

CNN (Convolutional Neural Networks)

까지 요약(모두의 딥러닝)

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CNN?

**Stride / Padding / 여러개의 filters /
Convolutional Layers**

Max Pooling

CNN case

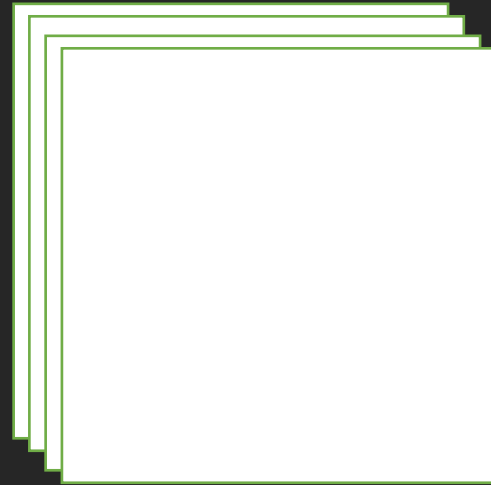
CNN?

**이미지를 학습할 때 사용하는
Neural Network**

CNN?

Input (Training Data)

Image (width * height * depth)

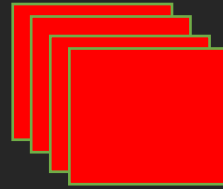


CNN?

Filter

(width * height * **depth**)

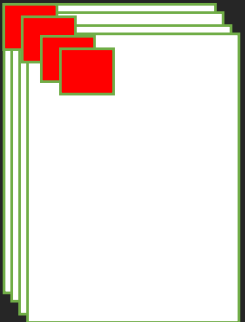
Input (Training Data)



→ 하나의 수

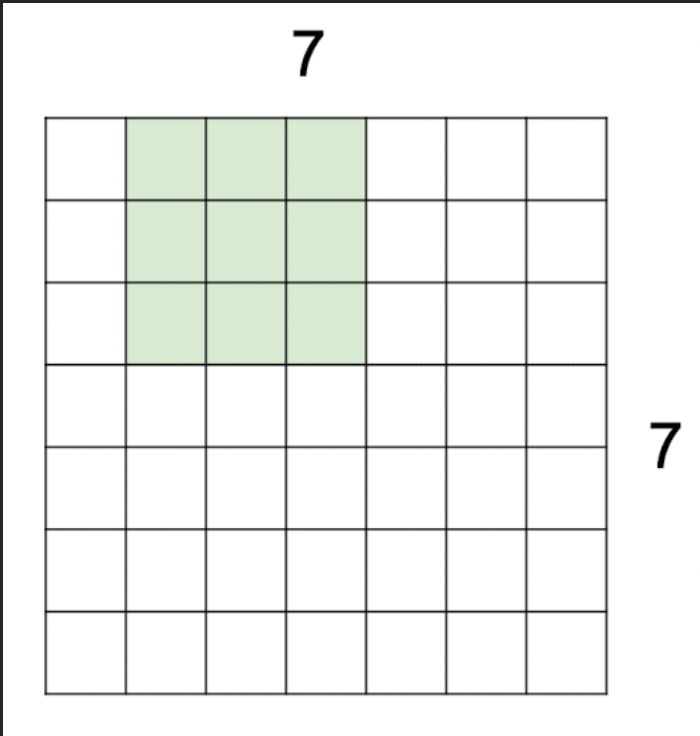
$$= WX + b$$

Image (width * height * **depth**)



Stride / Padding / 여러개의 filters & Convolutional Layers

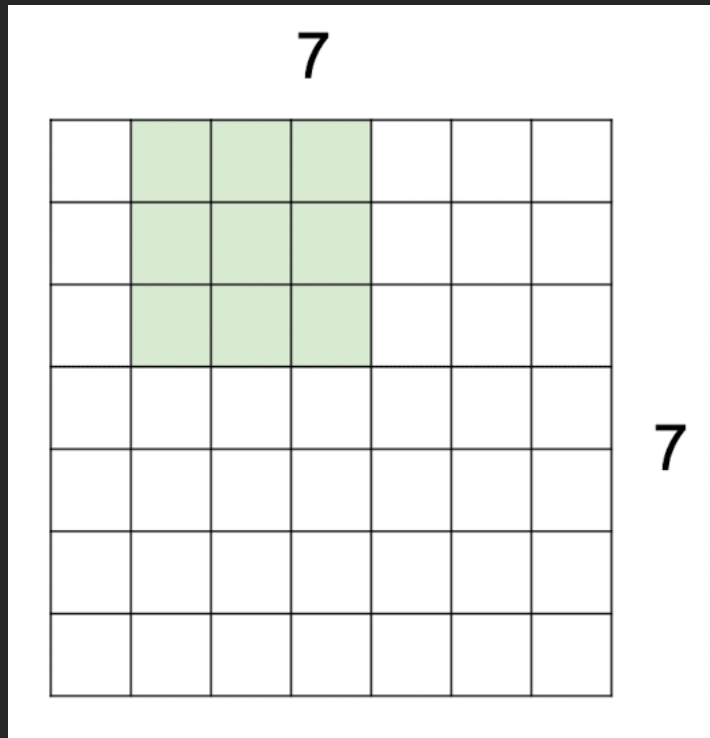
예시



Input : $7 * 7 * \text{depth}$
filter : $3 * 3 * \text{depth}$
strade : 1

Stride / Padding / 여러개의 filters & Convolutional Layers

예시



Input : $7 * 7 * \text{depth}$

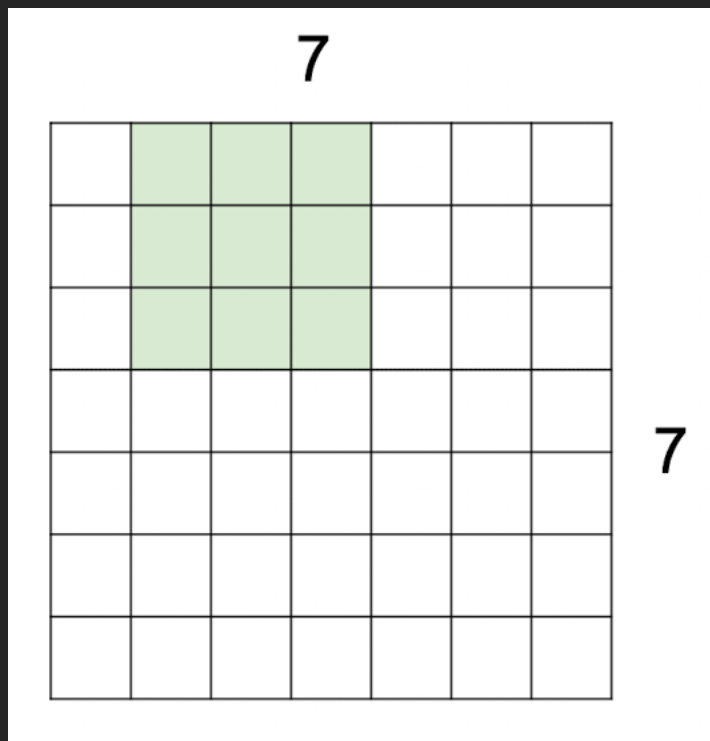
filter : $3 * 3 * \text{depth}$

stride : 1

Output : $5 * 5 * \text{depth}$

Stride / Padding / 여러개의 filters & Convolutional Layers

예시



Input : $N * N * \text{depth}$
filter : $F * F * \text{depth}$

stride : S

Output : $O * O * \text{depth}$

$$O = (N - F) / S + 1$$

Stride / Padding / 여러개의 filters & Convolutional Layers

문제 : 필터를 지나칠 수록 사이즈가 작아짐!

-> 정보의 손실

**Stride / Padding /
여러개의 filters & Convolutional Layers**

해결방법 : Padding

Stride / Padding / 여러개의 filters & Convolutional Layers

해결방법 : Padding

0	0	0	0	0	0			
0								
0								
0								
0								

Stride / Padding / 여러개의 filters & Convolutional Layers

Padding

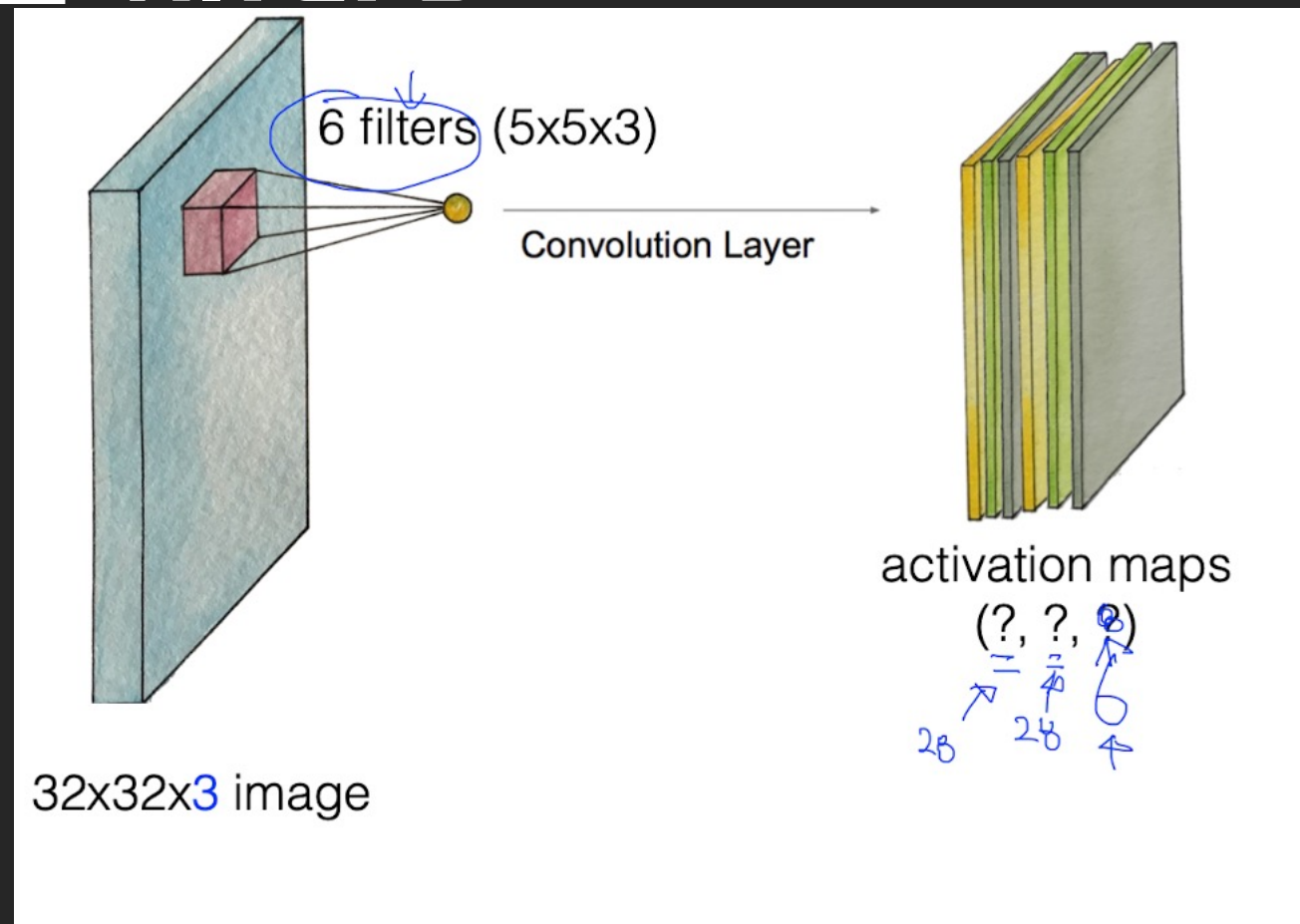
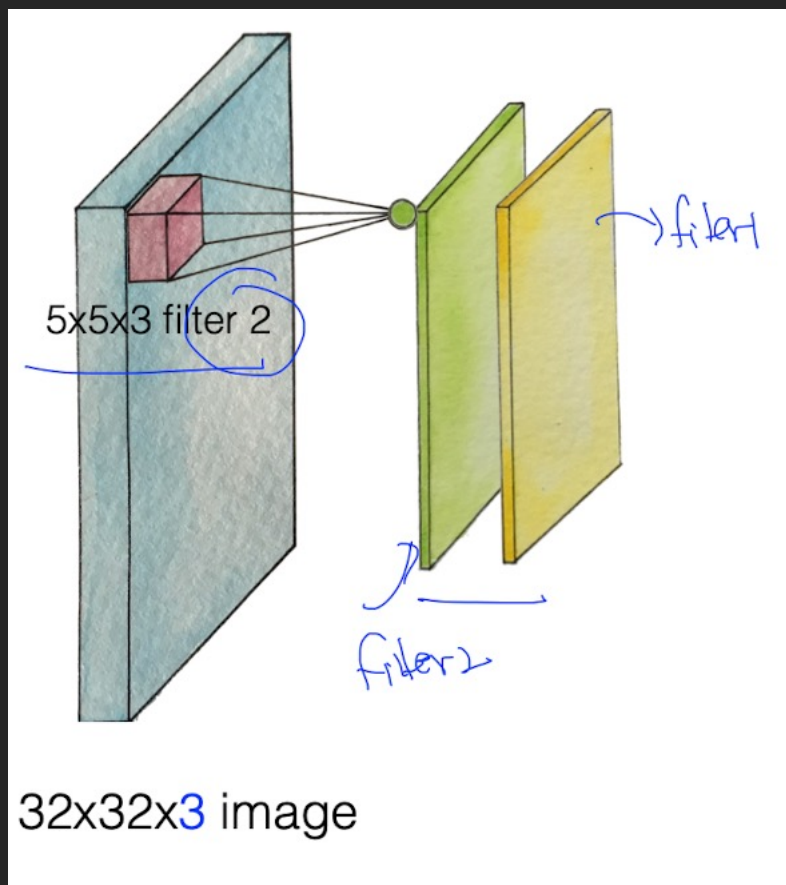
0	0	0	0	0	0			
0								
0								
0								
0								

장점

1. 이미지가 작아지는 것을 방지
2. model한테 이미지의 모서리 부분을 학습시키는 기능

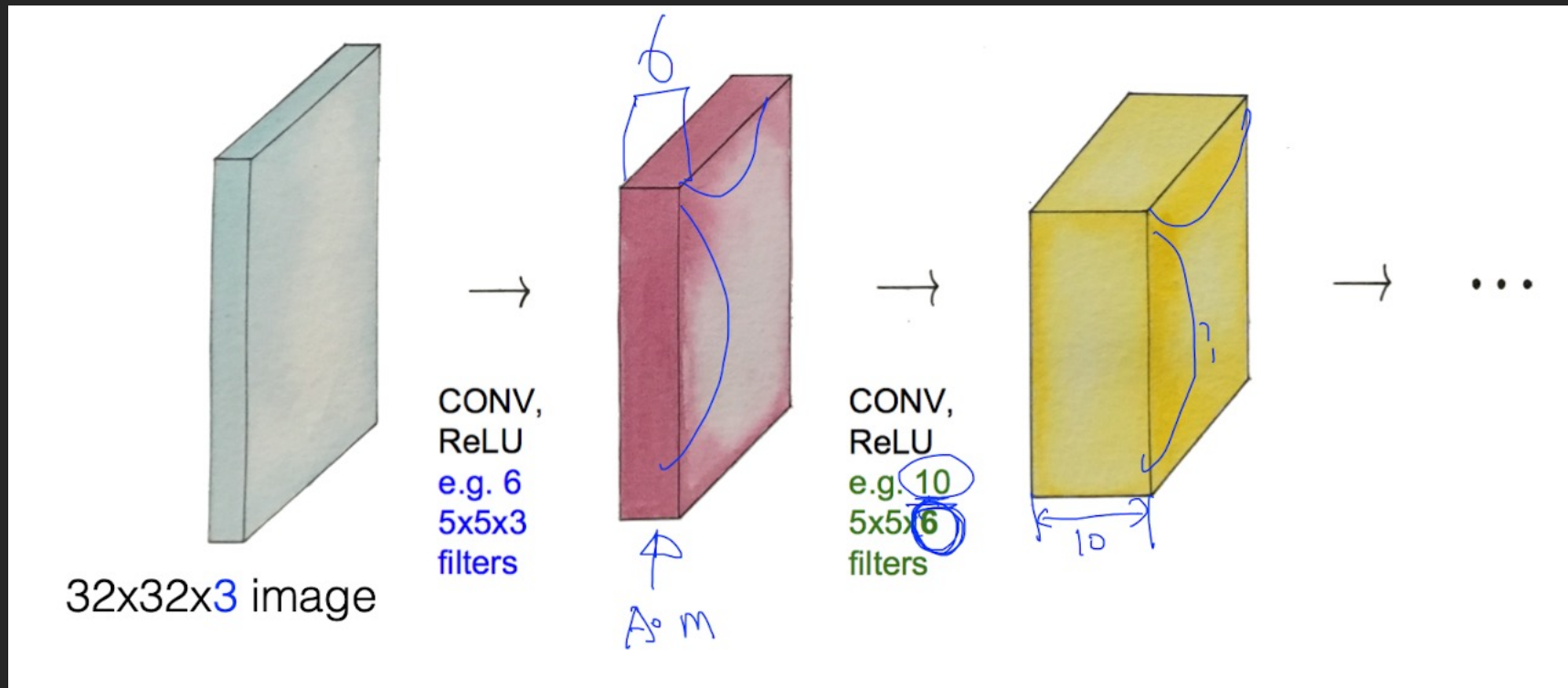
Stride / Padding / 여러개의 filters & Convolutional Layers

여러개의 filters



Stride / Padding / 여러개의 filters & Convolutional Layers

Convolutional Layers



Max Pooling

Pooling Layer

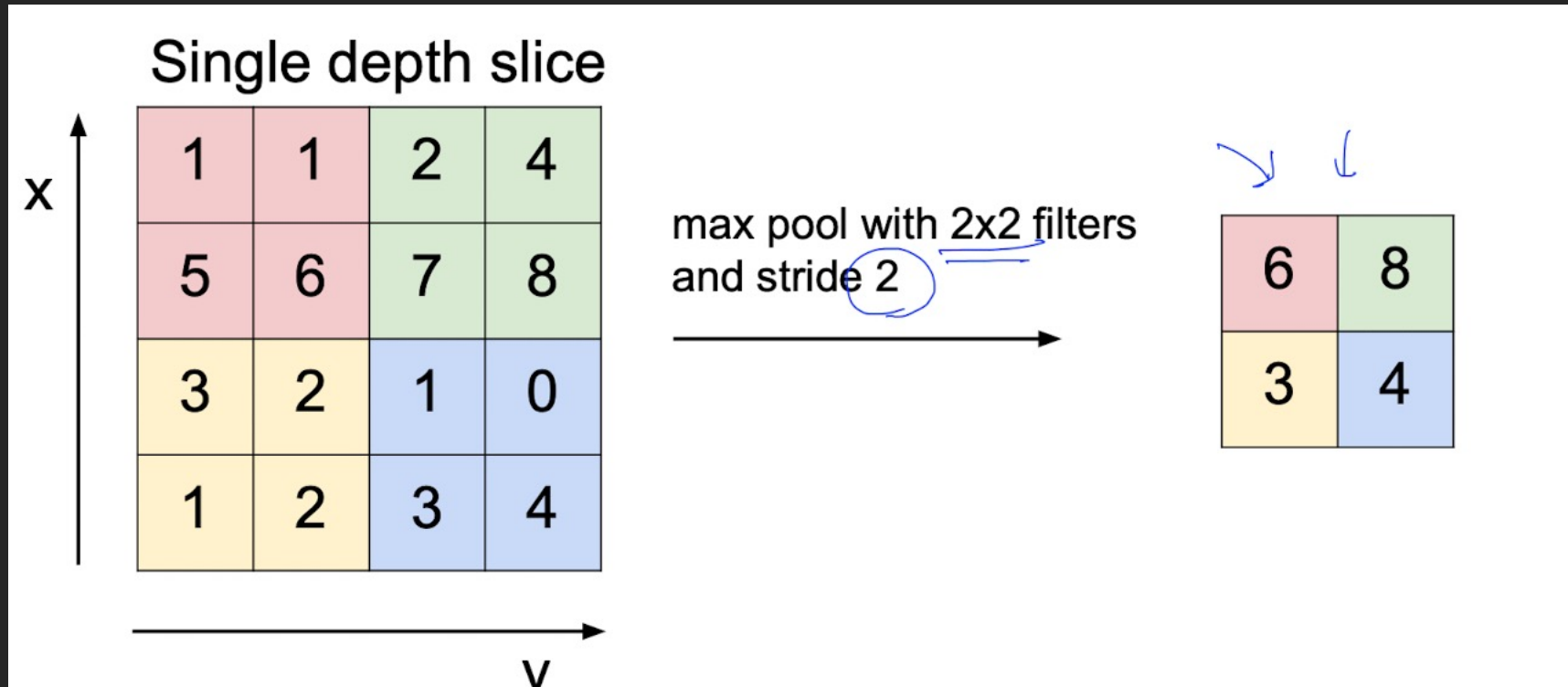
Weight를 곱해서 layer를 만드는
것이 아니라 다른 방식으로 만들어진
Layer

Max Pooling

max pooling은 필터 사이즈 안에서 가장 큰 값을 하나의 수로 취해서 오는 것

Max Pooling

max pooling은 필터 사이즈 안에서 가장 큰 값을 하나의 수로 취해서 오는 것

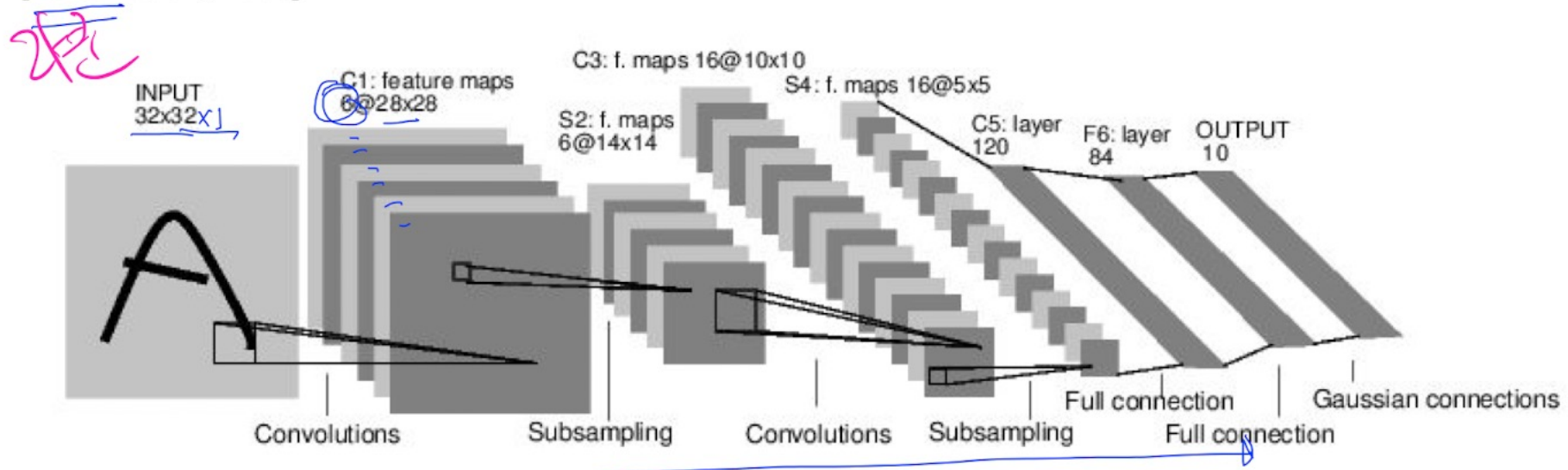


FC Layer

- CNN에서 마지막 Layer
- 일반적인 Neural Network
- FC Layer에서 마지막 Layer는 output (label과 비교해서 loss를 구하는)

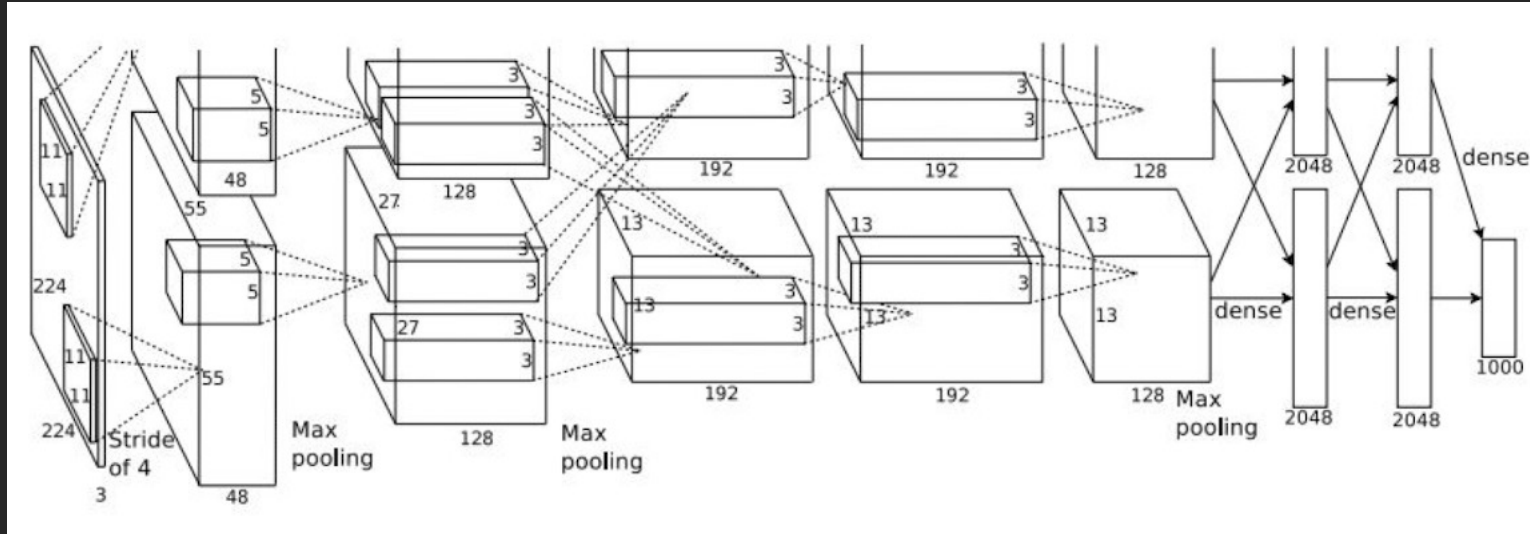
Case1- LeNet-5

[LeCun et al., 1998]



Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]

Case2- AlexNet



Full (simplified) AlexNet architecture:

[227x227x3] INPUT

[55x55x96] **CONV1**: 96 11x11 filters at stride 4, pad 0

[27x27x96] **MAX POOL1**: 3x3 filters at stride 2

[27x27x96] **NORM1**: Normalization layer

[27x27x256] **CONV2**: 256 5x5 filters at stride 1, pad 2

[13x13x256] **MAX POOL2**: 3x3 filters at stride 2

[13x13x256] **NORM2**: Normalization layer

[13x13x384] **CONV3**: 384 3x3 filters at stride 1, pad 1

[13x13x384] **CONV4**: 384 3x3 filters at stride 1, pad 1

[13x13x256] **CONV5**: 256 3x3 filters at stride 1, pad 1

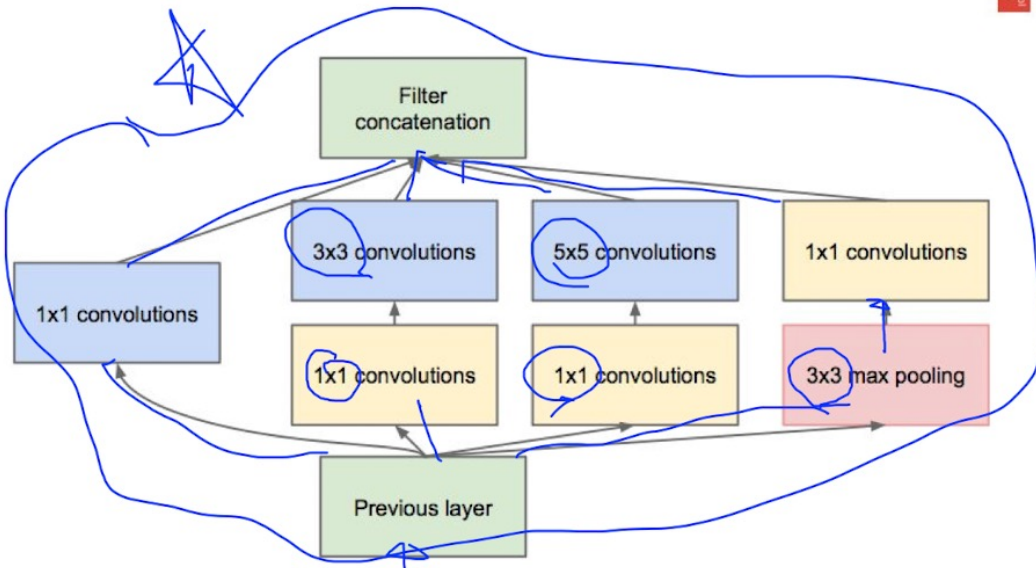
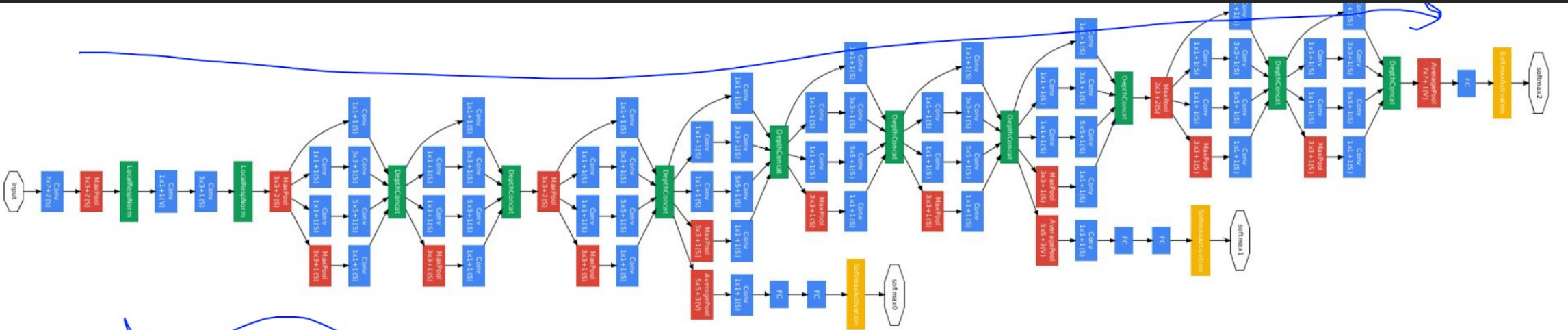
[6x6x256] **MAX POOL3**: 3x3 filters at stride 2

[4096] **FC6**: 4096 neurons

[4096] **FC7**: 4096 neurons

[1000] **FC8**: 1000 neurons (class scores)

Case3- GoogleLeNet



Inception module

ILSVRC 2014 winner (6.7% top 5 error)

Case4- ResNet

Revolution of Depth

AlexNet, 8 layers
(ILSVRC 2012)



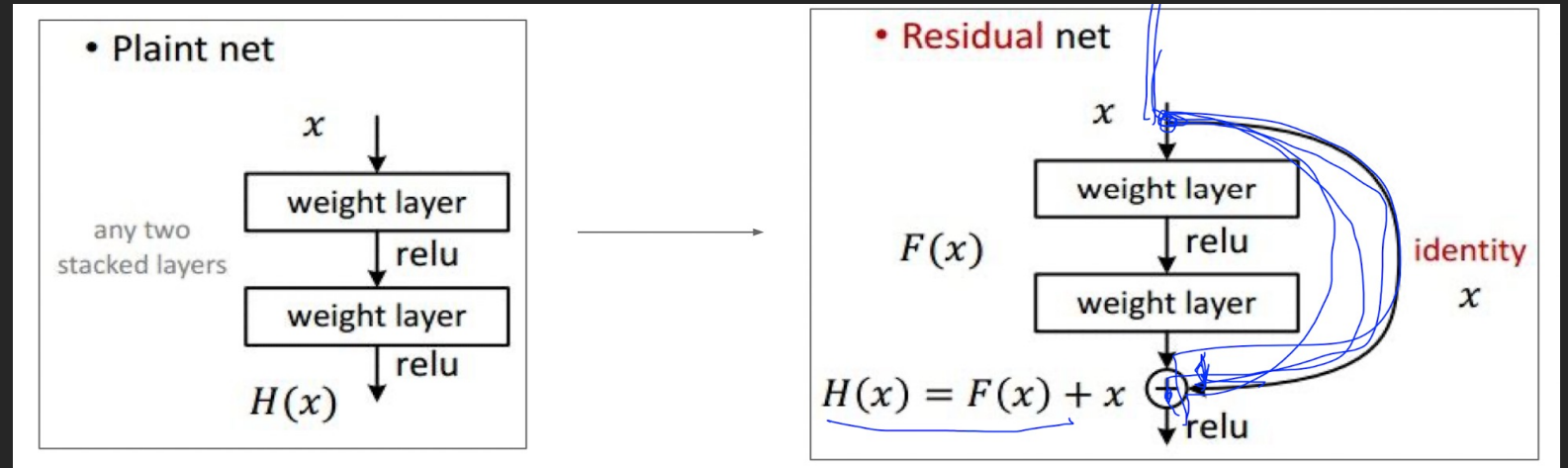
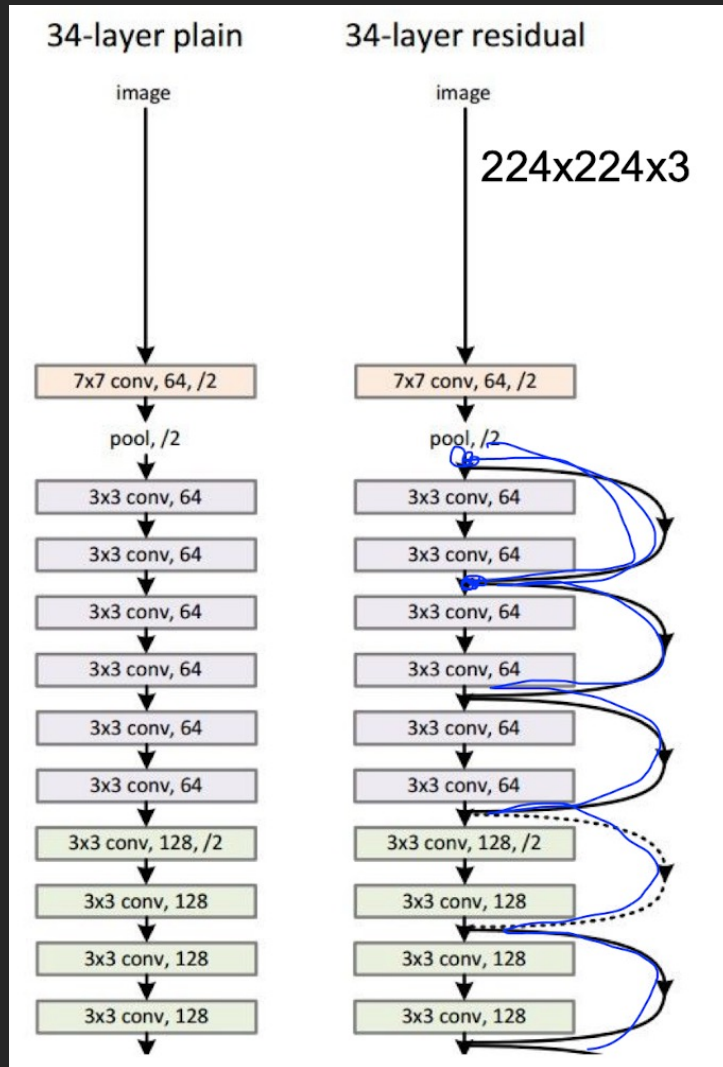
VGG, 19 layers
(ILSVRC 2014)



ResNet, 152 layers
(ILSVRC 2015)



Case4- ResNet



Case4- ResNet

