDataset</td>
<td>Dataset of images built from a list of paths to zip files.</td>
</tr>
</tbody>
</table>

**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 strs)** – 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.

c imprison.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 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 processess via ChainerMN.

Parameters

• zipfilename (str) – a string to point zipfile path
• 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):
```

(continues on next page)
...    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_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.

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.

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

class chainer.datasets.LabeledImageDataset(pairs, root='.', dtype=None, label_dtype=<class 'numpy.int32'>)

Dataset of image and label pairs built from a list of paths and labels.

This dataset reads an external image file like ImageDataset. The difference from ImageDataset 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_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
```

(continues on next page)
>>> 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.

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 filename 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.

---

**TextDataset**

Dataset of a line-oriented text file.

```python
chainer.datasets.TextDataset
```

**chainer.datasets.TextDataset**

Dataset of a line-oriented text file.

```python
class chainer.datasets.TextDataset(paths, encoding=None, errors=None, newline=None, filter_func=None)
```

**class chainer.datasets.TextDataset**

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.

---

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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

```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
```

(continues on next page)
Access by one-dimensional integer list

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.

get_example(idx)
Returns the i-th example.

Parameters
i (int) -- The index of the example.

Returns
The i-th example.

PickleDataset

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.

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
...     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.
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
    __enter__()
    __exit__(exc_type, exc_value, traceback)
    close()
    flush()
    write(x)
```

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
```

chainer.datasets.open_pickle_dataset_writer

```python
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`

### 4.8.4 Concrete Datasets

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.datasets.get_mnist</code></td>
<td>Gets the MNIST dataset.</td>
</tr>
<tr>
<td><code>chainer.datasets.get_fashion_mnist</code></td>
<td>Gets the Fashion-MNIST dataset.</td>
</tr>
<tr>
<td><code>chainer.datasets.get_cifar10</code></td>
<td>Gets the CIFAR-10 dataset.</td>
</tr>
<tr>
<td><code>chainer.datasets.get_cifar100</code></td>
<td>Gets the CIFAR-100 dataset.</td>
</tr>
<tr>
<td><code>chainer.datasets.get_ptb_words</code></td>
<td>Gets the Penn Tree Bank dataset as long word sequences.</td>
</tr>
<tr>
<td><code>chainer.datasets.get_ptb_words_vocabulary</code></td>
<td>Gets the Penn Tree Bank word vocabulary.</td>
</tr>
<tr>
<td><code>chainer.datasets.get_svhn</code></td>
<td>Gets the SVHN dataset.</td>
</tr>
</tbody>
</table>

### `chainer.datasets.get_mnist`

**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 \([0, \text{scale}]\).

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_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=..., ndim=..., scale=..., dtype=..., label_dtype=..., rgb_format=...)

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, 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]`. 

4.8. Datasets
• **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.VOC SemanticSegmentationDataset`

• **Instance Segmentation Datasets**
  - `chainercv.datasets.COCOInstanceSegmentationDataset`
  - `chainercv.datasets.VOCInstanceSegmentationDataset`

• **Classification Datasets**
  - `chainercv.datasets.CUBLabelDataset`
  - `chainercv.datasets.OnlineProductsDataset`

### 4.9 Iterator

Chainer provides some iterators that implement typical strategies to create mini-batches by iterating over datasets. `SerialIterator` is the simplest one, which extract mini-batches in the main thread. `MultiprocessIterator` and `MultithreadIterator` are a parallelized version of `SerialIterator`. It maintains worker subprocesses and subthreads to load the next mini-batch in parallel.

<table>
<thead>
<tr>
<th>Iterator</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.iterators.SerialIterator</code></td>
<td>Dataset iterator that serially reads the examples.</td>
</tr>
<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>
4.9.1 `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__()`**
  With statement context manager method

  This method does nothing by default. Implementation may override it to better handle the internal resources by with statement.

- **`__exit__(exc_type, exc_value, traceback)`**
  With statement context manager method

  This method does nothing by default. Implementation may override it to better handle the internal resources by with statement.

- **`__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.
next ()
Returns the next batch.

Returns 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 serializes what is set manually by users such as the batch size.

Attributes

epoch_detail
previous_epoch_detail
repeat

4.9.2 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)

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.

### Methods

__enter__ ()

With statement context manager method

This method does nothing by default. Implementation may override it to better handle the internal resources by with statement.

__exit__ (exc_type, exc_value, traceback)

With statement context manager method

This method does nothing by default. Implementation may override it to better handle the internal resources by with statement.

__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 ()

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 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.

**Attributes**

```
epoch_detail
previous_epoch_detail
```

### 4.9.3 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__()  
With statement context manager method

This method does nothing by default. Implementation may override it to better handle the internal resources by with statement.

__exit__(exc_type, exc_value, traceback)  
With statement context manager method

This method does nothing by default. Implementation may override it to better handle the internal resources by with statement.

__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.

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 serializer protocol of Chainer.

Note: It should only serialize the internal state that changes over the iteration. It should not serializes what is set manually by users such as the batch size.

Attributes

epoch_detail
previous_epoch_detail
repeat

4.9.4 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**

```python
__enter__()  # With statement context manager method
    This method does nothing by default. Implementation may override it to better handle the internal resources by with statement.
__exit__(exc_type, exc_value, traceback)  # With statement context manager method
    This method does nothing by default. Implementation may override it to better handle the internal resources by with statement.
__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.
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()  # Serializes the internal state of the iterator.
    This is a method to support serializer protocol of Chainer.
serialize(serializer)  # Serializes the internal state of the iterator.
    This is a method to support serializer protocol of Chainer.
```

**Note:** It should only serialize the internal state that changes over the iteration. It should not serializes what is set manually by users such as the batch size.

**Attributes**

- **batch_size**
- **epoch_detail**
- **previous_epoch_detail**
- **repeat**
4.9.5 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>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.iterators.OrderSampler</code></td>
<td>Base class of all order samplers.</td>
</tr>
<tr>
<td><code>chainer.iterators.ShuffleOrderSampler</code></td>
<td>Sampler that generates random orders.</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*

### chainer.iterators.ShuffleOrderSampler

class chainer.iterators.ShuffleOrderSampler

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**

### Methods

```python
__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`

---

### 4.10 Serializers

#### 4.10.1 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><code>chainer.serializers.NpzDeserializer</code></td>
<td>Deserializer for NPZ format.</td>
</tr>
<tr>
<td><code>chainer.serializers.save_npz</code></td>
<td>Saves an object to the file in NPZ format.</td>
</tr>
<tr>
<td><code>chainer.serializers.load_npz</code></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="")
```

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: As of v2.0.0, 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.

chainer.serializers.NpzDeserializer

class chainer.serializers.NpzDeserializer(npz, path=",", strict=True, ignore_names=None)

Deserializer 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:** As of v2.0.0, 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.

**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.
• 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()

4.10.2 Serialization in HDF5 format

<table>
<thead>
<tr>
<th>chainer.serializers.HDF5Serializer</th>
<th>Serializer for HDF5 format.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.serializers.HDF5Deserializer</td>
<td>Deserializer for HDF5 format.</td>
</tr>
<tr>
<td>chainer.serializers.save_hdf5</td>
<td>Saves an object to the file in HDF5 format.</td>
</tr>
<tr>
<td>chainer.serializers.load_hdf5</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: As of v2.0.0, 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.

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:** As of v2.0.0, 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.

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.
- **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()
```

### 4.10.3 Serializers base classes

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.Serializer</code></td>
<td>Base class of all serializers.</td>
</tr>
<tr>
<td><code>chainer.AbstractSerializer</code></td>
<td>Abstract base class of all serializers and deserializers.</td>
</tr>
<tr>
<td><code>chainer.Deserializer</code></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.

**Note:** As of v2.0.0, 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.

---

**4.10. Serializers**

---

**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.

**Note:** As of v2.0.0, 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.

```python
__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.

chainer.Deserializer

class chainer.Deserializer

Base class of all deserializers.

Methods

```python
__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:** As of v2.0.0, 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.

```python
__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.
```

### 4.11 Utilities

#### 4.11.1 Convolution/Deconvolution utilities

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<td>chainer.utils.get_conv_outsize</td>
<td>Calculates output size of convolution.</td>
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<td>chainer.utils.get_deconv_outsize</td>
<td>Calculates output size of deconvolution.</td>
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</table>

**chainer.utils.get_conv_outsize**

```python
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:

*get_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**

```python
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

## 4.11.2 CUDA and Backend Utilities

### Utilities across backends

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<th><strong>chainer.backend.copyto</strong></th>
<th>Copies the elements of an ndarray to those of another one.</th>
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**chainer.backend.copyto**

chainer.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 or ideep4py.mdarray)* – Destination array.
• **src** *(numpy.ndarray, cupy.ndarray or ideep4py.mdarray)* – Source array.

### CUDA

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).
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

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<td><code>chainer.backends.cuda.get_device</code></td>
<td>Gets the device from a device object, an ID integer or an array object.</td>
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<tr>
<td><code>chainer.backends.cuda.get_device_from_id</code></td>
<td>Gets the device from an ID integer.</td>
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<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>
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</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. 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.

**chainer.backends.cuda.get_device_from_id**

chainer.backends.cuda.get_device_from_id(device_id)

Gets the device from an ID integer.

**Parameters** `device_id` (*int* or *None*) – The ID of the device which this function returns.
chainer.backends.cuda.get_device_from_array

chainer.backends.cuda.get_device_from_array(*arrays)

Gets the device from a list of CuPy array or a single CuPy array.

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**

data (cupy.ndarray or list of cupy.ndarray) – A CuPy array which this function returns the device corresponding to. If a list of `cupy.ndarray` are given, it returns the first device object of an array in the list.

cupy array allocation and copy

chainer.backends.cuda.copy

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

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

**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** – Device specifier.
- **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

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<td>Makes a function memoizing the result for each argument and device.</td>
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<td>Clears the memoized results for all functions decorated by memoize.</td>
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<td><strong>chainer.backends.cuda.elementwise</strong></td>
<td>Creates an elementwise kernel function.</td>
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<td><strong>chainer.backends.cuda.raw</strong></td>
<td>Creates a raw kernel function.</td>
</tr>
<tr>
<td><strong>chainer.backends.cuda.reduce</strong></td>
<td>Creates a global reduction kernel function.</td>
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**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 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.

```python
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.

```python
chainer.backends.cuda.elementwise
```

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.

```python
chainer.backends.cuda.raw
```

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`.

```python
chainer.backends.cuda.reduce
```

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**

```python
chainer.backends.cuda.get_array_module
```

Gets an appropriate one from `numpy` or `cupy`. 

870 Chapter 4. API Reference
chainer.backends.cuda.get_array_module

chainer.backends.cuda.get_array_module(*args)

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.

Check “cuDNN Library User Guide” for detail.

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.

Check “cuDNN Library User Guide” for detail.

Returns

The workspace size for cuDNN.

Return type

int

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 | Returns if iDeep is available. |
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

4.11.3 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

sample(shape)
Generates a random sample based on given probabilities.

Parameters shape (tuple of int) – Shape of a return value.

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_cpu(shape)
sample_gpu(shape)
to_cpu()
Make a sampler CPU mode.
to_gpu()
Make a sampler GPU mode.

4.11.4 Reporter

Reporter

chainer.Reporter
Object to which observed values are reported.

chainer.get_current_reporter
Returns the current reporter object.

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<td><code>chainer.report</code></td>
<td>Reports observed values with the current reporter object.</td>
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<td><code>chainer.report_scope</code></td>
<td>Returns a report scope with the current reporter.</td>
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**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:

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

There are also a global API to add values:

```python
>>> observation = {}
>>> with report_scope(observation):
...    report({'x': 1}, observer)
...>>> observation
{'my Observer/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:** As of v2.0.0, 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.

**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.

Example

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(behavior)

Returns a report scope with the current reporter.

This is equivalent to `get_current_reporter().scope(behavior)`, except that it does not make the reporter current redundantly.

Summary and DictSummary
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)**

chainer.DictSummary

**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)  

4.11.5 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().

chainer.utils.CooMatrix  A sparse matrix in COO format.
chainer.utils.to_coo  Returns a single or a batch of matrices in COO format.

chainer.utils.CooMatrix

class  chainer.utils.CooMatrix(data, row, col, shape, 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.

#### 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)
```

#### 4.11.6 Experimental feature annotation

`chainer.utils.experimental` Declares that user is using an experimental feature.
chainer.utils.experimental

chainer.utils.experimental(api_name)

Declares that user is using an experimental feature.

The developer of an API can mark it as experimental by calling this function. When users call experimental APIs, `FutureWarning` is issued. The presentation of `FutureWarning` is disabled by setting `chainer.disable_experimental_feature_warning` to `True`, which is `False` by default.

The basic usage is to call it in the function or method we want to mark as experimental along with the API name.

```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.

```python
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.
4.12 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.

4.12.1 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 `float16`, `float32` or `float64`.

- `enable_backprop` (default: `True`) Flag to enable backpropagation support.

  If it is `True`, computational graphs are created during forward passes by `FunctionNodes`, 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`.
• **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 **chainer.functions.forget()**. See the documentation of **chainer.functions.forget()** for details.

### 4.12.2 User-defined Keys

Users can also define their own configurations. There are two ways:

1. Use Chainer’s configuration objects. In this case, it is strongly recommended to prefix the name 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 **chainer.configuration.GlobalConfig** and **chainer.configuration.LocalConfig**. In this case, there is no need to take care of the name conflicts.

### 4.12.3 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
```

(continues on next page)
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 `using_config()`. For example, if you only want to enable debug mode in a fragment of code, write as follows.

```python
>>> 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.

```python
>>> # 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>The plain object that represents the global configuration of Chainer.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chainer.config</td>
<td>Thread-local configuration of Chainer.</td>
</tr>
<tr>
<td>chainer.using_config</td>
<td>Context manager to temporarily change the thread-local configuration.</td>
</tr>
<tr>
<td>chainer.configuration.GlobalConfig</td>
<td>The plain object that represents the global configuration of Chainer.</td>
</tr>
<tr>
<td>chainer.configuration.LocalConfig</td>
<td>Thread-local configuration of Chainer.</td>
</tr>
</tbody>
</table>

**chainer.global_config**

```python
chainer.global_config = <chainer.configuration.GlobalConfig object>
```

The plain object that represents the global configuration of Chainer.
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
    The plain object that represents the global configuration of Chainer.

    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.

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()  # doctest: +SKIP
debug       False
enable_backprop True
train       True
type_check     True
```

**Related functions**

`chainer.get_dtype`  
Resolves Chainer’s default dtype.

chainer.get_dtype

chainer.get_dtype(dtype=None)  
Resolves Chainer’s default dtype.

**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.

### 4.12.4 Environment Variables

Here are the environment variables Chainer uses.
The following environment variables are only effective when running unit tests.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CHAINER_TEST_GPU</td>
<td>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.</td>
</tr>
<tr>
<td>CHAINER_TEST_RANDOM</td>
<td>Set to use non-fixed seed for random number generators, even for test cases annotated with fix_random.</td>
</tr>
</tbody>
</table>

## 4.13 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.

```python
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 `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>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.is_debug()</code></td>
<td>Returns if the debug mode is enabled or not in the current thread.</td>
</tr>
<tr>
<td><code>chainer.set_debug(debug)</code></td>
<td>Enables or disables the debug mode in the current thread.</td>
</tr>
</tbody>
</table>

### 4.13.1 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`

### 4.13.2 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.

### 4.13.3 Deprecated interface

As of v2.0.0, it is recommended to turn on the debug mode using `chainer.config.debug`. See *Configuring Chainer* for the way to use the config object. We leave the reference of the conventional way (which has been available since Chainer v1) as follows.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.DebugMode</code></td>
<td>Debug mode context.</td>
</tr>
</tbody>
</table>

**chainer.DebugMode**

- **class** `chainer.DebugMode(debug)`

  Debug mode context.

  This class provides a context manager for debug mode. When entering the context, it sets the debug mode to the value of `debug` parameter with memorizing its original value. When exiting the context, it sets the debug mode back to the original value.

  Deprecated since version v2.0.0: Use `chainer.using_config()` instead. See *Debug Mode* for details.

  - **Parameters**
    - `debug (bool)` – Debug mode used in the context.
4.14 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.
4.14.1 chainer.computational_graph.build_computational_graph

chainer.computational_graph.build_computational_graph(outputs, remove_split=True, variable_style={'fillcolor': '#E0E0E0', 'shape': 'octagon', 'style': 'filled'}, function_style={'fillcolor': '#6495ED', 'shape': 'record', 'style': 'filled'}, rankdir='TB', remove_variable=False, show_name=True)

Builds a graph of functions and variables backward-reachable from outputs.

Parameters

- **outputs (list)** – nodes 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)** – Dot node style for variable. Possible keys are ‘shape’, ‘color’, ‘fillcolor’, ‘style’, and etc.
- **function_style (dict)** – Dot node style for function.
- **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**
Chainer Documentation, Release 5.3.0

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.

4.14.2 chainer.computational_graph.ComputationalGraph

class chainer.computational_graph.ComputationalGraph(nodes, edges, variable_style={'fillcolor': '#E0E0E0', 'shape': 'octagon', 'style': 'filled'}, function_style={'fillcolor': '#6495ED', 'shape': 'record', 'style': 'filled'}, 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)** – Dot node style for variable.
- **function_style (dict)** – Dot node style for function.
- **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 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
Chainer Documentation, Release 5.3.0

- **format** (*str*) – The graph language name of the output.
- **it must be 'dot'.** *(Currently,)*

Returns The graph in specified format.

Return type *str*

### 4.15 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.

**chainer.static_graph**

Decorator to mark a Chain’s `__call__()` as a static sub-graph.

#### 4.15.1 chainer.static_graph

**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, \texttt{chainer.config.train}. If it is \texttt{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 \texttt{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 require 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 \texttt{chain.schedule_manager.end_forward()} after the end of each forward pass.

If test mode is active (\texttt{chainer.config.train} is \texttt{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 \texttt{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 \texttt{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**

- \texttt{force_test_define_by_run (bool)} – If \texttt{True}, disable static graph optimizations during test mode (that is, when \texttt{chainer.config.train} is \texttt{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 \texttt{False}.

- \texttt{minimize_cache_size (bool)} – If \texttt{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 \texttt{True}. 

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• **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.

### 4.15.2 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
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

        @staticmethod
        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.
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(). We expect there will rarely be a need to use side-effect code but for completeness, an example of a model that uses it is available in the MLPSideEffect Chain 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.

### 4.15.3 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.
4.15.4 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 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).

4.15.5 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 __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 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 __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.

4.15.6 Examples

For additional examples that use this feature, refer to the examples in examples/static_graph_optimizations.

4.16 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.
4.16.1 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.

4.16.2 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.

### 4.16.3 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

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
```

(continues on next page)
It should not be necessary to modify the `backward()` implementation. As of Chainer v3 when double-backward (i.e., grad of grad) support was added, the `backward()` method of `FunctionNode` actually calls the `forward()` method of other `FunctionNode`'s, and so it is only necessary that the `forward()` functions be wrapped.

For an example of how to add support to an existing function, see the `Linear` function.

### 4.16.4 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 `@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.

### 4.16.5 Reference

[1] Training deep nets with sublinear memory cost

### 4.17 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.

#### 4.17.1 Import

Chainer can import the reference models and emulate the network by `Link` implementations. This functionality is provided by the `chainer.links.caffe.CaffeFunction` class.

```python
chainer.links.caffe.CaffeFunction
```

Caffe emulator based on the model file of Caffe.

#### 4.17.2 Export

Chainer can export a model from `Link`.

```python
chainer.exporters.caffe.export
```

(Experimental) Export a computational graph as Caffe format.
(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 `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.
```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')
```

## 4.18 Assertion and Testing

Chainer provides some facilities to make debugging easy.

### 4.18.1 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.

<table>
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<tr>
<th>Module</th>
<th>Description</th>
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<tr>
<td>chainer.utils.type_check.Expr</td>
<td>Abstract syntax tree of an expression.</td>
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<td>chainer.utils.type_check.expect</td>
<td>Evaluates and tests all given expressions.</td>
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<td>chainer.utils.type_check.TypeInfo</td>
<td>Type information of an input/gradient array.</td>
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<td>chainer.utils.type_checkTypeInfo</td>
<td>Type information of input/gradient tuples.</td>
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#### chainer.utils.type_check.Expr

**class** chainer.utils.type_check.Expr\(\text{priority}\)

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

```python
>>> 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:

```python
>>> c.eval()
True
```

Call `str` function to get a representation of the original equation:

```python
>>> str(c)
'x == y'
```

You can actually compare an expression with a value:

```python
>>> (x == 1).eval()
True
```

Note that you can’t use boolean operators such as `and`, as they try to cast expressions to boolean values:

```python
>>> 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)`
- `__ne__(y)`
- `__lt__(y)`
- `__le__(y)`
- `__gt__(y)`
- `__ge__(y)`
- `__nonzero__()`
- `__bool__()`
- `__neg__()`
- `__add__(y)`
- `__radd__(y)`
- `__sub__(y)`
- `__rsub__(y)`
- `__mul__(y)`
- `__rmul__(y)`
- `__pow__(y)`
- `__rpow__(y)`
- `__truediv__(y)`
- `__rtruediv__(y)`
- `__floordiv__(y)`
- `__rfloordiv__(y)`
- `__mod__(y)`
- `__rmod__(y)`
- `__divmod__(y)`
- `__rdivmod__(y)`
- `__and__(y)`
- `__rand__(y)`
- `__or__(y)`
- `__ror__(y)`
- `__xor__(y)`
- `__rxor__(y)`
- `__invert__(y)`
- `__rshift__(y)`
- `__rrshift__(y)`
- `__lshift__(y)`
- `__rlshift__(y)`

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__mul__ (y)
__rmul__ (y)
__truediv__ (y)
__rtruediv__ (y)
__floordiv__ (y)
__rfloordiv__ (y)
__pow__ (y)

chainer.utils.type_check.expect

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.

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

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

count ()
Return number of occurrences of value.

index ()
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

4.18.2 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.

chainer.gradient_check.check_backward
chainer.gradient_check.numerical_grad

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:

```python
def func(xs):
    y, = MyFunc().apply(xs)
    return y

x1_data = xp.array(...)  # x_data
x2_data = xp.array(...)  # x2_data
gy_data = xp.array(...)  # y_grad
check_backward(func, (x1_data, x2_data), gy_data)
```

This method 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 \( g : \mathbb{R} \to \mathbb{R}^n \) 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:

```python
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:

```python
check_backward(my_loss_func,
               (x1_data, x2_data), None)
```

If `MyFunc` returns multiple outputs, pass all gradients for outputs as a tuple:

```python
gy1_data = xp.array(...)  
gy2_data = xp.array(...)  
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:

```python
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:

```python
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 ~chainer.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.numerical_grad`

```python
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 `chainer.functions`.

By default, `numerical_grad` computes the gradient to the first order of `eps`.

Parameters

• **f** *(callable)* – Python function with no arguments that runs forward computation and returns the result.

• **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.

• **grad_outputs** *(tuple of arrays or scalars)* – Tuple of arrays or scalars that are treated as output gradients.

• **eps** *(float)* – Epsilon value of finite differences.

• **detect_nondifferentiable** *(bool)* – False by default. If True, `numerical_grad` checks whether `f` is differentiable at `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 `eps`. If it turns out that `f` is non-differentiable at `input`, `numerical_grad` raises `NondifferentiableError`.

• **diff_atol** *(float)* – Absolute tolerance of fitting error of non-differentiable point detection.

• **diff_rtol** *(float)* – Tolerance of fitting error of non-differentiable point detection relative to the output values of `f`.

• **center_outputs** *(tuple of arrays or None)* – Only used if `detect_nondifferentiable` is True. If specified, these arrays are used as the outputs of `f` at `inputs`. Otherwise, it is calculated. It can be used to reduce the computation if these arrays are already calculated before calling `numerical_grad`.  

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Returns  Numerical gradient arrays corresponding to inputs.

Return type  tuple

4.18.3 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.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.testing.assert_allclose</code></td>
<td>Asserts if some corresponding element of x and y differs too much.</td>
</tr>
<tr>
<td><code>chainer.testing.assert_warns</code></td>
<td></td>
</tr>
</tbody>
</table>

**chainer.testing.assert_allclose**

`chainer.testing.assert_allclose(x, y, atol=1e-05, rtol=0.0001, verbose=True)`

Asserts if some corresponding element of x and y differs too much.

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.

**chainer.testing.assert_warns**

`chainer.testing.assert_warns(expected)`

4.18.4 Function testing utilities

Utilities for testing functions.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.testing.unary_math_function_unittest</code></td>
<td>Decorator for testing unary mathematical Chainer functions.</td>
</tr>
<tr>
<td><code>chainer.testing.unary_math_function_unittest</code></td>
<td></td>
</tr>
</tbody>
</table>

**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 ed 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 `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)
(continues on next page)
```

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Because the test methods are implicitly injected to `TestSin` class by the decorator, it is enough to place `pass` in the class definition.

To customize test data, `make_data` optional parameter can be used. The following is an example of testing `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
```

`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 `make_data` parameter.

### 4.18.5 Serialization testing utilities

Utilities for testing serializable objects.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>chainer.testing.save_and_load</code></td>
<td>Saves <code>src</code> and loads it to <code>dst</code> using a de/serializer.</td>
</tr>
<tr>
<td><code>chainer.testing.save_and_load_hdf5</code></td>
<td>Saves <code>src</code> to an HDF5 file and loads it to <code>dst</code>.</td>
</tr>
<tr>
<td><code>chainer.testing.save_and_load_npz</code></td>
<td>Saves <code>src</code> to an NPZ file and loads it to <code>dst</code>.</td>
</tr>
<tr>
<td><code>chainer.testing.get_trainer_with_mock_updater</code></td>
<td>Returns a <code>Trainer</code> object with mock updater.</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.

**chainer.testing.get_trainer_with_mock_updater**

chainer.testing.get_trainer_with_mock_updater(stop_trigger=(10, 'iteration'), iter_per_epoch=10, extensions=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.

**4.18.6 Trainer Extension Testing Utilities**

Utilities for testing trainer extensions.

**chainer.testing.get_trainer_with_mock_updater**

Returns a Trainer object with mock updater.

**4.18.7 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.
chainer.testing.condition.repeat_with_success_at_least

chainer.testing.condition.repeat_with_success_at_least(times, min_success)

Decorator for multiple trial of the test case.

The decorated test case is launched multiple times. The case is judged as passed at least specified number of trials. If the number of successful trials exceeds min_success, the remaining trials are skipped.

Parameters

- **times (int)** – The number of trials.
- **min_success (int)** – Threshold that the decorated test case is regarded as passed.

chainer.testing.condition.repeat

chainer.testing.condition.repeat(times)

Decorator that imposes the test to be successful in a row.

Decorated test case is launched multiple times. The case is regarded as passed only if it is successful specified times in a row.

Note: In current implementation, this decorator grasps the failure information of each trial.

Parameters **times (int)** – The number of trials.

chainer.testing.condition.retry

chainer.testing.condition.retry(times)

Decorator that imposes the test to be successful at least once.

Decorated test case is launched multiple times. The case is regarded as passed if it is successful at least once.

Note: In current implementation, this decorator grasps the failure information of each trial.

Parameters **times (int)** – The number of trials.

4.18.8 Unit test annotation

Decorators for annotating unit tests.
**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()*

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`.
4.18.9 Parameterized test

Decorators for making a unit test parameterized.

- `chainer.testing.parameterize`
- `chainer.testing.product`
- `chainer.testing.product_dict`

**chainer.testing.parameterize**

`chainer.testing.parameterize(*params)`

**chainer.testing.product**

`chainer.testing.product(parameter)`

**chainer.testing.product_dict**

`chainer.testing.product_dict(*parameters)`
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: 2.7.6+, 3.4.3+, 3.5.1+, 3.6.0+ and 3.7.0+.
- **NumPy**
  - Supported Versions: 1.9, 1.10, 1.11, 1.12, 1.13, 1.14, 1.15 and 1.16.
  - NumPy will be installed automatically during the installation of Chainer.

Before installing Chainer, we recommend you to upgrade **setuptools and pip**:

```
$ pip install -U setuptools pip
```
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.post1+ (2.0.0.post3+ is recommended)
  - 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:

```bash
$ 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:

```bash
$ 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:

```bash
$ nvidia-docker run -it chainer/chainer /bin/bash
```

Or run the interpreter directly:

```bash
$ 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:

```bash
# 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.
CHAPTER 6

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.

6.1 Installation

6.1.1 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 reinstallation.

MPI4py

You can install MPI4py by:
$ 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.

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 to 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, 3.5.1, 3.6.1
- MPI
  - openmpi 2.1.2
- MPI4py 3.0.0
- NCCL 2.2.13

Installation on Non-GPU Environments

Users who want to try ChainerMN in CPU-only environment may skip installation of CuPy. Non-GPU set up may not be performant as GPU-enabled set up, 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.

6.1.2 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:

```
$ 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 l1 lsf sge manual persist
Topology libraries available: hwloc
Resource management kernels available: user slurm l1 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 MVAPICHI (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.

```
/* check_cuda_aware.c */
#include <assert.h>
#include <stdio.h>
```
```c
#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);

  MPI_Finalize();
}
```

Save the code to a file named `check_cuda_aware.c`. You can compile and run it with the following command:

```
$ export MPICH_CC=nvcc # if you use Mvapich
$ export OMP_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:
# 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
host00 1
host00 2
host00 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 you 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 nosetests to check the single-node configuration is ready:

$ nosetests
......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>

(continues on next page)
**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):

```bash
$ 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:haGUMcCeC5A81Gh11pjpwL5dF4xCg1ZArhhxxxxxxxxxx.
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.

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:

```bash
$ 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()

(continues on next page)
```
for i in range(size):
    if i == rank:
        print("{} {}\n".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
host01 1
host02 2
host03 3
host04 4
host05 5
host06 6
host07 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:

(continues on next page)
-> Check the value of MV2_SMP_USE_CMA (see CUDA-Aware MPI and Check SSH connection and environment variables).

- Check the value of MV2_USE_CUDA (see CUDA-Aware MPI and Check SSH connection and environment variables)

6.2 Tutorial

6.2.1 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`.

### 6.2.2 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 paths 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.
6.2.3 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 worker 0 (i.e., 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 almost equal sizes 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:
6.2.4 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
class DoNothing:
    def __init__(self):
        pass

if comm.rank == 0:
    trainer.extend(extensions.dump_graph('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())
```

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
def func():
    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()
```

$ mpiexec -n 2 python test.py

`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
def global_except_hook(exctype, value, traceback):
    import sys
    try:
        import mpi4py.MPI
    $ 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:

```python
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.

### 6.3 Model Parallel

#### 6.3.1 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.

Synchronous model-parallelism suits well with MPI programming style and SPMD model.

References

- More Effective Distributed ML via a Stale Synchronous Parallel Parameter Server
6.3.2 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:

```python
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.

![Diagram of scatter_dataset](image)

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.
6.3. Model Parallel
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.
Model 0 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.
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 $\phi_2$:

```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

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
```

### 6.3.3 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:
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:

```python
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:
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))

class MLP0SubB(chainer.Chain):
    def __init__(self, comm):
        super(MLP0SubB, self).__init__()

    def __call__(self, y):
        return y

class MLP0(chainermn.MultiNodeChainList):
    # Model on worker 0.
    def __init__(self, comm, n_out):
        super(MLP0, self).__init__(comm=comm)
        self.add_link(MLP0SubA(comm, n_out), rank_in=None, rank_out=1)
        self.add_link(MLP0SubB(comm), rank_in=1, rank_out=None)

class MLP1Sub(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):
        h1 = F.relu(self.l2(h0))
        return self.l3(h1)

class MLP1(chainermn.MultiNodeChainList):
    # Model on worker 1.
    def __init__(self, comm, n_units, n_out):
        super(MLP1, self).__init__(comm=comm)
        self.add_link(MLP1Sub(n_units, n_out), rank_in=0, rank_out=0)

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.

### 6.3.4 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).

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.

### 6.3.5 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
        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):
```

(continues on next page)
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.

### 6.3.6 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:
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)
            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

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)
```

(continues on next page)
train_iter = chainer.iterators.SerialIterator(train, batchsize)
test_iter = chainermn.iterators.create_multi_node_iterator(
    chainer.iterators.SerialIterator(test, batchsize,
        repeat=False, shuffle=False),
    comm)

6.4 API Reference

6.4.1 Communicators

chainermn.create_communicator(communicator_name='hierarchical', mpi_comm=None, allreduce_grad_dtype=None)

Create a ChainerMN communicator.

Different communicators provide different approaches of communication, so they have different performance characteristics. The default communicator hierarchical is expected to generally perform well on a variety of environments, so one need not to change communicators in most cases. However, choosing proper communicator may give better performance. 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>OK</td>
<td>NCCL</td>
<td>pure_nccl is recommended when NCCL2 is available in the environment.</td>
</tr>
<tr>
<td>hierarchical</td>
<td>OK</td>
<td>OK</td>
<td>NCCL</td>
<td>Each node has a single NIC or HCA</td>
</tr>
<tr>
<td>two_dimensional</td>
<td>OK</td>
<td>OK</td>
<td>NCCL</td>
<td>Each node has multiple NICs or HCAs</td>
</tr>
<tr>
<td>single_node</td>
<td>OK</td>
<td>OK</td>
<td>NCCL</td>
<td>Single node with multiple GPUs</td>
</tr>
<tr>
<td>flat</td>
<td>OK</td>
<td>OK</td>
<td>NCCL</td>
<td>N/A</td>
</tr>
<tr>
<td>naive</td>
<td>OK</td>
<td>OK</td>
<td>NCCL</td>
<td>Testing on CPU mode</td>
</tr>
</tbody>
</table>

Parameters

- communicator_name – The name of communicator (naive, flat, hierarchical, two_dimensional, pure_nccl, or single_node)
- 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 scaler values. So the number of methods would be

[send, recv, bcast, gather, allreduce] × ['_obj', '']
(with single exception `alltoall, allreduce_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.

```python
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.

```python
allreduce_grad(model)
```
 Works as same as `allreduce_obj` but for Chainer model gradients

**Note:** this only supports `SUM` same as `allreduce_obj`.

```python
allreduce_obj(obj)
```
 Apply a reduce operation to all objects and spread the result.

For example of integers and summation, equivalent local code is:

```python
>>> 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` – 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.

```python
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)

```python
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)

**bcast_data**(model)
Broadcast Chainer model parameter data

**bcast_obj**(obj, max_buf_len=None, root=0)
Broadcasts an arbitrary object from root to all non-root processes.

**Parameters**

• **obj** – 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.

**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?

**gather_obj**(obj, root=0)
Gathers arbitrary objects from all non-root processes to root process.

**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.

**inter_rank**
The rank of this node in the cluster.

**inter_size**
Number of nodes that participates the cluster.

**intra_rank**
Intra rank (process id in the machine) of this process.

**rank**
Rank (process id in the cluster) of this process in integer.

**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

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.

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

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.

size

Number of processes of the cluster.

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
6.4.2 Optimizers and Evaluators

```python
chainermn.create_multi_node_optimizer(actual_optimizer, communicator, double_buffering=False)
```

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.

**Returns** The multi node optimizer based on `actual_optimizer`.

```python
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.

6.4.3 Dataset Utilities

```python
chainermn.scatter_dataset(dataset, comm, root=0, shuffle=False, seed=None, max_buf_len=268435456)
```

Scatter the given dataset to the workers in the communicator.

The dataset of worker 0 (i.e., the worker whose `comm.rank` is 0) 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.

**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.

**Returns** Scattered dataset.

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

### 6.4.4 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__(
            l1=L.Linear(n_in, n_hidden),
            l2=L.Linear(n_hidden, n_out))

    def __call__(self, x):
        h1 = F.relu(self.l1(x))
        return self.l2(h1)

class SimpleModel(chainermn.MultiNodeChainList):
    def __init__(self, comm, n_in, n_hidden, n_out):
        super(SimpleModel, self).__init__(comm)
        self.add_link(
```

(continues on next page)
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:
In this example, `Model_on_Process_0` sends two elemental tuple \((y_0, y_1)\) (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.

**class chainermn.links.MultiNodeBatchNormalization (size, comm, decay=0.9, eps=2e-05, dtype=<class 'numpy.float32'>, use_gamma=True, use_beta=True, initial_gamma=None, initial_beta=None, communication_backend='auto')**

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.

### 6.4.5 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. ([docs-cupy.chainer.org/en/stable/tutorial/basic.html#current-device](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)
```

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** 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)

**Parameters**

- \( \text{comm} \) – ChainerMN communicator.
- \( x \) (chainer.Variable) – Variable to be sent.

**Returns** Broadcasted variable.

**Return type** \( y \) (chainer.Variable)

```python
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**

- `comm` – ChainerMN communicator.
- `xs` *(list of chainer.Variables)* – Variables to send.

**Returns** Received variables.

**Return type** *ys* *(list of chainer.Variables)*

```python
ccharnermn.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)*

### 6.4.6 Iterators

```python
ccharnermn.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`.

---

### 6.4.7 Trainer extensions

#### class `chainermn.extensions.AllreducePersistent(model, comm)`

Chainer extension to averagize persists 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](https://docs.chainer.org/en/latest/reference/links.html#link)) – Target link object.
- `comm` ([ChainerMN communicator](https://github.com/chainer/chainermn)) – communicator to compute averages.

#### `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 agrees.

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.

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()
  ...
  checkpointer.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

### 6.4.8 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.
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.

### 7.1 Targeted Versions

This policy is applied to Chainer v2.0.0 and higher. Note that this policy is not applied to Chainer of lower versions. For older versions of Chainer, see the old version of API Compatibility Policy.

### 7.2 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.

### 7.3 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.

Note: Since Chainer v2, we have stopped adopting any solid processes to break backward compatibilities (e.g. a solid schedule for deprecating and removing a feature) in order to keep the development fast enough to support the cutting-edge research. It does not mean we stop taking care of maintainability of user codes. We are still paying much attention to not breaking user codes.

### 7.4 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.

### 7.5 Supported Backward Compatibility

This section defines backward compatibilities that revision updates must maintain.
7.5.1 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.

7.5.2 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.

7.5.3 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.

7.5.4 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.

7.5.5 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.

7.5.6 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.

### 7.6 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.

### 7.7 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.
CHAPTER 8

Contribution Guide

This is a guide for all contributions to Chainer. The development of Chainer is running on the official repository at GitHub. Anyone that wants to register an issue or to send a pull request should read through this document.

Note: Many points of this documentation are updated at v2. We strongly recommend all contributors of v1 to read through the documentation again.

8.1 Classification of Contributions

There are several ways to contribute to Chainer community:

1. Registering an issue
2. Sending a pull request (PR)
3. Sending a question/reply to StackOverflow (with chainer tag) or Chainer User Group
4. Open-sourcing an external example
5. Writing a post about Chainer

This documentation mainly focuses on 1 and 2, though other contributions are also appreciated.

8.2 Development Cycle

This section explains the development process of Chainer. Before contributing to Chainer, it is strongly recommended to understand the development cycle.
8.2.1 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 so that the version string is much friendly with Python eco-system.

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 API bug that we have to fix for the major version, we may add breaking changes to the major version up.

As for the backward compatibility, see API Compatibility Policy.

8.2.2 Release Cycle

Starting from v2.0.0, we are developing two tracks of versions at the same time. The first one is the track of stable versions, which is a series of revision updates for the latest major version. The second one is the track of development versions, which is a series of pre-releases for the upcoming major version.

Consider that X.0.0 is the latest major version and Y.0.0, Z.0.0 are the succeeding major versions. Then, the timeline of the updates is depicted by the following table.

<table>
<thead>
<tr>
<th>Date</th>
<th>ver X</th>
<th>ver Y</th>
<th>ver Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 weeks</td>
<td>X.0.0rc1</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>4 weeks</td>
<td>X.0.0</td>
<td>Y.0.0a1</td>
<td>–</td>
</tr>
<tr>
<td>8 weeks</td>
<td>X.1.0*</td>
<td>Y.0.0b1</td>
<td>–</td>
</tr>
<tr>
<td>12 weeks</td>
<td>X.2.0*</td>
<td>Y.0.0rc1</td>
<td>–</td>
</tr>
<tr>
<td>16 weeks</td>
<td>–</td>
<td>Y.0.0</td>
<td>Z.0.0a1</td>
</tr>
</tbody>
</table>

(* These might be revision releases)

The dates shown in the left-most column are relative to the release of X.0.0rc1. In particular, each revision/minor release is made four weeks after the previous one of the same major version, and the pre-release of the upcoming major version is made at the same time. Whether these releases are revision or minor is determined based on the contents of each update.

Note that there are only three stable releases for the versions X.x.x. During the parallel development of Y.0.0 and Z.0.0a1, the version Y is treated as an almost-stable version and Z is treated as a development version.

If there is a critical bug found in X.x.x after stopping the development of version X, we may release a hot-fix for this version at any time.

We create a milestone for each upcoming release at GitHub. The GitHub milestone is basically used for collecting the issues and PRs resolved in the release.

8.2.3 Git Branches

The master branch is used to develop pre-release versions. It means that alpha, beta, and RC updates are developed at the master branch. This branch contains the most up-to-date source tree that includes features newly added after the latest major version.

The stable version is developed at the individual branch named as vN where “N” reflects the version number (we call it a versioned branch). For example, v3.0.0, v3.0.1, and v3.0.2 will be developed at the v3 branch.
Notes for contributors: When you send a pull request, you basically have to send it to the master branch. If the change can also be applied to the stable version, a core team member will apply the same change to the stable version so that the change is also included in the next revision update.

If the change is only applicable to the stable version and not to the master branch, please send it to the versioned branch. We basically only accept changes to the latest versioned branch (where the stable version is developed) unless the fix is critical.

If you want to make a new feature of the master branch available in the current stable version, please send a backport PR to the stable version (the latest vN branch). See the next section for details.

Note: a change that can be applied to both branches should be sent to the master branch. Each release of the stable version is also merged to the development version so that the change is also reflected to the next major version.

8.2.4 Feature Backport PRs

We basically do not backport any new features of the development version to the stable versions. If you desire to include the feature to the current stable version and you can work on the backport work, we welcome such a contribution. In such a case, you have to send a backport PR to the latest vN branch. Note that we do not accept any feature backport PRs to older versions because we are not running quality assurance workflows (e.g. CI) for older versions so that we cannot ensure that the PR is correctly ported.

There are some rules on sending a backport PR.

- Start the PR title from the prefix [backport].
- Clarify the original PR number in the PR description (something like “This is a backport of #XXXX”).
- (optional) Write to the PR description the motivation of backporting the feature to the stable version.

Please follow these rules when you create a feature backport PR.

Note: PRs that do not include any changes/additions to APIs (e.g. bug fixes, documentation improvements) are usually backported by core dev members. It is also appreciated to make such a backport PR by any contributors, though, so that the overall development proceeds more smoothly!

8.3 Issues and Pull Requests

In this section, we explain how to file issues and send pull requests (PRs).

8.3.1 Issue/PR Labels

Issues and PRs are labeled by the following tags:

- **Bug**: bug reports (issues) and bug fixes (PRs)
- **Enhancement**: implementation improvements without breaking the interface
- **Feature**: feature requests (issues) and their implementations (PRs)
- **NoCompat**: disrupts backward compatibility
- **Test**: test fixes and updates
- **Document**: documentation fixes and improvements
- **Example**: fixes and improvements on the examples
- **Install**: fixes installation script
8.3.2 How to File an Issue

On registering an issue, write precise explanations on how you want Chainer to be. Bug reports must include necessary and sufficient conditions to reproduce the bugs. Feature requests must include what you want to do (and why you want to do, if needed) with Chainer. You can contain your thoughts on how to realize it into the feature requests, though what part is most important for discussions.

**Warning:** If you have a question on usages of Chainer, it is highly recommended to send a post to StackOverflow or Chainer User Group instead of the issue tracker. The issue tracker is not a place to share knowledge on practices. We may suggest these places and immediately close how-to question issues.

8.3.3 How to Send a Pull Request

If you can write code to fix an issue, we encourage to send a PR.

First of all, before starting to write any code, do not forget to confirm the following points.

- Read through the Coding Guidelines and Unit Testing.
- Check the appropriate branch that you should send the PR following Git Branches. If you do not have any idea about selecting a branch, please choose the master branch.

In particular, check the branch before writing any code. 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 you fix; it is the first documentation of your code that developers read, which is a very important part of your PR.

Once you send a PR, it is automatically tested on Travis CI for Linux and Mac OS X, and on AppVeyor for Windows. Your PR needs to pass at least the test for Linux on Travis CI. After the automatic test passes, some of the core developers will start reviewing your code. Note that this automatic PR test only includes CPU tests.

**Note:** We are also running continuous integration with GPU tests for the master branch and the versioned branch of the latest major version. Since this service is currently running on our internal server, we do not use it for automatic PR tests to keep the server secure.

If you are planning to add a new feature or modify existing APIs, it is recommended to open an issue and discuss the design first. The design discussion needs lower cost for the core developers than code review. Following the consequences of the discussions, you can send a PR that is smoothly reviewed in a shorter time.

Even if your code is not complete, you can send a pull request as a work-in-progress PR by putting the [WIP] prefix to the PR title. If you write a precise explanation about the PR, core developers and other contributors can join the discussion about how to proceed the PR. WIP PR is also useful to have discussions based on a concrete code.
8.4 Coding Guidelines

Note: Coding guidelines are updated at v3.0. Those who have contributed to older versions should read the guidelines again.

We use PEP 8 and a part of OpenStack Style Guidelines related to general coding style as our basic style guidelines.

You can use autopep8 and flake8 commands to check your code.

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 Chainer repository):

```
$ pip install -e '.[stylecheck]'
```

And check your code with:

```
$ autopep8 path/to/your/code.py
$ flake8 path/to/your/code.py
```

The autopep8 supports automatically correct Python code to conform to the PEP 8 style guide:

```
$ autopep8 --in-place path/to/your/code.py
```

The flake8 command lets you know the part of your code not obeying our style guidelines. Before sending a pull request, be sure to check that your code passes the flake8 checking.

Note that flake8 command is not perfect. It does not check some of the style guidelines. Here is a (not-complete) 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.

```
import chainer

class MyLink(chainer.Link): ...
```

Instead, import chainer.link and use that.

```
import chainer.link

class MyLink(chainer.link.Link): ...
```

If you feel the code too verbose, you can also use from import or import as.

```
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 is 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 with 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 you to use `import chainer.functions` and spell out like `chainer.functions.foo` in your methods.

Once you send a pull request, your coding style is automatically checked by Travis-CI. The reviewing process starts after the check passes.

8.5 Unit Testing

Testing is one of the most important part of your code. You must write test cases and verify your implementation by following our testing guide.

Note that we are using pytest and mock package for testing, so install them before writing your code:

```bash
$ pip install pytest mock
```

8.5.1 How to Run Tests

You can run unit tests simply by running `python -m pytest` command at the repository root:

```bash
$ python -m pytest
```

or specify the test script that you want to run:

```bash
$ python -m pytest path/to/your/test.py
```

You can also run all unit tests under a specified directory:

```bash
$ python -m pytest tests/chainer_tests/<directory name>
```

It requires CUDA and cuDNN by default. In order to run unit tests that do not require CUDA and cuDNN, use `CHAINER_TEST_GPU_LIMIT=0` environment variable and `-m='not cudnn'` option:

```bash
$ 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 have only one GPU, launch pytest by the following command to skip multi-GPU tests:

```bash
$ 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:
If you modify the code related to existing unit tests, you must run appropriate commands and confirm that the tests pass.

8.5.2 Test File and Directory Naming Conventions

Tests are put into the `tests/chainer_tests` directory. In order to enable test runner to find test scripts correctly, we are using 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`.

8.5.3 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 simply use the `unittest` package of the standard library, while some tests are using utilities from `chainer.testing`.

In addition to the **Coding Guidelines** mentioned above, the following rules are applied 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 by `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 by 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 by `cudnn` are skipped if `-m='not cudnn'` is given.
The test functions decorated by `gpu` must not depend on multiple GPUs. In order to write tests for multiple GPUs, use `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 `chainer.testing.attr.slow` decorator. The test functions decorated by `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.

Once you send a pull request, your code is automatically tested by Travis-CI except for tests annotated with ``gpu``, ``multi_gpu`` and ``slow``. Since Travis-CI does not support CUDA, we cannot check your CUDA-related code automatically. The reviewing process starts after the test passes. Note that reviewers will test your code without the option to check CUDA-related code.

**Note:** Some of numerically unstable tests might cause errors irrelevant to your changes. In such a case, we ignore the failures and go on to the review process, so do not worry about it!

### 8.6 Documentation

When adding a new feature to the framework, you also need to document it in the reference. For example, if you are adding a new function under `chainer.functions`, you need to add it to the `Functions` page.

**Note:** If you are unsure about how to fix the documentation, you can submit a pull request without doing so. Reviewers will help you fix the documentation appropriately.

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
```
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:** Docstrings (documentation comments in the source code) are collected from the installed Chainer module. If you modified docstrings, make sure to install the module (e.g., using `pip install -e .`) before building the documentation.
9.1 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 failing. 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.

9.2 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:

[openblas]
libraries = openblas
library_dirs = /usr/local/opt/openblas/lib
include_dirs = /usr/local/opt/openblas/include

Install NumPy from the source code

pip install --no-binary :all: numpy

Confirm NumPy has been installed with OpenBLAS by running this command:

$ python -c "import numpy; print(numpy.show_config())"

You should see the following information:

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.

### 9.3 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

x = np.arange(10) - 5
F.relu(x)
```
Chainer Documentation, Release 5.3.0

Traceback (most recent call last):
... 
chainer.utils.type_check.InvalidType:
Invalid operation is performed in: ReLU (Forward)

Expect: in_types[0].dtype.kind == f
Actual: i != f

In this case, kind of in_types[0] (which means the first input to the function, x) is expected to be f (floating-point), whereas the input was i (signed integer). You need to cast the input appropriately before passing to the function (e.g., 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 \( x.shape[0] \) is equal to \( y.shape[0] \), but actually it was 4 and 3, respectively.

See Type Checks for the detailed behavior of type checking system in Chainer.

### 9.4 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.

#### 9.4.1 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:** ideep4py v1.0.x is incompatible with v2.0.x, and is not supported in Chainer v5.0 or later.
9.4.2 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:

```
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'>

9.4.3 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.

9.4.4 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.

9.5 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.
CHAPTER 10

Performance Best Practices

This guide explains some tips and advice for maximizing the performance of Chainer.

10.1 Use the Latest Version

It is generally recommended to 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:

```python
chainer.print_runtime_info()
```

<table>
<thead>
<tr>
<th>Chainer: 4.0.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>NumPy: 1.14.3</td>
</tr>
</tbody>
</table>

CuPy:

<table>
<thead>
<tr>
<th>CuPy Version</th>
<th>4.0.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>CUDA Root</td>
<td>/usr/local/cuda</td>
</tr>
<tr>
<td>CUDA Build Version</td>
<td>9000</td>
</tr>
<tr>
<td>CUDA Driver Version</td>
<td>9000</td>
</tr>
<tr>
<td>CUDA Runtime Version</td>
<td>9000</td>
</tr>
<tr>
<td>cuDNN Build Version</td>
<td>7100</td>
</tr>
<tr>
<td>cuDNN Version</td>
<td>7100</td>
</tr>
<tr>
<td>NCCL Build Version</td>
<td>2102</td>
</tr>
</tbody>
</table>

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.
10.2 Enable Hardware Accelerations

10.2.1 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.

10.2.2 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.

10.3 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.

10.4 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.

## 10.5 Optimize cuDNN Convolution

### 10.5.1 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.

### 10.5.2 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.

### 10.6 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 to turn off the check only for well-tested code and input data.

See *Configuring Chainer* for detailed descriptions.

### 10.7 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.

### 10.8 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.

### 10.9 Use Multiple Nodes

You can scale-out the training process of your Chainer model to multiple-node cluster by using ChainerMN, an additional package for Chainer which enables distributed deep learning. See ChainerMN Official Documentation for details.
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.

11.1 Chainer v5

11.1.1 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*.

11.1.2 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 to 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.
11.1.3 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:

```
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)
```

11.1.4 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.

11.1.5 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).

### 11.1.6 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.

#### 11.1.7 `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>
```

### 11.1.8 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.

### 11.1.9 CuPy v5

Chainer v5 requires CuPy v5 if you need GPU support. Please see the `Upgrade Guide for CuPy v5` for details.

### 11.2 Chainer v4

#### 11.2.1 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.
11.2.2 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.

11.2.3 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.

11.2.4 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.

11.2.5 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.
11.2.6 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.

11.2.7 CuPy v4

Chainer v4 requires CuPy v4 if you need GPU support. Please see the Upgrade Guide for CuPy v4 for details.

11.3 Chainer v3

11.3.1 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.

11.3.2 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 deprecated by this change. You can rewrite it using chainer.functions.matmul().

11.3.3 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.

11.3.4 CuPy v2

Chainer v3 requires CuPy v2 if you need GPU support. Please see the Upgrade Guide for CuPy v2 for details.

11.4 Chainer v2

See Upgrade Guide from v1 to v2 for the changes introduced in Chainer v2.

11.4.1 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.zerogradbs 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 light-weight 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.

```python
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.

```python
class AddFunction(chainer.Function):
    def forward(self, inputs):
```

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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 to 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 memory overhead right now. It is recommended to 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.

```python
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.

```python
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 \(1/\sqrt{\text{fanin}}\). 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 \(\text{scale} \times \sqrt{2/\text{fanin}}\), 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):
```
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.

```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.links.GRU 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 to 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
# Chainer v1
class MyLink(chainer.Link):
    def __init__(self):
        super(MyLink, self).__init__()
        W=(10, 5),
        b=(5,),
        chainer.initializers.Normal(0.05)(self.W.data)
        self.b.data.fill(0)
```

is recommended to be updated as follows.

```python
# 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))
```

(continues on next page)
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 to 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.

```python
# Chainer v2
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 `UpdaterRule` 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.
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()`)

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Comparison with Other Frameworks

12.1 A table for quick comparison

This table compares Chainer with other actively developed deep learning frameworks. Content is current as of July 2017.
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12.2 Benchmarks

Benchmarks for convolutional networks can be found at convnet-benchmarks while some NLP benchmarks are at dynet-benchmark. Chainer wraps the latest available cuDNN kernels for CNNs and RNNs, so performance of most common networks that use these kernels is typically similar to that of other modern frameworks. As Chainer’s define-by-run approach means the user’s Python code is executed directly at runtime, particularly complex networks or those with very small tensor sizes may be slower than in static-graph frameworks.

---

1 Define-by-run is in development as of June 2017 and tracked in dmlc/mxnet#5705. It is also possible using the much slower MinPy extension.
2 Symbolic autograd is in development as of June 2017 and tracked in deeplearning4j/nd4j#1750.
3 Symbolic autograd is available only with ngraph backend (experimental).
4 Some functions do not support higher-order differentiation. See chainer/chainer#4449.
5 Nervana provides kernels that are meant to compete with cuDNN.
6 Multiprocessing provides a significant performance improvement only for frameworks that use Python at runtime.
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