Medical Image Analysis

3. Medical image classification(2)

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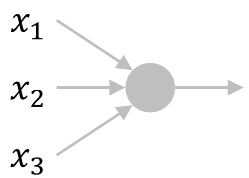
https://www.edwith.org/medical-20200327/joinLectures/30437

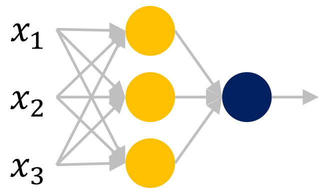
Contents

1. Property of Deep Neural Network

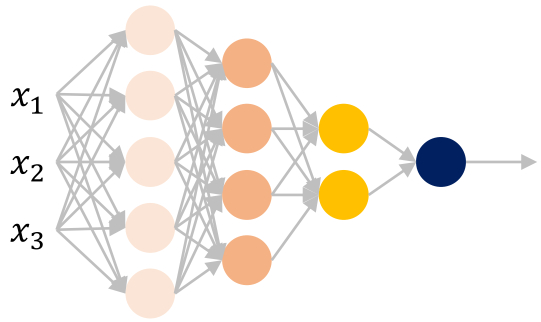
- Logistic regression



- Neural network

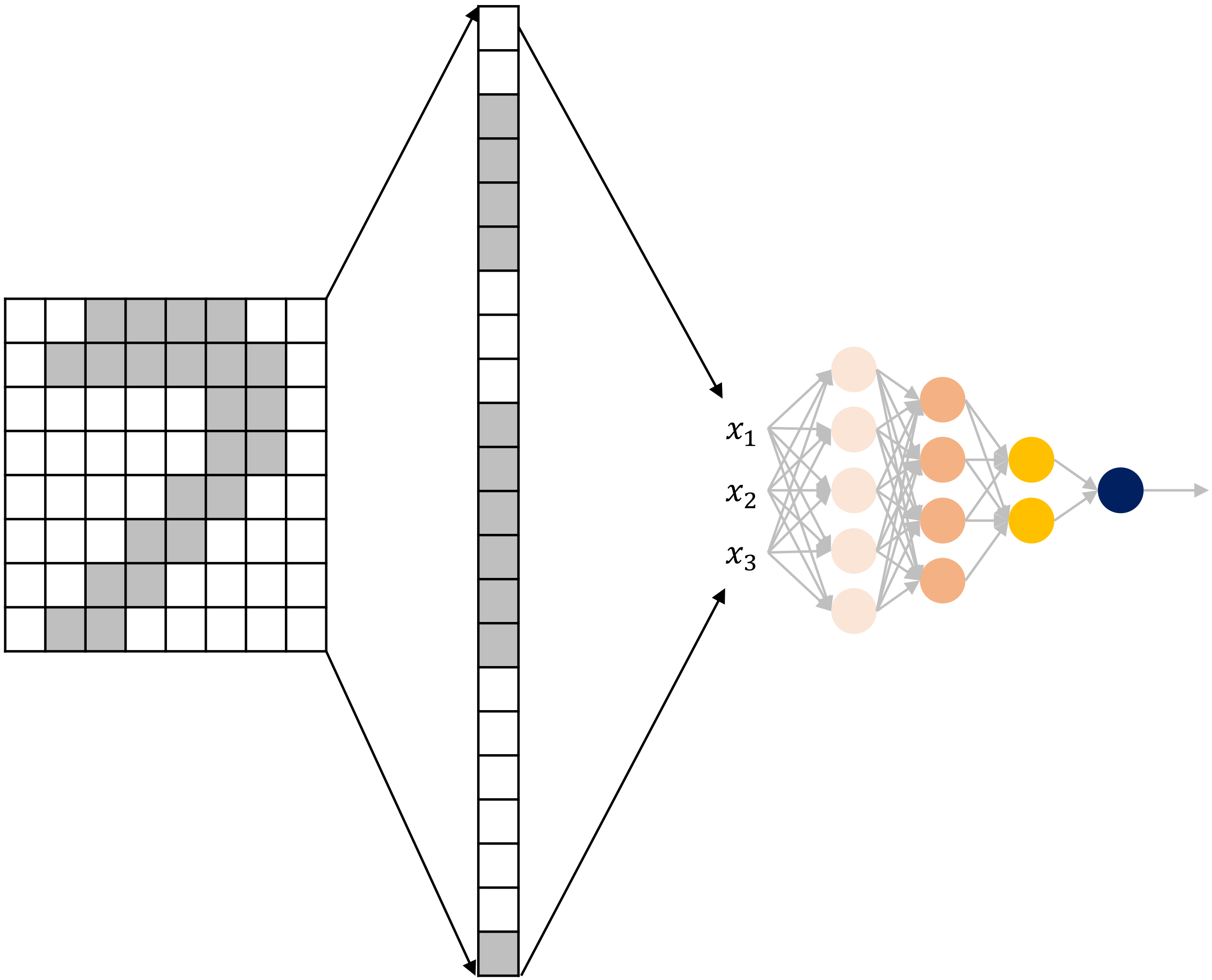


- Deep neural network



1. Property of Deep Neural Network

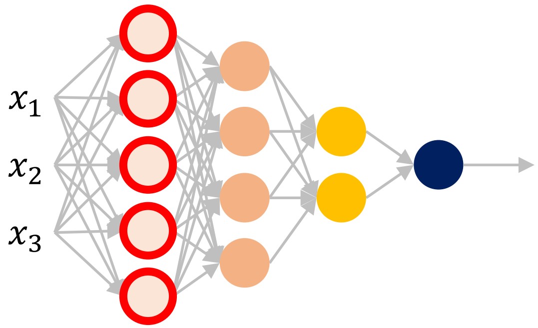
Image input

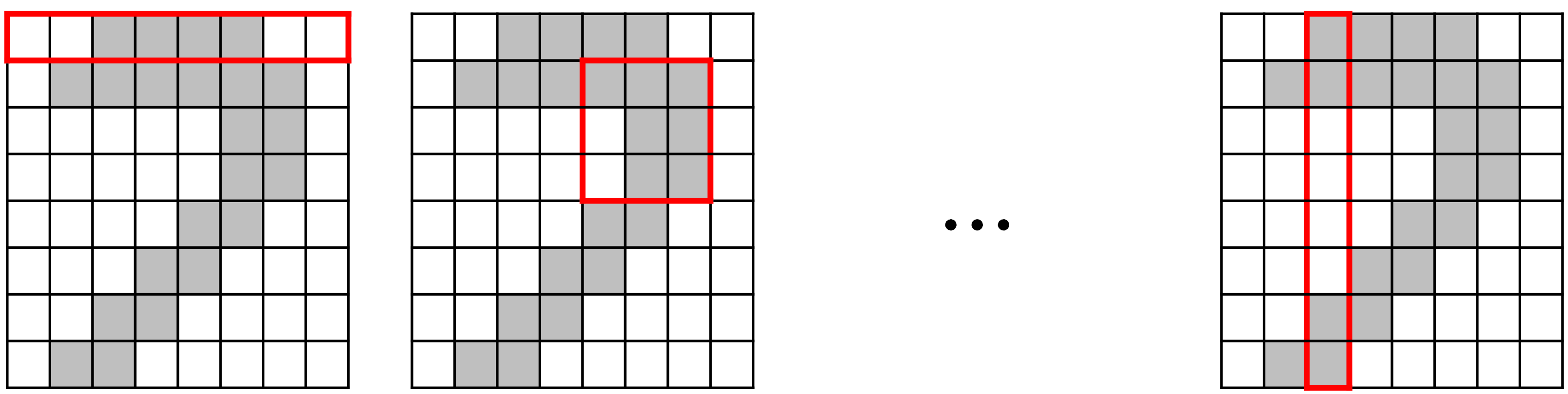


1. Property of Deep Neural Network

Role of Deep hidden layers

- 각각의 node들은 서로 다른 영역을 맡아 체크한다.
- Layer마다 체크하는 수준이 달라진다.
  - 1st layer: low level

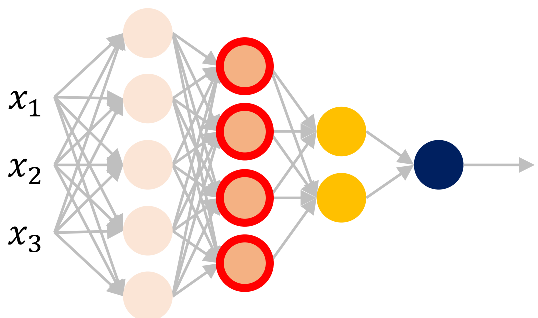


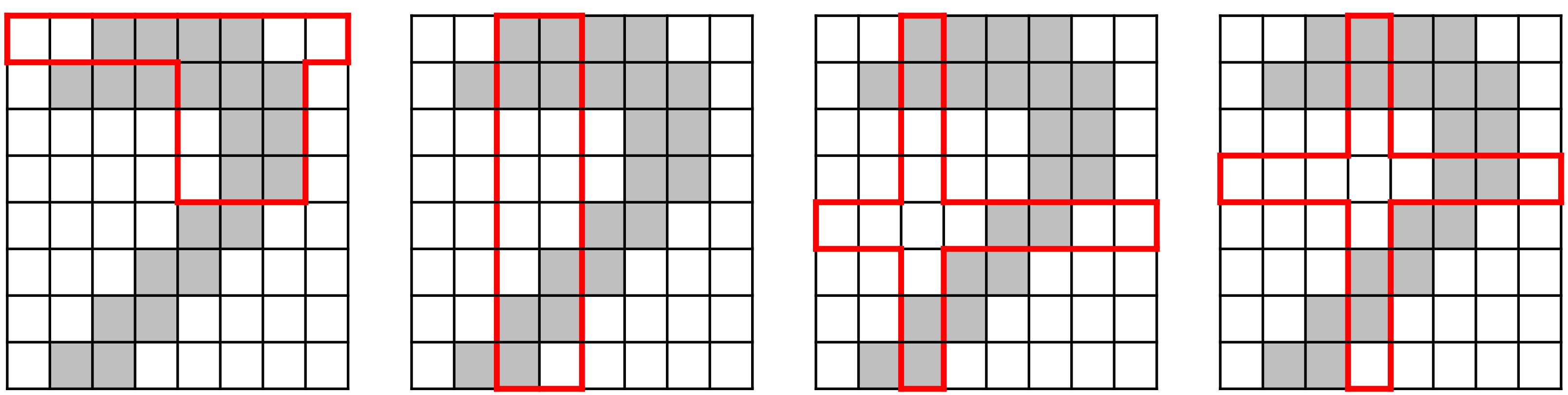


1. Property of Deep Neural Network

Role of Deep hidden layers

- 각각의 node들은 서로 다른 영역을 맡아 체크한다.
- Layer마다 체크하는 수준이 달라진다.
    - 2nd layer: high level

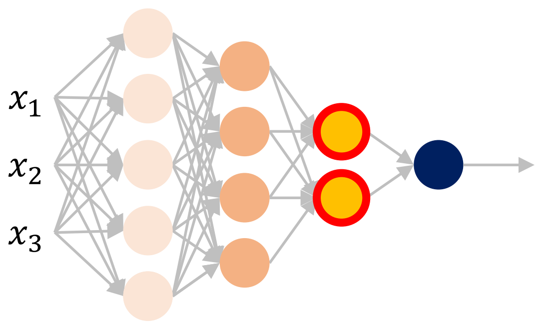


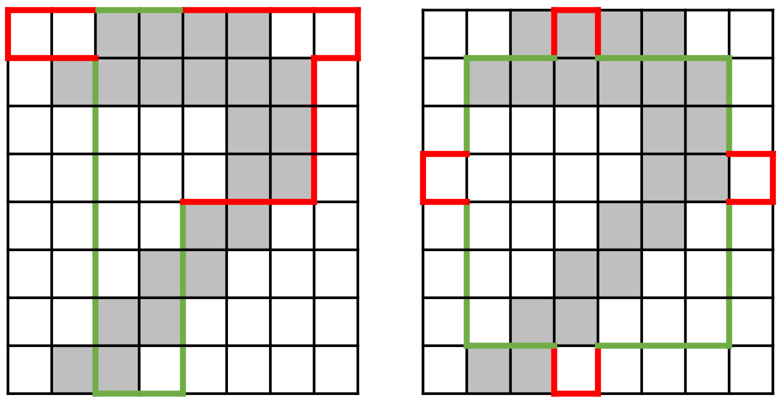


1. Property of Deep Neural Network

Role of Deep hidden layers

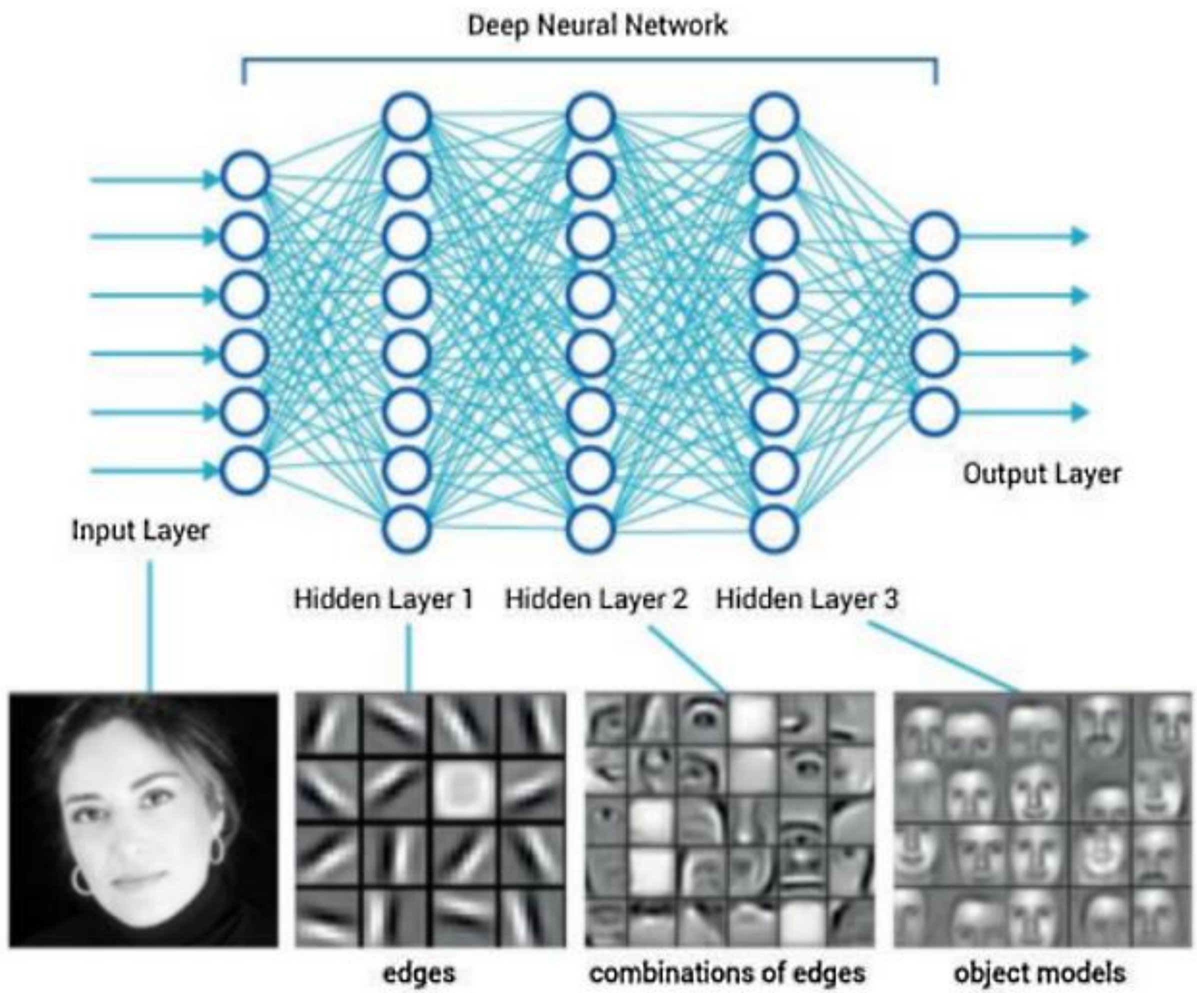
- 각각의 node들은 서로 다른 영역을 맡아 체크한다.
- Layer마다 체크하는 수준이 달라진다.
    - 3rd layer: higher level





1. Property of Deep Neural Network

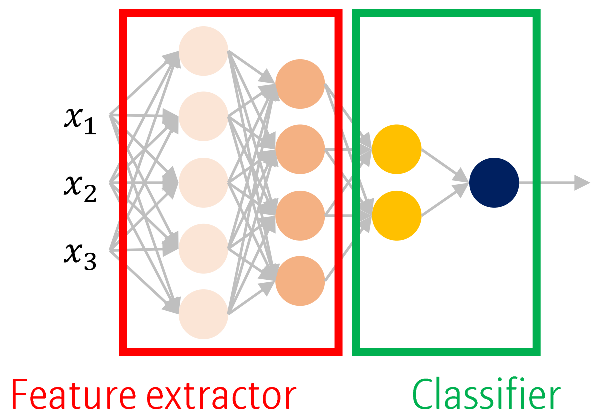
Role of Deep hidden layers



https://iq.opengenus.org/hidden-layers/

1. Property of Deep Neural Network

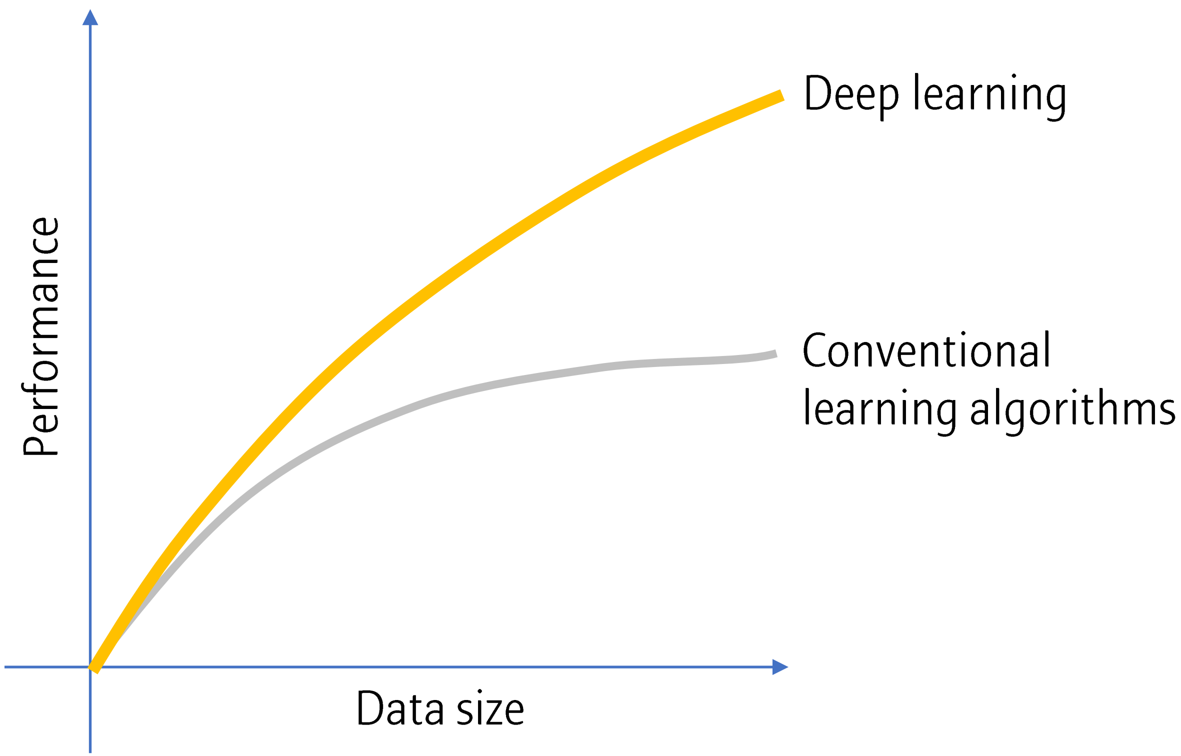
Deep neural network: End-to-end learning (Feature extractor + Classifier)



1. Property of Deep Neural Network

Important of data size

- Data size에 따라 점차 성능이 좋아지는 Deep neural network
    - Data size가 적은 의료영상 도메인 특성상 Conventional learning algorithm이 나은 경우도 많다.



1. Property of Deep Neural Network

Limitation of deep neural network

- Too many parameters

2. Convolution

Convolution filter

Data

9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0

Convolution filter

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

2. Convolution

Convolution

Data

9 1/9	9 1/9	9 1/9	0	0	0
9 1/9	9 1/9	9 1/9	0	0	0
9 1/9	9 1/9	9 1/9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0

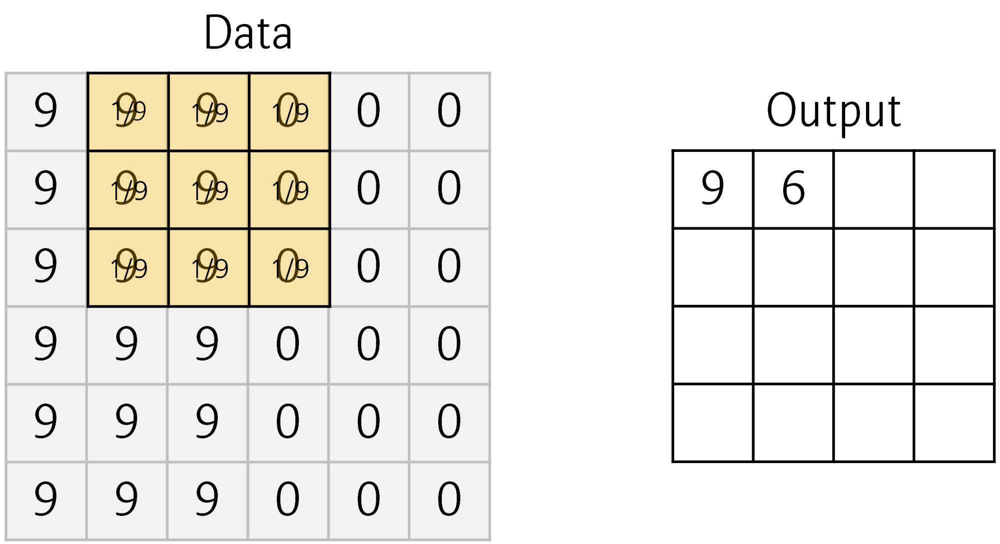
Output

9			

$$9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} = 9$$

2. Convolution

Convolution



$$9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 0 \times \frac{1}{9} + 0 \times \frac{1}{9} + 0 \times \frac{1}{9} = 6$$

2. Convolution

Convolution

Data

9	9	9 1/9	0 1/9	0 1/9	0
9	9	9 1/9	0 1/9	0 1/9	0
9	9	9 1/9	0 1/9	0 1/9	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0

Output

9	6	3	

$$9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 0 \times \frac{1}{9} + 0 \times \frac{1}{9} + 0 \times \frac{1}{9} + 0 \times \frac{1}{9} + 0 \times \frac{1}{9} + 0 \times \frac{1}{9} = 6$$

Convolution

Data

9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0 1/9	0 1/9	0 1/9
9	9	9	0 1/9	0 1/9	0 1/9
9	9	9	0 1/9	0 1/9	0 1/9

Output

9	6	3	0
9	6	3	0
9	6	3	0
9	6	3	0

$$9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 0 \times \frac{1}{9} + 0 \times \frac{1}{9} + 0 \times \frac{1}{9} + 0 \times \frac{1}{9} + 0 \times \frac{1}{9} + 0 \times \frac{1}{9} = 6$$

2. Convolution

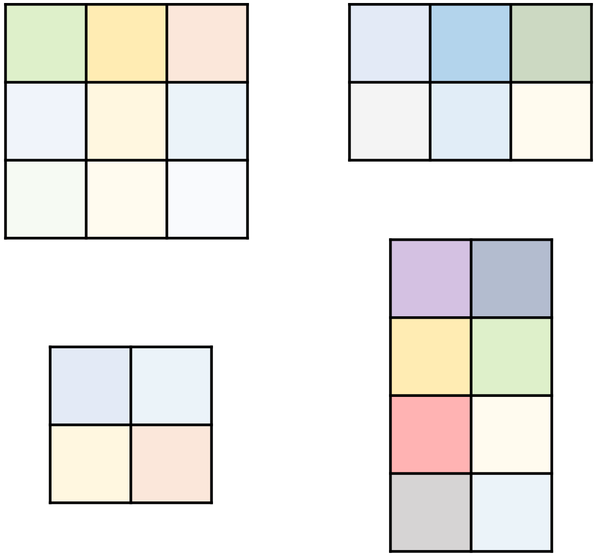
Different Convolution filter

1/9	1/9	1/9
1/9	-17/9	1/9
1/9	1/9	1/9

2. Convolution

Diverse Convolution filter

- 다양한 필터가 만들어질 수 있다.
- 단, 같은 레이어에서는 같은 크기의 필터가 사용된다.



2. Convolution

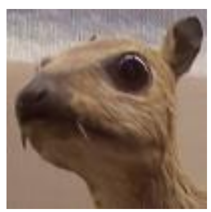
Convolution examples

- 각 필터는 다양한 역할을 수행한다

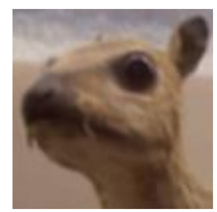
Input **Convolution filter** **Feature**

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

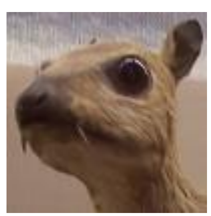
Edge



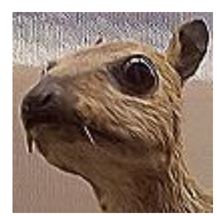
$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$



Blurred



$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$



Sharpen

3. Convolutional Neural Network (CNN)

Pooling layer

Data

9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0

Convolutional layer

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Output

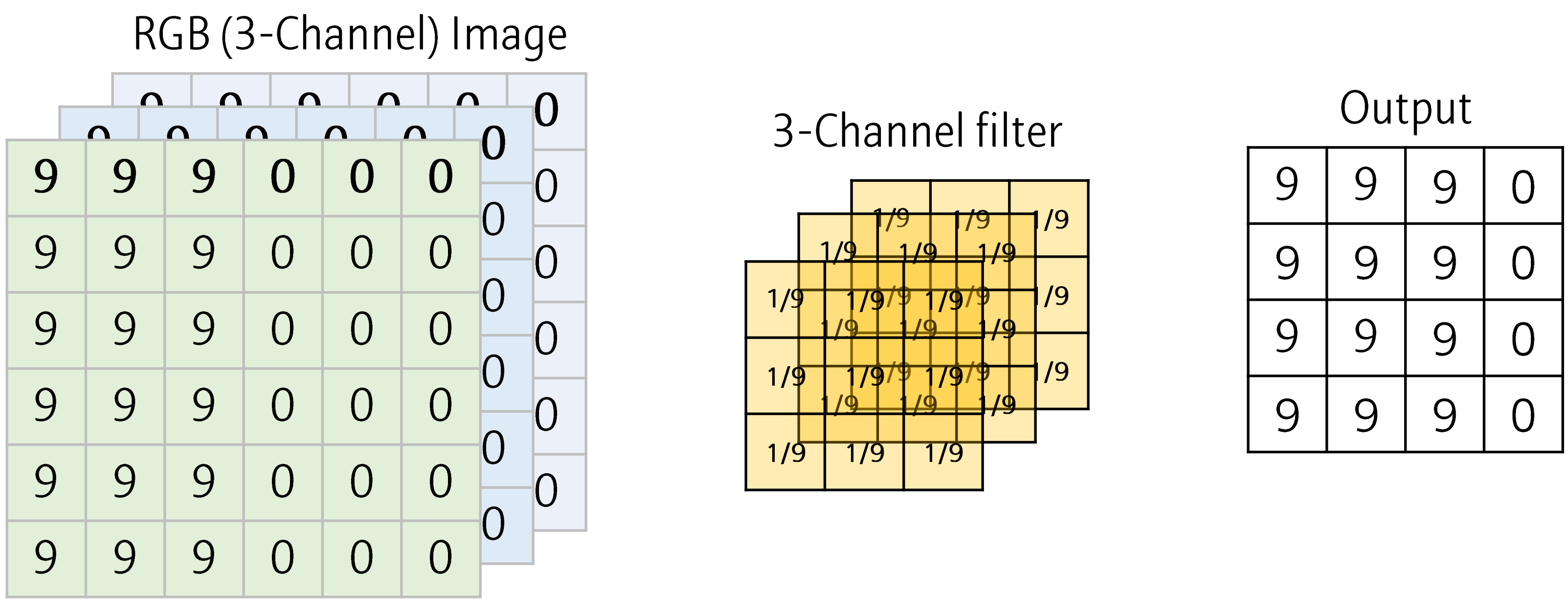
9	6	3	0
9	6	3	0
9	6	3	0
9	6	3	0

$$9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} + 9 \times \frac{1}{9} = 9$$

3. Convolutional Neural Network (CNN)

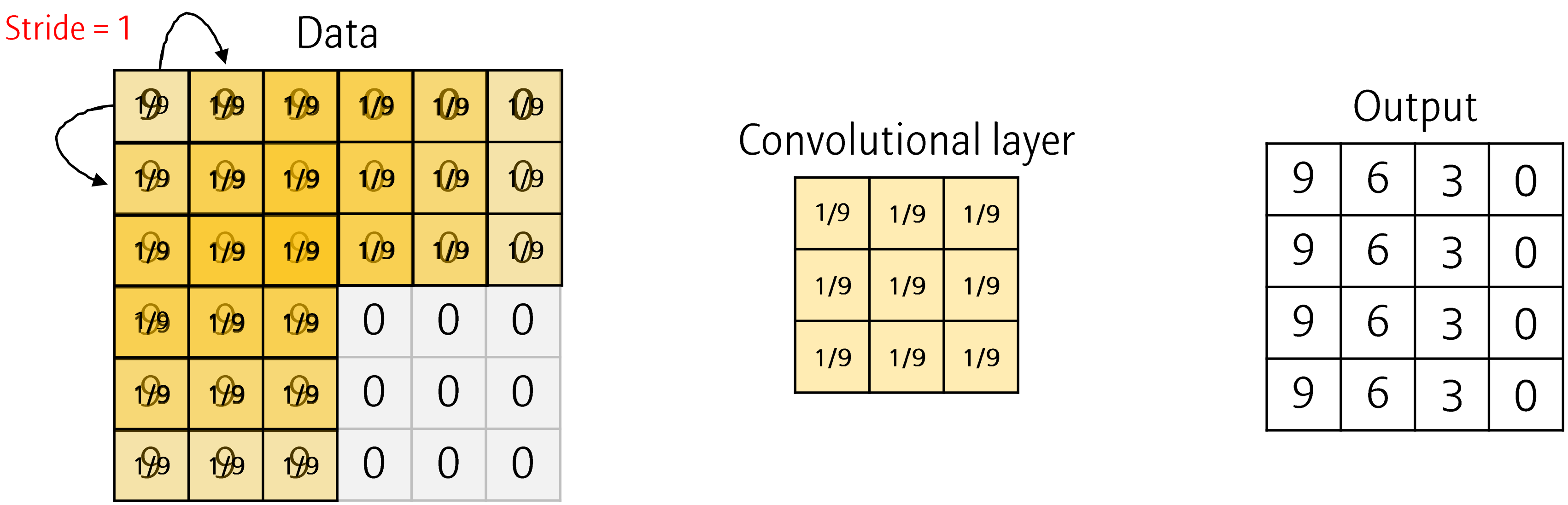
RGB image convolution

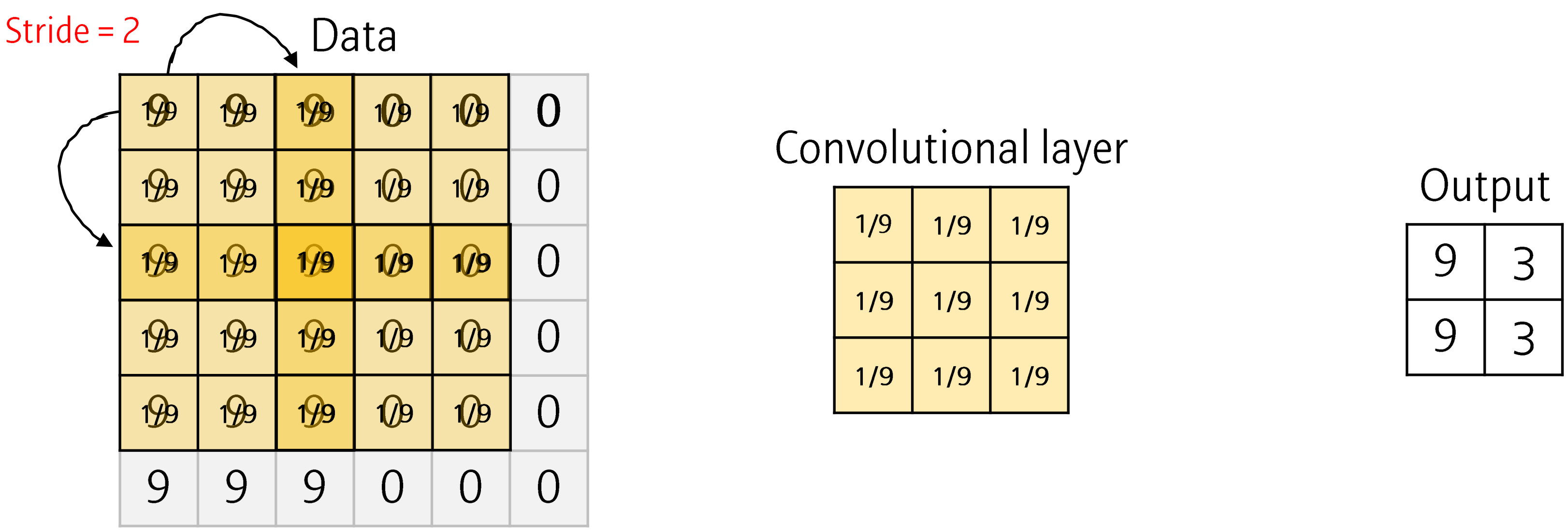
- 입력 이미지의 채널에 맞추어 Convolution filter의 크기도 조정된다



3. Convolutional Neural Network (CNN)

Strided convolution





3. Convolutional Neural Network (CNN)

Padding

Padding = 1

Data

0	0	0	0	0	0	0	0
0 1/9	9 1/9	9 1/9	9	0	0	0	0
0 1/9	9 1/9	9 1/9	9	0	0	0	0
0 1/9	9 1/9	9 1/9	9	0	0	0	0
0	9	9	9	0	0	0	0
0	9	9	9	0	0	0	0
0	9	9	9	0	0	0	0
0	0	0	0	0	0	0	0

Convolutional layer

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Output

4	6	4	2	0	0
6	9	6	3	0	0
6	9	6	3	0	0
6	9	6	3	0	0
6	9	6	3	0	0
4	6	4	2	0	0

3. Convolutional Neural Network (CNN)

Max Pooling layer

Data

9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0

Max Pooling layer

Output

9	9	9	0
9	9	9	0
9	9	9	0
9	9	9	0

$$\max(9,9,9,9,9,9,9,9,9) = 9$$

No parameter

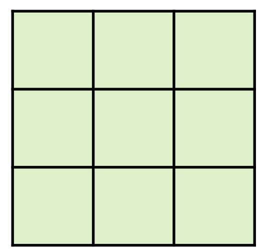
3. Convolutional Neural Network (CNN)

Average Pooling layer

Data

9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0
9	9	9	0	0	0

Average Pooling layer



Output

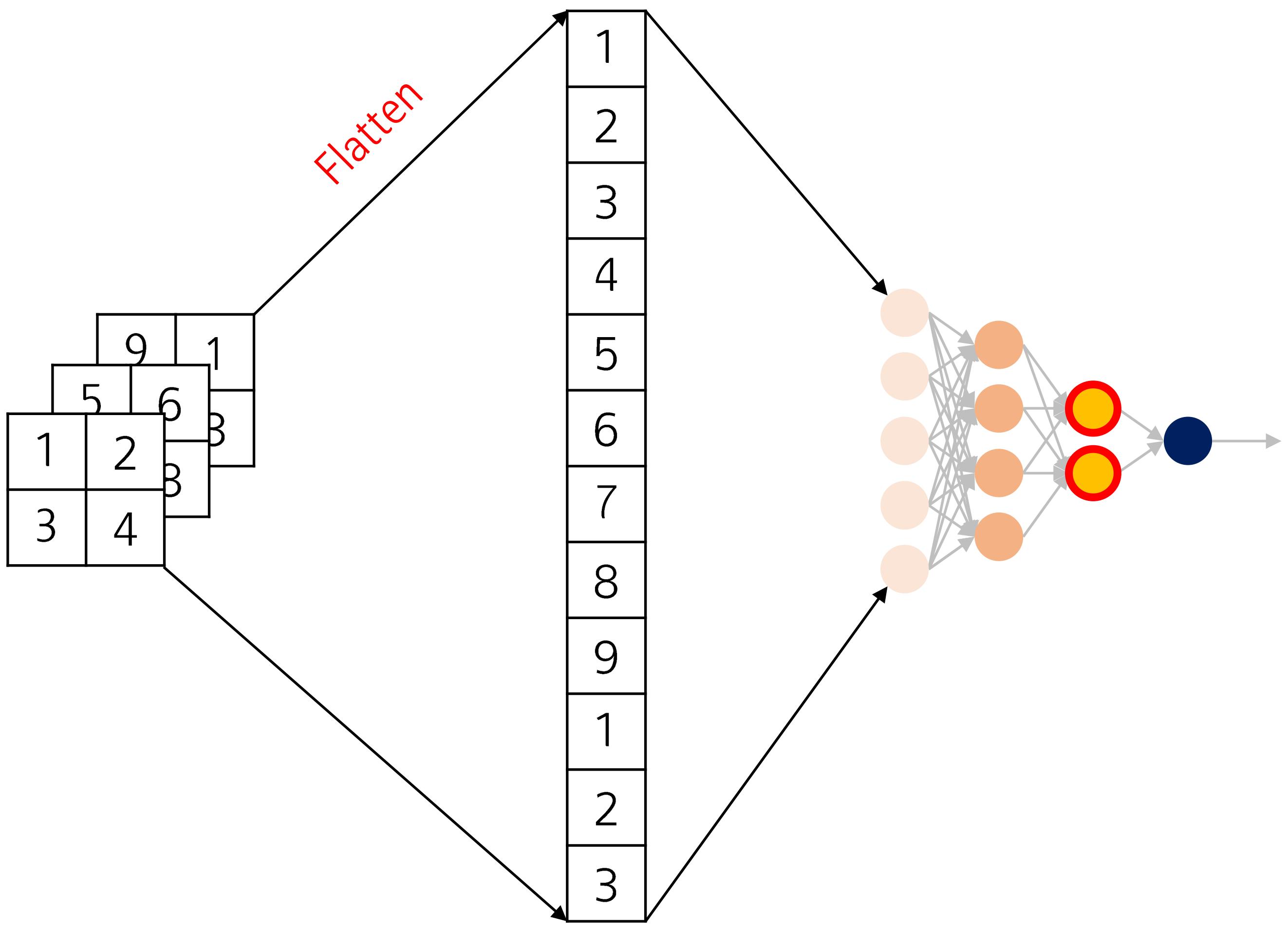
9	6	3	0
9	6	3	0
9	6	3	0
9	6	3	0

$$\frac{1}{9}(9+9+9+9+9+9+9+9+9) = 9$$

No parameter

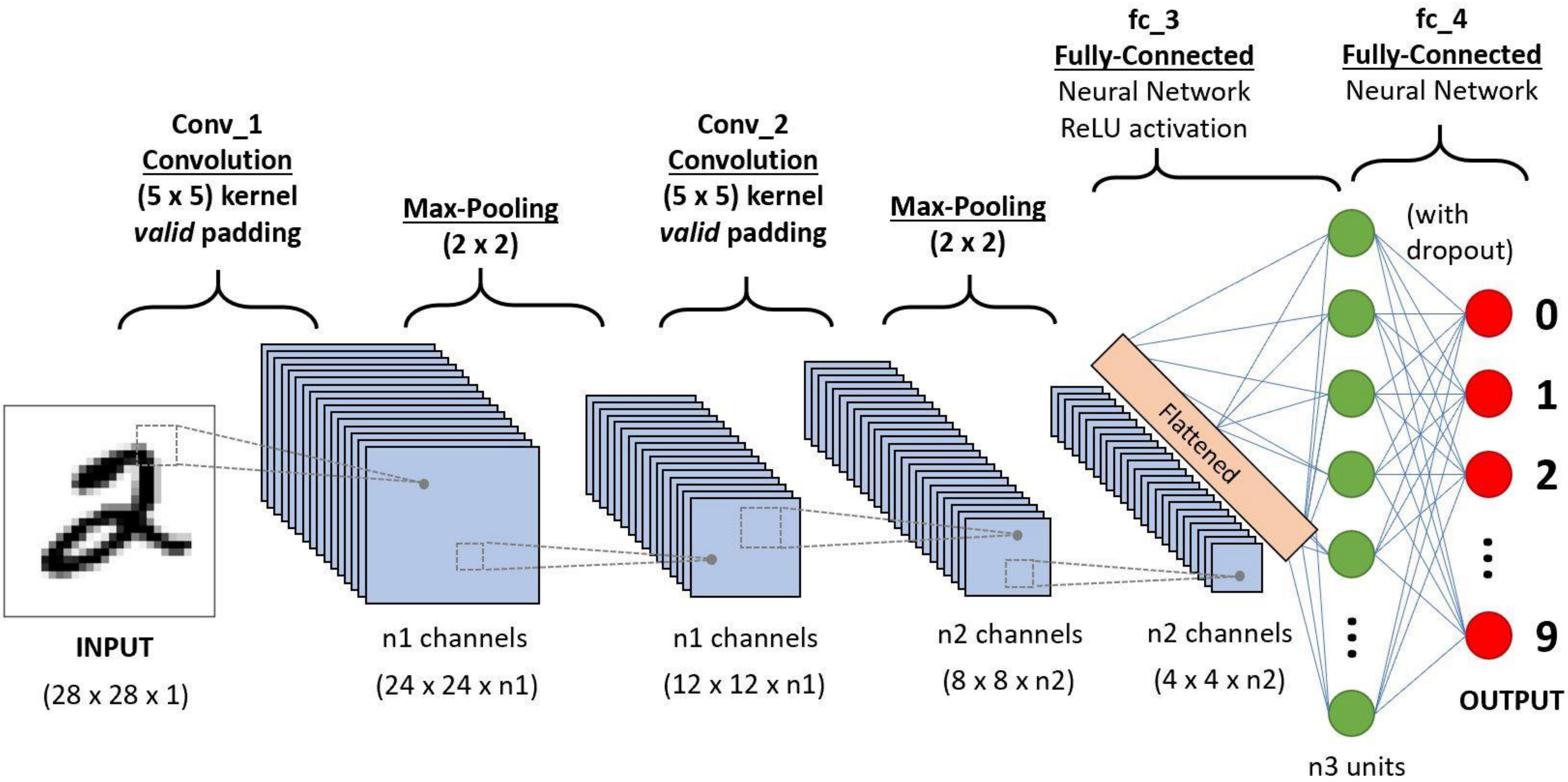
3. Convolutional Neural Network (CNN)

Fully-connected layer



3. Convolutional Neural Network (CNN)

Overall pipeline



6. 3D CNN with demographic scores

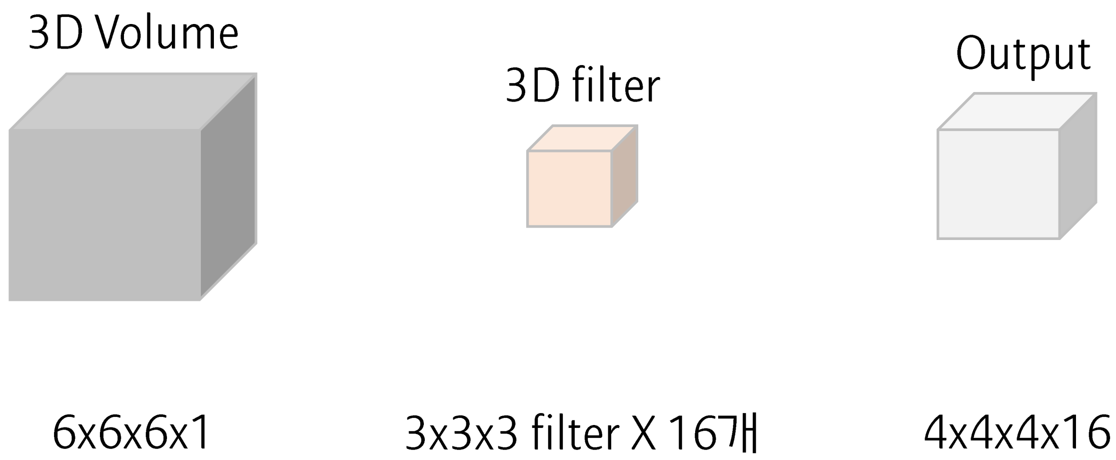
흐름상 여기가 더 어울려서 앞으로 가져옴

- 의료영상은 3D 이미지인 경우가 많음

6. 3D CNN with demographic scores

3D CNN

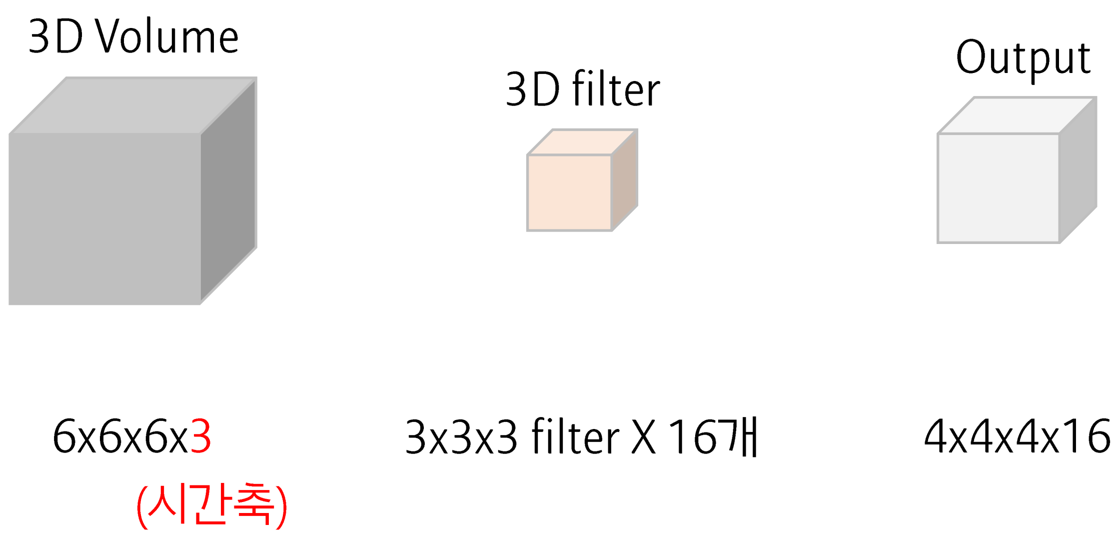
- 2D CNN과 거의 비슷하다



6. 3D CNN with demographic scores

3D CNN with multiple images

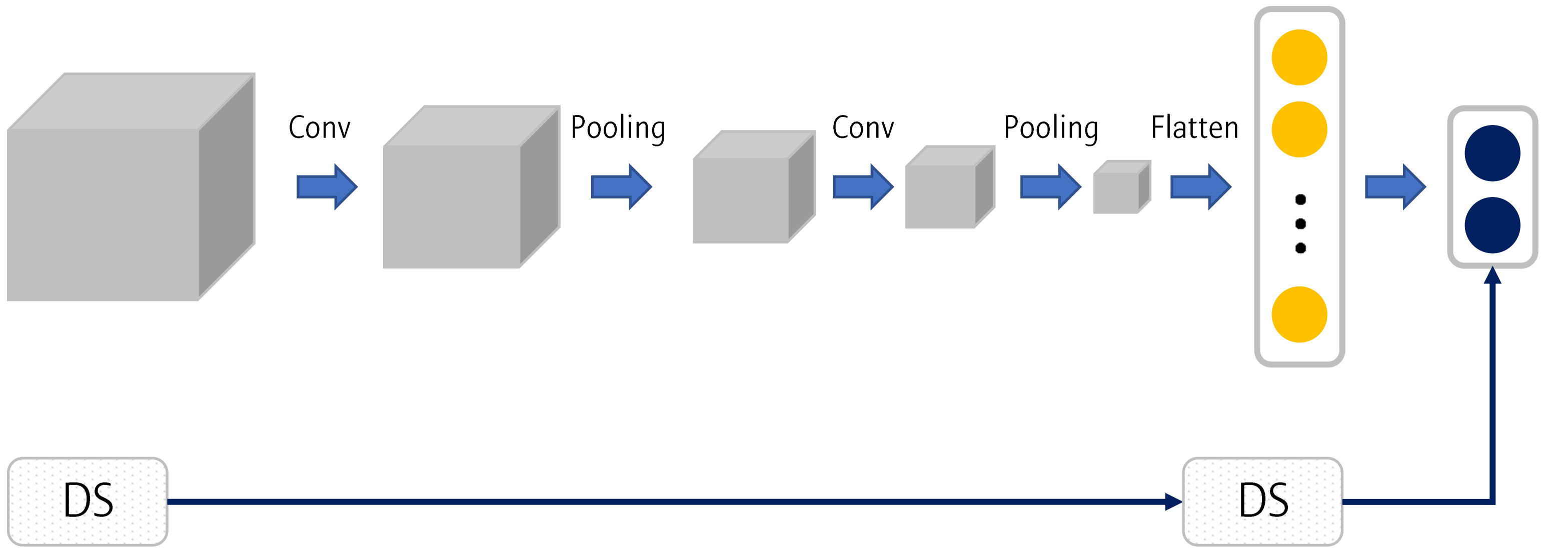
- T1-weighted, T2-weighted 등 여러 이미지를 사용하는 경우
  - 인풋 채널이 증가된다고 보면 됨 (2D 예시: 흑백 이미지 → RGB 이미지)



6. 3D CNN with demographic scores

3D CNN with demographic scores

- 이런 구조가 가능함. 마찬가지로 DS의 모든 분포에 대해 충분한 샘플이 있어야 함.



4. Advanced CNN

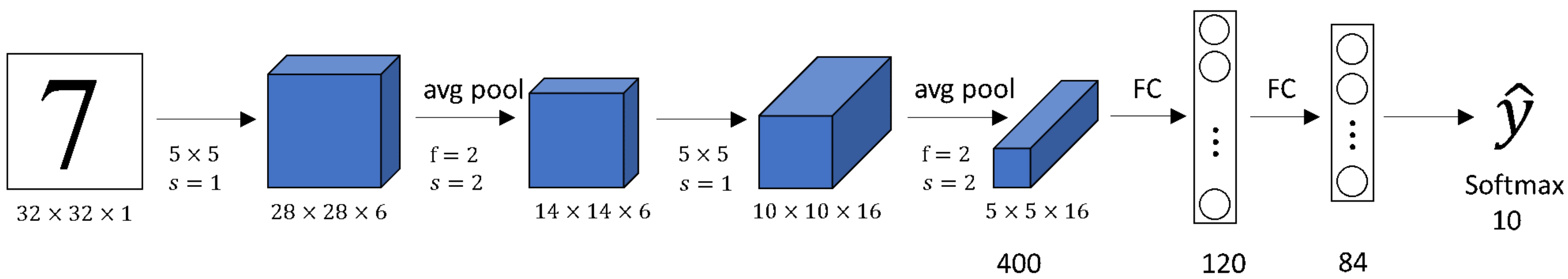
Advanced CNN architectures

- LeNet-5
- AlexNet
- Inception (GoogLeNet)
- VGGNet
  - VGG-16
  - VGG-19
- ResNet
- DenseNet

4. Advanced CNN

LeNet-5 (1998)

뒤로 갈 수록, Feature map의 사이즈가 줄어드는 대신, 채널 수 증가



60k parameters

$n_{h,} n_w \downarrow$ $\quad n_{c,} \uparrow$

conv pool conv pool FC FC output

Simple CNN architecture

4. Advanced CNN

AlexNet (2012)

초반: 큰 stride로 사이즈를 크게 줄임

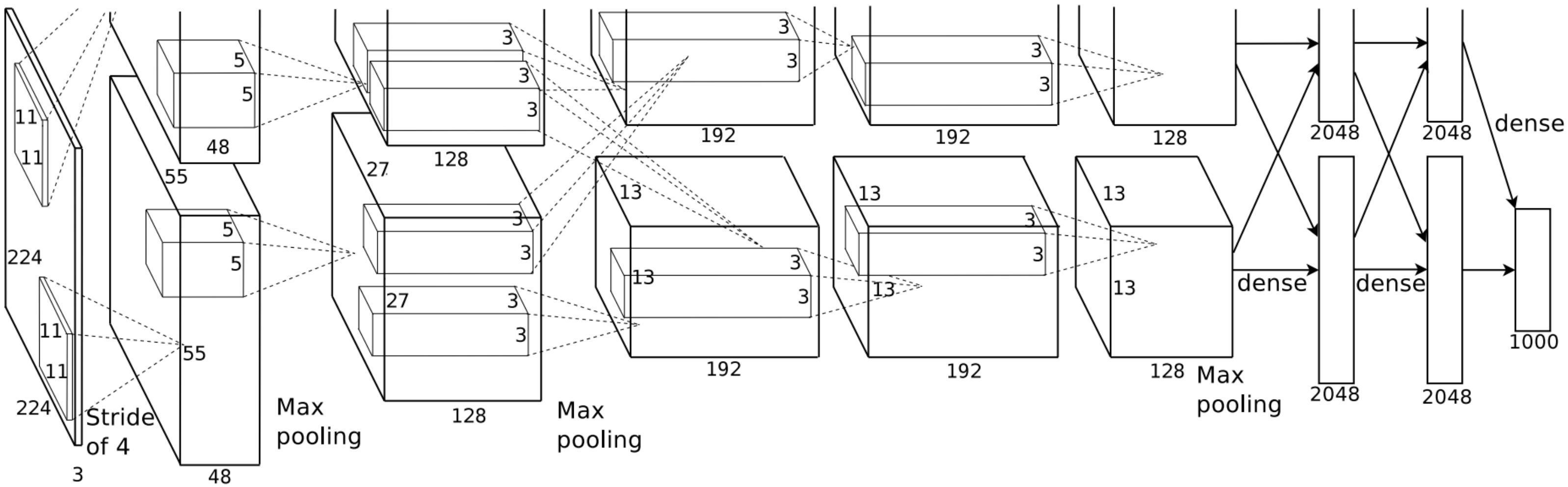


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

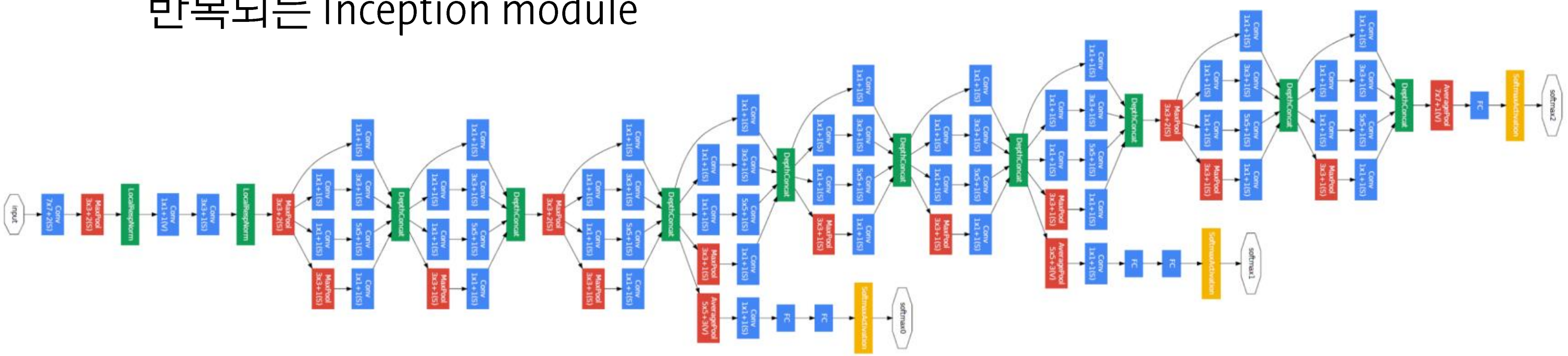
Max-pooling layer

ReLU activation function

4. Advanced CNN

Inception (2014)

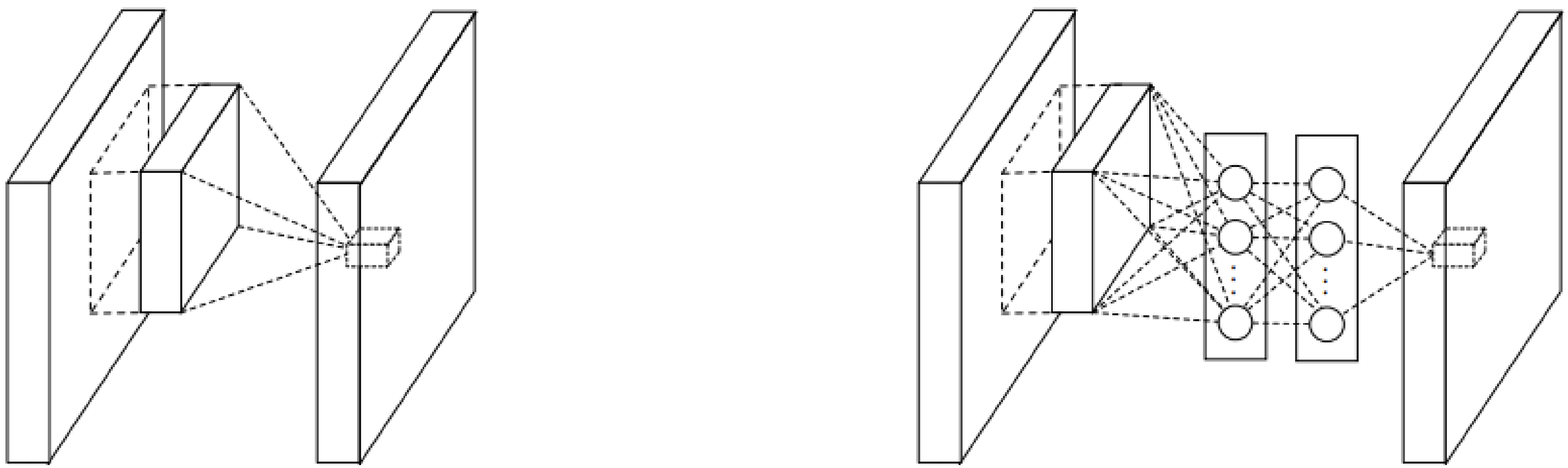
반복되는 Inception module



중간 중간 Cost 계산

4. Advanced CNN

Inception (2014) – Network In Network (2013)

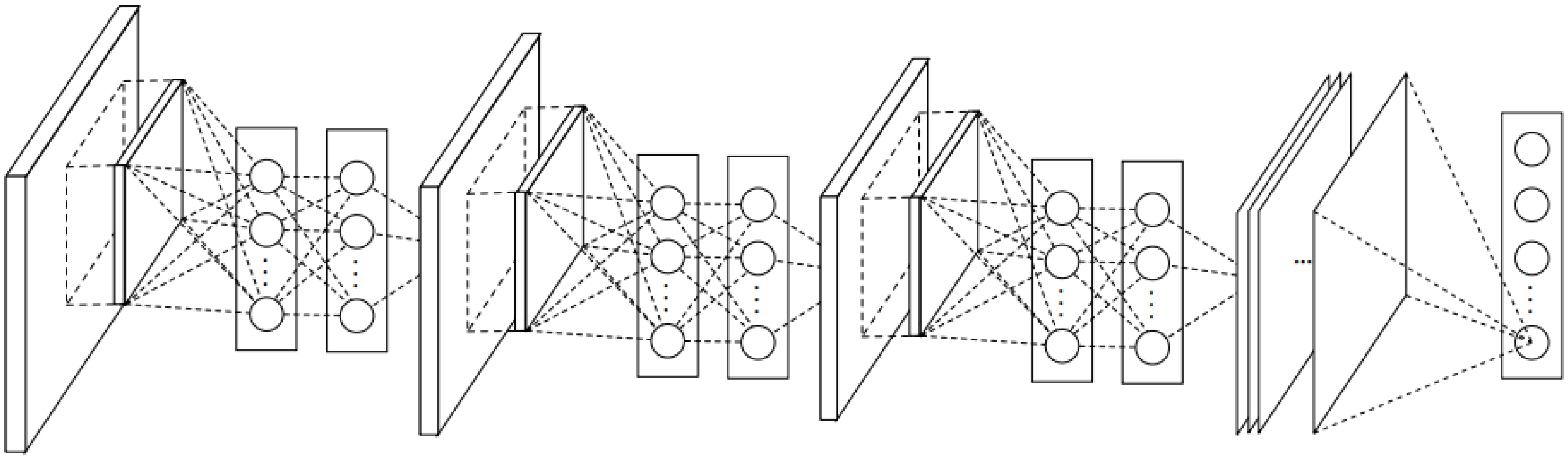


(a) Linear convolution layer

(b) Mlpconv layer

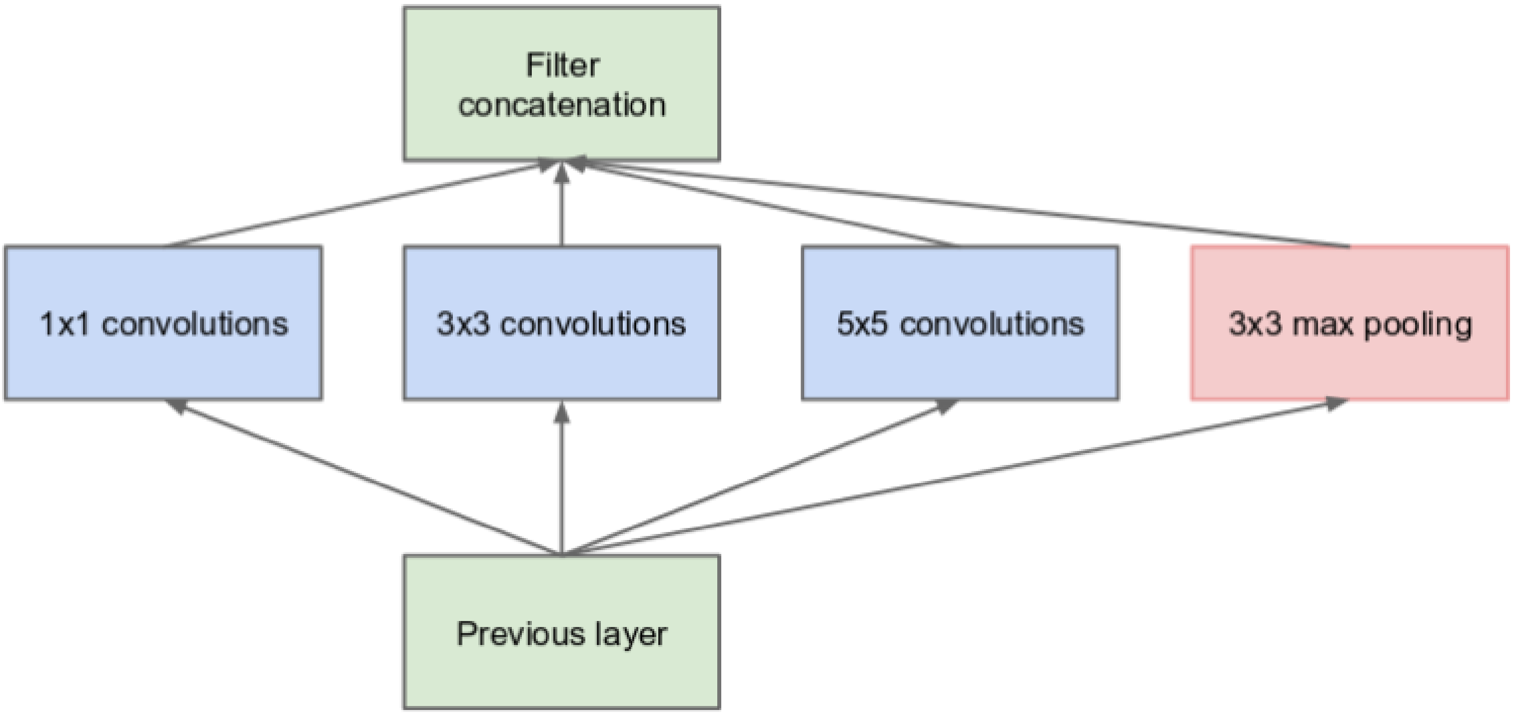
4. Advanced CNN

Inception (2014) – Network In Network (2013)



4. Advanced CNN

Inception (2014) – Inception module



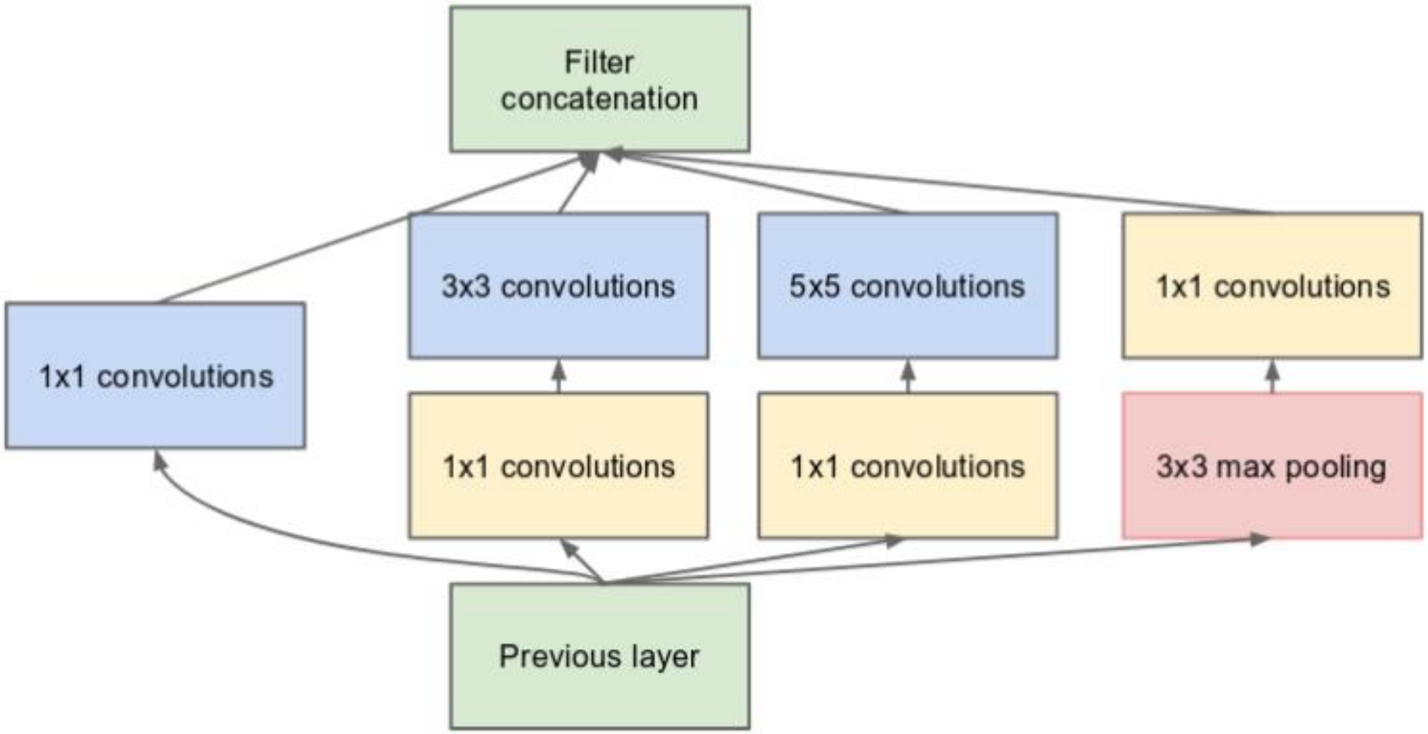
(a) Inception module, naïve version

다양한 크기의 필터를 만들어 이를 concatenate해서 사용

후반부 레이어에서는 depth (채널 개수)가 너무 깊어져서 computational cost가 너무 증가

4. Advanced CNN

Inception (2014) – Inception module with dimension reductions



(b) Inception module with dimension reductions

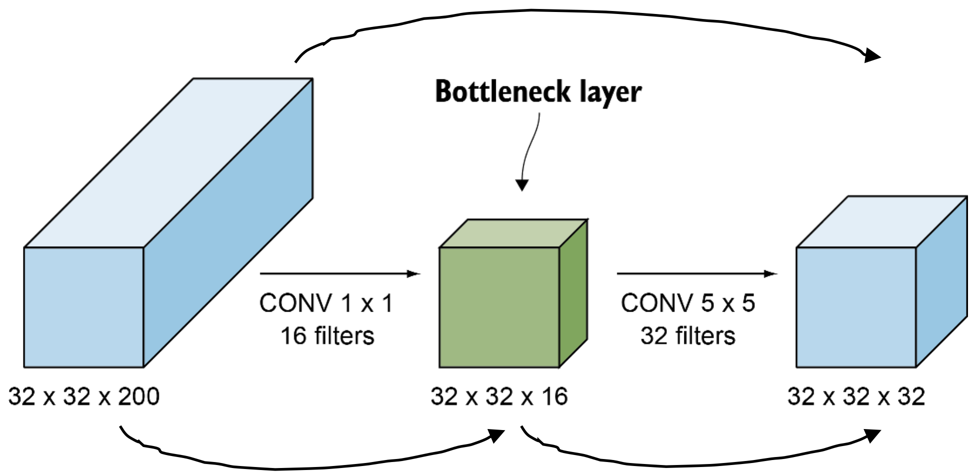
1x1 필터의 사용

4. Advanced CNN

Inception (2014) – 1x1 Conv filter

- 1x1 Conv filter
    - Depth 감소 (1x1보다 큰 필터를 써도 되긴 하지만, computational cost 최소를 위해 1x1 사용)
- 비선형성 증가
    - More activation functions
- Computational cost 감소
    - 163M ➔ 4.3M

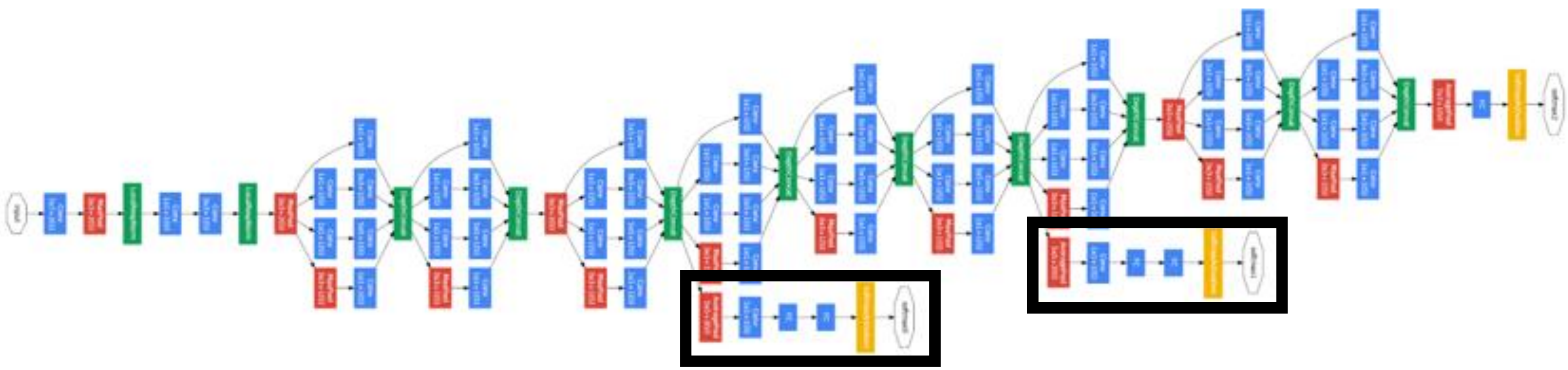
$$(5 \times 5 \times 200) \times (32 \times 32 \times 32) = 163\text{M}$$



$$(1 \times 1 \times 200) \times (32 \times 32 \times 16) = 3M \qquad (5 \times 5 \times 16) \times (32 \times 32 \times 32) = 1.3M$$

4. Advanced CNN

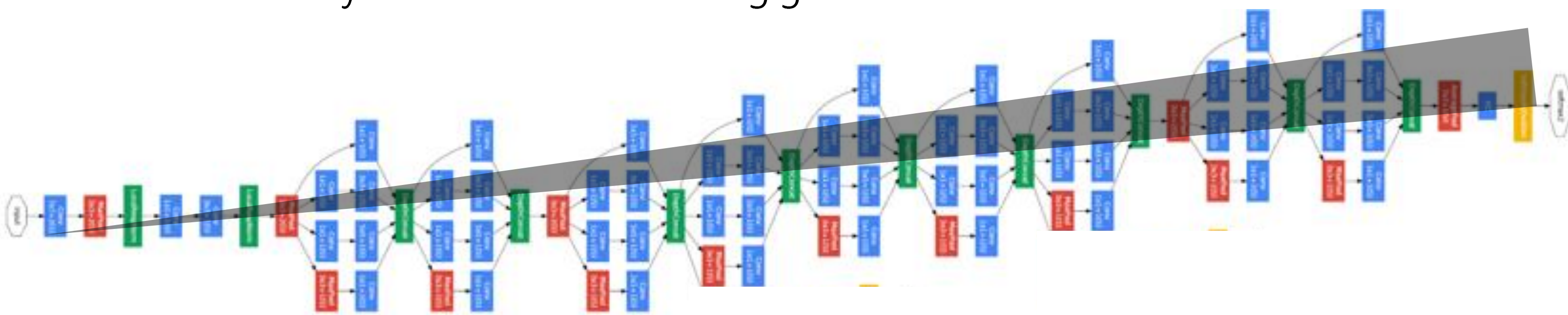
Inception (2014) – Auxiliary classifier



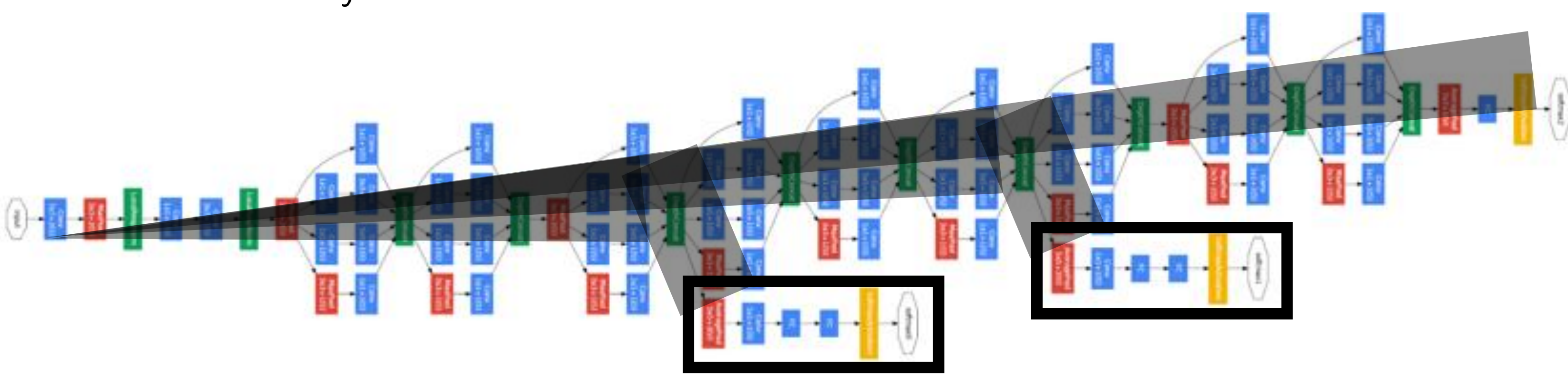
4. Advanced CNN

Inception (2014) – Auxiliary classifier

Without Auxiliary classifier ➔ Vanishing gradient

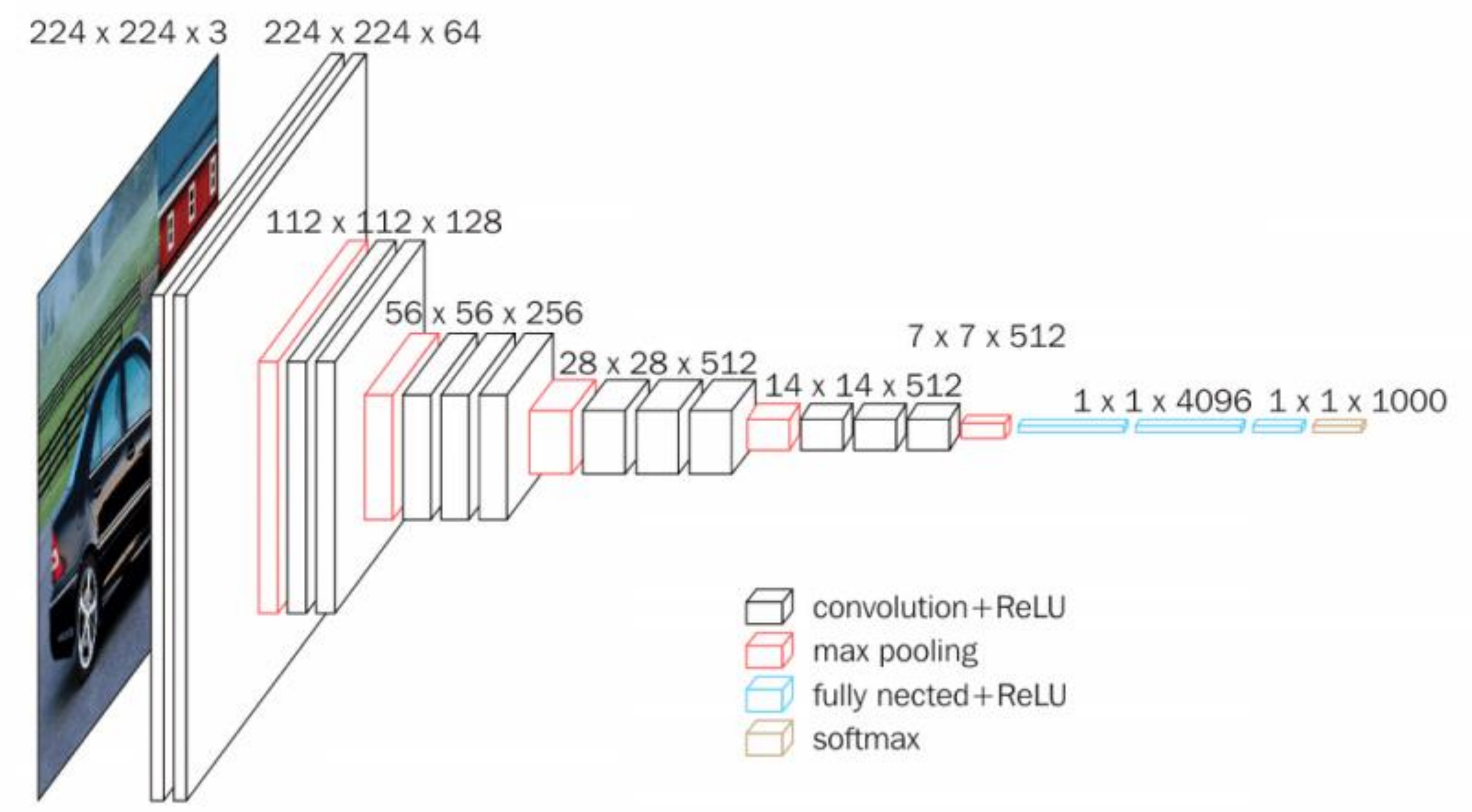


Without Auxiliary classifier



4. Advanced CNN

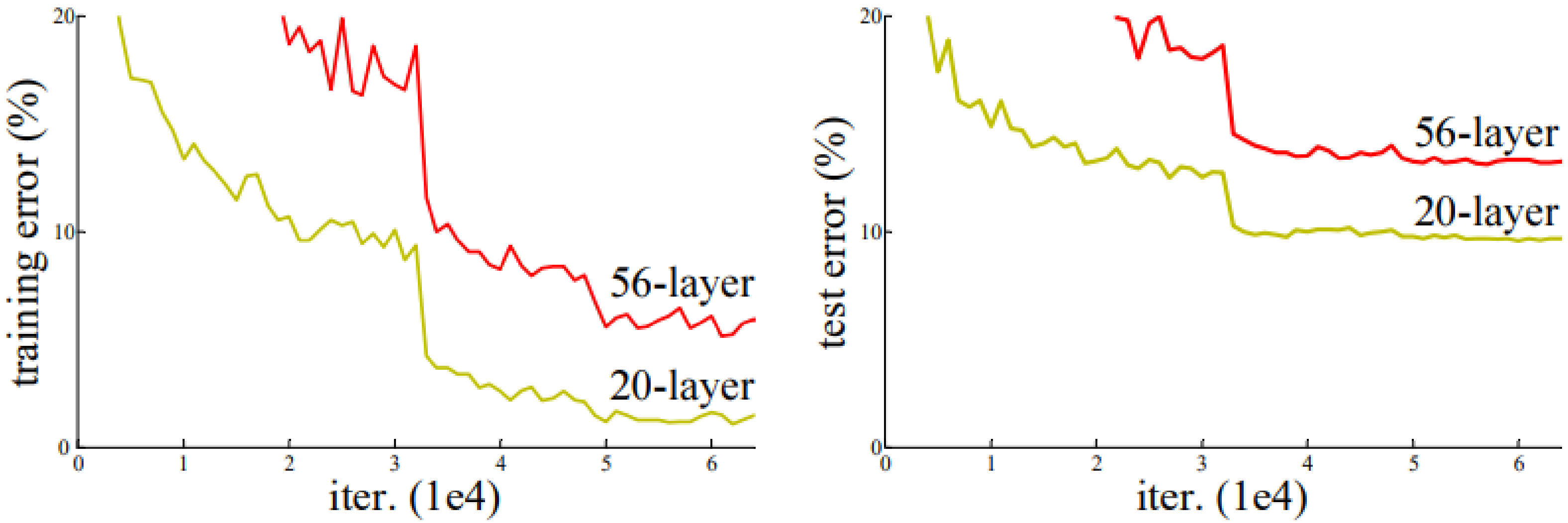
VGGNet (2014)



3x3 Convolution filter만 사용

4. Advanced CNN

ResNet (2015) - Motivation

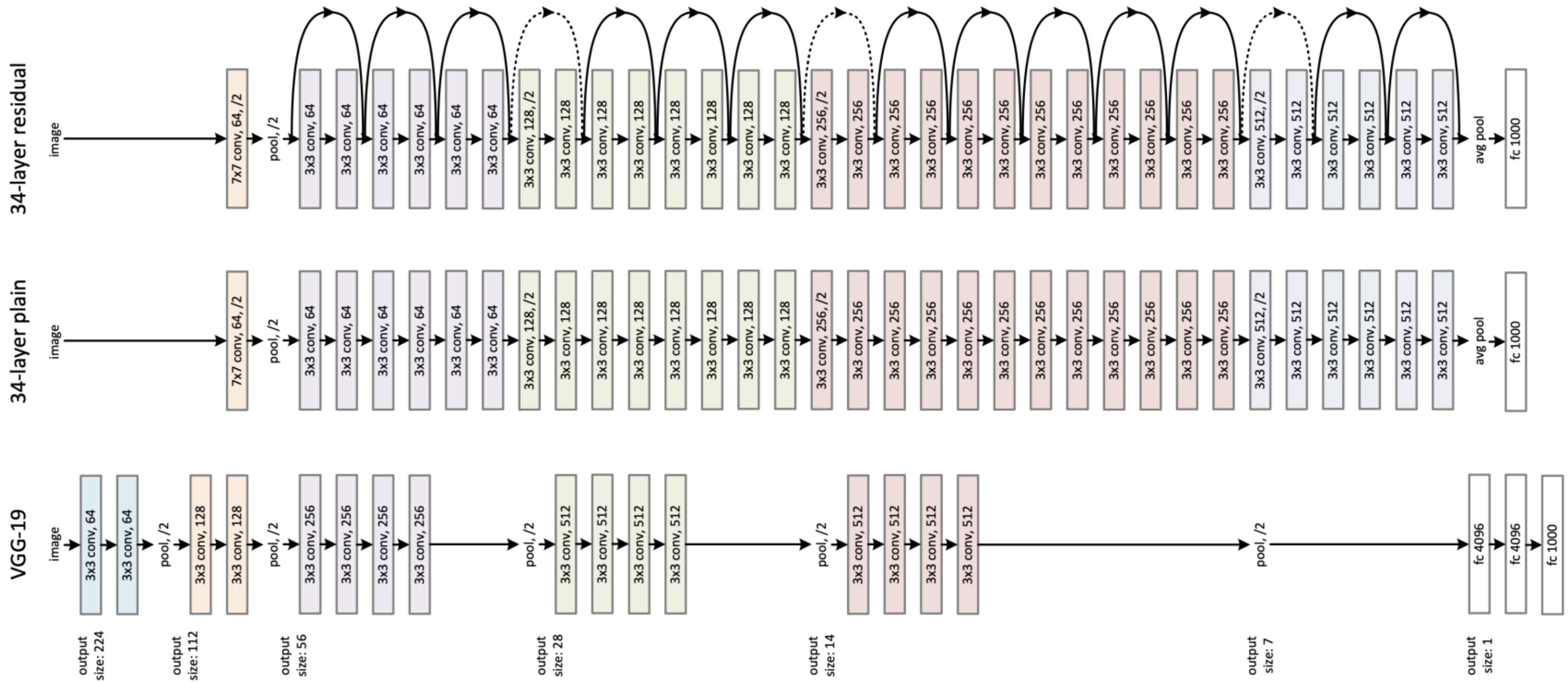


네트워크가 깊어졌음에도, Trainnig/Test 모두에서 성능이 더 안 좋다

https://arxiv.org/pdf/1512.03385.pdf

4. Advanced CNN

ResNet (2015)

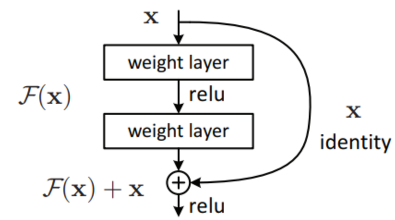


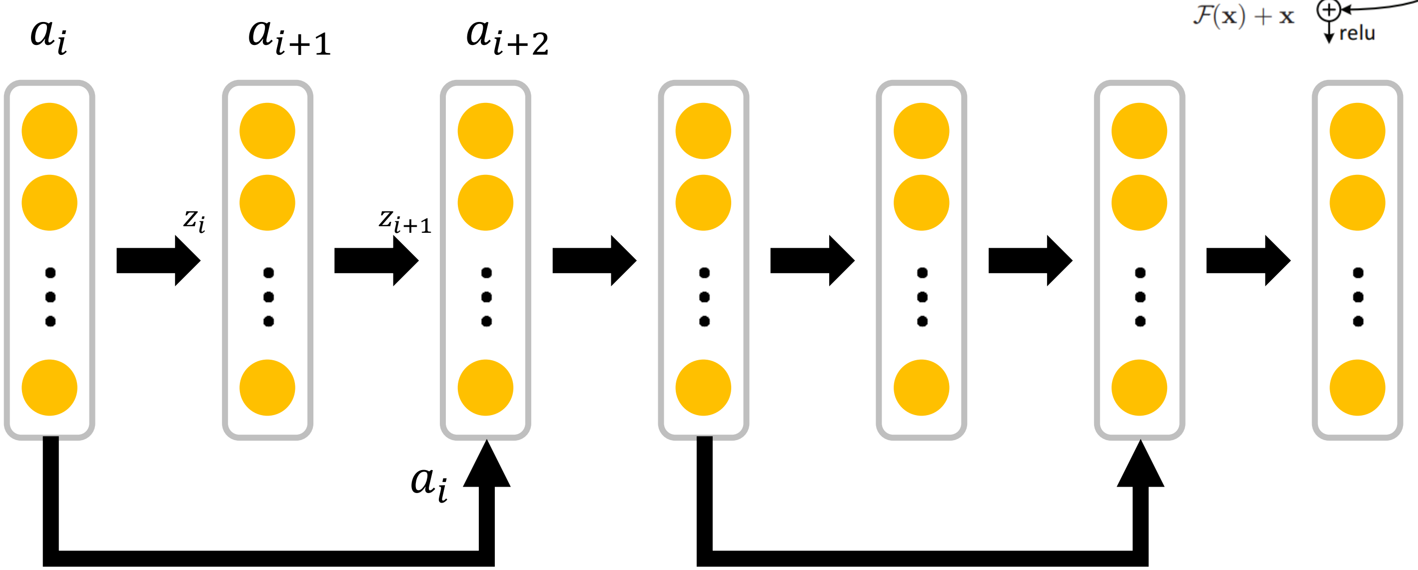
https://arxiv.org/pdf/1512.03385.pdf

4. Advanced CNN

ResNet (2015)

- 일반적으로 Test 할 때는, 레이어가 많으면 Overfitting 많이 됨.
- 그런데 일반적인 CNN 모델의 경우, 레이어가 너무 많으면 Training data에 대해서도 Error가 떨어짐.
- Residual block을 쓰면 이런 문제가 없음





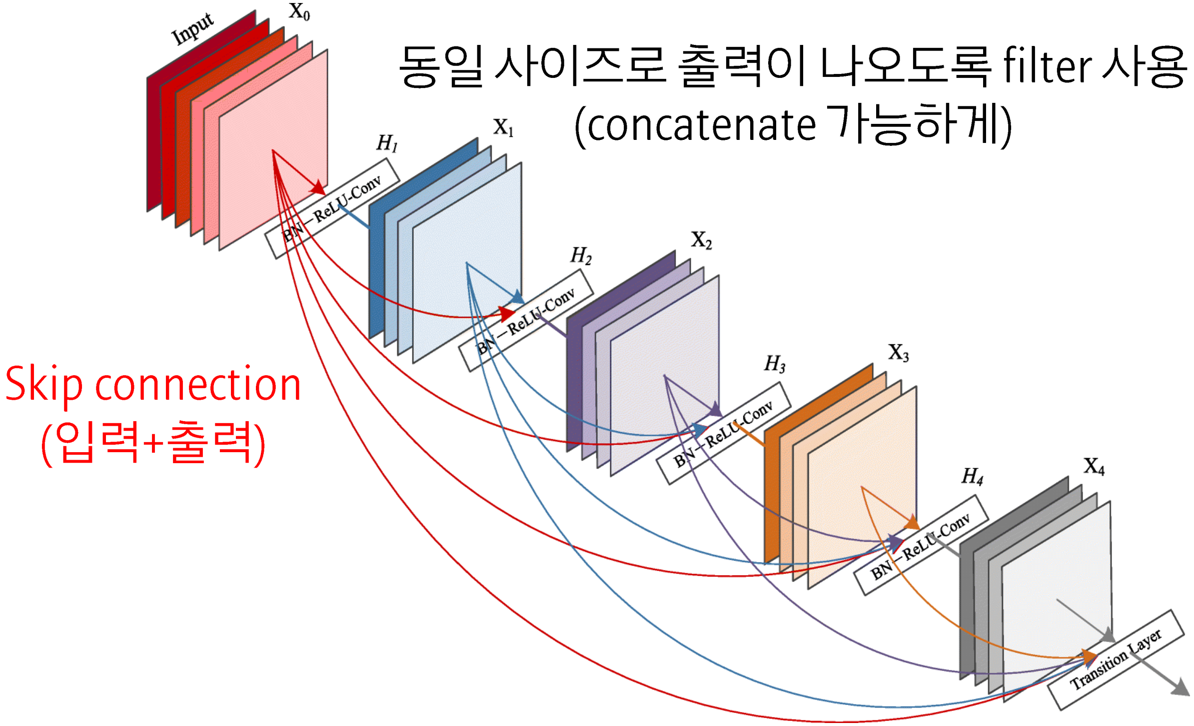
Skip connection

$$a_{i+2} = \sigma(z_{i+1} + a_i)$$

4. Advanced CNN

Dense Net (2017)

- Skip connection을 더 dense하게 사용



Gradient descent가 더 잘 일어남

4. Advanced CNN

성능 비교