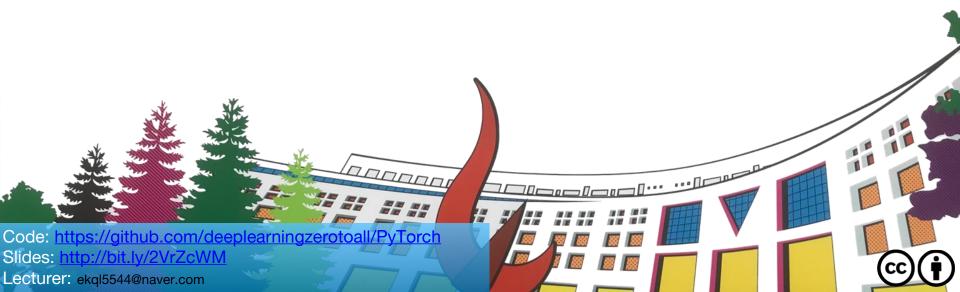
ML/DL for Everyone Season2

with PYTORCH

10-1 Convolution

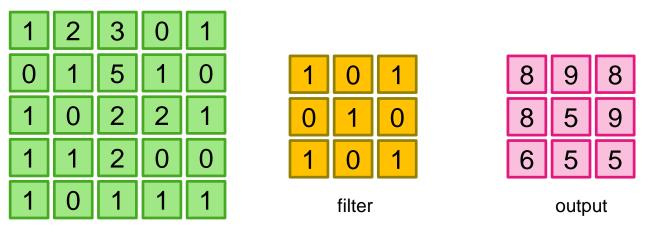


오늘의 목차

- Convolution?
- Neuron과 Convolution
- Pooling
- 다음시간에는?
- One more Thing!

Convolution?

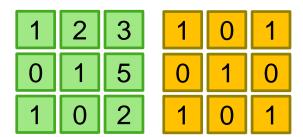
이미지 위에서 stride 값 만큼 filter(kernel)을 이동시키면서
 겹쳐지는 부분의 각 원소의 값을 곱해서 모두 더한 값을 출력으로
 하는 연산



input

Convolution?

이미지 위에서 stride 값 만큼 filter(kernel)을 이동시키면서 겹쳐지는 부분의 각 원소의 값을 곱해서 모두 더한 값을 출력으로 하는 연산



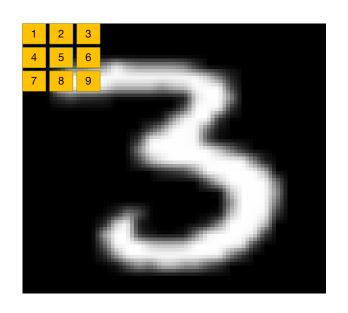
input

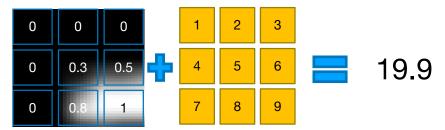
$$(1x1) + (2x0) + (3x1) +$$

 $(0x0) + (1x1) + (5x0) +$
 $(1x1) + (0x0) + (2x1) = 8$

8

계산해보기





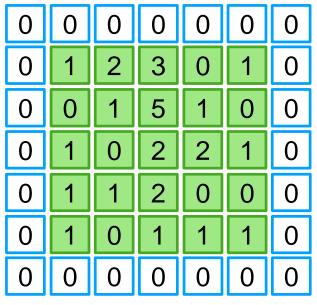
$$(0 * 1) + (0 * 2) + (0 * 3) +$$

 $(0 * 4) + (0.3 * 5) + (0.5 * 6) +$
 $(0 * 7) + (0.8 * 8) + (1 * 9) = 19.9$

Stride and Padding

• stride: filter를 한번에 얼마나 이동 할 것인가

padding : zero-padding



input + padding

Pytorch nn.Conv2d

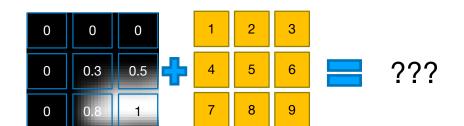
CLASS torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True)

[SOURCE] &

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

In the simplest case, the output value of the layer with input size $(N, C_{\rm in}, H, W)$ and output $(N, C_{\rm out}, H_{\rm out}, W_{\rm out})$ can be precisely described as:

$$\operatorname{out}(N_i, C_{\operatorname{out}_j}) = \operatorname{bias}(C_{\operatorname{out}_j}) + \sum_{k=0}^{C_{\operatorname{in}}-1} \operatorname{weight}(C_{\operatorname{out}_j}, k) \star \operatorname{input}(N_i, k)$$



ex) 입력 채널 1 /출력채널 1 / 커널 크기3x3

conv = nn.Conv2d(1,1,3)

입력의 형태

- input type : torch.Tensor
- input shape : (N x C x H x W)

(batch_size, channel, height, width)

직접 해볼까요?

Convolution의 output 크기

$$Output \ size = \frac{input \ size - filter \ size + (2*padding)}{Stride} + 1$$

```
예제 1)
input image size : 227 x 227
filter size = 11x11
stride = 4
padding = 0
output image size = ?
```

```
예제 4)
input image size : 32 x 64
filter size = 5x5
stride = 1
padding = 0
output image size = ?
```

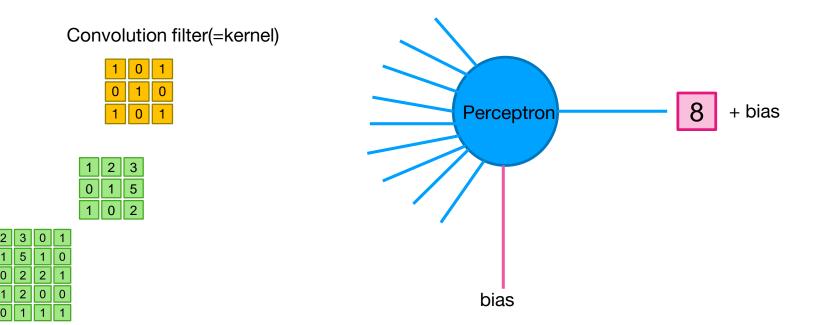
```
예제 2)
input image size : 64 x 64
filter size = 7x7
stride = 2
padding = 0
output image size = ?
```

```
예제 5)
input image size : 64 x 32
filter size = 3x3
stride = 1
padding = 1
output image size = ?
```

```
예제 3)
input image size : 32 x 32
filter size = 5x5
stride = 1
padding = 2
output image size = ?
```

Neuron과 Convolution

• Perceptron과 Convolution



직접 해볼까요?

- nn.Conv2d에 입력
- filter size 변경 (size = 1x1, 3x3, 5x5)
- bias
- stride
- padding

Pooling

Max Pooling





max pooling

Average Pooling





Average pooling

MaxPool2d

MaxPool2d ₽

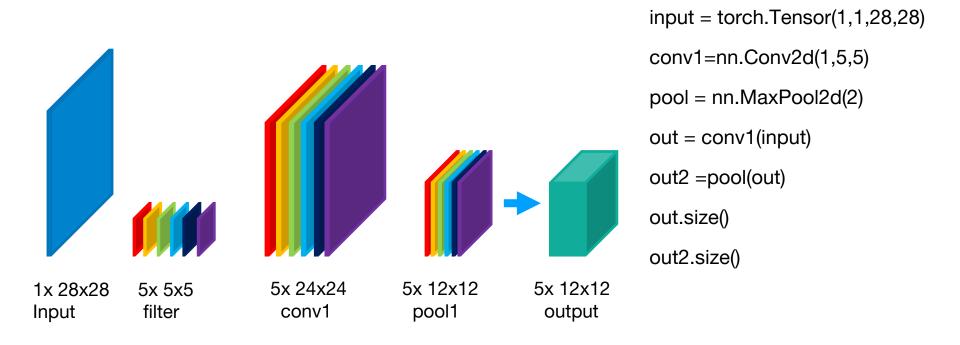
[SOURCE]

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

In the simplest case, the output value of the layer with input size (N,C,H,W), output (N,C,H_{out},W_{out}) and kernel_size (kH,kW) can be precisely described as:

$$out(N_i, C_j, h, w) = \max_{m=0,\dots,kH-1} \max_{n=0,\dots,kW-1} \max_{input(N_i, C_j, \operatorname{stride}[0] \times h + m, \operatorname{stride}[1] \times w + n)$$

CNN implementation



직접 해볼까요?

What's Next?

● 오늘은 Convolution 연산과 Pooling 연산을 배우고 직접 활용해봤습니다.

● 다음시간에는 MNIST dataset에 CNN을 적용해보도록 하겠습니다.

One More Thing!

CLASS torch.nn.Conv2d(<u>in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True</u>)

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

In the simplest case, the output value of the layer with input size $(N, C_{\rm in}, H, W)$ and output $(N, C_{\rm out}, H_{\rm out}, W_{\rm out})$ can be precisely described as:

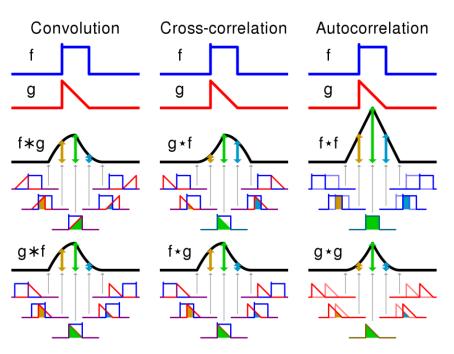
[SOURCE]

$$\operatorname{out}(N_i, C_{\operatorname{out}_j}) = \operatorname{bias}(C_{\operatorname{out}_j}) + \sum_{k=0}^{C_{\operatorname{in}}-1} \operatorname{weight}(C_{\operatorname{out}_j}, k) \star \operatorname{input}(N_i, k)$$

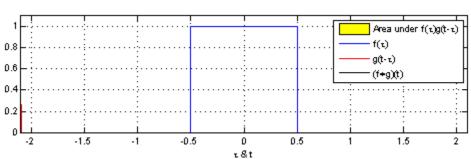
where \star is the valid 2D cross-correlation operator, N is a batch size, C denotes a number of channels, H is a height of input planes in pixels, and W is width in pixels.

- . stride controls the stride for the cross-correlation, a single number or a tuple.
- padding controls the amount of implicit zero-paddings on both sides for padding number of points for each dimension.
- dilation controls the spacing between the kernel points; also known as the à trous algorithm. It is harder to
 describe, but this link has a nice visualization of what dilation does.
- groups controls the connections between inputs and outputs. in_channels and out_channels must both be divisible by groups. For example,
 - At groups=1, all inputs are convolved to all outputs.
 - At groups=2, the operation becomes equivalent to having two conv layers side by side, each seeing half the input channels, and producing half the output channels, and both subsequently concatenated.
 - At groups= in_channels , each input channel is convolved with its own set of filters, of size: $\left| \frac{C_{\text{out}}}{C_{\text{in}}} \right|$.

What is Convolution?



$$(fst g)(t) \stackrel{ ext{def}}{=} \int_{-\infty}^{\infty} f(au)g(t- au)\,d au \ = \int_{-\infty}^{\infty} f(t- au)g(au)\,d au.$$



Cross-correlation

● Cross-correlation과 Convolution의 차이를 간단히 말하면...?

- 뒤집고 계산하면 => (Convolution)
- 안 뒤집고 계산하면 => (Cross-Correlation)

● 안 뒤집고 계산해서 Cross-Correlation!

