Deep learning

4.4. Convolutions

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If they were handled as normal “unstructured” vectors, large-dimension signals such as sound samples or images would require models of intractable size.

For instance a linear layer taking a $256 \times 256$ RGB image as input, and producing an image of same size would require

$$(256 \times 256 \times 3)^2 \approx 3.87e+10$$

parameters, with the corresponding memory footprint ($\approx 150Gb$ !), and excess of capacity.
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A convolution layer embodies this idea. It applies the same linear transformation locally, everywhere, and preserves the signal structure.
Input

\[ W = \begin{bmatrix} 1 & 4 & -1 & 0 & 2 & -2 & 1 & 3 & 3 & 1 \end{bmatrix} \]
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Input

\[
\begin{array}{cccccccc}
1 & 4 & -1 & 0 & 2 & -2 & 1 & 3 & 3 & 1 \\
\end{array}
\]

\[W\]

\[w\]

Output

\[
\begin{array}{c}
9 \\
\end{array}
\]

\[W - w + 1\]
\input{convolution}

The output is calculated as \( W - w + 1 \).
The diagram illustrates a convolution operation. The input sequence is: 1 4 -1 0 2 -2 1 3 3 1. The kernel (W) is: 1 2 0 -1. The output (W - w + 1) is: 9 0 1.
Input

\[
\begin{array}{cccccccccc}
1 & 4 & -1 & 0 & 2 & -2 & 1 & 3 & 3 & 1 \\
\end{array}
\]

\[
W \quad w \quad W - w + 1
\]

Output

\[
\begin{array}{cccc}
9 & 0 & 1 & 3 & -5 \\
\end{array}
\]
\[ W - w + 1 \]
\[ W - w + 1 \]

**Input**

\[
\begin{array}{cccccccccc}
1 & 4 & -1 & 0 & 2 & -2 & 1 & 3 & 3 & 1 \\
\end{array}
\]

**Kernel**

\[
\begin{array}{cccc}
1 & 2 & 0 & -1 \\
\end{array}
\]

**Output**

\[
\begin{array}{cccccccc}
9 & 0 & 1 & 3 & -5 & -3 & 6 \\
\end{array}
\]
Formally, in 1d, given

\[ x = (x_1, \ldots, x_W) \]

and a “convolution kernel” (or “filter”) of width \( w \)

\[ u = (u_1, \ldots, u_w) \]
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\[ x = (x_1, \ldots, x_W) \]
and a “convolution kernel” (or “filter”) of width \( w \)
\[ u = (u_1, \ldots, u_w) \]
the convolution \( x \odot u \) is a vector of size \( W - w + 1 \), with
\[
(x \odot u)_i = \sum_{j=1}^{w} x_{i-1+j} u_j \\
= (x_i, \ldots, x_{i+w-1}) \cdot u
\]
for instance
\[
(1, 2, 3, 4) \odot (3, 2) = (3 + 4, 6 + 6, 9 + 8) = (7, 12, 17).
\]
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\]

for instance

\[(1, 2, 3, 4) \odot (3, 2) = (3 + 4, 6 + 6, 9 + 8) = (7, 12, 17).\]

⚠️ This differs from the usual convolution since the kernel and the signal are both visited in increasing index order.
Convolution can implement in particular differential operators, e.g.

\[(0, 0, 0, 0, 1, 2, 3, 4, 4, 4) \ast (-1, 1) = (0, 0, 0, 1, 1, 1, 0, 0, 0).\]
Convolution can implement in particular differential operators, e.g.

\((0, 0, 0, 0, 1, 2, 3, 4, 4, 4) \odot (-1, 1) = (0, 0, 0, 1, 1, 1, 0, 0, 0)\).
Convolution can implement in particular differential operators, e.g.

\[(0, 0, 0, 0, 1, 2, 3, 4, 4, 4) \ast (-1, 1) = (0, 0, 0, 1, 1, 1, 0, 0, 0, 0)\].

or crude “template matcher”, e.g.
It generalizes naturally to a multi-dimensional input, although specification can become complicated.
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Its most usual form for “convolutional networks” processes a 3d tensor as input (i.e. a multi-channel 2d signal) to output a 2d tensor. The kernel is not swiped across channels, just across rows and columns.

In this case, if the input tensor is of size $C \times H \times W$, and the kernel is $C \times h \times w$, the output is $(H - h + 1) \times (W - w + 1)$. 
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In a standard convolution layer, $D$ such convolutions are combined to generate a $D \times (H - h + 1) \times (W - w + 1)$ output.
\[ D - h + 1 \]

\[ W - w + 1 \]

\[ C \]
Kernel $K$ is defined as a $D$ by $H$ by $W$ tensor of $C$ channels. The output at position $(h,w) = (D−h+1, W−w+1)$ is given by

$$
\text{Output}(h,w) = \sum_{d=1}^{D} \sum_{h'=1}^{H} \sum_{w'=1}^{W} \text{Input}(d,h',w') \cdot K(d,h',w')
$$

where $K(d,h',w')$ is the $d$th channel of the kernel at position $(h',w')$. The convolution operation slides the kernel over each input position, computing the weighted sum of the overlapping elements.
Kernel $K$ of size $D \times H \times W$ with strides $h \times w$ and padding $1$.
Kernel $D - h + 1 \times W - w + 1$

Input

Output
Kernel $K_h$ of size $D 	imes H 	imes W$ with stride $h$ and padding $w$ is applied to the input of size $C 	imes H 	imes W$ to produce the output of size $C'$. The formula for the output size is:

$$C' = \left\lfloor \frac{W - w + 1}{h} \right\rfloor$$
Kernel

\[ (D-h+1) \times (W-w+1) \times 1 \]

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\[ D \times H \times W - h + 1 \times w - 1 \]
Kernels $K$ of size $D \times H \times W$ are applied to the input $I$ of size $C \times h \times w \times 1$. The output $O$ is of size $C \times (H - h + 1) \times (W - w + 1)$. 

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\[ D - h + 1 \times W - w + 1 \]
\[(D - h + 1) \times (W - w + 1)
\]
Kernel

\[ Kernels \]

\[ H - h + 1 \]

\[ W - w + 1 \]

Input

\[ D \]

\[ H \]

\[ W \]

\[ C \]

\[ h \]

\[ w \]

Kernel

Output

\[ 1 \]
Kernel $K$:

$$
D \times H - h + 1
$$

Output:

$$
W - w + 1
$$

$$
H - h + 1
$$
Input

\[ \text{W} \]

\[ \text{H} \]

\[ \text{C} \]

Kernels

\[ \text{w} \]

\[ \text{h} \]

\[ \text{D} \]

Output

\[ \text{W} - w + 1 \]

\[ \text{H} - h + 1 \]

\[ \text{D} \]
The diagram illustrates a convolution operation in a neural network. The input and output layers are shown, with dimensions labeled as follows:

- **Input** layer:
  - **Height (H)**:
  - **Width (W)**:
  - **Depth (D)**:
  - **Channels (C)**:

- **Output** layer:
  - **Height (H)**:
  - **Width (W)**:
  - **Channels (C)**:

The convolution process is linear, as indicated by the red arrow. The output dimensions are computed as:

- **Height**: \(H - h + 1\)
- **Width**: \(W - w + 1\)
- **Depth**: \(D\)

Here, \(h\) and \(w\) are the height and width of the convolution kernel, respectively.
Note that a convolution preserves the signal support structure.

A 1d signal is converted into a 1d signal, a 2d signal into a 2d, and neighboring parts of the input signal influence neighboring parts of the output signal.
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A 1d signal is converted into a 1d signal, a 2d signal into a 2d, and neighboring parts of the input signal influence neighboring parts of the output signal.

A 3d convolution can be used if the channel index has some metric meaning, such as time for a series of grayscale video frames. Otherwise swiping across channels makes no sense.
We usually refer to one of the channels generated by a convolution layer as an activation map.

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The sub-area of an input map that influences a component of the output as the receptive field of the latter.

In the context of convolutional networks, a standard linear layer is called a fully connected layer since every input influences every output.
F.conv2d(input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1)

Implements a 2d convolution, where `weight` contains the kernels, and is
\[ D \times C \times h \times w, \]
`bias` is of dimension `D`, `input` is of dimension
\[ N \times C \times H \times W \]
and the result is of dimension
\[ N \times D \times (H - h + 1) \times (W - w + 1). \]
F.conv2d(input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1)

Implements a 2d convolution, where `weight` contains the kernels, and is $D \times C \times h \times w$, `bias` is of dimension $D$, `input` is of dimension $N \times C \times H \times W$

and the result is of dimension

$$N \times D \times (H - h + 1) \times (W - w + 1).$$

```python
>>> weight = torch.empty(5, 4, 2, 3).normal_()
>>> bias = torch.empty(5).normal_()
>>> input = torch.empty(117, 4, 10, 3).normal_()
>>> output = F.conv2d(input, weight, bias)
>>> output.size()
torch.Size([117, 5, 9, 1])
```
F.conv2d(input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1)

Implements a 2d convolution, where weight contains the kernels, and is $D \times C \times h \times w$, bias is of dimension $D$, input is of dimension $N \times C \times H \times W$

and the result is of dimension $N \times D \times (H - h + 1) \times (W - w + 1)$.

```python
>>> weight = torch.empty(5, 4, 2, 3).normal_()
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>>> output = F.conv2d(input, weight, bias)
>>> output.size()
torch.Size([117, 5, 9, 1])
```

Similar functions implement 1d and 3d convolutions.
x = mnist_train.data[12].float().view(1, 1, 28, 28)

weight = torch.empty(5, 1, 3, 3)

weight[0, 0] = torch.tensor([[0., 0., 0.],
                           [0., 1., 0.],
                           [0., 0., 0.]])

weight[1, 0] = torch.tensor([[1., 1., 1.],
                           [1., 1., 1.],
                           [1., 1., 1.]])

weight[2, 0] = torch.tensor([[-1., 0., 1.],
                           [-1., 0., 1.],
                           [-1., 0., 1.]])

weight[3, 0] = torch.tensor([[-1., -1., -1.],
                           [0., 0., 0.],
                           [1., 1., 1.]])

weight[4, 0] = torch.tensor([[0., -1., 0.],
                           [-1., 4., -1.],
                           [0., -1., 0.]])

y = F.conv2d(x, weight)
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class torch.nn.Conv2d(in_channels, out_channels, 
    kernel_size, stride=1, padding=0, dilation=1, 
    groups=1, bias=True)

Wraps the convolution into a Module, with the kernels and biases as Parameter properly randomized at creation.

The kernel size is either a pair \((h, w)\) or a single value \(k\) interpreted as \((k, k)\).
class torch.nn.Conv2d(in_channels, out_channels,
    kernel_size, stride=1, padding=0, dilation=1,
    groups=1, bias=True)

Wraps the convolution into a Module, with the kernels and biases as Parameter properly randomized at creation.

The kernel size is either a pair \((h, w)\) or a single value \(k\) interpreted as \((k, k)\).

```python
>>> f = nn.Conv2d(in_channels = 4, out_channels = 5, kernel_size = (2, 3))
>>> for n, p in f.named_parameters(): print(n, p.size())
... weight torch.Size([5, 4, 2, 3])
  bias torch.Size([5])
>>> x = torch.empty(117, 4, 10, 3).normal_()
>>> y = f(x)
>>> y.size()
torch.Size([117, 5, 9, 1])
```
Padding, stride, and dilation
Convolutions have three additional parameters:

- The **padding** specifies the size of a zeroed frame added around the input,
- the **stride** specifies a step size when moving the kernel across the signal,
- the **dilation** modulates the expansion of the filter without adding weights.
Here with $C \times 3 \times 5$ as input
Here with $C \times 3 \times 5$ as input, a padding of $(2, 1)$
Here with $C \times 3 \times 5$ as input, a padding of $(2, 1)$, a stride of $(2, 2)$
Here with $C \times 3 \times 5$ as input, a padding of $(2, 1)$, a stride of $(2, 2)$, and a kernel of size $C \times 3 \times 3$.
Here with $C \times 3 \times 5$ as input, a padding of $(2, 1)$, a stride of $(2, 2)$, and a kernel of size $C \times 3 \times 3$.
Here with $C \times 3 \times 5$ as input, a padding of $(2, 1)$, a stride of $(2, 2)$, and a kernel of size $C \times 3 \times 3$.
Here with $C \times 3 \times 5$ as input, a padding of $(2, 1)$, a stride of $(2, 2)$, and a kernel of size $C \times 3 \times 3$.
Here with $C \times 3 \times 5$ as input, a padding of $(2, 1)$, a stride of $(2, 2)$, and a kernel of size $C \times 3 \times 3$.
Here with $C \times 3 \times 5$ as input, a padding of $(2, 1)$, a stride of $(2, 2)$, and a kernel of size $C \times 3 \times 3$. 

Input

Output
Here with $C \times 3 \times 5$ as input, a padding of $(2,1)$, a stride of $(2,2)$, and a kernel of size $C \times 3 \times 3$.
Here with $C \times 3 \times 5$ as input, a padding of $(2, 1)$, a stride of $(2, 2)$, and a kernel of size $C \times 3 \times 3$
Here with $C \times 3 \times 5$ as input, a padding of $(2,1)$, a stride of $(2,2)$, and a kernel of size $C \times 3 \times 3$, the output is $1 \times 3 \times 3$. 

Input

Output
A convolution with a stride greater than 1 may not cover the input map entirely, hence may ignore some of the input values.
The dilation modulates the expansion of the filter support by adding rows and columns of zeros between coefficients (Yu and Koltun, 2015).

It is 1 for standard convolutions, but can be greater, in which case the resulting operation can be envisioned as a convolution with a regularly sparsified filter.
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It is 1 for standard convolutions, but can be greater, in which case the resulting operation can be envisioned as a convolution with a regularly sparsified filter.

This notion comes from signal processing, where it is referred to as *algorithme à trous*, hence the term sometime used of “convolution à trous”.
Dilation = 1

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Dilation = 1
Dilation = 1

Input

Output
Dilation = 1
Dilation = 1
Dilation = 1
Dilation = 1

Input

Output
Dilation = 2

Input

Output
Dilation = 2

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Dilation = 2

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Dilation = 2
Dilation = 2
Dilation = 2
Dilation = 2

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Input

Output

Dilation = 2
Dilation = 2

Input

Output
A convolution with a kernel of size $k$ and dilation $d$ can be interpreted as a convolution with a filter of size $1 + (k - 1)d$ with only $k$ non-zero coefficients.

For example with $k = 3$ and $d = 4$, the difference between the input map size and the output map size is $1 + (3 - 1)4 - 1 = 8$.

```python
>>> x = torch.empty(1, 1, 20, 30).normal_()
>>> l = nn.Conv2d(1, 1, kernel_size = 3, dilation = 4)
>>> l(x).size()
torch.Size([1, 1, 12, 22])
```
Having a dilation greater than one increases the units’ receptive field size without increasing the number of parameters.

Convolutions with stride or dilation strictly greater than one reduce the activation map size, for instance to make a final classification decision.
The end
References