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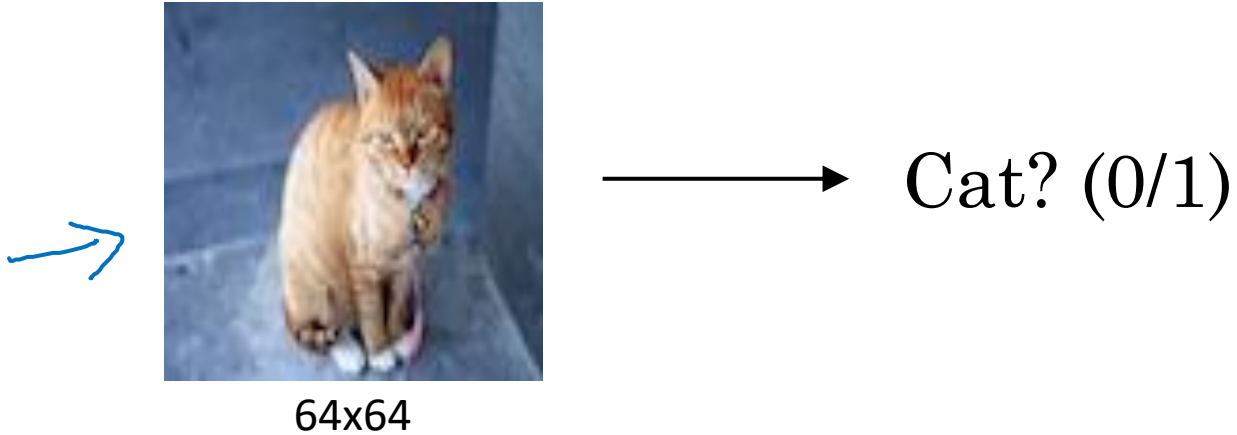
# Convolutional Neural Networks

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## Computer vision

# Computer Vision Problems

## Image Classification



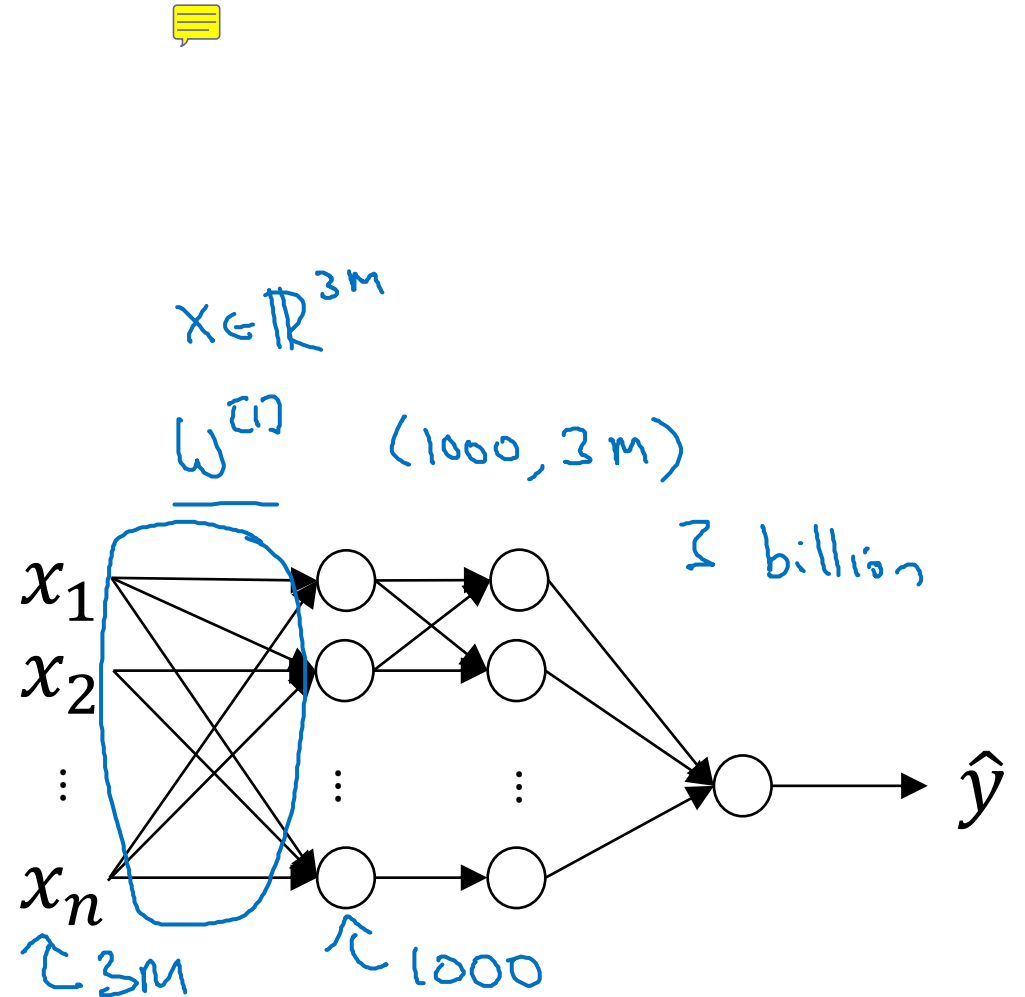
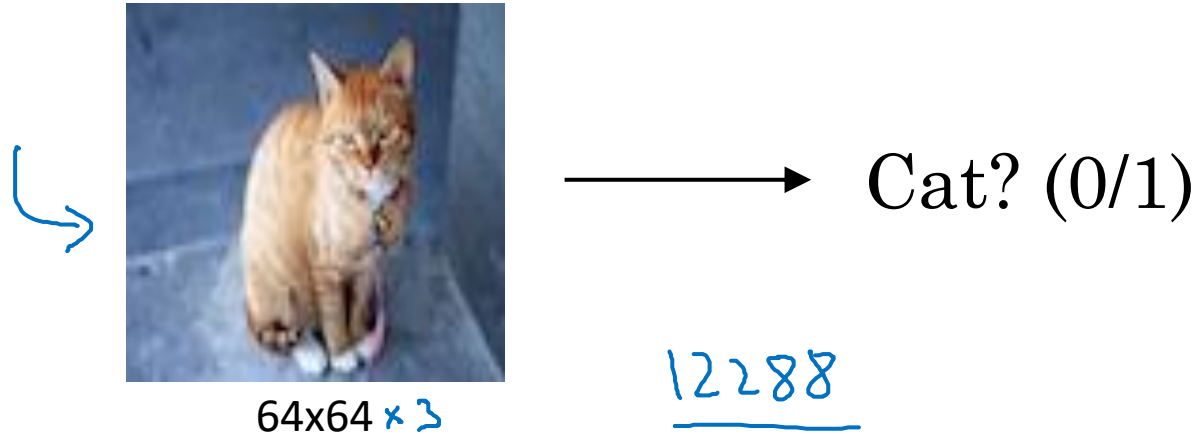
## Neural Style Transfer



## Object detection



# Deep Learning on large images





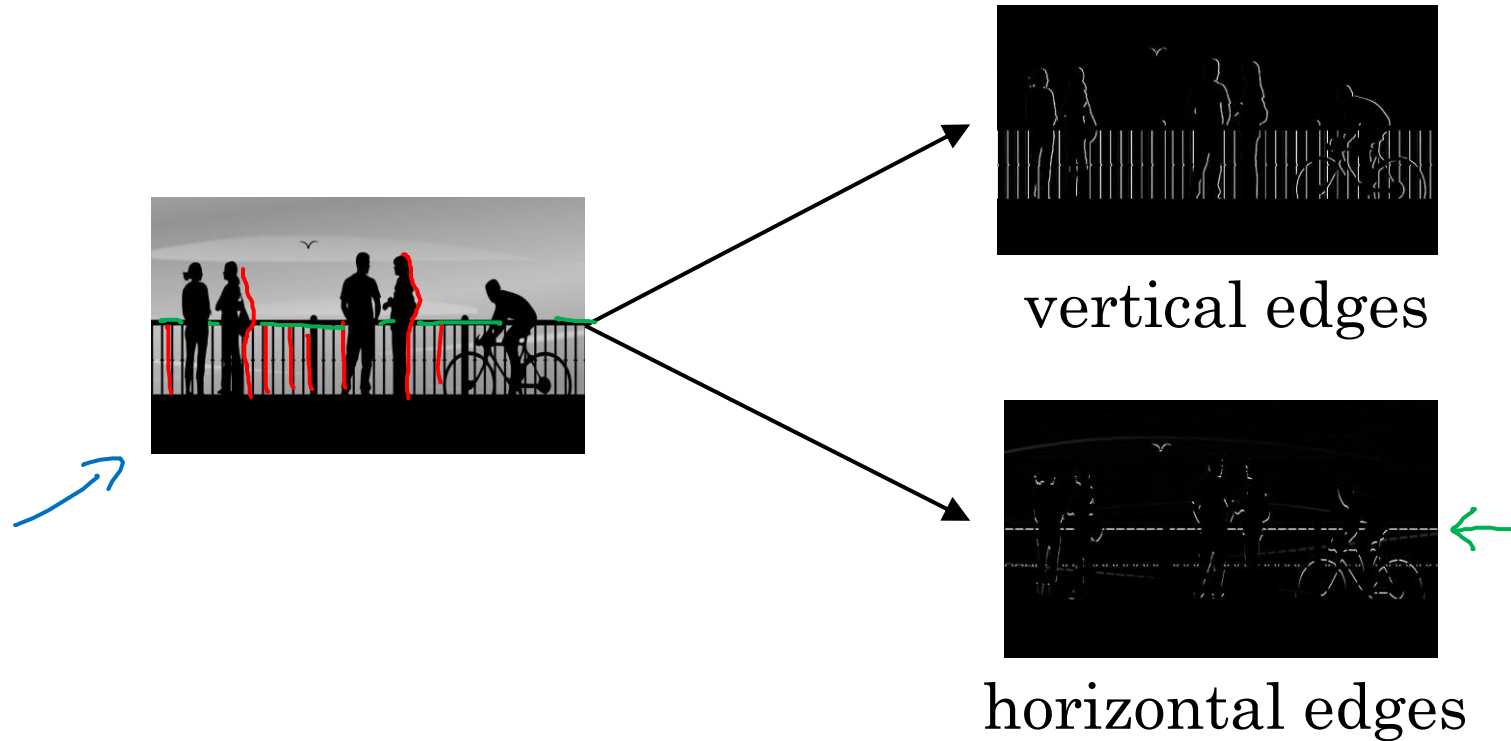
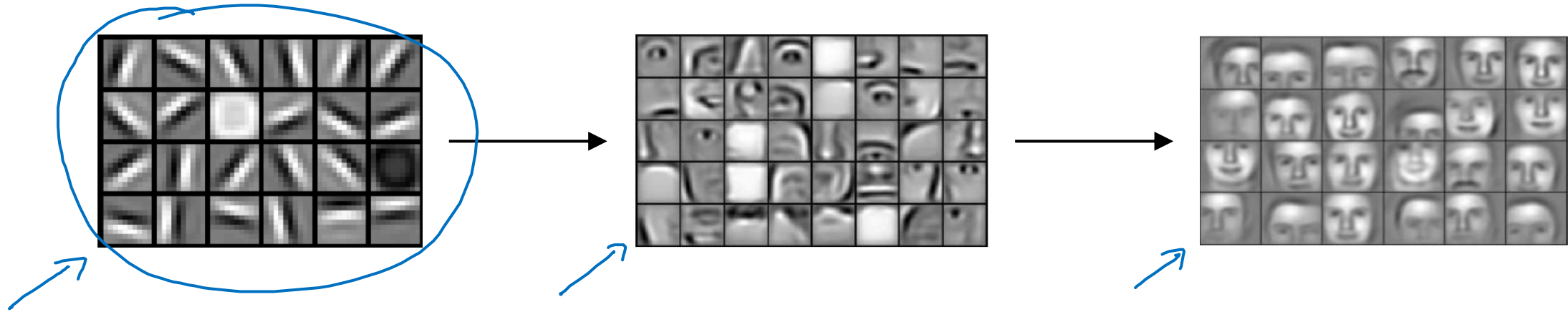
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# Convolutional Neural Networks

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## Edge detection example

# Computer Vision Problem

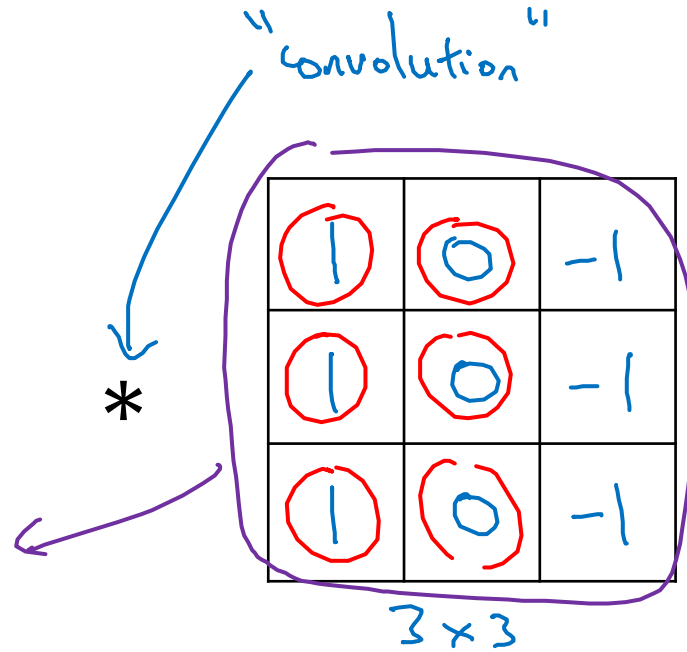


# Vertical edge detection

$$\rightarrow 3 \times 1 + 1 \times 1 + 2 \times 1 + 0 \times 0 + 5 \times 0 + 7 \times 0 + 1 \times -1 + 8 \times -1 + 2 \times -1 = -5$$

3 <sup>1</sup>	0 <sup>1</sup>	1 <sup>-1</sup>	2 <sup>-1</sup>	7 <sup>-0</sup>	4 <sup>-1</sup>
1 <sup>1</sup>	5 <sup>1</sup>	8 <sup>-1</sup>	9 <sup>-1</sup>	3 <sup>-0</sup>	1 <sup>-1</sup>
2 <sup>1</sup>	7 <sup>1</sup>	2 <sup>-1</sup>	5 <sup>-1</sup>	1 <sup>-0</sup>	3 <sup>-1</sup>
0 <sup>1</sup>	1 <sup>1</sup>	3 <sup>-1</sup>	1 <sup>-1</sup>	7 <sup>-0</sup>	8 <sup>-1</sup>
4	2	1	6	2	8
2	4	5	2	3	9

6x6



=

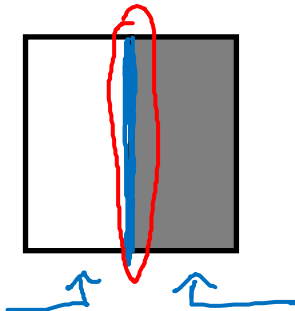
-5	-4	0	8
-10	-2	2	3
0	-2	-4	-7
-3	-2	-3	-16

4x4

# Vertical edge detection

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	<u>10</u>	<u>10</u>	<u>0</u>	0	0
10	<u>10</u>	<u>10</u>	<u>0</u>	0	0
10	<u>10</u>	<u>10</u>	<u>0</u>	0	0

6x6

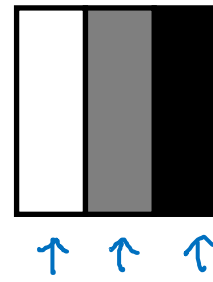


\*

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

3x3

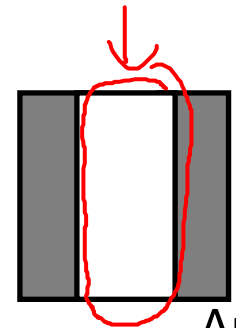
\*



=

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

4x4





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# Convolutional Neural Networks

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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



\*

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

=

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

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




\*

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

=


0	-30	-30	0
0	-30	-30	0
0	-30	-30	0
0	-30	-30	0

# Vertical and Horizontal Edge Detection



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

Vertical



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

Horizontal

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

6x6

\*



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

=

0	0	0	0
30	10	-10	-30
30	10	-10	-30
0	0	0	0

# Learning to detect edges

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



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



Sobel filter

3	0	-3
10	0	-10
3	0	-3

Scharr filter



3	0	1	2	7	4
1	5	8	9	3	1
2	7	2	5	1	3
0	1	3	1	7	8
4	2	1	6	2	8
2	4	5	2	3	9

convolution  
×

$W_1$	$W_2$	$W_3$
$W_4$	$W_5$	$W_6$
$W_7$	$W_8$	$W_9$

3x3

=

45°  
70°  
73°




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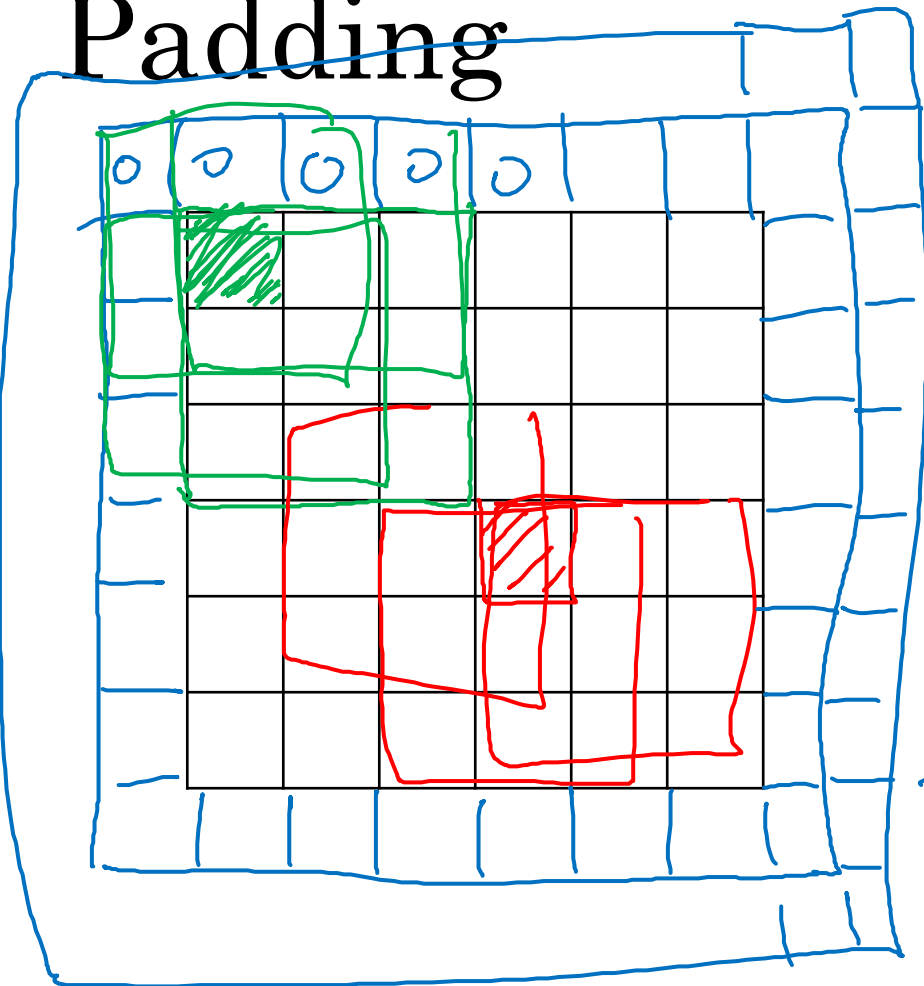
# Convolutional Neural Networks

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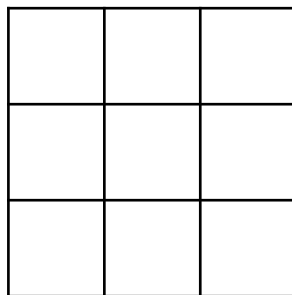
## Padding

# Padding

- shrinky output
- throw away info from edge

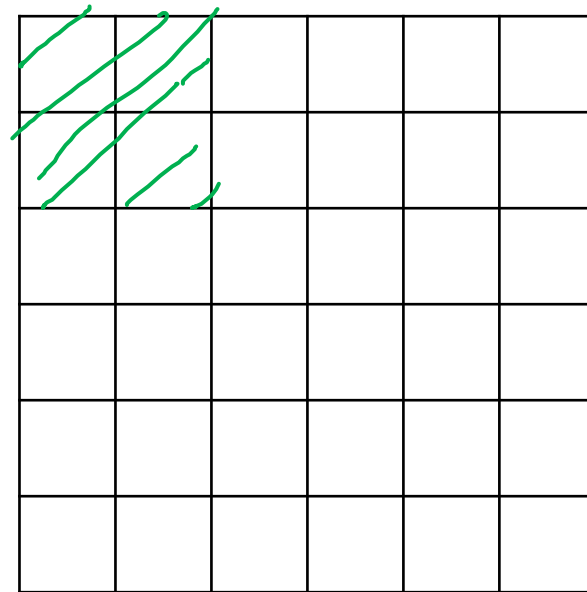


\*



3x3  
f x f

=



6x6

~~4x4~~

6x6 → 8x8  
n x n

$n - f + 1 \times n - f + 1$   
 $6 - 3 + 1 = 4$

$p = \text{padding} = \underline{1}$

$n + 2p - f + 1 \times n + 2p - f + 1$   
 $6 + 2 - 3 + 1 \times \underline{\quad} = 6 \times 6$

# Valid and Same convolutions

→ no padding

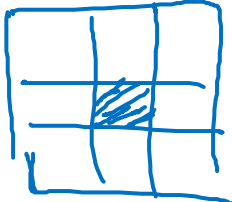
“Valid”:  $n \times n$   $\times$   $f \times f$   $\rightarrow \frac{n-f+1}{1} \times n-f+1$   
 $6 \times 6$   $\times$   $3 \times 3$   $\rightarrow 4 \times 4$

“Same”: Pad so that output size is the same as the input size.

$$n+2p-f+1 \times n+2p-f+1$$
$$\cancel{n+2p-f+1} = \cancel{n} \Rightarrow \boxed{p = \frac{f-1}{2}}$$
$$3 \times 3 \quad p = \frac{3-1}{2} = 1 \quad \left| \begin{array}{l} 5 \times 5 \\ f=5 \end{array} \right.$$

$f$  is usually odd

1x1  
3x3  
5x5  
7x7



$p=2$



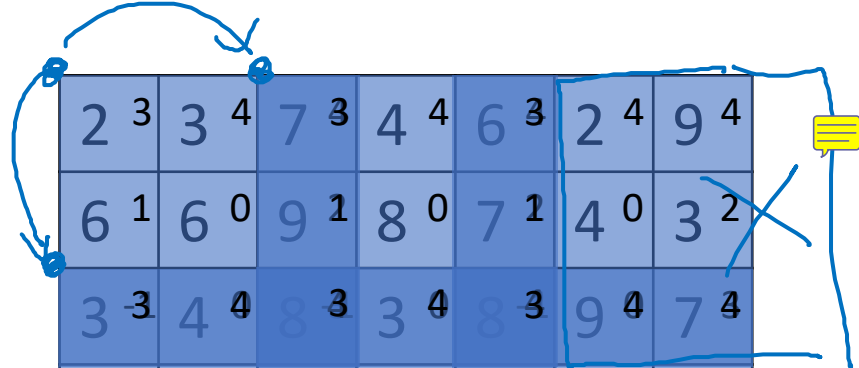
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# Convolutional Neural Networks

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## Strided convolutions

# Strided convolution



2	3	3	4	7	3	4	4	6	3	2	4	9	4
6	1	6	0	9	1	8	0	7	1	4	0	3	2
3	3	4	4	8	3	3	4	8	3	9	4	7	4
7	1	8	0	3	1	6	0	6	1	3	0	4	2
4	3	2	4	1	3	8	4	3	3	4	4	6	4
3	1	2	0	4	1	1	0	9	1	8	0	3	2
0	-1	1	0	3	-1	9	0	2	-1	1	0	4	3


7x7

\*

3	4	4
1	0	2
-1	0	3

3x3

=



91	100	83
69	91	127
44	72	74

3x3

Stride = 2

$\lfloor z \rfloor = \text{floor}(z)$

$n \times n$  \*  $f \times f$   
 padding  $p$       stride  $s$   
 $s = 2$

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

$$\frac{7 + 0 - 3}{2} + 1 = \frac{4}{2} + 1 = 3$$



# Summary of convolutions

$n \times n$  image       $f \times f$  filter

padding  $p$       stride  $s$



Output Size:

$$\left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor \times \left\lfloor \underbrace{\frac{n+2p-f}{s}} + 1 \right\rfloor$$

# Technical note on cross-correlation vs. convolution

Convolution in math textbook:

2 <sup>7</sup>	3 <sup>2</sup>	7 <sup>5</sup>	4	6	2
6 <sup>9</sup>	6 <sup>0</sup>	9 <sup>4</sup>	8	7	4
3 <sup>-1</sup>	4 <sup>1</sup>	8 <sup>3</sup>	3	8	9
7	8	3	6	6	3
4	2	1	8	3	4
3	2	4	1	9	8

3	4	5
1	0	2
-1	9	7

7	2	5
9	0	4
-1	1	3


$$(A * B) * C = A * (B * C)$$



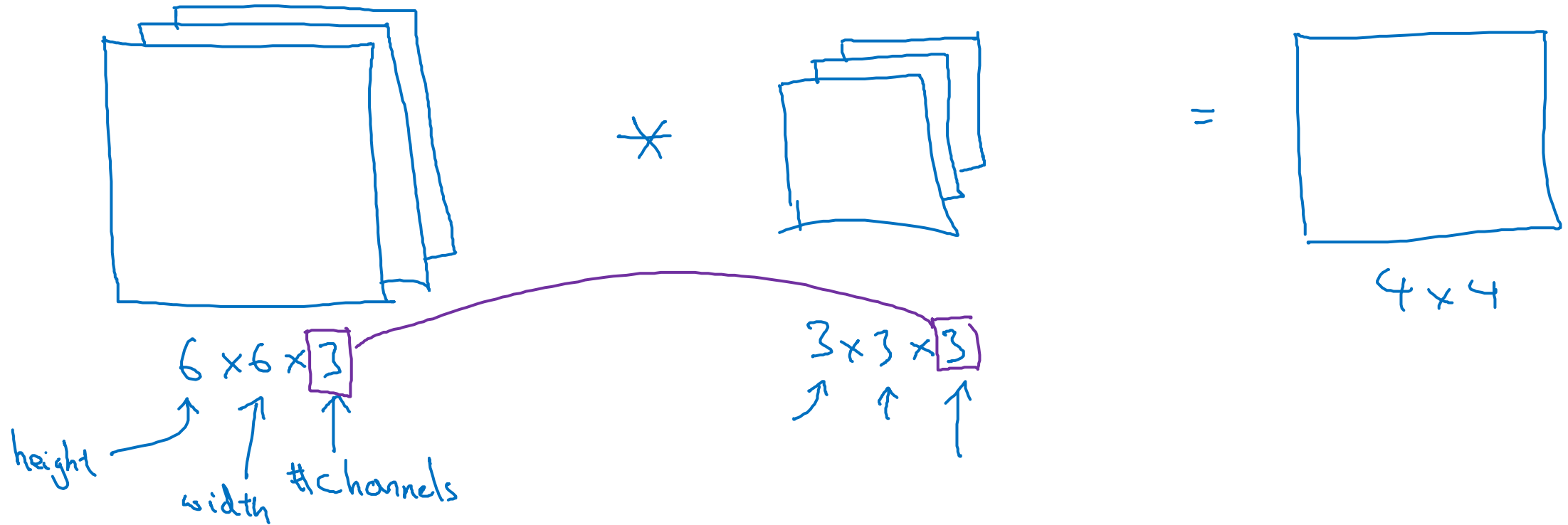
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# Convolutional Neural Networks

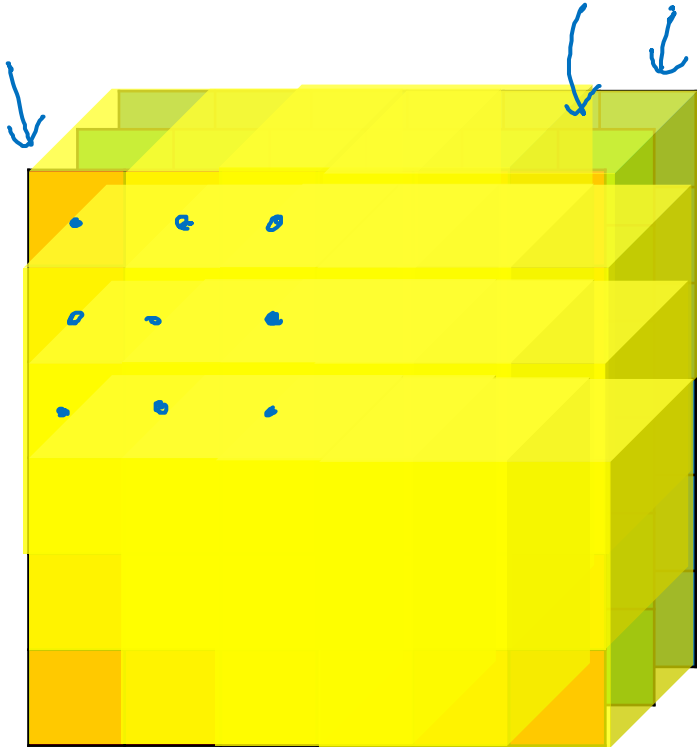
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## Convolutions over volumes

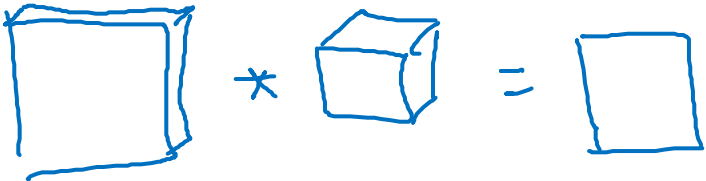
# Convolutions on RGB images



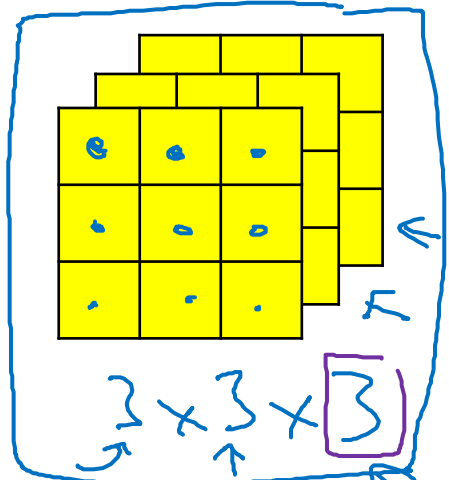
# Convolutions on RGB image



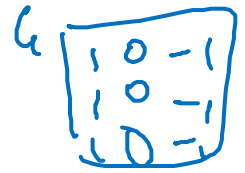
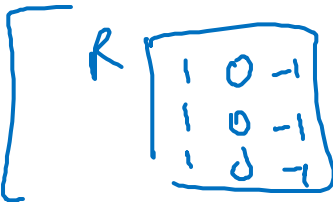
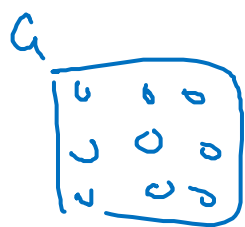
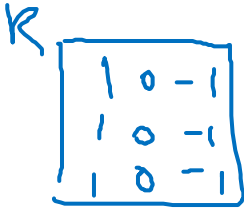
$6 \times 6 \times 3$   
↑    ↑    ↑



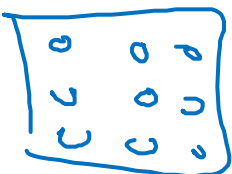
\*



27 numbers

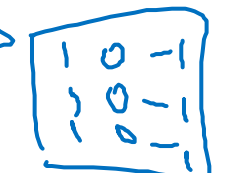


3

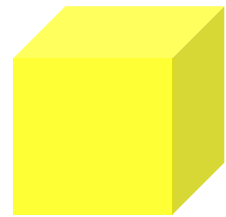


→ 3x3x3

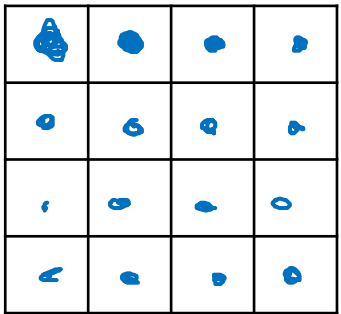
B



→ 3x3x3

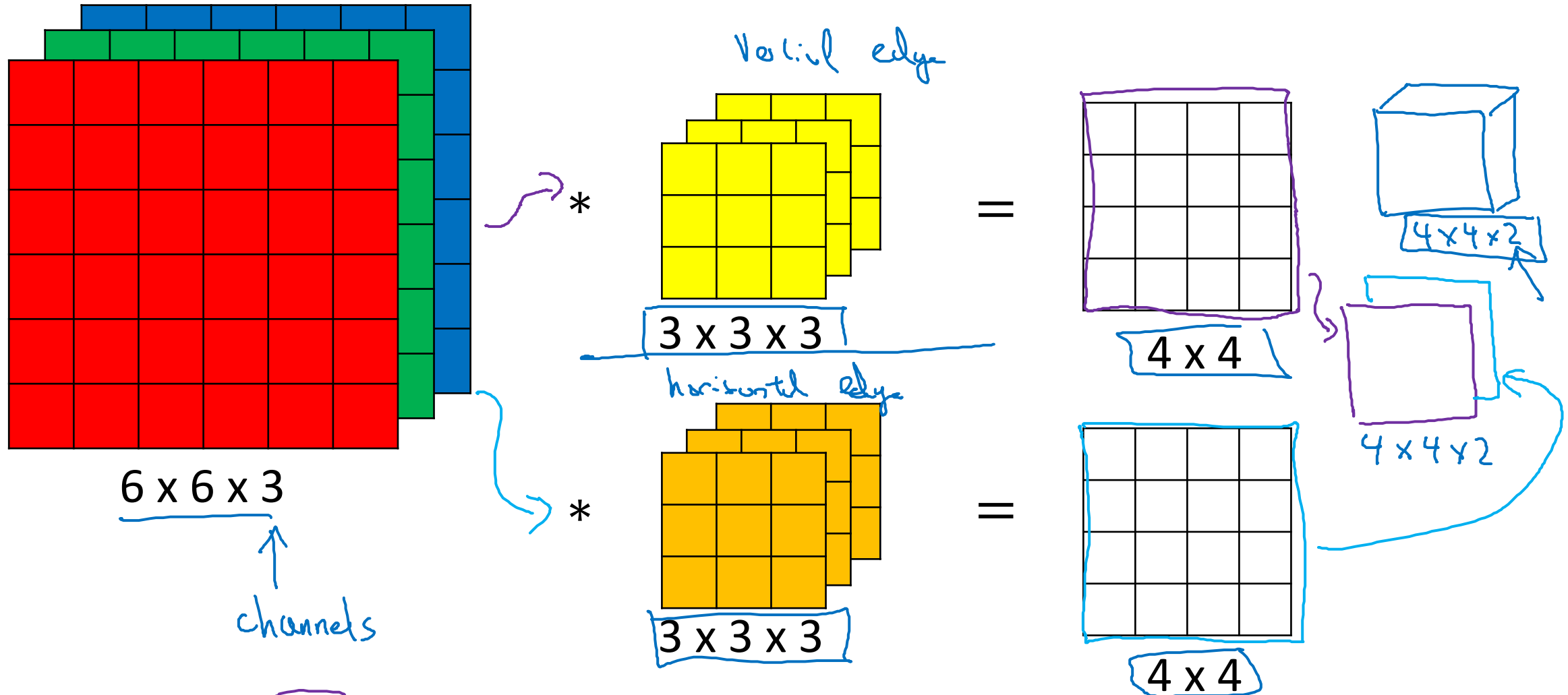


=



4 x 4

# Multiple filters



Summary:  $n \times n \times n_c$   $\times$   $f \times f \times n_c$   $\rightarrow$   $\frac{n-f+1}{4} \times \frac{n-f+1}{4} \times n_c'$

$6 \times 6 \times 3$   $3 \times 3 \times 3$   $4 \times 4 \times 2$   $\uparrow$  #filters



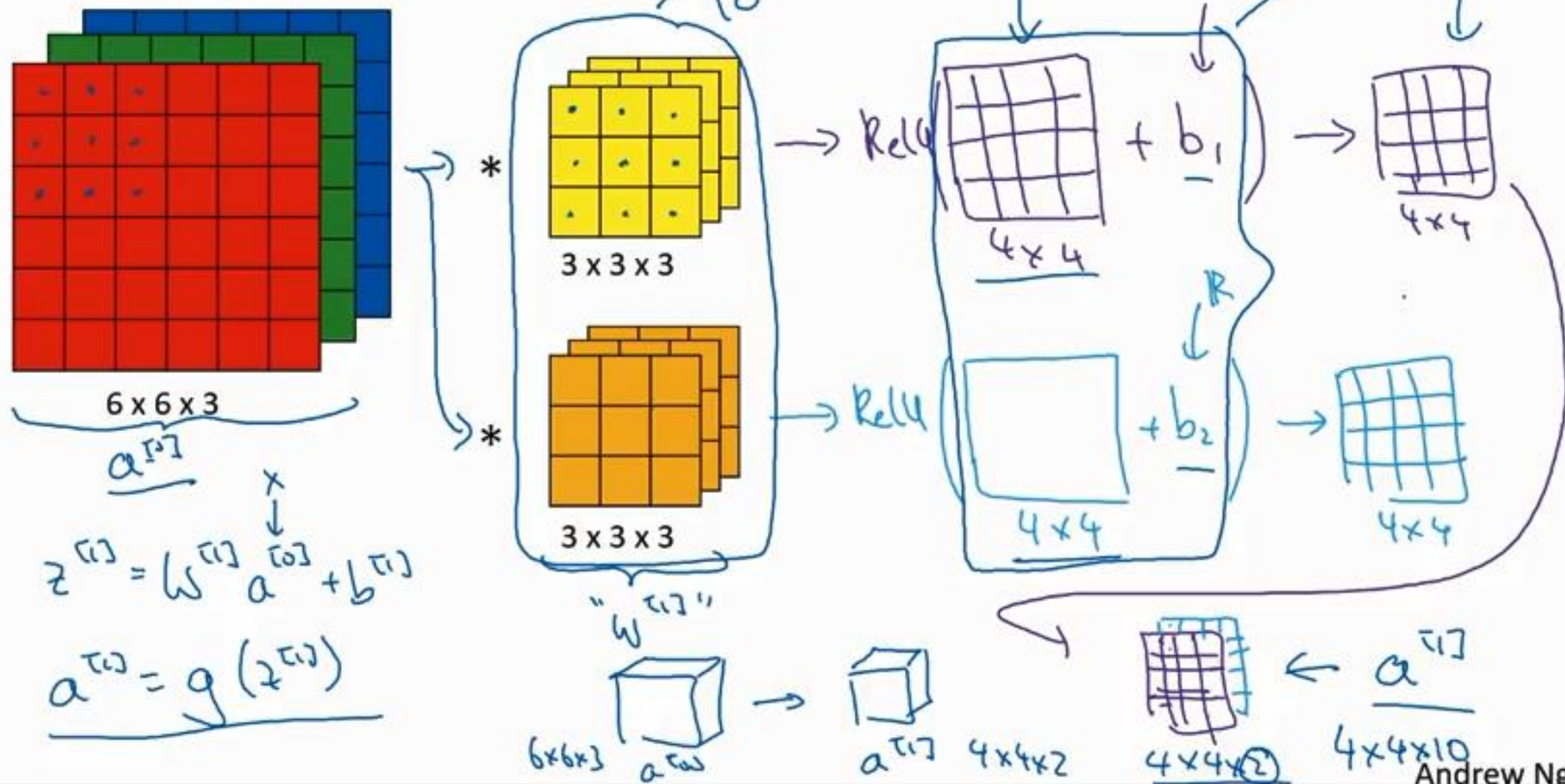
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# Convolutional Neural Networks

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One layer of a  
convolutional  
network

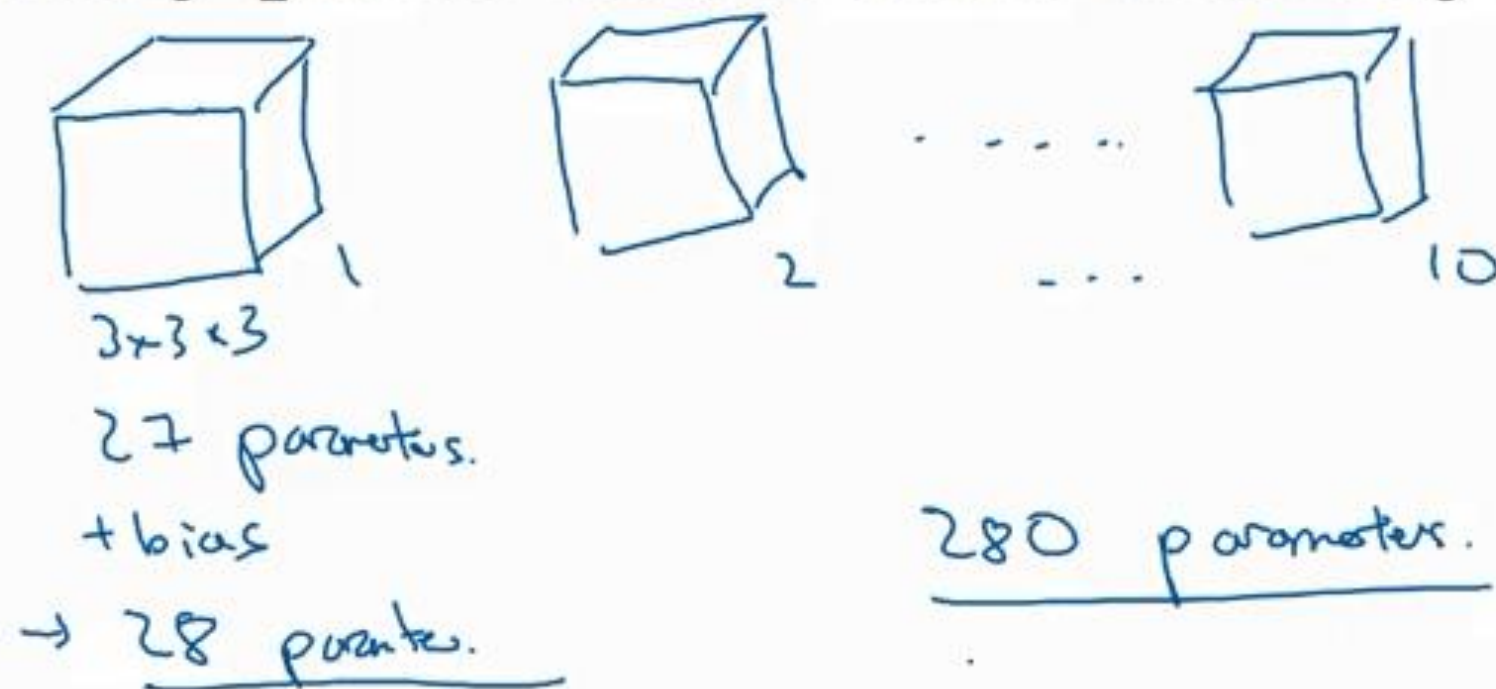
# Example of a layer





# Number of parameters in one layer

If you have 10 filters that are  $3 \times 3 \times 3$  in one layer of a neural network, how many parameters does that layer have?



# Summary of notation

If layer l is a convolution layer:

$f^{[l]}$  = filter size

$p^{[l]}$  = padding

$s^{[l]}$  = stride



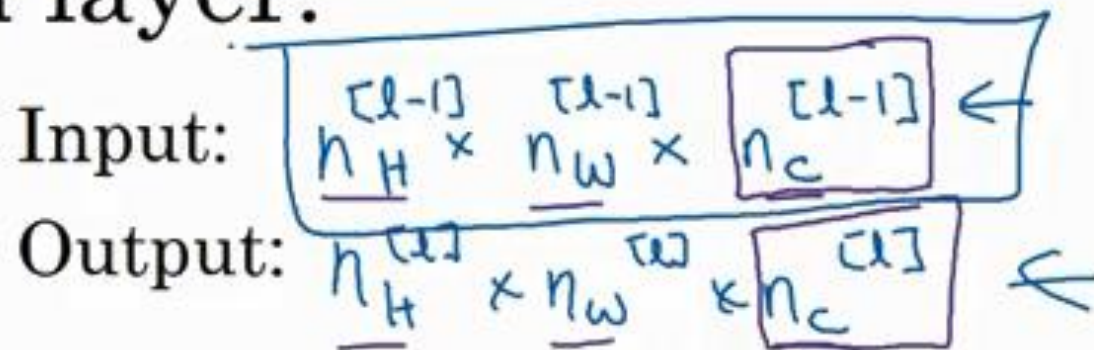
$n_c^{[l]}$  = number of filters

→ Each filter is:  $f^{[l]} \times f^{[l]} \times n_c^{[l-1]}$

Activations:  $A^{[l]} \rightarrow n_H^{[l]} \times n_W^{[l]} \times n_c^{[l]}$

Weights:  $f^{[l]} \times f^{[l]} \times n_c^{[l-1]} \times n_c^{[l]}$

bias:  $n_c^{[l]} - (1, 1, 1, n_c^{[l]})$  ← #f: (tors in layer l.



$$n_{HW}^{[l]} = \left\lfloor \frac{n_H^{[l-1]} + 2p^{[l]} - f^{[l]}}{s^{[l]}} + 1 \right\rfloor$$

$$A^{[l]} \rightarrow m \times \underbrace{n_H^{[l]} \times n_W^{[l]} \times n_c^{[l]}}_{n_c^{[l]} \times n_H^{[l]} \times n_W^{[l]}}$$



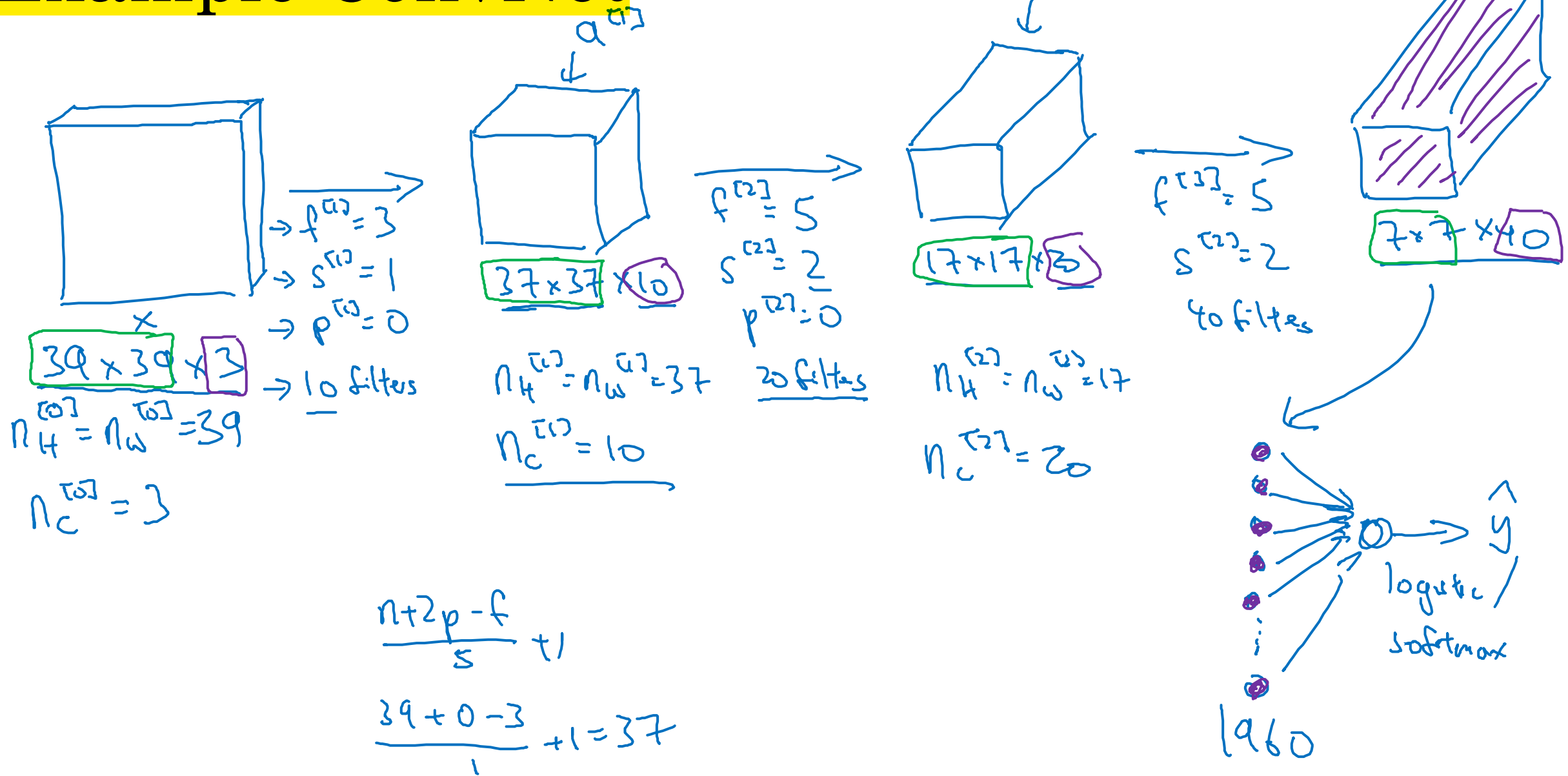
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# Convolutional Neural Networks

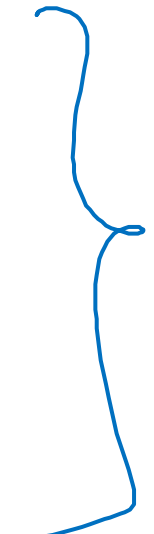
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A simple convolution  
network example

# Example ConvNet



# Types of layer in a convolutional network:

- Convolution (conv) ←
  - Pooling (pool) ←
  - Fully connected (Fc) ←
- 



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# Convolutional Neural Networks

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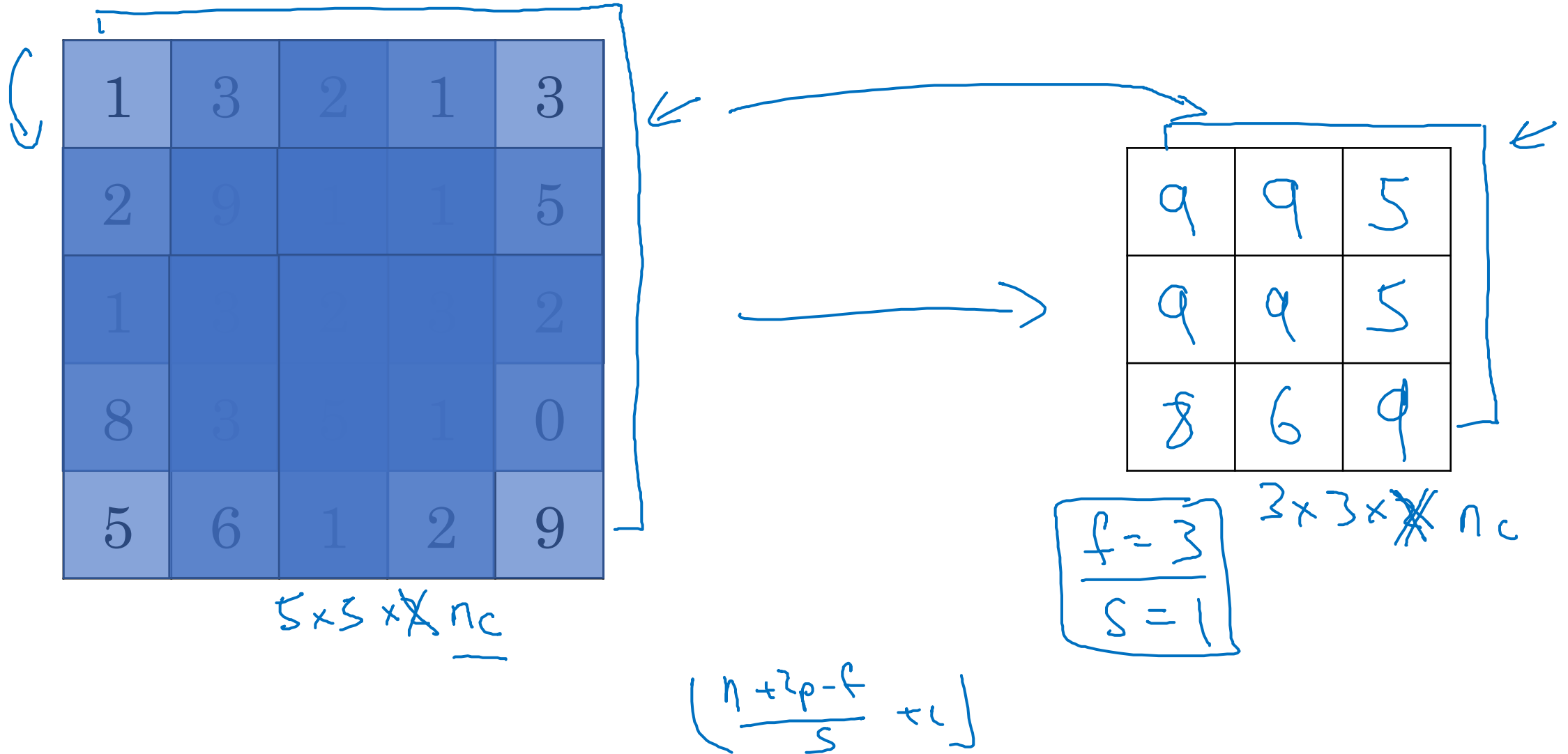
## Pooling layers

# Pooling layer: Max pooling



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

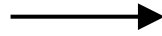

# Pooling layer: Max pooling





# Pooling layer: Average pooling

1	3	2	1
2	9	1	1
1	4	2	3
5	6	1	2



3.75	1.25
4	2

$$f=2$$

$$s=2$$

$$\underline{7 \times 7 \times 1000} \rightarrow 1 \times 1 \times 1000$$

# Summary of pooling

Hyperparameters:

f : filter size

$$f=2, s=2$$

s : stride

$$f=3, s=2$$

Max or average pooling

~~⇒ p: padding.~~

No parameters to learn!

$$n_H \times n_W \times \underline{n_C}$$

$$\downarrow$$
$$\left\lfloor \frac{n_H - f}{s} + 1 \right\rfloor \times \left\lfloor \frac{n_W - f}{s} + 1 \right\rfloor$$
$$\times \underline{n_C}$$



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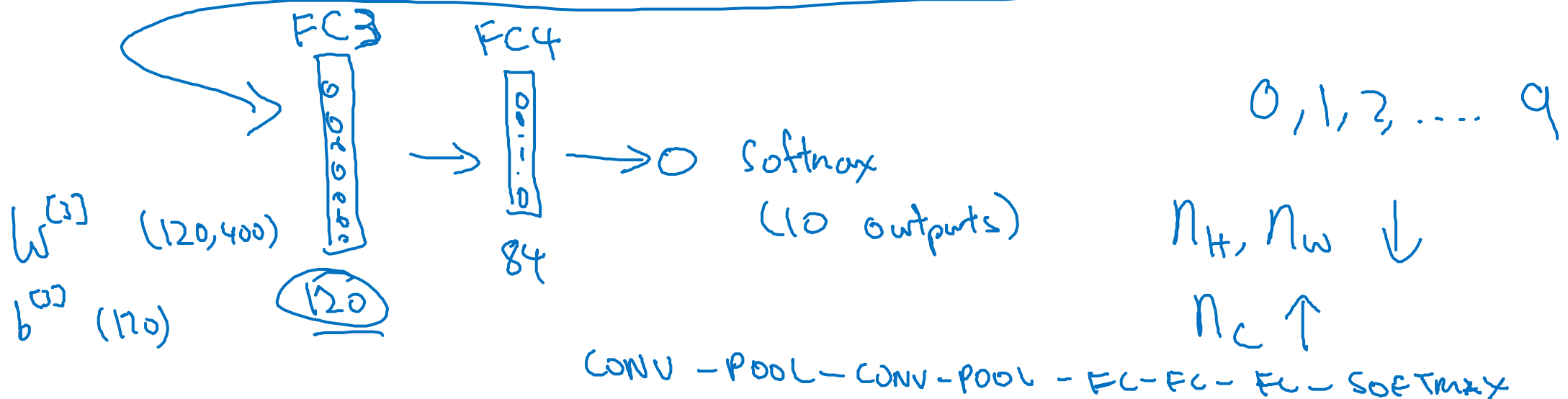
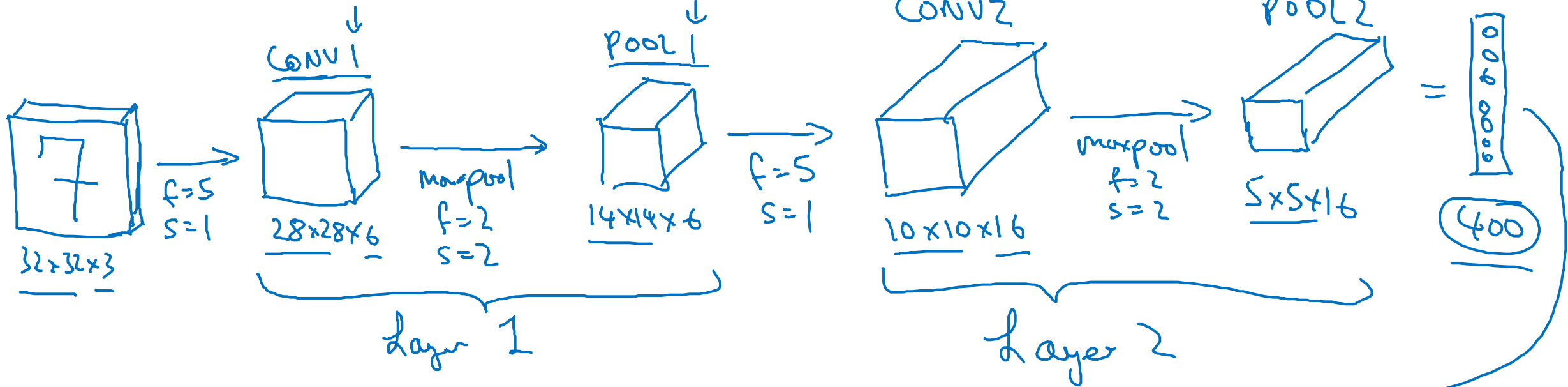
# Convolutional Neural Networks

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## Convolutional neural network example

# Neural network example

(LeNet-5)



# Neural network example

	Activation shape	Activation Size	# parameters
Input:	(32,32,3)	— 3,072 $a^{[0]}$	0
CONV1 (f=5, s=1)	(28,28,8)	6,272	$(5*5*3 + 1) * 8 = 608$
POOL1	(14,14,8)	1,568	0 ←
CONV2 (f=5, s=1)	(10,10,16)	1,600	$(5*5*8 + 1) * 16 = 3216$
POOL2	(5,5,16)	400	0 ←
FC3	(120,1)	120	$400*120 + 120 = 48120$
FC4	(84,1)	84	$120*84 + 84 \text{ (not 1) } = 10164$
Softmax	(10,1)	10	$84*10 + 10 = 850$



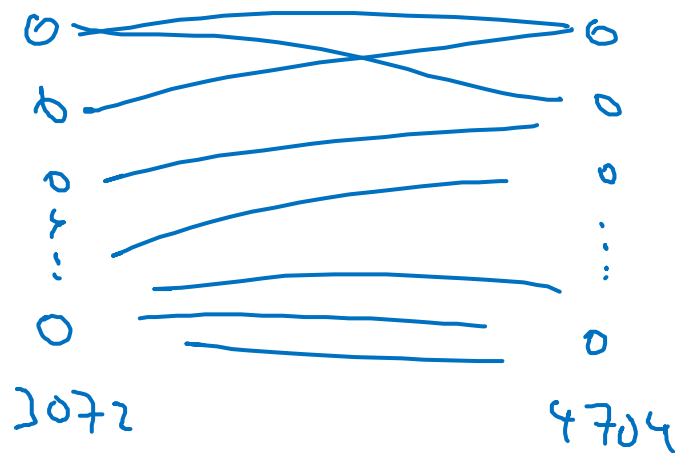
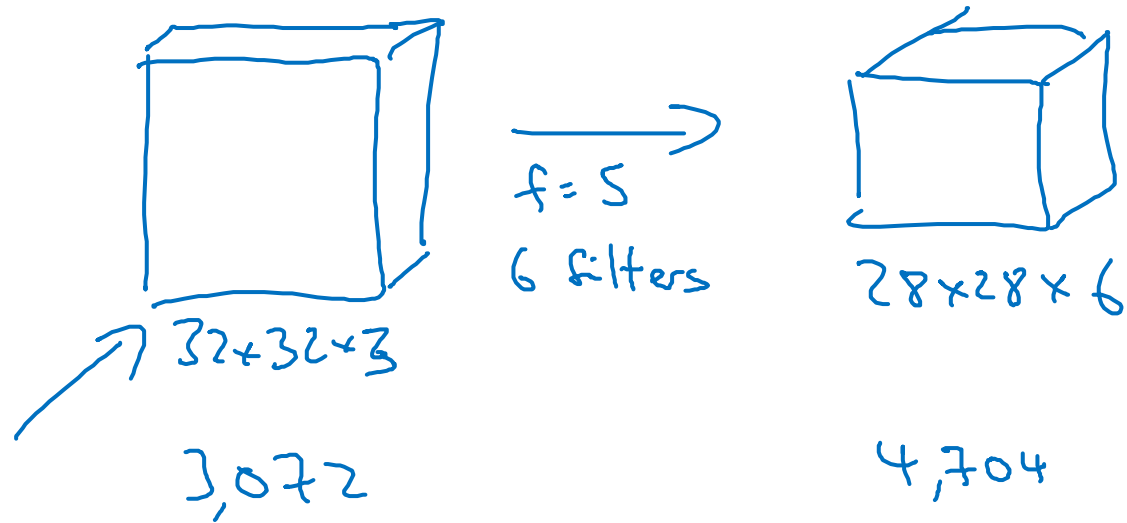
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# Convolutional Neural Networks

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## Why convolutions?

# Why convolutions



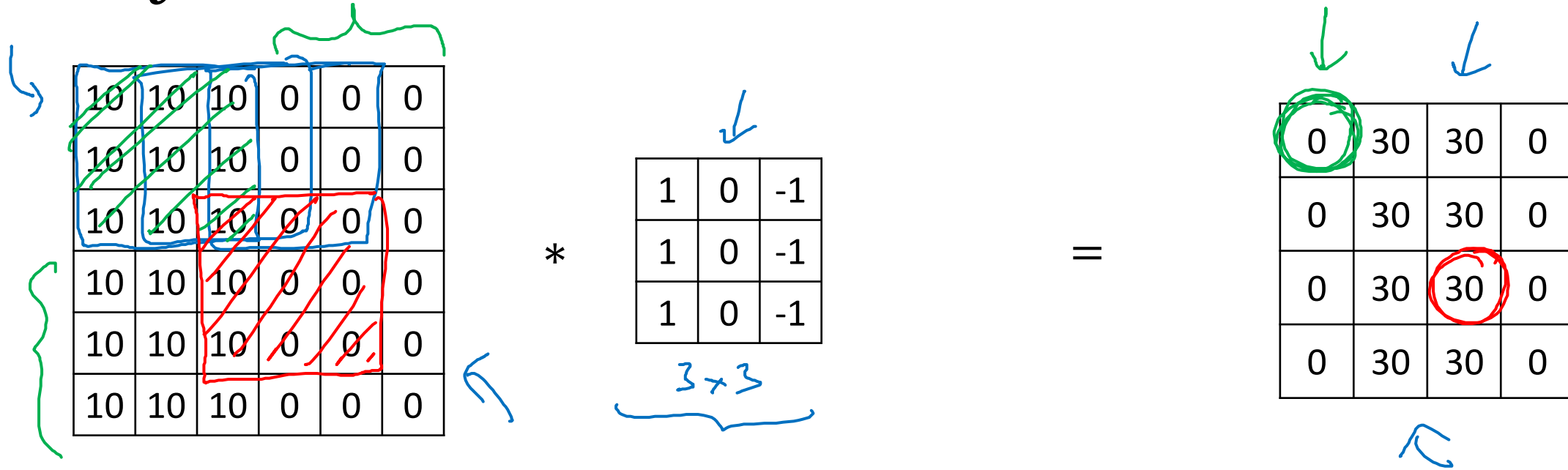
$$5 \times 5 = 25$$

$$26$$

$$6 \times 26 = 156 \text{ parameters}$$

$$3,072 \times 4,704 \approx \underline{14M}$$

# Why convolutions



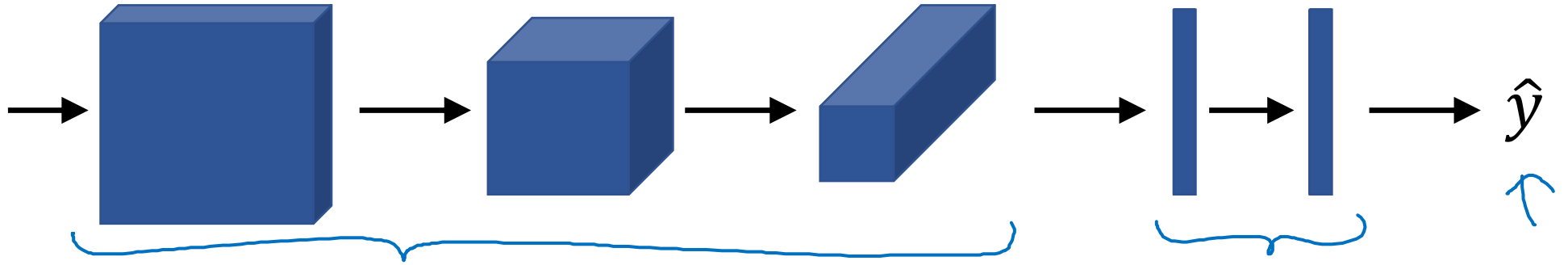
**Parameter sharing:** A feature detector (such as a vertical edge detector) that's useful in one part of the image is probably useful in another part of the image.

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



# Putting it together

Training set  $(x^{(1)}, y^{(1)}) \dots (x^{(m)}, y^{(m)})$ .



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

Use gradient descent to optimize parameters to reduce  $J$