

ML/DL for Everyone Season2

with  TensorFlow

Lab 11-0 CNN Basics Convolution

Code: <https://github.com/deeplearningzerotoall/TensorFlow>

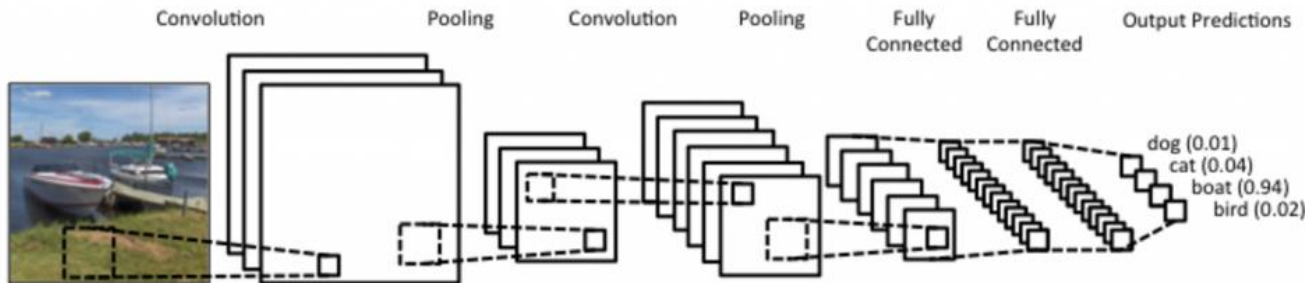
Slides: <http://bit.ly/2LQMKvk>

Lecturer: 이진원/JinWon Lee(wlee.ml25@gmail.com)



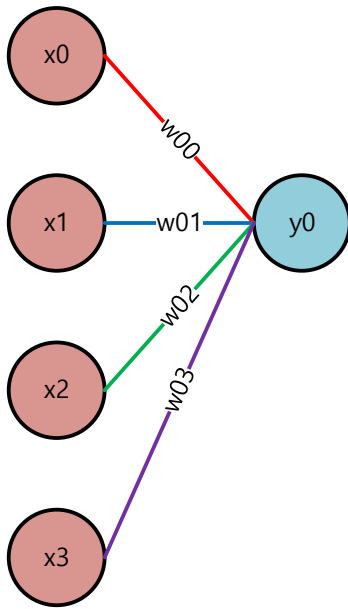
Convolutional Neural Network

- Most widely used for image classification.
- Generally, it consists of convolution layer, pooling layer and fully-connected layer.
- Weight(parameter, filter, kernel) sharing
- Convolution, Pooling layer – feature extraction
- Fully-connected layer – classification



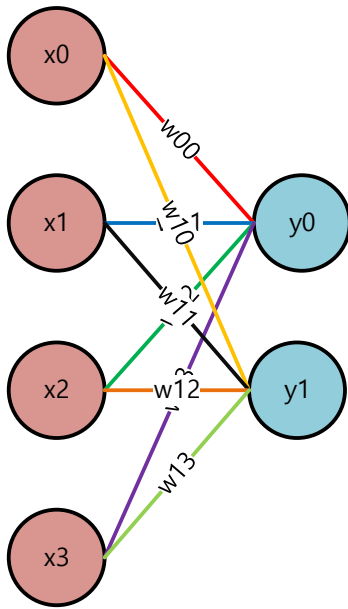
Dense Layer vs 1-D Convolution Layer

- Dense Layer(Fully Connected Layer)
 - $y_0 = x_0 \cdot w_{00} + x_1 \cdot w_{01} + x_2 \cdot w_{02} + x_3 \cdot w_{03}$



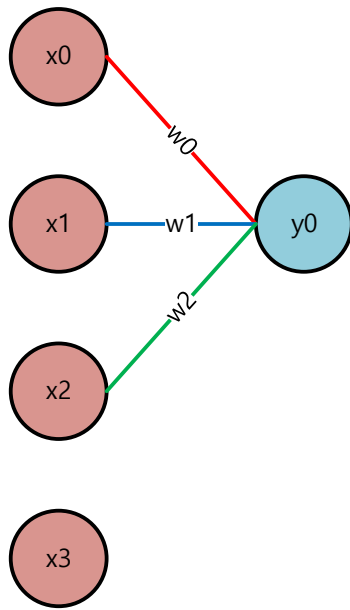
Dense Layer vs 1-D Convolution Layer

- Dense Layer(Fully Connected Layer)
 - $y_0 = x_0 \cdot w_{00} + x_1 \cdot w_{01} + x_2 \cdot w_{02} + x_3 \cdot w_{03}$
 - $y_1 = x_0 \cdot w_{10} + x_1 \cdot w_{11} + x_2 \cdot w_{12} + x_3 \cdot w_{13}$



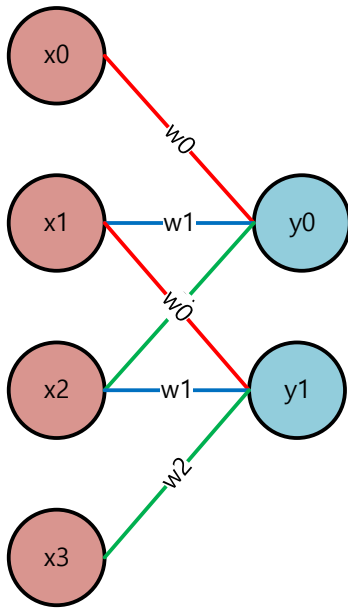
Dense Layer vs 1-D Convolution Layer

- 1-D Convolution Layer
 - $y_0 = x_0 \cdot w_0 + x_1 \cdot w_1 + x_2 \cdot w_2$



Dense Layer vs 1-D Convolution Layer

- 1-D Convolution Layer
 - $y_0 = x_0 \cdot w_0 + x_1 \cdot w_1 + x_2 \cdot w_2$
 - $y_0 = x_1 \cdot w_0 + x_2 \cdot w_1 + x_3 \cdot w_2$



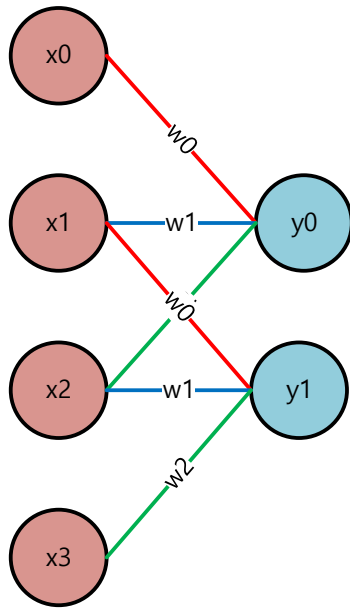
Dense Layer vs 1-D Convolution Layer

- 1-D Convolution Layer

- $y_0 = x_0 \cdot w_0 + x_1 \cdot w_1 + x_2 \cdot w_2$

- $y_0 = x_1 \cdot w_0 + x_2 \cdot w_1 + x_3 \cdot w_2$

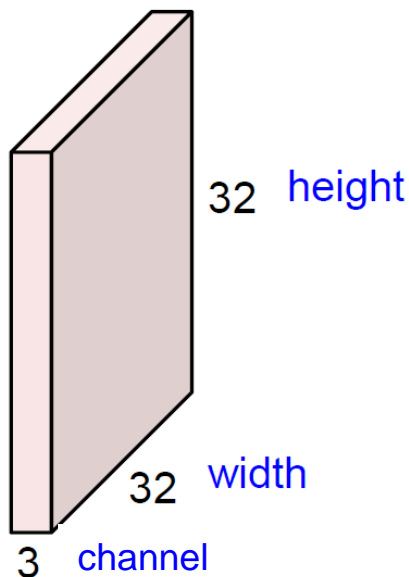
Weight sharing
&
Locally connected



2D Convolution Layer

Convolution Layer

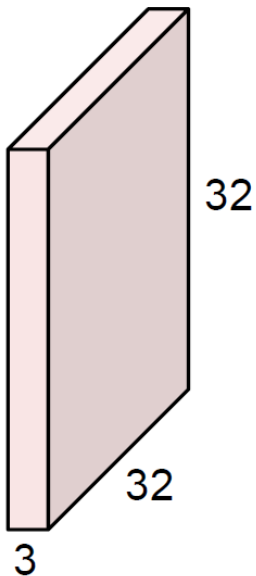
32x32x3 image



2D Convolution Layer

Convolution Layer

32x32x3 image



5x5x3 filter

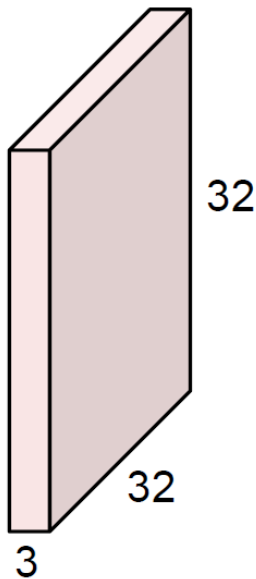


Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

2D Convolution Layer

Convolution Layer

32x32x3 image



Filters always extend the full channel of the input volume

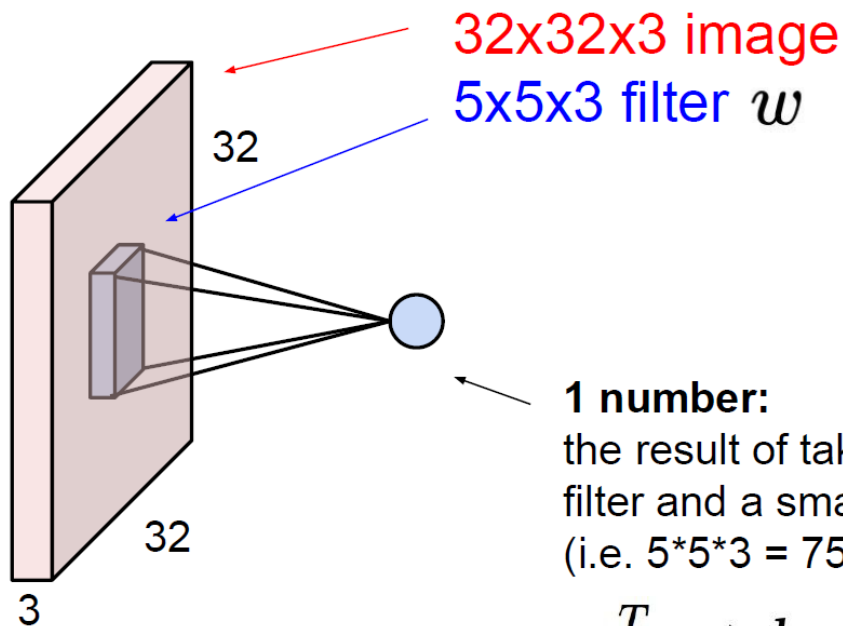
5x5x3 filter



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

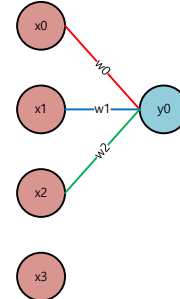
2D Convolution Layer

Convolution Layer



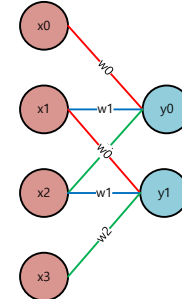
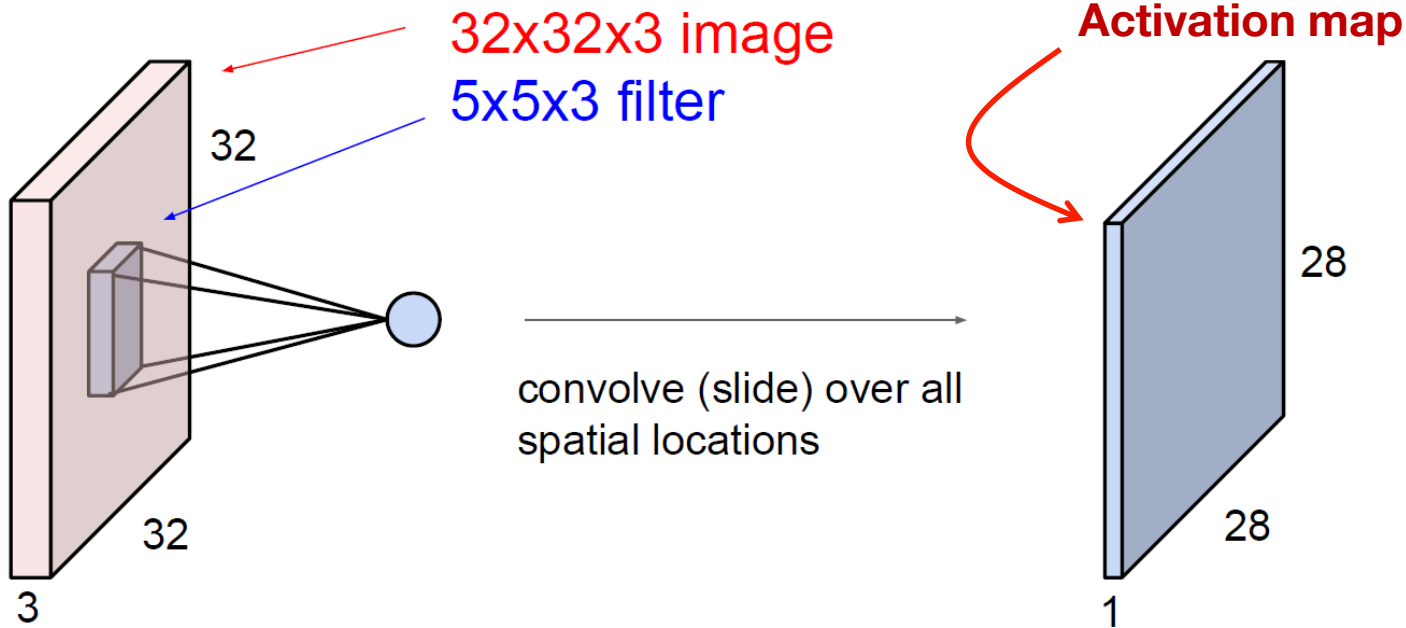
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image (i.e. $5 \cdot 5 \cdot 3 = 75$ -dimensional dot product + bias)

$$w^T x + b$$



2D Convolution Layer

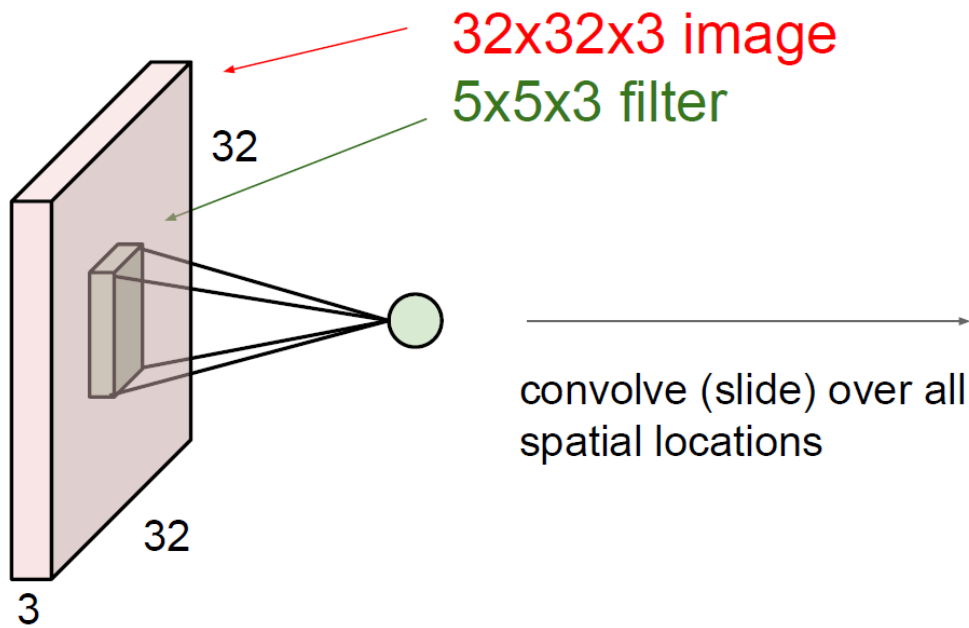
Convolution Layer



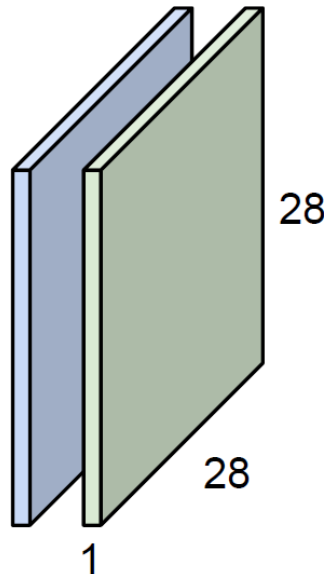
2D Convolution Layer

Convolution Layer

consider a second, **green** filter

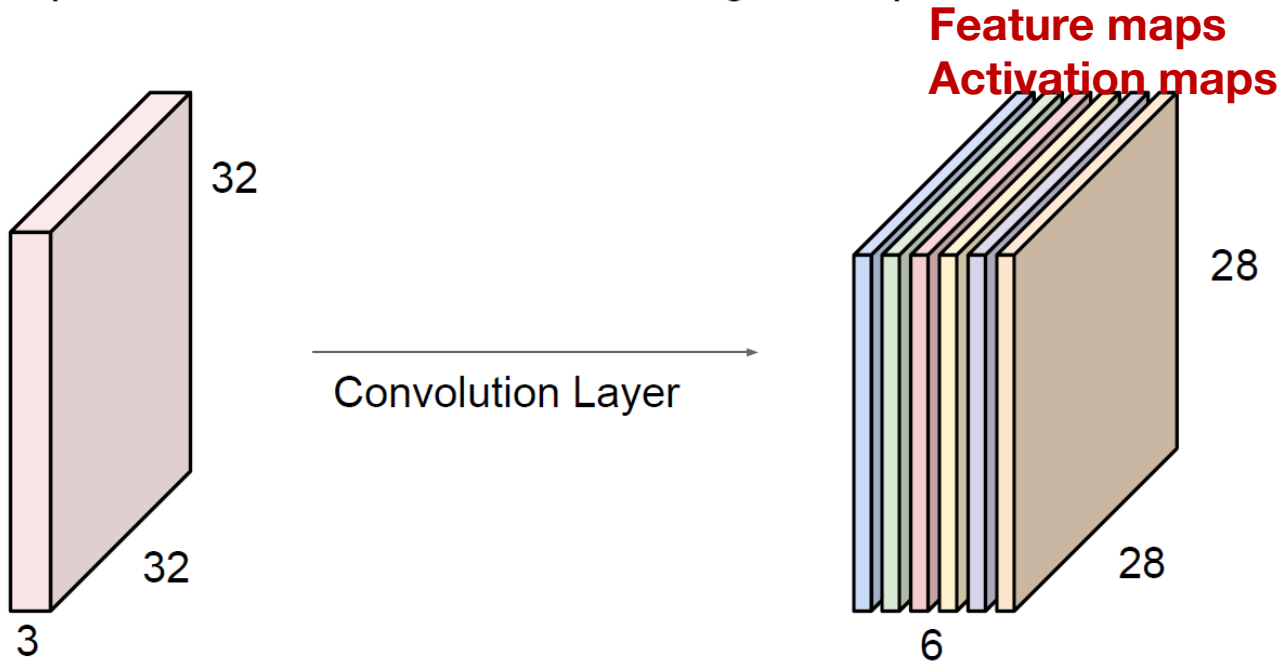


Feature maps
Activation maps



2D Convolution Layer

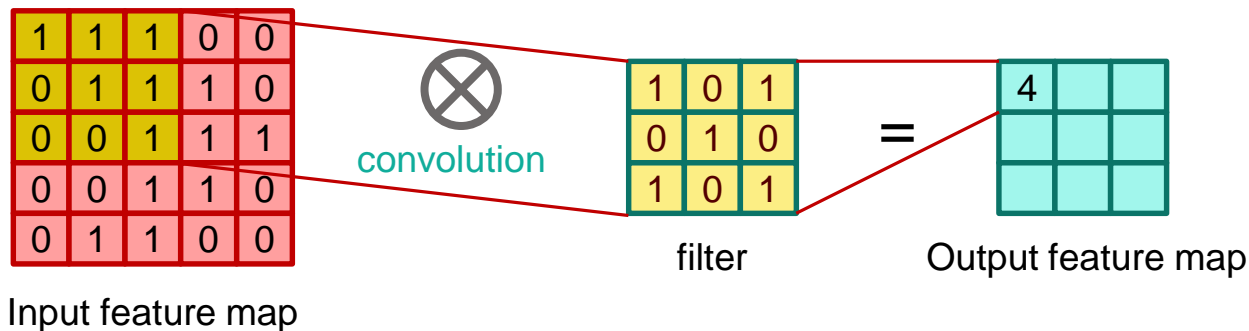
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



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

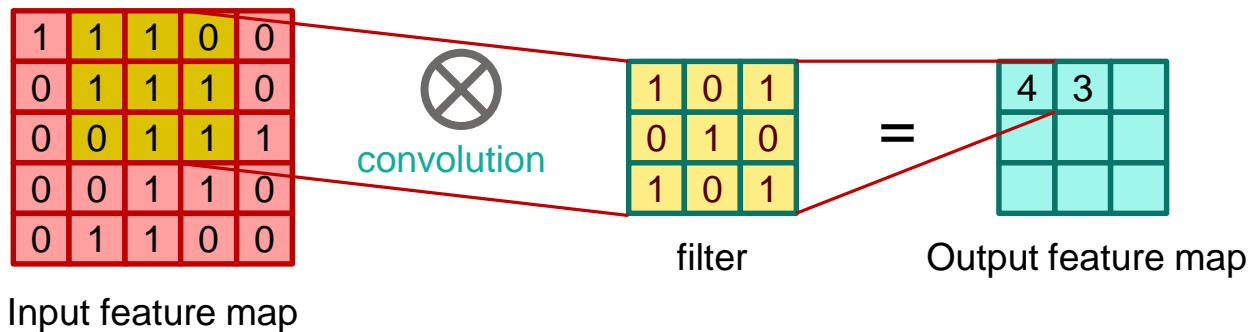
2D Convolution Layer – Computation

- $1 \times 1 + 1 \times 0 + 1 \times 1 + 0 \times 0 + 1 \times 1 + 1 \times 0 + 0 \times 1 + 0 \times 0 + 1 \times 1 = 4$



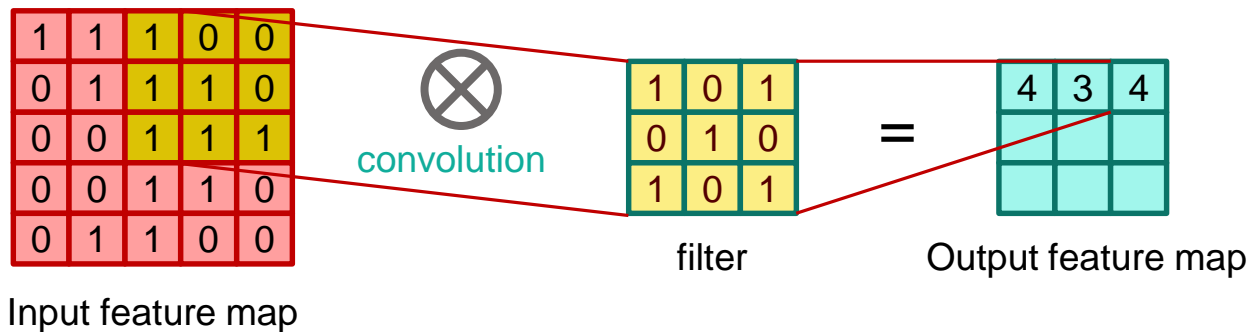
2D Convolution Layer – Computation

- $1 \times 1 + 1 \times 0 + 0 \times 1 + 1 \times 0 + 1 \times 1 + 1 \times 0 + 0 \times 1 + 1 \times 0 + 1 \times 1 = 3$



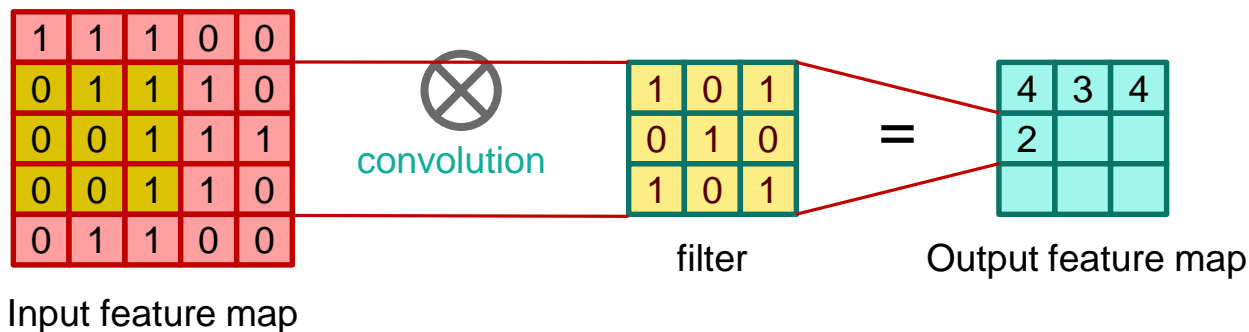
2D Convolution Layer – Computation

- $1 \times 1 + 0 \times 0 + 0 \times 1 + 1 \times 0 + 1 \times 1 + 0 \times 0 + 1 \times 1 + 1 \times 0 + 1 \times 1 = 4$



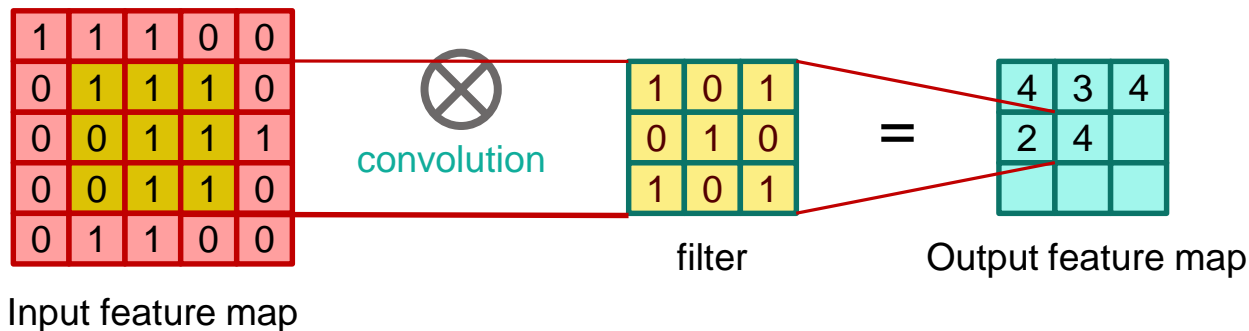
2D Convolution Layer – Computation

- $0 \times 1 + 1 \times 0 + 1 \times 1 + 0 \times 0 + 0 \times 1 + 1 \times 0 + 0 \times 1 + 0 \times 0 + 1 \times 1 = 2$



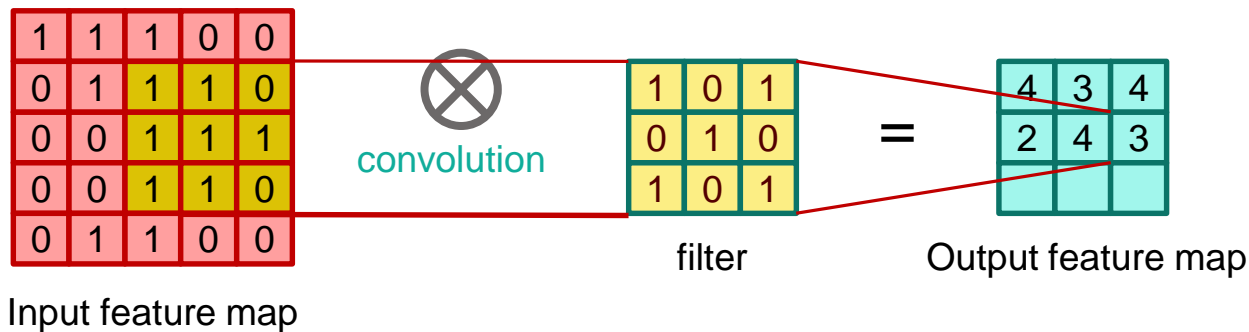
2D Convolution Layer – Computation

- $1 \times 1 + 1 \times 0 + 1 \times 1 + 0 \times 0 + 1 \times 1 + 1 \times 0 + 0 \times 1 + 1 \times 0 + 1 \times 1 = 4$



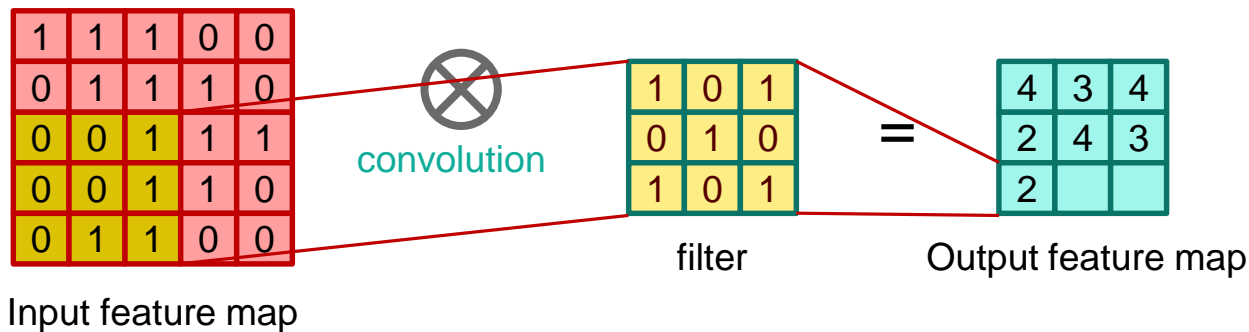
2D Convolution Layer – Computation

- $1 \times 1 + 1 \times 0 + 0 \times 1 + 1 \times 0 + 1 \times 1 + 1 \times 0 + 1 \times 1 + 1 \times 0 + 0 \times 1 = 3$



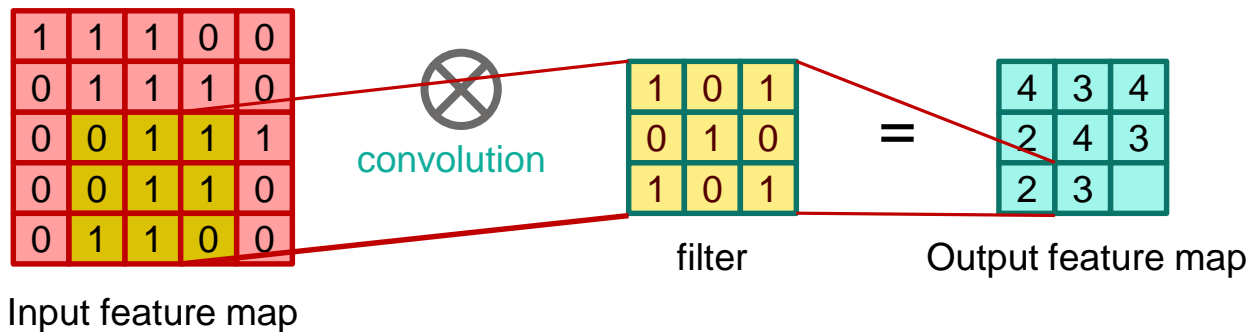
2D Convolution Layer – Computation

- $0 \times 1 + 0 \times 0 + 1 \times 1 + 0 \times 0 + 0 \times 1 + 1 \times 0 + 0 \times 1 + 1 \times 0 + 1 \times 1 = 2$



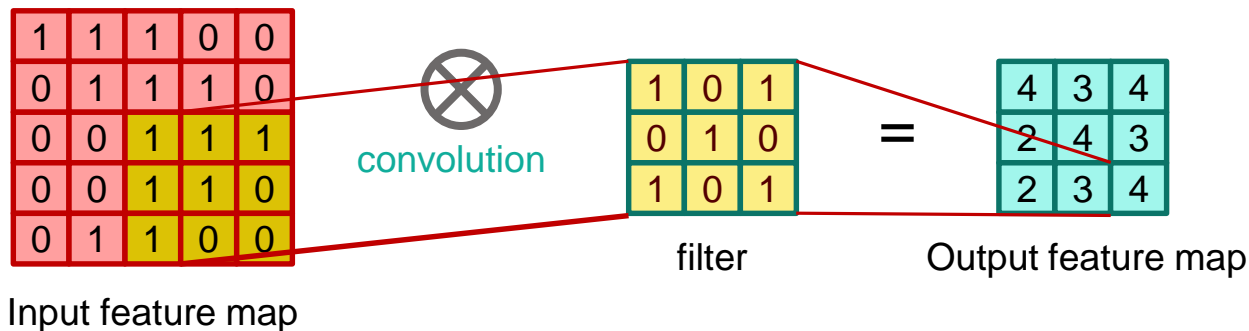
2D Convolution Layer – Computation

- $0 \times 1 + 1 \times 0 + 1 \times 1 + 0 \times 0 + 1 \times 1 + 1 \times 0 + 1 \times 1 + 1 \times 0 + 0 \times 1 = 3$



2D Convolution Layer – Computation

- $1 \times 1 + 1 \times 0 + 1 \times 1 + 1 \times 0 + 1 \times 1 + 0 \times 0 + 1 \times 1 + 0 \times 0 + 0 \times 1 = 4$



2D Convolution Layer – Computation

1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

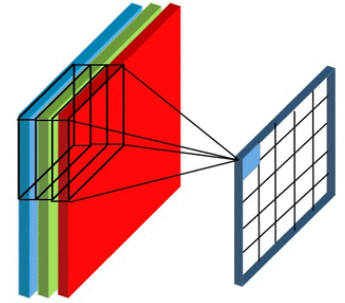
Image

4		

Convolved
Feature

2D Convolution Layer

– Multi Channel, Many Filters



1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Input channel : 3


convolution

1	0	1
0	1	0
1	0	1

1	0	1
0	-1	0
1	0	1

of filters : 2

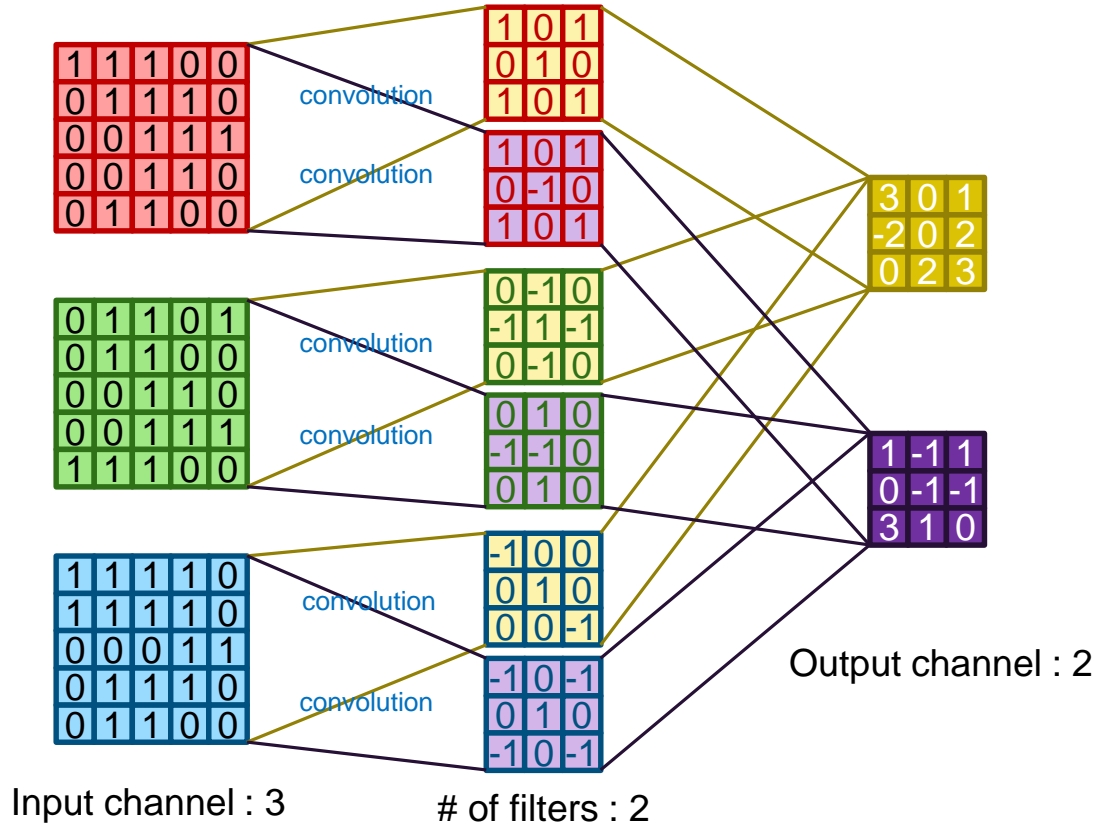
=

3	0	1
-2	0	2
0	2	3

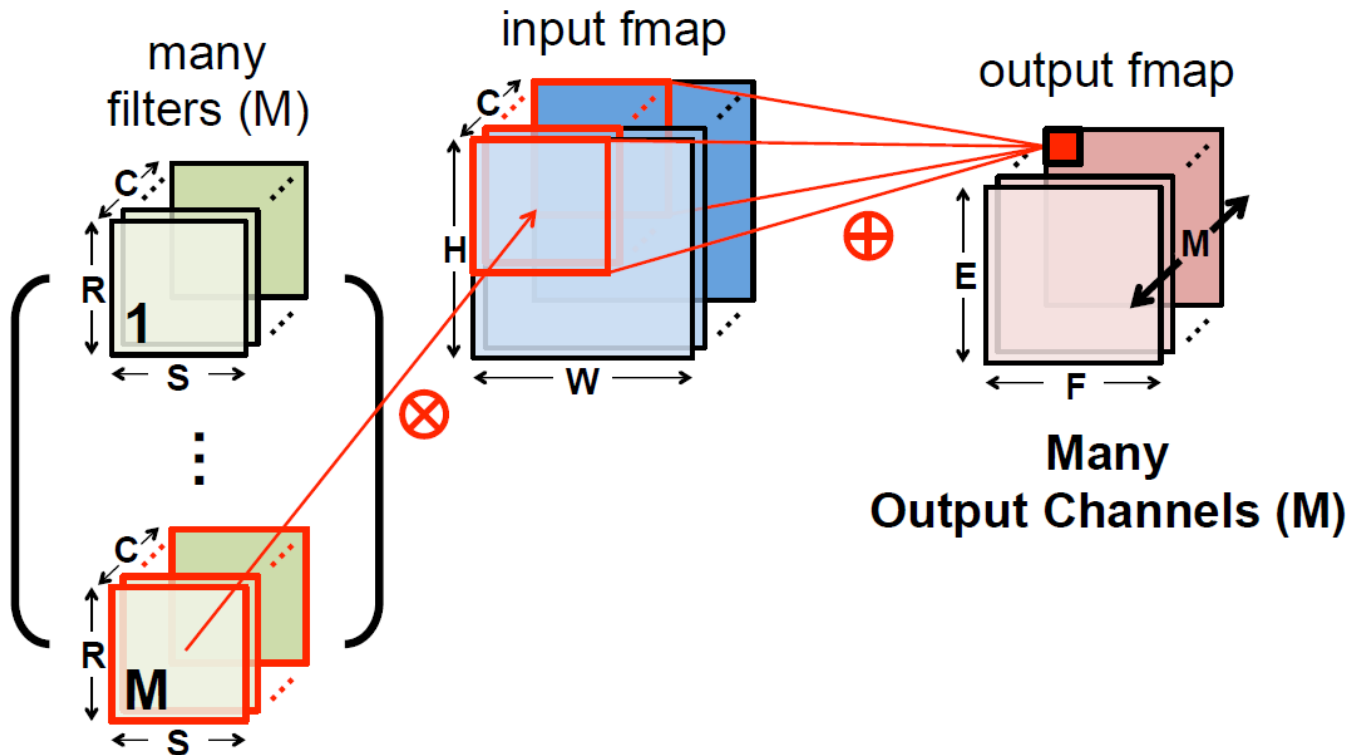
Output channel : 2

2D Convolution Layer

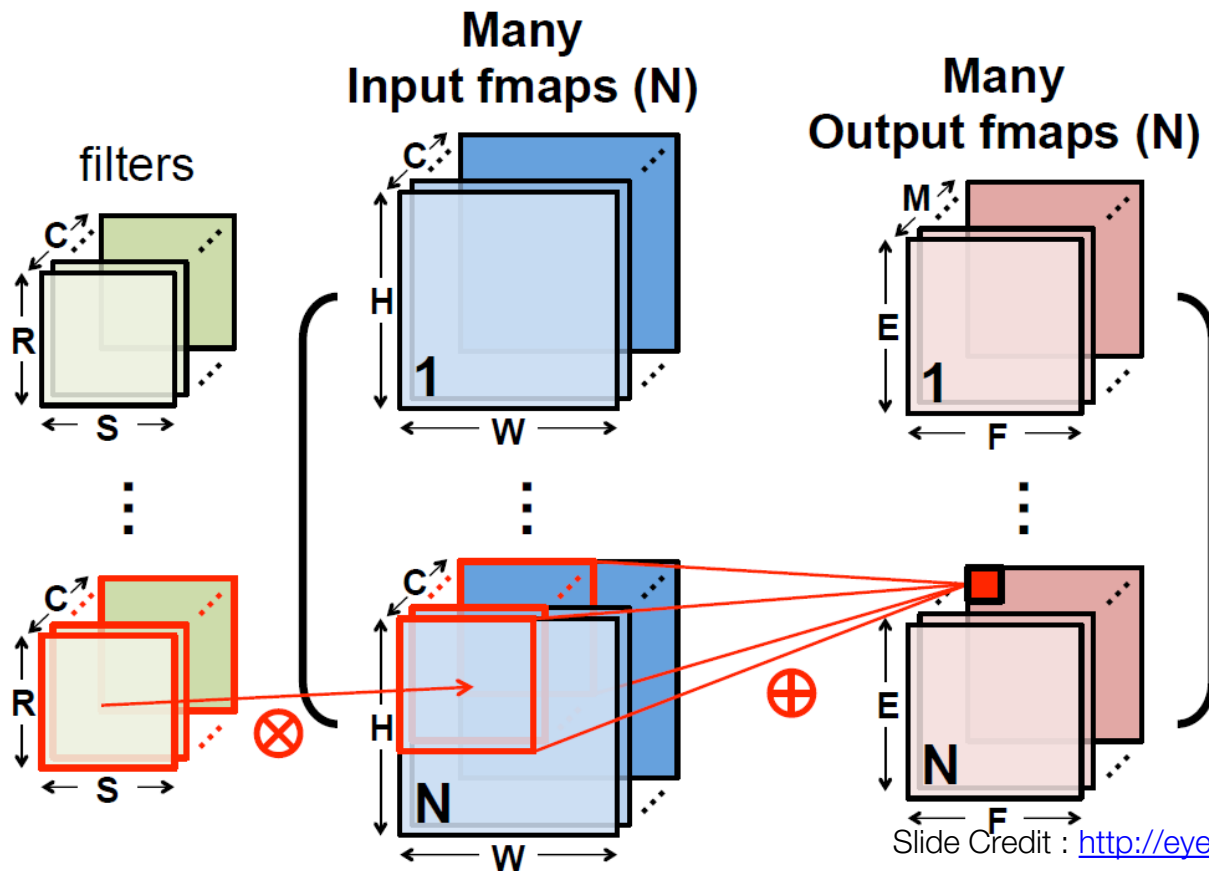
– Multi Channel, Many Filters



2D Convolution Layer

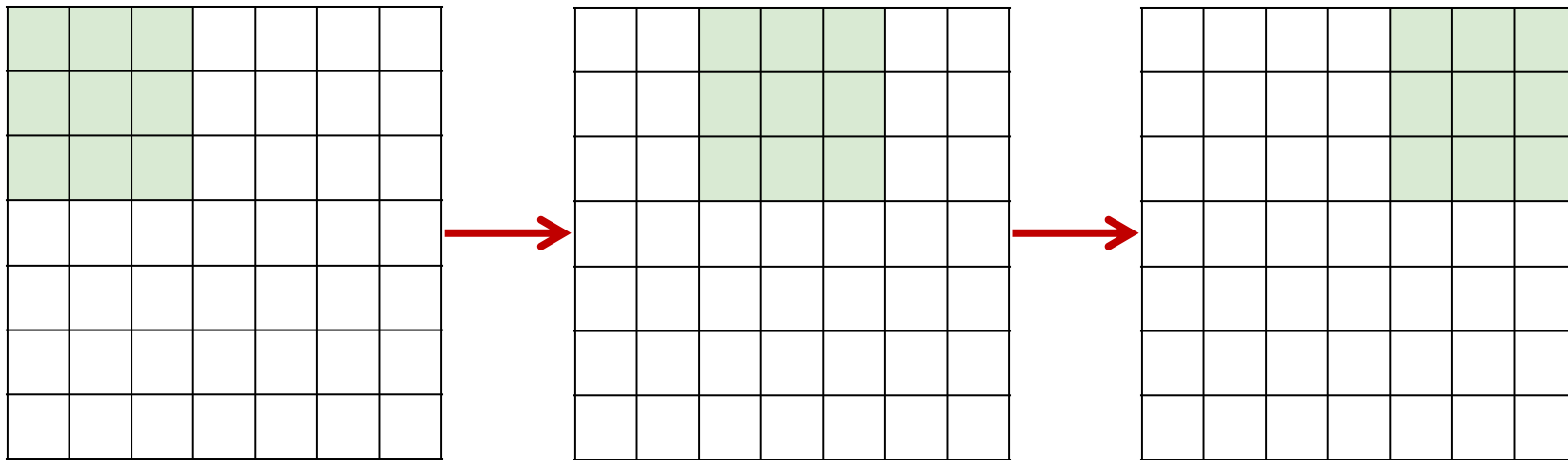


2D Convolution Layer – 4D Tensors



Options of Convolution

- Stride – How far to go to the right or the bottom to perform the next convolution
 - Ex) 7x7 input, 3x3 convolution filter with **stride 2** → 3x3 output



Options of Convolution

- Zero Padding

0	0	0	0	0	0			
0								
0								
0								
0								

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 $F \times F$, and zero-padding with $(F-1)/2$. (will preserve size spatially)

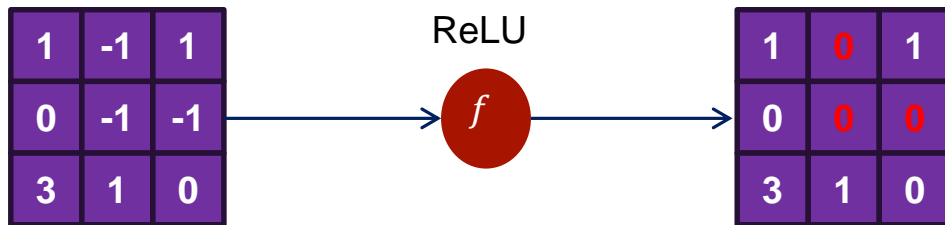
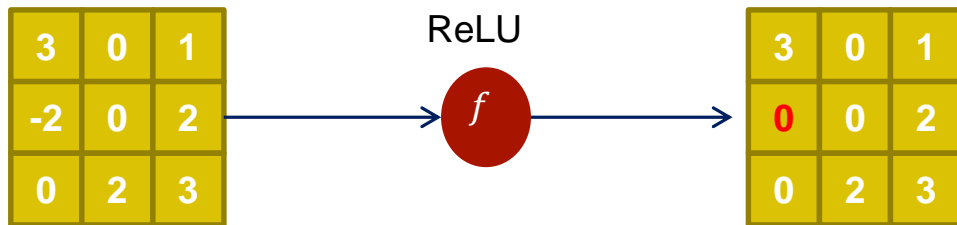
e.g. $F = 3 \Rightarrow$ zero pad with 1

$F = 5 \Rightarrow$ zero pad with 2

$F = 7 \Rightarrow$ zero pad with 3

Activation Function

- ReLU



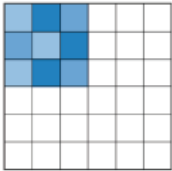
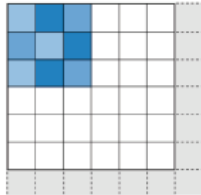
tf.keras.layers.Conv2D

```
__init__(  
    filters,  
    kernel_size,  
    strides=(1, 1),  
    padding='valid',  
    data_format=None,  
    dilation_rate=(1, 1),  
    activation=None,  
    use_bias=True,  
    kernel_initializer='glorot_uniform',  
    bias_initializer='zeros',  
    kernel_regularizer=None,  
    bias_regularizer=None,  
    activity_regularizer=None,  
    kernel_constraint=None,  
    bias_constraint=None,  
    **kwargs  
)
```


tf.keras.layers.Conv2D

- **filters**: Integer, the dimensionality of the output space (i.e. the number of output filters in the convolution).
- **kernel_size**: An integer or tuple/list of 2 integers, specifying the height and width of the 2D convolution window. Can be a single integer to specify the same value for all spatial dimensions.
- **strides**: An integer or tuple/list of 2 integers, specifying the strides of the convolution along the height and width. Can be a single integer to specify the same value for all spatial dimensions. Specifying any stride value != 1 is incompatible with specifying any **dilation_rate** value != 1.
- **padding**: one of "valid" or "same" (case-insensitive).
- **data_format**: A string, one of **channels_last** (default) or **channels_first**. The ordering of the dimensions in the inputs. **channels_last** corresponds to inputs with shape (batch, height, width, channels) while **channels_first** corresponds to inputs with shape (batch, channels, height, width). It defaults to the **image_data_format** value found in your Keras config file at ~/.keras/keras.json. If you never set it, then it will be "channels_last".

Padding – SAME vs VALID

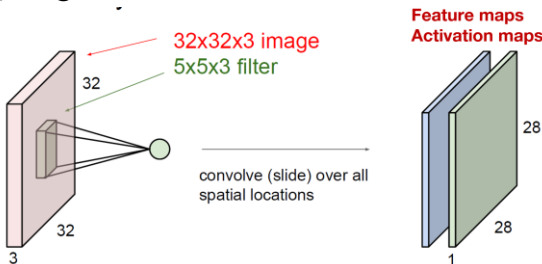
	Valid	Same
Value	$P = 0$	$P_{\text{start}} = \left\lfloor \frac{S \lceil \frac{I}{S} \rceil - I + F - S}{2} \right\rfloor$ $P_{\text{end}} = \left\lceil \frac{S \lceil \frac{I}{S} \rceil - I + F - S}{2} \right\rceil$
Illustration		
Purpose	<ul style="list-style-type: none"> - No padding - Drops last convolution if dimensions do not match 	<ul style="list-style-type: none"> - Padding such that feature map size has size $\left\lceil \frac{I}{S} \right\rceil$ - Output size is mathematically convenient - Also called 'half' padding

tf.keras.layers.Conv2D

- **activation** : Activation function to use. If you don't specify anything, no activation is applied (ie. "linear" activation: $a(x) = x$).
- **use_bias** : Boolean, whether the layer uses a bias vector.
- **kernel_initializer** : Initializer for the **kernel** weights matrix.
- **bias_initializer** : Initializer for the bias vector.
- **kernel_regularizer** : Regularizer function applied to the **kernel** weights matrix.
- **bias_regularizer** : Regularizer function applied to the bias vector.

kernel dimension : {height, width, in_channel, out_channel}

Ex) {5, 5, 3, 2}



Importing Libraries & Enable Eager Mode

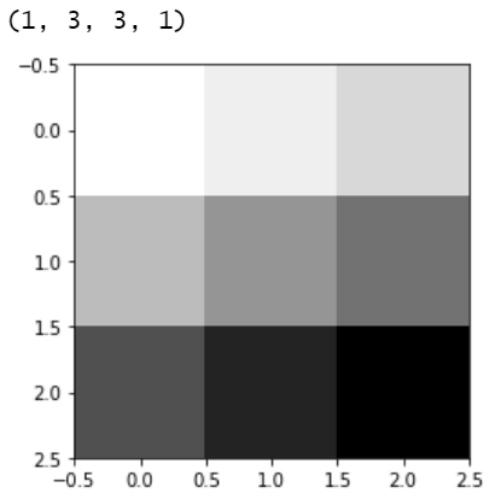
```
import numpy as np
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt
```

```
print(tf.__version__)
print(keras.__version__)
```

```
tf.enable_eager_execution()
```

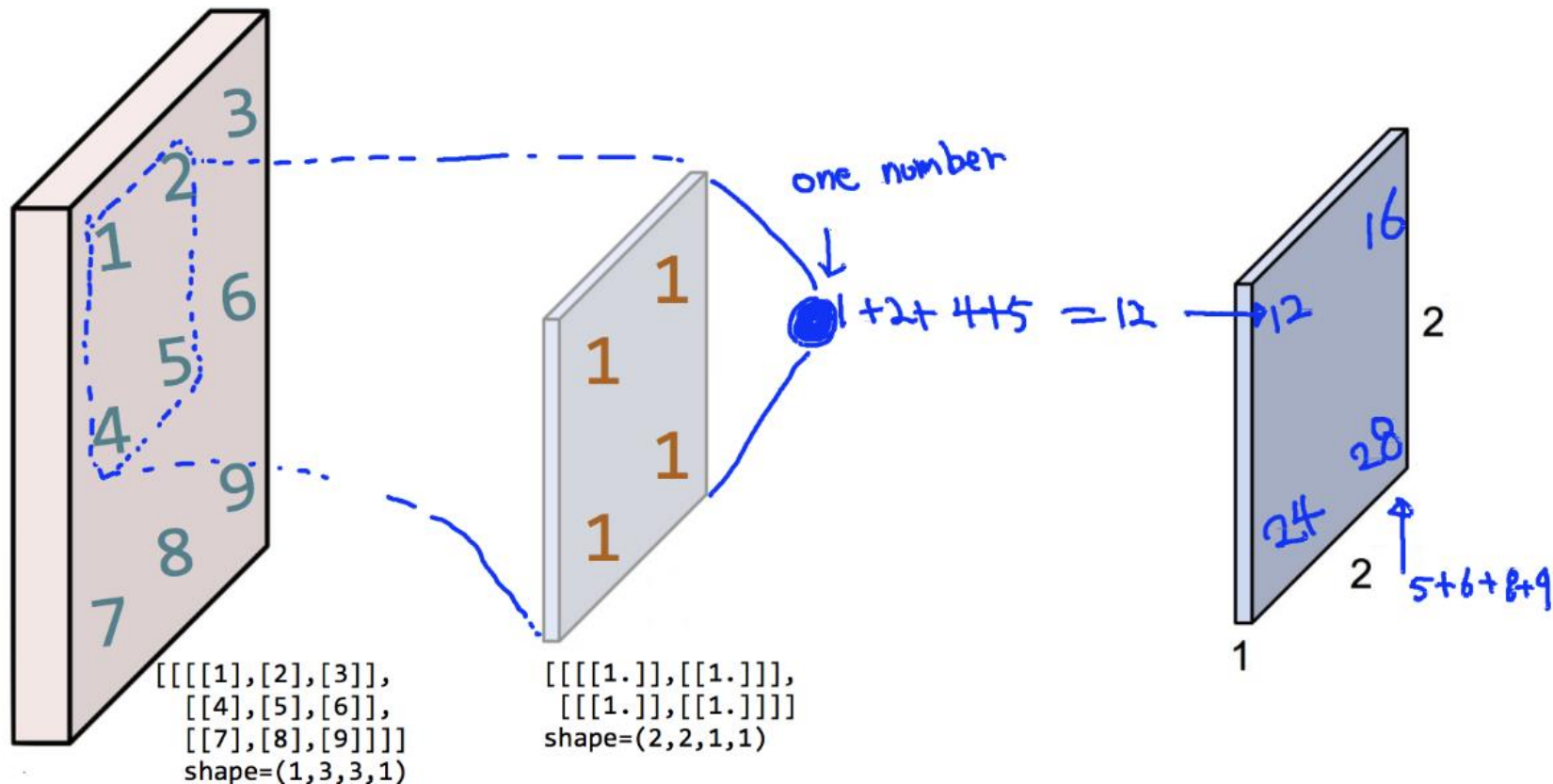
Toy Image

```
image = tf.constant([[[[1],[2],[3]],  
                      [[4],[5],[6]],  
                      [[7],[8],[9]]]], dtype=np.float32)  
print(image.shape)  
plt.imshow(image.numpy().reshape(3,3), cmap='Greys')  
plt.show()
```



Simple Convolution Layer

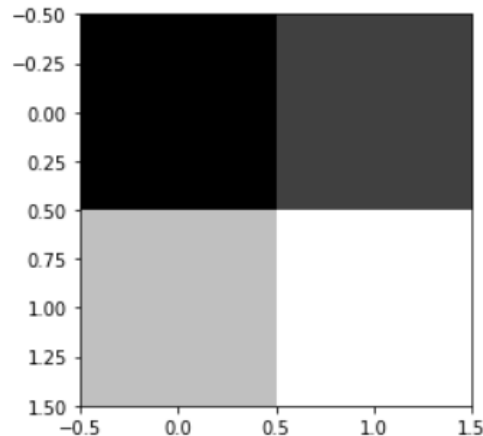
Image: 1,3,3,1 image, Filter: 2,2,1,1, Stride: 1x1, Padding: VALID



```
print("image.shape", image.shape)
weight = np.array([[[[1.]], [[1.]]],
                  [[[1.]], [[1.]]]])
print("weight.shape", weight.shape)
weight_init = tf.constant_initializer(weight)
conv2d = keras.layers.Conv2D(filters=1, kernel_size=2, padding='VALID',
                              kernel_initializer=weight_init)(image)

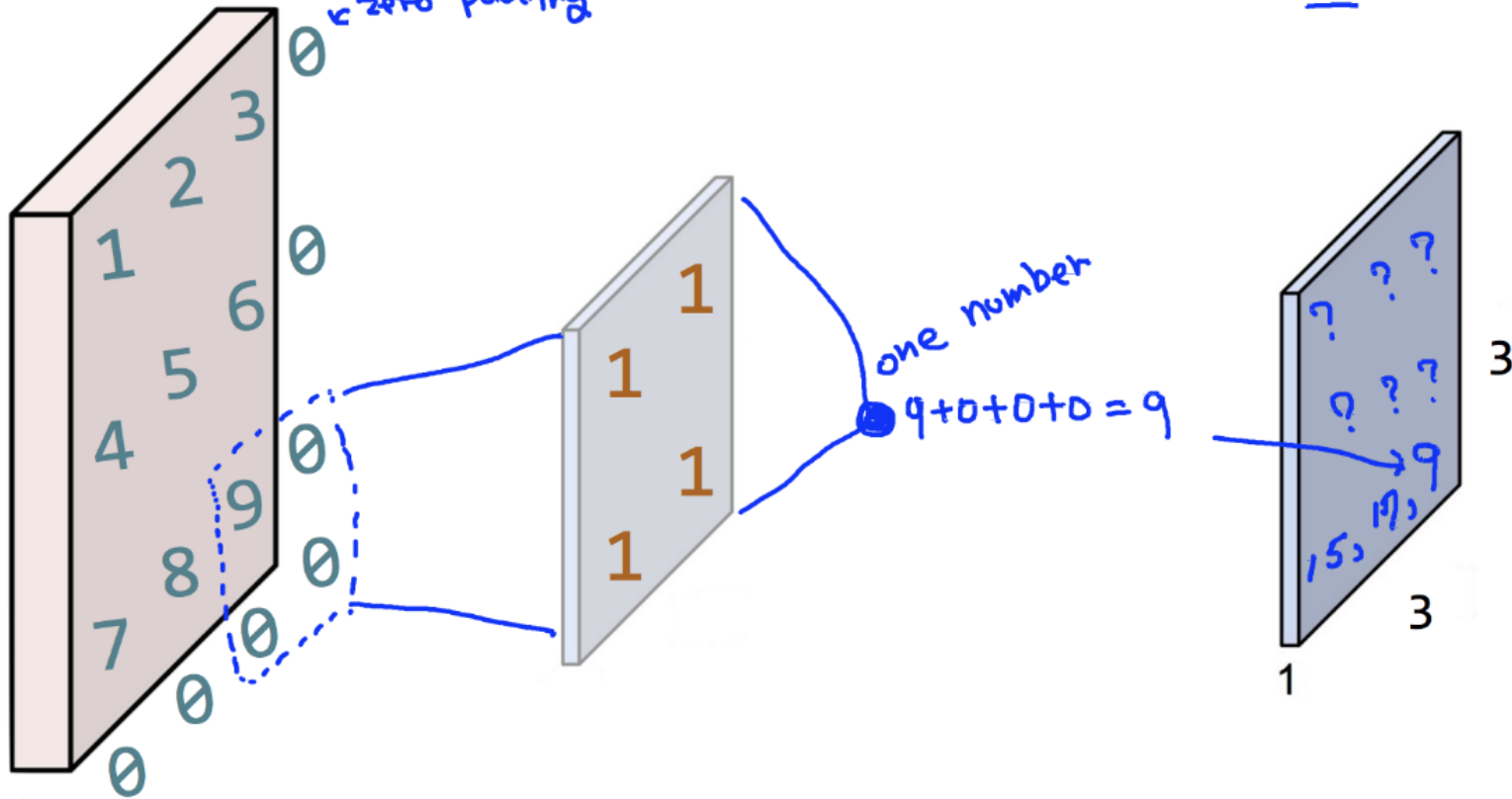
print("conv2d.shape", conv2d.shape)
print(conv2d.numpy().reshape(2,2))
plt.imshow(conv2d.numpy().reshape(2,2), cmap='gray')
plt.show()
```

```
image.shape (1, 3, 3, 1)
weight.shape (2, 2, 1, 1)
conv2d.shape (1, 2, 2, 1)
[[12. 16.]
 [24. 28.]]
```



Simple Convolution Layer

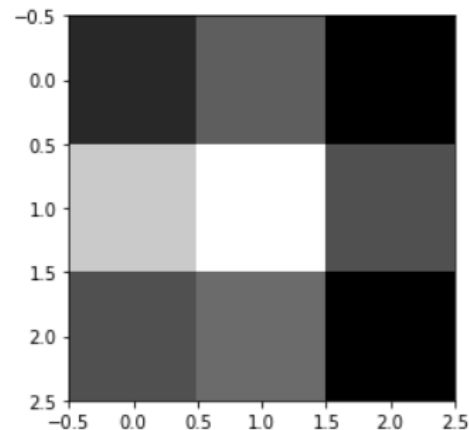
Image: 1,3,3,1 image, Filter: 2,2,1,1, Stride: 1x1, Padding: SAME *want 3x3*




```
print("image.shape", image.shape)
weight = np.array([[[[1.]], [[1.]]],
                  [[[1.]], [[1.]]]])
print("weight.shape", weight.shape)
weight_init = tf.constant_initializer(weight)
conv2d = keras.layers.Conv2D(filters=1, kernel_size=2, padding='SAME',
                              kernel_initializer=weight_init)(image)

print("conv2d.shape", conv2d.shape)
print(conv2d.numpy().reshape(3,3))
plt.imshow(conv2d.numpy().reshape(3,3), cmap='gray')
plt.show()
```

```
image.shape (1, 3, 3, 1)
weight.shape (2, 2, 1, 1)
conv2d.shape (1, 3, 3, 1)
[[12. 16.  9.]
 [24. 28. 15.]
 [15. 17.  9.]]
```



3 Filters (2, 2, 1, 3)

```
print("image.shape", image.shape)
```

```
weight = np.array([[[[1.,10.,-1.]], [[1.,10.,-1.]]],  
                  [[1.,10.,-1.]], [[1.,10.,-1.]]])
```

```
print("weight.shape", weight.shape)
```

```
weight_init = tf.constant_initializer(weight)
```

```
conv2d = keras.layers.Conv2D(filters=3, kernel_size=2, padding='SAME',  
                             kernel_initializer=weight_init)(image)
```

```
print("conv2d.shape", conv2d.shape)
```

```
feature_maps = np.swapaxes(conv2d, 0, 3)
```

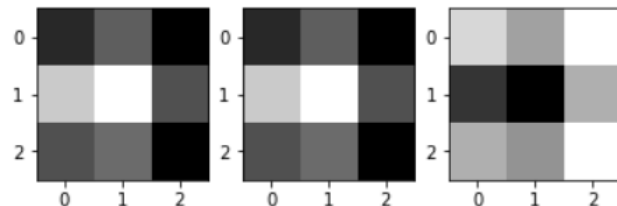
```
for i, feature_map in enumerate(feature_maps):
```

```
    print(feature_map.reshape(3,3))
```

```
    plt.subplot(1,3,i+1), plt.imshow(feature_map.reshape(3,3), cmap='gray')
```

```
plt.show()
```

```
image.shape (1, 3, 3, 1)  
weight.shape (2, 2, 1, 3)  
conv2d.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.]
```



What's Next?

- CNN Basics – Pooling