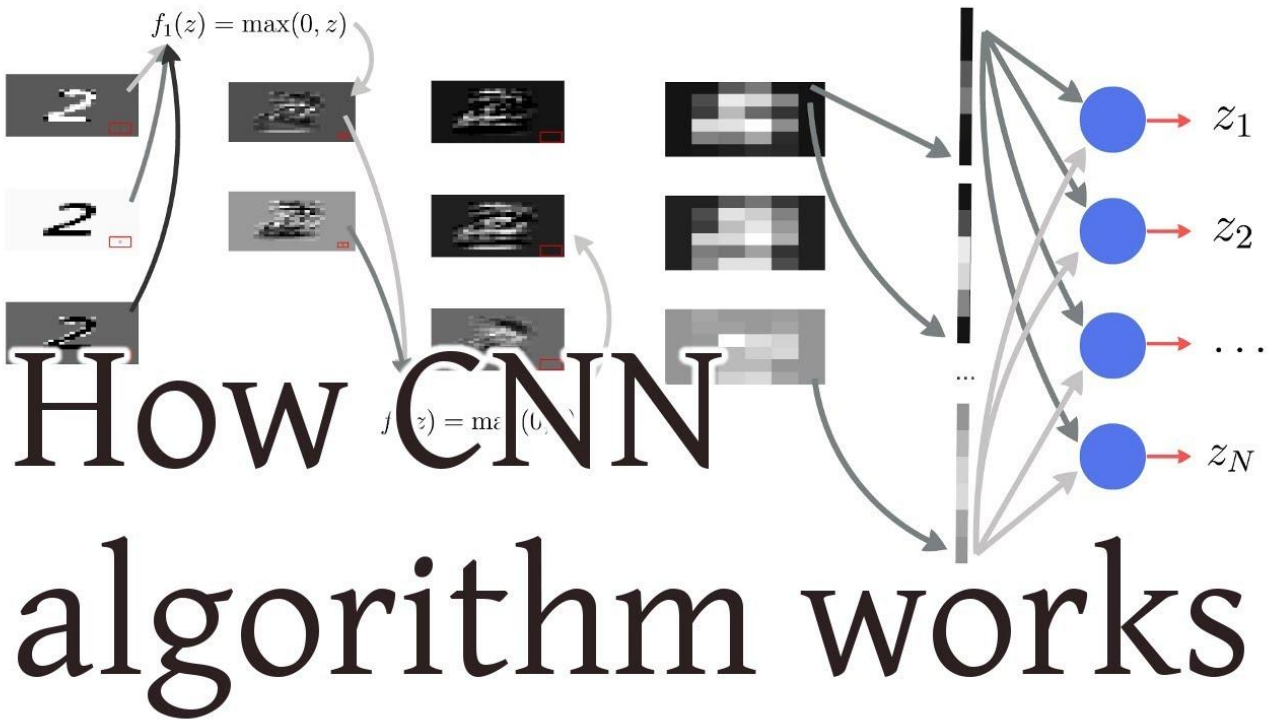
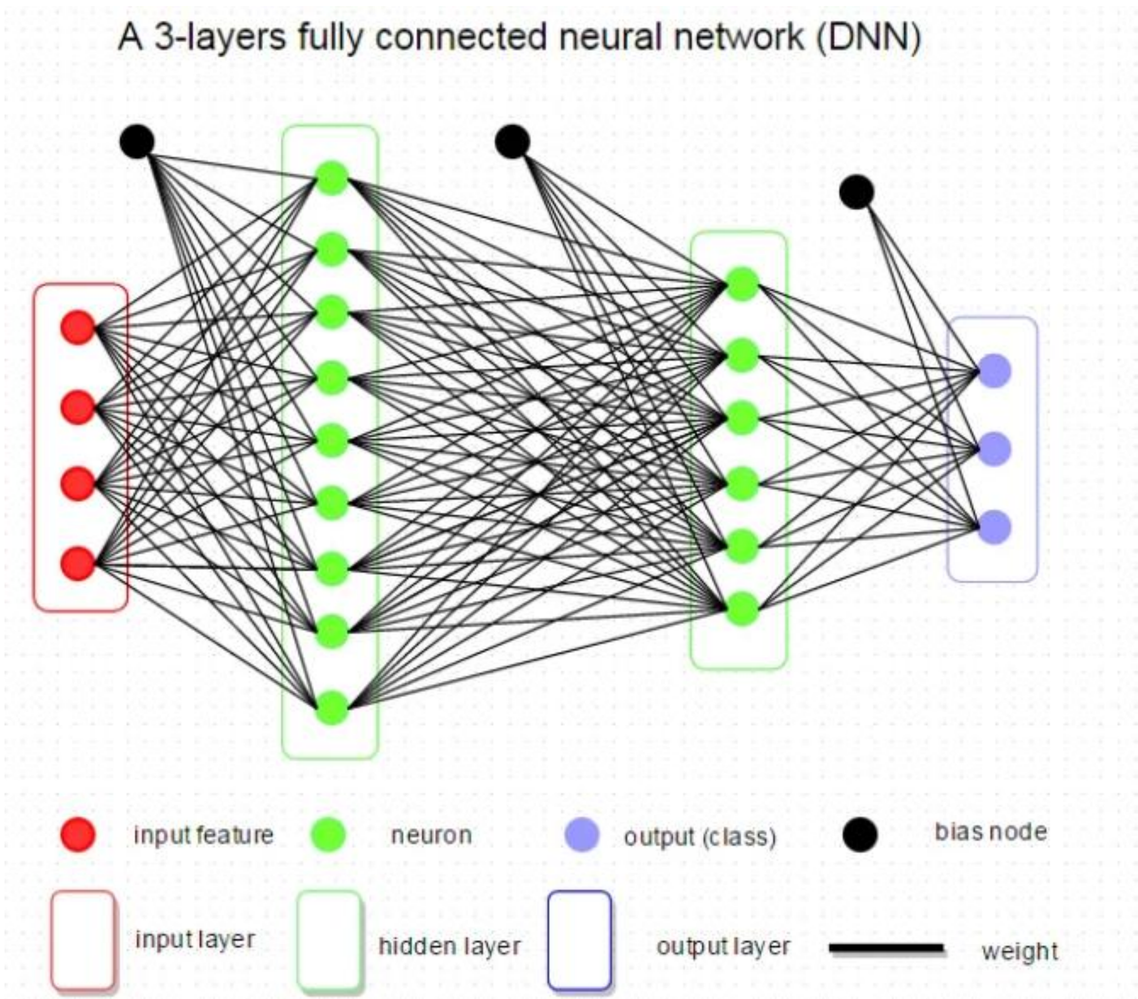
Convolutional Neural Network (CNN)

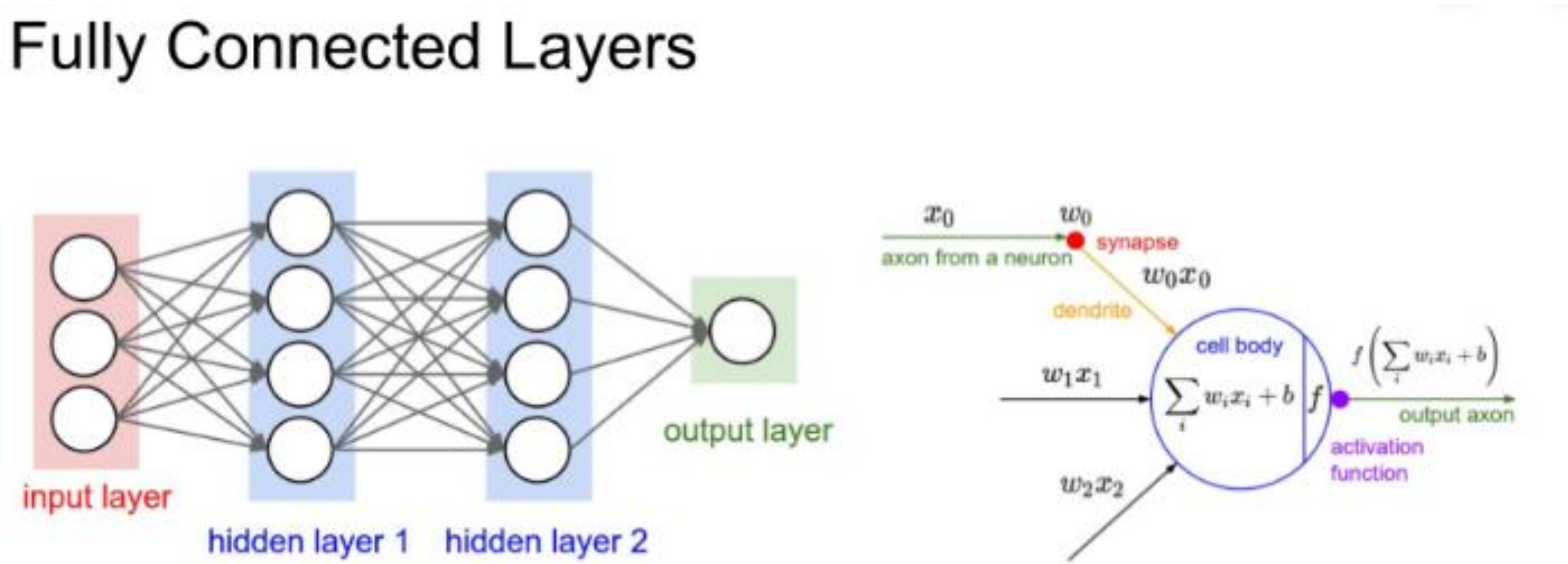


191127 이승한

[복습] Fully Connected Layer (전결합 계층)

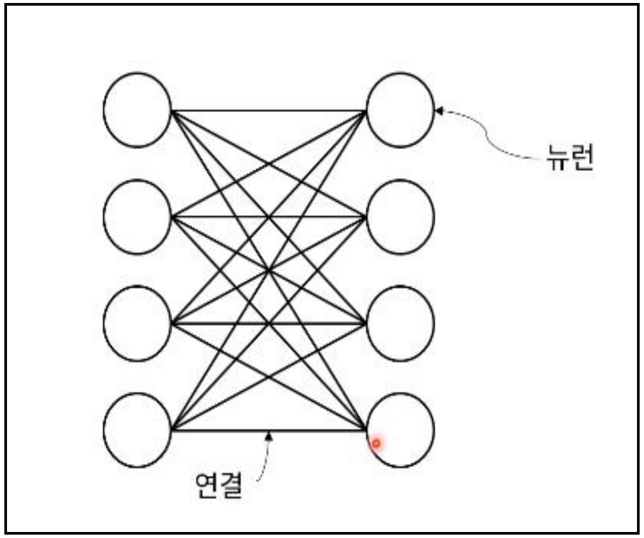


[복습] Fully Connected Layer (전결합 계층)

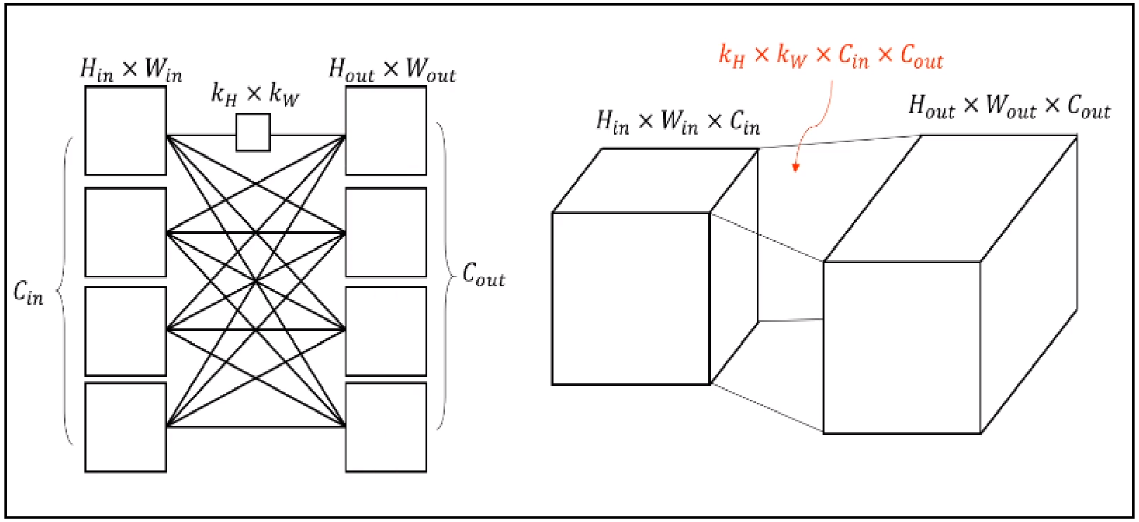


1. What is Convolutional Layer?

[Fully Connected Layer]
전결합 계층



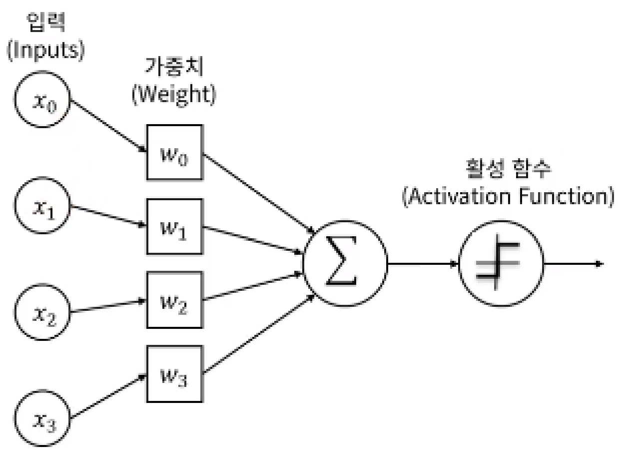
[Convolutional Layer]
합성곱 계층



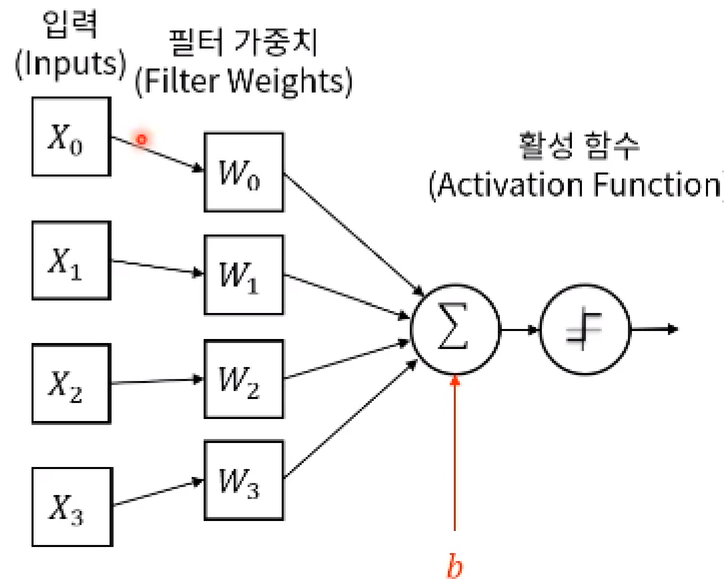
What's the difference?

1. What is Convolutional Layer?

[Fully Connected Layer]
전결합 계층



[Convolutional Layer]
합성곱 계층



(FC) 입력 -> (Conv) 입력 사진/영상

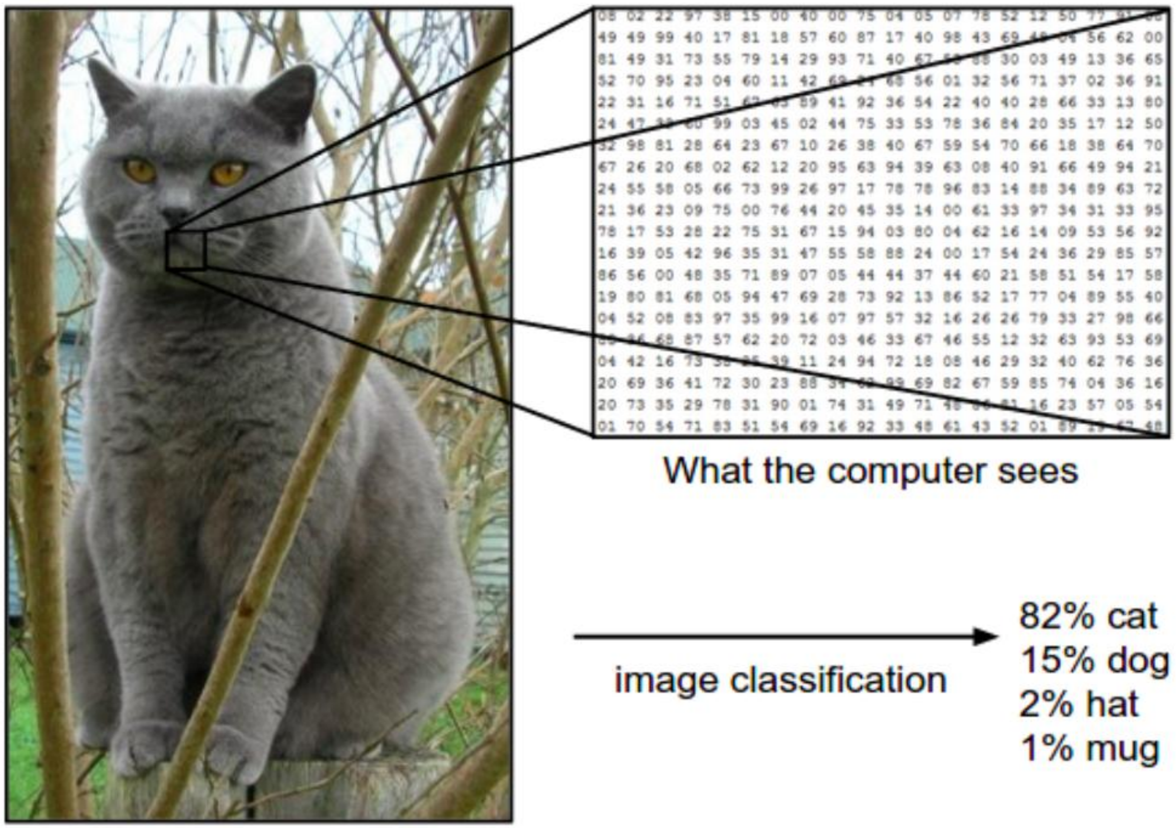
(FC) 가중치 -> (Conv) 필터

(FC) 곱 -> (Conv) 합성곱

Not so different!

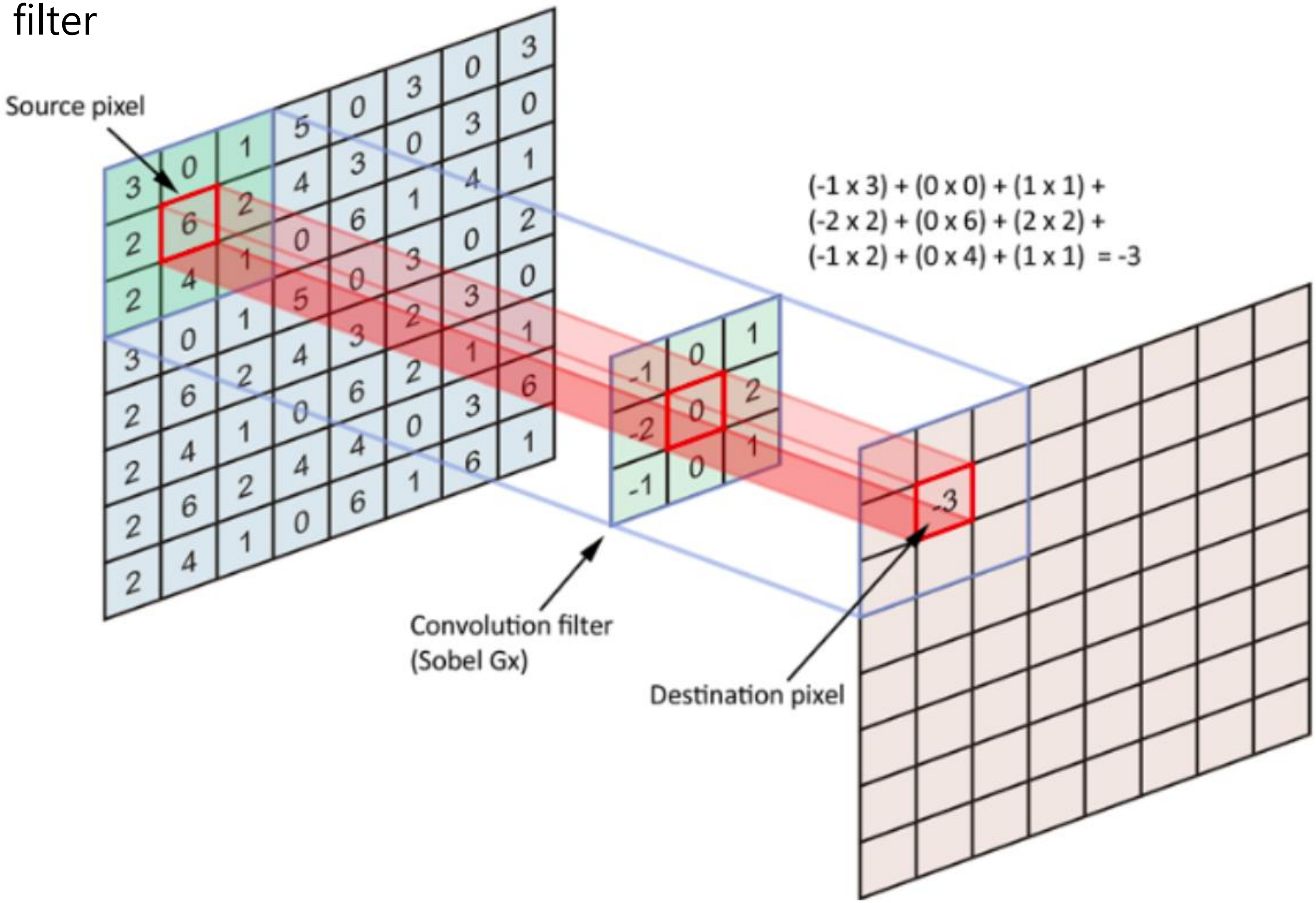
1. What is Convolutional Layer?

(1) input



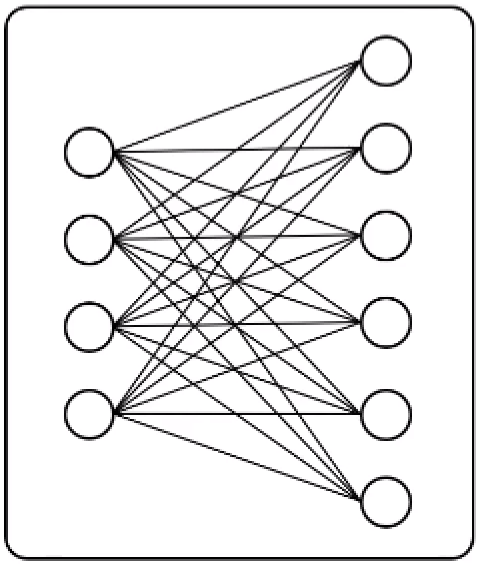
1. What is Convolutional Layer?

(2) filter



2. Convolutional Layer – 수식적 표현

(1) FC의 수식적 표현

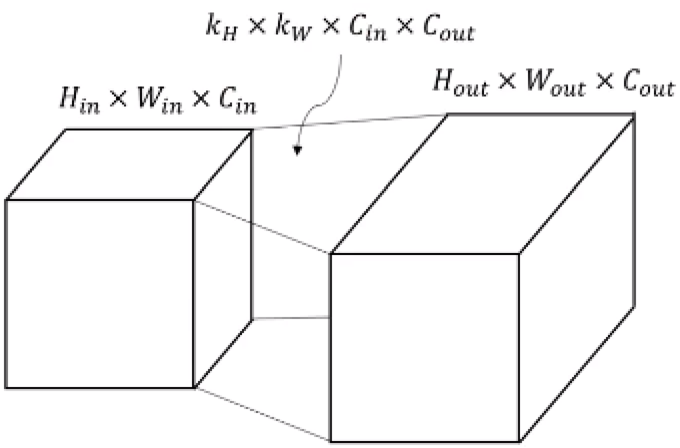


$$W = [\boldsymbol{w}_0, \boldsymbol{w}_1, \dots, \boldsymbol{w}_{M-1}]^T$$
$$\boldsymbol{b} = [b_0, b_1, \dots, b_{M-1}]^T$$

$$\left.\begin{aligned} y_0 &= a(\boldsymbol{w}_0^T\boldsymbol{x} + b_0) \\ y_1 &= a(\boldsymbol{w}_1^T\boldsymbol{x} + b_1) \\ &\vdots \\ y_{M-1} &= a(\boldsymbol{w}_{M-1}^T\boldsymbol{x} + b_{M-1}) \end{aligned}\right\} \boxed{\boldsymbol{y} = a(W\boldsymbol{x} + \boldsymbol{b})}$$

뉴런들이 곱해진 뒤, 모두 더해짐! (Matrix 곱 연산으로 표현)

(2) Conv의 수식적 표현



보통 3x3, 5x5, 7x7 등을 사용

$\mathbb{R}^{k_H \times k_W \times C_{in} \times C_{out}}$

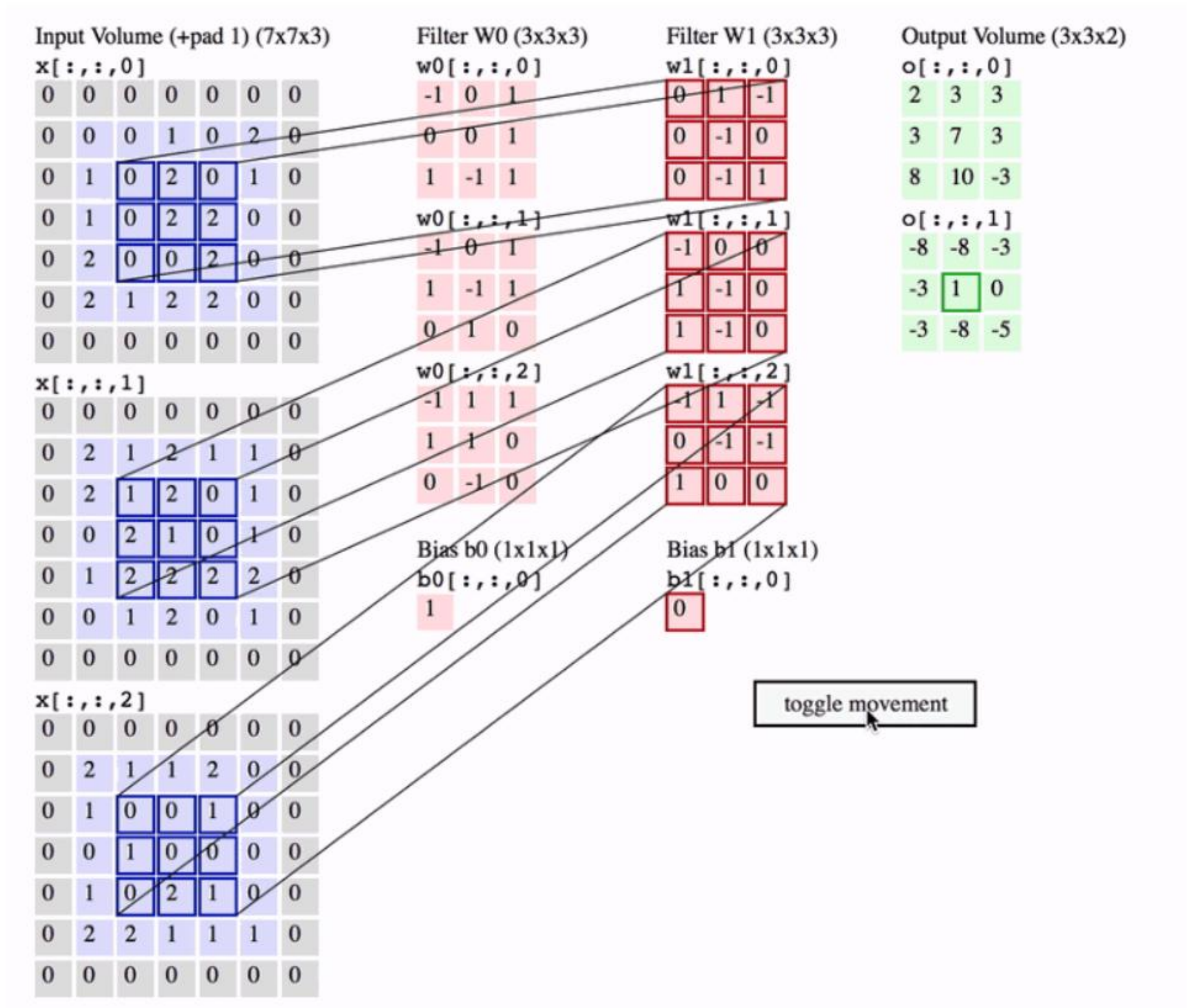
$$\boldsymbol{W} = \begin{bmatrix} \boxed{W_{0,0}} & \cdots & W_{0,M-1} \\ \vdots & \ddots & \vdots \\ W_{N-1,0} & \cdots & W_{N-1,M-1} \end{bmatrix}$$

$$\boldsymbol{b} = [b_0, b_1, \ldots, b_{M-1}]^T$$

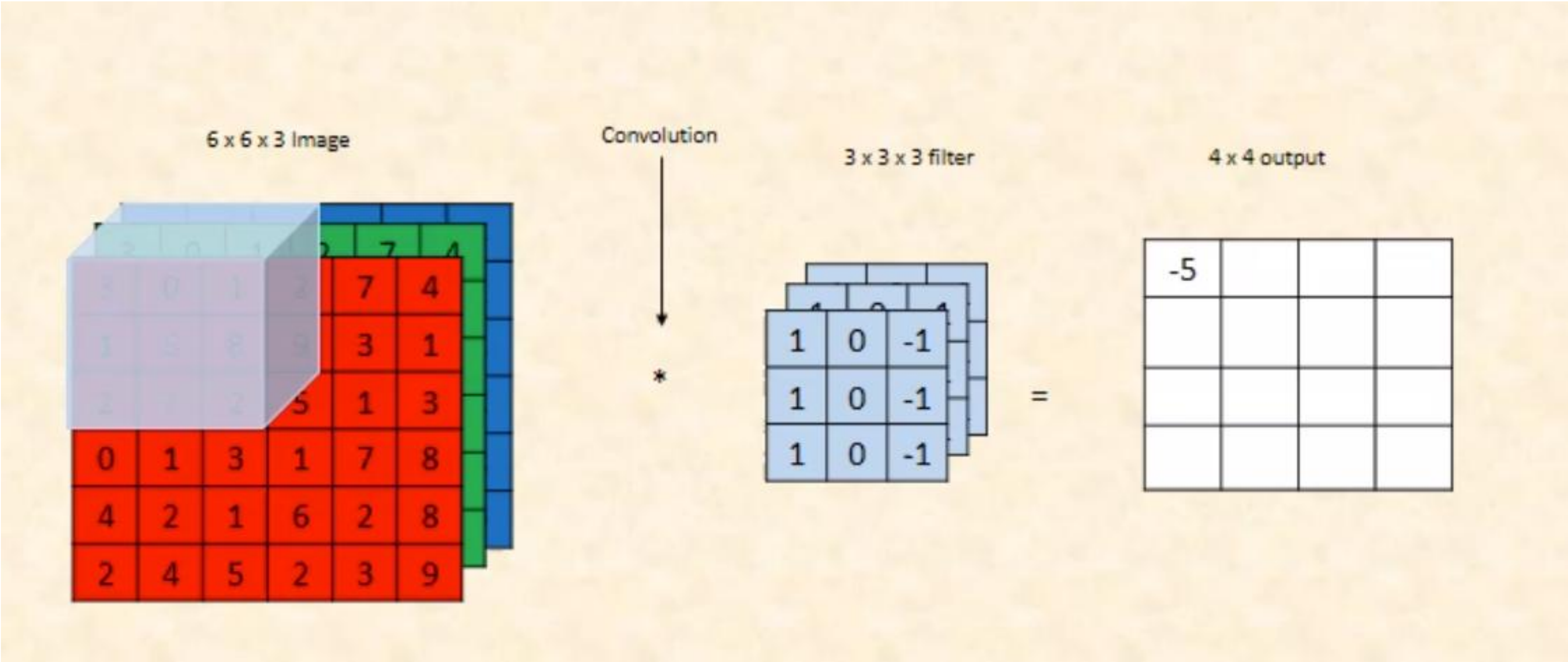
$$\boxed{Y_{i,j} = a\left(W_{i,j} * X_i + b_j\right)}$$

C(in) x C(out)번의 합성곱 연산이 이루어짐!

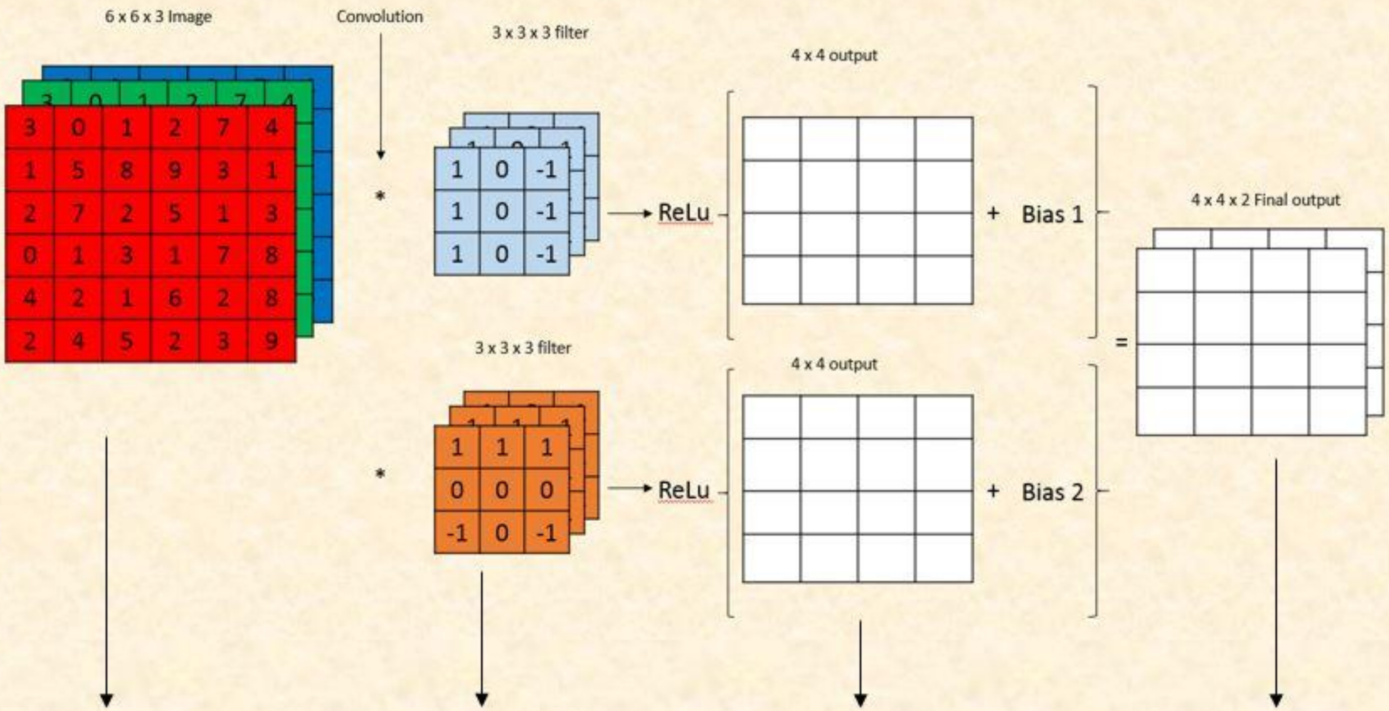
2. Convolutional Layer – 수식적 표현



2. Convolutional Layer – 수식적 표현



2. Convolutional Layer – 수식적 표현



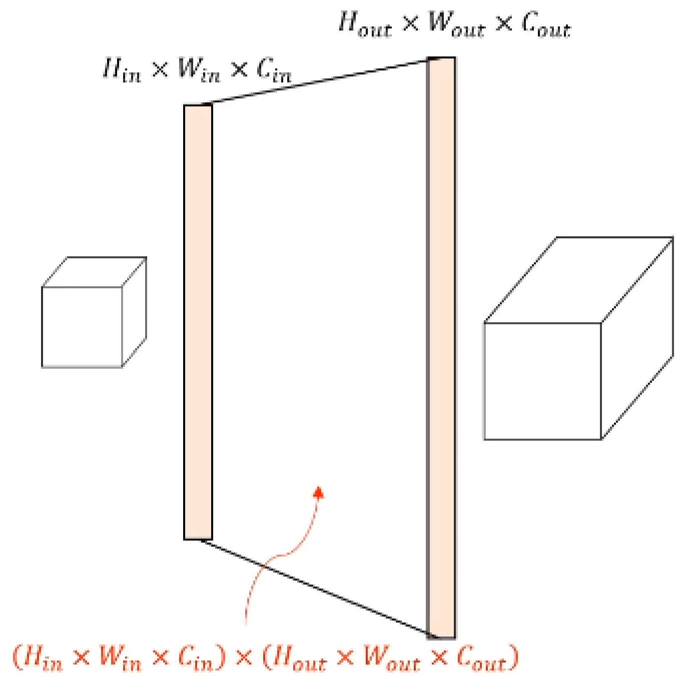
$A^{[0]}$ $W^{[1]}$ $\mathrm{ReLu}\,(\,W^{[1]} A^{[0]} + b\,)$ = $A^{[1]}$

Dimensions

Input	$n_H^{[l-1]} \times n_W^{[l-1]} \times n_c^{[l-1]}$
Activation $a^{[l]}$	$n_H^{[l]} \times n_W^{[l]} \times n_c^{[l]}$
Weights	$f^{[l]} \times f^{[l]} \times n_c^{[l-1]} \times n_c^{[l]}$
Bias	$n_c^{[l]}$

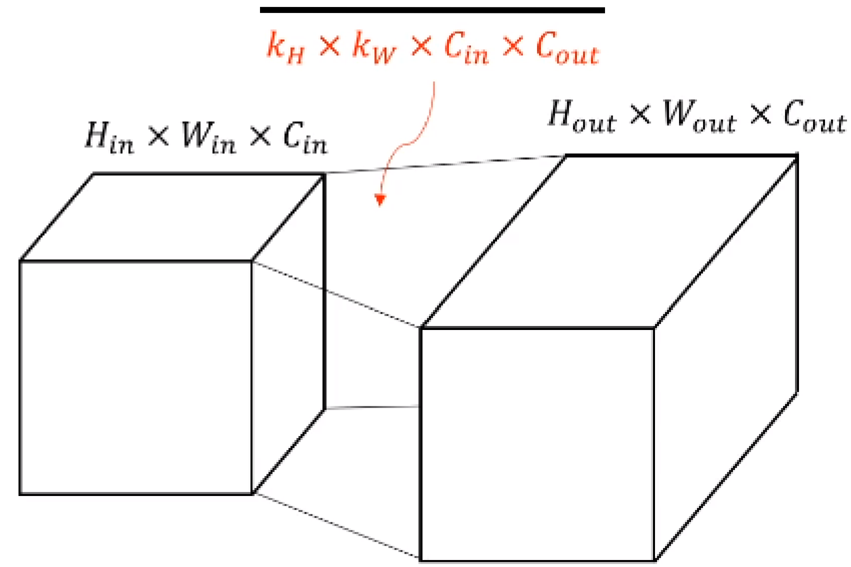
Where
$f^{[l]}$ = filter size
$p^{[l]}$ = padding
$s^{[l]}$ = stride
$n_c^{[l]}$ = number of filters
$n_c^{[l-1]}$ = color channels

3. Why Convolutional Layer?



(1024 x1024x16)

(3x3x16x32)

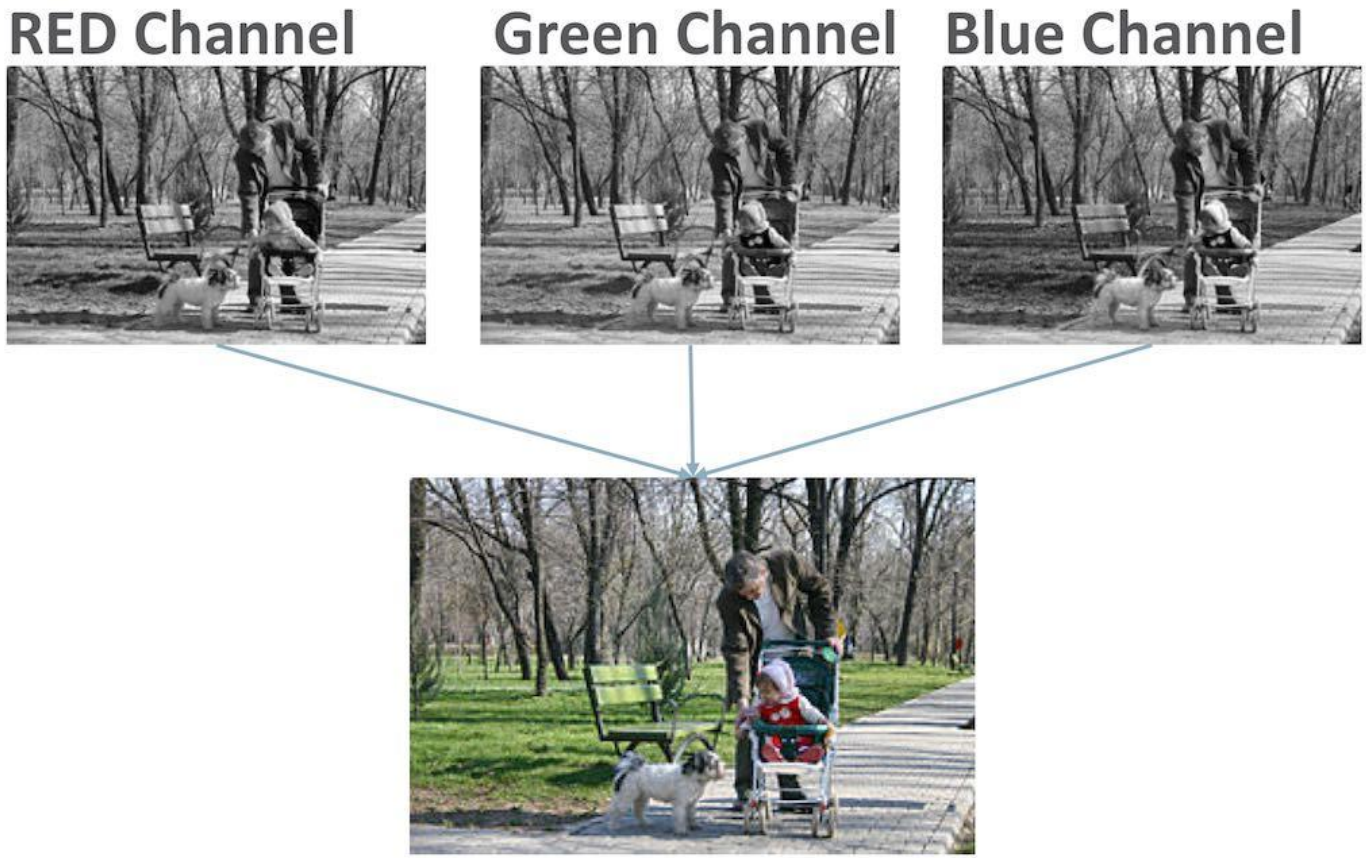


FC 대신 Convolutional Layer 써야하는 이유?

“Parameter 수의 감소!”

4. 용어 설명

(1) Channel

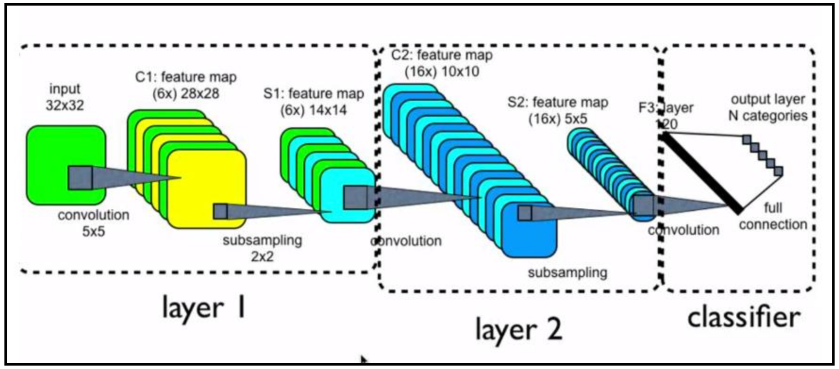


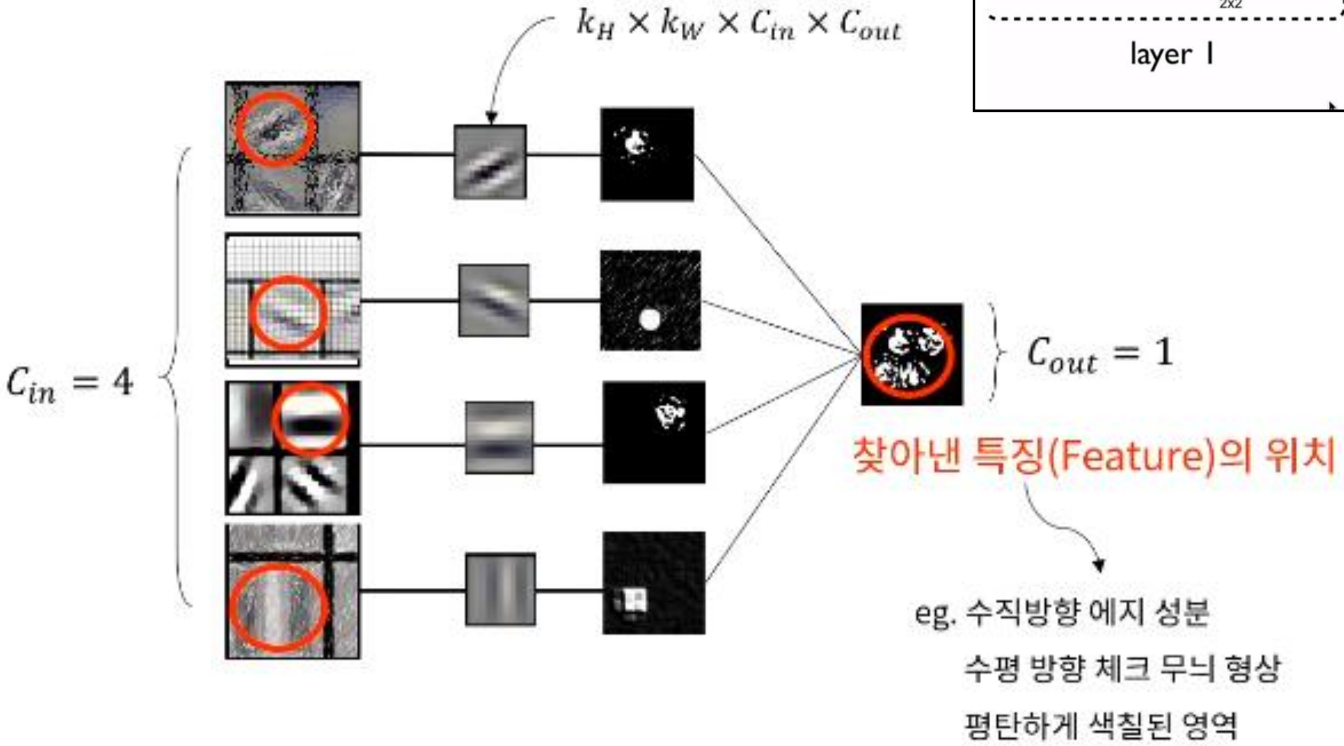
이미지 출처: https://en.wikipedia.org/wiki/Channel_(digital_image)

4. 용어 설명

(2) Feature Map

합성곱을 통해서 만들어진 출력!



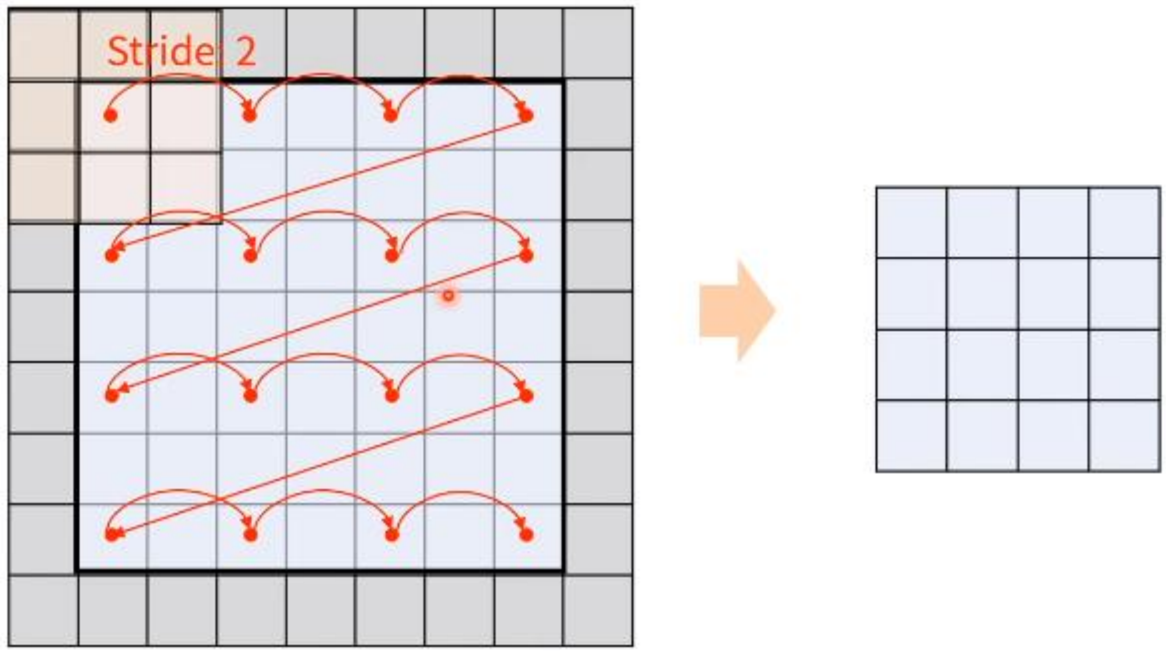


합성곱 계층의 의미?

여러 채널에서 특별한 "특징"이 나타내는 위치를 찾아내는 역할!

4. 용어 설명

(3) Stride



합성곱 계산시, 커널을 이동시키는 거리!

Stride를 크게 할 수록, 영상/사진의 크기는 줄어든다!

4. 용어 설명

(4) Padding

0	0	0	0	0	0
0	35	19	25	6	0
0	13	22	16	53	0
0	4	3	7	10	0
0	9	8	1	3	0
0	0	0	0	0	0

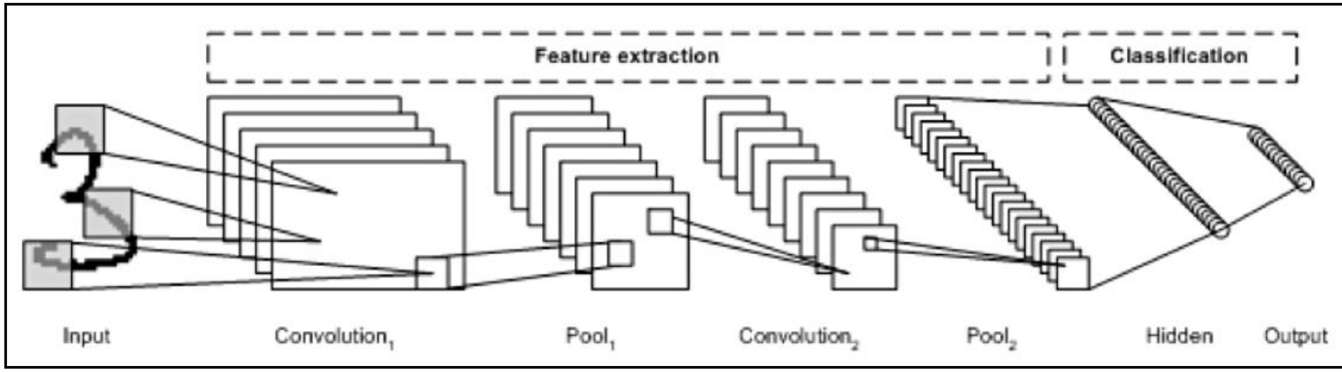
주위에 숫자(주로 0)을 둘러씌우는 것! (For 크기 보존)

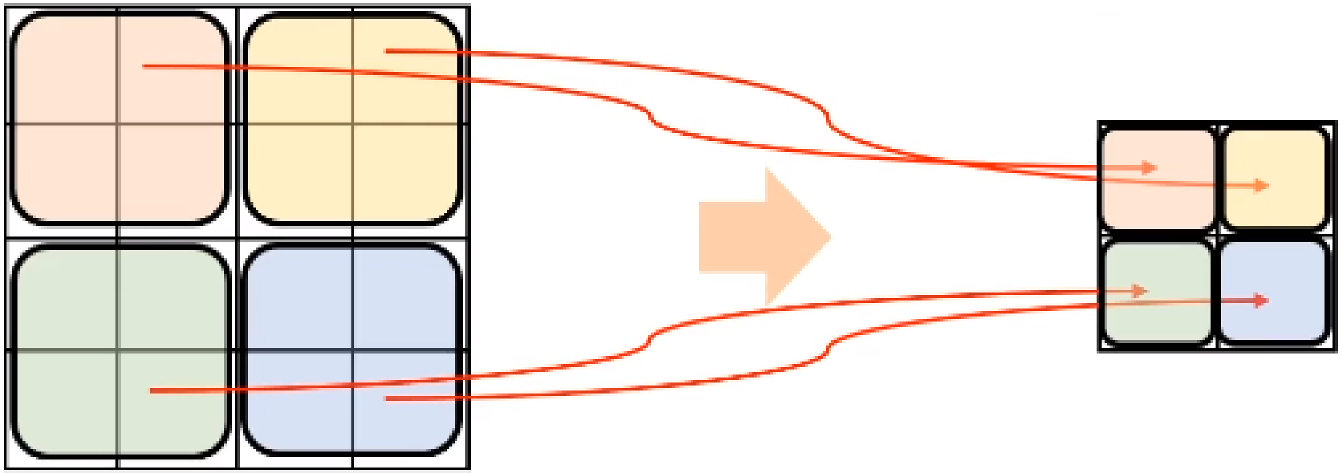
합성 곱 연산시, 필터(커널)의 크기에 따라 영상의 크기가 줄어드는 문제 발생

ex) 크기가 (2N+1)인 커널 -> 상하좌우로 N개의 zero-padding!

4. 용어 설명

(5) Pooling



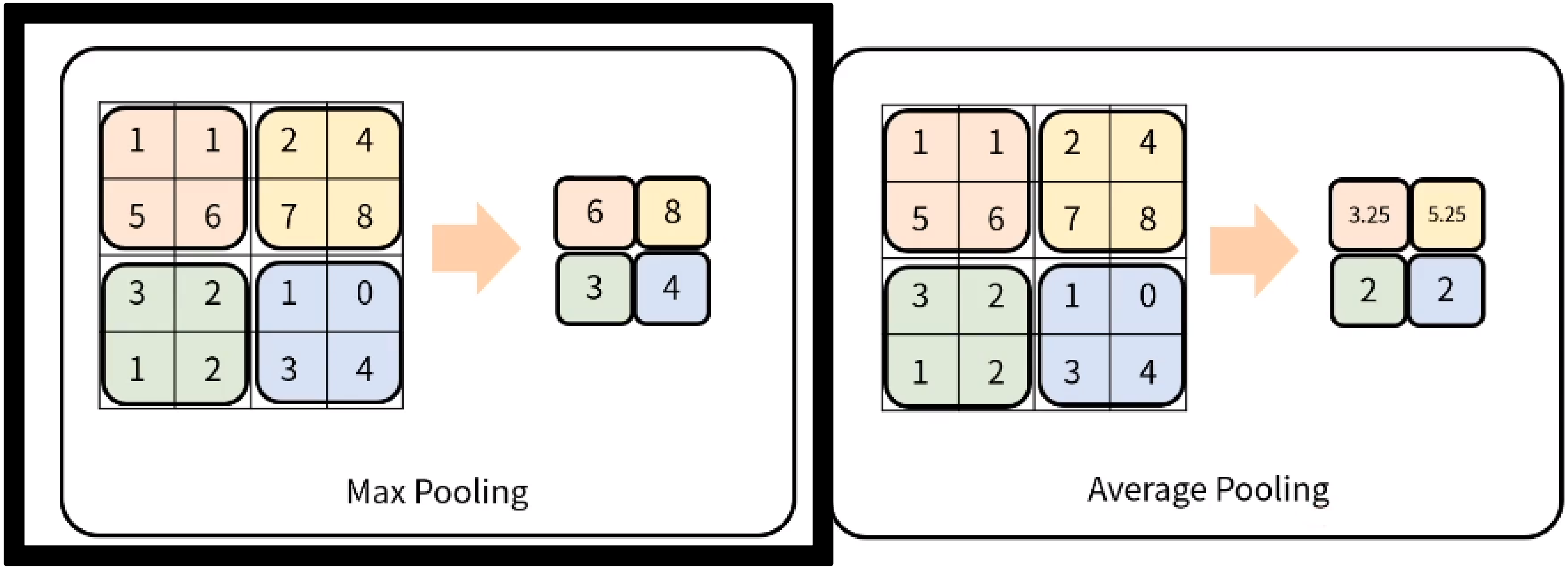


Sampling이라고 보면 됨! (여러 화소를 하나의 화소로 축약!)

즉, “영상/사진의 크기가 줄어들고, 정보가 종합(요약)된다!”

4. 용어 설명

(5) Pooling



Pooling Layer (vs Convolution Layer)

1) 학습대상 parameter 없음

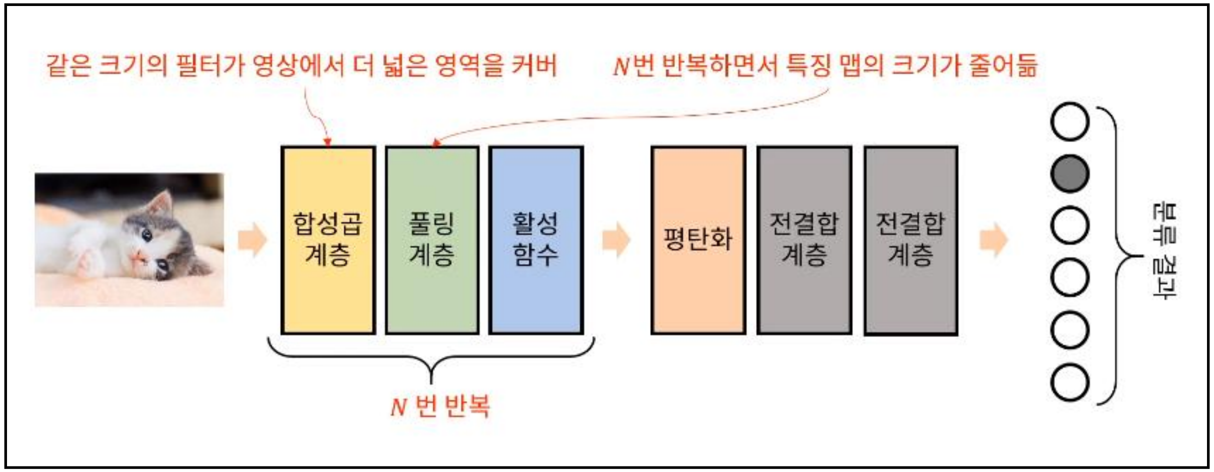
2) Pooling Layer를 통과하면 행렬의 크기 감소

3) Pooling Layer를 통해서 채널 수 변경 없음

4. 용어 설명

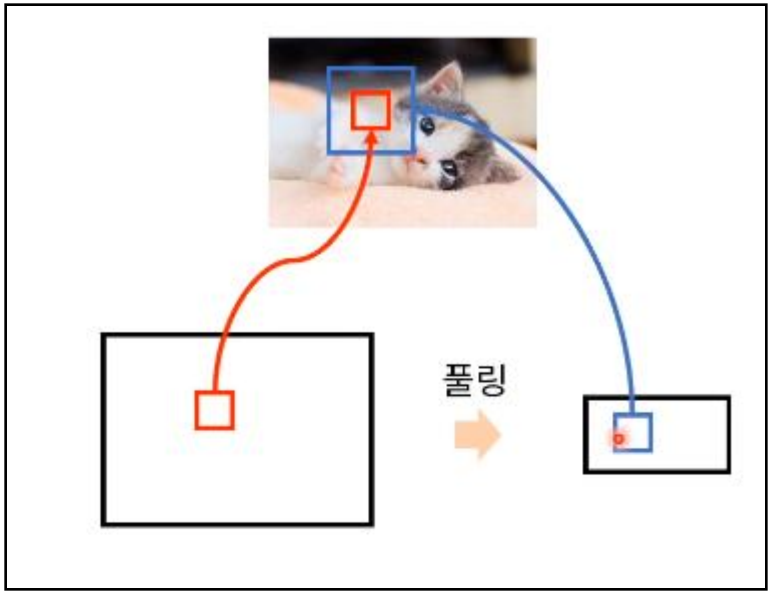
(5) Pooling

why pooling? Receptive Field?



(h,w)영상 크기 작아지고,

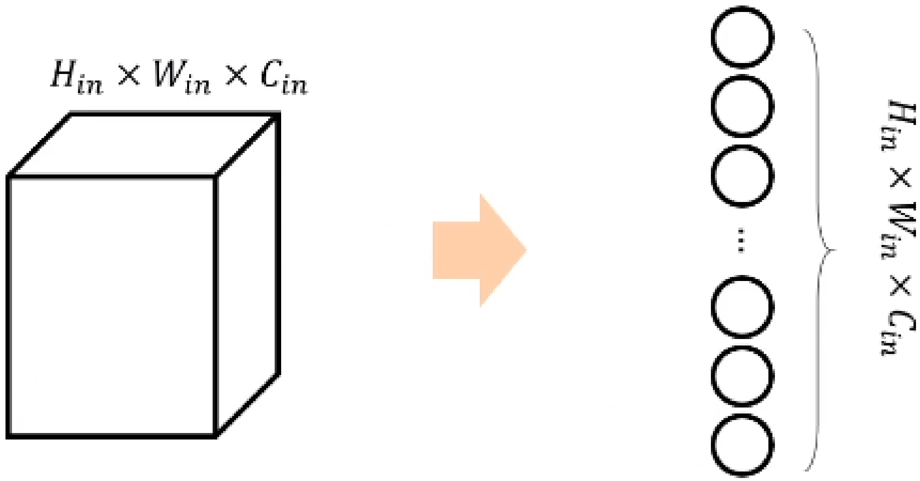
(c)채널 수 늘어나게 될 것!



같은 크기의 filter여도, Pooling에 의해 작아진 feature map에 적용되면, "원본 영상에서 차지하는 범위(=receptive field)"가 넓다

4. 용어 설명

(6) Flatten



평탄화! -> Vector로 만들어줌

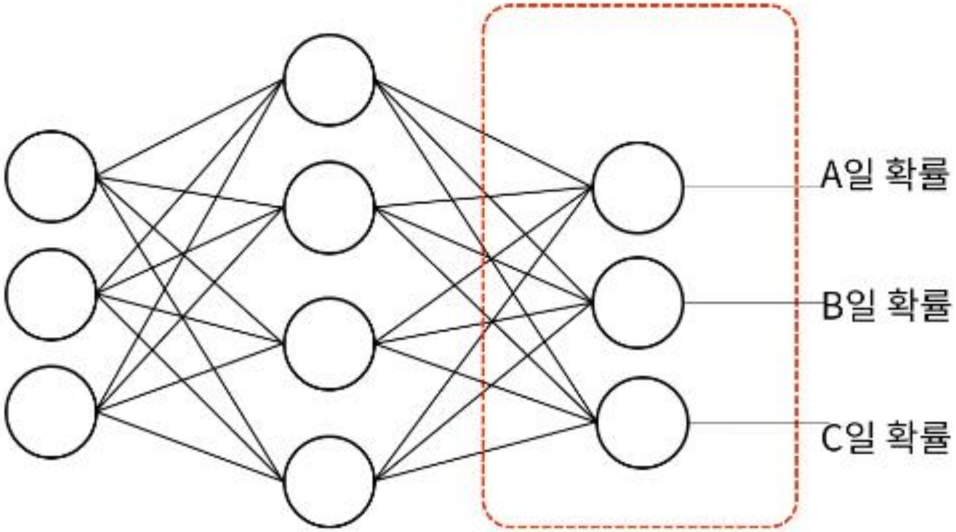
단지 쭉 피는 것을 의미! (연산 과정 X)

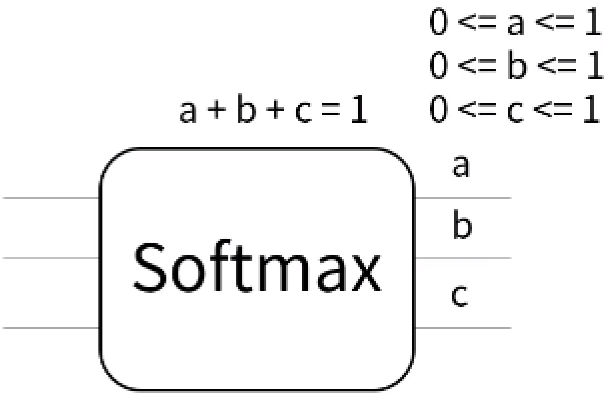
Conv & FC 연결해주는 역할

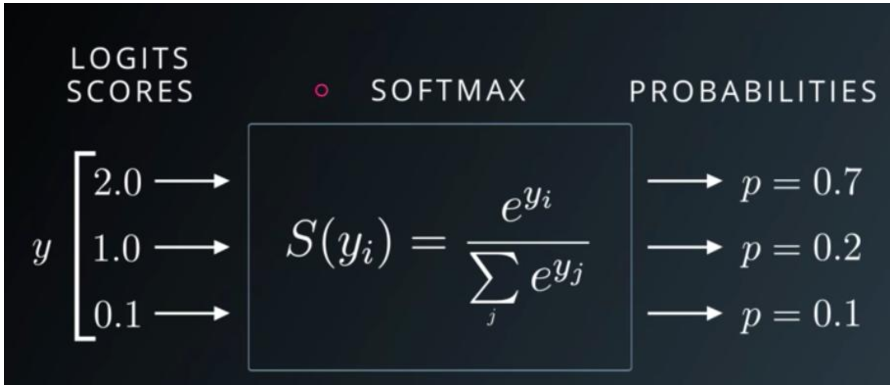
4. 용어 설명

(7) Softmax Function

for Multi-class Classification

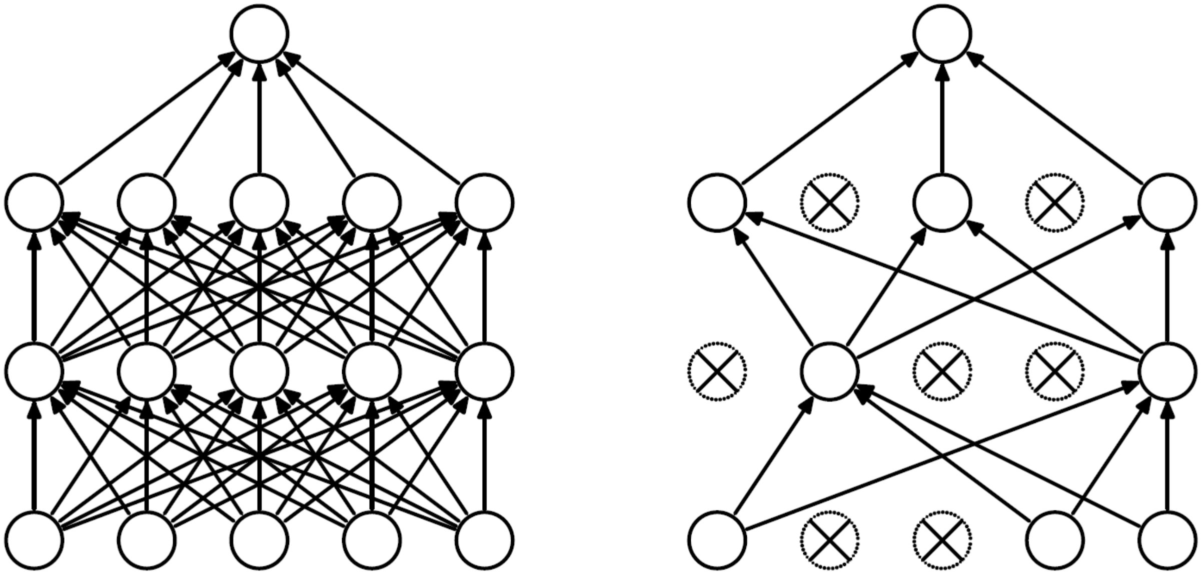






5. Dropout

To prevent overfitting!



(a) Standard Neural Net (b) After applying dropout.

Training 할 때만!

(testing할 때는 X)

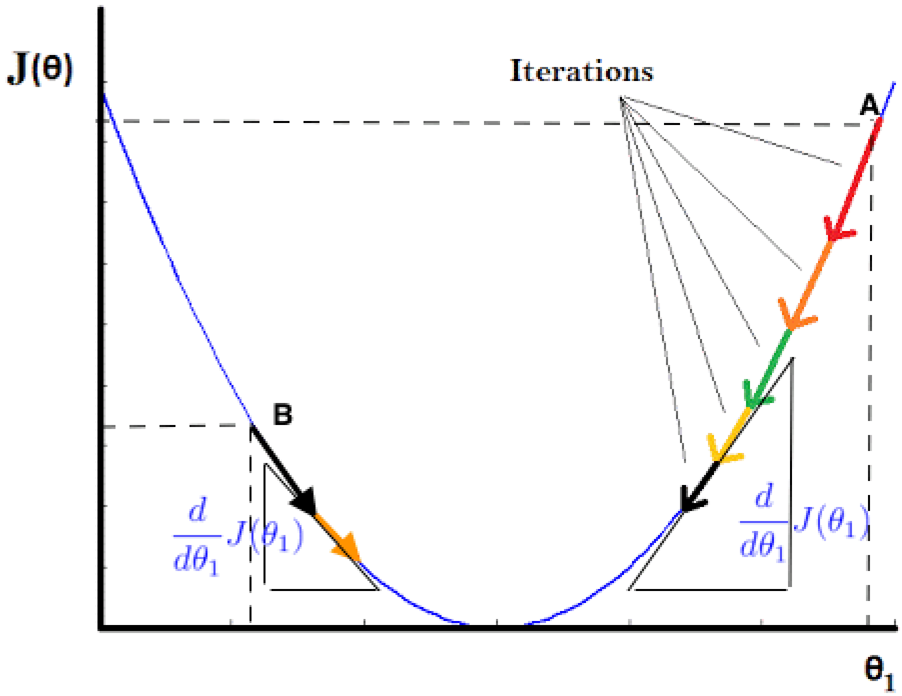
Ex) Dropout rate 0.3 : 30%의 node는 사용 X (less parameter)

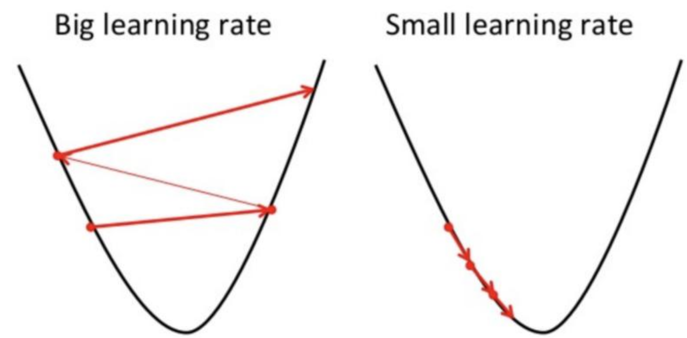
Overfitting 문제가 해결되는 이유를, 직관적으로 생각해보자!

100가지의 일, 100명의 사람이 하는 경우? 20명의 사람이 하는 경우?

6. Mini-Batch

[복습] Gradient Descent





Optimal point를 찾아가는 과정!

(too big, to small LR (X))

1 Iteration : dataset이 한번 반복되는 것을 의미!

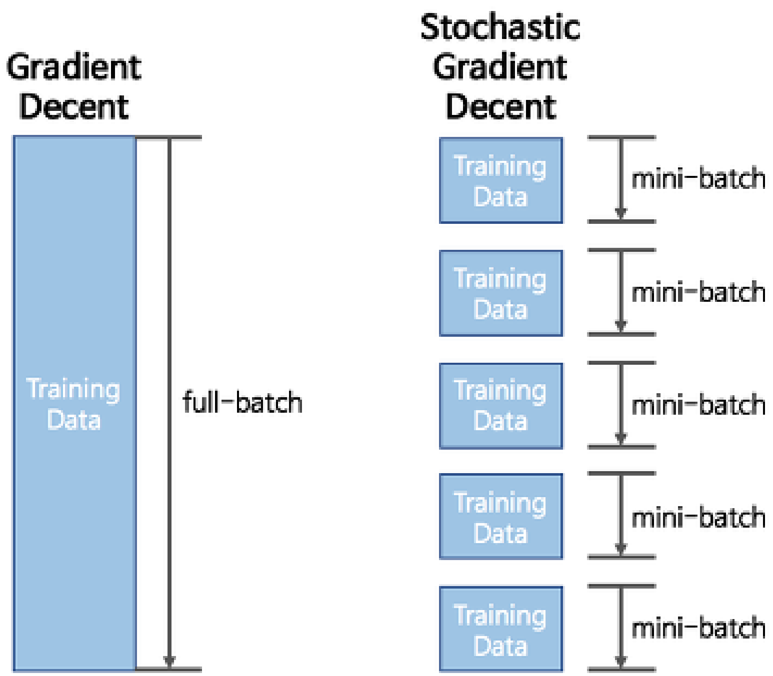
(iteration 한번 할 때마다 parameter 조정해 나감)

6. Mini-Batch

Vanilla(Batch) Gradient Descent
(일반 경사 하강법)

Gradient를 한번 update하기 위해,

“모든 training data”를 사용



Stochastic Gradient Descent
(확률적 경사 하강법)

Gradient를 한번 update하기 위해,

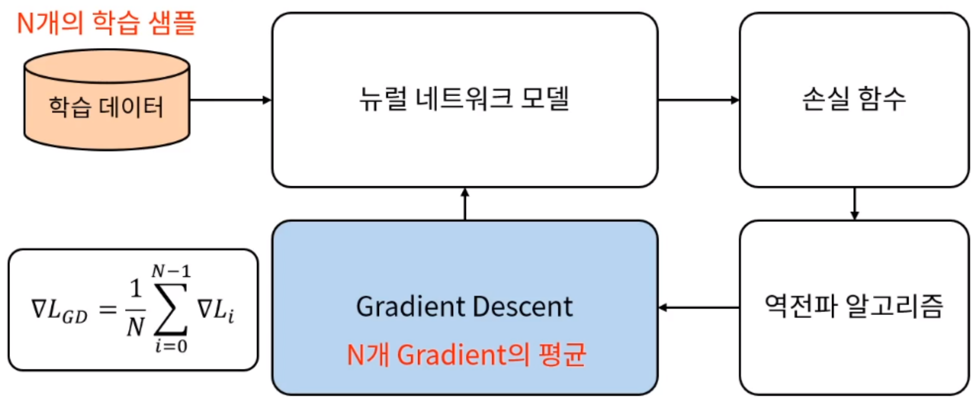
“일부의 training data”만 활용! (일단, 일부 = 1개라고 일단은 생각하자!)

(일부=m개인 경우가 ‘Mini-Batch’ Gradient Descent)

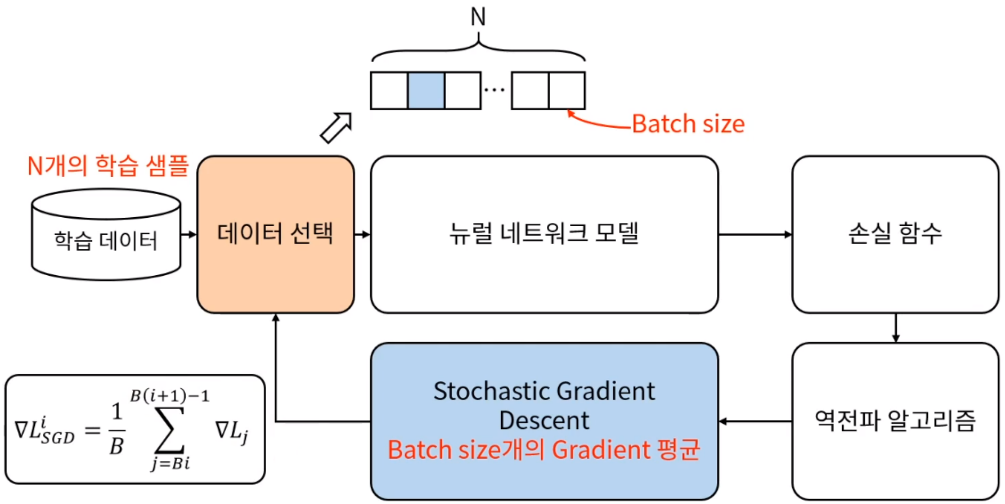
(SGD와 Mini-batch GD의 용어를 섞어 쓰기도)

6. Mini-Batch

Vanilla(Batch) Gradient Descent (일반 경사 하강법)



Stochastic Gradient Descent (확률적 경사 하강법)



6. Mini-Batch

	Vanilla Gradient Descent (일반 경사 하강법)	Stochastic Gradient Descent (확률적 경사 하강법)
장점	-전체 data에 대한 update가 "1번"이루어짐 -> SGD에 비 적은 update(계산) 횟수 필요 -전체 data에 대해 error gradient 계산! (optimal로 수렴이 안정적) - 병렬 처리 GOOD	-Local optimal에 빠질 위험 적음 - step에 걸리는 시간이 짧기 때문에 학습 - 속도(수렴 속도)가 빠름
단점	-학습이 오래 걸림! (한 스텝에 "전체 data"를 활용하여 학습하므로) - Local optimal에 빠질 위험	-Global Optimal를 찾기 어려움 - 병렬 처리 BAD

6. Mini-Batch

(Vanilla) Gradient Descent (GD)

TRAINING DATASET (1000개)

Mini-Batch Gradient Descent (MBGD)

32개	32개	....	32개	32개

(용어 구분해서 쓰지 않는 경우도!)

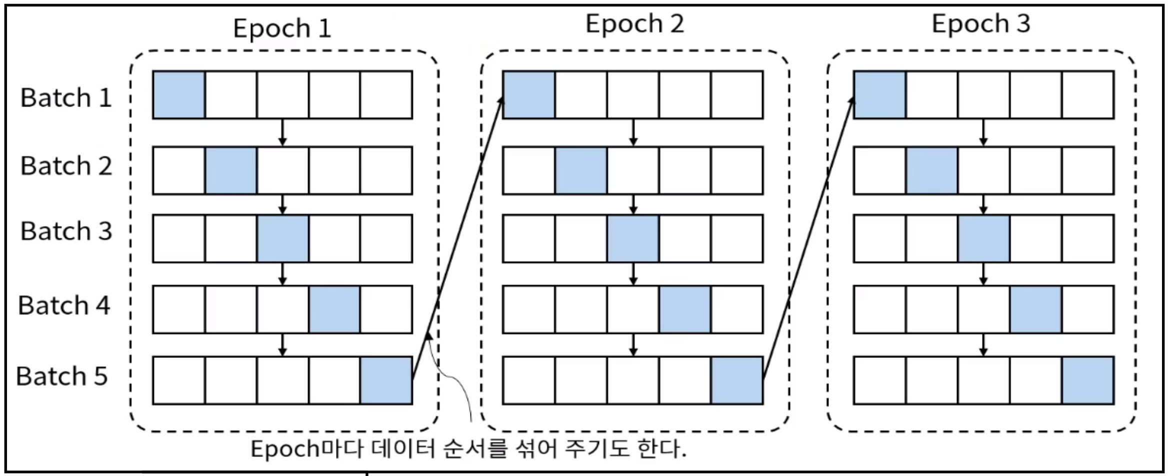
Stochastic Gradient Descent (SGD)

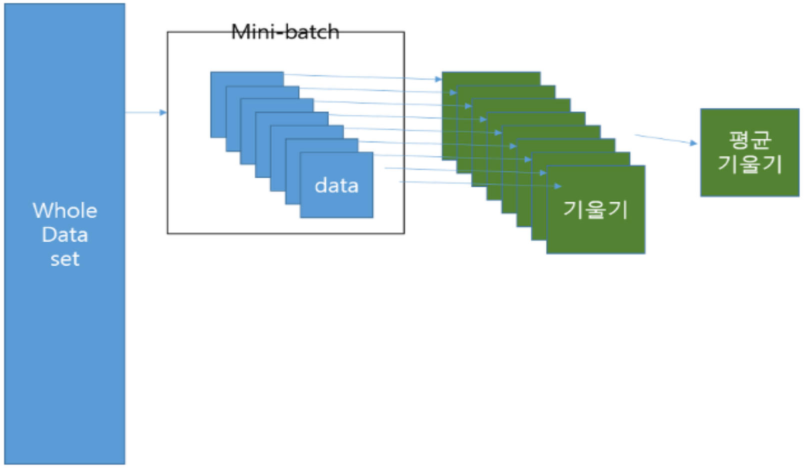
1개	1개	1개	..	..	..	..	..	1개	1개

6. Mini-Batch

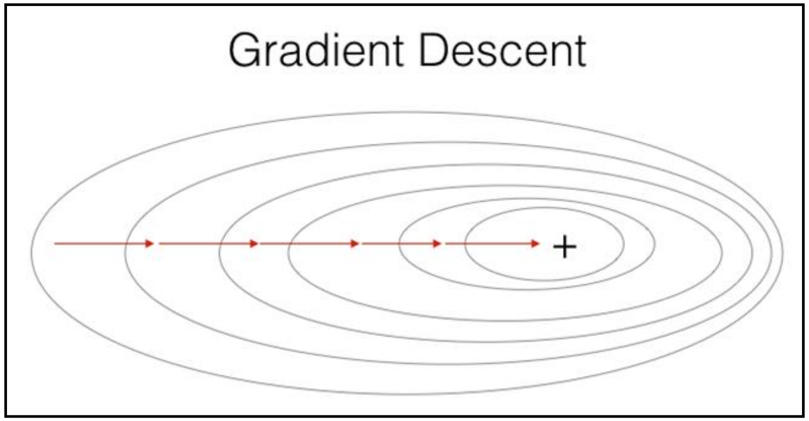
Training data 전체를 한번 학습 하는 것을 “Epoch”

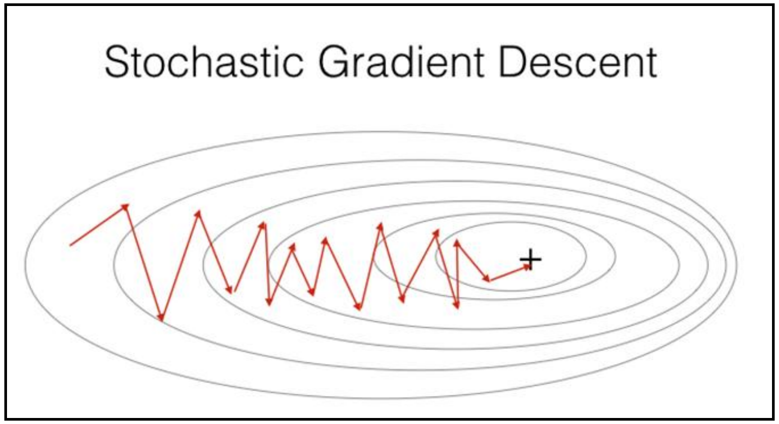
한 번 Gradient를 구하는 단위를 “Batch”라고 한다

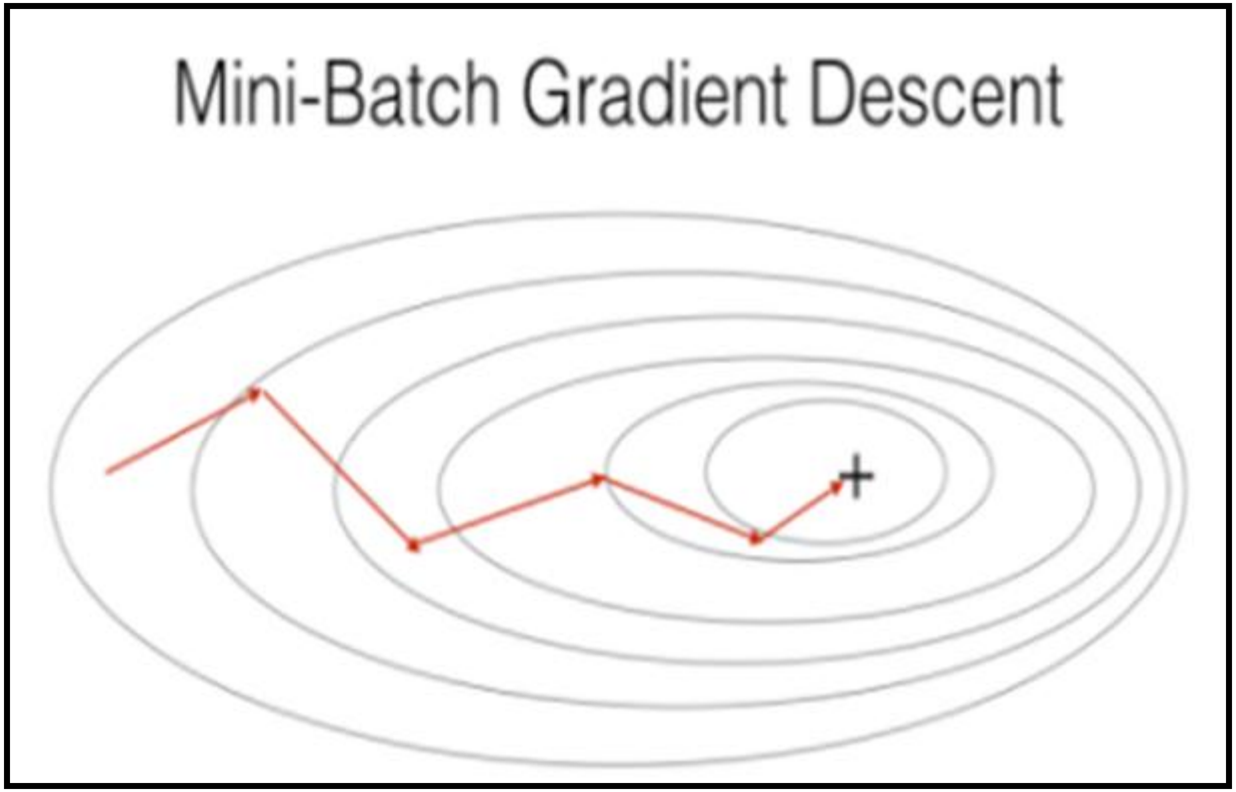




6. Mini-Batch


Gradient Descent

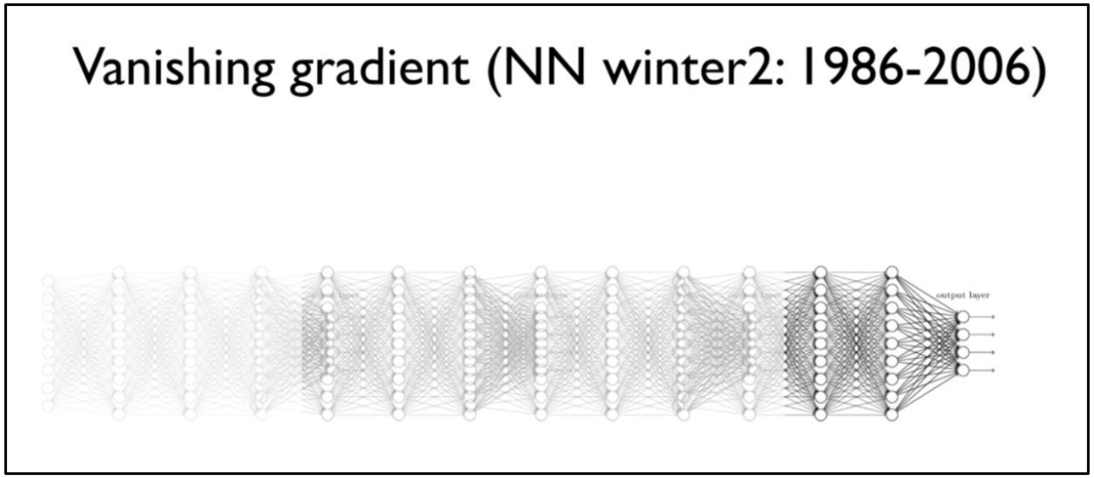

Stochastic Gradient Descent


Mini-Batch Gradient Descent

7. Batch Normalization

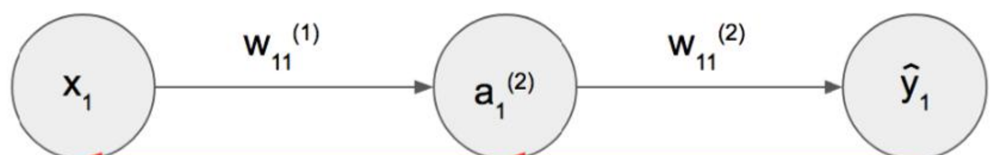
<u>Gradient Vanishing?</u>

(기울기 소실 문제)



DEEP 할수록 gradient vanishing! WHY?

(Backpropagation의 수식을 생각해보자)



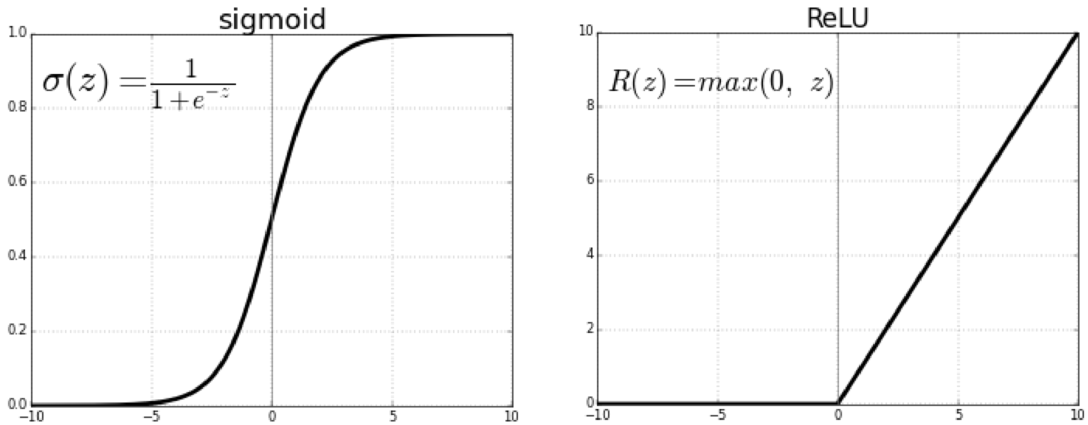
$$\frac{\partial E}{\partial w_{11}^{(1)}} = \frac{\partial E}{\partial \hat{y}_1} \frac{\partial \hat{y}_1}{\partial a_1^{(2)}} \frac{\partial a_1^{(2)}}{\partial w_{11}^{(1)}} \qquad \frac{\partial E}{\partial w_{11}^{(2)}} = \frac{\partial E}{\partial \hat{y}_1} \frac{\partial \hat{y}_1}{\partial w_{11}^{(2)}}$$

7. Batch Normalization

<u>Gradient Vanishing?</u>

How to Solve?

1) Activation Function으로 **<u>Sigmoid -> ReLU</u>**

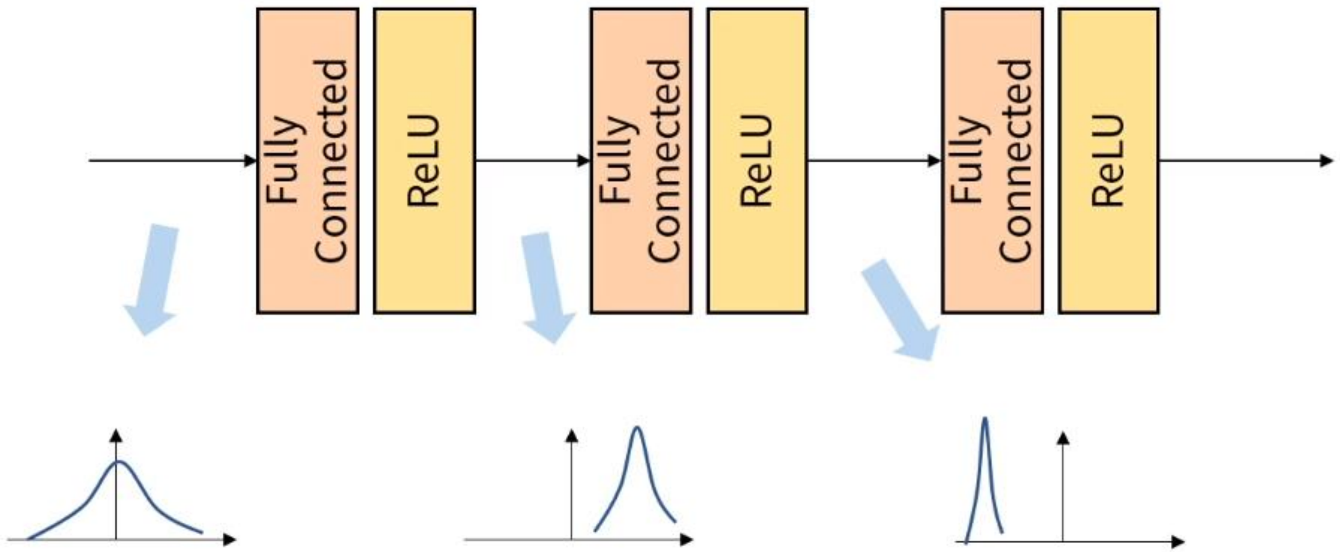


2) 적절한 weight 초기값 : **<u>Xavier Initialization, He Initialization</u>**

3) Batch Normalization

7. Batch Normalization

Internal Covariance Shift



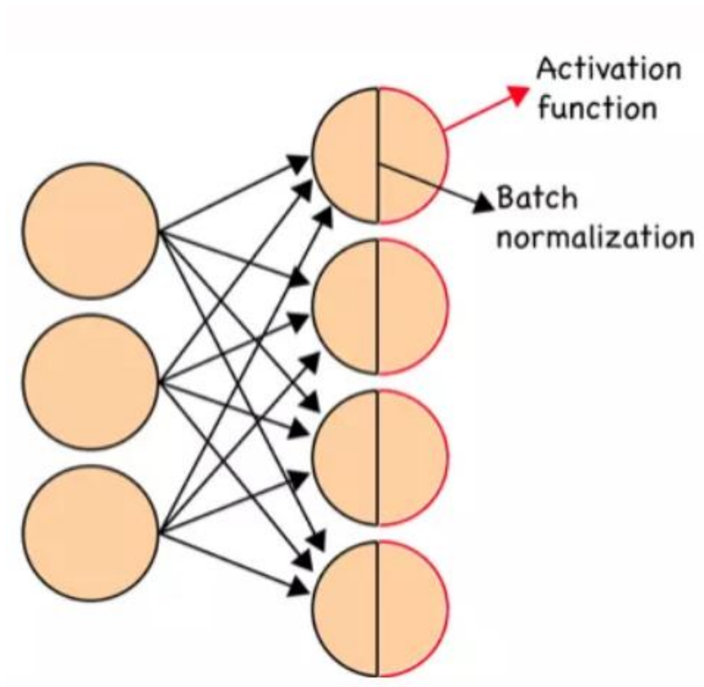
Training 과정에서, parameter의 변화로 인해 input data의 distribution이 달라지는 현상! -> 불안정한 training야기!

이 문제를 해결하는 방법이 **Batch Normalization**!

이로써 안정적인 training을 가능하게 하고, gradient vanishing problem해결!

7. Batch Normalization

Batch Normalization



Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_\mathcal{B} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_\mathcal{B}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_\mathcal{B})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_\mathcal{B}}{\sqrt{\sigma_\mathcal{B}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

training data 전체에 대하여 normalize하는 것이 좋겠지만, Mini-batch Gradient Descent방식을 사용하게 되면, parameter의 update가 Mini-batch단위로 이루어지기 때문에, Mini-batch를 단위로 Batch Normalization(BN) 실시!

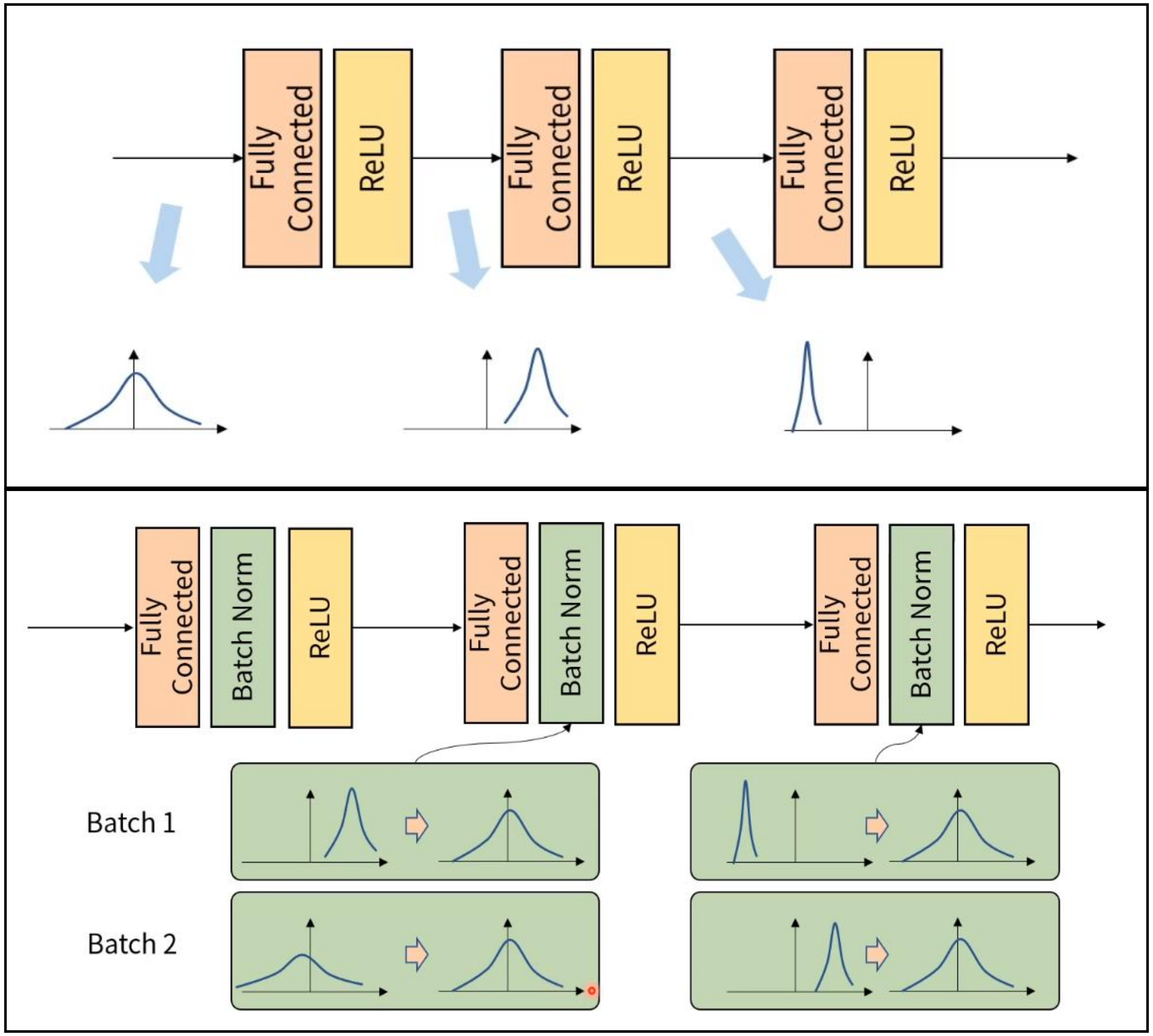
Internal Covariance Shift 문제를 해결하기 위해, "각 층의 input의 distribution을 평균 0, 표준편차 1인 input으로 normalize" 시키는 방법

7. Batch Normalization

Internal Covariance Shift

BN (X)

BN (O)



7. Batch Normalization

Batch Normalization

< BN의 장점 >

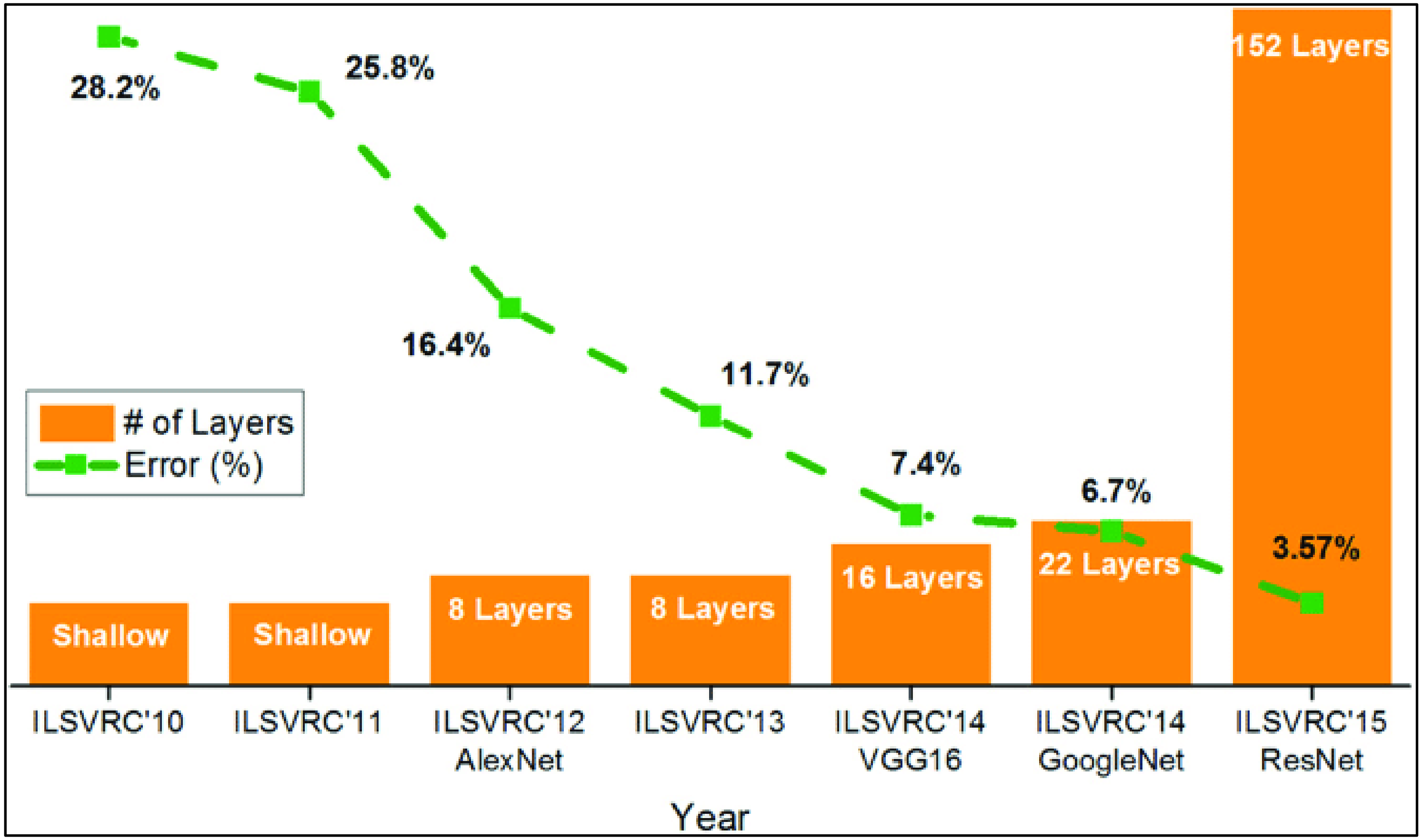
1) Gradient vanishing 문제 해결!

2) Regularization 효과가 있음 (overfitting 방지)

- (regularization 효과를 주는) Dropout을 제외할 수 있게 해줌
- Dropout 경우 효과는 좋지만 학습 속도가 느려진다는 단점!

3) Gradient의 scale 영향을 덜 받음!

7. 심화 CNN



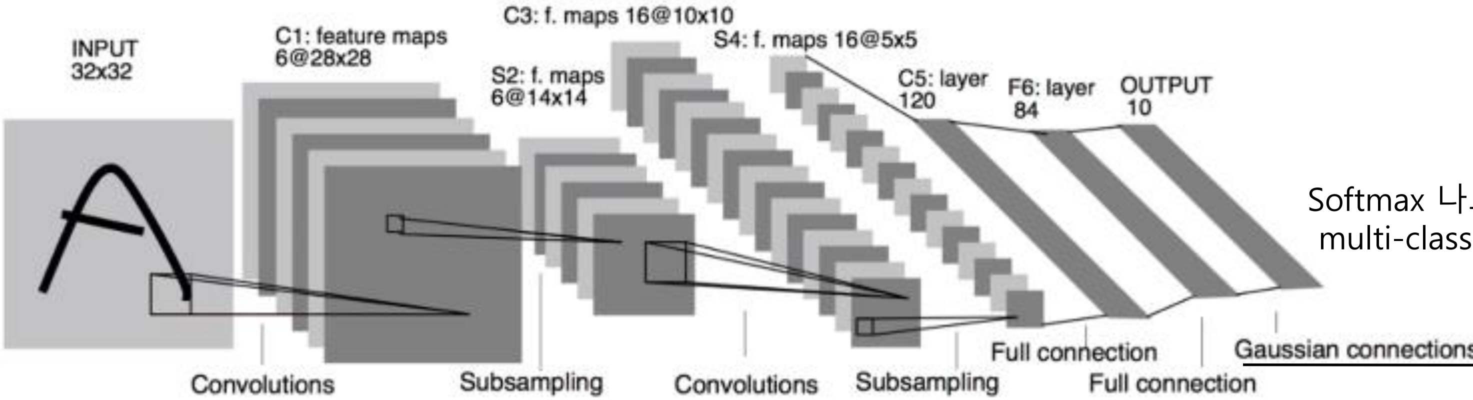
CNN의 대표 모델들에 대해 알아보자.

LeNet-5, AlexNet, VGG16, GoogLeNet, ResNet

7. 심화 CNN

1. LeNet-5

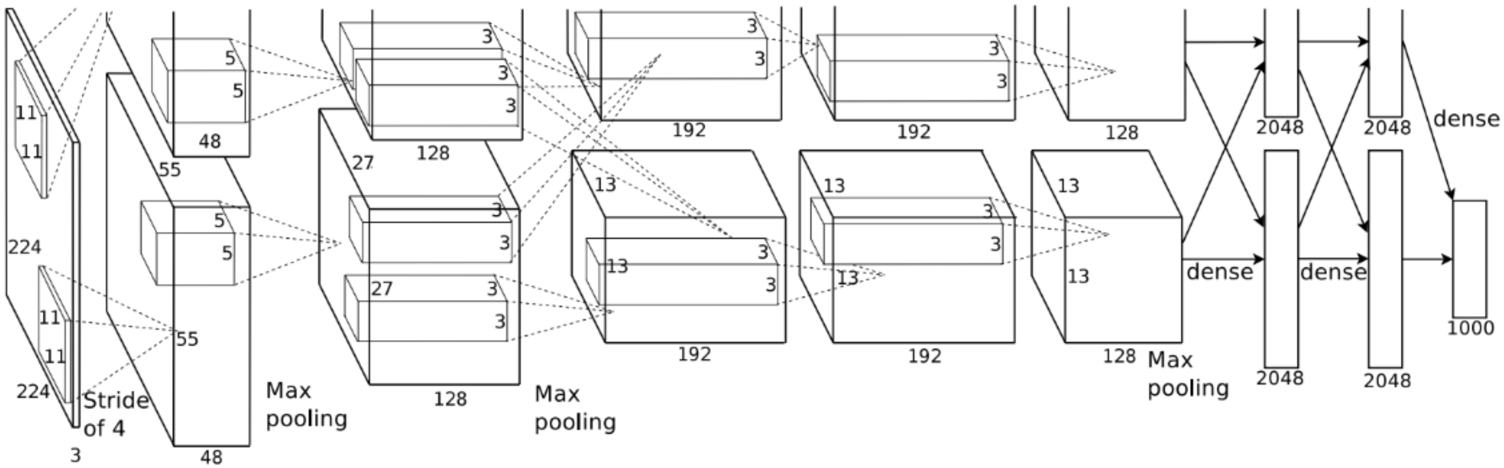
6채널의 28*28 feature map



Softmax 나오기 전에 사용한
multi-class classification

- 1998. CNN의 기본구조 창립
- MNIST data 사용

2. AlexNet



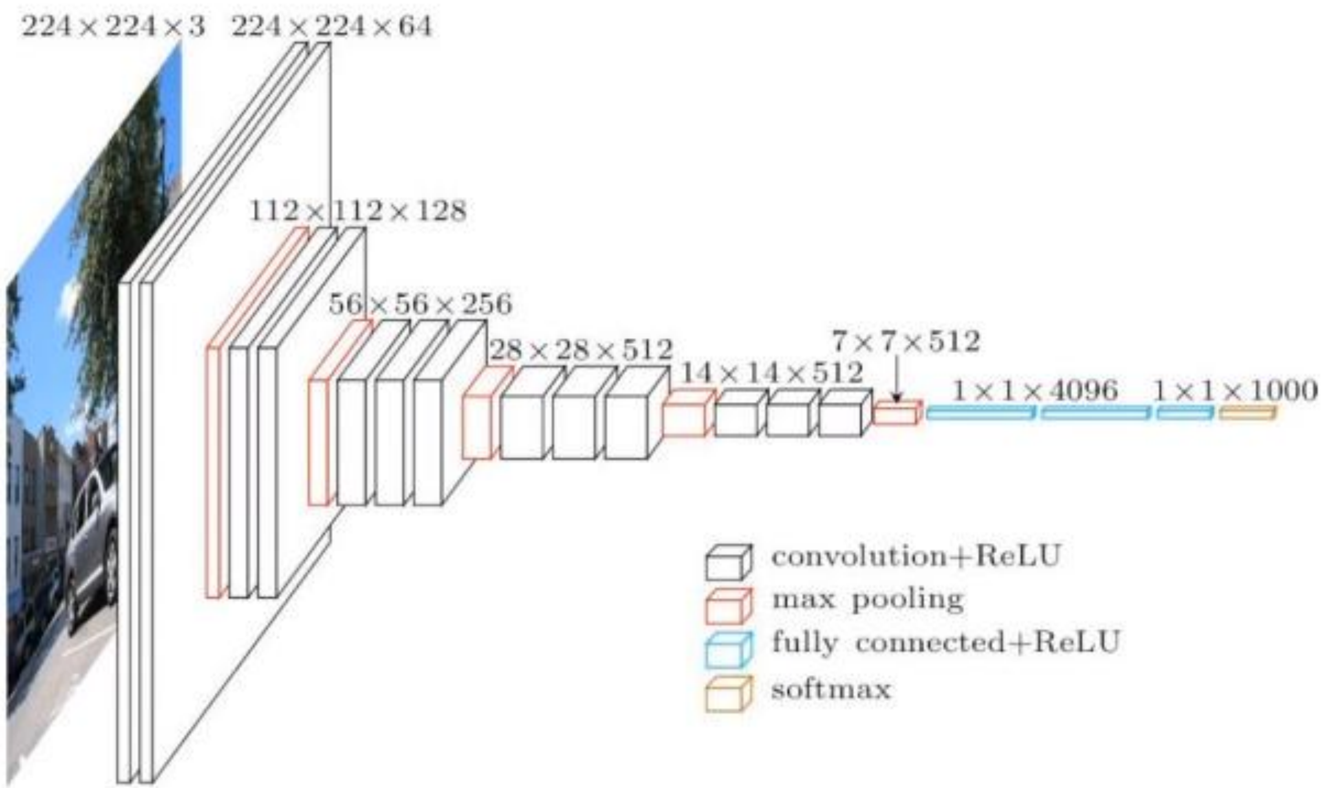
- Conv, Max Pooling, Dropout 5개

- Activation function : ReLU

- Batch Stochastic Gradient Descent

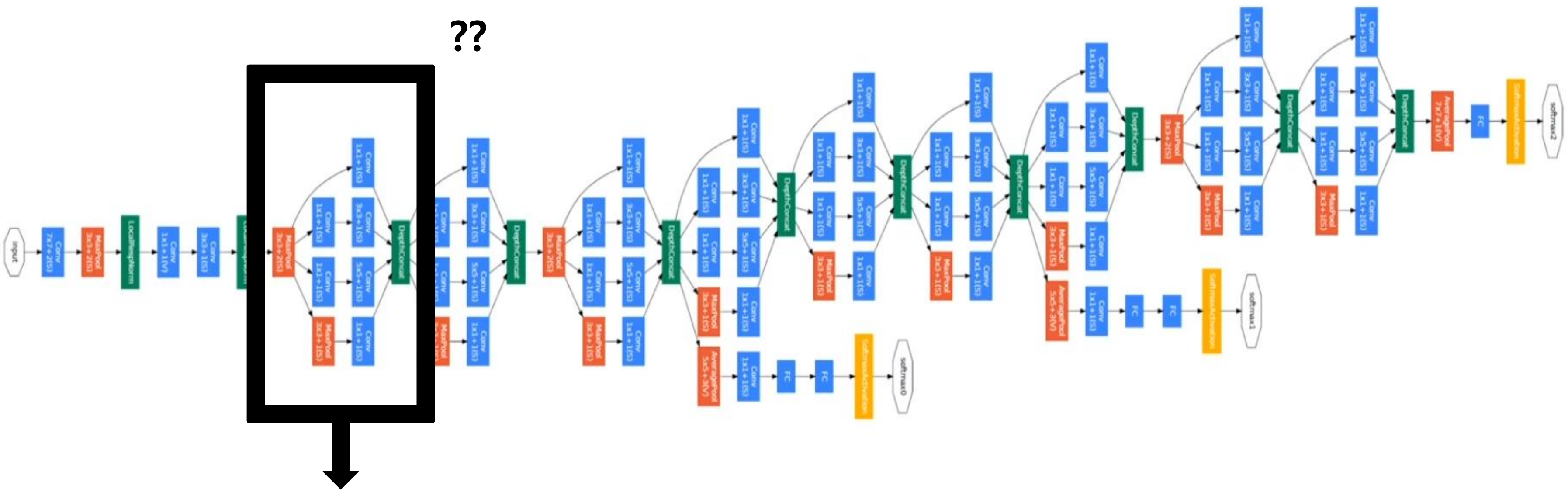
7. 심화 CNN

3. VGG-16



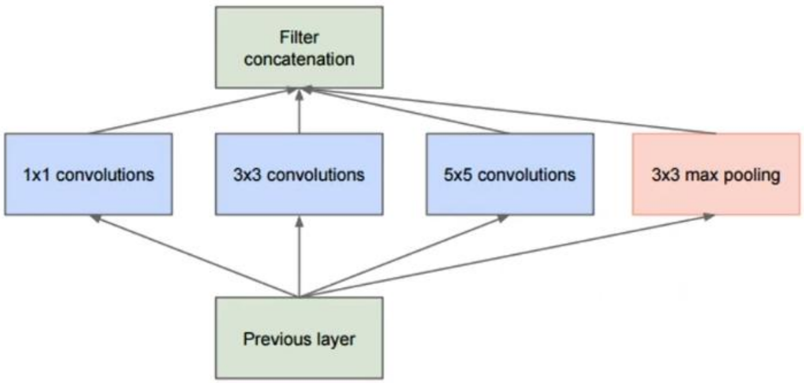
4. GoogLeNet (Inception)

"Let's go Deeper and Deeper"

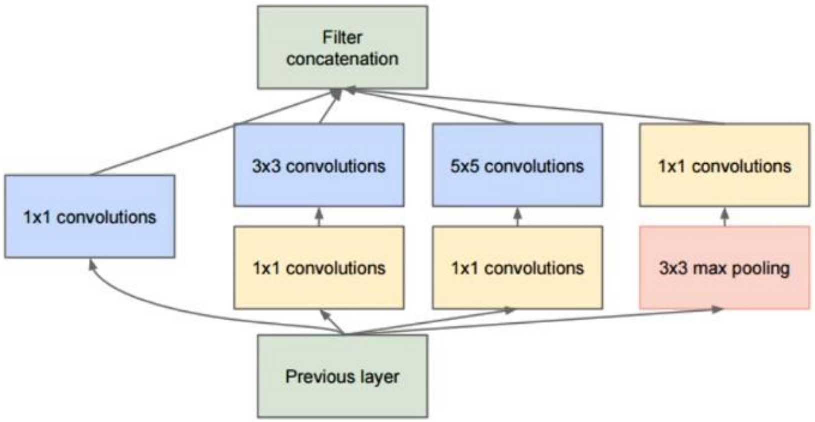


Inception 모듈에 대해 먼저 이해해야!

4. GoogLeNet (Inception)



(a) Inception module, naïve version



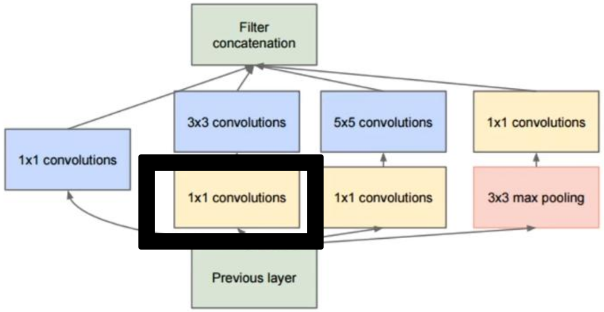
(b) Inception module with dimension reductions

Inception module : 다양한 크기의 합성곱 계층을 한번에 계산!

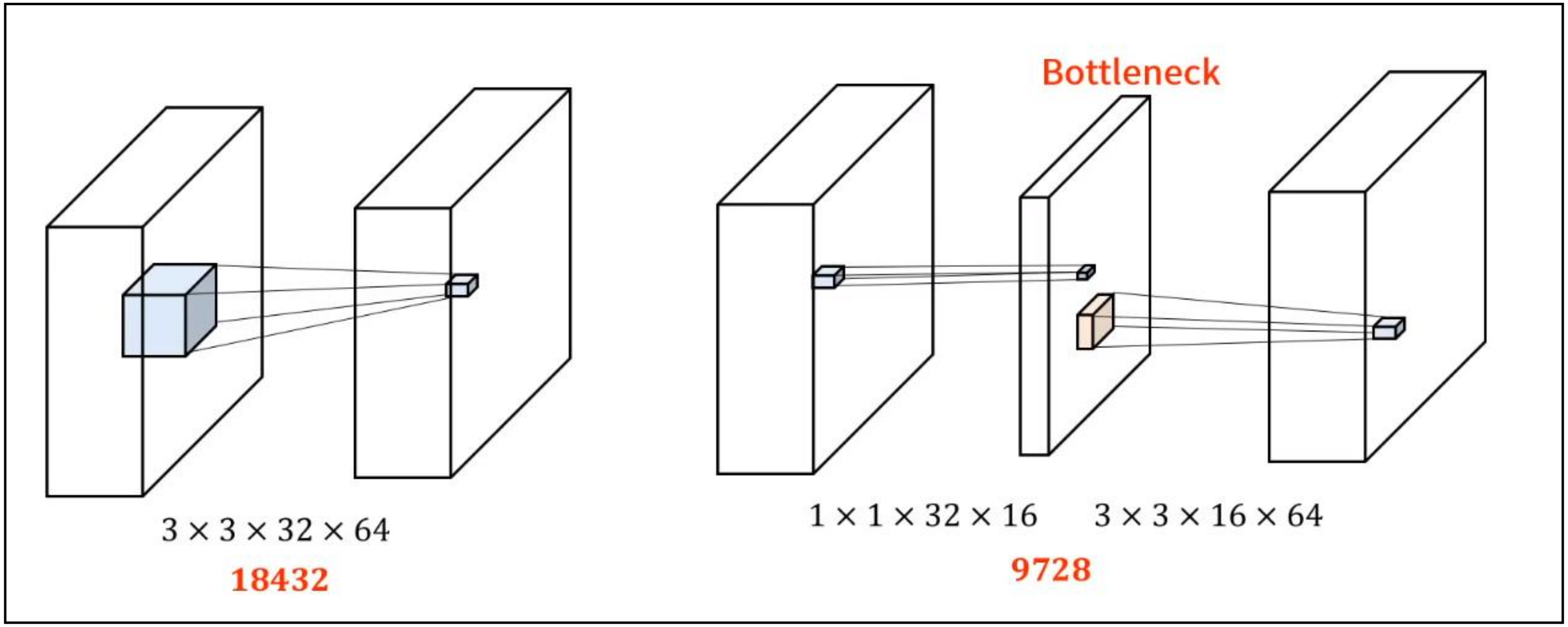
1x1 convolution : for 연산량 줄이기! (bottle neck 구조라고도 함)

7. 심화 CNN

4. GoogLeNet (Inception)



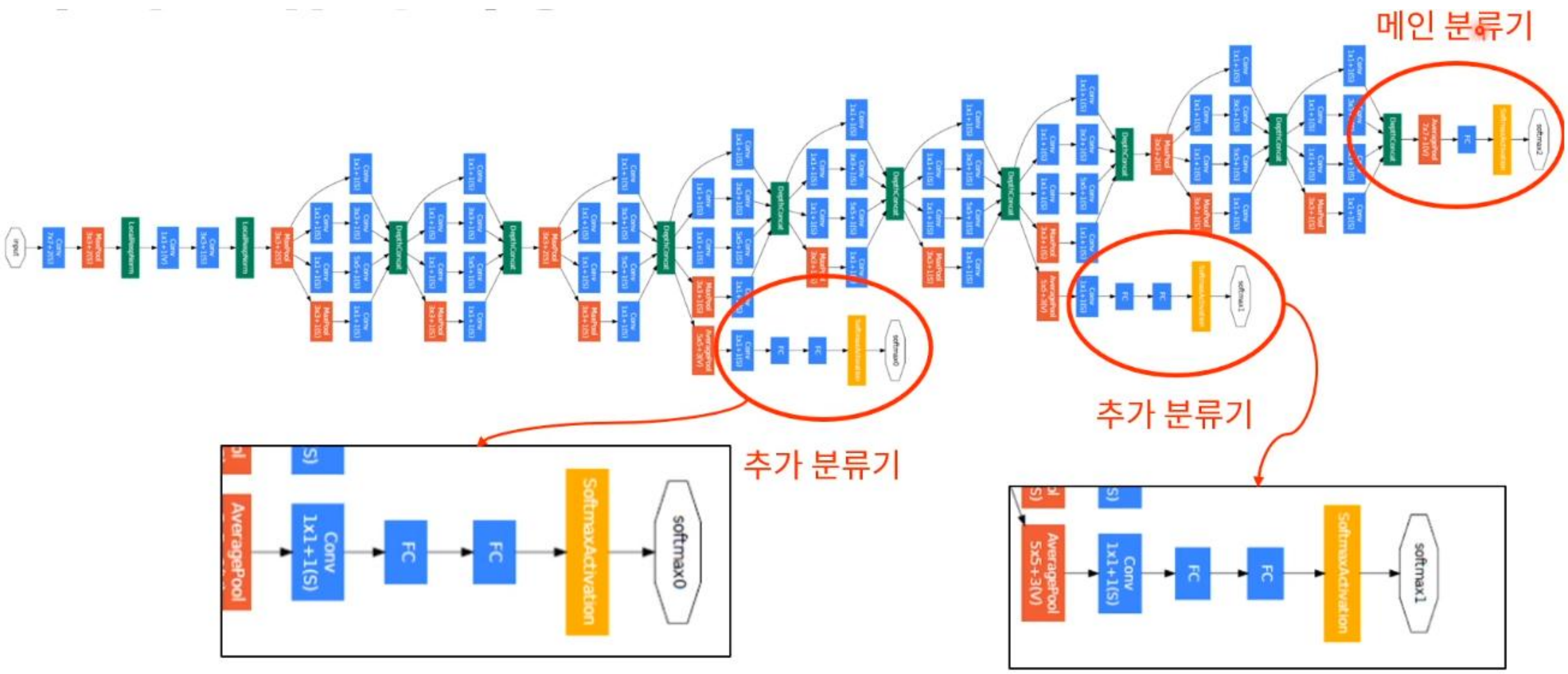
(b) Inception module with dimension reductions



1x1 Conv를 하면, 왜 연산량이 줄어들까?

7. 심화 CNN

4. GoogLeNet (Inception)

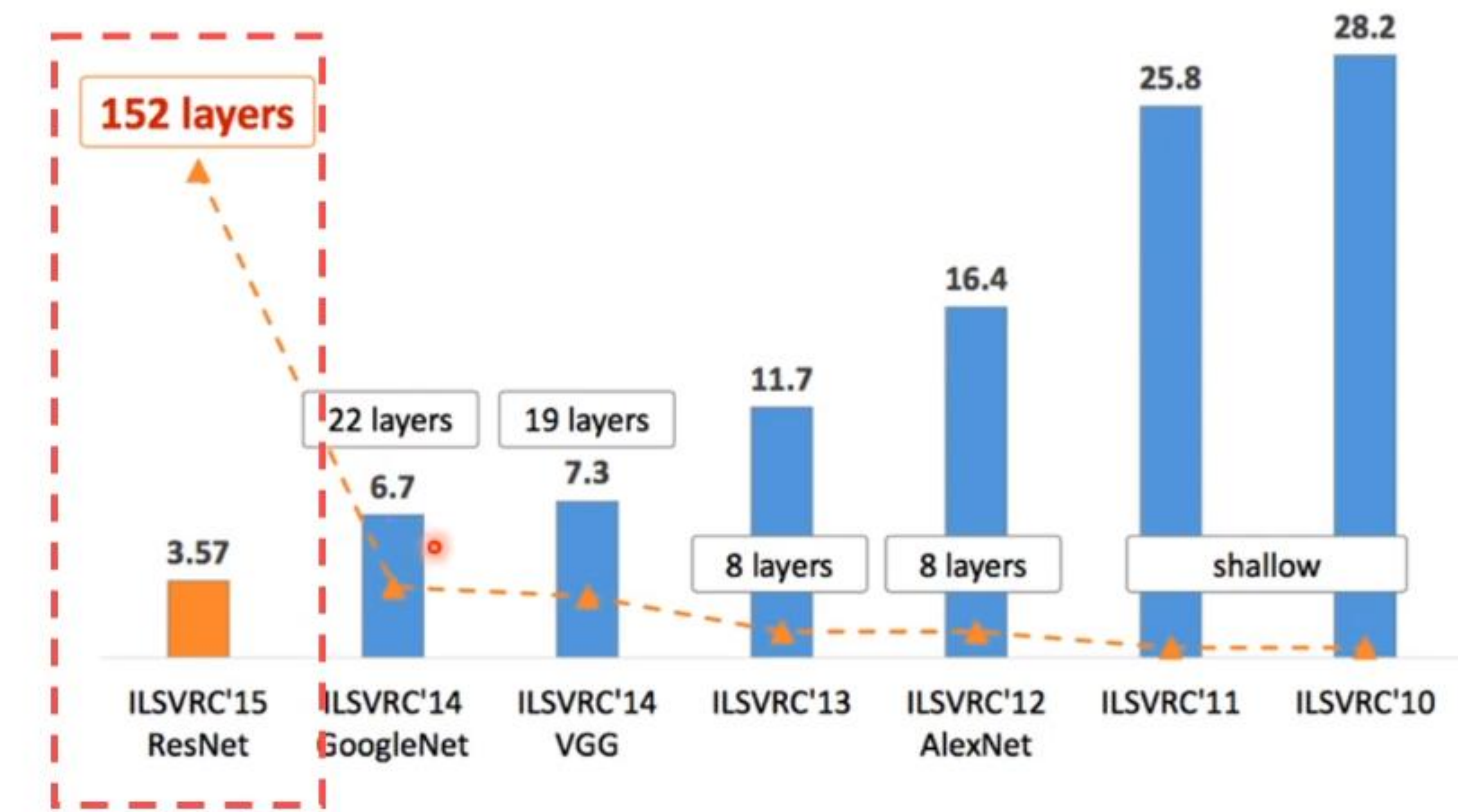


역전파에서 '기울기 소실이 발생하는 것을 방지'하기 위해 추가 분류기 존재

5. ResNet

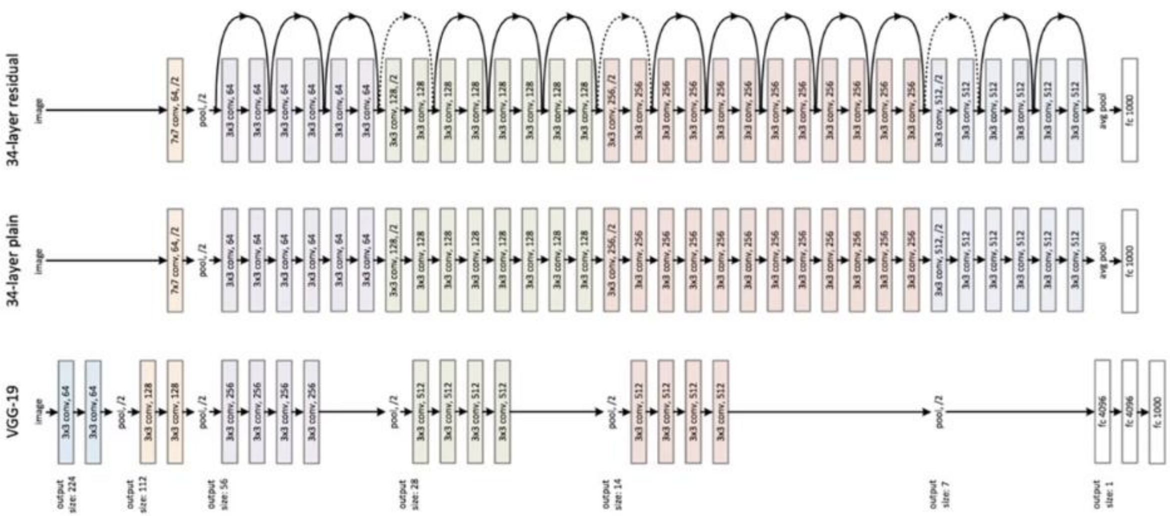
152 Layers? How that deep?

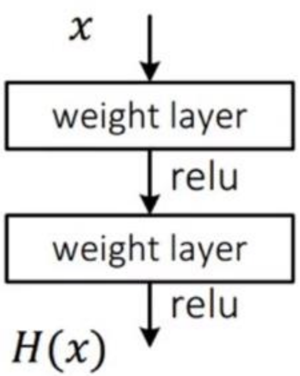
Residual Block



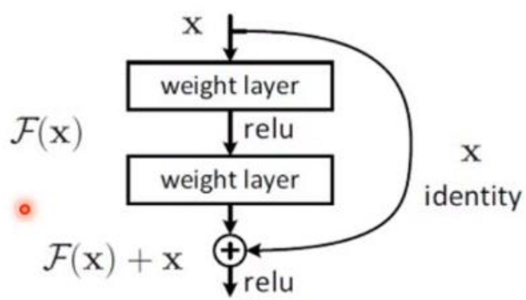
5. ResNet

사이사이에 있는 Skip-Connection이 한몫함!





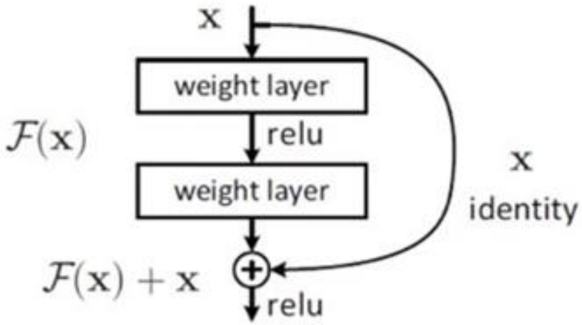
일반적인 구조



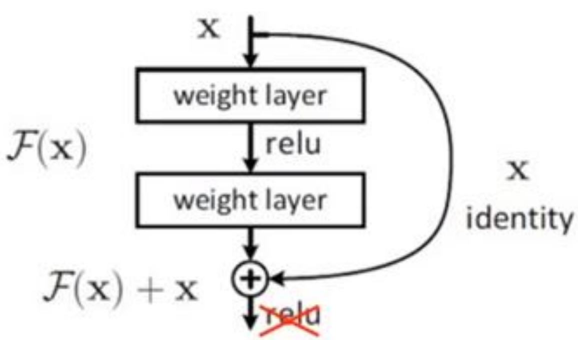
Residual 구조

Feature를 추출하기 전/후를 더함!

5. ResNet

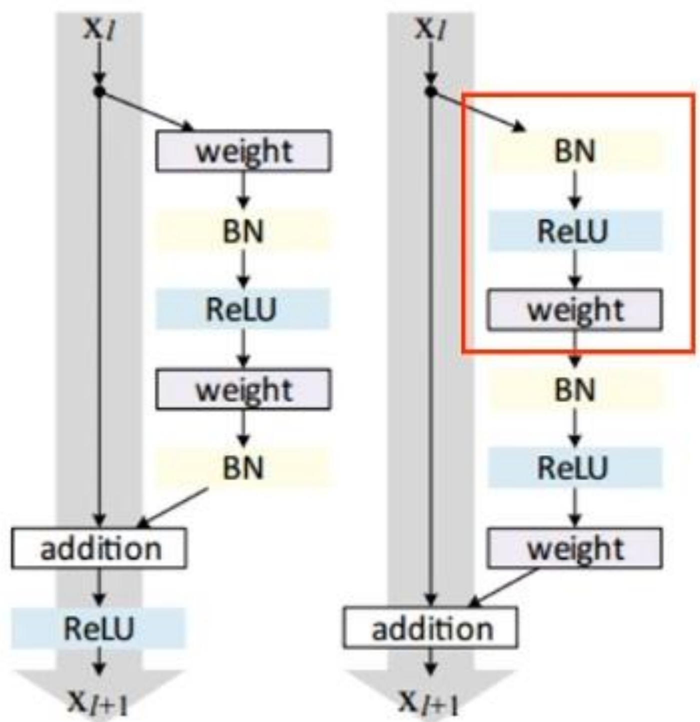


Residual 구조



Identity Mapping

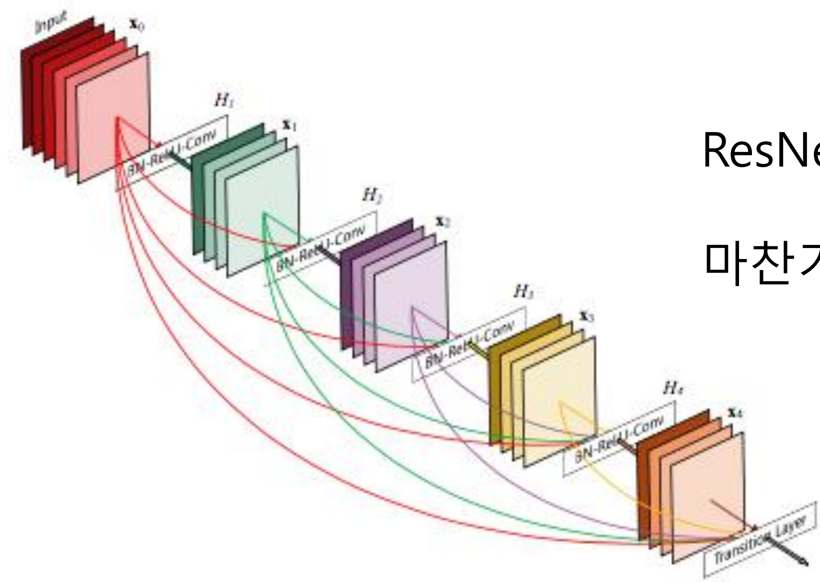
Feature map을 추출한 뒤, activation function을 하던 것이 일반적이었으나, 개선된 구조에서는 "Pre-Activation" (activation function이 먼저 들어감!)



(a) original (b) proposed

7. 심화 CNN

6. DenseNet



ResNet 아이디어의 연장선 상!

마찬가지로 Pre-Activation (BN-ReLU-Conv)

Figure 1: A 5-layer dense block with a growth rate of $k = 4$. Each layer takes all preceding feature-maps as input.

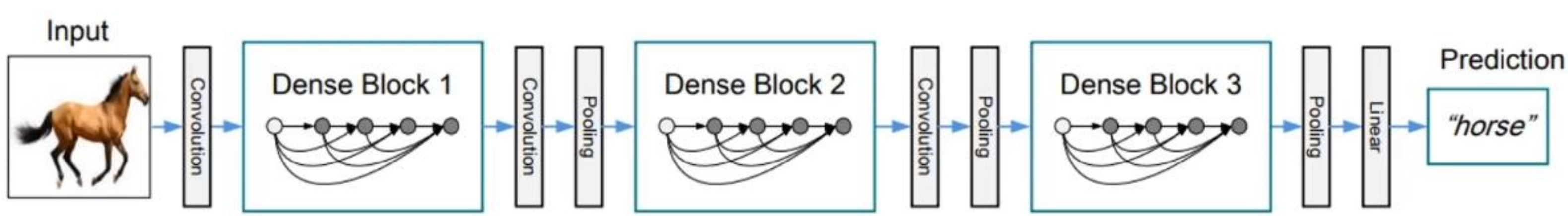
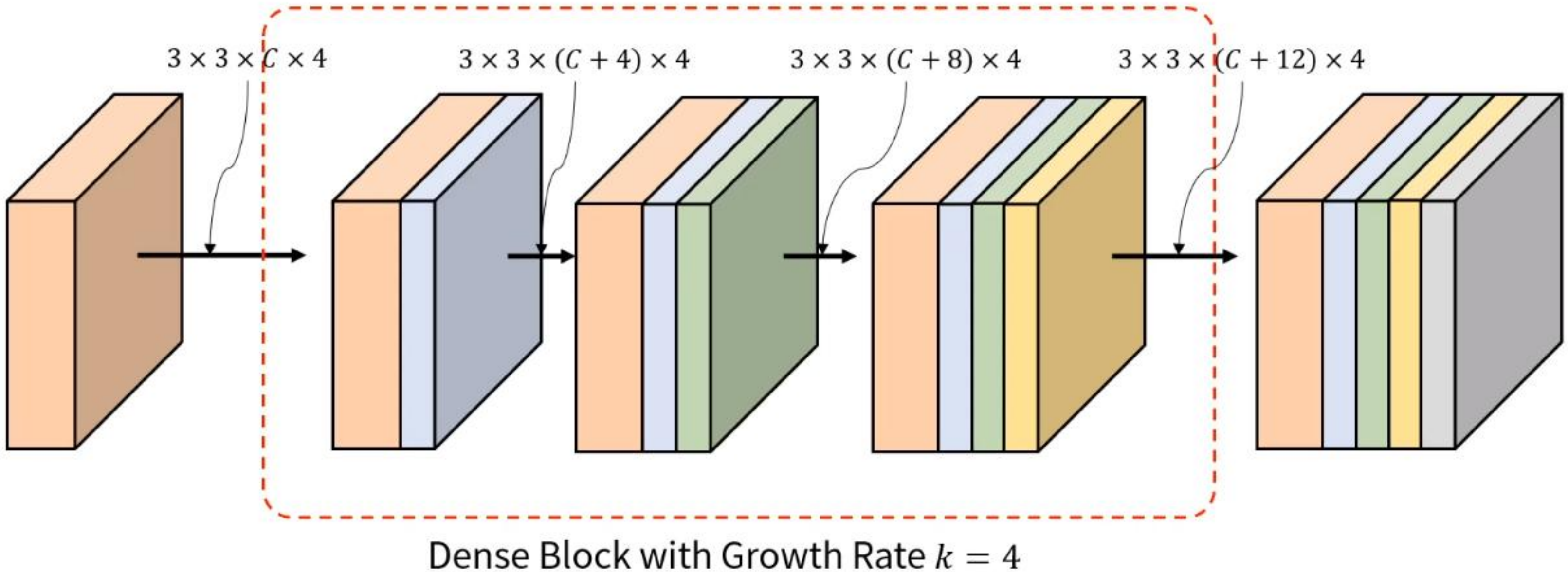


Figure 2: A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

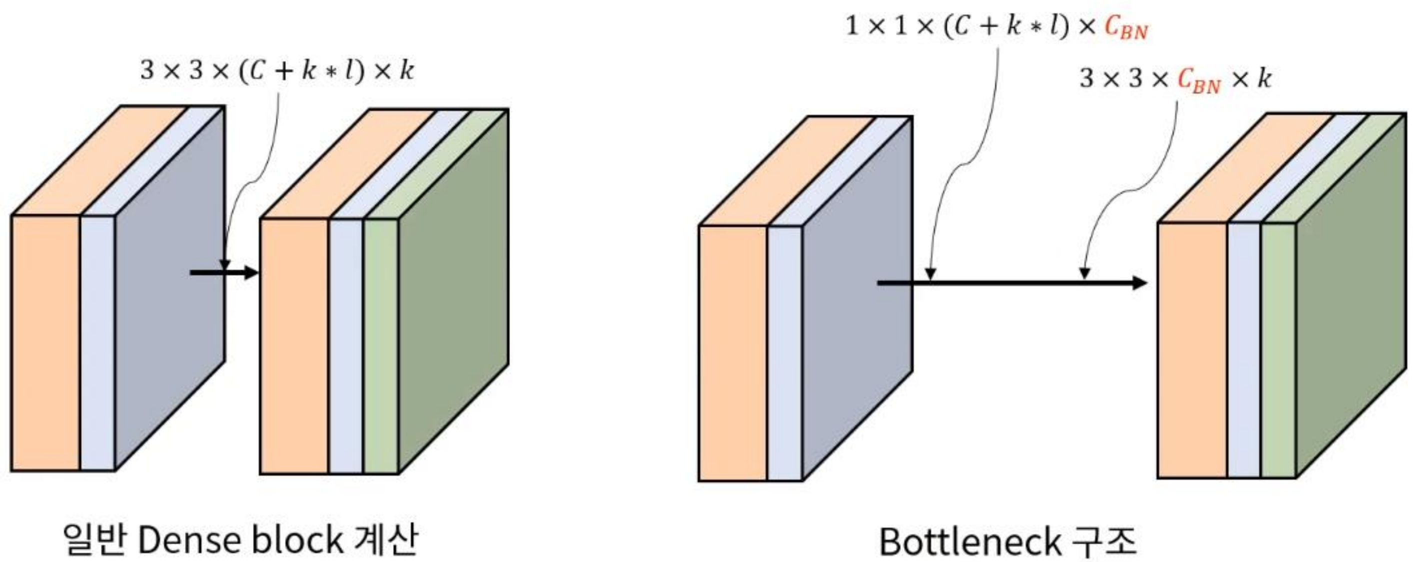
6. DenseNet



쉽게 말해, “이전 feature map에 누적해서 concatenate!”

7. 심화 CNN

6. DenseNet



Deep -> 연산량 too much!

그래서 “1x1 Conv (= Bottleneck Layer)” 사용함

8. Summary

CNN is good for image classification!