Artificial Intelligence

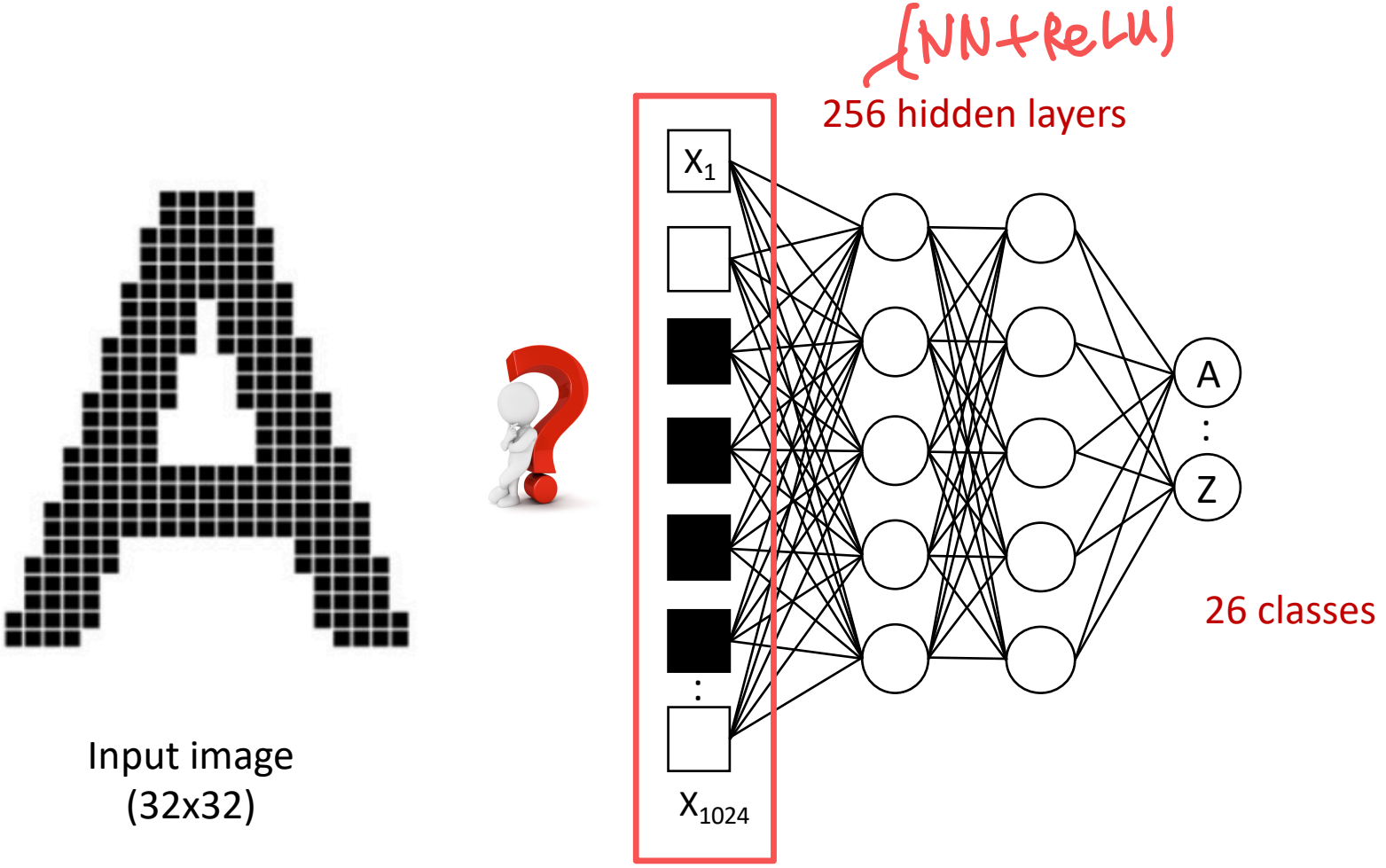
Yukyung Choi

Agenda

- Limitation of DNN
- Convolutional Neural Networks (CNN)
  - Kernel (filter, weight)
  - Receptive field
  - Stride
  - Padding
  - Pooling
    - Max / Average Pooling

Limitation of DNN

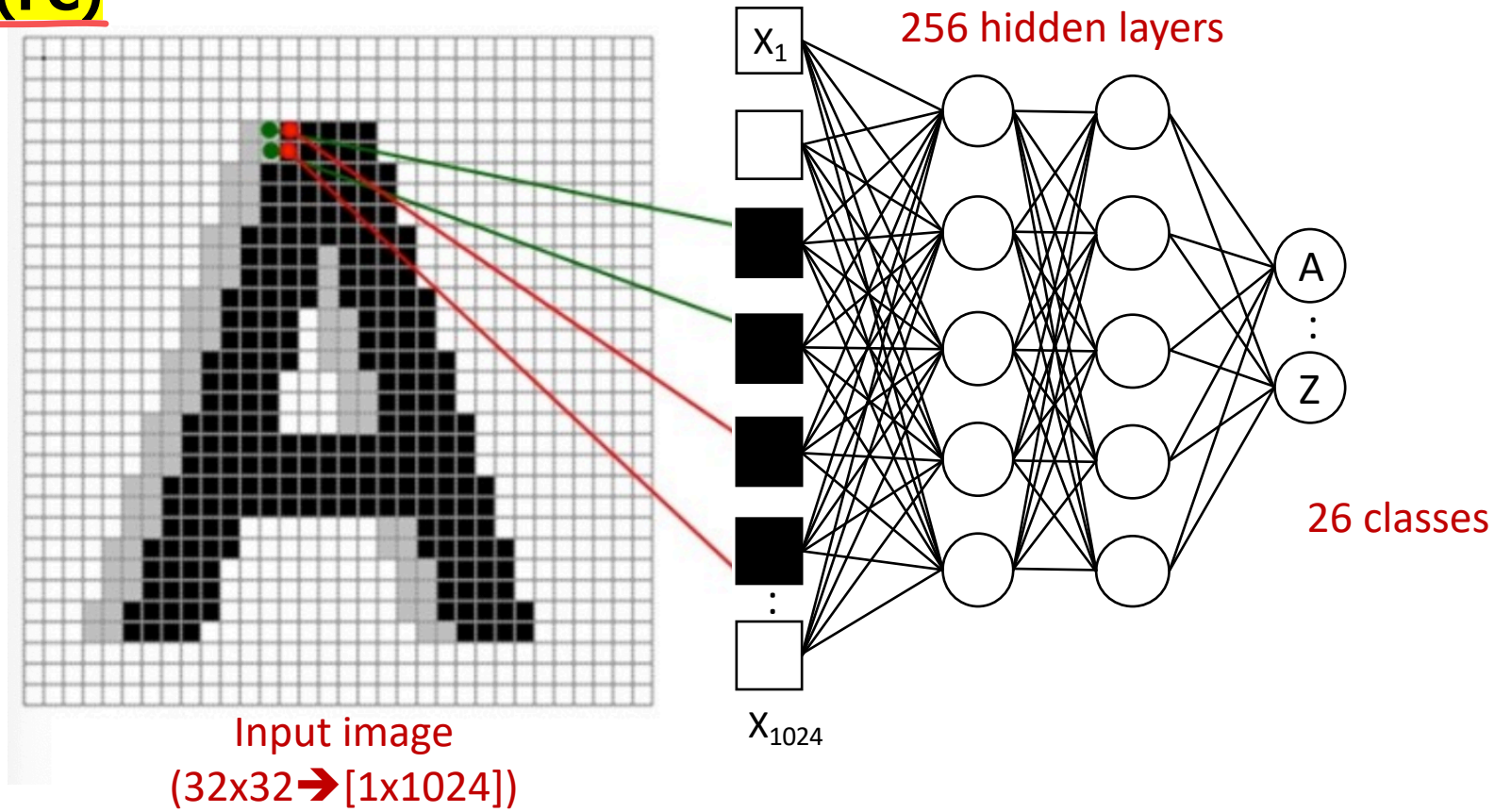
- **영상데이터(2D 데이터)에 DNN을 적용하여 분류 문제를 푼다면?**



Limitation of DNN

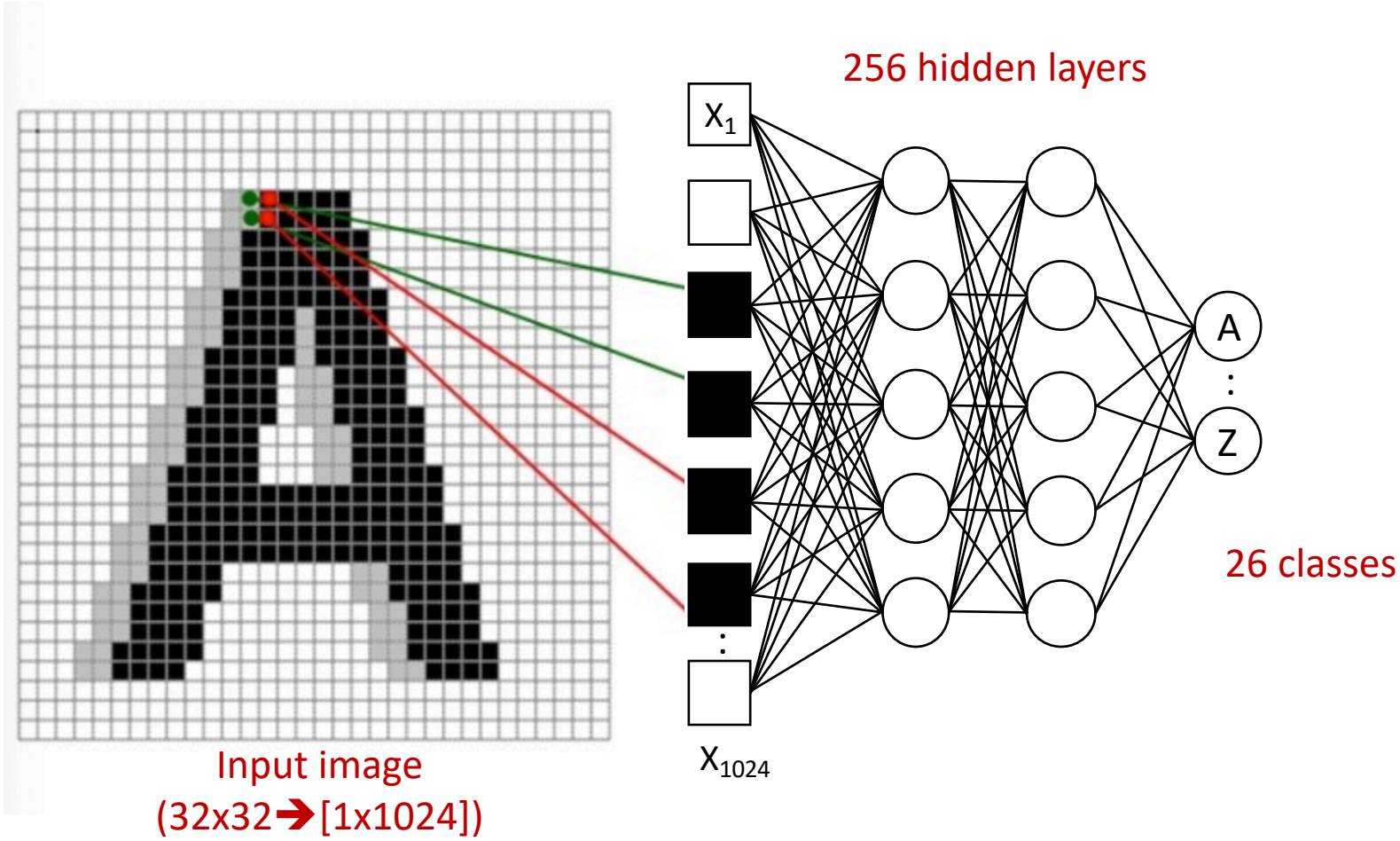
위치정보 중요

- **2D 데이터를 1D로 평탄화 하여 DNN 적용 가능**
- **위치에 상관없이 동일한 수준의 중요도를 갖음**
- **DNN = Multi-layer Perceptron = Feedforward NN = Fully Connected Layer (FC)**



Limitation of DNN

- 전체 글자가 2픽셀 이동만 하더라도 새로운 학습 데이터로 처리해야 함 (translation invariance 특성이 보장되지 않음)



Limitation of DNN

- 글자 크기(scale)가 달라지거나, 글자가 회전(rotation)하거나, 글자에 변형(distortion)이 생겨도 좋은 결과를 기대하기 어려움
  - Scale / Rotation / Distortion Invariance 특성이 보장되지 않음

Summary of Limitation (DNN)

- 학습시간 (training time) : 크기, 회전, 이동 등 모든 데이터 학습해야
- DNN 모델의 크기 (network size) : 입력영상수, layer 깊어짐
- 변수의 개수 (number of parameters)

→ 모델크기↑

→ 파라미터수↑

Convolutional Neural Network (CNN)

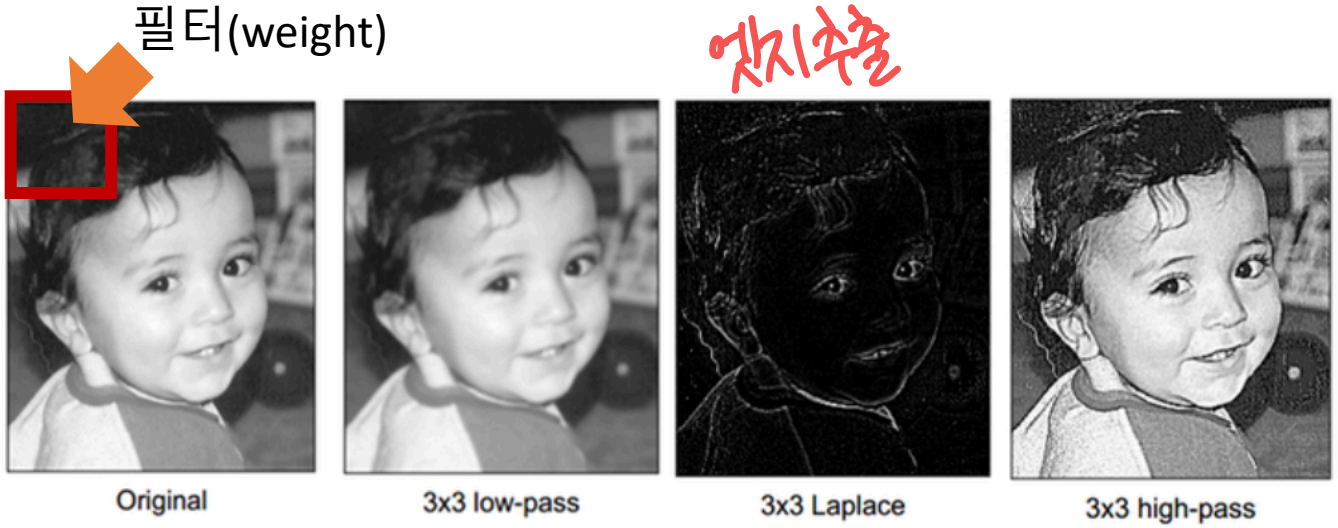
- CNN이란 무엇인가? (wikipedia)
  - **합성곱 신경망**(Convolutional neural network, CNN)은 시각적 이미지를 분석하는 데 사용되는 깊은 인공신경망의 한 종류이다.
  - CNN은 **변환 불변성 특성**에 기초하며, 이미지 및 비디오 인식, 추천 시스템, 이미지 분류, 의료 이미지 분석에 응용된다.
  - CNN은 다른 이미지 분류 알고리즘에 비해 상대적으로 **전처리를 거의 사용하지 않는다**. 이는 네트워크가 기존 알고리즘에서 수작업으로 제작된 여러 필터 역할을 스스로 학습한다는 것을 의미한다.

(DNN)

크기, 이동, 회전 등의 변화 X

Convolution

- 영상처리 혹은 컴퓨터비전 에서의 컨볼루션이란?
  - Convolution은 주로 filter연산에서 사용되며, 영상으로 부터 특정 feature를 추출하고 싶을 때 사용한다.



Convolution

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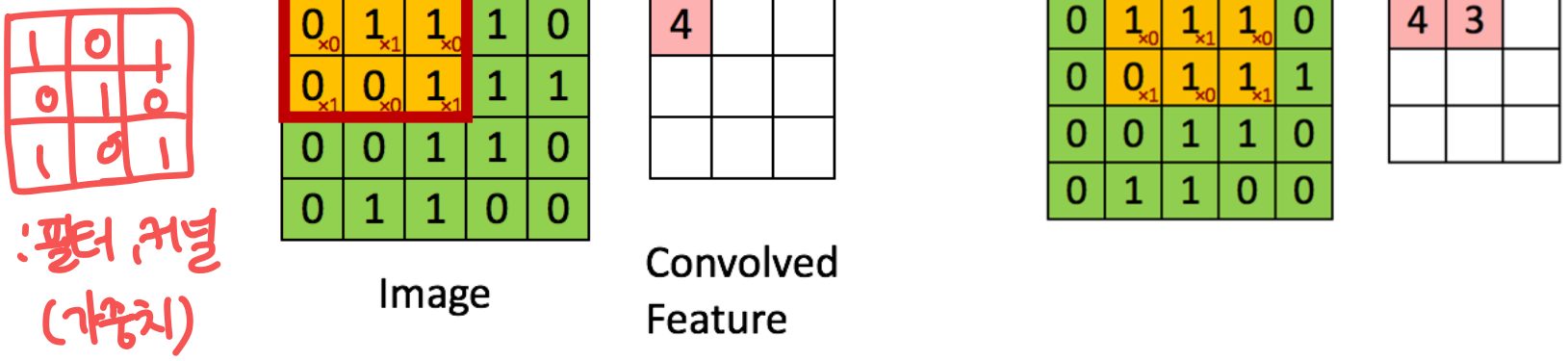
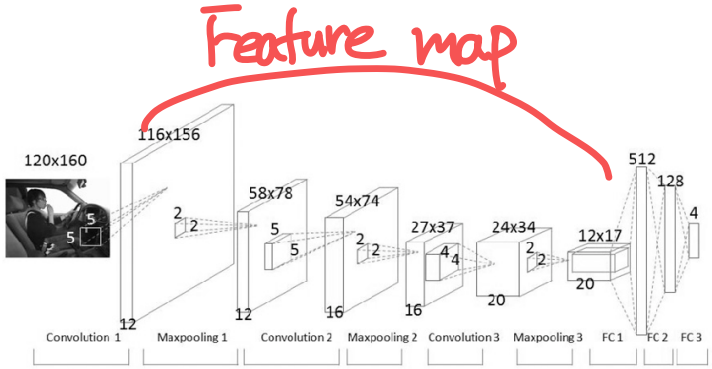


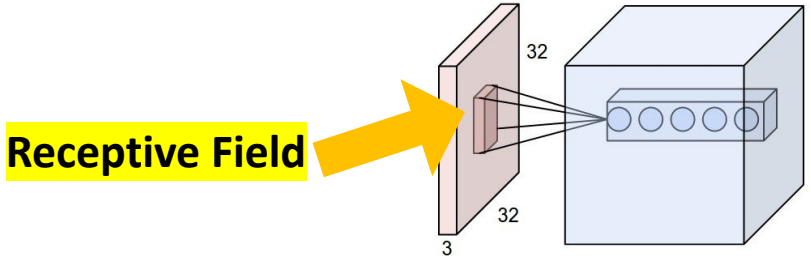
Green: 영상 이미지
Yellow: 컨볼루션이 일어나는 영역
Red: 컨볼루션 커널

Convolutional Neural Network (CNN)

- Convolution + Neural Network
  - CNN➔ Convolution특성을 살린 신경망 연산
  - 2번 이상의 CNN, 입력영상뿐만 아니라 중간 Feature map에도 Convolution 적용

- Receptive Field(수용영역)란 무엇인가?
  - **Receptive field** 는 출력 레이어의 뉴런 하나에 영향을 미치는 입력 뉴런들의 공간 크기이다.
  - 외부 자극이 전체 영향을 끼치는게 아니라 특정 영역에만 영향을 미친다.
  - 영상에서 특정 위치에 있는 픽셀들은 그 주변에 있는 일부 픽셀들과만 correlation 높을 뿐이며, 거리가 멀어질 수록 그 영향은 감소하게 된다.



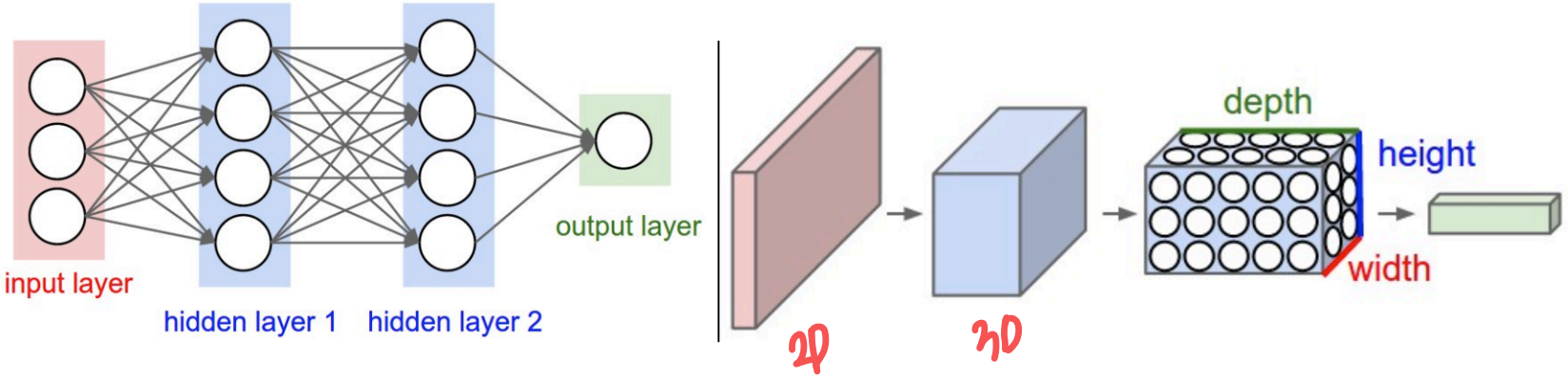


Advantage of CNN

- Conv layer는 형상을 유지한다.
- 즉, 입/출력 모두 3차원 데이터로 처리하기 때문에 공간적 정보를 유지할 수 있다.

평탄화 X

왼쪽은 일반적인 3-layer Neural Network(전결합), 오른쪽은 CNN을 3차원으로 표현한 그림이다.

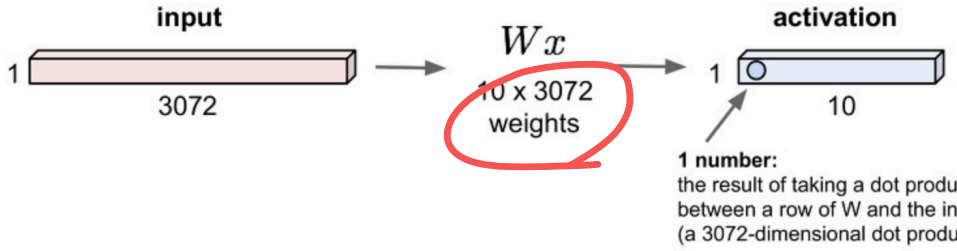


DNN **CNN**

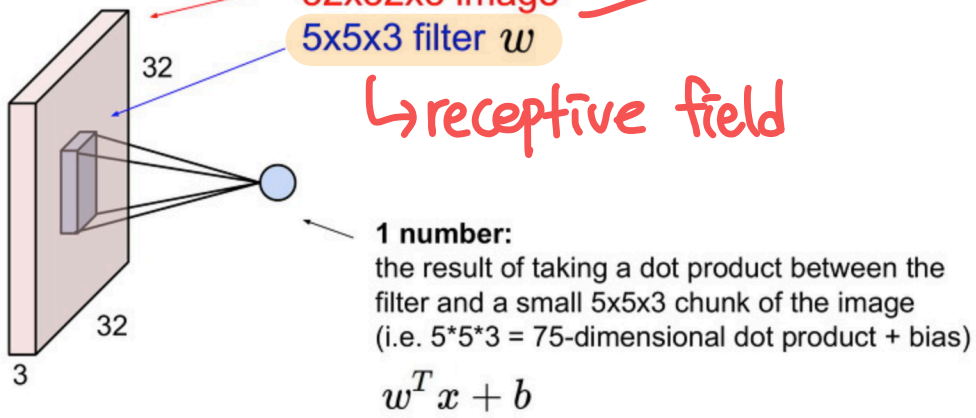
DNN vs CNN

Fully Connected Layer

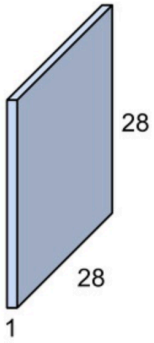
32x32x3 image -> stretch to 3072 x 1



Convolution Layer



↳receptive field

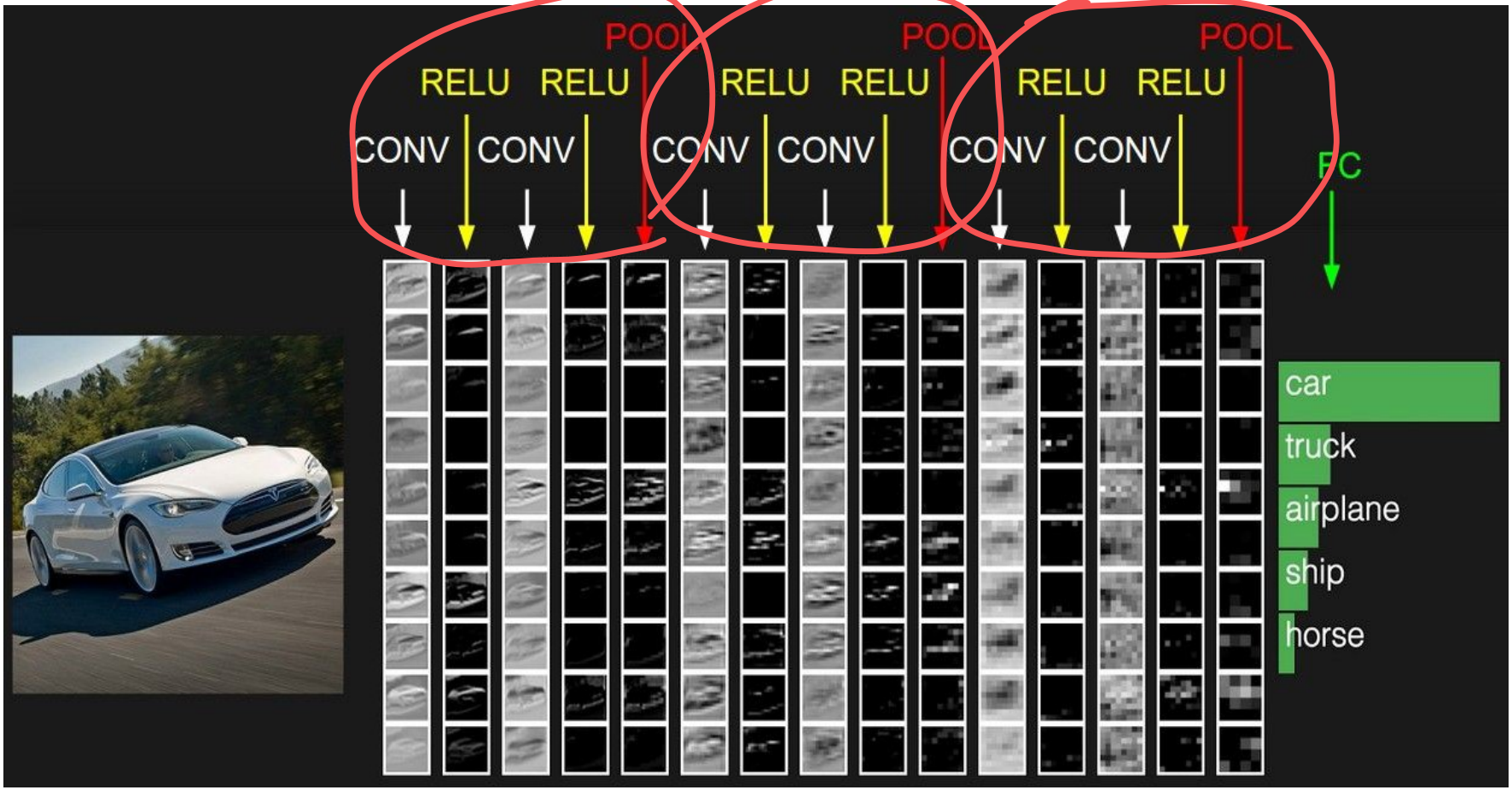


- 적은수의 가중치
- 부분의 합으로 판단하는 브레인 모사

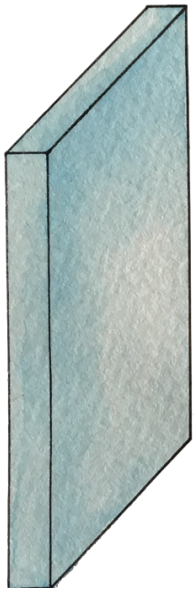
↓

kernel

Example: CNN based Classification



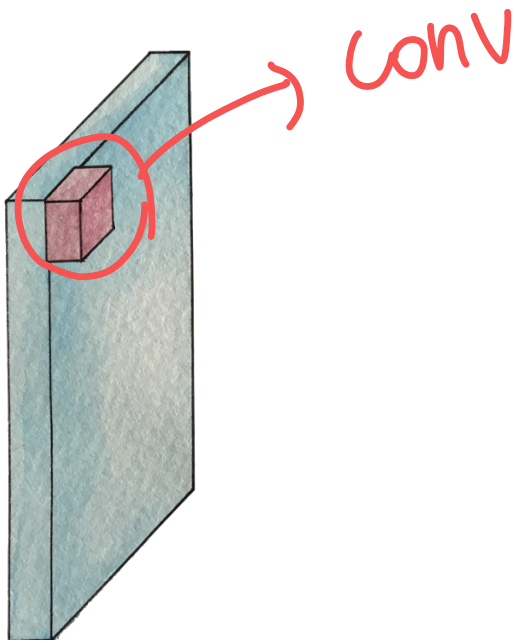
Start with an image (width x height x depth)



32x32x3 image

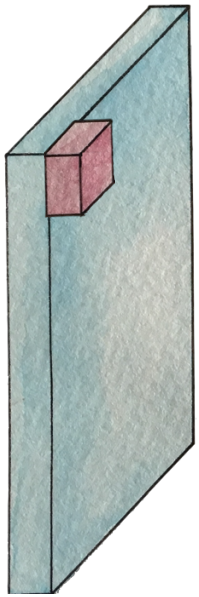
↳ color 채널

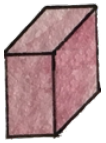
Let’s focus on a small area only



32x32x3 image

Let’s focus on a small area only (5x5x3)

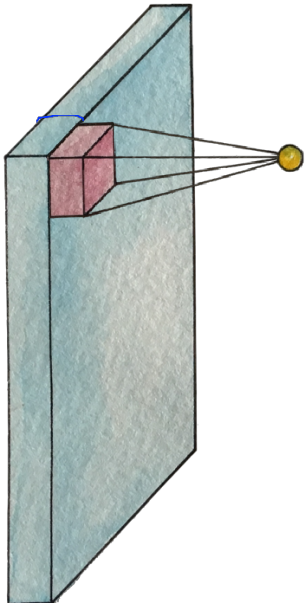




32x32x3 image

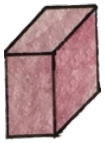
5x5x3 filter

Get one number using the filter (w)



one number!

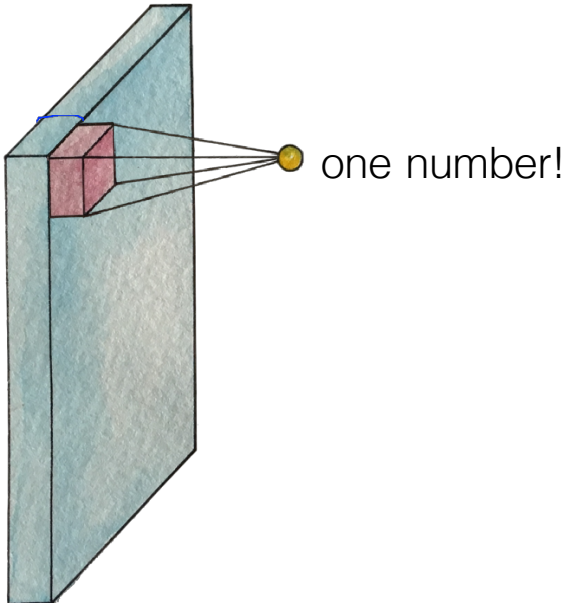
Wx+b [1]



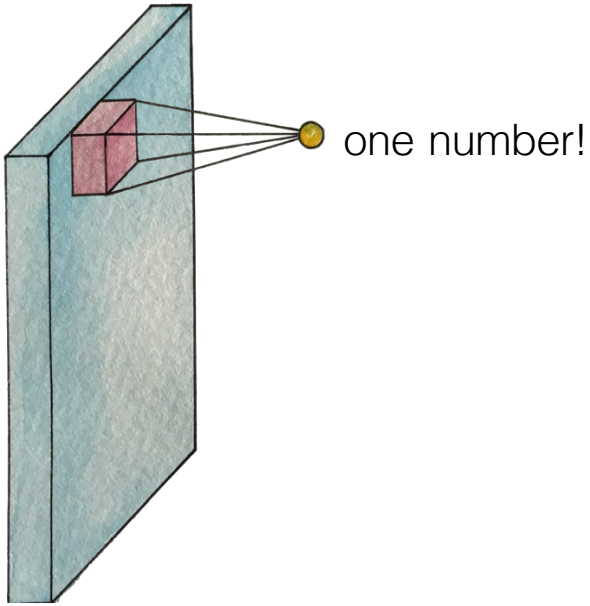
32x32x3 image

5x5x3 filter

Get one number using the filter (w)

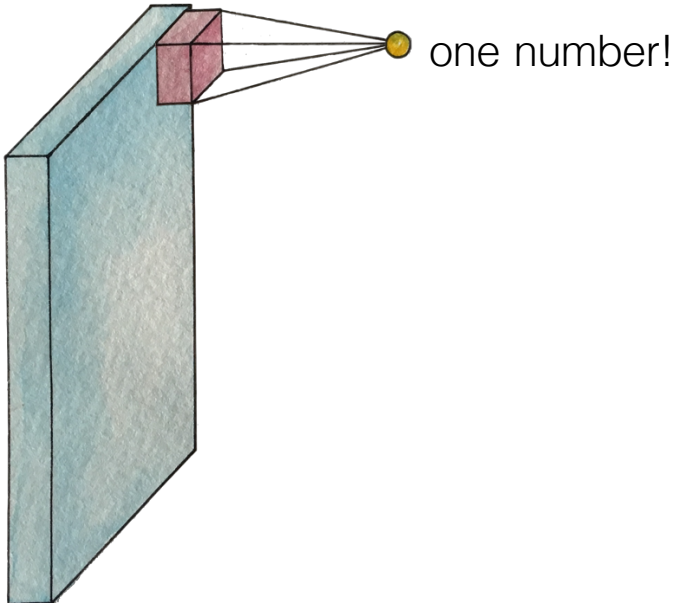


Get one number using the filter (w)



32x32x3 image

Get one number using the filter (w)



32x32x3 image

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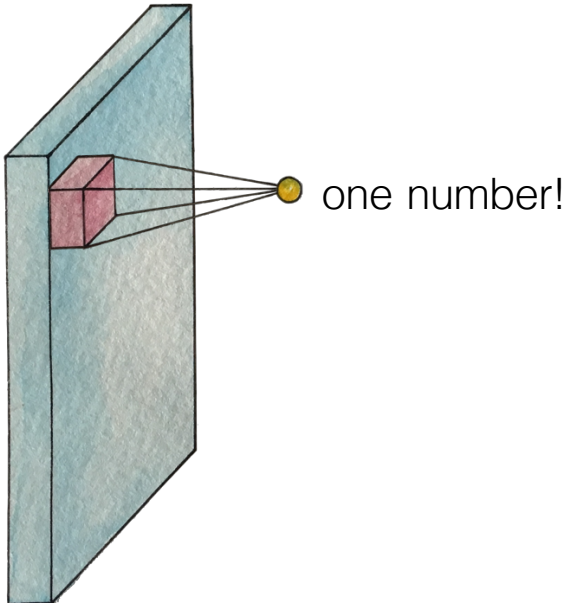

32x32x3 image

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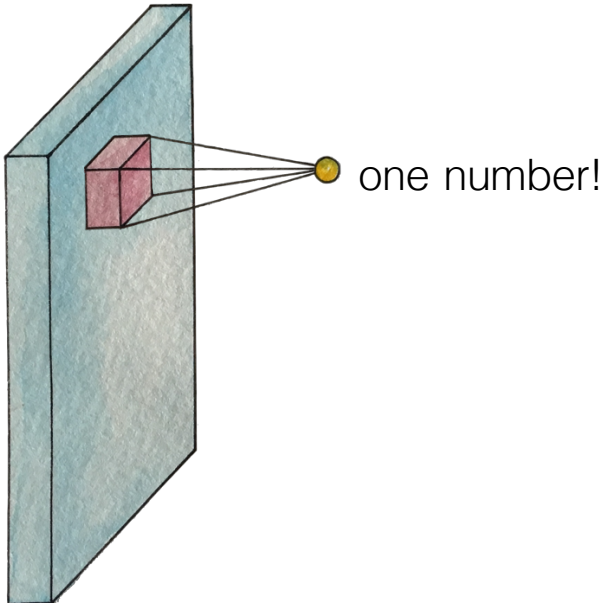
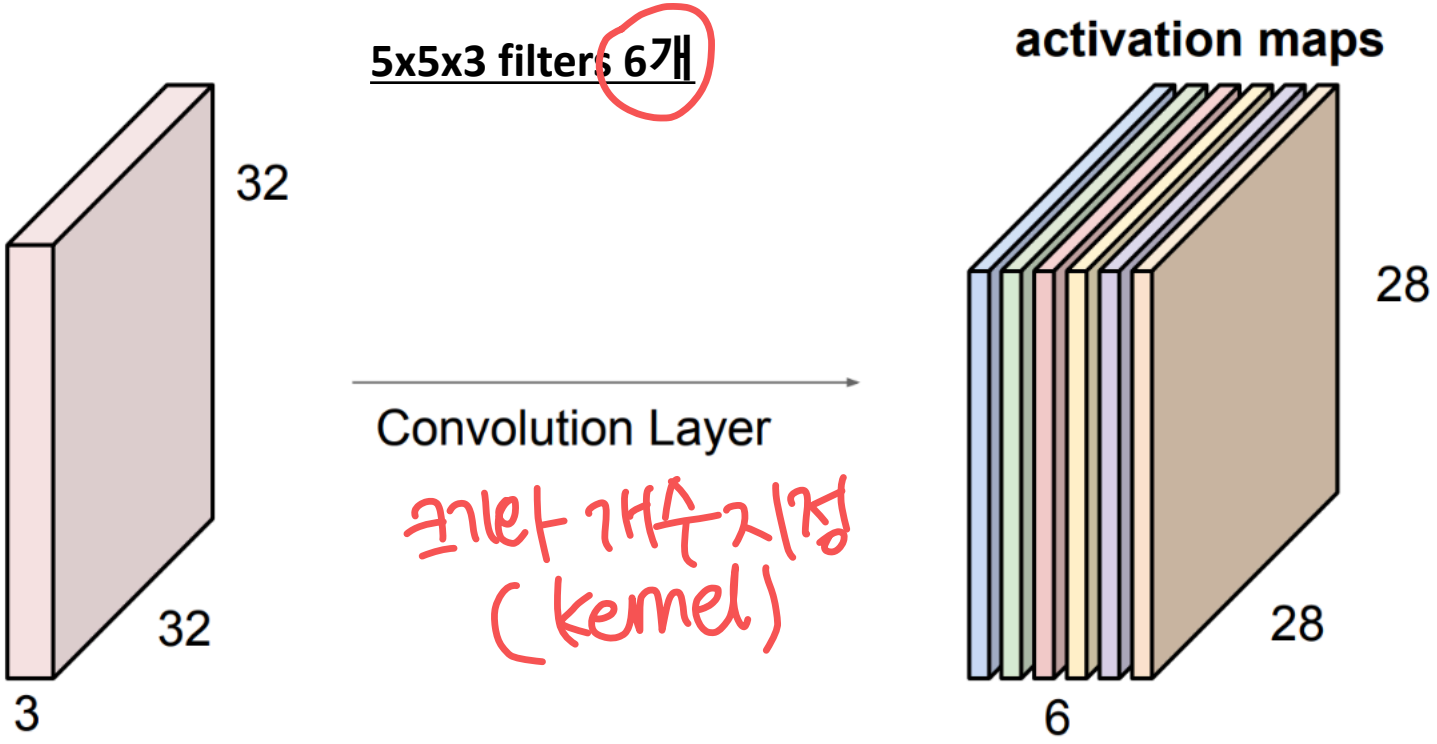


32x32x3 image

How many numbers can we get?

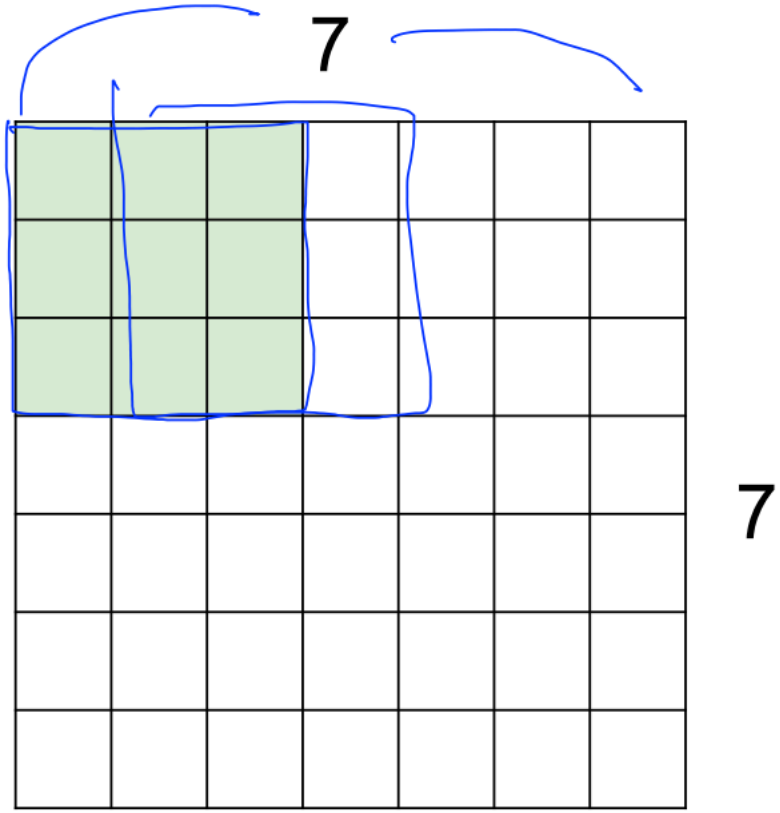
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a "new image" of size 28x28x6!

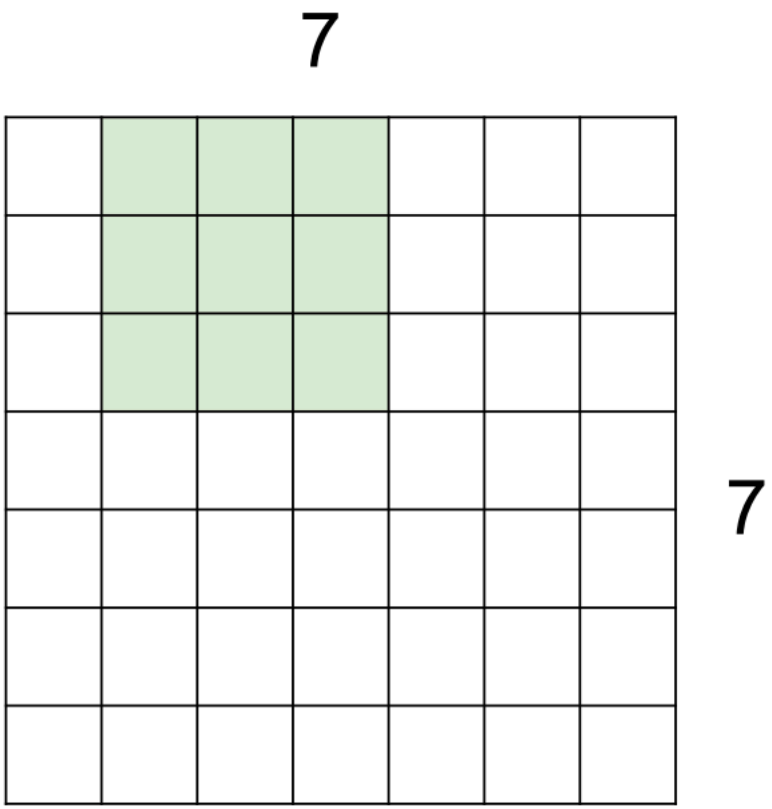
A closer look at spatial dimensions: stride==1

움직이는 칸수



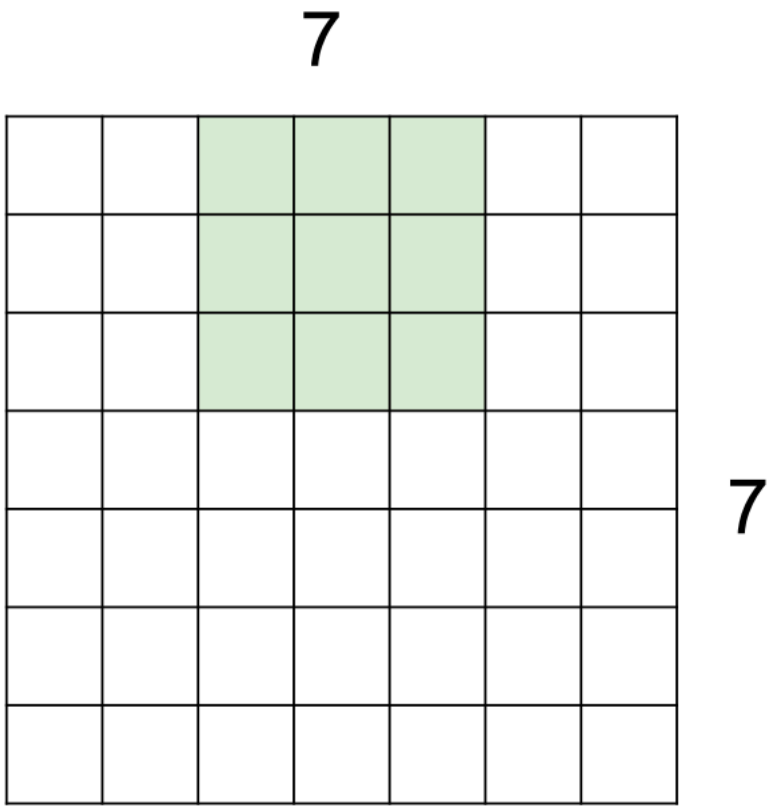
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



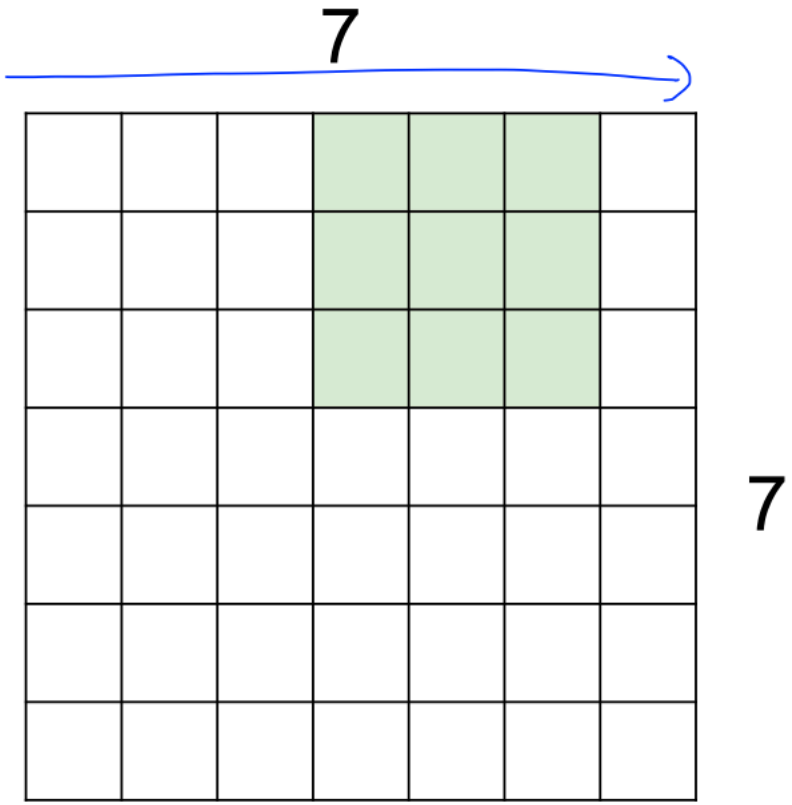
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

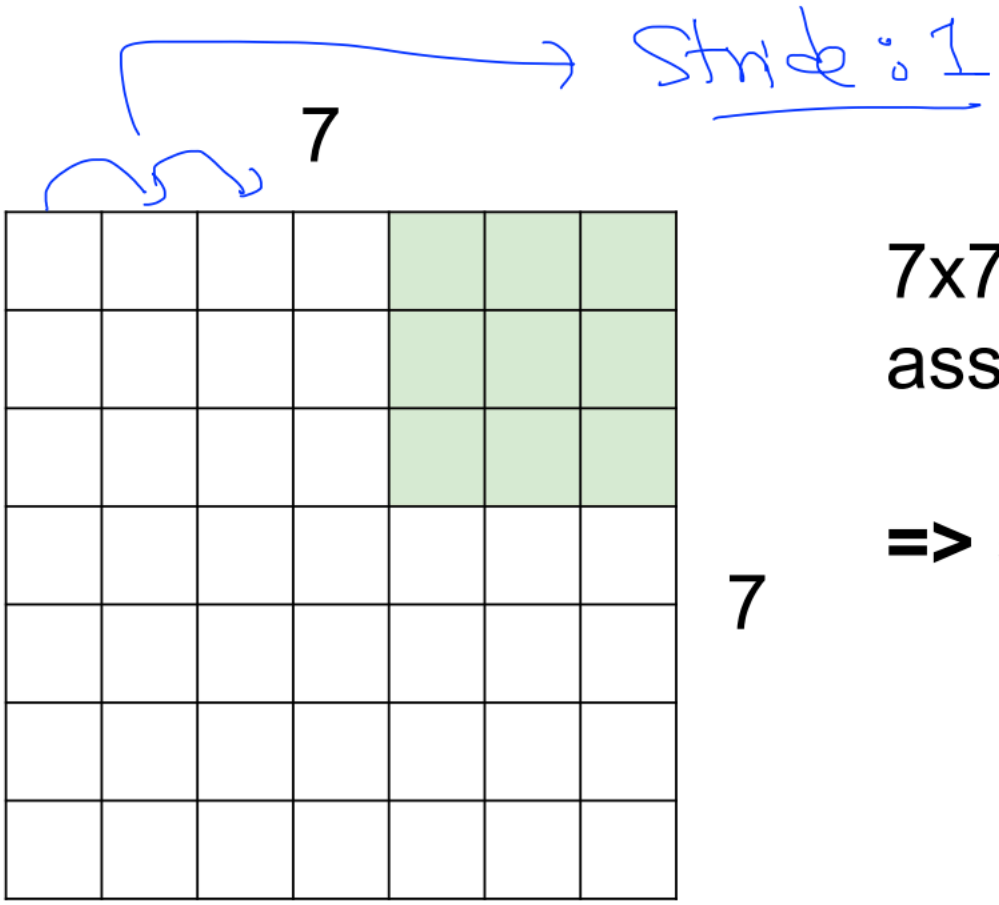
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

5x5

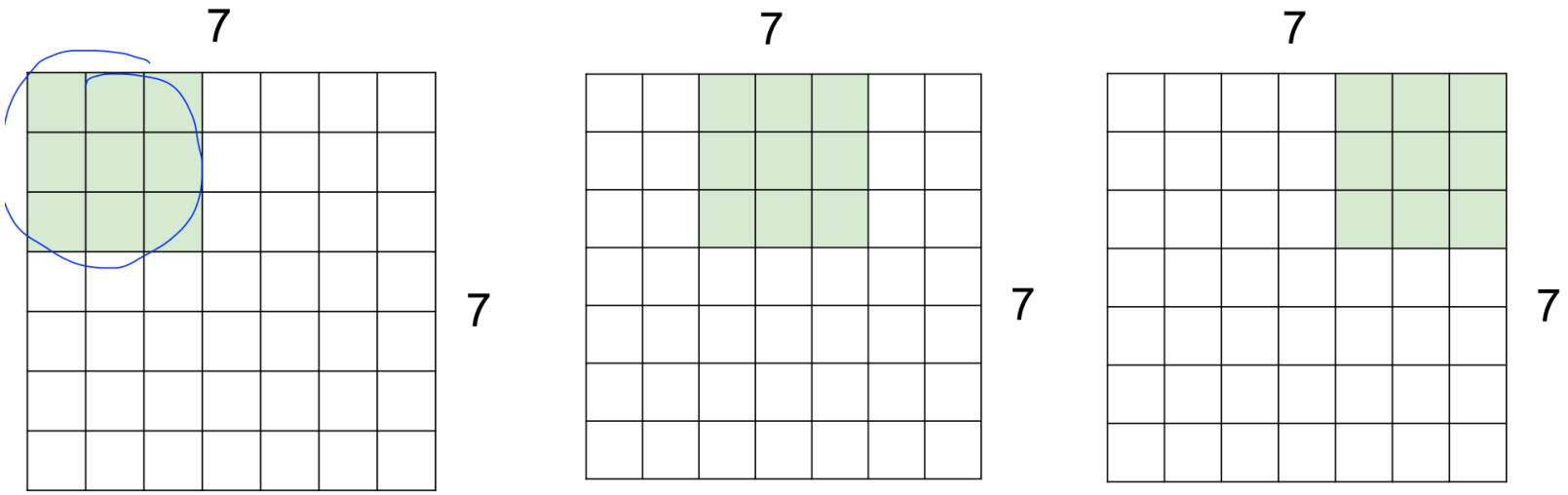
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

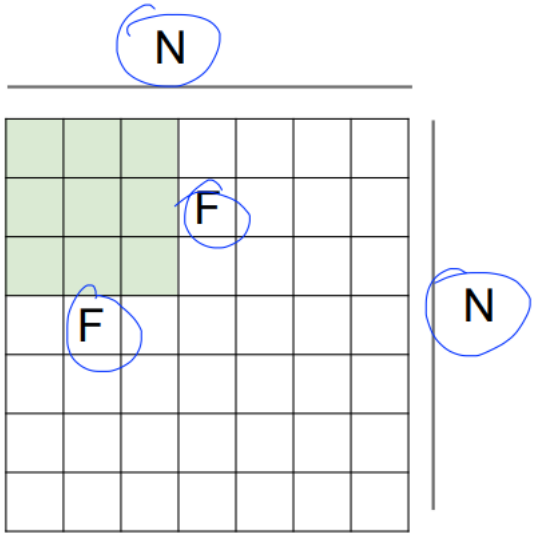
=> 5x5 output

A closer look at spatial dimensions: stride==2



7x7 input (spatially) assume 3x3 filter applied with stride 2 => **3x3 output!**

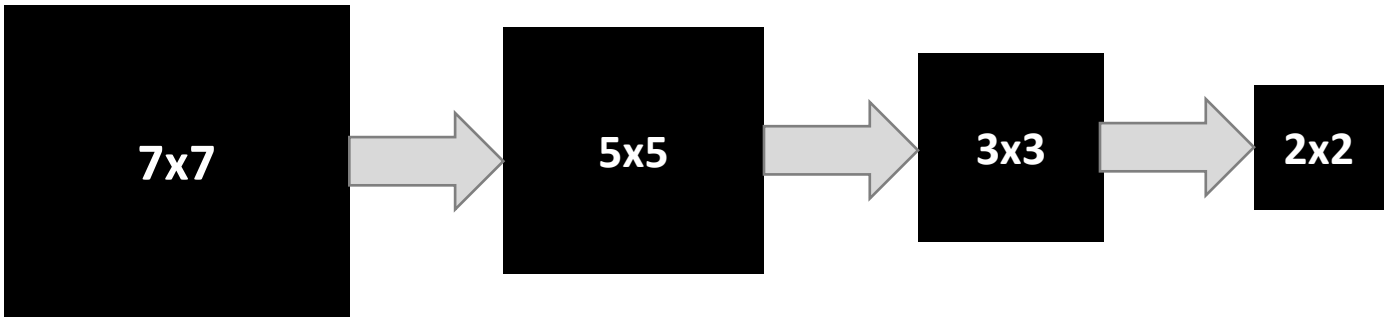
A closer look at spatial dimensions: stride==?



Output size:

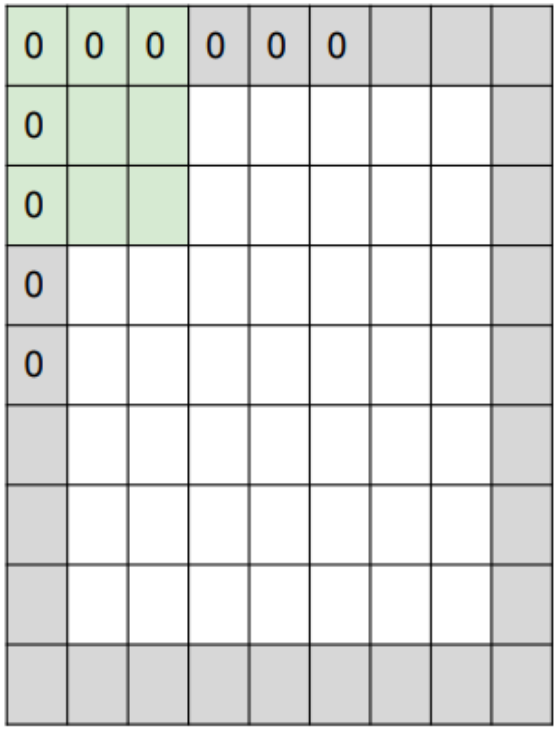
(N - F) / stride + 1

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = **5** (O)
stride 2 => (7 - 3)/2 + 1 = **3** (O)
stride 3 => (7 - 3)/3 + 1 = 2.33 (X)
Stride 4 => (7 - 3)/4 + 1 = **2** (O)



In practice: Common to zero pad the border

영상사이즈유지 → 패딩.



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

패딩사이즈 = [F/2]

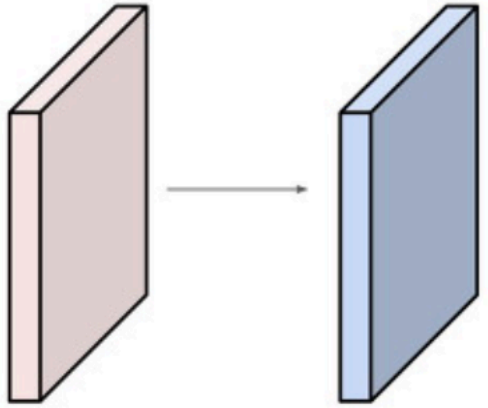
Question)

Examples time:

W H ch

Input volume: 32x32x3

10 5x5 filters with stride 1, pad 2



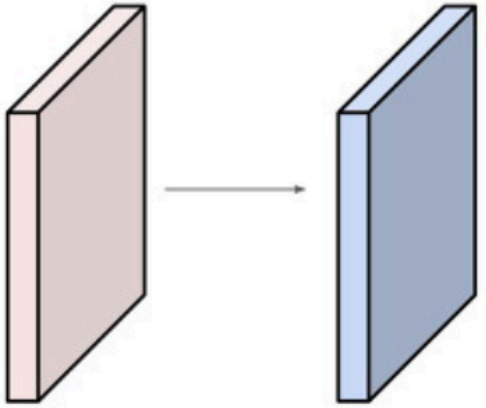
Number of parameters in this layer?

$(5 \times 5 \times 3 + 1) \times 10 = 760$개

weight bias 10개

Answer)

Examples time:



Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Number of parameters in this layer?
each filter has 5*5*3 + 1 = 76 params (+1 for bias)
=> 76*10 = **760**

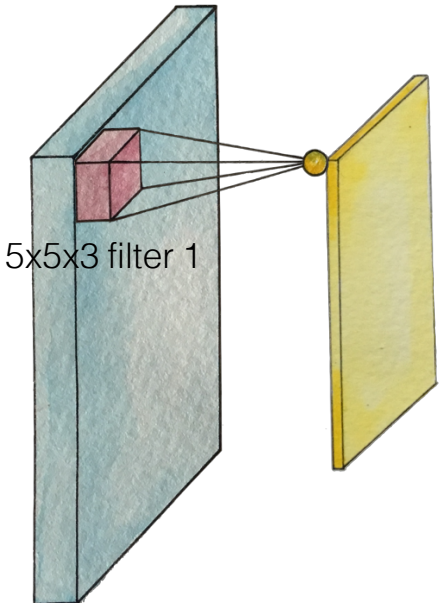
Summary

Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F + 2P)/S + 1$
  - $H_2 = (H_1 - F + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
  - $D_2 = K$
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.
- In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

① Convolution Layers

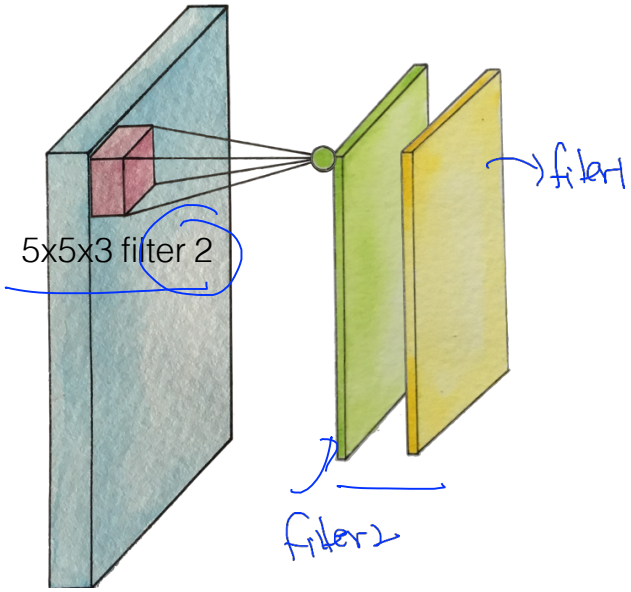
- Swiping the entire image



32x32x3 image

① Convolution Layers

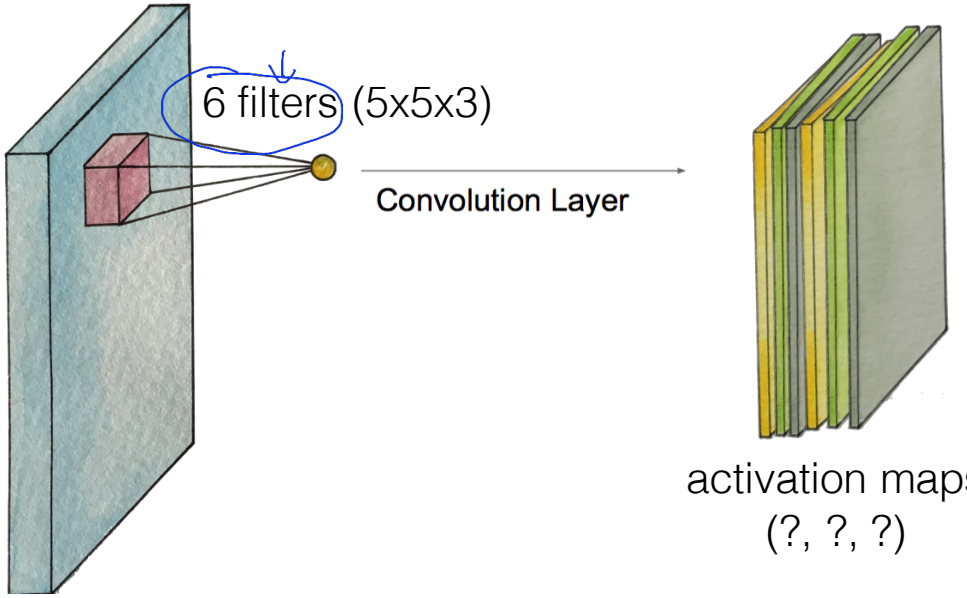
- Swiping the entire image



32x32x3 image

① Convolution Layers

- Swiping the entire image

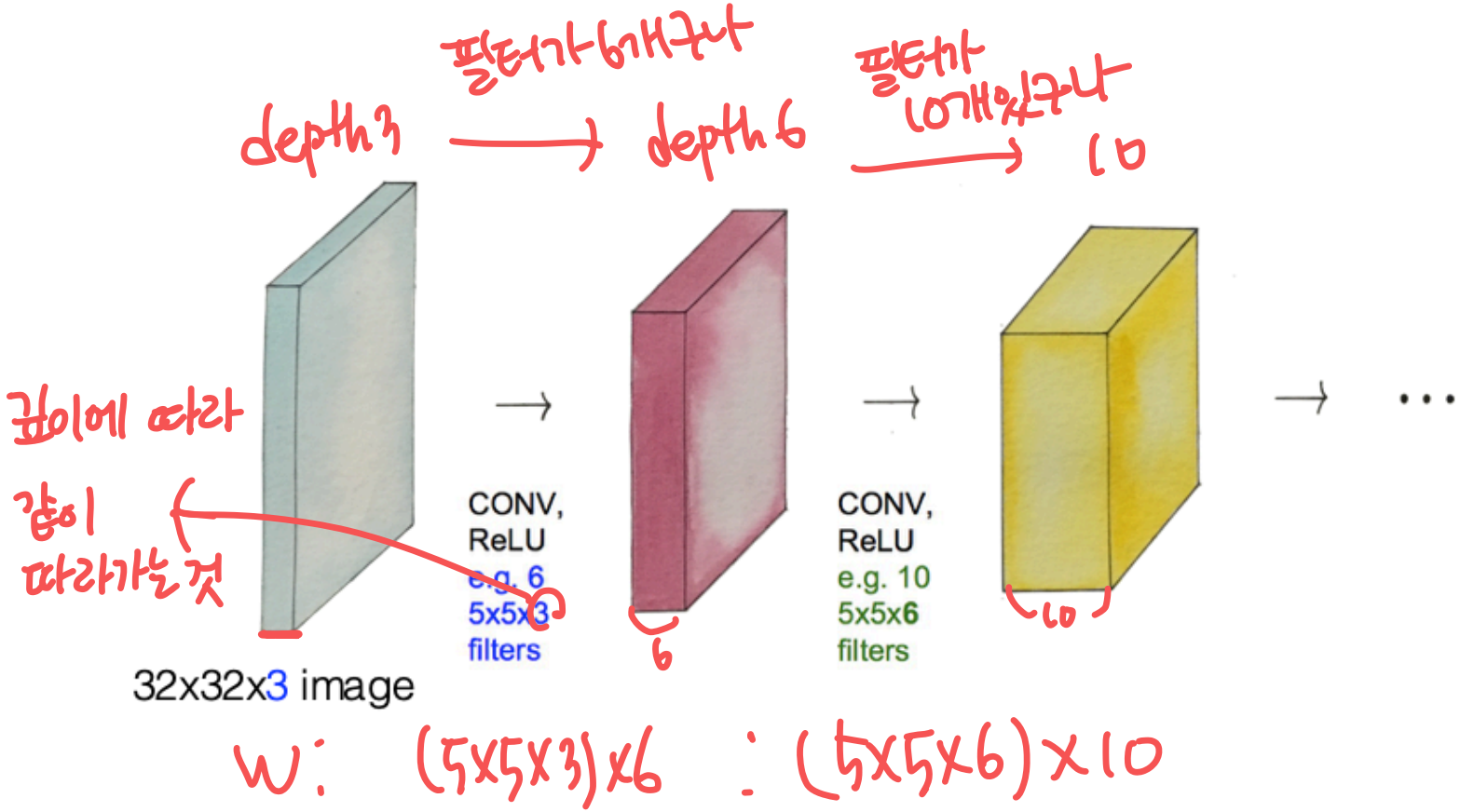


32x32x3 image

(28x28x6)

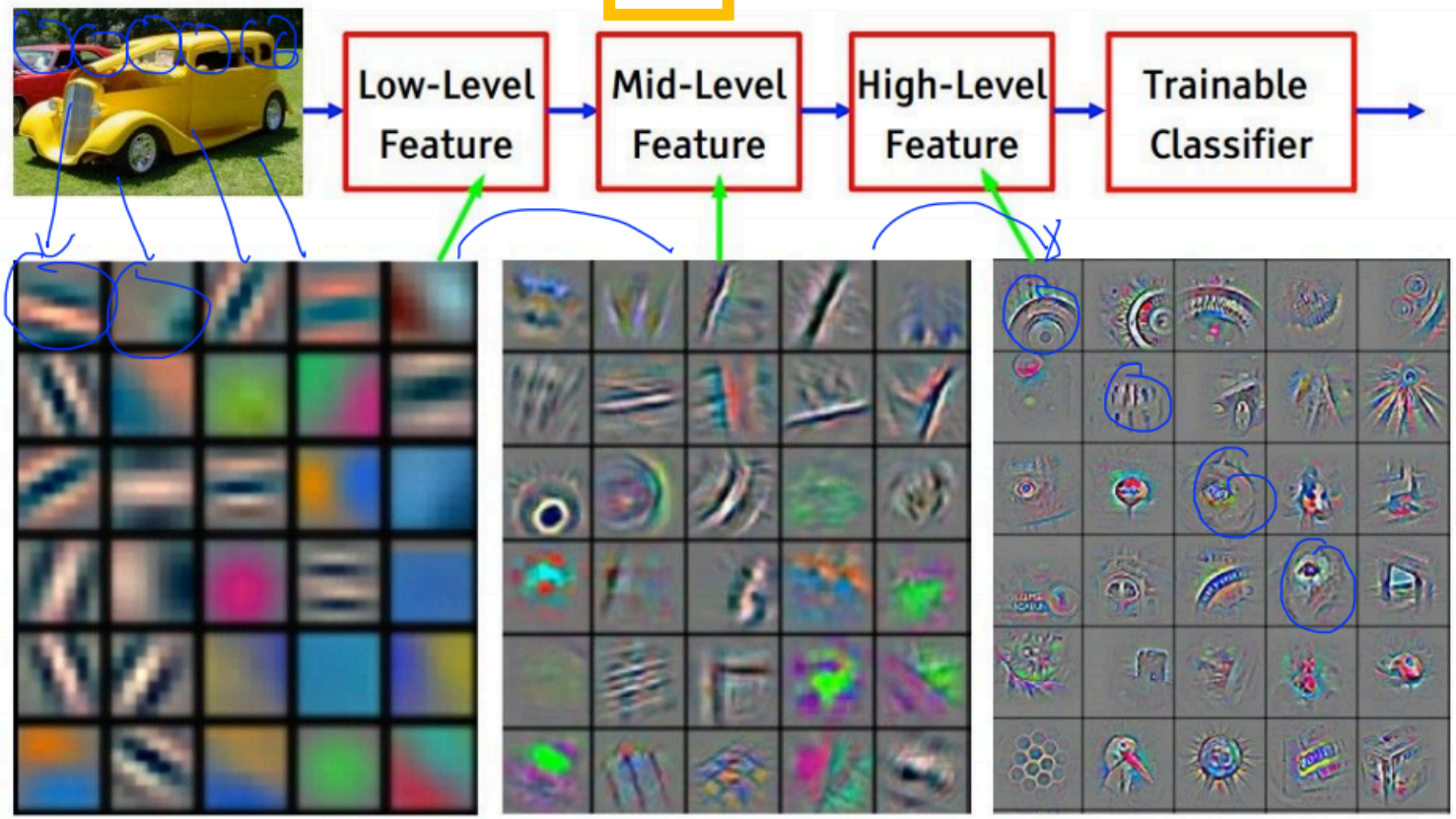
① Convolution Layers

- How many weight variables? How to set them?



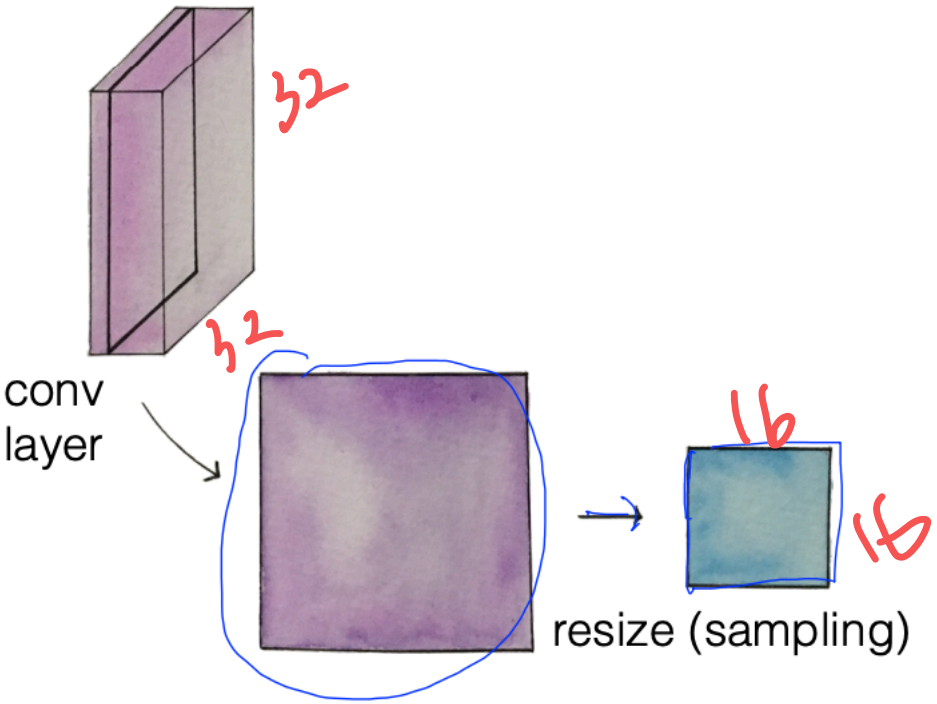
① Visualization of Activation Map (Feature Map)

[From recent Yann LeCun slides]

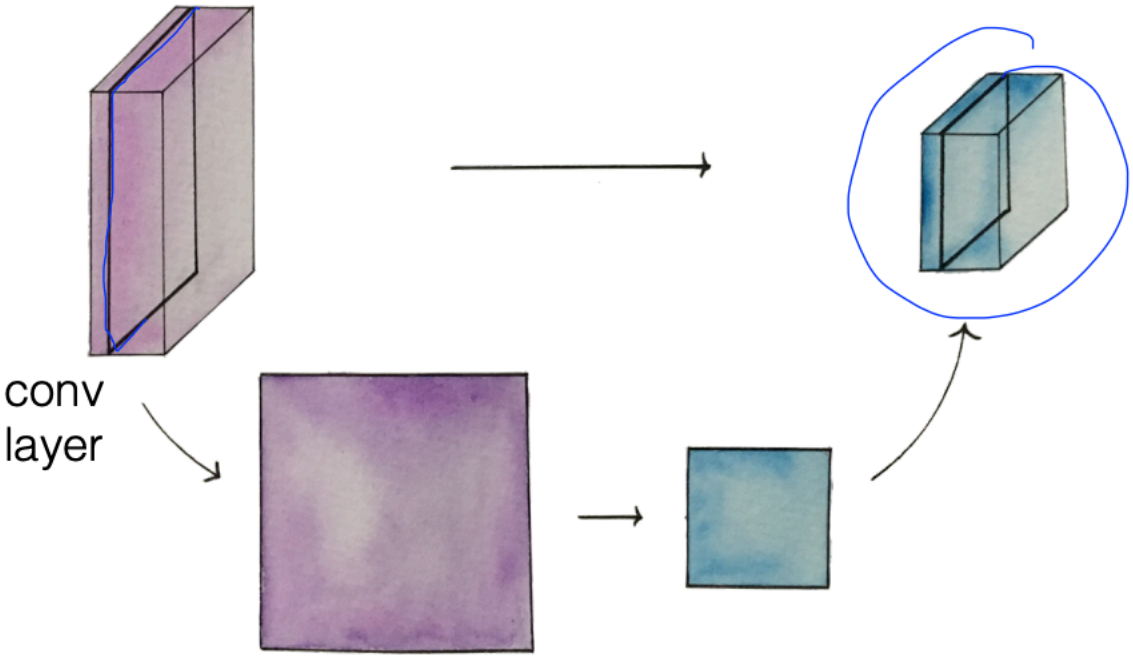


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

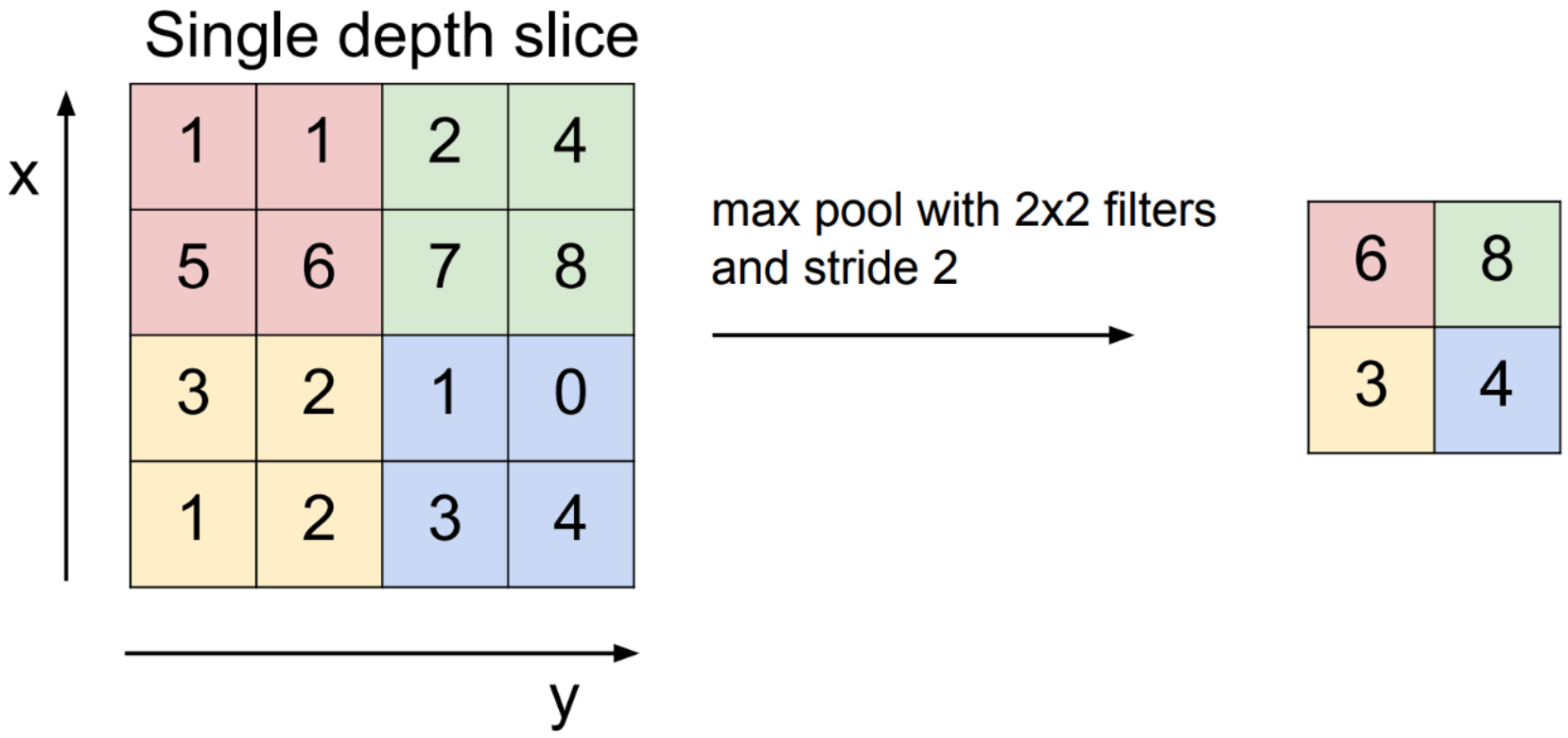
②Pooling Layer (sampling)



②Pooling Layer (sampling)



②Max Pooling



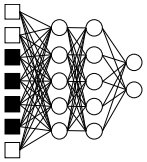
②Max Pooling

- (2x2 filter를 사용하는 경우) 전체 데이터의 75%를 버리고 25%만 선택
  - **Computational Complexity 감소**
- Filter 내에서 가장 큰 값을 선택
  - Average Pooling은 평균값을 선택.
  - Average Pooling은 Spatial Structure를 보존하되 이미지가 smooth해짐.
  - Max Pooling은 더 강한 특징만 남기는 방식
- Depth를 줄이지 않고 Spatially하게만 줄임(Height & Width)

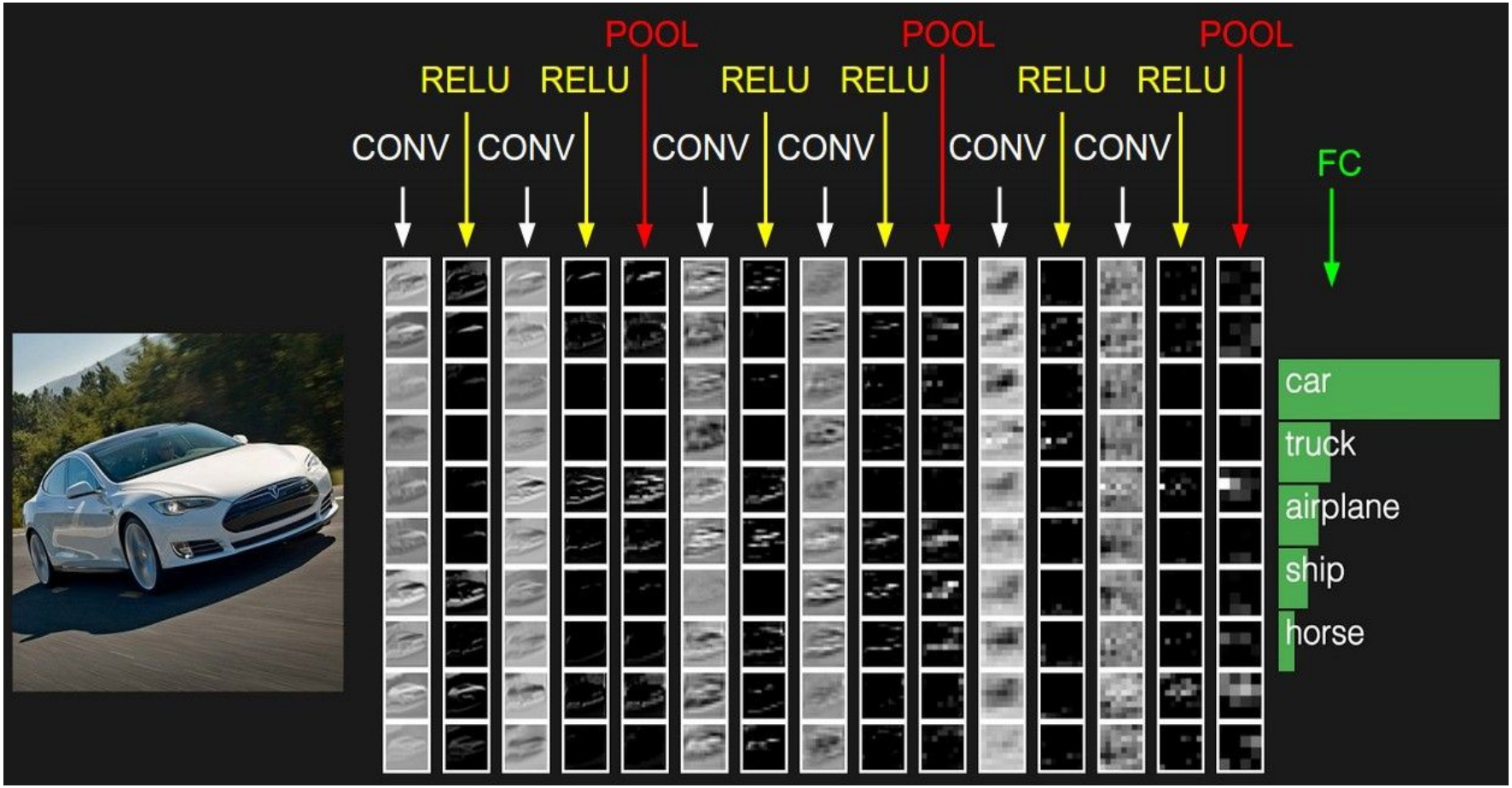
32x32x3 → 16x16x3 ⇒ depth 유지

- Q) stride와 pooling 모두 down-sampling인데 어떤 것을 사용해야 하나요?
- A) 최근 CNN 아키텍쳐는 stride를 사용하는 편이 많습니다. stride 추천합니다

③Fully Connected Layer (FC layer)



- Contains neurons that connect to the entire input volume, as in ordinary Neural Networks

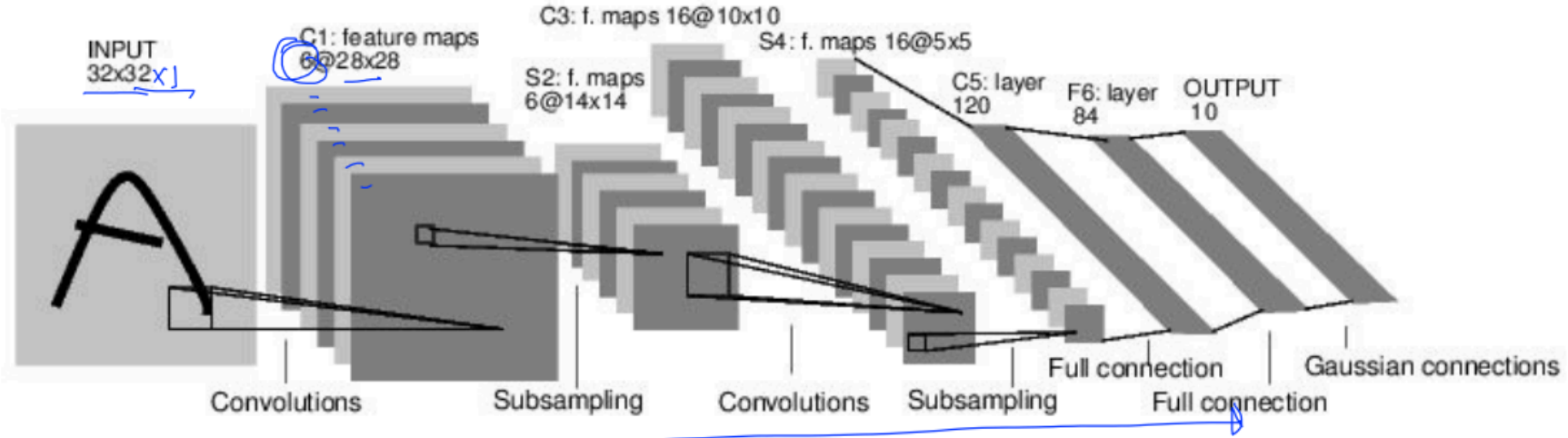


CNN Case Study

- LeNet-5
- AlexNet
- GoogLeNet
- ResNet

Case Study: LeNet-5

[LeCun et al., 1998]

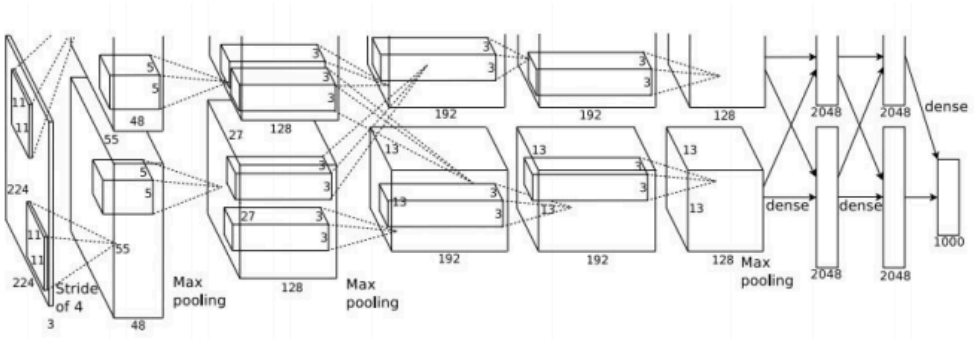


Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]

Case Study: AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4

=>

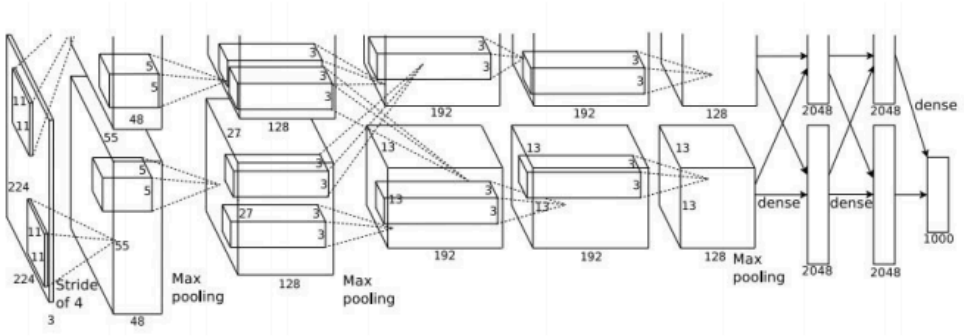
Output volume **[55x55x96]**

Parameters: (11*11*3)*96 = **35K**

Case Study: AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]



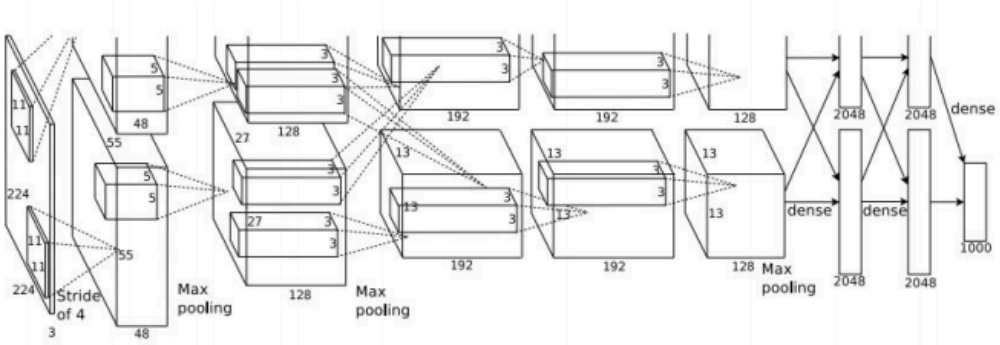
Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96
Parameters: 0!

Case Study: AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]

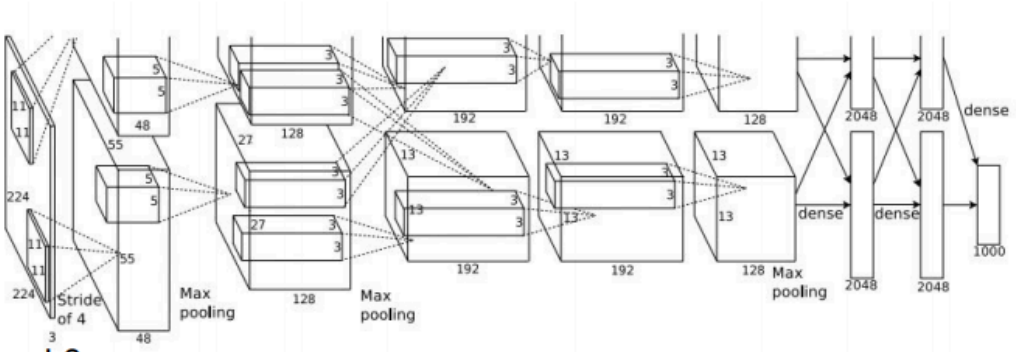


Input: 227x227x3 images
After CONV1: 55x55x96
After POOL1: 27x27x96
...

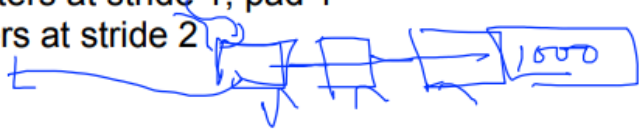
Case Study: AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]



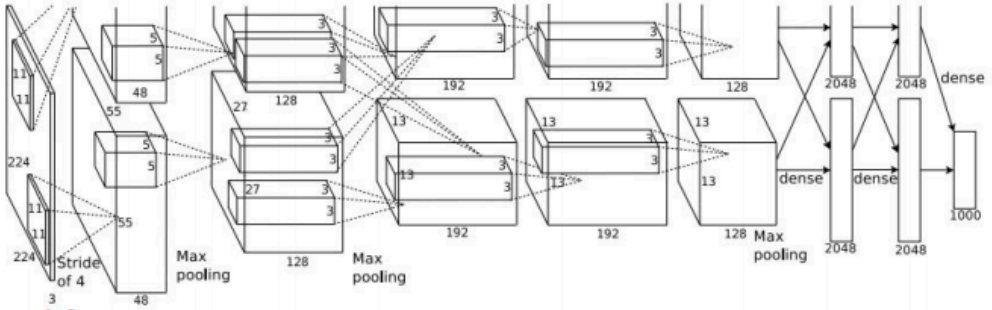
Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] ~~NORM1: Normalization layer~~
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[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)



Case Study: AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
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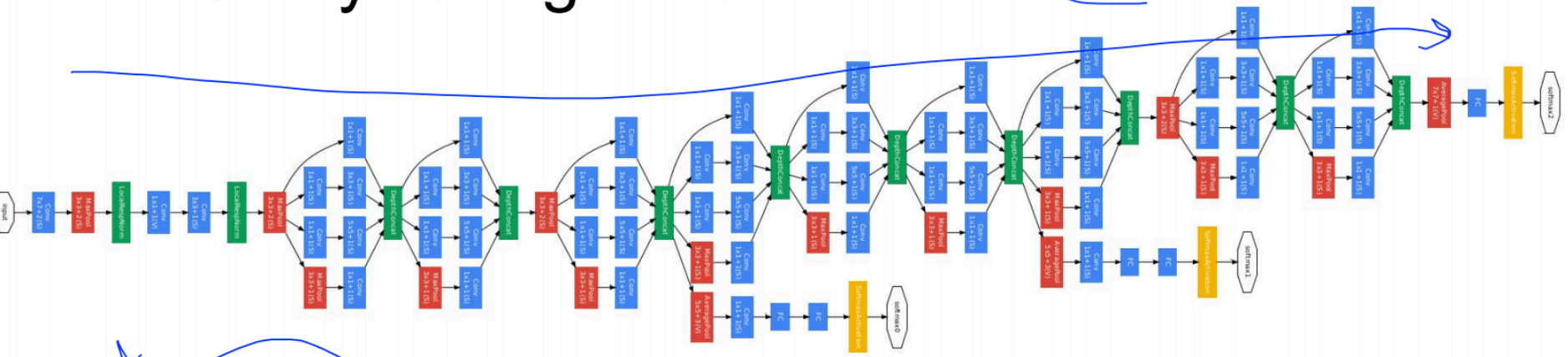
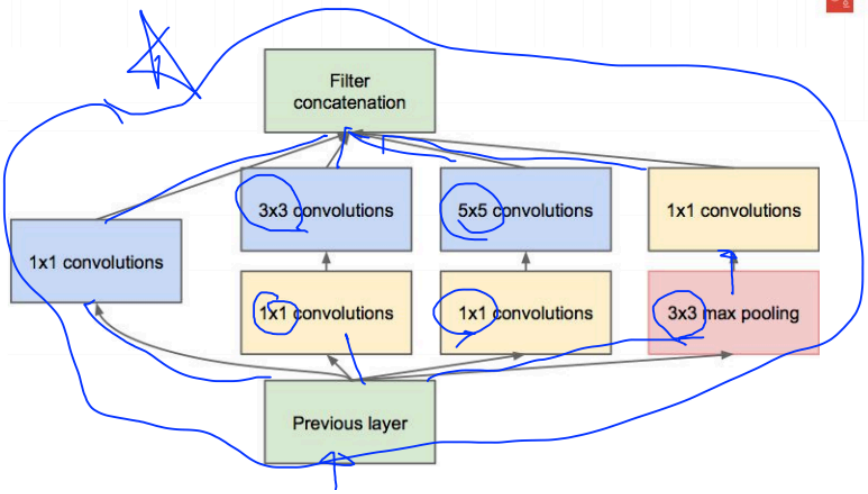
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 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)

Details/Retrospectives:
- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

Case Study: GoogLeNet

[Szegedy et al., 2014]



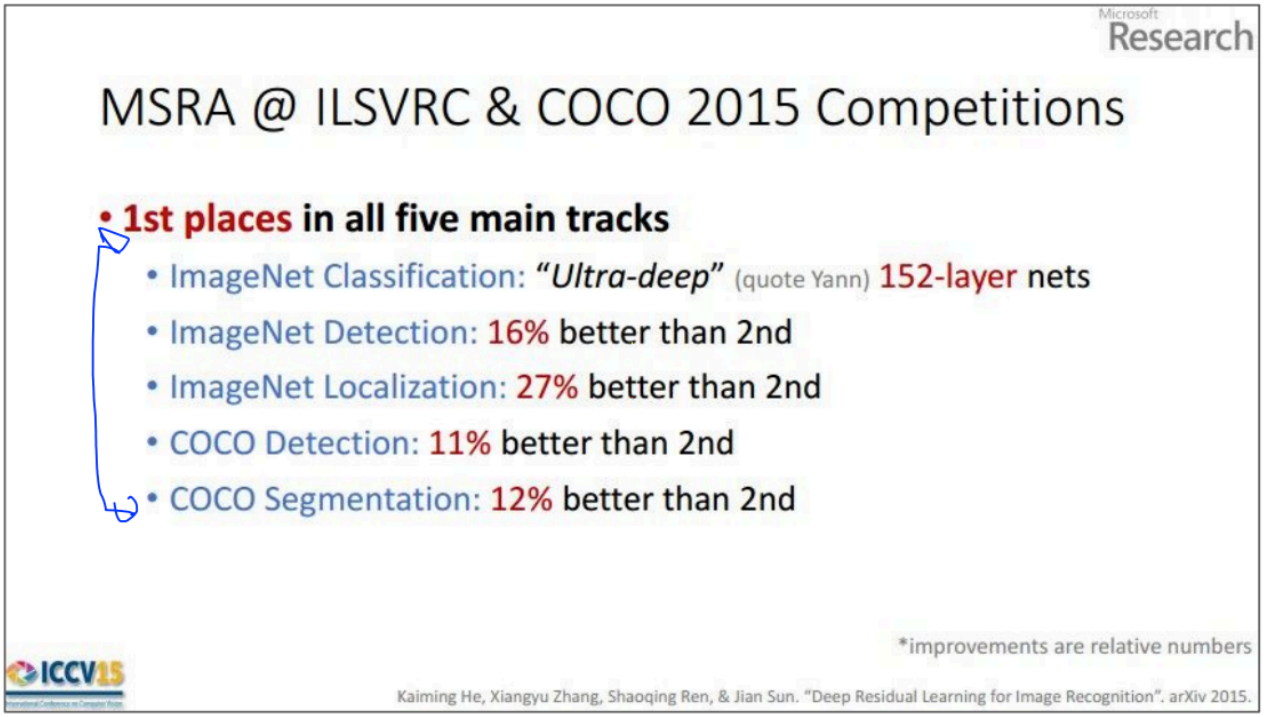


Inception module

ILSVRC 2014 winner (6.7% top 5 error)

Case Study: ResNet [He et al., 2015]

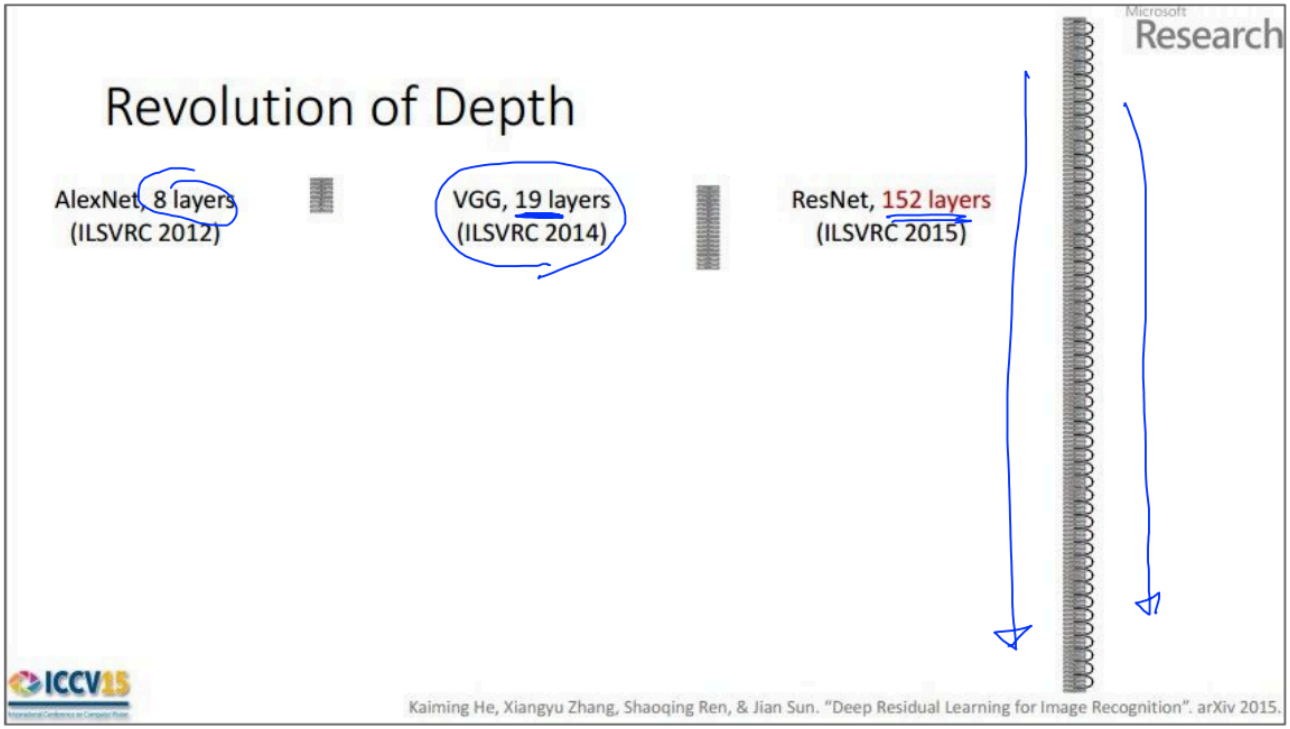
ILSVRC 2015 winner (3.6% top 5 error)



Slide from Kaiming He's recent presentation https://www.youtube.com/watch?v=1PGLj-uKT1w

Case Study: ResNet *[He et al., 2015]*

ILSVRC 2015 winner (3.6% top 5 error)



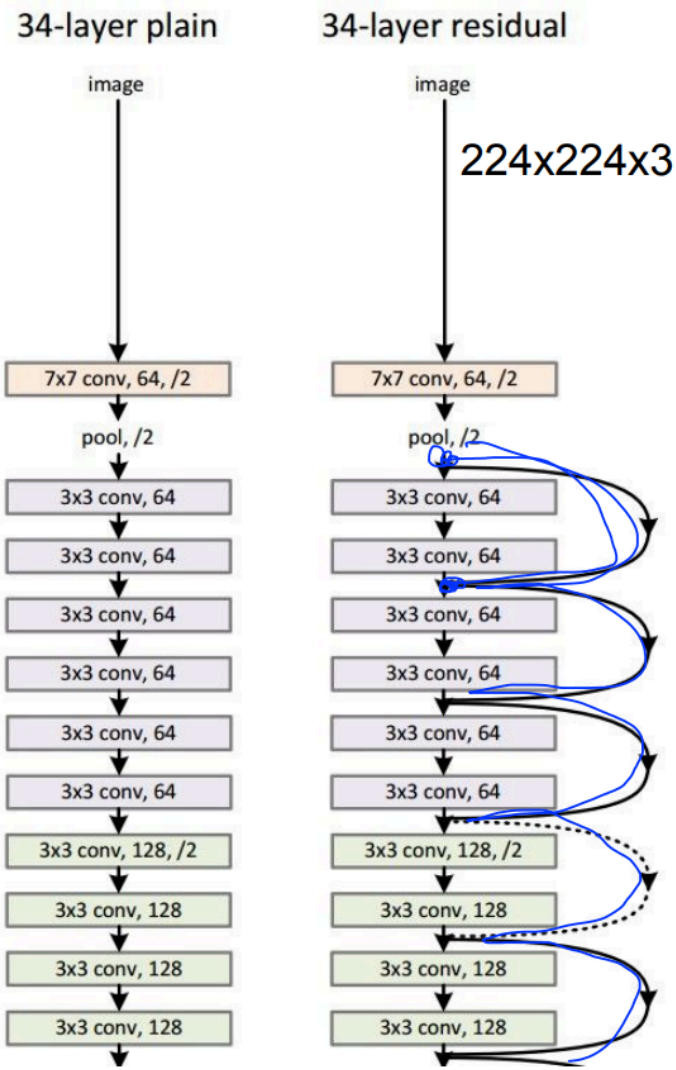
(slide from Kaiming He's recent presentation)

2-3 weeks of training on 8 GPU machine

at runtime: faster than a VGGNet! (even though it has 8x more layers)

Case Study: ResNet

[He et al., 2015]



Summary

- ConvNet stack “Conv+Pool+ReLU” + FC
- Trend towards smaller filters and deeper architectures
- Trend towards getting rid of Pool/FC layers