Deep learning

4.4. Convolutions

François Fleuret

https://fleuret.org/dlc/
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

$$(256 \times 256 \times 3)^2 \approx 3.87 \times 10^{10}$$

parameters, with the corresponding memory footprint ($\approx 150$Gb !), and excess of capacity.
Moreover, this requirement is inconsistent with the intuition that such large signals have some “invariance in translation”. A transformation meaningful at a certain location can / should be used everywhere.
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A convolution layer embodies this idea. It applies the same linear transformation locally, everywhere
Input

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

\[W\]
The diagram illustrates a convolution operation in deep learning. The input is a one-dimensional array: [1, 4, -1, 0, 2, -2, 1, 3, 3, 1]. The kernel is a smaller array: [1, 2, 0, -1]. The output is calculated by sliding the kernel over the input, performing element-wise multiplication, and summing the results. The output size is determined by the formula $W - w + 1$, where $W$ is the input size and $w$ is the kernel size.
The diagram illustrates the process of convolution in deep learning. The input consists of a sequence of numbers represented by a horizontal line. The kernel, a smaller sequence of numbers, slides across the input. The output is calculated by taking the dot product of the kernel with a segment of the input, shifted by one position at a time. The formula $W - w + 1$ represents the number of valid output values that can be obtained. For this example, the output is a single value, 9.
Input

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

\[W\]

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

\[W \]

Output

\[
\begin{array}{cc}
9 & 0 \\
\end{array}
\]

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

Input:

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

Kernel:

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

Output:

\[
\begin{array}{ccc}
9 & 0 & 1 \\
\end{array}
\]
$W - w + 1$
Input

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

\[
W
\]

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

\[
w
\]

Output

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

\[
W - w + 1
\]
Input

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

\[
W
\]

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

\[
w
\]

Output

\[
\begin{array}{cccccc}
9 & 0 & 1 & 3 & -5 & -3
\end{array}
\]

\[
W - w + 1
\]
The diagram illustrates the convolution operation in deep learning. The input sequence is:

\[ 1 \ 4 \ -1 \ 0 \ 2 \ -2 \ 1 \ 3 \ 3 \ 1 \]

The kernel is:

\[ 1 \ 2 \ 0 \ -1 \]

The output sequence is:

\[ 9 \ 0 \ 1 \ 3 \ -5 \ -3 \ 6 \]

The formula shown is:

\[ W \rightarrow W - w + 1 \]
\[
W - w + 1
\]
Formally, in 1d, given

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

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

\[ u = (u_1, \ldots, u_w) \]
Formally, in 1d, given
\[ x = (x_1, \ldots, x_W) \]
and a “convolution kernel” (or “filter”) of width \( w \)
\[ u = (u_1, \ldots, u_w) \]
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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\[ x = (x_1, \ldots, x_W) \]

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\[ u = (u_1, \ldots, u_w) \]

the convolution \( x \ast u \) is a vector of size \( W - w + 1 \), with

\[
(x \ast u)_i = \sum_{j=1}^{w} x_{i-1+j} u_j
\]

\[
= (x_i, \ldots, x_{i+w-1}) \cdot u
\]

for instance

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

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.

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

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

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

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.
Kernel

\[ \text{Input} \]

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

\[ C \]

Françoise Fleuret
Francois Fleuret

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\( D - h + 1 \)

\( W - w + 1 \)
Kernel

\[ D - h + 1 \]

\[ W - w + 1 \]

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Kernels

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

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The diagram illustrates the process of convolution in deep learning. The input is a multi-channel image represented by the dimensions $W$, $H$, and $C$. The kernel, with dimensions $h$, $w$, and $C$, slides over the input, producing an output with dimensions $W-h+1$, $H-w+1$, and $C$. The convolution operation involves element-wise multiplication and summation of the input and kernel elements, followed by an activation function.
Kernel

$$D - h + 1$$

$$W - w + 1$$
Kernel $K$ of size $D \times H \times W$ applied to an input of size $H \times W \times C$.

Output size is $W - w + 1 \times H - h + 1 \times C$.
Kernel:

\[
D - h + 1 \\
W - w + 1
\]

Output:

\[
W - w + 1 \\
H - h + 1
\]
Kernel $K$:

- $D$: depth
- $H$: height
- $W$: width
- $C$: channels
- $h$: kernel height
- $w$: kernel width

Input:

- $W$:
- $H$:
- $C$:

Kernels:

- $w$:
- $h$:
- $D$:

Output:

- $W - w + 1$:
- $H - h + 1$:
- $D$:
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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And a convolution is equivariant to a translation of the input signal, since its output is translated similarly.
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And a convolution is equivariant to a translation of the input signal, since its output is translated similarly.

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.

The sub-area of an input map that influences a component of the output as the receptive field of the latter.
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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, or a dense layer, since every input influences every output.
The autograd-compliant function

\[
\text{F.conv2d}(\text{input}, \text{weight}, \text{bias}=\text{None}, \text{stride}=1, \text{padding}=0, \text{dilation}=1, \text{groups}=1)
\]

Implements a 2d convolution, where \text{weight} is of dimension \(D \times C \times h \times w\) and contains the kernels, \text{bias} is of dimension \(D\), \text{input} is of dimension

\[
N \times C \times H \times W
\]

and the result is of dimension

\[
N \times D \times (H - h + 1) \times (W - w + 1).
\]
The autograd-compliant function

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F.\text{conv2d}(\text{input}, \text{weight}, \text{bias}=\text{None}, \text{stride}=1, \text{padding}=0, \text{dilation}=1, \text{groups}=1)
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\[
N \times C \times H \times W
\]
and the result is of dimension
\[
N \times D \times (H - h + 1) \times (W - w + 1).
\]

>>> weight = torch.randn(5, 4, 2, 3)
>>> bias = torch.randn(5)
>>> input = torch.randn(117, 4, 10, 3)
>>> output = F.conv2d(input, weight, bias)
>>> output.size()
torch.Size([117, 5, 9, 1])
The autograd-compliant function

\[ F.\text{conv2d}(\text{input}, \text{weight}, \text{bias}=\text{None}, \text{stride}=1, \text{padding}=0, \text{dilation}=1, \text{groups}=1) \]

Implements a 2d convolution, where \text{weight} is of dimension \( D \times C \times h \times w \) and contains the kernels, \text{bias} is of dimension \( D \), \text{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.randn(5, 4, 2, 3)
>>> bias = torch.randn(5)
>>> input = torch.randn(117, 4, 10, 3)
>>> output = F.conv2d(input, weight, bias)
>>> output.size()
torch.Size([117, 5, 9, 1])
```

Similar functions implement 1d and 3d convolutions.
```python
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)
```
Convolutional filters can combine simple shapes to create more complex ones.
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.randn(117, 4, 10, 3)
>>> 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 $(2, 2)$. 

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 $C \times 3 \times 3$. 

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

\[
\begin{array}{cccc}
\bigcirc & \bigcirc & \bigcirc & \bigcirc \\
\bigcirc & \bigcirc & \bigcirc & \bigcirc \\
\bigcirc & \bigcirc & \bigcirc & \bigcirc \\
\end{array}
\quad
\begin{array}{ccc}
\bigcirc & \bigcirc & \bigcirc \\
\bigcirc & \bigcirc & \bigcirc \\
\bigcirc & \bigcirc & \bigcirc \\
\end{array}
\]

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 $C \times 3 \times 3$. 

![Diagram](image_url)
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 $1 \times 3 \times 3$. 
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
Dilation = 1
Dilation = 1

Input

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

Input

Output
Dilation = 1

Input

Output
Dilation = 2

Input

Output
Dilation = 2

Input

Output
Dilation = 2

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Dilation = 2
Dilation = 2

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Dilation = 2

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Dilation = 2
Dilation = 2

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Dilation = 2

Input

Output
A 1d 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
generate code here
```
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