Chapter

1 CNN 개요

학습 목표

✓ CNN이 기본적으로 어떤 곳에 쓰일 수 있는지 이해한다
✓ Convolution 을 이해하고 레이어를 설계에 익숙해진다

주요 내용

✓ CNN의 정의와 필요성
✓ Convolution, Pooling Layer 설계 방법
✓ Binary, Multinomial Logistic Regression 을 통한 Cross Entropy 설명

강의에 앞서서..

❖ 본 문서는 아래의 자료들을 활용하여 만들어 졌음을 알립니다

❖ 모두를 위한 딥러닝 강좌

- 네이버 Search & Clova AI 부분 리더 김성훈 교수님
- https://www.youtube.com/playlist?list=PLlMkM4tgfjnLSOjrEJN31gZATbcj_MpUm
- https://www.edwith.org/boostcourse-dl-tensorflow/lecture/43739/

❖ 스탠포드 대학 CNN 강좌

- Fei-Fei Li & Andrej Karpathy & Justin Johnson
- http://cs231n.stanford.edu/slides/2020/

CS231n: Convolutional Neural Networks for Visual Recognition
- This course, Prof. Fei-Fei Li & Justin Johnson & Serena Yeung
- Focusing on applications of deep learning to computer vision

1

1. CNN 소개

Image Classification

(assume given set of discrete labels)
{dog, cat, truck, plane, ...}

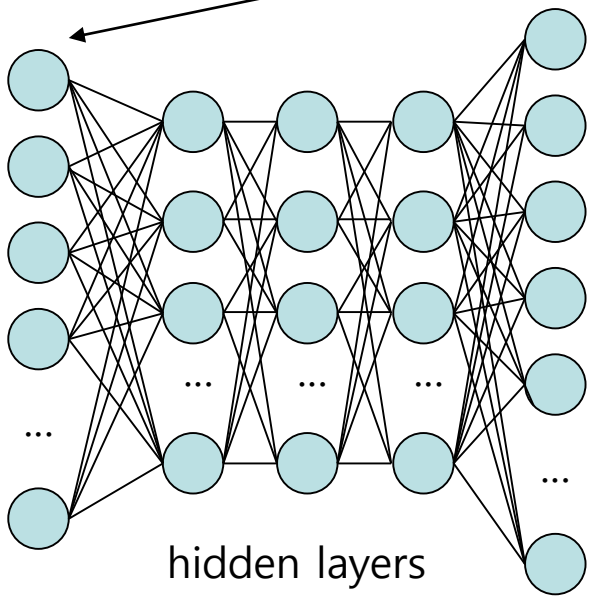
→ cat

MNIST with Neural Network

0	0	0	0	0	..	0.3	0.7	0.2	0	0	...	0	0	0	0

28 x 28
image

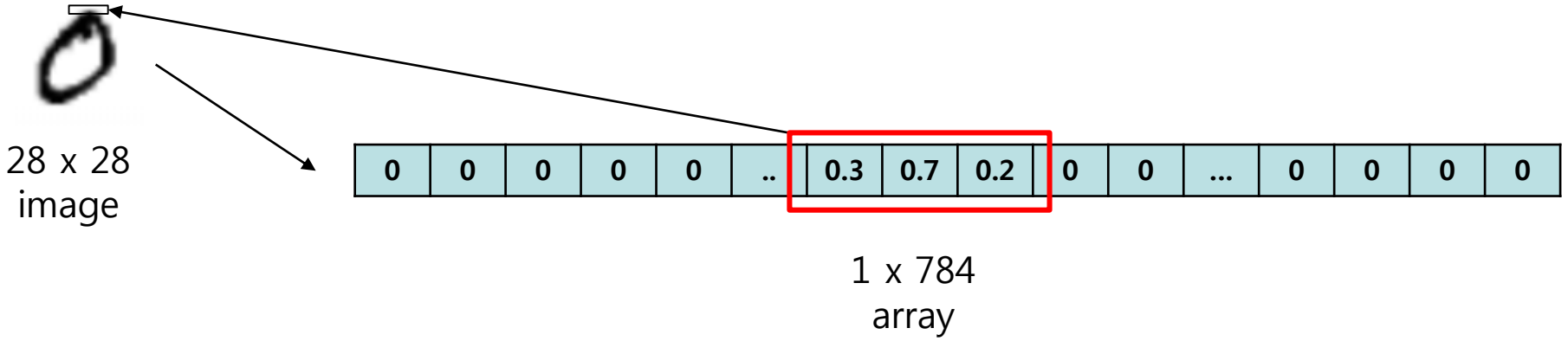
1 x 784
array




```
Epoch: 0001 cost = 0.266061549
Epoch: 0002 cost = 0.080796588
Epoch: 0003 cost = 0.049075800
Epoch: 0004 cost = 0.034772298
Epoch: 0005 cost = 0.024780529
Epoch: 0006 cost = 0.017072763
Epoch: 0007 cost = 0.014031383
Epoch: 0008 cost = 0.013763446
Epoch: 0009 cost = 0.009164047
Epoch: 0010 cost = 0.008291388
Epoch: 0011 cost = 0.007319742
Epoch: 0012 cost = 0.006434021
Epoch: 0013 cost = 0.005684378
Epoch: 0014 cost = 0.004781207
Epoch: 0015 cost = 0.004342310
Learning Finished!
Accuracy: 0.9742
```

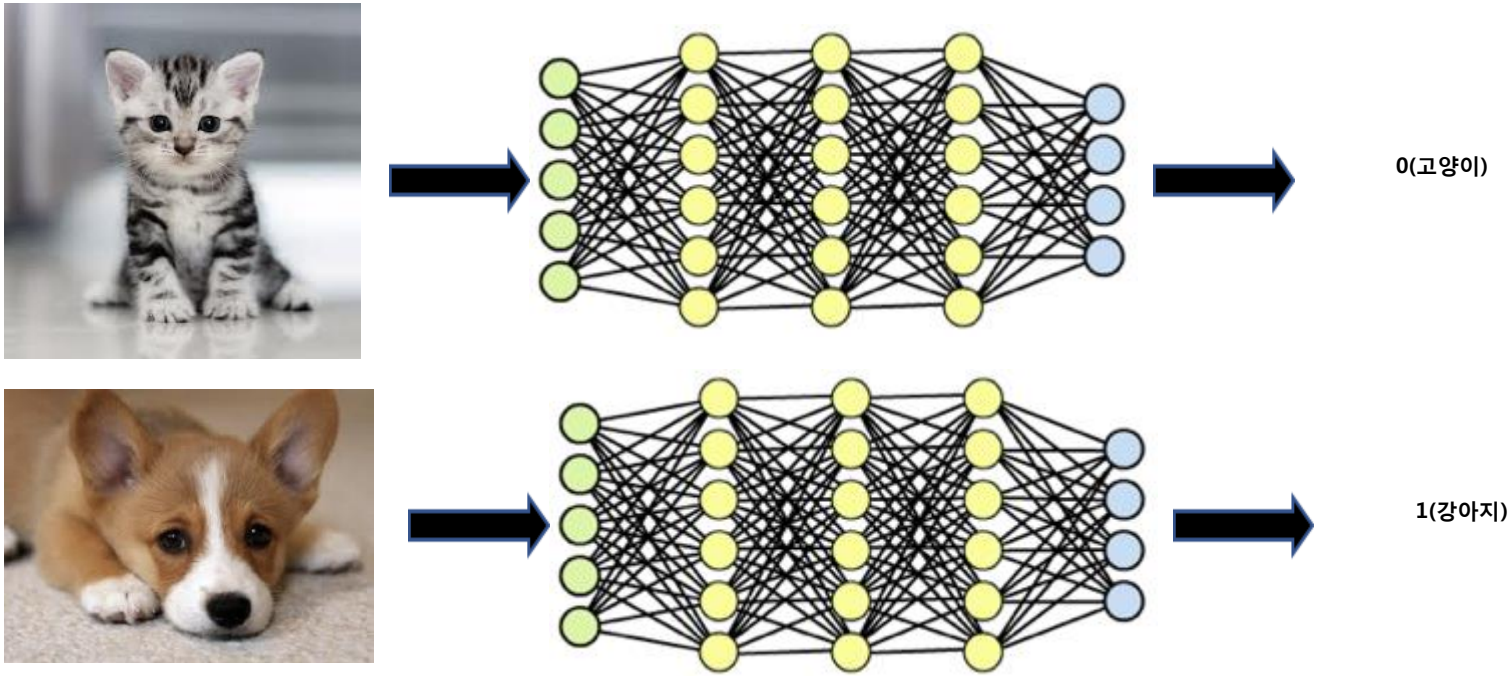
MNIST with Neural Network

❖ **Neural network은 매우 강력하지만 전체 데이터로는 feature selection이 어렵다**

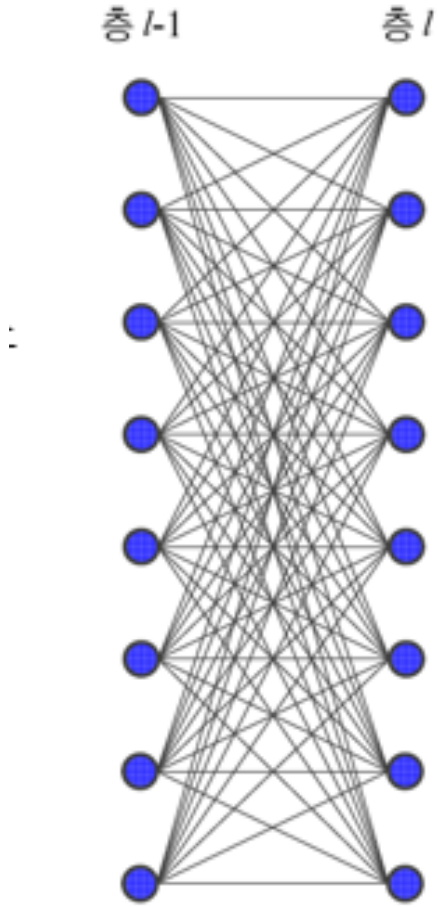


Deep Neural Network

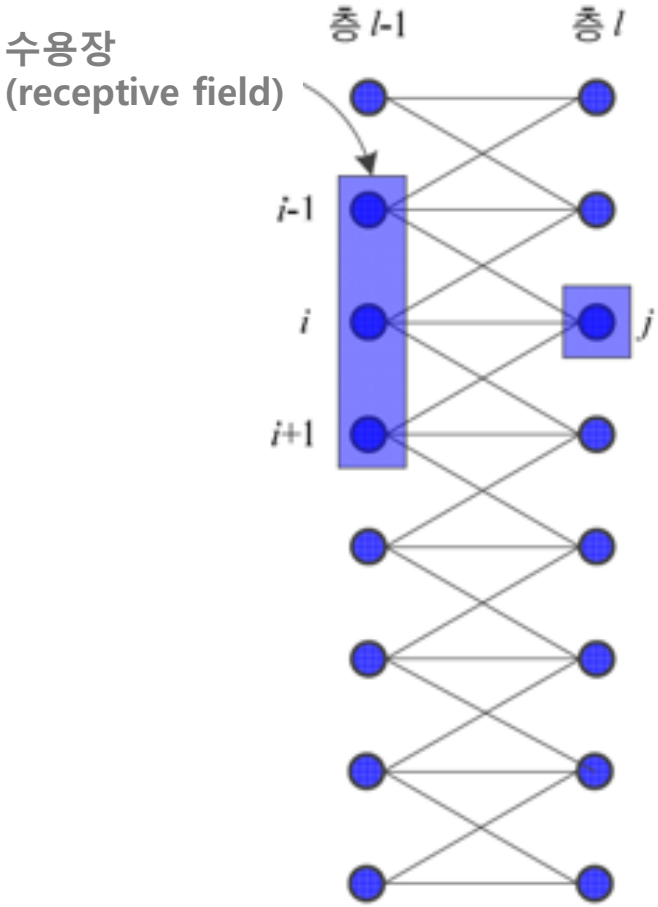
- 데이터의 크기가 클수록, 형태가 복잡할수록 학습이 어려워짐
  - 학습시간(training time), 네트워크 크기(network size), 매개변수의 개수(parameter)



Deep Neural Network & Convolutional Neural Network



(a)DNN (fully connected)



(b)CNN (sparse connected)

Visual Object Challenge

PASCAL Visual Object Challenge
(20 object categories)
[Everingham et al. 2006-2012]

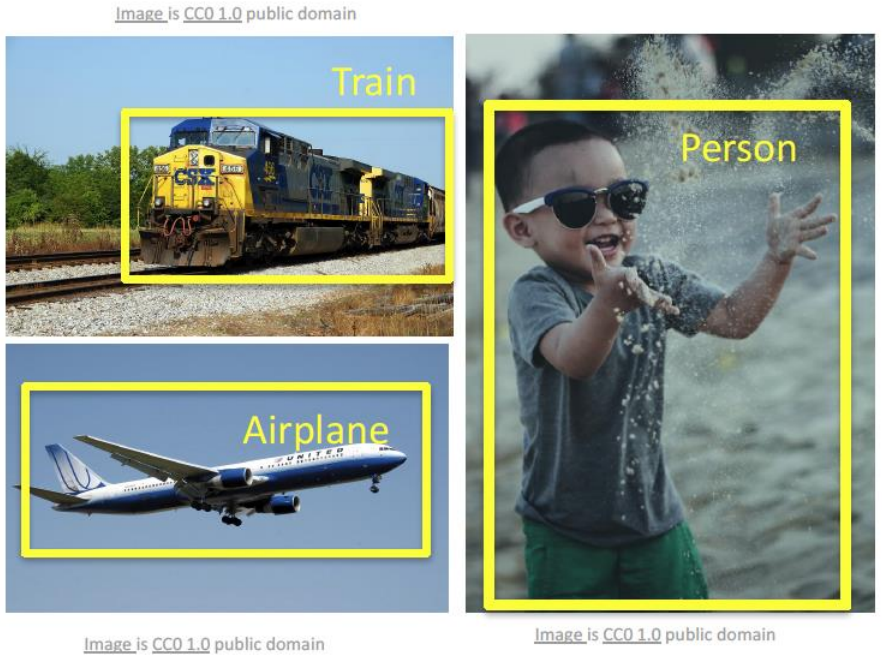
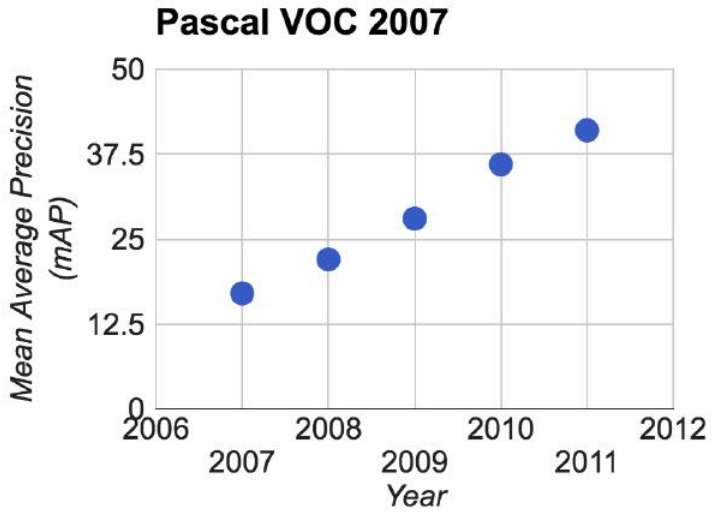


Image is CC0 1.0 public domain

Image is CC0 1.0 public domain

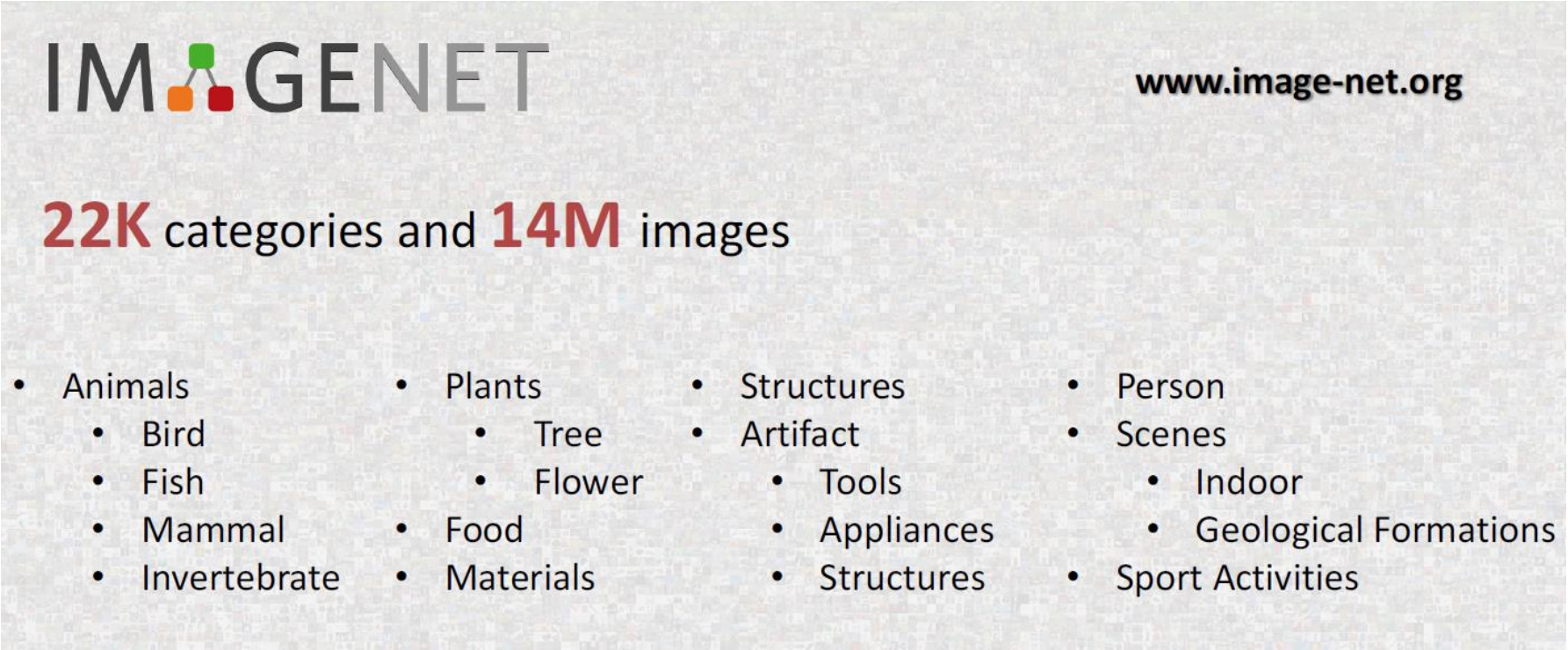
Image is CC0 1.0 public domain



Visual Object Challenge

❖ IMAGENET

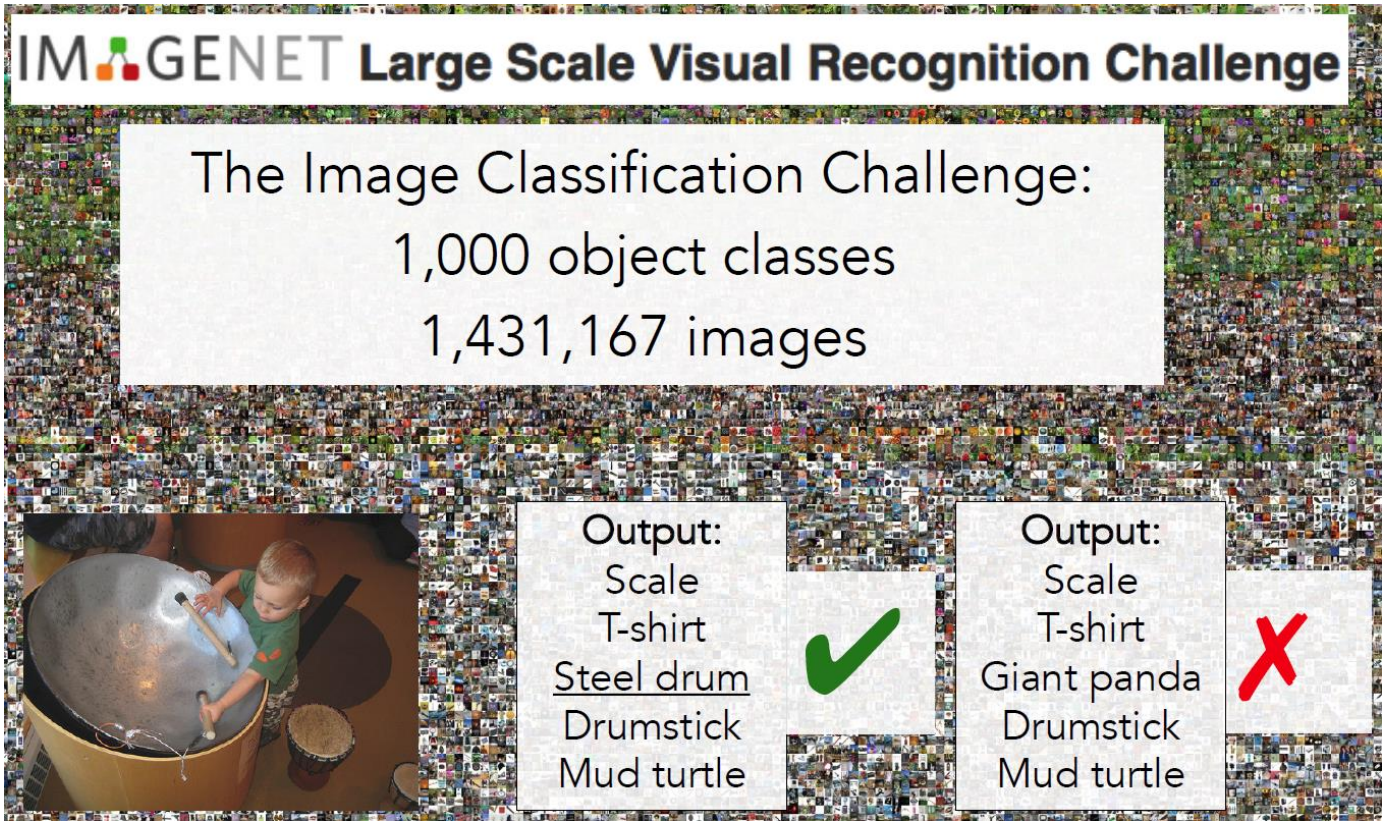
- Visual object recognition 연구를 위한 매우 큰 데이터베이스
- 22000 카테고리에 140만개의 이미지



Visual Object Challenge

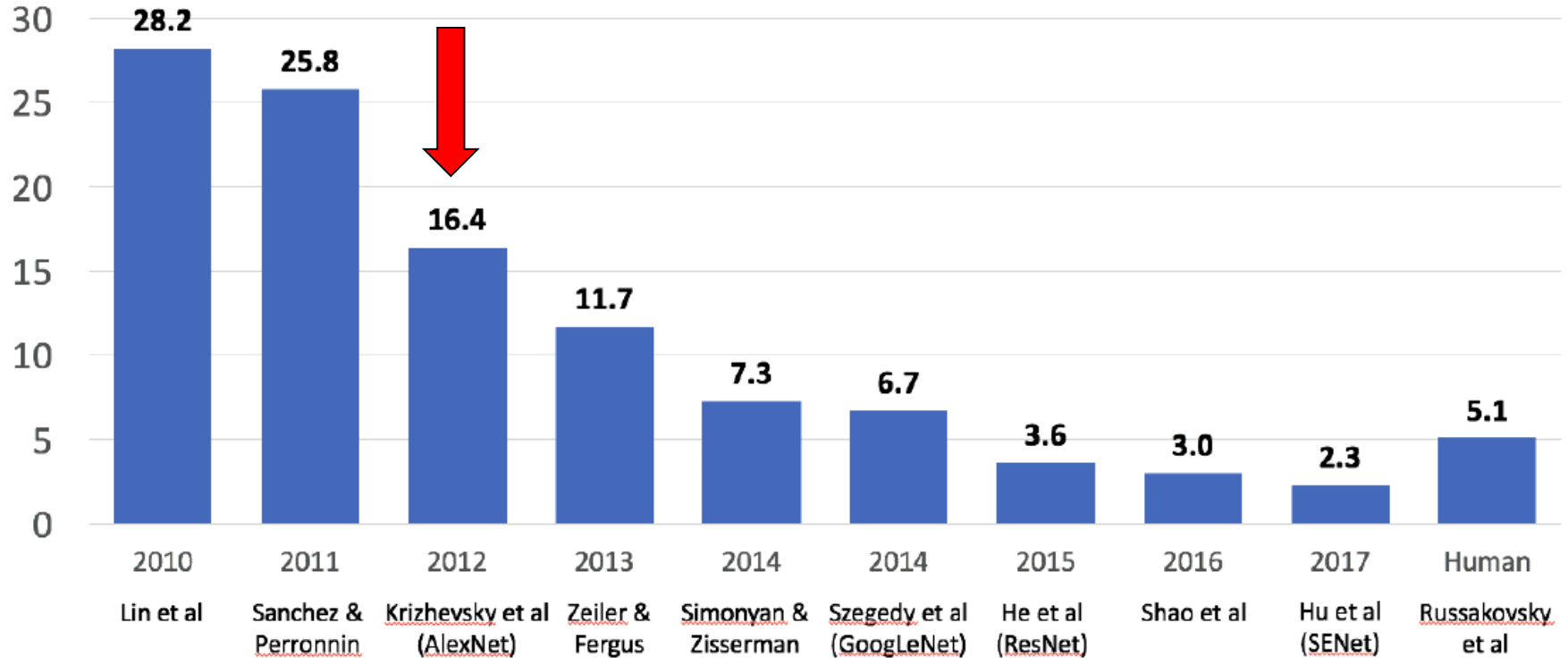
❖ ImageNet Large Scale Visual Recognition Competition(ILSVRC)

- 1000개의 카테고리, 140만개의 이미지로 이미지 인식 대회 개최

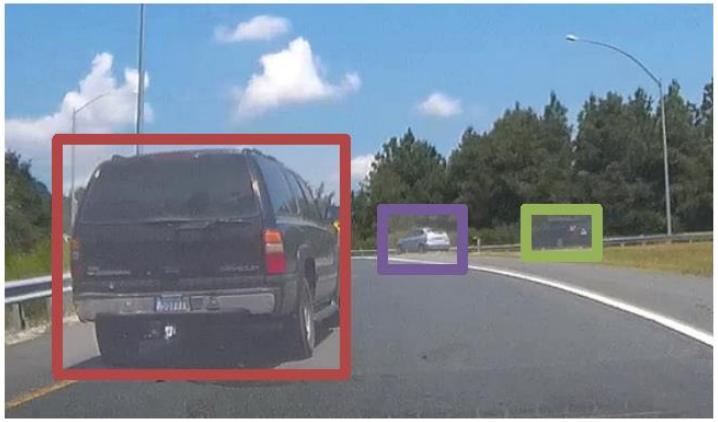


Visual Object Challenge

- 2012년 갑자기 16.4%로 오답률이 낮아짐 -> CNN
- 사람의 오답률이 5.1%인데 2015년에 사람을 뛰어넘음



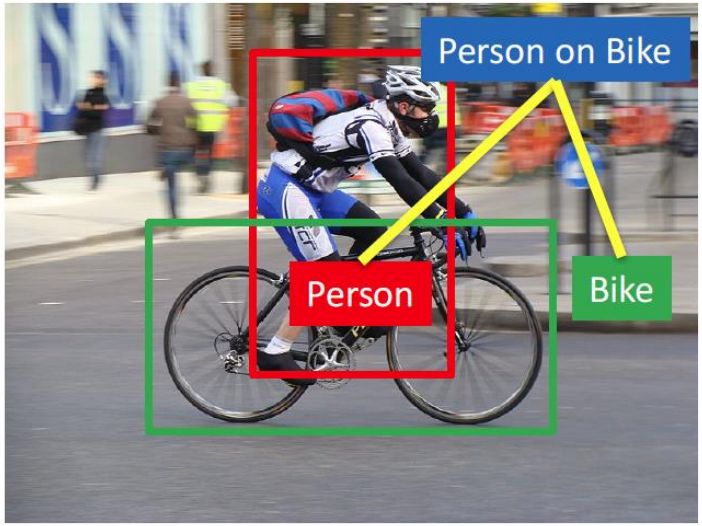
Visual Recognition Problems



- Object detection
- Action classification
- Image captioning
- …

Person

Hammer



Visual Recognition Problems

- ILSVRC에서 우승한 VGG, ResNet 등의 모델이 Keras에 공개

IMAGENET **Large Scale Visual Recognition Challenge**

Year 2010

NEC-UIUC

Dense descriptor grid: HOG, LBP

Coding: local coordinate, super-vector

Pooling, SPM

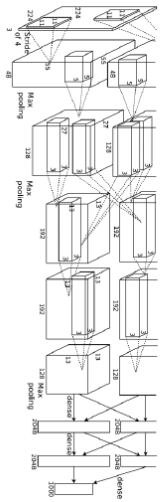
Linear SVM

[Lin CVPR 2011]

Year 2012

SuperVision

AlexNet

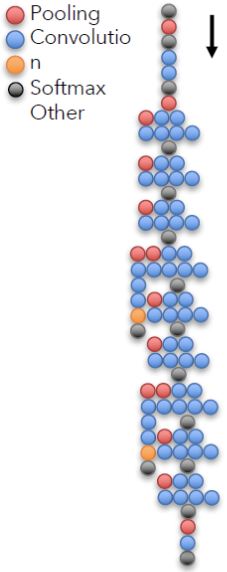


[Krizhevsky NIPS 2012]

Year 2014

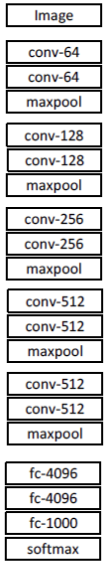
GoogLeNet

Inception



[Szegedy arxiv 2014]

VGG

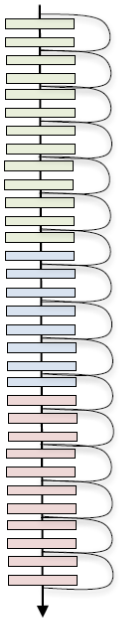


[Simonyan arxiv 2014]

Visual Geometry Group

Year 2015

MSRA **ResNet**



[He ICCV 2015]

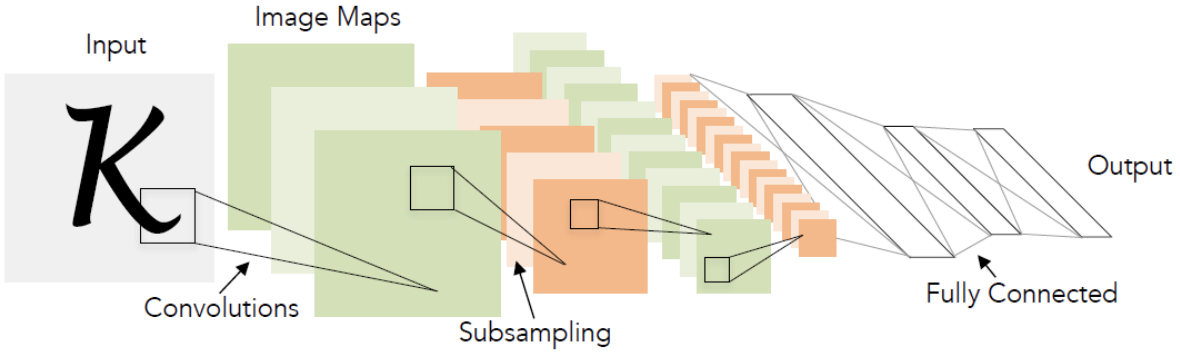
Microsoft Research

Visual Recognition Problems

Convolutional Neural Networks (CNN) have become an important tool for object recognition

Visual Recognition Problems

1998
LeCun et al.



LeNet-5
"Gradient-based learning applied to document recognition"논문에서 CNN을 이용하여 필기체를 성공적으로 인식

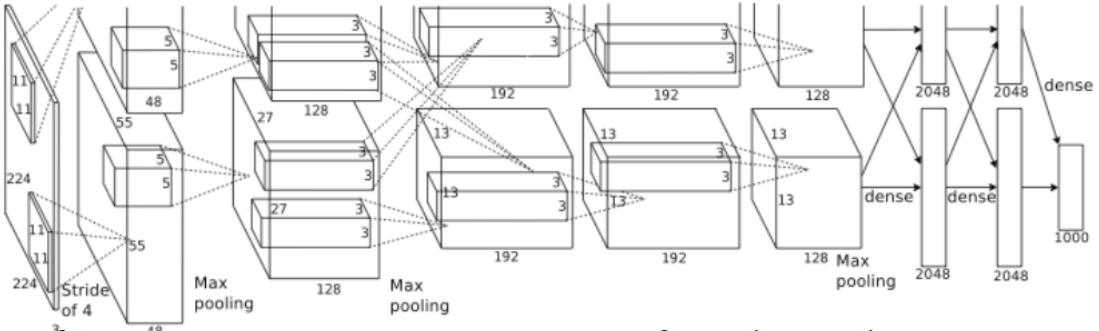
# of transistors

10^6

# of pixels used in training

10^7 NIST

2012
Krizhevsky et al.



AlexNet
"ImageNet Classification with Deep Convolutional Neural Networks"논문

# of transistors

10^9

GPUs

# of pixels used in training

10^{14} IMAGENET

Our Goal

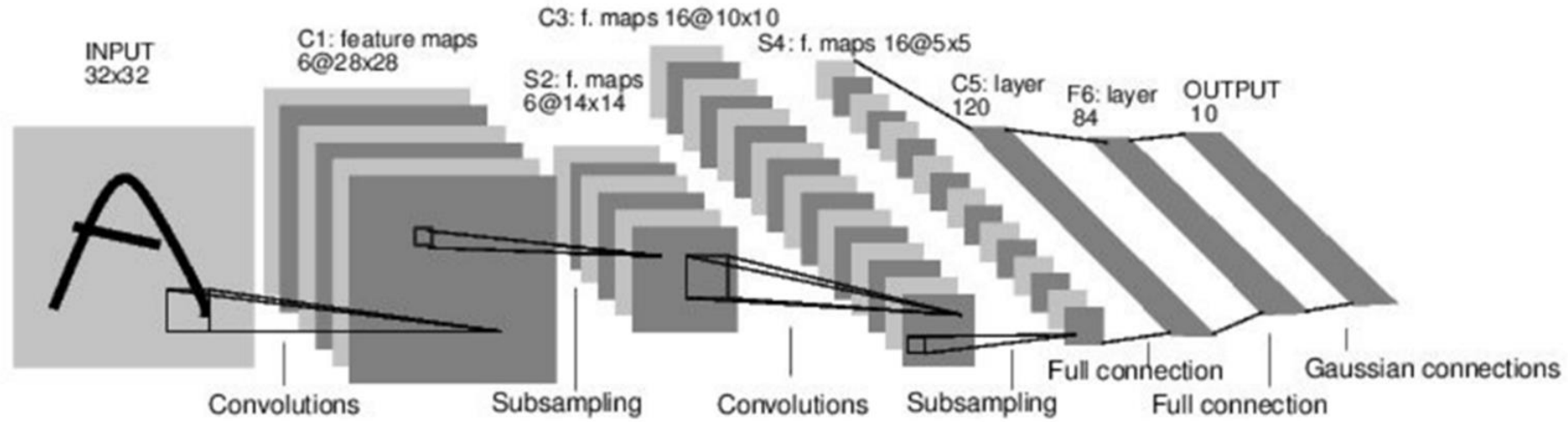
Deep Learning 기술 중

이미지 인식에 많이 활용되는

CNN에 대한 이해와 활용능력 습득

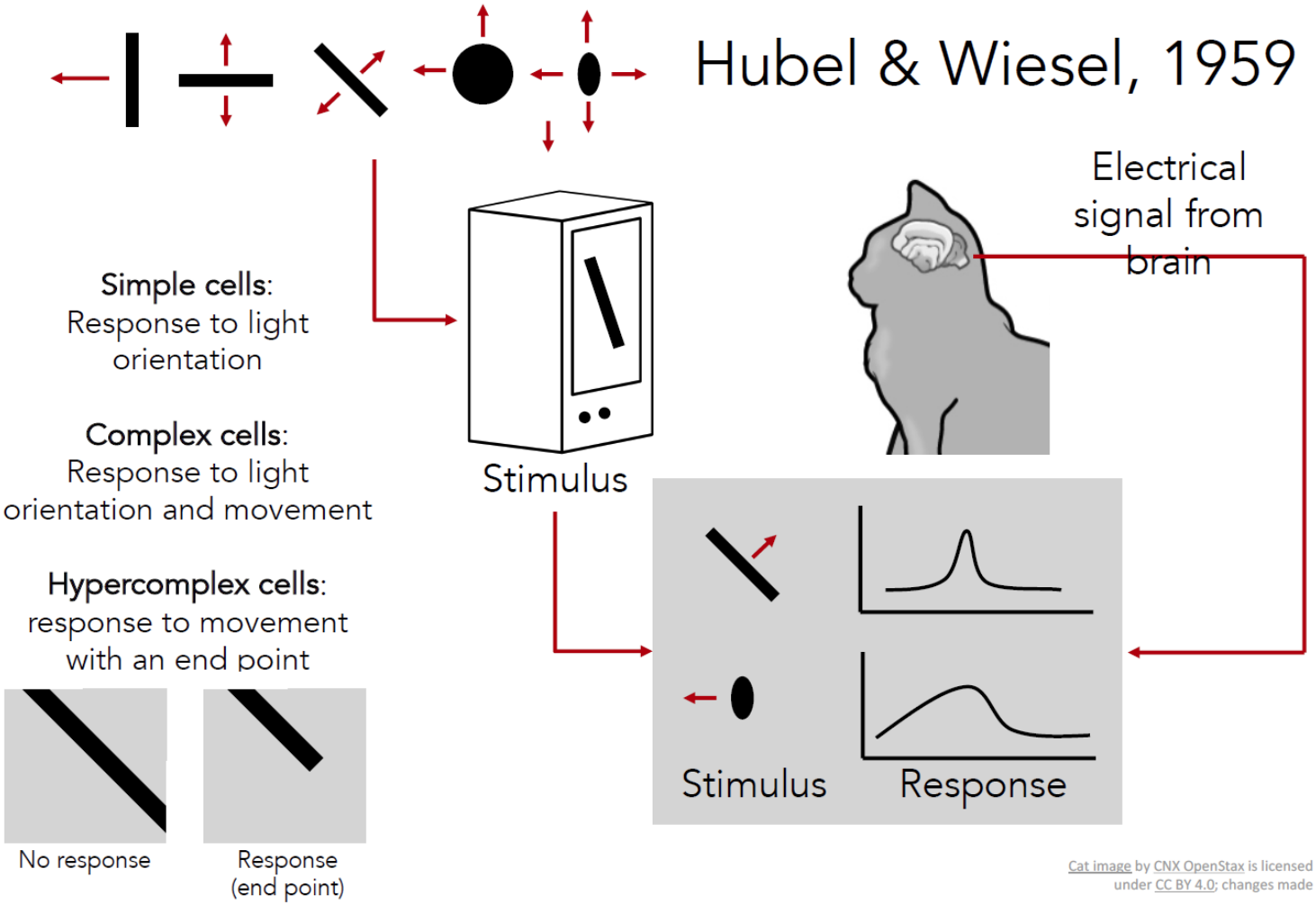
Convolutional Neural Network

❖ 이미지의 부분 부분을 샘플링 하여 특징을 추출



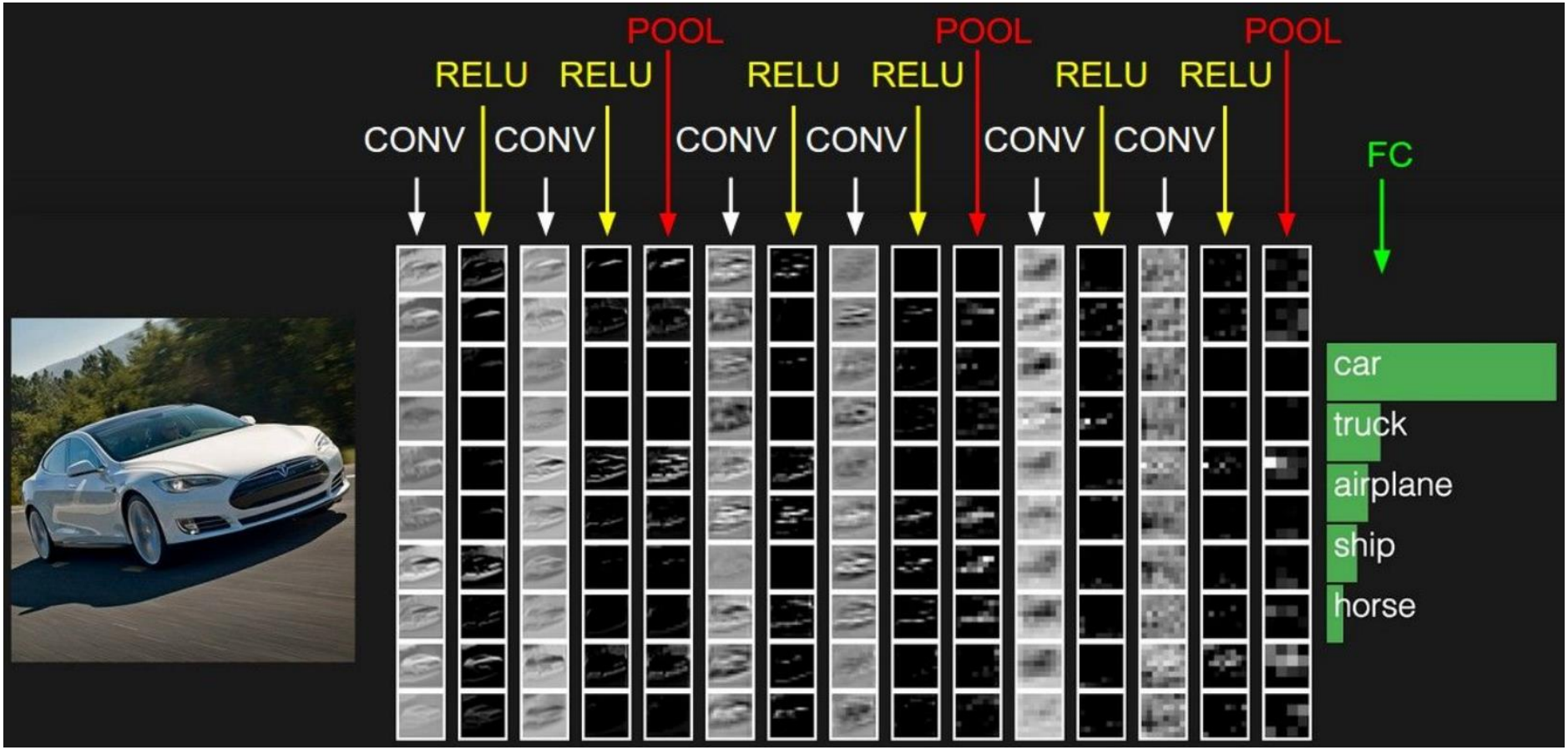
[LeNet-5, LeCun]

Convolutional Neural Network



간단한 자극 특징으로부터 시각 정보의 복잡한 표현을 설명

Convolutional Neural Network



Convolutional Neural Network

데이터들을 배열로 만든다

↓

각 데이터의 크기에 따른
hidden layer 들을 생성...

↓

분류

Deep neural network

데이터들을 배열로 만든다

↓

데이터를 적당히 분할한 후
필터를 입혀서 부표본(subsample) 생성

↓

샘플들을 또 적당히 분할한 후
필터를 입혀서 부표본(subsample) 생성...

↓

(Deep) neural network

↓

분류

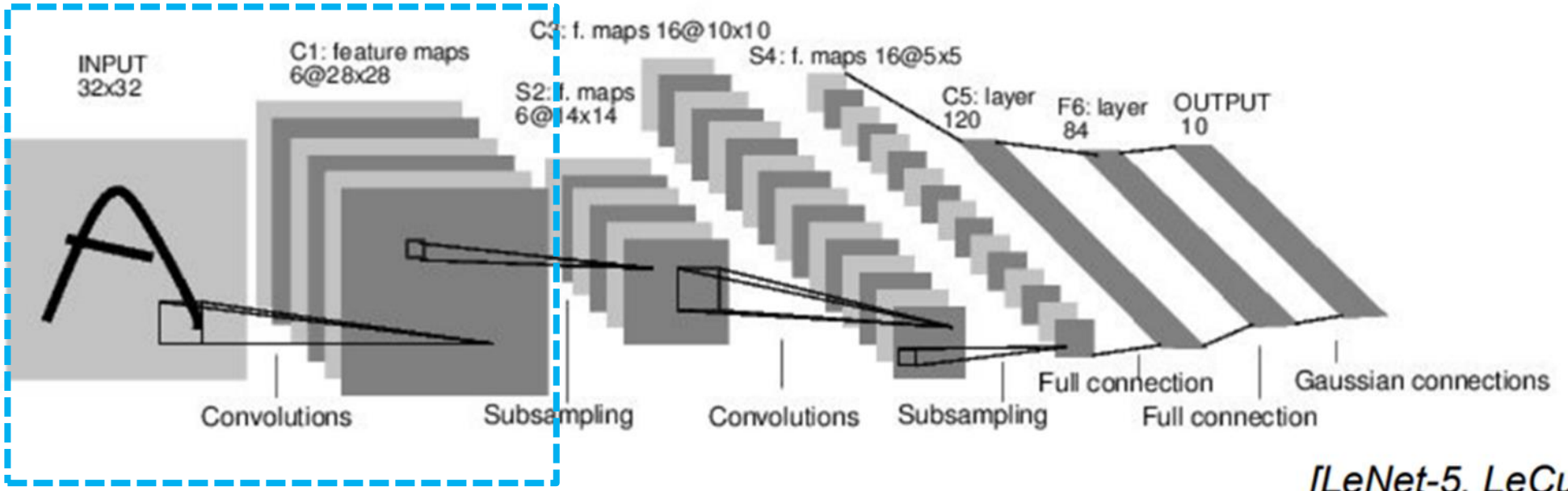
Convolutional neural network

1

2. CNN 기본

Convolution Layer

- ❖ Input 에서 feature(activation) map을 만드는 과정
- ❖ Convolution(합성곱) 연산으로 처리

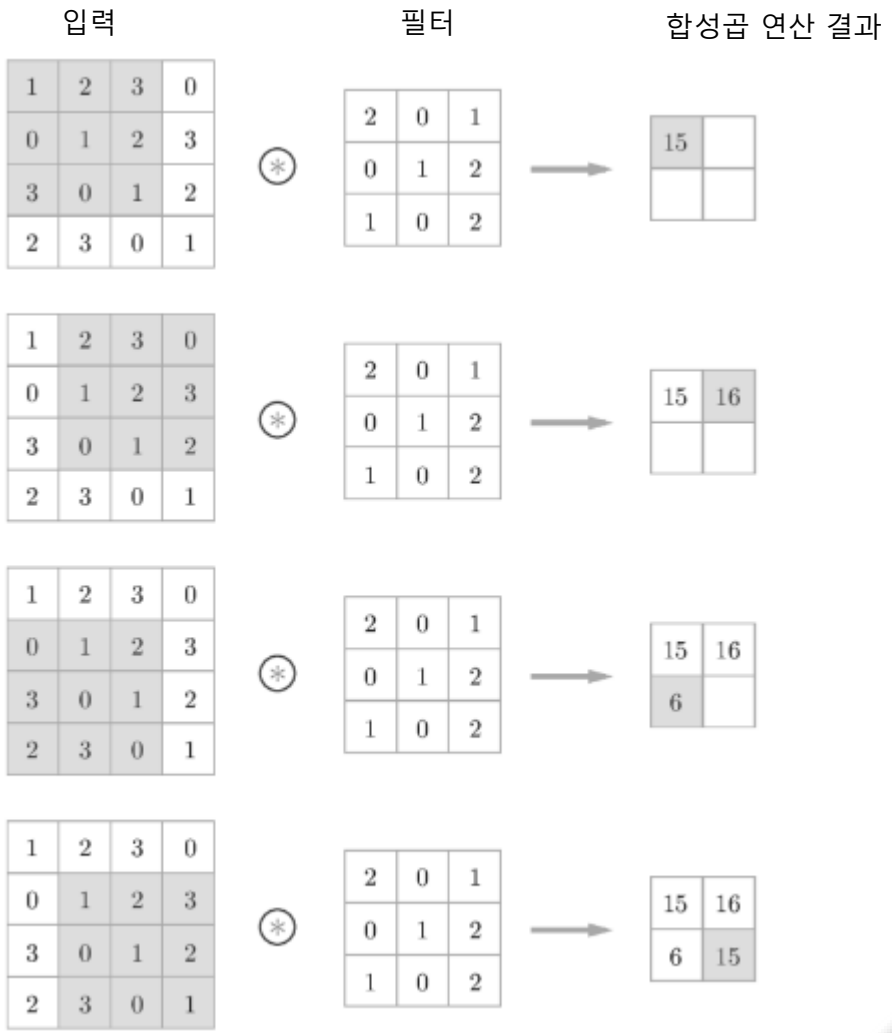


[LeNet-5, LeCun]

Convolution Layer

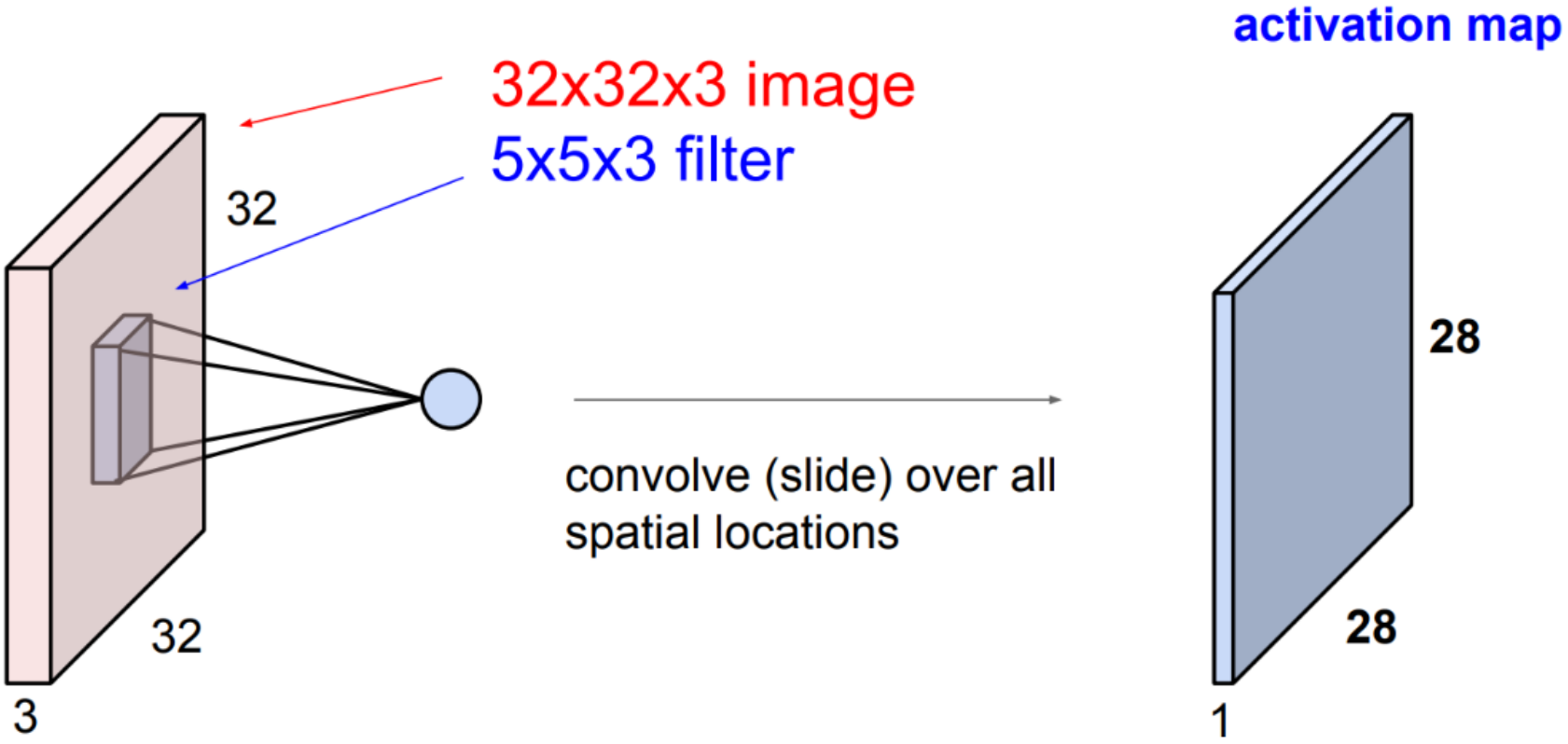
❖ Convolution(합성곱) 연산

- 필터(filter, kernel)의 윈도우를 일정 간격(stride) 이동시키면서 입력에 weighted sum을 적용
- weighted sum : 각 요소의 값을 곱하여 더함



Convolution Layer

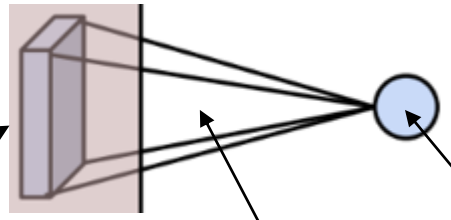
입력 이미지에 필터를 적용하여 작은 영역을 한 점으로 표현



Convolution Layer

❖ 이미지를 Filter의 크기만큼 조각 내어 weighted sum을 한다

이미지에서 하나의 셀 값이
하나인 경우 색을 나타내는 값이
하나라는 말이기 때문에
흑백 사진일 가능성이 높다



1	2	3
4	5	6
7	8	9

Sample (1x3x3x1)

Weighted Sum

10	10	10
1	1	1
-1	-1	-1

Filter (1x3x3x1)

= 10 + 20 + 30 +
4 + 5 + 6 +
(-7) + (-8) +(-9)
= 51

Convolution Layer

❖ 연습 문제

1	5	4	3
8	4	1	4
1	2	3	3
6	5	3	1

Sample(1x4x4x1)

Weighted Sum

1	1	1	1
-1	-1	-1	-1
2	2	2	2
3	3	3	3

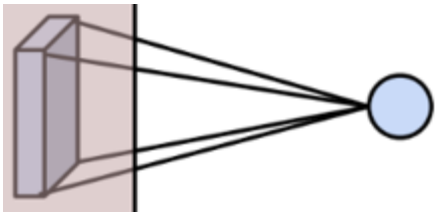
Filter(1x4x4x1)

=

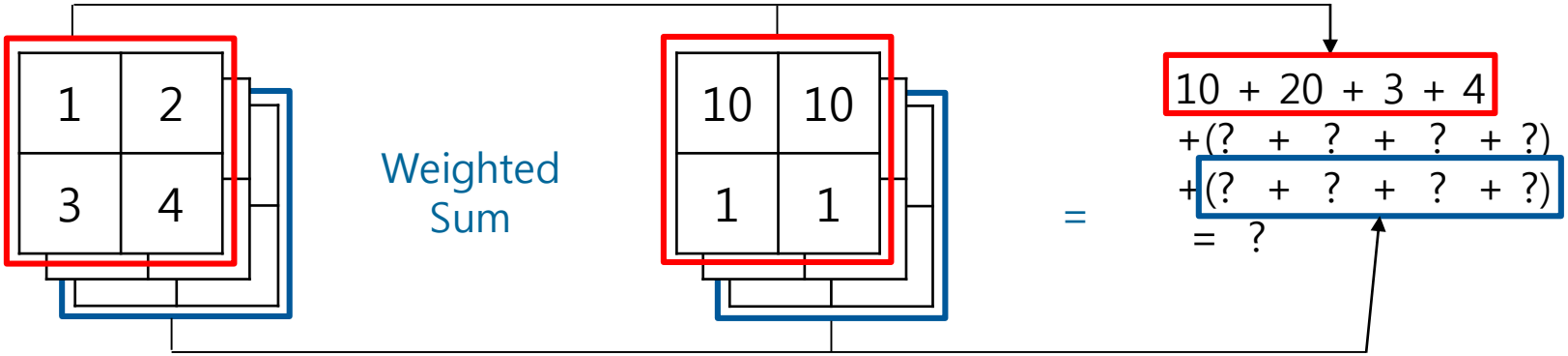
Convolution Layer

❖ Sample의 깊이에 대한 차원과 필터의 깊이에 대한 차원이 동일

각 깊이마다 합성곱연산을 수행하여



이미지에서 하나의 셀 값이
세 개인 경우 색을 나타내는 값이
세 개이고, 이는 보통 R,G,B 이기 때문에
컬러 사진일 가능성이 높다



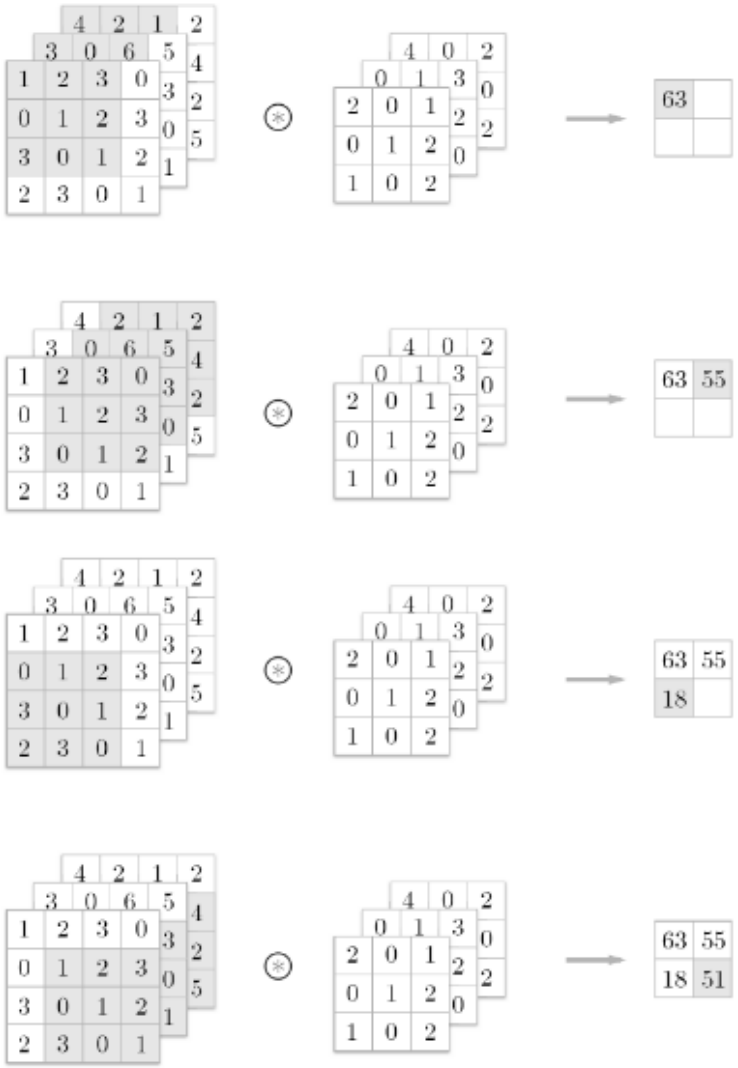
Sample(1x2x2x3)

Filter(1x2x2x3)

Convolution Layer

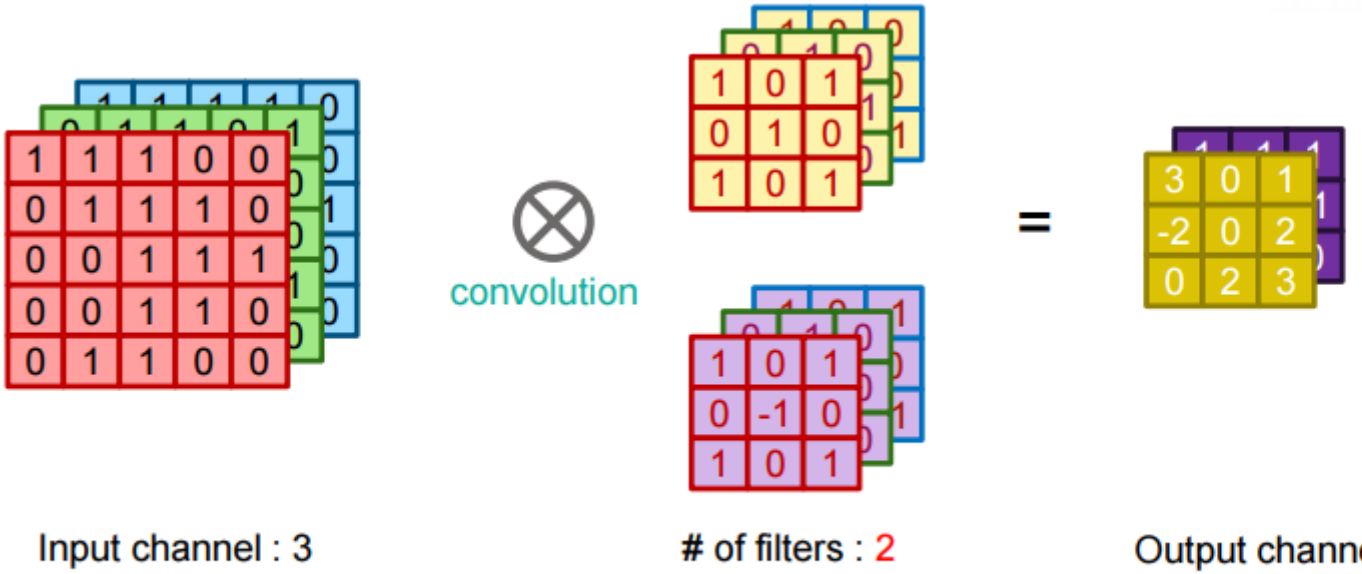
❖ 3차원 데이터의 합성곱

- 입력 데이터와 필터의 합성곱 연산을 깊이마다 수행하고 그 결과를 더해서 출력



Convolution Layer

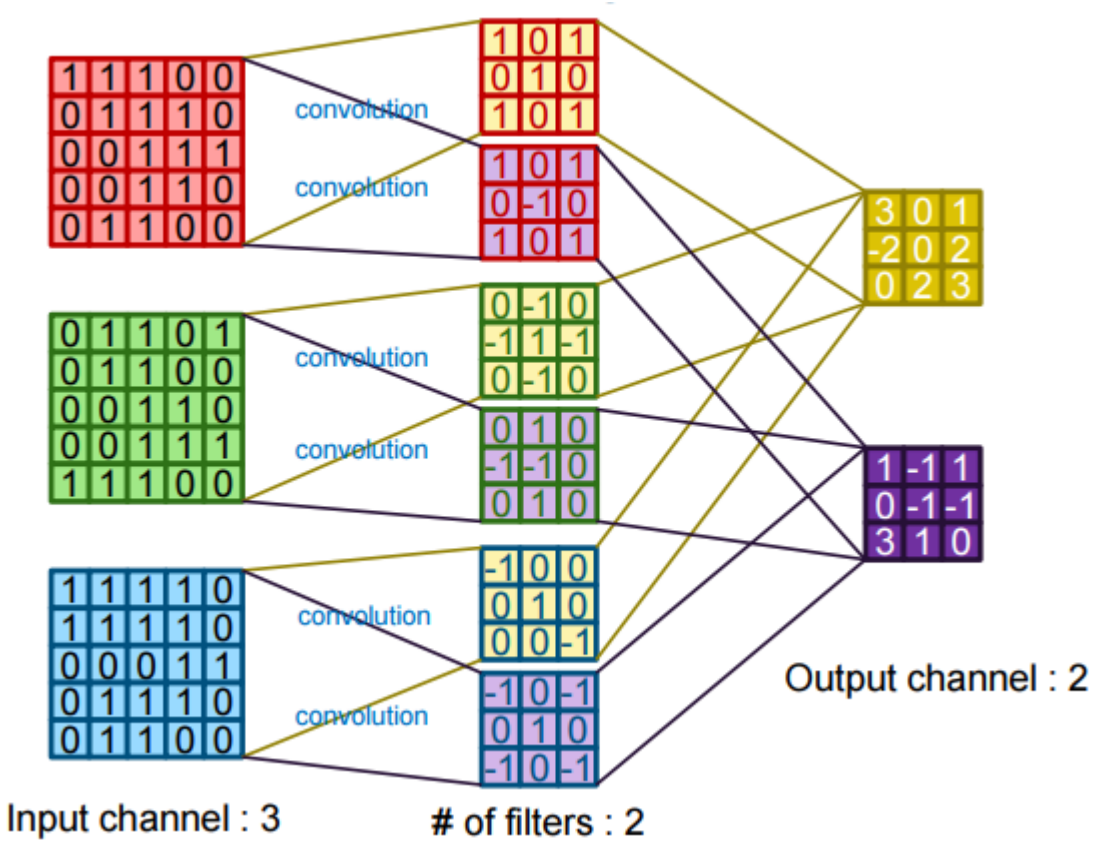
❖ Many filters, multi Channel



https://predictiveprogrammer.com/famous-convolutional-neural-network-architectures-1

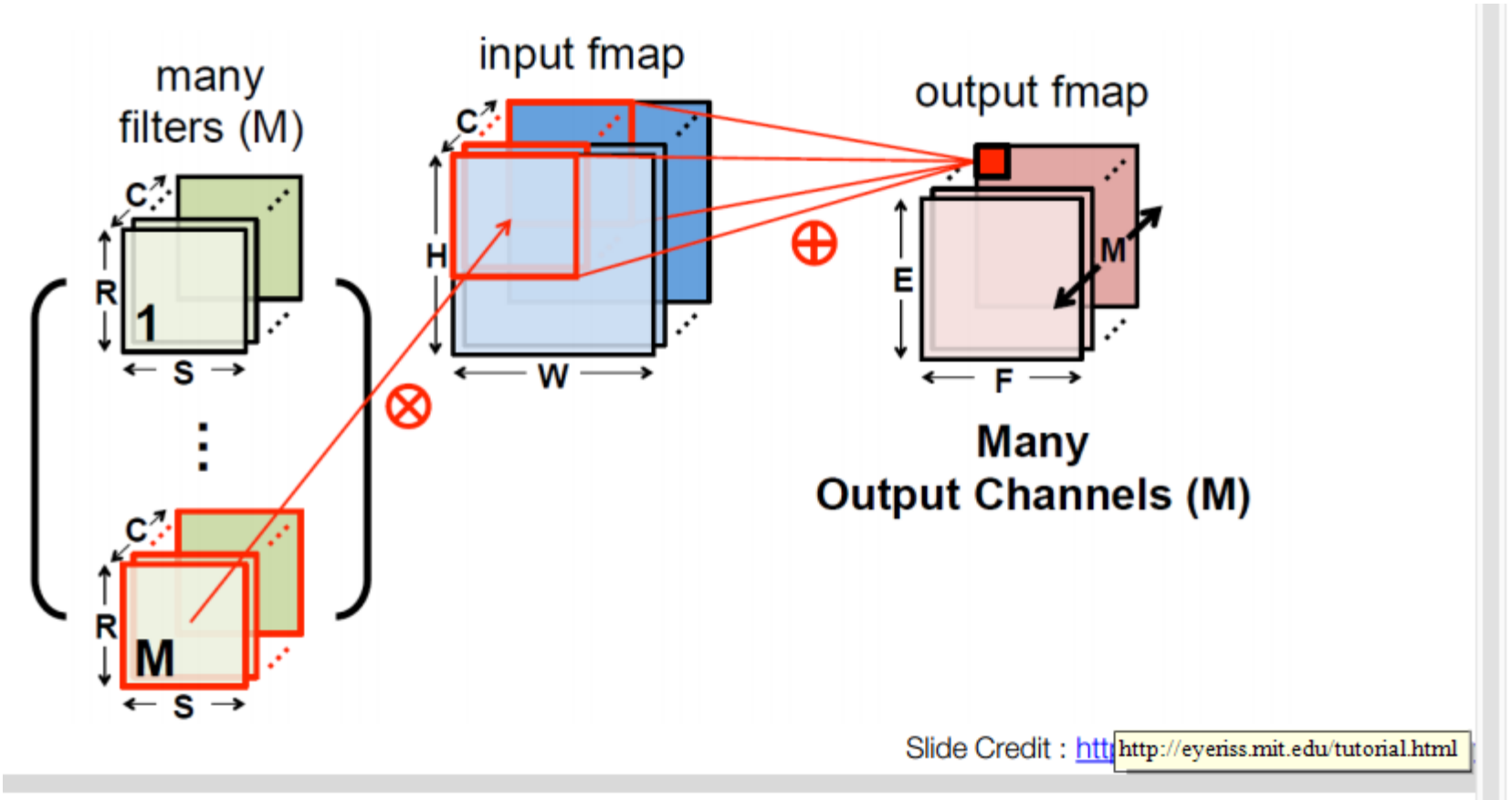
Convolution Layer

❖ Many filters, multi Channel



Convolution Layer

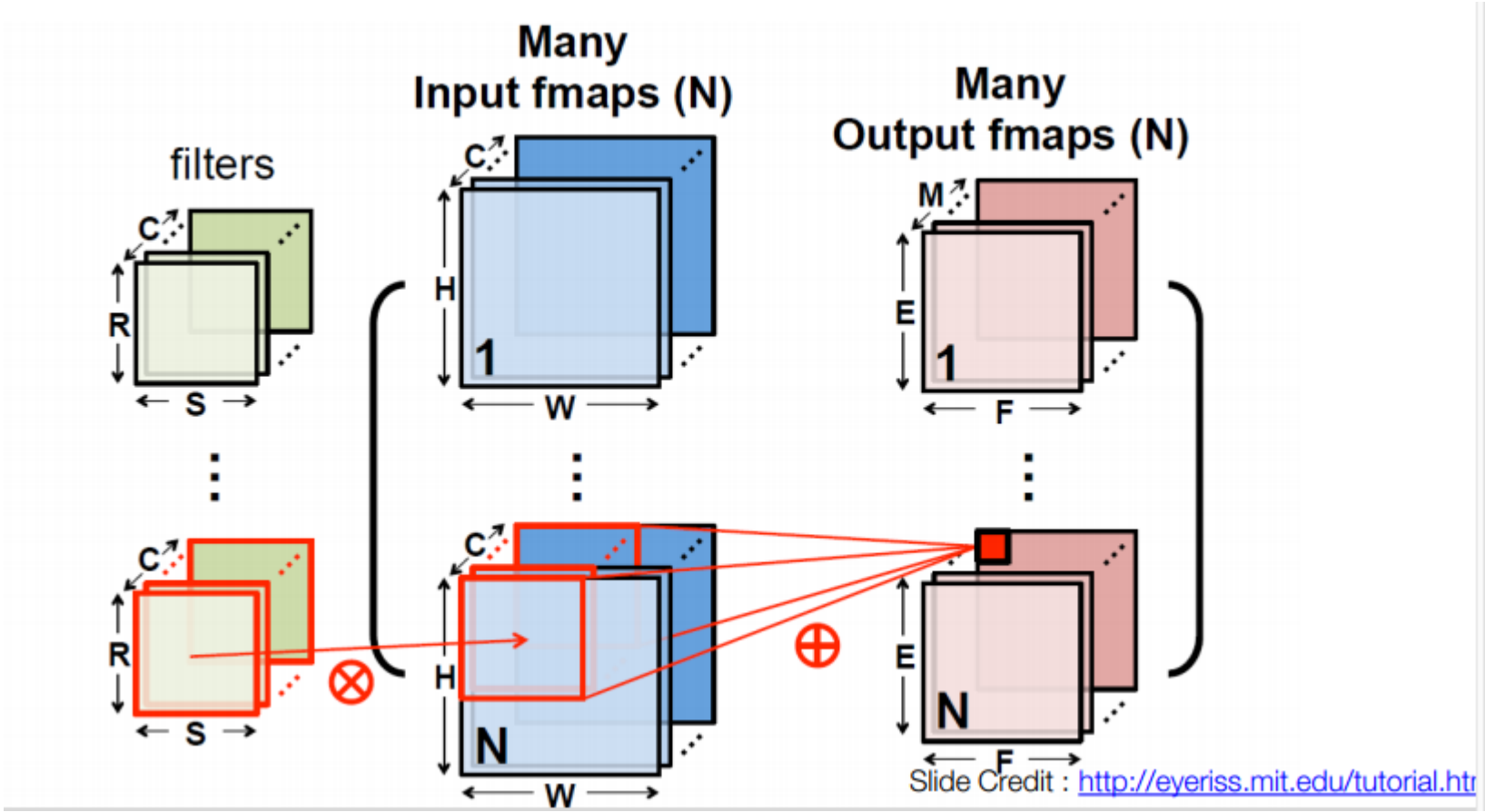
❖ Many filters, multi Channel



Convolution Layer

❖ Many input(batch size), Many filters, multi Channel

- Input(inN, H, W, C), filter(R,S,C,outN), Output(N,E,F,M)



Convolution Layer

❖ Activation map 이 28 x 28 이 되려면 어떻게 해야 할까?

Convolution Layer

❖ 쉬운 예

- 7x7 이미지에 3x3 필터를 적용하여 나올 수 있는 Activation map은?

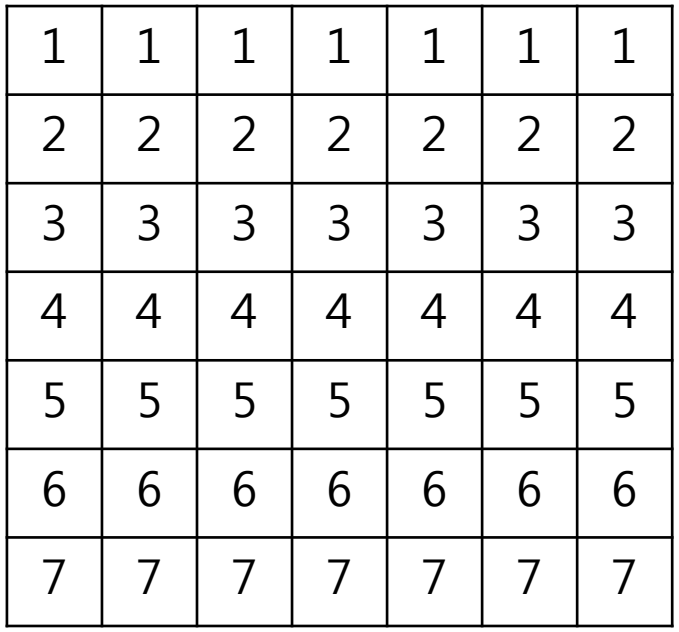
다음 페이지에서 예상해보세요

1	1	1	1	1	1	1
2	2	2	2	2	2	2
3	3	3	3	3	3	3
4	4	4	4	4	4	4
5	5	5	5	5	5	5
6	6	6	6	6	6	6
7	7	7	7	7	7	7

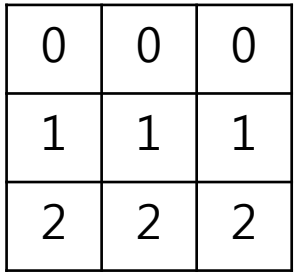
7 x 7 x 1 image

0	0	0
1	1	1
2	2	2

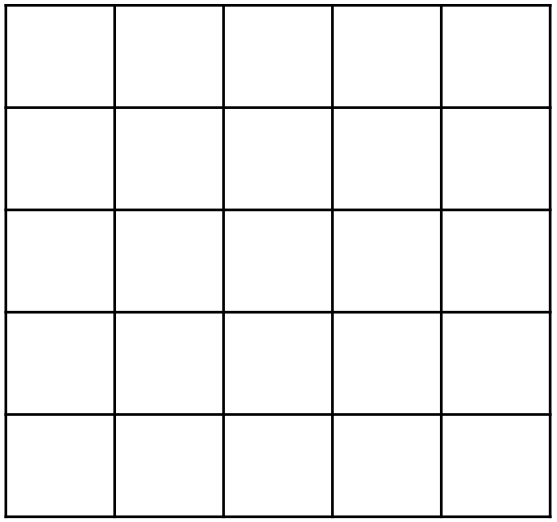
3 x 3 x 1 filter



7 x 7 x 1 image

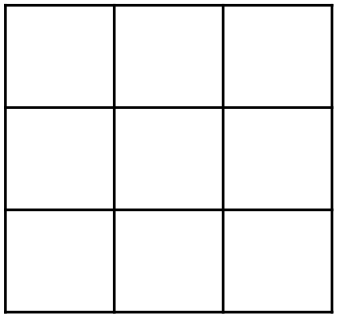


3 x 3 x 1 filter



5 x 5 x 1 activation map

or

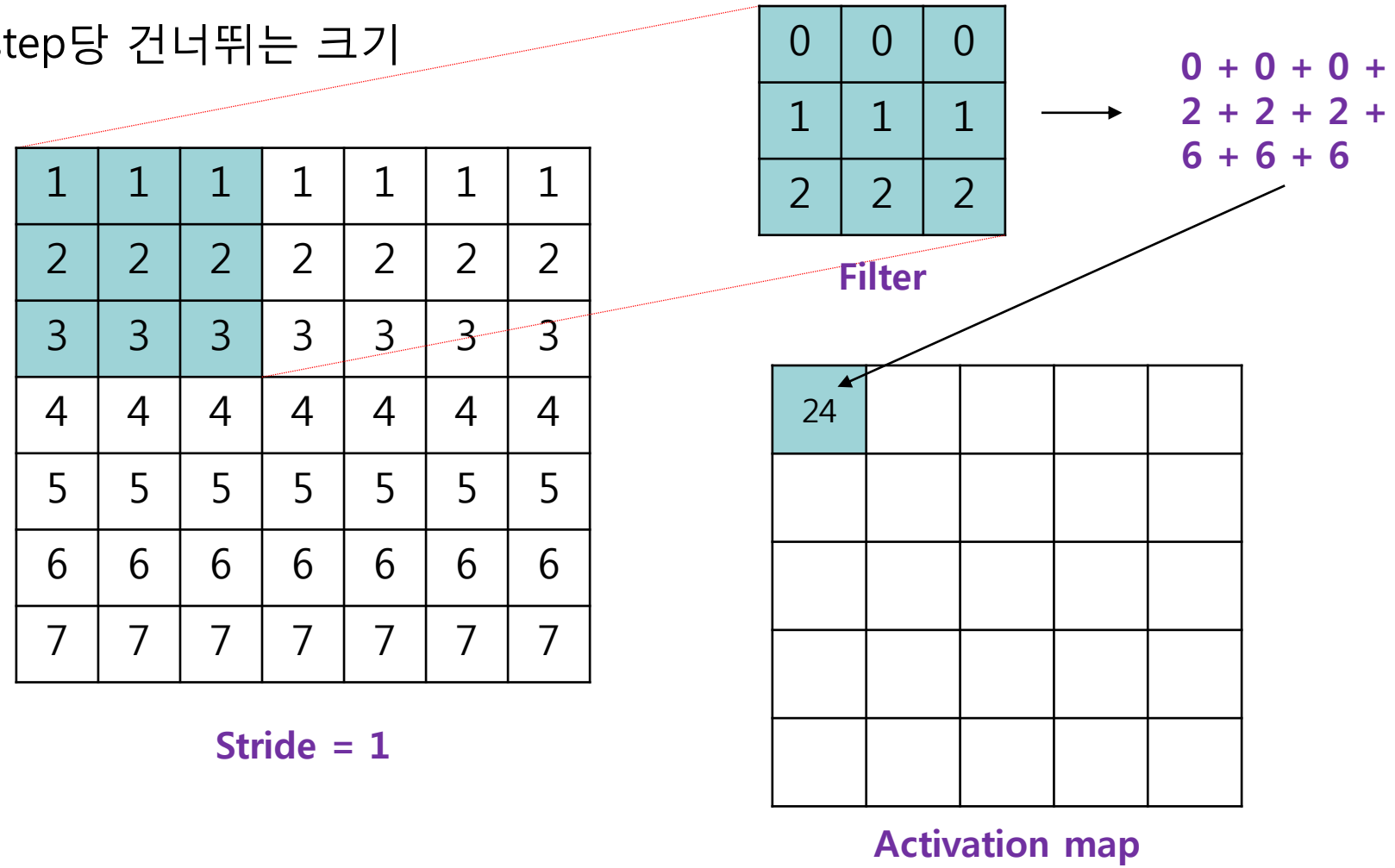


3 x 3 x 1 activation map

Convolution Layer

❖ Stride

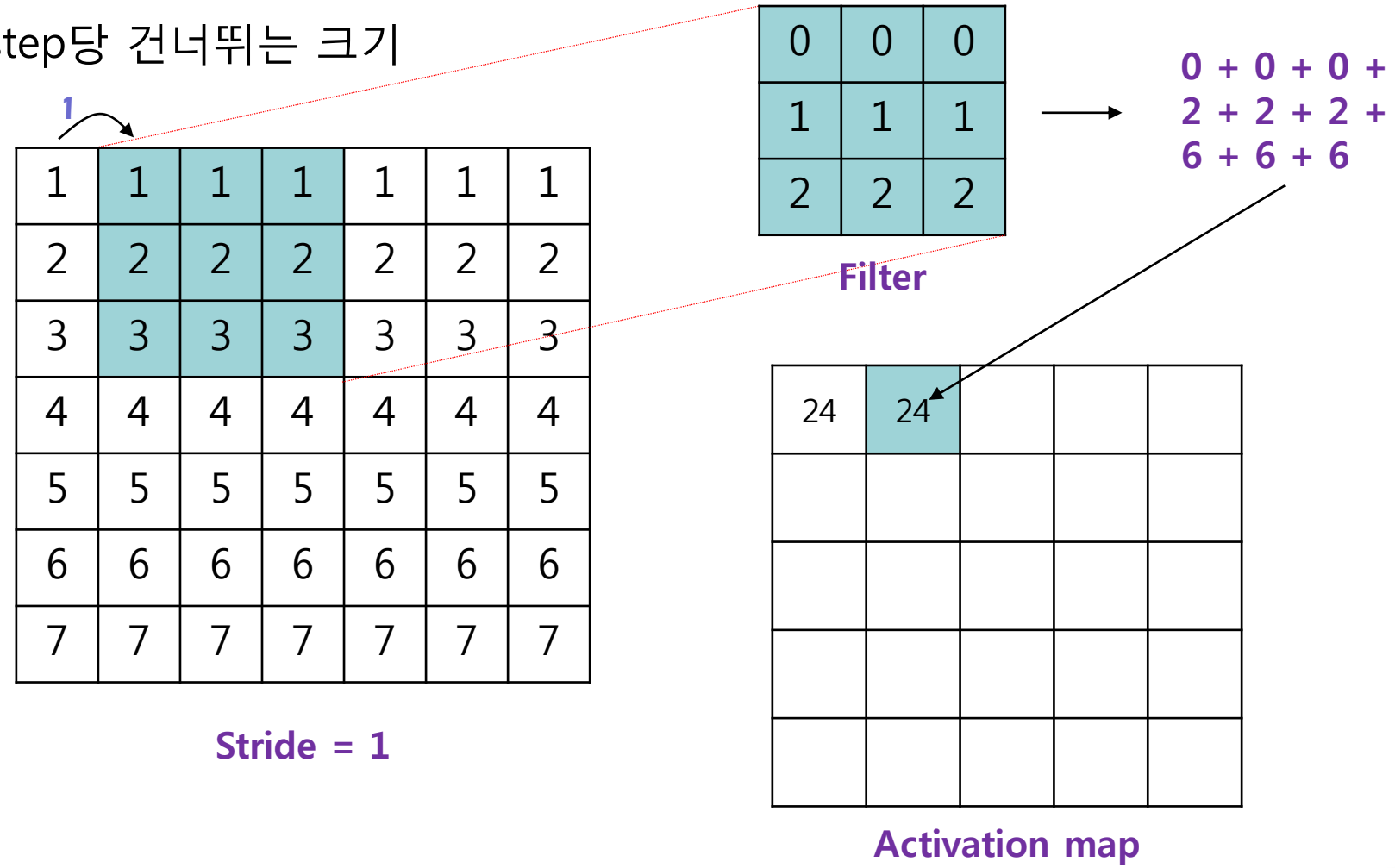
- step당 건너뛰는 크기



Convolution Layer

❖ Stride

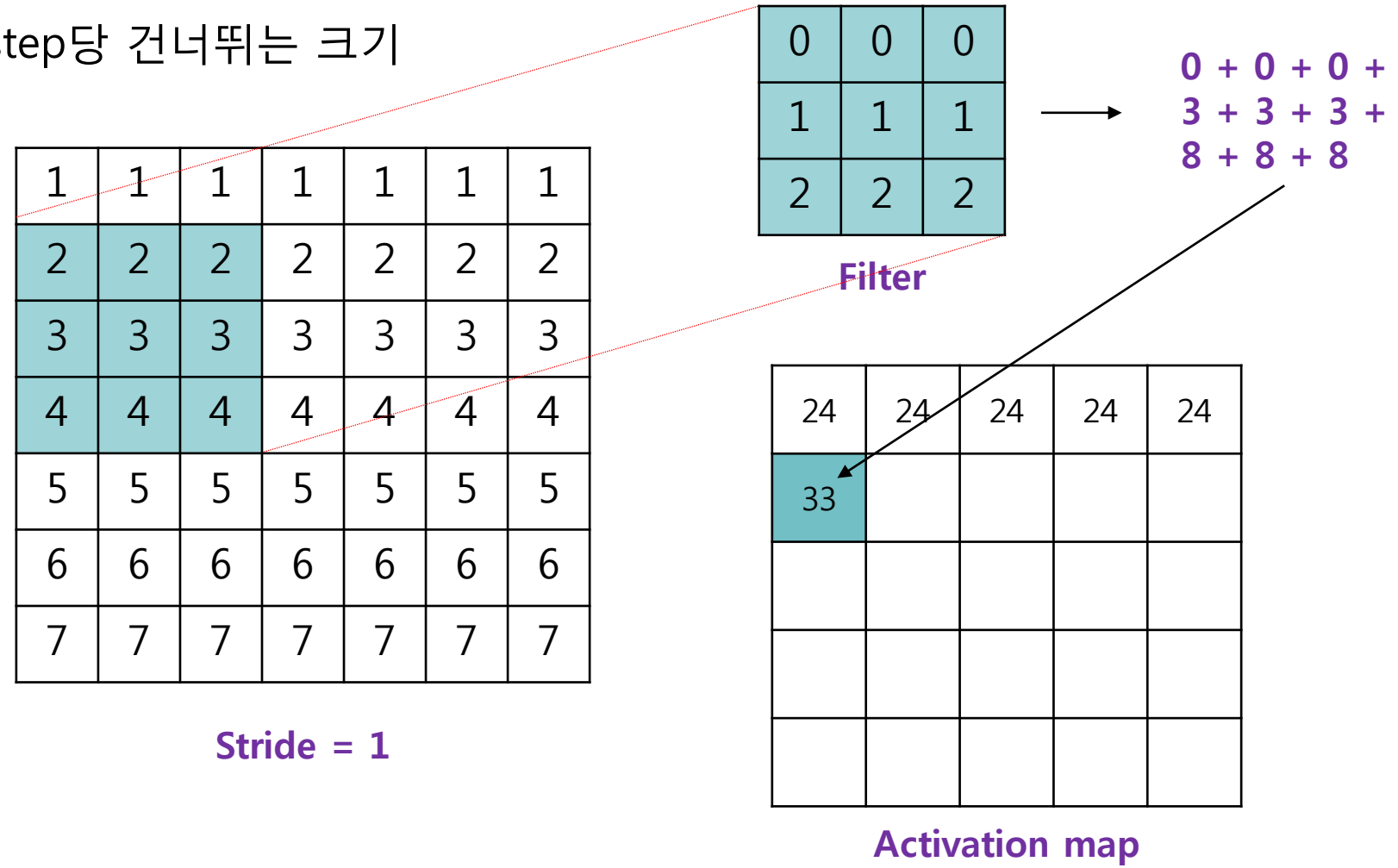
- step당 건너뛰는 크기



Convolution Layer

❖ Stride

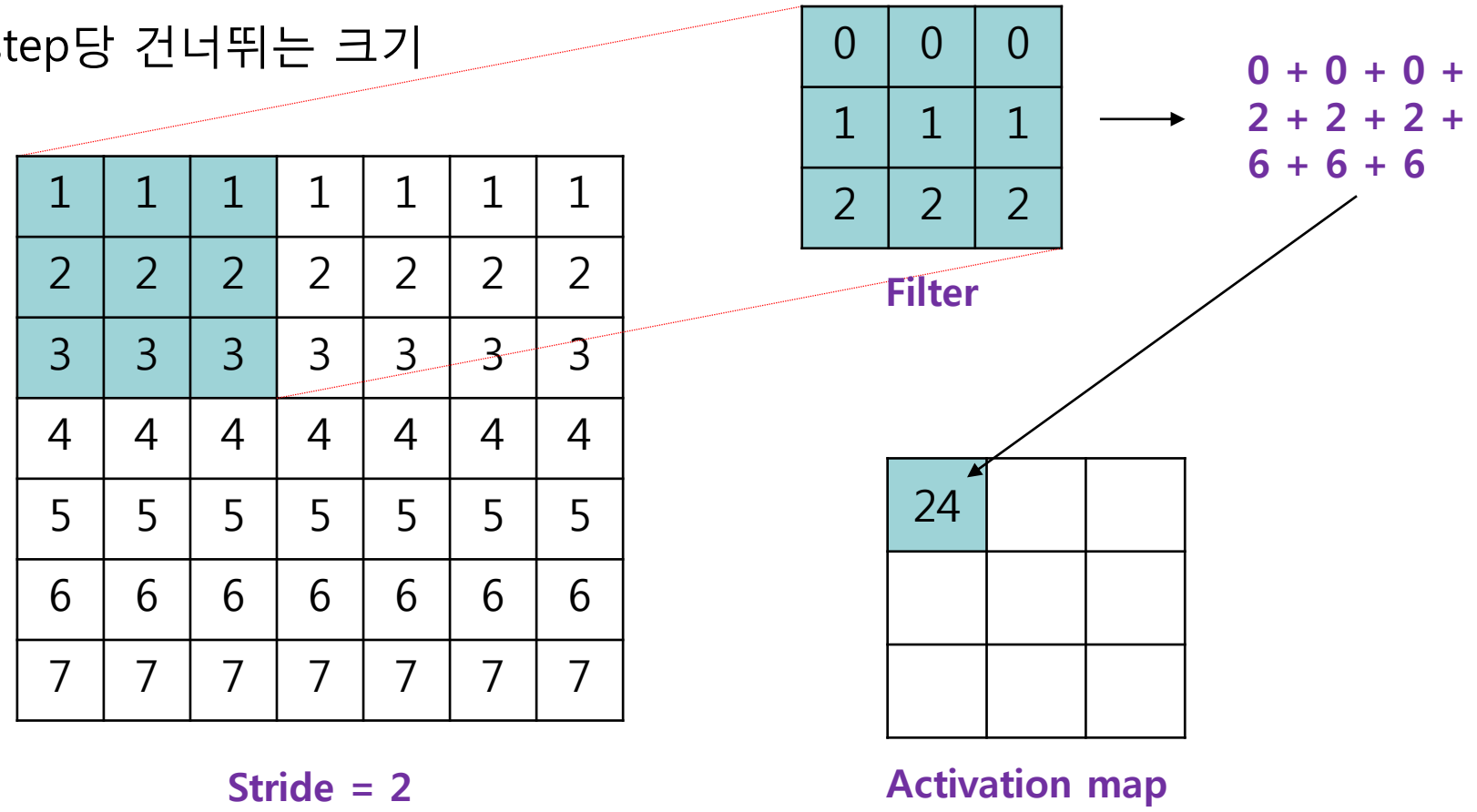
- step당 건너뛰는 크기



Convolution Layer

❖ Stride

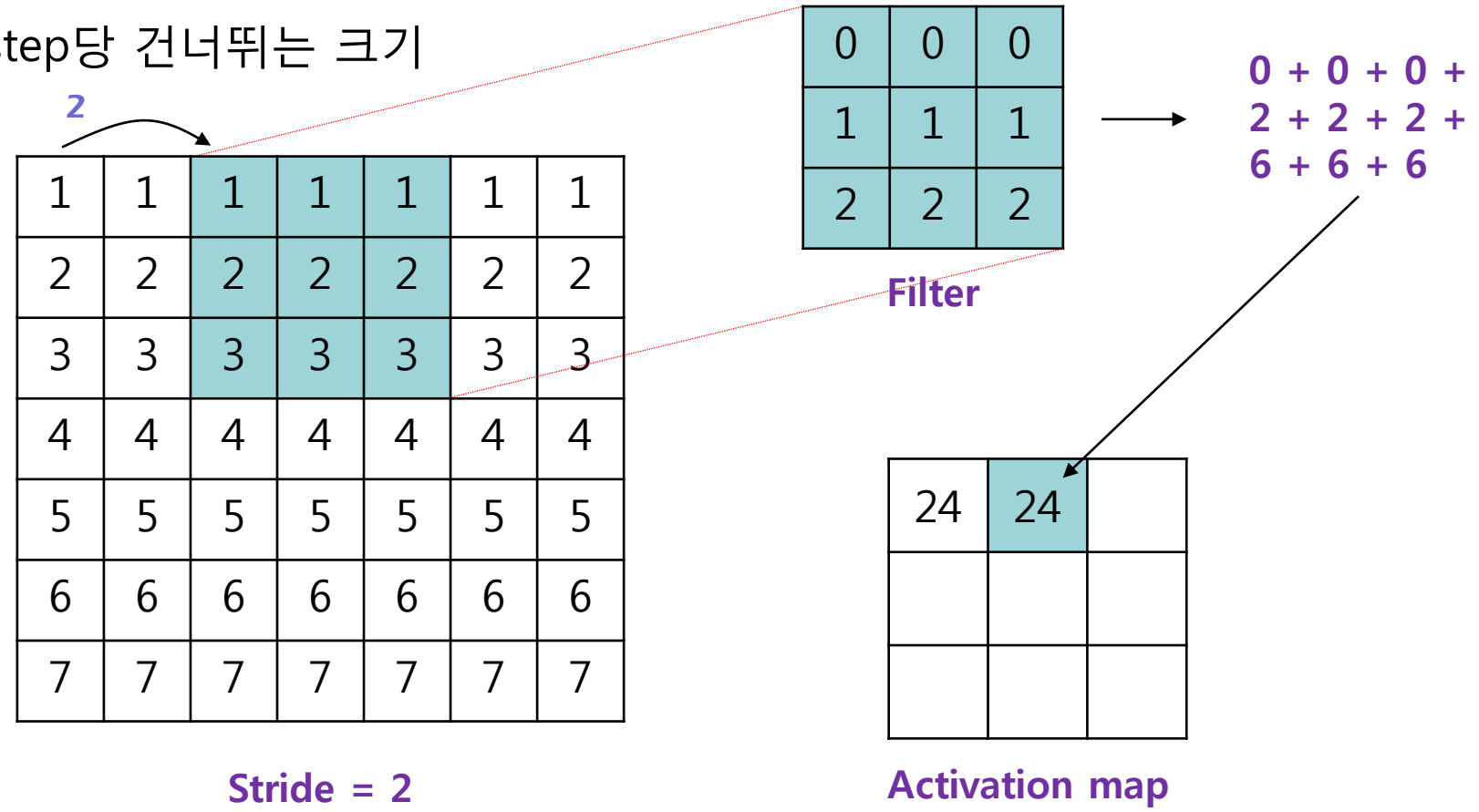
- step당 건너뛰는 크기



Convolution Layer

❖ Stride

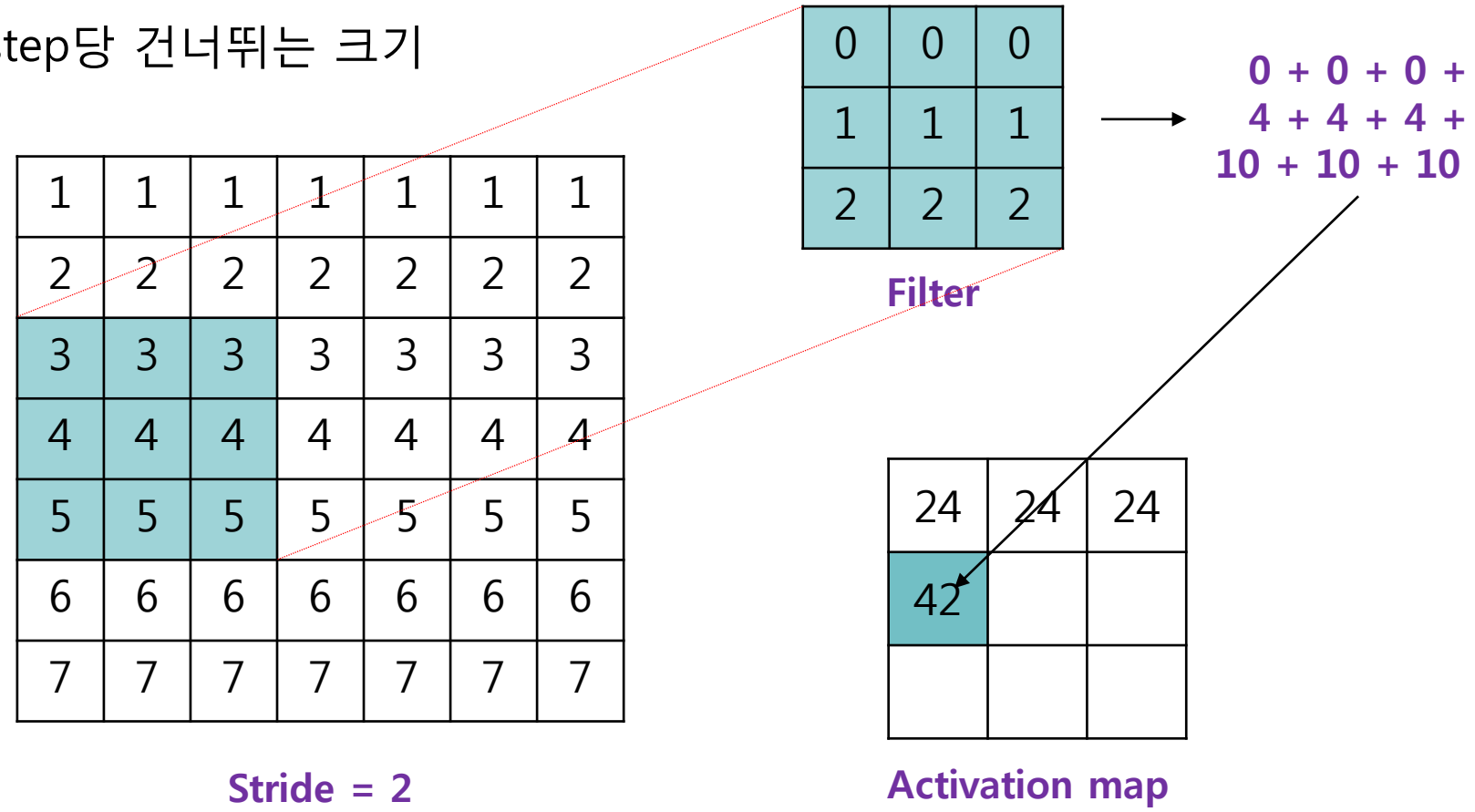
- step당 건너뛰는 크기



Convolution Layer

❖ Stride

- step당 건너뛰는 크기

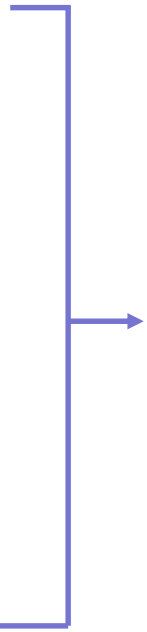


1	1	1	1	1	1	1
2	2	2	2	2	2	2
3	3	3	3	3	3	3
4	4	4	4	4	4	4
5	5	5	5	5	5	5
6	6	6	6	6	6	6
7	7	7	7	7	7	7

7 x 7 x 1 image

0	0	0
1	1	1
2	2	2

3 x 3 x 1 filter



24	24	24	24	24
33	33	33	33	33
42	42	42	42	42
51	51	51	51	51
60	60	60	60	60

5 x 5 x 1 activation map

or

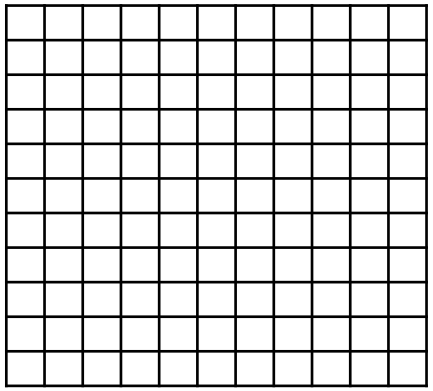
24	24	24
42	42	42
60	60	60

3 x 3 x 1 activation map

Exercise

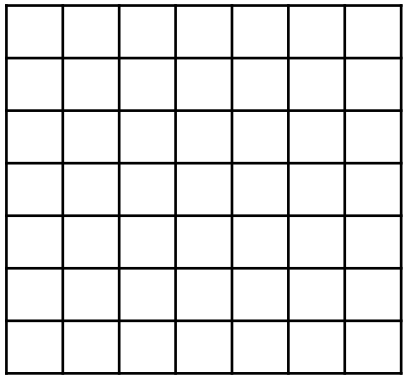
Q. 11 x 11 x 1 Sample, 3 x 3 x 1 Filter

- Stride = 1 일 때 activation map의 크기?
- Stride = 2 일 때 activation map의 크기?



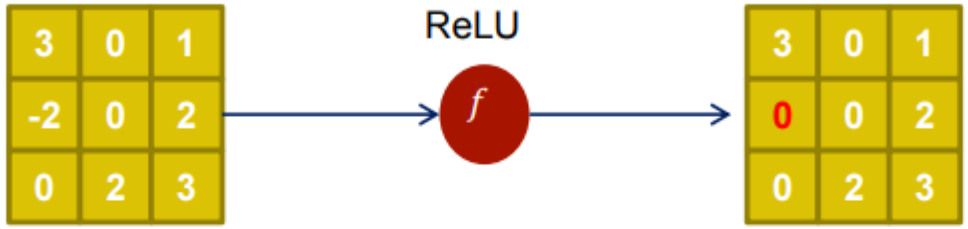
Q. 7 x 7 x 3 Sample 에서 5 x 5 x 1 의 activation map 생성

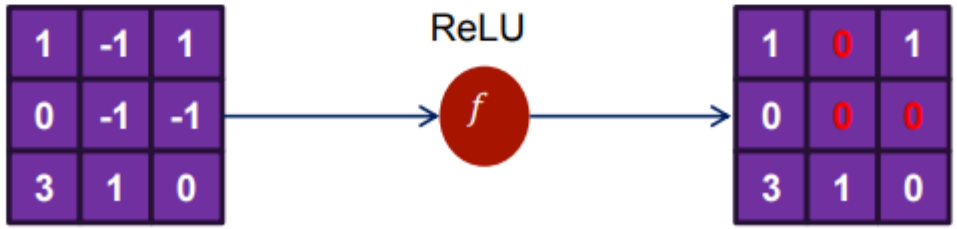
- Filter 의 크기는?
- Stride 의 크기는?



Activation function

- ReLU





tf.keras.layers.Conv2D

```
tf.keras.layers.Conv2D(
    filters, kernel_size, strides=(1, 1), padding='valid',
    data_format=None, dilation_rate=(1, 1), activation=None,
    use_bias=True,   kernel_initializer='glorot_uniform',
    bias_initializer='zeros',    kernel_regularizer=None,
    bias_regularizer=None, activity_regularizer=None,
     kernel_constraint=None, bias_constraint=None, **kwargs
    )
```

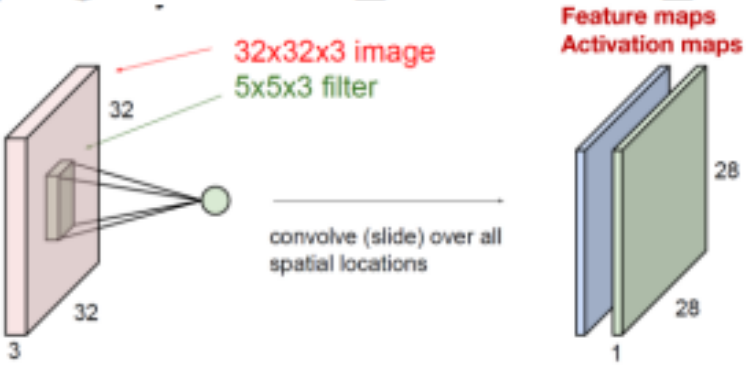
filters : 필터개수
kernel_size : 커널 크기
strides=(1, 1) : 폭, 높이로 컨볼루션 보폭 지정
padding='valid' (패딩 안함), 'same' (stride 가 1일 때, 입력과 출력 크기가 같아지도록)
data_format : 입력 데이터 구조의 순서 (batch_size, height, width, channels)
activation: 활성화함수 지정

https://www.tensorflow.org/api_docs/python/tf/keras/layers/Conv2D

tf.keras.layers.Conv2D

(출력 channel 개수 == 필터 개수)

kernel dimension : {height, width, in_channel, out_channel}
Ex) {5, 5, 3, 2}



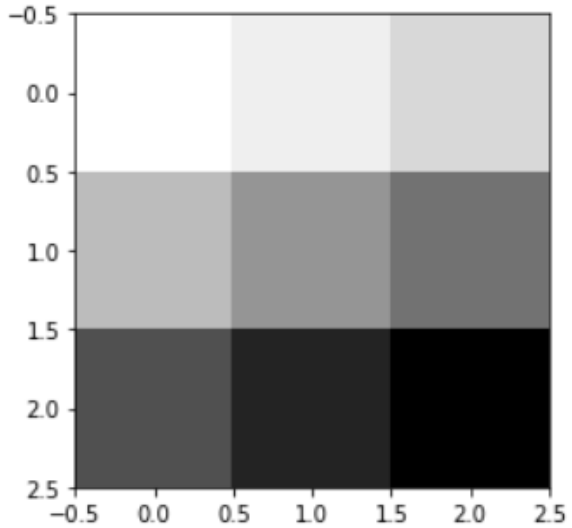
Input

```
import numpy as np
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt

print(tf.__version__)
print(keras.__version__)
```

```
image = tf.constant([[[[1],[2],[3]],
                      [[4],[5],[6]],
                      [[7],[8],[9]]]], dtype=np.float32)
print(image.shape)
plt.imshow(image.numpy().reshape(3,3), cmap='Greys')
plt.show()
```

```
(1, 3, 3, 1)
```

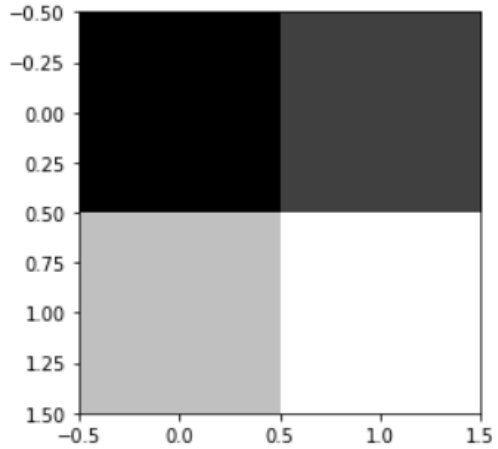


https://github.com/deeplearningzerotoall/TensorFlow/blob/master/tf_2.x/lab-11-0-cnn-basics-keras-eager.ipynb

Weight(filter)

```
print("image.shape", image.shape)
weight = np.array([[[[1.]],[[1.]]],
                   [[[1.]],[[1.]]]])
print("weight.shape", weight.shape)
weight_init = tf.constant_initializer(weight)
conv2d = keras.layers.Conv2D(filters=1, kernel_size=2, padding='VALID',
                             kernel_initializer=weight_init)(image)
print("conv2d.shape", conv2d.shape)
print(conv2d.numpy().reshape(2,2))
plt.imshow(conv2d.numpy().reshape(2,2), cmap='gray')
plt.show()
```

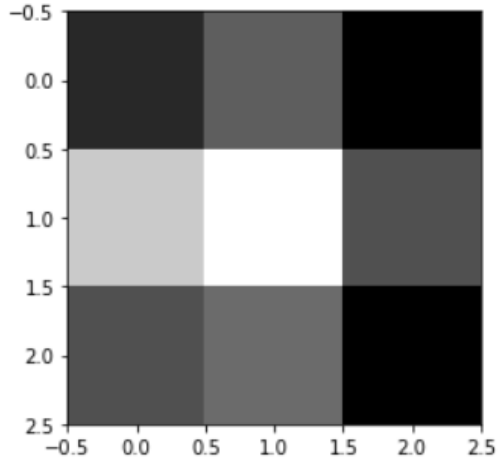
```
image.shape (1, 3, 3, 1)
weight.shape (2, 2, 1, 1)
conv2d.shape (1, 2, 2, 1)
[[12. 16.]
 [24. 28.]]
```



conv2d

```
print("image.shape", image.shape)
weight = np.array([[[[1.]],[[1.]]],
                   [[[1.]],[[1.]]]])
print("weight.shape", weight.shape)
weight_init = tf.constant_initializer(weight)
conv2d = keras.layers.Conv2D(filters=1, kernel_size=2, padding='SAME',
                             kernel_initializer=weight_init)(image)
print("conv2d.shape", conv2d.shape)
print(conv2d.numpy().reshape(3,3))
plt.imshow(conv2d.numpy().reshape(3,3), cmap='gray')
plt.show()
```

```
image.shape (1, 3, 3, 1)
weight.shape (2, 2, 1, 1)
conv2d.shape (1, 3, 3, 1)
[[12. 16.  9.]
 [24. 28. 15.]
 [15. 17.  9.]]
```

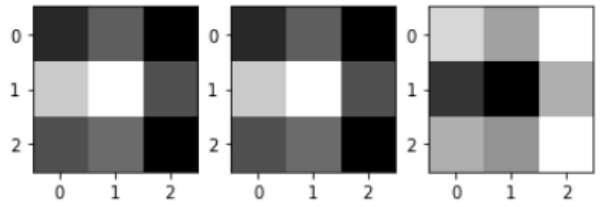


3 filters (2,2,1,3)

```
# print("imag:₩n", image)
print("image.shape", image.shape)

weight = np.array([[[[1.,10.,-1.]],[[1.,10.,-1.]]],
                   [[[1.,10.,-1.]],[[1.,10.,-1.]]]])
print("weight.shape", weight.shape)
weight_init = tf.constant_initializer(weight)
conv2d = keras.layers.Conv2D(filters=3, kernel_size=2, padding='SAME',
                             kernel_initializer=weight_init)(image)
print("conv2d.shape", conv2d.shape)
feature_maps = np.swapaxes(conv2d, 0, 3)
for i, feature_map in enumerate(feature_maps):
    print(feature_map.reshape(3,3))
    plt.subplot(1,3,i+1), plt.imshow(feature_map.reshape(3,3), cmap='gray')
plt.show()
```

```
image.shape (1, 3, 3, 1)
weight.shape (2, 2, 1, 3)
conv2d.shape (1, 3, 3, 3)
[[12. 16.  9.]
 [24. 28. 15.]
 [15. 17.  9.]]
[[120. 160.  90.]
 [240. 280. 150.]
 [150. 170.  90.]]
[[-12. -16.  -9.]
 [-24. -28. -15.]
 [-15. -17.  -9.]]
```



Padding

❖ Padding

- 이미지의 외각에 지정된 값만큼 특정 값으로 채워 넣는 작업

1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1

원본 5 x 5 x 1

Padding

❖ Padding

- 만일 외각 두께 1만큼 0으로 모두 채운다면 아래와 같은 형태가 된다

0	0	0	0	0	0	0
0	1	1	1	1	1	0
0	1	1	1	1	1	0
0	1	1	1	1	1	0
0	1	1	1	1	1	0
0	1	1	1	1	1	0
0	0	0	0	0	0	0

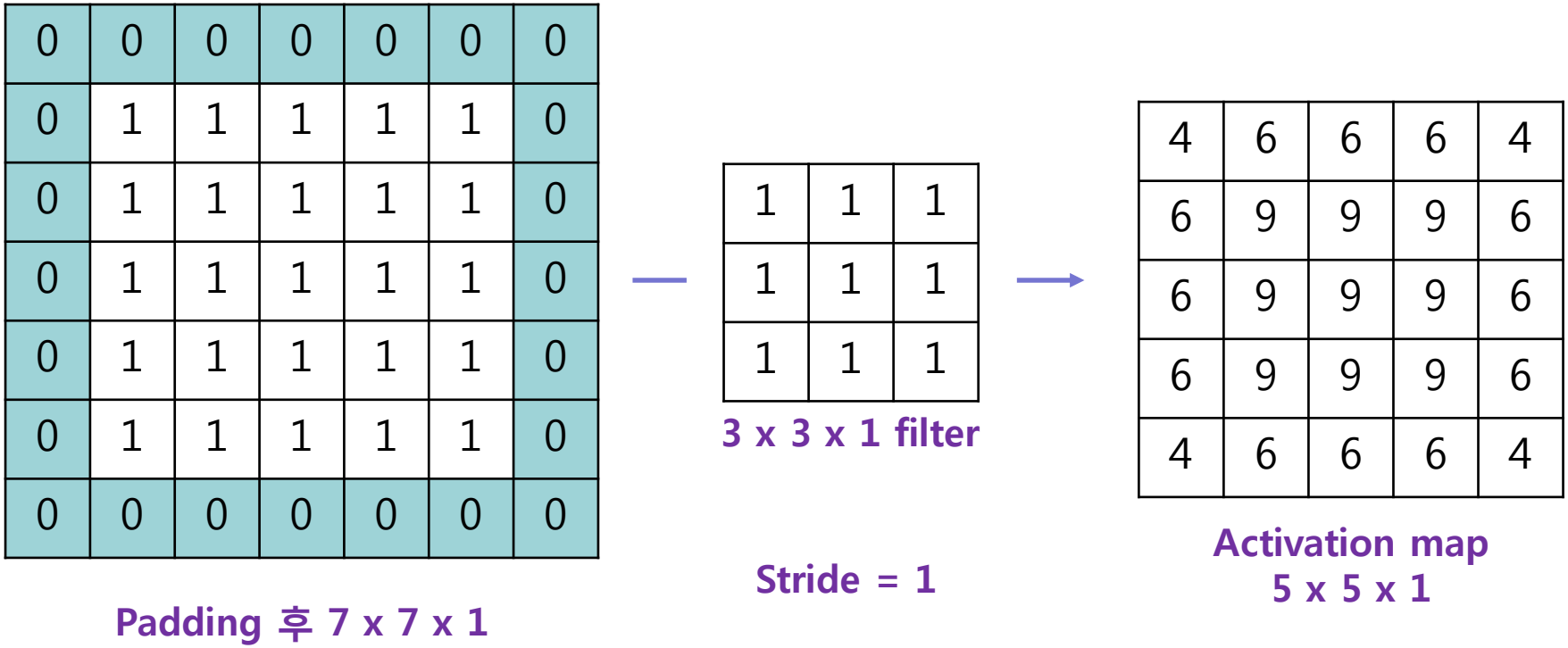
Padding 후 7 x 7 x 1

모두 0으로 채우는 것을 zero padding 이라고도 한다

Padding

❖ Padding

- filter = 3x3x1, stride = 1 을 진행하면 padding 을 하기 전과 크기가 같다



Padding

❖ Padding

- Weighted sum 을 데이터의 drop 없이 모두 수행
- Sample 의 크기가 너무 빨리 줄어드는 것을 방지
- 경계면의 정보를 유지
- 출력크기를 조정할 때 사용

0	0	0	0	0	0	0
0	1	1	1	1	1	0
0	1	1	1	1	1	0
0	1	1	1	1	1	0
0	1	1	1	1	1	0
0	1	1	1	1	1	0
0	0	0	0	0	0	0

Padding

❖ 입력 크기 (H,W), 필터 크기 (FH, FW), 출력 크기를 (OG, OW), 패딩 P, 스트라이드 S일 때 출력의 크기는 ?

OH=(H+2P-FH)/S+1

OW=(W+2P-FW)/S+1

예>(1)입력 (4,4) 필터(3,3) 패딩 1, 스트라이드 1

OH = (4 + 2*1 – 3) / 1 + 1 = 4

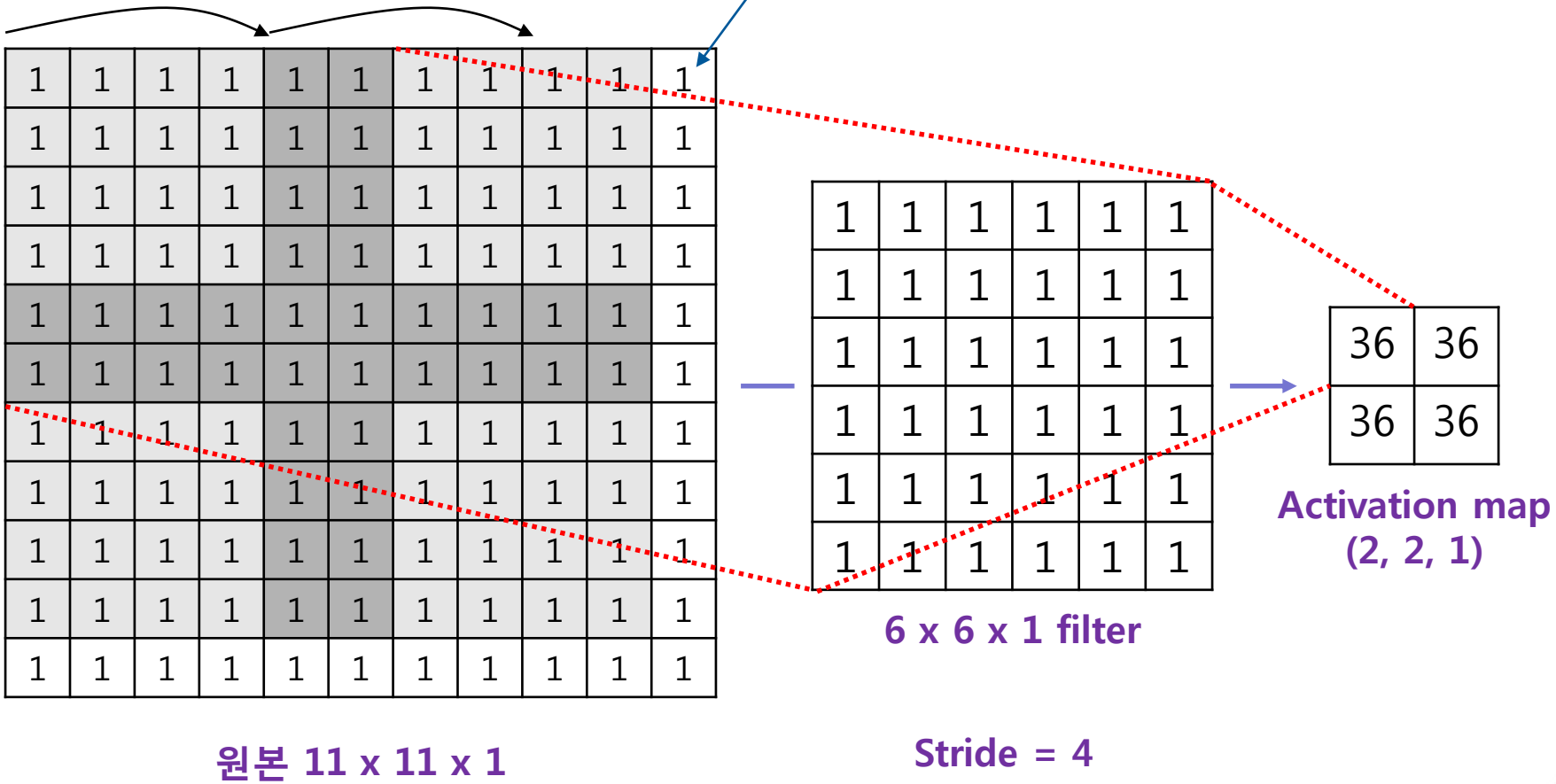
OW = (4 + 2*1 – 3) / 1 + 1 = 4

(2)입력 (28,32) 필터(5,5) 패딩 2, 스트라이드 2 ??

Padding

❖ Padding 고급

- padding = 'VALID'



Padding

❖ Padding 고급

- padding = 'SAME' -> stride = 4, filter = 6 x 6 을 완수하려면 3칸이 더 필요