

# 딥러닝 6

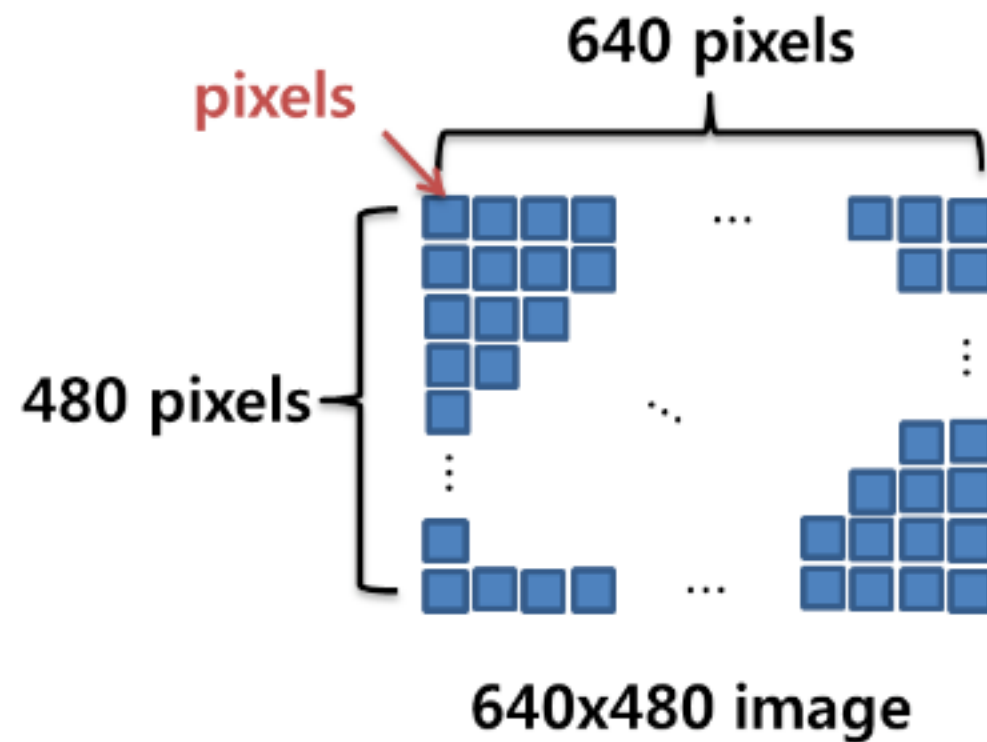
현운용

# Goals

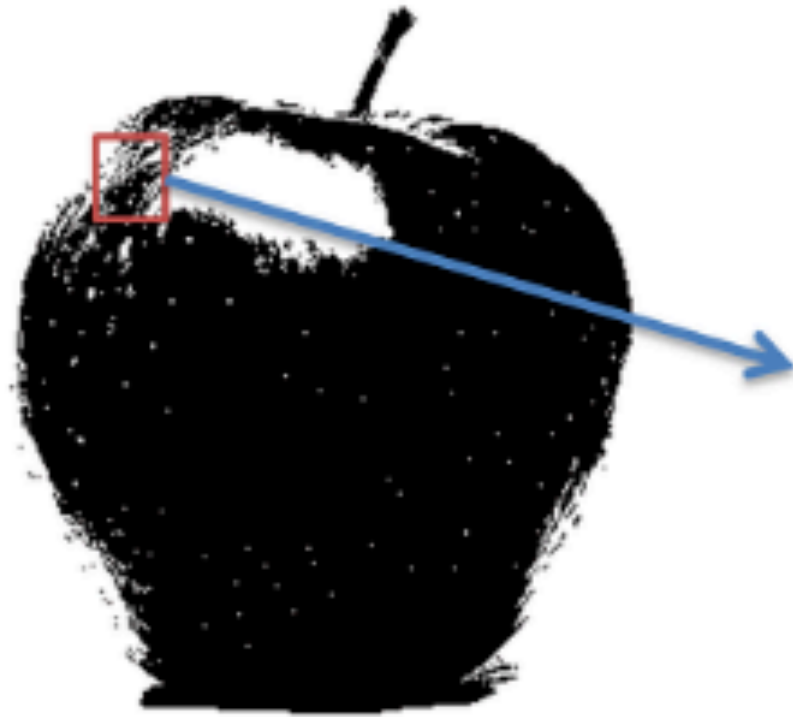
- 컴퓨터에서 이미지 처리
- 기초적인 이미지 분류 Computer vision
- Convolution neural network

# 컴퓨터에서 이미지 처리

픽셀로 표현.



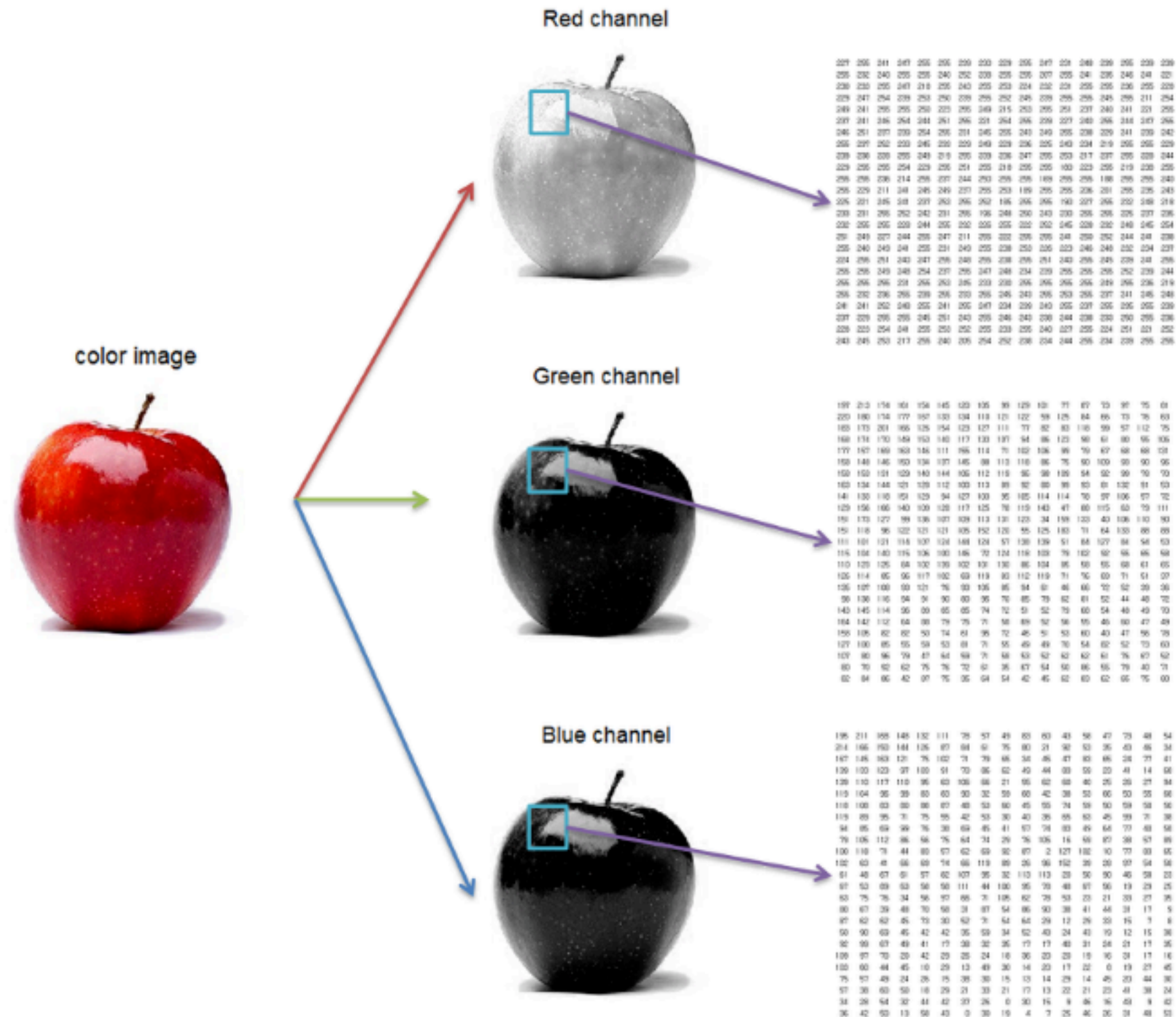
# 컴퓨터에서 이미지 처리



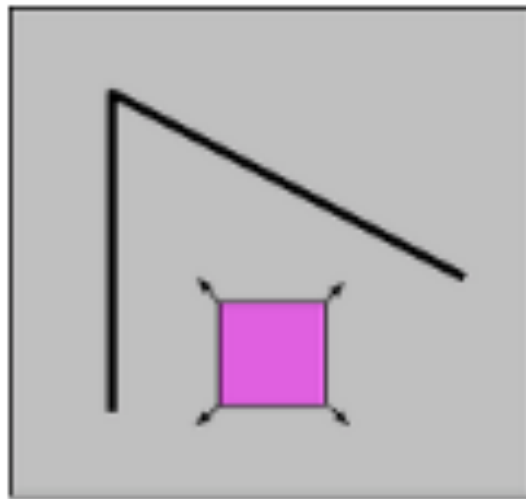
## Binary Image

|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |   |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |   |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 |   |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 |   |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |   |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 |   |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 |
| 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 |
| 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 |
| 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 |

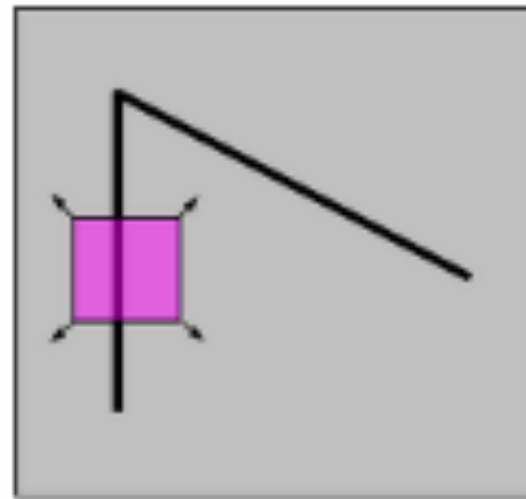
# 컴퓨터에서 이미지 처리



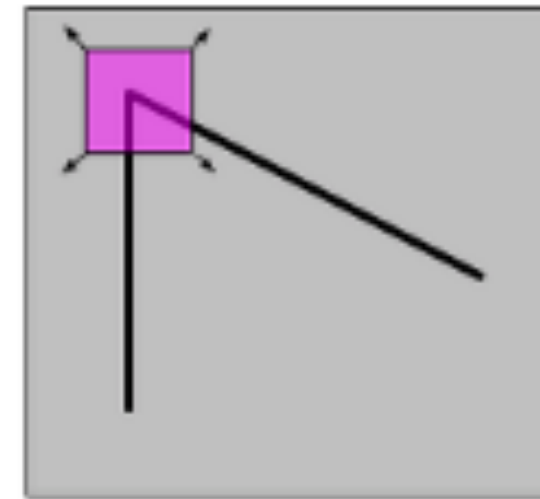
# 기초적인 이미지 분류



“flat” region:  
no change in all  
directions



“edge”:  
no change along the  
edge direction



“corner”:  
significant change in  
all directions

- 각 픽셀의 위치에 대해 윈도우를 수직, 수평, 좌대각선, 우대각선 이렇게 4개 방향으로 1픽셀씩 이동시켰을 때의 영상변화량(SSD)  $E$  를 계산한 후,  $E$ 의 최소값을 해당 픽셀의 영상 변화량 값으로 설정...

# 기초적인 이미지 분류

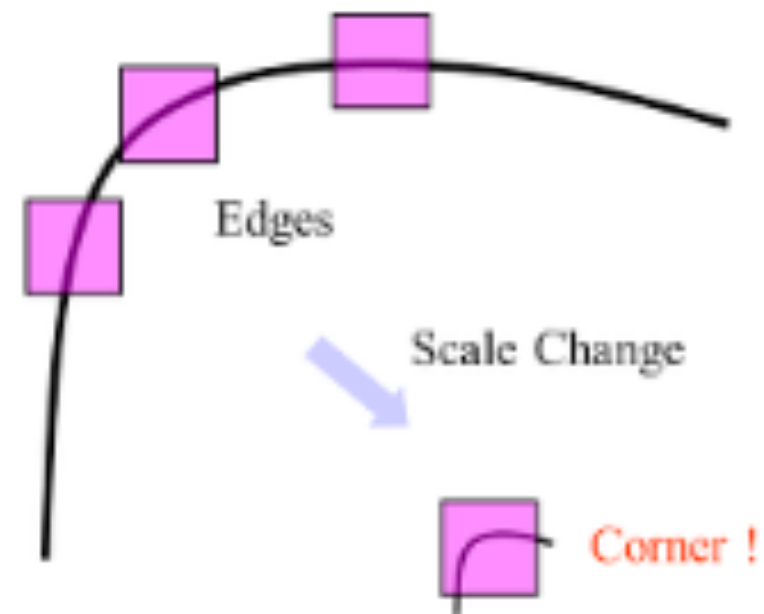
먼저,  $(\Delta x, \Delta y)$ 만큼 윈도우를 이동시켰을 때 영상의 SSD(sum of squared difference) 변화량  $E$ 는 다음과 같습니다 ( $W$ : 로컬 윈도우).

$$E(\Delta x, \Delta y) = \sum_W [I(x_i + \Delta x, y_i + \Delta y) - I(x_i, y_i)]^2 \quad \text{--- (1)}$$

이 때, shift값  $(\Delta x, \Delta y)$ 이 매우 작다고 가정하고 그레디언트(gradient)를 이용하여  $I$ 를 선형 근사하면 (1차 테일러 근사),

$$\begin{aligned} I(x_i + \Delta x, y_i + \Delta y) &\approx I(x_i, y_i) + [I_x(x_i, y_i) \ I_y(x_i, y_i)] \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \\ E(\Delta x, \Delta y) &= \sum_W [I(x_i + \Delta x, y_i + \Delta y) - I(x_i, y_i)]^2 \\ &\approx \sum_W [I(x_i, y_i) + [I_x(x_i, y_i) \ I_y(x_i, y_i)] \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} - I(x_i, y_i)]^2 \\ &= \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} \begin{bmatrix} \sum_W I_x(x_i, y_i)^2 & \sum_W I_x(x_i, y_i) I_y(x_i, y_i) \\ \sum_W I_x(x_i, y_i) I_y(x_i, y_i) & \sum_W I_y(x_i, y_i)^2 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \\ &= \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} M \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \quad \text{--- (2)} \end{aligned}$$

# 기초적인 이미지 분류



<그림 4> 출처: [Matching with Invariant Features](#), Lecture Notes 2004



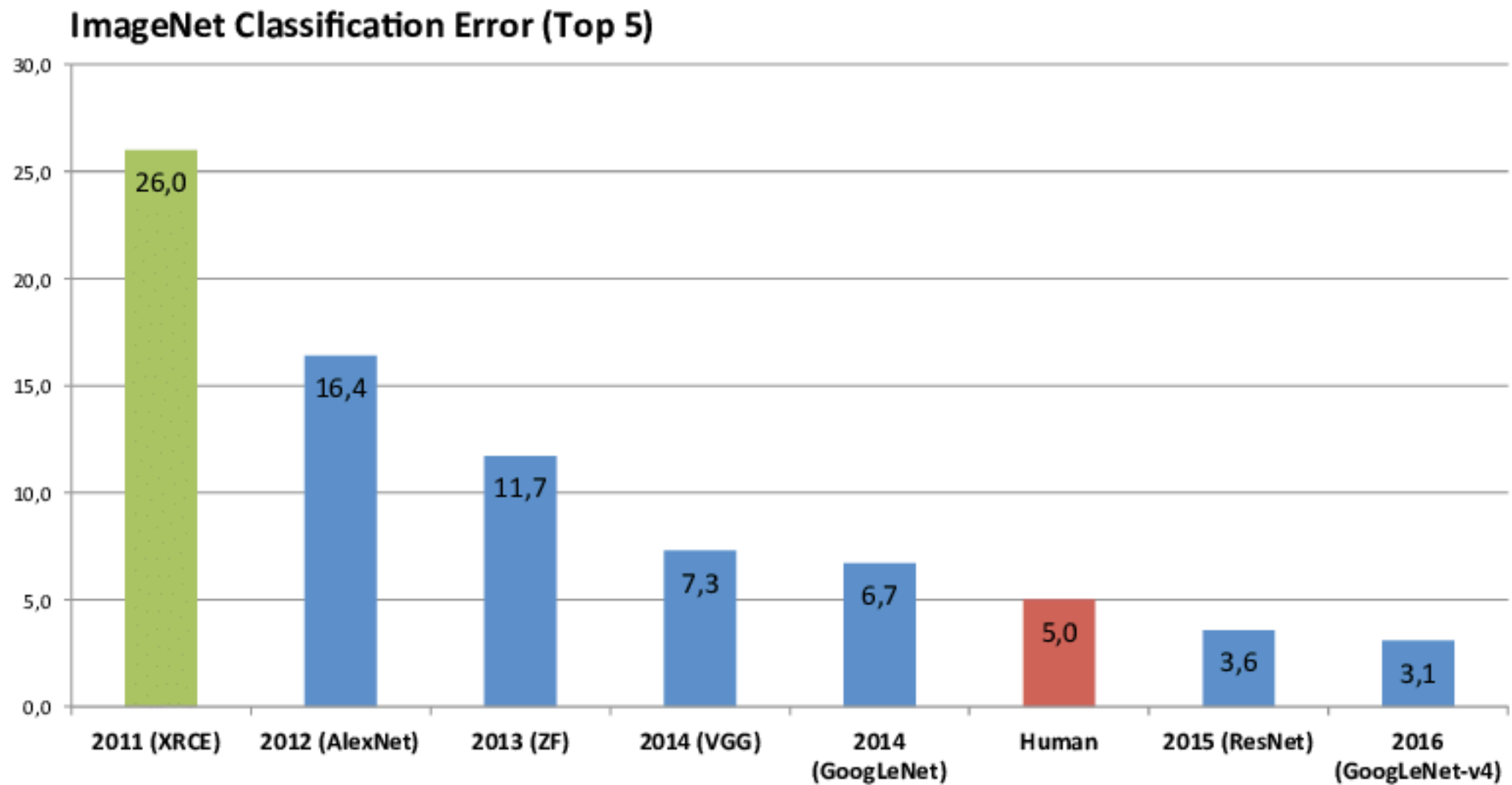
# 기초적인 이미지 분류

특징점을 수동으로 찾았음



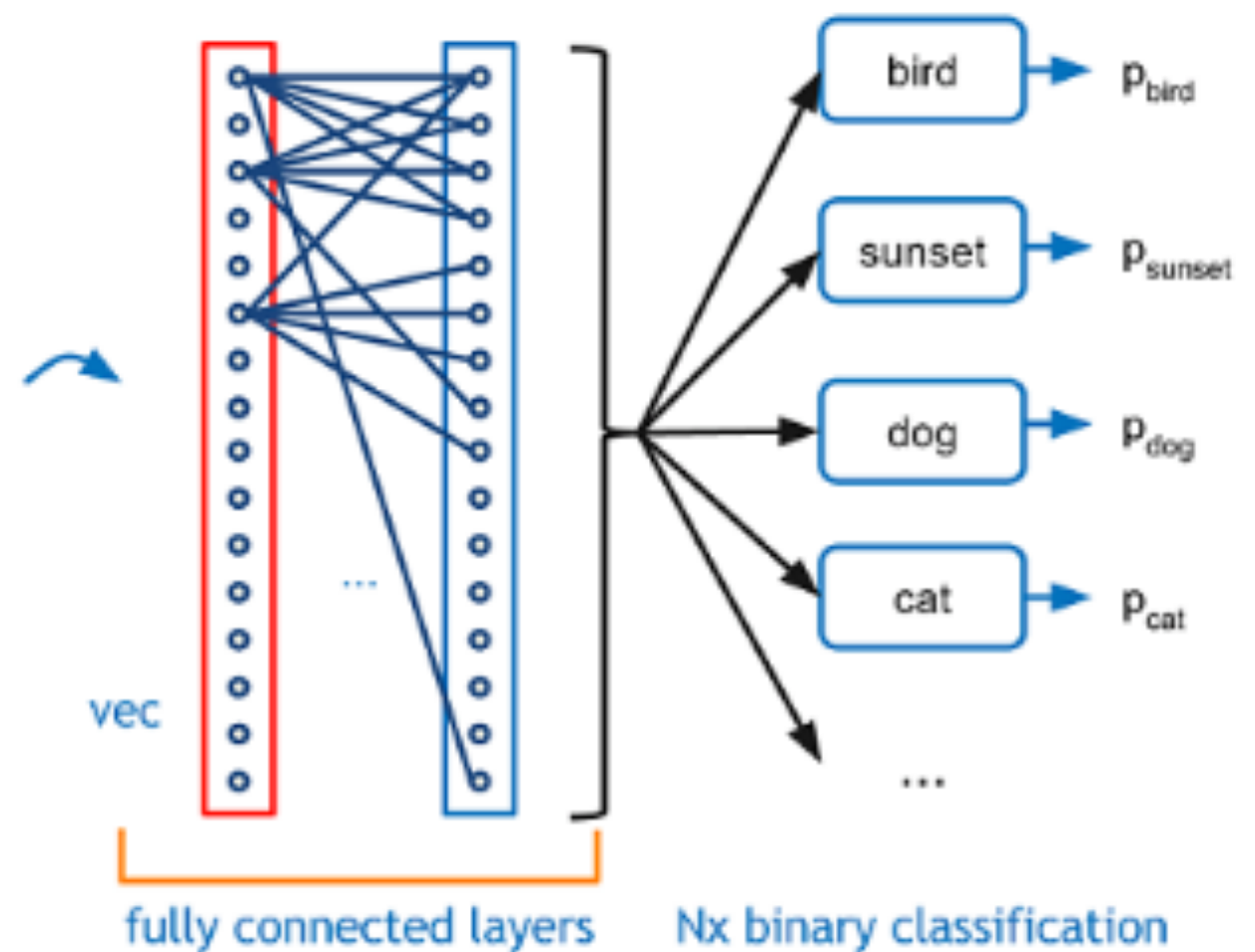
# 기초적인 이미지 분류

이런식의 분류가 오차율 26%



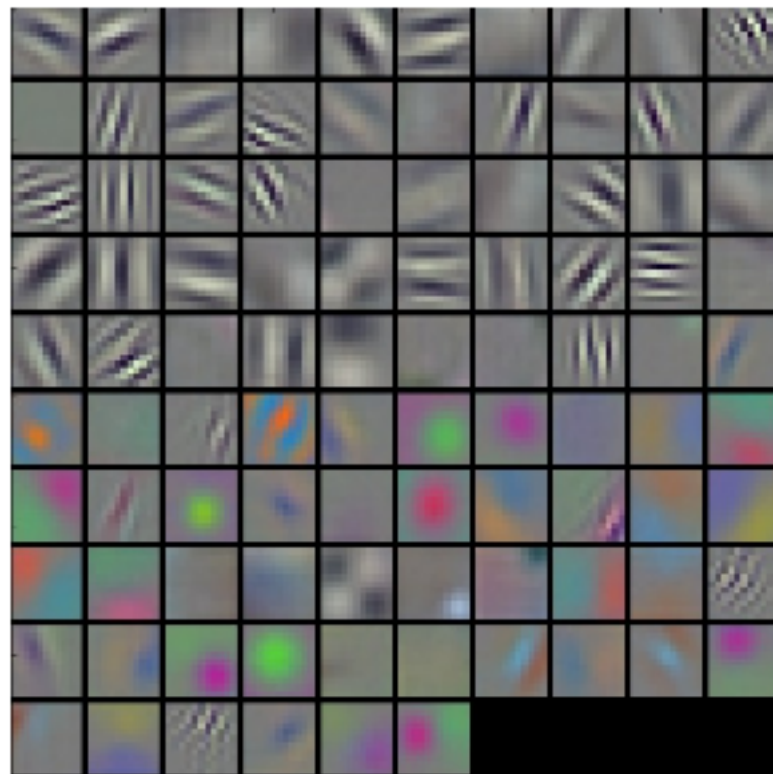
# Convolution neural network

스스로 특징점을 찾는 프로그램 CNN



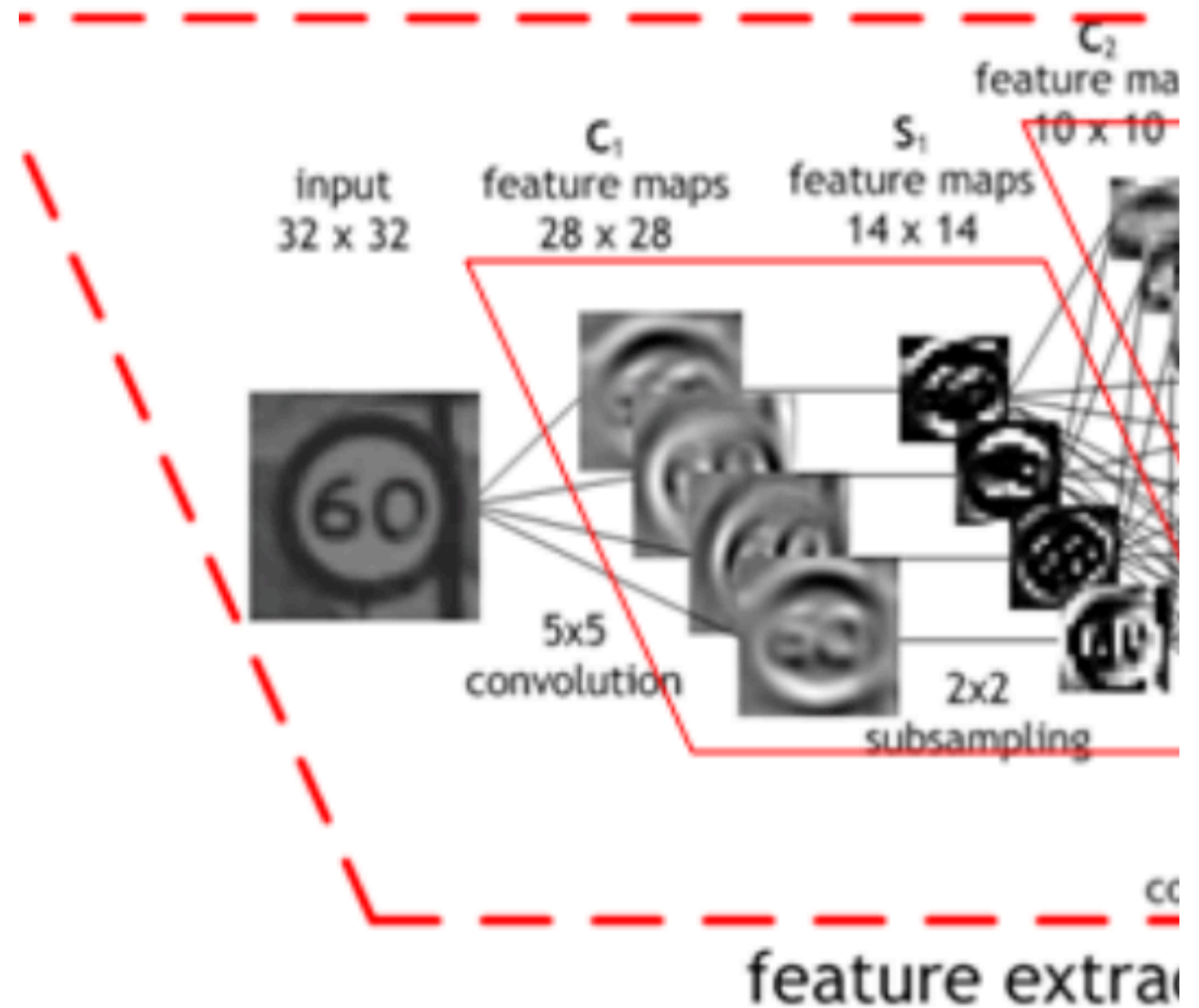
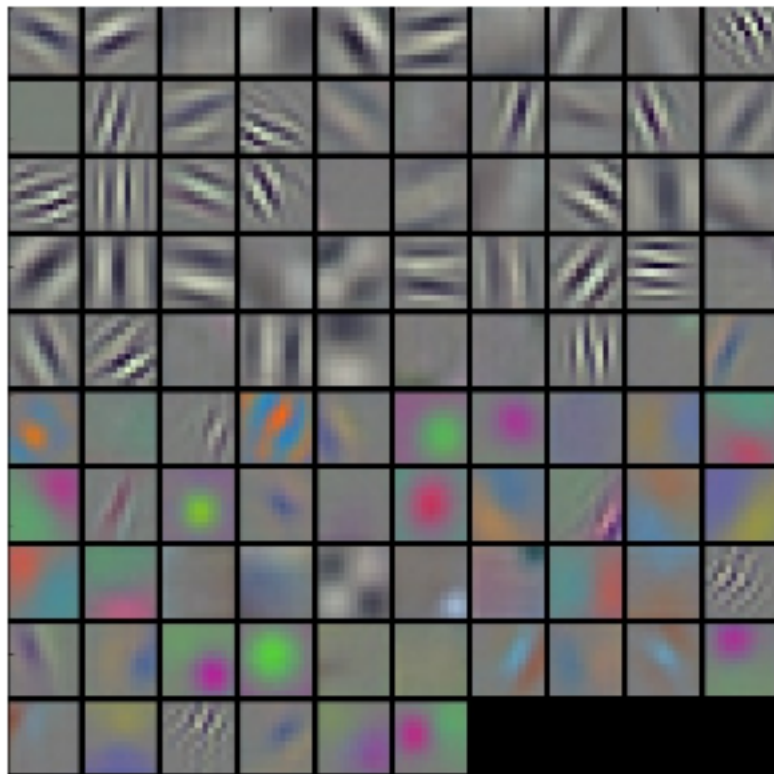
# Convolution neural network

스스로 특징점을 찾는 프로그램 CNN



# Convolution neural network

스스로 특징점을 찾는 프로그램 CNN

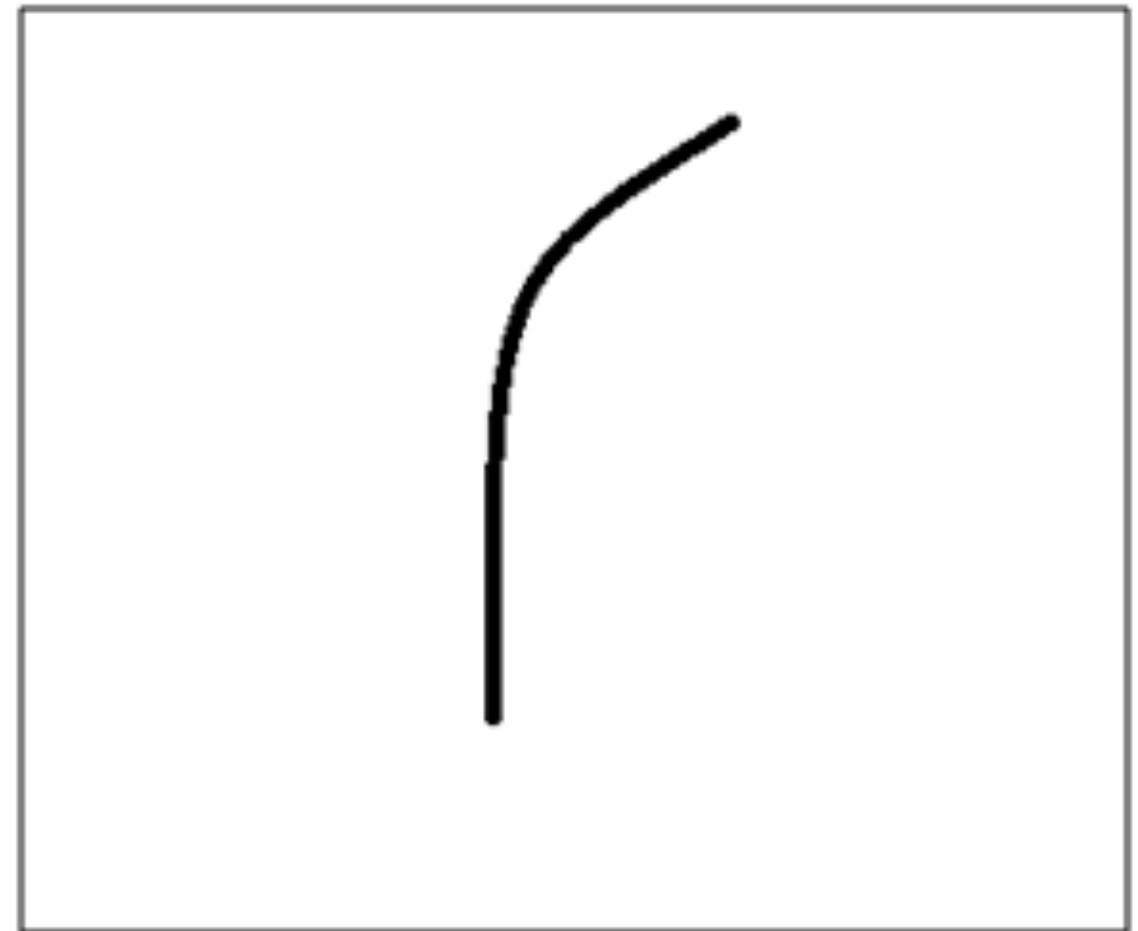


# Convolution neural network

스스로 특징점을 찾는 프로그램 CNN

|   |   |   |    |    |    |   |
|---|---|---|----|----|----|---|
| 0 | 0 | 0 | 0  | 0  | 30 | 0 |
| 0 | 0 | 0 | 0  | 30 | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 0  | 0  | 0  | 0 |

Pixel representation of filter



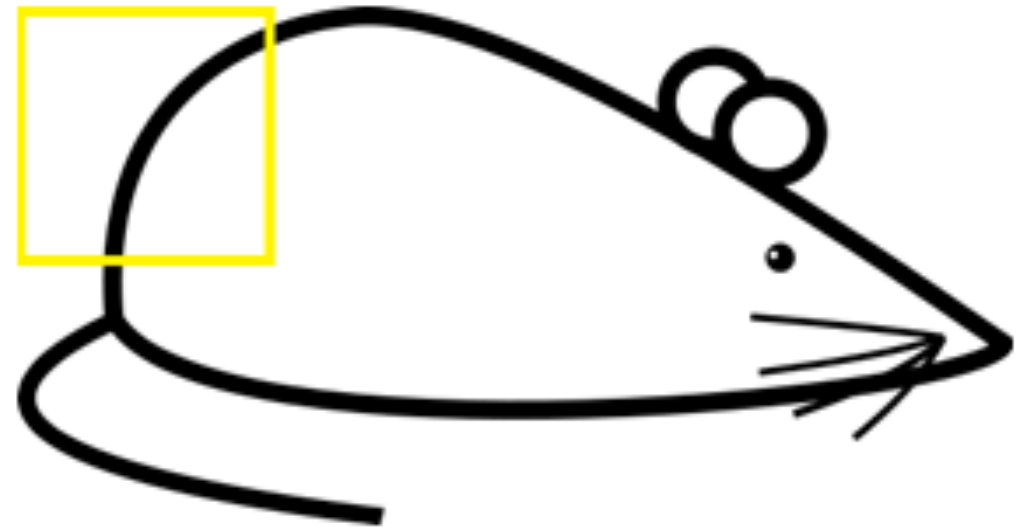
Visualization of a curve detector filter

# Convolution neural network

스스로 특징점을 찾는 프로그램 CNN



Original image



Visualization of the filter on the image

# Convolution neural network

스스로 특징점을 찾는 프로그램 CNN



Visualization of the receptive field

|   |   |   |    |    |    |    |
|---|---|---|----|----|----|----|
| 0 | 0 | 0 | 0  | 0  | 0  | 30 |
| 0 | 0 | 0 | 0  | 50 | 50 | 50 |
| 0 | 0 | 0 | 20 | 50 | 0  | 0  |
| 0 | 0 | 0 | 50 | 50 | 0  | 0  |
| 0 | 0 | 0 | 50 | 50 | 0  | 0  |
| 0 | 0 | 0 | 50 | 50 | 0  | 0  |
| 0 | 0 | 0 | 50 | 50 | 0  | 0  |

Pixel representation of the receptive field

\*

|   |   |   |    |    |    |   |
|---|---|---|----|----|----|---|
| 0 | 0 | 0 | 0  | 0  | 30 | 0 |
| 0 | 0 | 0 | 0  | 30 | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 0  | 0  | 0  | 0 |

Pixel representation of filter

Multiplication and Summation =  $(50*30)+(50*30)+(50*30)+(20*30)+(50*30) = 6600$  (A large number!)



# Convolution neural network

스스로 특징점을 찾는 프로그램 CNN



Visualization of the filter on the image

|    |    |    |    |   |   |   |
|----|----|----|----|---|---|---|
| 0  | 0  | 0  | 0  | 0 | 0 | 0 |
| 0  | 40 | 0  | 0  | 0 | 0 | 0 |
| 40 | 0  | 40 | 0  | 0 | 0 | 0 |
| 40 | 20 | 0  | 0  | 0 | 0 | 0 |
| 0  | 50 | 0  | 0  | 0 | 0 | 0 |
| 0  | 0  | 50 | 0  | 0 | 0 | 0 |
| 25 | 25 | 0  | 50 | 0 | 0 | 0 |

Pixel representation of receptive field

\*

|   |   |   |    |    |    |   |
|---|---|---|----|----|----|---|
| 0 | 0 | 0 | 0  | 0  | 30 | 0 |
| 0 | 0 | 0 | 0  | 30 | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 0  | 0  | 0  | 0 |

Pixel representation of filter

Multiplication and Summation = 0

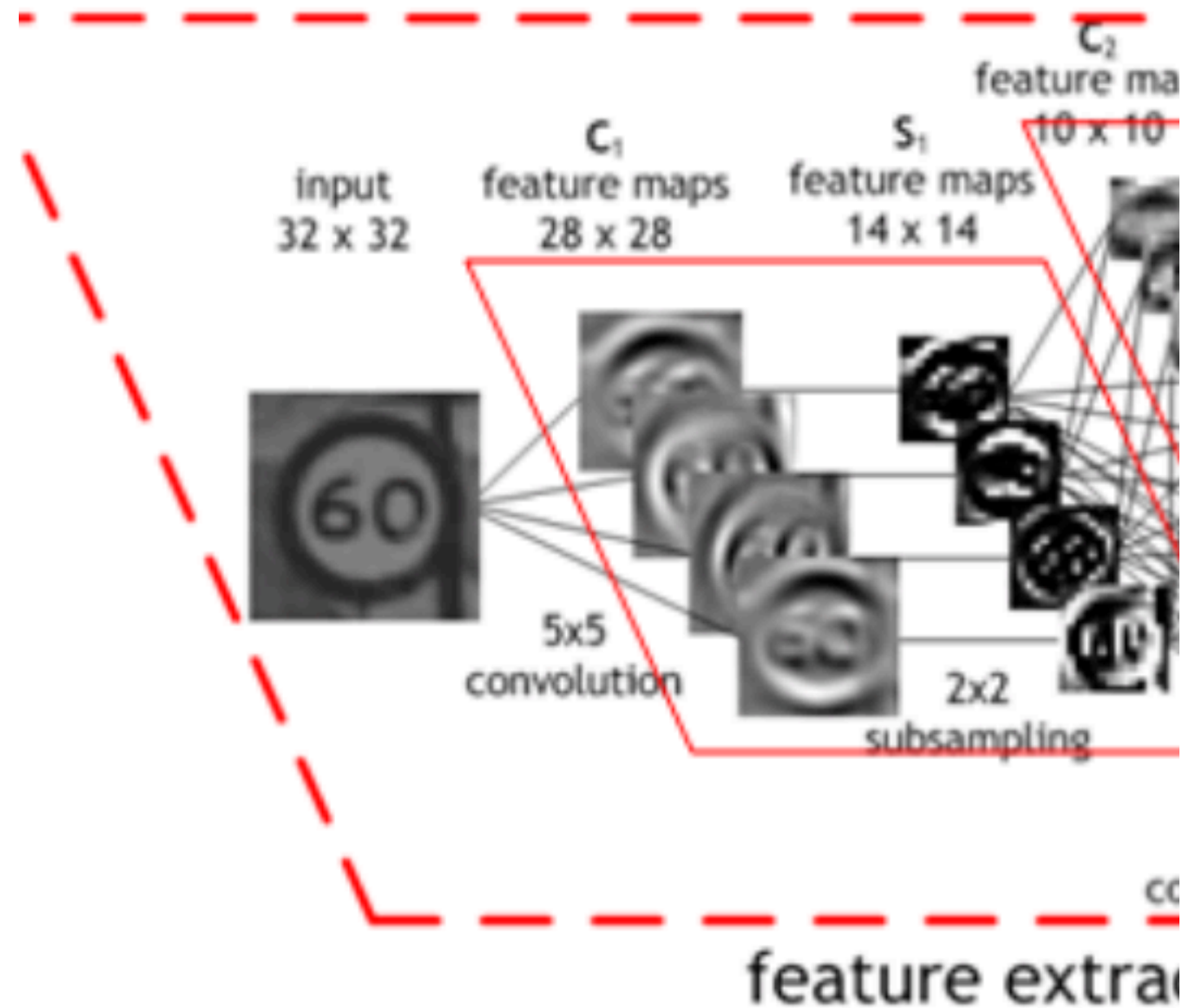
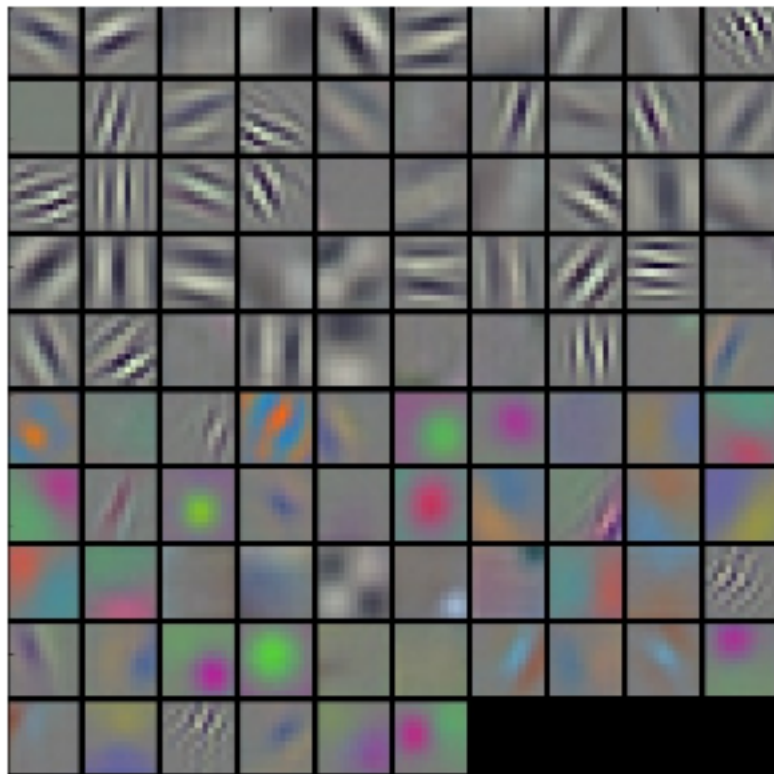
# Convolution neural network

스스로 특징점을 찾는 프로그램 CNN

<http://cs231n.github.io/convolutional-networks/>

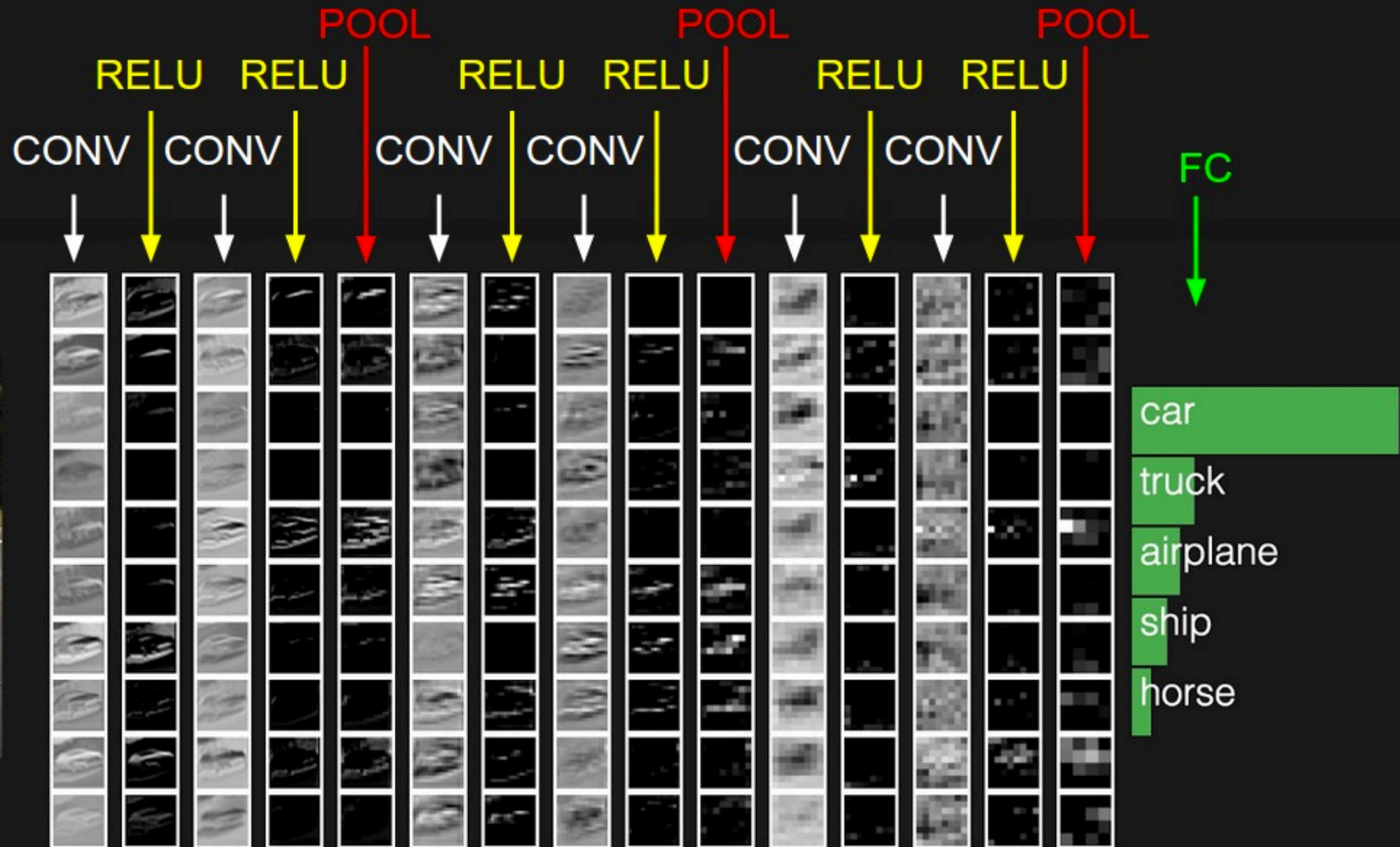
# Convolution neural network

스스로 특징점을 찾는 프로그램 CNN



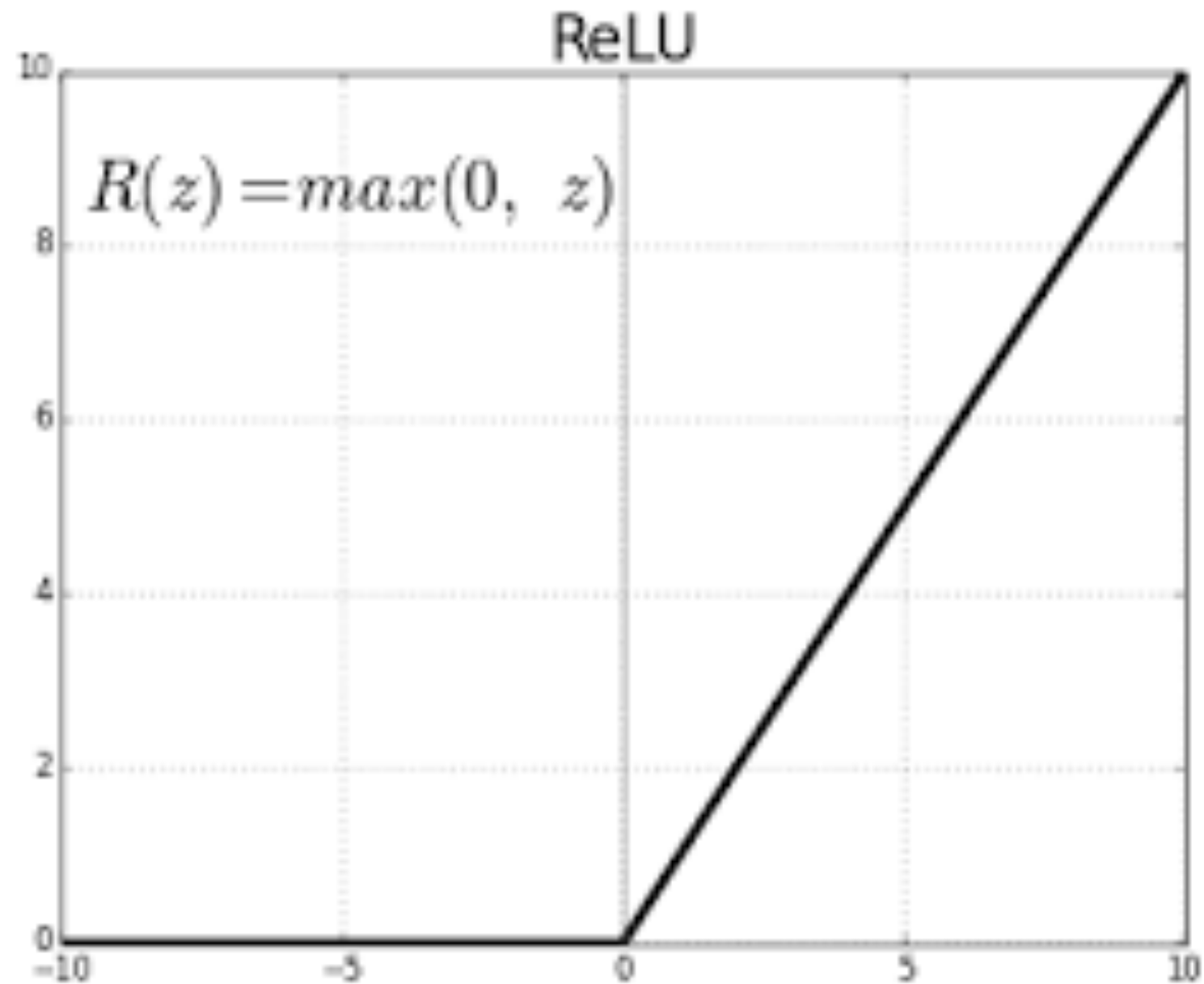
# Convolution neural network

스스로 특징점을 찾는 프로그램 CNN



# Convolution neural network

스스로 특징점을 찾는 프로그램 CNN



# Convolution neural network

- CNN의 핵심 Convolution Layer 있습니다.
- CNN에는 Convolution Layer 말고도 사용되는 계층
  1. Max Pooling Layer
  2. Flatten Layer

# Convolution neural network

## Max Poolin Layer

단순히 데이터의 사이즈를 줄여주는 것 뿐만 아니라,  
노이즈를 상쇄시킨다.

Single depth slice

|   |   |   |   |
|---|---|---|---|
| 1 | 1 | 2 | 4 |
| 5 | 6 | 7 | 8 |
| 3 | 2 | 1 | 0 |
| 1 | 2 | 3 | 4 |

max pool with 2x2 filters  
and stride 2



|   |   |
|---|---|
| 6 | 8 |
| 3 | 4 |

# Convolution neural network

Flatton Layer

2차원을 1차원으로

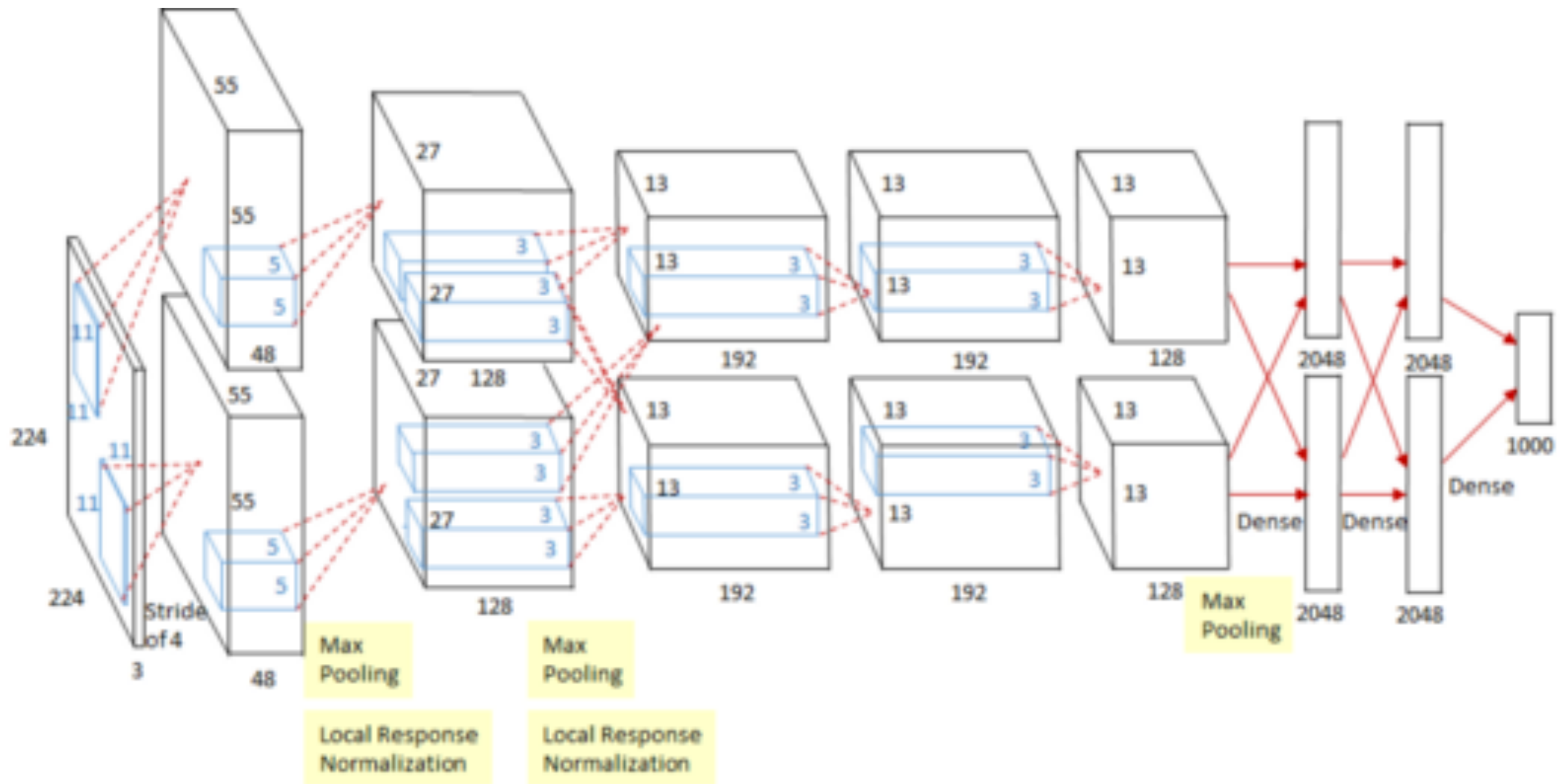
|    |    |    |
|----|----|----|
| 1  | 24 | 9  |
| 4  | 11 | 52 |
| 54 | 32 | 15 |

|    |
|----|
| 1  |
| 24 |
| 9  |
| 4  |

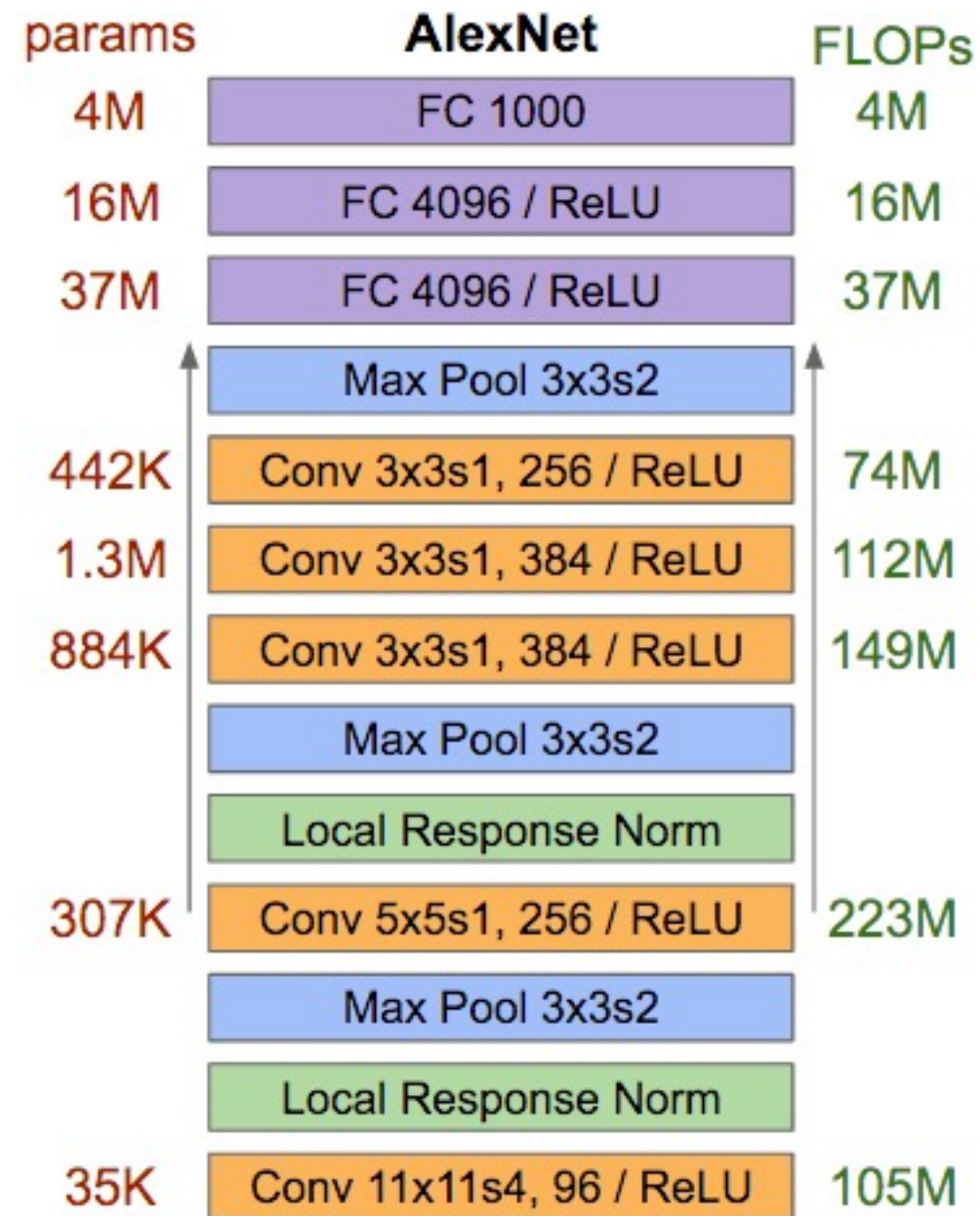
....



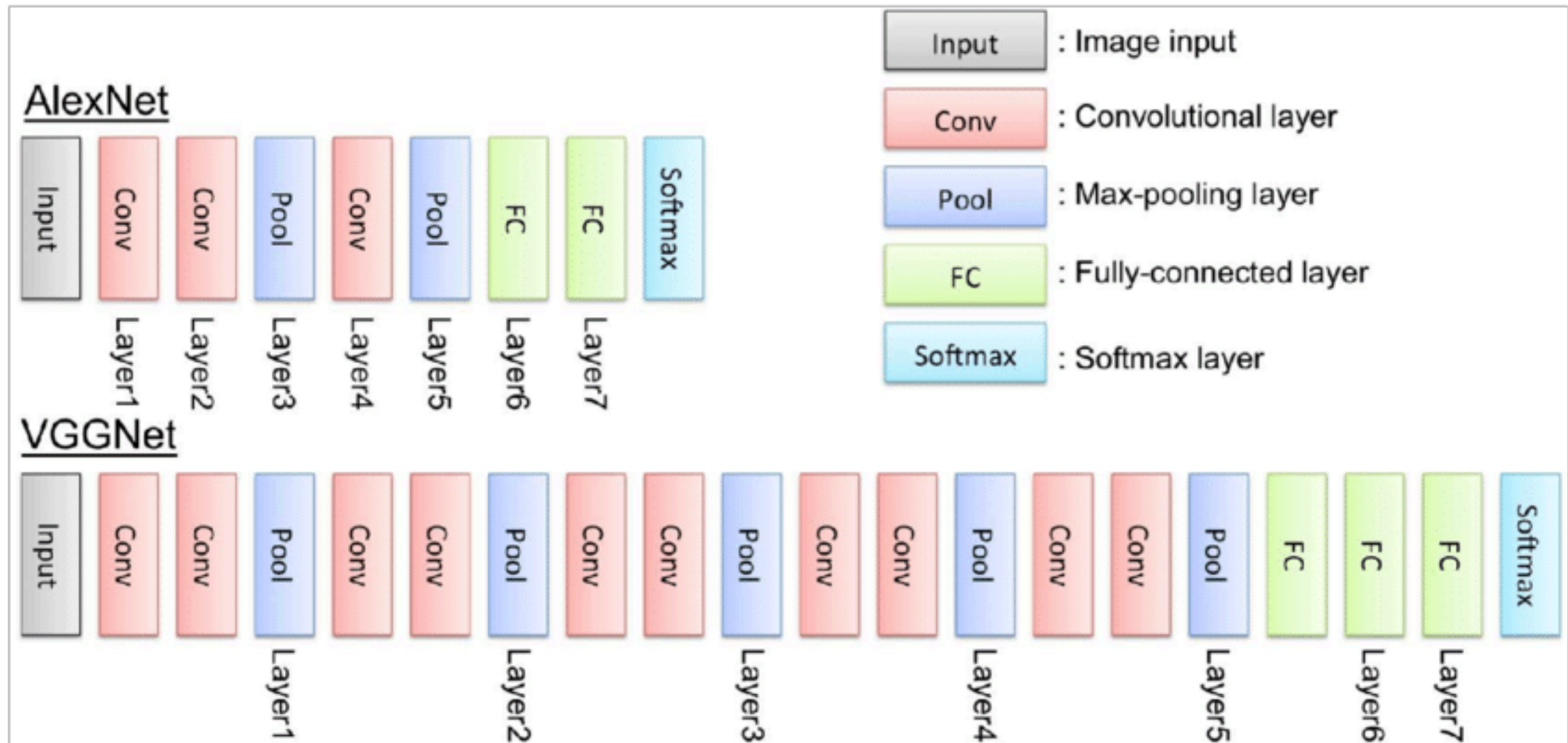
# Convolution neural network



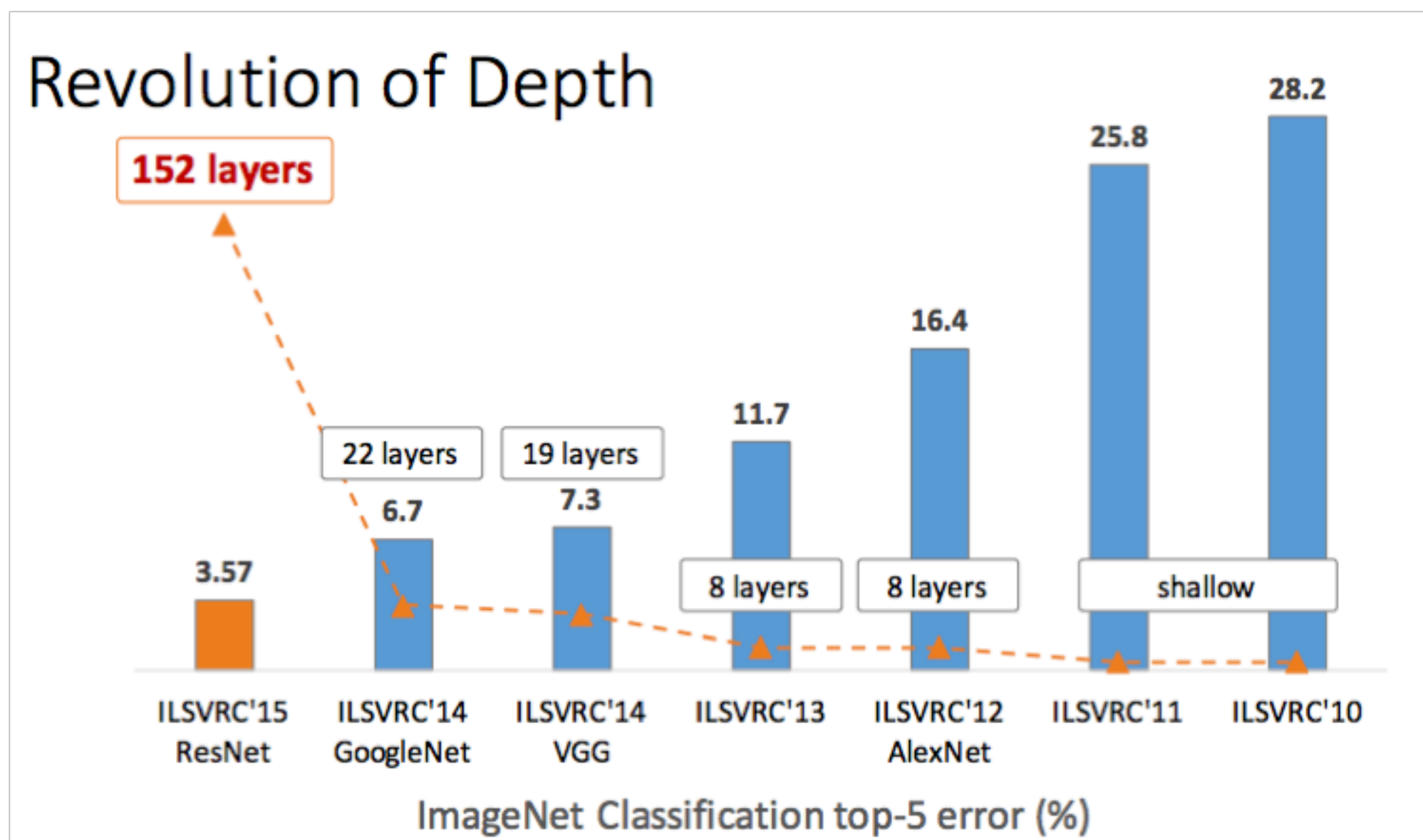
# Convolution neural network



# Convolution neural network



# Convolution neural network



# Convolution neural network

Triangle002.png



rectangle005.png



# 실습

```
conda install -c anaconda pillow
```

# 실습

```
import numpy as np  
from keras.models import Sequential  
from keras.layers import Dense  
from keras.layers import Flatten  
from keras.layers.convolutional import Conv2D  
from keras.layers.convolutional import MaxPooling2D  
from keras.preprocessing.image import ImageDataGenerator
```

# 실습

```
train_datagen = ImageDataGenerator(rescale=1./255)
```

```
train_generator = train_datagen.flow_from_directory(  
    './dataset/shape/train',  
    target_size=(24, 24),  
    batch_size=3,  
    class_mode='categorical')
```

```
test_datagen = ImageDataGenerator(rescale=1./255)
```

```
test_generator = test_datagen.flow_from_directory(  
    './dataset/shape/test',  
    target_size=(24, 24),  
    batch_size=3,  
    class_mode='categorical')
```



# 실습

```
model = Sequential()  
model.add(Conv2D(32, kernel_size=(3, 3),  
                activation='relu',  
                input_shape=(24,24,3)))  
model.add(Conv2D(64, (3, 3), activation='relu'))  
model.add(MaxPooling2D(pool_size=(2, 2)))  
model.add(Flatten())  
model.add(Dense(128, activation='relu'))  
model.add(Dense(3, activation='softmax'))
```

실습

```
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

# 실습

```
model.fit_generator(  
    train_generator,  
    steps_per_epoch=15,  
    epochs=50,  
    validation_data=test_generator,  
    validation_steps=5)
```

# 실습

```
print("-- Evaluate --")  
scores = model.evaluate_generator(test_generator, steps=5)  
print("%s: %.2f%%" %(model.metrics_names[1], scores[1]*100))
```

실습

```
print("-- Predict --")  
output = model.predict_generator(test_generator, steps=5)  
np.set_printoptions(formatter={'float': lambda x: "{0:0.3f}".format(x)})  
print(test_generator.class_indices)  
print(output)
```

# 실습

자기가 그린 도형과 좀 더 다르게 그림을 그려서 테스트한다면?

실습

과적합.

실습

# MNist





# 실습

```
# 영상 => 다중분류 컨볼루션  
# 0. 사용할 패키지 불러오기  
import numpy as np  
from keras.utils import np_utils  
from keras.datasets import mnist  
from keras.models import Sequential  
from keras.layers import Dense, Activation  
from keras.layers import Conv2D, MaxPooling2D, Flatten  
  
width = 28  
height = 28
```

# 실습

```
# 1. 데이터셋 생성하기
|
# 훈련셋과 시험셋 불러오기
(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train = x_train.reshape(60000, width, height, 1).astype('float32') / 255.0
x_test = x_test.reshape(10000, width, height, 1).astype('float32') / 255.0

# 훈련셋과 검증셋 분리
x_val = x_train[50000:]
y_val = y_train[50000:]
x_train = x_train[:50000]
y_train = y_train[:50000]

# 데이터셋 전처리 : one-hot 인코딩
y_train = np_utils.to_categorical(y_train)
y_val = np_utils.to_categorical(y_val)
y_test = np_utils.to_categorical(y_test)
```

# 실습

## # 2. 모델 구성하기

```
model = Sequential()  
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(width, height, 1)))  
model.add(MaxPooling2D(pool_size=(2, 2)))  
model.add(Conv2D(32, (3, 3), activation='relu'))  
model.add(MaxPooling2D(pool_size=(2, 2)))  
model.add(Flatten())  
model.add(Dense(256, activation='relu'))  
model.add(Dense(10, activation='softmax'))
```

# 실습

# 3. 모델 학습과정 설정하기

```
model.compile(loss='categorical_crossentropy', optimizer='sgd', metrics=['accuracy'])
```

# 4. 모델 학습시키기

```
hist = model.fit(x_train, y_train, epochs=3, batch_size=32, validation_data=(x_val, y_val))
```

# 5. 학습과정 살펴보기

```
%matplotlib inline
```

```
import matplotlib.pyplot as plt
```

```
fig, loss_ax = plt.subplots()
```

```
acc_ax = loss_ax.twinx()
```

```
loss_ax.plot(hist.history['loss'], 'y', label='train loss')
```

```
loss_ax.plot(hist.history['val_loss'], 'r', label='val loss')
```

```
loss_ax.set_ylim([0.0, 0.5])
```

```
acc_ax.plot(hist.history['acc'], 'b', label='train acc')
```

```
acc_ax.plot(hist.history['val_acc'], 'g', label='val acc')
```

```
acc_ax.set_ylim([0.8, 1.0])
```

```
loss_ax.set_xlabel('epoch')
```

```
loss_ax.set_ylabel('loss')
```

```
acc_ax.set_ylabel('accuracy')
```

```
loss_ax.legend(loc='upper left')
```

```
acc_ax.legend(loc='lower left')
```

```
plt.show()
```

# 실습

# 6. 모델 평가하기

```
loss_and_metrics = model.evaluate(x_test, y_test, batch_size=32)
print('## evaluation loss and_metrics ##')
print(loss_and_metrics)
```

# 7. 모델 사용하기

```
yhat_test = model.predict(x_test, batch_size=32)
```

```
# 7. 모델 사용하기
```

```
yhat_test = model.predict(x_test, batch_size=32)
```

```
%matplotlib inline
```

```
import matplotlib.pyplot as plt
```

```
plt_row = 5
```

```
plt_col = 5
```

```
plt.rcParams["figure.figsize"] = (10,10)
```

```
f, axarr = plt.subplots(plt_row, plt_col)
```

```
cnt = 0
```

```
i = 0
```

```
while cnt < (plt_row*plt_col):
```

```
    if np.argmax(y_test[i]) == np.argmax(yhat_test[i]):
```

```
        i += 1
```

```
        continue
```

```
    sub_plt = axarr[int(cnt/plt_row), int(cnt%plt_col)]
```

```
    sub_plt.axis('off')
```

```
    sub_plt.imshow(x_test[i].reshape(width, height))
```

```
    sub_plt_title = 'R: ' + str(np.argmax(y_test[i])) + ' P: ' + str(np.argmax(yhat_test[i]))
```

```
    sub_plt.set_title(sub_plt_title)
```

```
    i += 1
```

```
    cnt += 1
```

```
plt.show()
```