Lecture 12

CNN

A bit of history:

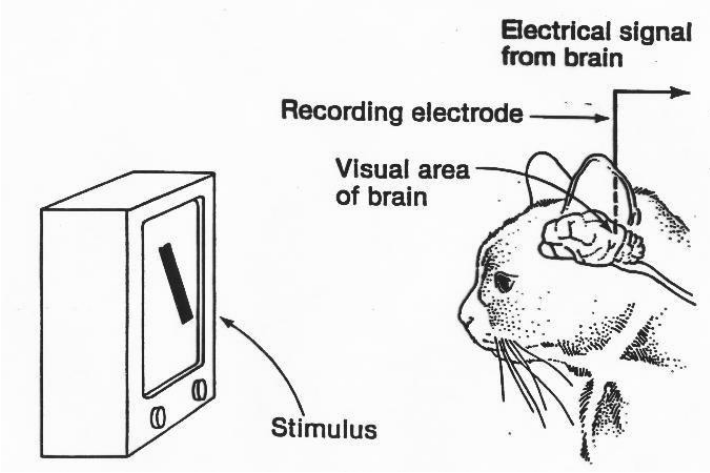
Hubel & Wiesel, 1959

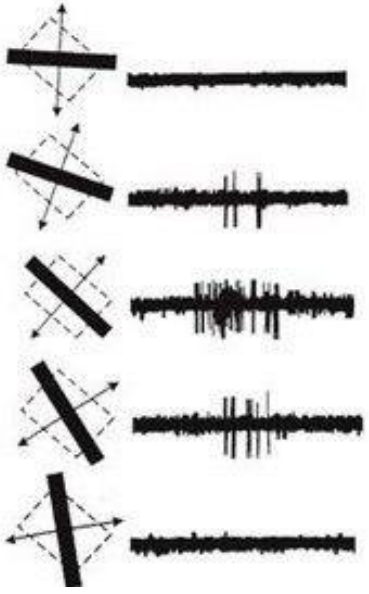
RECEPTIVE FIELDS OF SINGLE NEURONES IN
THE CAT'S STRIATE CORTEX

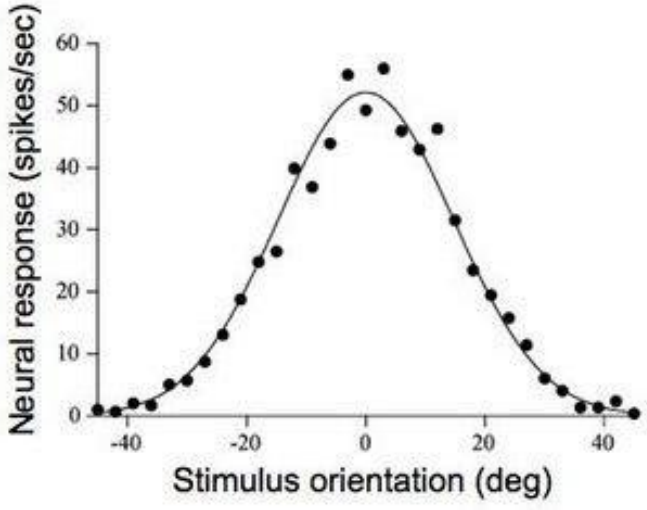
1962

RECEPTIVE FIELDS, BINOCULAR INTERACTION
AND FUNCTIONAL ARCHITECTURE IN
THE CAT'S VISUAL CORTEX

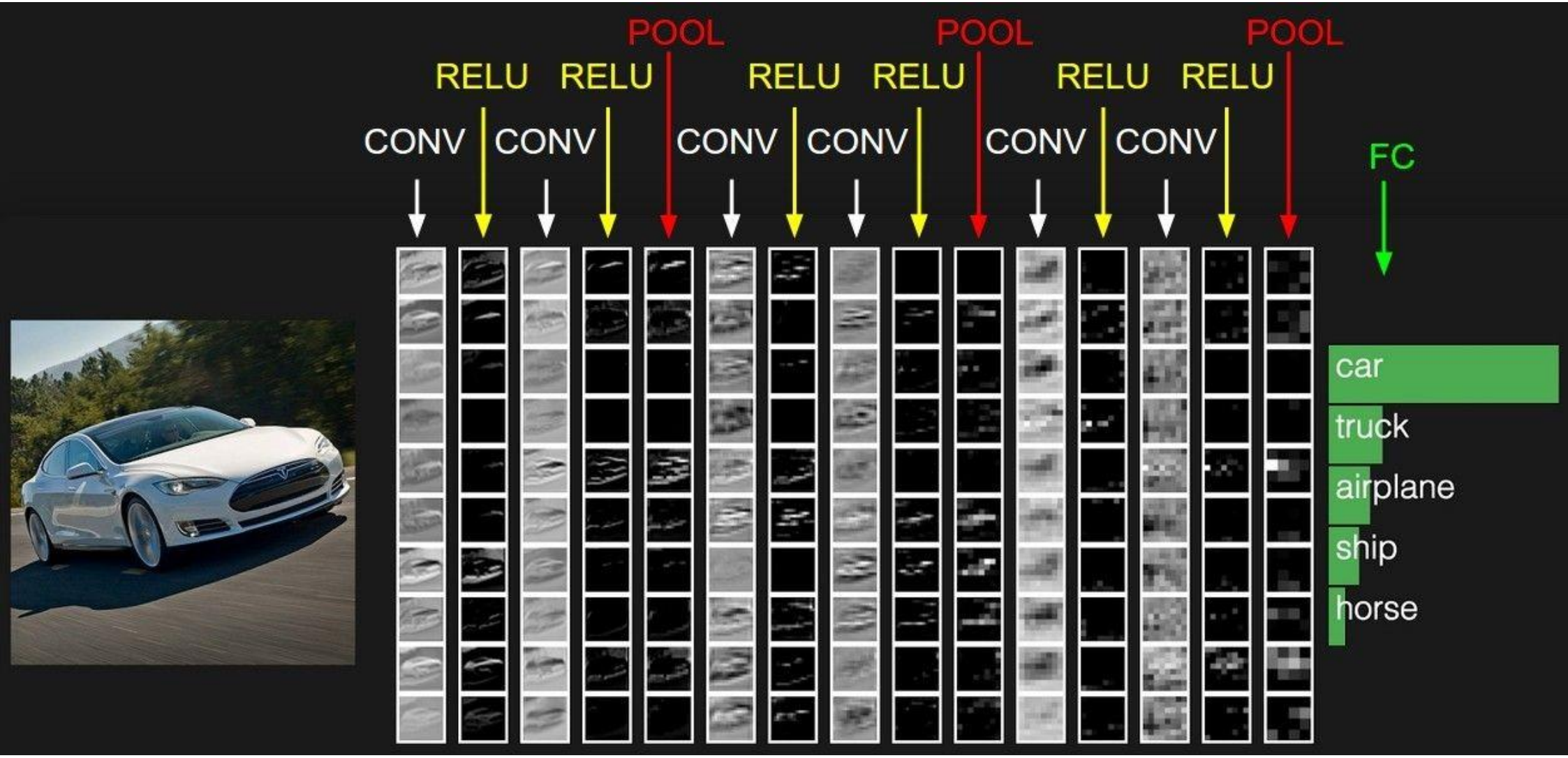
1968...



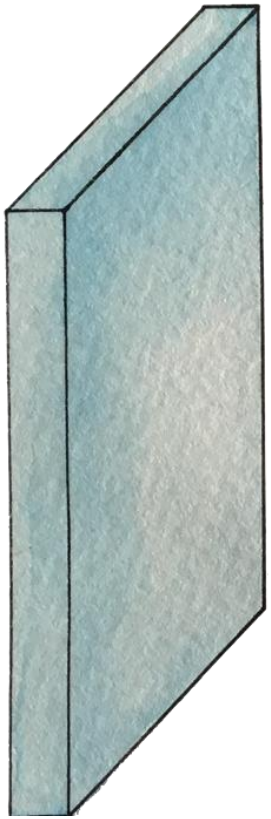




preview:

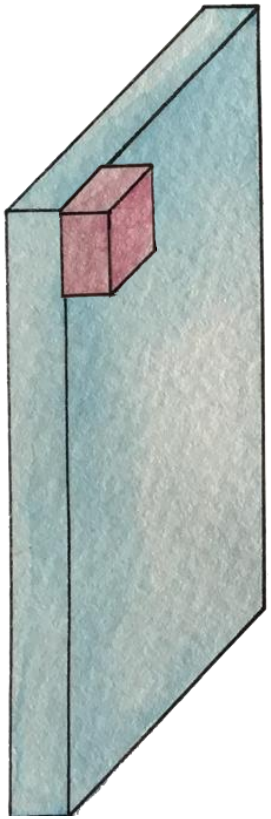

POOL
POOL
POOL
RELU
RELU
RELU
RELU
RELU
RELU
CONV
CONV
CONV
CONV
CONV
CONV
FC
car
truck
airplane
ship
horse

Start with an image (width x hight x depth)



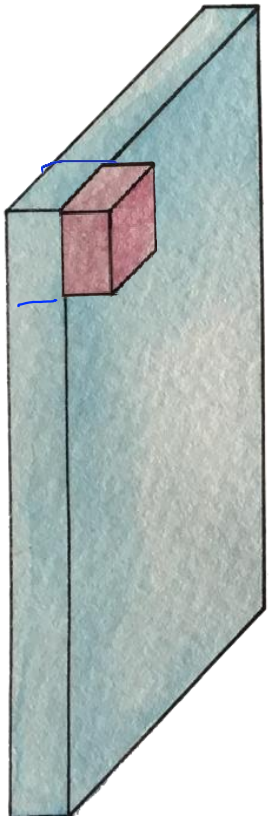
32x32x3 image

Let’s focus on a small area only



32x32x3 image

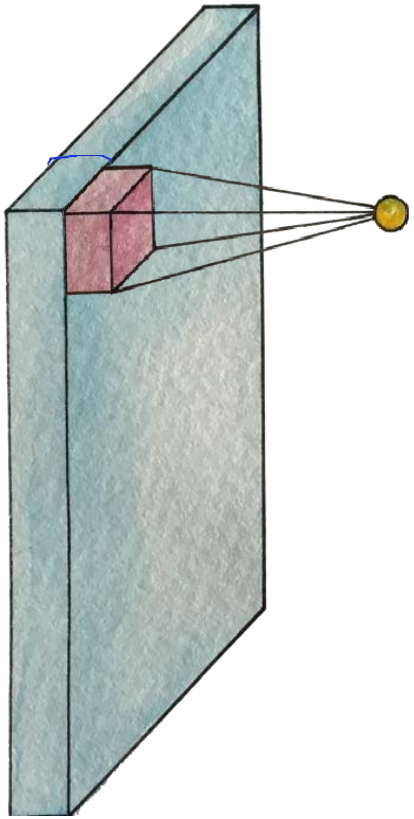
Let's focus on a small area only (5x5x3)



32x32x3 image

5x5x3 filter

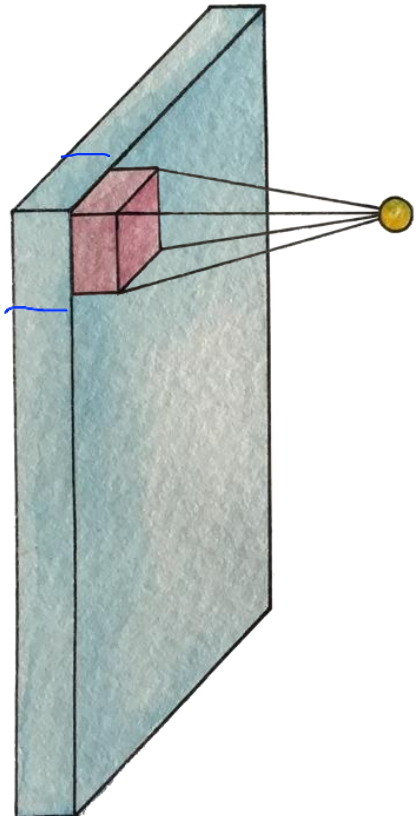
Get one number using the filter



one number!

32x32x3 image

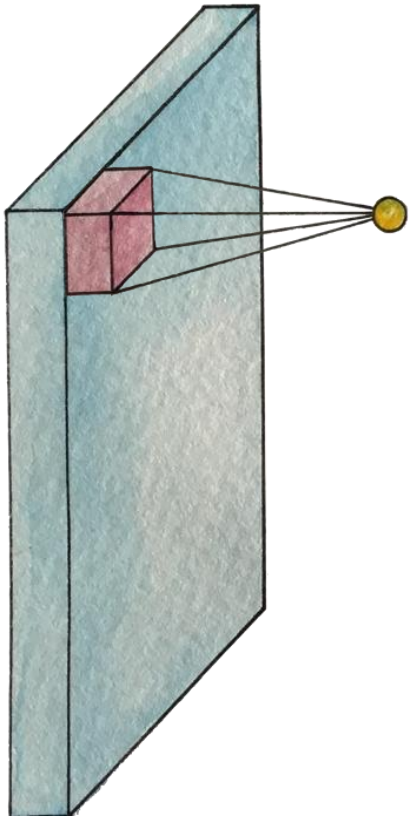
Get one number using the filter



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

5x5x3 filter

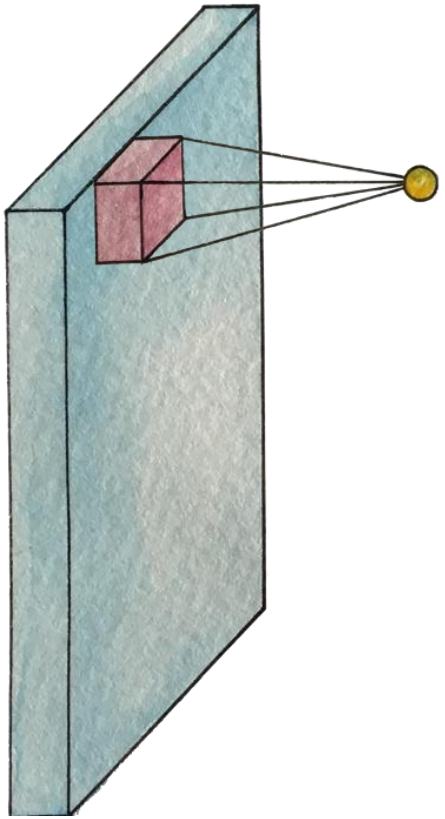
32x32x3 image



one number!

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

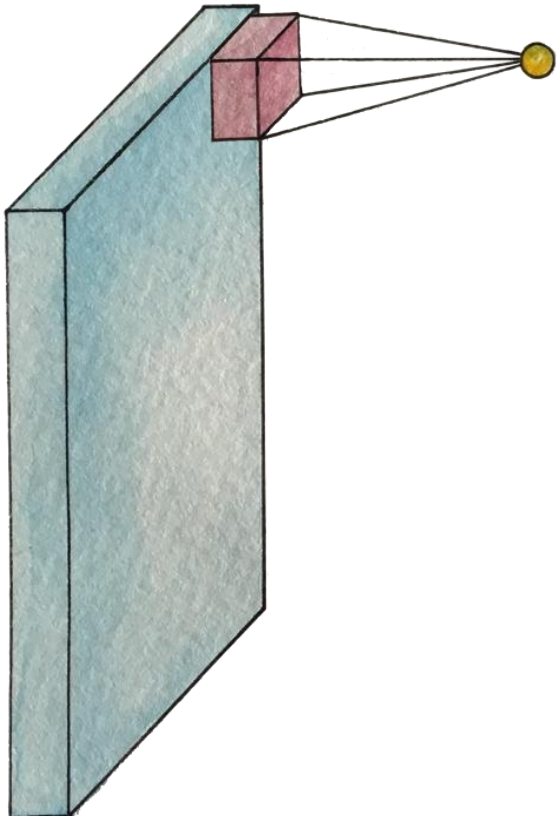
32x32x3 image



one number!

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

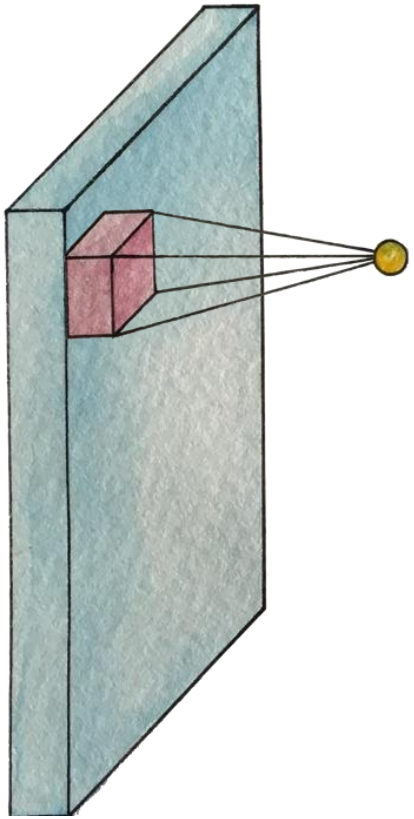
32x32x3 image



one number!

32x32x3 image

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

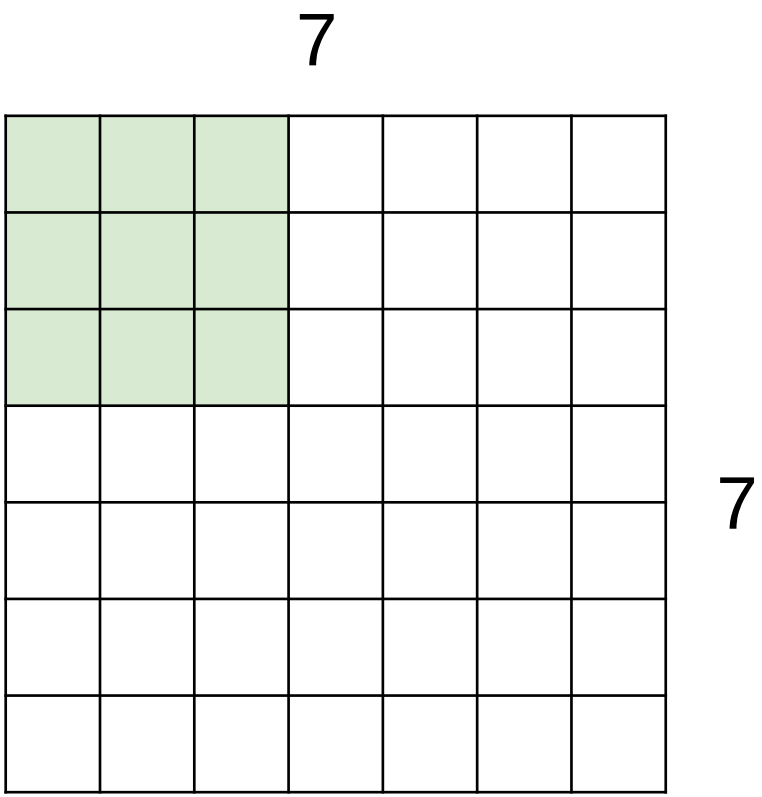


one number!

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

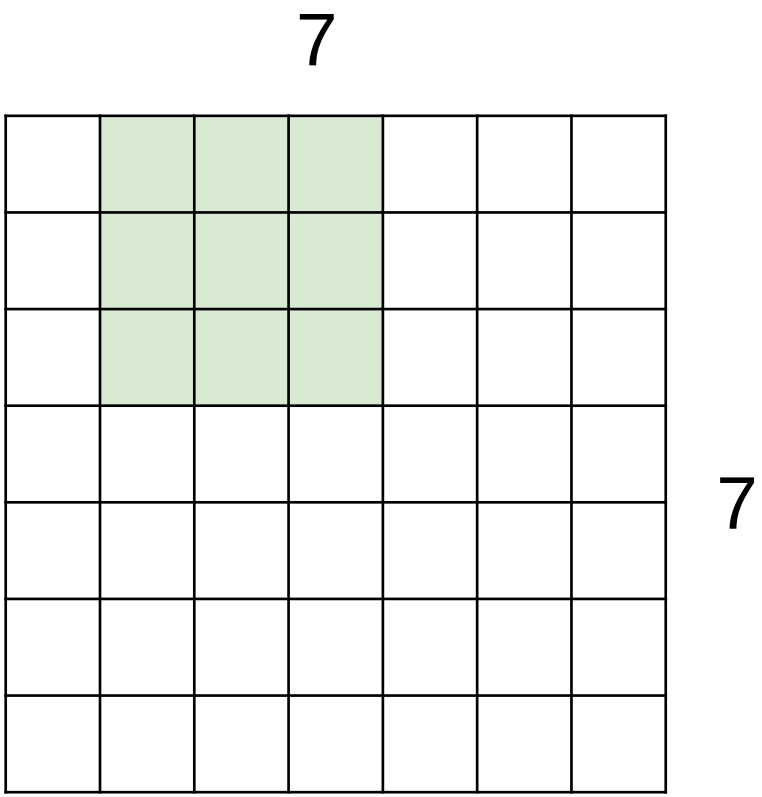
32x32x3 image

A closer look at spatial dimensions:



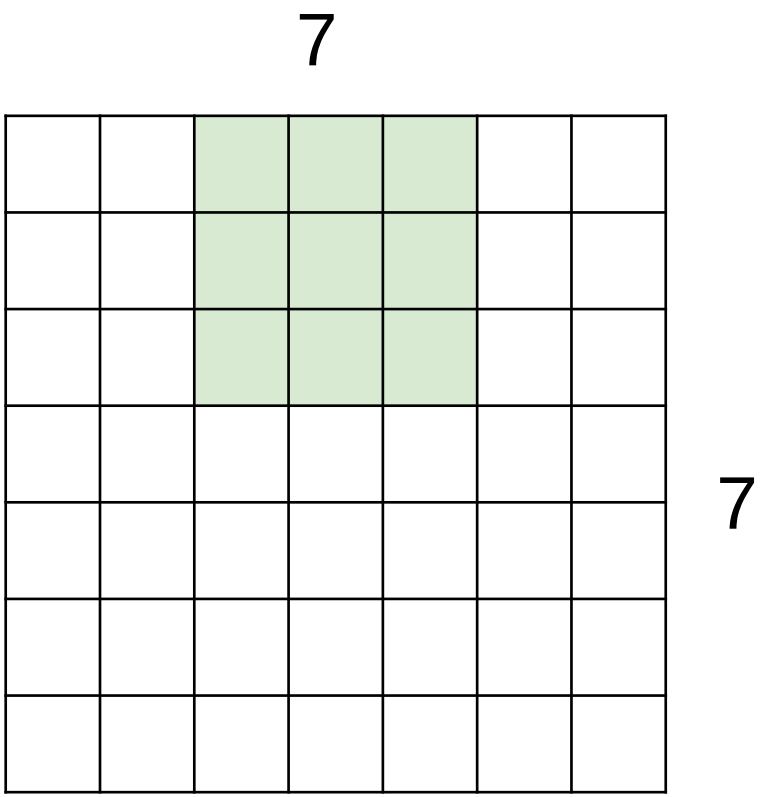
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



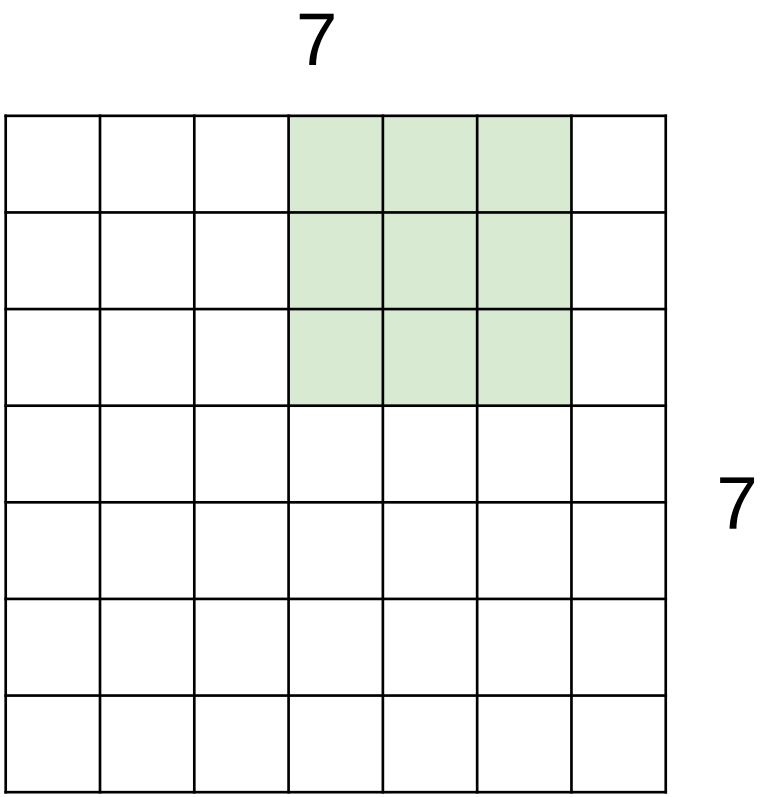
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



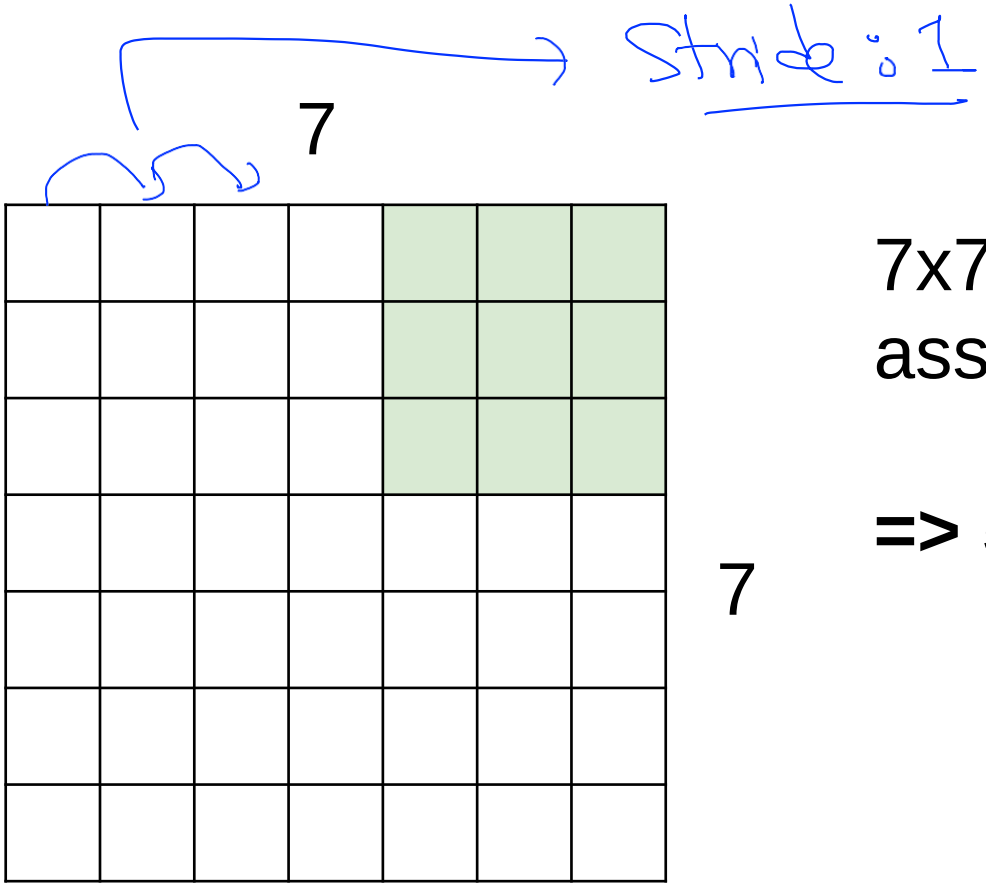
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

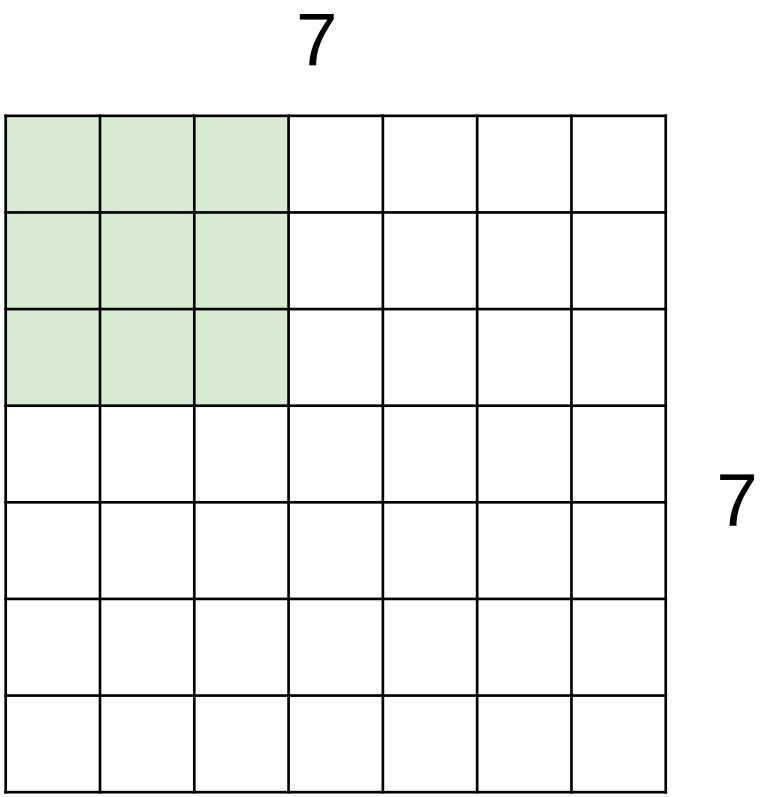
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

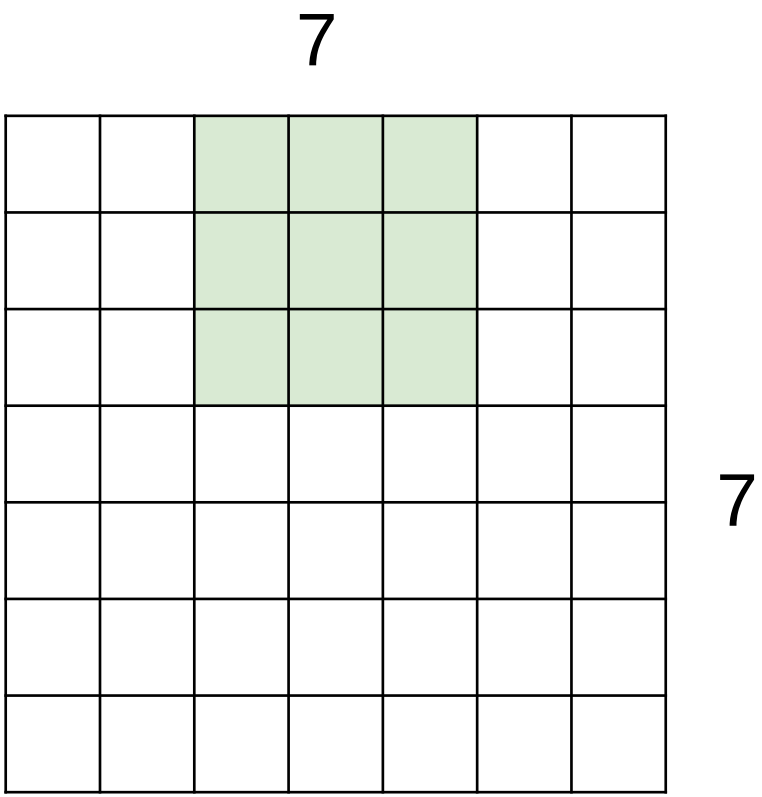
=> 5x5 output

A closer look at spatial dimensions:



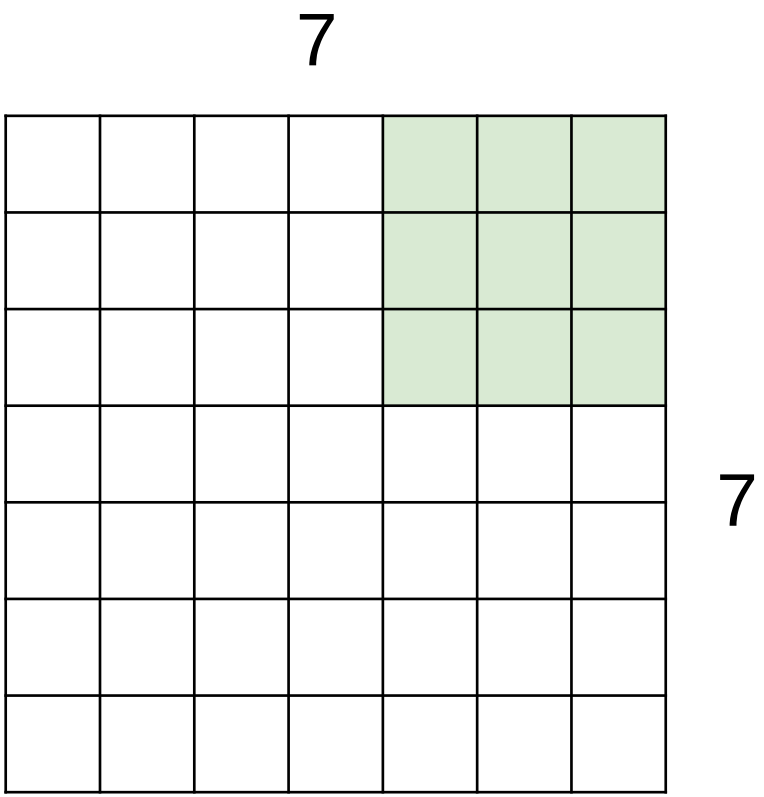
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



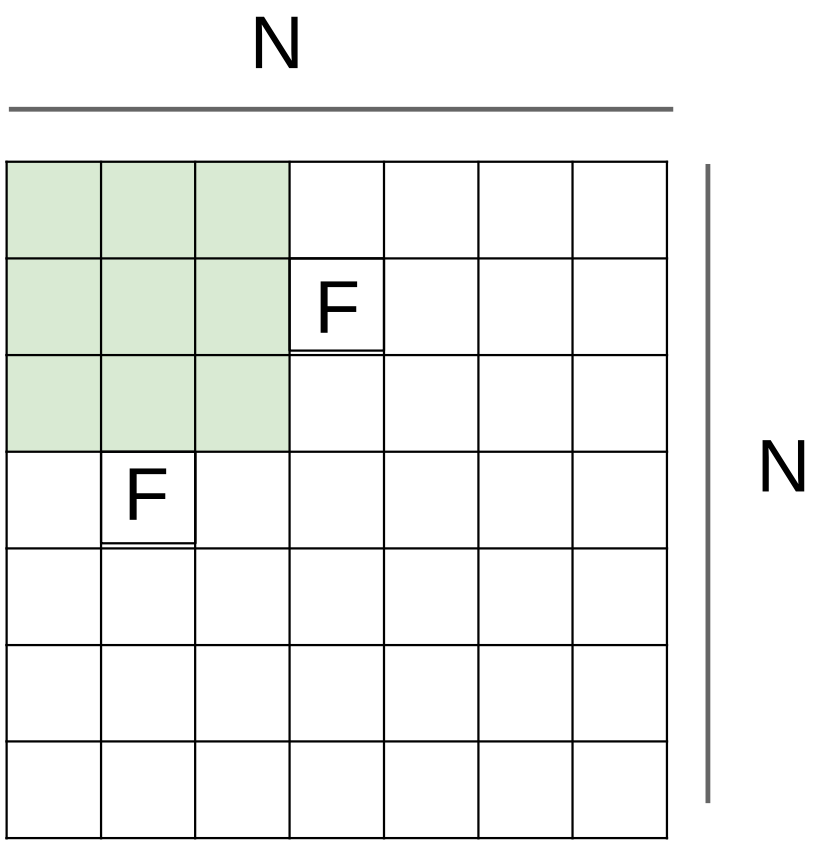
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



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

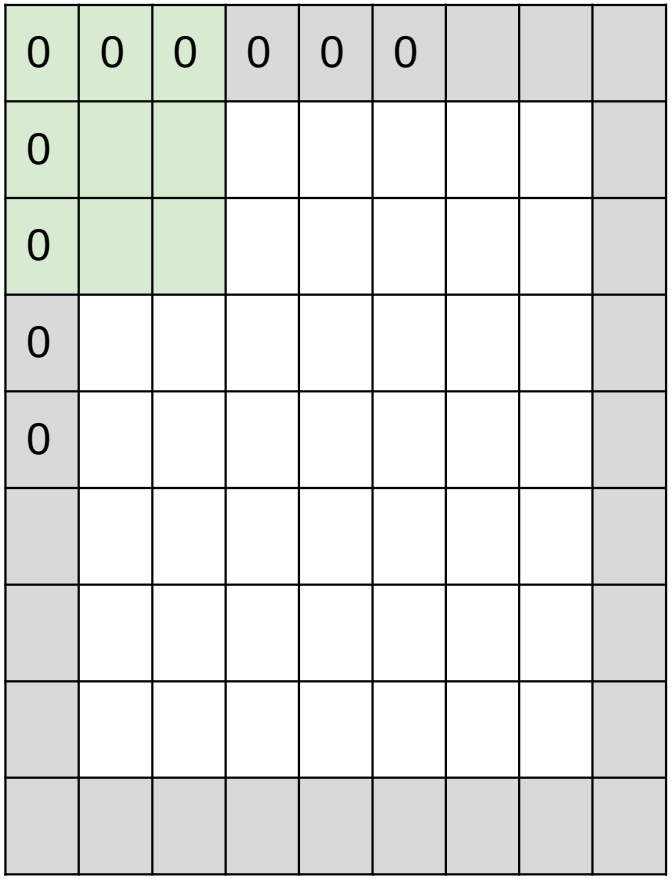
=> 3x3 output!



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 :\

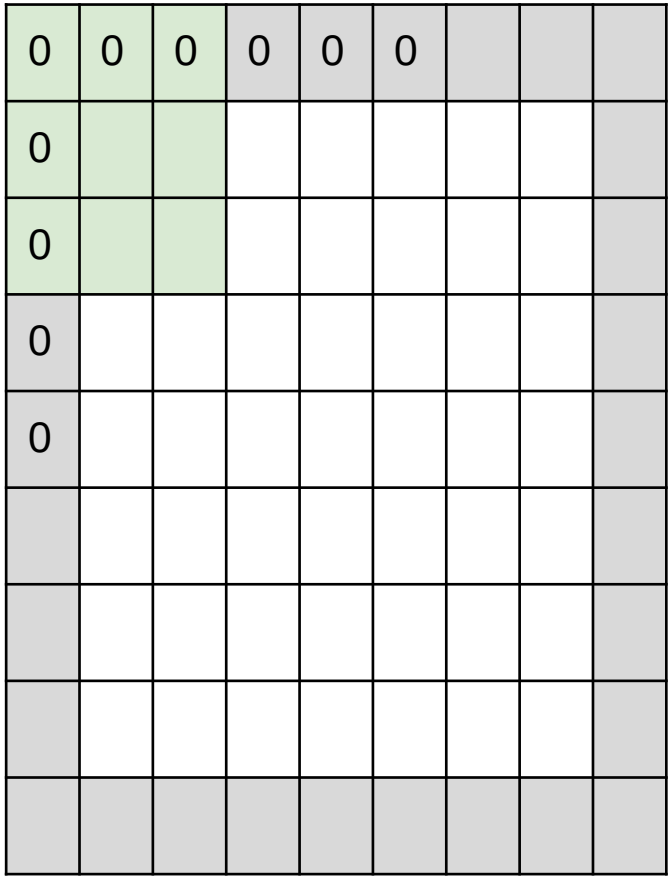
In practice: Common to zero pad the border



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

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

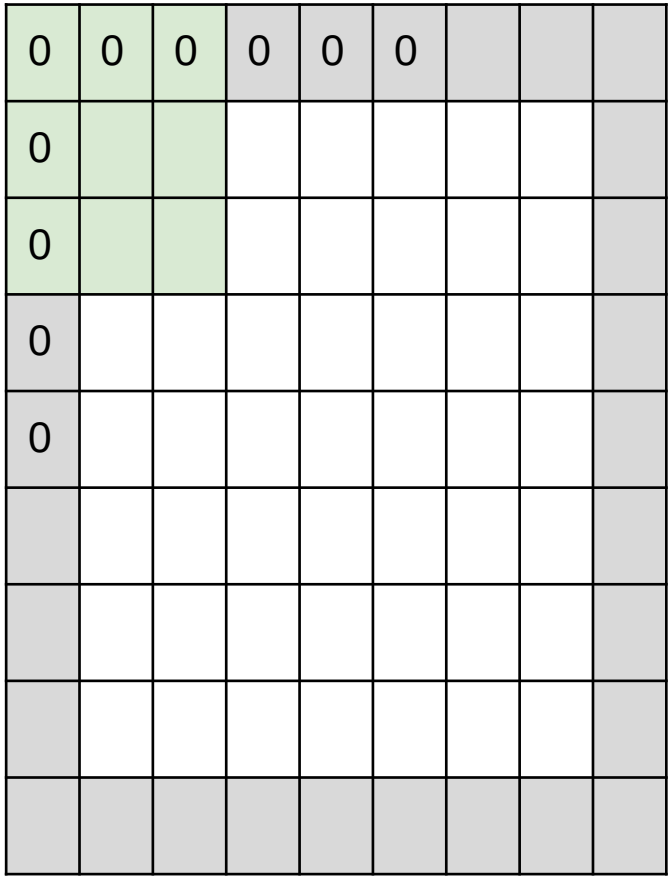
In practice: Common to zero pad the border



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

7x7 output!

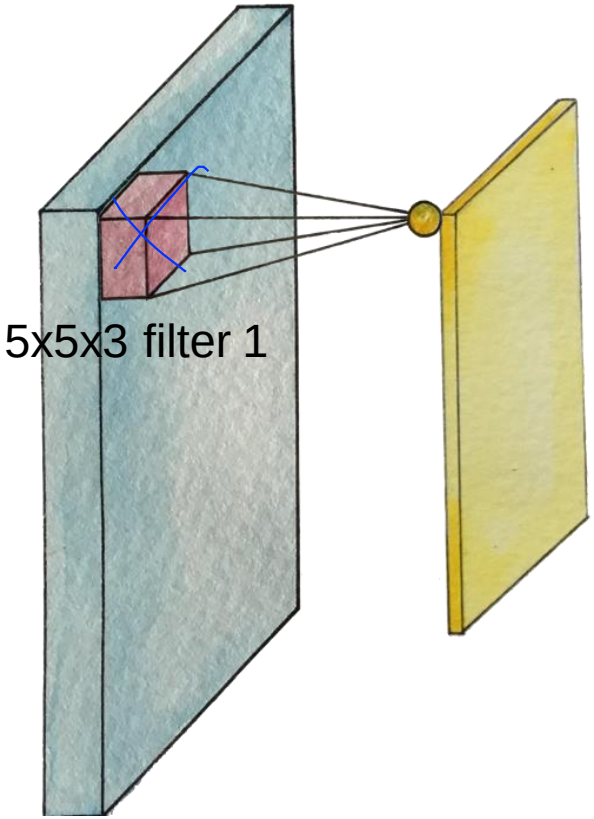
In practice: Common to zero pad the border



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

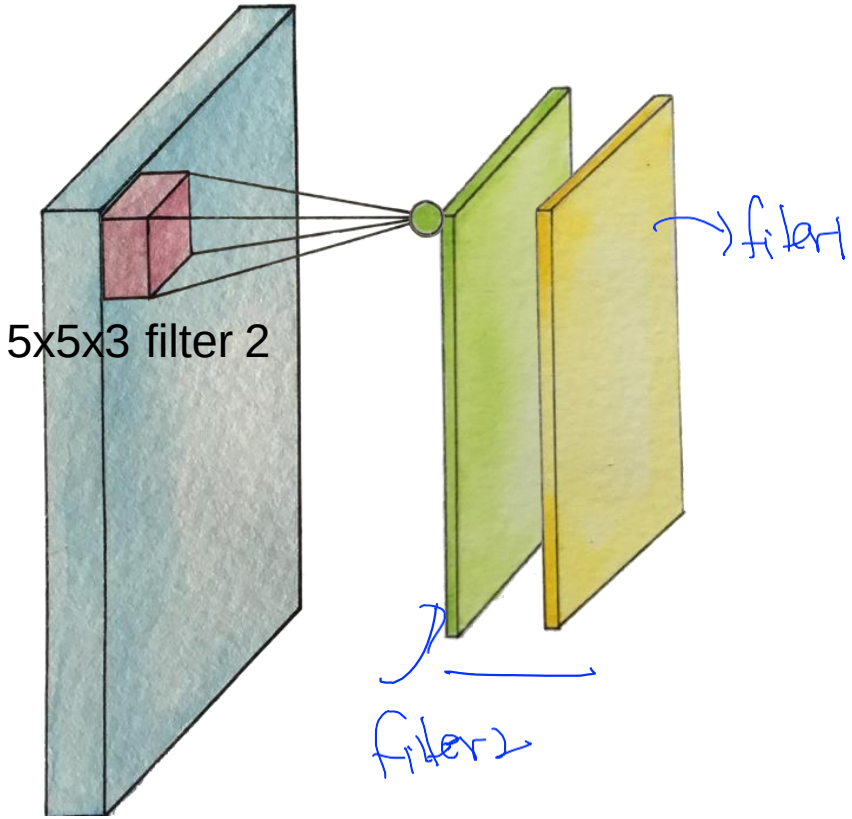
7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2 F = 7 => zero pad with 3

Swiping the entire image



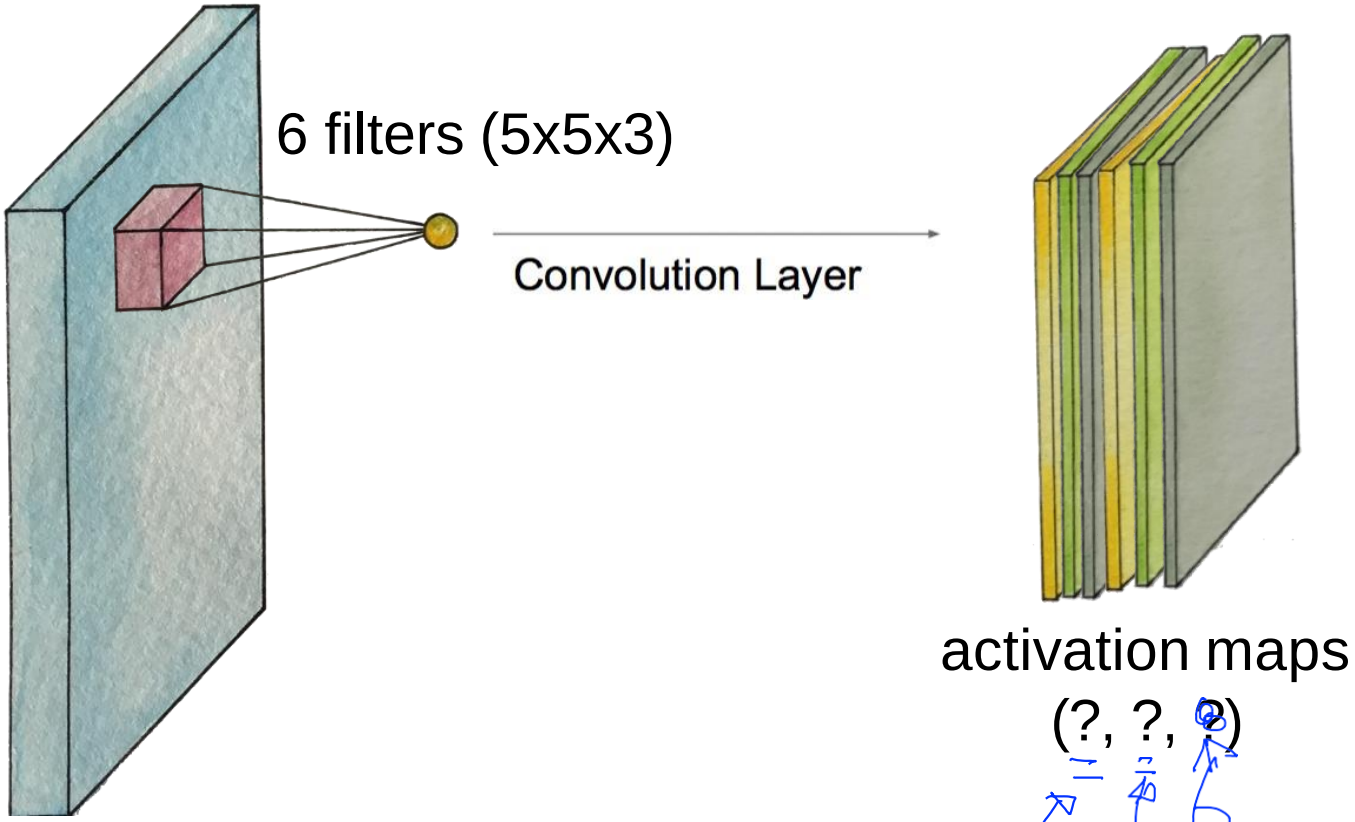
32x32x3 image

Swiping the entire image



32x32x3 image

Swiping the entire image

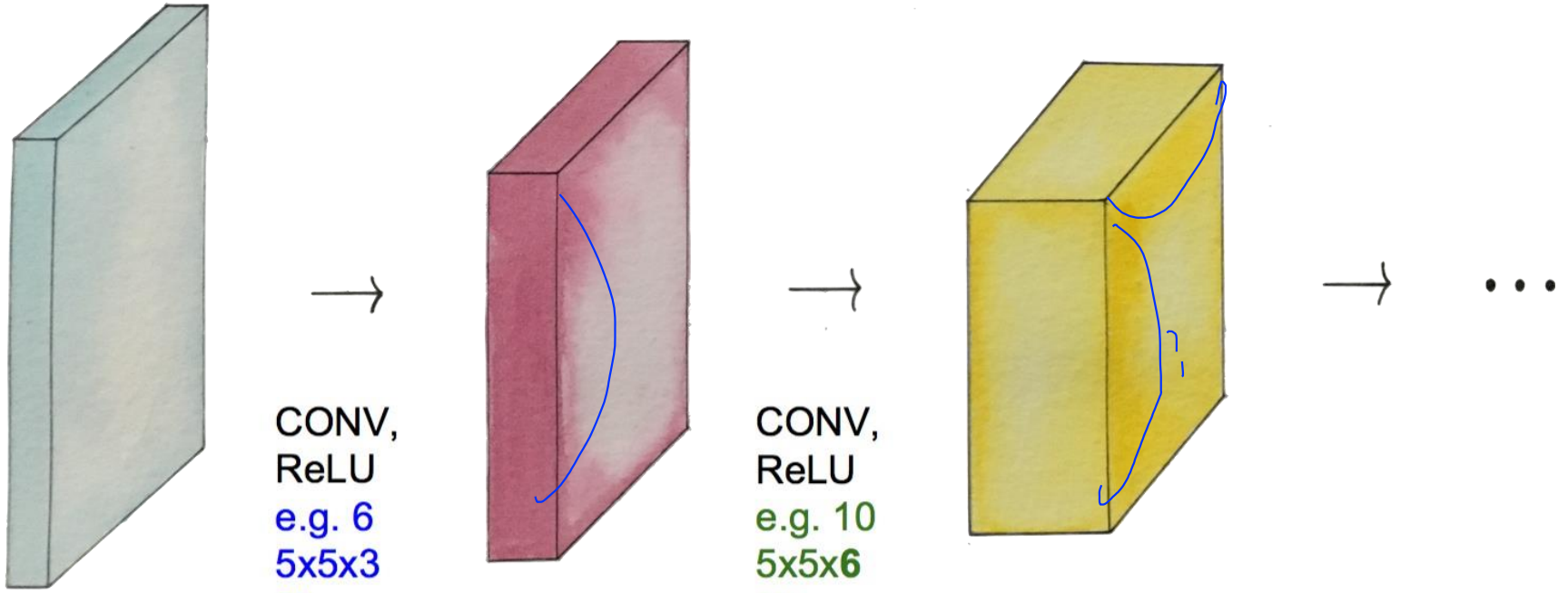


activation maps

(?, ?, 6)

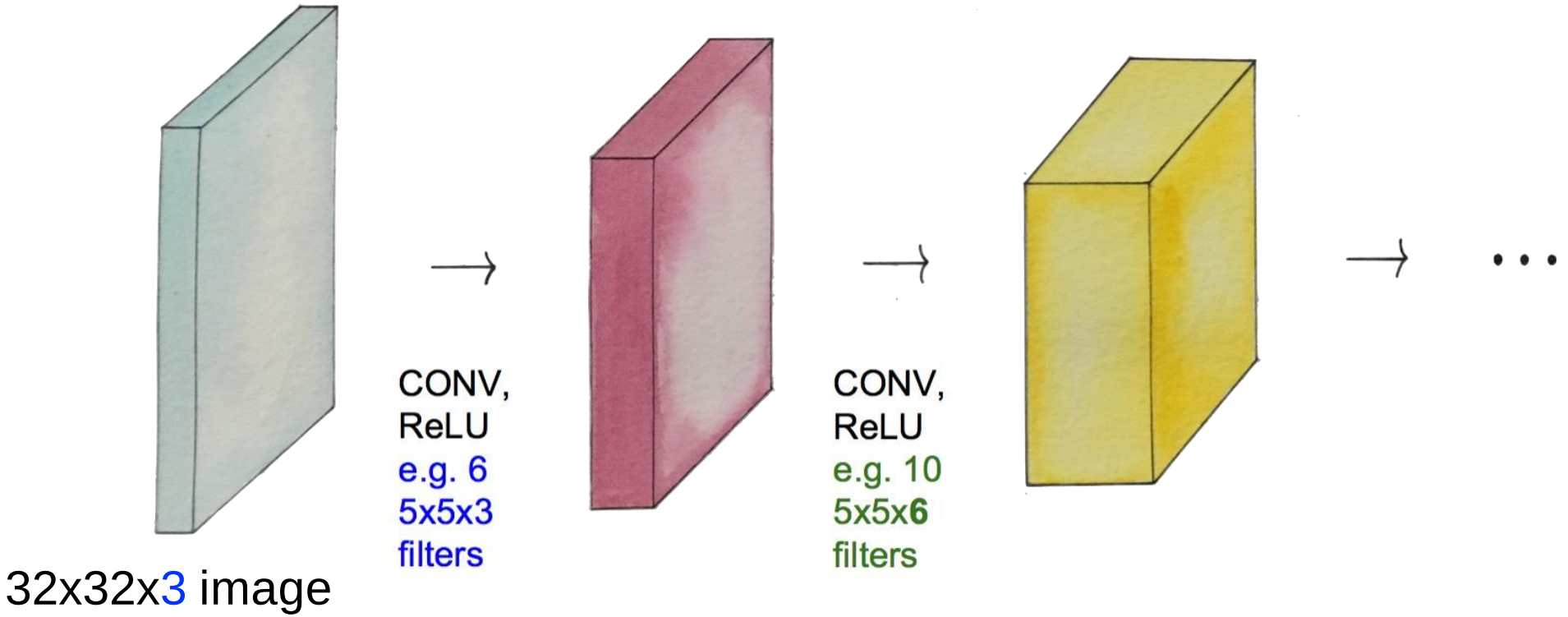
32x32x3 image

Convolution layers

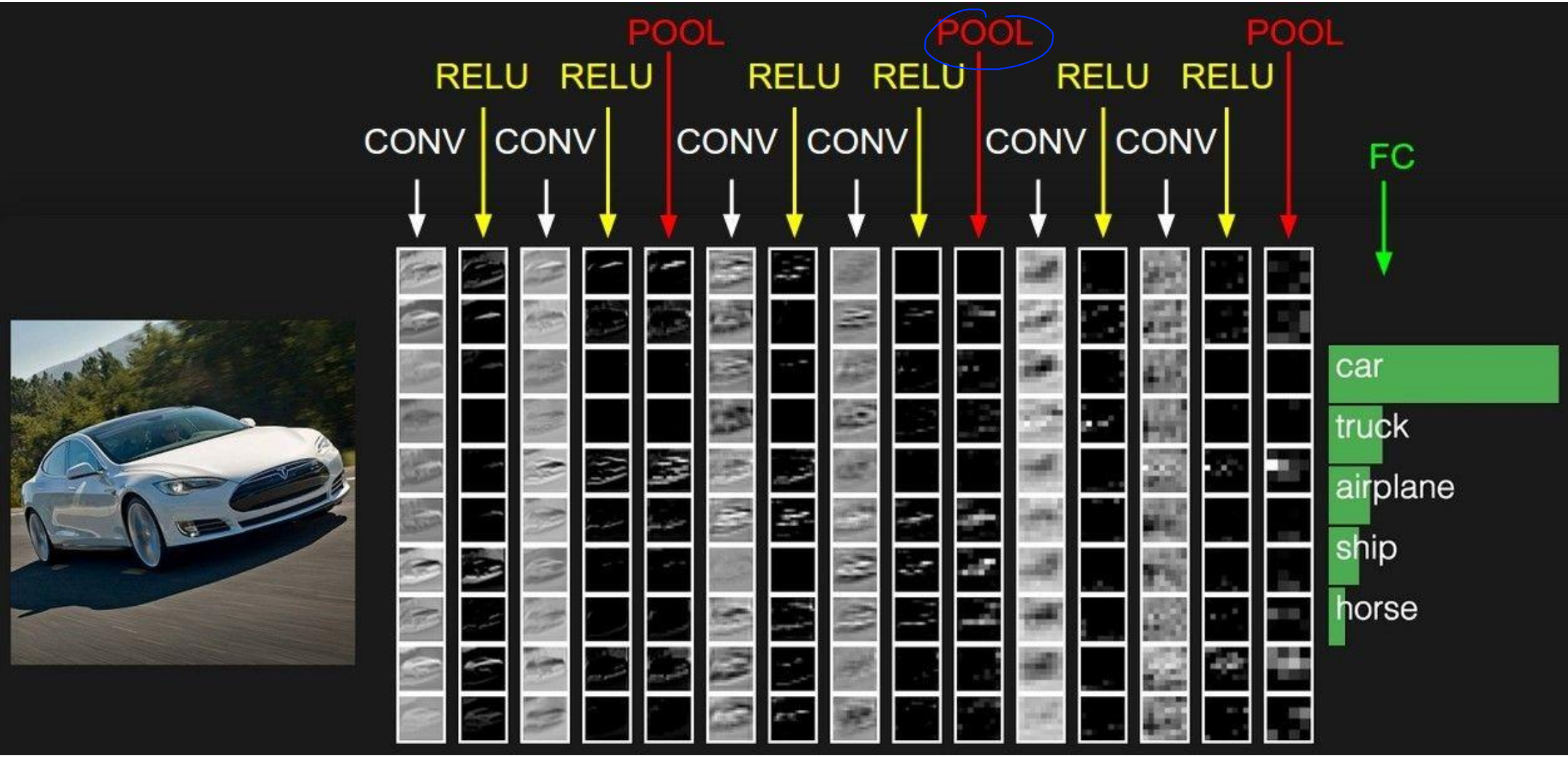


Convolution layers

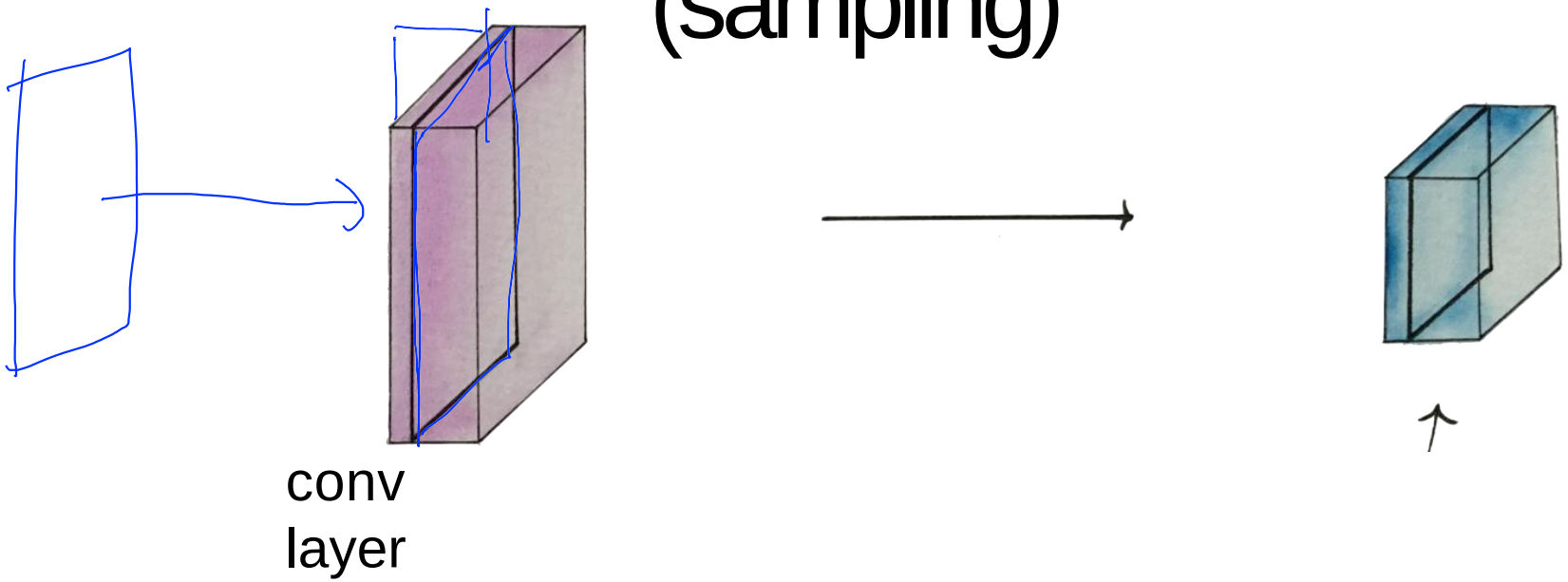
How many weight variables? How to set them?



preview:

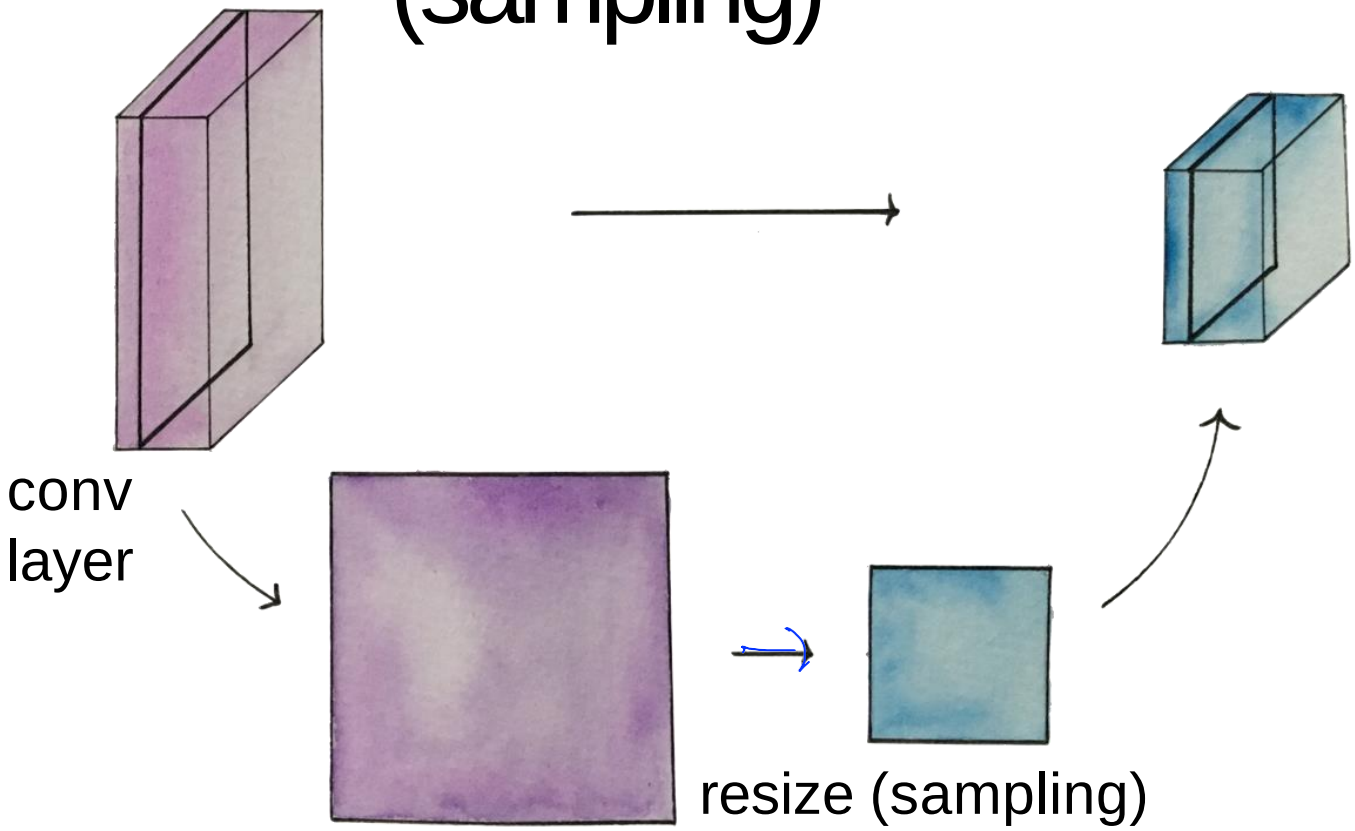

POOL
POOL
POOL
RELU
RELU
RELU
RELU
RELU
RELU
CONV
CONV
CONV
CONV
CONV
CONV
FC
car
truck
airplane
ship
horse

Pooling layer (sampling)



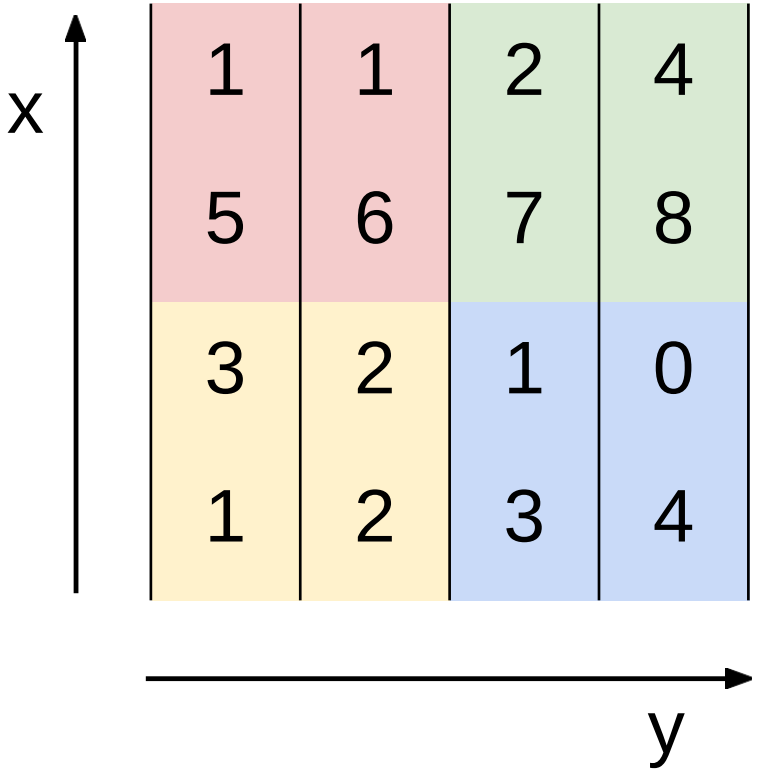
conv layer

Pooling layer (sampling)

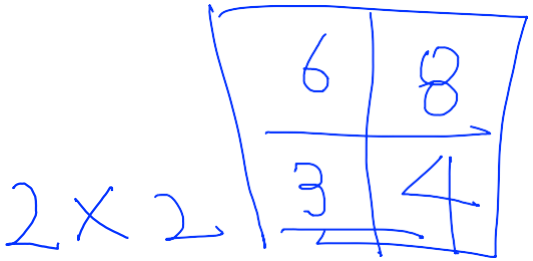


MAX POOLING

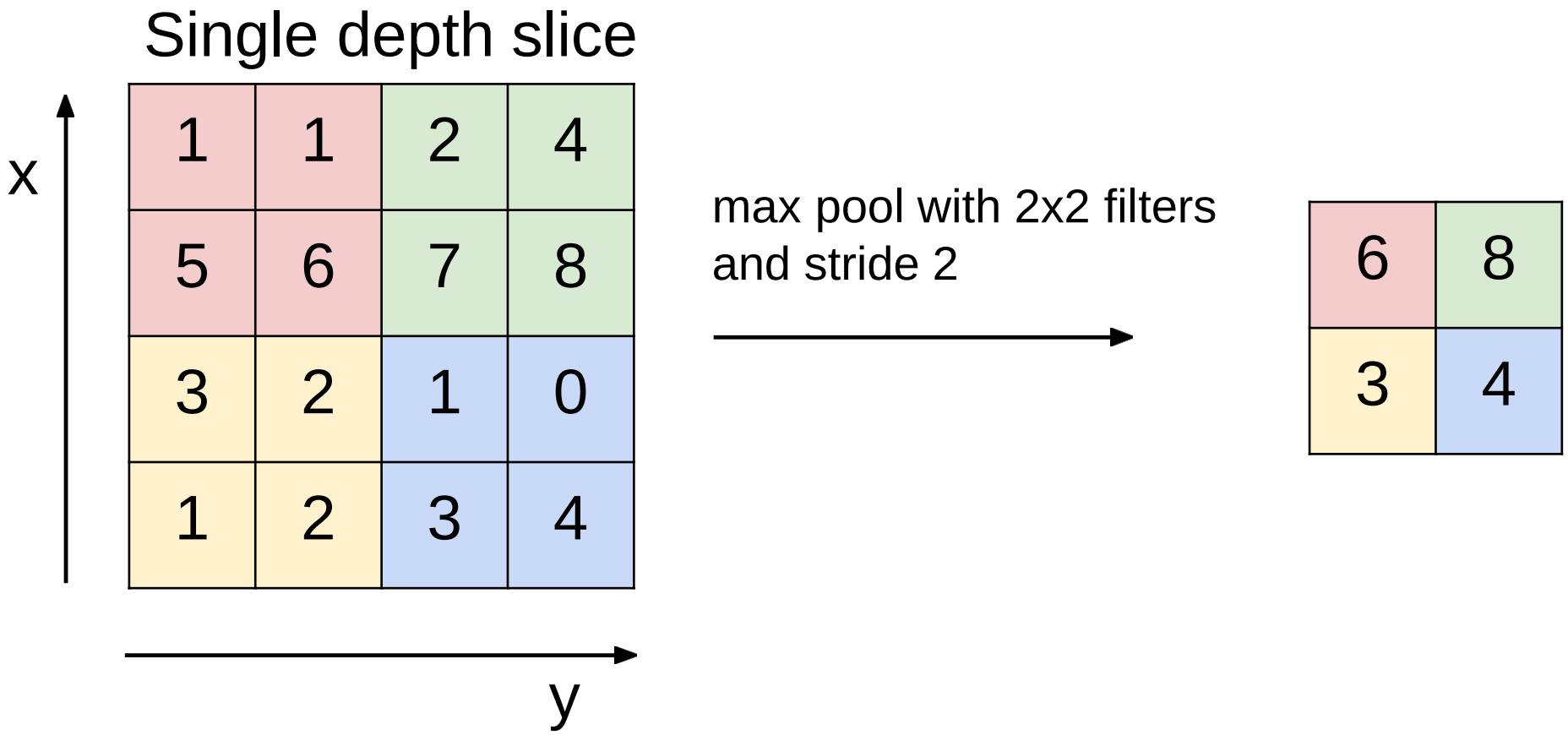
Single depth slice



max pool with 2x2 filters
and stride 2

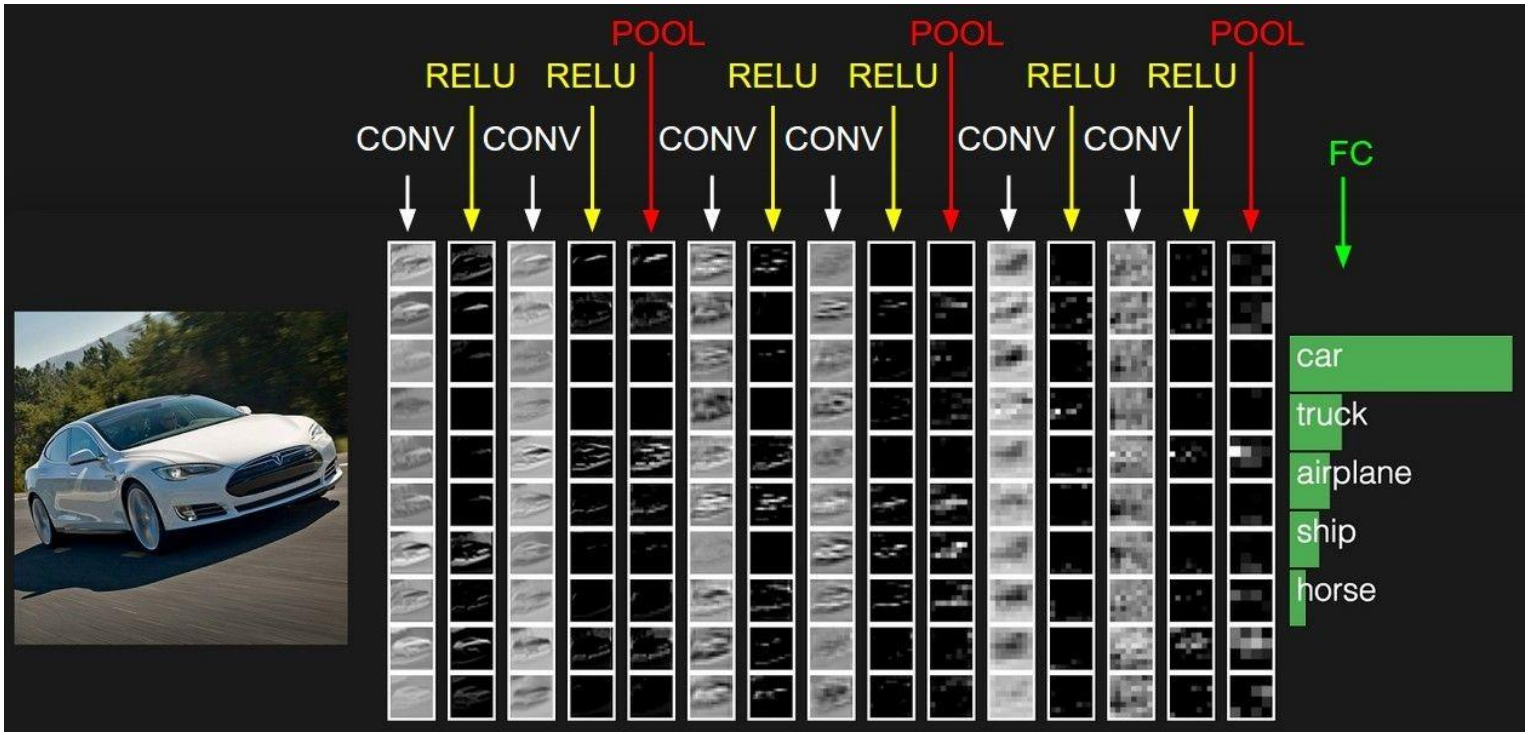


MAX POOLING


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

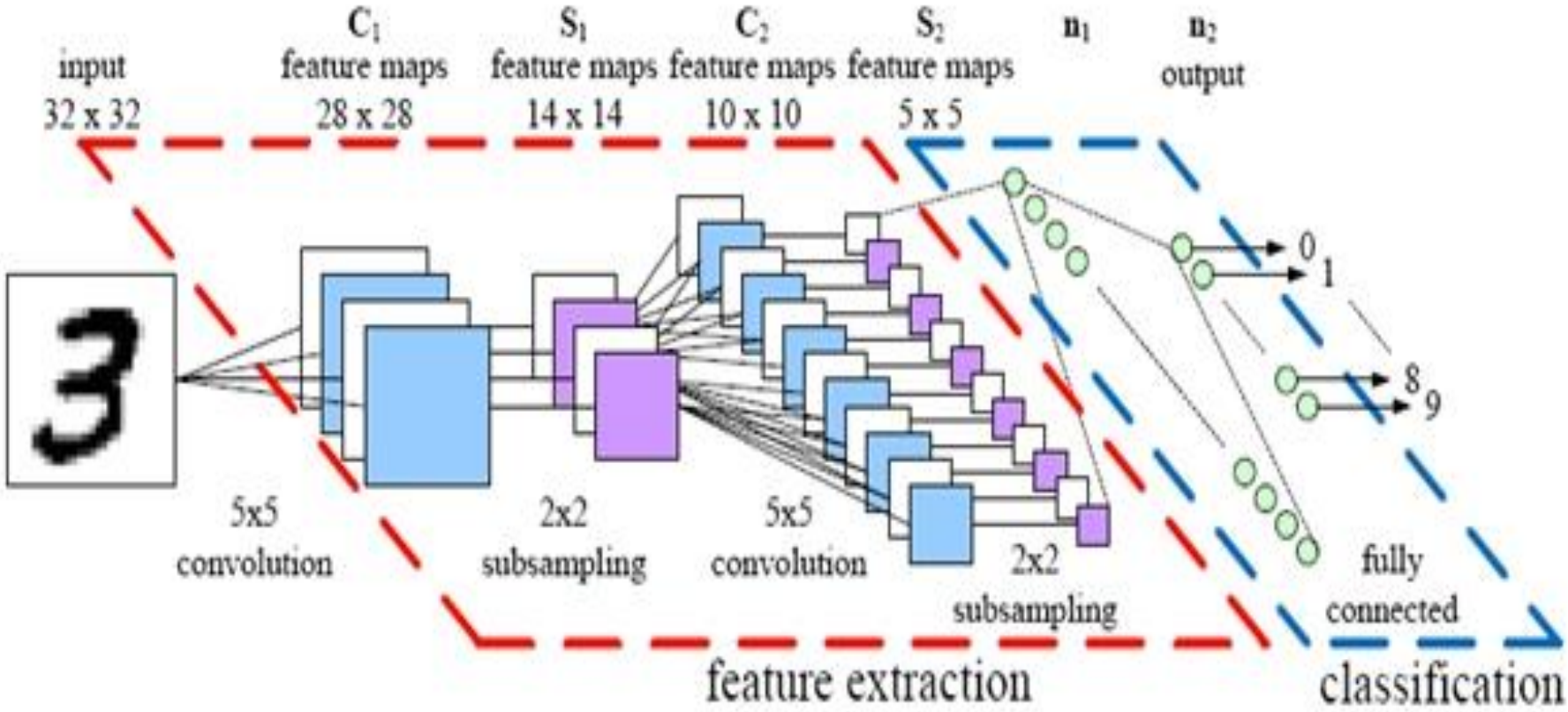
Fully Connected Layer (FC layer)

- Contains neurons that connect to the entire input volume, as in ordinary Neural Networks



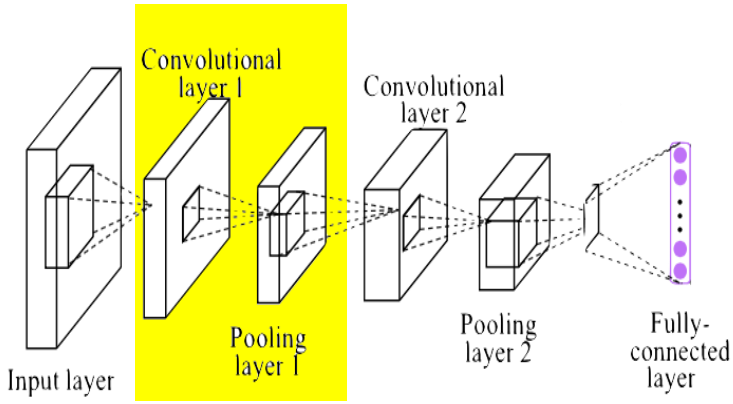
https://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html

CNN



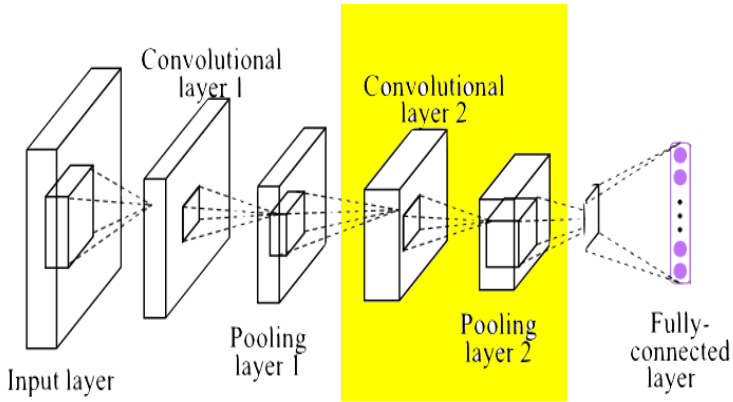
http://parse.ele.tue.nl/cluster/2/CNNArchitecture.jpg

Conv 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)
'''
```

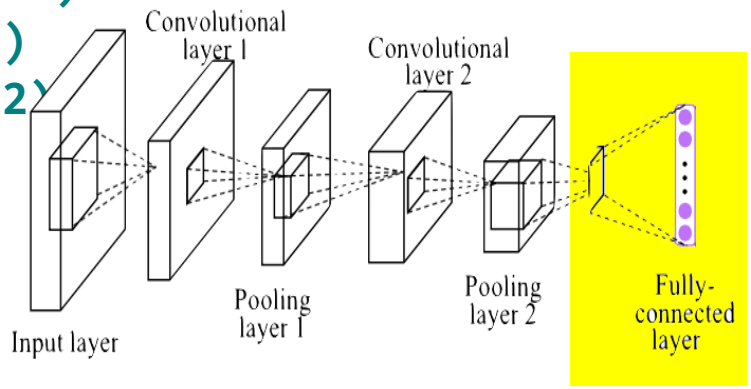
Conv layer 2




```
'''
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)
```

Fully Connected (FC, Dense) 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_initializer())
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)
```



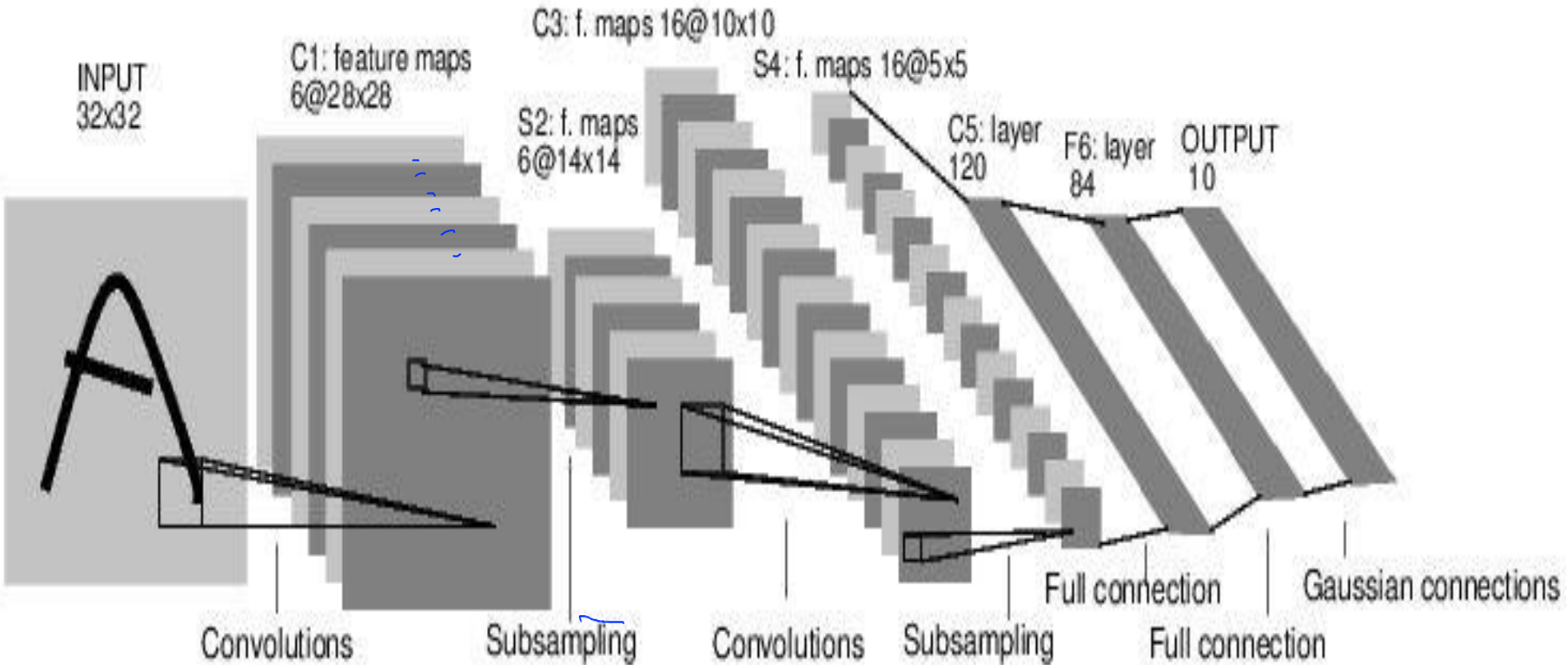
Training and Evaluation

```
# 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
```

Case Study: LeNet-5 (60K param)

[LeCun et al., 1998]

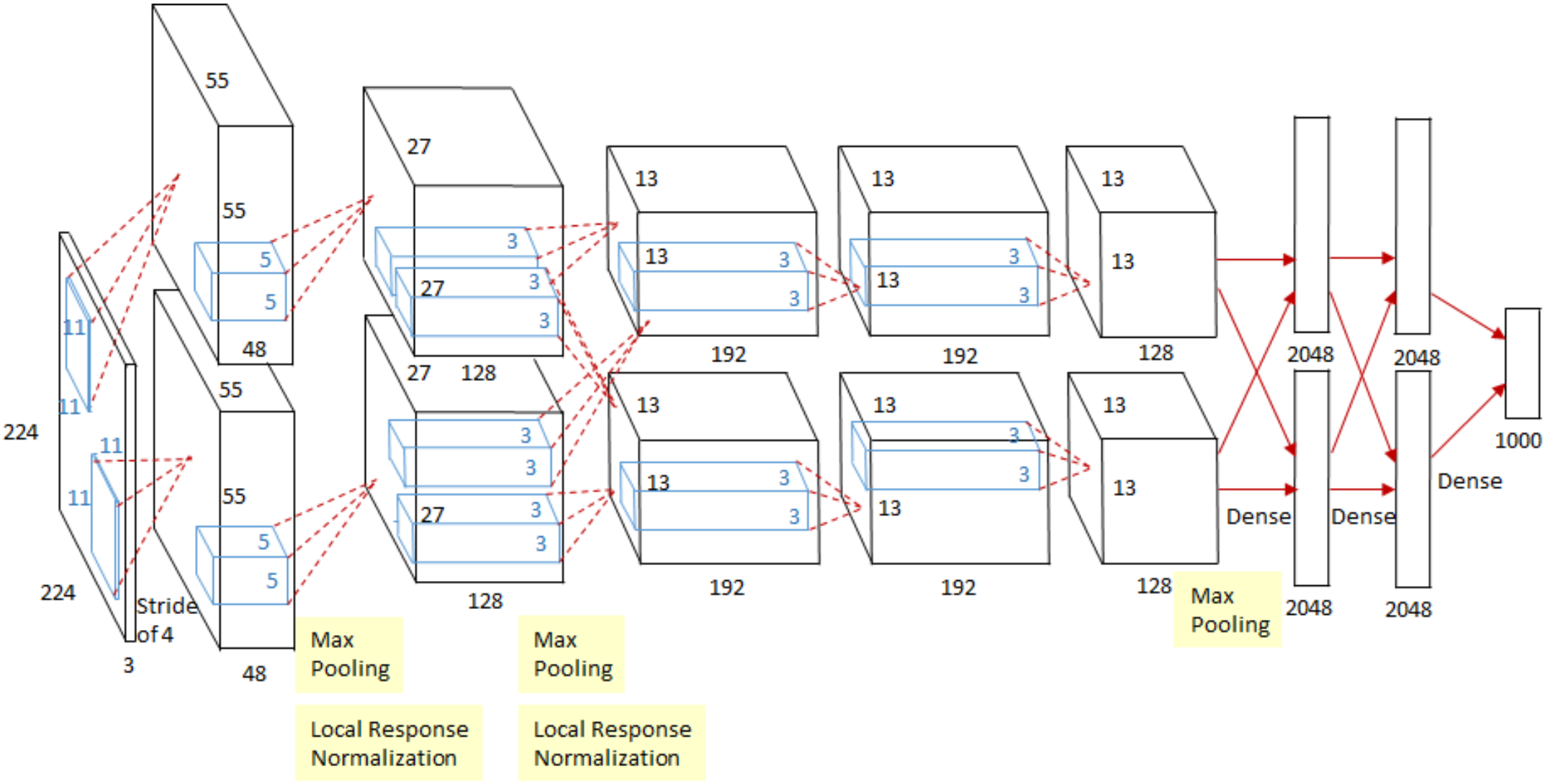


Conv filters were 5x5, applied at stride 1

Subsampling (Pooling) layers were 2x2 applied at stride 2

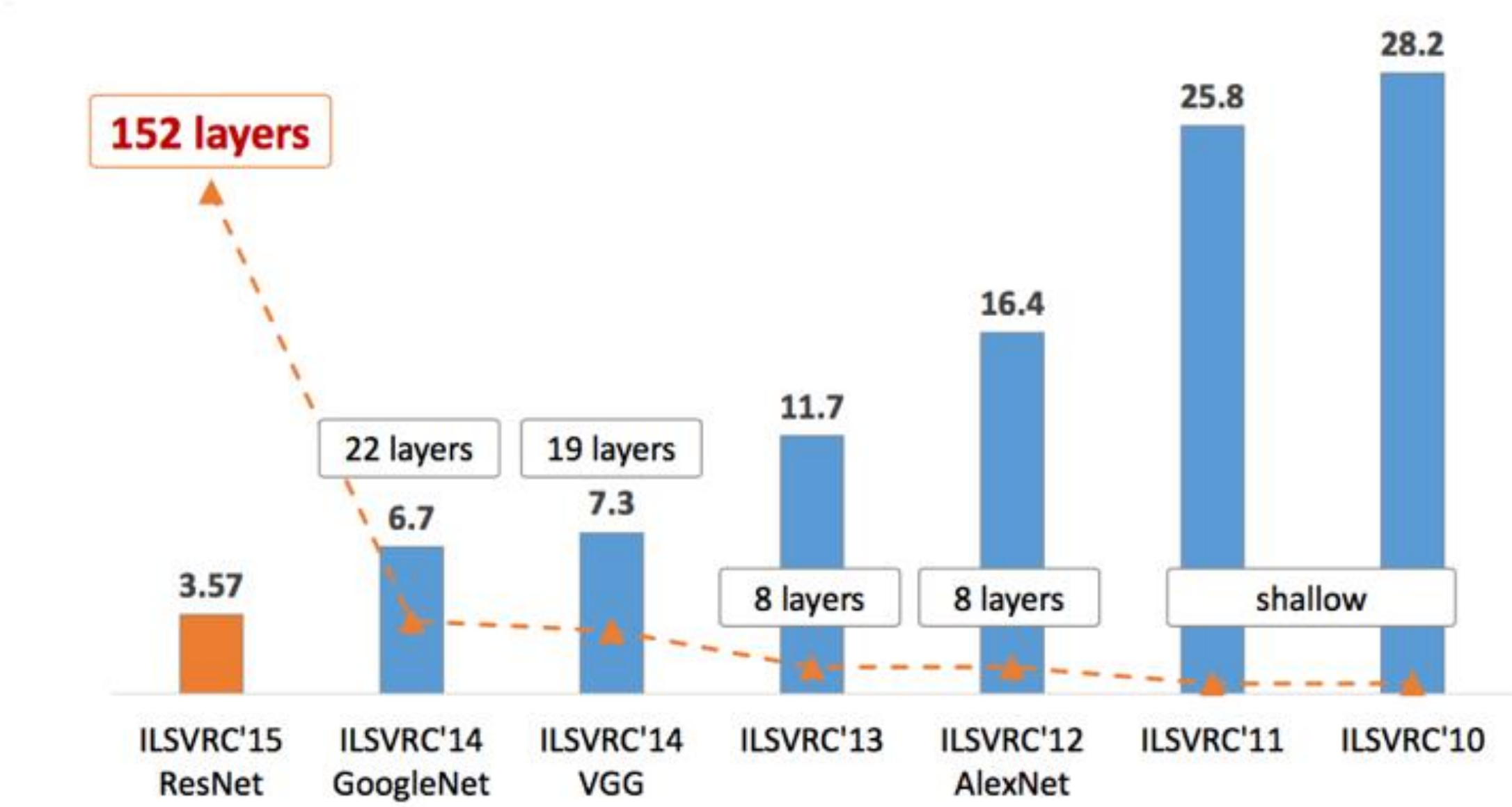
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]

AlexNet


55
55
48
55
55
48
224
224
11
11
11
11
Stride
of 4
3
5
5
5
5
27
27
27
27
128
128
3
3
3
3
3
3
3
3
13
13
13
13
13
13
13
13
13
13
192
192
192
192
128
128
2048
2048
2048
2048
1000
Dense
Dense
Dense
Max
Pooling
Max
Pooling
Max
Pooling
Local Response
Normalization
Local Response
Normalization

Classification Results (CLS)

CNN Architectures: LeNet, AlexNet, VGG, GoogLeNet, ResNet



Deep Visualization Toolbox

https://github.com/yosinski/deep-visualization-toolbox
https://www.youtube.com/watch?v=AgkfIQ4IGaM