Ⅰ. Introduction

2020. 11. 27
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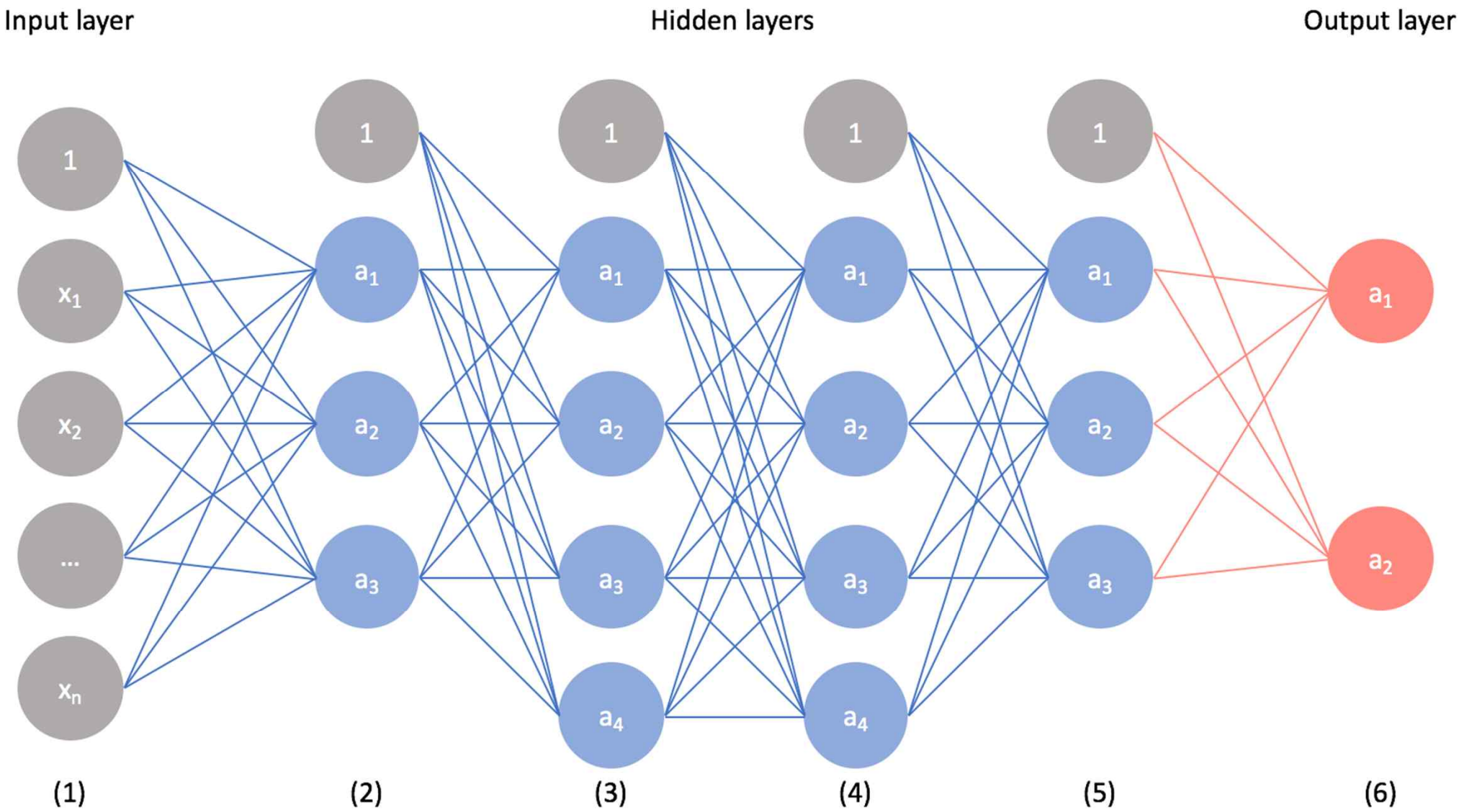
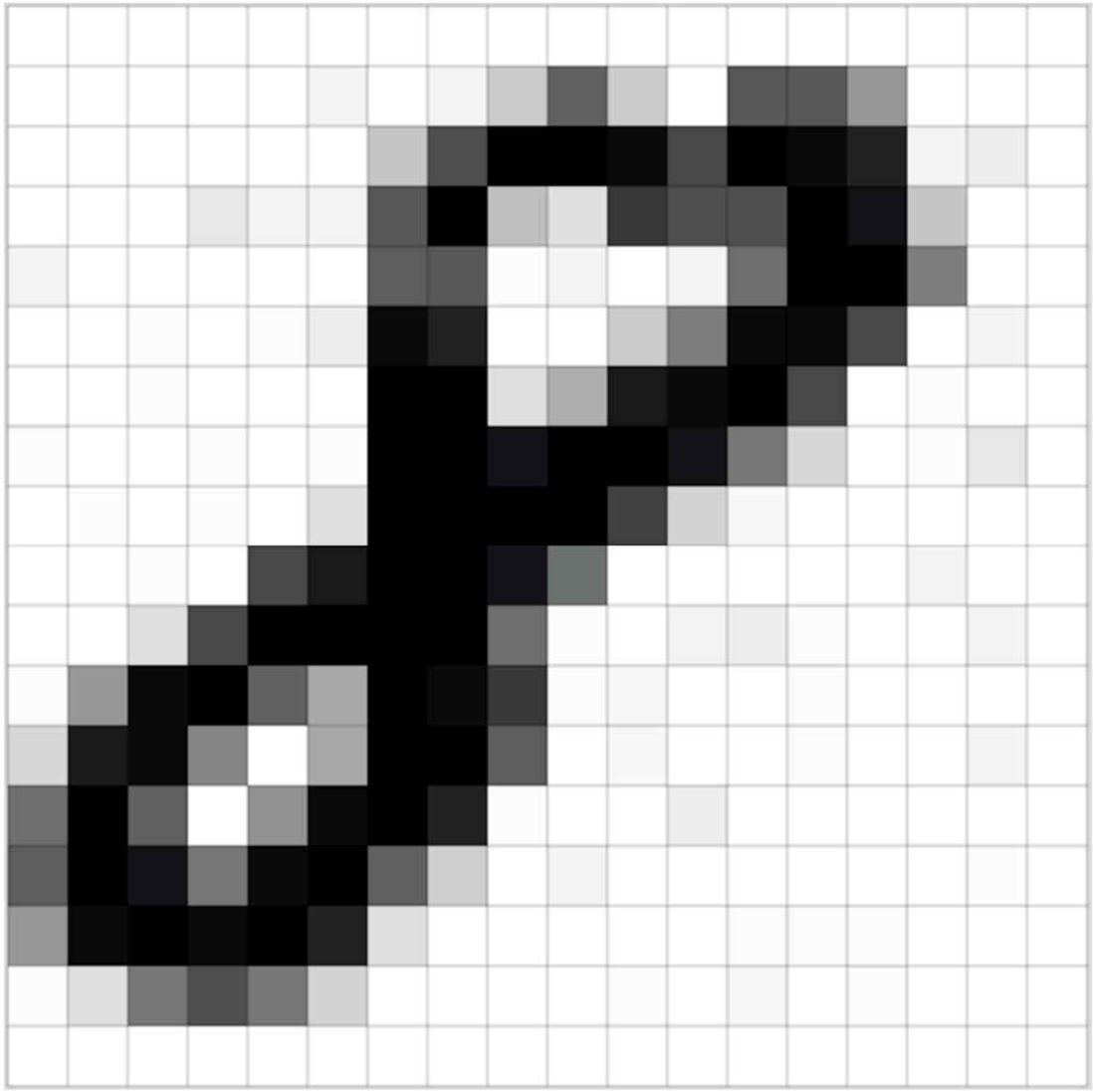
경남대학교
KYUNGNAM UNIVERSITY

01 Fully Connected Neural Network



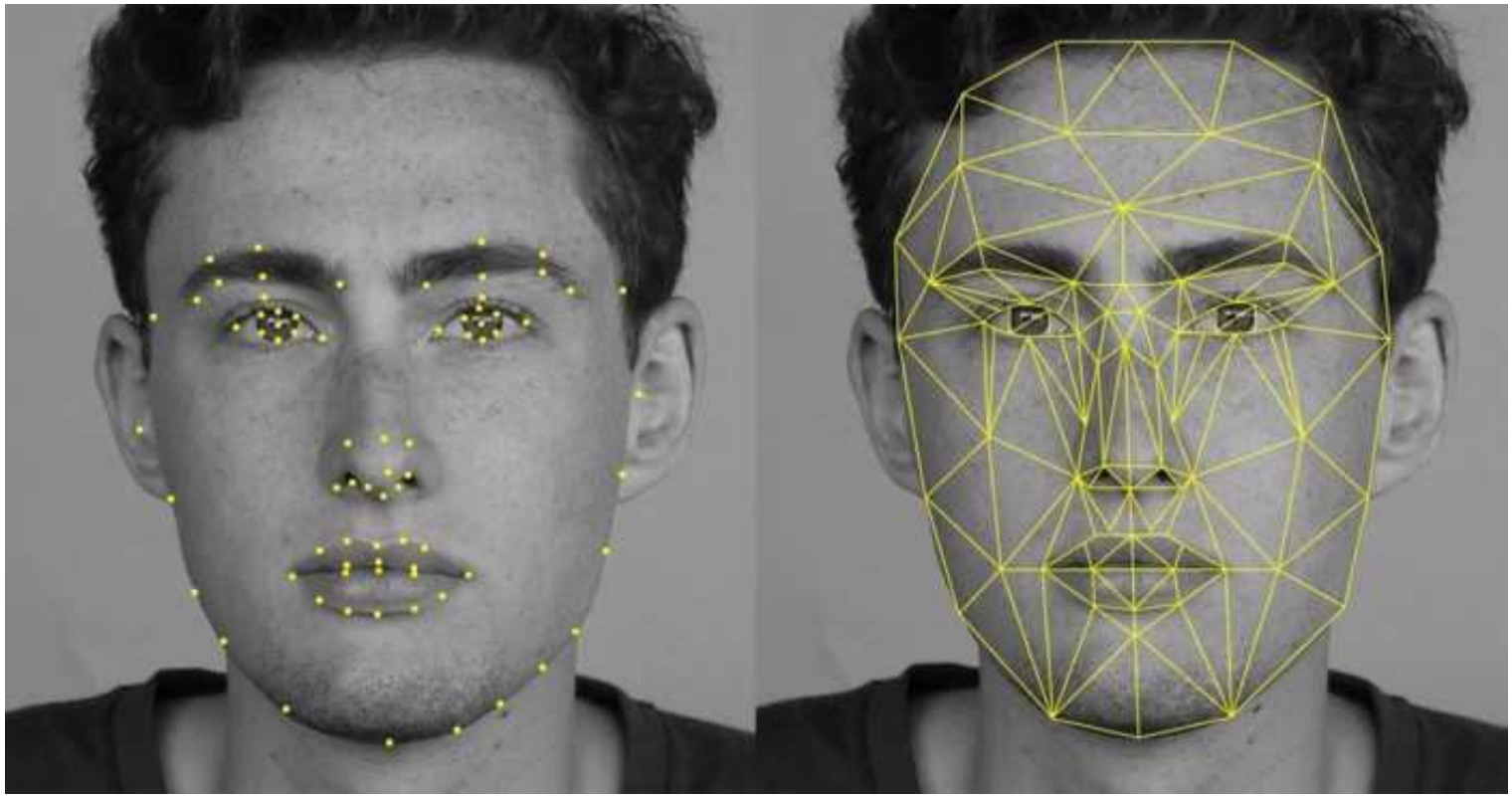
01 Fully Connected Neural Network

Grayscale images vs. Color images



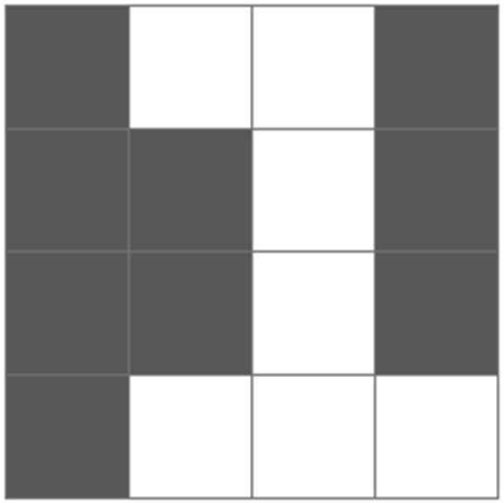
01 Fully Connected Neural Network

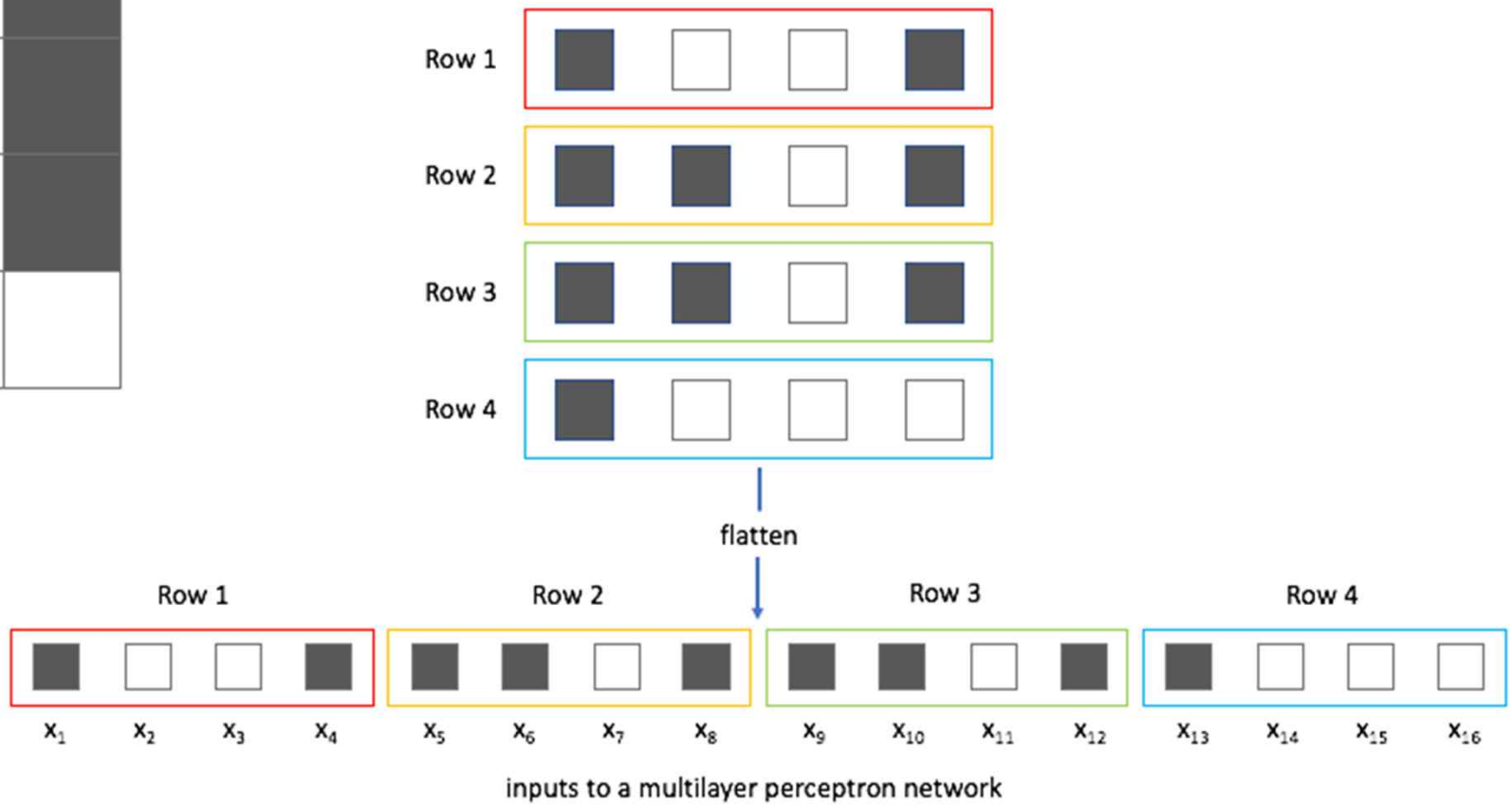
Spatial Relationships within the Data?



01 Fully Connected Neural Network

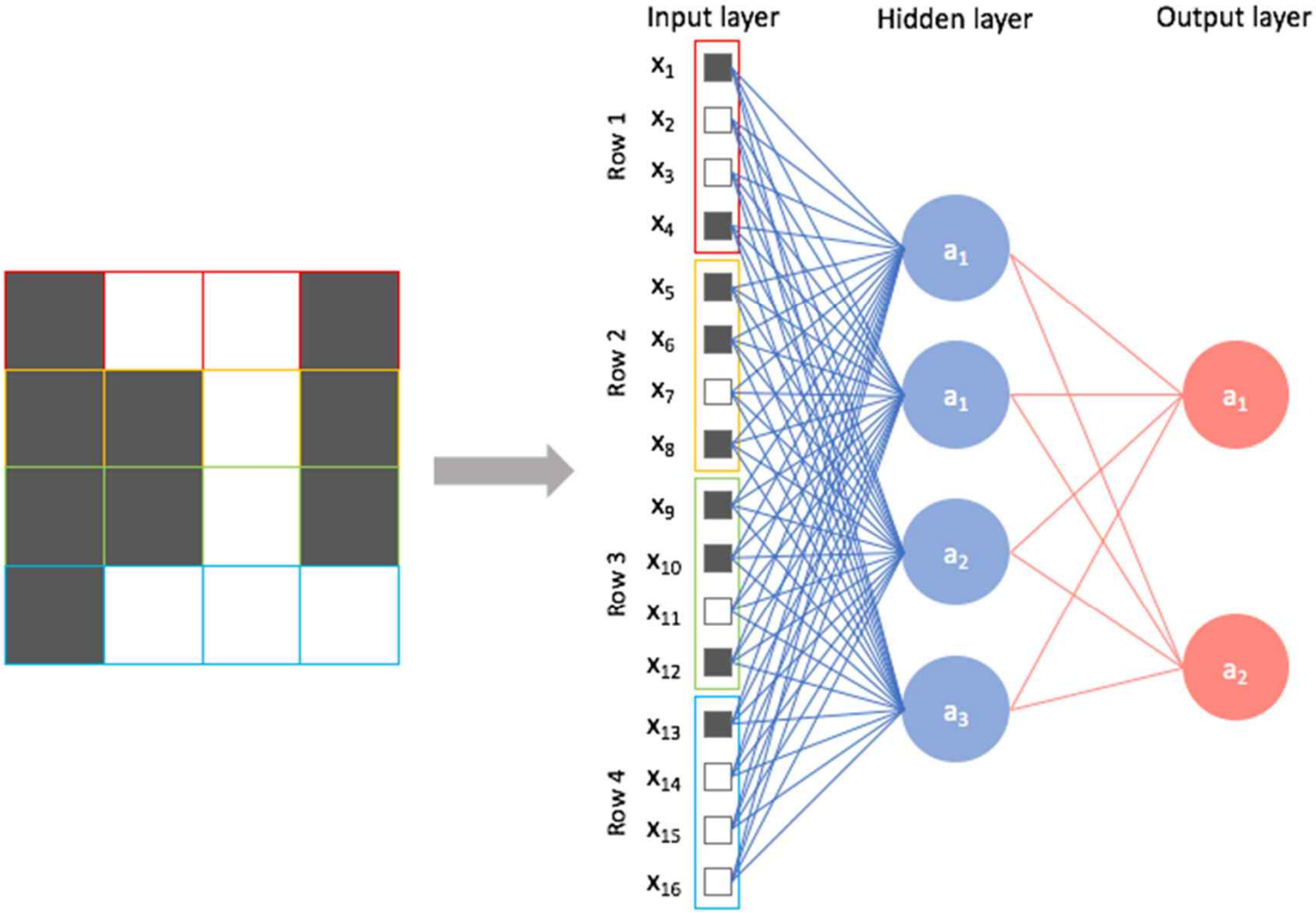
Spatial Relationships within the Data?





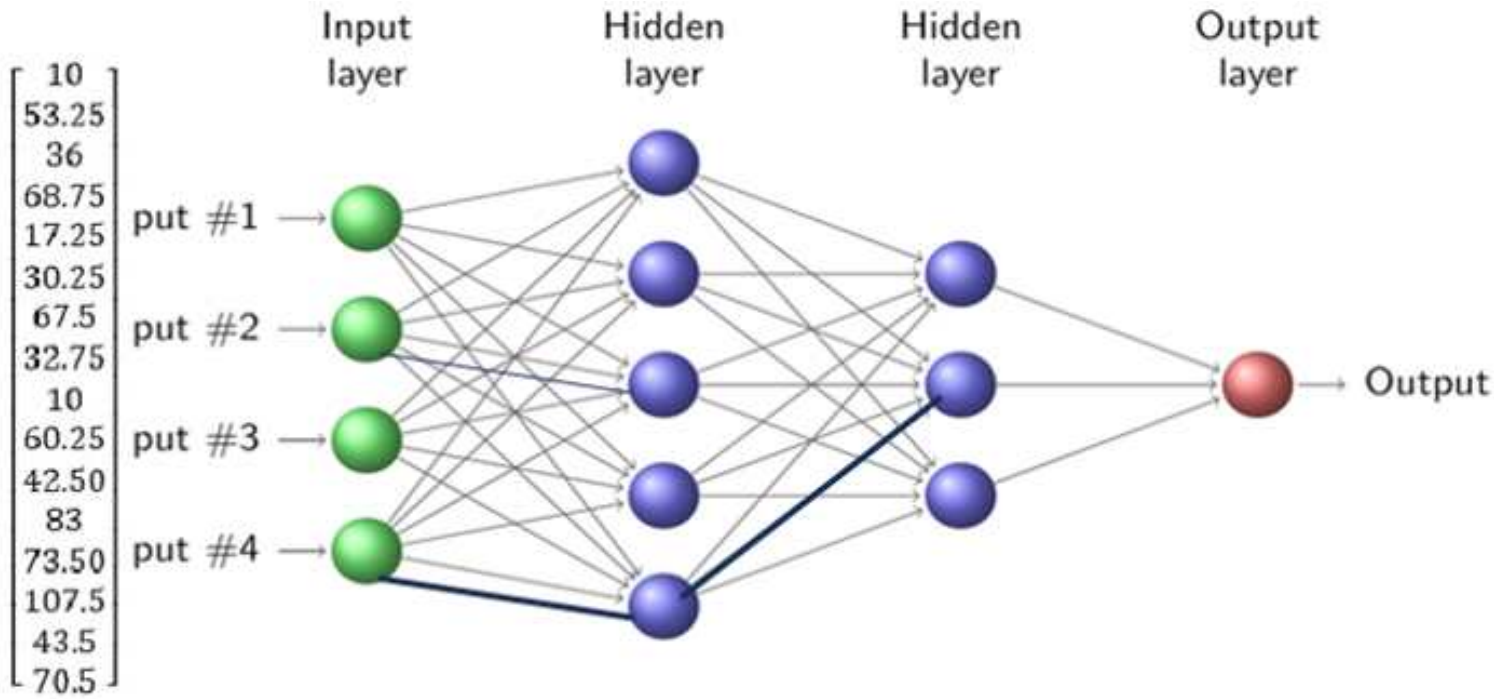
01 Fully Connected Neural Network

Spatial Relationships within the Data?

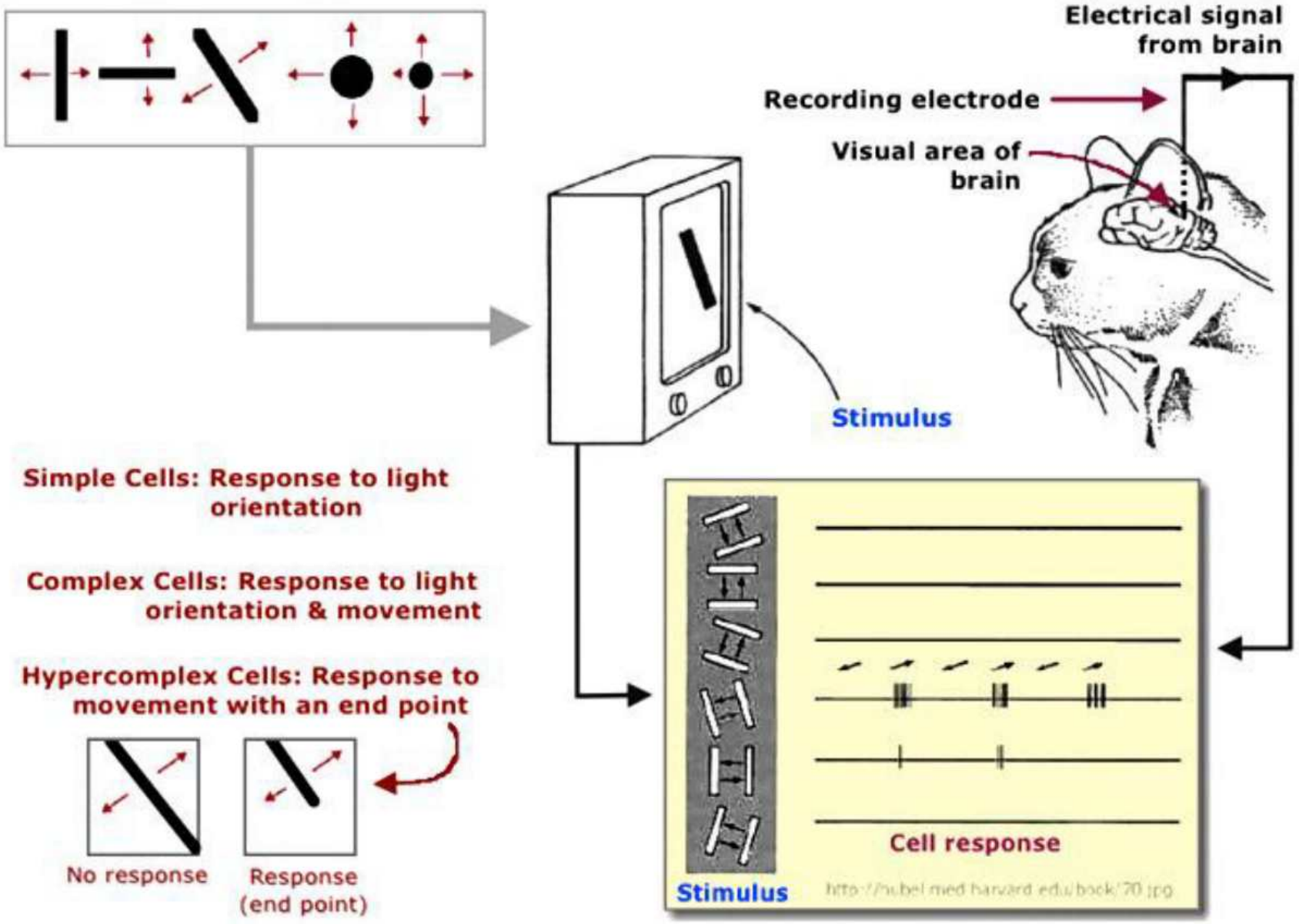


01 Fully Connected Neural Network

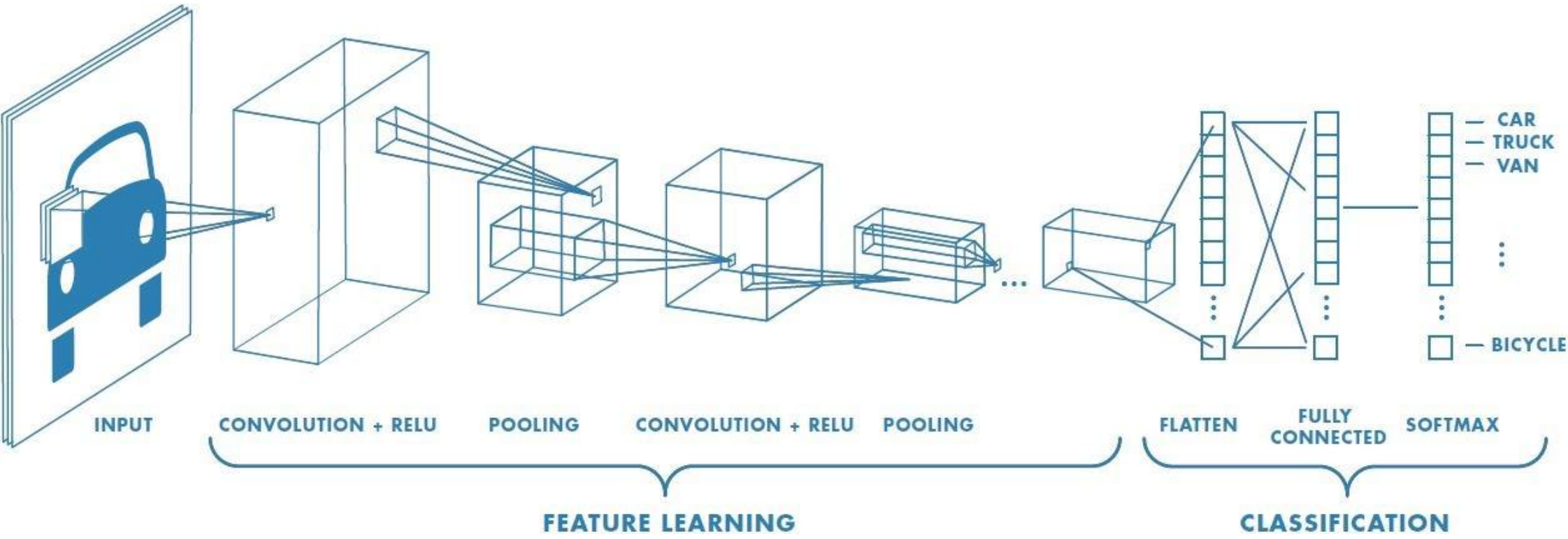
Number of Parameters?



02 Basic CNN

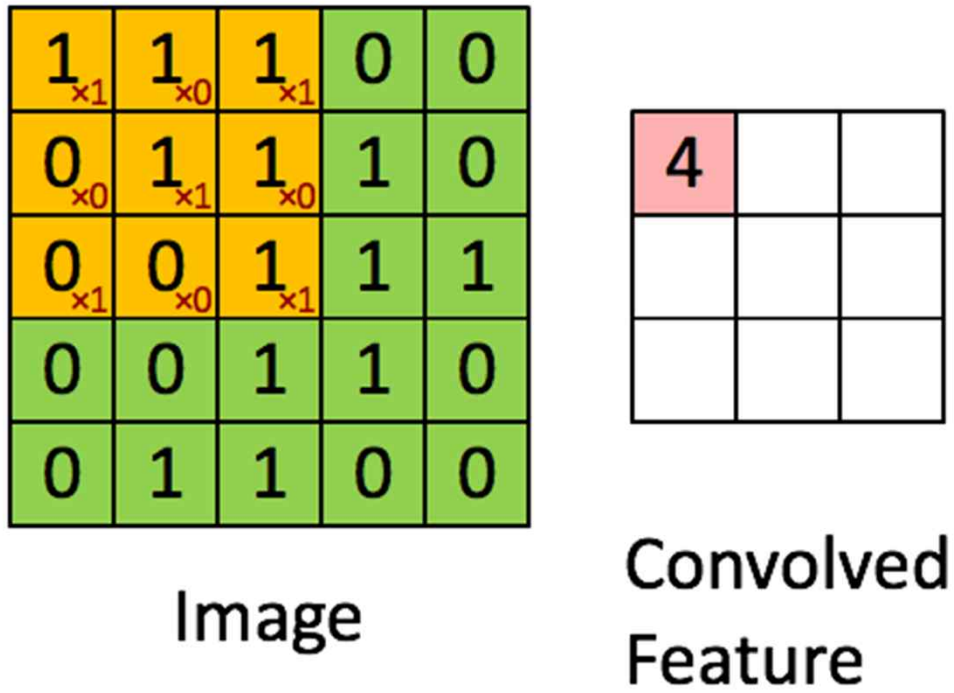

Electrical signal from brain
Recording electrode
Visual area of brain
Stimulus
Simple Cells: Response to light orientation
Complex Cells: Response to light orientation & movement
Hypercomplex Cells: Response to movement with an end point
No response
Response (end point)
Cell response
Stimulus

02 Basic CNN


CAR
TRUCK
VAN
BICYCLE
INPUT
CONVOLUTION + RELU
POOLING
CONVOLUTION + RELU
POOLING
FLATTEN
FULLY CONNECTED
SOFTMAX
FEATURE LEARNING
CLASSIFICATION

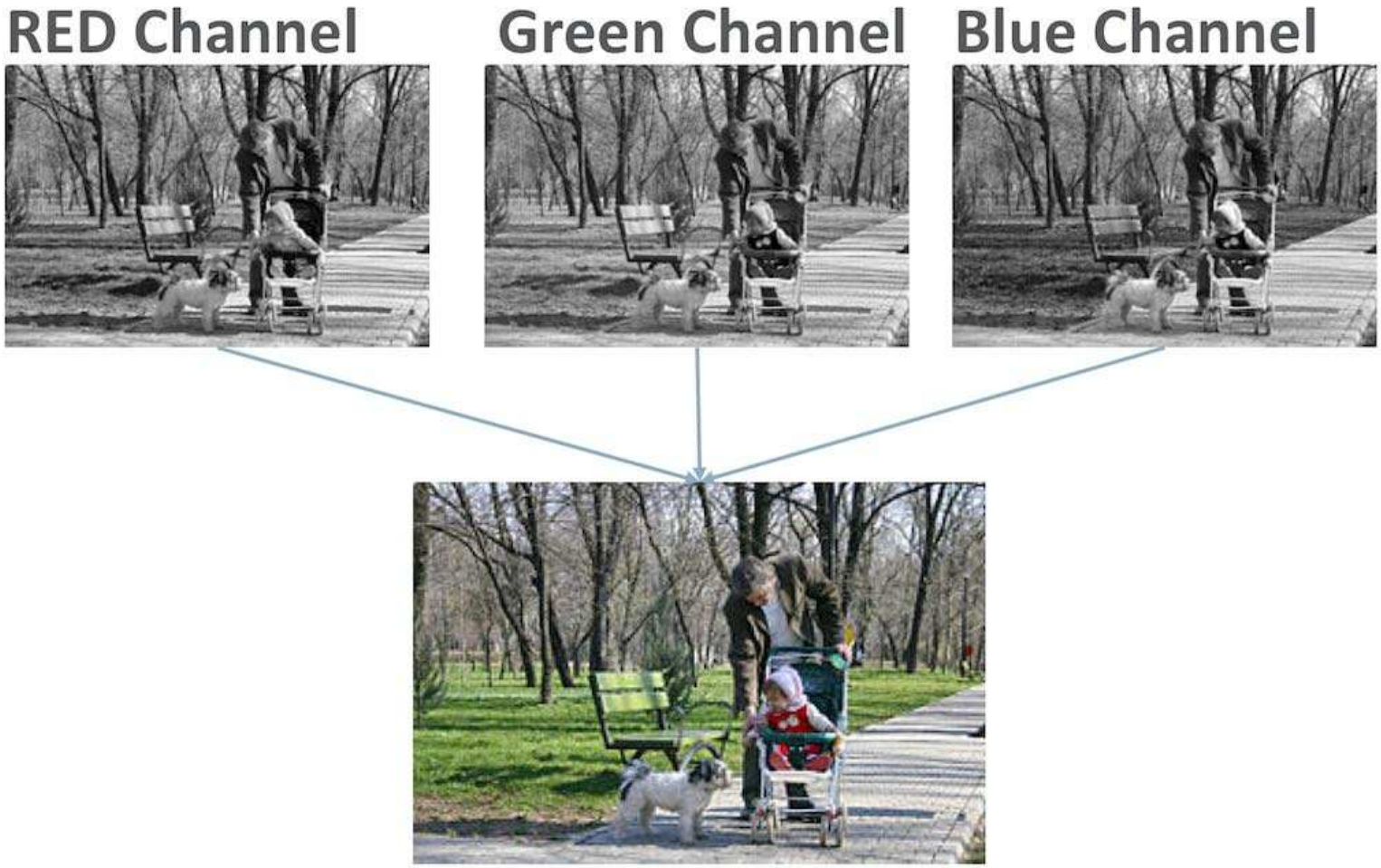
02 Basic CNN

Convolution



02 Basic CNN

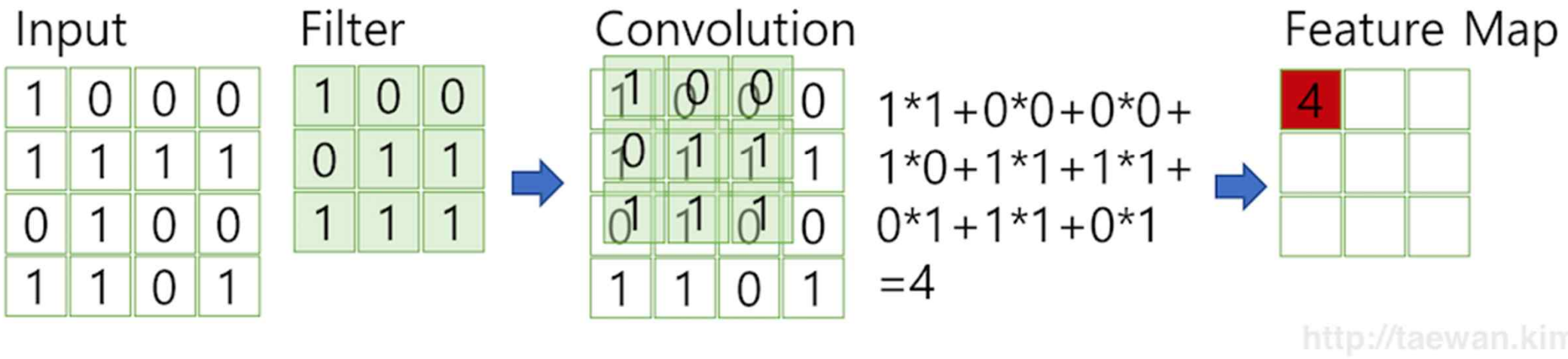
Channel



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

02 Basic CNN

Filter & Feature Map



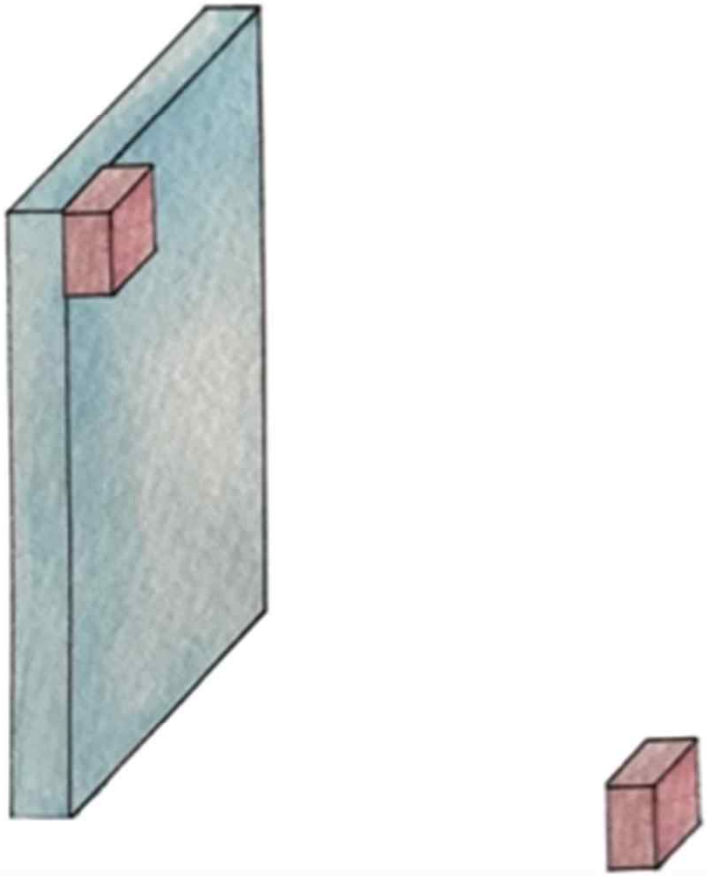
02 Basic CNN

Start with an image (width x hight x depth)

32x32x3 image

02 Basic CNN

Let's focus on a small area only (5x5x3)

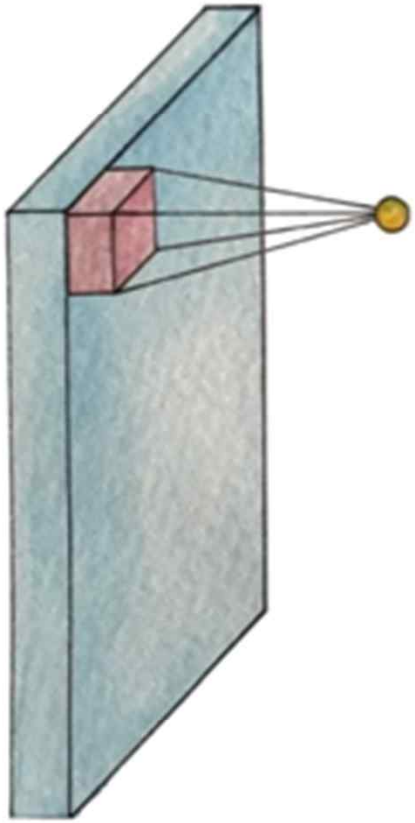


32x32x3 image

5x5x3 filter

02 Basic CNN

Get one number using the filter



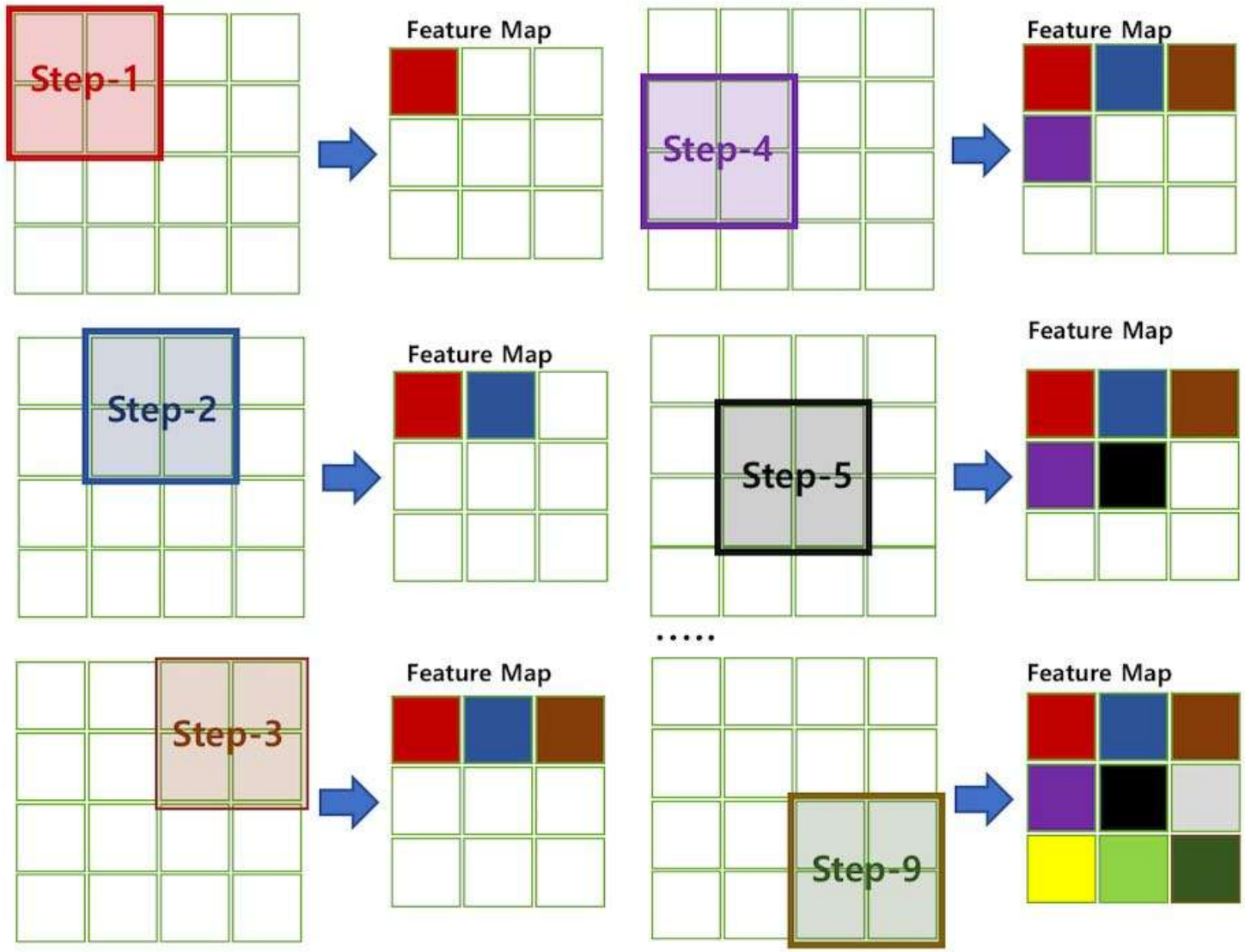
one number! =Wx+b =ReLU(Wx+b)

5x5x3 filter

32x32x3 image

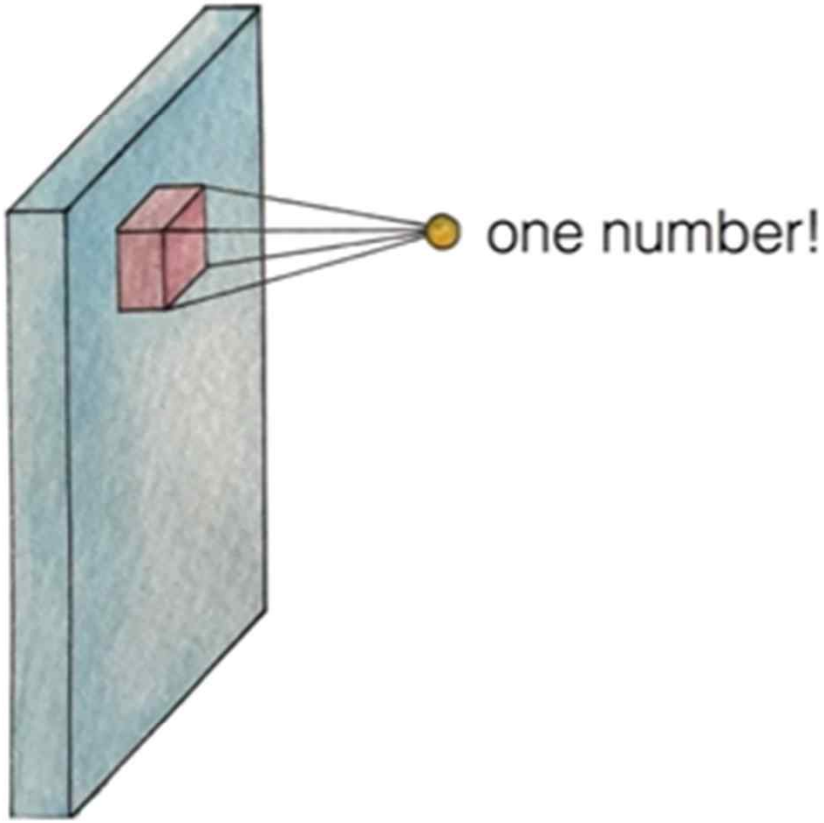
02 Basic CNN

Stride & Feature Map



02 Basic CNN

Let's look at other areas with the same filter (w)

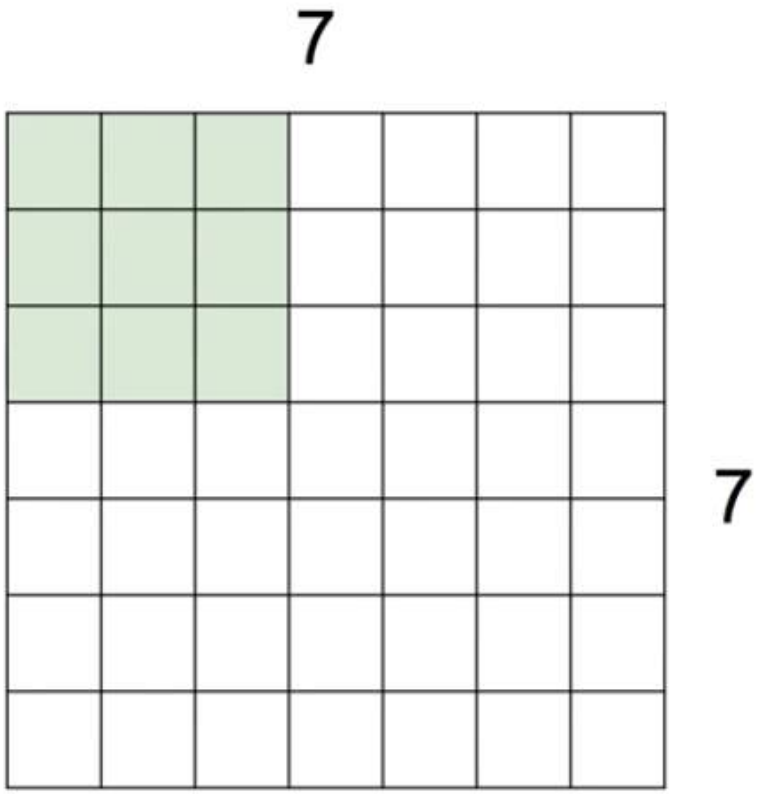


How many numbers can we get?

32x32x3 image

02 Basic CNN

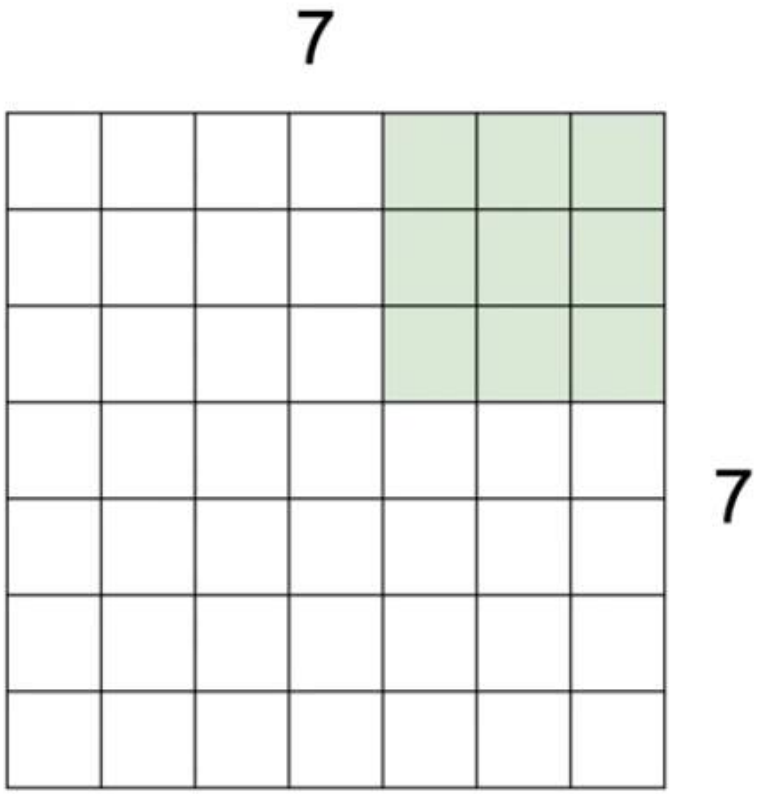
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

02 Basic CNN

A closer look at spatial dimensions:

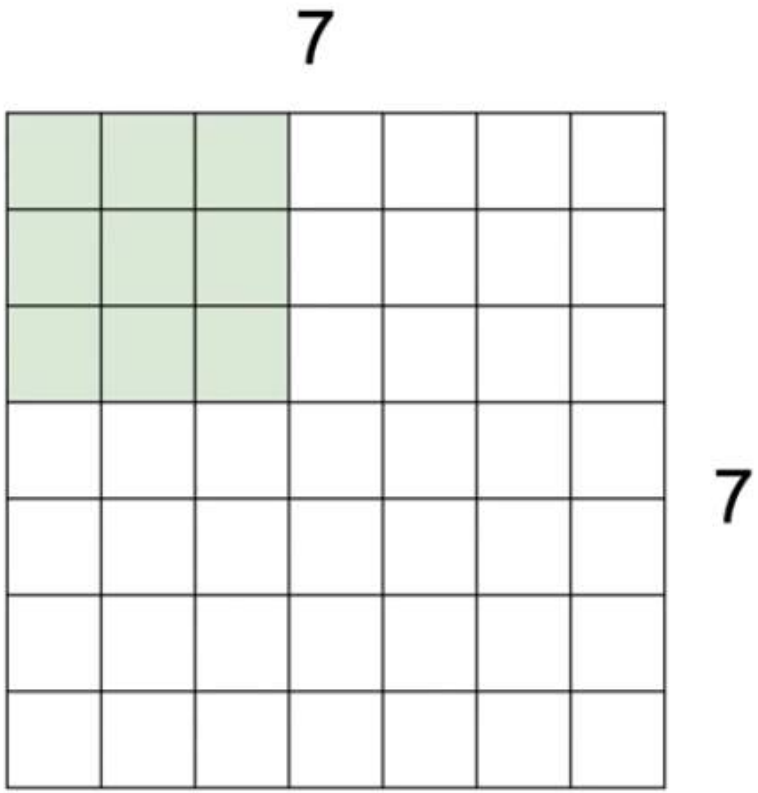


7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

02 Basic CNN

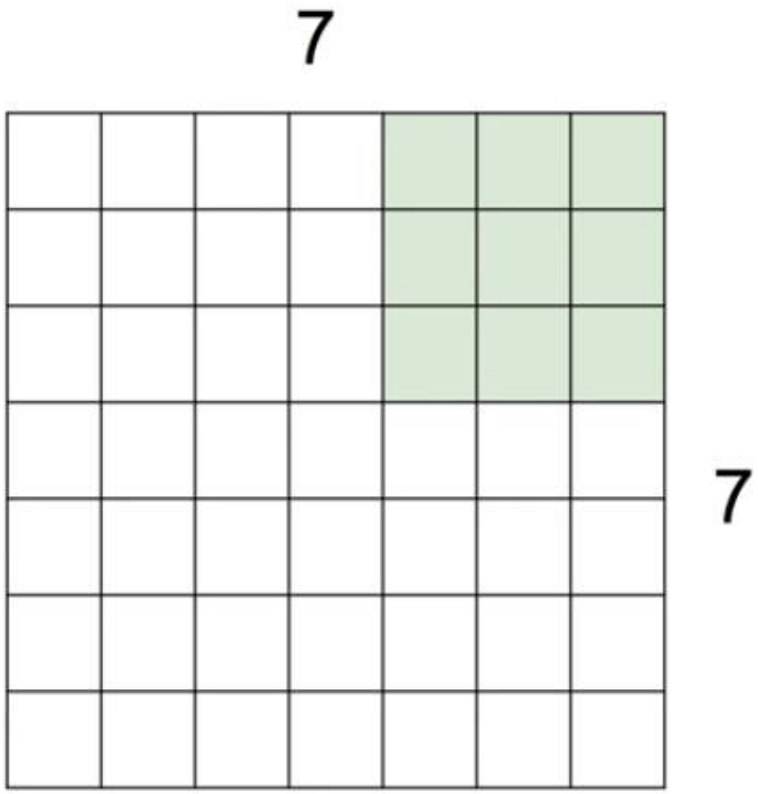
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

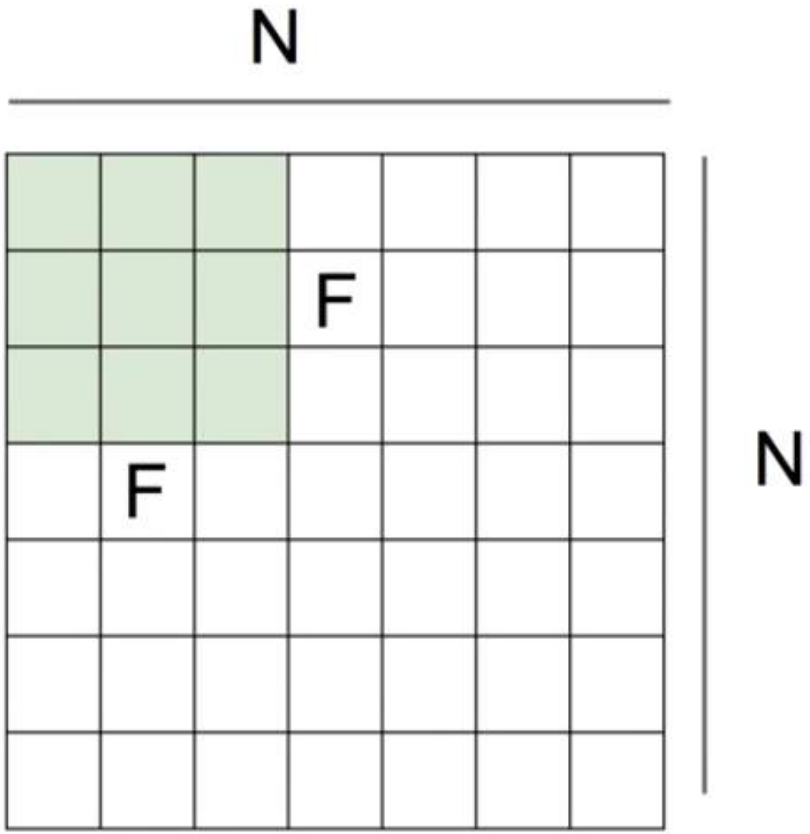
02 Basic CNN

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

02 Basic CNN

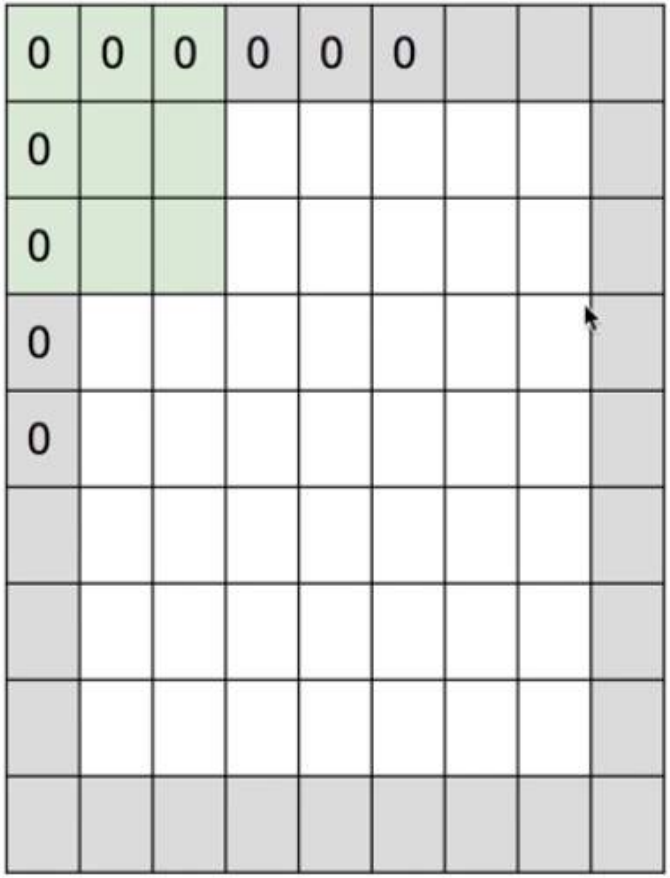


Output size:
(N - F) / stride + 1

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33 :\

02 Basic CNN

In practice: Common to zero pad the border

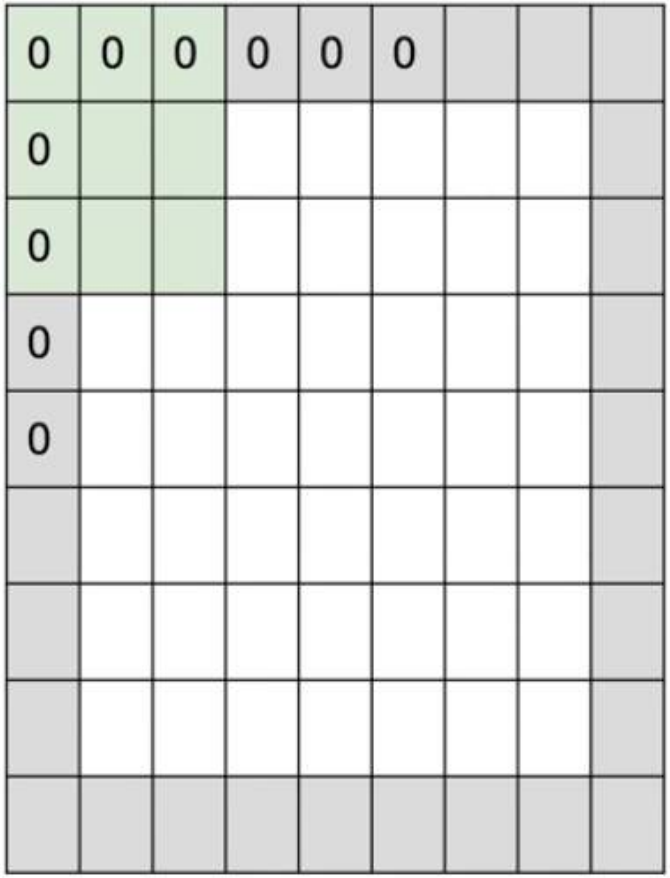


e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

(recall:)
(N - F) / stride + 1

02 Basic CNN

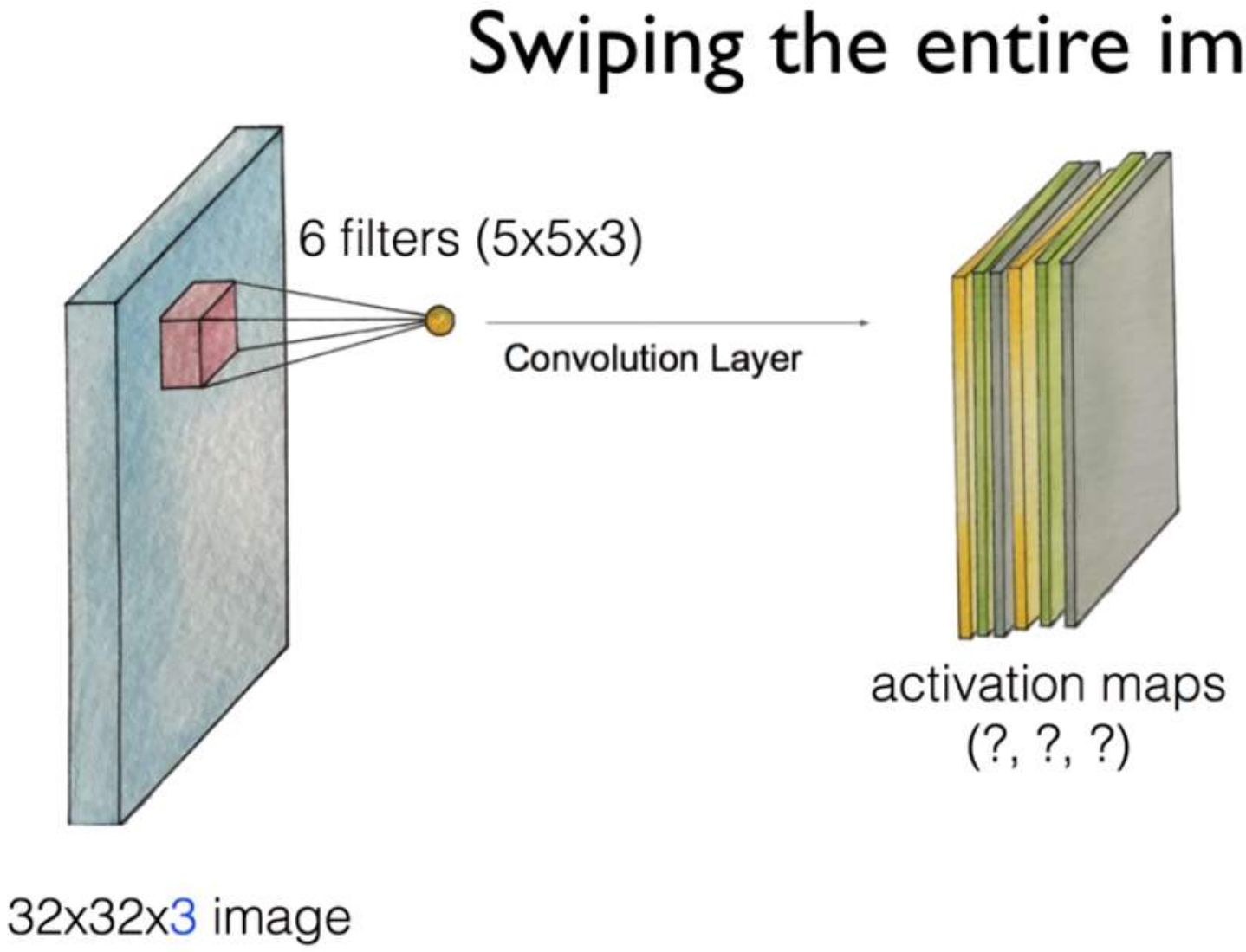
In practice: Common to zero pad the border



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

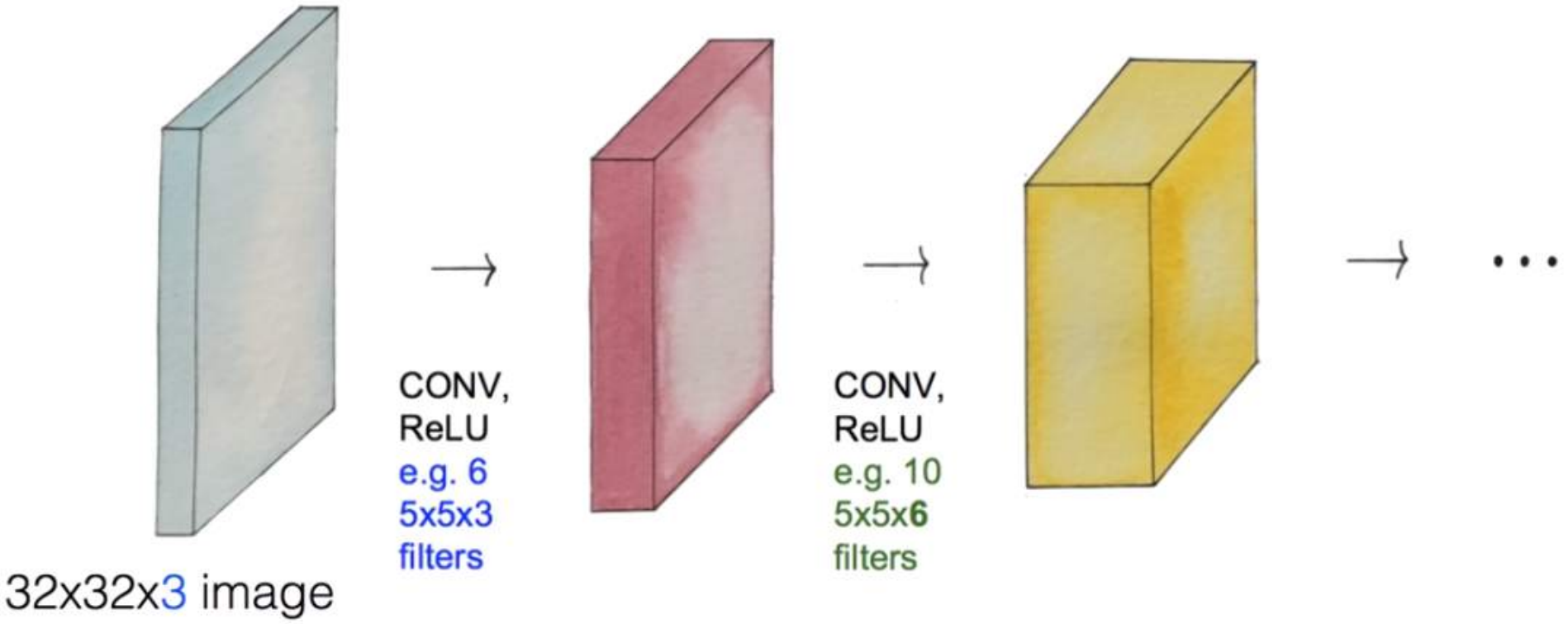
02 Basic CNN


Swiping the entire image
6 filters (5x5x3)
Convolution Layer
activation maps
(?, ?, ?)
32x32x3 image

02 Basic CNN

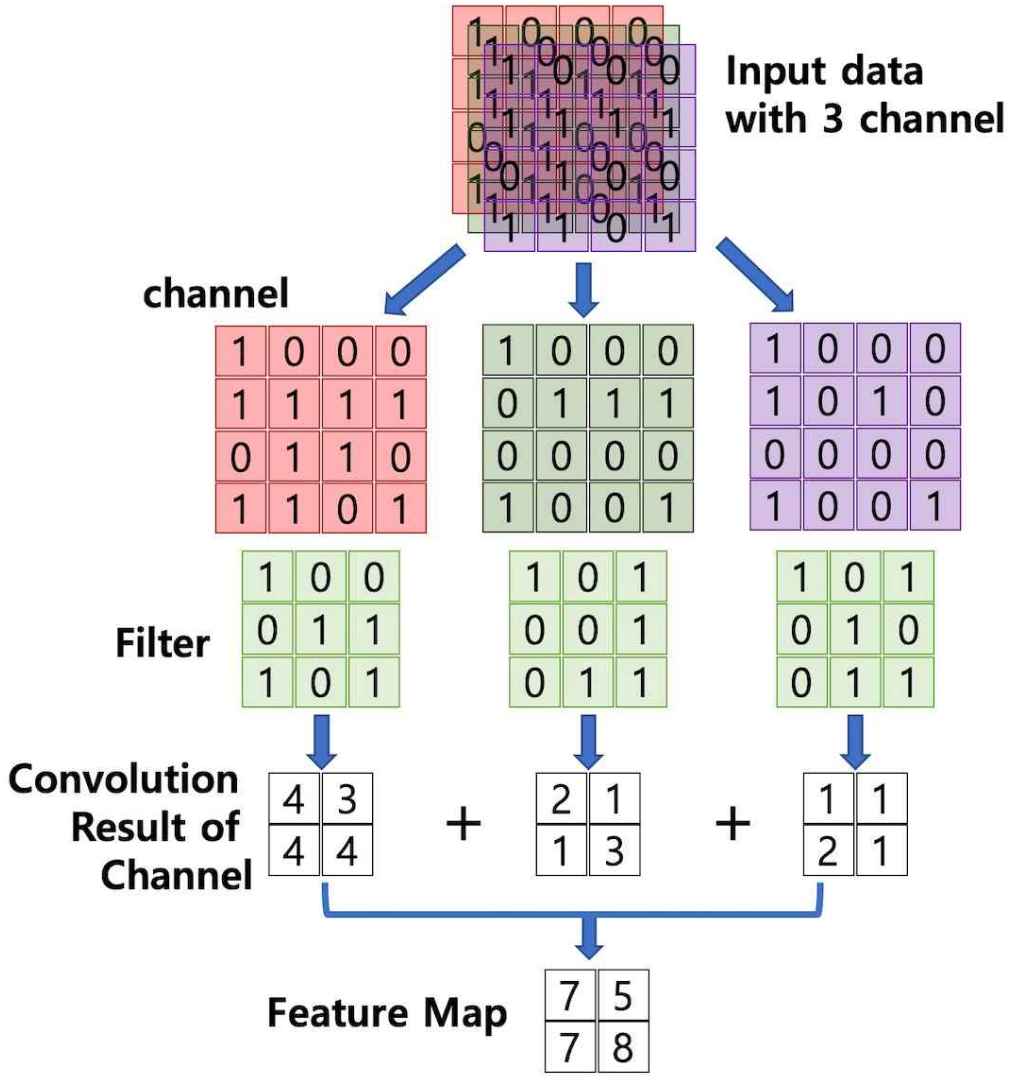
Convolution layers

How many weight variables? How to set them?



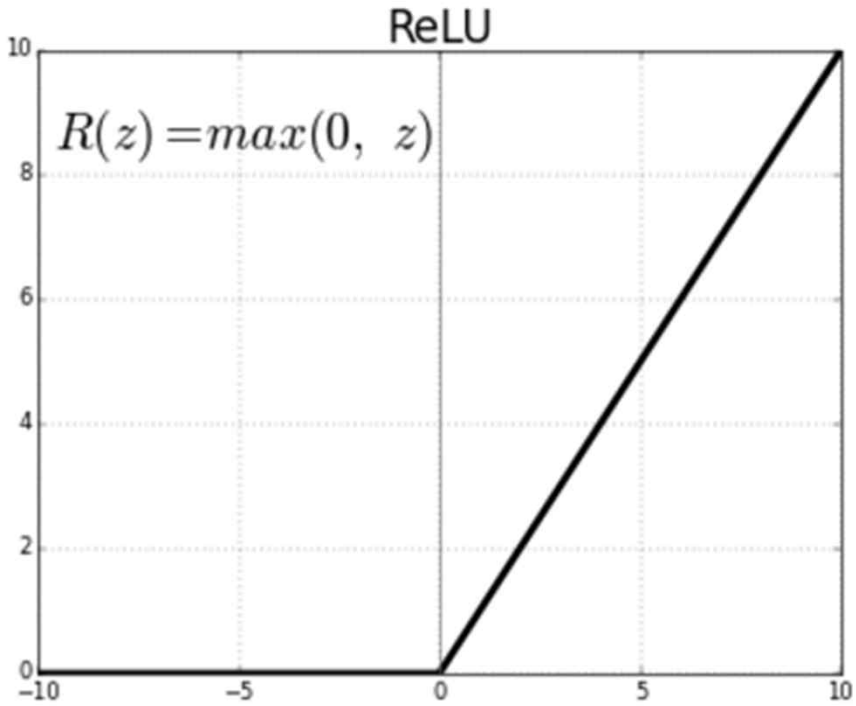
02 Basic CNN

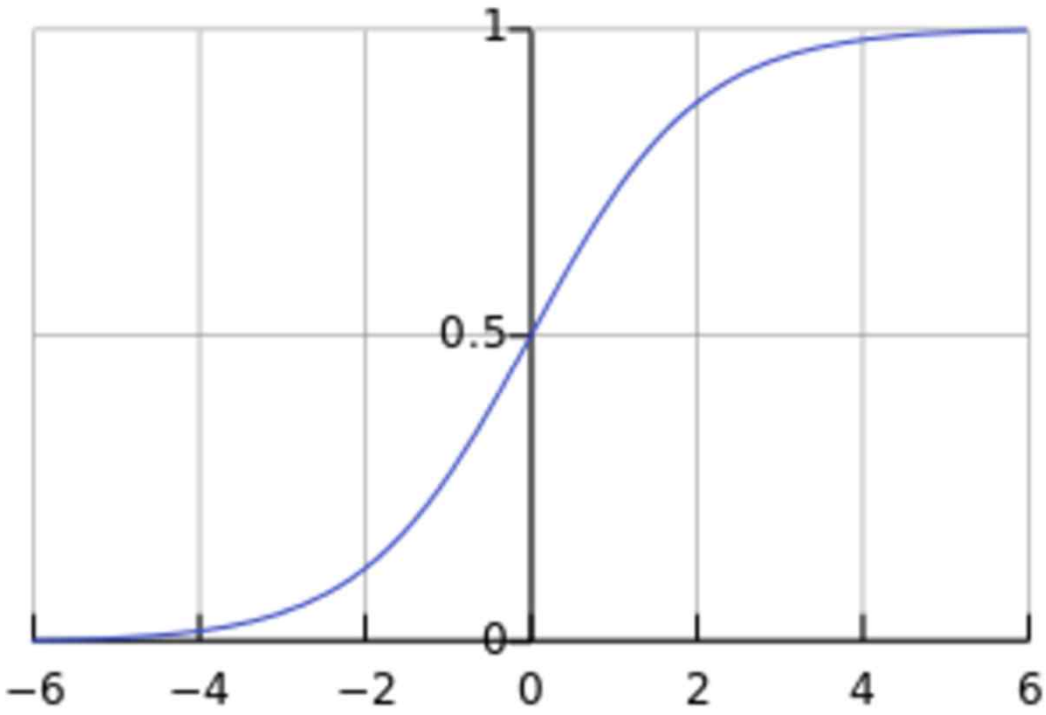
Convolution Result of Input Data with 3 Channel



02 Basic CNN

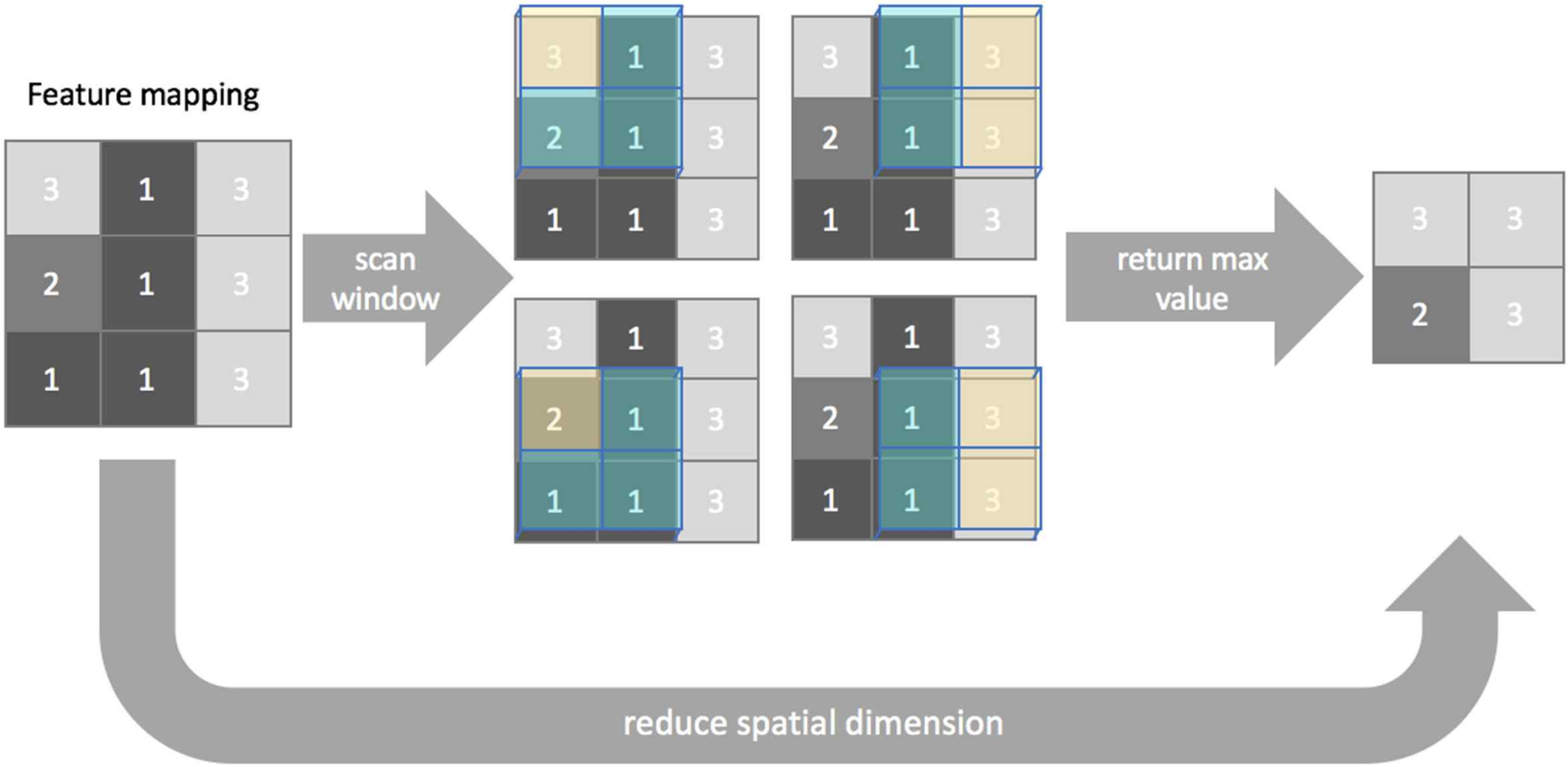
Activation Function(ReLU vs. Sigmoid)





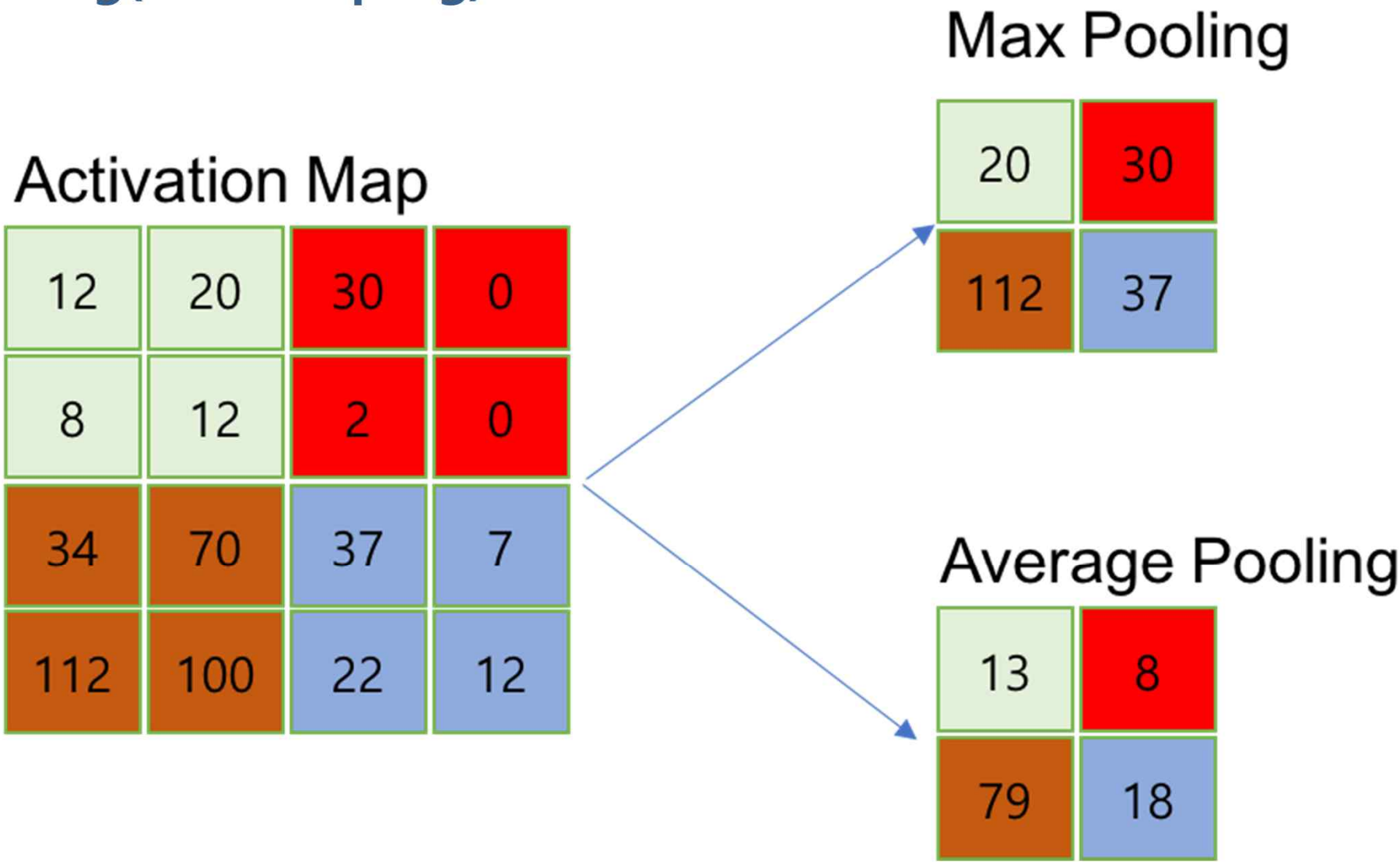
02 Basic CNN

Pooling(Sub Sampling)



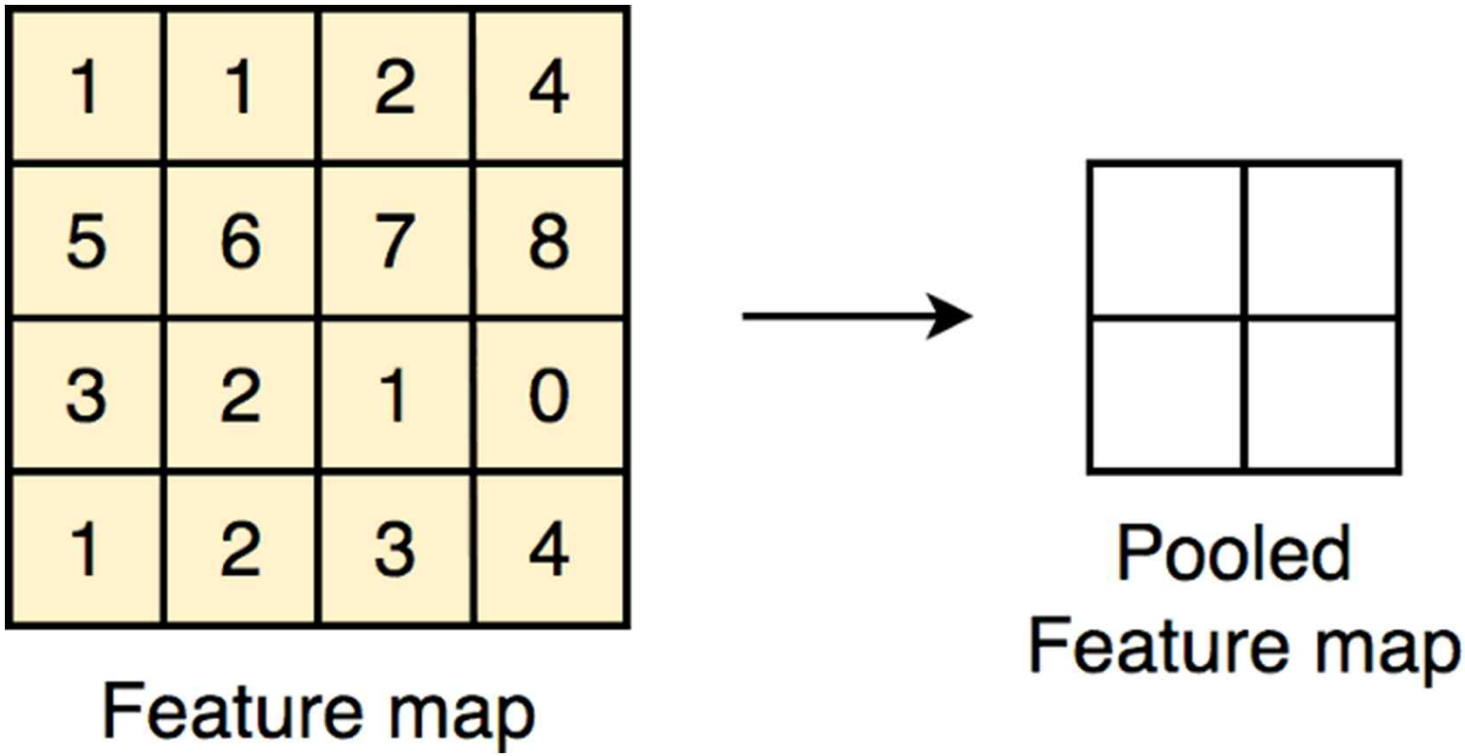
02 Basic CNN

Pooling(Sub Sampling)

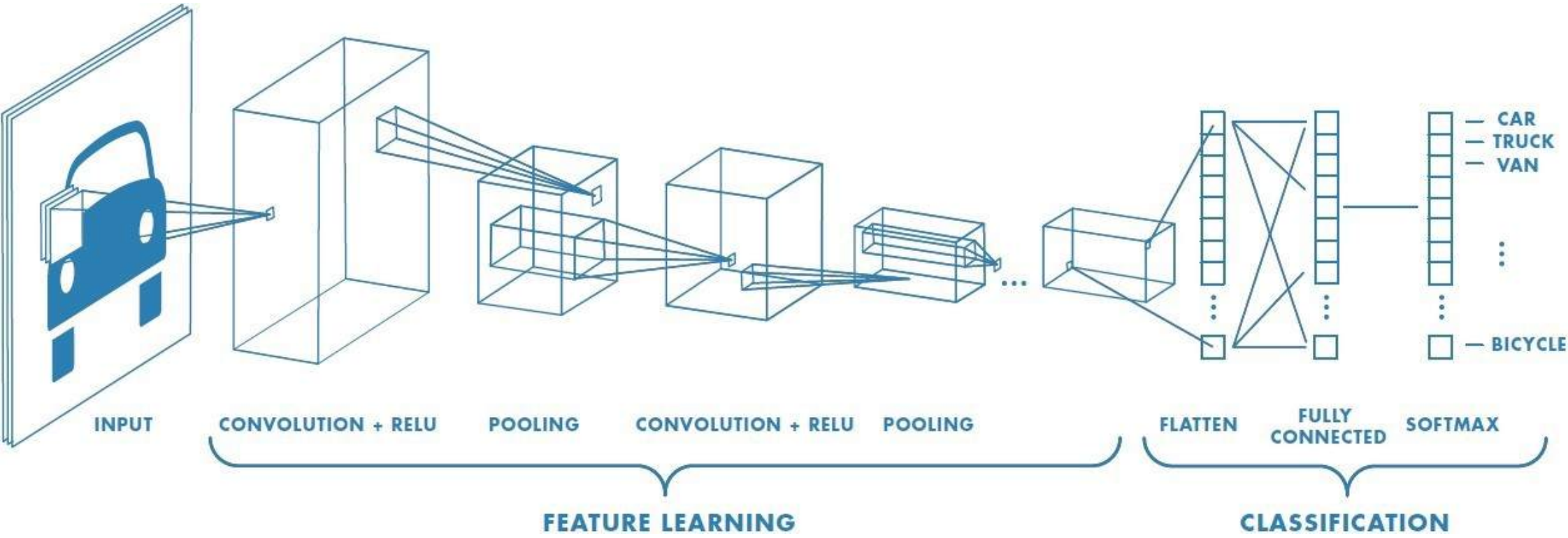


02 Basic CNN

Max Pooling

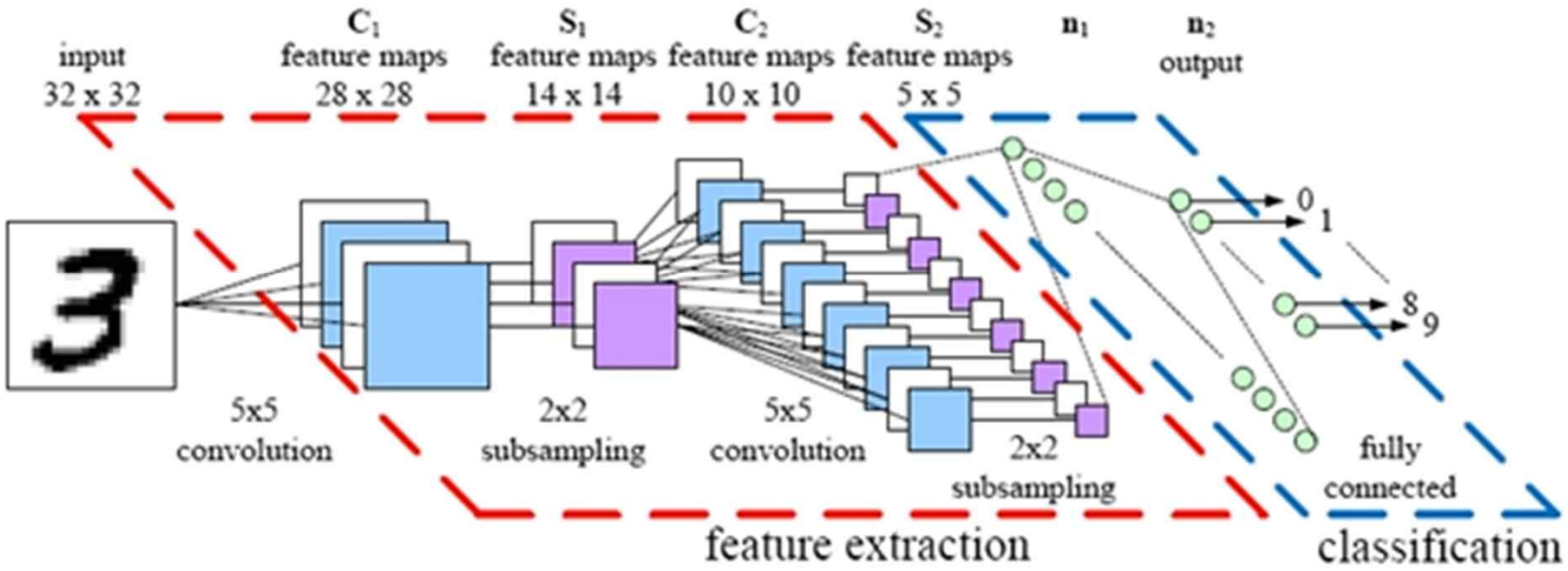


02 Basic CNN

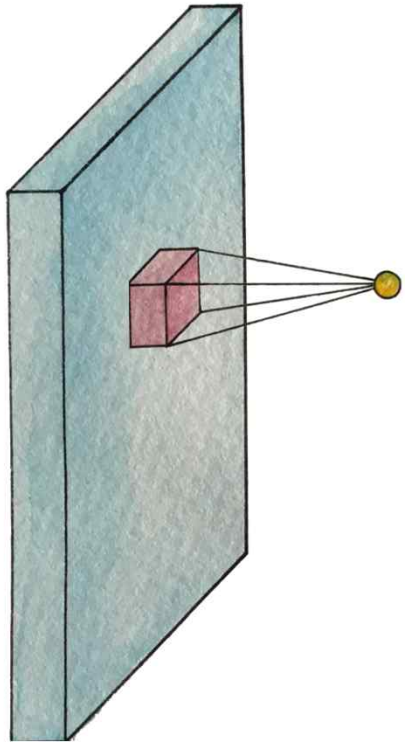

CAR
TRUCK
VAN
BICYCLE
INPUT
CONVOLUTION + RELU
POOLING
CONVOLUTION + RELU
POOLING
FLATTEN
FULLY CONNECTED
SOFTMAX
FEATURE LEARNING
CLASSIFICATION

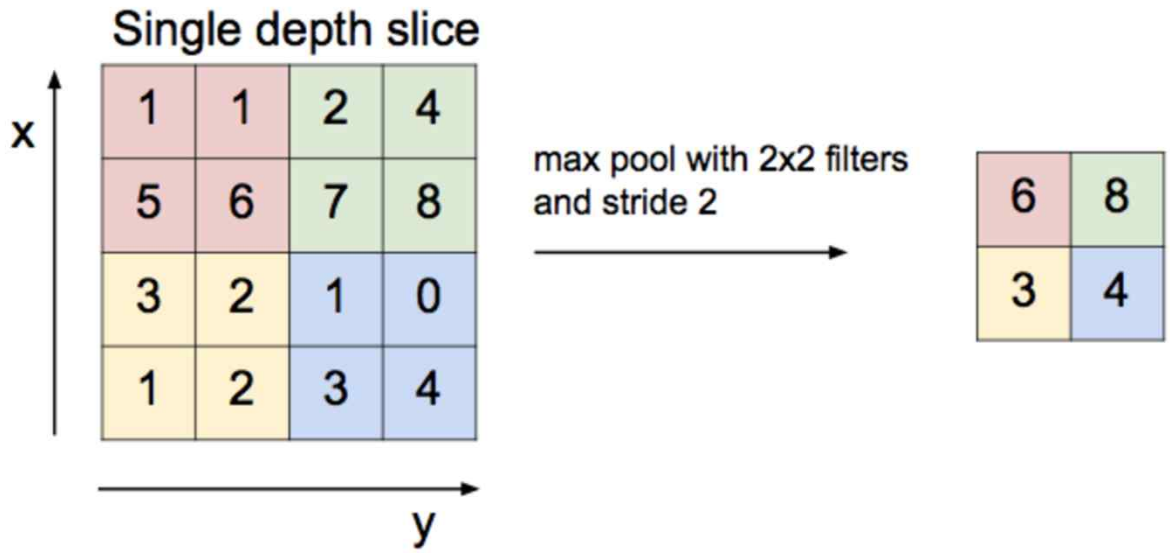
I -1. CNN Basics

01 CNN

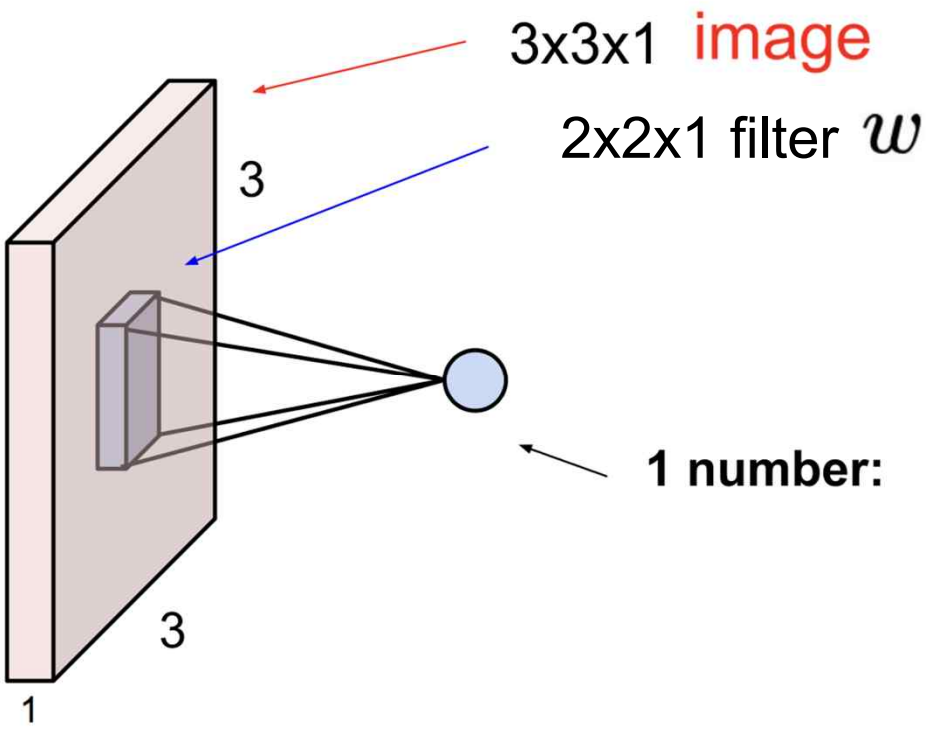

input
32 x 32
C1
feature maps
28 x 28
S1
feature maps
14 x 14
C2
feature maps
10 x 10
S2
feature maps
5 x 5
n1
n2
output
0
1
8
9
5x5
convolution
2x2
subsampling
5x5
convolution
2x2
subsampling
fully
connected
feature extraction
classification

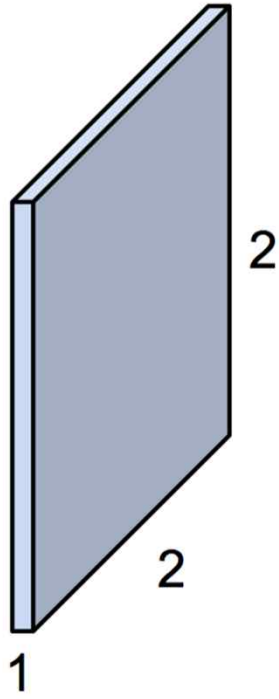
01 CNN




Single depth slice
x
y
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

02 Simple Convolution Layer



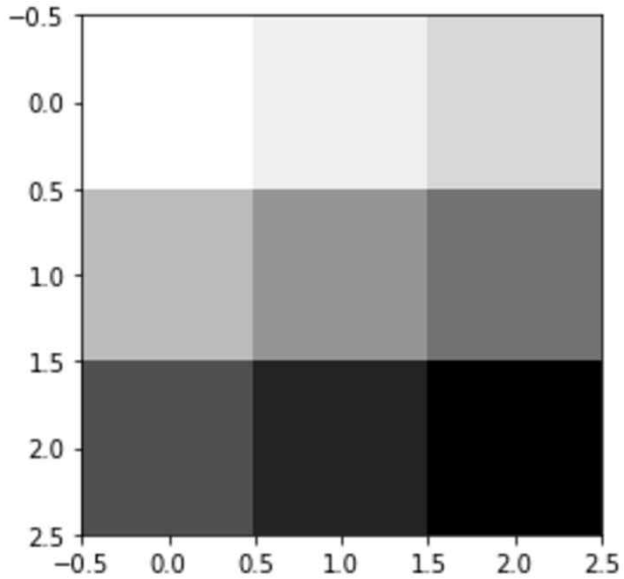


02 Simple Convolution Layer

In [2]:
```
sess = tf.InteractiveSession()
image = np.array([[[[1],[2],[3]],
                   [[4],[5],[6]],
                   [[7],[8],[9]]]], dtype=np.float32)
print(image.shape)
plt.imshow(image.reshape(3,3), cmap='Greys')
```

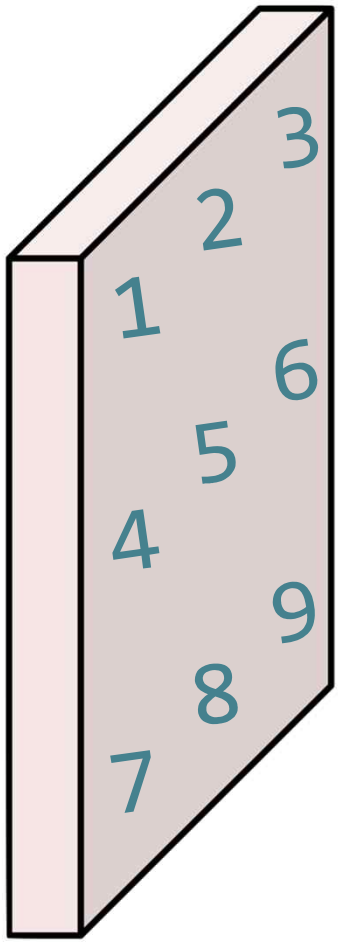
```
(1, 3, 3, 1)
```

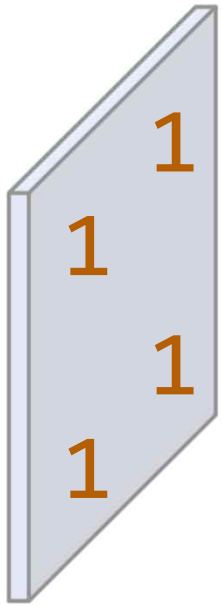
Out[2]:
```
<matplotlib.image.AxesImage at 0x10db67dd8>
```



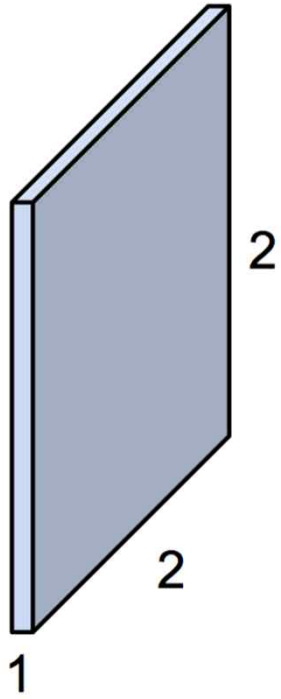
02 Simple Convolution Layer

Image: 1,3,3,1 image, Filter: 2,2,1,1, Stride: 1x1, Padding: VALID






```
[[[[1.]],[[1.]]],
 [[[1.]],[[1.]]]]
shape=(2,2,1,1)
```

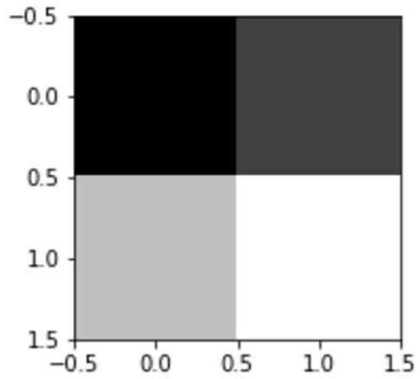


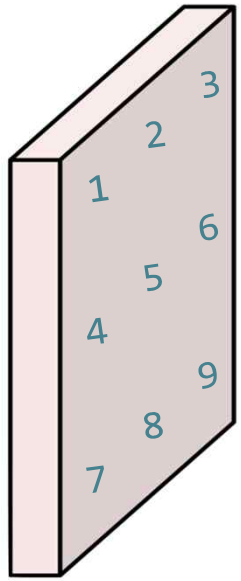
02 Simple Convolution Layer

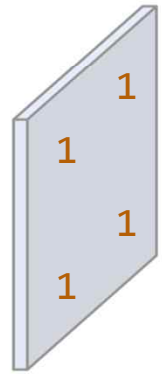
Image: 1,3,3,1 image, Filter: 2,2,1,1, Stride: 1x1, Padding: VALID

```
# print("imag:\n", image)
print("image.shape", image.shape)
weight = tf.constant([[[[1.]],[[1.]]],
                      [[[1.]],[[1.]]]])
print("weight.shape", weight.shape)
conv2d = tf.nn.conv2d(image, weight, strides=[1, 1, 1, 1], padding='VALID')
conv2d_img = conv2d.eval()
print("conv2d_img.shape", conv2d_img.shape)
conv2d_img = np.swapaxes(conv2d_img, 0, 3)
for i, one_img in enumerate(conv2d_img):
    print(one_img.reshape(2,2))
    plt.subplot(1,2,i+1), plt.imshow(one_img.reshape(2,2), cmap='gray')
```

```
image.shape (1, 3, 3, 1)
weight.shape (2, 2, 1, 1)
conv2d_img.shape (1, 2, 2, 1)
[[ 12.  16.]
 [ 24.  28.]]
```

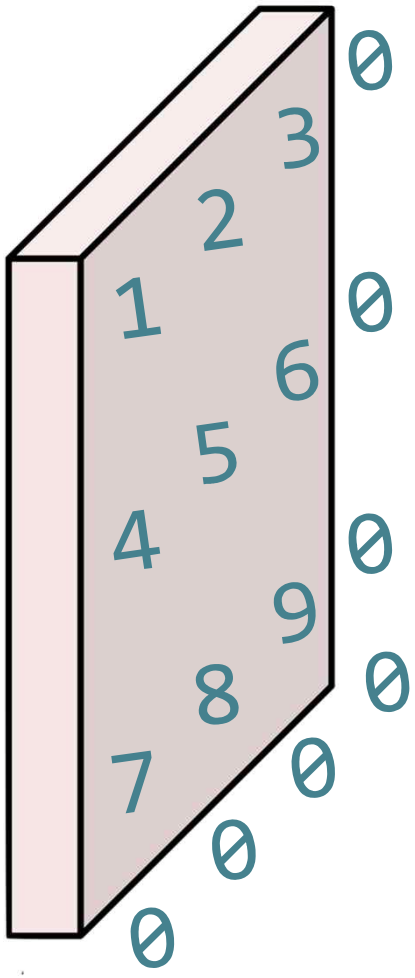


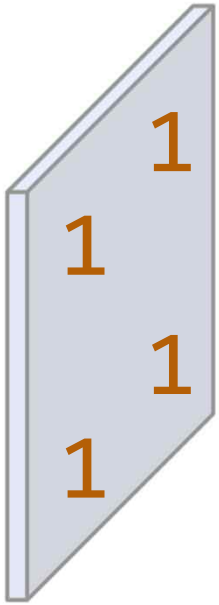


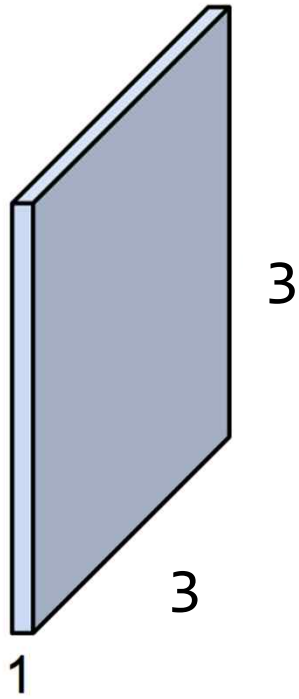


02 Simple Convolution Layer

Image: 1,3,3,1 image, Filter: 2,2,1,1, Stride: 1x1, Padding: **SAME**





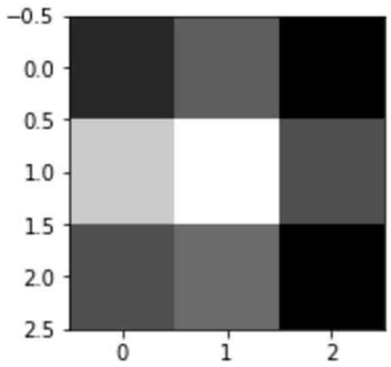


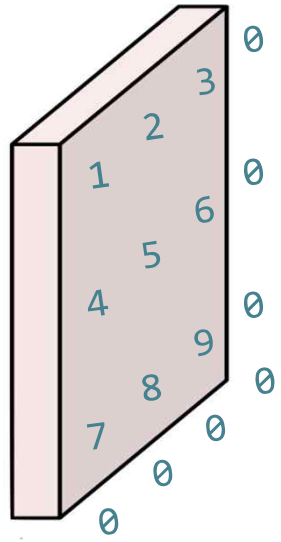
02 Simple Convolution Layer

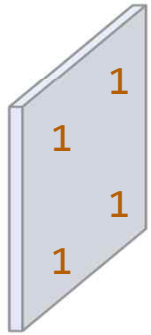
Image: 1,3,3,1 image, Filter: 2,2,1,1, Stride: 1x1, Padding: **SAME**

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

weight = tf.constant([[[[1.]],[[1.]]],
                      [[[1.]],[[1.]]]])
print("weight.shape", weight.shape)
conv2d = tf.nn.conv2d(image, weight, strides=[1, 1, 1, 1], padding='SAME')
conv2d_img = conv2d.eval()
print("conv2d_img.shape", conv2d_img.shape)
conv2d_img = np.swapaxes(conv2d_img, 0, 3)
for i, one_img in enumerate(conv2d_img):
    print(one_img.reshape(3,3))
    plt.subplot(1,2,i+1), plt.imshow(one_img.reshape(3,3), cmap='gray')
```

```
image.shape (1, 3, 3, 1)
weight.shape (2, 2, 1, 1)
conv2d_img.shape (1, 3, 3, 1)
[[ 12.  16.   9.]
 [ 24.  28.  15.]
 [ 15.  17.   9.]]
```





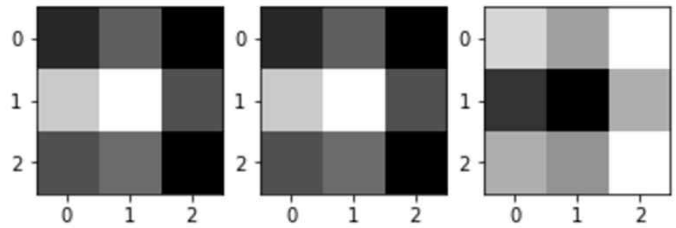


02 Simple Convolution Layer

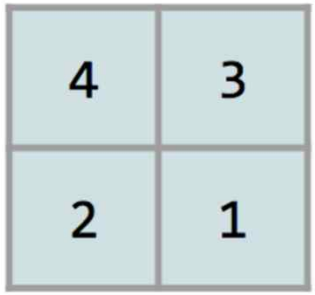
3 filters (2,2,1,3)

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

weight = tf.constant([[[[1.,10.,-1.]],[[1.,10.,-1.]]],
                      [[[1.,10.,-1.]],[[1.,10.,-1.]]]])
print("weight.shape", weight.shape)
conv2d = tf.nn.conv2d(image, weight, strides=[1, 1, 1, 1], padding='SAME')
conv2d_img = conv2d.eval()
print("conv2d_img.shape", conv2d_img.shape)
conv2d_img = np.swapaxes(conv2d_img, 0, 3)
for i, one_img in enumerate(conv2d_img):
    print(one_img.reshape(3,3))
    plt.subplot(1,3,i+1), plt.imshow(one_img.reshape(3,3), cmap='gray')
```

```
image.shape (1, 3, 3, 1)
weight.shape (2, 2, 1, 3)
conv2d_img.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.]]
```



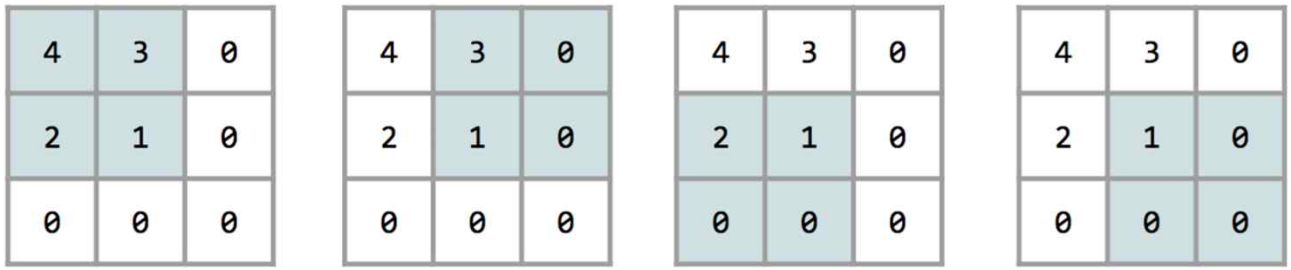
03 Max Pooling



In [19]:
```
image = np.array([[[[4],[3]],
                   [[2],[1]]]], dtype=np.float32)
pool = tf.nn.max_pool(image, ksize=[1, 2, 2, 1],
                      strides=[1, 1, 1, 1], padding='SAME')
print(pool.shape)
print(pool.eval())
```

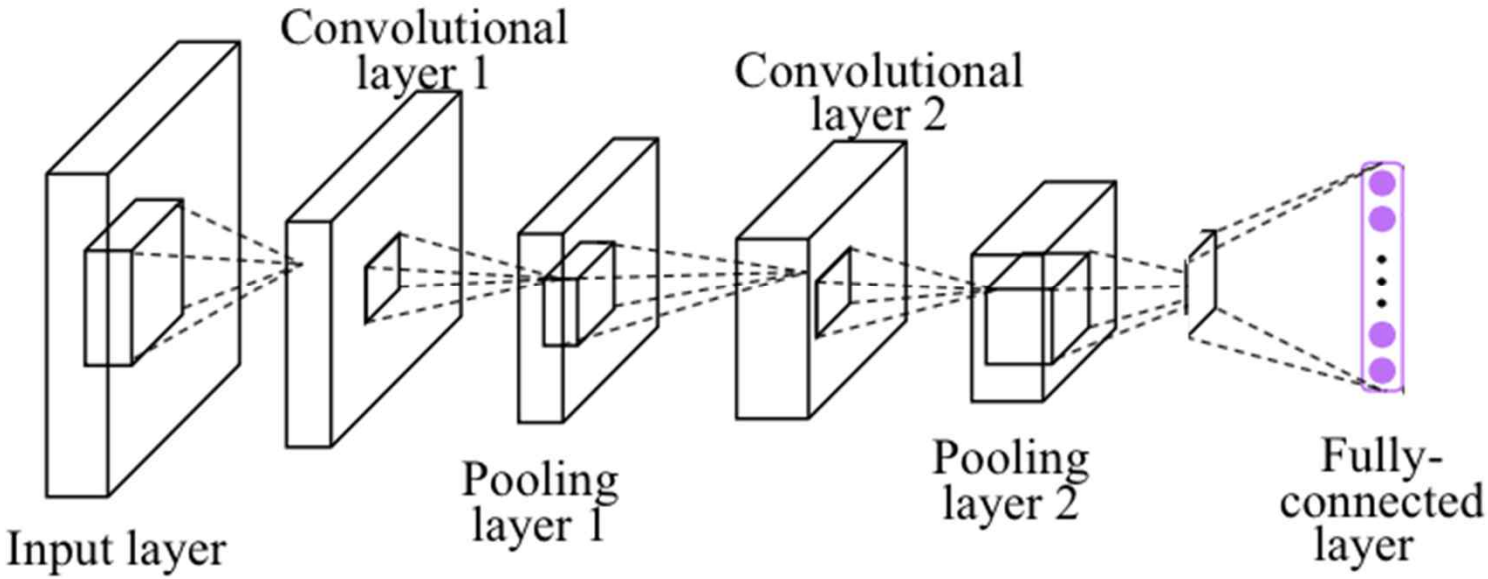
```
(1, 2, 2, 1)
[[[[ 4.]
   [ 3.]]

  [[ 2.]
   [ 1.]]]]
```

SAME: Zero paddings



I -2. CNN for MNIST

01 Simple CNN



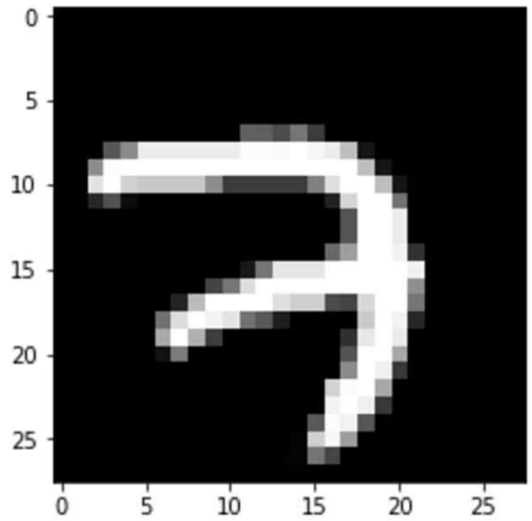
02 Image Loading

In [6]:
```
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
# Check out https://www.tensorflow.org/get_started/mnist/beginners for
# more information about the mnist dataset
```

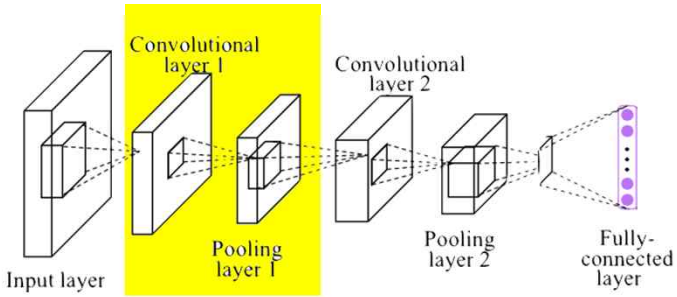
```
Extracting MNIST_data/train-images-idx3-ubyte.gz
Extracting MNIST_data/train-labels-idx1-ubyte.gz
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
```

In [7]:
```
img = mnist.train.images[0].reshape(28,28)
plt.imshow(img, cmap='gray')
```

Out[7]:
```
<matplotlib.image.AxesImage at 0x115029ac8>
```

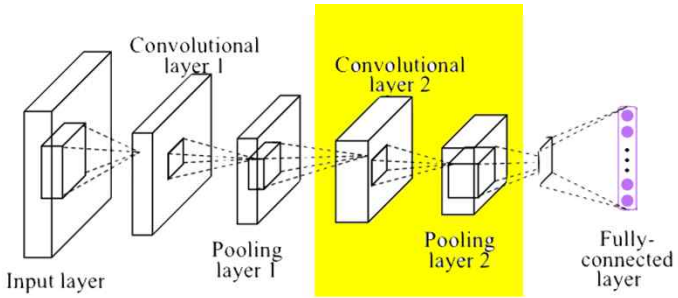


03 Convolution Layer - 1




```
# input placeholders
X = tf.placeholder(tf.float32, [None, 784])
X_img = tf.reshape(X, [-1, 28, 28, 1])   # img 28x28x1 (black/white)
Y = tf.placeholder(tf.float32, [None, 10])

# L1 ImgIn shape=(?, 28, 28, 1)
W1 = tf.Variable(tf.random_normal([3, 3, 1, 32], stddev=0.01))
#    Conv     -> (?, 28, 28, 32)
#    Pool     -> (?, 14, 14, 32)
L1 = tf.nn.conv2d(X_img, W1, strides=[1, 1, 1, 1], padding='SAME')
L1 = tf.nn.relu(L1)
L1 = tf.nn.max_pool(L1, ksize=[1, 2, 2, 1],
         strides=[1, 2, 2, 1], padding='SAME')
'''
Tensor("Conv2D:0", shape=(?, 28, 28, 32), dtype=float32)
Tensor("Relu:0", shape=(?, 28, 28, 32), dtype=float32)
Tensor("MaxPool:0", shape=(?, 14, 14, 32), dtype=float32)
'''
```

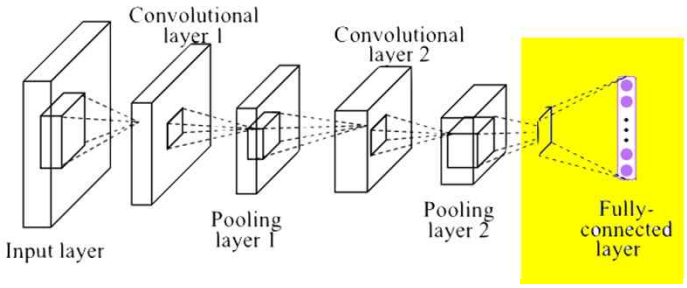
03 Convolution Layer - 2




```
'''
Tensor("Conv2D:0", shape=(?, 28, 28, 32), dtype=float32)
Tensor("Relu:0", shape=(?, 28, 28, 32), dtype=float32)
Tensor("MaxPool:0", shape=(?, 14, 14, 32), dtype=float32)
'''

# L2 ImgIn shape=(?, 14, 14, 32)
W2 = tf.Variable(tf.random_normal([3, 3, 32, 64], stddev=0.01))
#    Conv      ->(?, 14, 14, 64)
#    Pool      ->(?, 7, 7, 64)
L2 = tf.nn.conv2d(L1, W2, strides=[1, 1, 1, 1], padding='SAME')
L2 = tf.nn.relu(L2)
L2 = tf.nn.max_pool(L2, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SAME')
L2 = tf.reshape(L2, [-1, 7 * 7 * 64])
'''
Tensor("Conv2D_1:0", shape=(?, 14, 14, 64), dtype=float32)
Tensor("Relu_1:0", shape=(?, 14, 14, 64), dtype=float32)
Tensor("MaxPool_1:0", shape=(?, 7, 7, 64), dtype=float32)
Tensor("Reshape_1:0", shape=(?, 3136), dtype=float32)
```

04 Fully Connected Layer

```
'''
Tensor("Conv2D_1:0", shape=(?, 14, 14, 64), dtype=float32)
Tensor("Relu_1:0", shape=(?, 14, 14, 64), dtype=float32)
Tensor("MaxPool_1:0", shape=(?, 7, 7, 64), dtype=float32)
Tensor("Reshape_1:0", shape=(?, 3136), dtype=float32)
'''
L2 = tf.reshape(L2, [-1, 7 * 7 * 64])

# Final FC 7x7x64 inputs -> 10 outputs
W3 = tf.get_variable("W3", shape=[7 * 7 * 64, 10], initializer=tf.contrib.layers.xavier_in
itializer())
b = tf.Variable(tf.random_normal([10]))
hypothesis = tf.matmul(L2, W3) + b

# define cost/loss & optimizer
cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=hypothesis, labels=Y)
)
optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimize(cost)
```

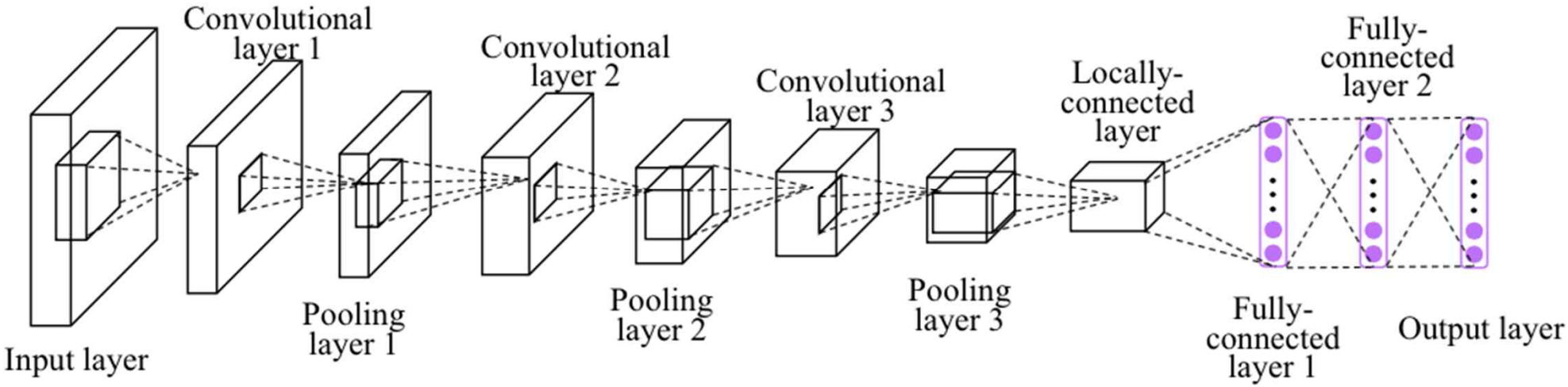


05 Training and Evaluation

```
# initialize
sess = tf.Session()
sess.run(tf.global_variables_initializer())

# train my model
print('Learning stared. It takes sometime.')
for epoch in range(training_epochs):
    avg_cost = 0
    total_batch = int(mnist.train.num_examples / batch_size)
    for i in range(total_batch):
        batch_xs, batch_ys = mnist.train.next_batch(batch_size)
        feed_dict = {X: batch_xs, Y: batch_ys}
        c, _, = sess.run([cost, optimizer], feed_dict=feed_dict)
        avg_cost += c / total_batch
    print('Epoch:', '%04d' % (epoch + 1), 'cost =', '{:.9f}'.format(avg_cost))

print('Learning Finished!')

# Test model and check accuracy
correct_prediction = tf.equal(tf.argmax(hypothesis, 1), tf.argmax(Y, 1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
print('Accuracy:', sess.run(accuracy, feed_dict={X: mnist.test.images, Y: mnist.test.labels})
)
```

```
Epoch: 0001 cost = 0.340291267
Epoch: 0002 cost = 0.090731326
Epoch: 0003 cost = 0.064477619
Epoch: 0004 cost = 0.050683064
…
Epoch: 0011 cost = 0.017758641
Epoch: 0012 cost = 0.014156652
Epoch: 0013 cost = 0.012397016
Epoch: 0014 cost = 0.010693789
Epoch: 0015 cost = 0.009469977
Learning Finished!
Accuracy: 0.9885
```

06 Deep CNN


Convolutional layer 1
Convolutional layer 2
Convolutional layer 3
Locally-connected layer
Fully-connected layer 2
Input layer
Pooling layer 1
Pooling layer 2
Pooling layer 3
Fully-connected layer 1
Output layer

06 Deep CNN

```
# L1 ImgIn shape=(?, 28, 28, 1)
W1 = tf.Variable(tf.random_normal([ 3, 3, 1, 32], stddev=0.01))
#    Conv      -> (?, 28, 28, 32)
#    Pool      -> (?, 14, 14, 32)
L1 = tf.nn.conv2d(X_img, W1, strides=[1, 1, 1, 1], padding='SAME')
L1 = tf.nn.relu(L1)
L1 = tf.nn.max_pool(L1, ksize=[1, 2, 2, 1],
                    strides=[1, 2, 2, 1], padding='SAME')
L1 = tf.nn.dropout(L1, keep_prob=keep_prob)
'''Tensor("Conv2D:0", shape=(?, 28, 28, 32), dtype=float32)
   Tensor("Relu:0", shape=(?, 28, 28, 32), dtype=float32)
   Tensor("MaxPool:0", shape=(?, 14, 14, 32), dtype=float32)
   Tensor("dropout/mul:0", shape=(?, 14, 14, 32), dtype=float32)'''

# L2 ImgIn shape=(?, 14, 14, 32)
W2 = tf.Variable(tf.random_normal([ 3, 3, 32, 64], stddev=0.01))
#    Conv      ->(?, 14, 14, 64)
#    Pool      ->(?, 7, 7, 64)
L2 = tf.nn.conv2d(L1, W2, strides=[1, 1, 1, 1], padding='SAME')
L2 = tf.nn.relu(L2)
L2 = tf.nn.max_pool(L2, ksize=[1, 2, 2, 1],
                    strides=[1, 2, 2, 1], padding='SAME')
L2 = tf.nn.dropout(L2, keep_prob=keep_prob)
'''Tensor("Conv2D_1:0", shape=(?, 14, 14, 64), dtype=float32)
   Tensor("Relu_1:0", shape=(?, 14, 14, 64), dtype=float32)
   Tensor("MaxPool_1:0", shape=(?, 7, 7, 64), dtype=float32)
   Tensor("dropout_1/mul:0", shape=(?, 7, 7, 64), dtype=float32)'''
```

```
# L3 ImgIn shape=(?, 7, 7, 64)
W3 = tf.Variable(tf.random_normal([ 3, 3, 64, 128], stddev=0.01))
#    Conv      ->(?, 7, 7, 128)
#    Pool      ->(?, 4, 4, 128)
#    Reshape   ->(?, 4 * 4 * 128) # Flatten them for FC
L3 = tf.nn.conv2d(L2, W3, strides=[1, 1, 1, 1], padding='SAME')
L3 = tf.nn.relu(L3)
L3 = tf.nn.max_pool(L3, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], pad
ding='SAME')
L3 = tf.nn.dropout(L3, keep_prob=keep_prob)
L3 = tf.reshape(L3, [-1, 128 * 4 * 4])
'''Tensor("Conv2D_2:0", shape=(?, 7, 7, 128), dtype=float32)
   Tensor("Relu_2:0", shape=(?, 7, 7, 128), dtype=float32)
   Tensor("MaxPool_2:0", shape=(?, 4, 4, 128), dtype=float32)
   Tensor("dropout_2/mul:0", shape=(?, 4, 4, 128), dtype=float32)
   Tensor("Reshape_1:0", shape=(?, 2048), dtype=float32)'''
# L4 FC 4x4x128 inputs  -> 625 outputs
W4 = tf.get_variable("W4", shape=[128 * 4 * 4, 625], initializer=tf.c
ontrib.layers.xavier_initializer())
b4 = tf.Variable(tf.random_normal([ 625]))
L4 = tf.nn.relu(tf.matmul(L3, W4) + b4)
L4 = tf.nn.dropout(L4, keep_prob=keep_prob)
'''Tensor("Relu_3:0", shape=(?, 625), dtype=float32)
   Tensor("dropout_3/mul:0", shape=(?, 625), dtype=float32)'''
# L5 Final FC 625 inputs  -> 10 outputs
W5 = tf.get_variable("W5", shape=[625, 10],    initializer=tf.contrib
.layers.xavier_initializer())
b5 = tf.Variable(tf.random_normal([ 10]))
hypothesis = tf.matmul(L4, W5) + b5
'''Tensor("add_1:0", shape=(?, 10), dtype=float32)'''
```

06 Deep CNN

```
# L1 ImgIn shape=(?, 28, 28, 1)
W1 = tf.Variable(tf.random_normal([ 3, 3, 1, 32], stddev=0.01))
#    Conv     -> (?, 28, 28, 32)
#    Pool     -> (?, 14, 14, 32)
L1 = tf.nn.conv2d(X_img, W1, strides=[1, 1, 1, 1], padding='SAME')
L1 = tf.nn.relu(L1)
L1 = tf.nn.max_pool(L1, ksize=[1, 2, 2, 1],
                    strides=[1, 2, 2, 1], padding='SAME')
L1 = tf.nn.dropout(L1, keep_prob=keep_prob)
'''Tensor("Conv2D:0", shape=(?, 28, 28, 32), dtype=float32)
   Tensor("Relu:0", shape=(?, 28, 28, 32), dtype=float32)
   Tensor("MaxPool:0", shape=(?, 14, 14, 32), dtype=float32)
   Tensor("dropout/mul:0", shape=(?, 14, 14, 32), dtype=float32)'''
...
...
# L4 FC 4x4x128 inputs  -> 625 outputs
W4 = tf.get_variable("W4", shape=[128 * 4 * 4, 625], initializer=tf.
contrib.layers.xavier_initializer())
b4 = tf.Variable(tf.random_normal([ 625]))
L4 = tf.nn.relu(tf.matmul(L3, W4) + b4)
L4 = tf.nn.dropout(L4, keep_prob=keep_prob)
'''Tensor("Relu_3:0", shape=(?, 625), dtype=float32)
   Tensor("dropout_3/mul:0", shape=(?, 625), dtype=float32)'''
# L5 Final FC 625 inputs  -> 10 outputs
W5 = tf.get_variable("W5", shape=[625, 10],    initializer=tf.contri
b.layers.xavier_initializer())
b5 = tf.Variable(tf.random_normal([ 10]))
hypothesis = tf.matmul(L4, W5) + b5
'''Tensor("add_1:0", shape=(?, 10), dtype=float32)'''
```

```
# Test model and check accuracy
correct_prediction = tf.equal(tf.argmax(hypothesis, 1),
         tf.argmax(Y, 1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction,tf.
float32))
print('Accuracy:', sess.run(accuracy,
feed_dict={X: mnist.test.images,
           Y: mnist.test.labels, keep_prob: 1}))
```

```
Epoch: 0013 cost = 0.027188021
Epoch: 0014 cost = 0.023604777
Epoch: 0015 cost = 0.024607201
Learning Finished!
Accuracy: 0.9938
```

I -3. Class, Layers, Ensemble

01 CNN

```
# L1 ImgIn shape=(?, 28, 28, 1)
W1 = tf.Variable(tf.random_normal([ 3, 3, 1, 32], stddev=0.01))
#    Conv     -> (?, 28, 28, 32)
#    Pool     -> (?, 14, 14, 32)
L1 = tf.nn.conv2d(X_img, W1, strides=[1, 1, 1, 1], padding='SAME')
L1 = tf.nn.relu(L1)
L1 = tf.nn.max_pool(L1, ksize=[1, 2, 2, 1],
                    strides=[1, 2, 2, 1], padding='SAME')
L1 = tf.nn.dropout(L1, keep_prob=keep_prob)
'''Tensor("Conv2D:0", shape=(?, 28, 28, 32), dtype=float32)
   Tensor("Relu:0", shape=(?, 28, 28, 32), dtype=float32)
   Tensor("MaxPool:0", shape=(?, 14, 14, 32), dtype=float32)
   Tensor("dropout/mul:0", shape=(?, 14, 14, 32), dtype=float32)'''
...
...
# L4 FC 4x4x128 inputs  -> 625 outputs
W4 = tf.get_variable("W4", shape=[128 * 4 * 4, 625], initializer=tf.
contrib.layers.xavier_initializer())
b4 = tf.Variable(tf.random_normal([ 625]))
L4 = tf.nn.relu(tf.matmul(L3, W4) + b4)
L4 = tf.nn.dropout(L4, keep_prob=keep_prob)
'''Tensor("Relu_3:0", shape=(?, 625), dtype=float32)
   Tensor("dropout_3/mul:0", shape=(?, 625), dtype=float32)'''
# L5 Final FC 625 inputs  -> 10 outputs
W5 = tf.get_variable("W5", shape=[625, 10],    initializer=tf.contri
b.layers.xavier_initializer())
b5 = tf.Variable(tf.random_normal([ 10]))
hypothesis = tf.matmul(L4, W5) + b5
'''Tensor("add_1:0", shape=(?, 10), dtype=float32)'''
```

```
# Test model and check accuracy
correct_prediction = tf.equal(tf.argmax(hypothesis, 1),
        tf.argmax(Y, 1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction,tf.
float32))
print('Accuracy:', sess.run(accuracy,
feed_dict={X: mnist.test.images,
           Y: mnist.test.labels, keep_prob: 1}))
```

```
Epoch: 0013 cost = 0.027188021
Epoch: 0014 cost = 0.023604777
Epoch: 0015 cost = 0.024607201
Learning Finished!
Accuracy: 0.9938
```

01 CNN using Class

```
class Model:

    def __init__(self, sess, name):
        self.sess = sess
        self.name = name
        self._build_net()

    def _build_net(self):
        with tf.variable_scope(self.name):
            # input place holders
            self.X = tf.placeholder(tf.float32, [None, 784])
            # img 28x28x1 (black/white)
            X_img = tf.reshape(self.X, [-1, 28, 28, 1])
            self.Y = tf.placeholder(tf.float32, [None, 10])

            # L1 ImgIn shape=(?, 28, 28, 1)
            W1 = tf.Variable(tf.random_normal([3, 3, 1, 32],
                                              stddev=0.01))
            ...
def predict(self, x_test, keep_prop=1.0):
    return self.sess.run(self.logits,
         feed_dict={self.X: x_test, self.keep_prob: keep_prop})

def get_accuracy(self, x_test, y_test, keep_prop=1.0):
    return self.sess.run(self.accuracy,
     feed_dict={self.X: x_test, self.Y: y_test, self.keep_prob: keep_prop})

def train(self, x_data, y_data, keep_prop=0.7):
    return self.sess.run([self.cost, self.optimizer], feed_dict={
        self.X: x_data, self.Y: y_data, self.keep_prob: keep_prop})
```

```
# initialize
sess = tf.Session()
m1 = Model(sess, "m1")

sess.run(tf.global_variables_initializer())

print('Learning Started!')

# train my model
for epoch in range(training_epochs):
    avg_cost = 0
    total_batch = int(mnist.train.num_examples / batch_size)

    for i in range(total_batch):
        batch_xs, batch_ys = mnist.train.next_batch(batch_size)
        c, _ = m1.train(batch_xs, batch_ys)
        avg_cost += c / total_batc
```

02 tf.layers

`average_pooling1d(...)` : Average Pooling layer for 1D inputs.

`average_pooling2d(...)` : Average pooling layer for 2D inputs (e.g. images).

`average_pooling3d(...)` : Average pooling layer for 3D inputs (e.g. volumes).

`batch_normalization(...)` : Functional interface for the batch normalization layer.

`conv1d(...)` : Functional interface for 1D convolution layer (e.g. temporal convolution).

`conv2d(...)` : Functional interface for the 2D convolution layer.

`conv2d_transpose(...)` : Transposed convolution layer (sometimes called Deconvolution).

`conv3d(...)` : Functional interface for the 3D convolution layer.

`dense(...)` : Functional interface for the densely-connected layer.

`dropout(...)` : Applies Dropout to the input.

`max_pooling1d(...)` : Max Pooling layer for 1D inputs.

`max_pooling2d(...)` : Max pooling layer for 2D inputs (e.g. images).

`max_pooling3d(...)` : Max pooling layer for 3D inputs (e.g. volumes).

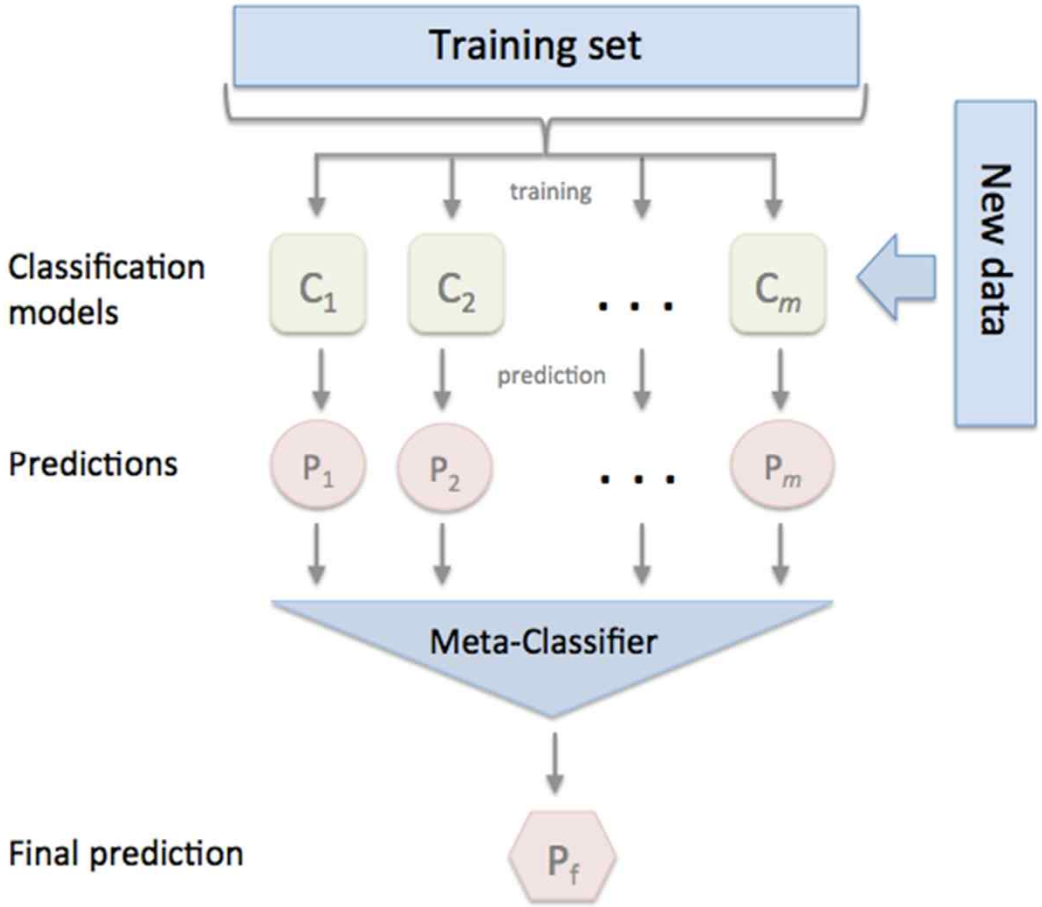
`separable_conv2d(...)` : Functional interface for the depthwise separable 2D convolution layer.

02 tf.layers

```
# L1 ImgIn shape=(?, 28, 28, 1)
W1 = tf.Variable(tf.random_normal([3, 3, 1, 32], stddev=0.01))
#    Conv     -> (?, 28, 28, 32)
#    Pool     -> (?, 14, 14, 32)
L1 = tf.nn.conv2d(X_img, W1, strides=[1, 1, 1, 1], padding='SAME')
L1 = tf.nn.relu(L1)
L1 = tf.nn.max_pool(L1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SAME')
L1 = tf.nn.dropout(L1, keep_prob=self.keep_prob)
…
# L2 ImgIn shape=(?, 14, 14, 32)
W2 = tf.Variable(tf.random_normal([3, 3, 32, 64], stddev=0.01))
```

```
# Convolutional Layer #1
conv1 = tf.layers.conv2d(inputs=X_img,filters=32,kernel_size=[3,3],padding="SAME",activation=tf.nn.relu)
pool1 = tf.layers.max_pooling2d(inputs=conv1, pool_size=[2, 2], padding="SAME", strides=2)
dropout1 = tf.layers.dropout(inputs=pool1,rate=0.7, training=self.training)

# Convolutional Layer #2
conv2 = tf.layers.conv2d(inputs=dropout1,filters=64,kernel_size=[3,3],padding="SAME",activation=tf.nn.relu)
…
flat = tf.reshape(dropout3, [-1, 128 * 4 * 4])
dense4 = tf.layers.dense(inputs=flat, units=625, activation=tf.nn.relu)
dropout4 = tf.layers.dropout(inputs=dense4, rate=0.5, training=self.training)
...
```

03 Ensemble


Training set
training
New data
Classification models
C_1
C_2
C_m
prediction
Predictions
P_1
P_2
P_m
Meta-Classifier
Final prediction
P_f

03 Ensemble

```python
class Model:

  def __init__(self, sess, name):
    self.sess = sess
    self.name = name
    self._build_net()

  def _build_net(self):
    with tf.variable_scope(self.name):

  ...
```

```python
models = []
num_models = 7
for m in range(num_models):
    models.append(Model(sess, "model" + str(m)))

sess.run(tf.global_variables_initializer())
print('Learning Started!')

# train my model
for epoch in range(training_epochs):
    avg_cost_list = np.zeros(len(models))
    total_batch = int(mnist.train.num_examples / batch_size)
    for i in range(total_batch):
        batch_xs, batch_ys =mnist.train.next_batch(batch_size)

        # train each model
        for m_idx, m in enumerate(models):
            c, _ = m.train(batch_xs, batch_ys)
            avg_cost_list[m_idx] += c / total_batch

    print('Epoch:','%04d'%(epoch + 1),'cost =', avg_cost_list)

print('Learning Finished!')
```

03 Ensemble

	0	1	2	3	4	5	6	7	8	9
C_1	0.1	0.01	0.02	0.8	...	...	...	...	...	...
C_2	0.01	0.5	0.02	0.4	...	...	...	...	...	...
.										
.										
.										
C_m	0.01	0.01	0.1	0.7	...	...	...	...	...	...
Sum	0.12	0.52	0.14	**1.9**	...	...	...	...	...	...

argmax

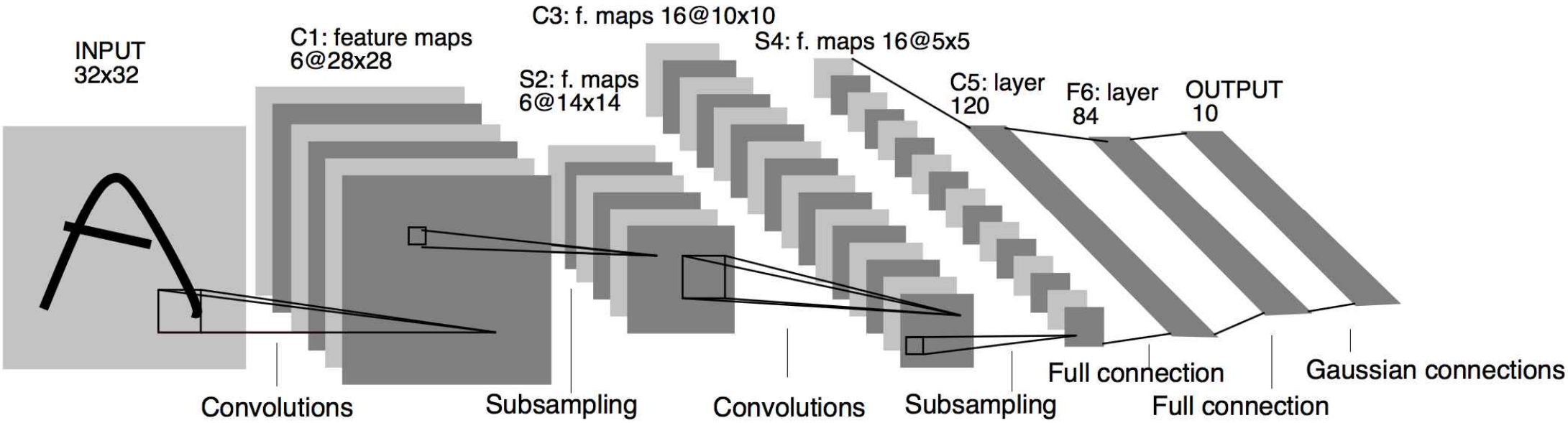
03 Ensemble

```
# Test model and check accuracy
test_size = len(mnist.test.labels)
predictions = np.zeros(test_size * 10).reshape(test_size, 10)


for m_idx, m in enumerate(models):
    print(m_idx, 'Accuracy:', m.get_accuracy(mnist.test.images, mnist.test.labels))
    p = m.predict(mnist.test.images)
    predictions += p

ensemble_correct_prediction = tf.equal(
     tf.argmax(predictions, 1), tf.argmax(mnist.test.labels, 1))
ensemble_accuracy = tf.reduce_mean(
    tf.cast(ensemble_correct_prediction, tf.float32))
print('Ensemble accuracy:', sess.run(ensemble_accuracy))
```

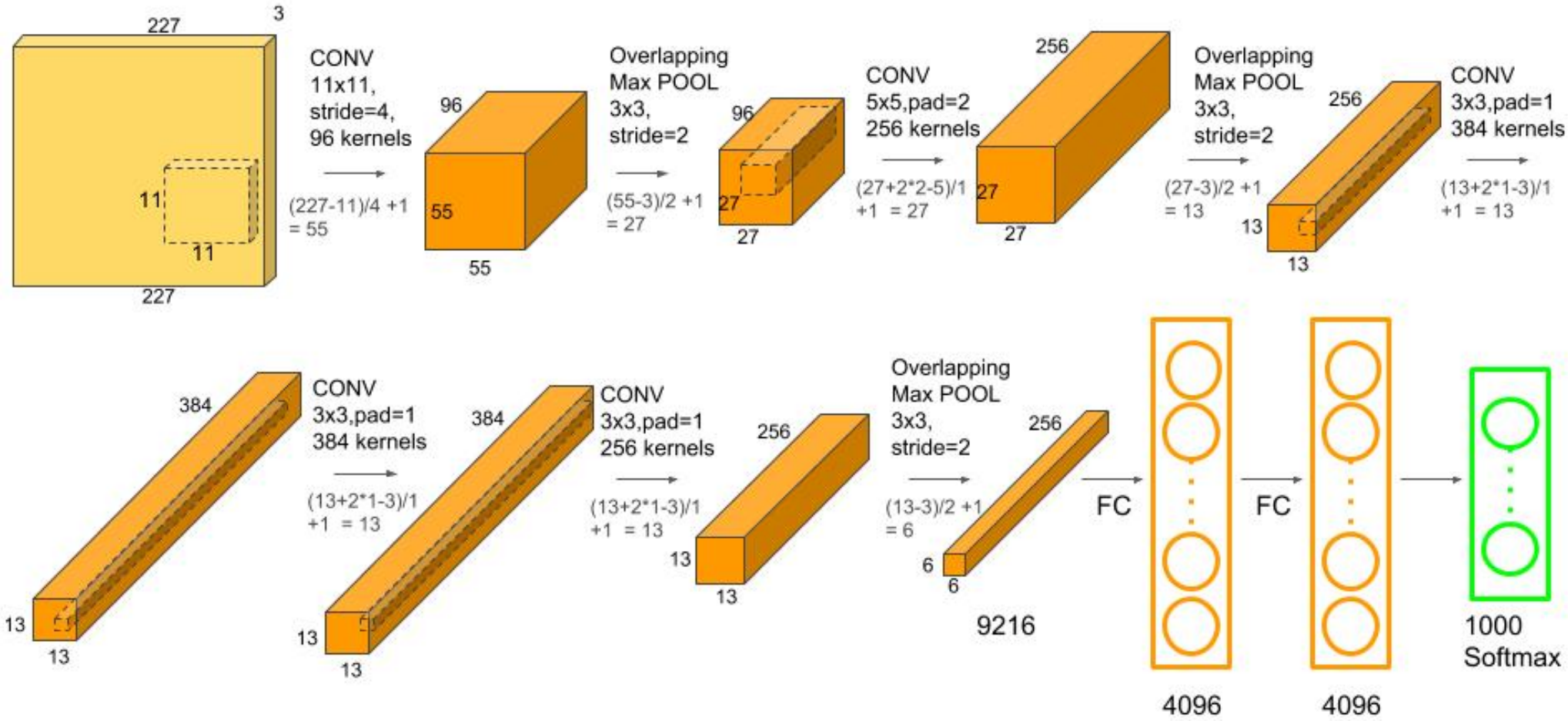
```
0 Accuracy: 0.9933
1 Accuracy: 0.9946
2 Accuracy: 0.9934
3 Accuracy: 0.9935
4 Accuracy: 0.9935
5 Accuracy: 0.9949
6 Accuracy: 0.9941

Ensemble accuracy: 0.9952
```

Ⅱ. Case Study

01 LeNet-5


INPUT
32x32
C1: feature maps
6@28x28
S2: f. maps
6@14x14
C3: f. maps 16@10x10
S4: f. maps 16@5x5
C5: layer
120
F6: layer
84
OUTPUT
10
Convolutions
Subsampling
Convolutions
Subsampling
Full connection
Full connection
Gaussian connections

02 AlexNet


227
3
11
11
227
CONV
11x11,
stride=4,
96 kernels
(227-11)/4 +1
= 55
96
55
55
Overlapping
Max POOL
3x3,
stride=2
(55-3)/2 +1
= 27
96
27
27
CONV
5x5,pad=2
256 kernels
(27+2*2-5)/1
+1 = 27
256
27
27
Overlapping
Max POOL
3x3,
stride=2
(27-3)/2 +1
= 13
256
13
13
CONV
3x3,pad=1
384 kernels
(13+2*1-3)/1
+1 = 13
384
13
13
CONV
3x3,pad=1
384 kernels
(13+2*1-3)/1
+1 = 13
384
13
13
CONV
3x3,pad=1
256 kernels
(13+2*1-3)/1
+1 = 13
256
13
13
Overlapping
Max POOL
3x3,
stride=2
(13-3)/2 +1
= 6
256
6
6
9216
FC
4096
FC
4096
1000
Softmax

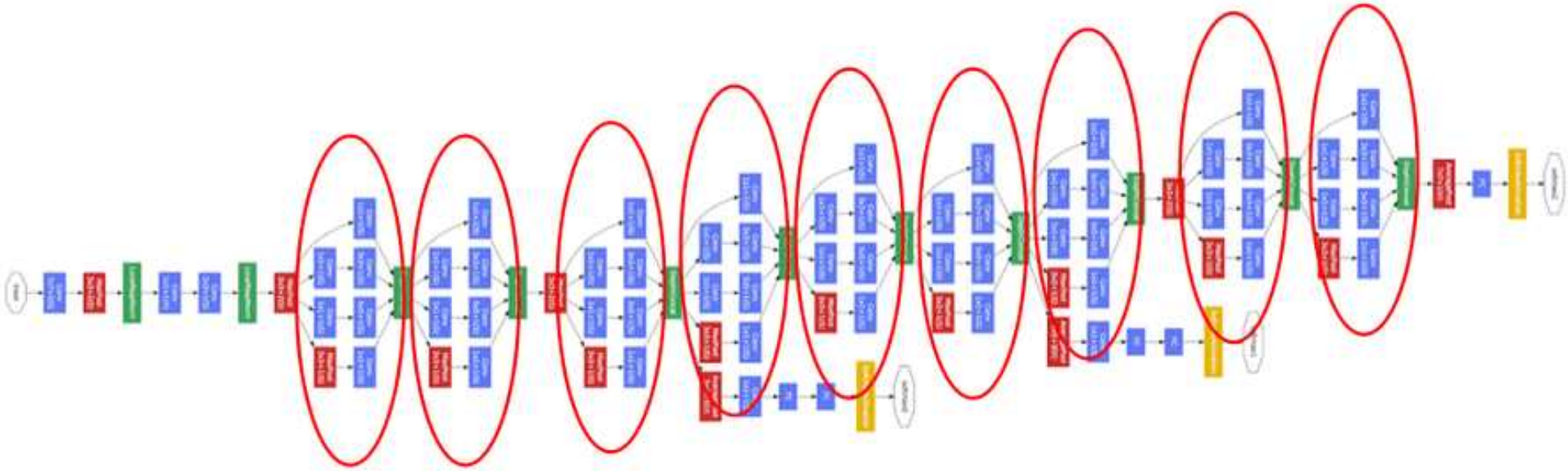
02 AlexNet

Layer	Type	Maps	Size	Kernel size	Stride	Padding	Activation
Out	Fully Connected	–	1,000	–	–	–	Softmax
F9	Fully Connected	–	4,096	–	–	–	ReLU
F8	Fully Connected	–	4,096	–	–	–	ReLU
C7	Convolution	256	13 × 13	3 × 3	1	SAME	ReLU
C6	Convolution	384	13 × 13	3 × 3	1	SAME	ReLU
C5	Convolution	384	13 × 13	3 × 3	1	SAME	ReLU
S4	Max Pooling	256	13 × 13	3 × 3	2	VALID	–
C3	Convolution	256	27 × 27	5 × 5	1	SAME	ReLU
S2	Max Pooling	96	27 × 27	3 × 3	2	VALID	–
C1	Convolution	96	55 × 55	11 × 11	4	SAME	ReLU
In	Input	3 (RGB)	224 × 224	–	–	–	–

02 AlexNet

- First use of ReLU
- used Norm layers (not common anymore)
- Dropout 0.5
- Batch size 128
- Learning rate 1e-2
- 7 CNN ensemble: 18.2 -> 15.4%

03 GoogLeNet

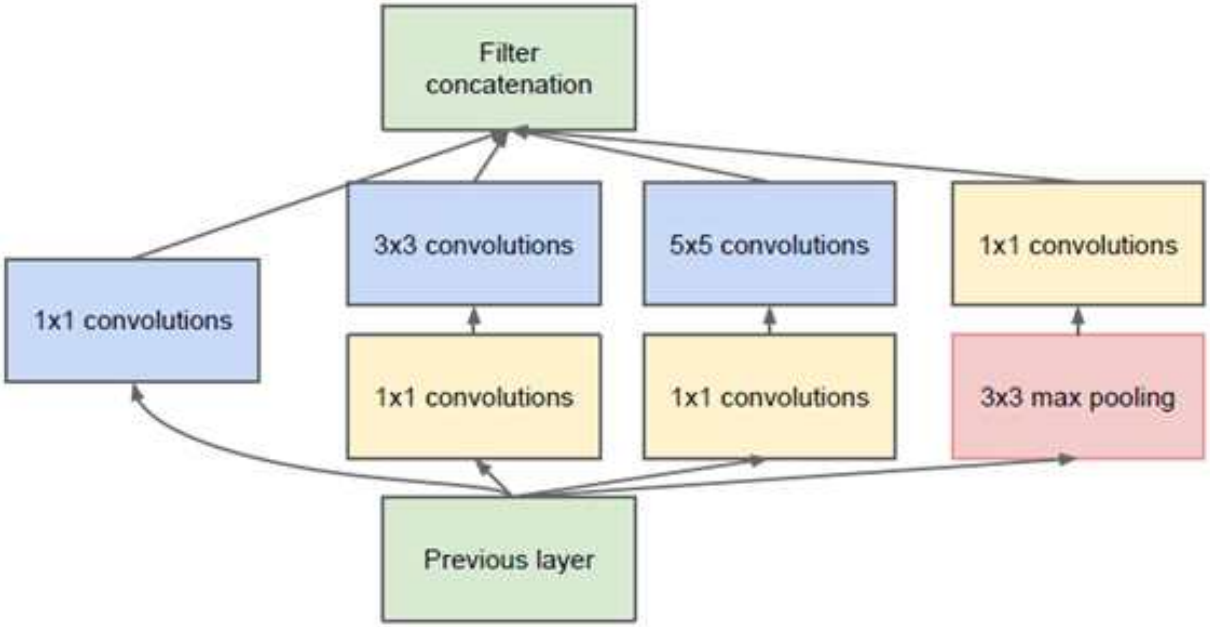


9 **Inception** modules

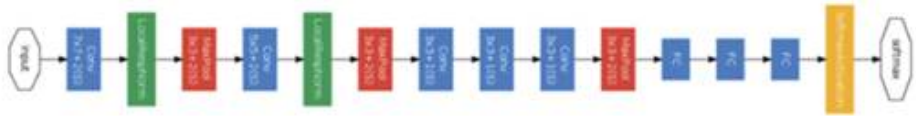
Network in a network in a network...

Convolution
Pooling
Softmax
Other

03 GoogLeNet

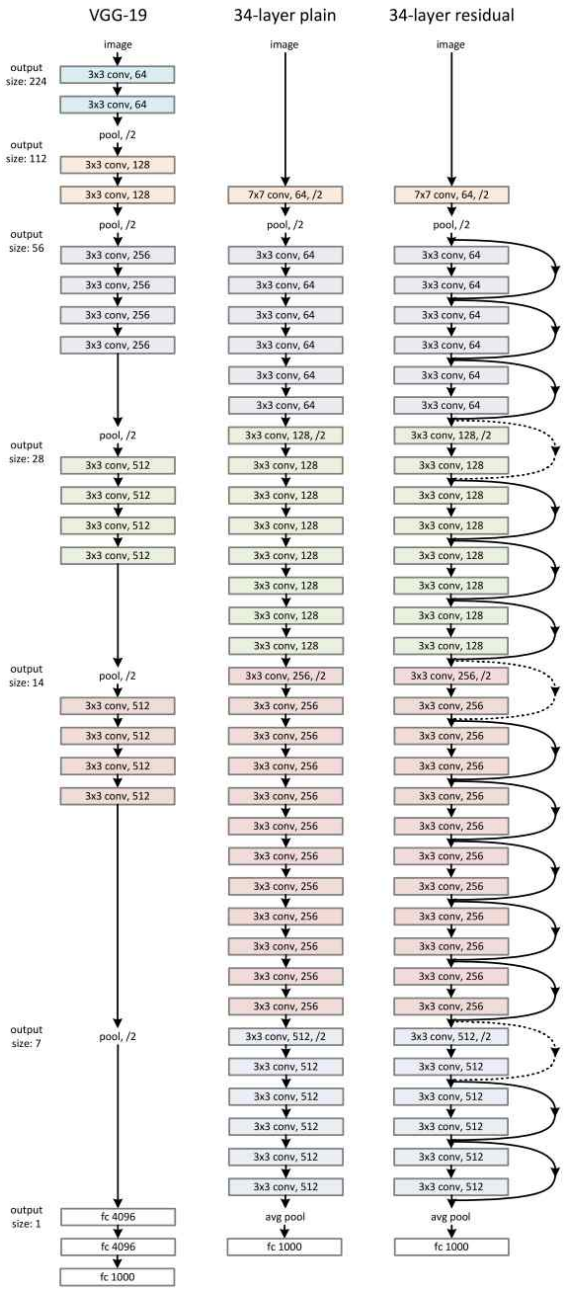


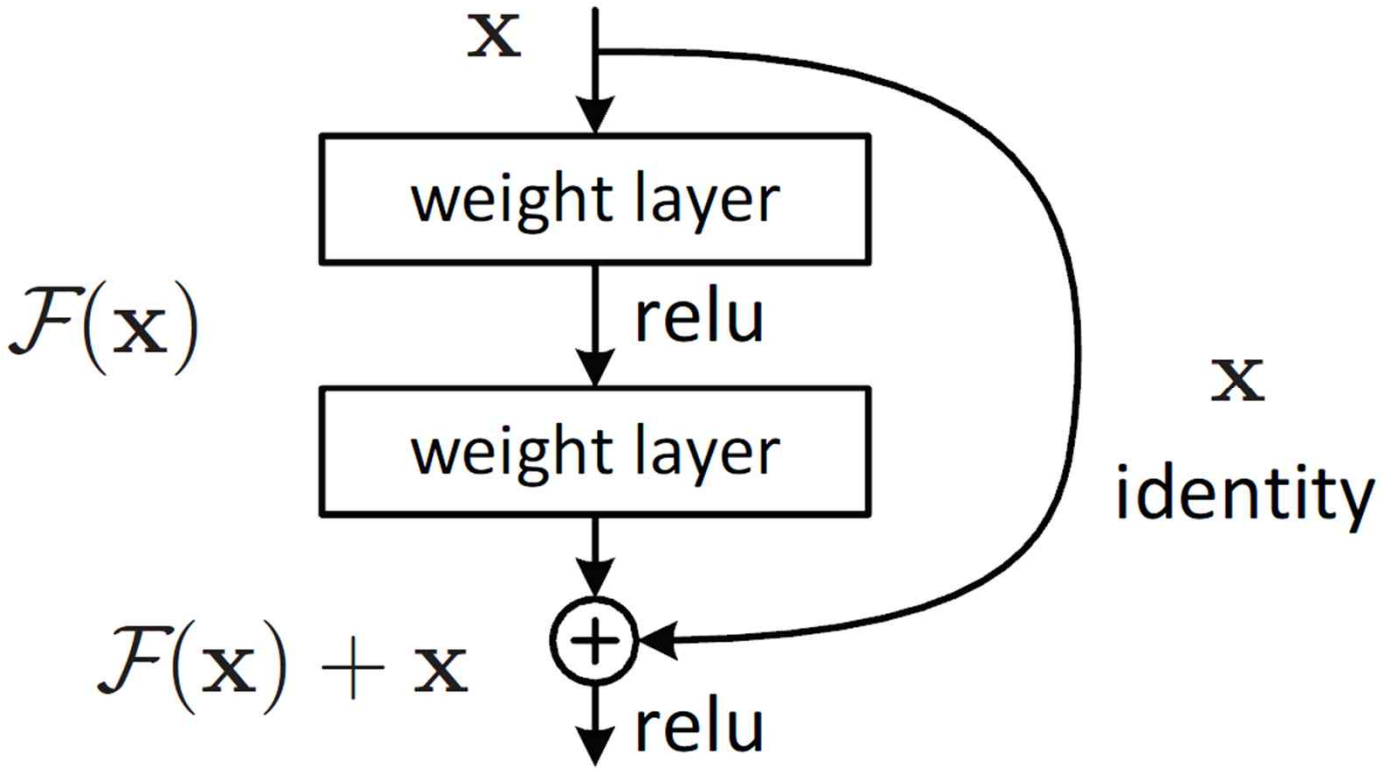
	params	*FLOPs*
Suskever and Hinton (2012)	60M	2B



Szegedy et al (2014)	5M	1.5B

04 ResNet


VGG-19
34-layer plain
34-layer residual
image
output size: 224
3x3 conv, 64
3x3 conv, 64
pool, /2
output size: 112
3x3 conv, 128
3x3 conv, 128
pool, /2
output size: 56
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
pool, /2
output size: 28
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
pool, /2
output size: 14
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
pool, /2
output size: 7
fc 4096
fc 4096
fc 1000
output size: 1
7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 128, /2
3x3 conv, 128
3x3 conv, 256, /2
3x3 conv, 256
3x3 conv, 512, /2
3x3 conv, 512
avg pool
fc 1000


x
weight layer
relu
weight layer
$\mathcal{F}(\mathbf{x})$
x
identity
$\mathcal{F}(\mathbf{x}) + \mathbf{x}$
relu

05 Various CNN Architecture