

TORCH.NN.F NCTIONAL

Convolution functions

conv1

`torch.nn.functional.conv1d(input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1) → Tensor`

Applies a 1D convolution over an input signal compose of several input planes.

This operator supports **TensorFloat32**.

See `Conv1d` for etails an output shape.

• NOTE

In some circumstances when using the C DA cken with CuDNN, this operator may select a non eterministic algorithm to increase performance. If this is un esira le, you can try to make the operation eterministic (potentially at a performance cost) y setting `torch.backends.cudnn.deterministic = True`. Please see the notes on **Repro uci ility** for ackgroun .

Parameters

- **in ut** – input tensor of shape (minibatch, in_channels, iW)
- **weight** – filters of shape (out_channels, $\frac{\text{in_channels}}{\text{groups}}$, kW)
- **ias** – optional ias of shape (out_channels) . Default: `None`
- **stri e** – the stri e of the convolving kernel. Can e a single num er or a one-element tuple (sW,). Default: 1
- **a ing** – implicit pa ings on oth si es of the input. Can e a single num er or a one-element tuple (padW,). Default: 0
- **ilation** – the spacing etween kernel elements. Can e a single num er or a one-element tuple (dW,). Default: 1
- **grou s** – split input into groups, in_channels shoul e ivisi le y the num er of groups. Default: 1

Examples:

```
>>> filters = torch.randn(33, 16, 3)
>>> inputs = torch.randn(20, 16, 50)
>>> F.conv1d(inputs, filters)
```

conv2

`torch.nn.functional.conv2d(input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1) → Tensor`

Applies a 2D convolution over an input image compose of several input planes.

This operator supports **TensorFloat32**.

See `Conv2d` for etails an output shape.

• NOTE

In some circumstances when using the C DA cken with CuDNN, this operator may select a non eterministic algorithm to increase performance. If this is un esira le, you can try to make the operation eterministic (potentially at a performance cost) y setting `torch.backends.cudnn.deterministic = True`. Please see the notes on **Repro uci ility** for ackgroun .

Parameters

- **in ut** – input tensor of shape (minibatch, in_channels, iH, iW)
- **weight** – filters of shape (out_channels, $\frac{\text{in_channels}}{\text{groups}}$, kH, kW)
- **ias** – optional ias tensor of shape (out_channels) . Default: `None`
- **stri e** – the stri e of the convolving kernel. Can e a single num er or a tuple (sH, sW). Default: 1
- **a ing** – implicit pa ings on oth si es of the input. Can e a single num er or a tuple (padH, padW). Default: 0
- **ilation** – the spacing etween kernel elements. Can e a single num er or a tuple (dH, dW). Default: 1
- **grou s** – split input into groups, in_channels shoul e ivisi le y the num er of groups. Default: 1

Examples:

```
>>> # With square kernels and equal stride
>>> filters = torch.randn(8,4,3,3)
>>> inputs = torch.randn(1,4,5,5)
>>> F.conv2d(inputs, filters, padding=1)
```

conv2

`torch.nn.functional.conv3d(input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1) → Tensor`

Applies a 3D convolution over an input image compose of several input planes.

This operator supports [TensorFloat32](#).

See `Conv3d` for details an output shape.

• NOTE

In some circumstances when using the C_{UDA} `ackenn` with CuDNN, this operator may select a non deterministic algorithm to increase performance. If this is undesirable, you can try to make the operation deterministic (potentially at a performance cost) by setting `torch.backends.cudnn.deterministic = True`. Please see the notes on [Reproducibility](#) for background.

Parameters

- **input** – input tensor of shape $(\text{minibatch}, \text{in_channels}, \text{iT}, \text{iH}, \text{iW})$
- **weight** – filters of shape $(\text{out_channels}, \frac{\text{in_channels}}{\text{groups}}, \text{kT}, \text{kH}, \text{kW})$
- **bias** – optional bias tensor of shape (out_channels) . Default: None
- **stride** – the stride of the convolving kernel. Can be a single number or a tuple $(\text{sT}, \text{sH}, \text{sW})$. Default: 1
- **padding** – implicit padding on both sides of the input. Can be a single number or a tuple $(\text{padT}, \text{padH}, \text{padW})$. Default: 0
- **dilation** – the spacing between kernel elements. Can be a single number or a tuple $(\text{dT}, \text{dH}, \text{dW})$. Default: 1
- **groups** – split input into groups, `in_channels` should be divisible by the number of groups. Default: 1

Examples:

```
>>> filters = torch.randn(33, 16, 3, 3, 3)
>>> inputs = torch.randn(20, 16, 50, 10, 20)
>>> F.conv3d(inputs, filters)
```

conv_transpose1

`torch.nn.functional.conv_transpose1d(input, weight, bias=None, stride=1, padding=0, output_padding=0, groups=1, dilation=1) → Tensor`

Applies a 1D transpose convolution operator over an input signal compose of several input planes, sometimes also called “deconvolution”.

This operator supports [TensorFloat32](#).

See `ConvTranspose1d` for details an output shape.

• NOTE

In some circumstances when using the C_{UDA} `ackenn` with CuDNN, this operator may select a non deterministic algorithm to increase performance. If this is undesirable, you can try to make the operation deterministic (potentially at a performance cost) by setting `torch.backends.cudnn.deterministic = True`. Please see the notes on [Reproducibility](#) for background.

Parameters

- **input** – input tensor of shape $(\text{minibatch}, \text{in_channels}, \text{iW})$
- **weight** – filters of shape $(\text{in_channels}, \frac{\text{out_channels}}{\text{groups}}, \text{kW})$
- **bias** – optional bias of shape (out_channels) . Default: None
- **stride** – the stride of the convolving kernel. Can be a single number or a tuple $(\text{sw},)$. Default: 1
- **padding** – $\text{dilation} * (\text{kernel_size} - 1) - \text{padding}$ zero-padding will be added to both sides of each dimension in the input. Can be a single number or a tuple $(\text{padW},)$. Default: 0
- **output_padding** – additional size added to one side of each dimension in the output shape. Can be a single number or a tuple $(\text{out_padW},)$. Default: 0
- **groups** – split input into groups, `in_channels` should be divisible by the number of groups. Default: 1
- **dilation** – the spacing between kernel elements. Can be a single number or a tuple $(\text{dW},)$. Default: 1

Examples:

```
>>> inputs = torch.randn(20, 16, 50)
>>> weights = torch.randn(16, 33, 5)
>>> F.conv_transpose1d(inputs, weights)
```

conv_transpose2

`torch.nn.functional.conv_transpose2d(input, weight, bias=None, stride=1, padding=0, output_padding=0, groups=1, dilation=1) → Tensor`

Applies a 2D transpose convolution operator over an input image compose of several input planes, sometimes also called “deconvolution”.

This operator supports [TensorFloat32](#).

See `ConvTranspose2d` for details an output shape.

• NOTE

In some circumstances when using the C_{UDA} `ackenn` with CuDNN, this operator may select a non deterministic algorithm to increase performance. If this is undesirable, you can try to make the operation deterministic (potentially at a performance cost) by setting `torch.backends.cudnn.deterministic = True`. Please see the notes on [Reproducibility](#) for background.

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Parameters

- input** – input tensor of shape $(\text{minibatch}, \text{in_channels}, \text{iH}, \text{iW})$
- weight** – filters of shape $(\text{in_channels}, \frac{\text{out_channels}}{\text{groups}}, \text{kH}, \text{kW})$
- bias** – optional biases of shape (out_channels) . Default: None
- stride** – the stride of the convolving kernel. Can be a single number or a tuple (sH, sW) . Default: 1
- dilation** – $\text{dilation} * (\text{kernel_size} - 1) - \text{padding}$ zero-padding will be added to both sides of each dimension in the input. Can be a single number or a tuple $(\text{padH}, \text{padW})$. Default: 0
- output_padding** – additional size added to one side of each dimension in the output shape. Can be a single number or a tuple $(\text{out_padH}, \text{out_padW})$. Default: 0
- groups** – split input into groups, `in_channels` should be divisible by the number of groups. Default: 1
- dilation** – the spacing between kernel elements. Can be a single number or a tuple (dH, dW) . Default: 1

Examples:

```
>>> # With square kernels and equal stride
>>> inputs = torch.randn(1, 4, 5, 5)
>>> weights = torch.randn(4, 8, 3, 3)
>>> F.conv_transpose2d(inputs, weights, padding=1)
```

conv_transpose3

`torch.nn.functional.conv_transpose3d(input, weight, bias=None, stride=1, padding=0, output_padding=0, groups=1, dilation=1) → Tensor`

Applies a 3D transpose convolution operator over an input image composed of several input planes, sometimes also called “deconvolution”.

This operator supports [TensorFloat32](#).

See [ConvTranspose3d](#) for details on output shape.

• NOTE

In some circumstances when using the CUDA backend with CuDNN, this operator may select a non-deterministic algorithm to increase performance. If this is undesirable, you can try to make the operation deterministic (potentially at a performance cost) by setting `torch.backends.cudnn.deterministic = True`. Please see the notes on [Reproducibility](#) for background.

Parameters

- input** – input tensor of shape $(\text{minibatch}, \text{in_channels}, \text{iT}, \text{iH}, \text{iW})$
- weight** – filters of shape $(\text{in_channels}, \frac{\text{out_channels}}{\text{groups}}, \text{kT}, \text{kH}, \text{kW})$
- bias** – optional biases of shape (out_channels) . Default: None
- stride** – the stride of the convolving kernel. Can be a single number or a tuple $(\text{sT}, \text{sH}, \text{sW})$. Default: 1
- dilation** – $\text{dilation} * (\text{kernel_size} - 1) - \text{padding}$ zero-padding will be added to both sides of each dimension in the input. Can be a single number or a tuple $(\text{padT}, \text{padH}, \text{padW})$. Default: 0
- output_padding** – additional size added to one side of each dimension in the output shape. Can be a single number or a tuple $(\text{out_padT}, \text{out_padH}, \text{out_padW})$. Default: 0
- groups** – split input into groups, `in_channels` should be divisible by the number of groups. Default: 1
- dilation** – the spacing between kernel elements. Can be a single number or a tuple $(\text{dT}, \text{dH}, \text{dW})$. Default: 1

Examples:

```
>>> inputs = torch.randn(20, 16, 50, 10, 20)
>>> weights = torch.randn(16, 33, 3, 3, 3)
>>> F.conv_transpose3d(inputs, weights)
```

unfold

`torch.nn.functional.unfold(input, kernel_size, dilation=1, padding=0, stride=1)`

[SOURCE]

Extracts sliding local blocks from an `attn` input tensor.

• WARNING

Currently, only 4-D input tensors (image-like tensors) are supported.

• WARNING

More than one element of the unfolded tensor may refer to a single memory location. As a result, in-place operations (especially ones that are vectorized) may result in incorrect behavior. If you need to write to the tensor, please clone it first.

See [torch.nn.Unfold](#) for details

fold

`torch.nn.functional.fold(input, output_size, kernel_size, dilation=1, padding=0, stride=1)` [SOURCE]

Comines an array of sliding local blocks into a large containing tensor.

• WARNING

Currently, only 3-D output tensors (unfolded batched image-like tensors) are supported.

See `torch.nn.Fold` for details

Pooling functions

avg_pool1d

`torch.nn.functional.avg_pool1d(input, kernel_size, stride=None, padding=0, ceil_mode=False, count_include_pad=True)` → Tensor

Applies a 1D average pooling over an input signal composed of several input planes.

See `AvgPool1d` for details and output shape.

Parameters

- **input** – input tensor of shape (minibatch, in_channels, iW)
- **kernel_size** – the size of the window. Can be a single number or a tuple (kW),
- **stride** – the stride of the window. Can be a single number or a tuple (sW). Default: `kernel_size`
- **padding** – implicit zero padding on both sides of the input. Can be a single number or a tuple (padW). Default: 0
- **ceil_mode** – when True, will use *ceil* instead of *floor* to compute the output shape. Default: `False`
- **count_include_pad** – when True, will include the zero-padding in the averaging calculation. Default: `True`

Examples:

```
>>> # pool of square window of size=3, stride=2
>>> input = torch.tensor([[[[1, 2, 3, 4, 5, 6, 7]]], dtype=torch.float32)
>>> F.avg_pool1d(input, kernel_size=3, stride=2)
tensor([[[[ 2.,  4.,  6.]]])
```

avg_pool2d

`torch.nn.functional.avg_pool2d(input, kernel_size, stride=None, padding=0, ceil_mode=False, count_include_pad=True, divisor_override=None)` → Tensor

Applies 2D average-pooling operation in $kH \times kW$ regions by step size $sH \times sW$ steps. The number of output features is equal to the number of input planes.

See `AvgPool2d` for details and output shape.

Parameters

- **input** – input tensor (minibatch, in_channels, iH, iW)
- **kernel_size** – size of the pooling region. Can be a single number or a tuple (kH, kW)
- **stride** – stride of the pooling operation. Can be a single number or a tuple (sH, sW). Default: `kernel_size`
- **padding** – implicit zero padding on both sides of the input. Can be a single number or a tuple (padH, padW). Default: 0
- **ceil_mode** – when True, will use *ceil* instead of *floor* in the formula to compute the output shape. Default: `False`
- **count_include_pad** – when True, will include the zero-padding in the averaging calculation. Default: `True`
- **divisor_override** – if specified, it will be used as divisor, otherwise size of the pooling region will be used. Default: `None`

avg_pool3d

`torch.nn.functional.avg_pool3d(input, kernel_size, stride=None, padding=0, ceil_mode=False, count_include_pad=True, divisor_override=None)` → Tensor

Applies 3D average-pooling operation in $kT \times kH \times kW$ regions by step size $sT \times sH \times sW$ steps. The number of output features is equal to $\lfloor \frac{\text{input planes}}{sT} \rfloor$.

See `AvgPool3d` for details and output shape.

Parameters

- **input** – input tensor (minibatch, in_channels, iT × iH, iW)
- **kernel_size** – size of the pooling region. Can be a single number or a tuple (kT, kH, kW)
- **stride** – stride of the pooling operation. Can be a single number or a tuple (sT, sH, sW). Default: `kernel_size`
- **padding** – implicit zero padding on both sides of the input. Can be a single number or a tuple (padT, padH, padW), Default: 0
- **ceil_mode** – when True, will use *ceil* instead of *floor* in the formula to compute the output shape
- **count_include_pad** – when True, will include the zero-padding in the averaging calculation
- **divisor_override** – if specified, it will be used as divisor, otherwise size of the pooling region will be used. Default: `None`

max_pool1d

`torch.nn.functional.max_pool1d(*args, **kwargs)`

Applies a 1D max pooling over an input signal composed of several input planes.

See `MaxPool1d` for details.

max_pool2

```
torch.nn.functional.max_pool2d(*args, **kwargs)
```

Applies a 2D max pooling over an input signal composed of several input planes.

See `MaxPool2d` for details.

max_pool3

```
torch.nn.functional.max_pool3d(*args, **kwargs)
```

Applies a 3D max pooling over an input signal composed of several input planes.

See `MaxPool3d` for details.

max_unpool1

```
torch.nn.functional.max_unpool1d(input, indices, kernel_size, stride=None, padding=0, output_size=None)
```

[SO RCE]

Computes a partial inverse of `MaxPool1d`.

See `MaxUnpool1d` for details.

max_unpool2

```
torch.nn.functional.max_unpool2d(input, indices, kernel_size, stride=None, padding=0, output_size=None)
```

[SO RCE]

Computes a partial inverse of `MaxPool2d`.

See `MaxUnpool2d` for details.

max_unpool3

```
torch.nn.functional.max_unpool3d(input, indices, kernel_size, stride=None, padding=0, output_size=None)
```

[SO RCE]

Computes a partial inverse of `MaxPool3d`.

See `MaxUnpool3d` for details.

l_pool1

```
torch.nn.functional.lp_pool1d(input, norm_type, kernel_size, stride=None, ceil_mode=False)
```

[SO RCE]

Applies a 1D power-average pooling over an input signal composed of several input planes. If the sum of all inputs to the power of p is zero, the gradient is set to zero as well.

See `LPPool1d` for details.

l_pool2

```
torch.nn.functional.lp_pool2d(input, norm_type, kernel_size, stride=None, ceil_mode=False)
```

[SO RCE]

Applies a 2D power-average pooling over an input signal composed of several input planes. If the sum of all inputs to the power of p is zero, the gradient is set to zero as well.

See `LPPool2d` for details.

adaptive_max_pool1

```
torch.nn.functional.adaptive_max_pool1d(*args, **kwargs)
```

Applies a 1D adaptive max pooling over an input signal composed of several input planes.

See `AdaptiveMaxPool1d` for details and output shape.

Parameters

- **output_size** – the target output size (single integer)
- **return_indices** – whether to return pooling indices. Default: `False`

adaptive_max_pool2

```
torch.nn.functional.adaptive_max_pool2d(*args, **kwargs)
```

Applies a 2D adaptive max pooling over an input signal composed of several input planes.

See `AdaptiveMaxPool2d` for details and output shape.

Parameters

- **output_size** – the target output size (single integer or double-integer tuple)
- **return_indices** – whether to return pooling indices. Default: `False`

adaptive_max_pool3

```
torch.nn.functional.adaptive_max_pool3d(*args, **kwargs)
```

`torch.nn.functional.adaptive_max_pool1d(*args, **kwargs)`

Applies a 3D adaptive max pooling over an input signal composed of several input planes.

See `AdaptiveMaxPool1d` for details and output shape.

Parameters

- **output_size** – the target output size (single integer or triple-integer tuple)
- **return_indices** – whether to return pooling indices. Default: `False`

adaptive_avg_pool1d

`torch.nn.functional.adaptive_avg_pool1d(input, output_size) → Tensor`

Applies a 1D adaptive average pooling over an input signal composed of several input planes.

See `AdaptiveAvgPool1d` for details and output shape.

Parameters

output_size – the target output size (single integer)

adaptive_avg_pool2d

`torch.nn.functional.adaptive_avg_pool2d(input, output_size)`

[SO RCE]

Applies a 2D adaptive average pooling over an input signal composed of several input planes.

See `AdaptiveAvgPool2d` for details and output shape.

Parameters

output_size – the target output size (single integer or double-integer tuple)

adaptive_avg_pool3d

`torch.nn.functional.adaptive_avg_pool3d(input, output_size)`

[SO RCE]

Applies a 3D adaptive average pooling over an input signal composed of several input planes.

See `AdaptiveAvgPool3d` for details and output shape.

Parameters

output_size – the target output size (single integer or triple-integer tuple)

Non-linear activation functions

threshold

`torch.nn.functional.threshold(input, threshold, value, inplace=False)`

Thresholds each element of the input Tensor.

See `Threshold` for more details.

`torch.nn.functional.threshold_(input, threshold, value) → Tensor`

In-place version of `threshold()`.

relu

`torch.nn.functional.relu(input, inplace=False) → Tensor`

[SO RCE]

Applies the rectified linear unit function element-wise. See `ReLU` for more details.

`torch.nn.functional.relu_(input) → Tensor`

In-place version of `relu()`.

hardtanh

`torch.nn.functional.hardtanh(input, min_val=-1., max_val=1., inplace=False) → Tensor`

[SO RCE]

Applies the Hard Tanh function element-wise. See `Hardtanh` for more details.

`torch.nn.functional.hardtanh_(input, min_val=-1., max_val=1.) → Tensor`

In-place version of `hardtanh()`.

hardswish

`torch.nn.functional.hardswish(input: torch.Tensor, inplace: bool = False) → torch.Tensor`

[SO RCE]

Applies the hard swish function, element-wise, as described in the paper:

Searching for MobileNetV3.

$$\text{Hardswish}(x) = \begin{cases} 0 & \text{if } x \leq -3, \\ x & \text{if } x \geq +3, \\ x \cdot (x + 3)/6 & \text{otherwise} \end{cases}$$

See [Hardswish](#) for more details.

relu6

`torch.nn.functional.relu6(input, inplace=False)` → Tensor [SO RCE]

Applies the element-wise function $\text{ReLU6}(x) = \min(\max(0, x), 6)$.

See [ReLU6](#) for more details.

elu

`torch.nn.functional.elu(input, alpha=1.0, inplace=False)` [SO RCE]

Applies element-wise, $\text{ELU}(x) = \max(0, x) + \min(0, \alpha * (\exp(x) - 1))$.

See [ELU](#) for more details.

`torch.nn.functional.elu_(input, alpha=1.)` → Tensor

In-place version of `elu()`.

selu

`torch.nn.functional.selu(input, inplace=False)` → Tensor [SO RCE]

Applies element-wise, $\text{SELU}(x) = \text{scale} * (\max(0, x) + \min(0, \alpha * (\exp(x) - 1)))$, with $\alpha = 1.6732632423543772848170429916717$ and $\text{scale} = 1.0507009873554804934193349852946$.

See [SELU](#) for more details.

celu

`torch.nn.functional.celu(input, alpha=1., inplace=False)` → Tensor [SO RCE]

Applies element-wise, $\text{CELU}(x) = \max(0, x) + \min(0, \alpha * (\exp(x/\alpha) - 1))$.

See [CELU](#) for more details.

leaky_relu

`torch.nn.functional.leaky_relu(input, negative_slope=0.01, inplace=False)` → Tensor [SO RCE]

Applies element-wise, $\text{LeakyReLU}(x) = \max(0, x) + \text{negative_slope} * \min(0, x)$

See [LeakyReLU](#) for more details.

`torch.nn.functional.leaky_relu_(input, negative_slope=0.01)` → Tensor

In-place version of `leaky_relu()`.

relu

`torch.nn.functional.prelu(input, weight)` → Tensor [SO RCE]

Applies element-wise the function $\text{PReLU}(x) = \max(0, x) + \text{weight} * \min(0, x)$ where `weight` is a learnable parameter.

See [PReLU](#) for more details.

rrelu

`torch.nn.functional.rrelu(input, lower=1./8, upper=1./3, training=False, inplace=False)` → Tensor [SO RCE]

Randomize Leaky ReLU.

See [RReLU](#) for more details.

`torch.nn.functional.rrelu_(input, lower=1./8, upper=1./3, training=False)` → Tensor

In-place version of `rrelu()`.

glu

`torch.nn.functional.glu(input, dim=-1)` → Tensor [SO RCE]

The gate linear unit. Computes:

$$\text{GLU}(a, b) = a \otimes \sigma(b)$$

where `input` is split in half along `dim` to form `a` and `b`, σ is the sigmoid function and \otimes is the element-wise product between matrices.

See [Language Modeling with Gate Convolutional Networks](#).

Parameters

- **input** (*Tensor*) – input tensor
- **dim** (*int*) – dimension on which to split the input. Default: -1

gelu

`torch.nn.functional.gelu(input) → Tensor` [Source]

Applies element-wise the function $\text{GELU}(x) = x * \Phi(x)$ where $\Phi(x)$ is the Cumulative Distribution Function for Gaussian Distribution.

See [Gaussian Error Linear Units \(GELUs\)](#).

logsigmoid

`torch.nn.functional.logsigmoid(input) → Tensor`

Applies element-wise $\text{LogSigmoid}(x_i) = \log\left(\frac{1}{1+\exp(-x_i)}\right)$

See [LogSigmoid](#) for more details.

hard shrink

`torch.nn.functional.hardshrink(input, lambd=0.5) → Tensor` [Source]

Applies the hard shrinkage function element-wise

See [Hardshrink](#) for more details.

tanhshrink

`torch.nn.functional.tanhshrink(input) → Tensor` [Source]

Applies element-wise, $\text{Tanhshrink}(x) = x - \tanh(x)$

See [Tanhshrink](#) for more details.

softsign

`torch.nn.functional.softsign(input) → Tensor` [Source]

Applies element-wise, the function $\text{SoftSign}(x) = \frac{x}{1+|x|}$

See [Softsign](#) for more details.

softplus

`torch.nn.functional.softplus(input, beta=1, threshold=20) → Tensor`

Applies element-wise, the function $\text{Softplus}(x) = \frac{1}{\beta} * \log(1 + \exp(\beta * x))$.

For numerical stability the implementation reverts to the linear function when $\text{input} * \beta > \text{threshold}$.

See [Softplus](#) for more details.

softmax

`torch.nn.functional.softmax(input, dim=None, _stacklevel=3, dtype=None)` [Source]

Applies a softmax function.

Note that $\text{Softmin}(x) = \text{Softmax}(-x)$. See [softmax](#) definition for mathematical formula.

See [Softmin](#) for more details.

Parameters

- **input** (*Tensor*) – input
- **dim** (*int*) – A dimension along which softmax will be computed (so every slice along dim will sum to 1).
- **dtype** (`torch.dtype`, optional) – the desired data type of returned tensor. If specified, the input tensor is casted to `dtype` before the operation is performed. This is useful for preventing data type overflows. Default: None.

softmax

`torch.nn.functional.softmax(input, dim=None, _stacklevel=3, dtype=None)` [Source]

Applies a softmax function.

Softmax is defined as:

$$\text{Softmax}(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$

It is applied to all slices along dim, and will re-scale them so that the elements lie in the range $[0, 1]$ and sum to 1.

See [Softmax](#) for more details.

Parameters

- **in ut** (*Tensor*) – input
- **im** (*int*) – A dimension along which softmax will be computed.
- **dtype** (`torch.dtype`, optional) – the desired data type of returned tensor. If specified, the input tensor is casted to `dtype` before the operation is performed. This is useful for preventing data type overflows. Default: None.

• NOTE

This function doesn't work directly with `NLLLoss`, which expects the Log to be computed between the Softmax and itself. Use `log_softmax` instead (it's faster and has better numerical properties).

softshrink

`torch.nn.functional.softshrink(input, lambd=0.5) → Tensor`

Applies the soft shrinkage function elementwise

See `Softshrink` for more details.

gumbel_softmax

`torch.nn.functional.gumbel_softmax(logits, tau=1, hard=False, eps=1e-10, dim=-1)` [SO RCE]

Samples from the Gumbel-Softmax distribution ([Link 1](#) [Link 2](#)) and optionally discretizes.

Parameters

- **logits** – [..., *num_features*] unnormalized log probabilities
- **tau** – non-negative scalar temperature
- **hard** – if `True`, the returned samples will be discretized as one-hot vectors, but will be differentiable as if it is the soft sample in autograd
- **im** (*int*) – A dimension along which softmax will be computed. Default: -1.

Returns

Sample tensor of same shape as *logits* from the Gumbel-Softmax distribution. If `hard=True`, the returned samples will be one-hot, otherwise they will be probabilities distributions that sum to 1 across *dim*.

• NOTE

This function is here for legacy reasons, may be removed from `nn.Functional` in the future.

• NOTE

The main trick for *hard* is to do `y_hard - y_soft.detach() + y_soft`

It achieves two things: - makes the output value exactly one-hot (since we add then subtract `y_soft` value) - makes the gradient equal to `y_soft` gradient (since we strip all other gradients)

Examples::

```
>>> logits = torch.randn(20, 32)
>>> # Sample soft categorical using reparametrization trick:
>>> F.gumbel_softmax(logits, tau=1, hard=False)
>>> # Sample hard categorical using "Straight-through" trick:
>>> F.gumbel_softmax(logits, tau=1, hard=True)
```

log_softmax

`torch.nn.functional.log_softmax(input, dim=None, _stacklevel=3, dtype=None)` [SO RCE]

Applies a softmax followed by a logarithm.

While mathematically equivalent to `log(softmax(x))`, doing these two operations separately is slower, and numerically unstable. This function uses an alternative formulation to compute the output and gradient correctly.

See `LogSoftmax` for more details.

Parameters

- **in ut** (*Tensor*) – input
- **im** (*int*) – A dimension along which `log_softmax` will be computed.
- **dtype** (`torch.dtype`, optional) – the desired data type of returned tensor. If specified, the input tensor is casted to `dtype` before the operation is performed. This is useful for preventing data type overflows. Default: None.

tanh

`torch.nn.functional.tanh(input) → Tensor` [SO RCE]

Applies element-wise, $\text{Tanh}(x) = \tanh(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)}$

See `Tanh` for more details.

sigmoid

`torch.nn.functional.sigmoid(input) → Tensor`

[SO RCE]

Applies the element-wise function $\text{Sigmoid}(x) = \frac{1}{1 + \exp(-x)}$

See `Sigmoid` for more details.

hard sigmoid

`torch.nn.functional.hardsigmoid(input) → Tensor`

[SO RCE]

Applies the element-wise function

$$\text{Hardsigmoid}(x) = \begin{cases} 0 & \text{if } x \leq -3, \\ 1 & \text{if } x \geq +3, \\ x/6 + 1/2 & \text{otherwise} \end{cases}$$

Parameters

inplace – If set to `True`, will do this operation in-place. Default: `False`

See `Hardsigmoid` for more details.

silu

`torch.nn.functional.silu(input, inplace=False)`

[SO RCE]

Applies the silu function, element-wise.

$$\text{silu}(x) = x * \sigma(x), \text{ where } \sigma(x) \text{ is the logistic sigmoid.}$$

- NOTE

See [Gaussian Error Linear Units \(GELUs\)](#) where the SiLU (Sigmoid Linear Unit) was originally coined, and see [Sigmoid-Weighted Linear Units for Neural Network Function Approximation in Reinforcement Learning](#) and [Swish: a Self-Gate Activation Function](#) where the SiLU was experimented with later.

See `SiLU` for more details.

Normalization functions

batch_norm

`torch.nn.functional.batch_norm(input, running_mean, running_var, weight=None, bias=None, training=False, momentum=0.1, eps=1e-05)`

[SO RCE]

Applies Batch Normalization for each channel across a batch of data.

See `BatchNorm1d`, `BatchNorm2d`, `BatchNorm3d` for details.

instance_norm

`torch.nn.functional.instance_norm(input, running_mean=None, running_var=None, weight=None, bias=None, use_input_stats=True, momentum=0.1, eps=1e-05)`

[SO RCE]

Applies Instance Normalization for each channel in each data sample in a batch.

See `InstanceNorm1d`, `InstanceNorm2d`, `InstanceNorm3d` for details.

layer_norm

`torch.nn.functional.layer_norm(input, normalized_shape, weight=None, bias=None, eps=1e-05)`

[SO RCE]

Applies Layer Normalization for last certain number of dimensions.

See `LayerNorm` for details.

local_response_norm

`torch.nn.functional.local_response_norm(input, size, alpha=0.0001, beta=0.75, k=1.0)`

[SO RCE]

Applies local response normalization over an input signal composed of several input planes, where channels occupy the second dimension. Applies normalization across channels.

See `LocalResponseNorm` for details.

normalize

`torch.nn.functional.normalize(input, p=2, dim=1, eps=1e-12, out=None)`

[SO RCE]

Performs L_p normalization of inputs over specific dimension.

For a tensor `input` of sizes $(n_0, \dots, n_{\text{dim}}, \dots, n_k)$, each n_{dim} -element vector `v` along dimension `dim` is transformed as

$$v = \frac{v}{\max(\|v\|_p, \epsilon)}.$$

With the default arguments it uses the Euclidean norm over vectors along dimension 1 for normalization.

Parameters

- **input** – input tensor of any shape
- **norm** (*float*) – the exponent value in the norm formulation. Default: 2
- **dim** (*int*) – the dimension to reduce. Default: 1
- **eps** (*float*) – small value to avoid division by zero. Default: 1e-12
- **out** (*Tensor, optional*) – the output tensor. If `out` is used, this operation won't be differentiable.

Linear functions

linear

```
torch.nn.functional.linear(input, weight, bias=None)
```

[SO RCE]

Applies a linear transformation to the incoming data: $y = xA^T + b$.

This operator supports `TensorFloat32`.

Shape:

- Input: $(N, *, \text{in_features})$ N is the batch size, $*$ means any number of additional dimensions
- Weight: $(\text{out_features}, \text{in_features})$
- Bias: (out_features)
- Output: $(N, *, \text{out_features})$

lilinear

```
torch.nn.functional.bilinear(input1, input2, weight, bias=None)
```

[SO RCE]

Applies a bilinear transformation to the incoming data: $y = x_1^T A x_2 + b$

Shape:

- input1: $(N, *, H_{\text{in}1})$ where $H_{\text{in}1} = \text{in1_features}$ and $*$ means any number of additional dimensions. All but the last dimension of the inputs should be the same.
- input2: $(N, *, H_{\text{in}2})$ where $H_{\text{in}2} = \text{in2_features}$
- weight: $(\text{out_features}, \text{in1_features}, \text{in2_features})$
- bias: (out_features)
- output: $(N, *, H_{\text{out}})$ where $H_{\text{out}} = \text{out_features}$ and all but the last dimension are the same shape as the input.

Dropout functions

Dropout

```
torch.nn.functional.dropout(input, p=0.5, training=True, inplace=False)
```

[SO RCE]

During training, randomly zeroes some of the elements of the input tensor with probability p using samples from a Bernoulli distribution.

See `Dropout` for details.

Parameters

- **p** – probability of an element to be zeroed. Default: 0.5
- **training** – apply dropout if is `True`. Default: `True`
- **inplace** – If set to `True`, will do this operation in-place. Default: `False`

alpha_dropout

```
torch.nn.functional.alpha_dropout(input, p=0.5, training=False, inplace=False)
```

[SO RCE]

Applies alpha dropout to the input.

See `AlphaDropout` for details.

feature_alpha_dropout

```
torch.nn.functional.feature_alpha_dropout(input, p=0.5, training=False, inplace=False)
```

[SO RCE]

Randomly masks out entire channels (a channel is a feature map, e.g. the j -th channel of the i -th sample in the batch input is a tensor `input[i, j]`) of the input tensor). Instead of setting activations to zero, as in regular Dropout, the activations are set to the negative saturation value of the SELU activation function.

Each element will be masked independently on every forward call with probability p using samples from a Bernoulli distribution. The elements to be masked are randomized on every forward call, and scaled and shifted to maintain zero mean and unit variance.

See `FeatureAlphaDropout` for details.

Parameters

- `p` – dropout probability of a channel to be zeroed. Default: 0.5
- **training** – apply dropout if is `True`. Default: `True`
- **inplace** – If set to `True`, will do this operation in-place. Default: `False`

Dropout2d

`torch.nn.functional.dropout2d(input, p=0.5, training=True, inplace=False)` [Source]

Randomly zero out entire channels (a channel is a 2D feature map, e.g., the j -th channel of the i -th sample in the batch) of the input is a 2D tensor `input[i, j]` of the input tensor). Each channel will be zeroed out independently on every forward call with probability `p` using samples from a Bernoulli distribution.

See `Dropout2d` for details.

Parameters

- `p` – probability of a channel to be zeroed. Default: 0.5
- **training** – apply dropout if is `True`. Default: `True`
- **inplace** – If set to `True`, will do this operation in-place. Default: `False`

Dropout3d

`torch.nn.functional.dropout3d(input, p=0.5, training=True, inplace=False)` [Source]

Randomly zero out entire channels (a channel is a 3D feature map, e.g., the j -th channel of the i -th sample in the batch) of the input is a 3D tensor `input[i, j]` of the input tensor). Each channel will be zeroed out independently on every forward call with probability `p` using samples from a Bernoulli distribution.

See `Dropout3d` for details.

Parameters

- `p` – probability of a channel to be zeroed. Default: 0.5
- **training** – apply dropout if is `True`. Default: `True`
- **inplace** – If set to `True`, will do this operation in-place. Default: `False`

Sparse functions

Embedding

`torch.nn.functional.embedding(input, weight, padding_idx=None, max_norm=None, norm_type=2.0, scale_grad_by_freq=False, sparse=False)` [Source]

A simple lookup table that looks up embeddings in a fixed dictionary and size.

This module is often used to retrieve word embeddings using indices. The input to the module is a list of indices, and the embedding matrix, and the output is the corresponding word embeddings.

See `torch.nn.Embedding` for more details.

Parameters

- **input** (`LongTensor`) – Tensor containing indices into the embedding matrix
- **weight** (`Tensor`) – The embedding matrix with number of rows equal to the maximum possible index + 1, and number of columns equal to the embedding size
- **padding_idx** (`int, optional`) – If given, pads the output with the embedding vector at `padding_idx` (initialize to zeros) whenever it encounters the index.
- **max_norm** (`float, optional`) – If given, each embedding vector with norm larger than `max_norm` is renormalized to have norm `max_norm`. Note: this will modify `weight` in-place.
- **norm_type** (`float, optional`) – The p of the p -norm to compute for the `max_norm` option. Default: 2.
- **scale_grad_by_freq** (`boolean, optional`) – If given, this will scale gradients by the inverse of frequency of the words in the mini-batch. Default: `False`.
- **sparse** (`bool, optional`) – If `True`, gradient w.r.t. `weight` will be a sparse tensor. See Notes under `torch.nn.Embedding` for more details regarding sparse gradients.

Shape:

- Input: `LongTensor` of arbitrary shape containing the indices to extract
- **Weight**: Embedding matrix of floating point type with shape $(V, embedding_dim)$,

where V = maximum index + 1 and `embedding_dim` = the embedding size
- Output: $(*, embedding_dim)$, where $*$ is the input shape

Examples:

```
>>> # a batch of 2 samples of 4 indices each
>>> input = torch.tensor([[1,2,4,5],[4,3,2,9]])
>>> # an embedding matrix containing 10 tensors of size 3
>>> embedding_matrix = torch.rand(10, 3)
>>> F.embedding(input, embedding_matrix)
tensor([[[ 0.8490,  0.9625,  0.6753],
          [ 0.9666,  0.7761,  0.6108],
          [ 0.6246,  0.9751,  0.3618],
          [ 0.4161,  0.2419,  0.7383]],
        [[ 0.6246,  0.9751,  0.3618],
          [ 0.0237,  0.7794,  0.0528],
          [ 0.9666,  0.7761,  0.6108],
          [ 0.3385,  0.8612,  0.1867]]]])

>>> # example with padding_idx
>>> weights = torch.rand(10, 3)
>>> weights[0, :].zero_()
>>> embedding_matrix = weights
>>> input = torch.tensor([[0,2,0,5]])
>>> F.embedding(input, embedding_matrix, padding_idx=0)
tensor([[[ 0.0000,  0.0000,  0.0000],
          [ 0.5609,  0.5384,  0.8720],
          [ 0.0000,  0.0000,  0.0000],
          [ 0.6262,  0.2438,  0.7471]]]])
```

embedding_bag

`torch.nn.functional.embedding_bag(input, weight, offsets=None, max_norm=None, norm_type=2, scale_grad_by_freq=False, mode='mean', sparse=False, per_sample_weights=None, include_last_offset=False)`

[SO RCE]

Computes sums, means or maxes of *bags* of embeddings, without instantiating the intermediate embeddings.

See `torch.nn.EmbeddingBag` for more details.

• NOTE

When using the CUDA backend, this operation may induce non-deterministic behaviour in its backward pass that is not easily switched off. Please see the notes on [Reproducibility](#) for background.

Parameters

- input** (*LongTensor*) – Tensor containing bags of indices into the embedding matrix
- weight** (*Tensor*) – The embedding matrix with number of rows equal to the maximum possible index + 1, and number of columns equal to the embedding size
- offsets** (*LongTensor, optional*) – Only use when `input` is 1D. `offsets` determines the starting index position of each bag (sequence) in `input`.
- max_norm** (*float, optional*) – If given, each embedding vector with norm larger than `max_norm` is renormalized to have norm `max_norm`. Note: this will modify `weight` in-place.
- norm_type** (*float, optional*) – The `p` in the `p`-norm to compute for the `max_norm` option. Default `2`.
- scale_grad_by_freq** (*boolean, optional*) – if given, this will scale gradients by the inverse of frequency of the words in the minibatch. Default `False`. Note: this option is not supported when `mode="max"`.
- mode** (*string, optional*) – `"sum"`, `"mean"` or `"max"`. Specifies the way to reduce the bag. Default: `"mean"`
- sparse** (*bool, optional*) – if `True`, gradient w.r.t. `weight` will be a sparse tensor. See Notes under `torch.nn.Embedding` for more details regarding sparse gradients. Note: this option is not supported when `mode="max"`.
- per_sample_weights** (*Tensor, optional*) – a tensor of float/ double weights, or `None` to indicate all weights should be taken to be 1. If specified, `per_sample_weights` must have exactly the same shape as `input` and is treated as having the same `offsets`, if those are not `None`.
- include_last_offset** (*bool, optional*) – if `True`, the size of offsets is equal to the number of bags + 1.
- last element is the size of the input, or the ending index position of the last bag** (*The*) –

Shape:

- input** (*LongTensor*) and **offsets** (*LongTensor, optional*)
 - If `input` is 2D of shape (B, N) , it will be treated as `B` bags (sequences) each of fixed length `N`, and this will return `B` values aggregated in a way depending on the `mode`. `offsets` is ignored and required to be `None` in this case.
 - If `input` is 1D of shape (N) , it will be treated as a concatenation of multiple bags (sequences). `offsets` is required to be a 1D tensor containing the starting index positions of each bag in `input`. Therefore, for `offsets` of shape (B) , `input` will be viewed as having `B` bags. Empty bags (i.e., having 0-length) will have returned vectors filled with zeros.
- weight** (*Tensor*): the learnable weights of the module of shape $(num_embeddings, embedding_dim)$
- per_sample_weights** (*Tensor, optional*). Has the same shape as `input`.
- output**: aggregated embedding values of shape $(B, embedding_dim)$

Examples:

```
>>> # an Embedding module containing 10 tensors of size 3
>>> embedding_matrix = torch.rand(10, 3)
>>> # a batch of 2 samples of 4 indices each
>>> input = torch.tensor([1,2,4,5,4,3,2,9])
>>> offsets = torch.tensor([0,4])
>>> F.embedding_bag(embedding_matrix, input, offsets)
tensor([[ 0.3397,  0.3552,  0.5545],
        [ 0.5893,  0.4386,  0.5882]])
```

one_hot

`torch.nn.functional.one_hot(tensor, num_classes=-1) → LongTensor`

Takes LongTensor with indices values of shape $(*)$ and returns a tensor of shape $(*, \text{num_classes})$ that have zeros everywhere except where the index of last dimension matches the corresponding value of the input tensor, in which case it will be 1.

See also [One-hot on Wikipedia](#).

Parameters

- tensor** (*LongTensor*) – class values of any shape.
- num_classes** (*int*) – Total number of classes. If set to -1, the number of classes will be inferred as one greater than the largest class value in the input tensor.

Returns

LongTensor that has one more dimension with 1 values at the index of last dimension indicating the input, and 0 everywhere else.

Examples

```
>>> F.one_hot(torch.arange(0, 5) % 3)
tensor([[1, 0, 0],
        [0, 1, 0],
        [0, 0, 1],
        [1, 0, 0],
        [0, 1, 0]])
>>> F.one_hot(torch.arange(0, 5) % 3, num_classes=5)
tensor([[1, 0, 0, 0, 0],
        [0, 1, 0, 0, 0],
        [0, 0, 1, 0, 0],
        [1, 0, 0, 0, 0],
        [0, 1, 0, 0, 0]])
>>> F.one_hot(torch.arange(0, 6).view(3,2) % 3)
tensor([[[1, 0, 0],
         [0, 1, 0]],
        [[0, 0, 1],
         [1, 0, 0]],
        [[0, 1, 0],
         [0, 0, 1]]])
```

Distance functions

pairwise_distance

`torch.nn.functional.pairwise_distance(x1, x2, p=2.0, eps=1e-06, keepdim=False)`

[SOURCE]

See `torch.nn.PairwiseDistance` for details

cosine_similarity

`torch.nn.functional.cosine_similarity(x1, x2, dim=1, eps=1e-8) → Tensor`

Returns cosine similarity between x_1 and x_2 , computed along dim .

$$\text{similarity} = \frac{x_1 \cdot x_2}{\max(\|x_1\|_2 \cdot \|x_2\|_2, \epsilon)}$$

Parameters

- x1** (*Tensor*) – First input.
- x** (*Tensor*) – Second input (of size matching x_1).
- dim** (*int, optional*) – Dimension of vectors. Default: 1
- eps** (*float, optional*) – Small value to avoid division by zero. Default: 1e-8

Shape:

- Input: $(*_1, D, *_2)$ where D is at position dim .
- Output: $(*_1, *_2)$ where 1 is at position dim .

Example:

```
>>> input1 = torch.randn(100, 128)
>>> input2 = torch.randn(100, 128)
>>> output = F.cosine_similarity(input1, input2)
>>> print(output)
```

ist

`torch.nn.functional.pdist(input, p=2) → Tensor`

Computes the p-norm distance between every pair of row vectors in the input. This is identical to the upper triangular portion, excluding the diagonal, of `torch.norm(input[:, None] - input, dim=2, p=p)`. This function will be faster if the rows are contiguous.

If input has shape $N \times M$ then the output will have shape $\frac{1}{2}N(N - 1)$.

This function is equivalent to `scipy.spatial.distance.pdist(input, 'minkowski', p=p)` if $p \in (0, \infty)$. When $p = 0$ it is equivalent to `scipy.spatial.distance.pdist(input, 'hamming') * M`. When $p = \infty$, the closest scipy function is `scipy.spatial.distance.pdist(xn, lambda x, y: np.abs(x - y).max())`.

Parameters

- **input** – input tensor of shape $N \times M$.
- **p** – p value for the p-norm distance to calculate between each vector pair $\in [0, \infty]$.

Loss functions

binary_cross_entropy

`torch.nn.functional.binary_cross_entropy(input, target, weight=None, size_average=None, reduce=None, reduction='mean')`

[SO RCE]

Function that measures the Binary Cross Entropy between the target and the output.

See `BCELoss` for details.

Parameters

- **input** – Tensor of arbitrary shape
- **target** – Tensor of the same shape as input
- **weight** (*Tensor, optional*) – a manual rescaling weight if provided it's repeated to match input tensor shape
- **size_average** (*bool, optional*) – Deprecate (see `reduction`). By default, the losses are averaged over each loss element in the batch. Note that for some losses, there multiple elements per sample. If the field `size_average` is set to `False`, the losses are instead summed for each minibatch. Ignore when reduce is `False`. Default: `True`
- **reduce** (*bool, optional*) – Deprecate (see `reduction`). By default, the losses are averaged or summed over observations for each minibatch depending on `size_average`. When `reduce` is `False`, returns a loss per batch element instead and ignores `size_average`. Default: `True`
- **reduction** (*string, optional*) – Specifies the reduction to apply to the output: 'none' | 'mean' | 'sum'. 'none': no reduction will be applied, 'mean': the sum of the output will be divided by the number of elements in the output, 'sum': the output will be summed. Note: `size_average` and `reduce` are in the process of being deprecated, and in the meantime, specifying either of those two args will override `reduction`. Default: 'mean'

Examples:

```
>>> input = torch.randn((3, 2), requires_grad=True)
>>> target = torch.rand((3, 2), requires_grad=False)
>>> loss = F.binary_cross_entropy(F.sigmoid(input), target)
>>> loss.backward()
```

binary_cross_entropy_with_logits

`torch.nn.functional.binary_cross_entropy_with_logits(input, target, weight=None, size_average=None, reduce=None, reduction='mean', pos_weight=None)`

[SO RCE]

Function that measures Binary Cross Entropy between target and output logits.

See `BCEWithLogitsLoss` for details.

Parameters

- **input** – Tensor of arbitrary shape
- **target** – Tensor of the same shape as input
- **weight** (*Tensor, optional*) – a manual rescaling weight if provided it's repeated to match input tensor shape
- **size_average** (*bool, optional*) – Deprecate (see `reduction`). By default, the losses are averaged over each loss element in the batch. Note that for some losses, there multiple elements per sample. If the field `size_average` is set to `False`, the losses are instead summed for each minibatch. Ignore when reduce is `False`. Default: `True`
- **reduce** (*bool, optional*) – Deprecate (see `reduction`). By default, the losses are averaged or summed over observations for each minibatch depending on `size_average`. When `reduce` is `False`, returns a loss per batch element instead and ignores `size_average`. Default: `True`
- **reduction** (*string, optional*) – Specifies the reduction to apply to the output: 'none' | 'mean' | 'sum'. 'none': no reduction will be applied, 'mean': the sum of the output will be divided by the number of elements in the output, 'sum': the output will be summed. Note: `size_average` and `reduce` are in the process of being deprecated, and in the meantime, specifying either of those two args will override `reduction`. Default: 'mean'
- **pos_weight** (*Tensor, optional*) – a weight of positive examples. Must be a vector with length equal to the number of classes.

weight (*Tensor*, optional) – a weight of positive examples. Must be a vector with length equal to the number of classes.

Examples:

```
>>> input = torch.randn(3, requires_grad=True)
>>> target = torch.empty(3).random_(2)
>>> loss = F.binary_cross_entropy_with_logits(input, target)
>>> loss.backward()
```

oisson_nll_loss

`torch.nn.functional.poisson_nll_loss(input, target, log_input=True, full=False, size_average=None, eps=1e-08, reduce=None, reduction='mean')`

[SO RCE]

Poisson negative log likelihood loss.

See `PoissonNLLLoss` for details.

Parameters

- in ut** – expectation of underlying Poisson distribution.
- target** – random sample $\text{target} \sim \text{Poisson}(\text{input})$.
- log_in ut** – if `True` the loss is computed as $\exp(\text{input}) - \text{target} * \text{input}$, if `False` then loss is $\text{input} - \text{target} * \log(\text{input} + \text{eps})$. Default: `True`
- full** – whether to compute full loss, i.e. to add the Stirling approximation term. Default: `False` $\text{target} * \log(\text{target}) - \text{target} + 0.5 * \log(2 * \pi * \text{target})$.
- size_average** (*bool*, optional) – Deprecate (see `reduction`). By default, the losses are averaged over each loss element in the batch. Note that for some losses, there are multiple elements per sample. If the field `size_average` is set to `False`, the losses are instead summed for each minibatch. Ignore when `reduce` is `False`. Default: `True`
- eps** (*float*, optional) – Small value to avoid evaluation of $\log(0)$ when `log_input='False'`. Default: `1e-8`
- reduce** (*bool*, optional) – Deprecate (see `reduction`). By default, the losses are averaged or summed over observations for each minibatch depending on `size_average`. When `reduce` is `False`, returns a loss per batch element instead and ignores `size_average`. Default: `True`
- reduction** (*string*, optional) – Specifies the reduction to apply to the output: 'none' | 'mean' | 'sum'. 'none': no reduction will be applied, 'mean': the sum of the output will be divided by the number of elements in the output, 'sum': the output will be summed. Note: `size_average` and `reduce` are in the process of being deprecated, and in the meantime, specifying either of those two args will override `reduction`. Default: `'mean'`

cosine_embedding_loss

`torch.nn.functional.cosine_embedding_loss(input1, input2, target, margin=0, size_average=None, reduce=None, reduction='mean') → Tensor`

[SO RCE]

See `CosineEmbeddingLoss` for details.

cross_entropy

`torch.nn.functional.cross_entropy(input, target, weight=None, size_average=None, ignore_index=-100, reduce=None, reduction='mean')`

[SO RCE]

This criterion combines `log_softmax` and `nll_loss` in a single function.

See `CrossEntropyLoss` for details.

Parameters

- input** (*Tensor*) – (N, C) where $C = \text{number of classes}$ or (N, C, H, W) in case of 2D Loss, or $(N, C, d_1, d_2, \dots, d_K)$ where $K \geq 1$ in the case of K -dimensional loss.
- target** (*Tensor*) – (N) where each value is $0 \leq \text{targets}[i] \leq C - 1$, or $(N, d_1, d_2, \dots, d_K)$ where $K \geq 1$ for K -dimensional loss.
- weight** (*Tensor*, optional) – a manual rescaling weight given to each class. If given, has to be a Tensor of size C
- size_average** (*bool*, optional) – Deprecate (see `reduction`). By default, the losses are averaged over each loss element in the batch. Note that for some losses, there are multiple elements per sample. If the field `size_average` is set to `False`, the losses are instead summed for each minibatch. Ignore when `reduce` is `False`. Default: `True`
- ignore_index** (*int*, optional) – Specifies a target value that is ignored and does not contribute to the input gradient. When `size_average` is `True`, the loss is averaged over non-ignored targets. Default: `-100`
- reduce** (*bool*, optional) – Deprecate (see `reduction`). By default, the losses are averaged or summed over observations for each minibatch depending on `size_average`. When `reduce` is `False`, returns a loss per batch element instead and ignores `size_average`. Default: `True`
- reduction** (*string*, optional) – Specifies the reduction to apply to the output: 'none' | 'mean' | 'sum'. 'none': no reduction will be applied, 'mean': the sum of the output will be divided by the number of elements in the output, 'sum': the output will be summed. Note: `size_average` and `reduce` are in the process of being deprecated, and in the meantime, specifying either of those two args will override `reduction`. Default: `'mean'`

Examples:

```
>>> input = torch.randn(3, 5, requires_grad=True)
>>> target = torch.randint(5, (3,), dtype=torch.int64)
>>> loss = F.cross_entropy(input, target)
>>> loss.backward()
```

ctc_loss

`torch.nn.functional.ctc_loss(log_probs, targets, input_lengths, target_lengths, blank=0, reduction='mean', zero_infinity=False)`

[SO RCE]

The Connectionist Temporal Classification (CTC) loss function.

See `CTCLoss` for details.

• NOTE

In some circumstances when using the CUDA backend with CuDNN, this operator may select a non-deterministic algorithm to increase performance. If this is undesirable, you can try to make the operation deterministic (potentially at a performance cost) by setting `torch.backends.cudnn.deterministic = True`. Please see the notes on [Reproducibility](#) for background.

• NOTE

When using the CUDA backend, this operation may induce non-deterministic behaviour in its backward pass that is not easily switched off. Please see the notes on [Reproducibility](#) for background.

Parameters

- **log_probs** – (T, N, C) where C = number of characters in alphabet including blank, T = input length, and N = batch size. The logarithmized probabilities of the outputs (e.g. obtainable with `torch.nn.functional.log_softmax()`).
- **targets** – (N, S) or $(\text{sum}(\text{target_lengths}))$. Targets cannot be blank. In the second form, the targets are assumed to be concatenated.
- **input_lengths** – (N) . Lengths of the inputs (must each be $\leq T$).
- **target_lengths** – (N) . Lengths of the targets.
- **blank** (*int, optional*) – Blank label. Default: 0.
- **reduction** (*string, optional*) – Specifies the reduction to apply to the output: 'none' | 'mean' | 'sum'. 'none': no reduction will be applied, 'mean': the output losses will be divided by the target lengths and then the mean over the batch is taken, 'sum': the output will be summed. Default: 'mean'.
- **zero_infinity** (*bool, optional*) – Whether to zero infinite losses and the associated gradients. Default: False. Infinite losses mainly occur when the inputs are too short to be aligned to the targets.

Example:

```
>>> log_probs = torch.randn(50, 16, 20).log_softmax(2).detach().requires_grad_()
>>> targets = torch.randint(1, 20, (16, 30), dtype=torch.long)
>>> input_lengths = torch.full((16,), 50, dtype=torch.long)
>>> target_lengths = torch.randint(10, 30, (16,), dtype=torch.long)
>>> loss = F.ctc_loss(log_probs, targets, input_lengths, target_lengths)
>>> loss.backward()
```

hinge_embedding_loss

`torch.nn.functional.hinge_embedding_loss(input, target, margin=1.0, size_average=None, reduce=None, reduction='mean')` → Tensor [SO RCE]

See `HingeEmbeddingLoss` for details.

kl_div

`torch.nn.functional.kl_div(input, target, size_average=None, reduce=None, reduction='mean', log_target=False)` [SO RCE]

The **Kullback-Leibler Divergence Loss**

See `KLDivLoss` for details.

Parameters

- **input** – Tensor of arbitrary shape
- **target** – Tensor of the same shape as input
- **size_average** (*bool, optional*) – Deprecate (see `reduction`). By default, the losses are averaged over each loss element in the batch. Note that for some losses, there are multiple elements per sample. If the field `size_average` is set to False, the losses are instead summed for each minibatch. Ignored when reduce is False. Default: True
- **reduce** (*bool, optional*) – Deprecate (see `reduction`). By default, the losses are averaged or summed over observations for each minibatch depending on `size_average`. When `reduce` is False, returns a loss per batch element instead and ignores `size_average`. Default: True
- **reduction** (*string, optional*) – Specifies the reduction to apply to the output: 'none' | 'batchmean' | 'sum' | 'mean'. 'none': no reduction will be applied, 'batchmean': the sum of the output will be divided by the batchsize, 'sum': the output will be summed, 'mean': the output will be divided by the number of elements in the output. Default: 'mean'
- **log_target** (*bool*) – A flag indicating whether `target` is passed in the log space. It is recommended to pass certain distributions (like `softmax`) in the log space to avoid numerical issues caused by explicit `log`. Default: False

• NOTE

`size_average` and `reduce` are in the process of being deprecated, and in the meantime, specifying either of those two args will override `reduction`.

• NOTE

`attn: reduction = 'mean'` doesn't return the true KL divergence value, please use `attn: reduction = 'batchmean'` which aligns with KL math definition. In the next major release, 'mean' will be changed to be the same as 'batchmean'.

torch.nn.functional.l1_loss(input, target, size_average=None, reduce=None, reduction='mean') → Tensor

[SO RCE]

Function that takes the mean element-wise absolute value difference.

See `L1Loss` for details.

mse_loss

torch.nn.functional.mse_loss(input, target, size_average=None, reduce=None, reduction='mean') → Tensor

[SO RCE]

Measures the element-wise mean square error.

See `MSELoss` for details.

margin_ranking_loss

torch.nn.functional.margin_ranking_loss(input1, input2, target, margin=0, size_average=None, reduce=None, reduction='mean') → Tensor

[SO RCE]

See `MarginRankingLoss` for details.

multilabel_margin_loss

torch.nn.functional.multilabel_margin_loss(input, target, size_average=None, reduce=None, reduction='mean') → Tensor

[SO RCE]

See `MultiLabelMarginLoss` for details.

multilabel_soft_margin_loss

torch.nn.functional.multilabel_soft_margin_loss(input, target, weight=None, size_average=None) → Tensor

[SO RCE]

See `MultiLabelSoftMarginLoss` for details.

multi_margin_loss

torch.nn.functional.multi_margin_loss(input, target, p=1, margin=1.0, weight=None, size_average=None, reduce=None, reduction='mean')

[SO RCE]

multi_margin_loss(input, target, p=1, margin=1, weight=None, size_average=None, reduce=None, reduction='mean') -> Tensor

See `MultiMarginLoss` for details.

nll_loss

torch.nn.functional.nll_loss(input, target, weight=None, size_average=None, ignore_index=-100, reduce=None, reduction='mean')

[SO RCE]

The negative log likelihood loss.

See `NLLLoss` for details.

Parameters

- **input** – (N, C) where $C = \text{number of classes}$ or (N, C, H, W) in case of 2D Loss, or $(N, C, d_1, d_2, \dots, d_K)$ where $K \geq 1$ in the case of K -dimensional loss.
- **target** – (N) where each value is $0 \leq \text{targets}[i] \leq C - 1$, or $(N, d_1, d_2, \dots, d_K)$ where $K \geq 1$ for K -dimensional loss.
- **weight** (*Tensor, optional*) – a manual rescaling weight given to each class. If given, has to be a Tensor of size C
- **size_average** (*bool, optional*) – Deprecate (see `reduction`). By default, the losses are averaged over each loss element in the batch. Note that for some losses, there are multiple elements per sample. If the field `size_average` is set to `False`, the losses are instead summed for each minibatch. Ignore when `reduce` is `False`. Default: `True`
- **ignore_index** (*int, optional*) – Specifies a target value that is ignored and does not contribute to the input gradient. When `size_average` is `True`, the loss is averaged over non-ignored targets. Default: `-100`
- **reduce** (*bool, optional*) – Deprecate (see `reduction`). By default, the losses are averaged or summed over observations for each minibatch depending on `size_average`. When `reduce` is `False`, returns a loss per batch element instead and ignores `size_average`. Default: `True`
- **reduction** (*string, optional*) – Specifies the reduction to apply to the output: `'none'` | `'mean'` | `'sum'`. `'none'`: no reduction will be applied, `'mean'`: the sum of the output will be divided by the number of elements in the output, `'sum'`: the output will be summed. Note: `size_average` and `reduce` are in the process of being deprecated, and in the meantime, specifying either of those two args will override `reduction`. Default: `'mean'`

Example:

```
>>> # input is of size N x C = 3 x 5
>>> input = torch.randn(3, 5, requires_grad=True)
>>> # each element in target has to have 0 <= value < C
>>> target = torch.tensor([1, 0, 4])
>>> output = F.nll_loss(F.log_softmax(input), target)
>>> output.backward()
```

smooth_l1_loss

torch.nn.functional.smooth_l1_loss(input, target, size_average=None, reduce=None, reduction='mean', beta=1.0)

[SO RCE]

Function that uses a squared term if the absolute element-wise error falls below `beta` and an L1 term otherwise.

See `SmoothL1Loss` for details.

soft_margin_loss

`torch.nn.functional.soft_margin_loss(input, target, size_average=None, reduce=None, reduction='mean')` → Tensor [SO RCE]

See `SoftMarginLoss` for details.

triplet_margin_loss

`torch.nn.functional.triplet_margin_loss(anchor, positive, negative, margin=1.0, p=2, eps=1e-06, swap=False, size_average=None, reduce=None, reduction='mean')` [SO RCE]

See `TripletMarginLoss` for details

triplet_margin_with_distance_loss

`torch.nn.functional.triplet_margin_with_distance_loss(anchor, positive, negative, *, distance_function=None, margin=1.0, swap=False, reduction='mean')` [SO RCE]

See `TripletMarginWithDistanceLoss` for details.

Vision functions

pixel_shuffle

`torch.nn.functional.pixel_shuffle()`

Rearranges elements in a tensor of shape $(*, C \times r^2, H, W)$ to a tensor of shape $(*, C, H \times r, W \times r)$.

See `PixelShuffle` for details.

Parameters

- input** (*Tensor*) – the input tensor
- scale_factor** (*int*) – factor to increase spatial resolution

Examples:

```
>>> input = torch.randn(1, 9, 4, 4)
>>> output = torch.nn.functional.pixel_shuffle(input, 3)
>>> print(output.size())
torch.Size([1, 1, 12, 12])
```

pad

`torch.nn.functional.pad(input, pad, mode='constant', value=0)`

Padding tensor.

Padding size:

The padding size `pad` which to pad some dimensions of `input` are described starting from the last dimension and moving forward. $\left\lfloor \frac{\text{len}(\text{pad})}{2} \right\rfloor$ dimensions of `input` will be padded. For example, to pad only the last dimension of the input tensor, then `pad` has the form `(padding_left, padding_right)`; to pad the last 2 dimensions of the input tensor, then use `(padding_left, padding_right, padding_top, padding_bottom)`; to pad the last 3 dimensions, use `(padding_left, padding_right, padding_top, padding_bottom, padding_front, padding_back)`.

Padding mode:

See `torch.nn.ConstantPad2d`, `torch.nn.ReflectionPad2d`, and `torch.nn.ReplicationPad2d` for concrete examples on how each of the padding modes works.

Constant padding is implemented for arbitrary dimensions. Replicate padding is implemented for padding the last 3 dimensions of 5D input tensor, or the last 2 dimensions of 4D input tensor, or the last dimension of 3D input tensor. Reflect padding is only implemented for padding the last 2 dimensions of 4D input tensor, or the last dimension of 3D input tensor.

NOTE

When using the CUDA backend, this operation may induce non-deterministic behaviour in its backward pass that is not easily switched off. Please see the notes on [Reproducibility](#) for background.

Parameters

- input** (*Tensor*) – N-dimensional tensor
- padding** (*tuple*) – m-elements tuple, where $\frac{m}{2} \leq$ input dimensions and `m` is even.
- mode** – `'constant'`, `'reflect'`, `'replicate'` or `'circular'`. Default: `'constant'`
- value** – fill value for `'constant'` padding. Default: `0`

Examples:

```
>>> t4d = torch.empty(3, 3, 4, 2)
>>> p1d = (1, 1) # pad last dim by 1 on each side
>>> out = F.pad(t4d, p1d, "constant", 0) # effectively zero padding
>>> print(out.size())
torch.Size([3, 3, 4, 4])
>>> p2d = (1, 1, 2, 2) # pad last dim by (1, 1) and 2nd to last by (2, 2)
>>> out = F.pad(t4d, p2d, "constant", 0)
>>> print(out.size())
torch.Size([3, 3, 8, 4])
>>> t4d = torch.empty(3, 3, 4, 2)
>>> p3d = (0, 1, 2, 1, 3, 3) # pad by (0, 1), (2, 1), and (3, 3)
>>> out = F.pad(t4d, p3d, "constant", 0)
>>> print(out.size())
torch.Size([3, 9, 7, 3])
```

inter olate

`torch.nn.functional.interpolate(input, size=None, scale_factor=None, mode='nearest', align_corners=None, recompute_scale_factor=None)` [SO RCE]

Down/up samples the input to either the given `size` or the given `scale_factor`

The algorithm use for interpolation is determine by `mode`.

Currently temporal, spatial and volumetric sampling are supported, i.e. expected inputs are 3-D, 4-D or 5-D in shape.

The input dimensions are interpreted in the form: *mini-batch* \times *channels* \times [*optional depth*] \times [*optional height*] \times *width*.

The modes available for resizing are: *nearest*, *linear* (3D-only), *bilinear*, *bicubic* (4D-only), *trilinear* (5D-only), *area*

Parameters

- **input** (*Tensor*) – the input tensor
- **size** (*int* or *tuple[int]* or *tuple[int, int]* or *tuple[int, int, int]*) – output spatial size.
- **scale_factor** (*float* or *tuple[float]*) – multiplier for spatial size. Has to match input size if it is a tuple.
- **mode** (*str*) – algorithm used for upsampling: 'nearest' | 'linear' | 'bilinear' | 'bicubic' | 'trilinear' | 'area'. Default: 'nearest'
- **align_corners** (*bool*, *optional*) – Geometrically, we consider the pixels of the input and output as squares rather than points. If set to `True`, the input and output tensors are aligned by the center points of their corner pixels, preserving the values at the corner pixels. If set to `False`, the input and output tensors are aligned by the corner points of their corner pixels, and the interpolation uses edge value padding for out-of-boundary values, making this operation *independent* of input size when `scale_factor` is kept the same. This only has an effect when `mode` is 'linear', 'bilinear', 'bicubic' or 'trilinear'. Default: `False`
- **recompute_scale_factor** (*bool*, *optional*) – recompute the `scale_factor` for use in the interpolation calculation. When `scale_factor` is passed as a parameter, it is used to compute the *output_size*. If `recompute_scale_factor` is `False` or not specified, the passed-in `scale_factor` will be used in the interpolation computation. Otherwise, a new `scale_factor` will be computed based on the output and input sizes for use in the interpolation computation (i.e. the computation will be identical to if the computed *output_size* were passed-in explicitly). Note that when `scale_factor` is floating-point, the recomputed `scale_factor` may differ from the one passed in due to rounding and precision issues.

• NOTE

With `mode='bicubic'`, it's possible to cause overshoot, in other words it can produce negative values or values greater than 255 for images. Explicitly call `result.clamp(min=0, max=255)` if you want to reduce the overshoot when displaying the image.

• WARNING

With `align_corners = True`, the linearly interpolating modes (*linear*, *bilinear*, and *trilinear*) don't proportionally align the output and input pixels, and thus the output values can depend on the input size. This was the default behavior for these modes up to version 0.3.1. Since then, the default behavior is `align_corners = False`. See [Upsample](#) for concrete examples on how this affects the outputs.

• WARNING

When `scale_factor` is specified, if `recompute_scale_factor=True`, `scale_factor` is used to compute the *output_size* which will then be used to infer new scales for the interpolation. The default behavior for `recompute_scale_factor` changed to `False` in 1.6.0, and `scale_factor` is used in the interpolation calculation.

• NOTE

When using the CUDA backend, this operation may induce non-deterministic behaviour in its backward pass that is not easily switched off. Please see the notes on [Reproducibility](#) for background.

upsample

`torch.nn.functional.upsample(input, size=None, scale_factor=None, mode='nearest', align_corners=None)` [SO RCE]

Upsamples the input to either the given `size` or the given `scale_factor`

• WARNING

This function is deprecated in favor of `torch.nn.functional.interpolate()`. This is equivalent with `nn.functional.interpolate(...)`.

• NOTE

When using the C_{UDA} backend, this operation may induce non-deterministic behaviour in its backward pass that is not easily switched off. Please see the notes on [Reproducibility](#) for background.

The algorithm used for upsampling is determined by `mode`.

Currently temporal, spatial and volumetric upsampling are supported, i.e. expected inputs are 3-D, 4-D or 5-D in shape.

The input dimensions are interpreted in the form: *mini-batch x channels x [optional depth] x [optional height] x width*.

The modes available for upsampling are: *nearest*, *linear* (3D-only), *bilinear*, *bicubic* (4D-only), *trilinear* (5D-only)

Parameters

- input** (*Tensor*) – the input tensor
- size** (*int* or *Tuple[int]* or *Tuple[int, int]* or *Tuple[int, int, int]*) – output spatial size.
- scale_factor** (*float* or *Tuple[float]*) – multiplier for spatial size. Has to match input size if it is a tuple.
- mode** (*string*) – algorithm used for upsampling: 'nearest' | 'linear' | 'bilinear' | 'bicubic' | 'trilinear'. Default: 'nearest'
- align_corners** (*bool*, *optional*) – Geometrically, we consider the pixels of the input and output as squares rather than points. If set to `True`, the input and output tensors are aligned by the center points of their corner pixels, preserving the values at the corner pixels. If set to `False`, the input and output tensors are aligned by the corner points of their corner pixels, and the interpolation uses edge value padding for out-of-boundary values, making this operation *independent* of input size when `scale_factor` is kept the same. This only has an effect when `mode` is 'linear', 'bilinear', 'bicubic' or 'trilinear'. Default: `False`

• NOTE

With `mode='bicubic'`, it's possible to cause overshoot, in other words it can produce negative values or values greater than 255 for images. Explicitly call `result.clamp(min=0, max=255)` if you want to reduce the overshoot when displaying the image.

• WARNING

With `align_corners = True`, the linearly interpolating modes (*linear*, *bilinear*, and *trilinear*) don't proportionally align the output and input pixels, and thus the output values can depend on the input size. This was the default behavior for these modes up to version 0.3.1. Since then, the default behavior is `align_corners = False`. See [Upsample](#) for concrete examples on how this affects the outputs.

upsample_nearest

```
torch.nn.functional.upsample_nearest(input, size=None, scale_factor=None) [SOURCE]
```

Upsamples the input, using nearest neighbors' pixel values.

• WARNING

This function is deprecated in favor of `torch.nn.functional.interpolate()`. This is equivalent with `nn.functional.interpolate(..., mode='nearest')`.

Currently spatial and volumetric upsampling are supported (i.e. expected inputs are 4 or 5 dimensional).

Parameters

- input** (*Tensor*) – input
- size** (*int* or *Tuple[int, int]* or *Tuple[int, int, int]*) – output spatial size.
- scale_factor** (*int*) – multiplier for spatial size. Has to be an integer.

• NOTE

When using the C_{UDA} backend, this operation may induce non-deterministic behaviour in its backward pass that is not easily switched off. Please see the notes on [Reproducibility](#) for background.

upsample_bilinear

```
torch.nn.functional.upsample_bilinear(input, size=None, scale_factor=None) [SOURCE]
```

Upsamples the input, using bilinear upsampling.

• WARNING

This function is deprecated in favor of `torch.nn.functional.interpolate()`. This is equivalent with `nn.functional.interpolate(..., mode='bilinear', align_corners=True)`.

Expected inputs are spatial (4 dimensional). Use *upsample_trilinear* for volumetric (5 dimensional) inputs.

Parameters

- input** (*Tensor*) – input
- size** (*int* or *Tuple[int, int]*) – output spatial size.
- scale_factor** (*int* or *Tuple[int, int]*) – multiplier for spatial size

• NOTE

When using the C_{UDA} backend, this operation may induce non-deterministic behaviour in its backward pass that is not easily switched off. Please see the notes on [Reproducibility](#) for background.

When using the CUDA backend, this operation may induce non-deterministic behaviour in its backward pass that is not easily switched off. Please see the notes on [Reproducibility](#) for background.

grid_sample

```
torch.nn.functional.grid_sample(input, grid, mode='bilinear', padding_mode='zeros', align_corners=None)
```

[Source]

Given an `input` and a flow-field `grid`, computes the `output` using `input` values at pixel locations from `grid`.

Currently, only spatial (4-D) and volumetric (5-D) `input` are supported.

In the spatial (4-D) case, for `input` with shape (N, C, H_{in}, W_{in}) and `grid` with shape $(N, H_{out}, W_{out}, 2)$, the output will have shape (N, C, H_{out}, W_{out}) .

For each output location `output[n, :, h, w]`, the size-2 vector `grid[n, h, w]` specifies `input` pixel locations `x` and `y`, which are used to interpolate the output value `output[n, :, h, w]`. In the case of 5D inputs, `grid[n, d, h, w]` specifies the `x`, `y`, `z` pixel locations for interpolating `output[n, :, d, h, w]`. `mode` argument specifies `nearest` or `bilinear` interpolation method to sample the input pixels.

`grid` specifies the sampling pixel locations normalized by the `input` spatial dimensions. Therefore, it should have most values in the range of `[-1, 1]`. For example, values `x = -1`, `y = -1` is the left-top pixel of `input`, and values `x = 1`, `y = 1` is the right-bottom pixel of `input`.

If `grid` has values outside the range of `[-1, 1]`, the corresponding outputs are handled as defined by `padding_mode`. Options are

- `padding_mode="zeros"`: use 0 for out-of-bound grid locations,
- `padding_mode="border"`: use border values for out-of-bound grid locations,
- `padding_mode="reflection"`: use values at locations reflected by the border for out-of-bound grid locations. For location far away from the border, it will keep being reflected until coming in-bound, e.g., (normalized) pixel location `x = -3.5` reflects by border `-1` and becomes `x' = 1.5`, then reflects by border `1` and becomes `x'' = -0.5`.

NOTE

This function is often used in conjunction with `affine_grid()` to build [Spatial Transformer Networks](#).

NOTE

When using the CUDA backend, this operation may induce non-deterministic behaviour in its backward pass that is not easily switched off. Please see the notes on [Reproducibility](#) for background.

NOTE

NaN values in `grid` would be interpreted as `-1`.

Parameters

- input** (*Tensor*) – input of shape (N, C, H_{in}, W_{in}) (4-D case) or $(N, C, D_{in}, H_{in}, W_{in})$ (5-D case)
- grid** (*Tensor*) – flow-field of shape $(N, H_{out}, W_{out}, 2)$ (4-D case) or $(N, D_{out}, H_{out}, W_{out}, 3)$ (5-D case)
- mode** (*str*) – interpolation mode to calculate output values `'bilinear'` | `'nearest'`. Default: `'bilinear'` Note: When `mode='bilinear'` and the input is 5-D, the interpolation mode used internally will actually be trilinear. However, when the input is 4-D, the interpolation mode will legitimately be bilinear.
- padding_mode** (*str*) – padding mode for out-of-grid values `'zeros'` | `'border'` | `'reflection'`. Default: `'zeros'`
- align_corners** (*bool, optional*) – Geometrically, we consider the pixels of the input as squares rather than points. If set to `True`, the extrema (`-1` and `1`) are considered as referring to the center points of the input's corner pixels. If set to `False`, they are instead considered as referring to the corner points of the input's corner pixels, making the sampling more resolution agnostic. This option parallels the `align_corners` option in `interpolate()`, and so whichever option is used here should also be used there to resize the input image before grid sampling. Default: `False`

Returns

output Tensor

Return type

output (*Tensor*)

WARNING

When `align_corners = True`, the grid positions depend on the pixel size relative to the input image size, and so the locations sampled by `grid_sample()` will differ for the same input given at different resolutions (that is, after being upsampled or downsampled). The default behavior up to version 1.2.0 was `align_corners = True`. Since then, the default behavior has been changed to `align_corners = False`, in order to bring it in line with the default for `interpolate()`.

affine_grid

```
torch.nn.functional.affine_grid(theta, size, align_corners=None)
```

[Source]

Generates a 2D or 3D flow field (sampling grid), given a batch of affine matrices `theta`.

NOTE

This function is often used in conjunction with `grid_sample()` to build [Spatial Transformer Networks](#).

Parameters

- **theta** (*Tensor*) – input batch of affine matrices with shape $(N \times 2 \times 3)$ for 2D or $(N \times 3 \times 4)$ for 3D
- **size** (*torch.Size*) – the target output image size. $(N \times C \times H \times W)$ for 2D or $(N \times C \times D \times H \times W)$ for 3D) Example: `torch.Size((32, 3, 24, 24))`
- **align_corners** (*bool, optional*) – if `True`, consider `-1` and `1` to refer to the centers of the corner pixels rather than the image corners. Refer to `grid_sample()` for a more complete description. A grid generated by `affine_grid()` should be passed to `grid_sample()` with the same setting for this option. Default: `False`

Returns

output Tensor of size $(N \times H \times W \times 2)$

Return type

output (*Tensor*)

• WARNING

When `align_corners = True`, the grid positions depend on the pixel size relative to the input image size, and so the locations sampled by `grid_sample()` will differ for the same input given at different resolutions (that is, after being upsampled or downsampled). The default behavior up to version 1.2.0 was `align_corners = True`. Since then, the default behavior has been changed to `align_corners = False`, in order to bring it in line with the default for `interpolate()`.

• WARNING

When `align_corners = True`, 2D affine transforms on 1D data and 3D affine transforms on 2D data (that is, when one of the spatial dimensions has unit size) are ill-defined, and not an intended use case. This is not a problem when `align_corners = False`. Up to version 1.2.0, all grid points along a unit dimension were considered arbitrarily to be at `-1`. From version 1.3.0, under `align_corners = True` all grid points along a unit dimension are considered to be at `0` (the center of the input image).

DataParallel functions (multi-GPU, distributed)

data_parallel

```
torch.nn.parallel.data_parallel(module, inputs, device_ids=None, output_device=None, dim=0, module_kwargs=None) [SOURCE]
```

Evaluates module(input) in parallel across the GPUs given in device_ids.

This is the functional version of the DataParallel module.

Parameters

- **module** (*Module*) – the module to evaluate in parallel
- **inputs** (*Tensor*) – inputs to the module
- **device_ids** (*list of python:int or torch.device*) – GPUs on which to replicate module
- **output_device** (*list of python:int or torch.device*) – GPU location of the output, -1 to indicate the CPU. (default: device_ids[0])

Returns

a Tensor containing the result of module(input) located on output_device

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