Convolutional Neural Networks
-Basic-

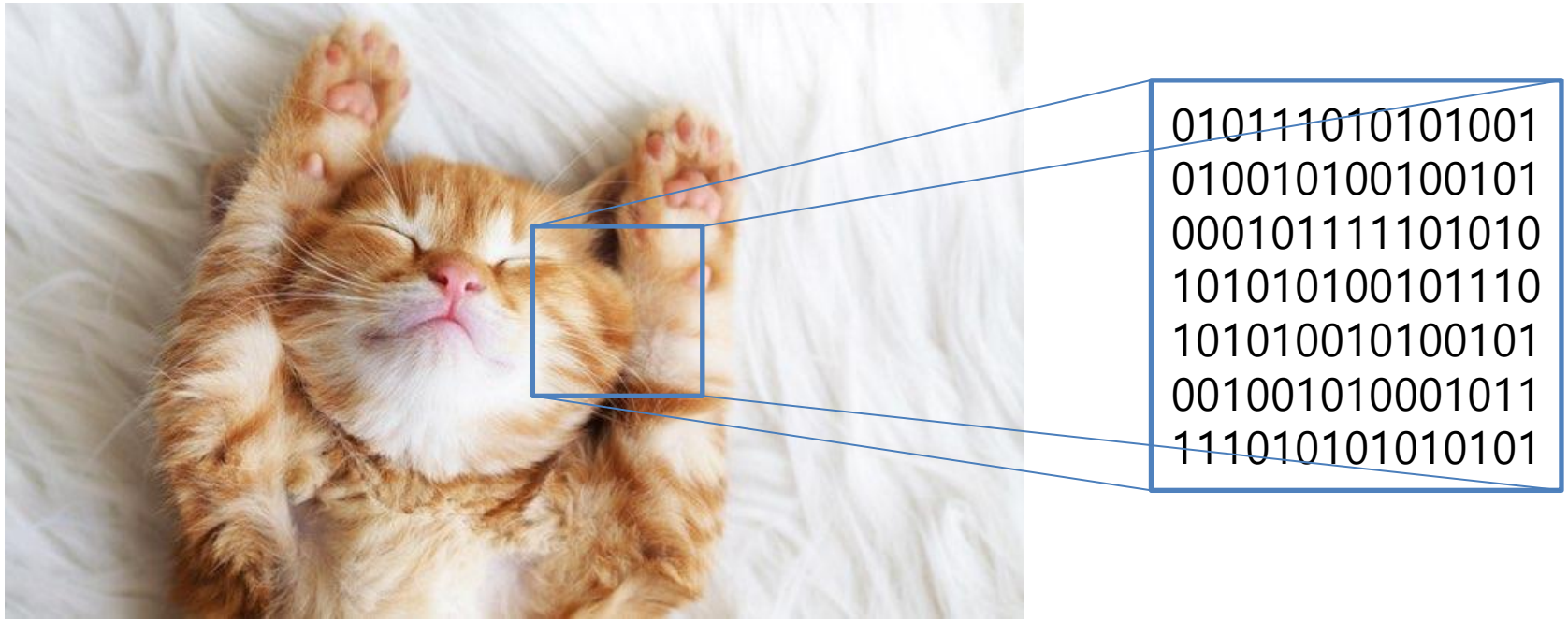
2017.10.28

최건호

INDEX

Before CNN

Before CNN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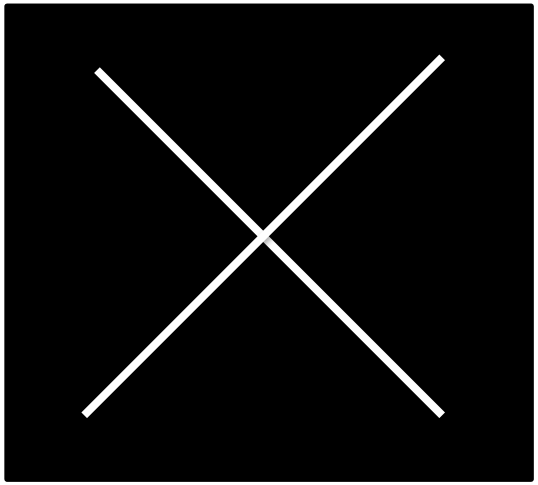
Before CNN



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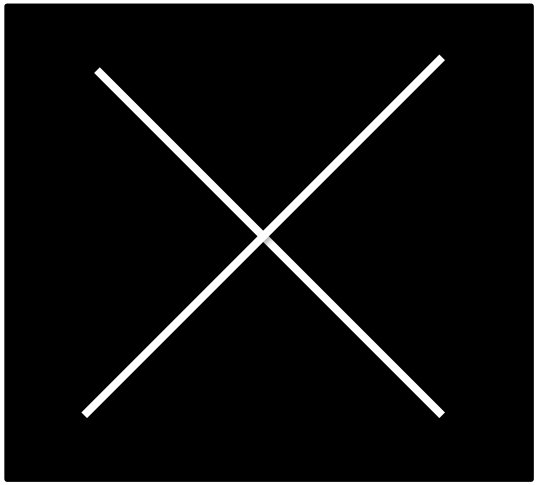
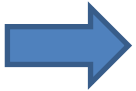
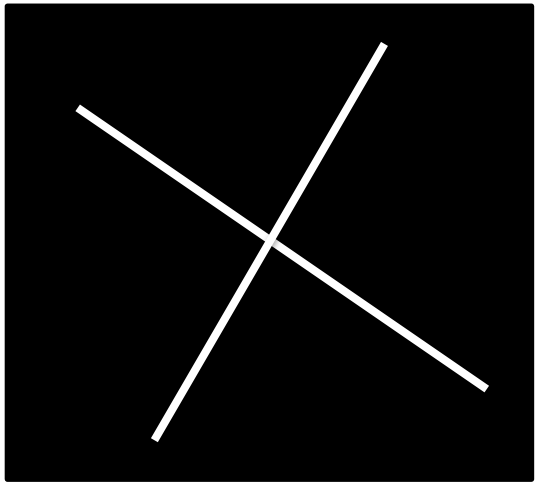
Before CNN







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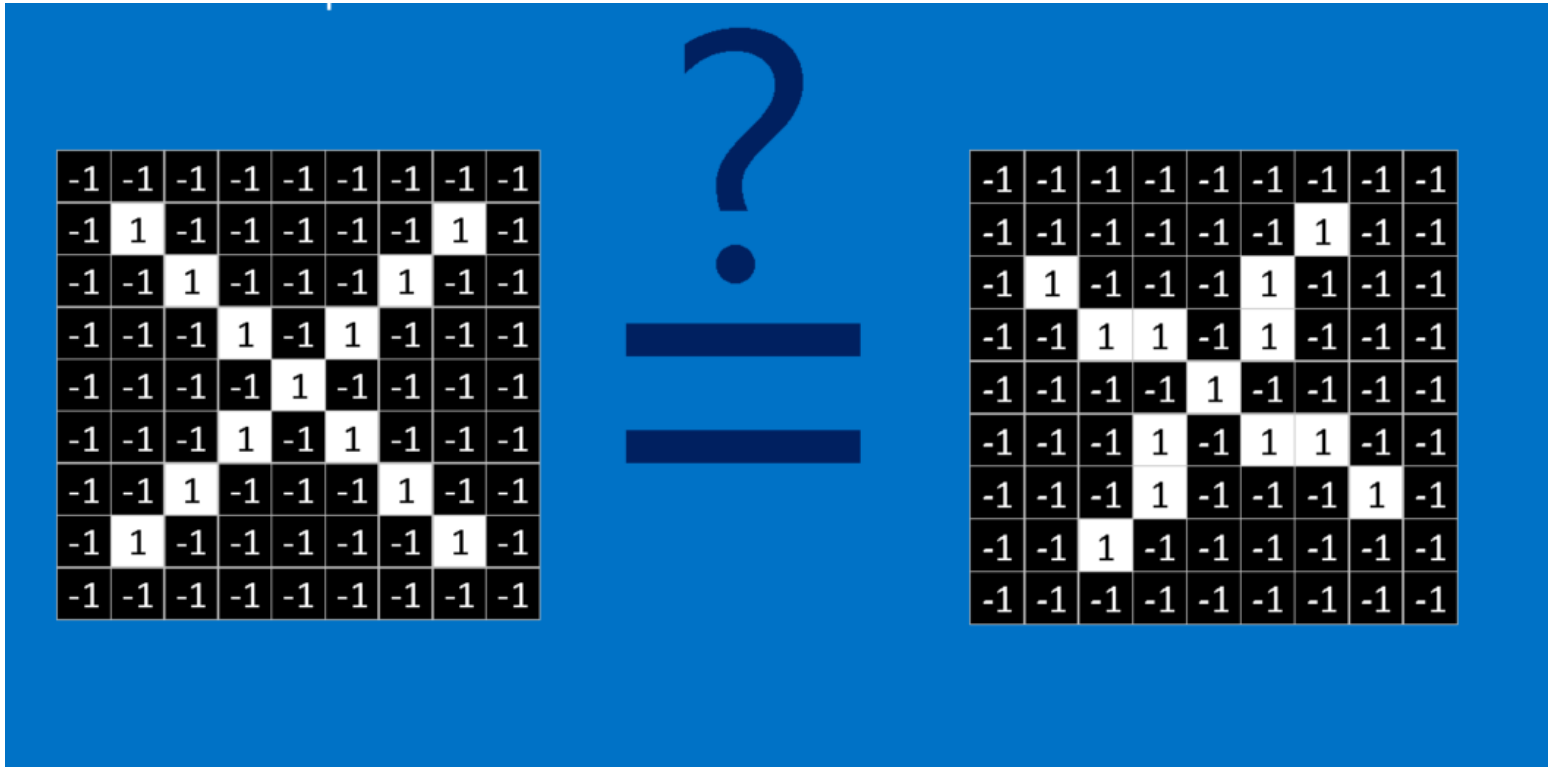
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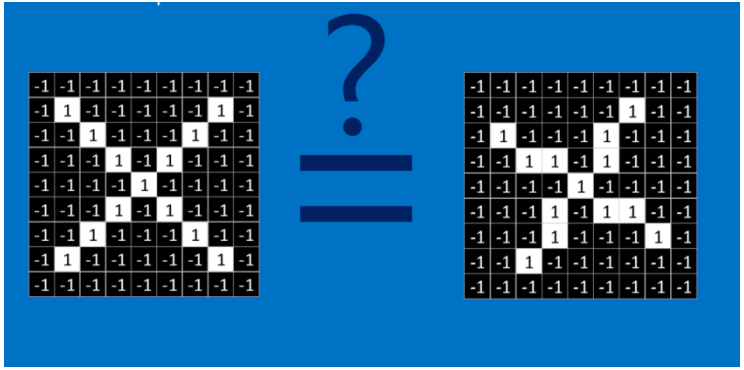

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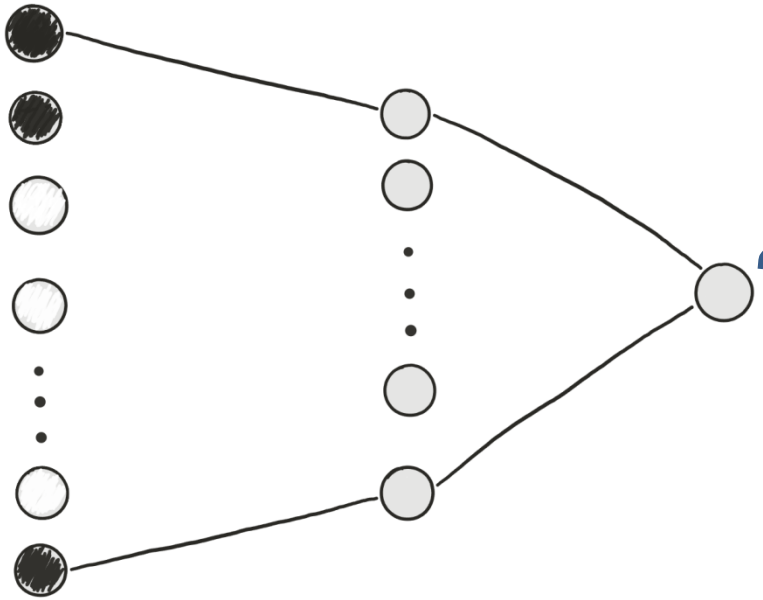
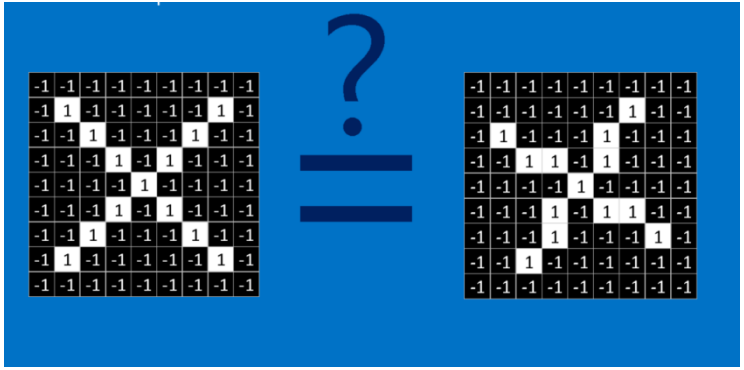


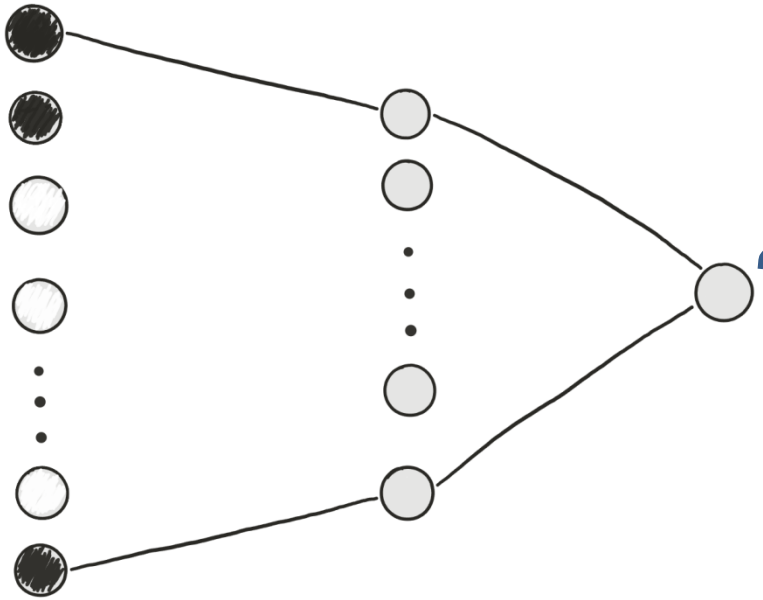
모양이 X인가
아닌가에 대한 결과값

9x9=81

Before CNN



Input

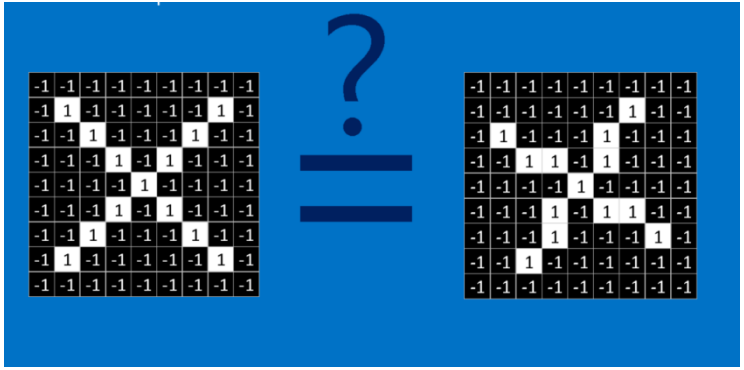


9x9=81

모양이 X인가
아닌가에 대한 결과값

하지만 그림이 기울어진다거나
하면 완전히 다른 입력 값이
들어오는 것

Before CNN



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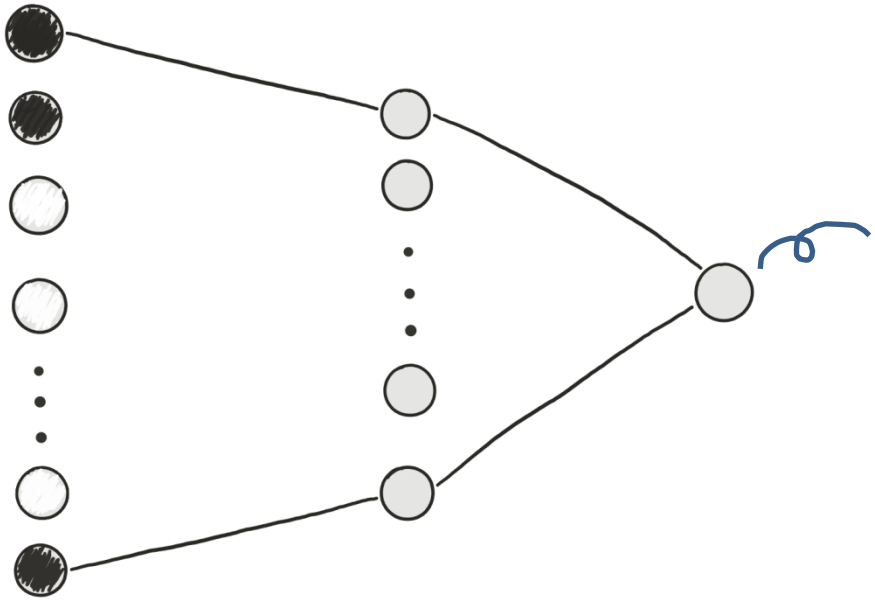

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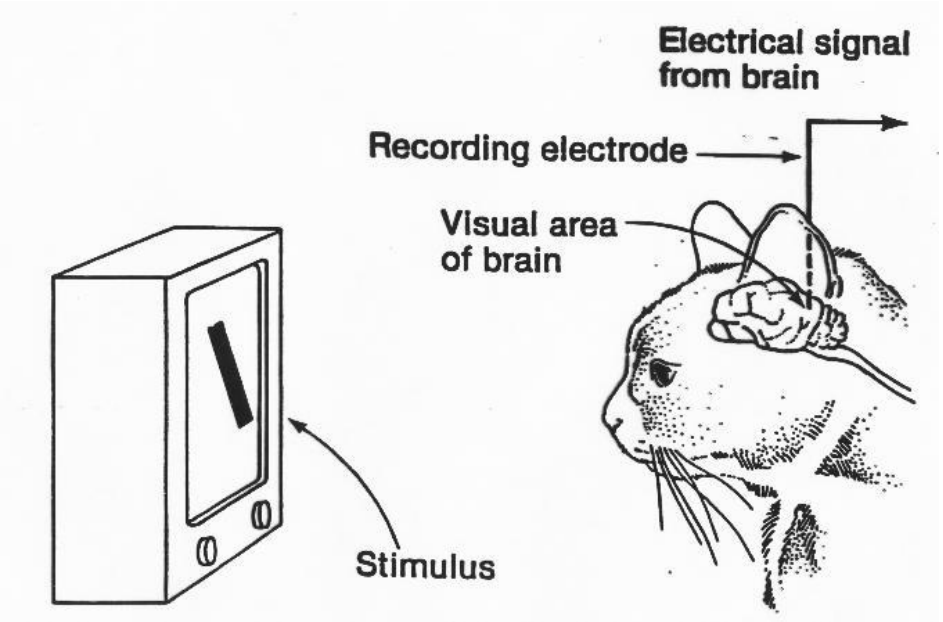
들어오는 것

보기에는 같은 모양이지만
기계는 전혀 다르게 인식

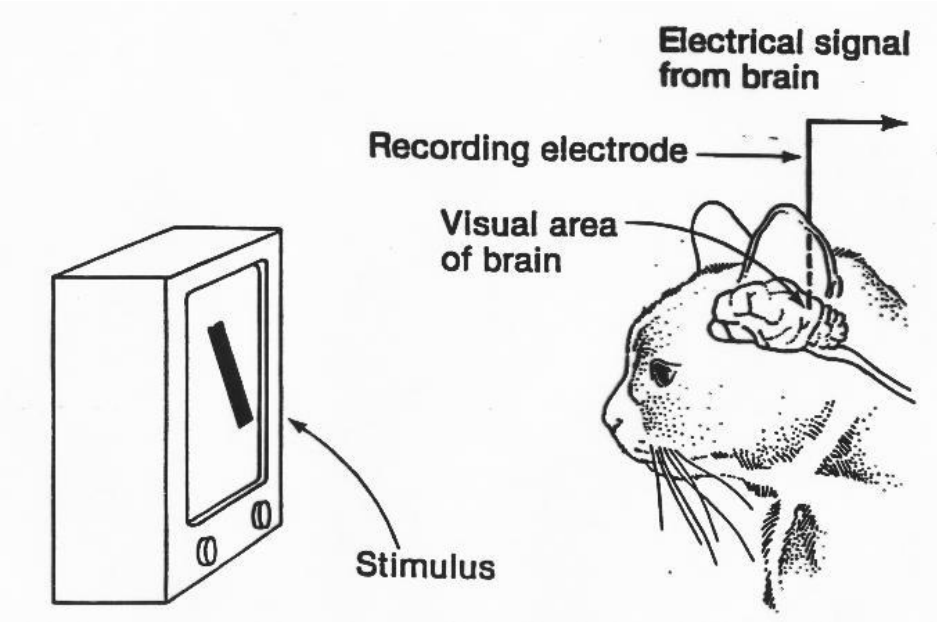
Before CNN

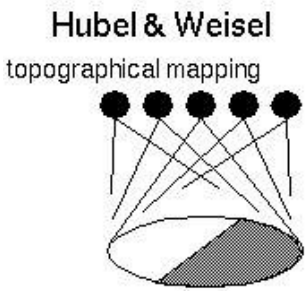
Hubel & Wiesel (1950s)

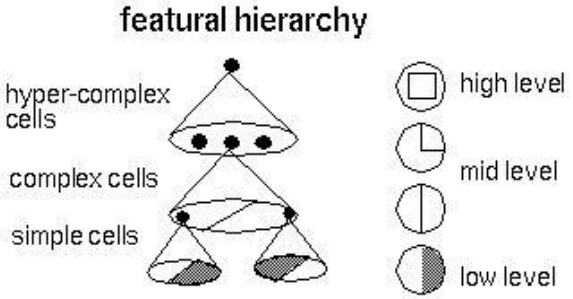


Before CNN

Hubel & Wiesel (1950s)



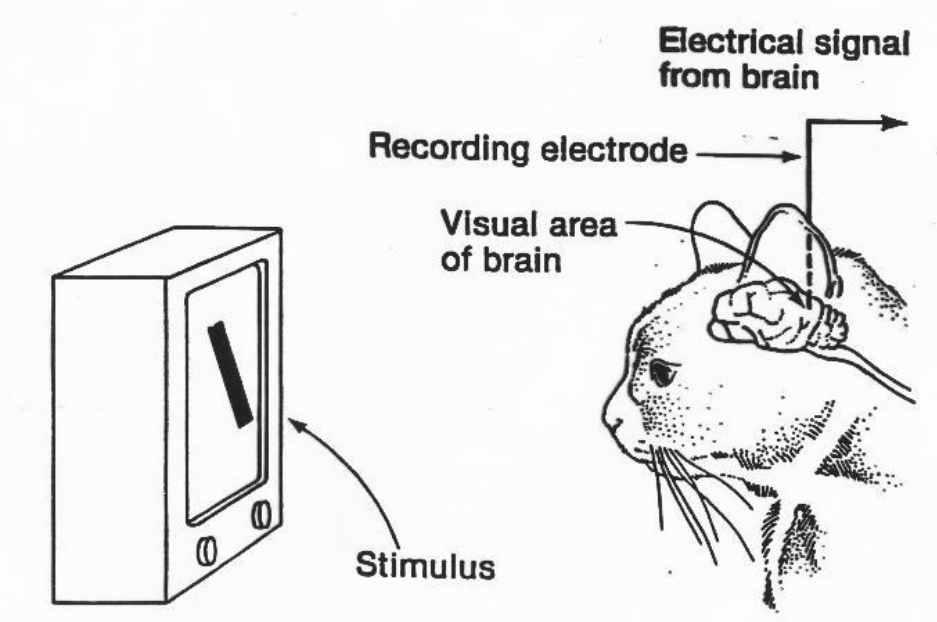


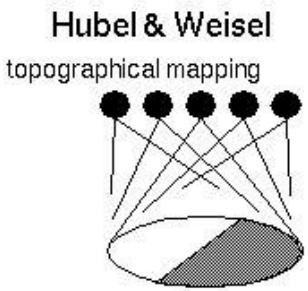


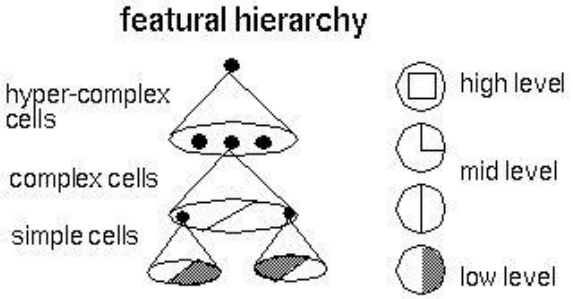
출처(http://cns-alumni.bu.edu/~slehar/webstuff/pcave/hubel.html)

Before CNN

Hubel & Wiesel (1950s)





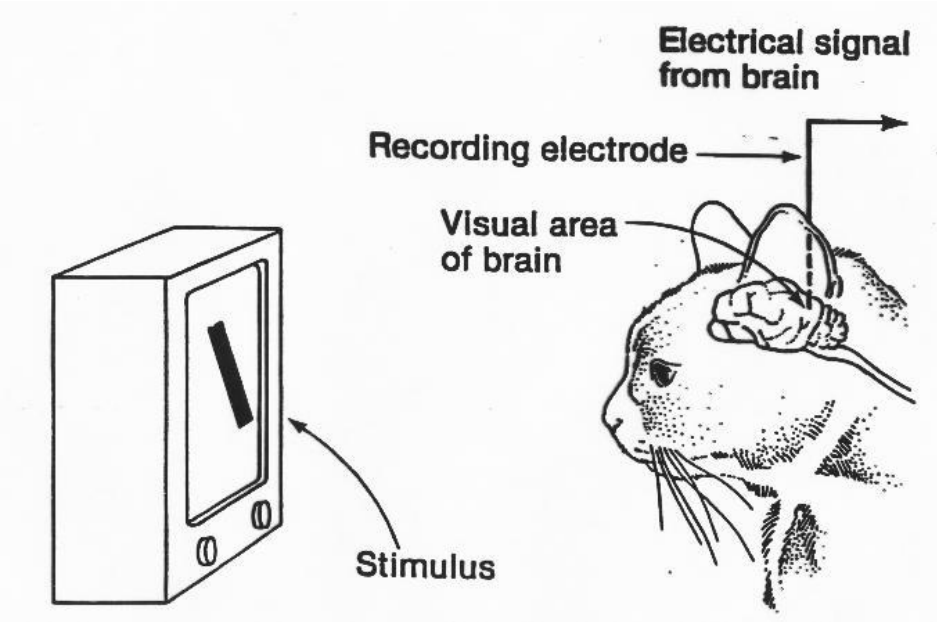


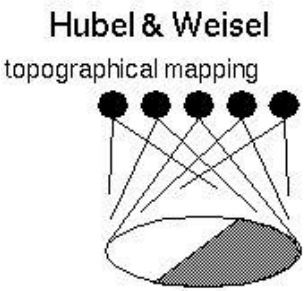
1. 뉴런들은 국소적으로 자극을 받는다.

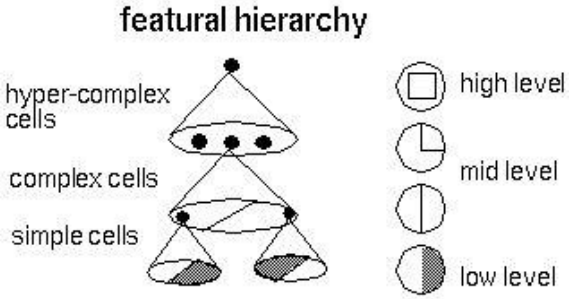
출처(http://cns-alumni.bu.edu/~slehar/webstuff/pcave/hubel.html)

Before CNN

Hubel & Wiesel (1950s)





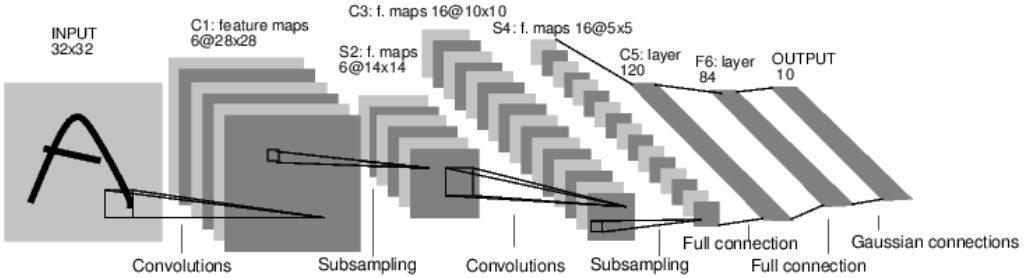


1. 뉴런들은 국소적으로 자극을 받는다.
2. 단순한 모양에 자극 받는 low level 뉴런이 있는가 하면 여기에서 받은 정보를 조합한 복잡한 모양에 자극 받는 complex cell 이 존재한다.

출처(http://cns-alumni.bu.edu/~slehar/webstuff/pcave/hubel.html)

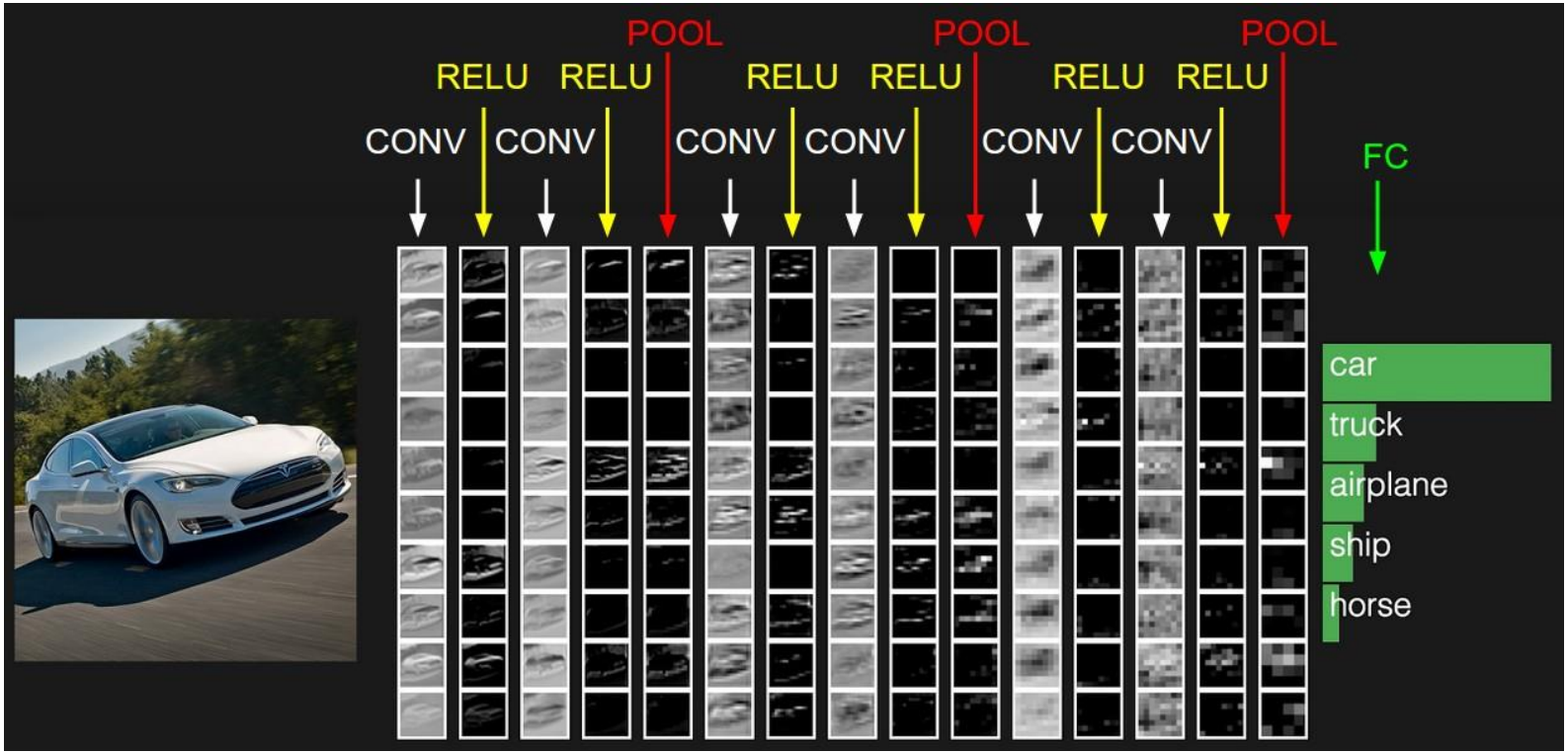
Before CNN

LeNet-5 (1998)



Convolutional Neural Network의 시초

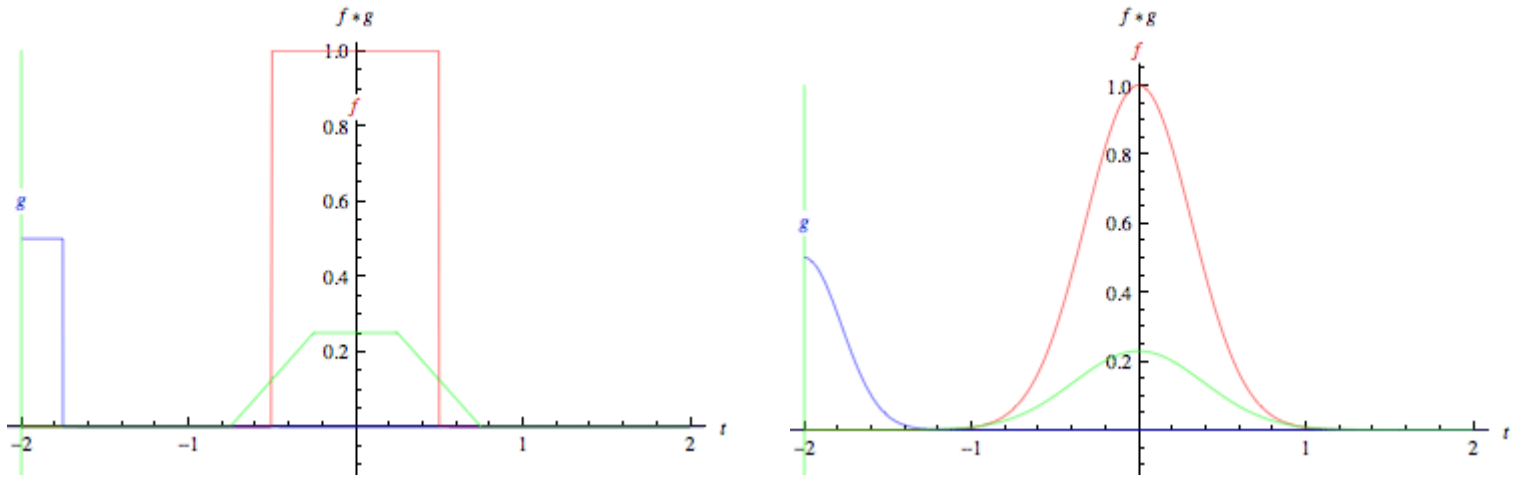
Before CNN



(출처: http://cs231n.github.io/convolutional-networks/)

Convolution Layer

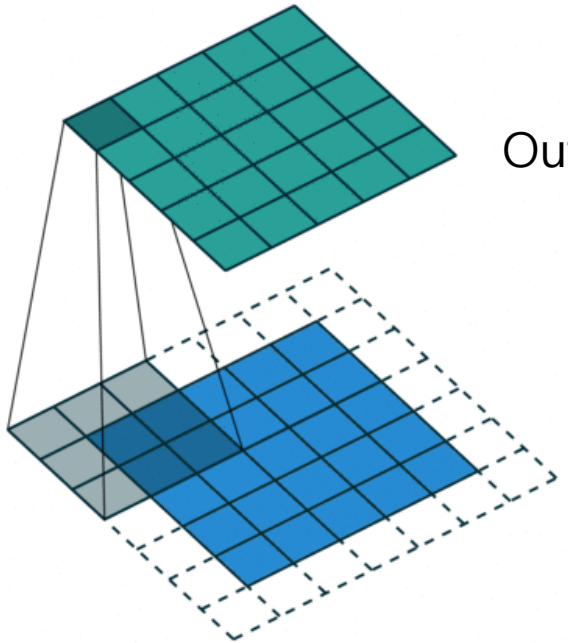
Convolution 연산?



함수 f 에 대하여 함수 g가 얼마나 겹치는가

(출처:http://mathworld.wolfram.com/Convolution.html)

Convolution Layer

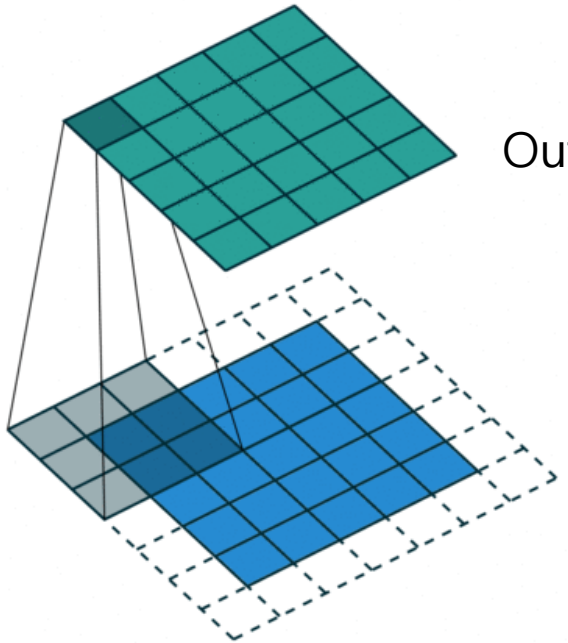


Output Image

Input Image

(출처: https://github.com/vdumoulin/conv_arithmetic)

Convolution Layer



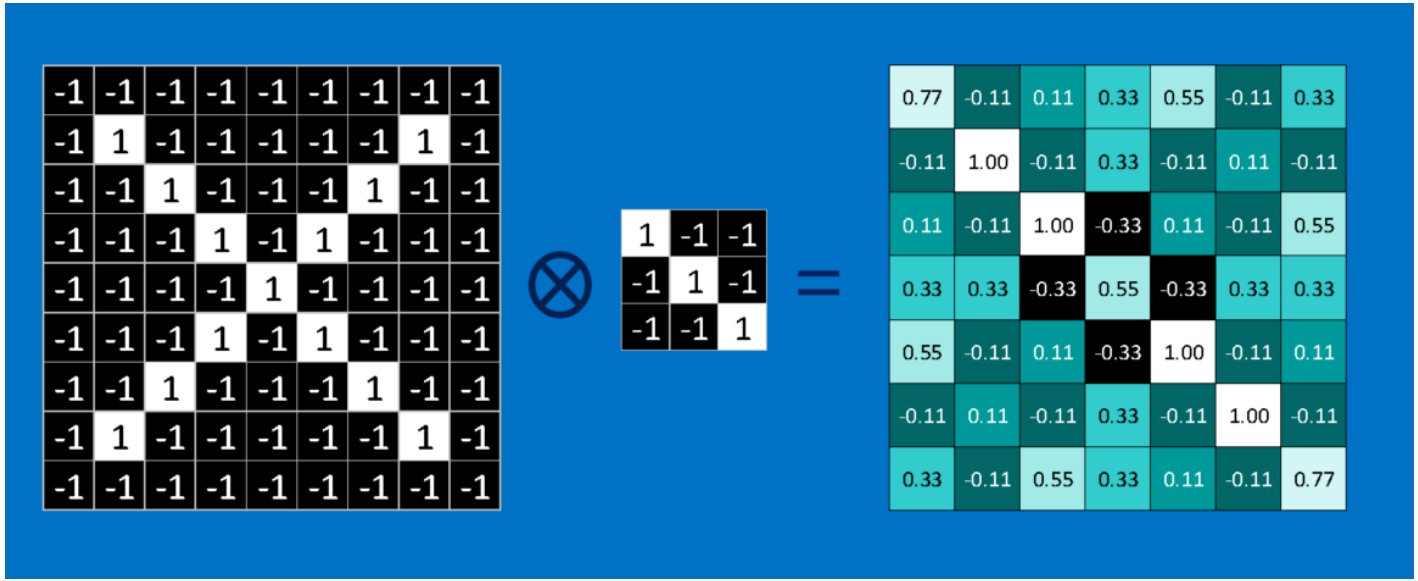
Output Image

Input Image

1. Kernel(or filter)
2. Stride
3. Padding

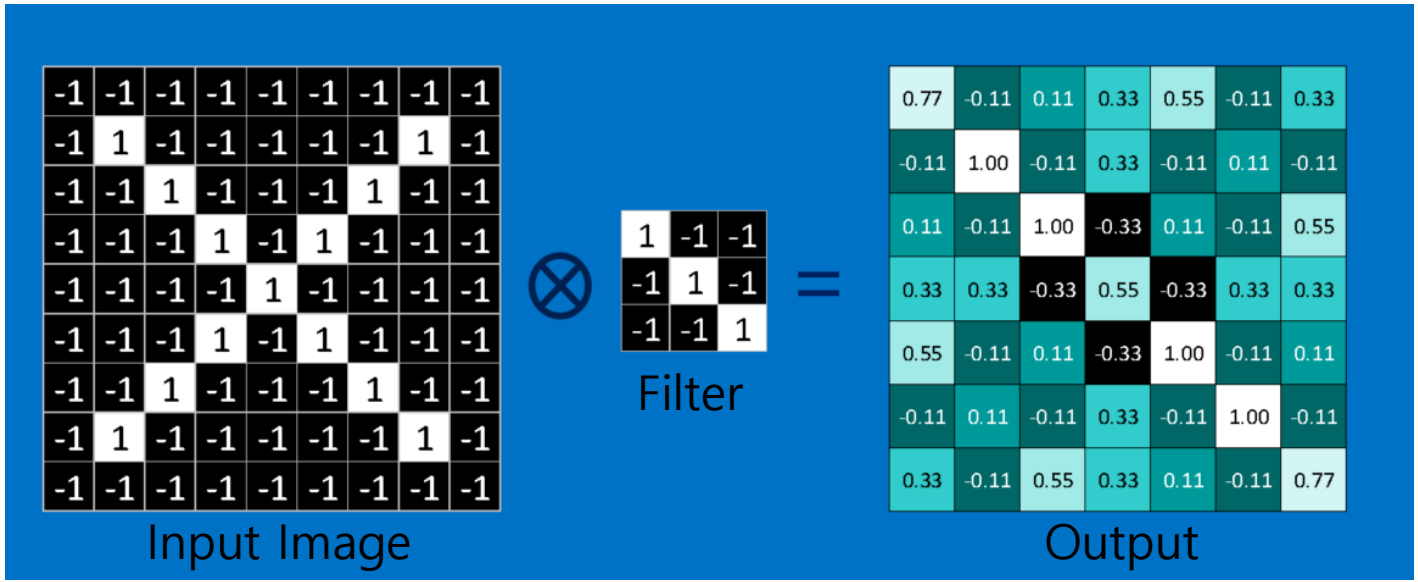
(출처: https://github.com/vdumoulin/conv_arithmetic)

Convolution Layer



(출처:https://brohrer.github.io/how_convolutional_neural_networks_work.html)

Convolution Layer



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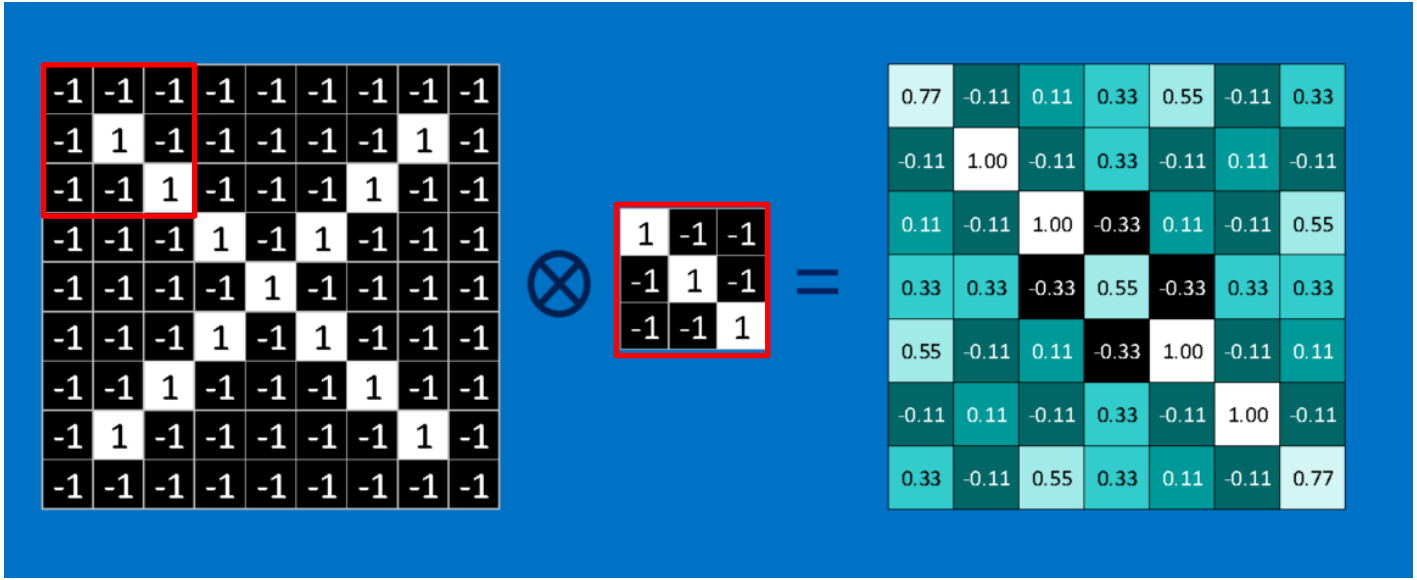
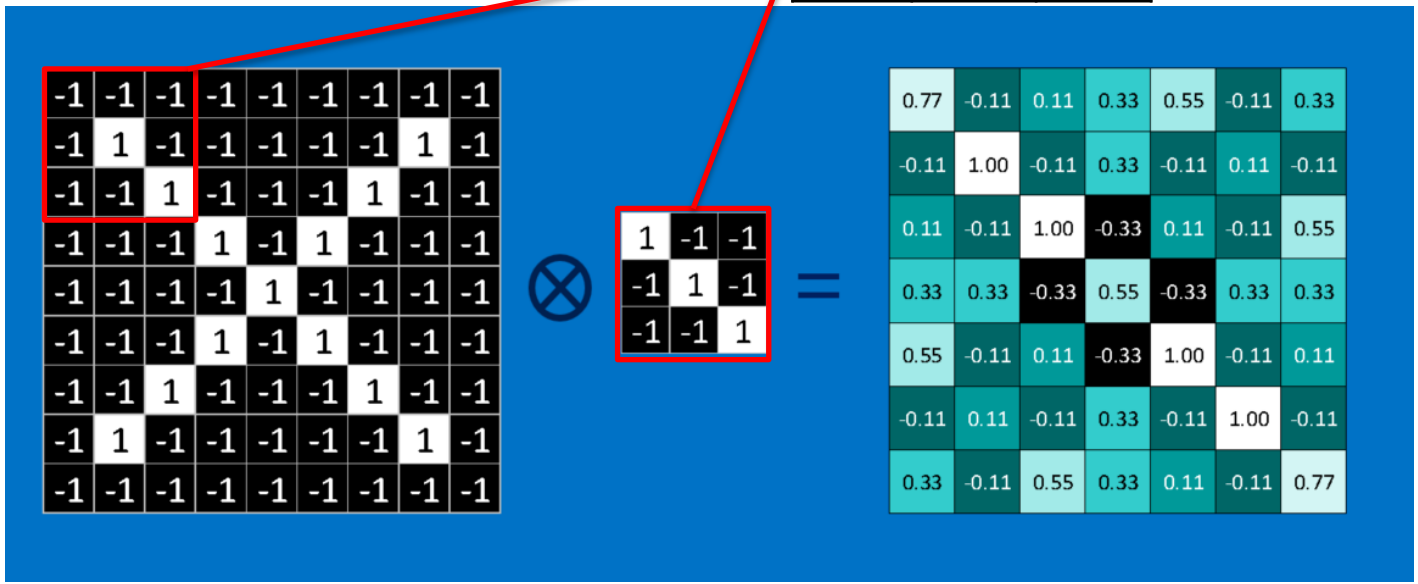


(출처:https://brohrer.github.io/how_convolutional_neural_networks_work.html)

Convolution Layer

-1*1	-1*-1	-1*-1
-1*-1	1*1	-1*-1
-1*-1	-1*-1	1*1



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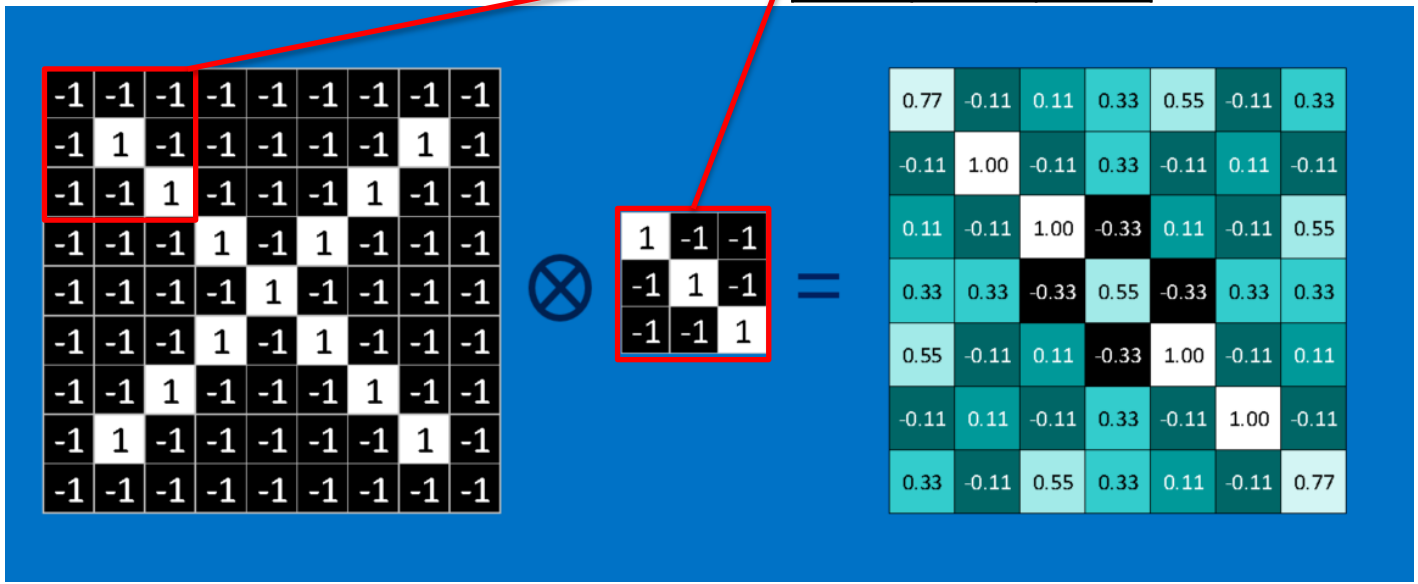
Convolution Layer

-1*1	-1*-1	-1*-1
-1*-1	1*1	-1*-1
-1*-1	-1*-1	1*1

$$= \frac{7}{9} = 0.7777$$



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Convolution Layer

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-1*-1	1*1	-1*-1
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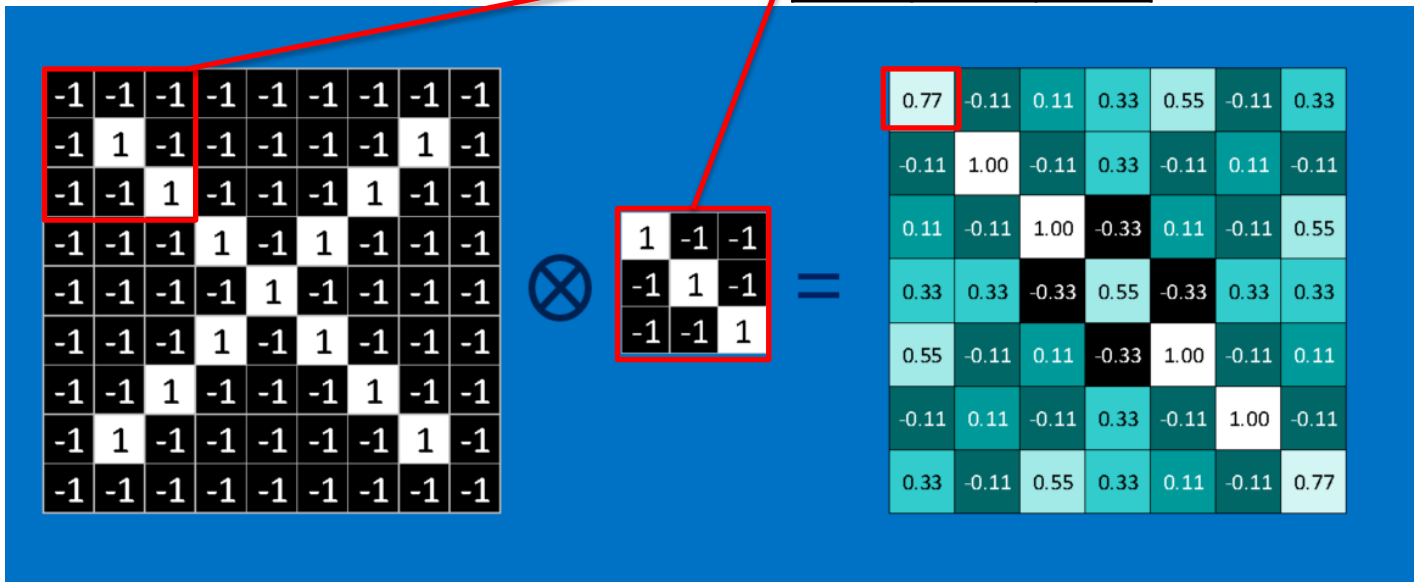
$$= \frac{7}{9} = 0.7777$$



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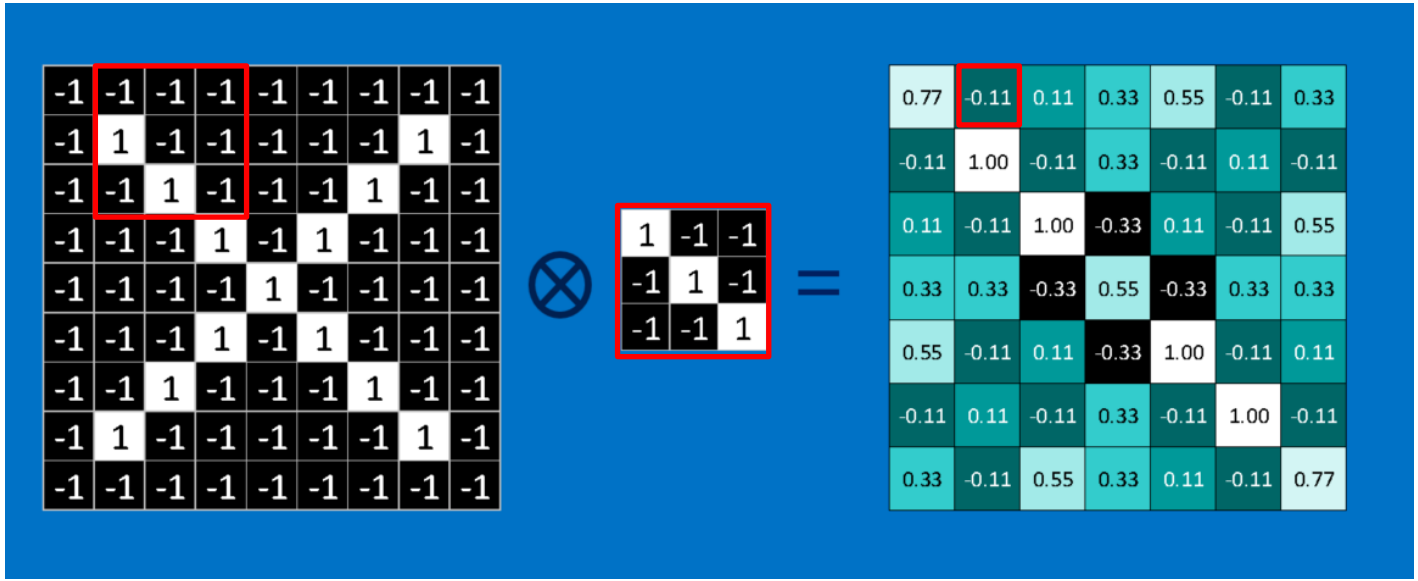
Convolution Layer



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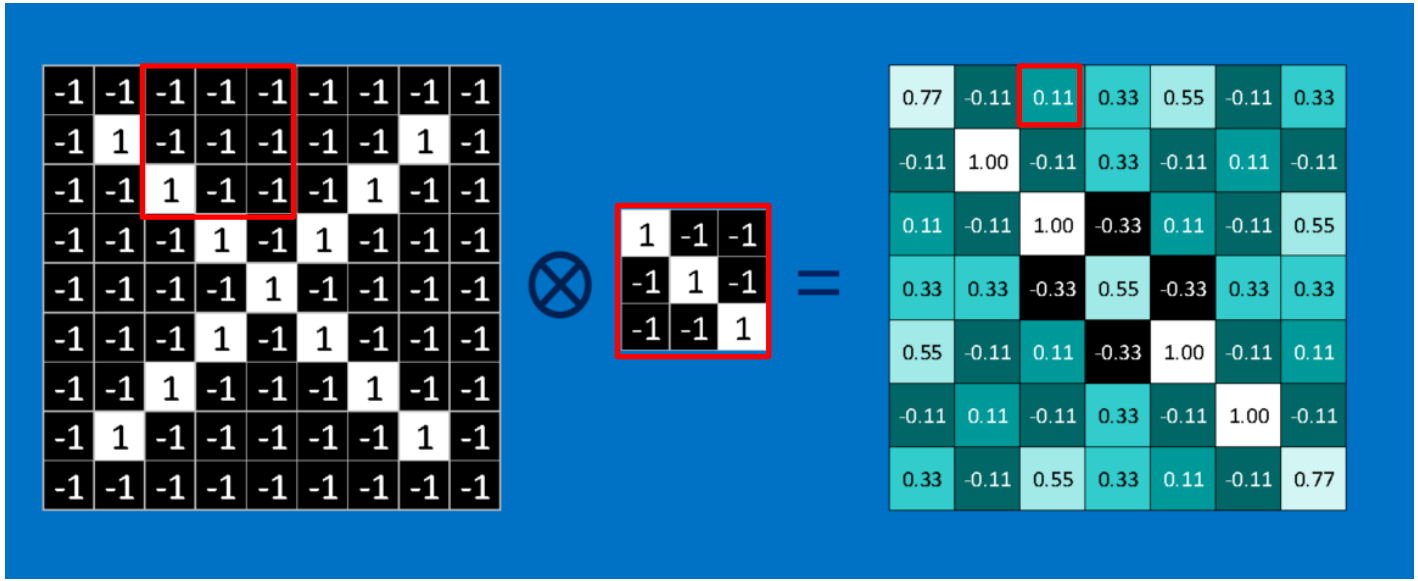

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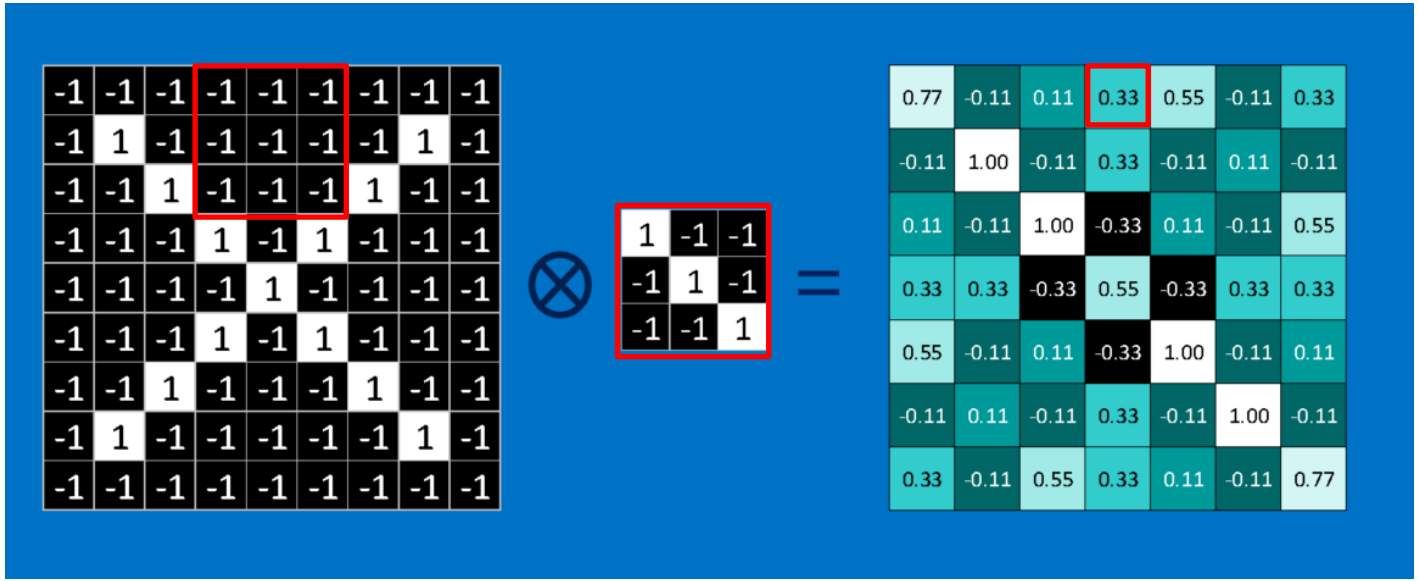

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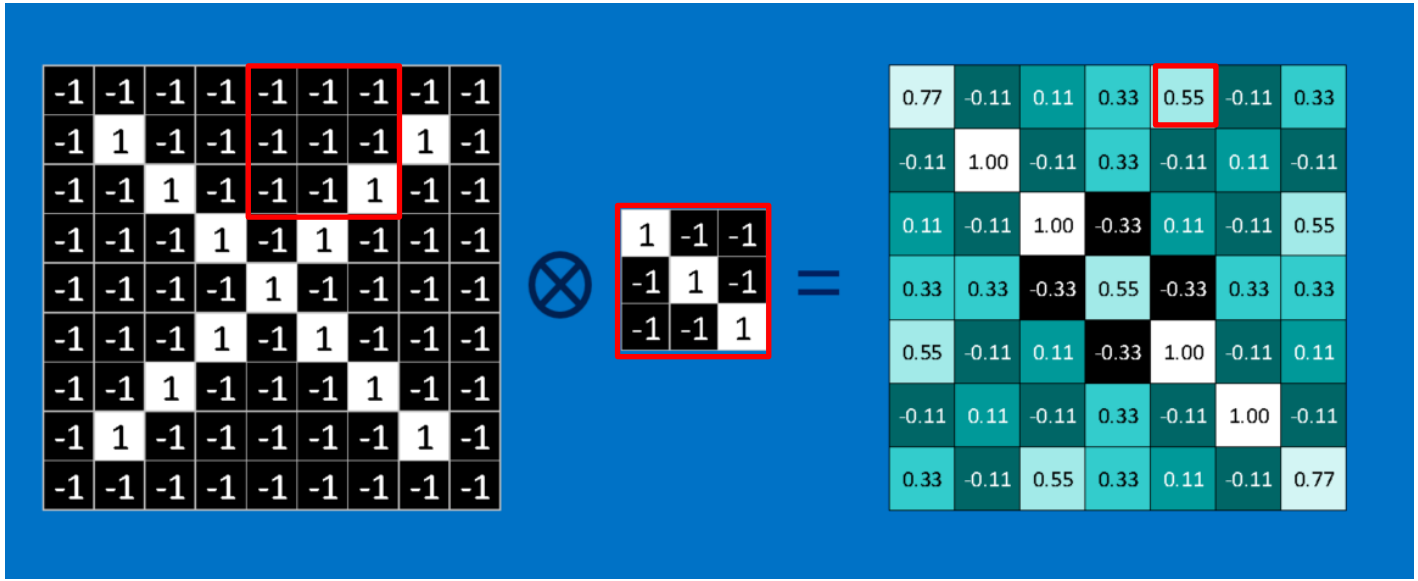

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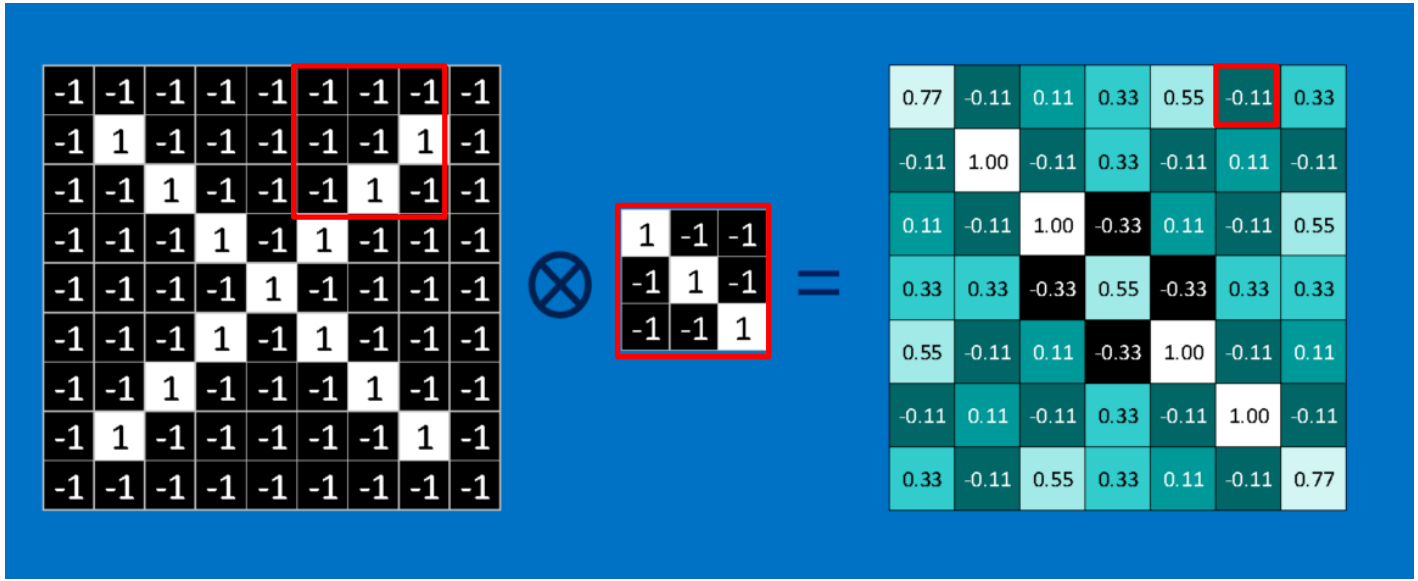
Convolution Layer



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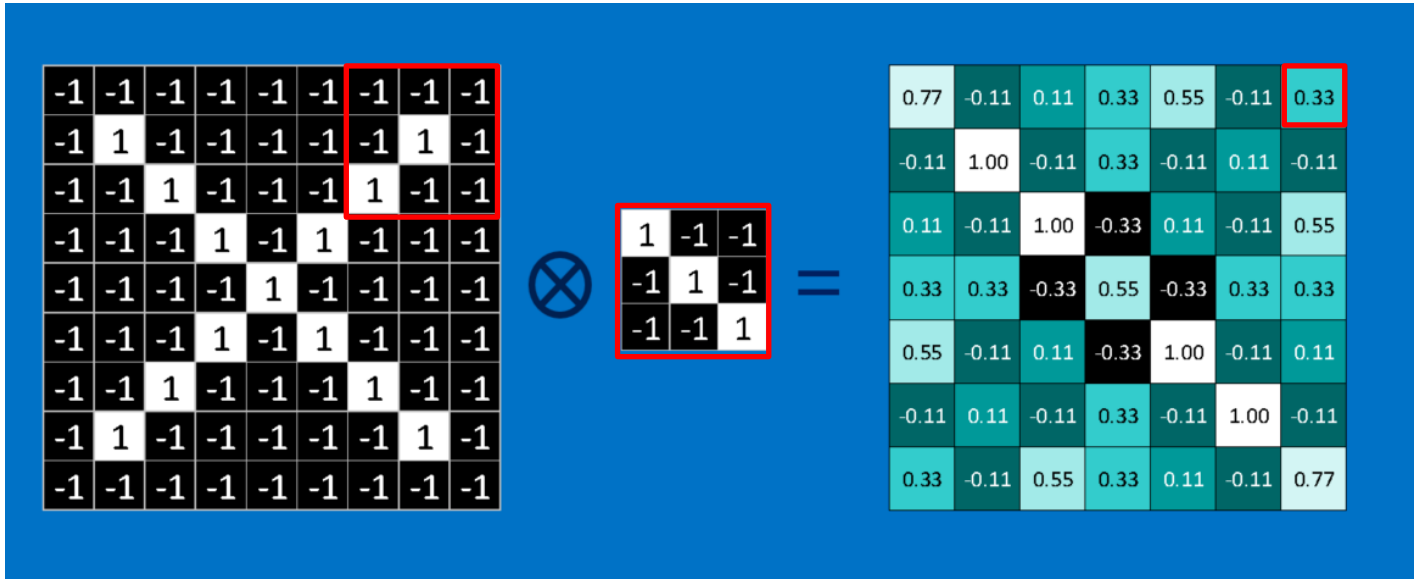
Convolution Layer



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Convolution Layer

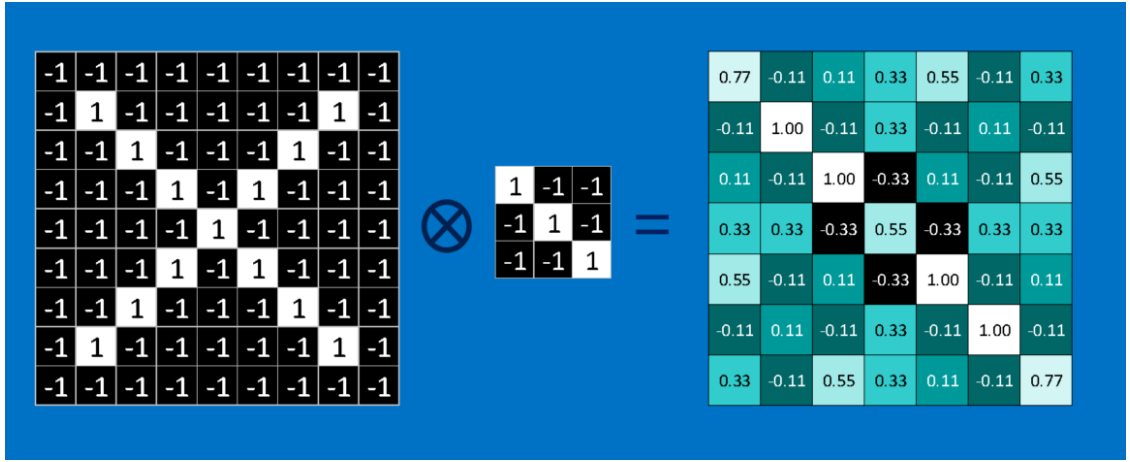


Image size를 I, kernel size를 K, stride를 S라고 하면 output size O는 아래의 식과 같음.

(출처:https://brohrer.github.io/how_convolutional_neural_networks_work.html)

Convolution Layer

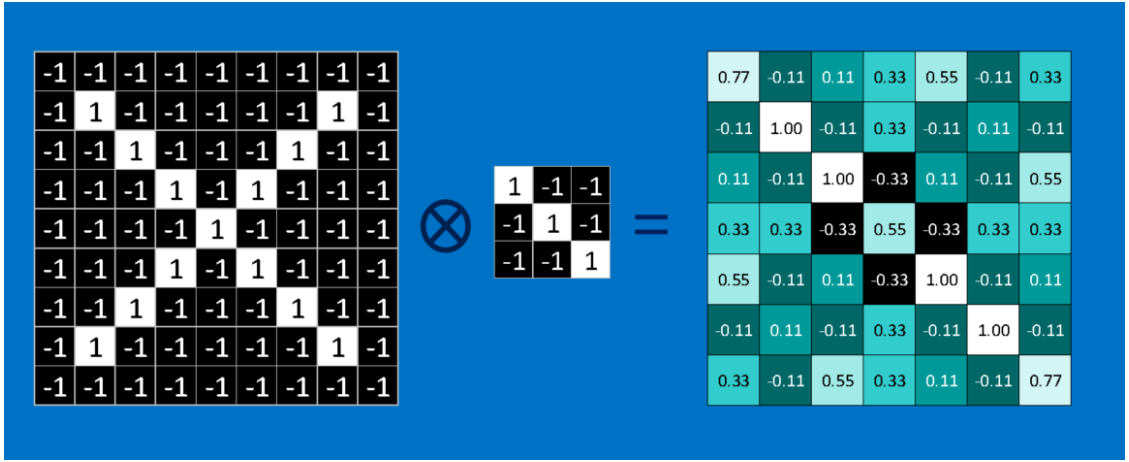
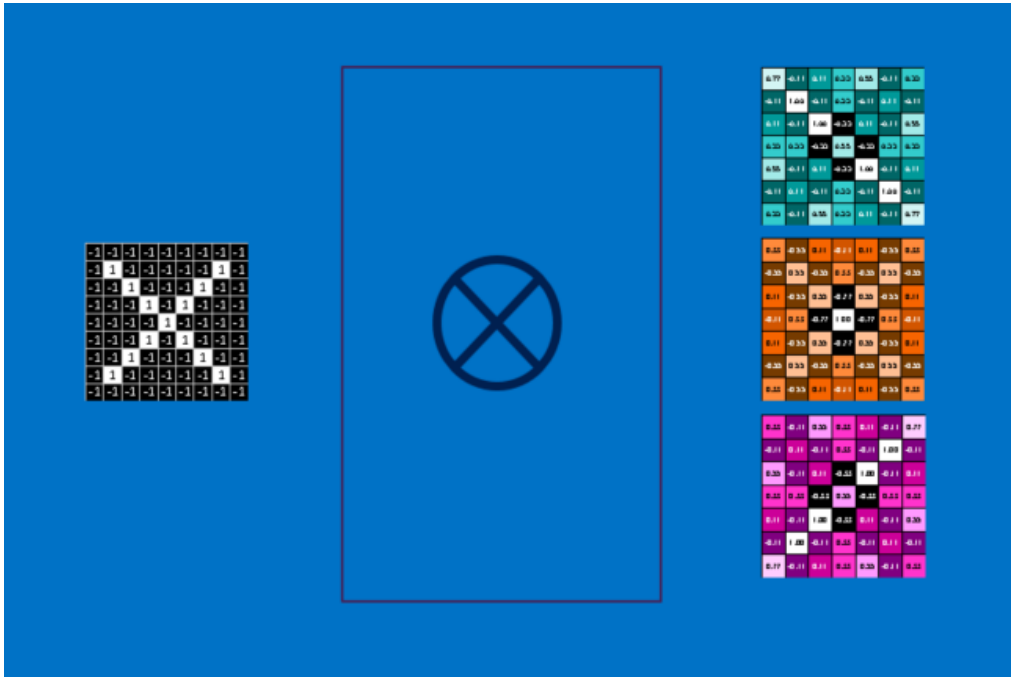


Image size를 I, kernel size를 K, stride를 S라고 하면 output size O는 아래의 식과 같음.

$$O = floor(\frac{I - K}{S} + 1)$$

(출처:https://brohrer.github.io/how_convolutional_neural_networks_work.html)

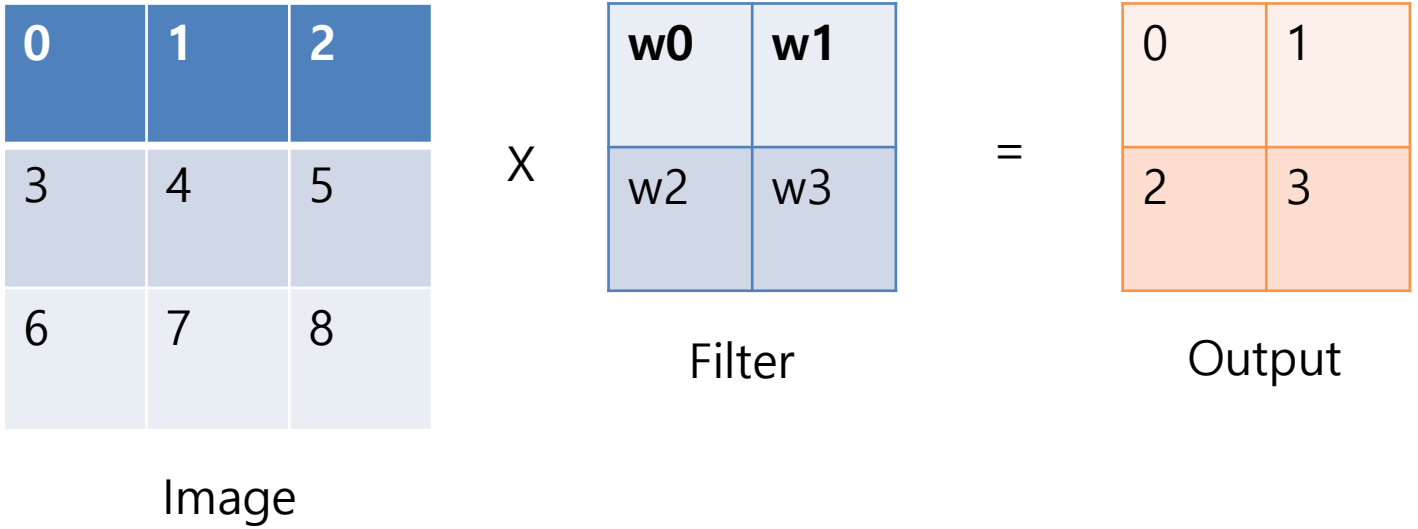
Convolution Layer



하나의 이미지에 대해서 여러 종류의 필터를 적용할 수 있음

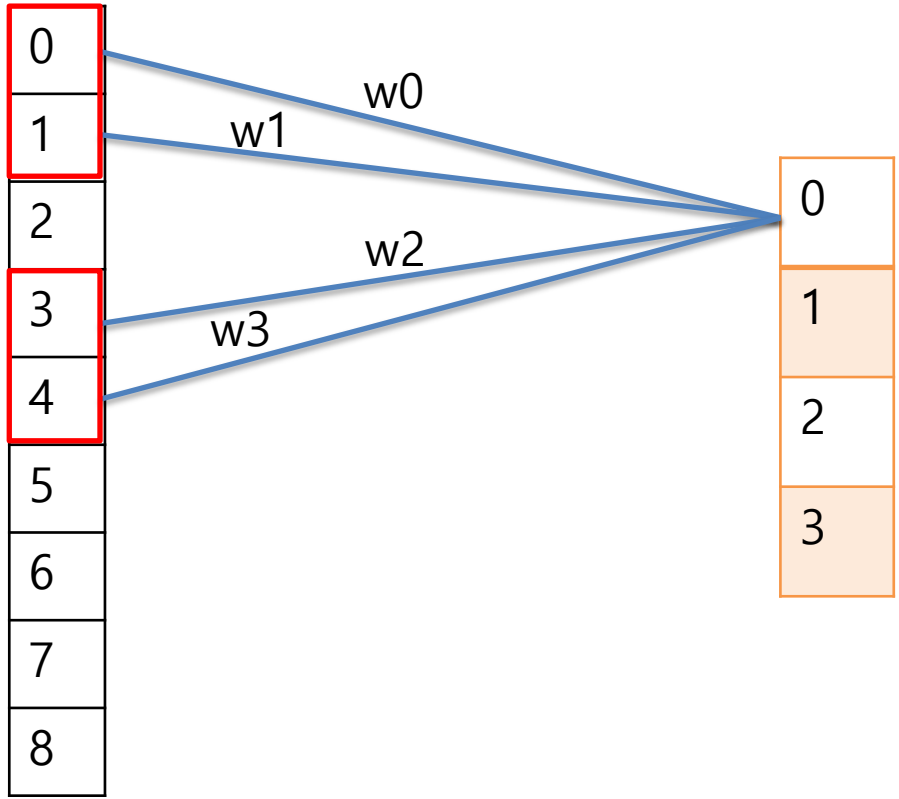
(출처:https://brohrer.github.io/how_convolutional_neural_networks_work.html)

Basic Architecture



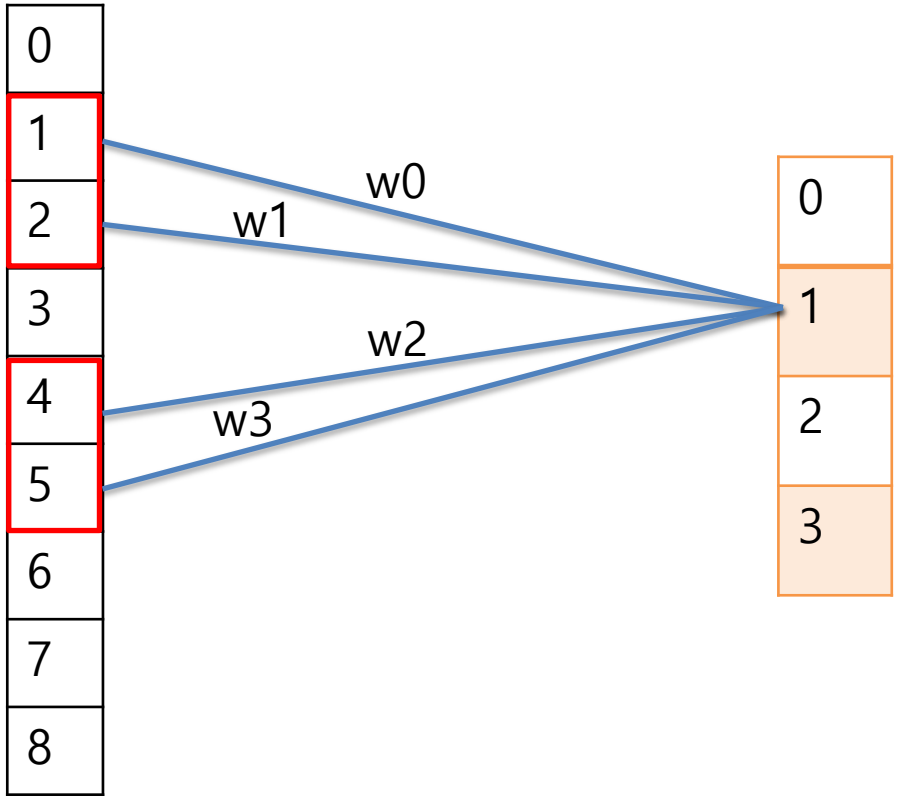
Basic Architecture

0	1	2
3	4	5
6	7	8



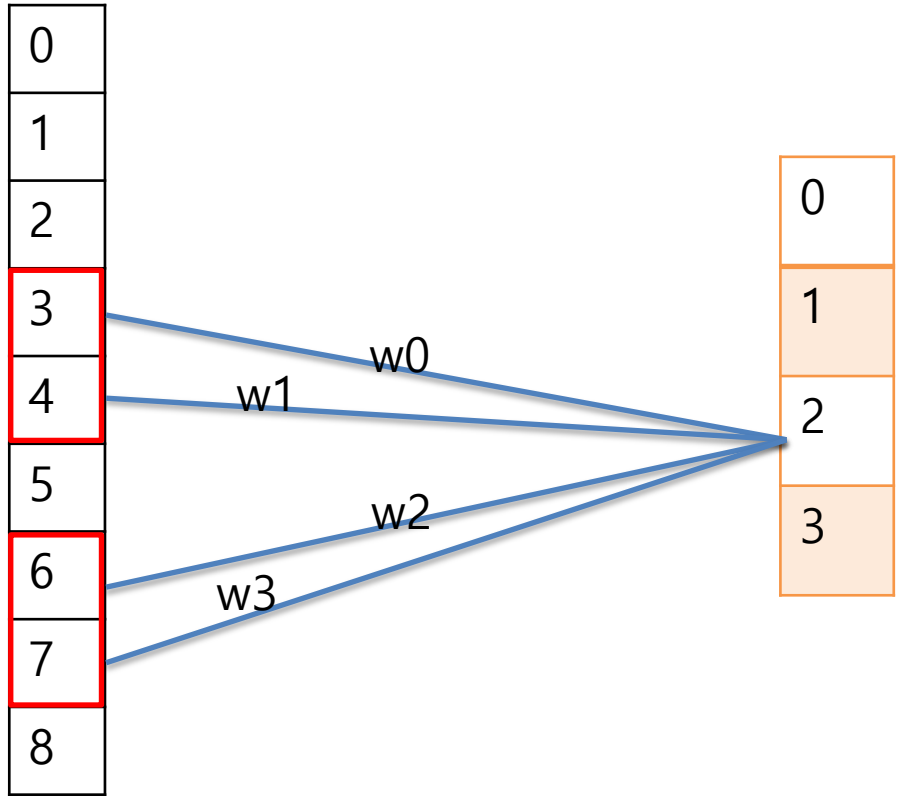
Basic Architecture

0	1	2
3	4	5
6	7	8



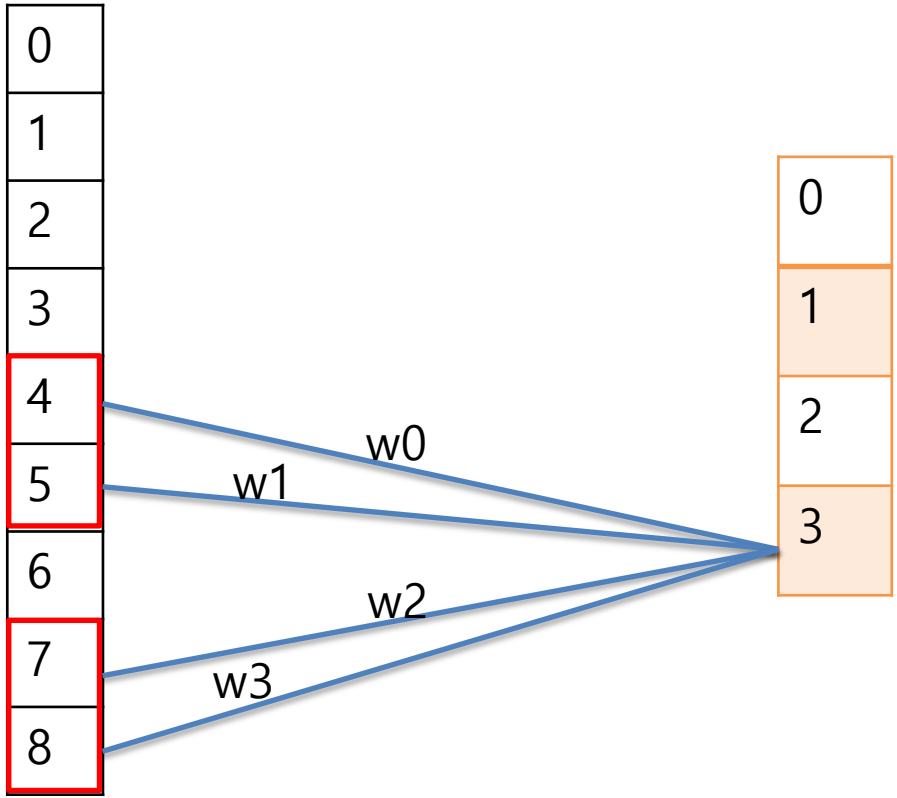
Basic Architecture

0	1	2
3	4	5
6	7	8

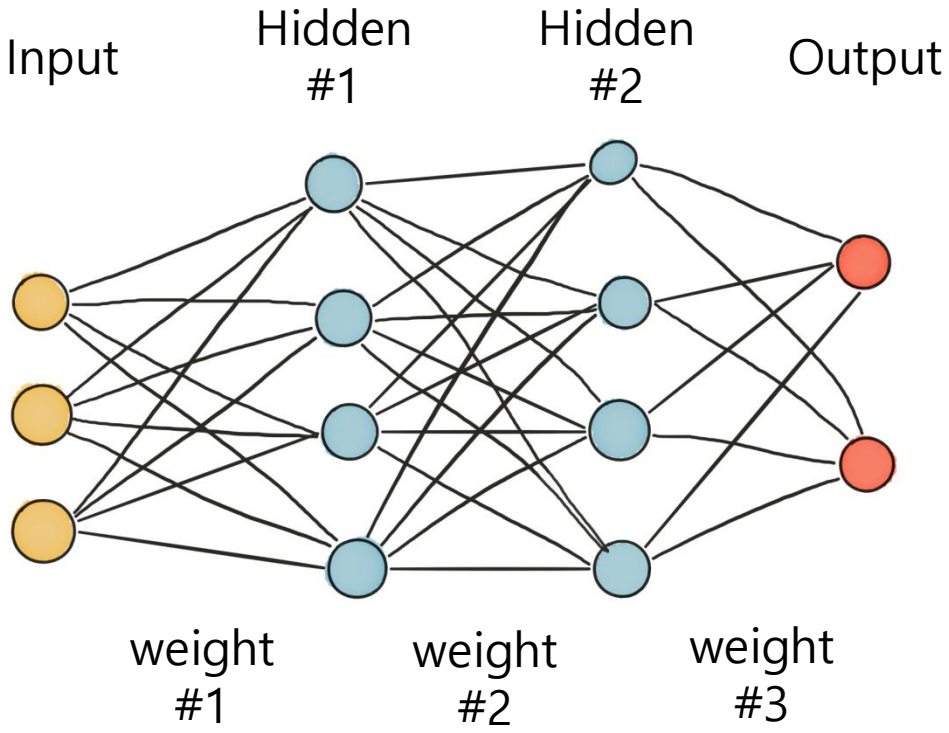


Basic Architecture

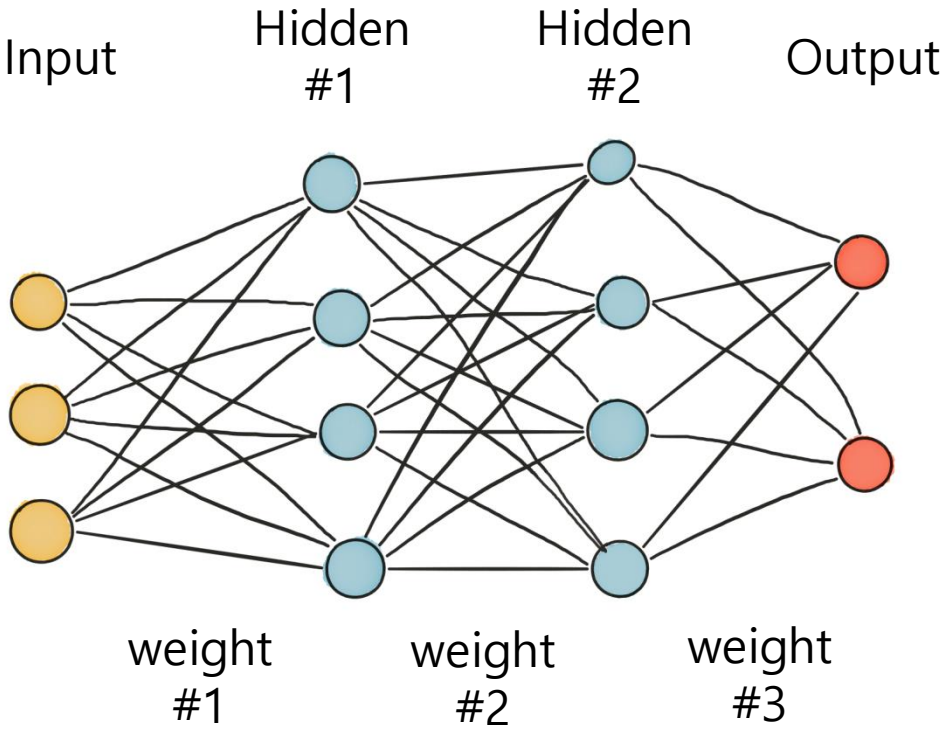
0	1	2
3	4	5
6	7	8



Basic Architecture

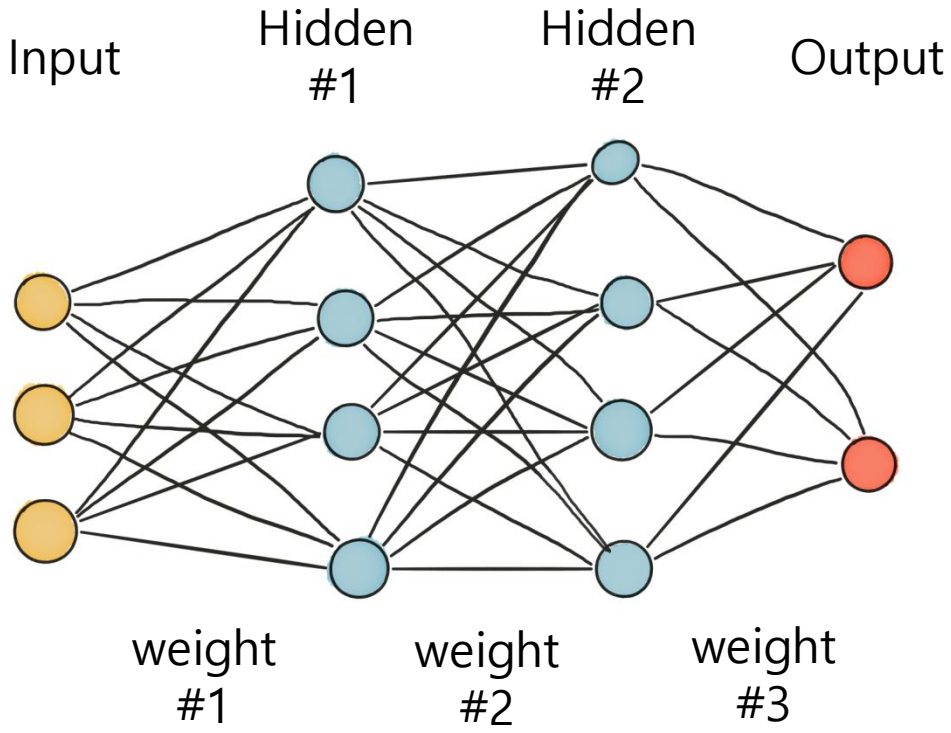


Basic Architecture



Convolutional Neural Network 역시 일반 뉴럴넷과 유사한 구조

Basic Architecture



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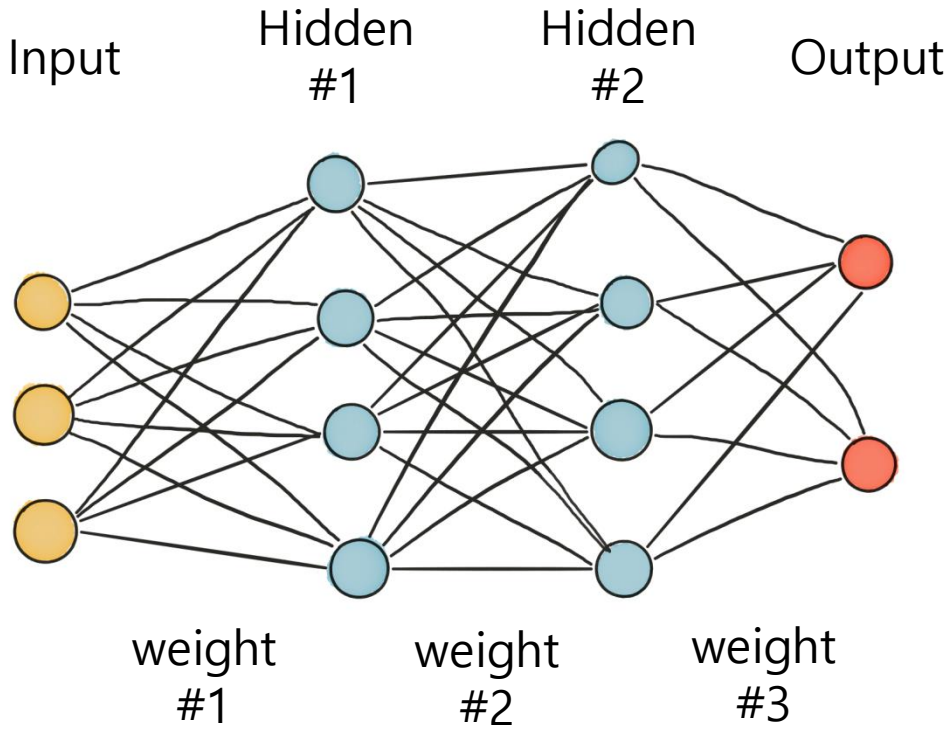
Basic Architecture

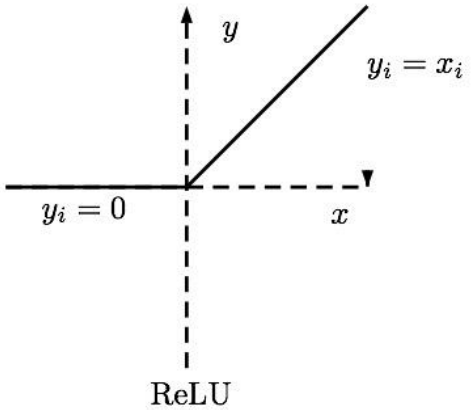


Convolutional Neural Network 역시 일반 뉴럴넷과 유사한 구조

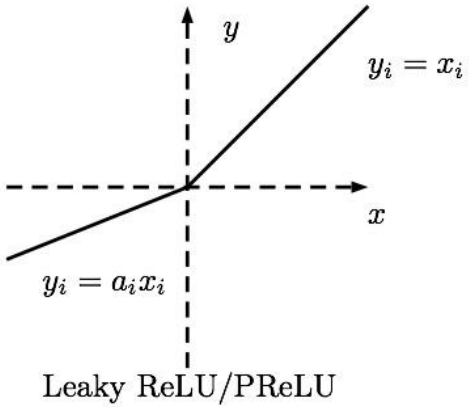
그렇다면 activation function은?

Basic Architecture

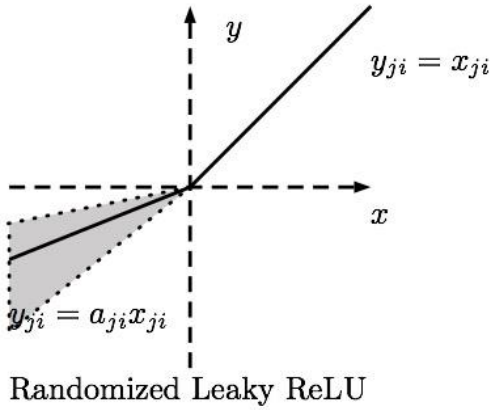
Rectified Linear Unit (ReLU)



f(x)=max(0,x)



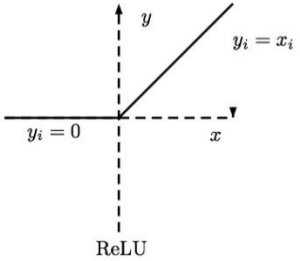
f(x)=max(ax,x)



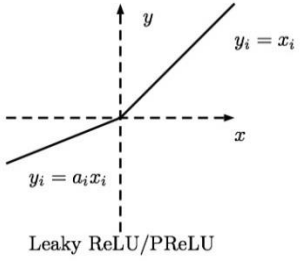
f(x)=max(ax,x)

(출처:http://www.datasciencecentral.com/m/blogpost?id=6448529%3ABlogPost%3A408853)

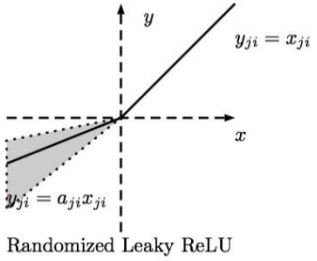
Basic Architecture



ReLU



Leaky ReLU/PReLU



Randomized Leaky ReLU

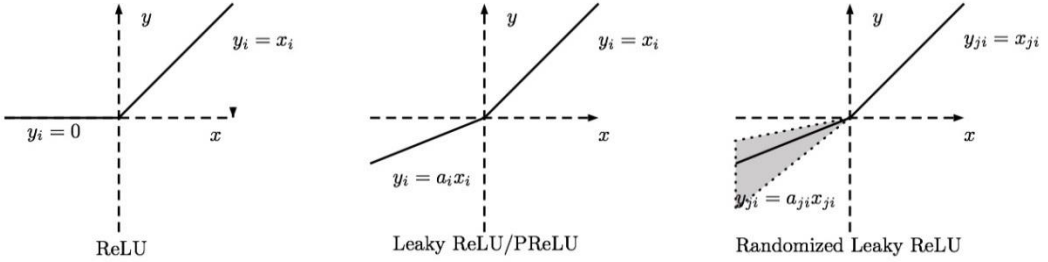
장점

- 학습이 빠름
- 연산면에서 효율적

단점

- Dying Neuron

Basic Architecture



장점

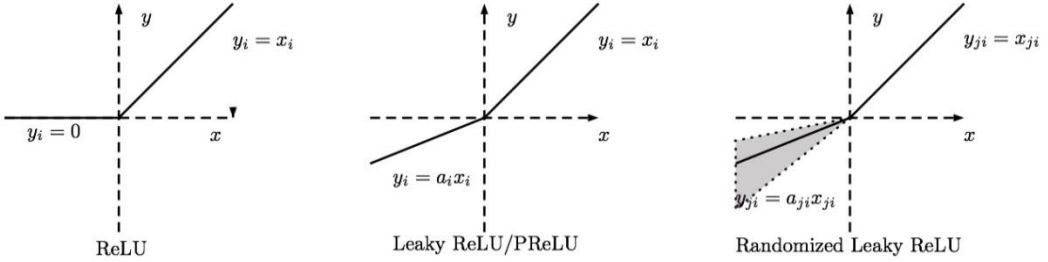
- 학습이 빠름
- 연산면에서 효율적

$y = x$ 를 미분하면 $gradient$가 1이니까 loss * gradient하면 sigmoid나 tanh보다 gradient가 크게 전달됨.

단점

- Dying Neuron

Basic Architecture



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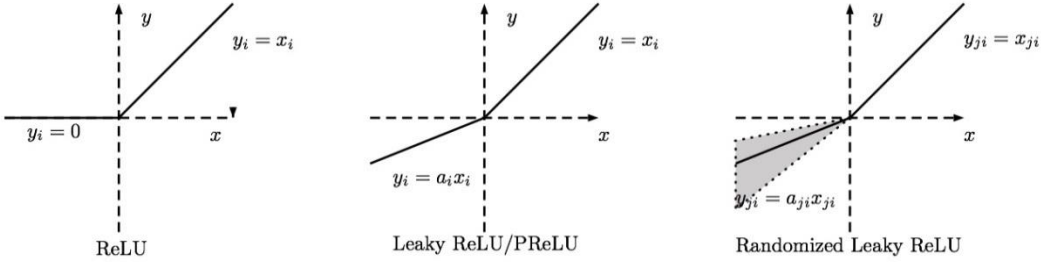
ex)

$$sigmoid'(x) = sigmoid(x) * (1 - sigmoid(x))$$

$$0 \leq sigmoid(x) \leq 1$$

$$0 \leq sigmoid'(x) \leq 1$$

Basic Architecture



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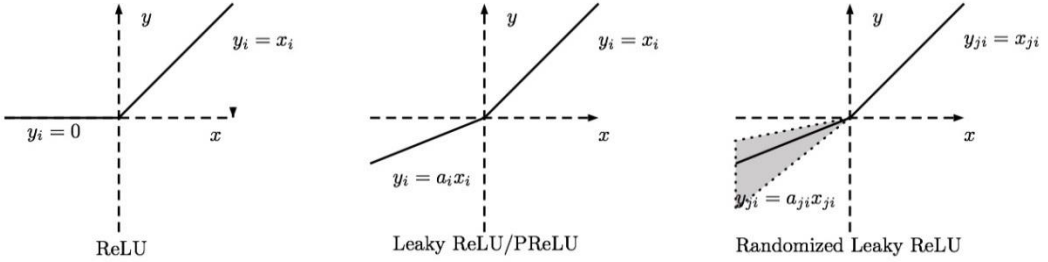
그렇기 때문에 업데이트도 비교적 크다

단점

- Dying Neuron

Basic Architecture



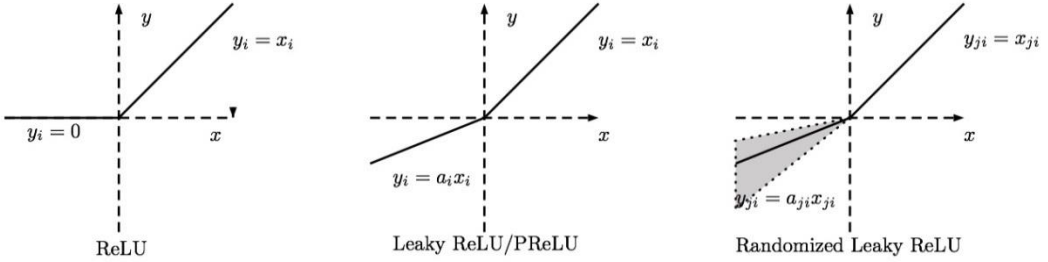
장점

- 학습이 빠름
- 연산면에서 효율적 → exponential이 들어간 연산보다는 ReLU가 더 간단하기 때문에 연산 속도가 빠름.

단점

- Dying Neuron

Basic Architecture



장점

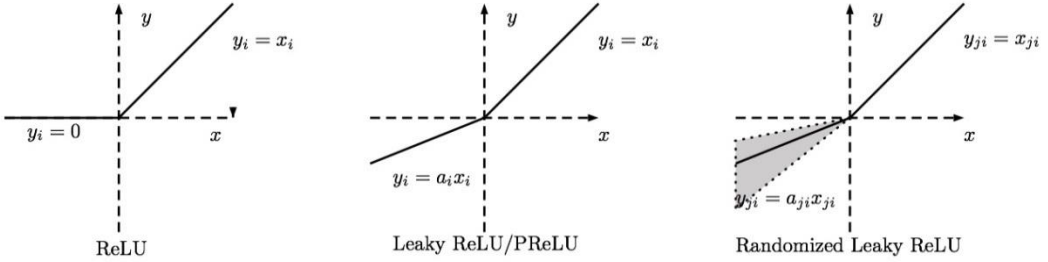
- 학습이 빠름
- 연산면에서 효율적

단점

- Dying Neuron

ReLU가 값이 0 이하인 값들은 무조건 gradient를 0로 만들어 버리고 back propagation이 일어나지 않음.

Basic Architecture



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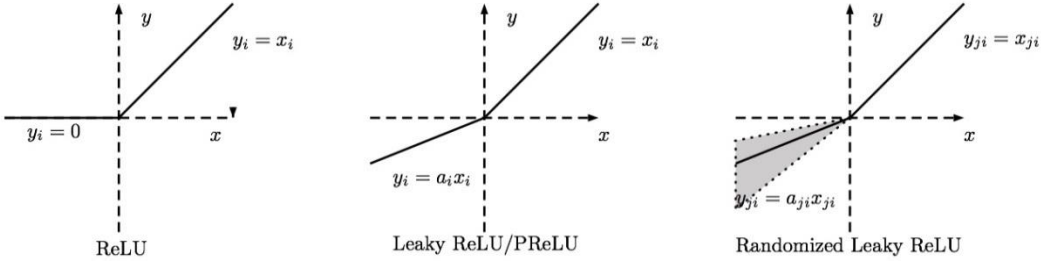
어쩌다 loss가 커지면 weight, bias가 크게 업데이트 됨.

Basic Architecture



장점

- 학습이 빠름
- 연산면에서 효율적

단점

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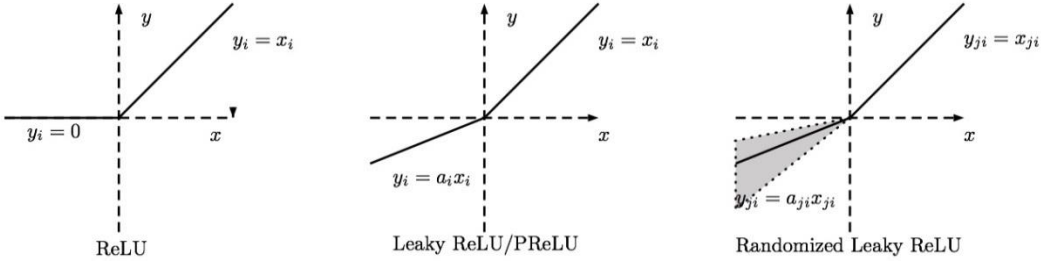
어쩌다 loss가 커지면 weight, bias가 크게 업데이트 됨.

ex) $y = -3x - 5$면 -1~1로 normalize된 input이 들어오면 무조건 0 이하. 영원히 업데이트 안됨.

Basic Architecture



장점

- 학습이 빠름
- 연산면에서 효율적

단점

- Dying Neuron

해결책으로 나온게 Leaky ReLU, PReLU
$x < 0$일 때도 update가 이루어 지도록 개선

Convolution Layer

(출처:http://setosa.io/ev/image-kernels/)

Convolution Layer

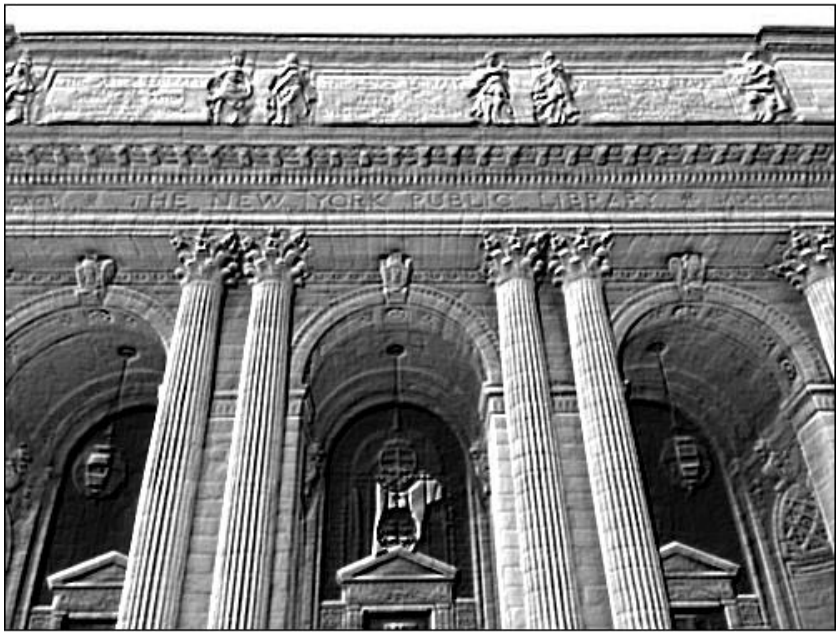
-1	-1	-1
-1	8	-1
-1	-1	-1

outline

(출처:http://setosa.io/ev/image-kernels/)

Convolution Layer

-2	-1	0
-1	1	1
0	1	2



emboss

(출처:http://setosa.io/ev/image-kernels/)

Convolution Layer

0.0625	0.125	0.0625
0.125	0.25	0.125
0.0625	0.125	0.0625

blur

(출처:http://setosa.io/ev/image-kernels/)

Convolution Layer

위의 예시는 하나의 필터만 적용됐을 때

Convolution Layer

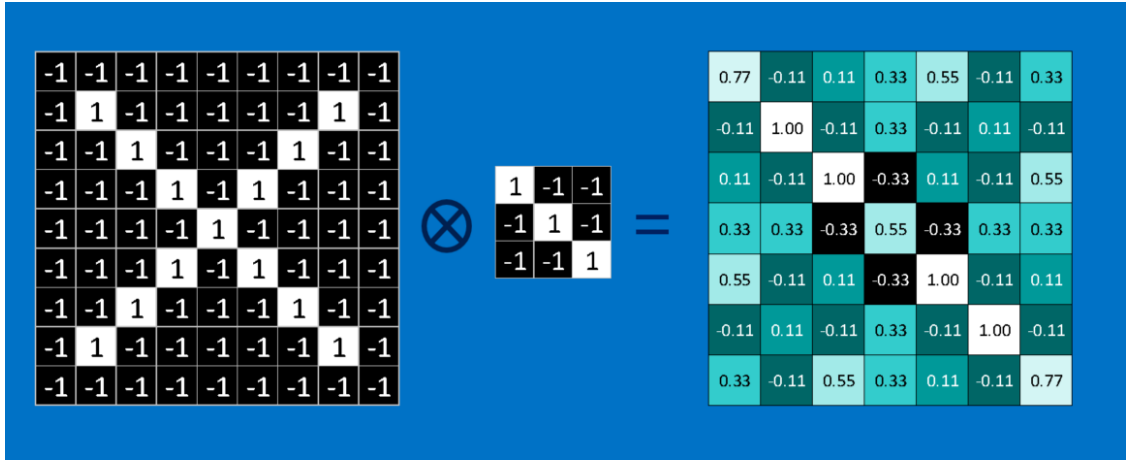
Hubel & Wiesel의 연구를 통해
단순한 필터로 뽑힌 feature들의
조합으로 complex feature를 뽑아낼
수 있다는 것을 배움

Convolution Layer

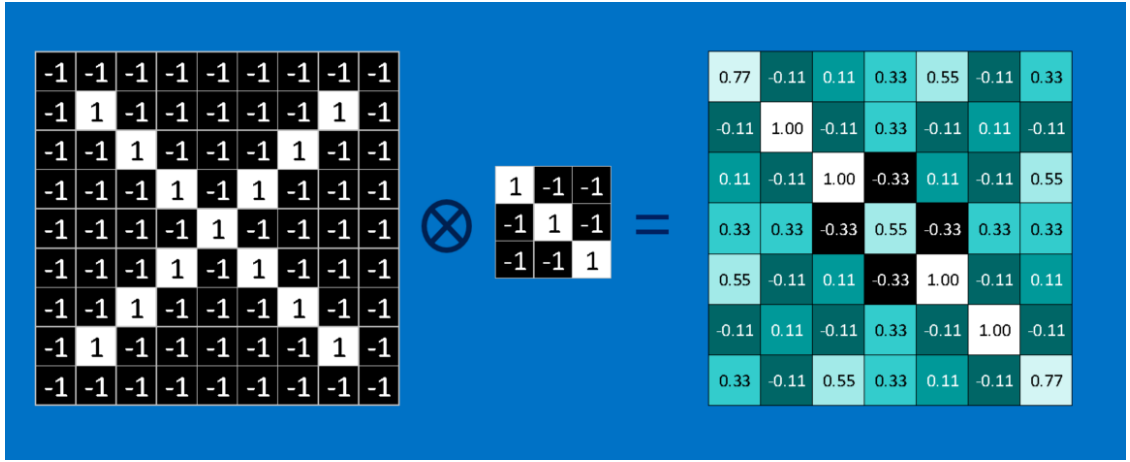
Hubel & Wiesel의 연구를 통해 단순한 필터로 뽑힌 feature들의 조합으로 complex feature를 뽑아낼 수 있다는 것을 배움

다양하고 많은 층의 Convolution layer가 있으면 더 복잡한 모양도 구분할 수 있음.

Convolution Layer

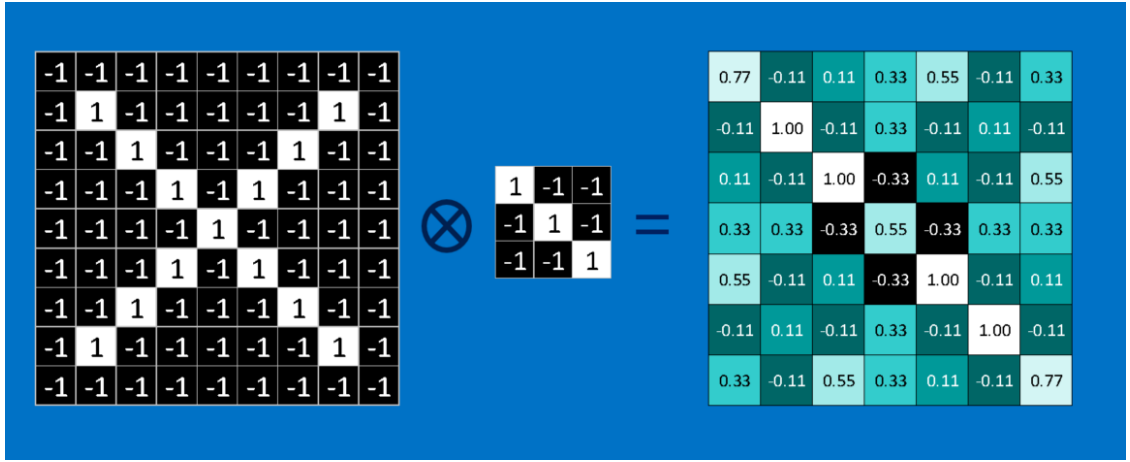


Convolution Layer



9x9 이미지의 경우
3x3 커널을
1번 적용: 7x7
2번 적용: 5x5
3번 적용: 3x3
4번 적용: 1x1

Convolution Layer



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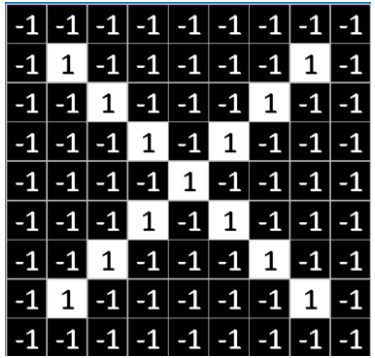
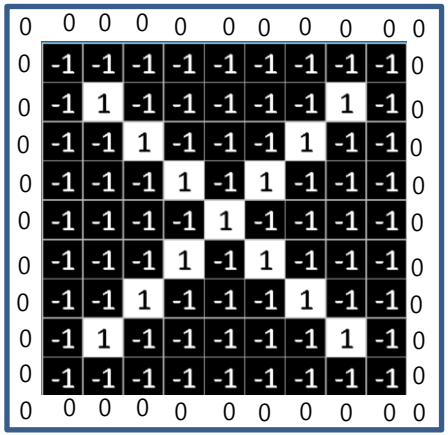
3번 적용: 3x3
4번 적용: 1x1

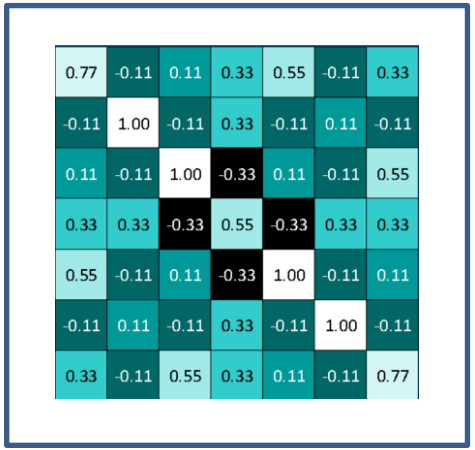
단순한 X자 모양이면 모르겠지만 만약 복잡한 모양을 구분해야 한다면 더 많은 층이 필요하지 않을까?

Convolution Layer



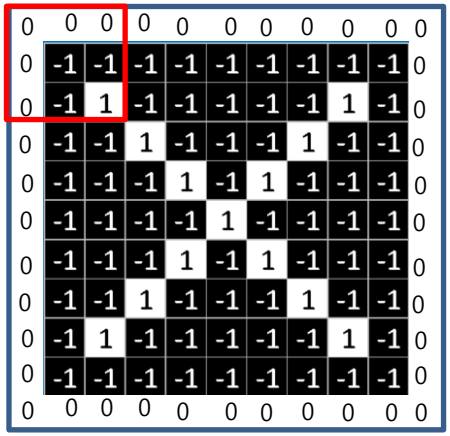
Convolution Layer

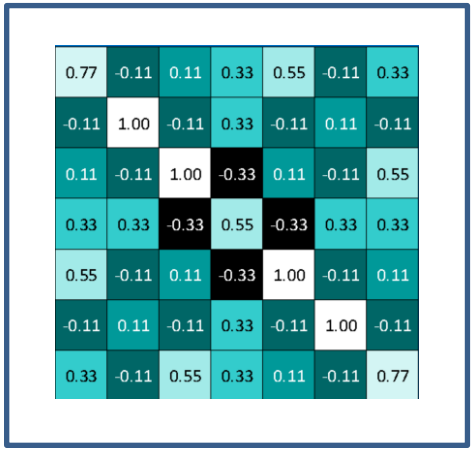




padding = 1

Convolution Layer

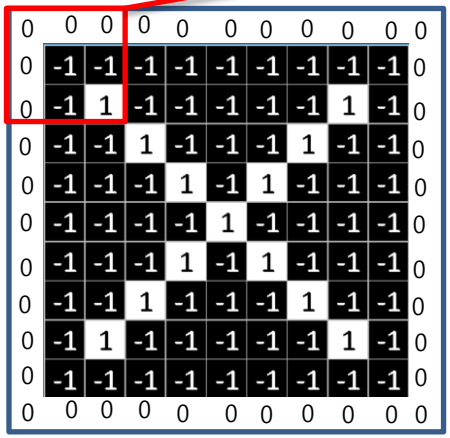


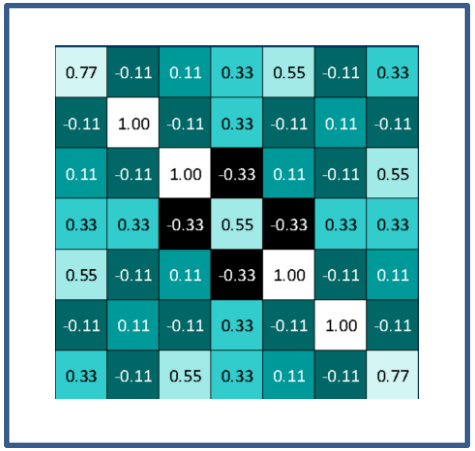


padding = 1

Convolution Layer

(-1+1+1+1)/9=0.2222

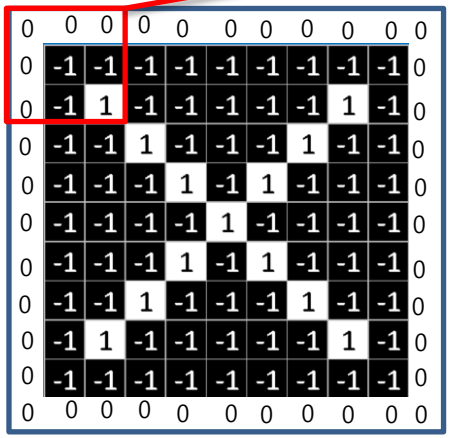


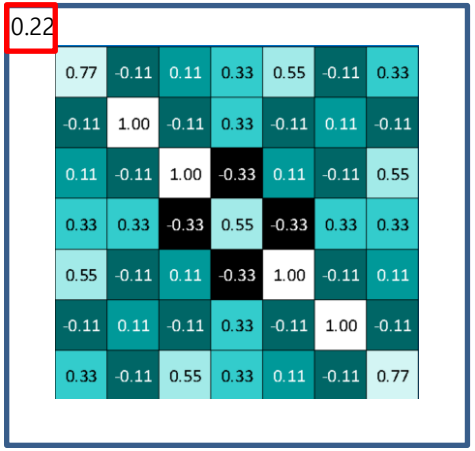


padding = 1

Convolution Layer

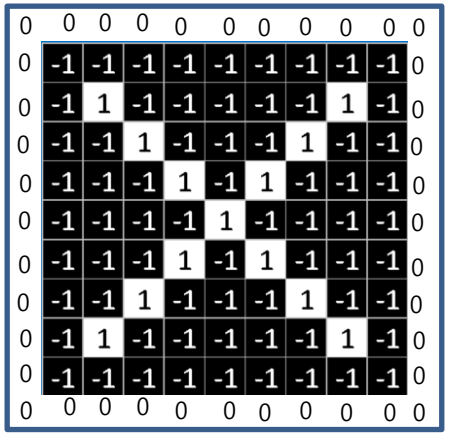
(-1+1+1+1)/9=0.2222





padding = 1

Convolution Layer



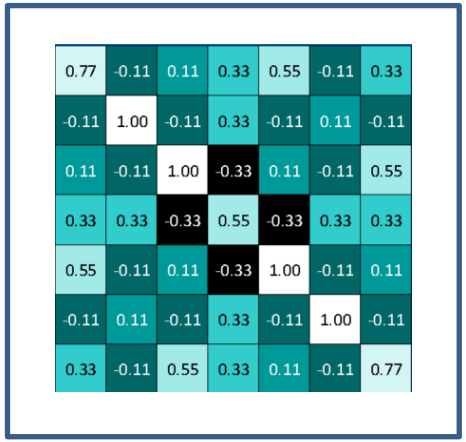
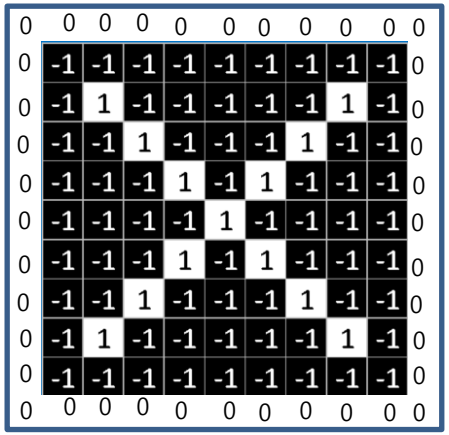


Image size를 I, kernel size를 K, stride를 S, padding을 P라고 하면 output size O는 아래의 식과 같음.

Convolution Layer



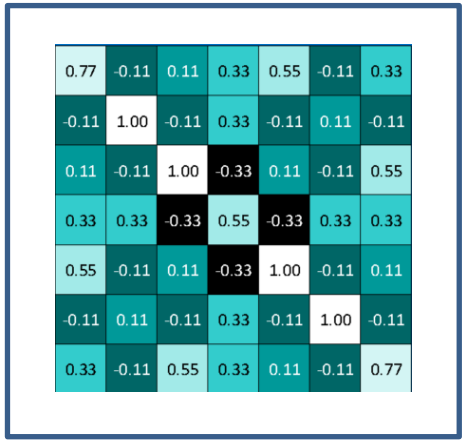


Image size를 I, kernel size를 K, stride를 S, padding을 P라고 하면 output size O는 아래의 식과 같음.

$$O = floor(\frac{I - K + 2P}{S} + 1)$$

Convolution Layer

이미 충분한 정보를 뽑아냈다면?

1800

3600

Convolution Layer

이미 충분한 정보를 뽑아냈다면?

3600

1800

3x3 Kernel로 특성을 300단계 뽑아내도 3000 x 1200
이렇게 큰 이미지에 3x3 필터를 적용하면 연산량도
너무 많고 뽑힌 필터로 결과값을 내는 것도 비효율적

Convolution Layer

이미 충분한 정보를 뽑아냈다면?

3600

1800

그래서 필요한 게 Subsampling(≈Downsampling)

Convolution Layer

이미지에서 충분한 정보를 뽑아냈다면 해당 정보를 전부 전달하는 것이 아니라 중요한 정보만 또는 평균적 정보를 전달해도 결정을 내릴 수 있다.

Convolution Layer

이미지에서 충분한 정보를 뽑아냈다면 해당 정보를 전부 전달하는 것이 아니라 중요한 정보만 또는 평균적 정보를 전달해도 결정을 내릴 수 있다.

Convolution Layer

이미지에서 충분한 정보를 뽑아냈다면 해당 정보를 전부 전달하는 것이 아니라 중요한 정보만 또는 평균적 정보를 전달해도 결정을 내릴 수 있다.

Convolution Layer

이미지에서 충분한 정보를 뽑아냈다면 해당 정보를 전부 전달하는 것이 아니라 중요한 정보만 또는 평균적 정보를 전달해도 결정을 내릴 수 있다.

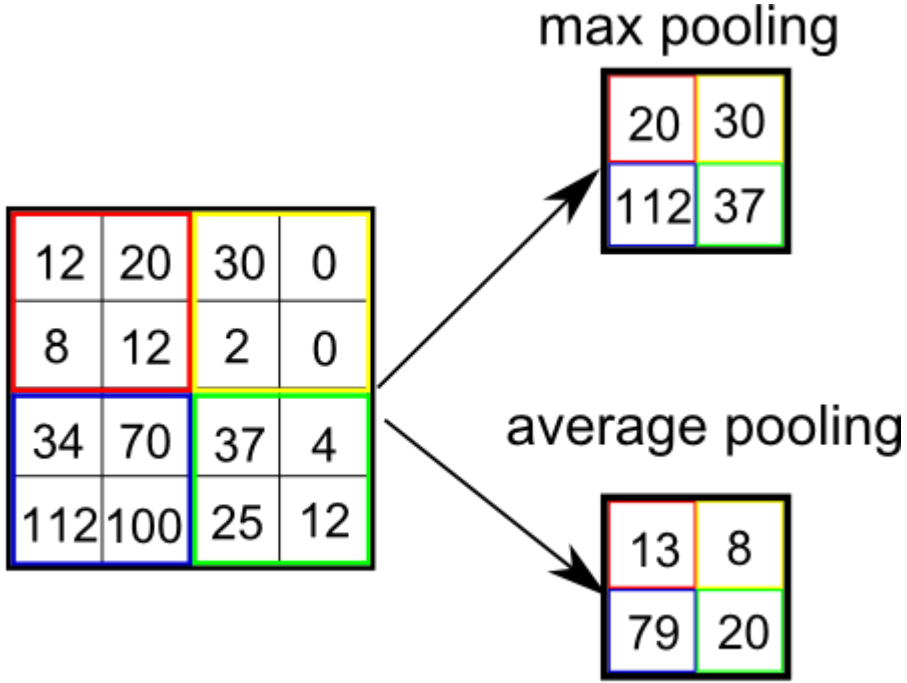
정보의 압축 및 축소

Convolution Layer

어떻게 축소시킬 것인가?

Convolution Layer

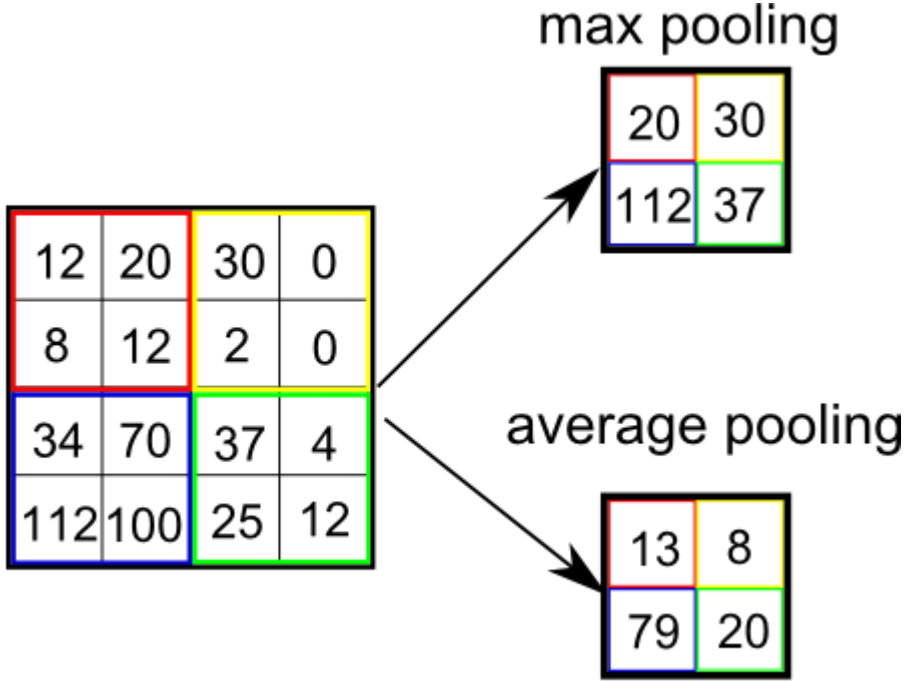
어떻게 축소시킬 것인가?



(출처: https://stackoverflow.com/questions/44287965/trying-to-confirm-average-pooling-is-equal-to-dropping-high-frequency-fourier-co)

Convolution Layer

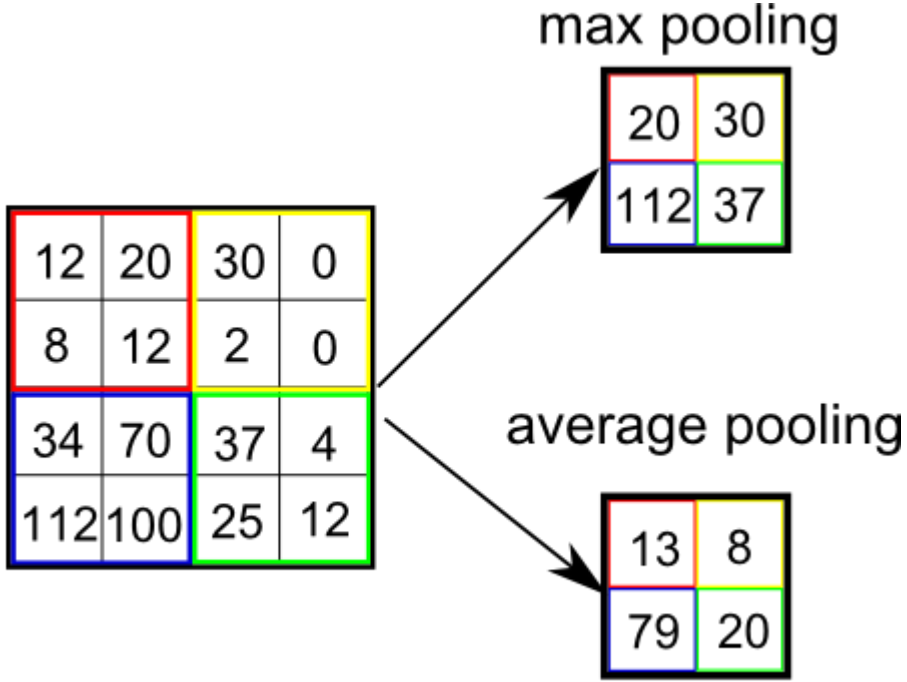
어떻게 축소시킬 것인가?



2x2 grid, stride 2로
최대값을 뽑아내서 축소
-> 강한 자극만 기억

Convolution Layer

어떻게 축소시킬 것인가?



2x2 grid, stride 2로
최대값을 뽑아내서 축소
-> 강한 자극만 기억

2x2 grid, stride 2로
평균값을 뽑아내서 축소
-> 평균적 자극을 기억

Basic Architecture

Convolution

- Kernel
- Stride
- Padding

Basic Architecture

Convolution

- Kernel
- Stride
- Padding

Subsampling

- Max Pooling
- Average Pooling

Basic Architecture

Convolution

- Kernel
- Stride
- Padding

Subsampling

- Max Pooling
- Average Pooling

Activation Function

- ReLU
- Leaky ReLU

Basic Architecture

Convolution

- Kernel
- Stride
- Padding

Subsampling

- Max Pooling
- Average Pooling

Activation Function

- ReLU
- Leaky ReLU

하나하나는 대충 알겠는데
대체 어떤 순서로 배열해야 할까?

Basic Architecture

$$conv$$

Basic Architecture

$$conv * \alpha$$

Basic Architecture

$$conv * \alpha + Activation$$

Basic Architecture

$$(conv * \alpha + Activation) * \beta$$

Basic Architecture

$$(conv * \alpha + Activation) * \beta + Pooling$$

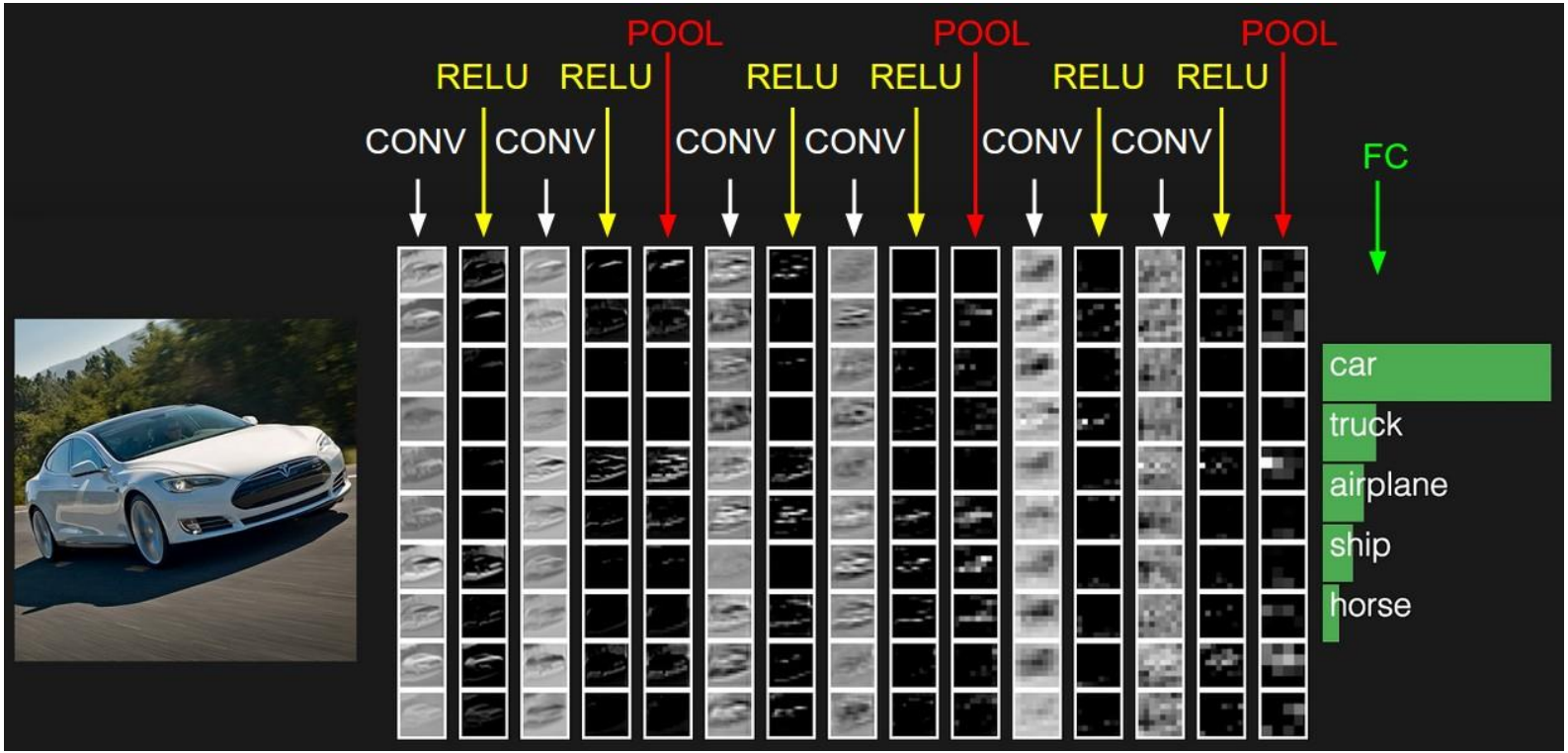
Basic Architecture

$$[(conv * \alpha + Activation) * \beta + Pooling] * \gamma$$

Basic Architecture

$$[(conv * \alpha + Activation) * \beta + Pooling] * \gamma + Fully\ Connected\ Layer$$

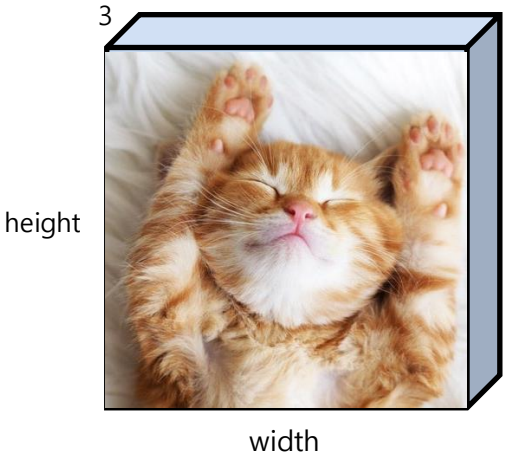
Basic Architecture



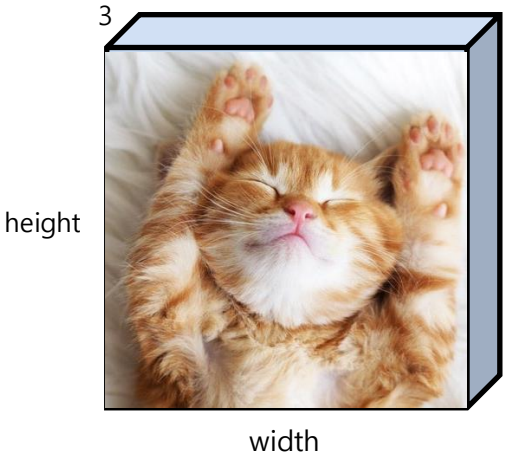
(출처: http://cs231n.github.io/convolutional-networks/)

Basic Architecture

CNN 연산의 3차원적 이해



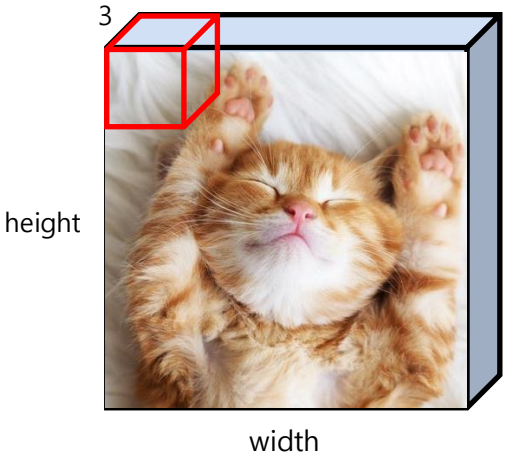
Basic Architecture



Convolution

3x3 filter
stride 1
padding 1
channel 16

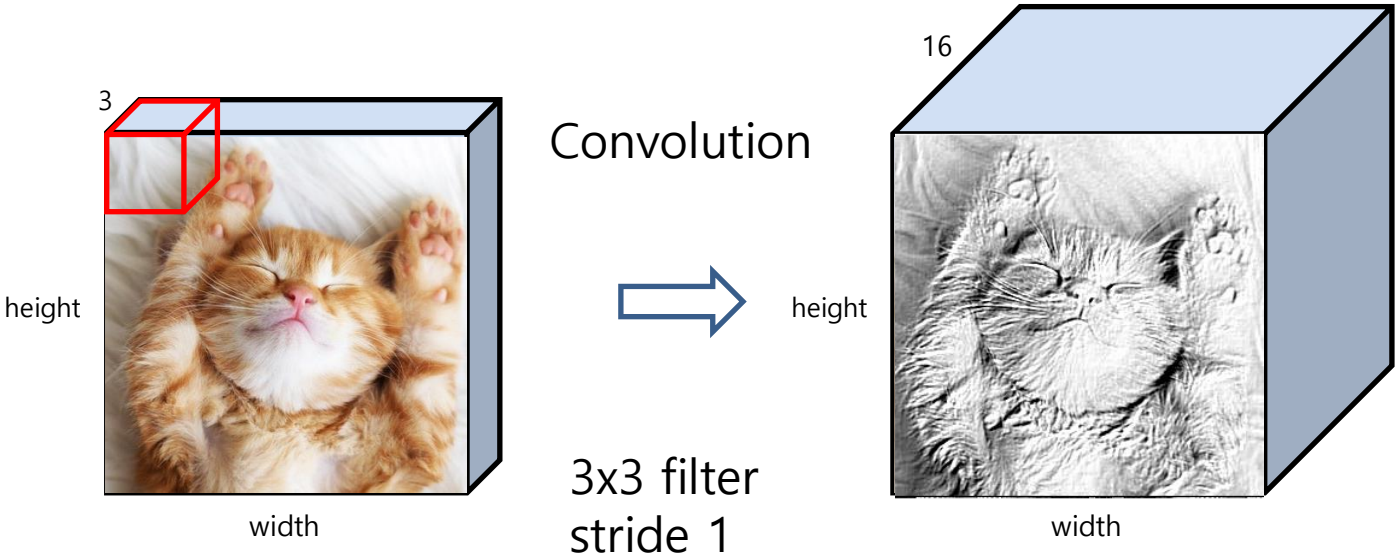
Basic Architecture



Convolution

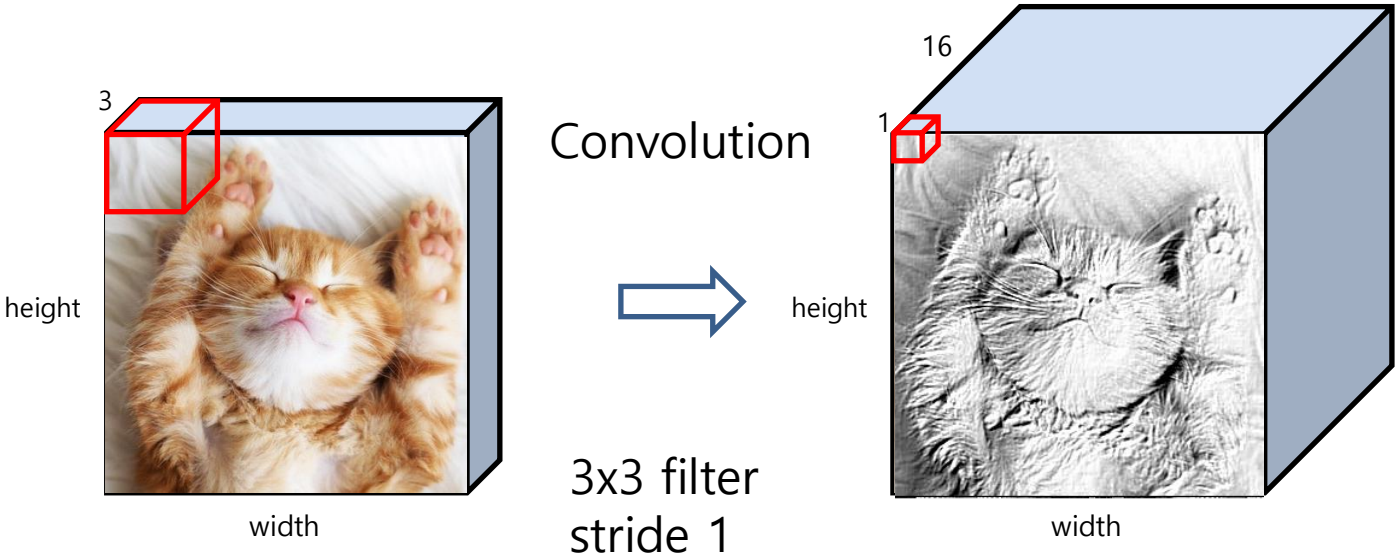
3x3 filter
stride 1
padding 1
channel 16

Basic Architecture



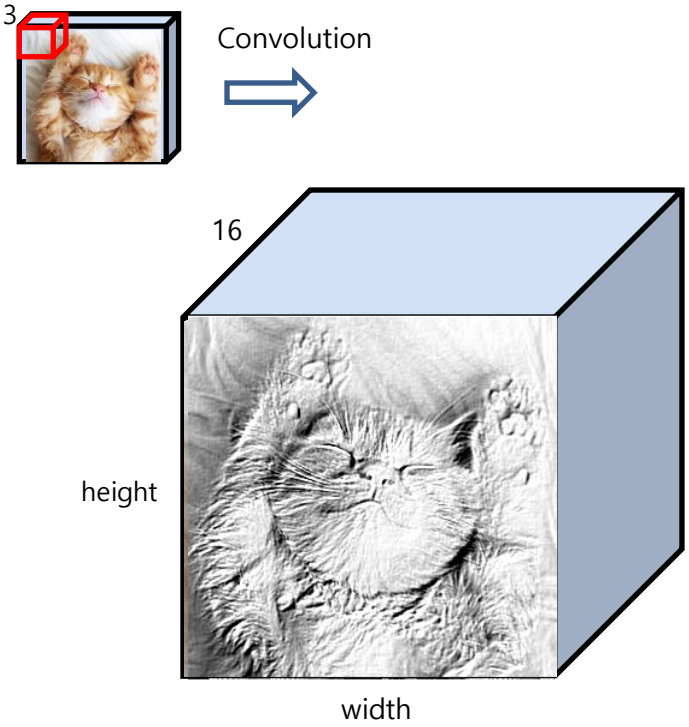
3x3 filter
stride 1
padding 1
channel 16

Basic Architecture

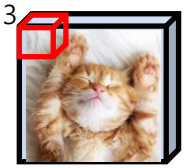


3x3 filter
stride 1
padding 1
channel 16

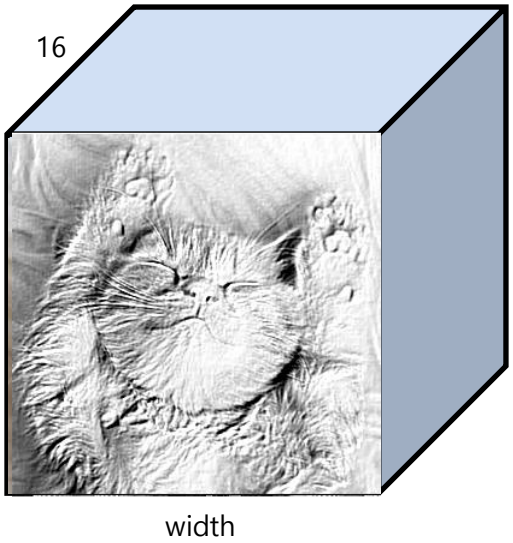
Basic Architecture



Basic Architecture



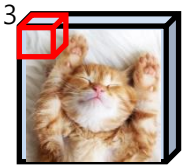
Convolution



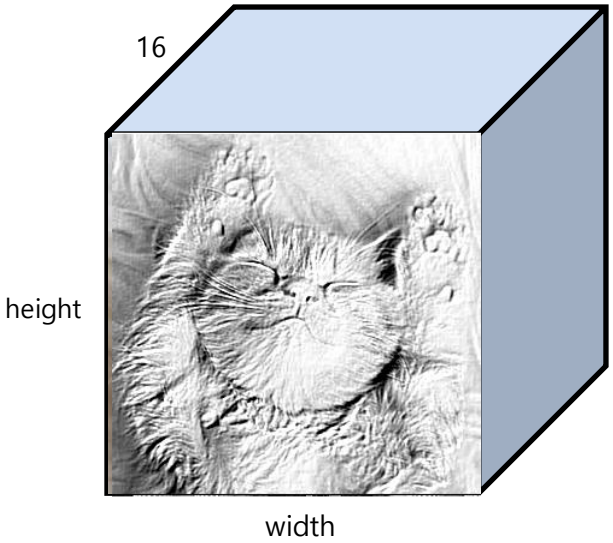
Activation

ReLU

Basic Architecture

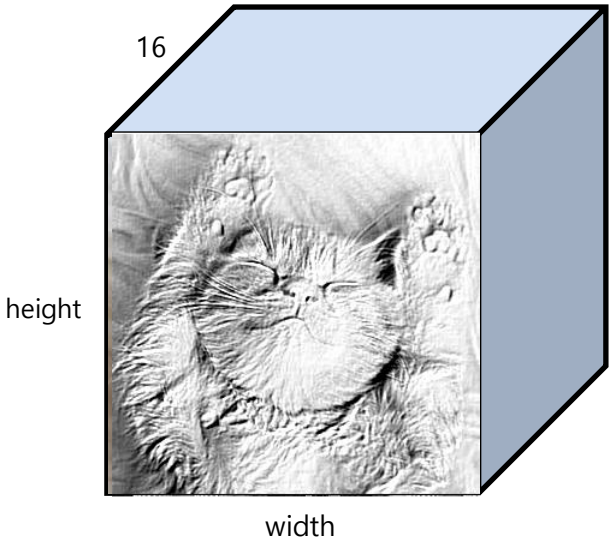


Convolution

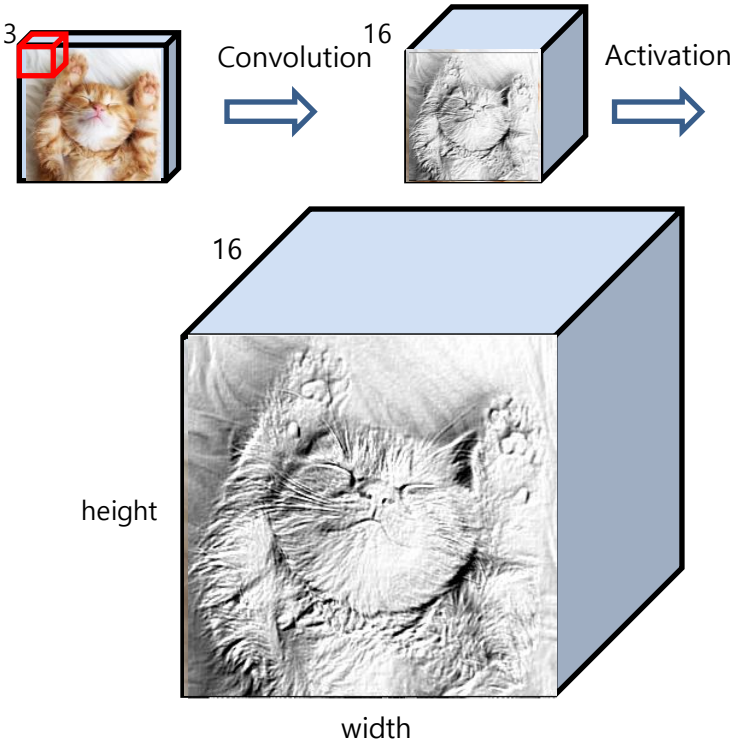


Activation

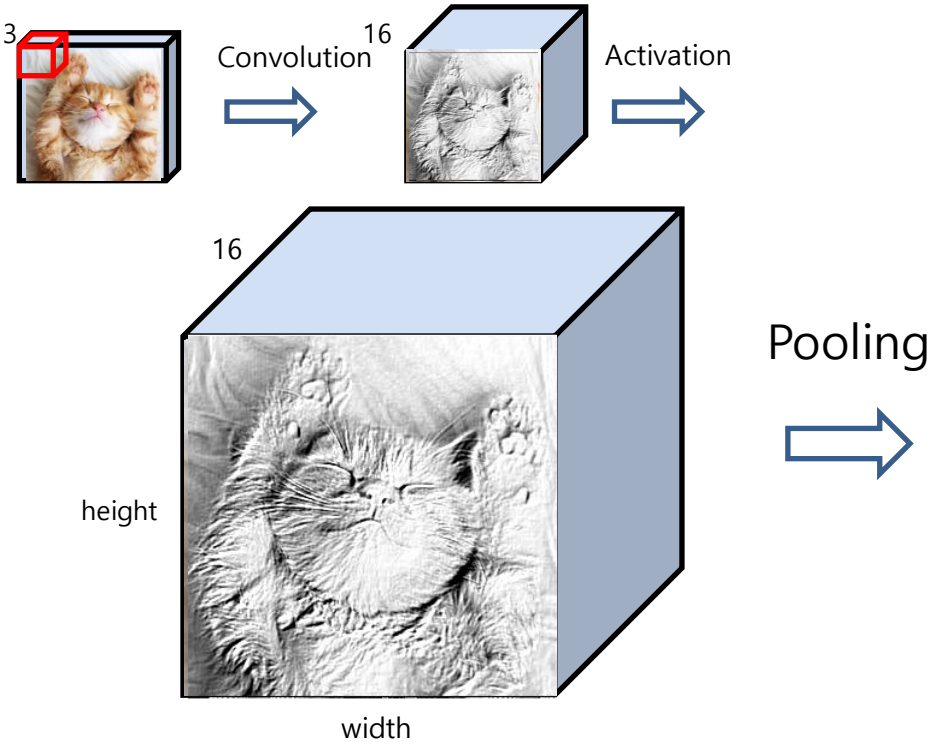
ReLU



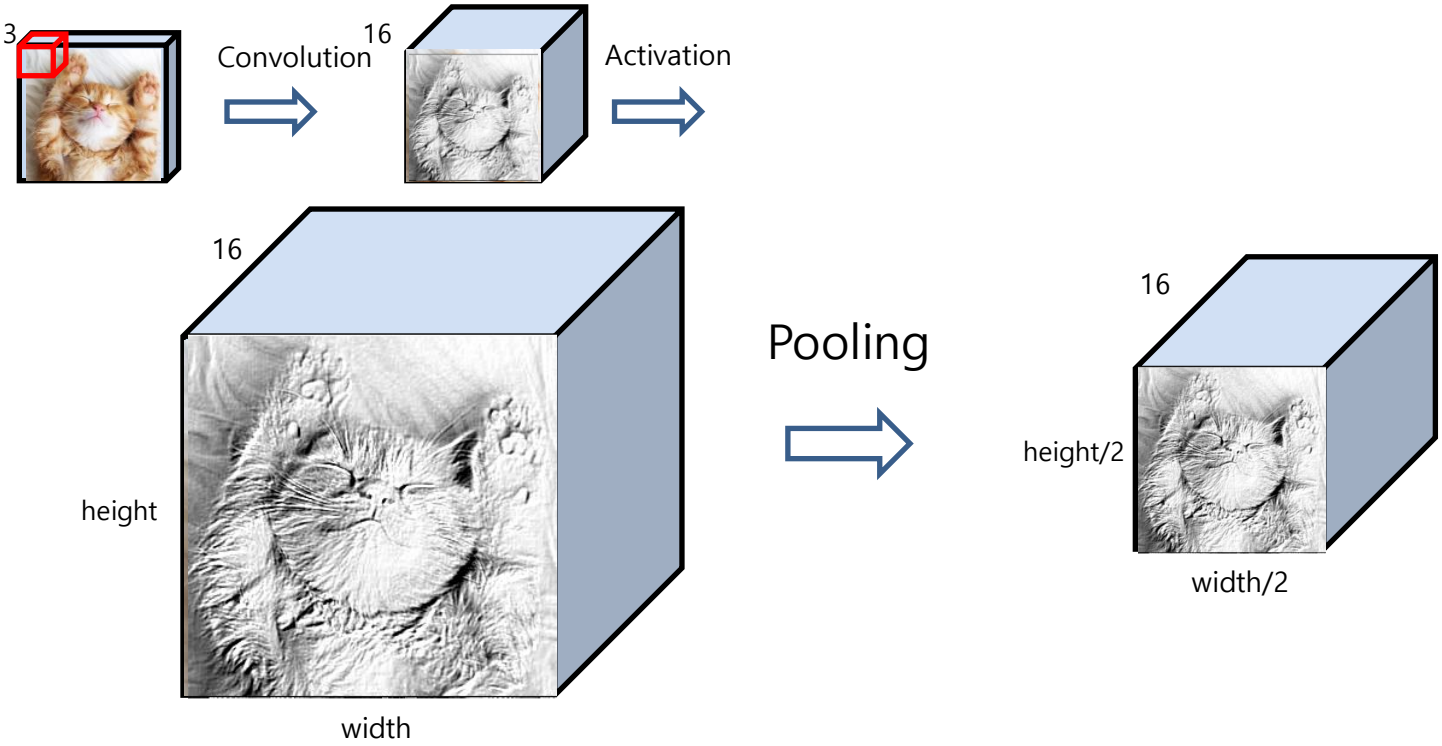
Basic Architecture



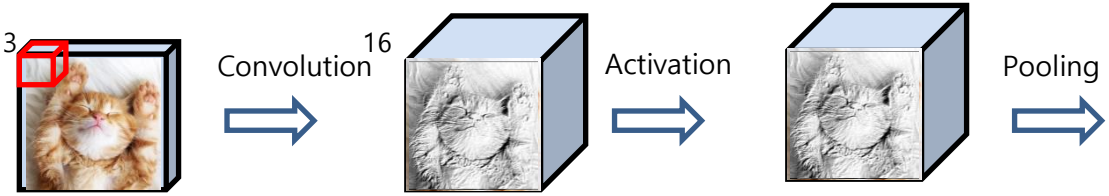
Basic Architecture

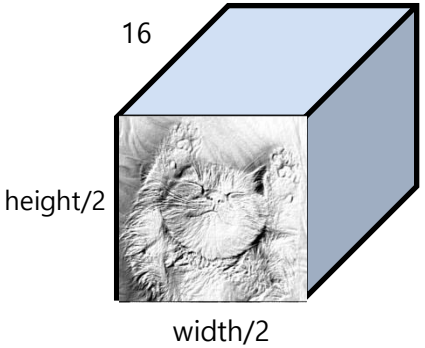


Basic Architecture

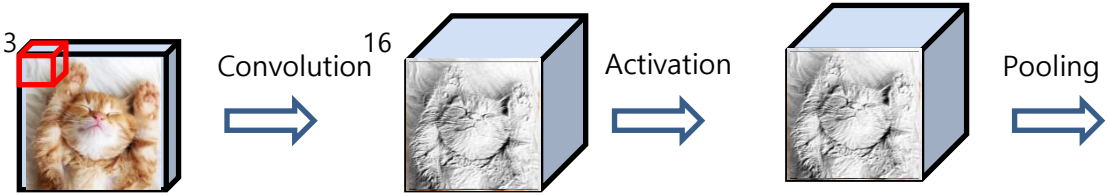


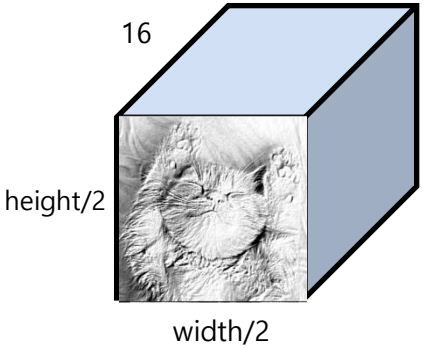
Basic Architecture





Basic Architecture

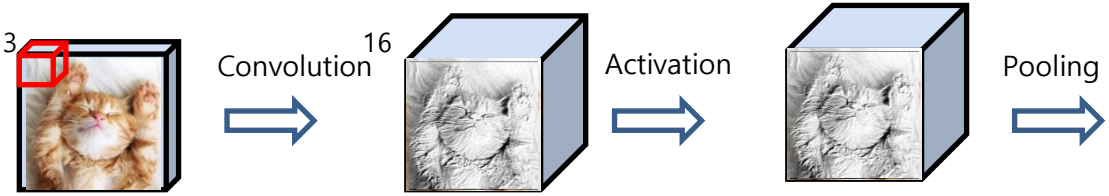


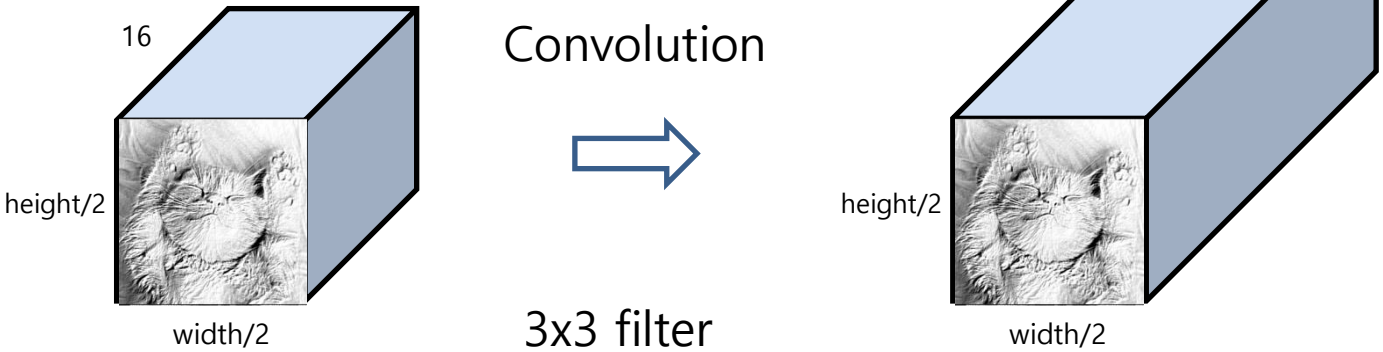


Convolution

3x3 filter
stride 1
padding 1
channel 32

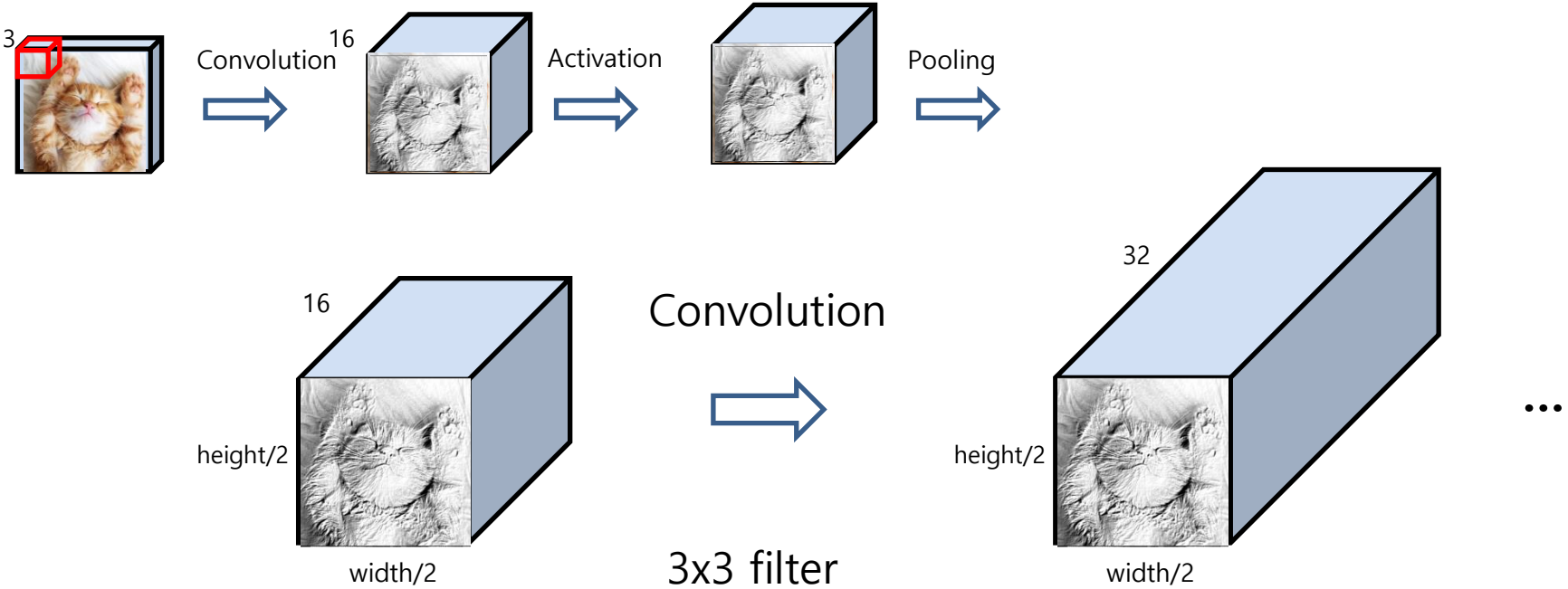
Basic Architecture





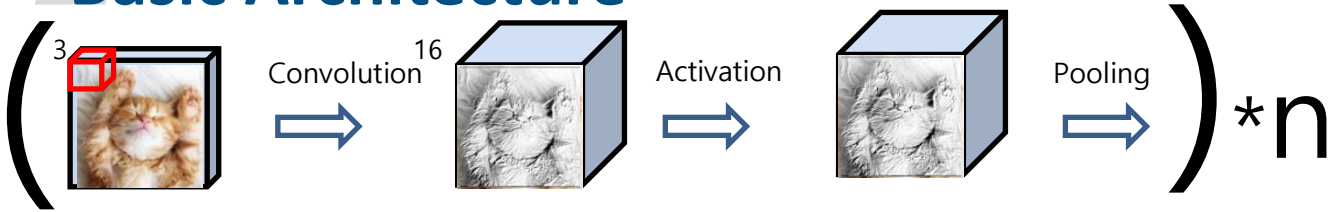
3x3 filter
stride 1
padding 1
channel 32

Basic Architecture



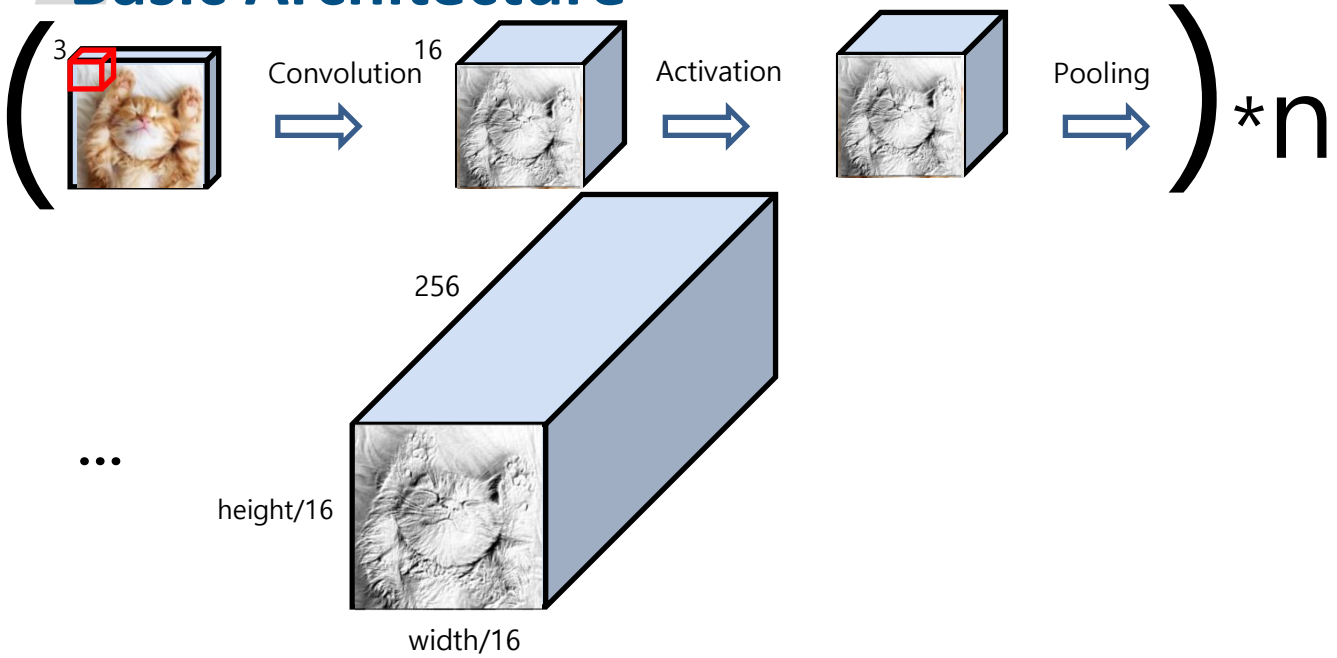
3x3 filter
stride 1
padding 1
channel 32

Basic Architecture



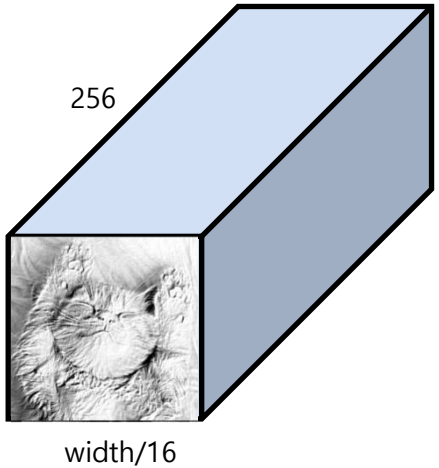
...

Basic Architecture



Basic Architecture

...



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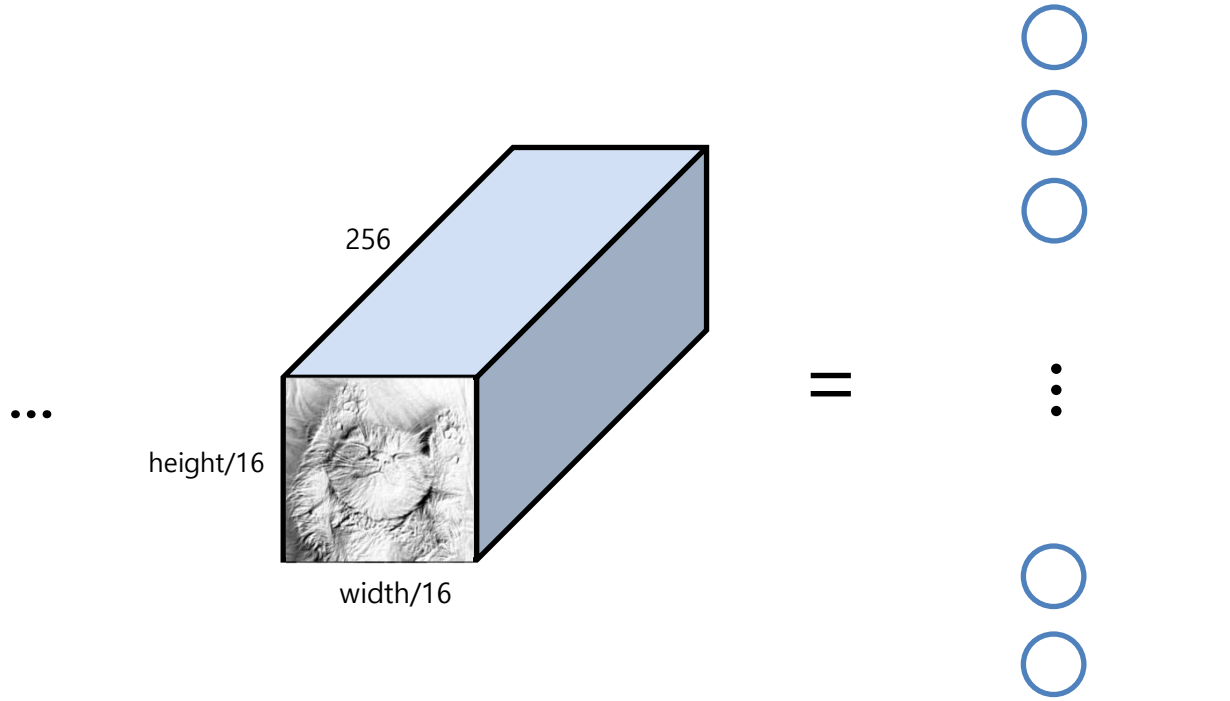
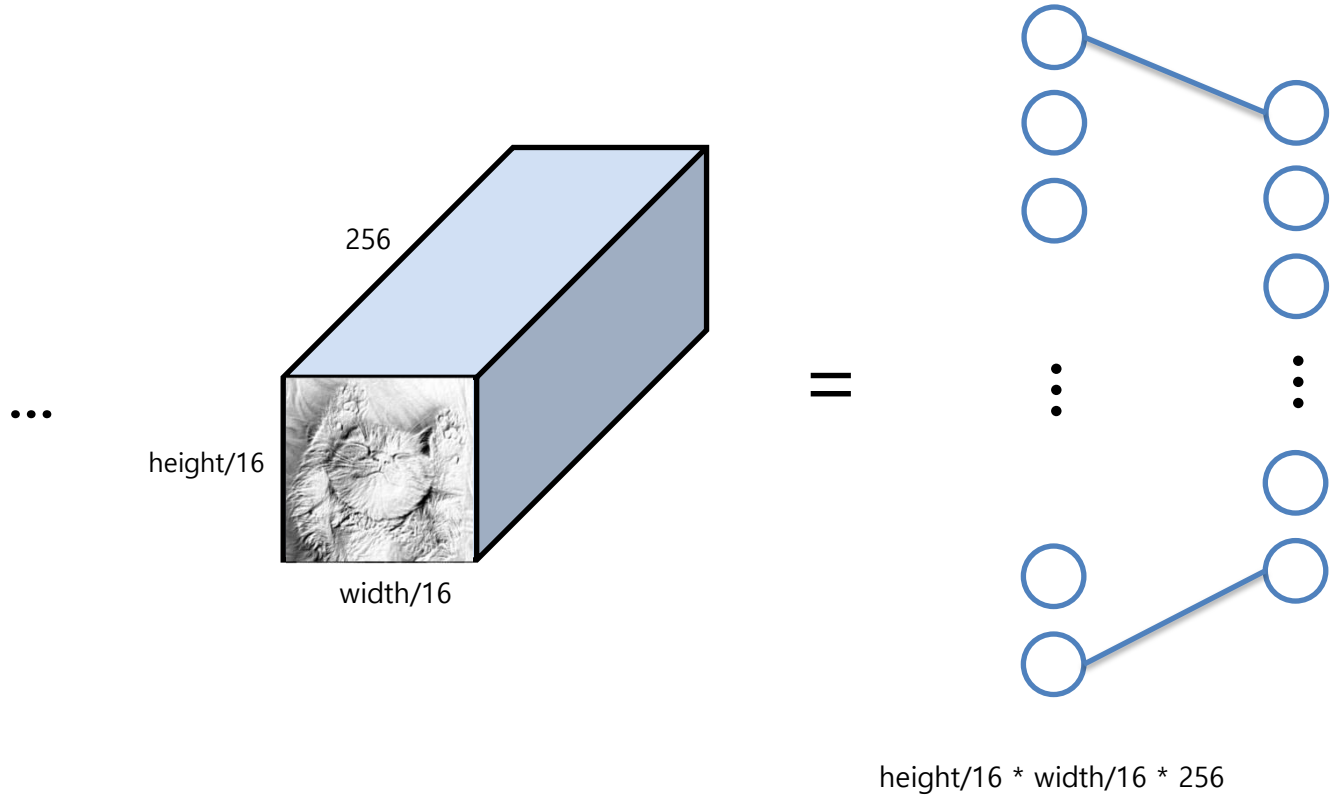
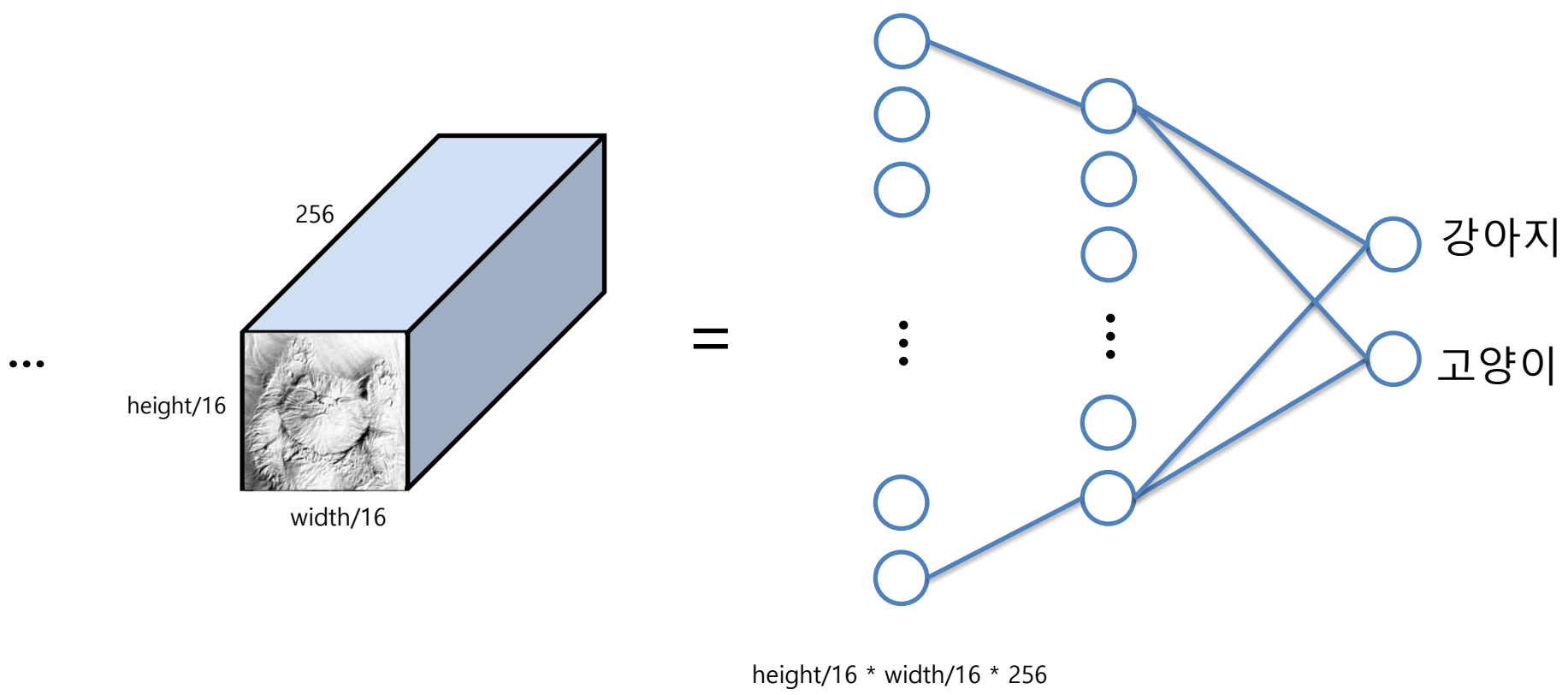
Basic Architecture



Basic Architecture

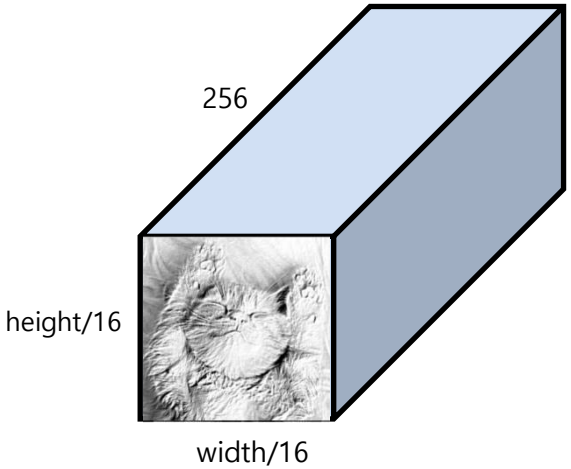


Basic Architecture



Basic Architecture

...



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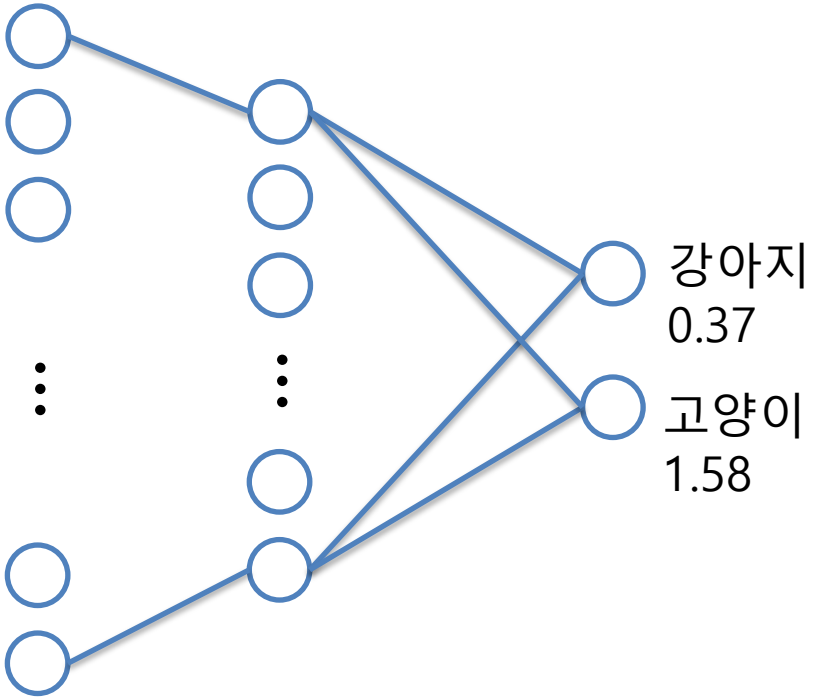
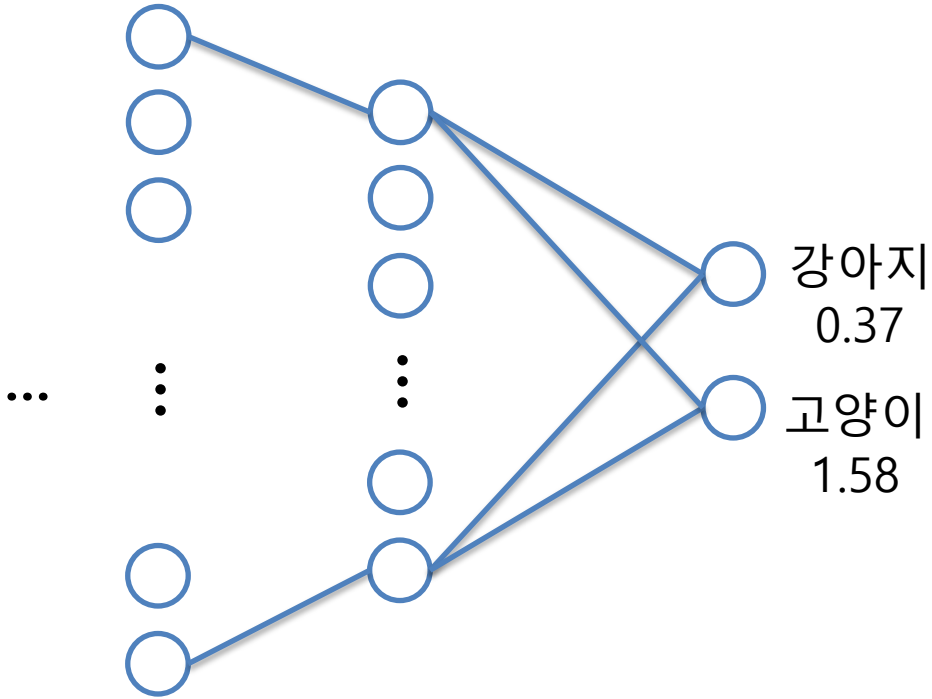


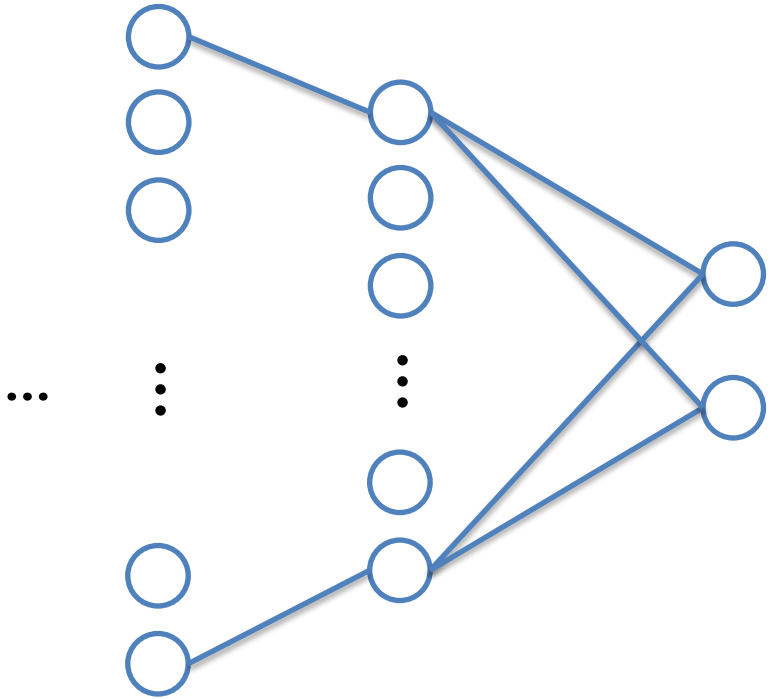
height/16 * width/16 * 256

Basic Architecture

loss function은?



Basic Architecture



loss function은?
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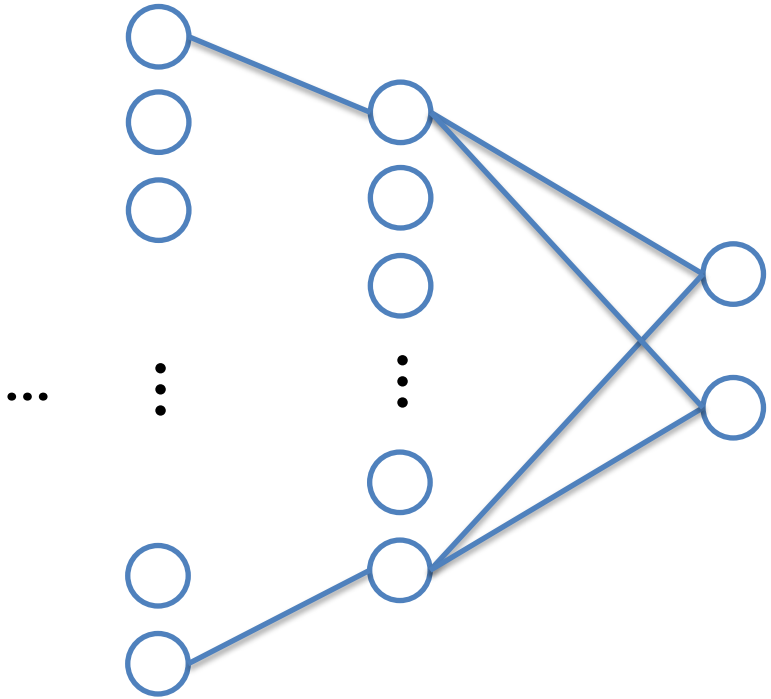
Basic Architecture



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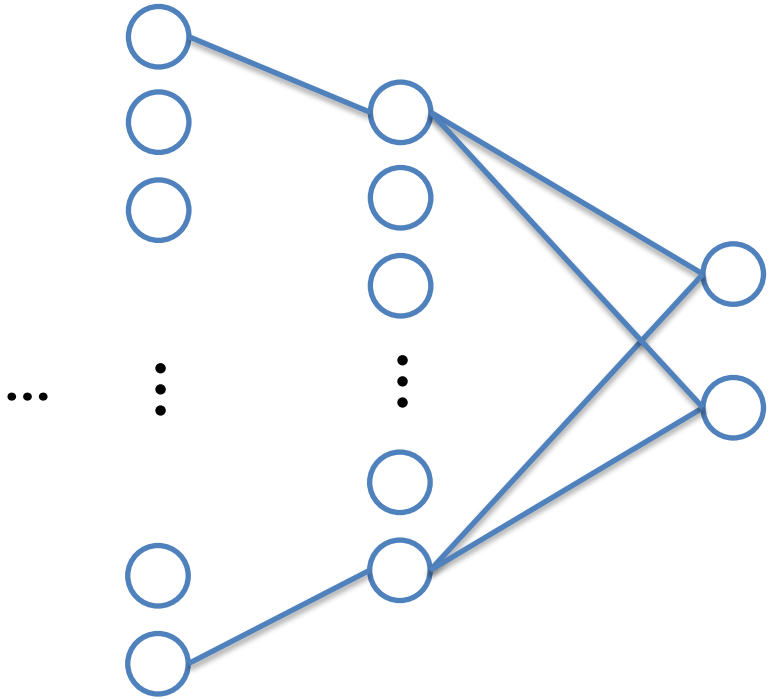
one-hot vector

0

1

Basic Architecture



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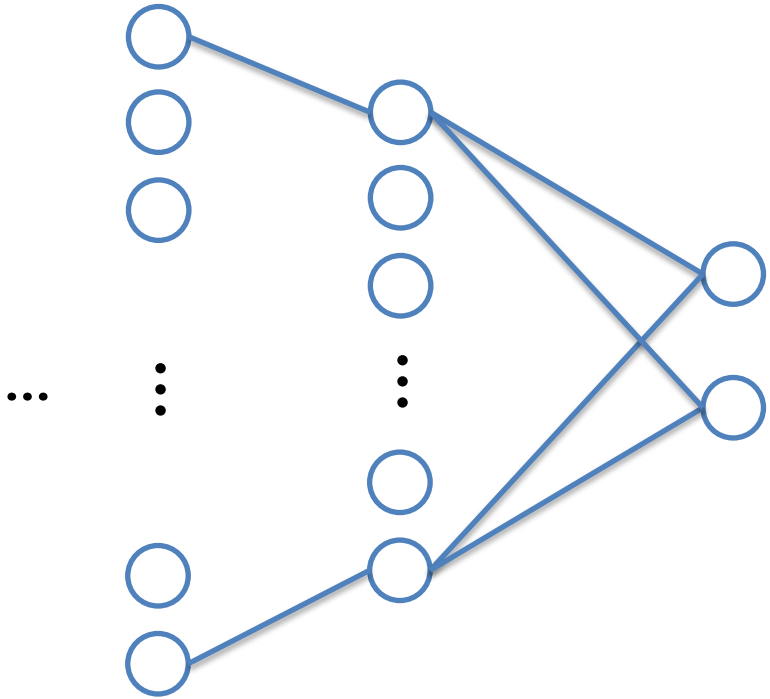
	one-hot vector
강아지	0
0.37	
고양이	1
1.58	
수치	확률

Basic Architecture



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0.37

고양이
1.58

수치 → 확률

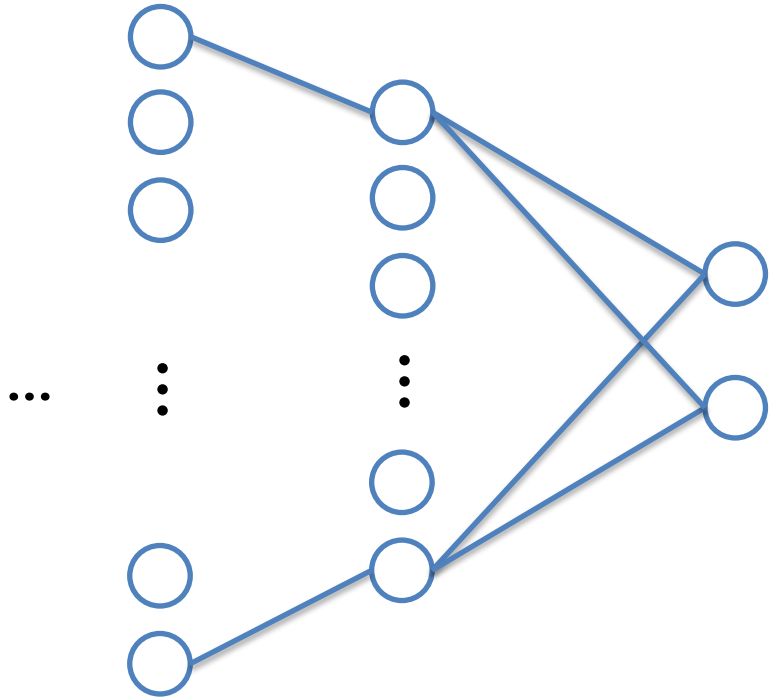
one-hot vector

0

1

확률

Basic Architecture



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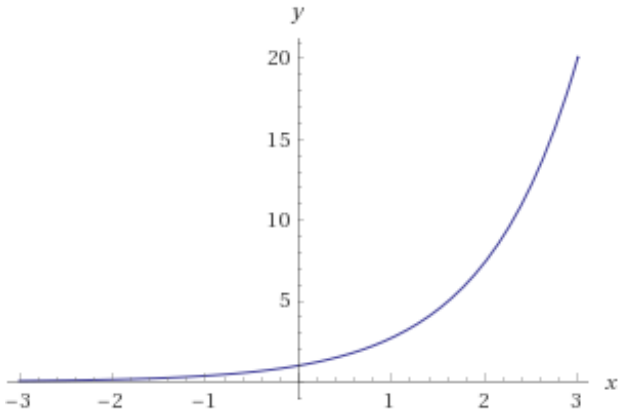
수치	→ 확률	확률

softmax!

Basic Architecture

$$\mathrm{softmax}(\mathrm{y})_i = \frac{\exp(\mathrm{y}_i)}{\sum_j \exp(\mathrm{y}_j)}$$

수치적 결과를 확률로 바꿔줌



(x from −3 to 3)

Basic Architecture

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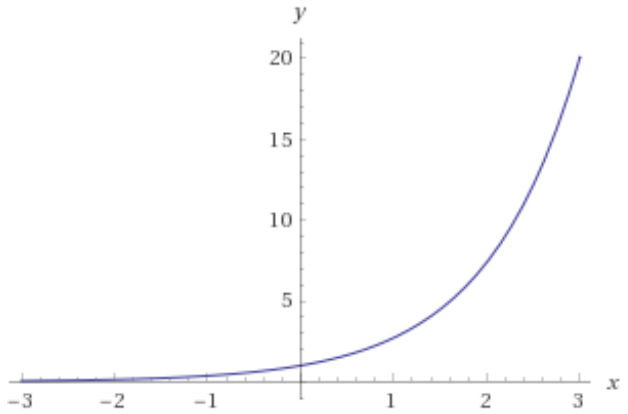
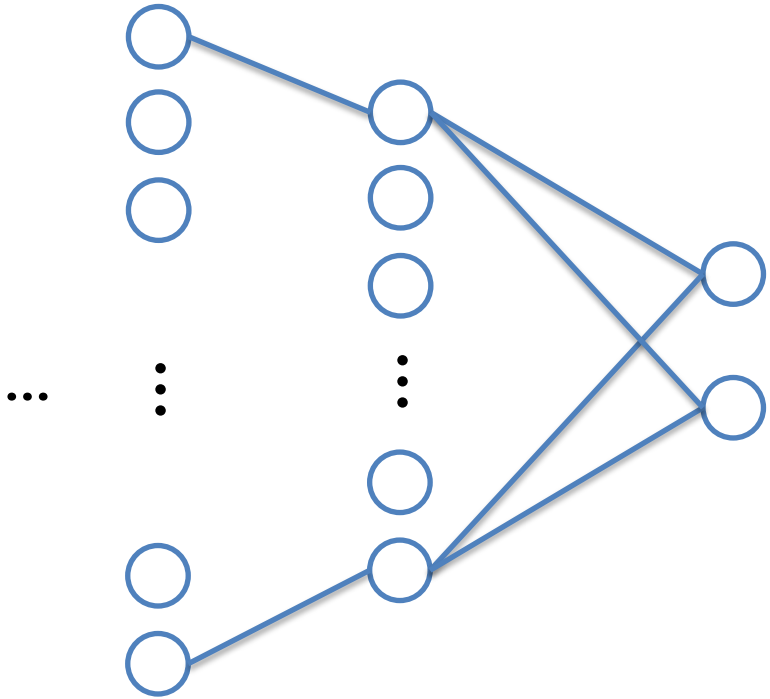


(x from −3 to 3)

사용되는 이유에는 Information Theory, Probabilistic Theory 및 Numerical Stability적 근거들이 있지만 시간관계상 링크로 대체

http://cs231n.github.io/linear-classify/#softmax

Basic Architecture



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수치

one-hot vector

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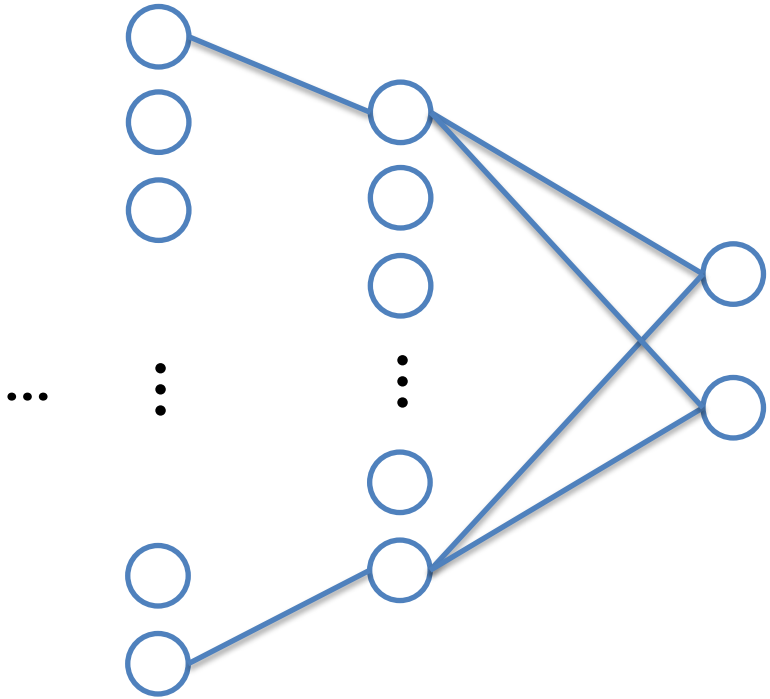
확률

softmax!

Basic Architecture



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강아지		
0.37	1.4477	0
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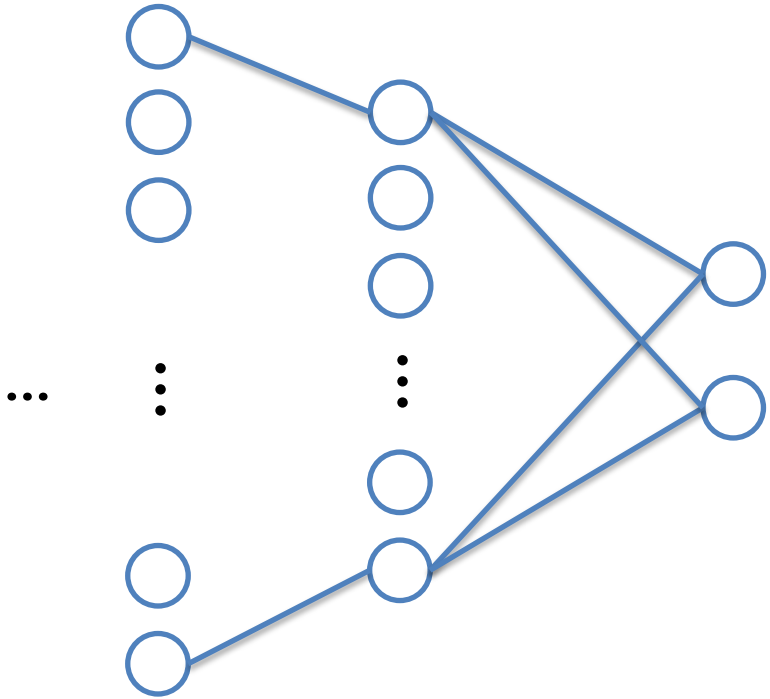
1.58	4.8549	1
수치 →	exp	확률

softmax!

Basic Architecture



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고양이			
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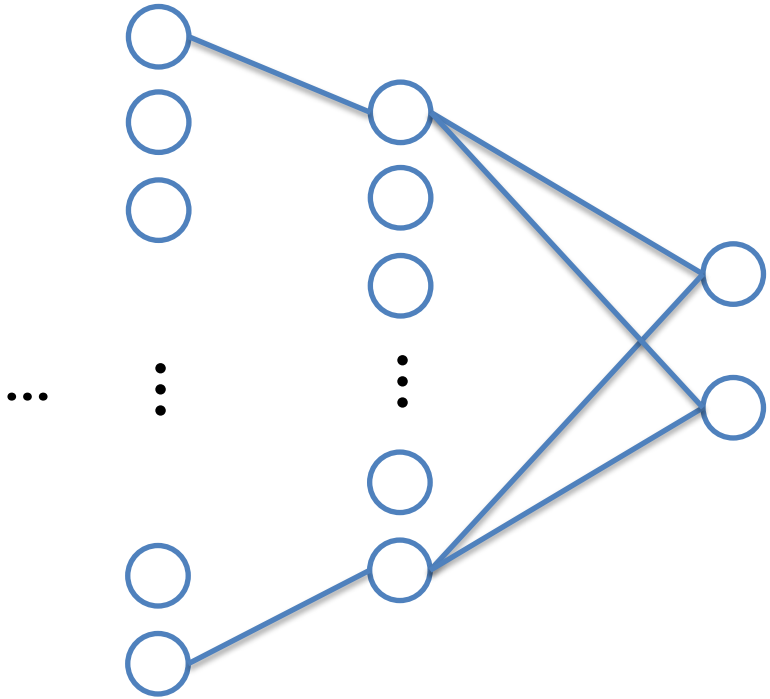
수치 →	exp →	확률	확률

softmax!

Basic Architecture



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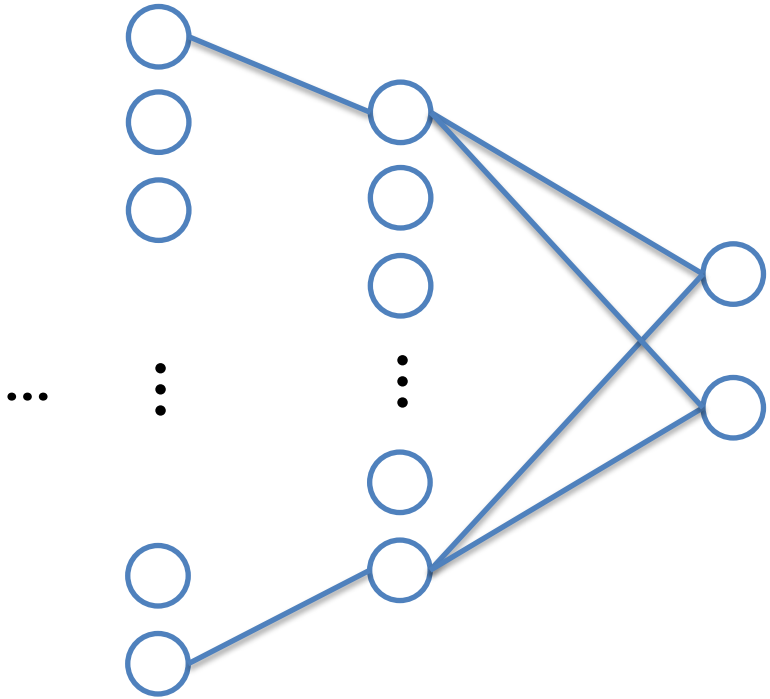
수치 → exp → 확률 ↔ 확률

softmax!

Basic Architecture



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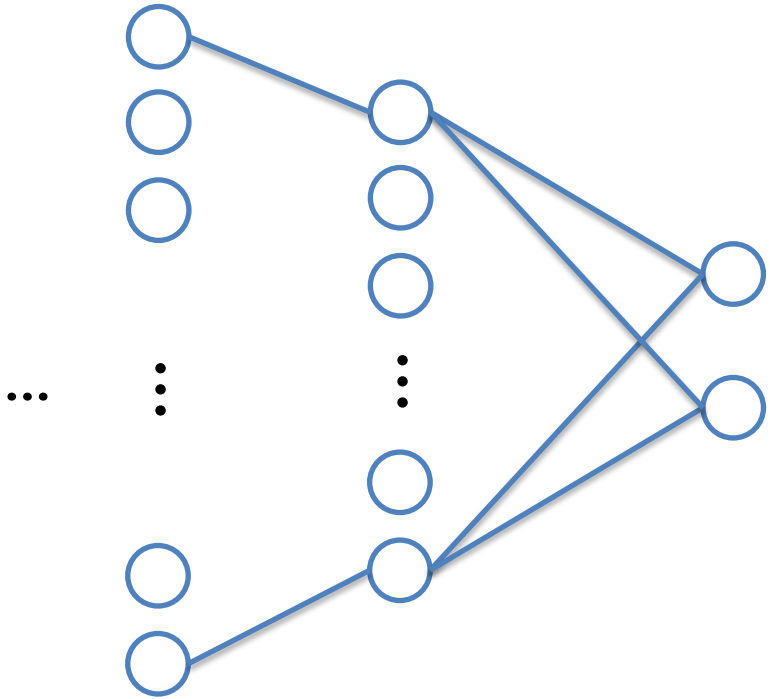
softmax!

L1? L2?

Basic Architecture



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softmax!

Cross Entropy Loss!

Basic Architecture

Entropy?

Basic Architecture

Entropy? $\mathrm{H}(X) = \mathrm{E}[\mathrm{I}(X)] = \mathrm{E}[-\ln(\mathrm{P}(X))].$ 정보량의 기대값

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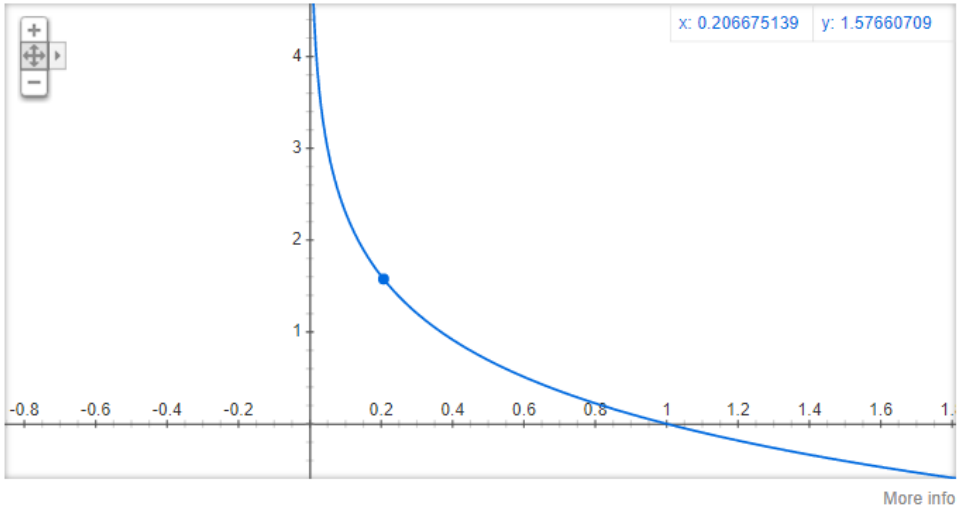
Graph for -ln(x)



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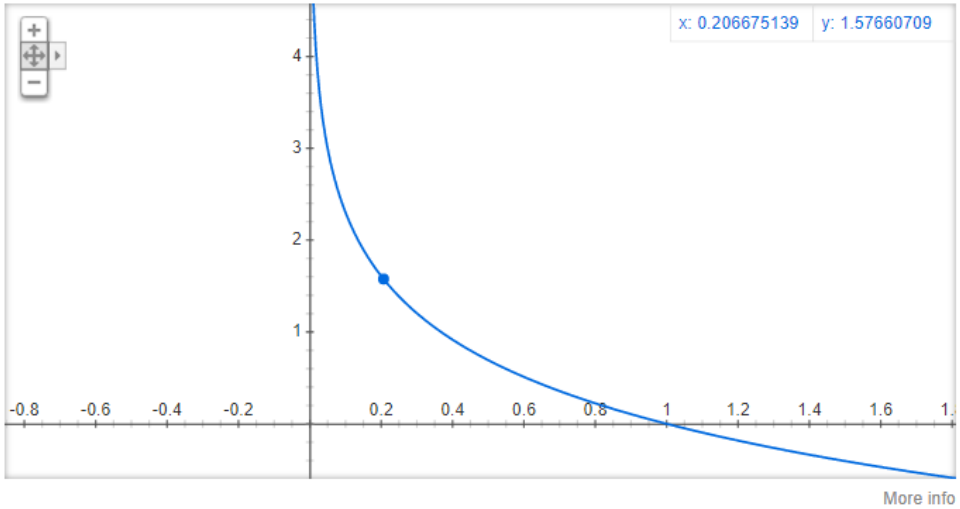

만약 항상 일어나는 사건이라면 p=1이고 이것이 가지고 있는 정보는 0.

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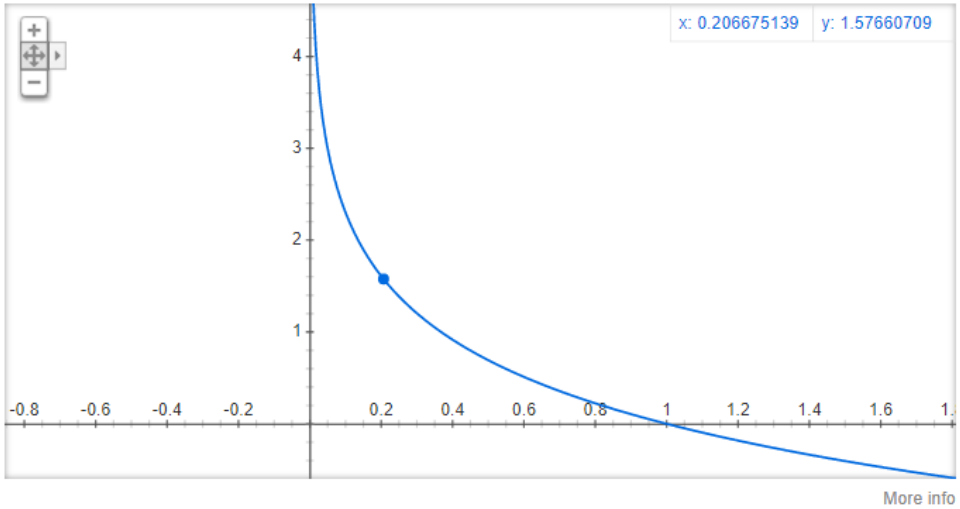

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일어날 확률이 적은 사건일수록 많은 정보를 담고 있다.

Basic Architecture

discrete 한 경우

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Basic Architecture

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ex) 동전 던지기

P(앞)=1/2
P(뒤)=1/2

$$H(X) = 0.5 * (-\log_2 0.5) + 0.5 * (-\log_2 0.5)$$
$$= 0.5 + 0.5$$
$$= 1$$

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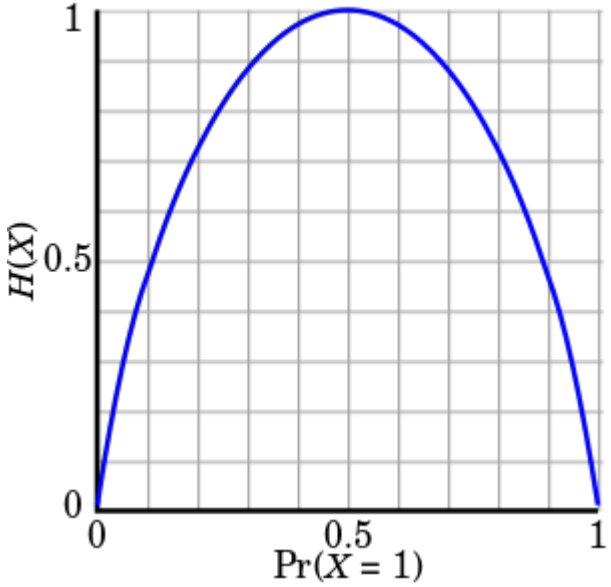

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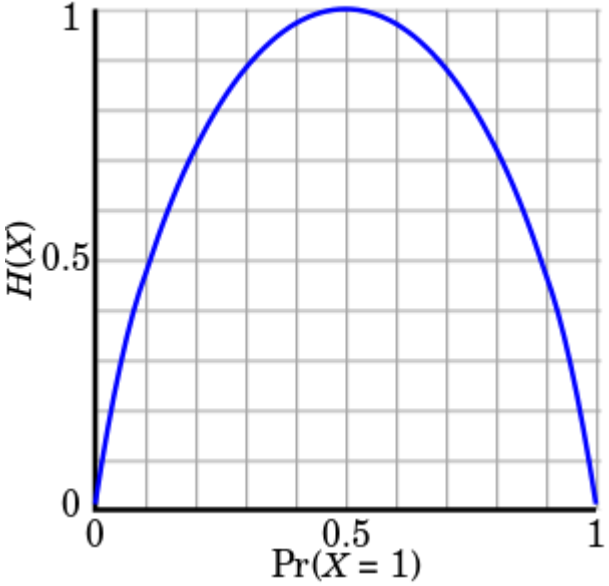
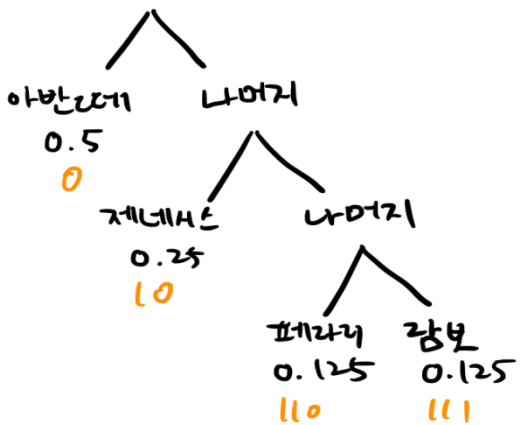
이 확률 분포를 표현하기 위해 서는 1 bit가 필요하다



Basic Architecture

ex) 길에서 아반떼, 제네시스, 페라리, 람보르기니를 볼 확률이 각각 1/2, 1/4, 1/8, 1/8 일 때 entropy는 얼마인가?

그림으로 그려보면

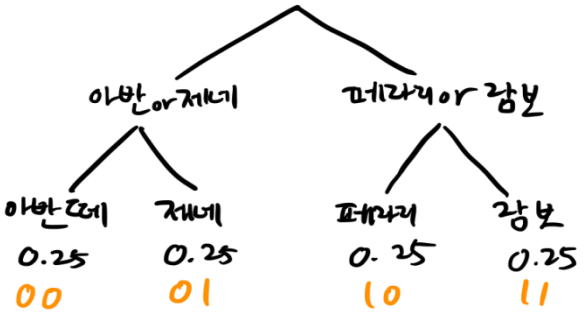


$1 \times 0.5 + 2 \times 0.25 + 3 \times 0.125 + 3 \times 0.125$

$= 0.5 + 0.5 + 0.75$

$= 1.75$

만약 전부 1/4 이었다면?



$2 \times 0.25 + 2 \times 0.25 + 2 \times 0.25 + 2 \times 0.25$

$= 0.5 \times 4$

$= 2$

Basic Architecture

Cross Entropy는?

Basic Architecture

Cross Entropy는?

원래 분포 y를 $\hat{y}$으로 인코딩했을때 필요한 비트의 수

$$\Rightarrow H(y, \hat{y}) = -\sum_{i=1}^{n} y_i \log \hat{y}_i$$

Basic Architecture

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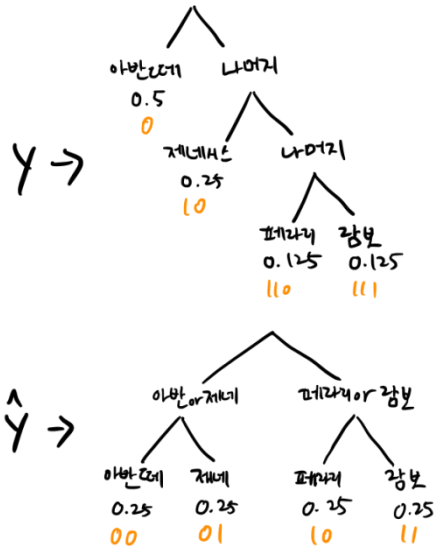

$y = [0.5, 0.25, 0.125, 0.125]$

$\hat{y} = [0.25, 0.25, 0.25, 0.25]$

$\hat{y}$ 기준으로 모든 차는 2bit.

y를 $\hat{y}$ 기준으로 표현하면

$2\text{bit} \times 0.5 + 2 \times 0.25 + 2 \times 0.125 + 2 \times 0.125$

$= 1 + 0.5 + 0.5 = 2\text{bit}$ ← 원래는 1.75

Basic Architecture

Cross Entropy

$$H(y,\hat{y}) = -\sum_{i=1}^{n} y_i \log \hat{y}_i$$

cf) $H(y) = -\sum_{i=1}^{n} y_i \log y_i$

$$= -\sum_{i=1}^{n} y_i \log \hat{y} - \sum_{i=1}^{n} y_i \log y_i + \sum_{i=1}^{n} y_i \log y_i$$

$$= H(y) + \sum_{i=1}^{n} y_i \log y_i - \sum_{i=1}^{n} y_i \log \hat{y}_i$$

$$= H(y) + \sum_{i=1}^{n} y_i \log \frac{y_i}{\hat{y}_i}$$

$$\Rightarrow H(y,\hat{y}) - H(y) = \sum_{i=1}^{n} y_i \log \frac{y_i}{\hat{y}_i}$$

By def. KL Divergence
= Cross Entropy - Entropy

결과적으로 Cross Entropy를 minimize 하는것은 $H(y)$가 고정이기 때문에 KL Divergence 를 Minimize 하는것과 같다.

Basic Architecture

true distribution p,
unnatural distribution q

Cross Entropy Loss

$$H(p, q) = \mathrm{E}_p[-\log q] = H(p) + D_{\mathrm{KL}}(p \| q),$$
$$= -\sum_x p(x) \log q(x).$$

실제 p의 distribution을 갖는 정보
를 q로 표현했을 때 드는 정보량

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Cross Entropy Loss

p 자체의 엔트로피

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Cross Entropy Loss

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p를 기준으로 q 가 얼마나 다른가

Basic Architecture

true distribution p,
unnatural distribution q

Cross Entropy Loss

p 자체의 엔트로피

결국 Cross Entropy를 minimize 하는 것은 p, q의 분포가 가까워 -지도록 만드는 것

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$$= -\sum_x p(x) \log q(x).$$

실제 p의 distribution을 갖는 정보를 q로 표현했을 때 드는 정보량

$$D_{\mathrm{KL}}(P \| Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)}.$$

p를 기준으로 q 가 얼마나 다른가

Basic Architecture

true distribution p,
unnatural distribution q

Cross Entropy Loss

$$H(p, q) = -\sum_{x} p(x) \log q(x).$$

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L1 Loss 였다면
Loss = 0.1
Loss = 0.7
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L1 Loss 였다면
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잘못된 예측에 대하여 penalty가 더 크기 때문에
Classification task에 대해서는 Cross Entropy Loss를 씀

MNIST Example

```
4  import torch
5  import torch.nn as nn
6  import torch.utils as utils
7  from torch.autograd import Variable
8  import torchvision.datasets as dset
9  import torchvision.transforms as transforms
10 import matplotlib.pyplot as plt
11
12 # Set Hyperparameters
13
14 epoch = 1000
15 batch_size = 16
16 learning_rate = 0.001
17
18 # Download Data
19
20 mnist_train = dset.MNIST("./", train=True, transform=transforms.ToTensor(), target_transform=None, download=True)
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23 # Check the datasets downloaded
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MNIST Example

Import Libraries

Hyperparameter setting

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MNIST Example

Import Libraries

Hyperparameter setting

Download Data

Check Data

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MNIST Example

Import Libraries

Hyperparameter setting

Download Data

Check Data

Data to Batch

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```

MNIST Example

```
47  class CNN(nn.Module):
48      def __init__(self):
49          super(CNN,self).__init__()
50          self.layer1 = nn.Sequential(
51                          nn.Conv2d(1,16,5),   # batch x 16 x 24 x 24
52                          nn.ReLU(),
53                          nn.Conv2d(16,32,5),  # batch x 32 x 20 x 20
54                          nn.ReLU(),
55                          nn.MaxPool2d(2,2)    # batch x 32 x 10 x 10
56          )
57          self.layer2 = nn.Sequential(
58                          nn.Conv2d(32,64,5),  # batch x 64 x 6 x 6
59                          nn.ReLU(),
60                          nn.Conv2d(64,128,5),  # batch x 128 x 2 x 2
61                          nn.ReLU()
62          )
63          self.fc = nn.Linear(2*2*128,10)
64
65      def forward(self,x):
66          out = self.layer1(x)
67          out = self.layer2(out)
68          out = out.view(batch_size, -1)
69          out = self.fc(out)
70          return out
71
72  cnn = CNN().cuda()
73
74  loss_func = nn.CrossEntropyLoss()
75  optimizer = torch.optim.SGD(cnn.parameters(), lr=learning_rate)
```

MNIST Example

Define Model
conv->relu->pool
(이 예시에는 패딩X)
cf) super는 base class 접근에 관한 것

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Forward 함수는 모델을 쭉 이어서 실행하는 부분. Forward라는 이름은 관습

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Initialize Model

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```

MNIST Example

Define Model
conv->relu->pool
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Forward 함수는 모델을 쭉 이어서 실행하는 부분. Forward라는 이름은 관습

Initialize Model

Loss Function & Optimizer

```
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MNIST Example

```
81  for i in range(epoch):
82      for j,[image,label] in enumerate(train_loader):
83          image = Variable(image).cuda()
84          label = Variable(label).cuda()
85
86
87          optimizer.zero_grad()
88          result = cnn.forward(image)
89          loss = loss_func(result,label)
90          loss.backward()
91          optimizer.step()
92
93          if j % 100 == 0:
94              print(loss)
95
96  # Test with test data
97
98  cnn.eval()
99  correct= 0
100 total = 0
101
102 for image, label in test_loader:
103     image = Variable(image).cuda()
104     result = cnn(image).cuda()
105     _, predicted = torch.max(result.data, 1)
106     total += label.size(0)
107     correct += (predicted == label.cuda()).sum()
108
109 print('Test Accuracy of the model on the 10000 test images: %f %%' % (100 * correct / total))
```

MNIST Example

Train Model

```
for i in range(epoch):
    for j,[image,label] in enumerate(train_loader):
        image = Variable(image).cuda()
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        optimizer.zero_grad()
        result = cnn.forward(image)
        loss = loss_func(result,label)
        loss.backward()
        optimizer.step()

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# Test with test data

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MNIST Example

Train Model

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Q&A