

CSCI 1470/2470
Spring 2024

Ritambhara Singh

February 16, 2024
Friday

CNNs contd.

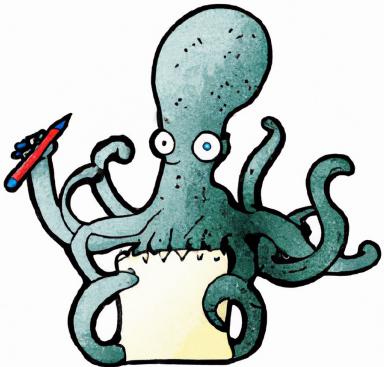
Deep Learning



Final project formation forms are
due today (6PM)!!!

Recap

Building multi-layer
neural networks



Introduction
to CNNs

Hidden layers

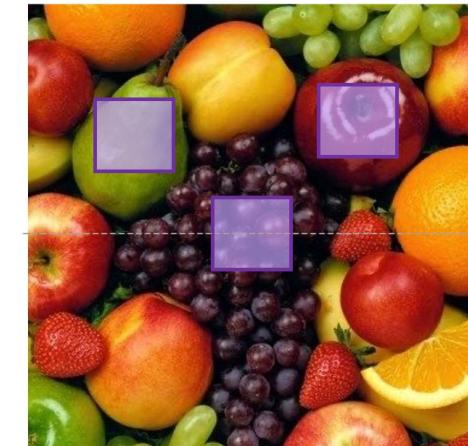
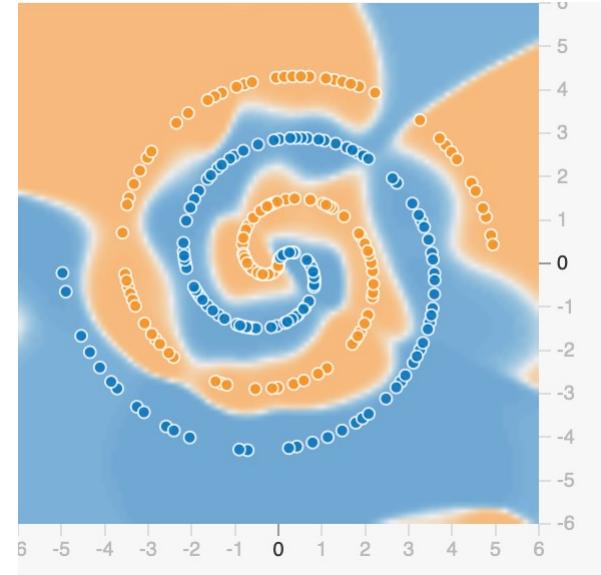
What a one-hidden layer
network can learn

What a multi-layer network can
learn

Partially connected networks
are useful (e.g., for images!)

Fully connected networks are
not translationally invariant

Convolutional filter



Today's goal – continue to learn about CNNs

- (1) Convolution (contd.) – stride
- (2) Learning convolutional filters – connection to partially connected networks
- (3) Convolution in Tensorflow – padding and other considerations

What Convolution Does (Visually)

In summary:

image	filter/kernel	output																													
<table border="1" style="border-collapse: collapse; width: 100%;"><tr><td style="padding: 5px;">2</td><td style="padding: 5px;">0</td><td style="padding: 5px;">1</td><td style="padding: 5px;">3</td></tr><tr><td style="padding: 5px;">7</td><td style="padding: 5px;">1</td><td style="padding: 5px;">1</td><td style="padding: 5px;">0</td></tr><tr><td style="padding: 5px;">0</td><td style="padding: 5px;">2</td><td style="padding: 5px;">5</td><td style="padding: 5px;">0</td></tr><tr><td style="padding: 5px;">0</td><td style="padding: 5px;">5</td><td style="padding: 5px;">1</td><td style="padding: 5px;">4</td></tr></table>	2	0	1	3	7	1	1	0	0	2	5	0	0	5	1	4	\otimes	<table border="1" style="border-collapse: collapse; width: 100%;"><tr><td style="padding: 5px;">1</td><td style="padding: 5px;">1</td><td style="padding: 5px;">1</td></tr><tr><td style="padding: 5px;">0</td><td style="padding: 5px;">0</td><td style="padding: 5px;">0</td></tr><tr><td style="padding: 5px;">-1</td><td style="padding: 5px;">-1</td><td style="padding: 5px;">-1</td></tr></table> $=$ <table border="1" style="border-collapse: collapse; width: 100%;"><tr><td style="padding: 5px;">-4</td><td style="padding: 5px;">-3</td></tr><tr><td style="padding: 5px;">3</td><td style="padding: 5px;">-8</td></tr></table>	1	1	1	0	0	0	-1	-1	-1	-4	-3	3	-8
2	0	1	3																												
7	1	1	0																												
0	2	5	0																												
0	5	1	4																												
1	1	1																													
0	0	0																													
-1	-1	-1																													
-4	-3																														
3	-8																														

What Convolution Does (Mathematically)

$$V(x, y) = (I \otimes K)(x, y) = \sum_m \sum_n I(x + m, y + n)K(m, n)$$

The output at pixel (x, y)

"Image I convolved with kernel K "

m

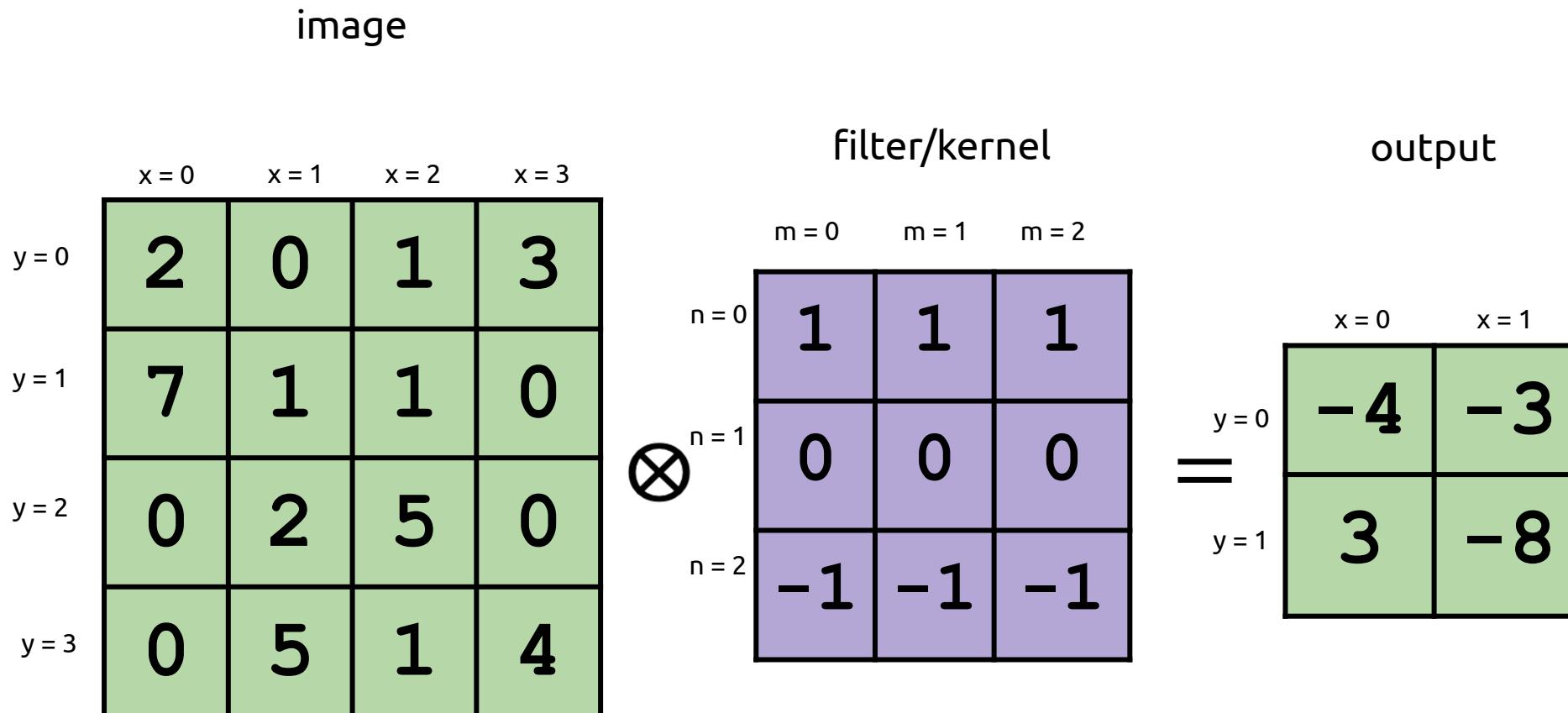
n

Sum over kernel columns

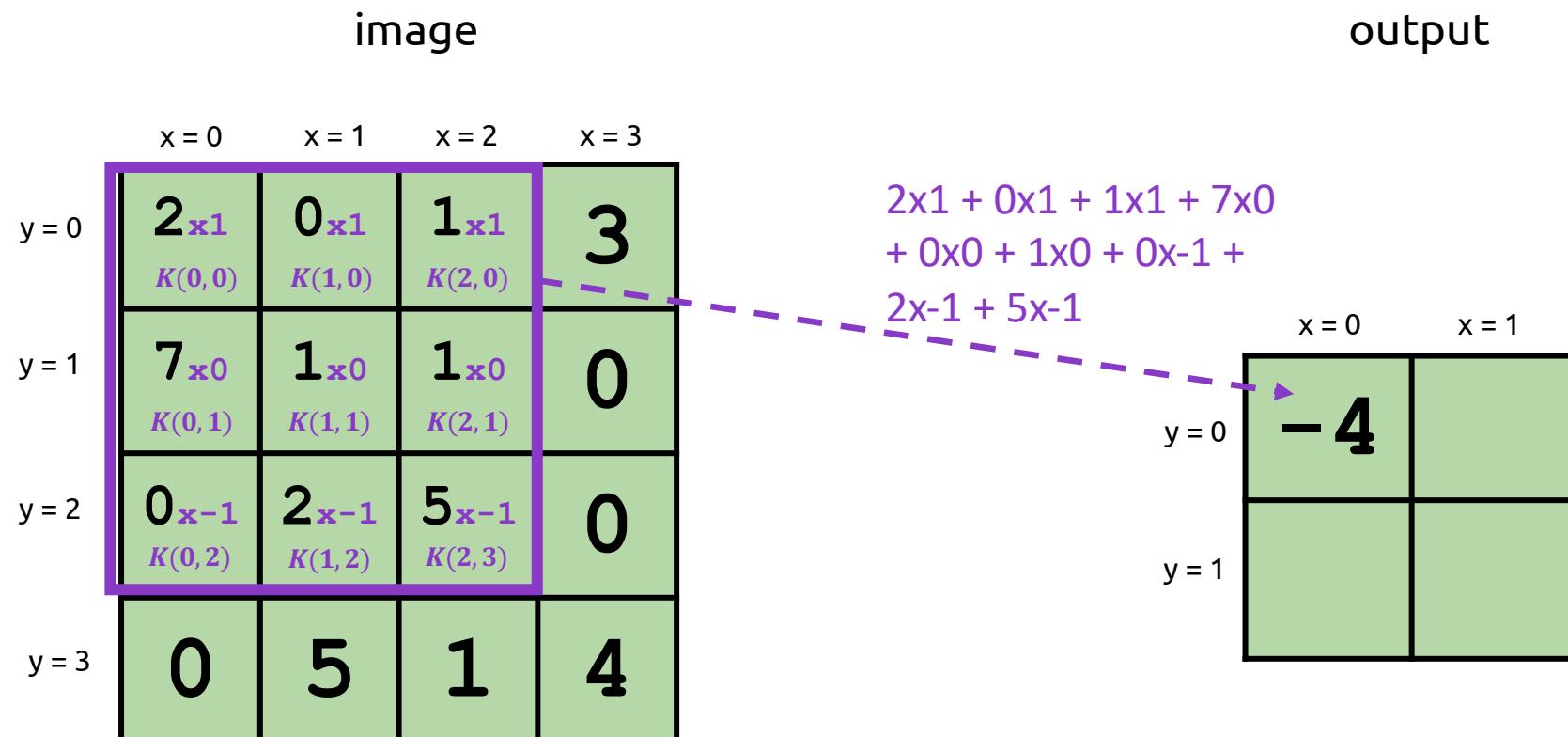
Sum over kernel rows

Multiply kernel value with corresponding image pixel value

What Convolution Does (Mathematically)

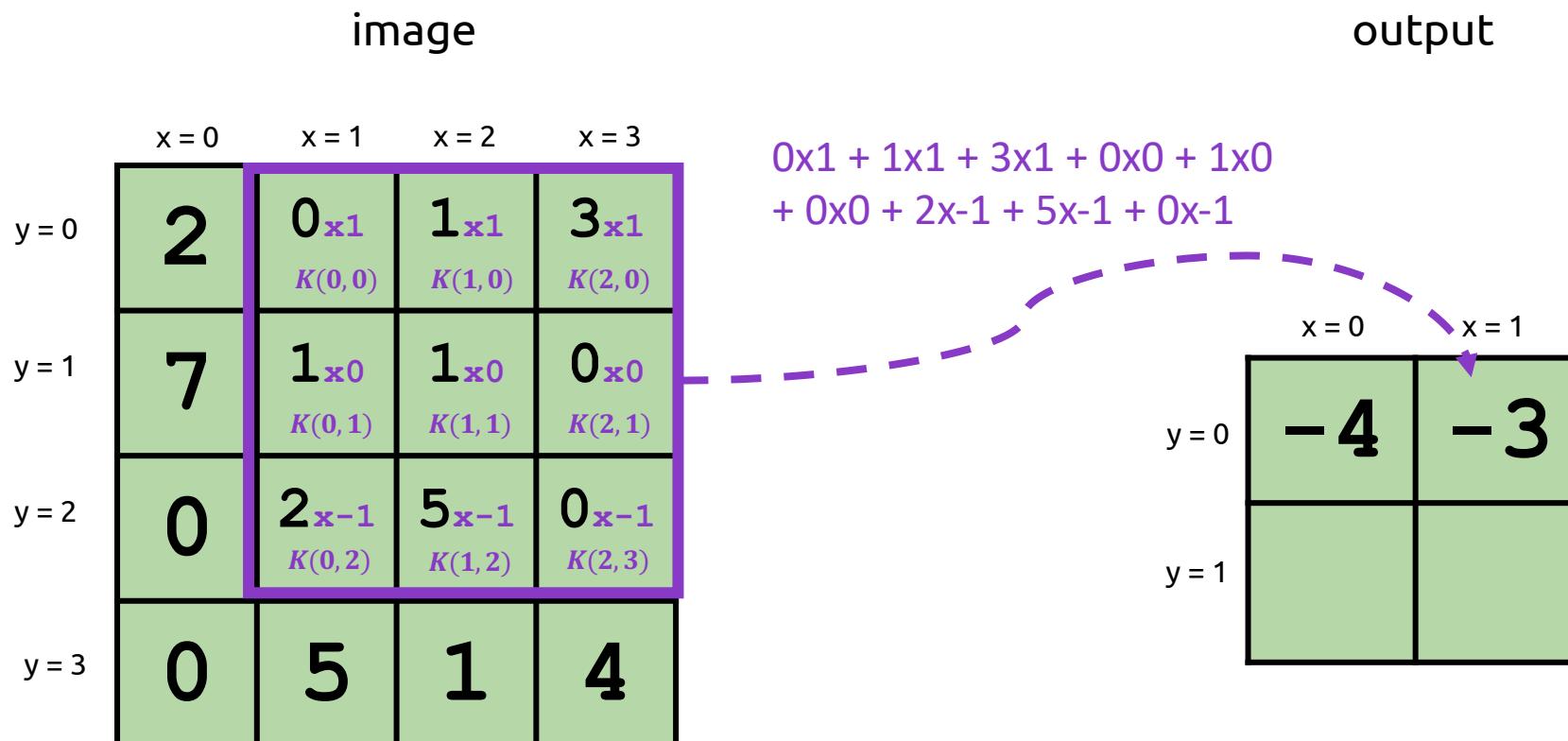


What Convolution Does (Mathematically)



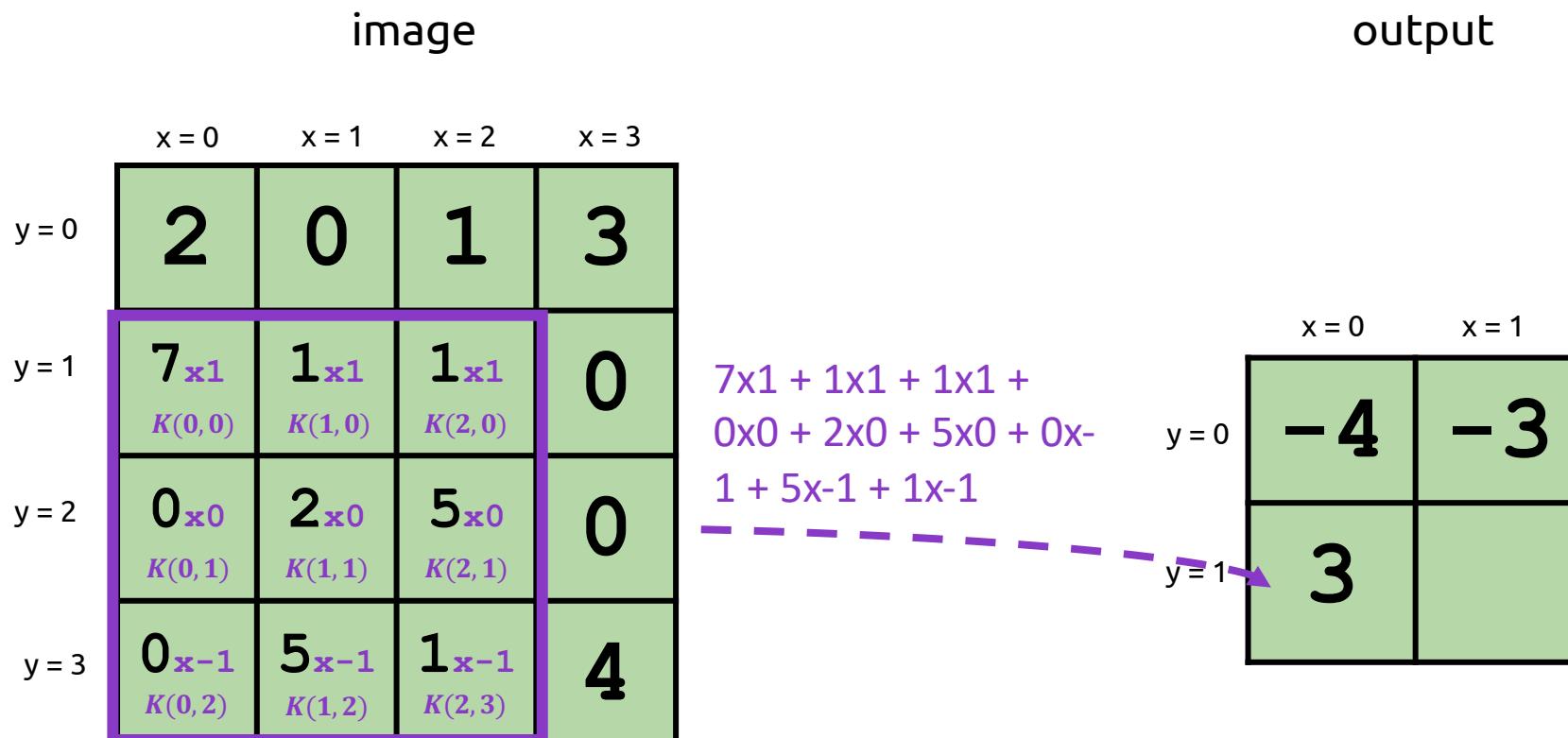
$$V(0, 0) = (I \otimes K)(0, 0) = \sum_{m=0}^2 \sum_{n=0}^2 I(0 + m, 0 + n)K(m, n)$$

What Convolution Does (Mathematically)



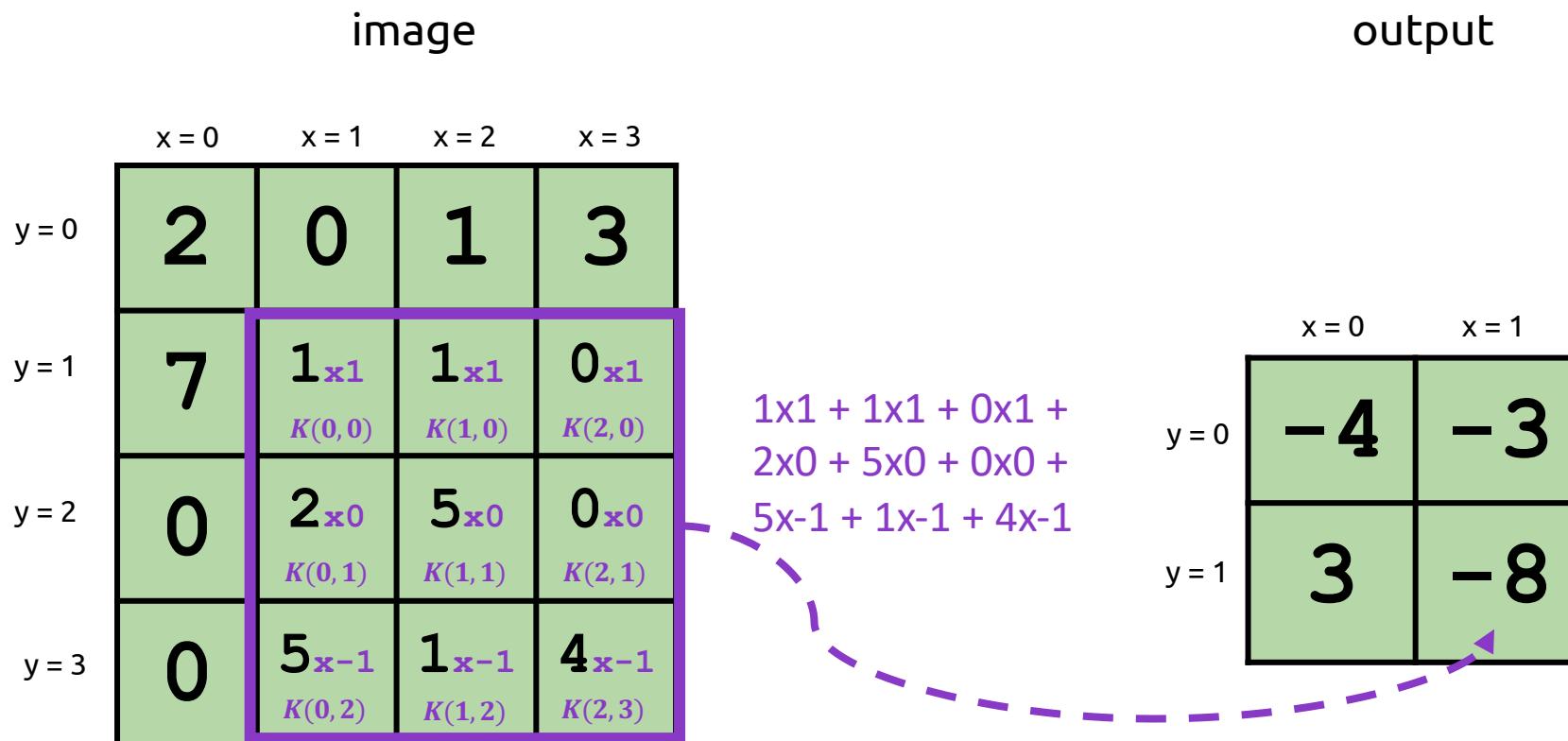
$$V(1, 0) = (I \otimes K)(1, 0) = \sum_{m=0}^2 \sum_{n=0}^2 I(1 + m, 0 + n)K(m, n)$$

What Convolution Does (Mathematically)



$$V(0, 1) = (I \otimes K)(0, 1) = \sum_{m=0}^2 \sum_{n=0}^2 I(0 + m, 1 + n)K(m, n)$$

What Convolution Does (Mathematically)



$$V(1, 1) = (I \otimes K)(1, 1) = \sum_{m=0}^2 \sum_{n=0}^2 I(1 + m, 1 + n)K(m, n)$$

What Convolution Does (In Code)

```
// Input: Image I, Kernel K, Output V, pixel index x,y  
// Assumes K is 3x3  
function apply_kernel(I, K, V, x, y)  
    for m = 0 to 2:  
        for n = 0 to 2:  
            V(x,y) += K(m,n) * I(m+x, n+y)
```

$$Equation: V(x, y) = (I \otimes K)(x, y) = \sum_m \sum_n I(x + m, y + n)K(m, n)$$

Different filters = different effects

<https://setosa.io/ev/image-kernels/>

Blur

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9



Edge Detection / Outline Kernel

0	-1	0
-1	5	-1
0	-1	0



Shift

0	0	0
1	0	0
0	0	0

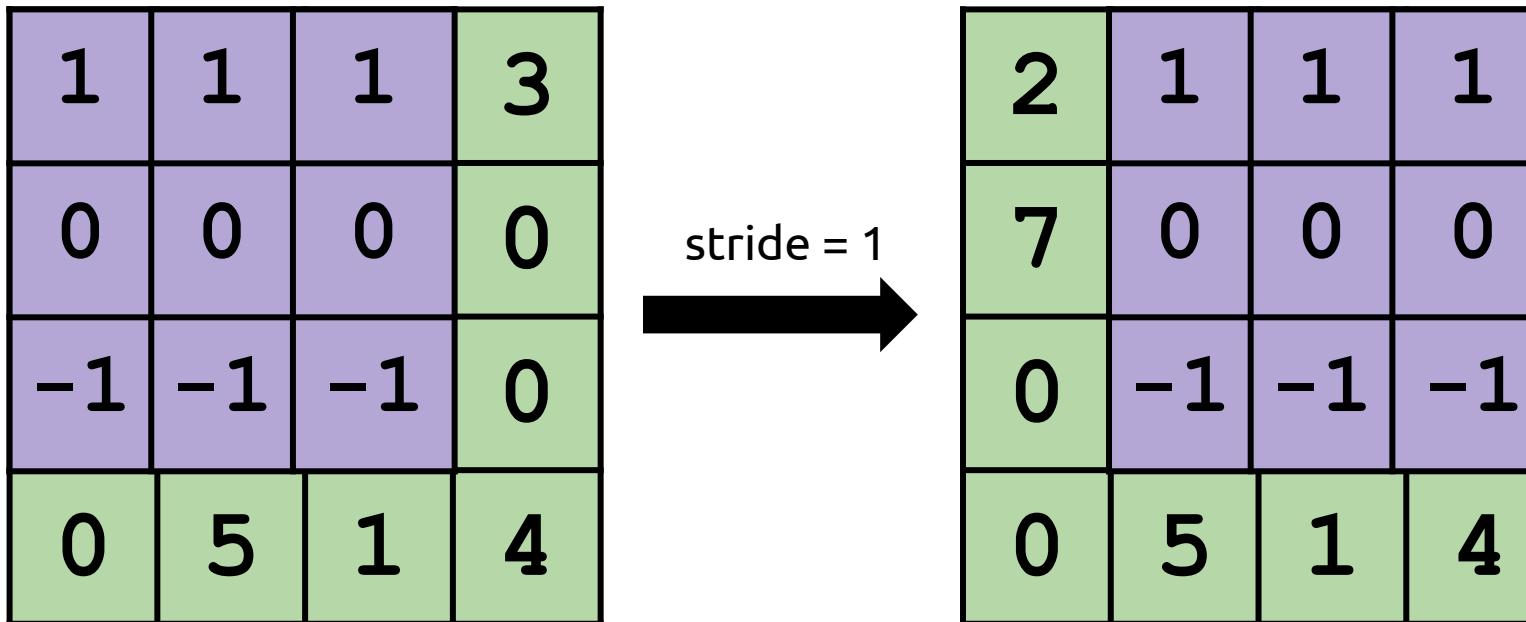


* exaggerated

*

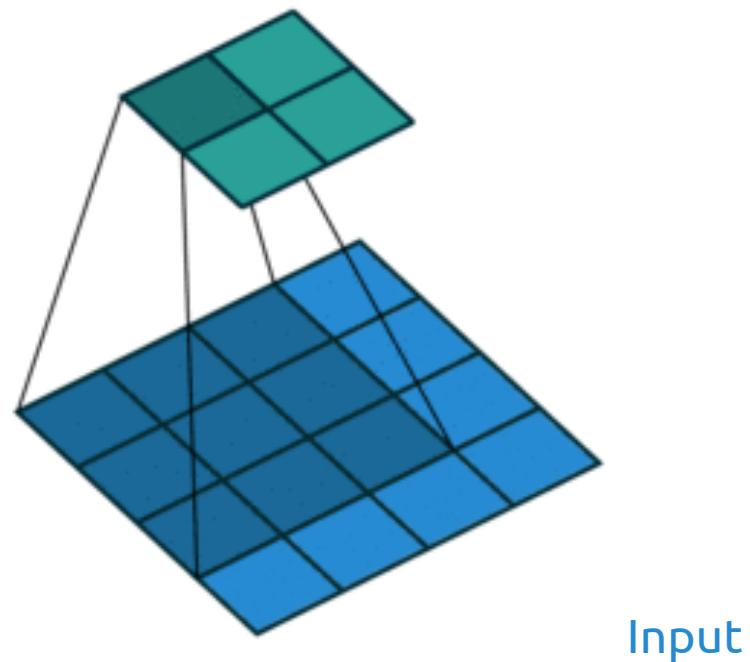
Stride

- We don't just have to slide the filter by one pixel every time
- The distance we slide a filter by is called ***stride***
 - All the examples we've seen thus far have been stride = 1



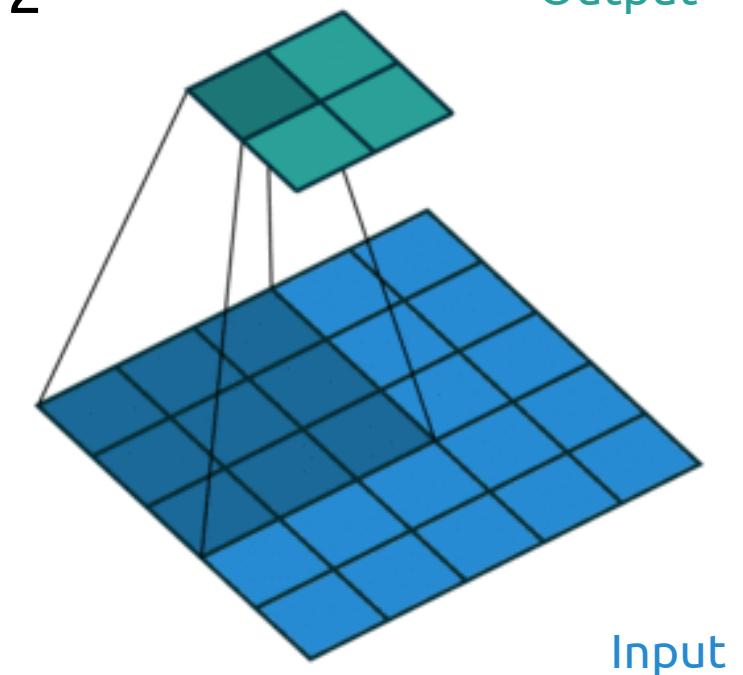
Stride in Action

Stride: 1



Output

Stride: 2

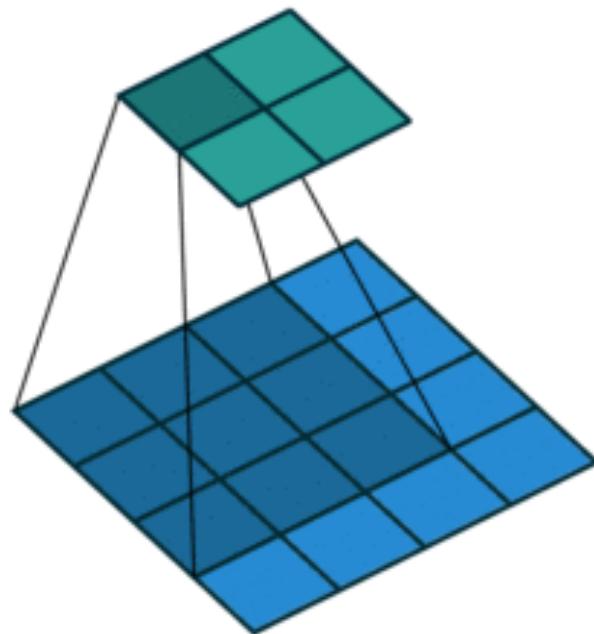


Output

Input

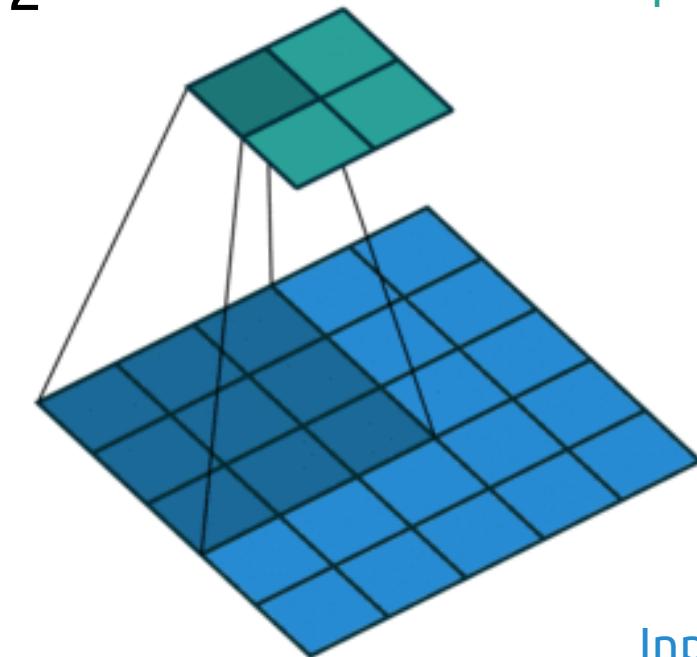
Why would we want stride > 1?

Stride: 1



Output

Stride: 2



Output

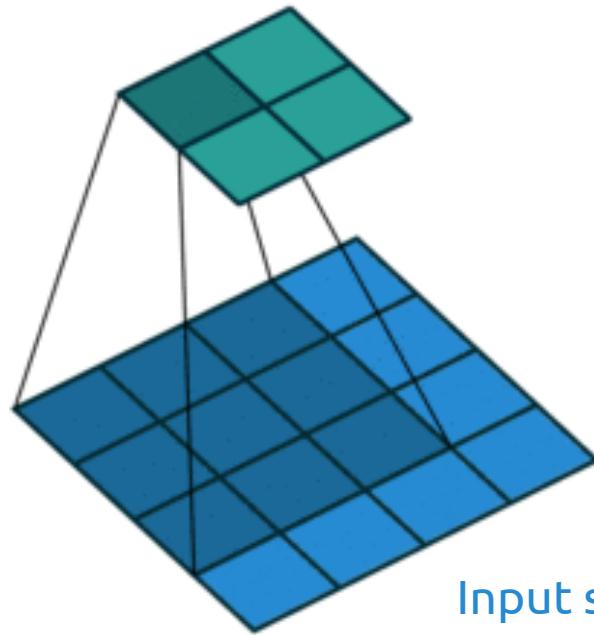
Input

Input

Any connection
between input and
output size?

Why would we want stride > 1?

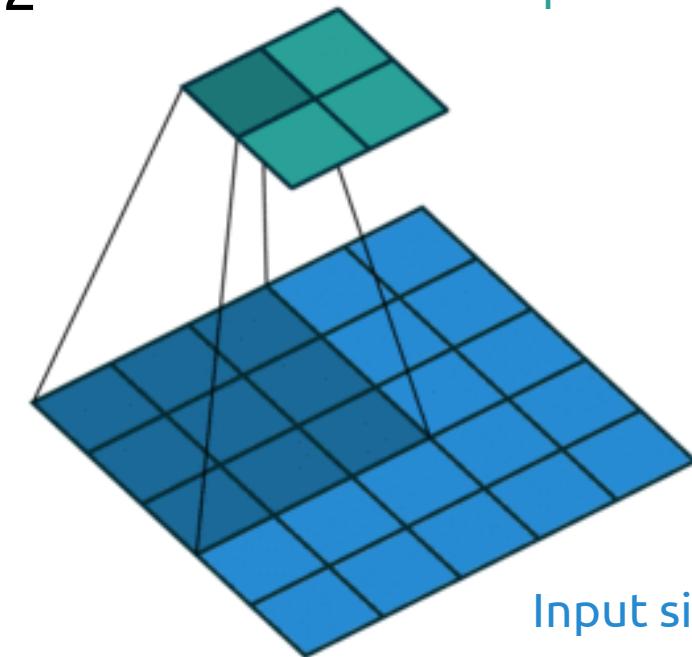
Stride: 1



Input size: 4x4

Output size: 2x2

Stride: 2



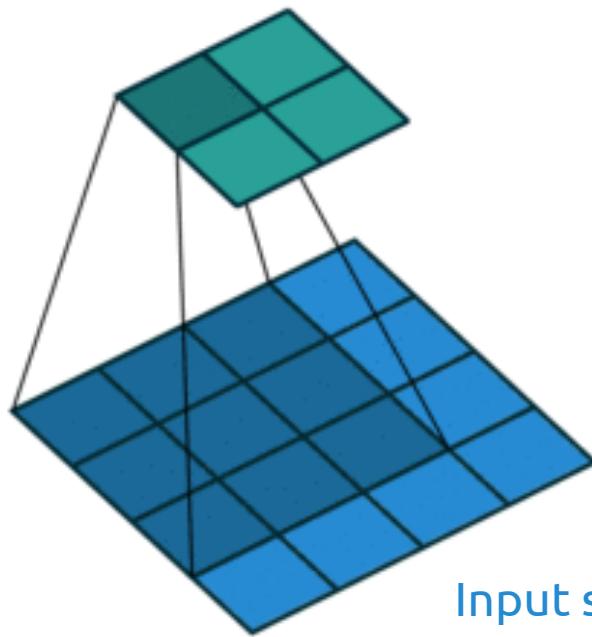
Input size: 5x5

Output size: 2x2

Larger stride turns a bigger input into the same size output

Why would we want stride > 1?

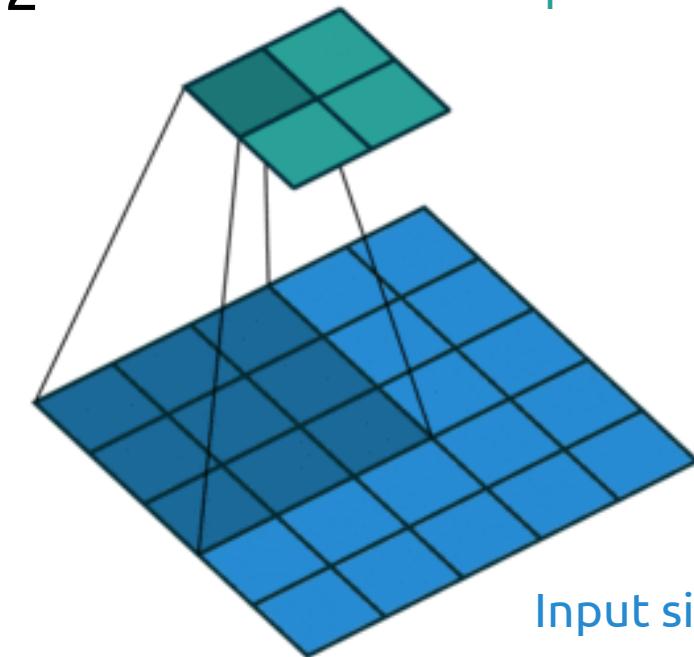
Stride: 1



Input size: 4x4

Output size: 2x2

Stride: 2



Input size: 5x5

Output size: 2x2

Larger stride turns a bigger input into the same size output

Corollary: Larger stride turns the same size input into a *smaller* output

Use this to (controllably) decrease image resolution!

OK but...where's the *learning*?

Can you guess what do we learn in
CNNs? (what are our parameters?)



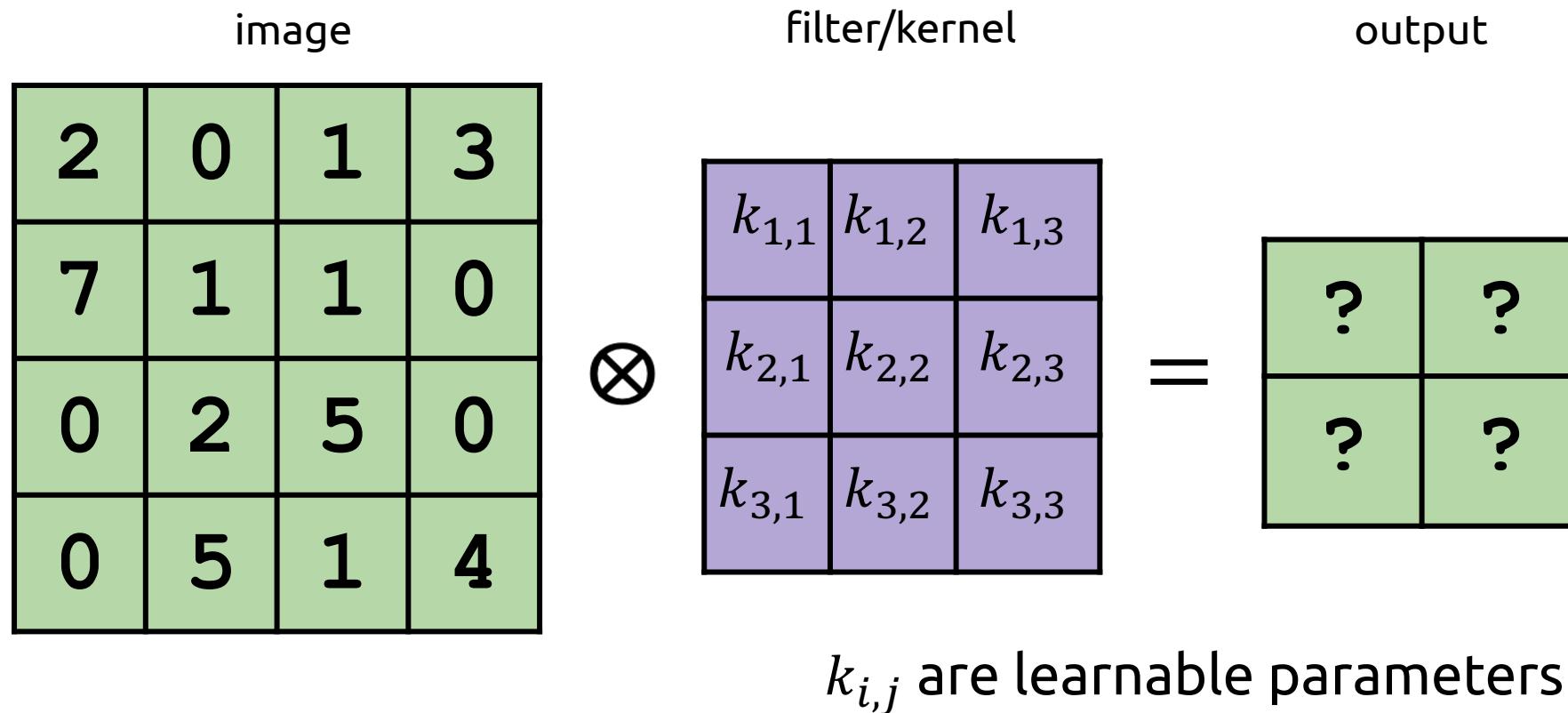
WHERE IS IT?

Key Idea 1: Filters are *Learnable*

image filter/kernel output

$$\begin{array}{|c|c|c|c|} \hline 2 & 0 & 1 & 3 \\ \hline 7 & 1 & 1 & 0 \\ \hline 0 & 2 & 5 & 0 \\ \hline 0 & 5 & 1 & 4 \\ \hline \end{array} \otimes \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 0 & 0 & 0 \\ \hline -1 & -1 & -1 \\ \hline \end{array} = \begin{array}{|c|c|} \hline -4 & -3 \\ \hline 2 & -9 \\ \hline \end{array}$$

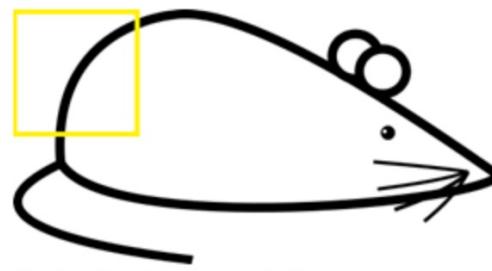
Key Idea 1: Filters are *Learnable*



Key Idea 1: Filters are *Learnable*



Original image



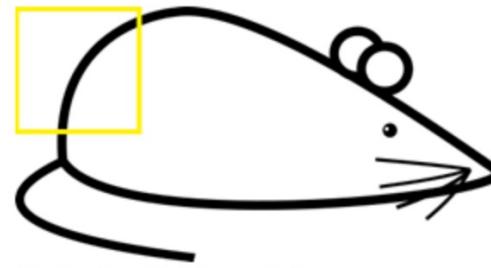
Visualization of the filter on the image

Label="Mouse"

Detecting patterns using learned filters



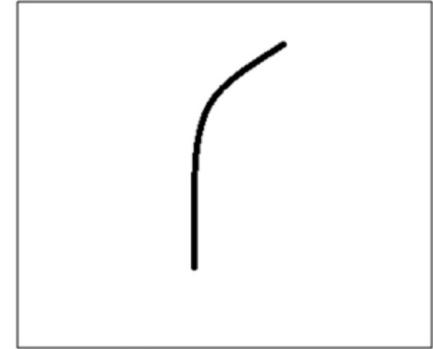
Original image



Visualization of the filter on the image

0	0	0	0	0	0	30	0
0	0	0	0	0	30	0	0
0	0	0	30	0	0	0	0
0	0	0	30	0	0	0	0
0	0	0	30	0	0	0	0
0	0	0	30	0	0	0	0
0	0	0	0	0	0	0	0

Pixel representation of filter



Visualization of a curve detector filter



Visualization of the receptive field

0	0	0	0	0	0	30	
0	0	0	0	50	50	50	
0	0	0	20	50	0	0	
0	0	0	50	50	0	0	
0	0	0	50	50	0	0	
0	0	0	50	50	0	0	
0	0	0	50	50	0	0	

Pixel representation of the receptive field

*

0	0	0	0	0	0	30	0
0	0	0	0	30	0	0	0
0	0	0	30	0	0	0	0
0	0	0	30	0	0	0	0
0	0	0	30	0	0	0	0
0	0	0	30	0	0	0	0
0	0	0	0	0	0	0	0

Pixel representation of filter

$$\text{Multiplication and Summation} = (50*30)+(50*30)+(50*30)+(20*30)+(50*30) = 6600 \text{ (A large number!)}$$

Detecting patterns using learned filters

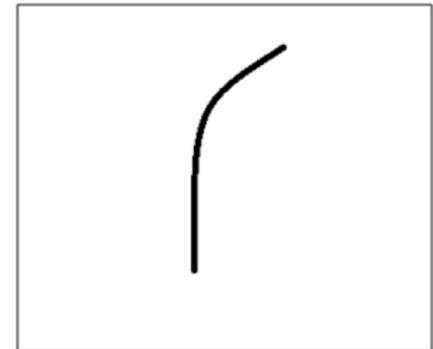


Original image

How to detect other patterns?

0	0	0	0	0	0	30	0
0	0	0	0	0	30	0	0
0	0	0	0	30	0	0	0
0	0	0	30	0	0	0	0
0	0	0	0	0	30	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Pixel representation of filter



Visualization of a curve detector filter



Visualization of the filter on the image

0	0	0	0	0	0	0
0	40	0	0	0	0	0
40	0	40	0	0	0	0
40	20	0	0	0	0	0
0	50	0	0	0	0	0
0	0	50	0	0	0	0
25	25	0	50	0	0	0

Pixel representation of receptive field

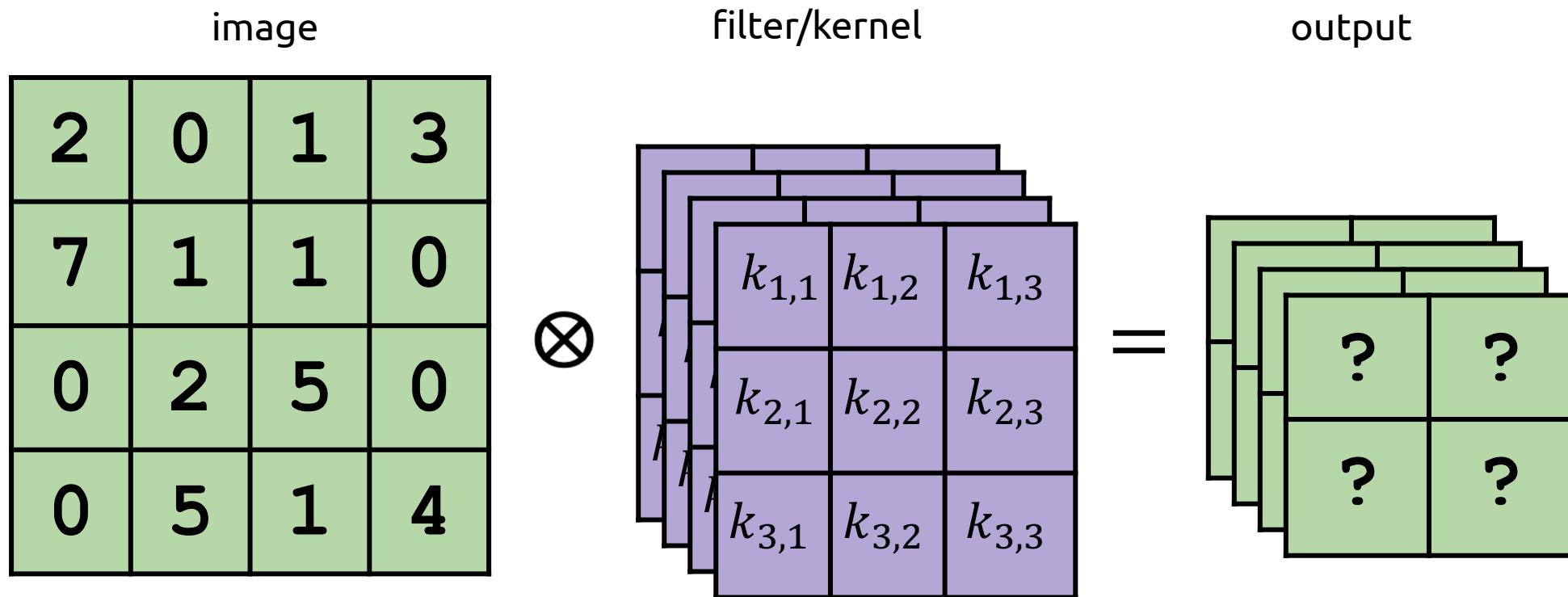
*

0	0	0	0	0	0	30	0
0	0	0	0	0	30	0	0
0	0	0	30	0	0	0	0
0	0	0	30	0	0	0	0
0	0	0	30	0	0	0	0
0	0	0	30	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Pixel representation of filter

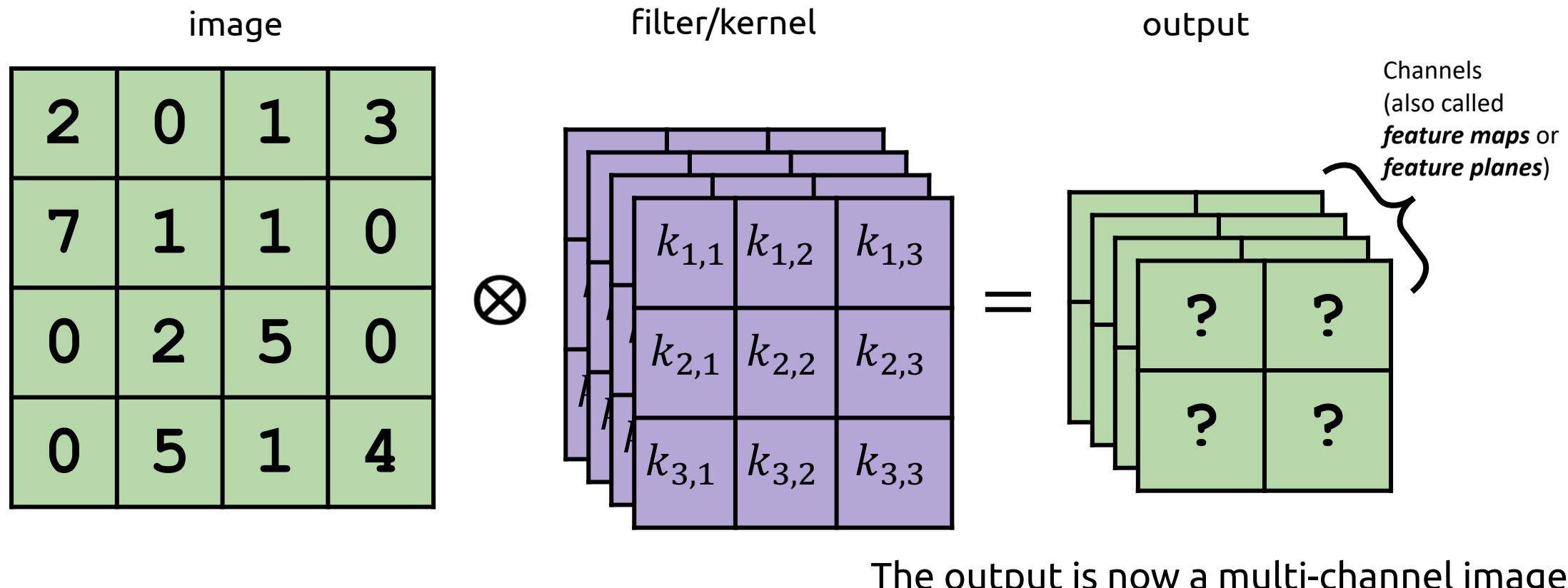
Multiplication and Summation = 0

Key Idea 2: Learn *many* filters



This block of filters is called a ***filter bank***

Key Idea 2: Learn *many* filters



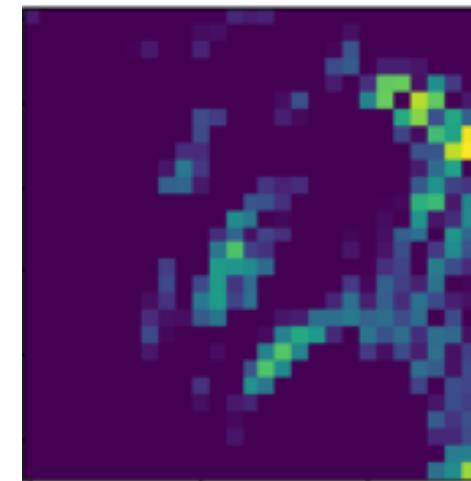


Key Idea 2: Learn *many* filters

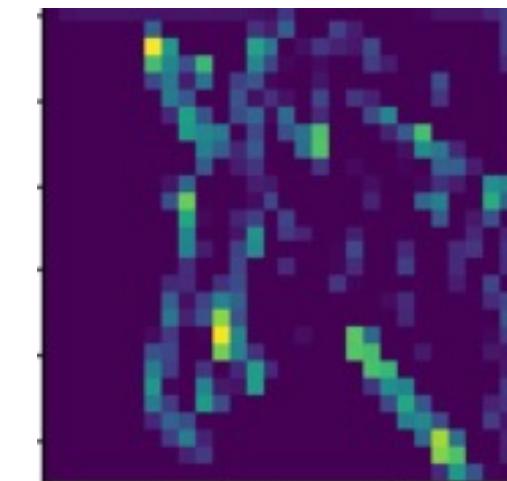
- Why are multiple filters a good idea?
 - Can learn to extract different ***features*** of the image



Input image



Output of filter 1

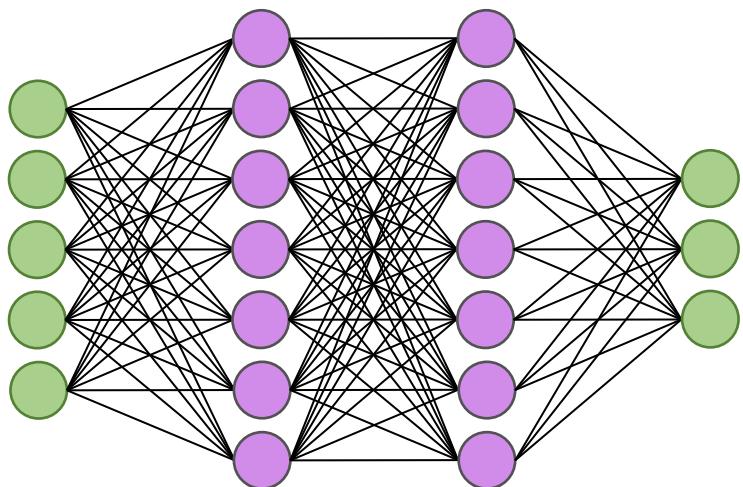


Output of filter 2

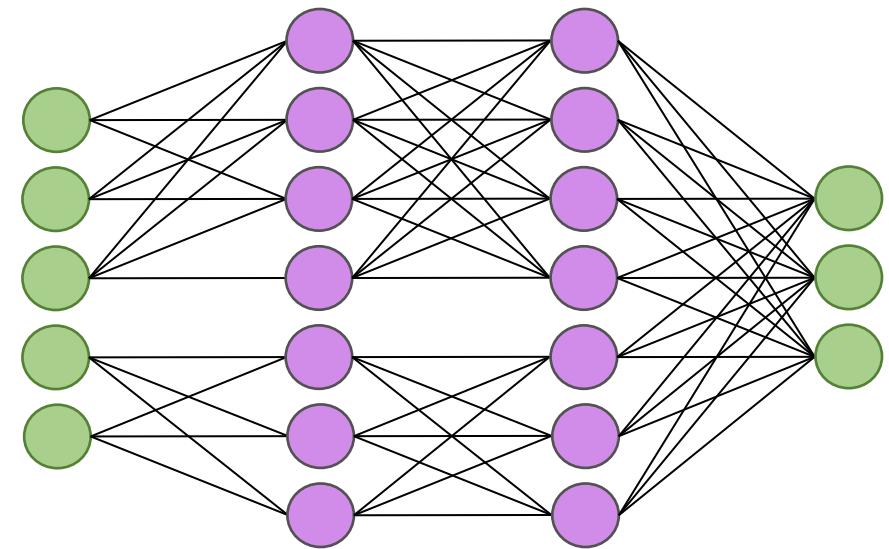
You will explore this more in lab!

How is convolution “partially connected?”

Fully Connected



Partially Connected



Only certain input pixels are “connected” to certain output pixels

image	filter/kernel	output																									
<table border="1" style="border-collapse: collapse; width: 100%;"><tr><td style="padding: 5px;">2</td><td style="padding: 5px;">0</td><td style="padding: 5px;">1</td><td style="padding: 5px;">3</td></tr><tr><td style="padding: 5px;">7</td><td style="padding: 5px;">1</td><td style="padding: 5px;">1</td><td style="padding: 5px;">0</td></tr><tr><td style="padding: 5px;">0</td><td style="padding: 5px;">2</td><td style="padding: 5px;">5</td><td style="padding: 5px;">0</td></tr><tr><td style="padding: 5px;">0</td><td style="padding: 5px;">5</td><td style="padding: 5px;">1</td><td style="padding: 5px;">4</td></tr></table>	2	0	1	3	7	1	1	0	0	2	5	0	0	5	1	4	\otimes	<table border="1" style="border-collapse: collapse; width: 100%;"><tr><td style="padding: 5px;">1</td><td style="padding: 5px;">1</td><td style="padding: 5px;">1</td></tr><tr><td style="padding: 5px;">0</td><td style="padding: 5px;">0</td><td style="padding: 5px;">0</td></tr><tr><td style="padding: 5px;">-1</td><td style="padding: 5px;">-1</td><td style="padding: 5px;">-1</td></tr></table>	1	1	1	0	0	0	-1	-1	-1
2	0	1	3																								
7	1	1	0																								
0	2	5	0																								
0	5	1	4																								
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-4	-3																										
2	-9																										

Only certain input pixels are “connected” to certain output pixels

image			
2	0	1	3
7	1	1	0
0	2	5	0
0	5	1	4

Colored dots in the input pixels represent which output pixels that input pixel contributes to

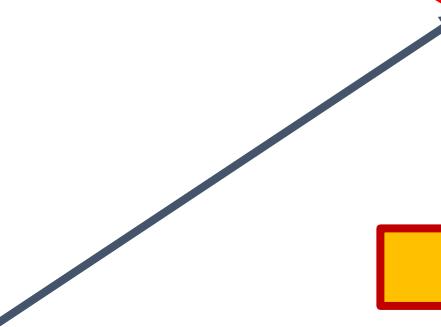
**If this were fully connected,
every input pixel would have
all four output colors**

output

-4	-3
2	-9

Convolution in Tensorflow

`tf.nn.conv2d(input, filter, strides, padding)`



Can you guess the shape?

Input Image (4-D Tensor)

Shape:

`[batchSz, input_height, input_width, input_channels]`

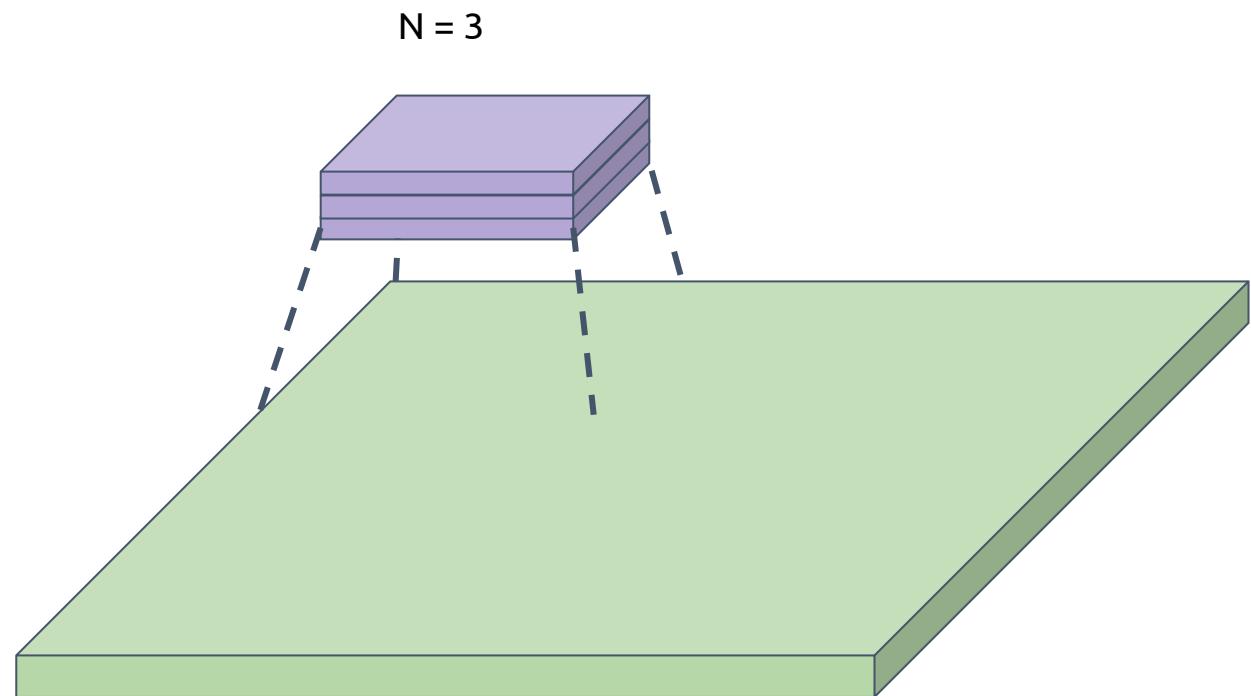
Full documentation here:

https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/nn/conv2d

Output Size of a Convolution Layer

The output size of a convolution layer depends on 4 Hyperparameters:

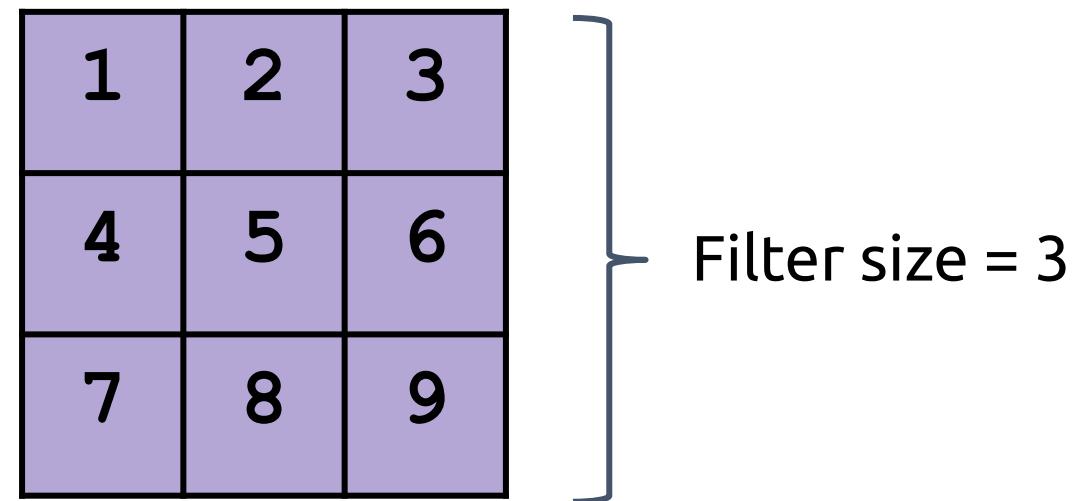
- Number of filters, \mathbf{N}



Output Size of a Convolution Layer

The output size of a convolution layer depends on 4 Hyperparameters:

- Number of filters, N
- The size of these filters, F



Convolution in Tensorflow

```
tf.nn.conv2d(input, filter, strides, padding)
```



Can you guess the shape?

Kernel (4-D Tensor)
Shape:

$[f_height, f_width, in_channels, out_channels]$

Full documentation here:

https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/nn/conv2d

Output Size of a Convolution Layer

The output size of a convolution layer depends on 4 Hyperparameters:

- Number of filters, N
- The size of these filters, F
- The stride, S

2	0	3	1	0
2	4	5	2	3
0	0	3	3	1
2	9	9	7	8
3	4	7	2	1

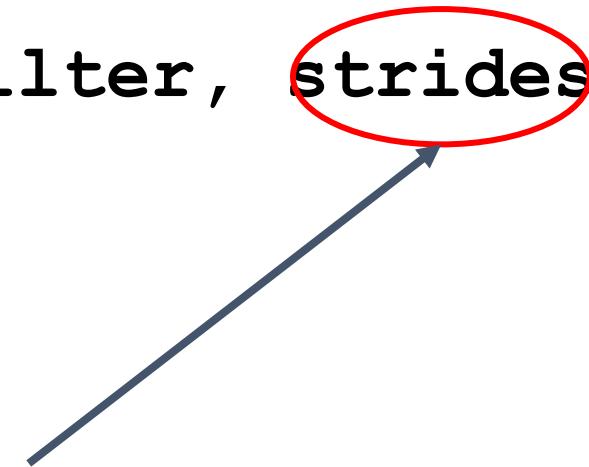
Stride = 2



2	0	3	1	0
2	4	5	2	3
0	0	3	3	1
2	9	9	7	8
3	4	7	2	1

Convolution in Tensorflow

```
tf.nn.conv2d(input, filter, strides, padding)
```



List of ints of length 4

Represents the strides along each dimension of the input

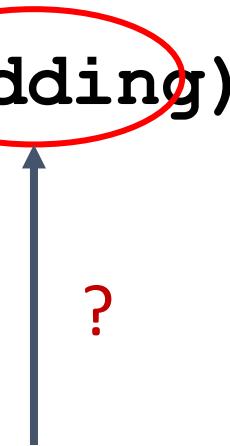
[batch_stride, stride_along_height, stride_along_width, stride_along_input_channels]

Full documentation here:

https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/nn/conv2d

Convolution in Tensorflow

```
tf.nn.conv2d(input, filter, strides, padding)
```



Full documentation here:

https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/nn/conv2d

“Problem” With Convolution

$$\begin{array}{|c|c|c|c|} \hline 2 & 0 & 1 & 3 \\ \hline 0 & 1 & 1 & 0 \\ \hline 0 & 0 & 2 & 0 \\ \hline 0 & 1 & 1 & 1 \\ \hline \end{array} \otimes \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 0 & 0 & 0 \\ \hline -1 & -1 & -1 \\ \hline \end{array} = \begin{array}{|c|c|} \hline 1 & 2 \\ \hline 0 & -1 \\ \hline \end{array}$$

- Output of convolution is always smaller than the input
- Why might we want the output size to be the same?
 - To avoid the filter “eating at the border” of the image when applying multiple conv layers

Solution: Padding

Apply the kernel to ‘imaginary’ pixels surrounding the image

2	0	3	1	1
1	1	0	0	2
4	3	2	0	1
1	0	5	2	0
0	1	0	3	0

Solution: Padding

Apply the kernel to ‘imaginary’ pixels surrounding the image

?	?	?	?	?	?	?	?
?	2	0	3	1	1	?	?
?	1	1	0	0	2	?	?
?	4	3	2	0	1	?	?
?	1	0	5	2	0	?	?
?	0	1	0	3	0	?	?
?	?	?	?	?	?	?	?

What Values to Use For These Pixels?

?	?	?	?	?	?	?	?
?	2	0	3	1	1	?	
?	1	1	0	0	2	?	
?	4	3	2	0	1	?	
?	1	0	5	2	0	?	
?	0	1	0	3	0	?	
?	?	?	?	?	?	?	?

What Values to Use For These Pixels?

Standard practice: fill with zeroes

0	0	0	0	0	0	0
0	2	0	3	1	1	0
0	1	1	0	0	2	0
0	4	3	2	0	1	0
0	1	0	5	2	0	0
0	0	1	0	3	0	0
0	0	0	0	0	0	0

What Values to Use For These Pixels?

Standard practice: fill with zeroes

- Zero-valued padding pixels just result in some terms in the convolution sum being zero

$$V(x, y) = (I \otimes K)(x, y) = \sum_m \sum_n I(x + m, y + n)K(m, n)$$

This is zero for a padding pixel

- End result: equivalent to applying a ‘masked’ version of the filter that only covers the valid pixels

0	0	0	0	0	0	0	0
0	2	0	3	1	1	0	0
0	1	1	0	0	2	0	0
0	4	3	2	0	1	0	0
0	1	0	5	2	0	0	0
0	0	1	0	3	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Padding Modes in Tensorflow

2 available options: ‘VALID’ and ‘SAME’:

Valid

Filter only slides over
“Valid” regions of the
data

2	0	1	3
0	1	1	0
0	0	2	0
0	1	1	1

Same

Filter slides over the bounds of the
data, ensuring output size is the
“Same” as input size (when stride = 1)

0	0	0	0	0	0
0	2	0	1	3	0
0	1	1	2	3	0
0	4	3	2	1	0
0	8	3	1	3	0
0	0	0	0	0	0

VALID Padding in Tensorflow

```
tf.nn.conv2d(input, filter, strides,  
            padding='VALID')
```

2	0	1	3
0	1	1	0
0	0	2	0
0	1	1	1

VALID Padding in Tensorflow

```
tf.nn.conv2d(input, filter, strides,  
            padding='VALID')
```

2	0	1	3
0	1	1	0
0	0	2	0
0	1	1	1

VALID Padding in Tensorflow

```
tf.nn.conv2d(input, filter, strides,  
            padding='VALID')
```

2	0	1	3
0	1	1	0
0	0	2	0
0	1	1	1

VALID Padding in Tensorflow

```
tf.nn.conv2d(input, filter, strides,  
            padding='VALID')
```

2	0	1	3
0	1	1	0
0	0	2	0
0	1	1	1

We already tried this! (reduced output size)

2	0	3	1
1	1	0	0
1	0	2	0
1	0	1	2



"VALID"
Stride = 1

1	0	-1
2	0	-2
1	0	-1

=

0	1
-1	-1

SAME Padding in Tensorflow

```
tf.nn.conv2d(input, filter, strides,  
            padding='SAME')
```

0	0	0	0	0	0
0	2	0	1	3	0
0	1	1	2	3	0
0	4	3	2	1	0
0	8	3	1	3	0
0	0	0	0	0	0

SAME Padding in Tensorflow

```
tf.nn.conv2d(input, filter, strides,  
            padding='SAME')
```

0	0	0	0	0	0
0	2	0	1	3	0
0	1	1	2	3	0
0	4	3	2	1	0
0	8	3	1	3	0
0	0	0	0	0	0

SAME Padding in Tensorflow

```
tf.nn.conv2d(input, filter, strides,  
            padding='SAME')
```

0	0	0	0	0	0
0	2	0	1	3	0
0	1	1	2	3	0
0	4	3	2	1	0
0	8	3	1	3	0
0	0	0	0	0	0

SAME Padding in Tensorflow

```
tf.nn.conv2d(input, filter, strides,  
            padding='SAME')
```

0	0	0	0	0	0
0	2	0	1	3	0
0	1	1	2	3	0
0	4	3	2	1	0
0	8	3	1	3	0
0	0	0	0	0	0

SAME padding Example (Try it as HW)

2	0	3	1
1	1	0	0
1	0	2	0
1	0	1	2



"Same"
Stride = 1

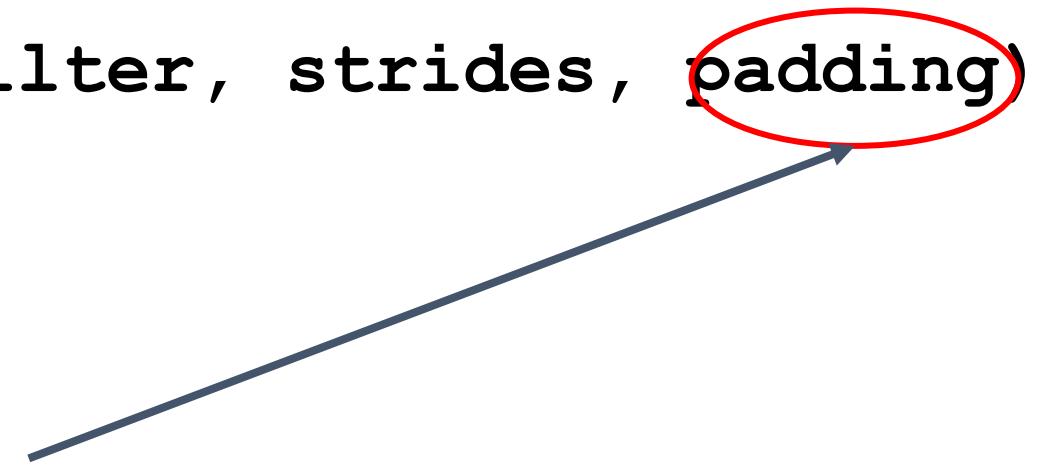
1	0	-1
2	0	-2
1	0	-1

=

-1	-1	-1	6
-2	0	1	5
-1	-1	-1	5
0	-1	-4	4

Convolution in Tensorflow

```
tf.nn.conv2d(input, filter, strides, padding)
```



The mode of padding to use (String)
Either “Valid” or “Same”
Case-insensitive

Full documentation here:

https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/nn/conv2d

Output Size of a Convolution Layer

The output size of a convolution layer depends on 4 Hyperparameters:

- Number of filters, N
- The size of these filters, F
- The stride, S
- The amount of padding, P

0	0	0	0	0	0
0	0	0	0	0	0
0	0	2	3	0	0
0	0	9	2	0	0
0	0	0	0	0	0
0	0	0	0	0	0

} Padding = 2

Output Size of a Convolution Layer

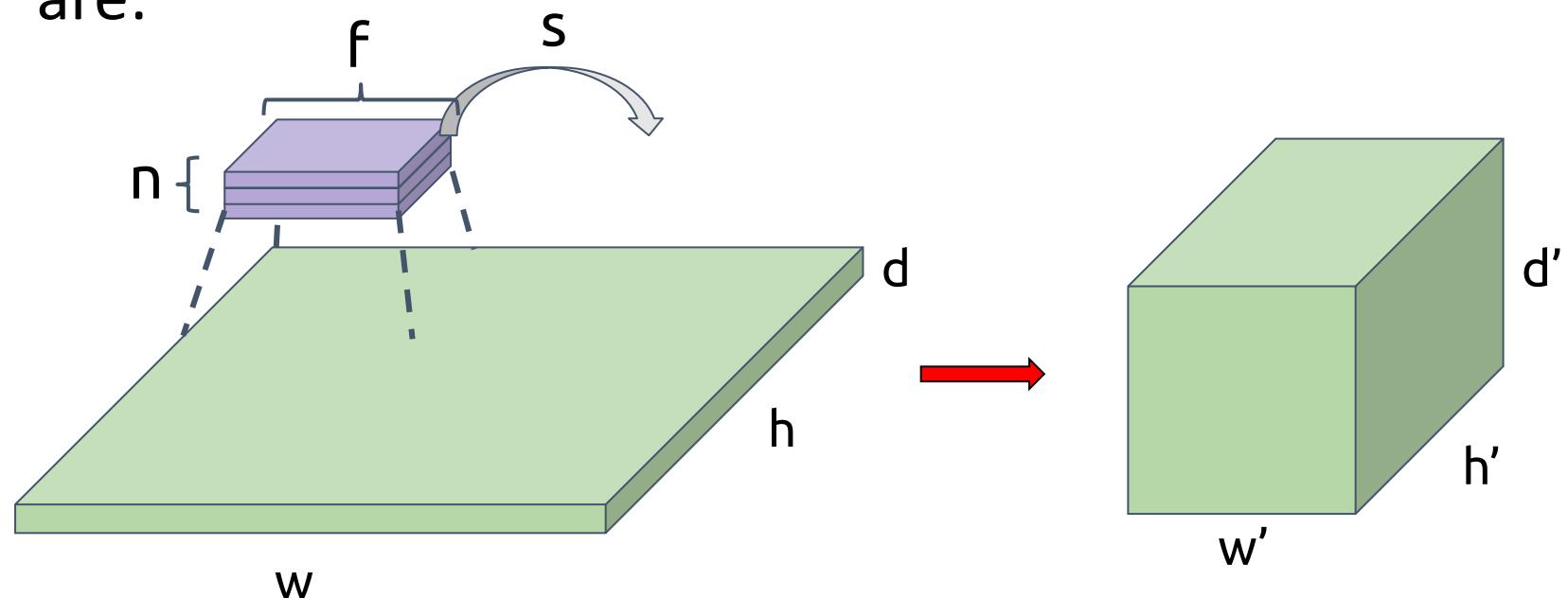
Suppose we know the number of filters, their size, the stride, and padding (n, f, s, p).

Then for a convolution layer with input dimension $w \times h \times d$, the output dimensions $w' \times h' \times d'$ are:

$$w' = \frac{w - f + 2p}{s} + 1$$

$$h' = \frac{h - f + 2p}{s} + 1$$

$$d' = n$$



Output Size for “VALID” Padding

$$w' = \frac{w - f + 2p}{s} + 1$$

Let $w = 4$

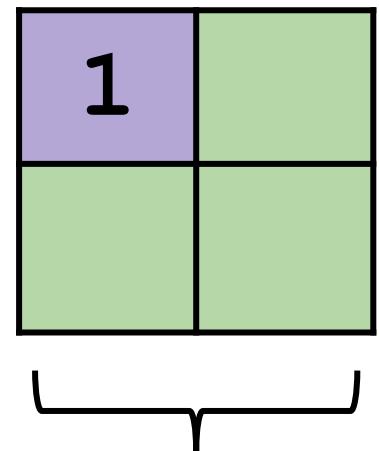
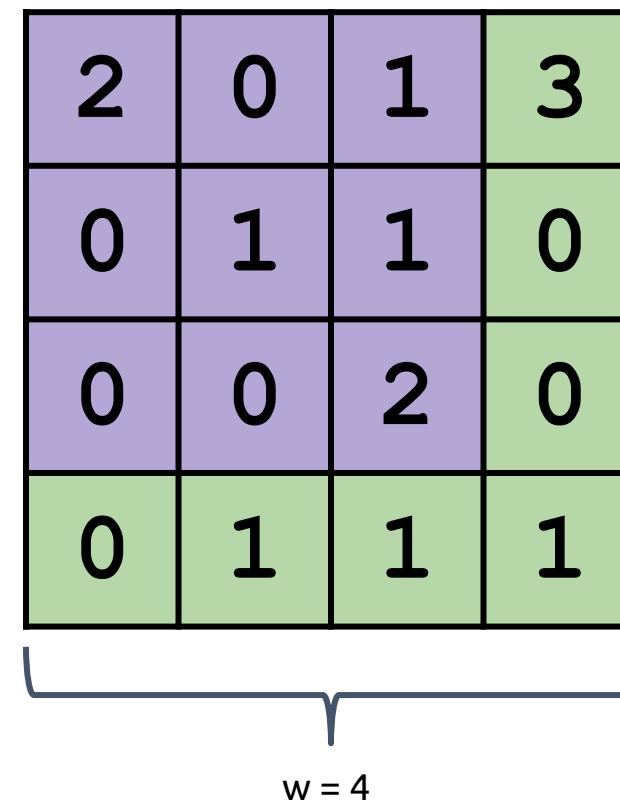
num filters $n = 1$
filter size $f = 3$
stride $s = 1$
padding $p = 0$

$$\begin{aligned} w' &= \frac{4 - 3 + 2 \cdot 0}{1} + 1 \\ &= 1 + 1 = 2 \end{aligned}$$

Output Size for “VALID” Padding

$$w' = \frac{w - f + 2p}{s} + 1$$

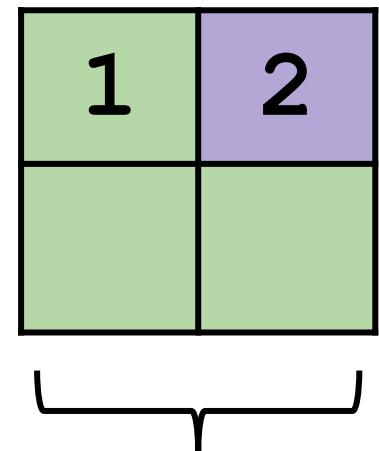
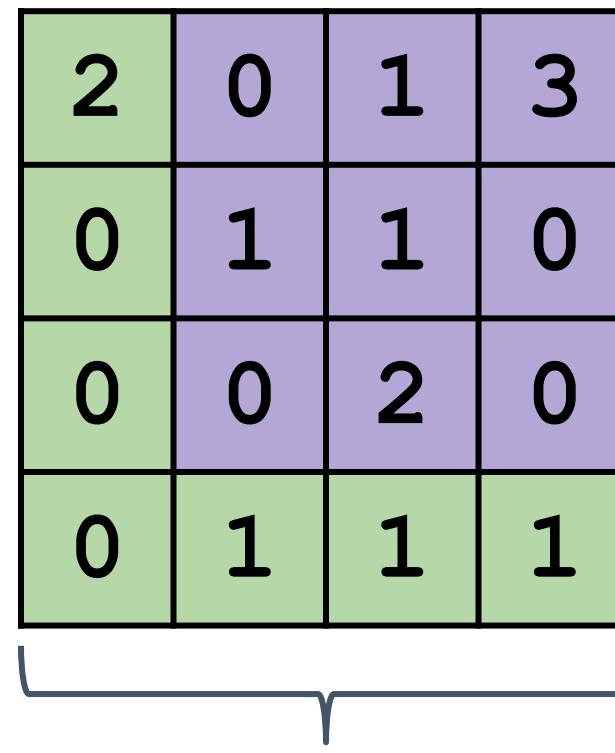
num filters $n = 1$
filter size $f = 3$
stride $s = 1$
padding $p = 0$



Output Size for “VALID” Padding

$$w' = \frac{w - f + 2p}{s} + 1$$

num filters $n = 1$
filter size $f = 3$
stride $s = 1$
padding $p = 0$

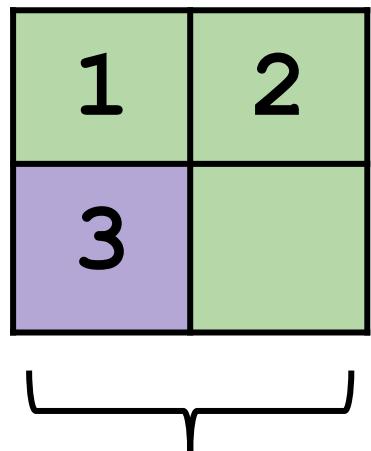
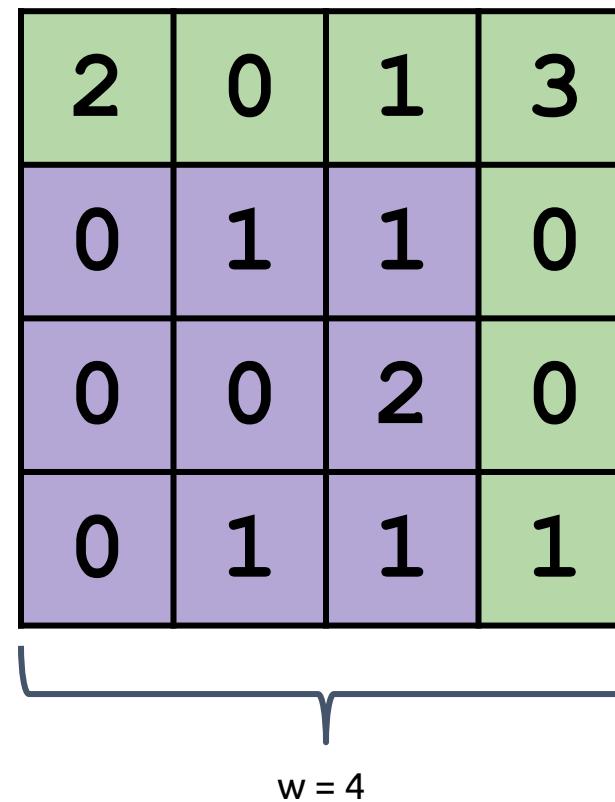


$w' = 2$

Output Size for “VALID” Padding

$$w' = \frac{w - f + 2p}{s} + 1$$

num filters $n = 1$
filter size $f = 3$
stride $s = 1$
padding $p = 0$

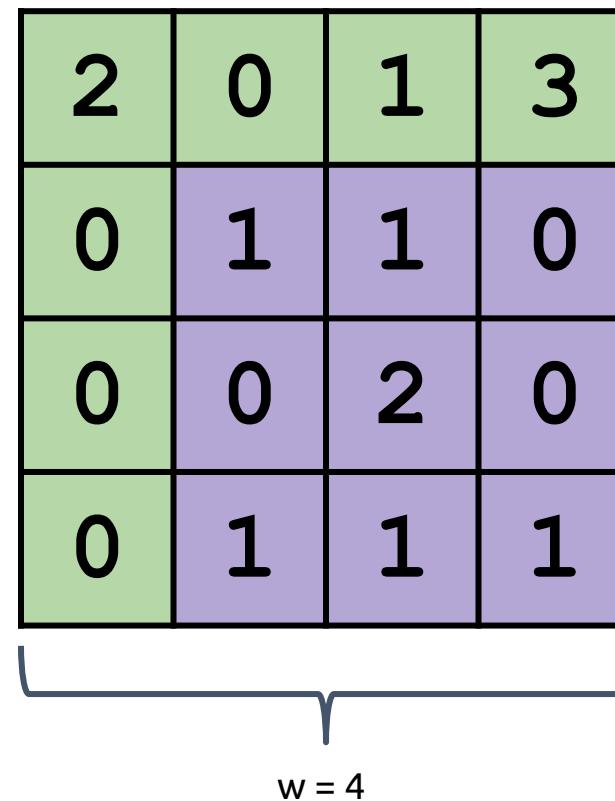


$$w' = 2$$

Output Size for “VALID” Padding

$$w' = \frac{w - f + 2p}{s} + 1$$

num filters $n = 1$
filter size $f = 3$
stride $s = 1$
padding $p = 0$



Output Size for “SAME” Padding

$$w' = \frac{w - f + 2p}{s} + 1$$

num filters $n = 1$
filter size $f = 3$
stride $s = 1$
padding $p = 1^*$

Let $w = 4$

$$\begin{aligned} w' &= \frac{4 - 3 + 2 \cdot 1}{1} + 1 \\ &= 3 + 1 = 4 \end{aligned}$$

*Chosen so output size is the same

Output Size for “SAME” Padding

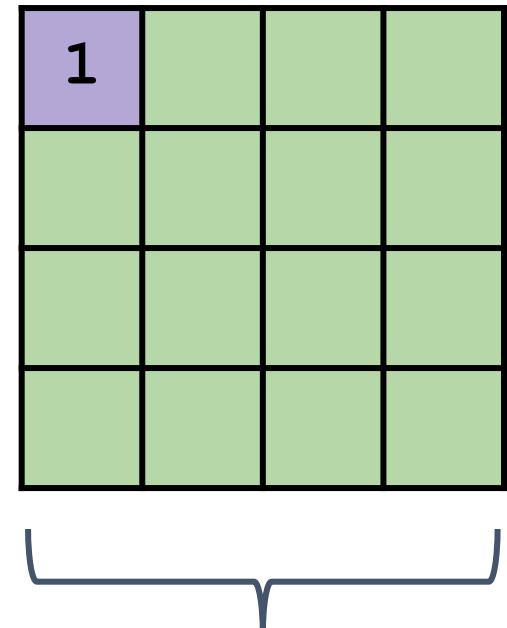
$$w' = \frac{w - f + 2p}{s} + 1$$

num filters $n = 1$
filter size $f = 3$
stride $s = 1$
padding $p = 1^*$

*Chosen so output size is the same

0	0	0	0	0	0
0	2	0	1	3	0
0	1	1	2	3	0
0	4	3	2	1	0
0	8	3	1	3	0
0	0	0	0	0	0

$w = 4$



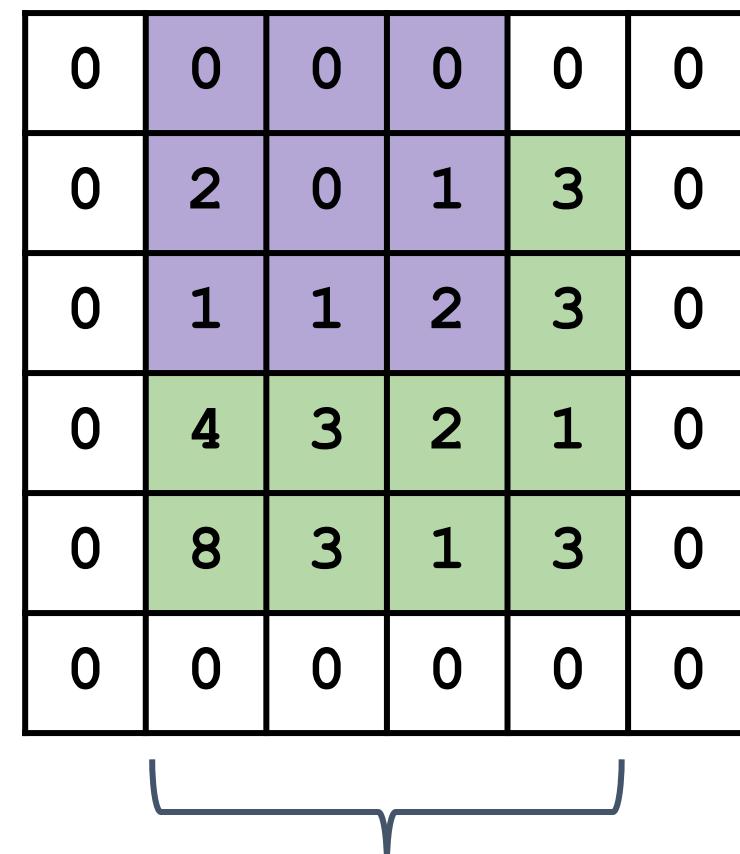
$w' = 4$

Output Size for “SAME” Padding

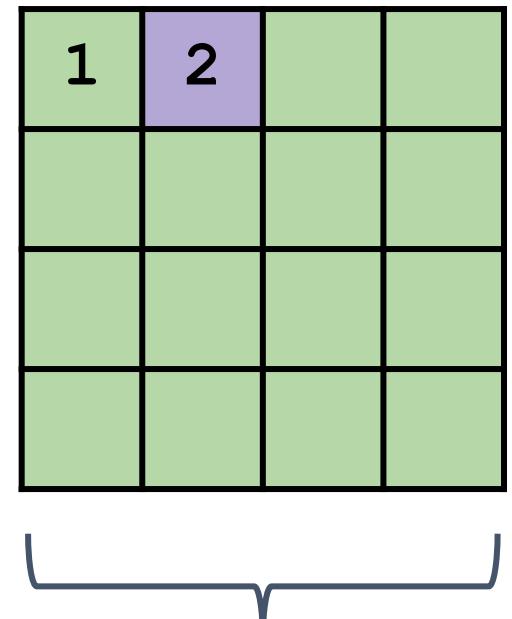
$$w' = \frac{w - f + 2p}{s} + 1$$

num filters $n = 1$
filter size $f = 3$
stride $s = 1$
padding $p = 1^*$

*Chosen so output size is the same



w = 4



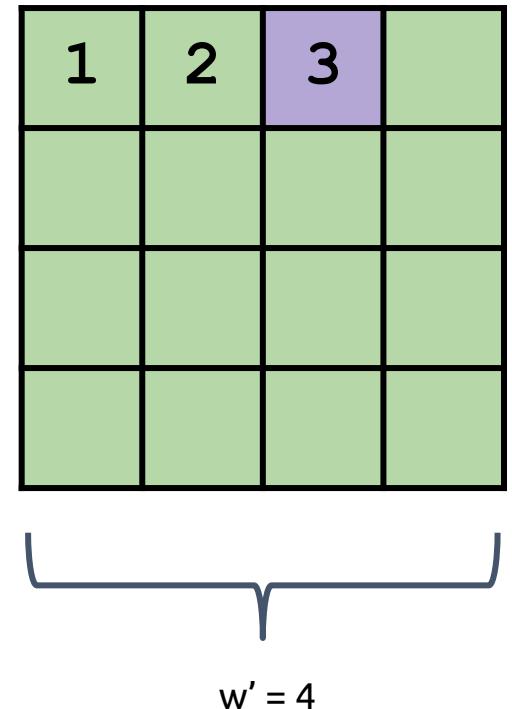
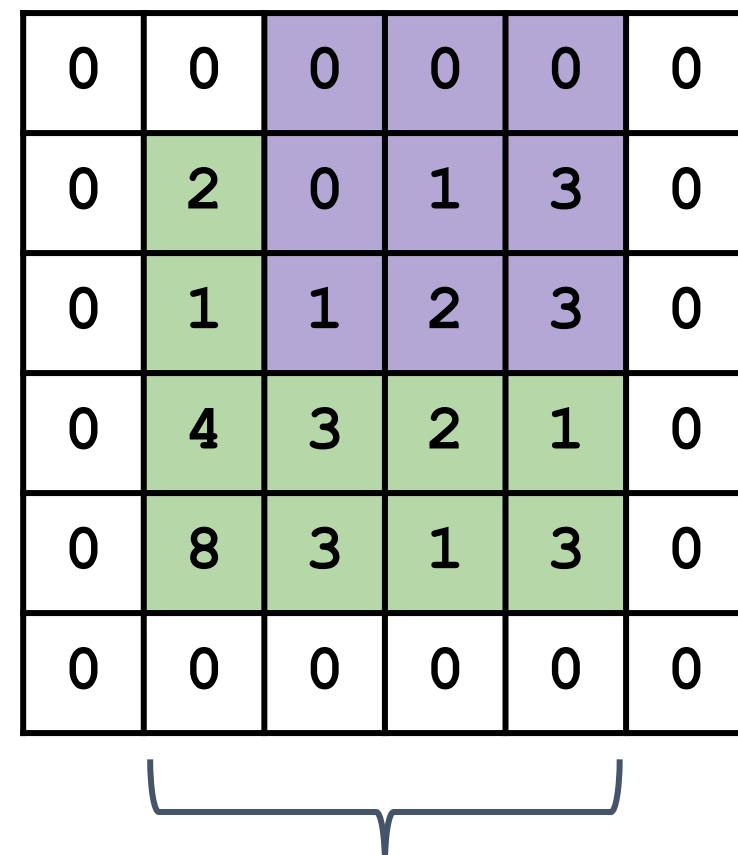
w' = 4

Output Size for “SAME” Padding

$$w' = \frac{w - f + 2p}{s} + 1$$

num filters $n = 1$
filter size $f = 3$
stride $s = 1$
padding $p = 1^*$

*Chosen so output size is the same



Any questions?

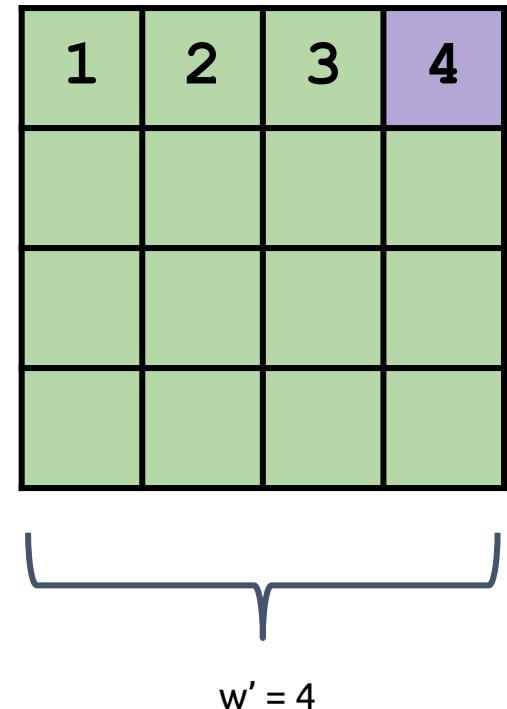
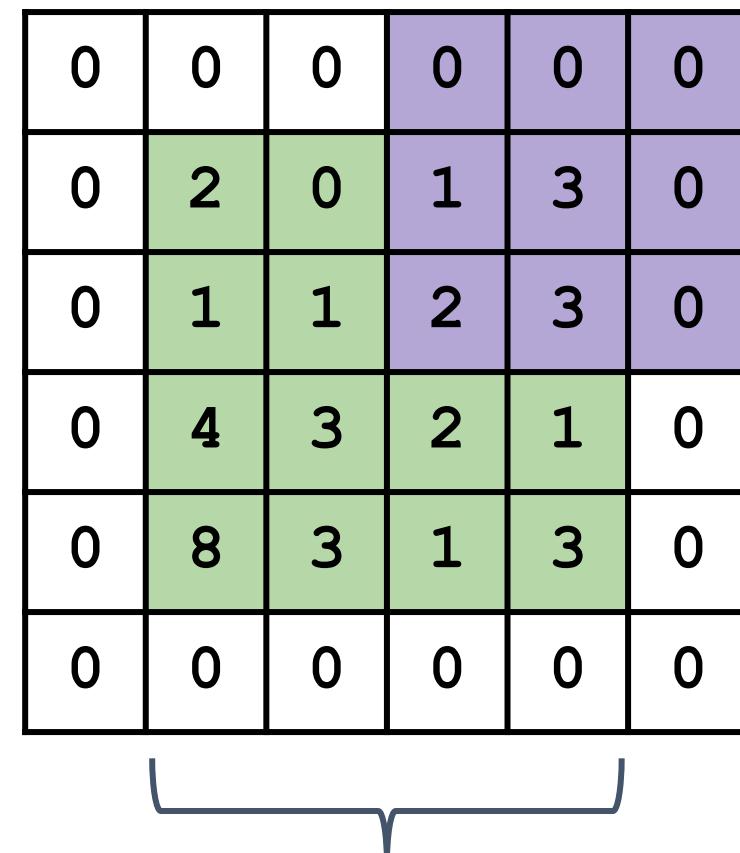


Output Size for “SAME” Padding

$$w' = \frac{w - f + 2p}{s} + 1$$

num filters $n = 1$
filter size $f = 3$
stride $s = 1$
padding $p = 1^*$

*Chosen so output size is the same



Convolution in Tensorflow

`tf.nn.conv2d(input, filter, strides, padding)`

Input Image
(4-D Tensor)

Filter/Kernel
(4-D Tensor)

Strides along
each dimension

Type of Padding
(String "Valid" or
"Same")

Full documentation here:

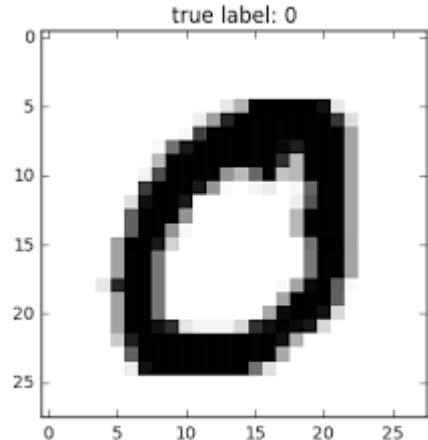
https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/nn/conv2d

Application to Real World Data (MNIST)

```
# Should be of shape (batch_sz, 28, 28, 1) for MNIST
inputs = MNIST_image_batch

# Sets up a 5x5 filter with 1 input channels and 16 output channels
self.filter = tf.Variable(tf.random.normal([5, 5, 1, 16], stddev=0.1))

# Convolves the input batch with our defined filter
conv = tf.nn.conv2d(inputs, self.filter, [1, 2, 2, 1], padding="SAME")
```



Application to Real World Data (CIFAR)



```
# Should be of shape (batch_sz, 32, 32, 3) for CIFAR10
inputs = CIFAR_image_batch

# Sets up a 5x5 filter with ? input channels and 16 output channels
self.filter = tf.Variable(tf.random.normal([?, ?, ?, ?, ?], stddev=0.1))

# Convolves the input batch with our defined filter
conv = tf.nn.conv2d(?, ?, ?, ?, ?)
```

Application to Real World Data (CIFAR)

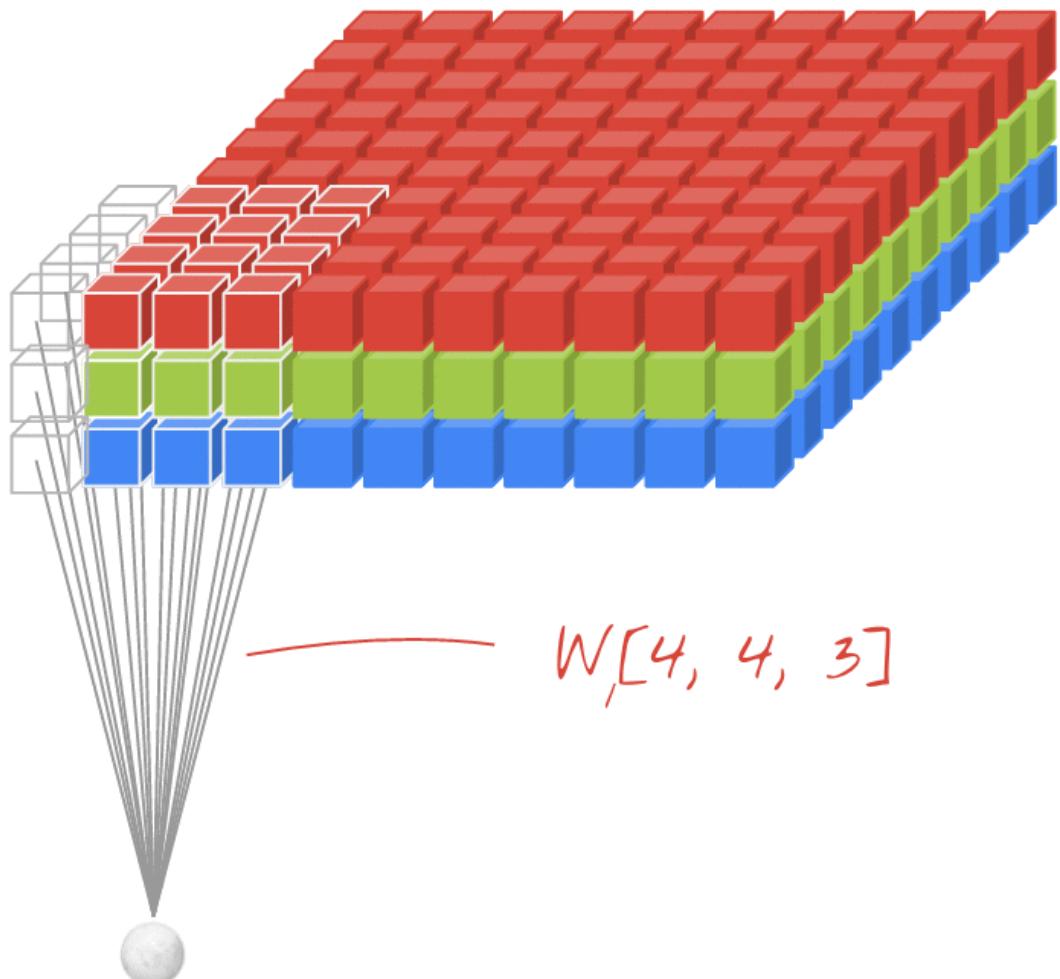


```
# Should be of shape (batch_sz, 32, 32, 3) for CIFAR10
inputs = CIFAR_image_batch

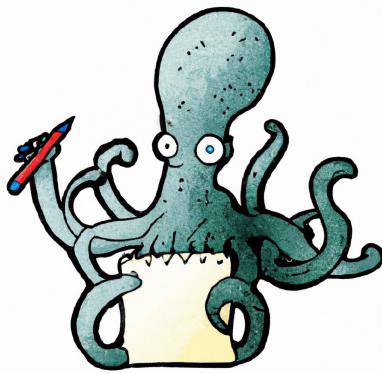
# Sets up a 5x5 filter with 3 input channels and 16 output channels
self.filter = tf.Variable(tf.random.normal([5, 5, 3, 16], stddev=0.1))

# Convolves the input batch with our defined filter
conv = tf.nn.conv2d(inputs, self.filter, [1, 2, 2, 1], padding="SAME")
```

2D Convolution for 3D Image



Recap



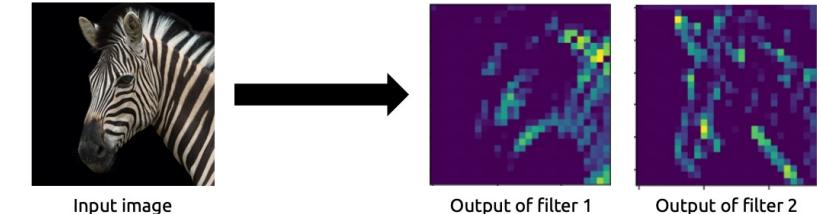
Convolution
in Tensorflow

Convolution

Filters/Kernels and Stride

Learning filters

CNNs are partially connected networks



Input image

Output of filter 1

Output of filter 2

Tensorflow conv2d function

Padding

Application to
MNIST/CIFAR

```
tf.nn.conv2d(input, filter, strides, padding)
```

Input Image
(4-D Tensor)

Filter/Kernel
(4-D Tensor)

Strides along
each dimension

Type of Padding
(String "Valid" or
"Same")