EE-559 – Deep learning

9.1. Transposed convolutions

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Generative processes that consist of optimizing the input rely on back-propagation to expend the signal from a low-dimension representation to the high-dimension signal space.

The same can be done in the forward pass with **transposed convolution layers** whose forward operation corresponds to a convolution layer's backward pass.

Consider a 1d convolution with a kernel κ

$$\begin{aligned} y_i &= (x \circledast \kappa)_i \\ &= \sum_a x_{i+a-1} \, \kappa_a \\ &= \sum_u x_u \, \kappa_{u-i+1}. \end{aligned}$$

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We get

$$\begin{aligned} \left[\frac{\partial \ell}{\partial x}\right]_u &= \frac{\partial \ell}{\partial x_u} \\ &= \sum_i \frac{\partial \ell}{\partial y_i} \frac{\partial y_i}{\partial x_u} \\ &= \sum_i \frac{\partial \ell}{\partial y_i} \kappa_{u-i+1}. \end{aligned}$$

which looks a lot like a standard convolution layer, except that the kernel coefficients are visited in reverse order.

This is actually the standard convolution operator from signal processing. If $*$ denotes this operation, we have

$$(x * \kappa)_i = \sum_a x_a \, \kappa_{i-a+1}.$$

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Coming back to the backward pass of the convolution layer, if

$$y = x \circledast \kappa$$

then

$$\left[\frac{\partial \ell}{\partial x}\right] = \left[\frac{\partial \ell}{\partial y}\right] * \kappa.$$

In the deep-learning field, since it corresponds to transposing the weight matrix of the equivalent fully-connected layer, it is called a **transposed convolution**.

$$\begin{pmatrix} \kappa_1 & \kappa_2 & \kappa_3 & 0 & 0 & 0 & 0 \\ 0 & \kappa_1 & \kappa_2 & \kappa_3 & 0 & 0 & 0 \\ 0 & 0 & \kappa_1 & \kappa_2 & \kappa_3 & 0 & 0 \\ 0 & 0 & 0 & \kappa_1 & \kappa_2 & \kappa_3 & 0 \\ 0 & 0 & 0 & 0 & \kappa_1 & \kappa_2 & \kappa_3 \end{pmatrix}^T = \begin{pmatrix} \kappa_1 & 0 & 0 & 0 & 0 \\ \kappa_2 & \kappa_1 & 0 & 0 & 0 \\ \kappa_3 & \kappa_2 & \kappa_1 & 0 & 0 \\ 0 & \kappa_3 & \kappa_2 & \kappa_1 & 0 \\ 0 & 0 & \kappa_3 & \kappa_2 & \kappa_1 \\ 0 & 0 & 0 & \kappa_3 & \kappa_2 \\ 0 & 0 & 0 & 0 & \kappa_3 \end{pmatrix}$$

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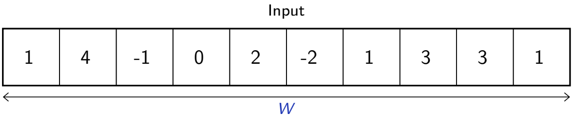
$$\begin{pmatrix} \kappa_1 & \kappa_2 & \kappa_3 & 0 & 0 & 0 & 0 \\ 0 & \kappa_1 & \kappa_2 & \kappa_3 & 0 & 0 & 0 \\ 0 & 0 & \kappa_1 & \kappa_2 & \kappa_3 & 0 & 0 \\ 0 & 0 & 0 & \kappa_1 & \kappa_2 & \kappa_3 & 0 \\ 0 & 0 & 0 & 0 & \kappa_1 & \kappa_2 & \kappa_3 \end{pmatrix}^T = \begin{pmatrix} \kappa_1 & 0 & 0 & 0 & 0 \\ \kappa_2 & \kappa_1 & 0 & 0 & 0 \\ \kappa_3 & \kappa_2 & \kappa_1 & 0 & 0 \\ 0 & \kappa_3 & \kappa_2 & \kappa_1 & 0 \\ 0 & 0 & \kappa_3 & \kappa_2 & \kappa_1 \\ 0 & 0 & 0 & \kappa_3 & \kappa_2 \\ 0 & 0 & 0 & 0 & \kappa_3 \end{pmatrix}$$

A convolution can be seen as a series of inner products, a transposed convolution can be seen as a weighted sum of translated kernels.

Convolution layer

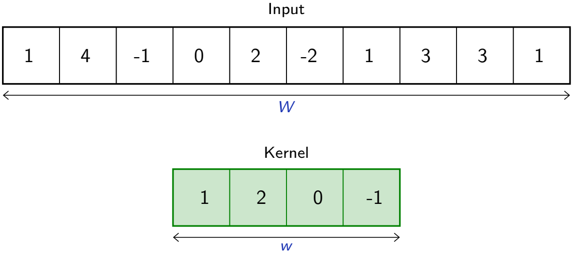


Input

1	4	-1	0	2	-2	1	3	3	1

W

Convolution layer



Input

1	4	-1	0	2	-2	1	3	3	1

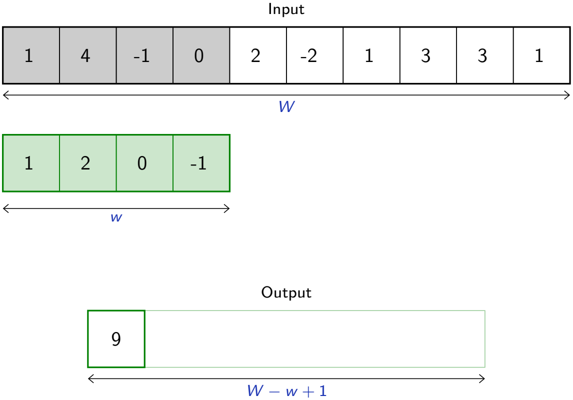
W

Kernel

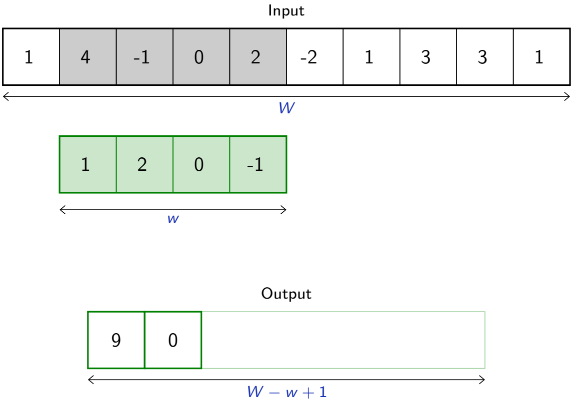
1	2	0	-1

w

Convolution layer



Convolution layer



Input

1	4	-1	0	2	-2	1	3	3	1

W

1	2	0	-1

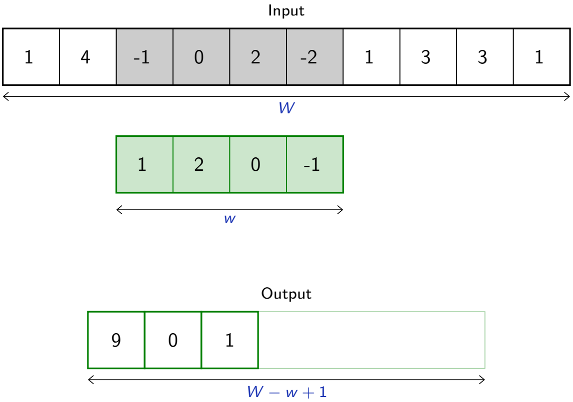
w

Output

9	0

$W - w + 1$

Convolution layer



Input

1	4	-1	0	2	-2	1	3	3	1

W

1	2	0	-1

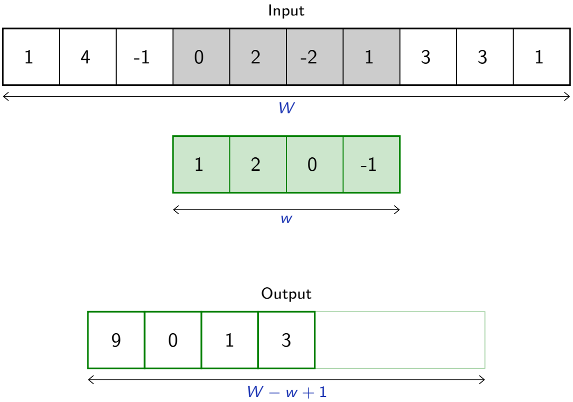
w

Output

9	0	1

$W - w + 1$

Convolution layer



Input

1	4	-1	0	2	-2	1	3	3	1

W

1	2	0	-1

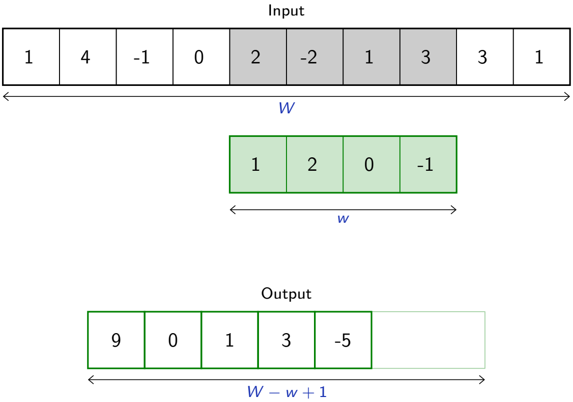
w

Output

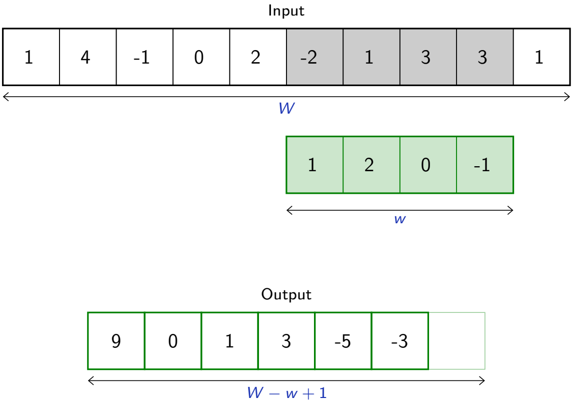
9	0	1	3

$W - w + 1$

Convolution layer



Convolution layer



Input

1	4	-1	0	2	-2	1	3	3	1

W

1	2	0	-1

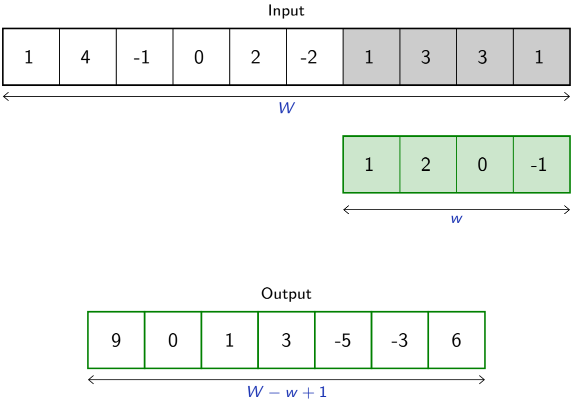
w

Output

9	0	1	3	-5	-3	

$W - w + 1$

Convolution layer



Input

1	4	-1	0	2	-2	1	3	3	1

W

1	2	0	-1

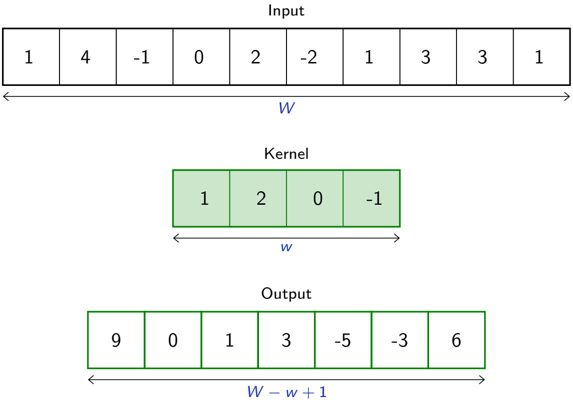
w

Output

9	0	1	3	-5	-3	6

$W - w + 1$

Convolution layer



Input

1	4	-1	0	2	-2	1	3	3	1

W

Kernel

1	2	0	-1

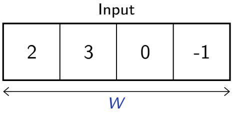
w

Output

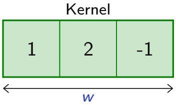
9	0	1	3	-5	-3	6

$W - w + 1$

Transposed convolution layer

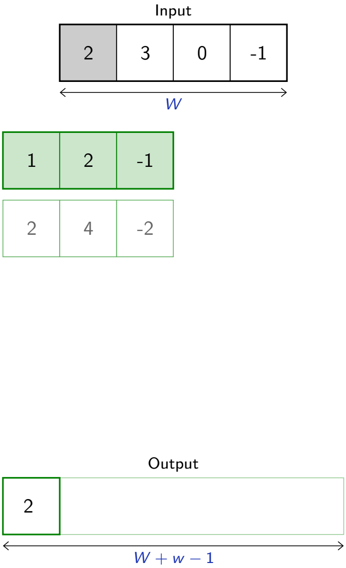

Input

2	3	0	-1


Kernel

1	2	-1

Transposed convolution layer



Input

2	3	0	-1

W

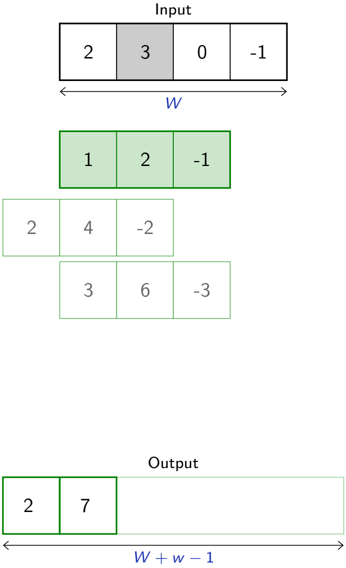
1	2	-1
2	4	-2

Output

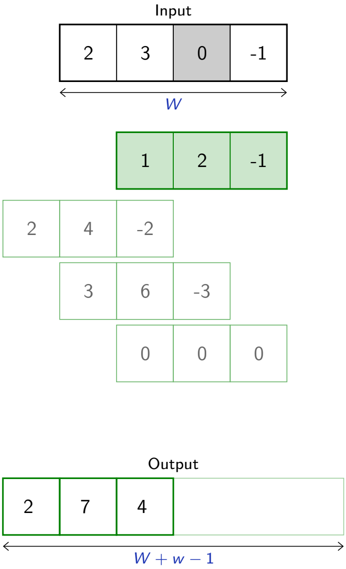
2

$W + w - 1$

Transposed convolution layer



Transposed convolution layer



Input

2	3	0	-1

W

1	2	-1

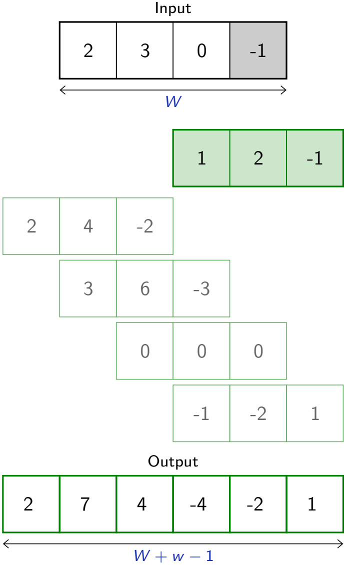
2	4	-2		
	3	6	-3	
		0	0	0

Output

2	7	4			

$W + w - 1$

Transposed convolution layer



Input

2	3	0	-1

W

1	2	-1

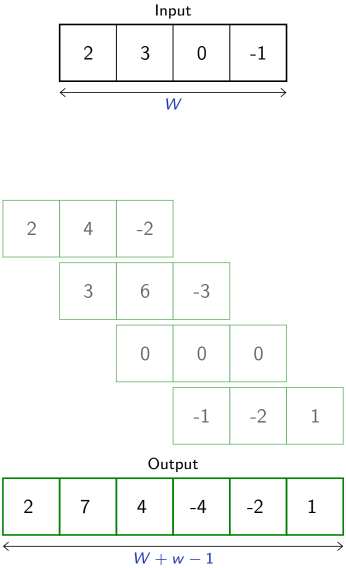
2	4	-2			
	3	6	-3		
		0	0	0	
			-1	-2	1

Output

2	7	4	-4	-2	1

$W + w - 1$

Transposed convolution layer



Input

2	3	0	-1

W

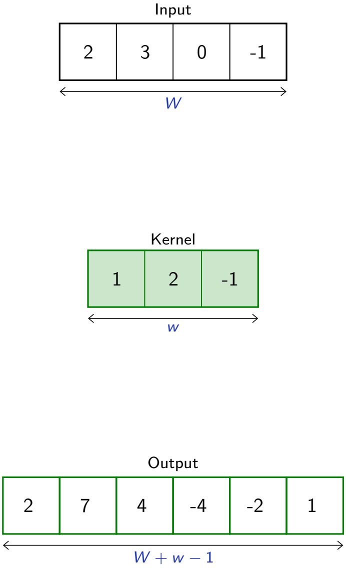
2	4	-2			
	3	6	-3		
		0	0	0	
			-1	-2	1

Output

2	7	4	-4	-2	1

$W + w - 1$

Transposed convolution layer



Input

2	3	0	-1

W

Kernel

1	2	-1

w

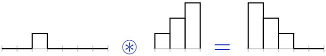
Output

2	7	4	-4	-2	1

$W + w - 1$

`torch.nn.functional.conv_transpose1d` implements the operation we just described. It takes as input a batch of multi-channel samples, and produces a batch of multi-channel samples.

```
>>> x = torch.tensor([[[0., 0., 1., 0., 0., 0., 0.]]])
>>> k = torch.tensor([[[1., 2., 3.]]])
>>> F.conv1d(x, k)
tensor([[[ 3.,  2.,  1.,  0.,  0.]]])
```



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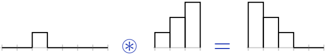
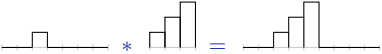
tensor([[[ 3.,  2.,  1.,  0.,  0.]]])
```



```
>>> F.conv_transpose1d(x, k)
tensor([[[ 0.,  0.,  1.,  2.,  3.,  0.,  0.,  0.,  0.]]])
```



The class `torch.nn.ConvTranspose1d` embeds that operation into a `torch.nn.Module`.

```
>>> x = torch.tensor([[[ 2., 3., 0., -1.]]])
>>> m = nn.ConvTranspose1d(1, 1, kernel_size=3)
>>> m.bias.data.zero_()
tensor([0.])
>>> m.weight.data.copy_(torch.tensor([ 1, 2, -1 ]))
tensor([[[ 1.,  2., -1.]]])
>>> y = m(x)
>>> y
tensor([[[ 2.,  7.,  4., -4., -2.,  1.]]], grad_fn=<SqueezeBackward1>)
```

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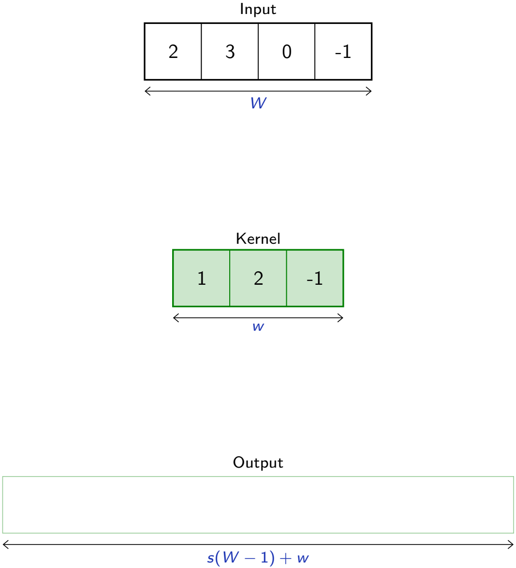
They also have a `stride` and `padding` parameters, however, due to the relation between convolutions and transposed convolutions:

⚠ While for convolutions `stride` and `padding` are defined in the input map, for transposed convolutions these parameters are defined in the output map, and the latter modulates a cropping operation.

Transposed convolution layer (stride $= 2$)



Input

2	3	0	-1

W

Kernel

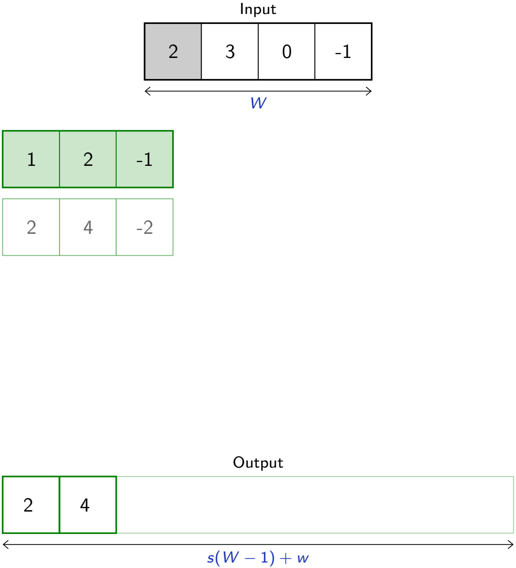
1	2	-1

w

Output

$s(W-1)+w$

Transposed convolution layer (stride $= 2$)



Input

2	3	0	-1

W

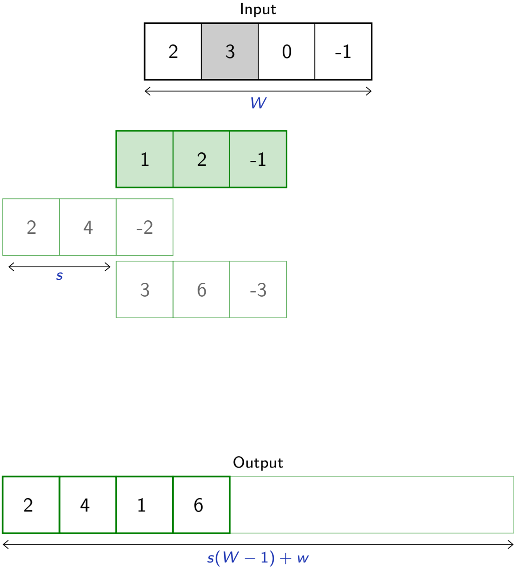
1	2	-1
2	4	-2

Output

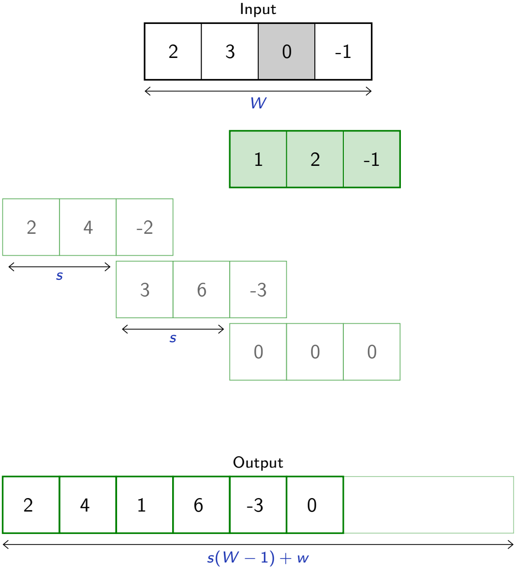
2	4

$s(W-1)+w$

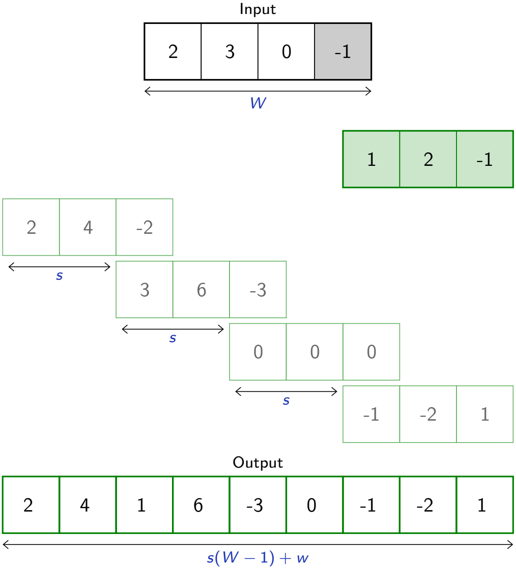
Transposed convolution layer (stride $= 2$)



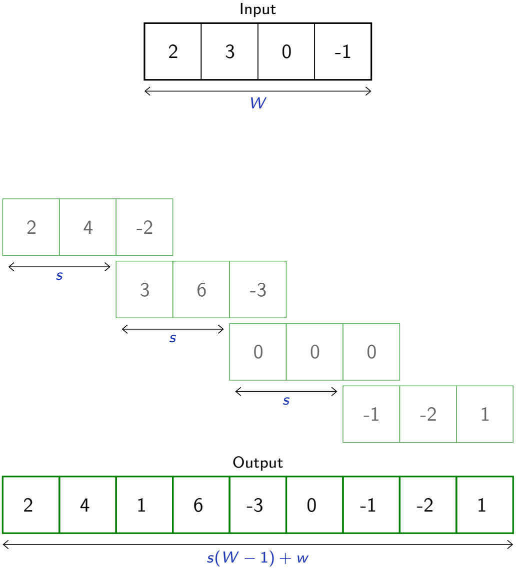
Transposed convolution layer (stride $= 2$)



Transposed convolution layer (stride $= 2$)



Transposed convolution layer (stride $= 2$)



Transposed convolution layer (stride $= 2$)

Input

2	3	0	-1

W

Kernel

1	2	-1

w

Output

2	4	1	6	-3	0	-1	-2	1

$s(W-1)+w$

The composition of a convolution and a transposed convolution of same parameters keep the signal size [roughly] unchanged.

⚠ A convolution with a stride greater than one may ignore parts of the signal. Its composition with the corresponding transposed convolution generates a map **of the size of the observed area**.

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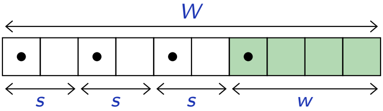
⚠ A convolution with a stride greater than one may ignore parts of the signal. Its composition with the corresponding transposed convolution generates a map **of the size of the observed area**.

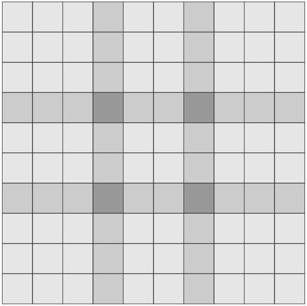
For instance, a 1d convolution of kernel size w and stride s composed with the transposed convolution of same parameters maintains the signal size W, only if

$$\exists q \in \mathbb{N}, \; W = w + s\,q.$$



It has been observed that transposed convolutions may create some grid-structure artifacts, since generated pixels are not all covered similarly.

For instance with a 4×4 kernel and stride 3



An alternative is to use an analytic up-scaling, implemented in the PyTorch functional `nn.functional.interpolate`.

```
>>> x = torch.tensor([[[[ 1., 2. ], [ 3., 4. ]]]])
>>> nn.functional.interpolate(x, scale_factor = 3, mode = 'bilinear')
tensor([[[[1.0000, 1.0000, 1.3333, 1.6667, 2.0000, 2.0000],
          [1.0000, 1.0000, 1.3333, 1.6667, 2.0000, 2.0000],
          [1.6667, 1.6667, 2.0000, 2.3333, 2.6667, 2.6667],
          [2.3333, 2.3333, 2.6667, 3.0000, 3.3333, 3.3333],
          [3.0000, 3.0000, 3.3333, 3.6667, 4.0000, 4.0000],
          [3.0000, 3.0000, 3.3333, 3.6667, 4.0000, 4.0000]]]])
```

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>>> nn.functional.interpolate(x, scale_factor = 3, mode = 'bilinear')
tensor([[[[1.0000, 1.0000, 1.3333, 1.6667, 2.0000, 2.0000],
          [1.0000, 1.0000, 1.3333, 1.6667, 2.0000, 2.0000],
          [1.6667, 1.6667, 2.0000, 2.3333, 2.6667, 2.6667],
          [2.3333, 2.3333, 2.6667, 3.0000, 3.3333, 3.3333],
          [3.0000, 3.0000, 3.3333, 3.6667, 4.0000, 4.0000],
          [3.0000, 3.0000, 3.3333, 3.6667, 4.0000, 4.0000]]]])

>>> nn.functional.interpolate(x, scale_factor = 3, mode = 'nearest')
tensor([[[[1., 1., 1., 2., 2., 2.],
          [1., 1., 1., 2., 2., 2.],
          [1., 1., 1., 2., 2., 2.],
          [3., 3., 3., 4., 4., 4.],
          [3., 3., 3., 4., 4., 4.],
          [3., 3., 3., 4., 4., 4.]]]])
```

Such module is usually combined with a convolution to learn local corrections to undesirable artifacts of the up-scaling.

In practice, a transposed convolution such as

```
tconv = nn.ConvTranspose2d(nic, noc,
                           kernel_size = 3, stride = 2,
                           padding = 1, output_padding = 1),

y = tconv(x)
```

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In practice, a transposed convolution such as

```
tconv = nn.ConvTranspose2d(nic, noc,
                           kernel_size = 3, stride = 2,
                           padding = 1, output_padding = 1),

y = tconv(x)
```

can be replaced by

```
conv = nn.Conv2d(nic, noc, kernel_size = 3, padding = 1)

u = nn.functional.interpolate(x, scale_factor = 2, mode = 'bilinear')
y = conv(u)
```

The end