

# Computer vision

### Computer Vision Problems

#### Image Classification









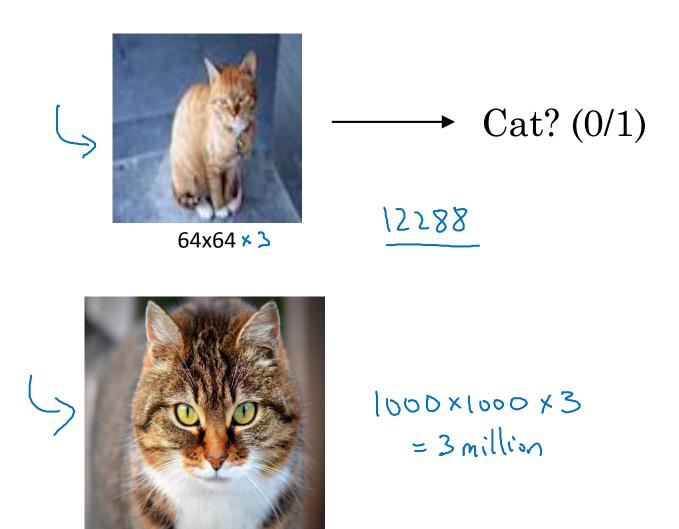


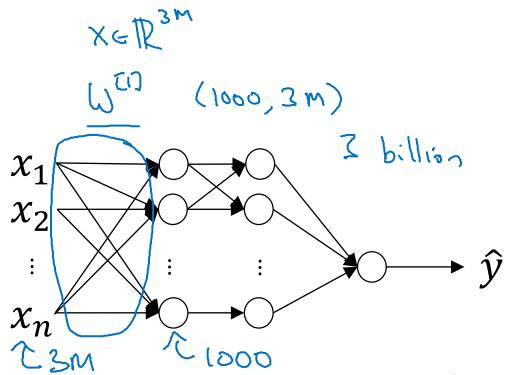
Object detection





### Deep Learning on large images

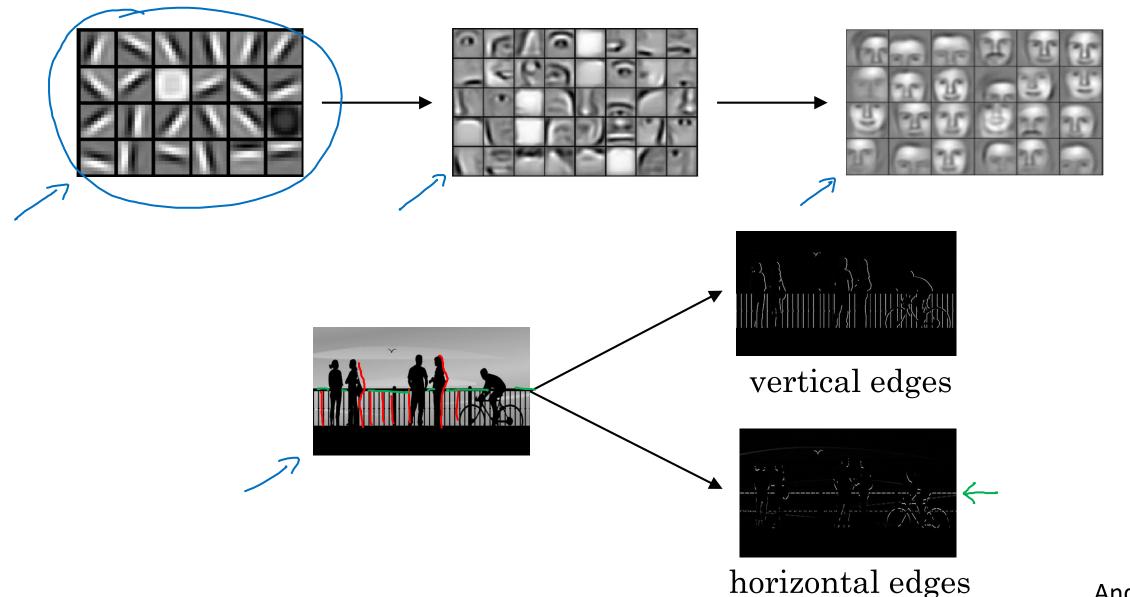






# Edge detection example

### Computer Vision Problem



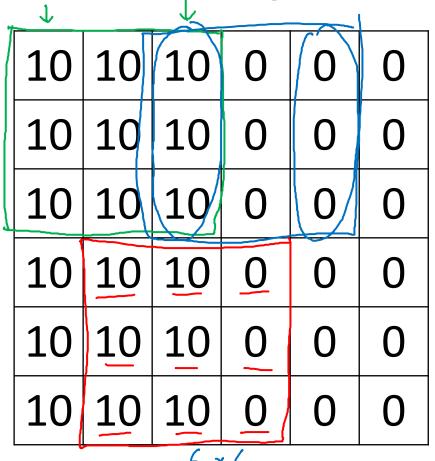
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### Vertical edge detection

1-5 3x1 + 1x1 +2+1 + 0x0 + 5x0 +7x0+1x+ +8x-1+2x-1=-5

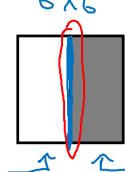
3	0	1	2 -	7 <sup>-0</sup>	4-1	Convolution				
1	5	8	9	3-0	1-1		-5	-4	0	8
2		2	5	1	3	*	-10	-2	2	3
01	1	3	1	7	8 <sup>-1</sup>		0	-2	-4	-7
4	2	1	6	2	8	3×3	-3	-2	-3(	-16
2	4	5	2	3	9	-> filta		4x	4	
		6×6				kenel				

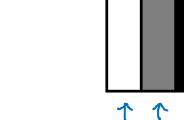
### Vertical edge detection

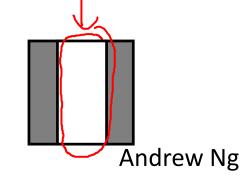


		<u>ს</u>	
		0	<u>-1</u>
*	1	0	-1
	1	0	-1
		7×3	

<u> </u>					
0	30	30	0		
0	30	30	0		
0	30	30	0		
0	30	30	0		
14x4					





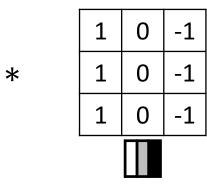




# More edge detection

### Vertical edge detection examples

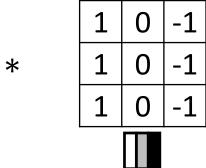
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

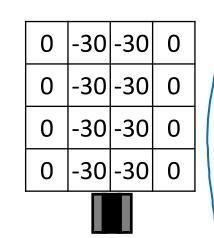


0	30	30	0		
0	30	30	0		
0	30	30	0		
0	30	30	0		

<b>→</b> >	
· ·	

0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

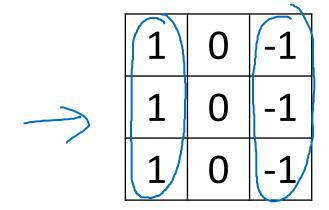




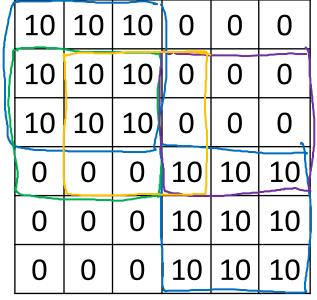


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### Vertical and Horizontal Edge Detection







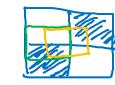
1 1 1 0 0 0 -1 -1 -1

Horizontal

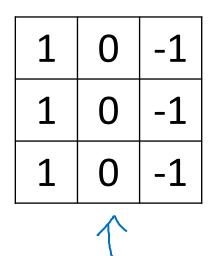
1	1	1
0	0	0
-1	-1	-1

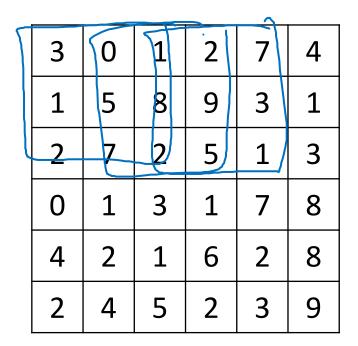
30 10 -10 -30 30 10 -10 -30

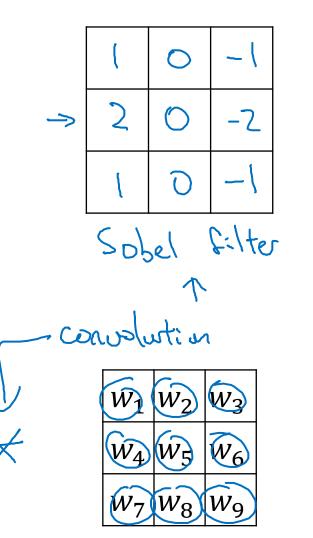
0



### Learning to detect edges

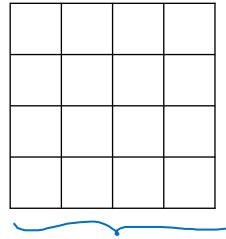






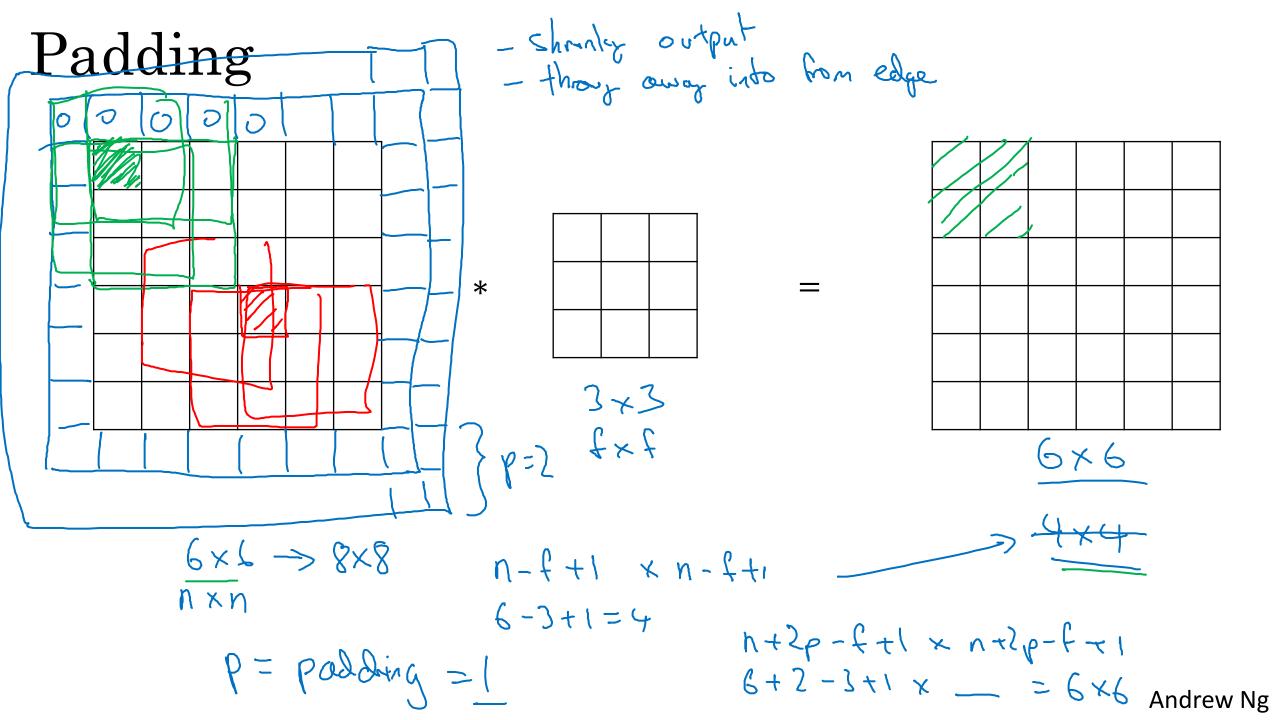
$\sim$	0	-3
10	0	0
7	∩ ∩	-3







Padding



#### Valid and Same convolutions

"Valid": 
$$n \times n \rightarrow \frac{n-f+1}{4} \times n-f+1$$

$$6 \times 6 \rightarrow 3+3 \rightarrow 4 \times 4$$

"Same": Pad so that output size is the <u>same</u> as the input size.

nt2p-ft1 ×n+2p-ft1

$$p=\frac{f-1}{2}$$
 $p=\frac{f-1}{2}$ 
 $p=\frac{3-1}{2}=1$ 

SxS

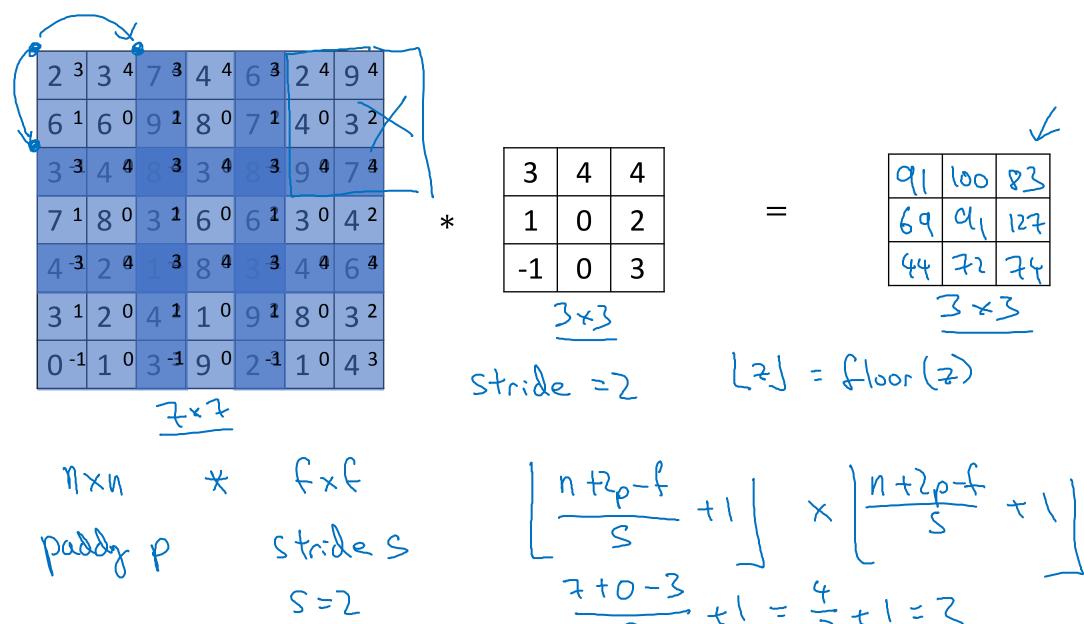
 $p=2$ 

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# Strided convolutions

#### Strided convolution



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### Summary of convolutions

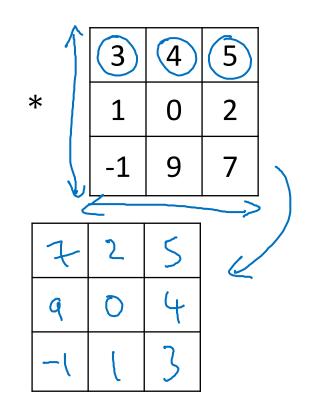
$$n \times n \text{ image}$$
  $f \times f \text{ filter}$  padding  $p$  stride  $s$ 

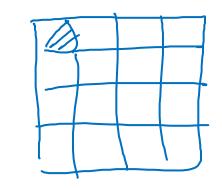
$$\left[\frac{n+2p-f}{s}+1\right] \times \left[\frac{n+2p-f}{s}+1\right]$$

# Technical note on <u>cross-correlation</u> vs. convolution

#### Convolution in math textbook:

		(	$\mathcal{L}$		
2	3	7 <sup>5</sup>	4	6	2
69	60	94	8	7	4
<b>T</b> 3	4	83	3	8	9
7	8	3	6	6	3
4	2	1	8	3	4
3	2	4	1	9	8



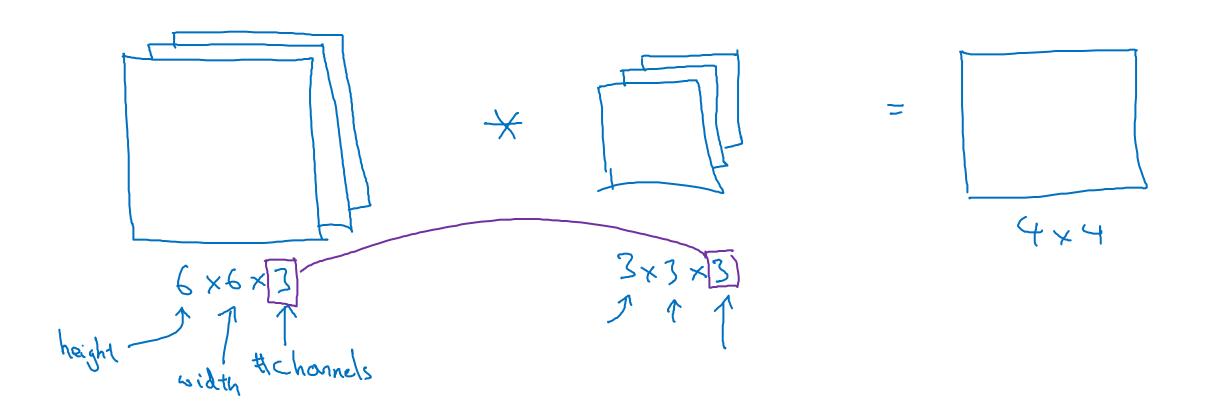


$$(A \times B) \times C = A \times (B \times C)$$

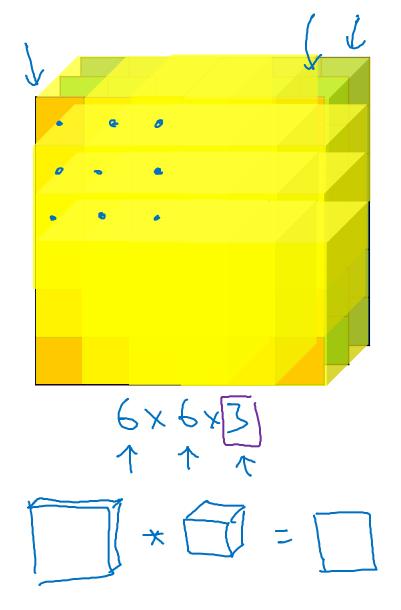


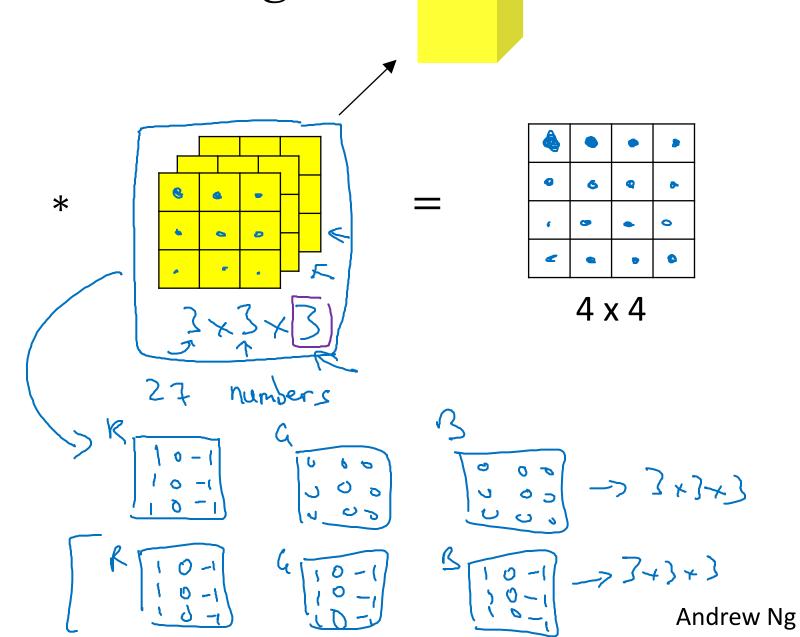
# Convolutions over volumes

### Convolutions on RGB images

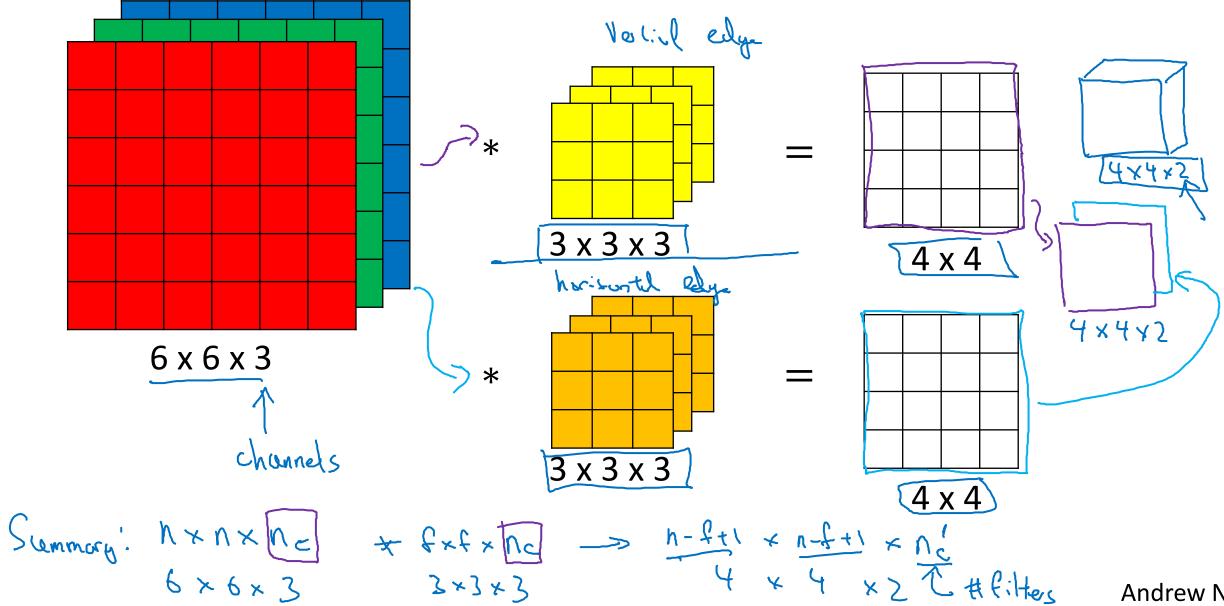


### Convolutions on RGB image





### Multiple filters

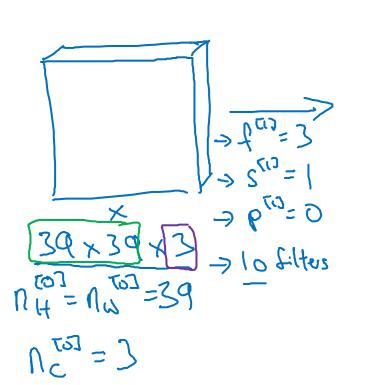


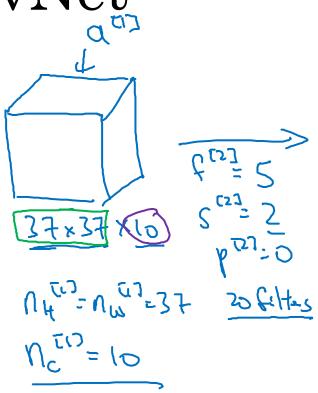
**Andrew Ng** 

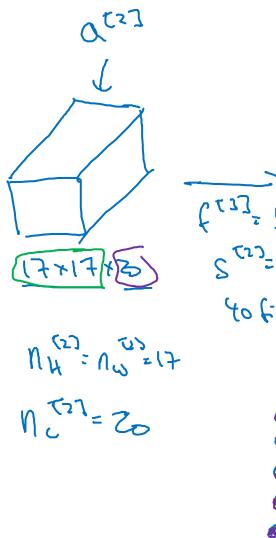


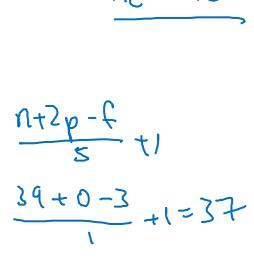
A simple convolution network example

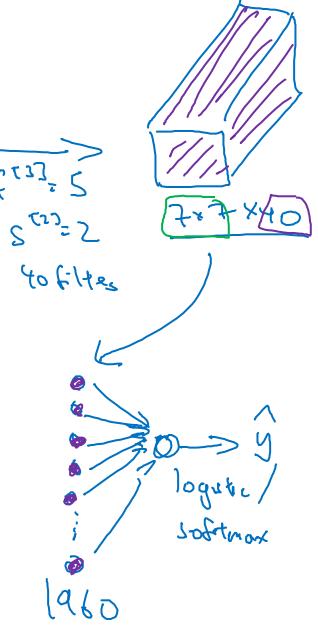
Example ConvNet











### Types of layer in a convolutional network:

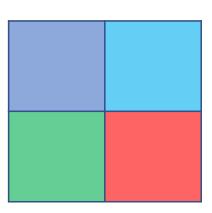
```
- Convolution (CONV) ←
- Pooling (POOL) ←
- Fully connected (FC) ←
```



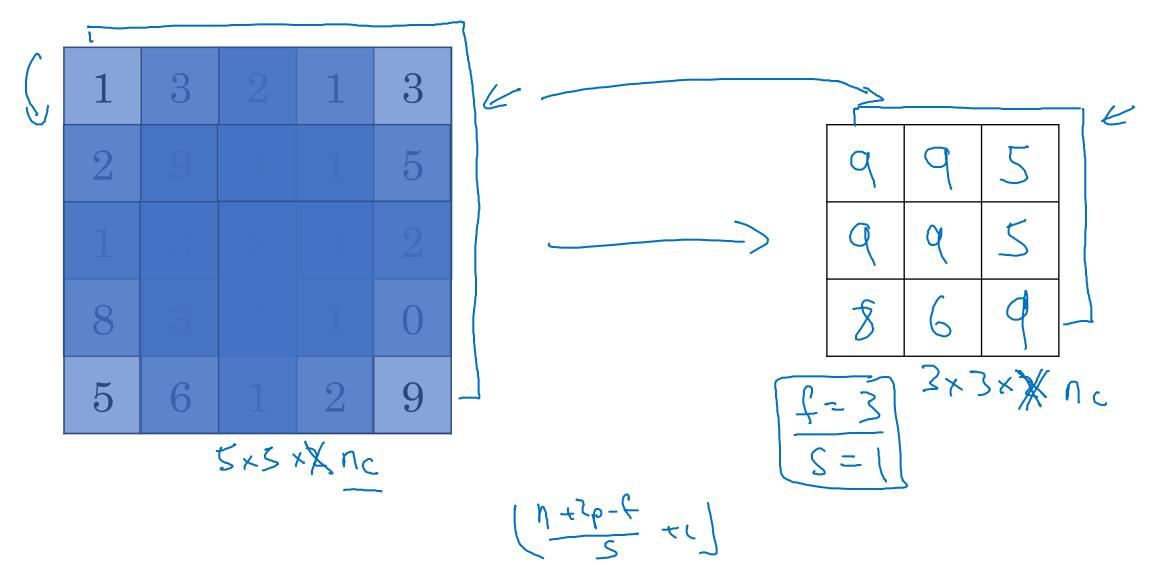
# Pooling layers

### Pooling layer: Max pooling

1	3	2	1
2	9	1	1
1	3	2	3
5	6	1	2

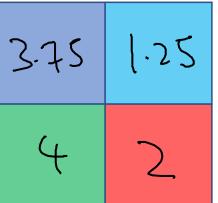


### Pooling layer: Max pooling



### Pooling layer: Average pooling

T	3	2	1	
2	9	1	1	
1	4	2	3	<b>→</b>
5	6	1	2	



### Summary of pooling

#### Hyperparameters:

f: filter size s: stride

Max or average pooling

$$N_{H} \times N_{W} \times N_{C}$$

$$N_{H} - f + f + f \times N_{S} + f$$

$$\times N_{C}$$



# Convolutional neural network example

Neural network example CONVZ POOLS POOL (DNV) Mospus 28×28×6 10×10×16 32+32×3 0,1,2,....9 NH, NW (120,400)

CONU-POOL-CONV-POOL-EC-EC- FL-SOFTMAX

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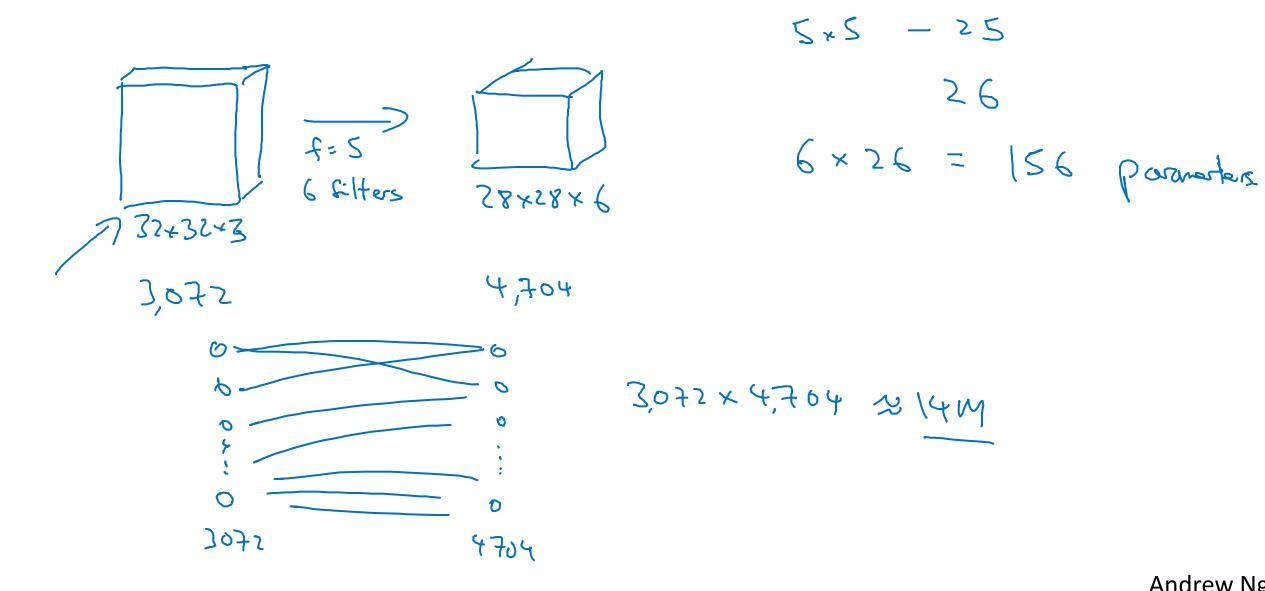
### Neural network example

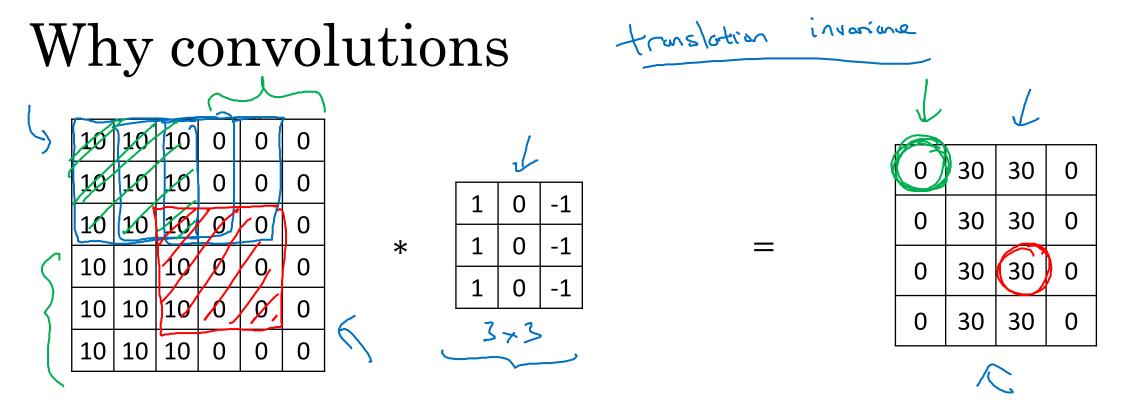
	Activation shape	Activation Size	# parameters
Input:	(32,32,3)	_ 3,072 a <sup>76]</sup>	0
			<del></del>



# Why convolutions?

### Why convolutions





**Parameter sharing:** A feature detector (such as a vertical edge detector) that's useful in one part of the image is probably useful in another part of the image.

→ **Sparsity of connections:** In each layer, each output value depends only on a small number of inputs.

### Putting it together

Cost 
$$J = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

Use gradient descent to optimize parameters to reduce J