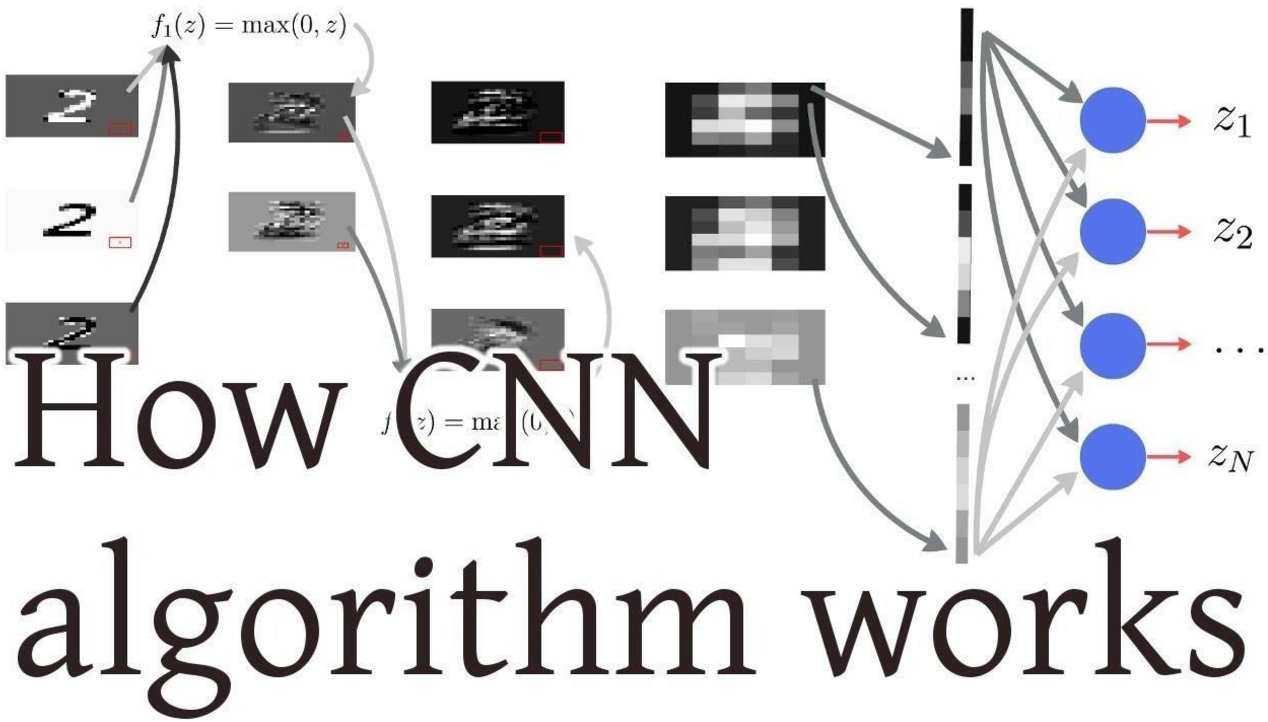
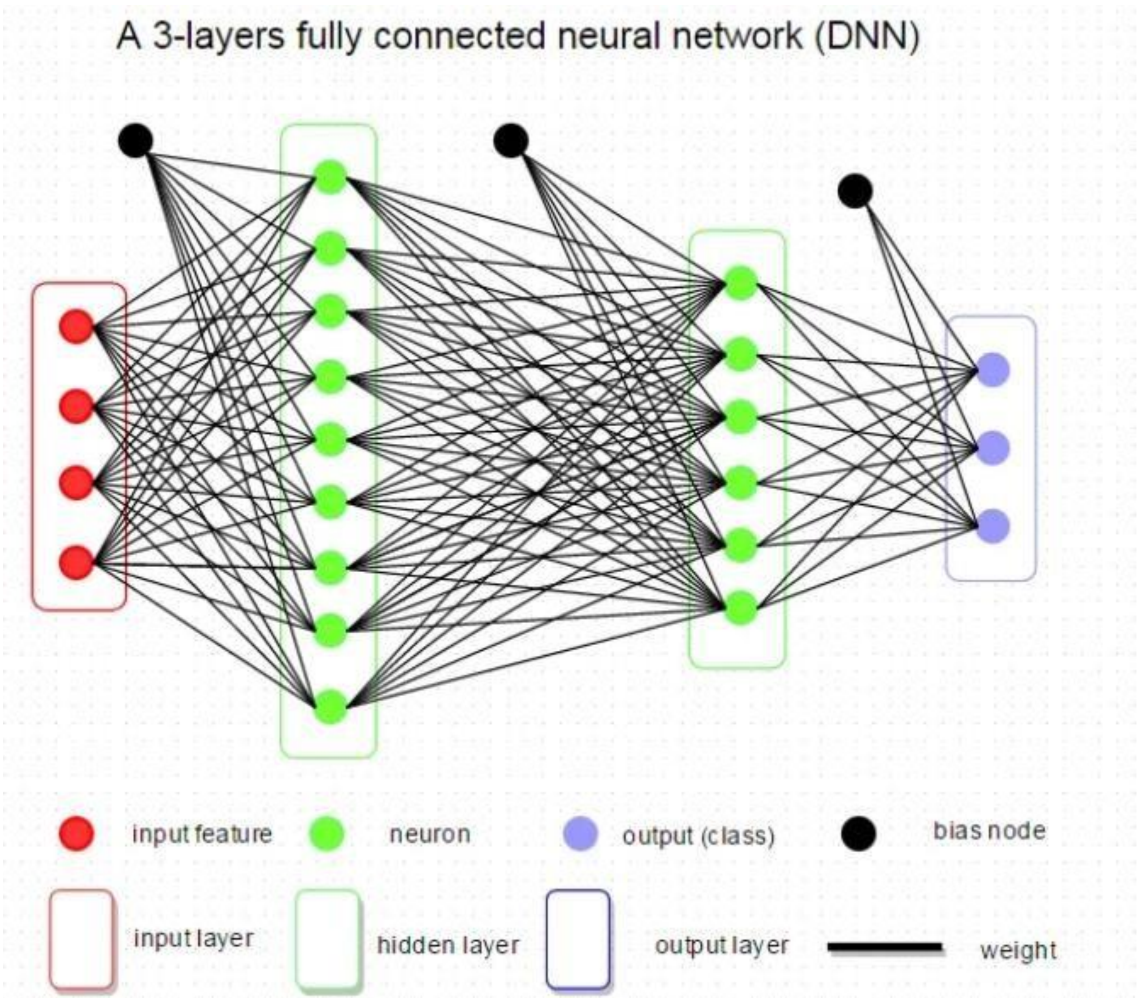
Convolutional Neural Network (CNN)

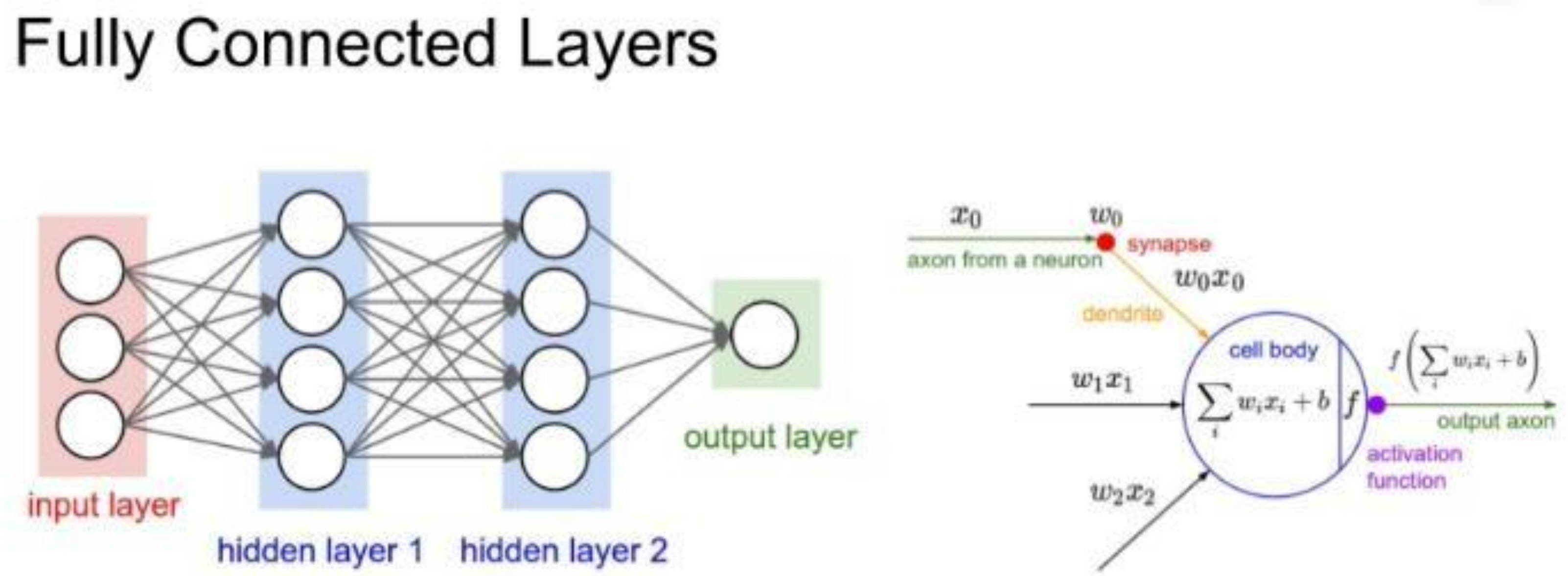


191127 이 승 한

[복 습] Fully Connected Layer (전 결 합 계 층)

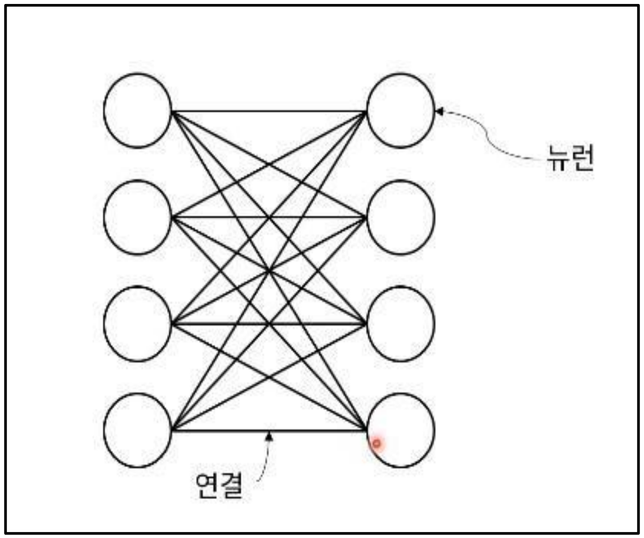


[복습] Fully Connected Layer (전결합 계층)

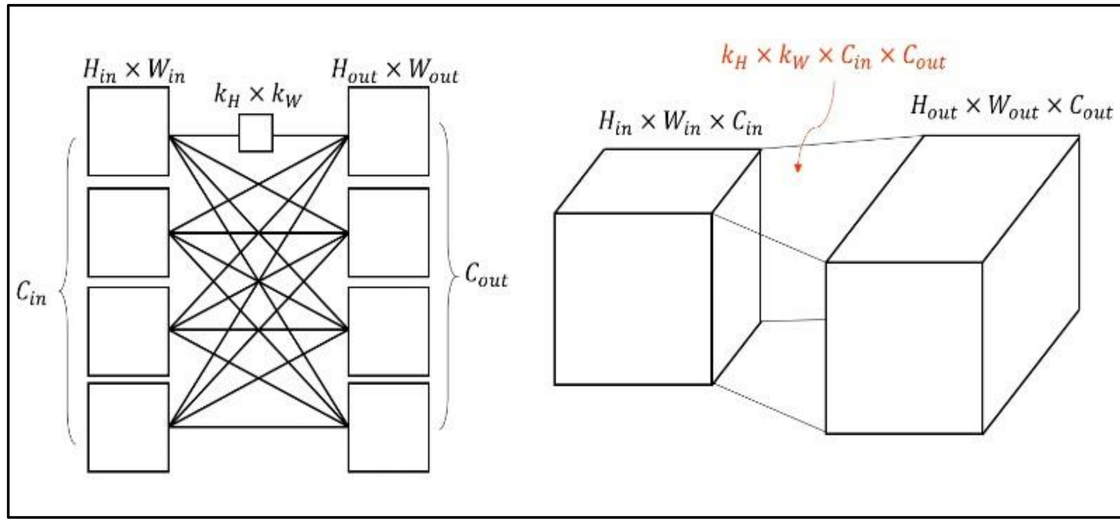


1. What is Convolutional Layer?

[Fully Connected Layer] 전결
합 계층



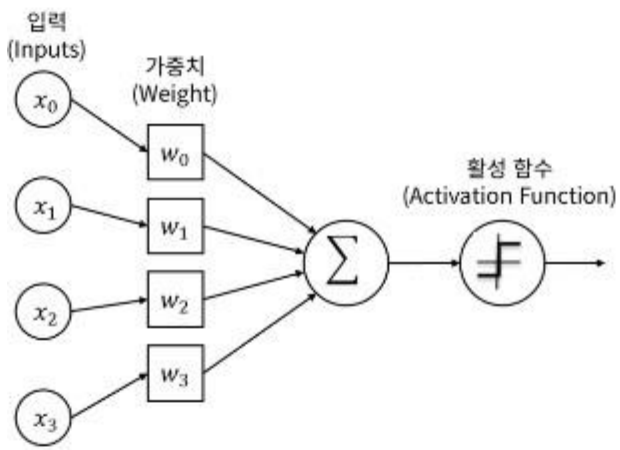
[Convolutional Layer] 합
성곱 계층



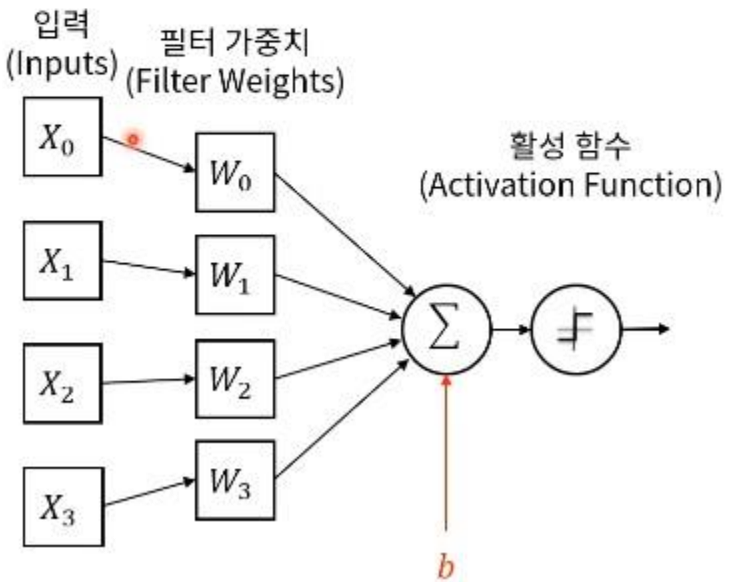
What's the difference?

1. W h a t is Convolutional Layer?

[Fully Connected Layer] 적 결
합 계층



[Convolutional Layer] 합
성곱 계층



(FC) 입 력 -> (Conv) 사 진 / 영 상

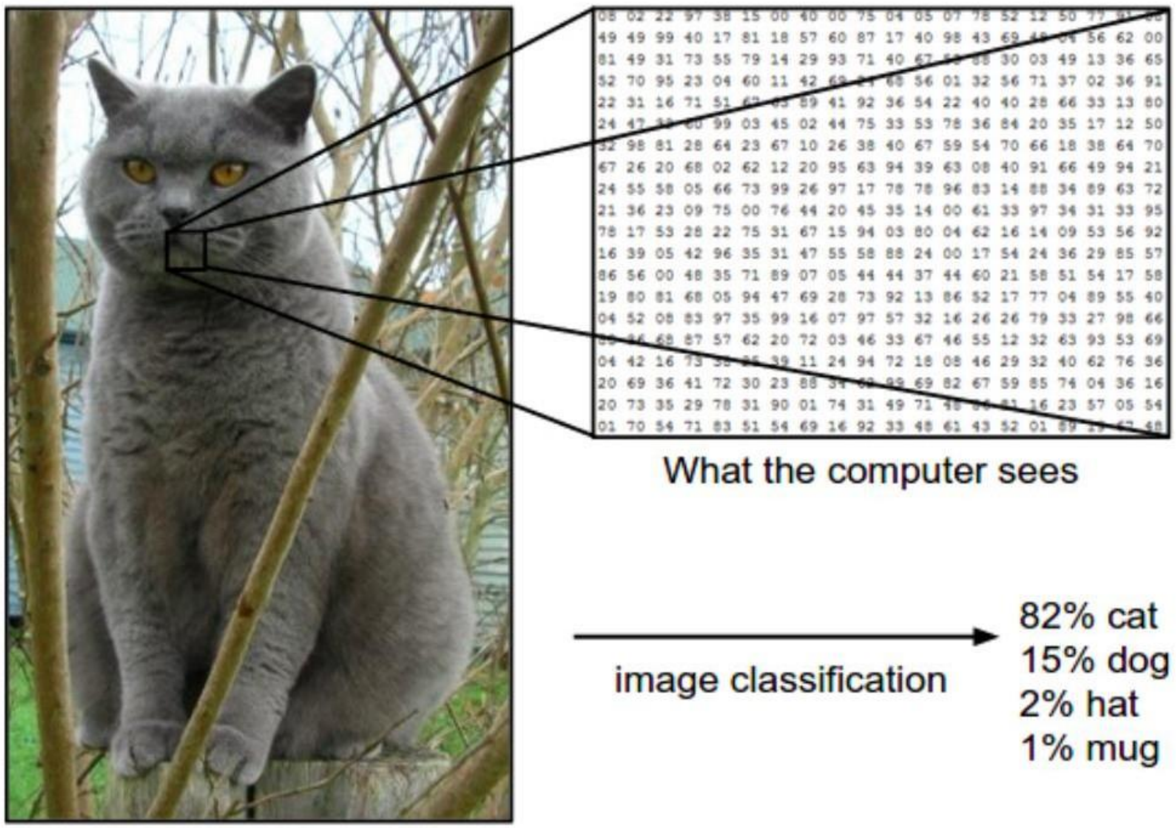
(FC) 가 중 치 -> (Conv) 필 터

(FC) 곱 -> (Conv) 합 성 곱

N o t so different!

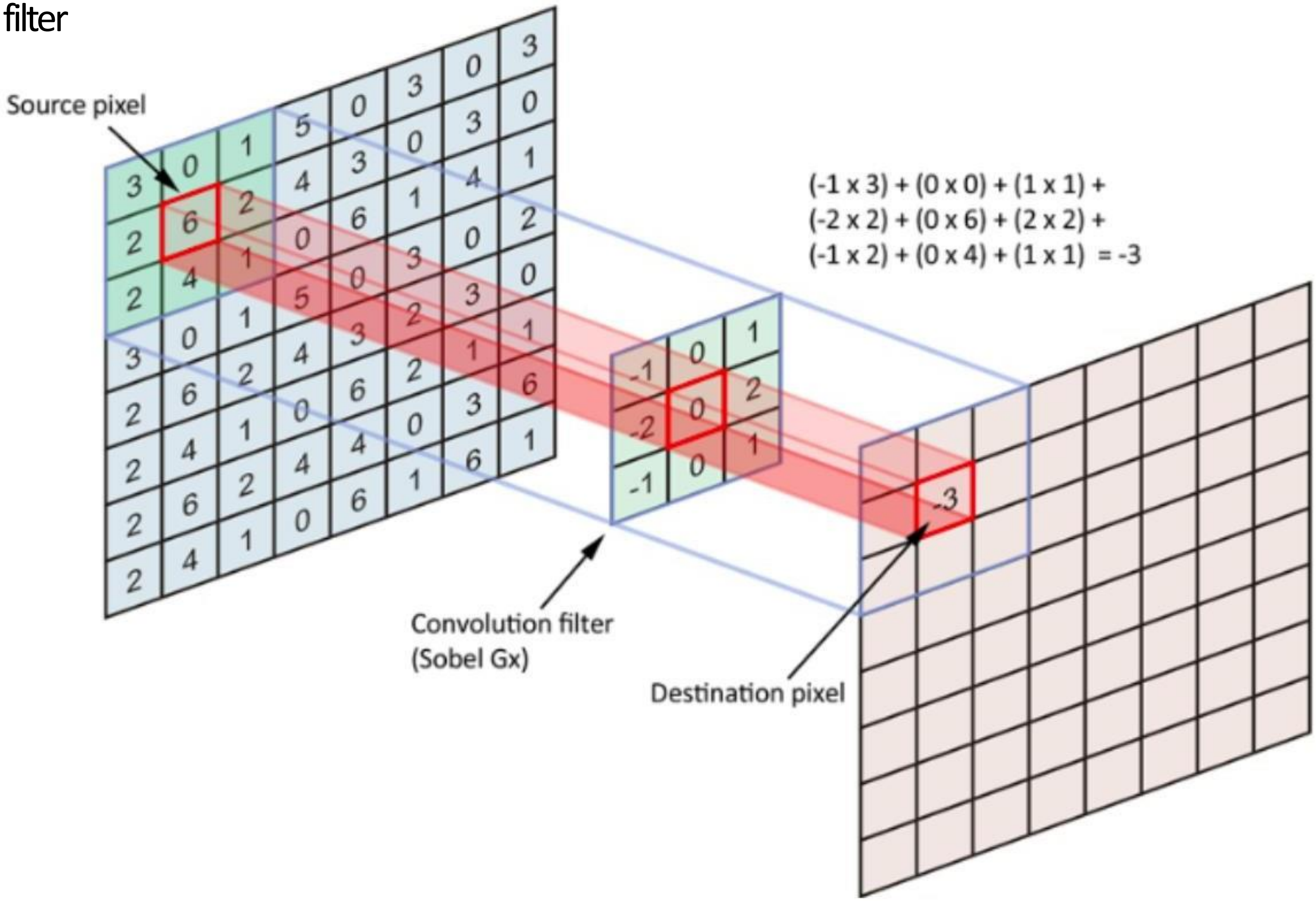
1. What is Convolutional Layer?

(1) input



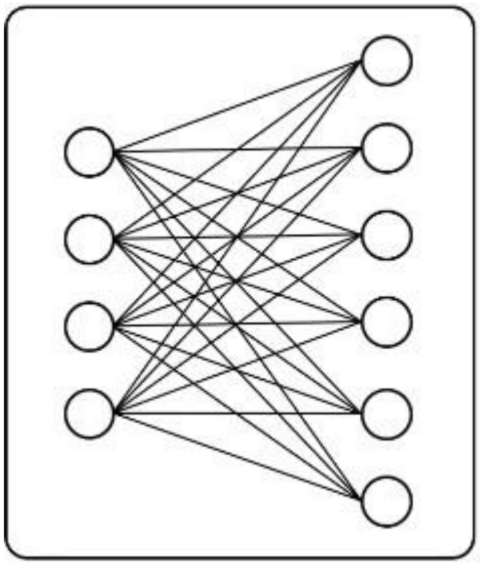
1. What is Convolutional Layer?

(2) filter



2. Convolutional Layer – 수 식 적 표 현

(1) FC의 수 식 적 표 현



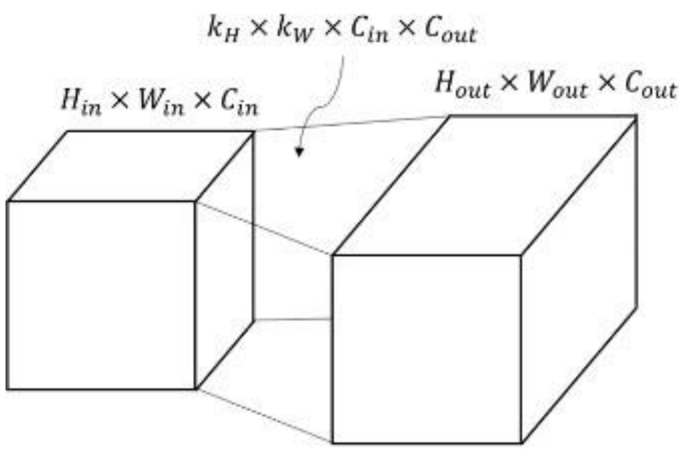
$$W = [\mathbf{w}_0, \mathbf{w}_1, \dots, \mathbf{w}_{M-1}]^T$$
$$\mathbf{b} = [b_0, b_1, \dots, b_{M-1}]^T$$

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

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

2. Convolutional Layer – 수 식 적 표 현

(2) Conv의 수 식 적 표 현



보통 3x3, 5x5, 7x7 등을 사용

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

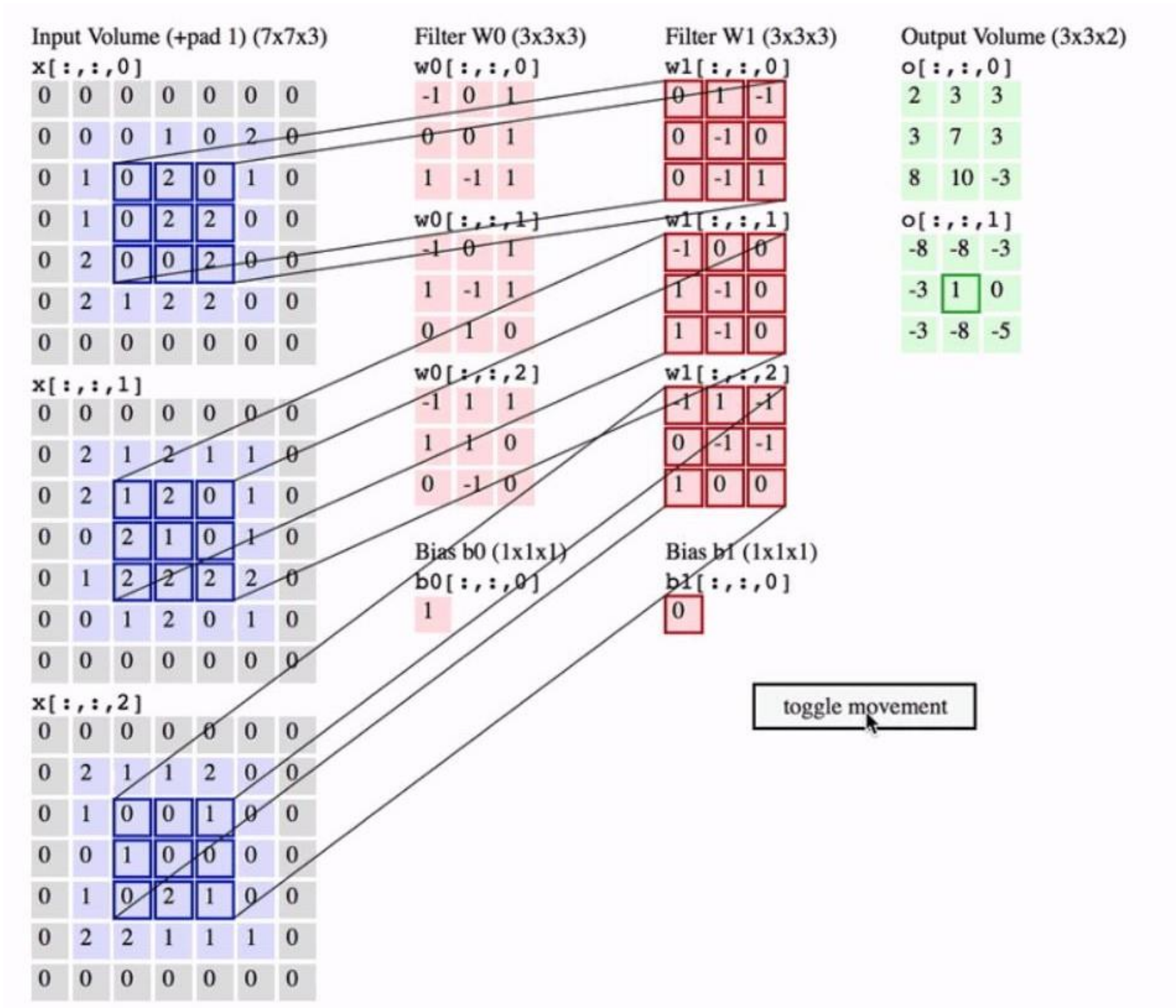
$$\boldsymbol{W} = \begin{bmatrix} \boxed{W_{0,0}} & \cdots & W_{0,M-1} \\ \vdots & \ddots & \vdots \\ W_{N-1,0} & \cdots & W_{N-1,M-1} \end{bmatrix}$$

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

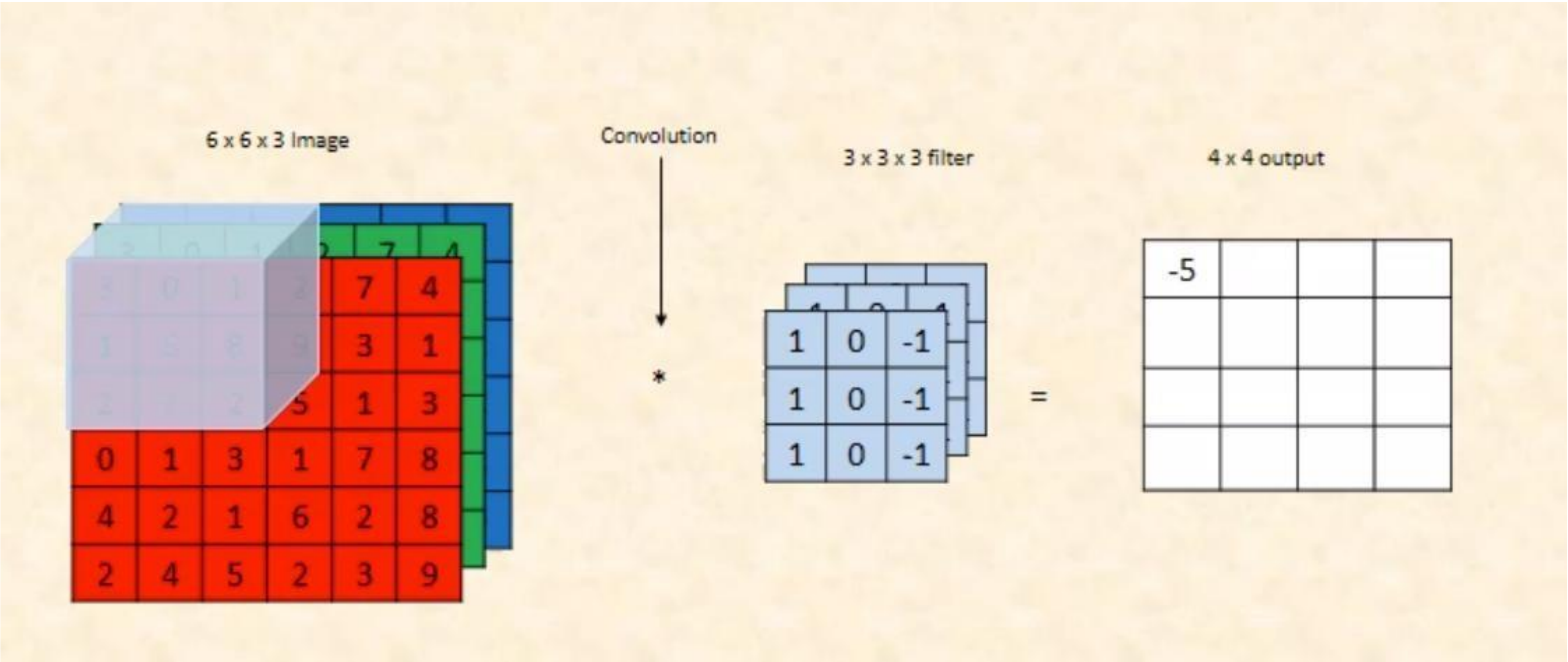
$$\boxed{Y_{i,j} = a\left(W_{i,j} * X_i + b_j\right)}$$

C(in) x C(out)번의 합성곱 연산이 이루어짐!

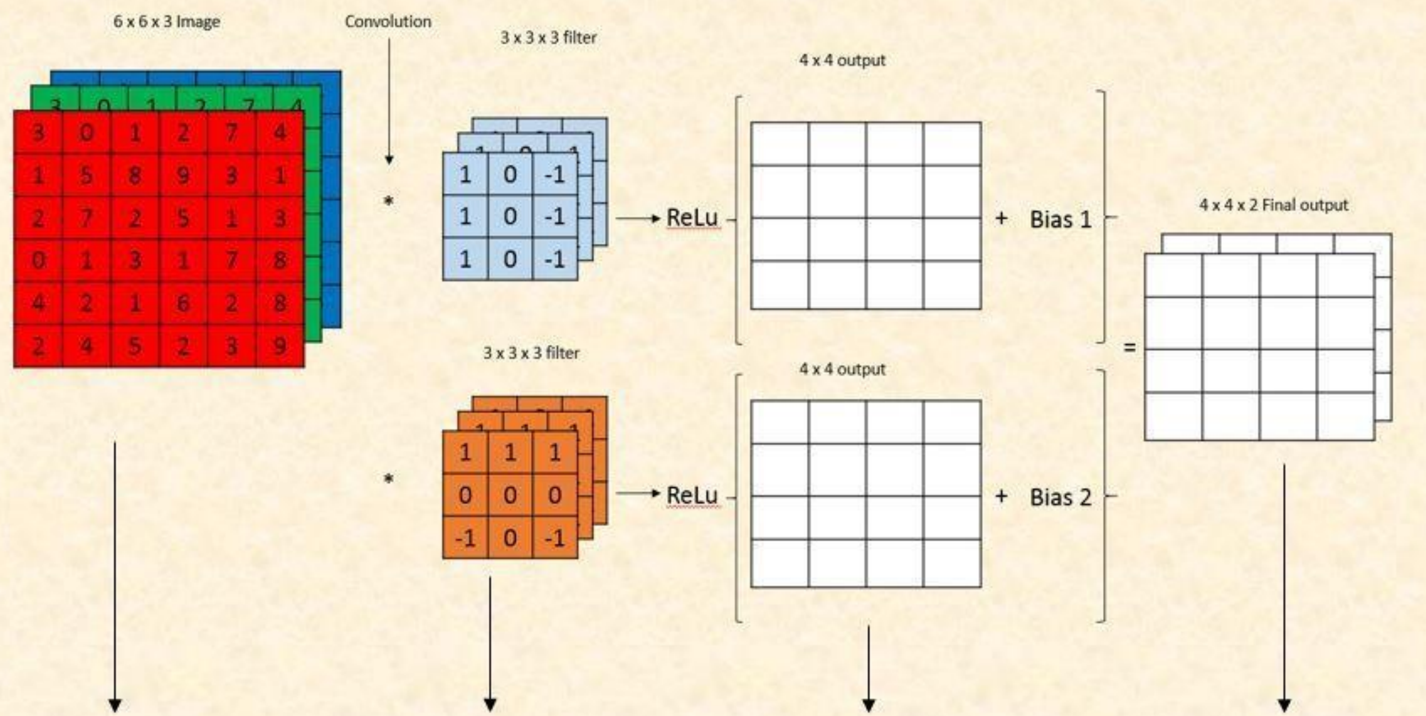
2. Convolutional Layer – 수 식 적 표 현



2. Convolutional Layer – 수 식 적 표 현



2. Convolutional Layer – 수 식 적 표 현



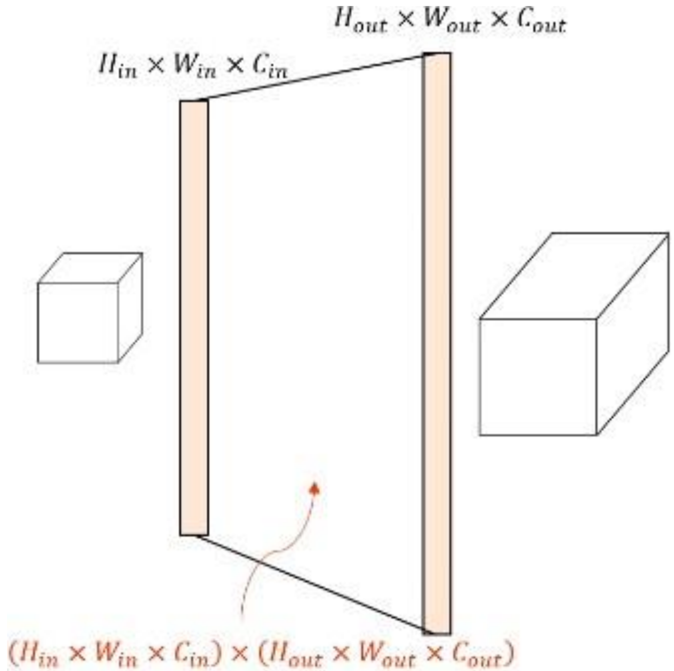
$A^{[0]}$ $W^{[1]}$ ReLu $(W^{[1]} A^{[0]} + b)$ $=$ $A^{[1]}$

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	$n_c^{[l]}$

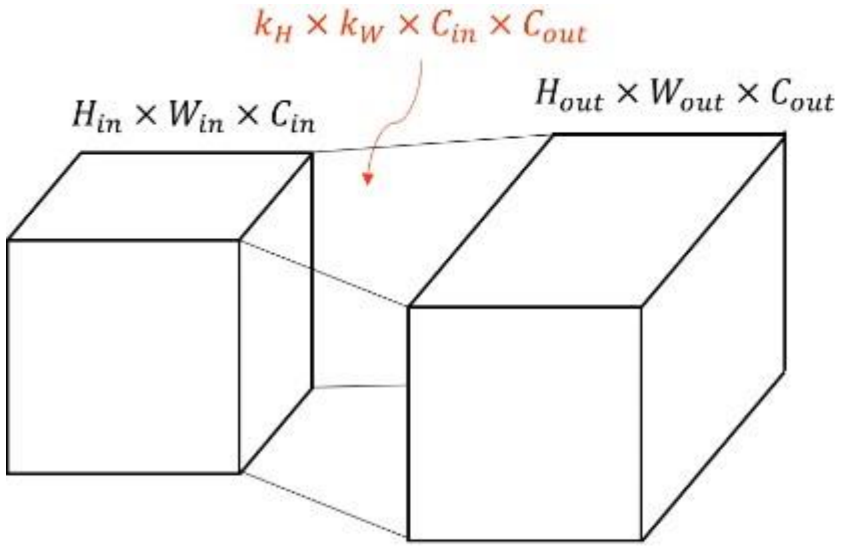
Where
$f^{[l]}$ = filter size
$p^{[l]}$ = padding
$s^{[l]}$ = stride
$n_c^{[l]}$ = number of filters
$n_c^{[l-1]}$ = color channels

3. Why Convolutional Layer?



(1024 x1024x16)

(3x3x16x32)

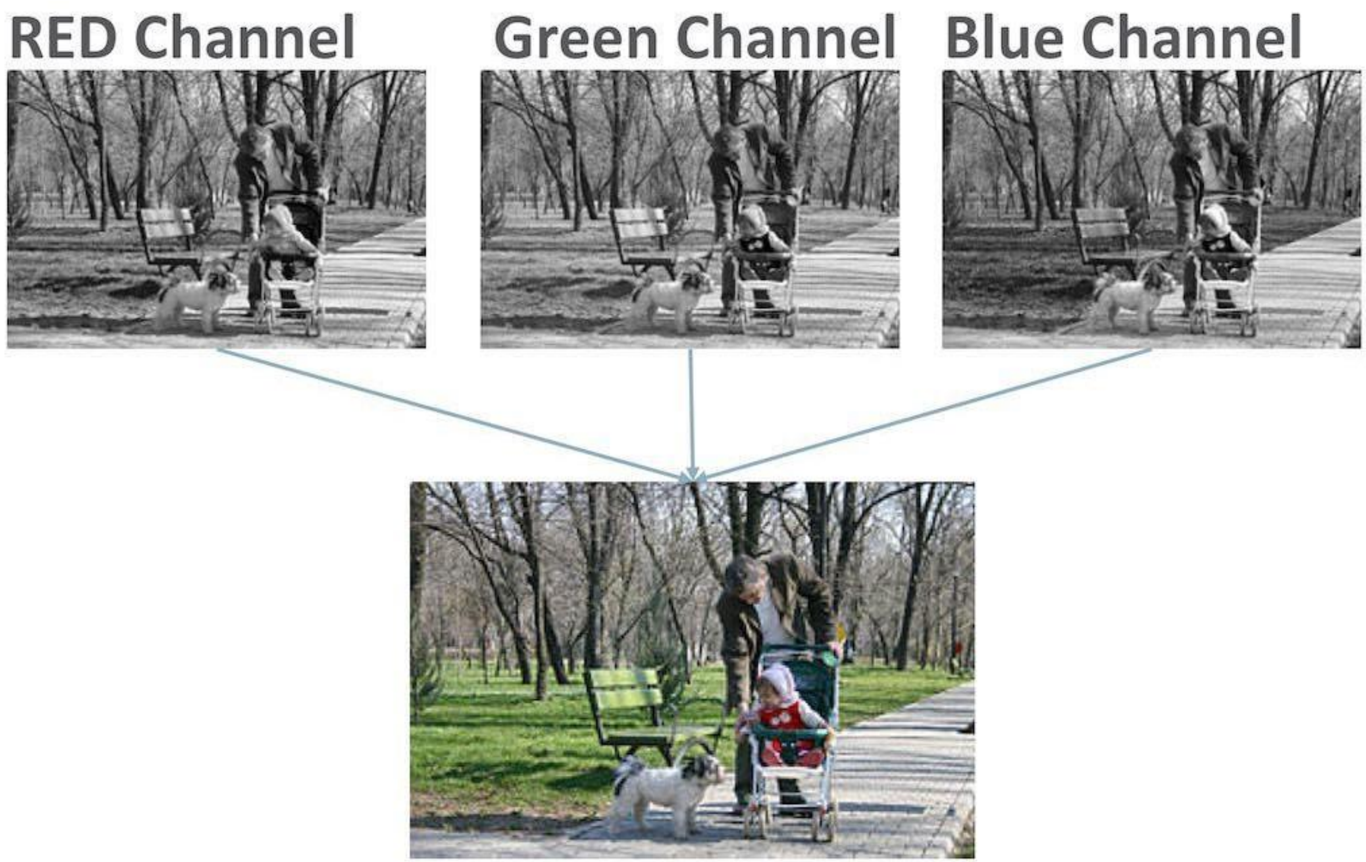


FC 대신 Convolutional Layer 써야하는 이유?

"Parameter 수의 감소!"

4. 용 어 설 명

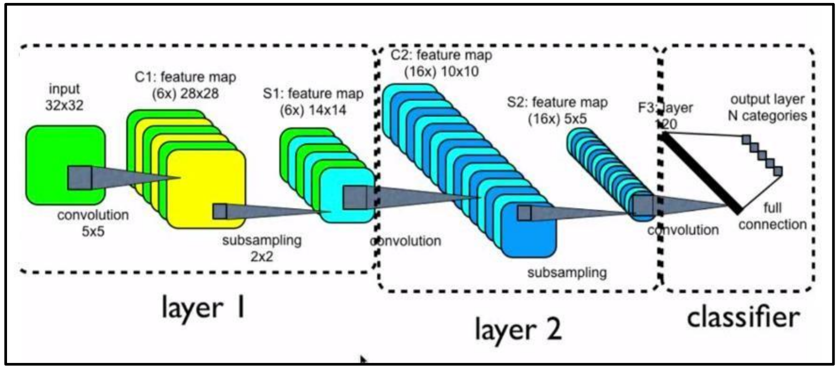
(1) Channel

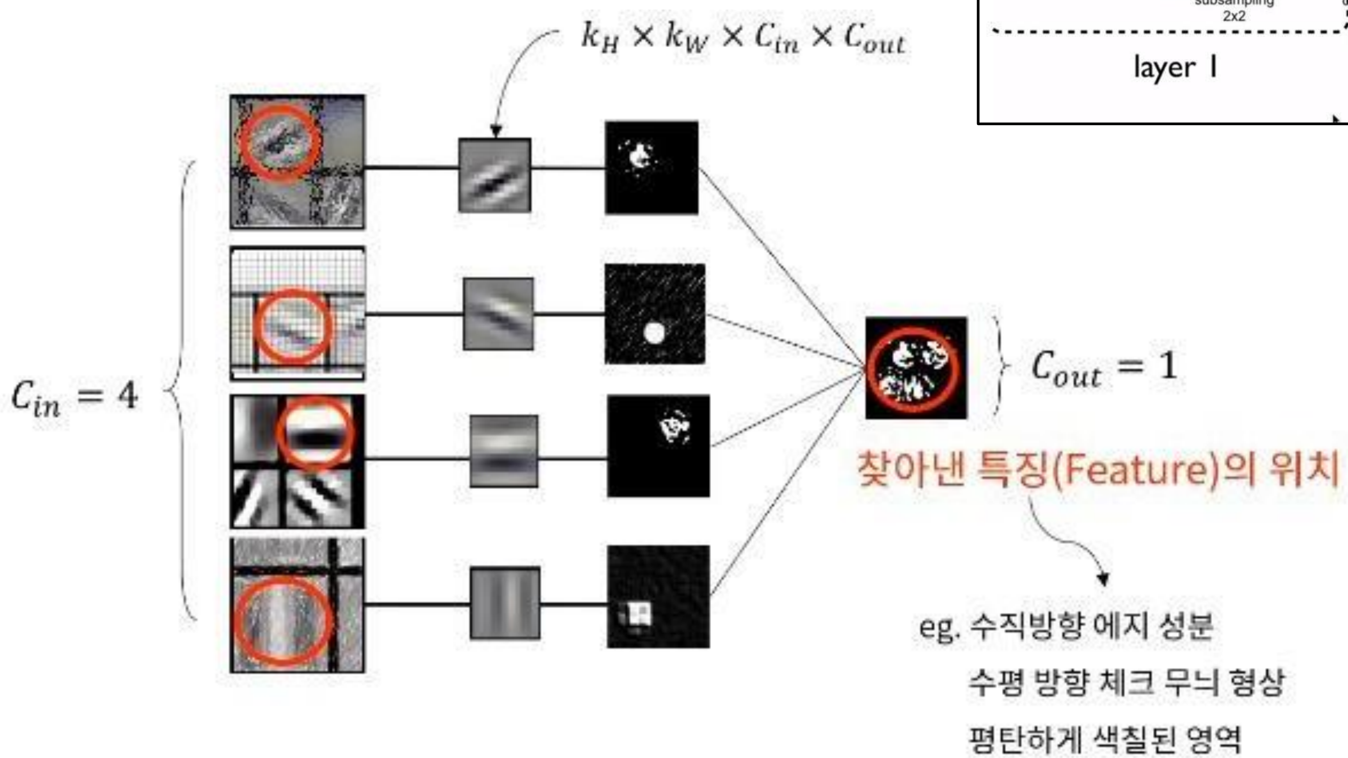


이미지 출처: https://en.wikipedia.org/wiki/Channel_(digital_image)

(2) FeatureM a p

합성곱을 통해서 만들어진 출력!



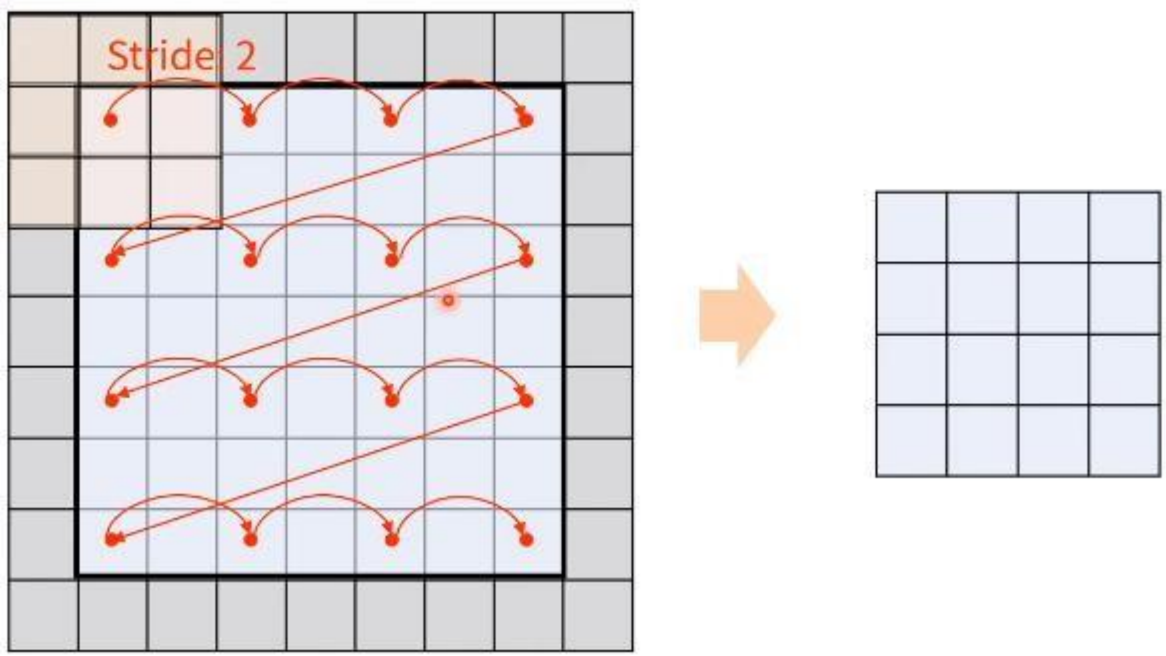


합성곱 계층의 의미?

여러 채널에서 특별한 "특징"이나타내는 위치를 찾아내는 역할!

4. 용 어 설 명

(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

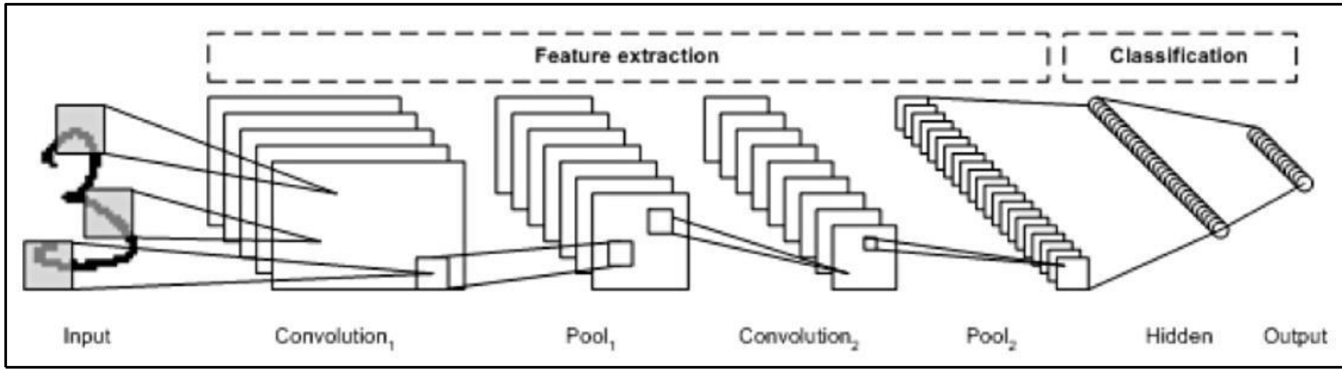
주위에 숫자(주로 0)을 둘러씌우는 것! (For 크기 보존)

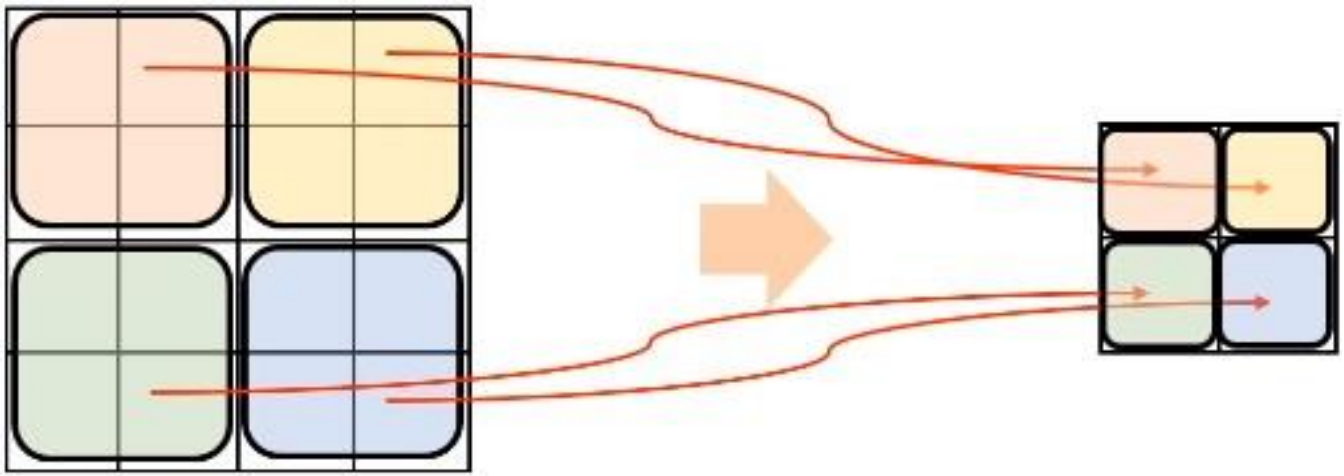
합성 곱 연산시, 필터(커널)의 크기에 따라 영상의 크기가 줄어드는 문제 발생

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

4. 용 어 설 명

(5) Pooling



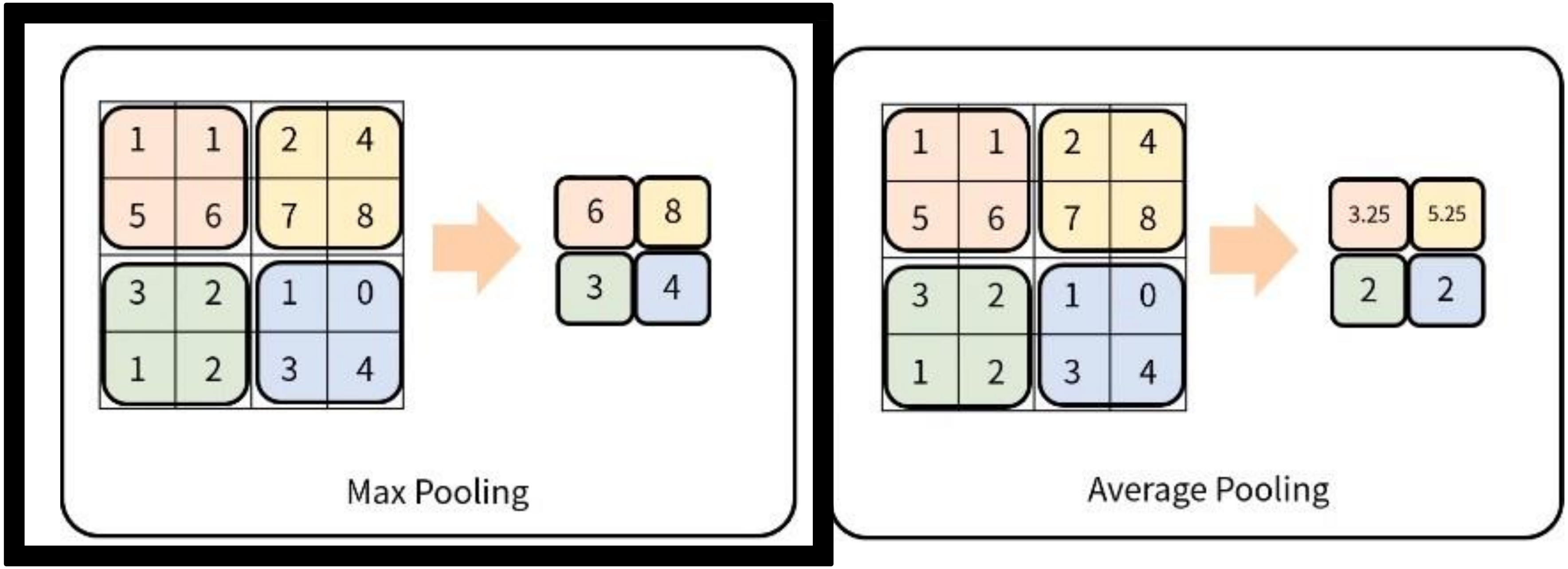


Sampling이라고 보면 됨! (여러 화소를 하나의 화소로 축약!)

즉, “영상/사진의 크기가 줄어들고, 정보가 종합(요약)된다!”

4. 용 어 설 명

(5) Pooling



Pooling Layer (vs Convolution Layer)

1) 학습대상 parameter 없음

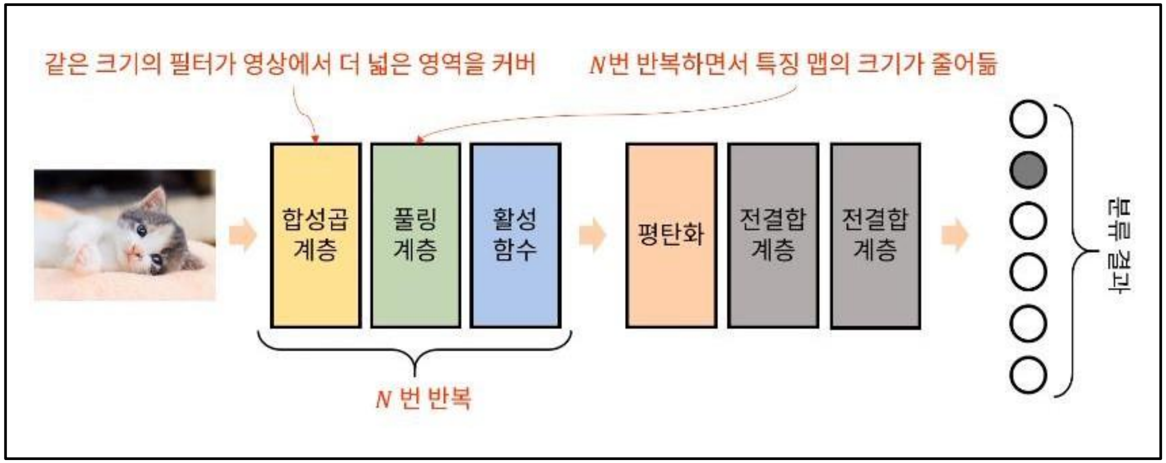
2) Pooling Layer를 통과하면 행렬의 크기 감소

3) Pooling Layer를 통해서 채널 수 변경 없음

4. 용 어 설 명

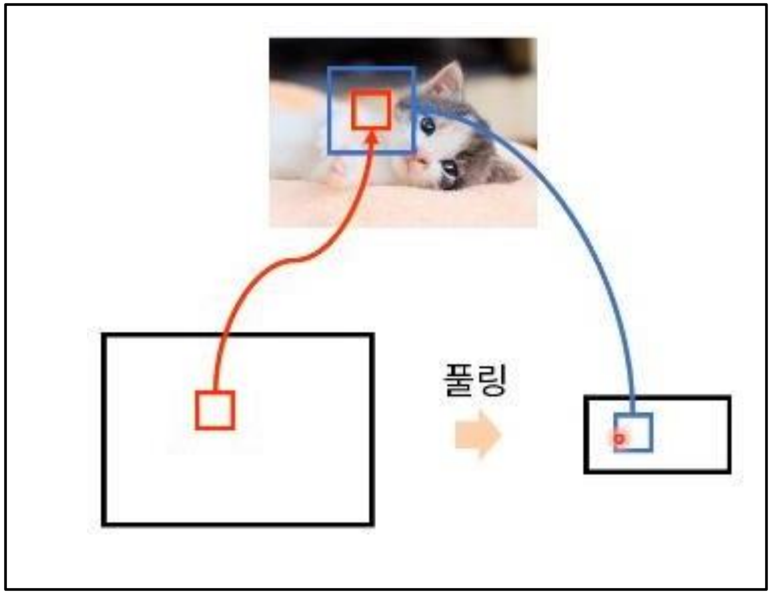
(5) Pooling

why pooling? Receptive Field?



(h,w)영상 크기 작아지고,

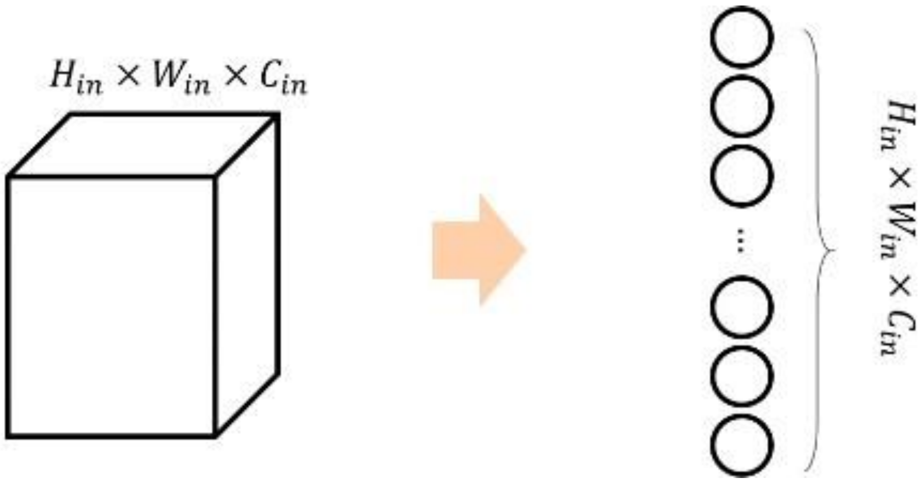
(c)채널 수 늘어나게 될 것!



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

4. 용 어 설 명

(6) Flatten



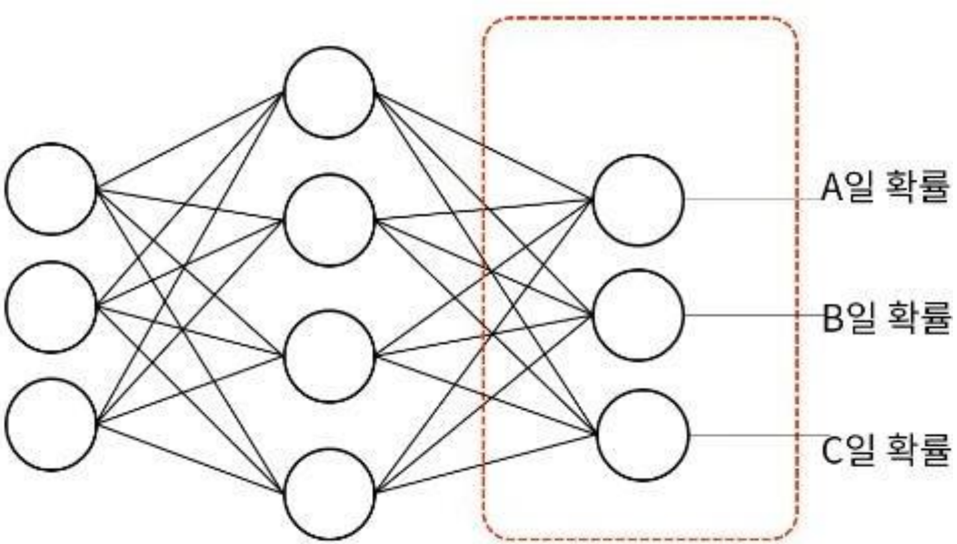
평탄화! -> Vector로 만들어줌

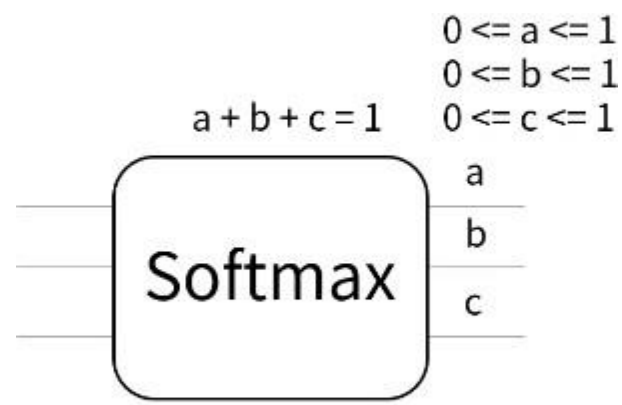
단지 쭉 피는 것을 의미! (연산 과정 X)

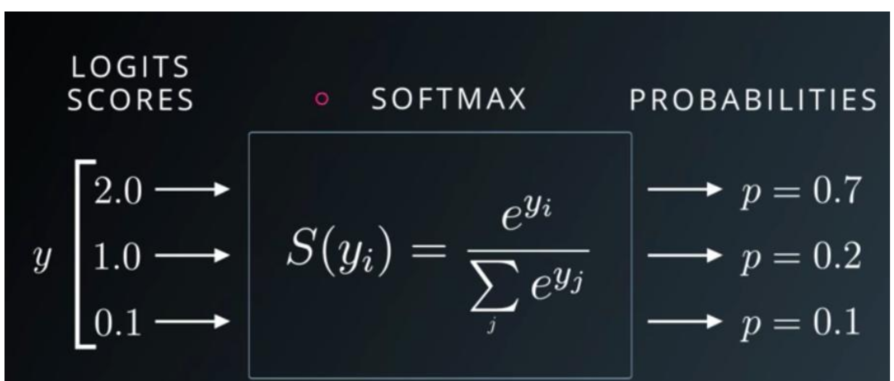
Conv & FC 연결해주는 역할

(7) Softmax Function

for Multi-class Classification

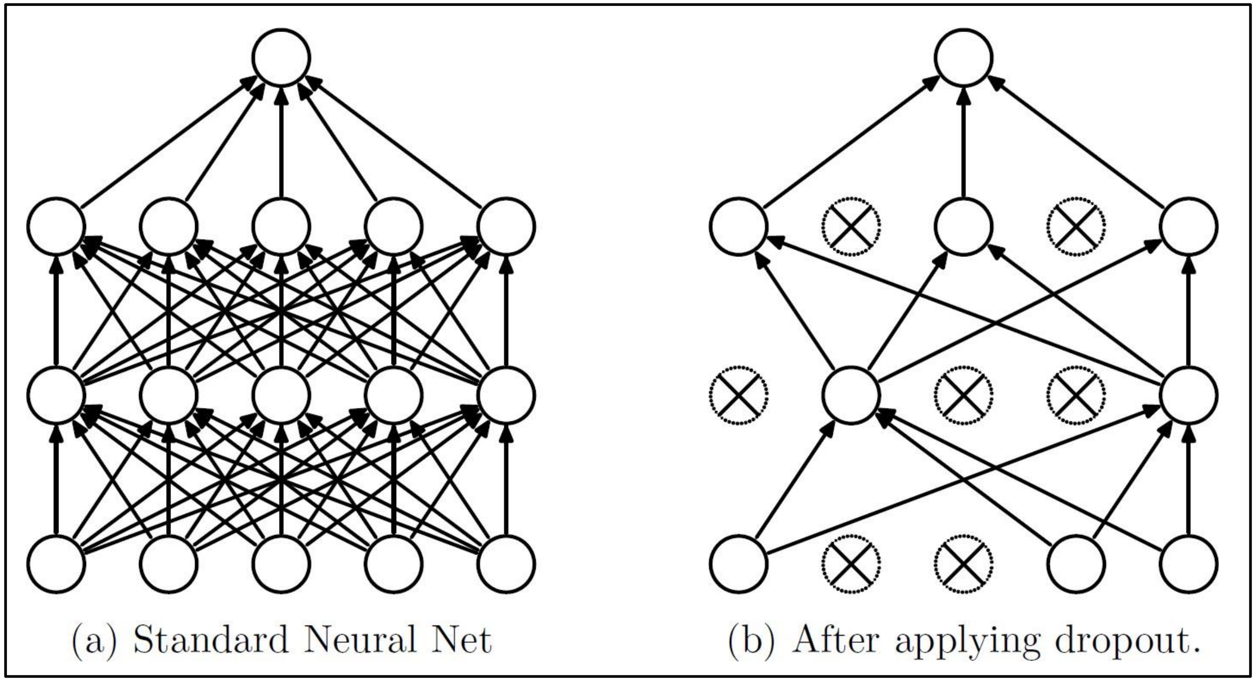






5. Dropout

To prevent overfitting!



Training할 때만!

(testing할 때는 X)

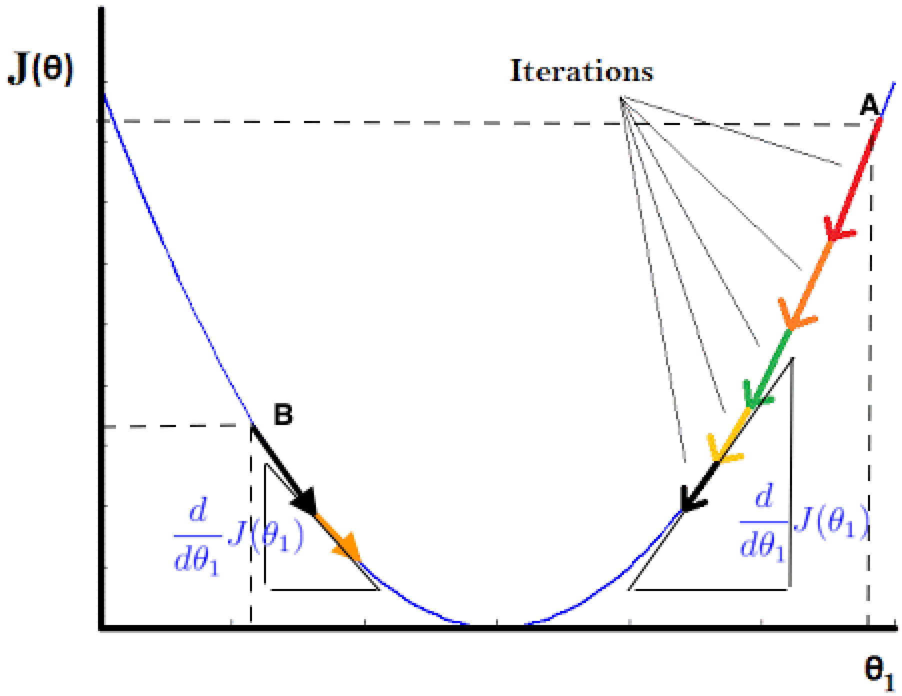
Ex) Dropout rate 0.3 : 30%의 node는 사용 X (less parameter)

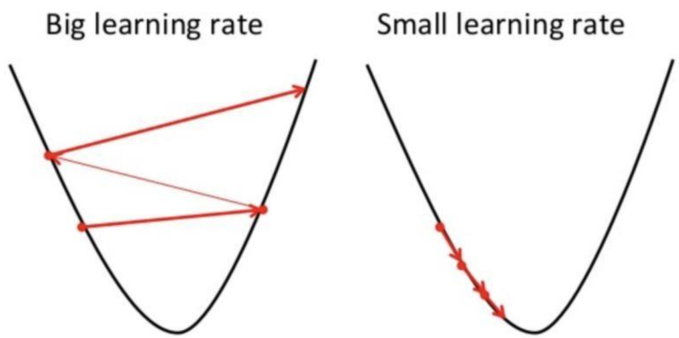
Overfitting 문제가 해결되는 이유를, 직관적으로 생각해보자!

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 한 번 반복되는 것을 의미!

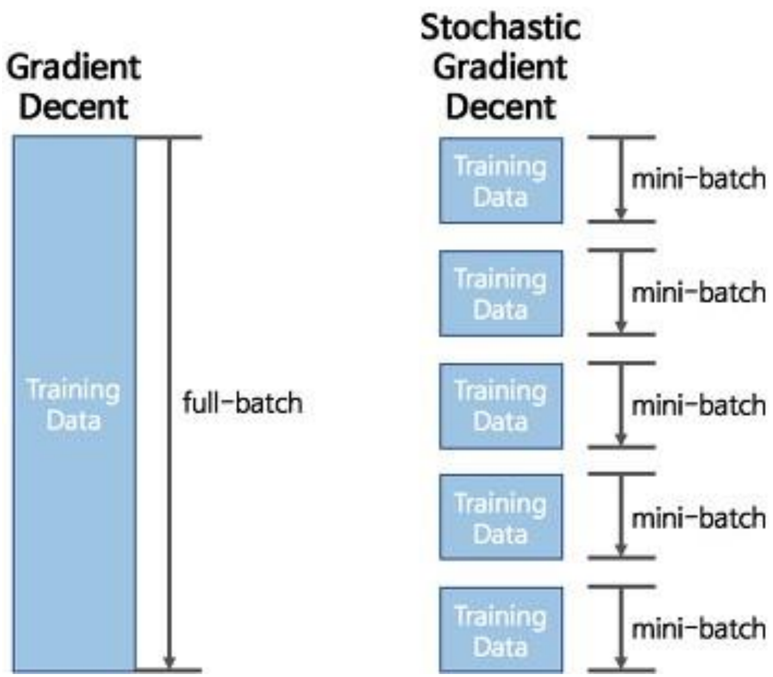
(iteration 한 번 할 때마다 parameter 조정해 나감)

6. Mini-Batch

Vanilla(Batch) Gradient Descent
(일반 경사 하강법)

Gradient를 한 번 update하기 위해, “

모든 training data”를 사용



Stochastic Gradient Descent
(확률적 경사 하강법)

Gradient를 한 번 update하기 위해,

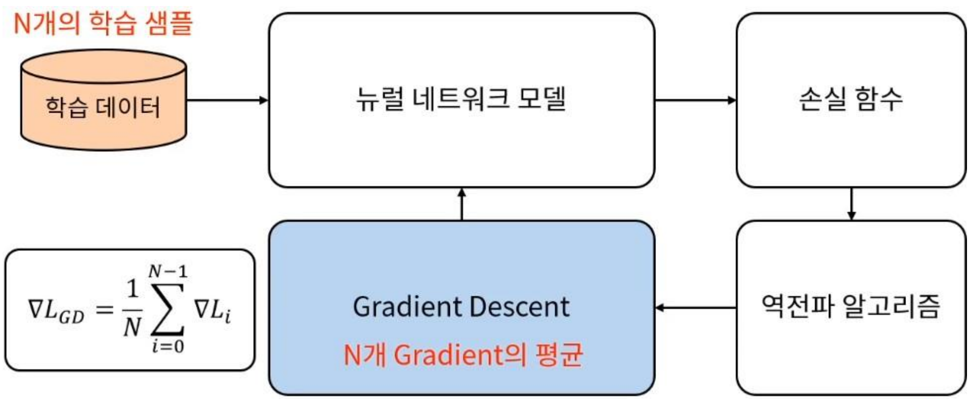
“일부의 training data”만 활용! (일단, 일부 = 1개라고 일단은 생각하자!)

(일부=m개인 경우가 „Mini-Batch Gradient Descent)

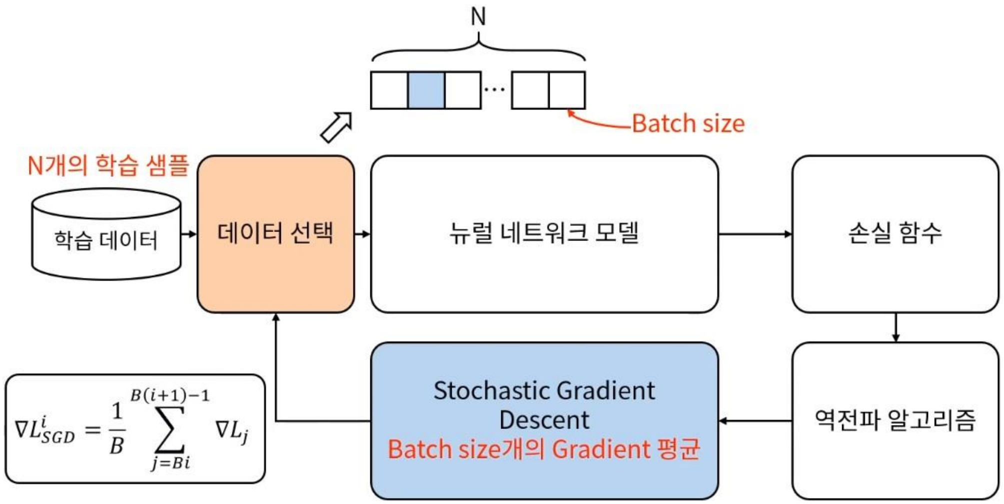
(SGD와 Mini-batch GD의 용어를 섞어 쓰기도)

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 대핚 update가 “1번”이루어짐 -> SGD에 비해 적은 update(계산) 횟수 필요 -전체 data에 대해 error gradient 계산! (optimal로 수렴이 안정적) - 병렬 처리 GOOD	-Local optimal에 빠질 위험 적음 - step에 걸리는 시갂이 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(M B G D)

32개	32개	…. .	32개	32개

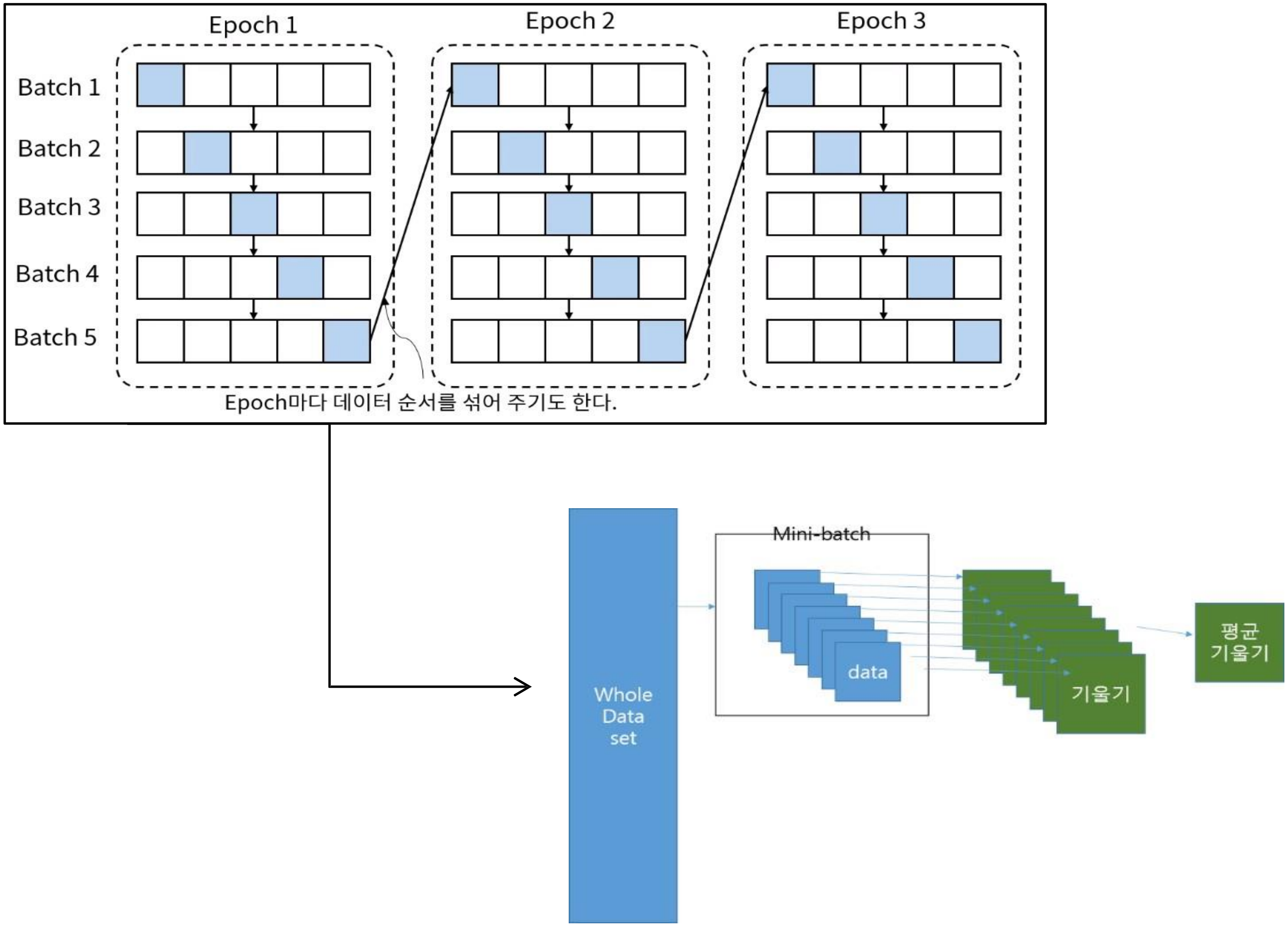
(용어 구분해서 쓰지 않는 경우도!)

Stochastic Gradient Descent (SGD)

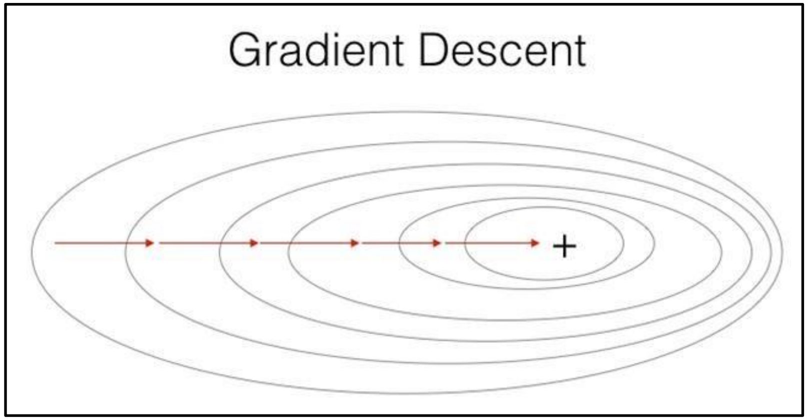
1개	1개	1개	..	..	..	..	..	1개	1개

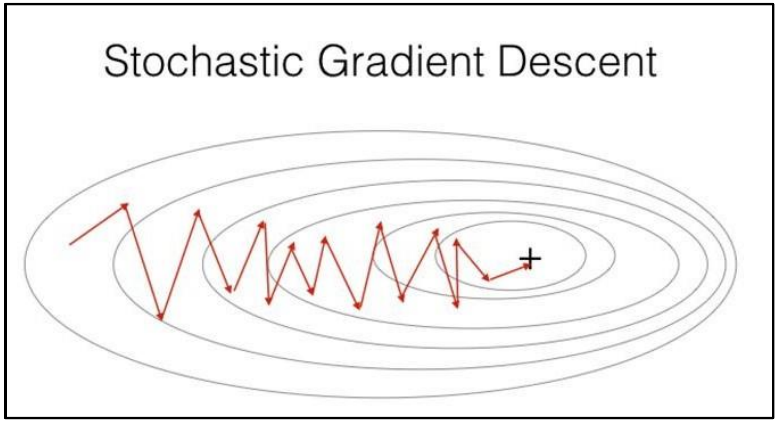
6. Mini-Batch

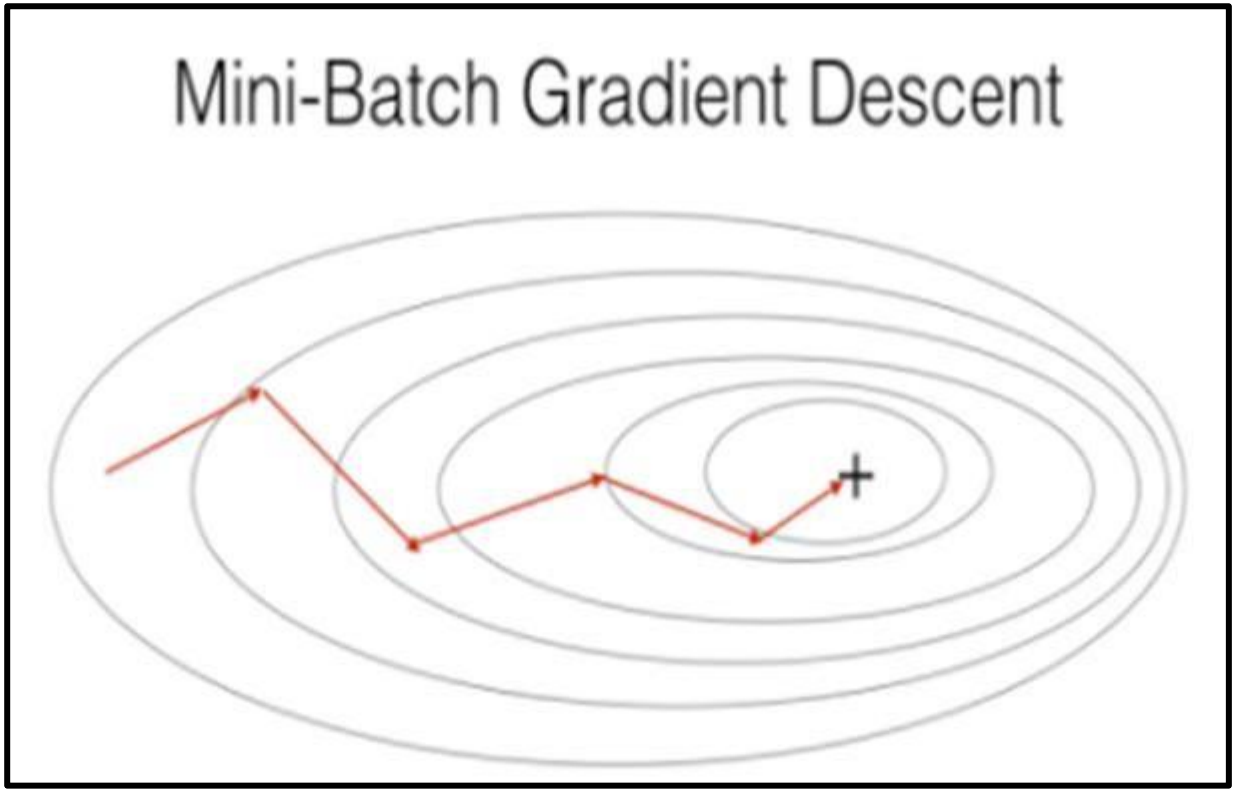
Training data 전체를 한 번 학습 하는 것을 “Epoch” 한 번 Gradient를 구하는 단위를 “Batch”라고 한다



6. Mini-Batch


Gradient Descent

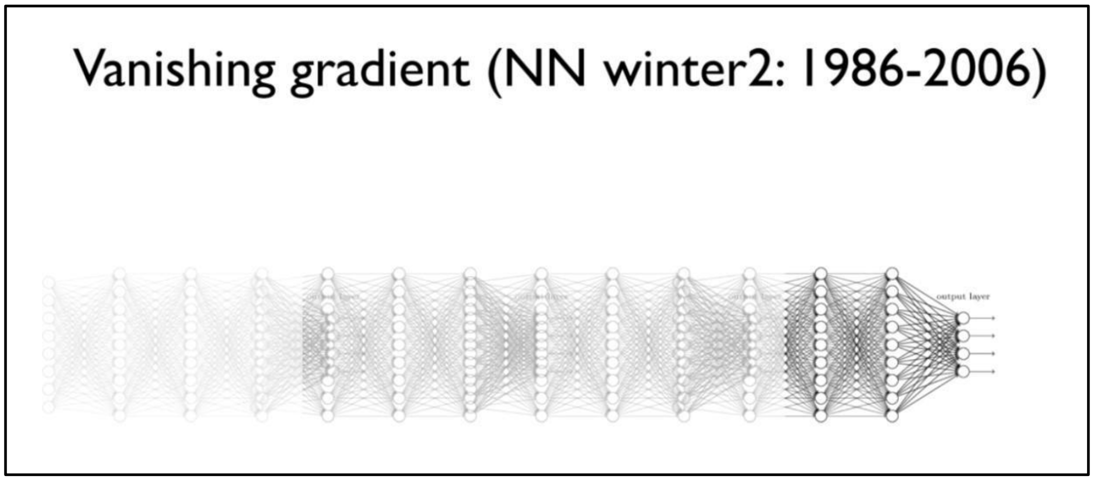

Stochastic Gradient Descent


Mini-Batch Gradient Descent

7. BatchNormalization

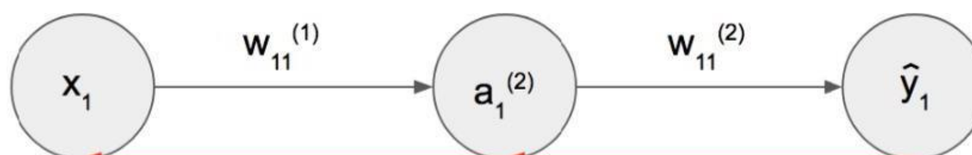
Gradient Vanishing?

(기울기 소실 문제)



DEEP할수록 gradient vanishing! WHY?

(Backpropagation의 수식을 생각해보자)



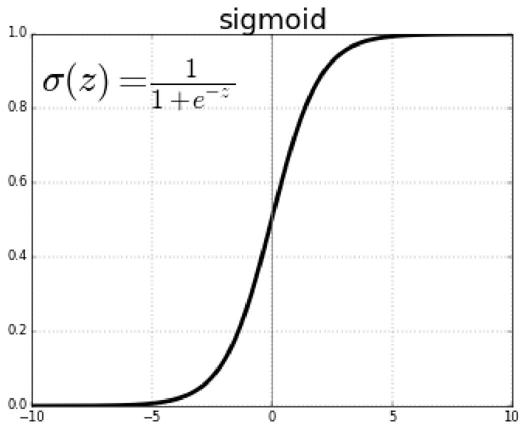
$$\frac{\partial E}{\partial w_{11}^{(1)}} = \frac{\partial E}{\partial \hat{y}_1} \frac{\partial \hat{y}_1}{\partial a_1^{(2)}} \frac{\partial a_1^{(2)}}{\partial w_{11}^{(1)}} \qquad \frac{\partial E}{\partial w_{11}^{(2)}} = \frac{\partial E}{\partial \hat{y}_1} \frac{\partial \hat{y}_1}{\partial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

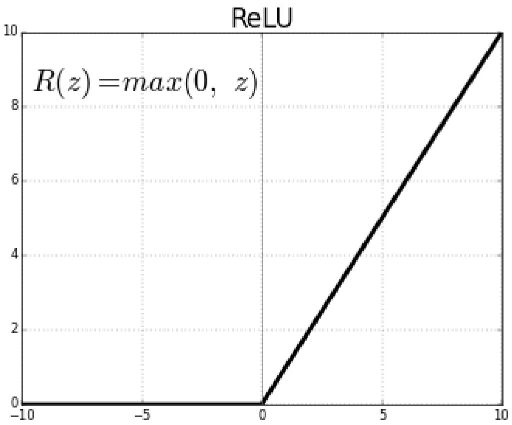
7. BatchNormalization

Gradient Vanishing?

How to Solve?

1) Activation Function으로 Sigmoid ->ReLU



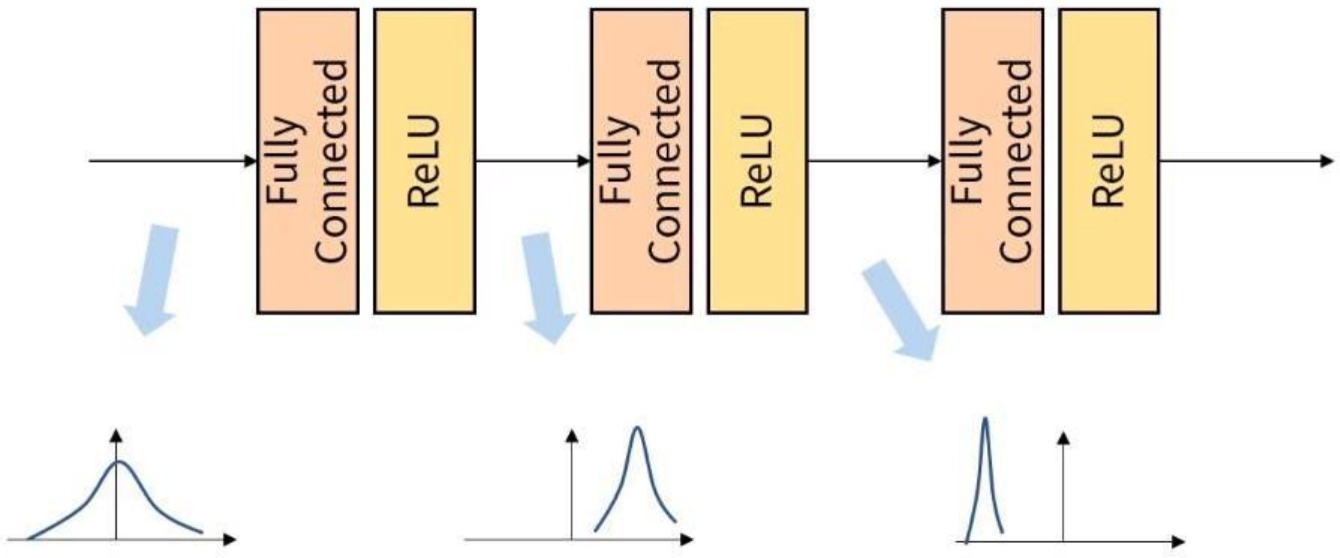


2) 적절한 weight초기값 :Xavier Initialization, He Initialization

3) Batch Normalization

7. BatchNormalization

<u>Internal Covariance Shift</u>



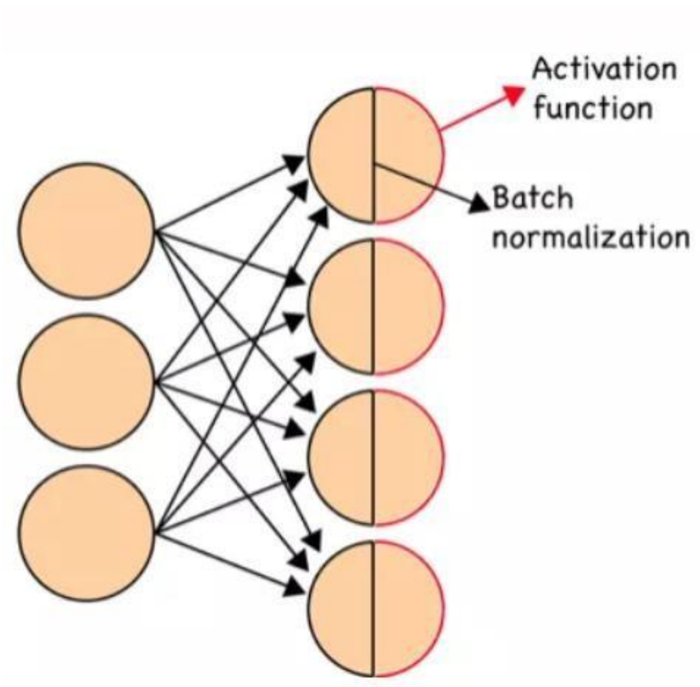
Training과정에서, parameter의 변화로 인해 input data의 distribution이 달라지는 현상! -> 불안정한 training야기!

이 문제를 해결하는 방법이 Batch Normalization!

이로써 안정적인 training을 가능하게 하고, gradient vanishing problem 해결!

7. BatchNormalization

Batch Normalization



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

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

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

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

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

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

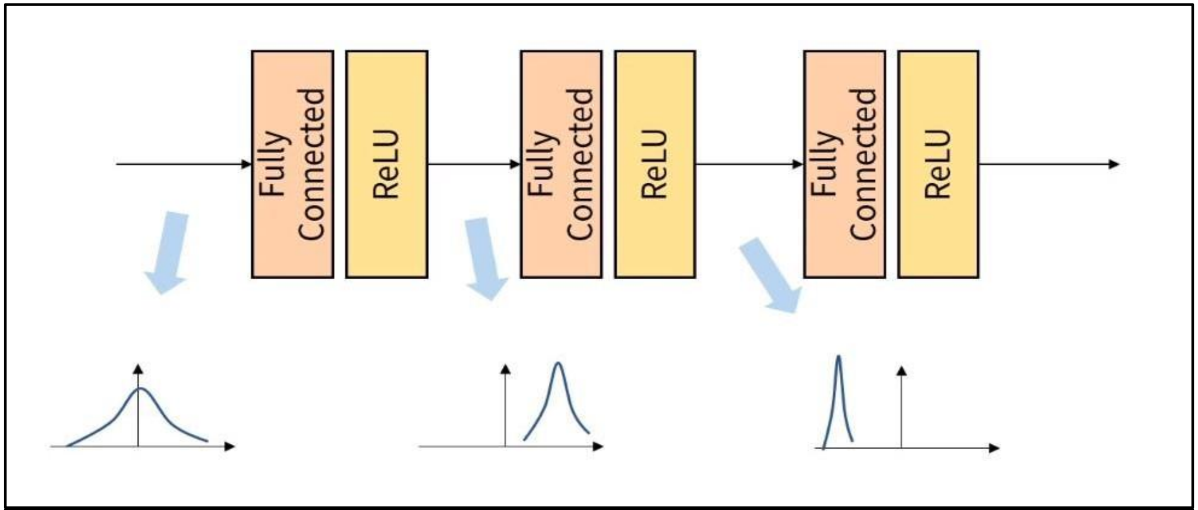
training data 전체에 대하여 normalize하는 것이 좋겠지만, Mini-batch Gradient Descent방식을 사용하게 되면, parameter의 update가 Mini-batch단위로 이루어지기 때문에, Mini-batch를 단위로 Batch Normalization(BN) 실시!

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

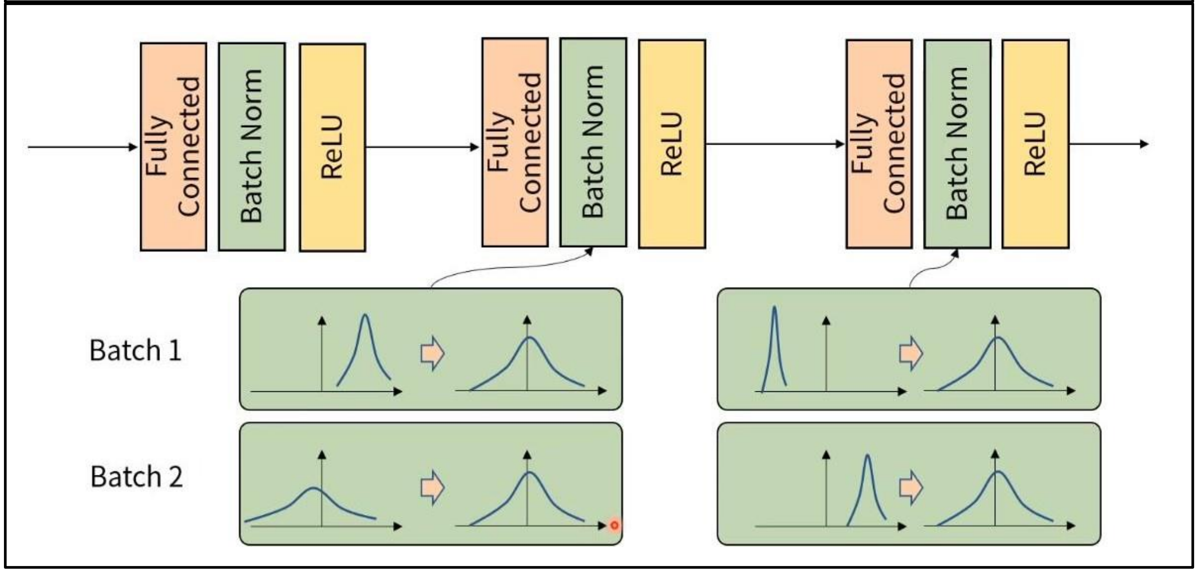
7. BatchNormalization

<u>Internal Covariance Shift</u>

B N (X)



B N (O)



7. BatchNormalization

Batch Normalization

< BN의 장점 >

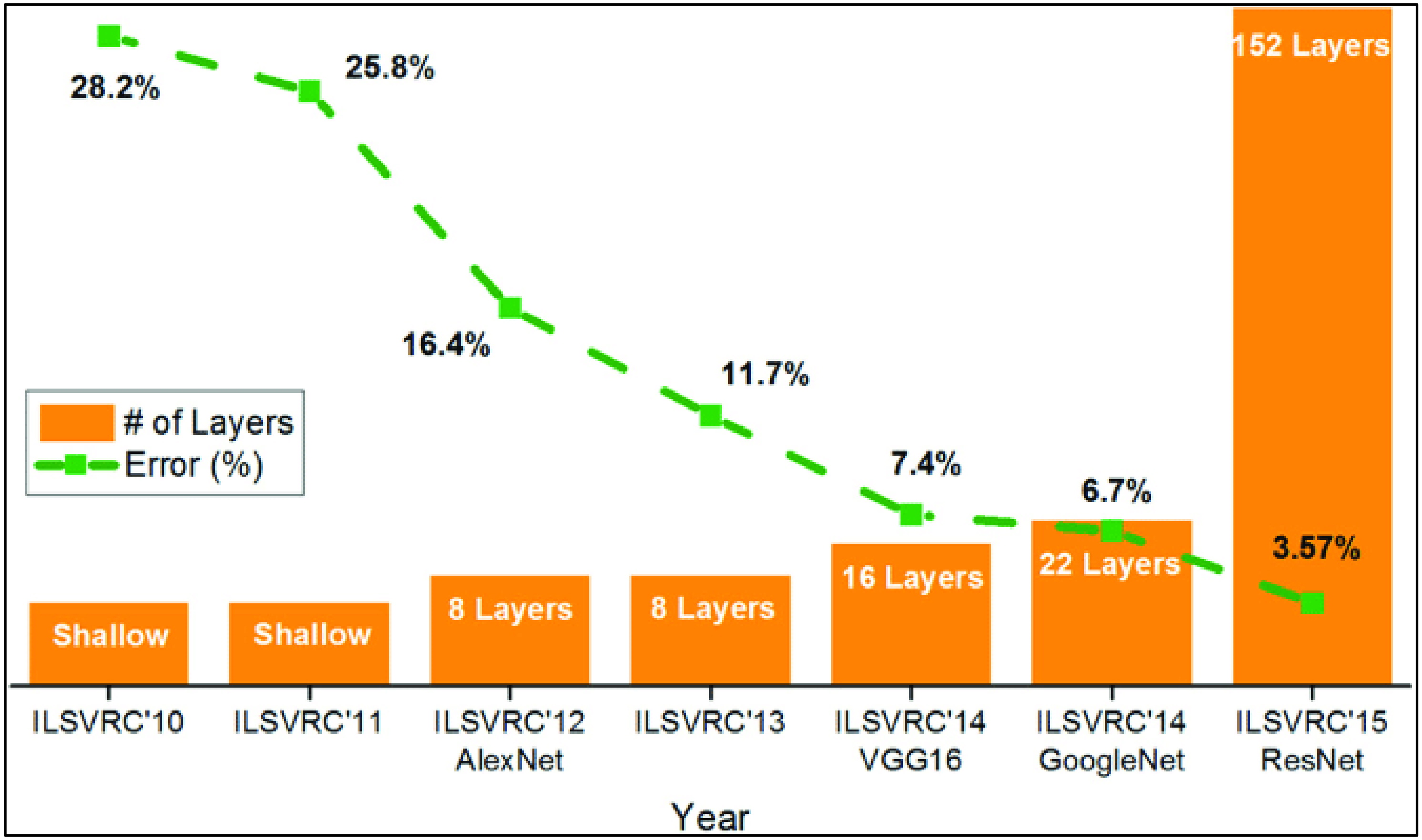
1) Gradient vanishing 문제 해결!

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



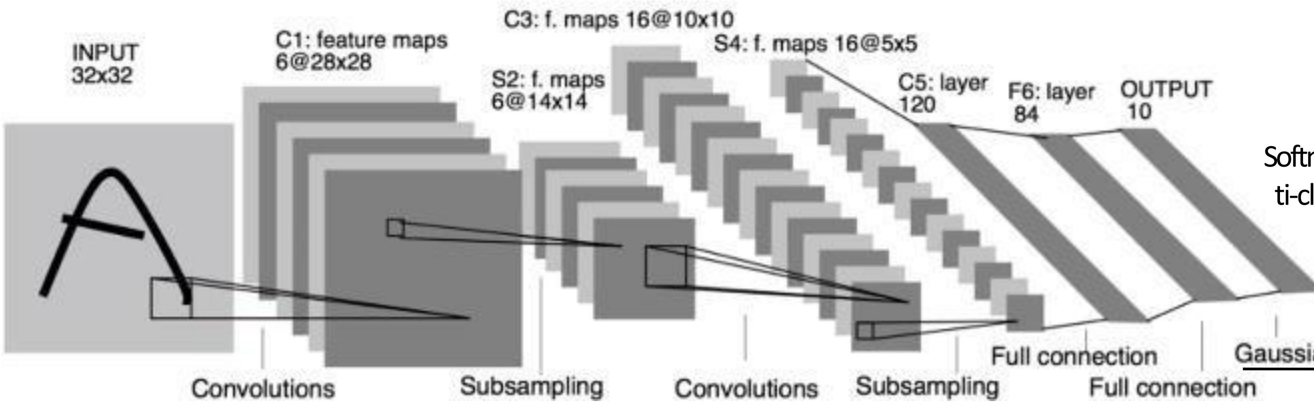
CNN의 대표 모델들에 대해 알아보자.

LeNet-5, AlexNet, VGG16, GoogLeNet, ResNet

7. 심 화 C N N

1. LeNet-5

6채 널의 28*28 feature map

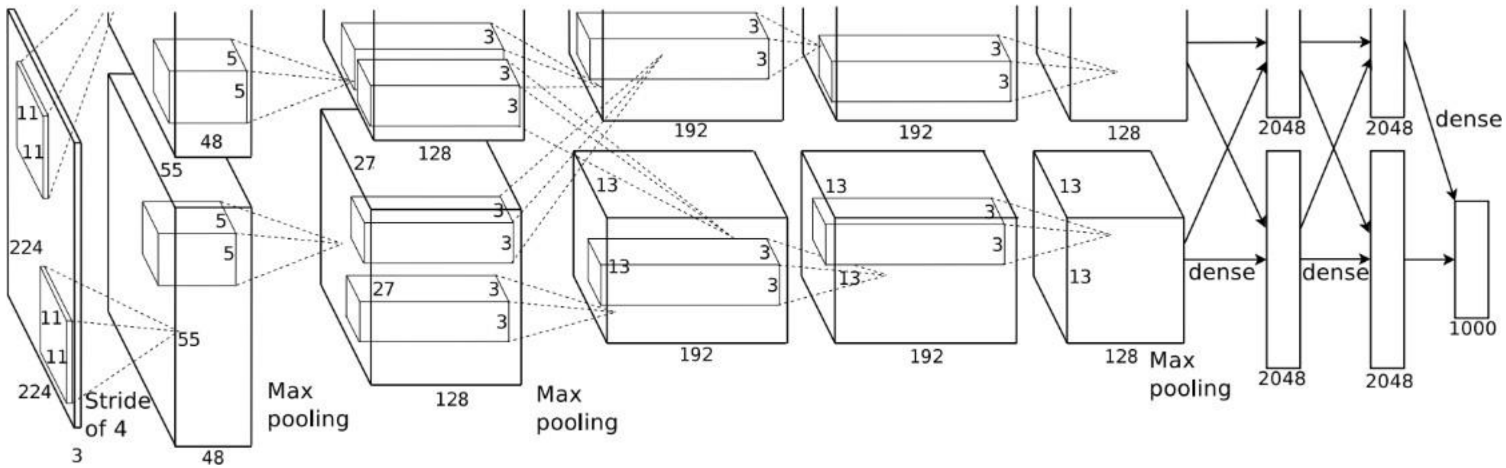


Softmax 나 오 기 전에 사용한 mul ti-class classification

- 1998. CNN의 기본구조 창 립
- MNIST data 사 용

7. 심 화 C N N

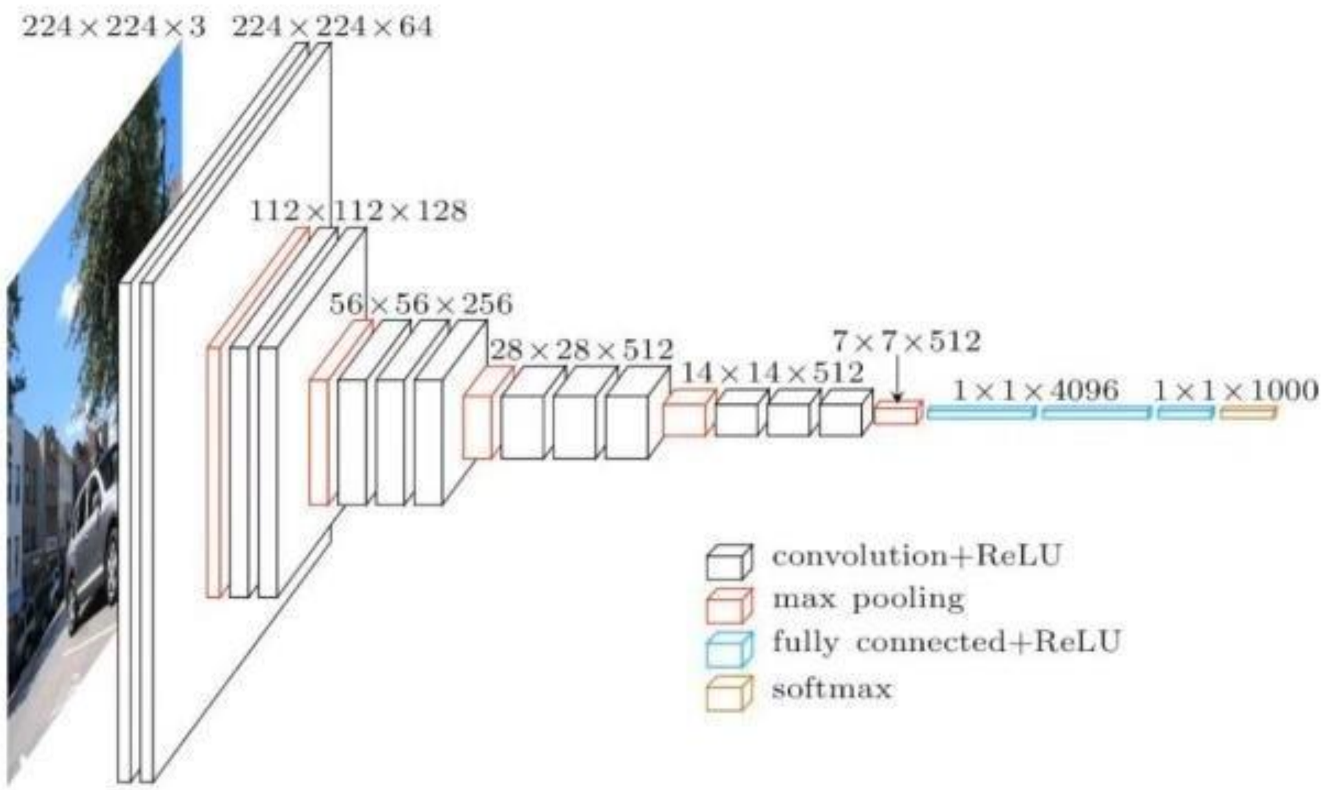
2. AlexNet



- Conv, Max Pooling, Dropout 5개
- Activation function : ReLU
- Batch Stochastic Gradient Descent

7. 심 화 C N N

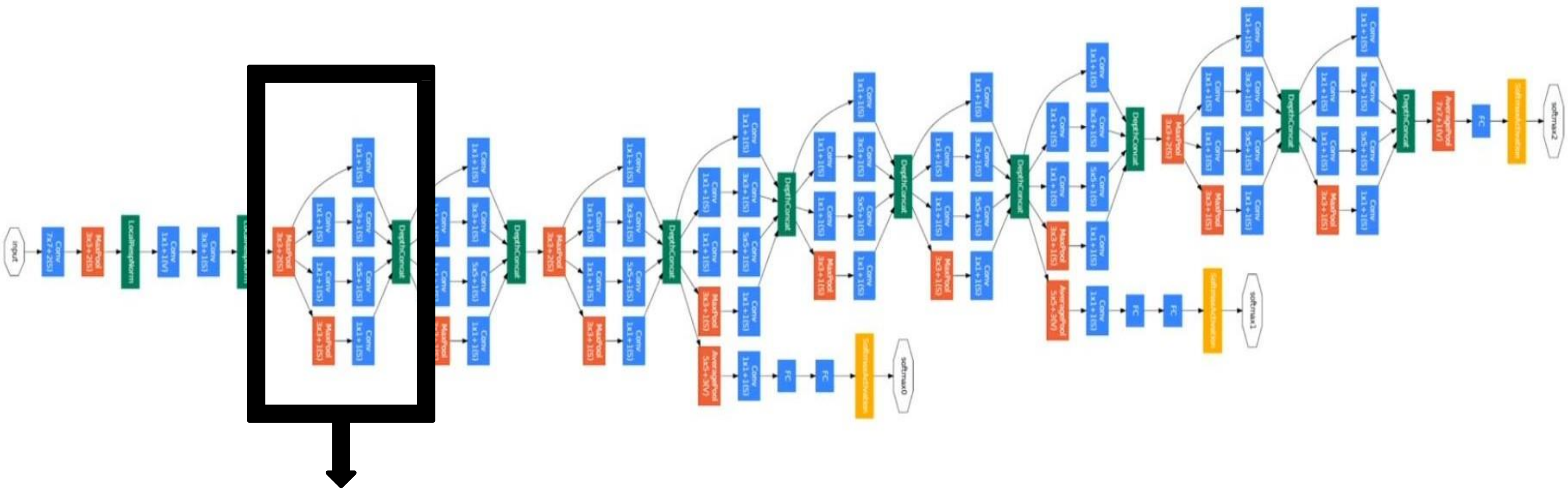
3. VGG-16



7. 심화 CNN

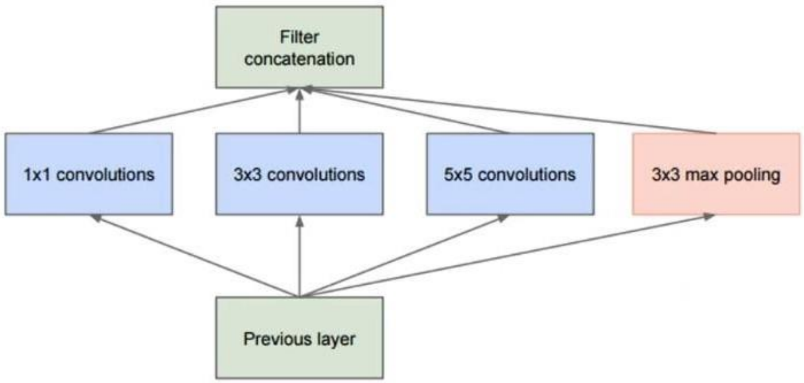
4. GoogLeNet (Inception)

"Let's go Deeper and Deeper"

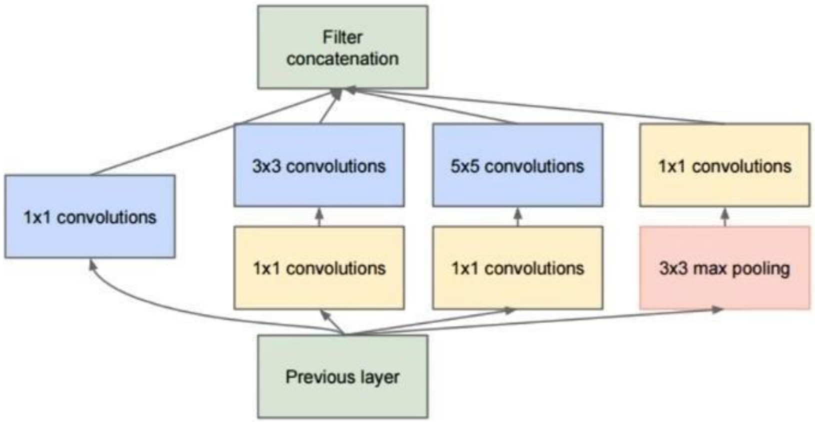


Inception 모듈에 대해 먼저 이해해야!

4. GoogLeNet (Inception)



(a) Inception module, naïve version



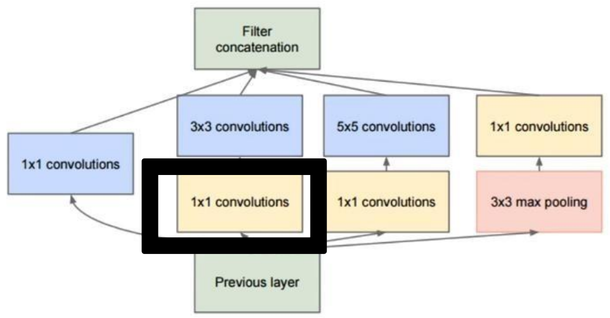
(b) Inception module with dimension reductions

Inception module : 다양한 크기의 합성곱 계층을 한 번에 계산!

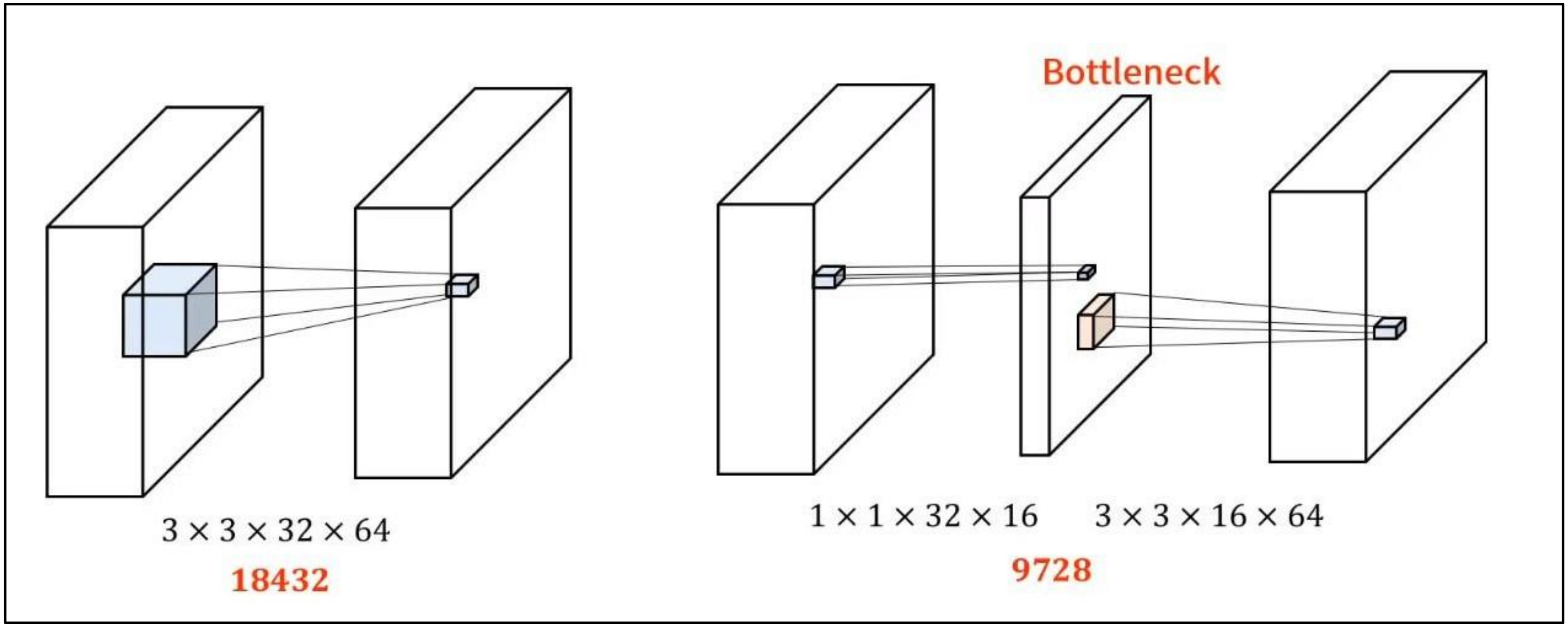
1x1 convolution : for 연산량 줄이기! (bottle neck 구조라고도 함)

7. 심화 CNN

4. GoogLeNet (Inception)



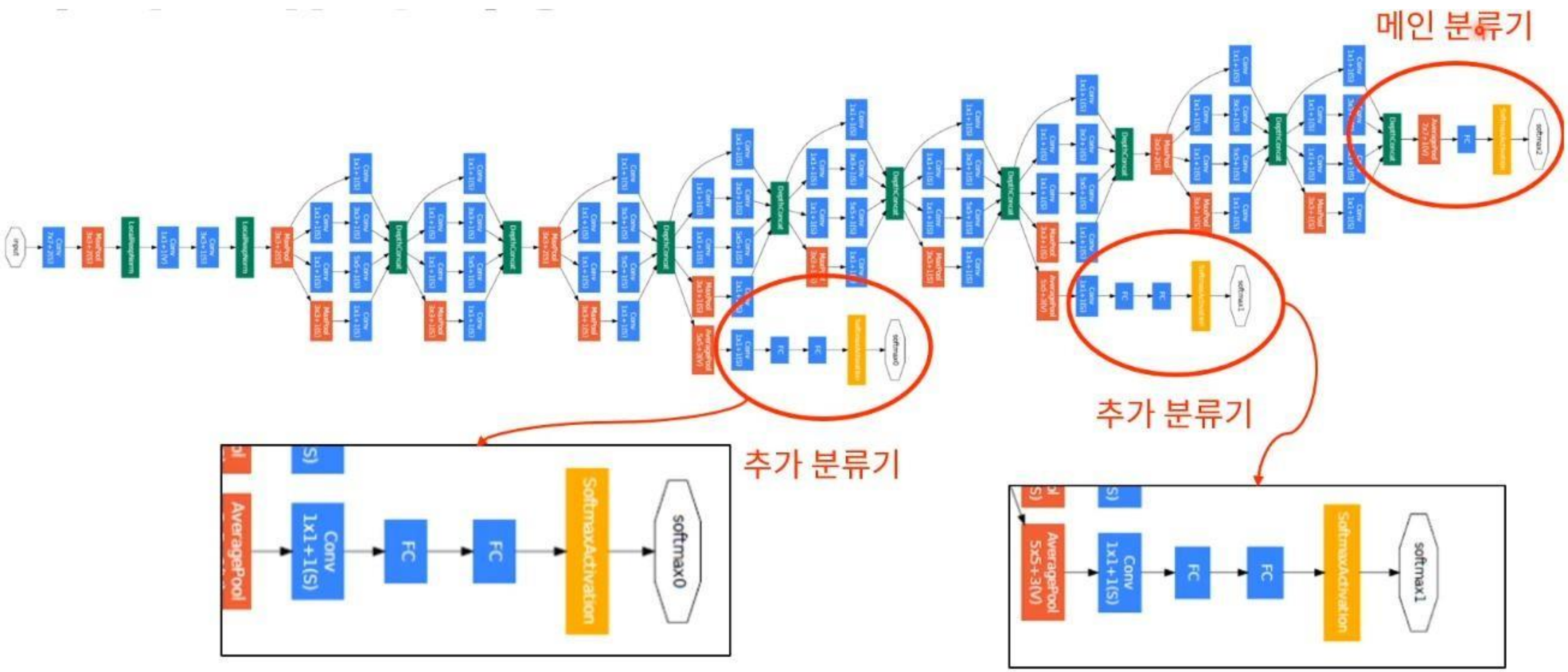
(b) Inception module with dimension reductions



1x1 Conv를 하면, 왜 연산량이 줄어들까?

7. 심화 CNN

4. GoogLeNet (Inception)

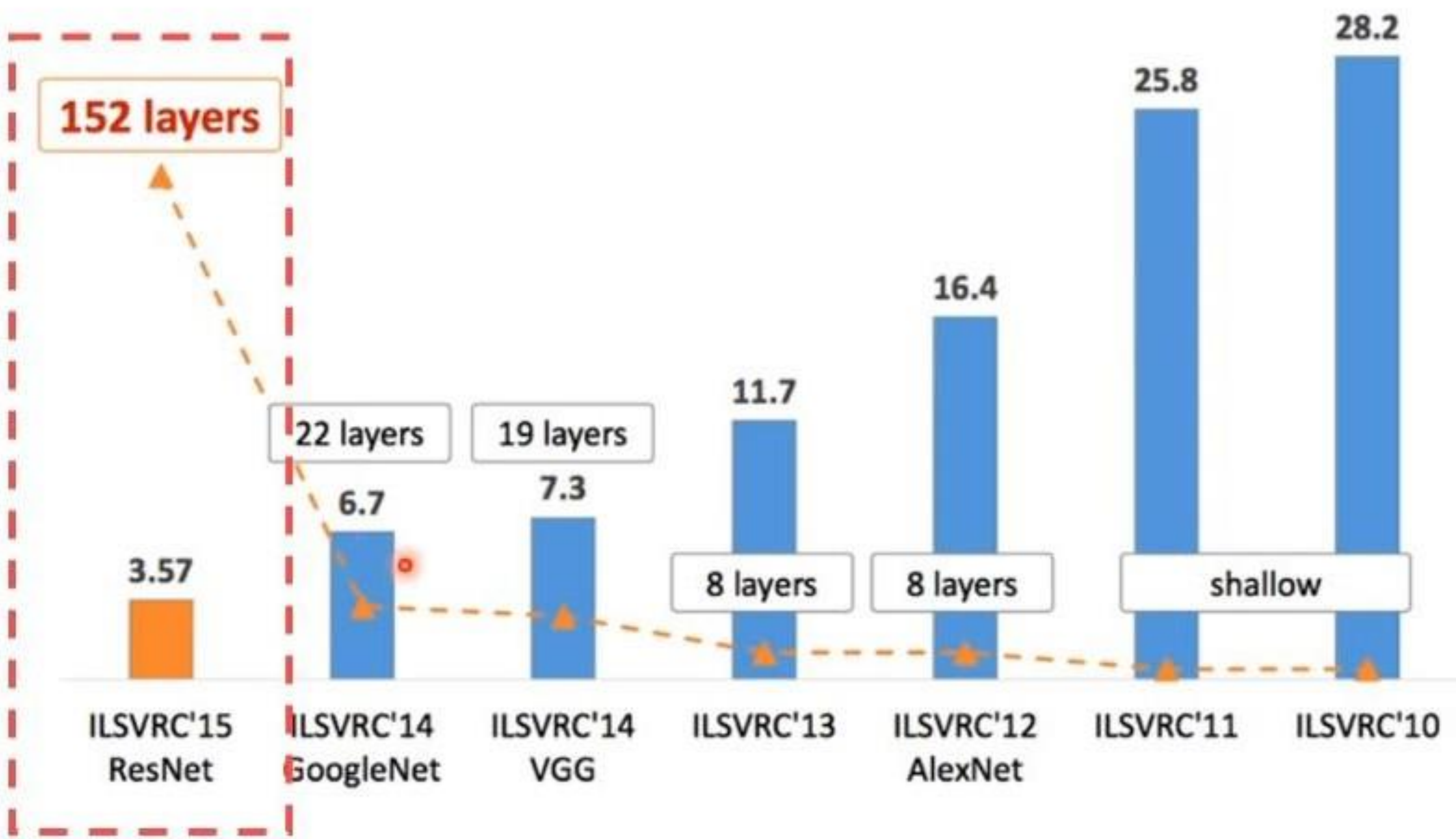


역전파에서 기울기소실이 발생하는 것을 방지하기위해 추가 분류기 존재

5. ResNet

152 Layers? H o w that deep?

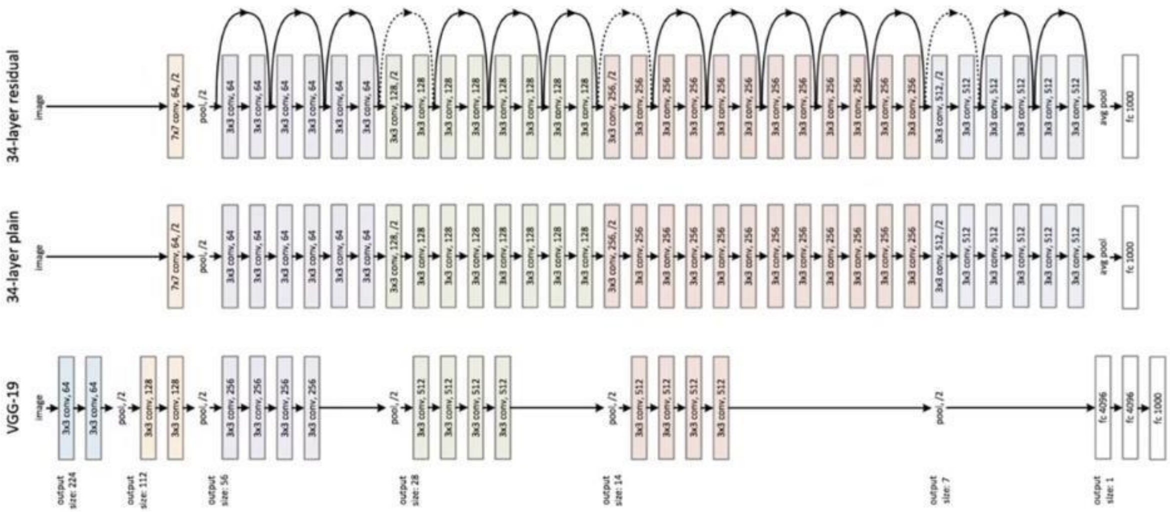
Residual Block

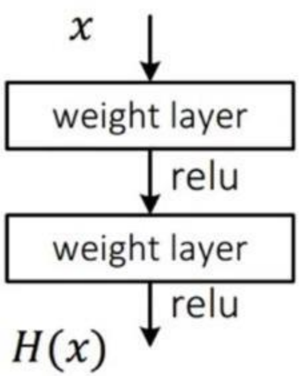


7. 심화 CNN

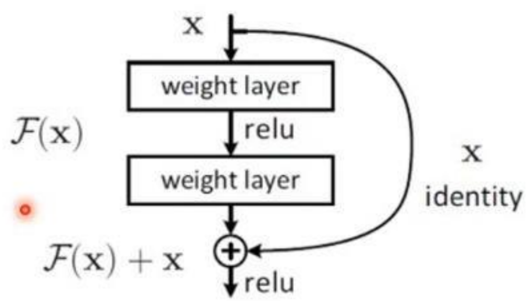
5. ResNet

사이사이에 있는 Skip-Connection이 한 몫함!





일반적인 구조

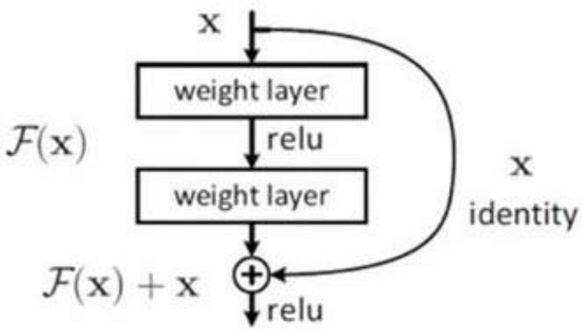


Residual 구조

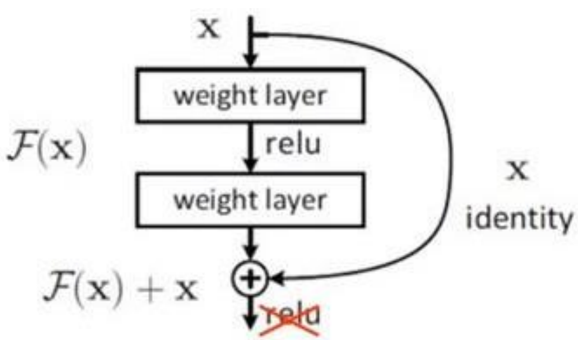
Feature를 추출하기 전/후를 더함!

7. 심화 CNN

5. ResNet

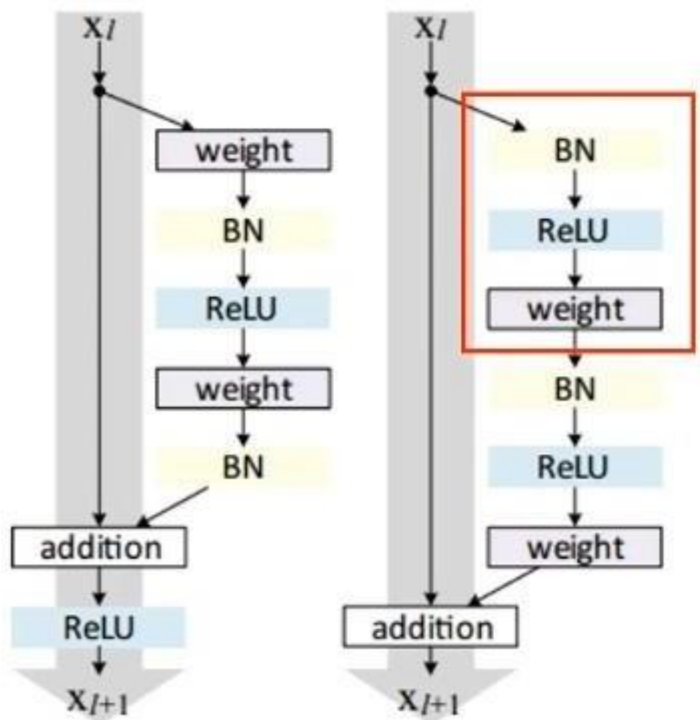


Residual 구조



Identity Mapping

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



(a) original (b) proposed

7. 심 화 C N N

6. DenseNet

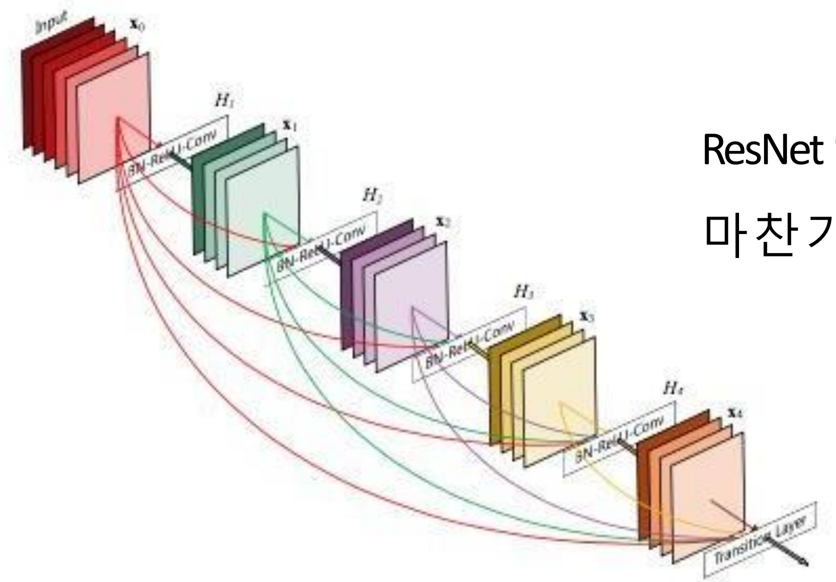


Figure 1: A 5-layer dense block with a growth rate of $k = 4$. Each layer takes all preceding feature-maps as input.

ResNet 아이디어의 연장선 상!

마찬가지로 Pre-Activation (BN-ReLU-Conv)

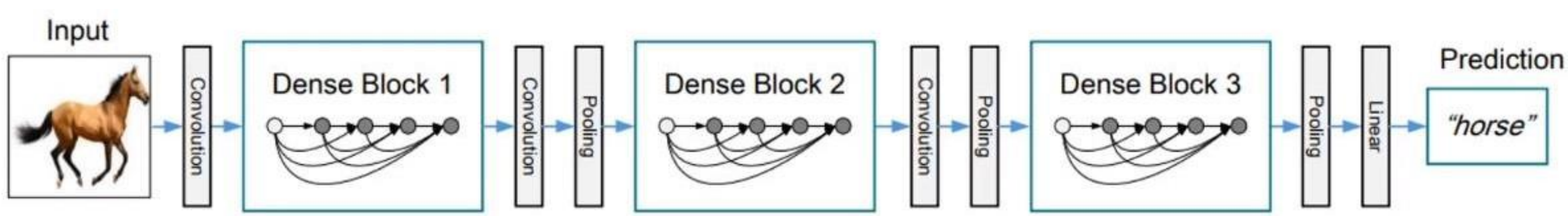
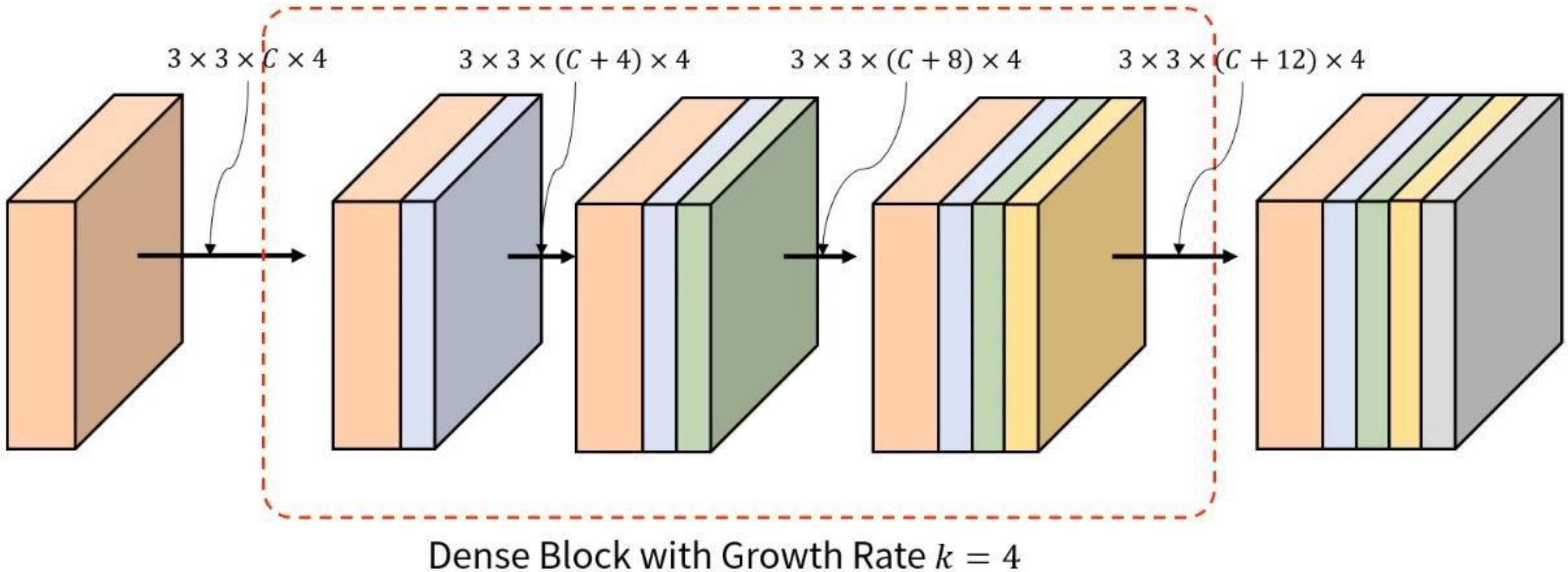


Figure 2: A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

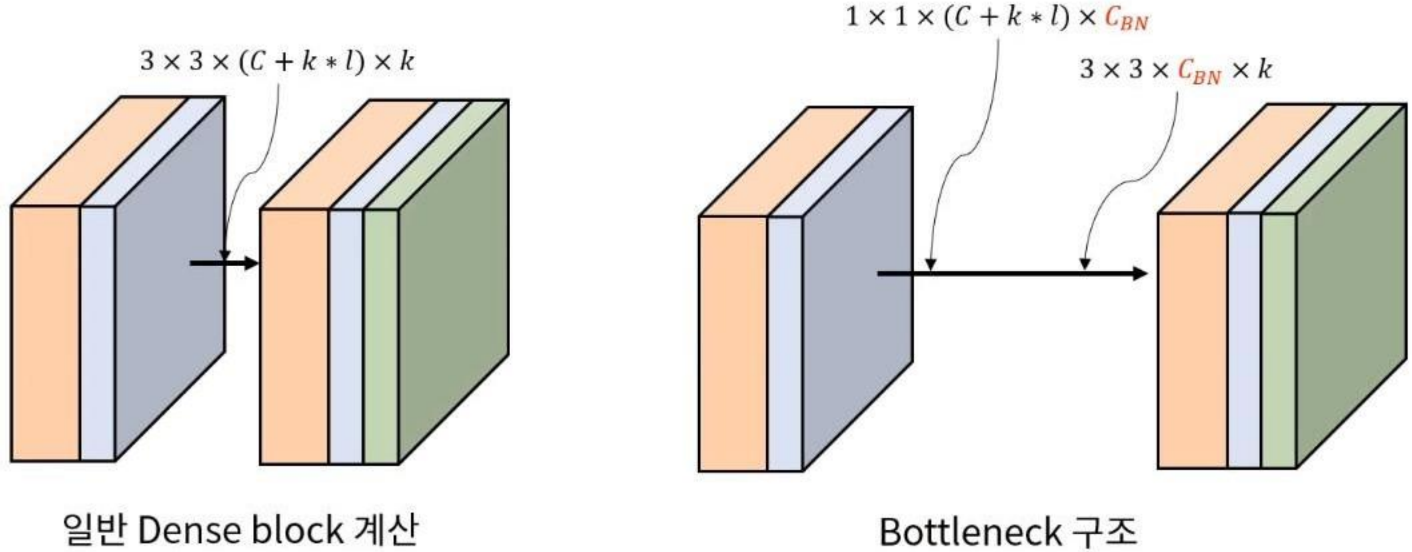
6. DenseNet



쉽게 말해, "이전 feature map에 누적해서 concatenate!"

7. 심 화 C N N

6. DenseNet



Deep -> 연 산 량 too much!

그 래 서 "1x1Conv (= Bottleneck Layer)"사 용 함

8. Summary

CNN is good for image classification!