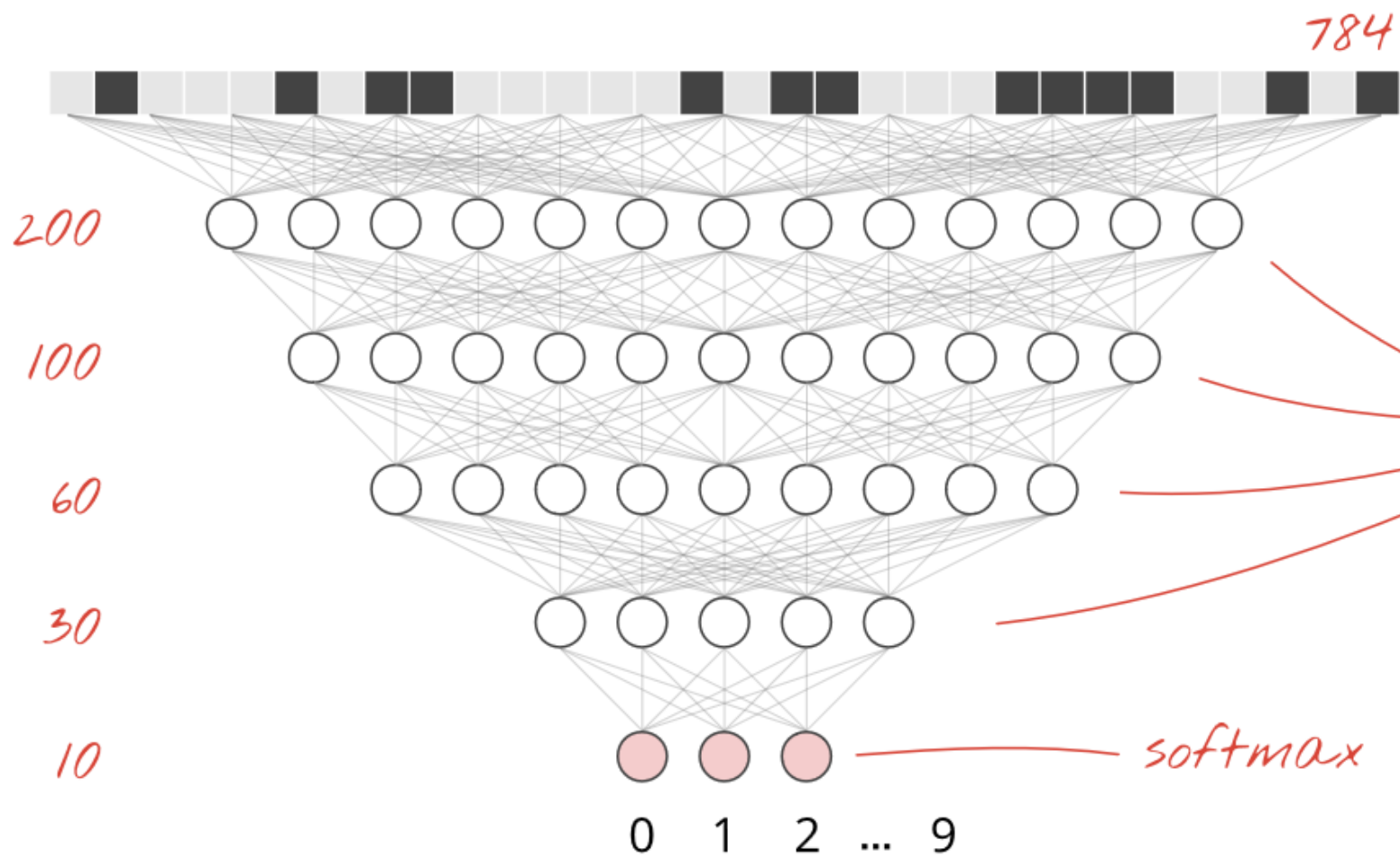




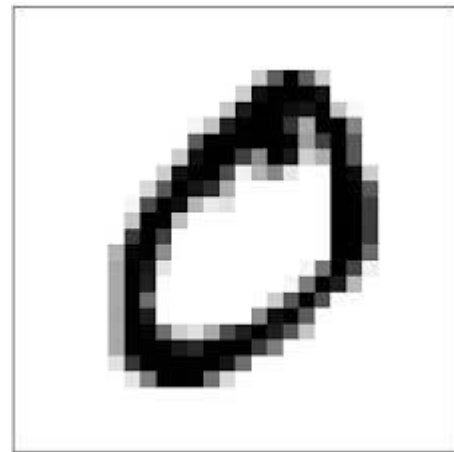
# CONVOLUTION NEURAL NETWORK

# Review Prev Lab

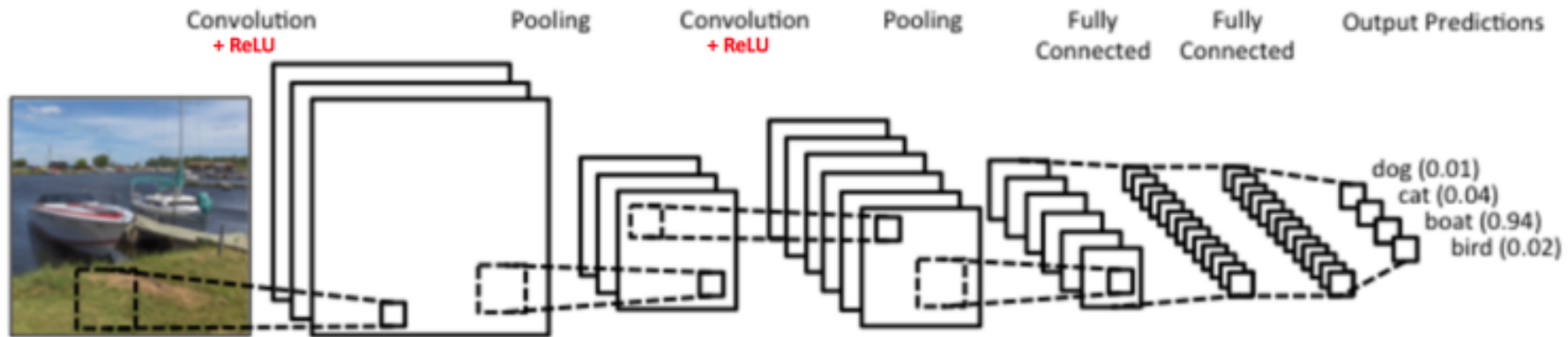
- We add 4 hidden layers.
- We change from sigmoid to ReLU
- But we didn't gain more accuracy as expected.
- Why ?
  - code errors or bugs?
  - machine mistake?
  - Take a look closer, what happen.



ReLU



# CONVOLUTION NEURAL NETWORK



Wait!, Let's learn some basic background

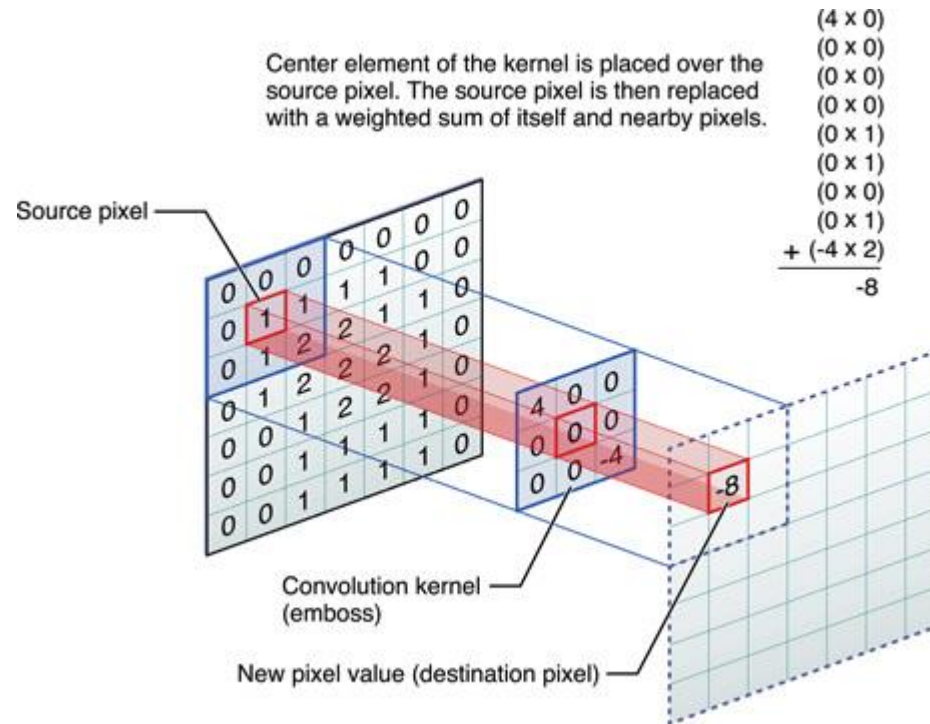


# What's convolutions



In Photoshop dose anyone try Image Effect before?  
Yes! that is some case of Convolution

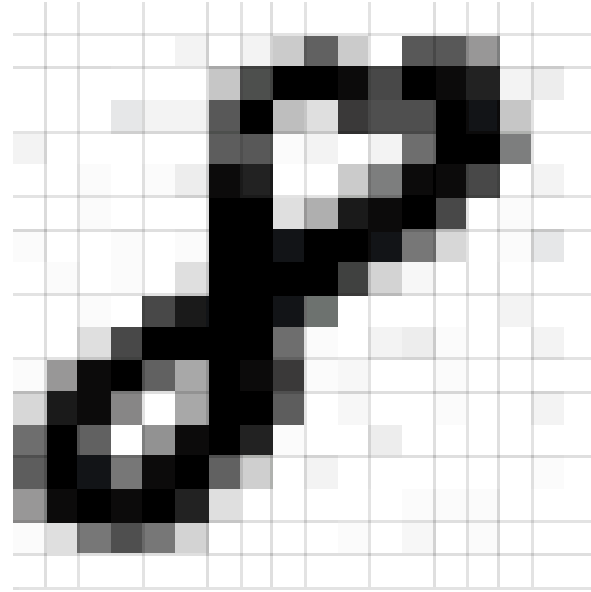
# How convolution work



$$f(x) * g(x) = \int_{-\infty}^{\infty} f(\tau) \cdot g(x - \tau) d\tau$$

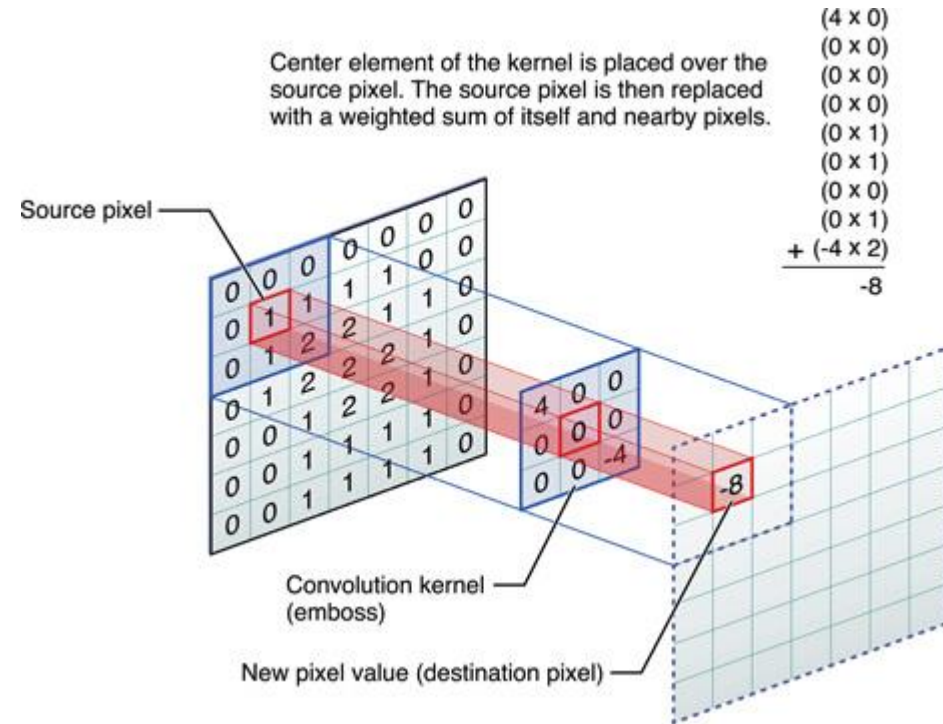


# How convolution work



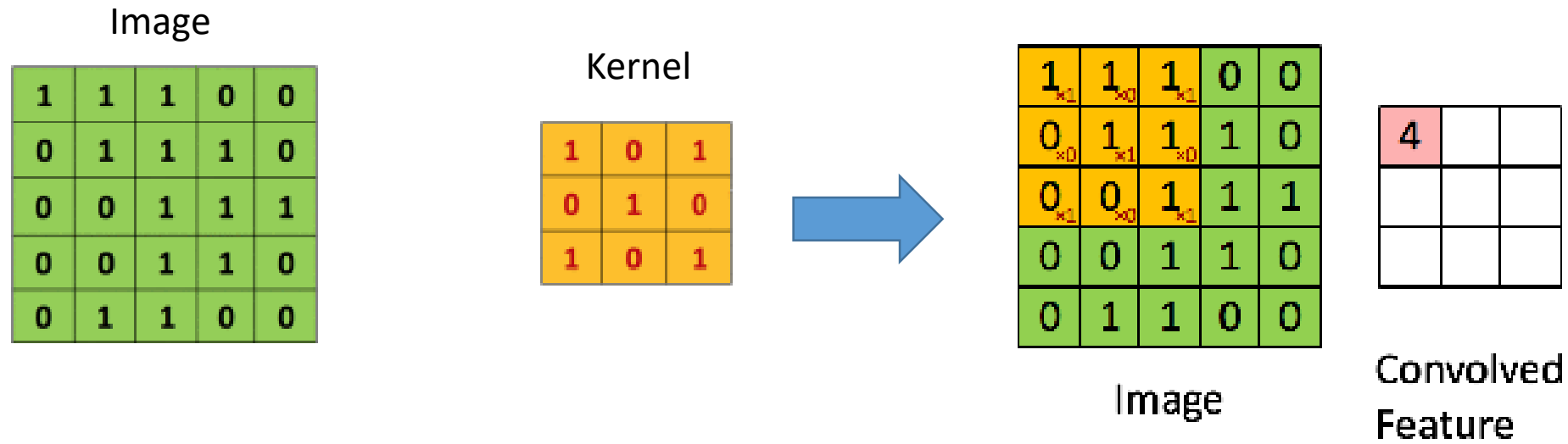
We has an images and represent as matrix of pixel

# How convolution work





# How convolution work



# How convolution work



Example of same input image  
but difference kernel

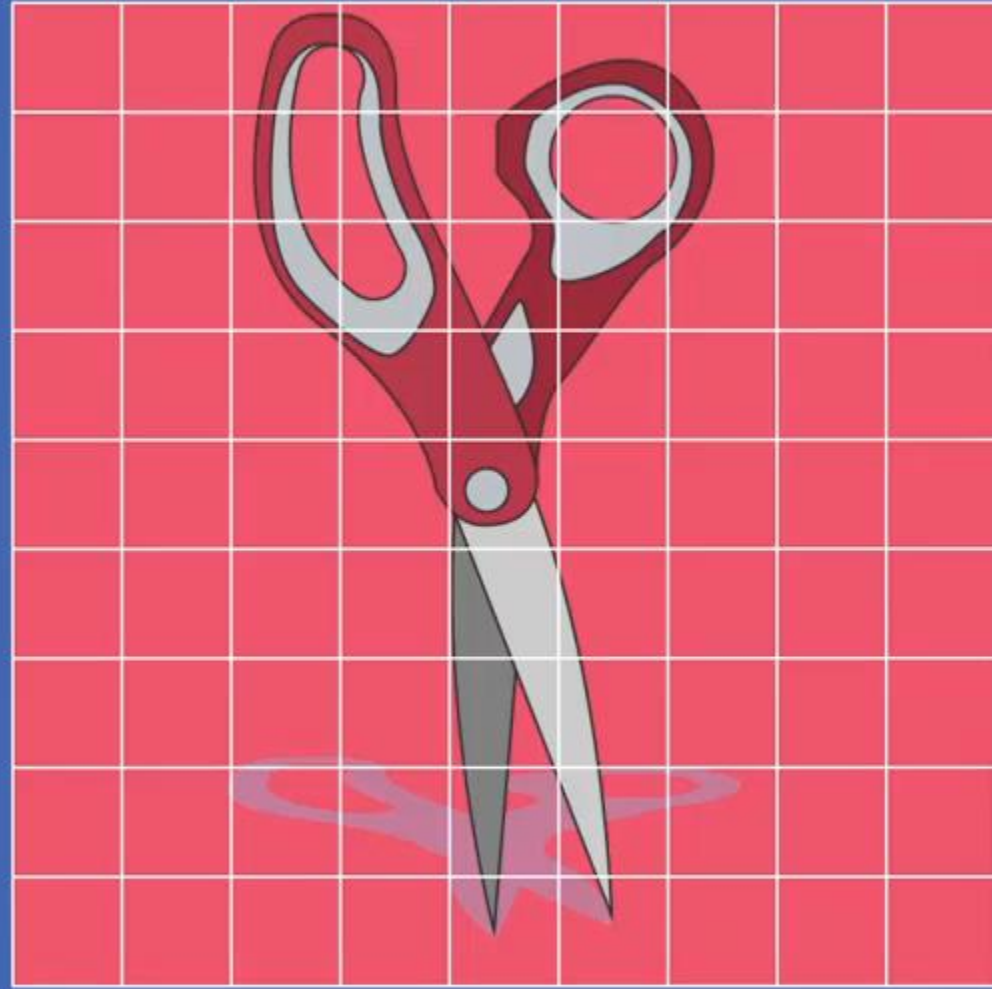
Operation	Filter	Convolved Image
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur (approximation)	$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

# How convolution has been involved



Kernel presented as weight, if we update it to find proper filter  
Extract features from image before training it, that can increase accuracy

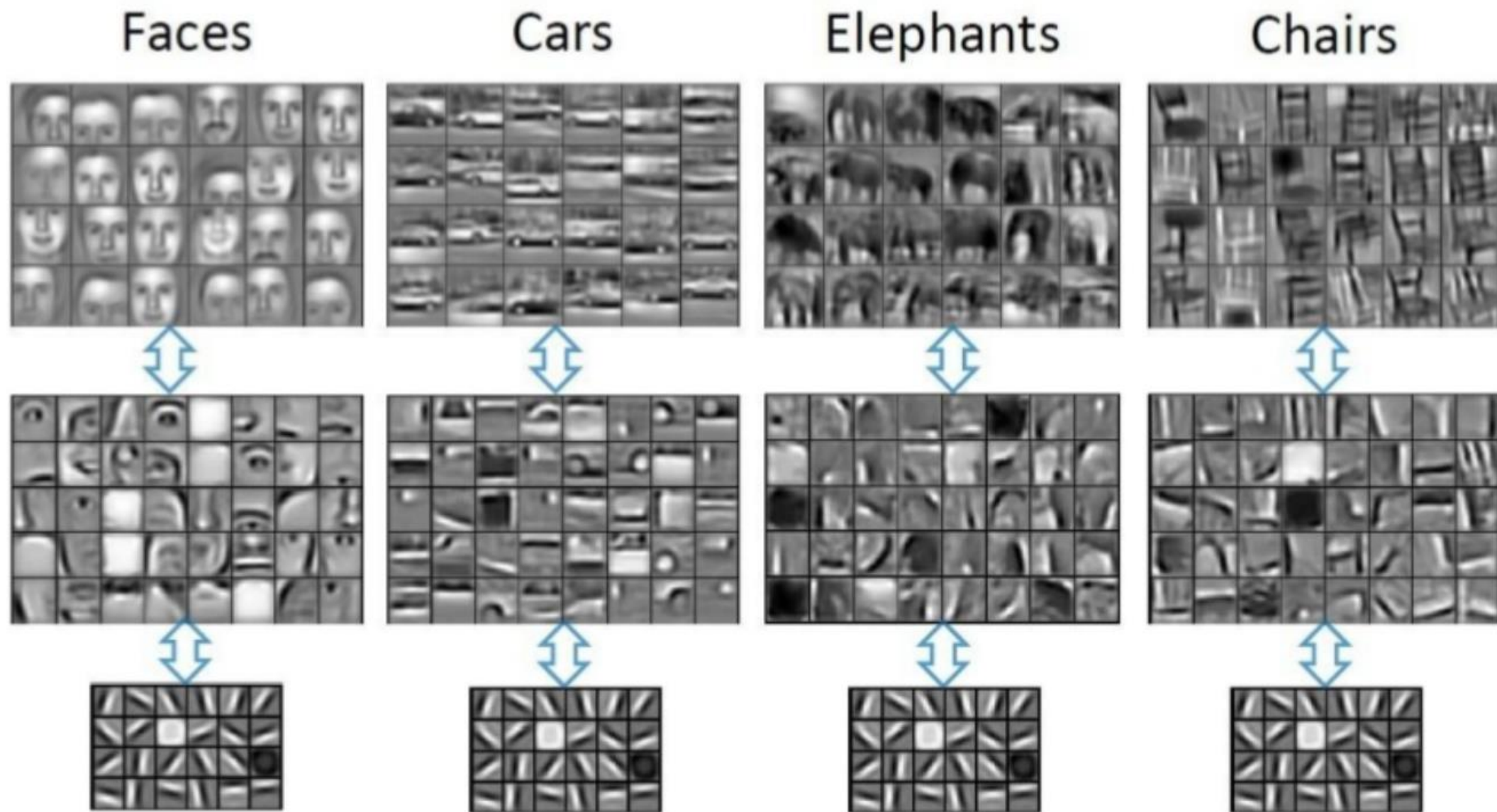








# Hierarchical Feature Learning



0123456789

Output  
Layer

FC  
Layer 2

FC  
Layer 1

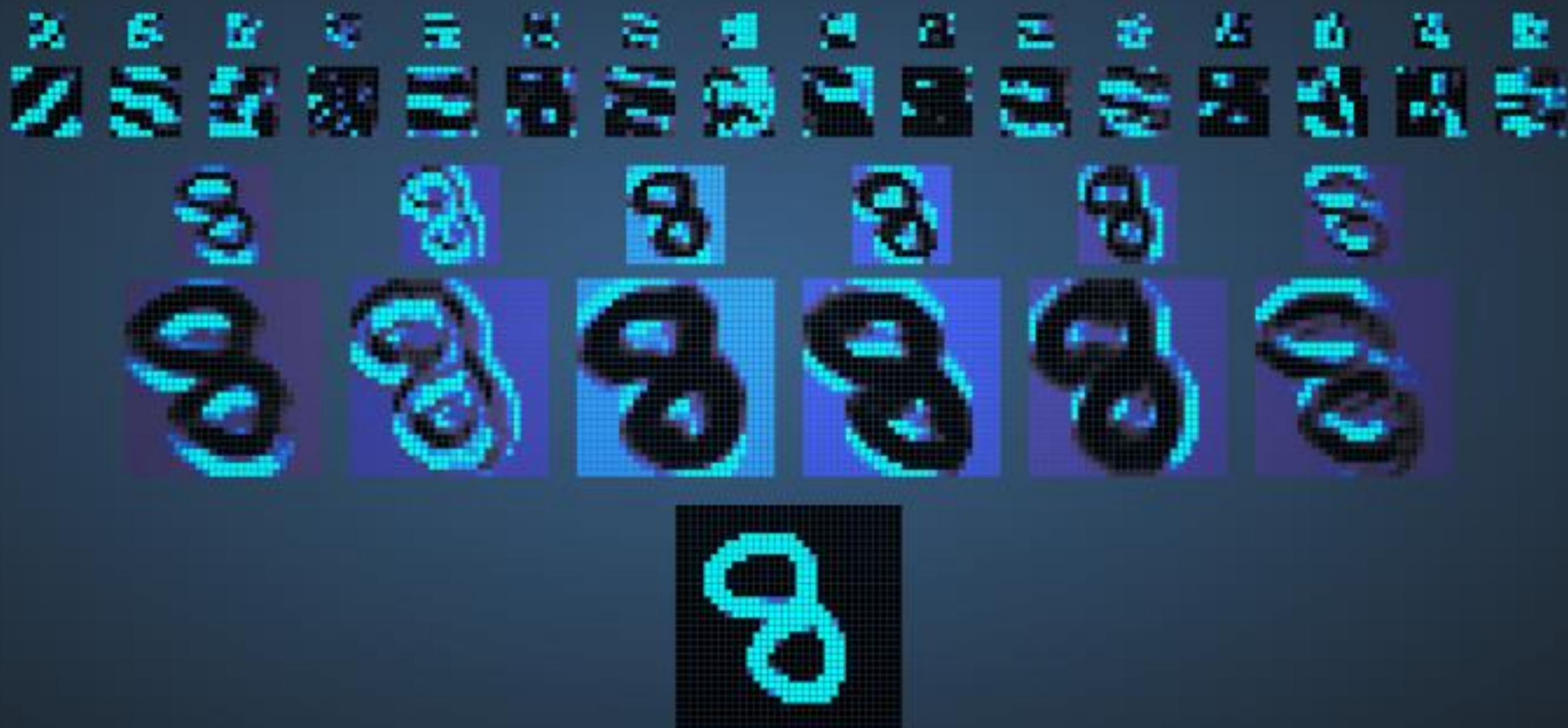
Pooling  
Layer 2

Convolution  
Layer 2

Pooling  
Layer 1

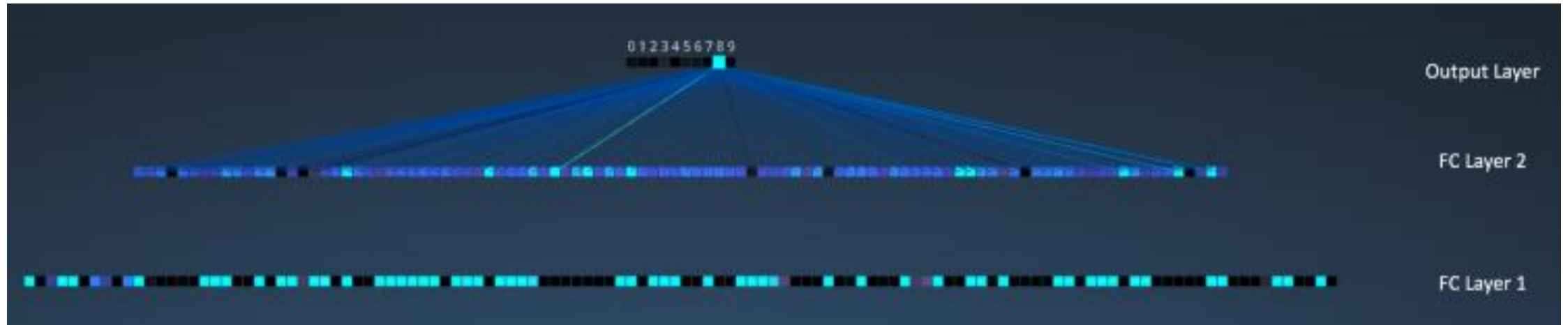
Convolution  
Layer 1

Input Layer



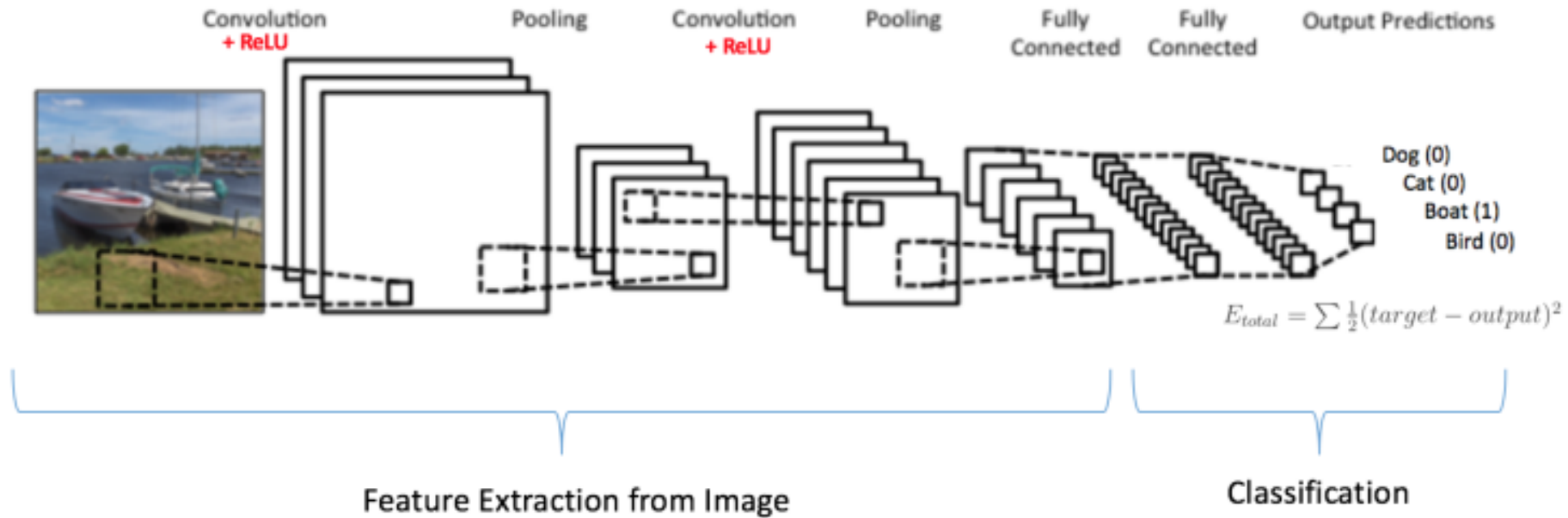


# How convolution has been involved



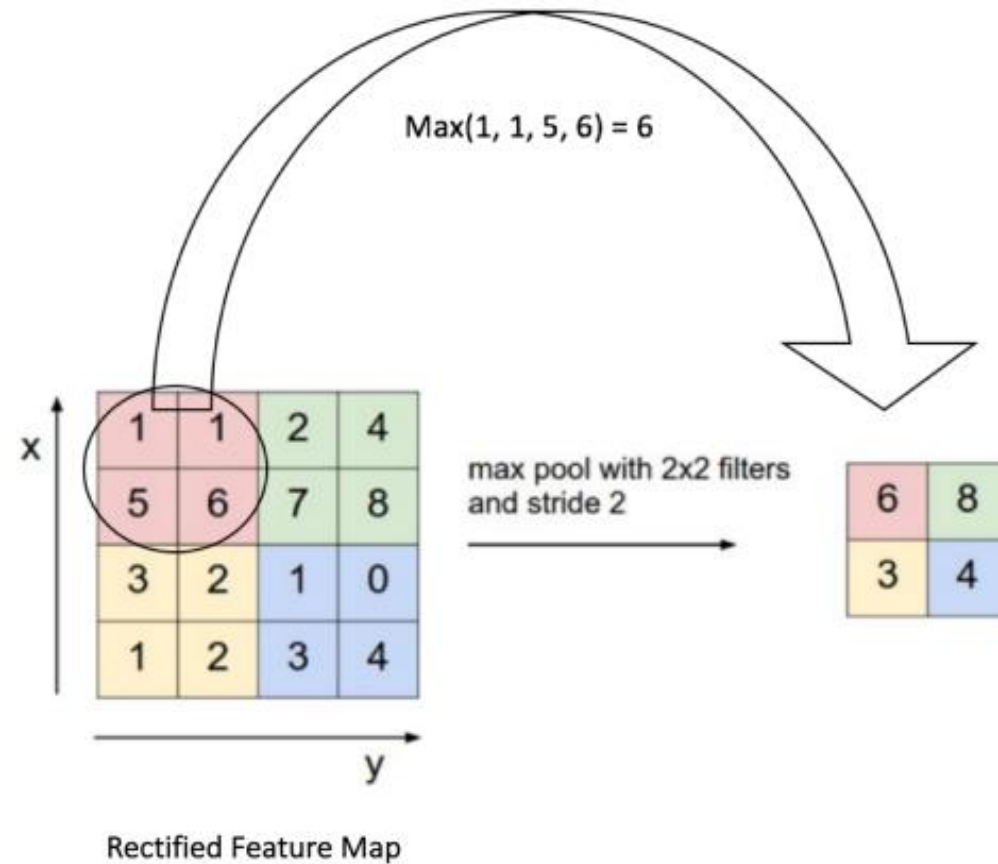
At the end we use fully connected (MLP)

# CONVOLUTION NEURAL NETWORK



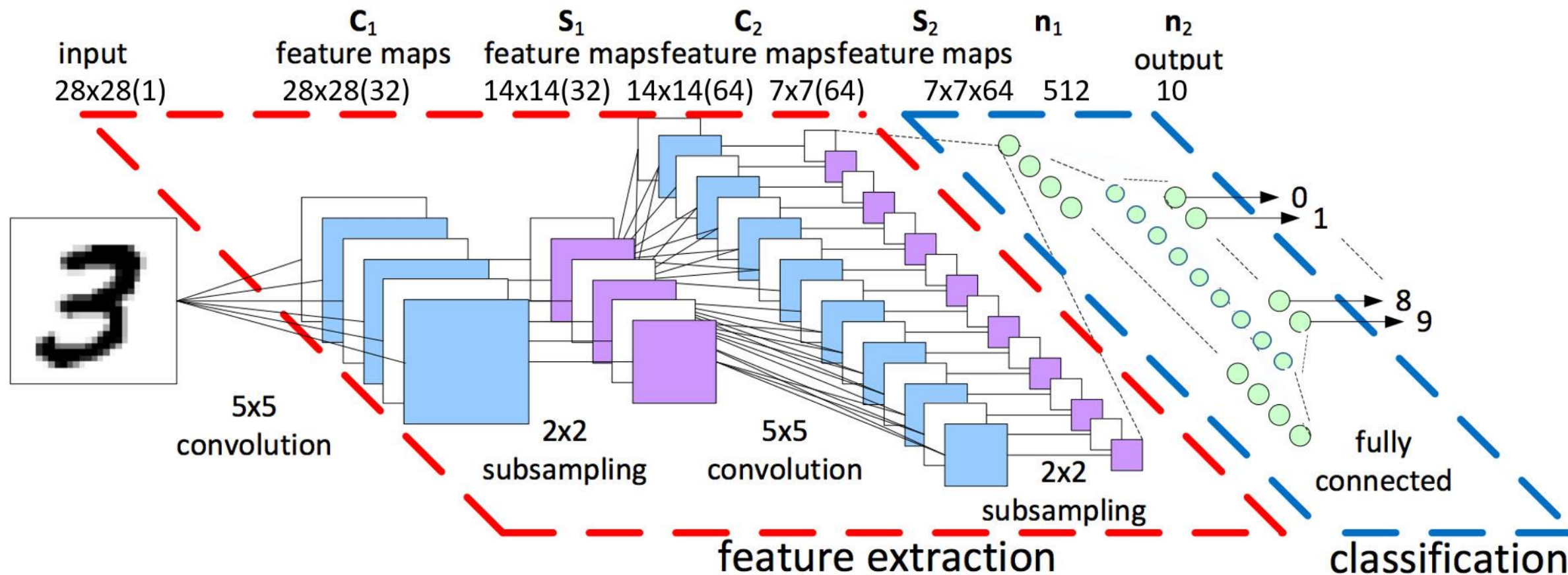


# Max pooling



- makes the input representations (feature dimension) smaller and more manageable
- reduces the number of parameters and computations in the network
- makes the network invariant to small transformations, distortions and translations in the input image (a small distortion in input will not change the output of Pooling – since we take the maximum / average value in a local neighborhood).
- helps us arrive at an almost scale invariant representation of our image (the exact term is “equivariant”). This is very powerful since we can detect objects in an image no matter where they are located.

# Max pooling



Input image 28x28 (ขาวดำ 1 มิติ)

```
1 X = tf.placeholder(tf.float32, [None, 28, 28, 1])
2 Y_ = tf.placeholder(tf.float32, [None, 10])
3
4 conv1_weights = tf.Variable(tf.truncated_normal([5, 5, 1, 32], # 5x5 filter, depth 32.
5                                     stddev=0.1))
6 conv1_biases = tf.Variable(tf.zeros([32]))
7
8 conv2_weights = tf.Variable(tf.truncated_normal([5, 5, 32, 64], #5x5 filter, depth 32.
9                                     stddev=0.1))
10 conv2_biases = tf.Variable(tf.constant(0.1, shape=[64]))
11
12 fc1_weights = tf.Variable( # fully connected, depth 512.
13     tf.truncated_normal([7 * 7 * 64, 512], stddev=0.1))
14 fc1_biases = tf.Variable(tf.constant(0.1, shape=[512]))
15
16
17 fc2_weights = tf.Variable(tf.truncated_normal([512, 10],
18     stddev=0.1))
19 fc2_biases = tf.Variable(tf.constant(0.1, shape=[10]))
```

Weight convo1 5x5 input 1 output 32

Weight convo2 5x5 input 32 output 64

Fully connected from 7x7x64

Output 512 hidden to 10 class numbers

```
conv = tf.nn.conv2d(X,
                    conv1_weights, strides=[1, 1, 1, 1],
                    padding='SAME')
```

```
relu = tf.nn.relu(tf.nn.bias_add(conv, conv1_biases))
```

```
pool = tf.nn.max_pool(relu,
                      ksize=[1, 2, 2, 1],
                      strides=[1, 2, 2, 1],
                      padding='SAME')
```

```
conv = tf.nn.conv2d(pool,
                    conv2_weights,
                    strides=[1, 1, 1, 1],
                    padding='SAME')
```

```
relu = tf.nn.relu(tf.nn.bias_add(conv, conv2_biases))
```

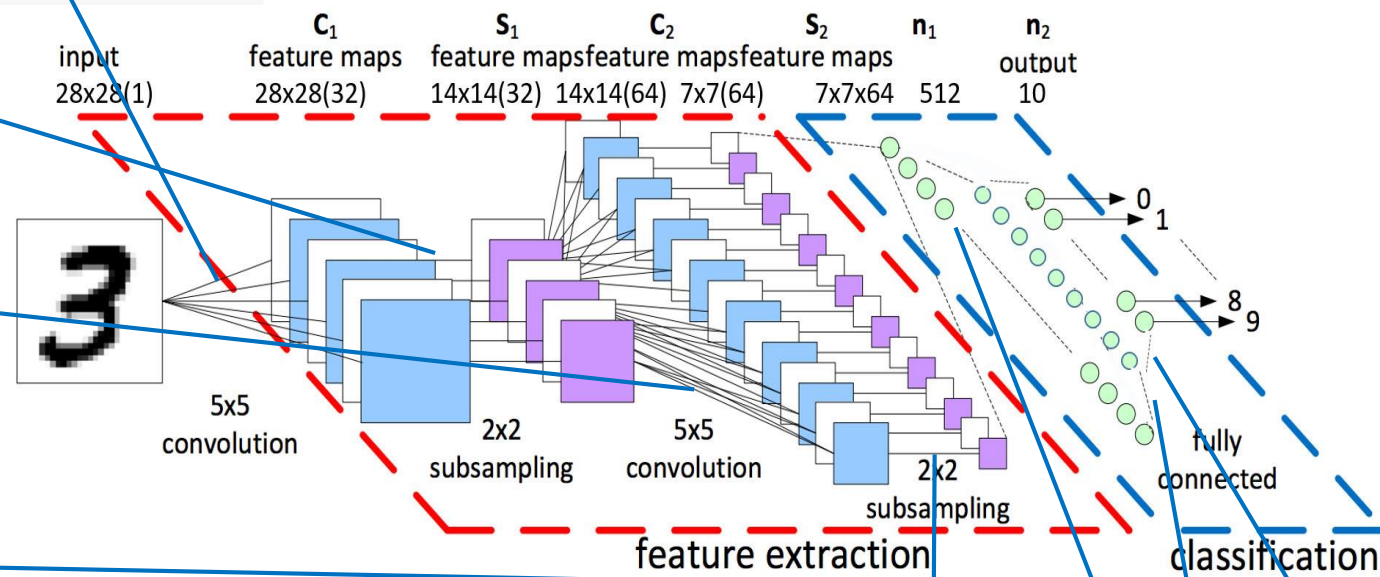
```
pool = tf.nn.max_pool(relu,
                      ksize=[1, 2, 2, 1],
                      strides=[1, 2, 2, 1],
                      padding='SAME')
```

```
reshape = tf.reshape(pool, shape=[-1, 7 * 7 * 64])
```

```
hidden = tf.nn.relu(tf.matmul(reshape, fc1_weights) + fc1_biases)
```

```
Ylogits = tf.matmul(hidden, fc2_weights) + fc2_biases
```

```
Y = tf.nn.softmax(Ylogits)
```



Run & open tensorboard  
tensorboard --logdir="logs"  
and see what happen!



Ummm...we should know helper.

# tflearn

A screenshot of a Windows terminal window titled "MINGW64:/k/MachineLearningClass". The window has standard Windows window controls (minimize, maximize, close) in the top right corner. The terminal text shows the user "Comdet Phaudphut@comdet" in a "MINGW64" environment at the directory "/k/MachineLearningClass" on the "master" branch. The command "\$ pip install tflearn\_" is entered at the prompt, with a cursor at the end of the line. The terminal background is black, and the text is in a monospaced font with some color coding (green for the prompt, purple for the shell, yellow for the path, and cyan for the branch name).

```
MINGW64:/k/MachineLearningClass

Comdet Phaudphut@comdet MINGW64 /k/MachineLearningClass (master)
$ pip install tflearn_
```