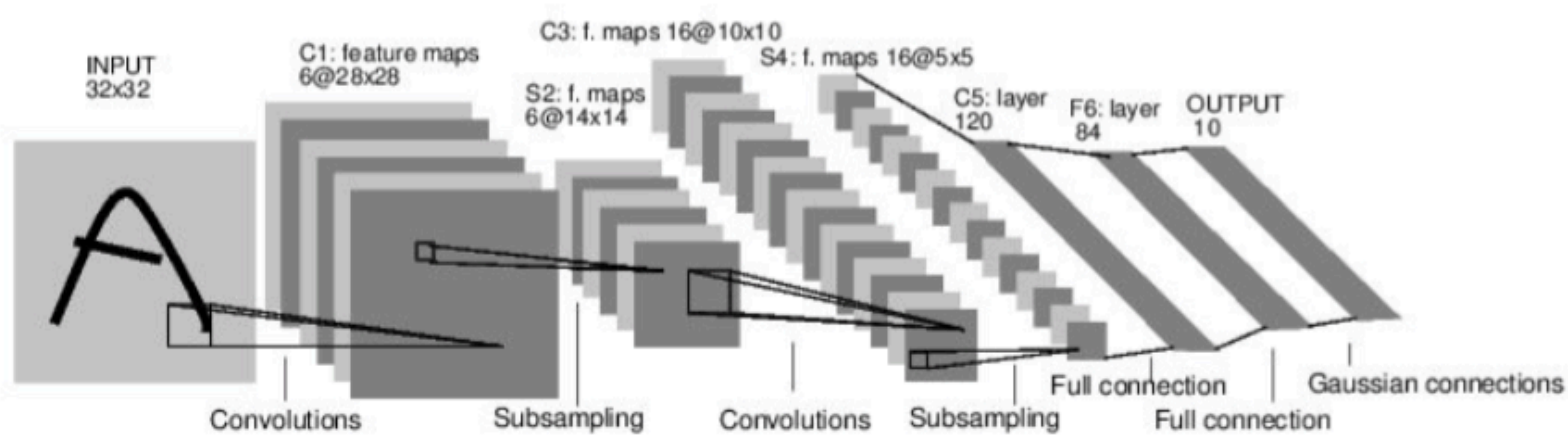
Tensorflow CNN turorial

2017/03/10

Lenet-5

[LeCun et al., 1998]



Today's example

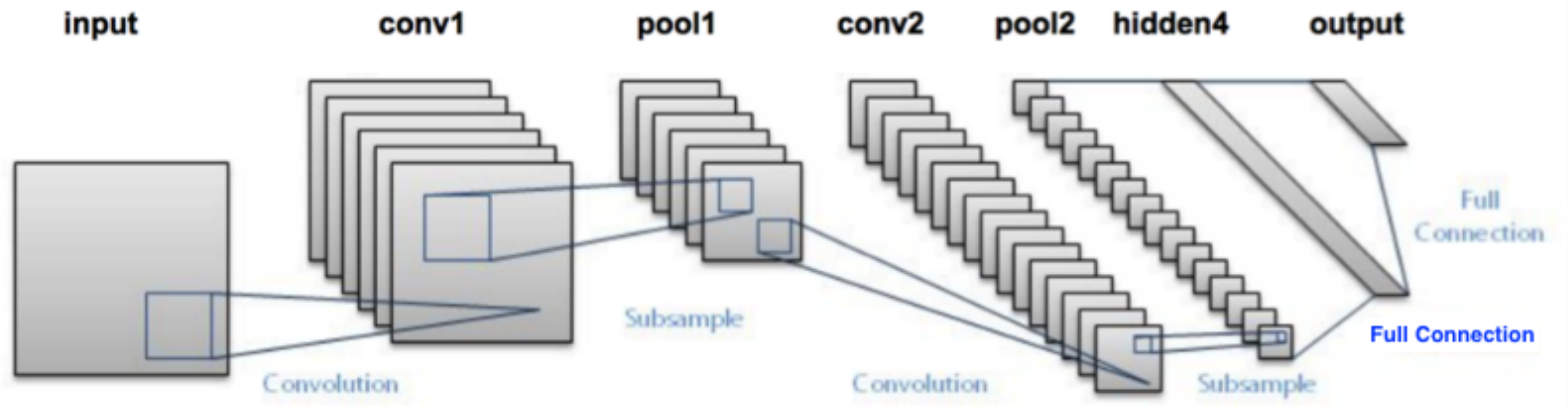
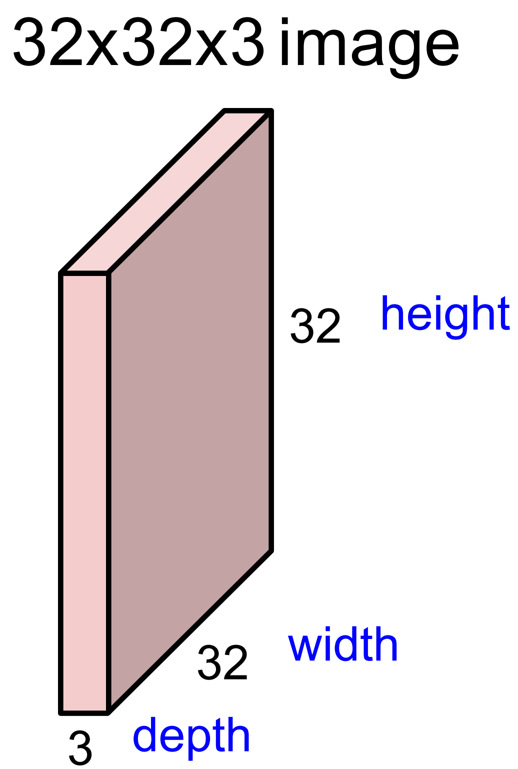


Image source

The slides are from

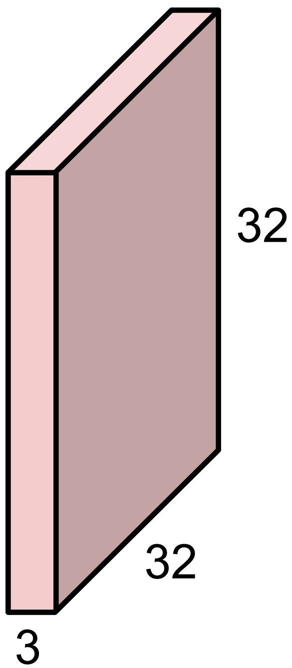
1. “Lecture 13: Neural networks for machine vision, Dr. Richard E. Turner”
2. Lecture 7 & 12 in Stanford CS231n

Convolution Layer

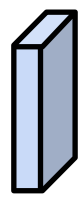


Convolution Layer

32x32x3 image



5x5x3 filter

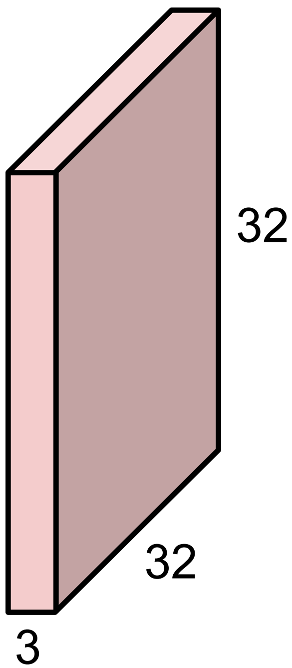


Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”

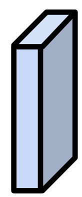
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image

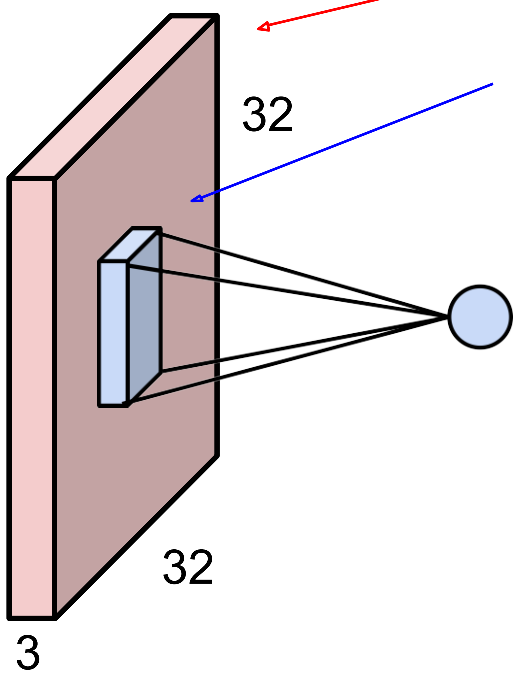


5x5x3 filter



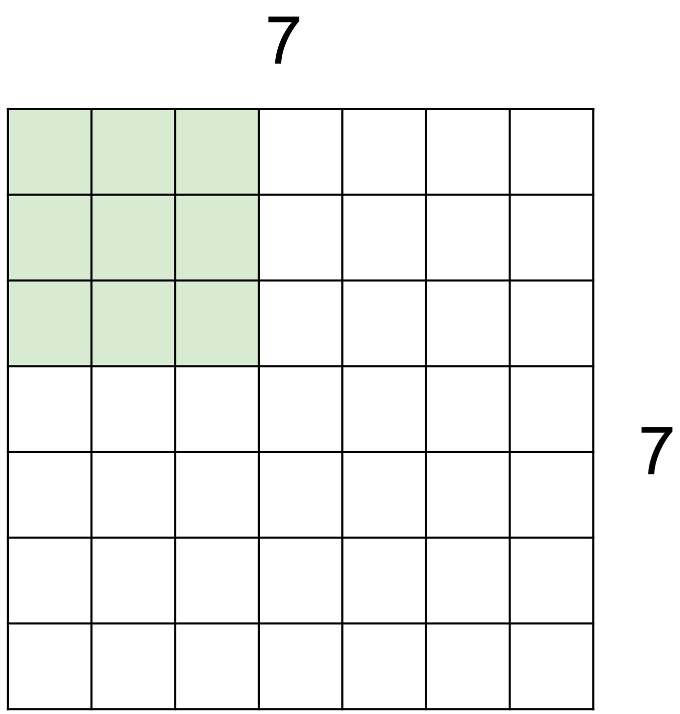
Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”

Convolution Layer

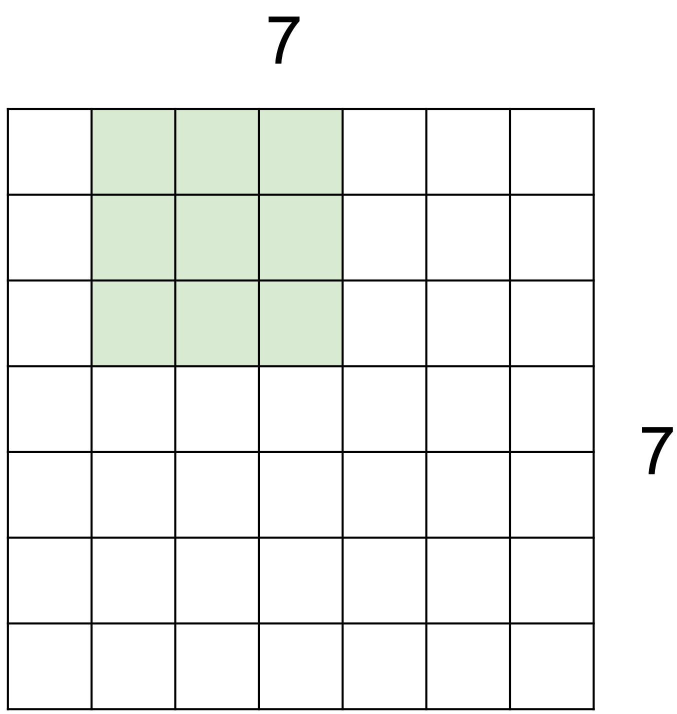


1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

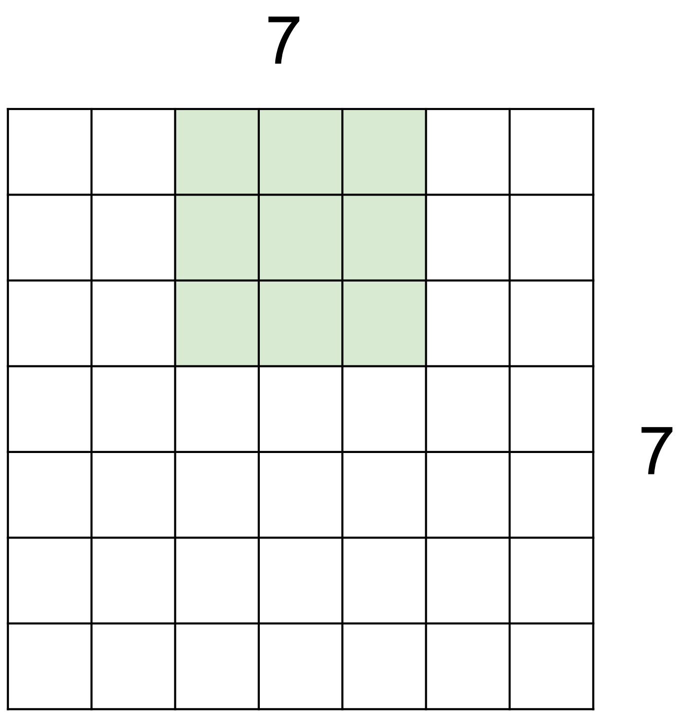
$$w^T x + b$$



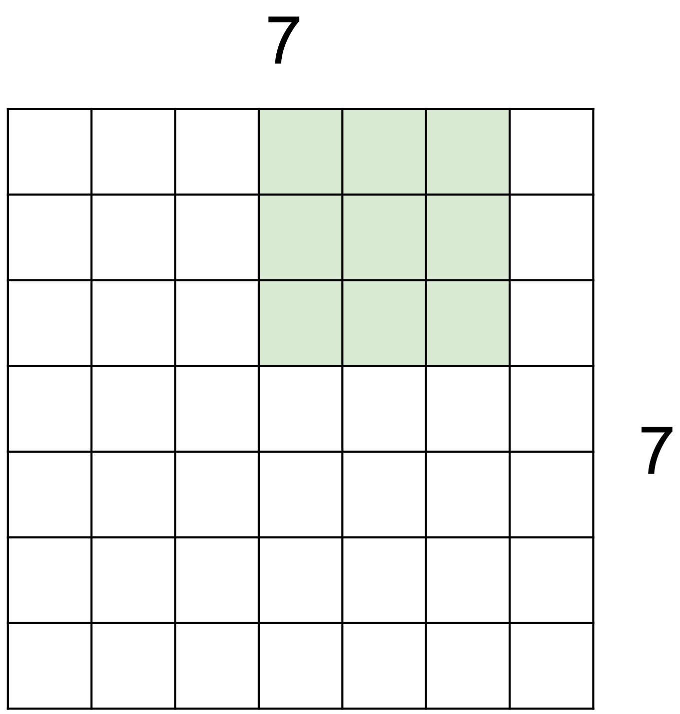
7x7 input (spatially)
assume 3x3 filter



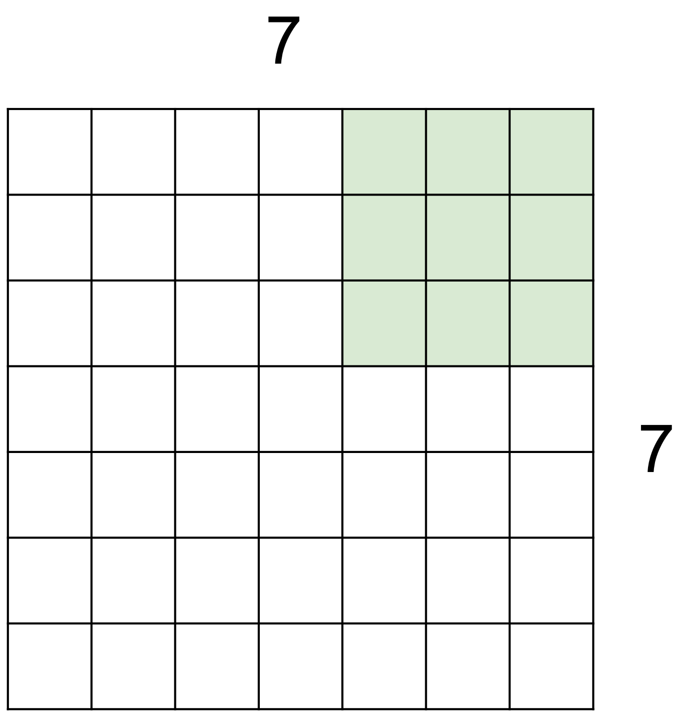
7x7 input (spatially)
assume 3x3 filter



7x7 input (spatially)
assume 3x3 filter



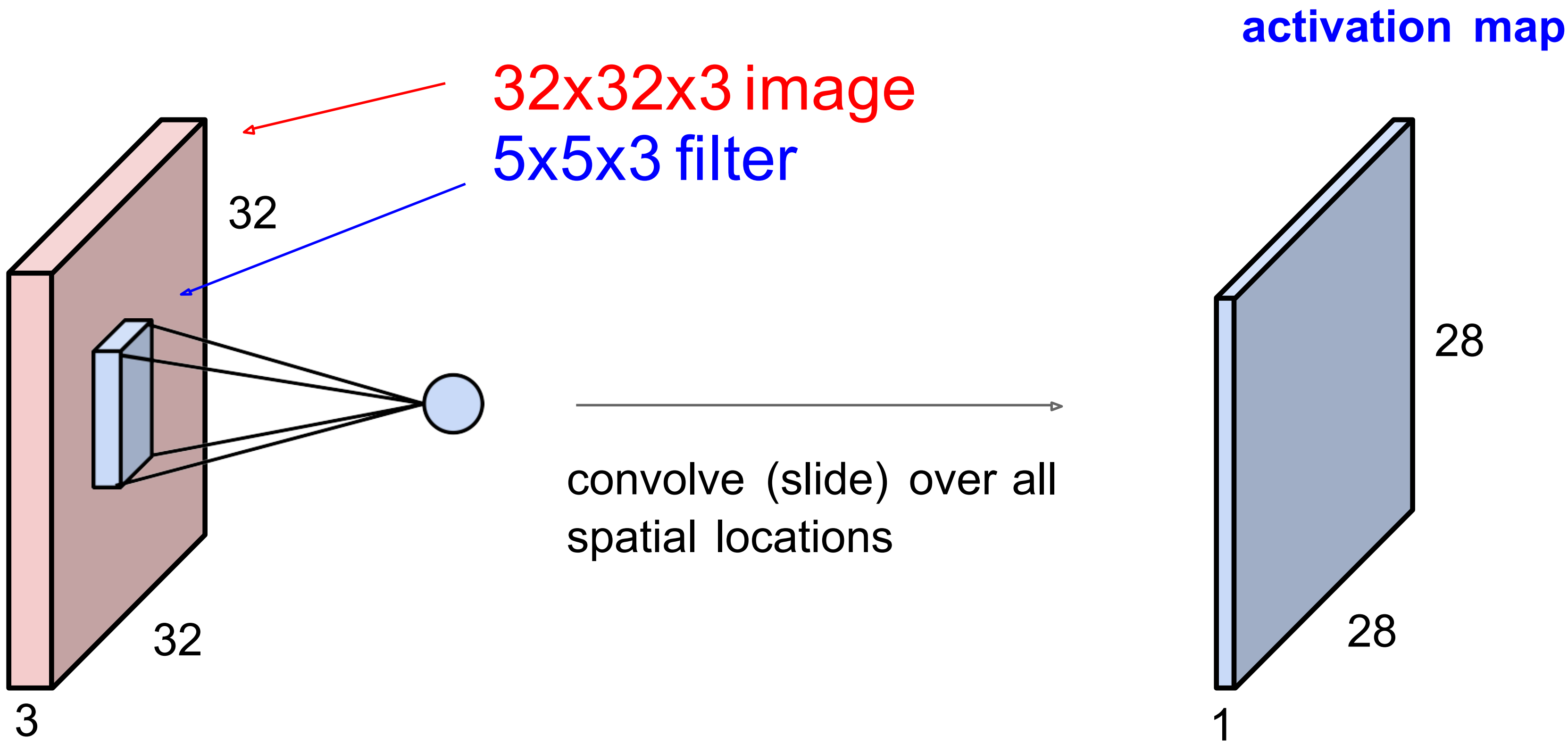
7x7 input (spatially)
assume 3x3 filter



7x7 input (spatially)
assume 3x3 filter

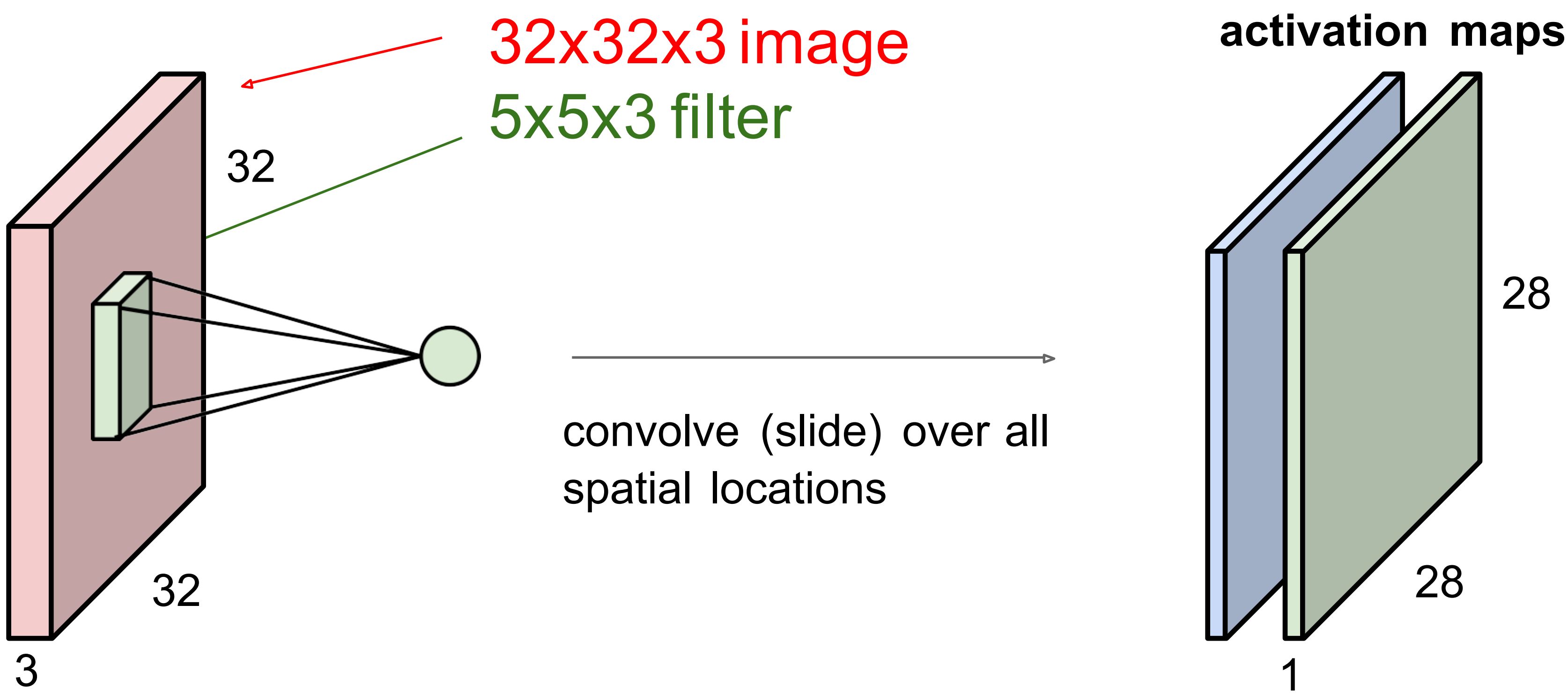
=> 5x5 output

Convolution Layer

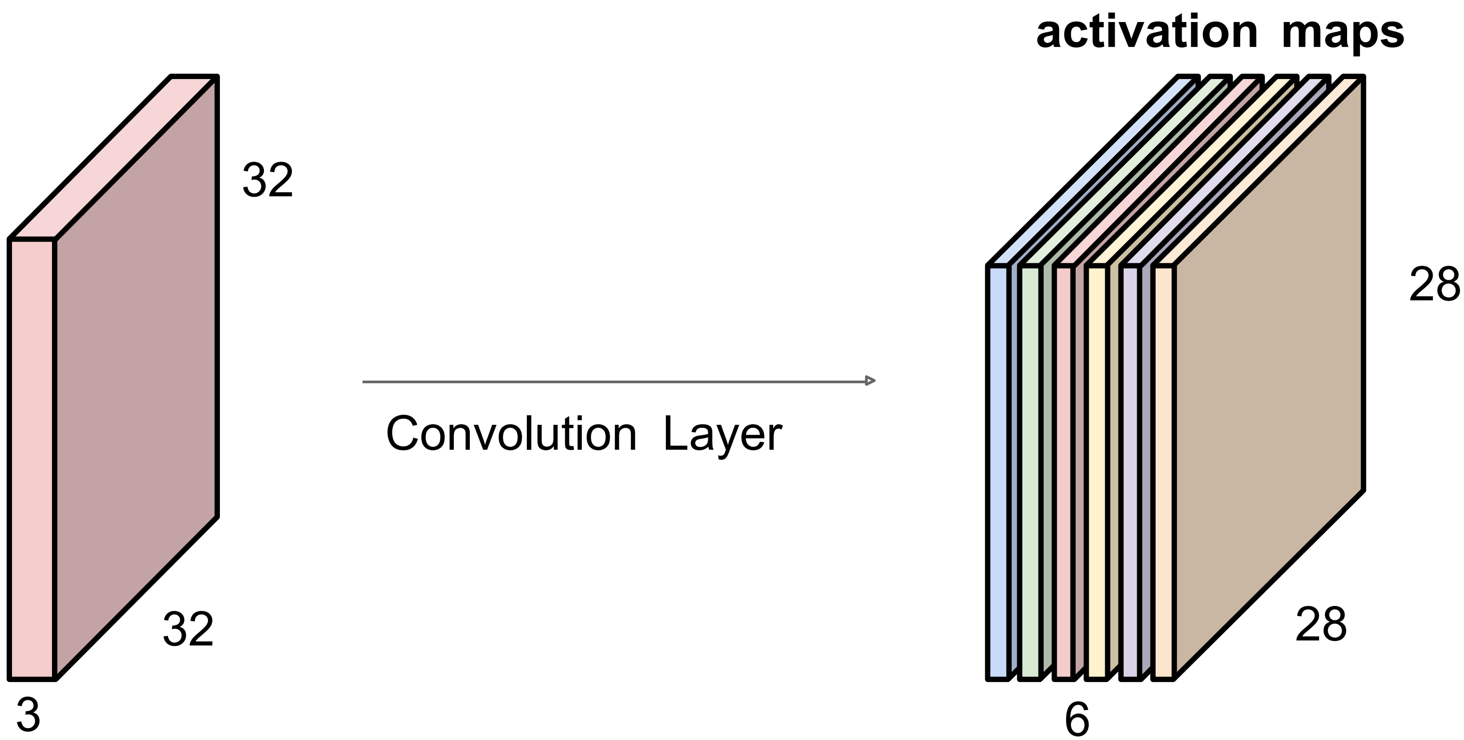


Convolution Layer

consider a second, green filter

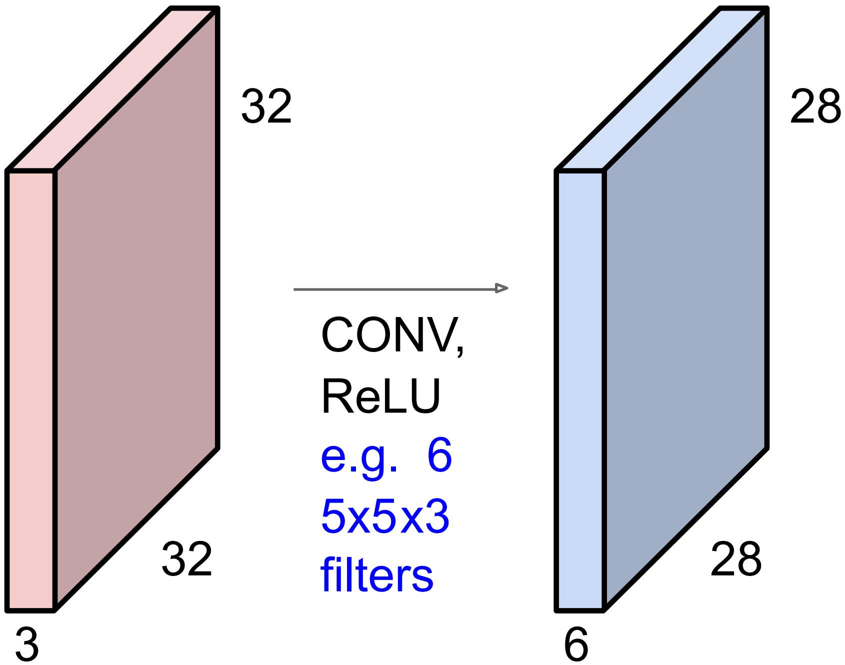


For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

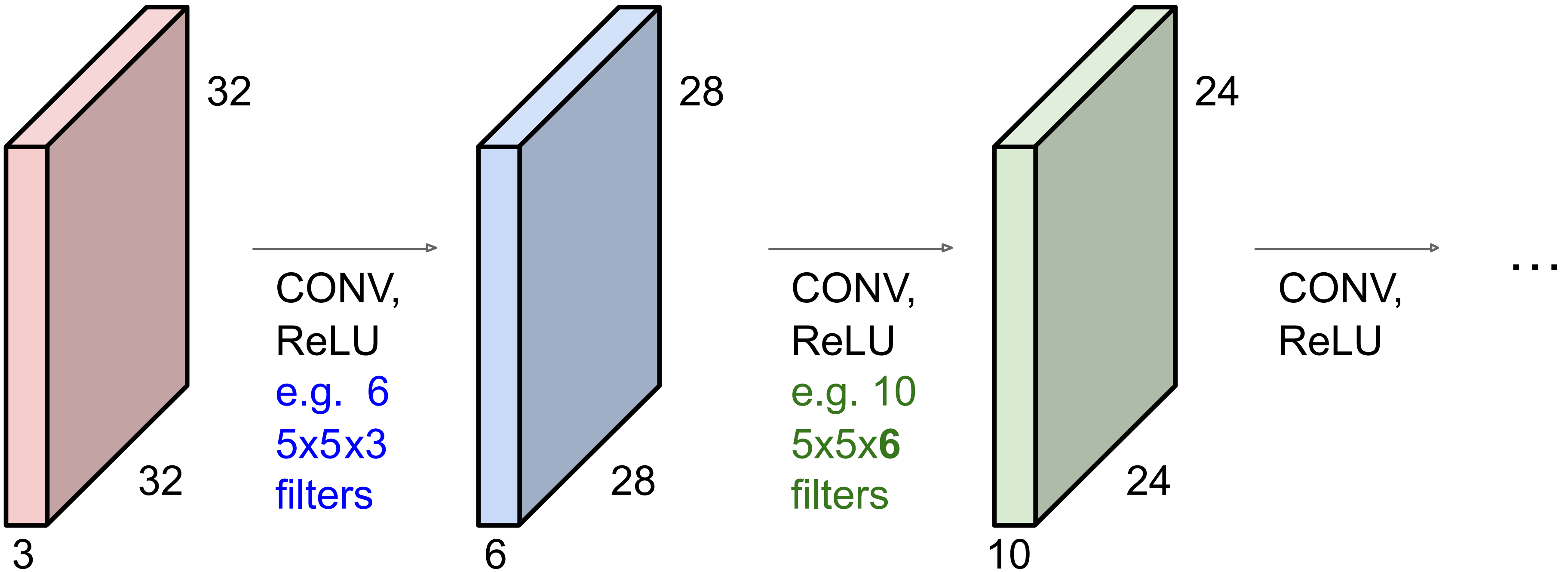


We stack these up to get a "new image" of size 28x28x6!

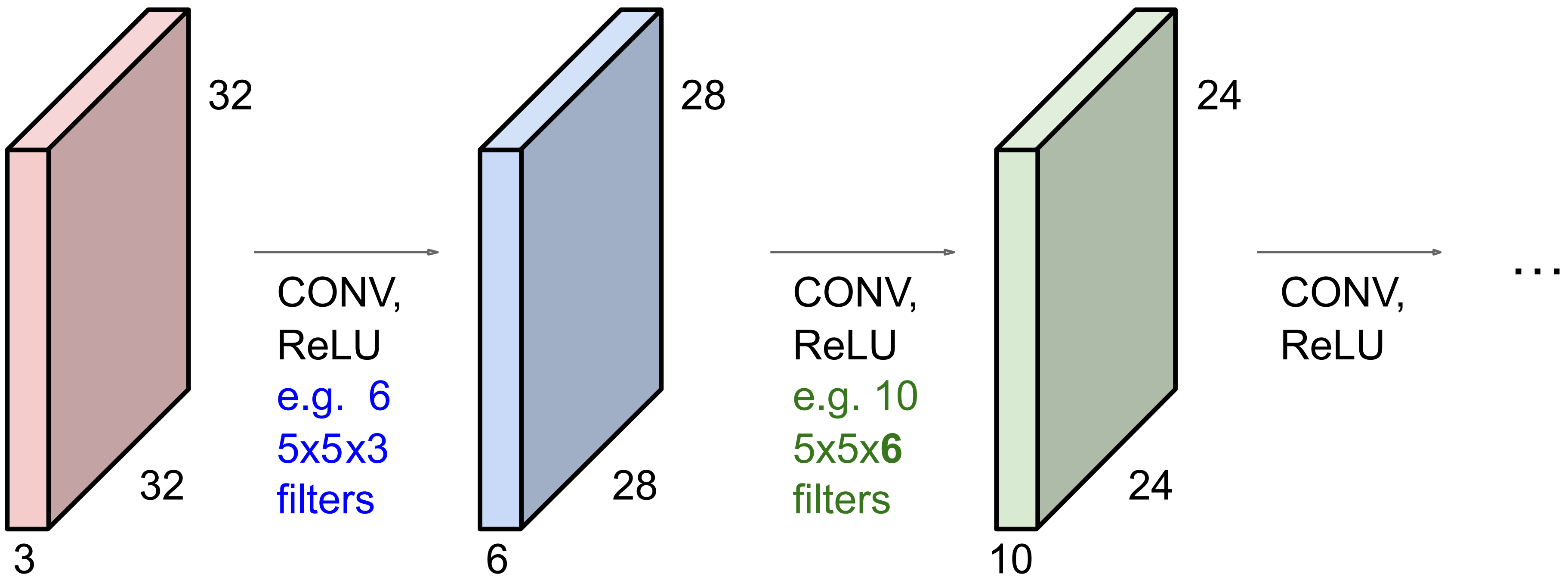
Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



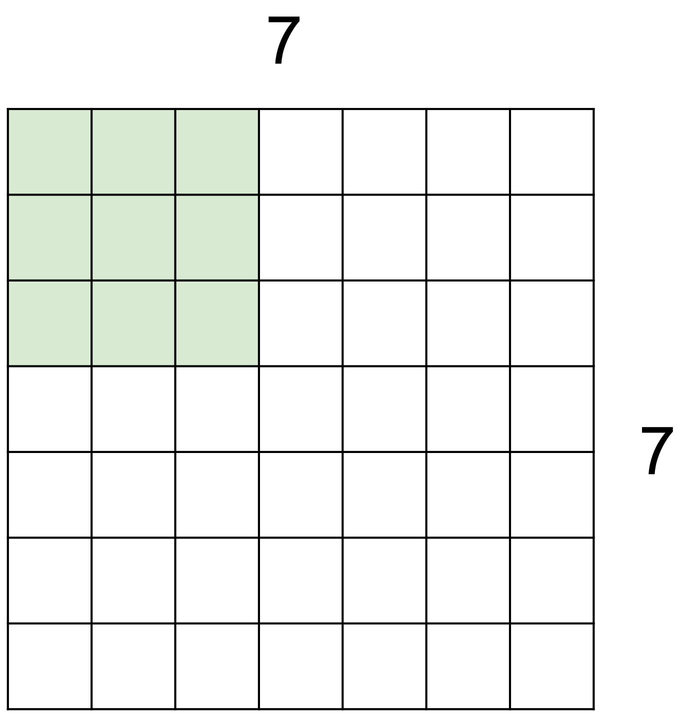
Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



32x32 input convolved repeatedly with 5x5 filters shrinks volumes spatially! (32 -> 28 -> 24 ...). Shrinking too fast is not good, doesn't work well.

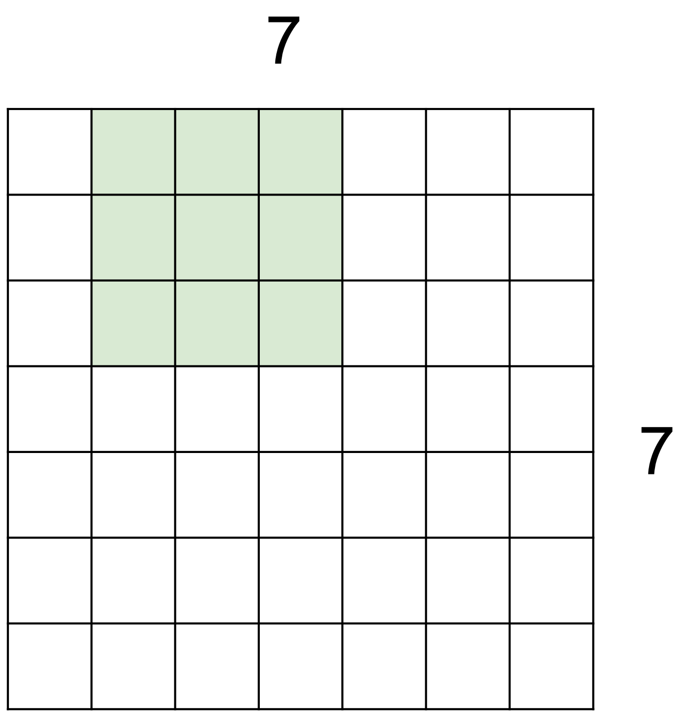


A closer look at spatial dimensions:



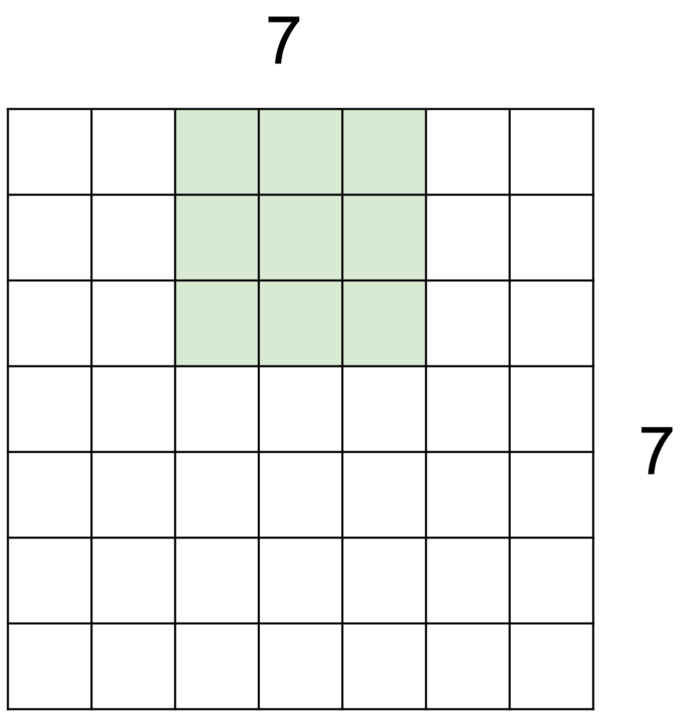
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



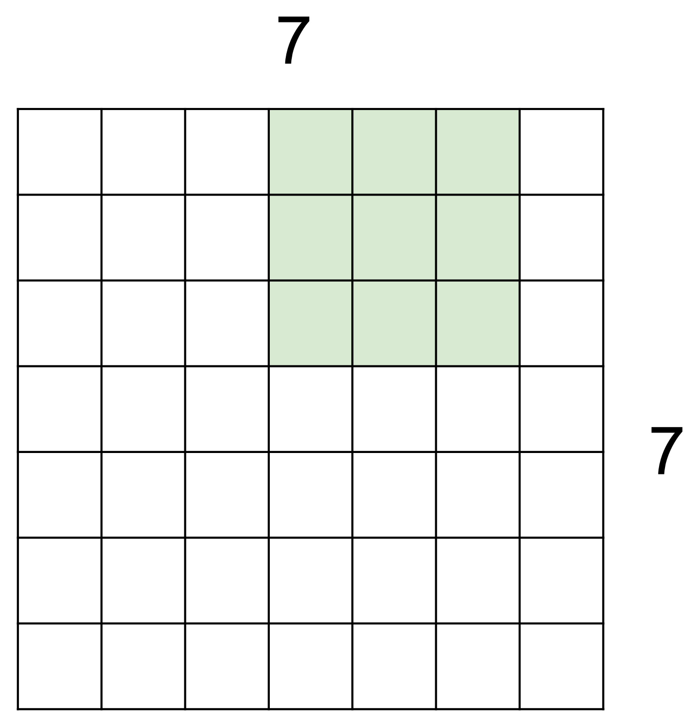
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



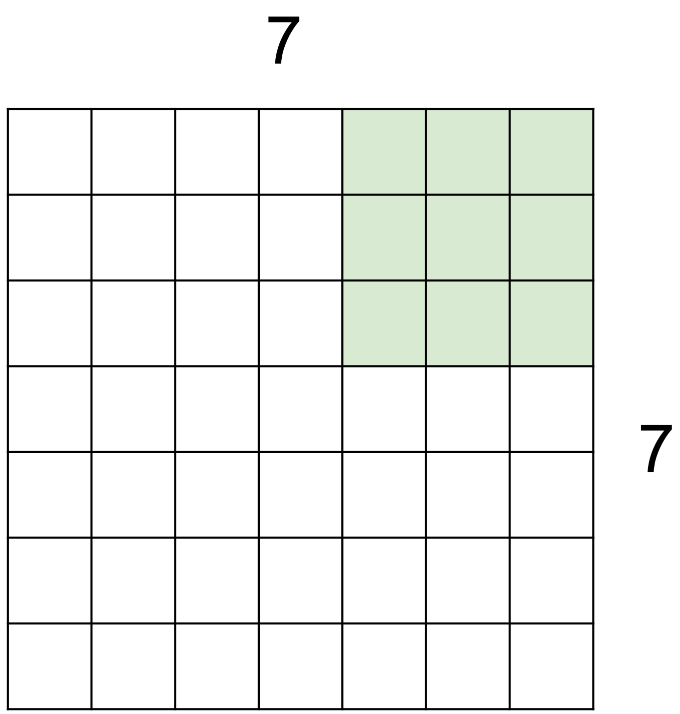
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

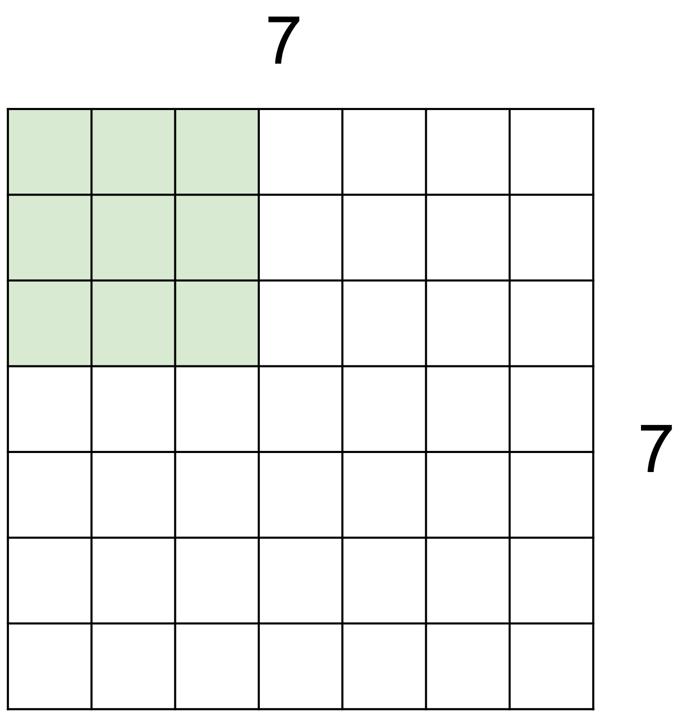
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

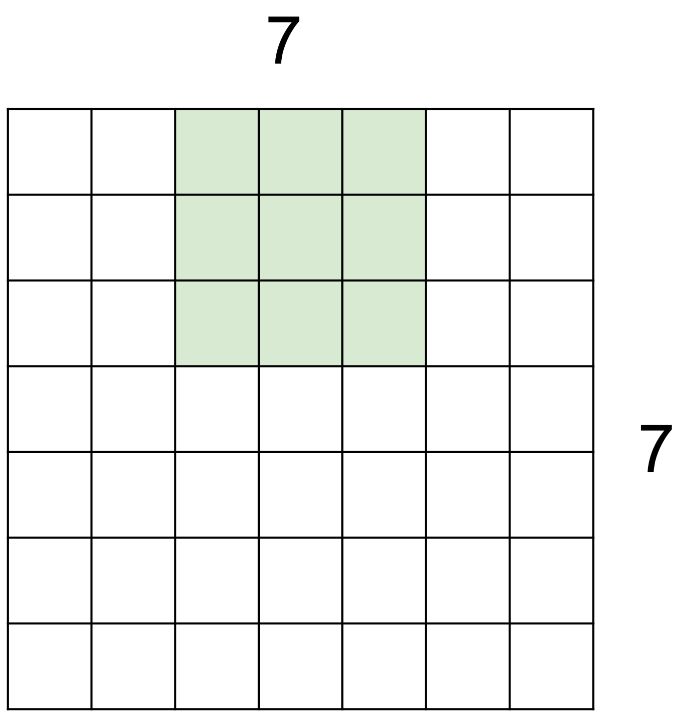
=> 5x5 output

A closer look at spatial dimensions:



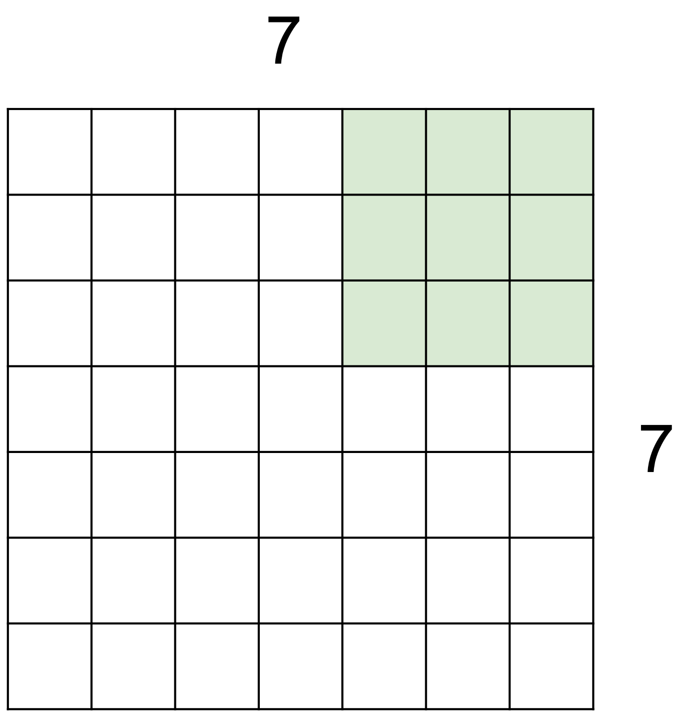
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



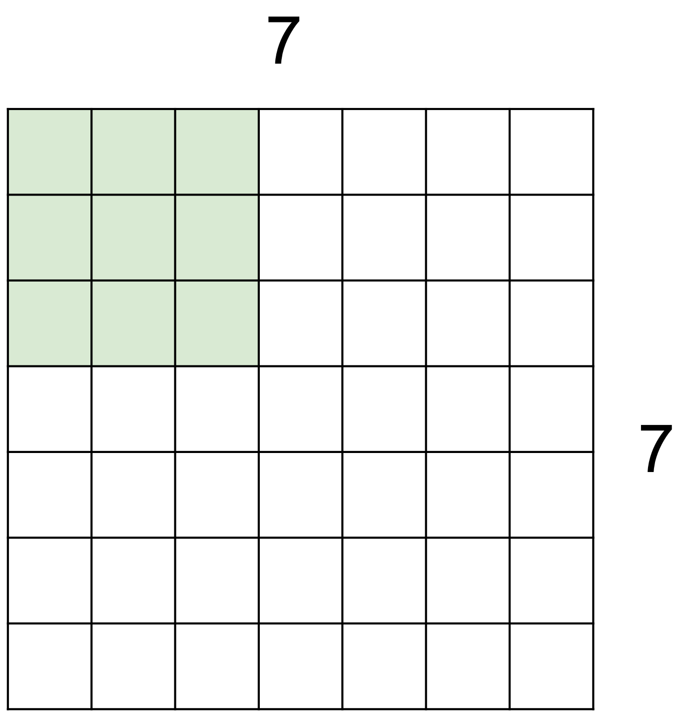
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



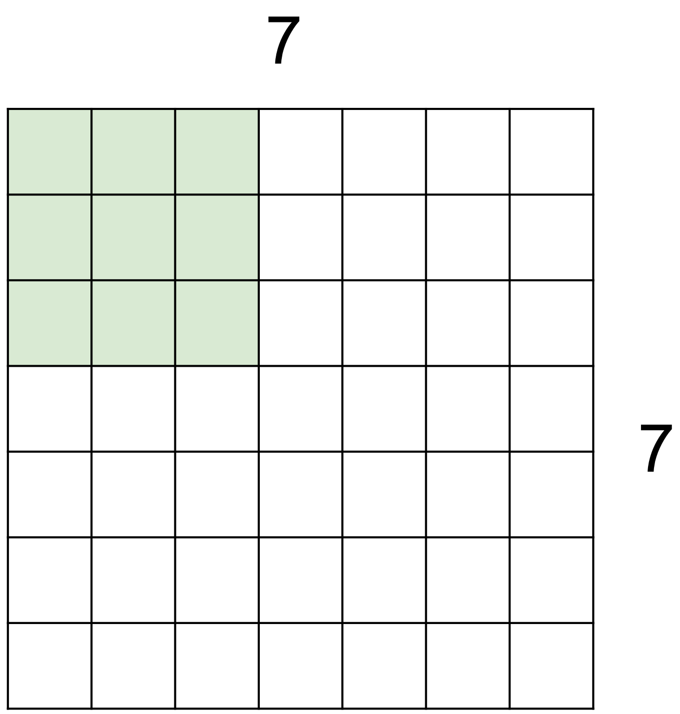
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

A closer look at spatial dimensions:



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

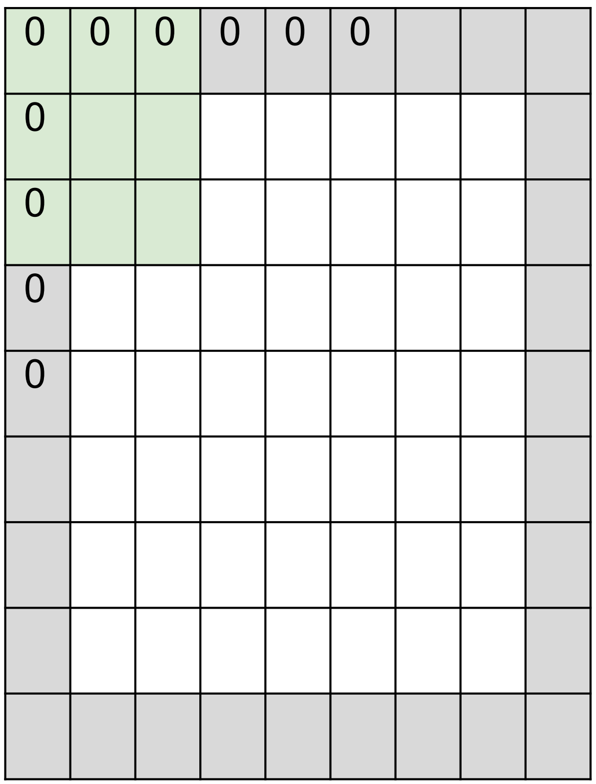
A closer look at spatial dimensions:



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

doesn't fit!
cannot apply 3x3 filter on
7x7 input with stride 3.

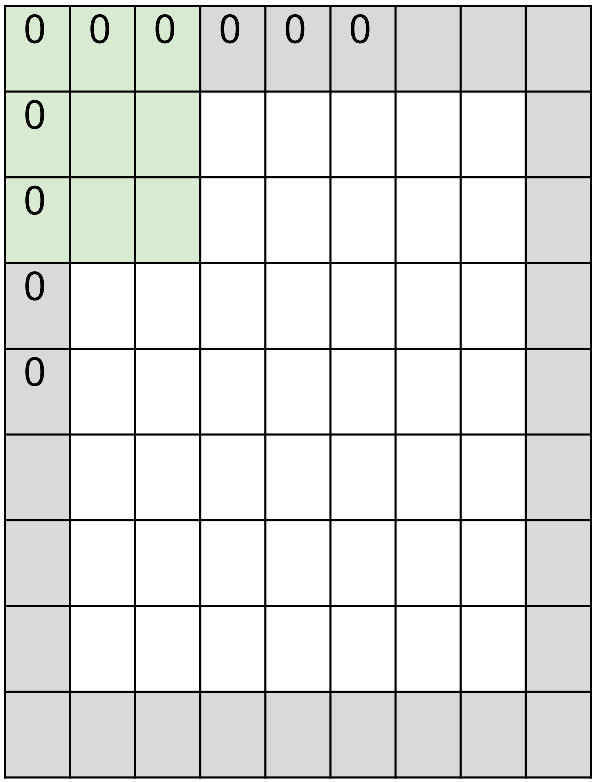
In practice: Common to zero pad the border



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

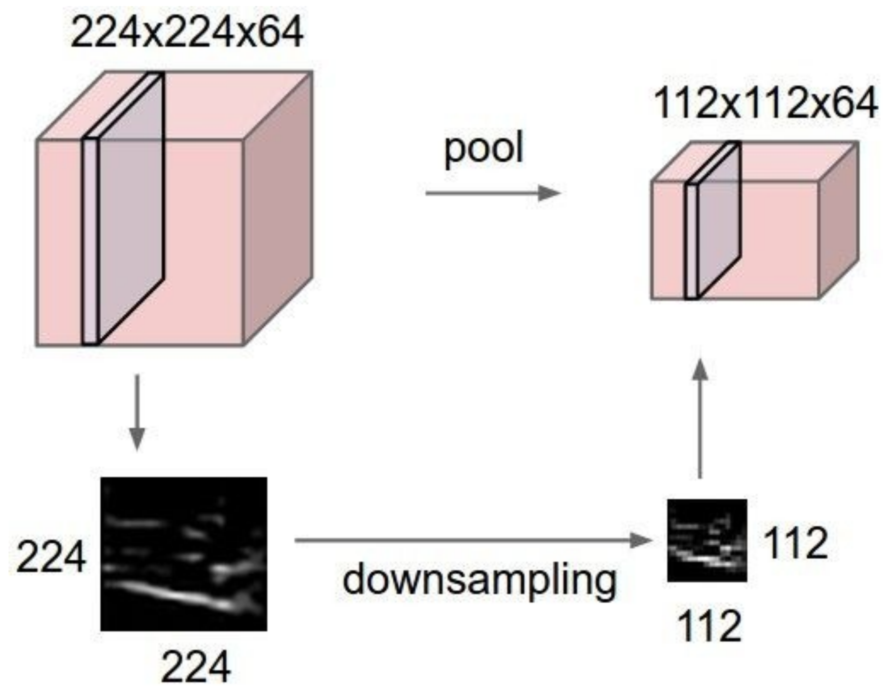


e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

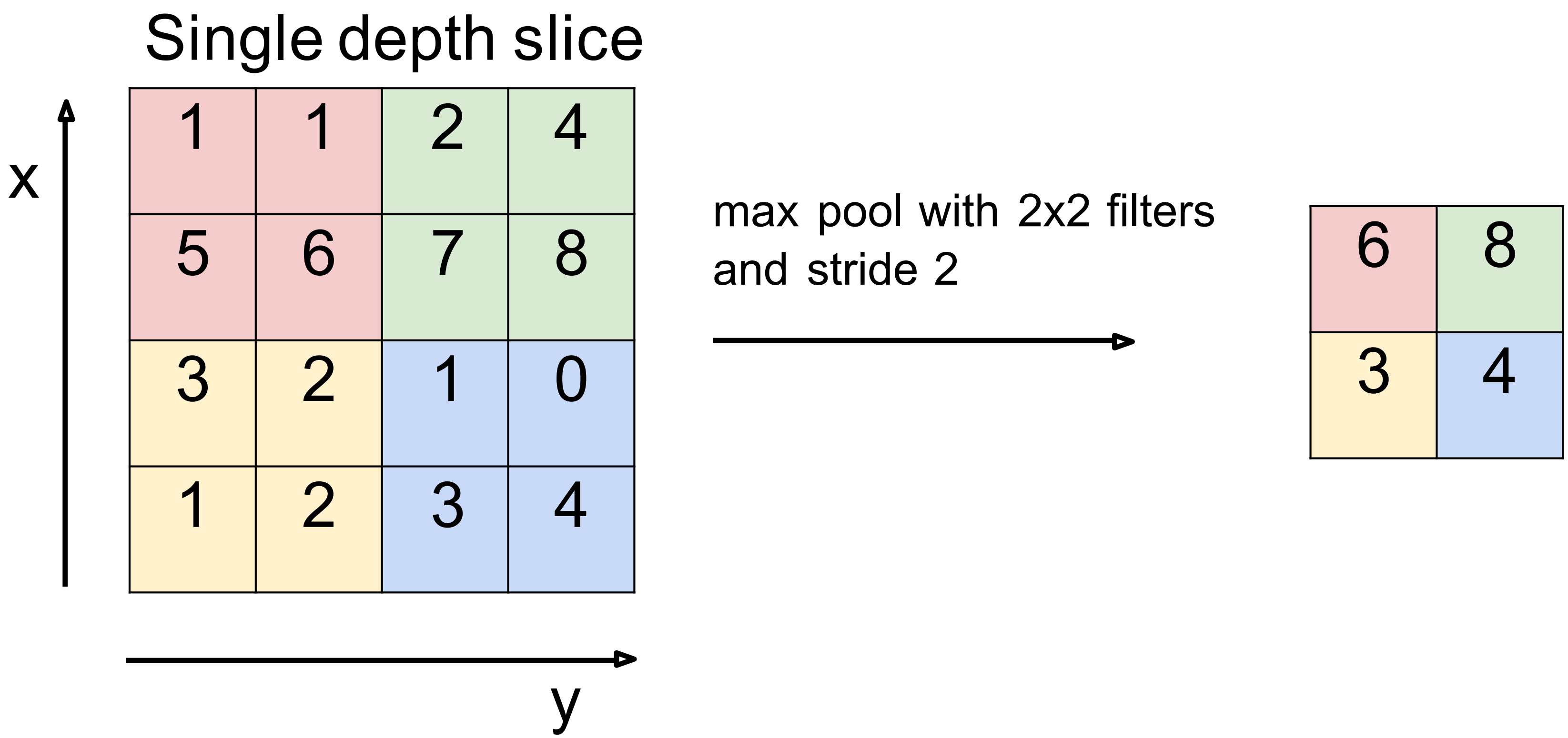
7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

Pooling layer

- makes the representations smaller and more manageable
- operates over each activation map independently:



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

Tensorflow implementation

- Weight Initialization
- Convolution and Pooling
- Convolution layer
- Fully connected layer
- Readout Layer

- Reference and image source: https://www.tensorflow.org/get_started/mnist/pros

  (See section 'Build a Multilayer Convolutional Network')

Input (placeholder)

```
x = tf.placeholder(tf.float32, shape=[None, input_size])
y = tf.placeholder(tf.float32, shape=[None, classes_num])
```

x is placeholder for input image.
y is label with one-hot representation, so second dimension of y is equal to number of classes.

None indicates that the first dimension, corresponding to the batch size, which can be any size.

[tf.placeholder]()

Weight Initialization

```
def weight_variable(shape):
    initial = tf.truncated_normal(shape, stddev=0.1)
    return tf.Variable(initial)

def bias_variable(shape):
    initial = tf.constant(0.1, shape=shape)
    return tf.Variable(initial)
```

tf.truncated_normal

These variable will be initialized when user run ‘tf.global_variables_initializer’.
Now they are just nodes in a graph without any value.

Convolution and Pooling

```
def conv2d(x, W):
    return tf.nn.conv2d(x, W, strides=[1, 1, 1, 1], padding='SAME')

def max_pool_2x2(x):
    return tf.nn.max_pool(x, ksize=[1, 2, 2, 1],
                          strides=[1, 2, 2, 1], padding='SAME')
```

Strides is 4-d, following NHWC format.
(Num_samples x Height x Width x Channels)

Recall strides and padding.
padding = 'SAME' means apply padding to keep output size as same as input size.

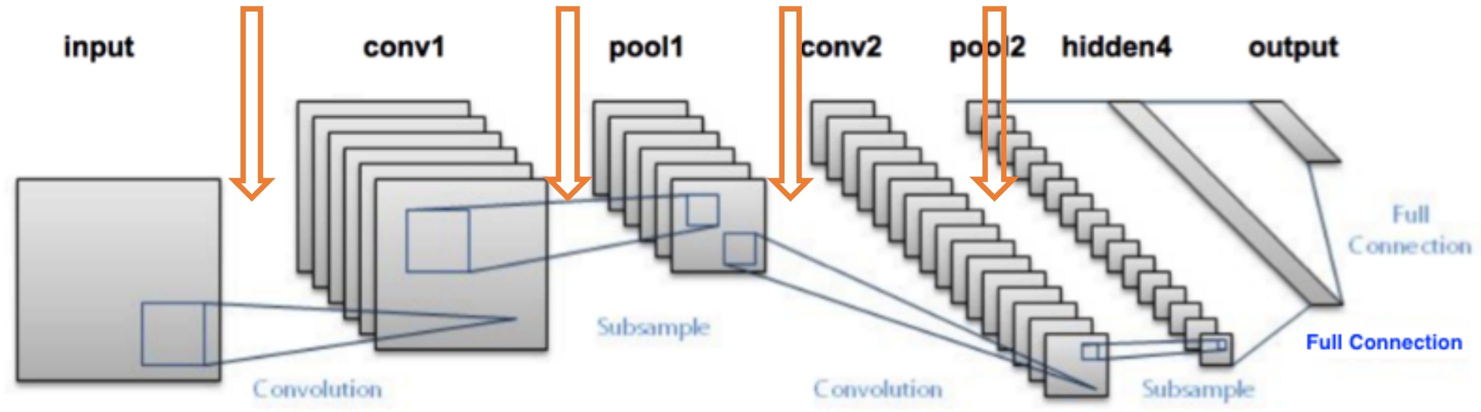
Conv2d pads with zeros and max_pool pads with –inf.

tf.nn.conv2d
tf.nn.max_pool

Convolution layer

```
W_conv1 = weight_variable([5, 5, 1, 32])
b_conv1 = bias_variable([32])
x_image = tf.reshape(x, [-1,28,28,1])
h_conv1 = tf.nn.relu(conv2d(x_image, W_conv1) + b_conv1)
h_pool1 = max_pool_2x2(h_conv1)
W_conv2 = weight_variable([5, 5, 32, 64])
b_conv2 = bias_variable([64])

h_conv2 = tf.nn.relu(conv2d(h_pool1, W_conv2) + b_conv2)
h_pool2 = max_pool_2x2(h_conv2)
```



tf.reshape

Convolution layer

```
W_conv1 = weight_variable([5, 5, 1, 32])
b_conv1 = bias_variable([32])
x_image = tf.reshape(x, [-1,28,28,1])
h_conv1 = tf.nn.relu(conv2d(x_image, W_conv1) + b_conv1)
h_pool1 = max_pool_2x2(h_conv1)
W_conv2 = weight_variable([5, 5, 32, 64])
b_conv2 = bias_variable([64])

h_conv2 = tf.nn.relu(conv2d(h_pool1, W_conv2) + b_conv2)
h_pool2 = max_pool_2x2(h_conv2)
```

See how the code creates a model by wrapping layers.
Be care of shape of each layer.
-1 means match the size of that dimension is computed
so that the total size remains constant.

[tf.reshape]()

Reshape

For example:

tensor ‘t’ is [[1, 2], [3, 4], [5, 6], [7, 8]] , so t has shape [4, 2]

(1) reshape(t, [2,4]) ➔ [[1, 2, 3, 4], [5, 6, 7, 8]]
(2) reshape(t, [-1, 4]) ➔ [[1, 2, 3, 4], [5, 6, 7, 8]]

-1 would be computed and becomes ‘2’

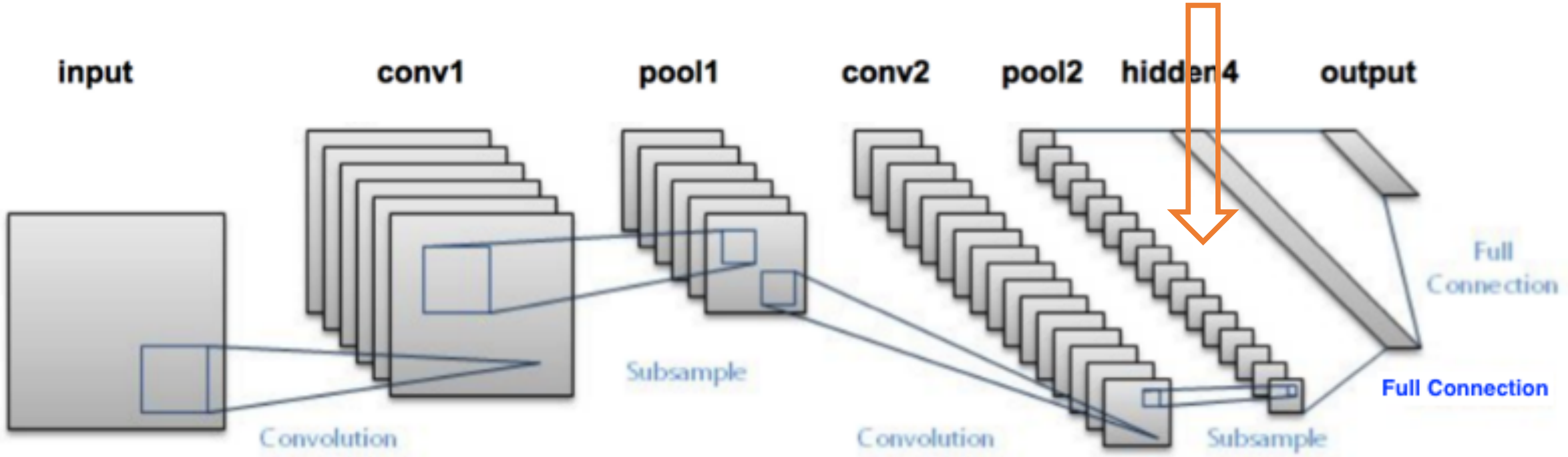
tf.reshape

Fully connected layer

```
W_fc1 = weight_variable([7 * 7 * 64, 1024])
b_fc1 = bias_variable([1024])

h_pool2_flat = tf.reshape(h_pool2, [-1, 7*7*64])
h_fc1 = tf.nn.relu(tf.matmul(h_pool2_flat, W_fc1) + b_fc1)
```

Flatten all the maps and connect them with fully connected layer.
Again, be care of shape.

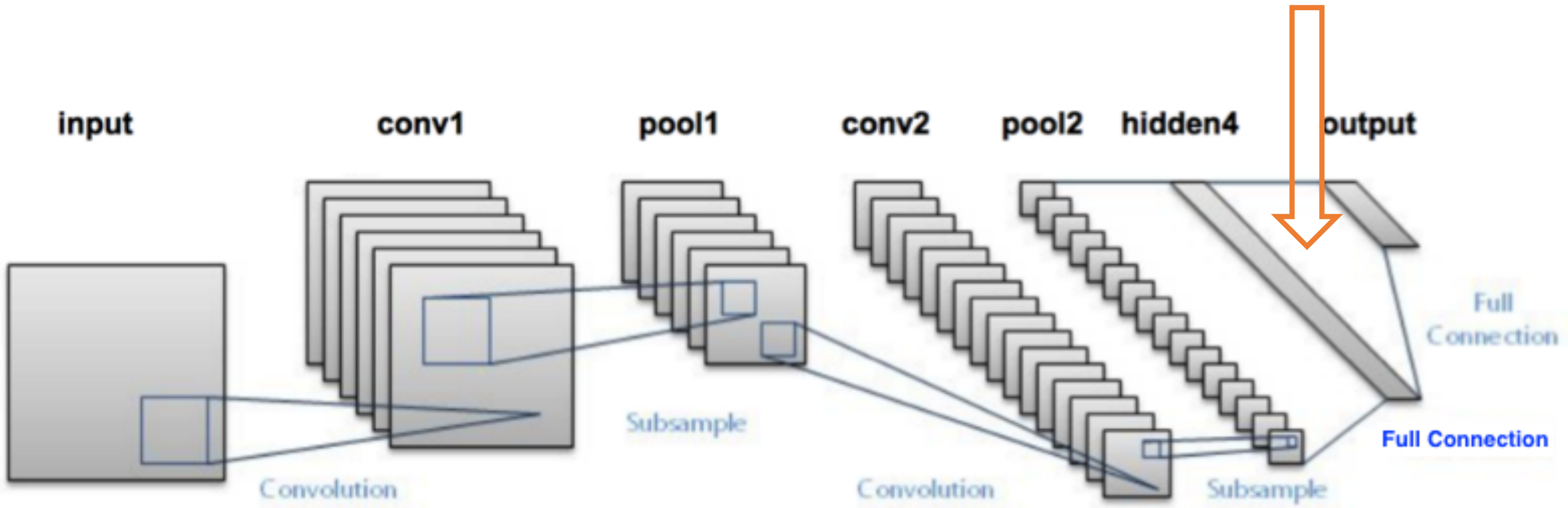


Readout Layer

```
W_fc2 = weight_variable([1024, 10])
b_fc2 = bias_variable([10])

y_conv = tf.matmul(h_fc1_drop, W_fc2) + b_fc2
```

Use a layer to match output size.
Done!



Training and Evaluation (optional)

```
cross_entropy = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(y_conv, y_))
train_step = tf.train.AdamOptimizer(1e-4).minimize(cross_entropy)
correct_prediction = tf.equal(tf.argmax(y_conv,1), tf.argmax(y_,1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
sess.run(tf.global_variables_initializer())
for i in range(20000):
    batch = mnist.train.next_batch(50)
    if i%100 == 0:
        train_accuracy = accuracy.eval(feed_dict={
            x:batch[0], y_: batch[1], keep_prob: 1.0})
        print("step %d, training accuracy %g"%(i, train_accuracy))
    train_step.run(feed_dict={x: batch[0], y_: batch[1], keep_prob: 0.5})

print("test accuracy %g"%accuracy.eval(feed_dict={
   x: mnist.test.images, y_: mnist.test.labels, keep_prob: 1.0}))
```

Recommendation

- Search for each function, and you’ll what’s everything going on.