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Convolutional Neural Networks

Computer vision

Computer Vision Problems

Image Classification

64x64

→ Cat? (0/1)

Object detection

Neural Style Transfer

Andrew Ng

Deep Learning on large images

64x64 × 3

→ Cat? (0/1)

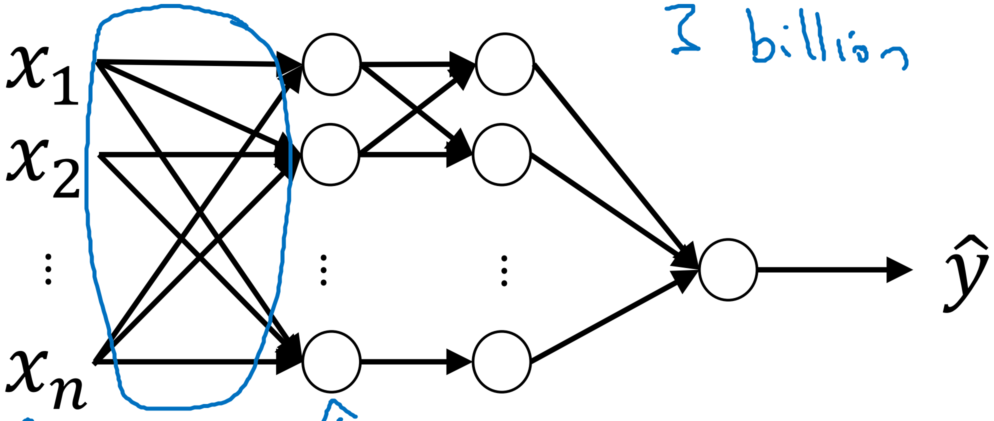
12288

1000 × 1000 × 3
= 3 million

$x \in \mathbb{R}^{3M}$

$W^{[1]}$ (1000, 3M)

3 billion



3M

1000

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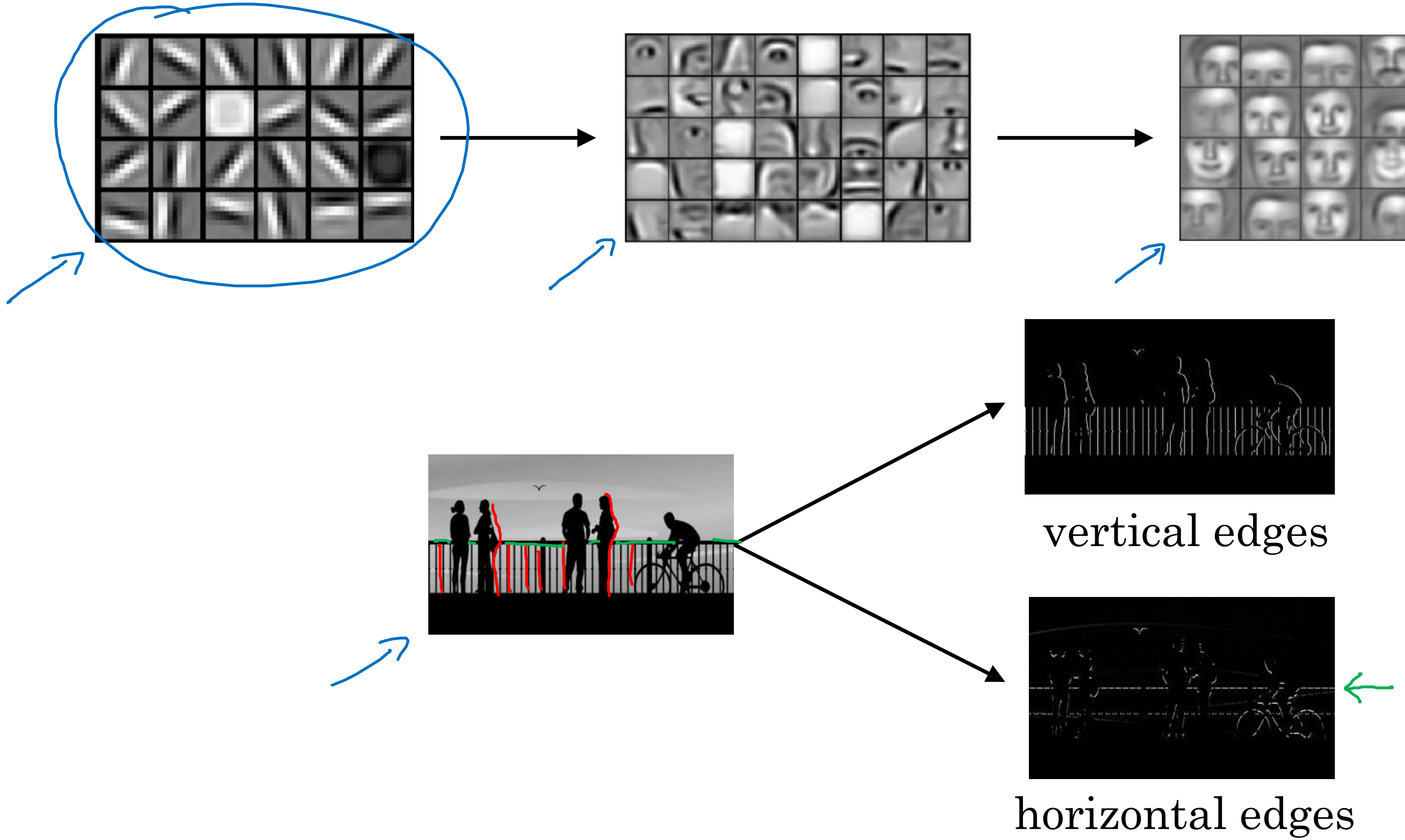
Convolutional Neural Networks

Edge detection example

Computer Vision Problem



Vertical edge detection

$3\times1 + 1\times1 + 2\times1 + 0\times0 + 5\times0 + 7\times0 + 1\times-1 + 8\times-1 + 2\times-1 = -5$

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

6×6

"convolution"

*

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

3×3

→ filter

kernel

=

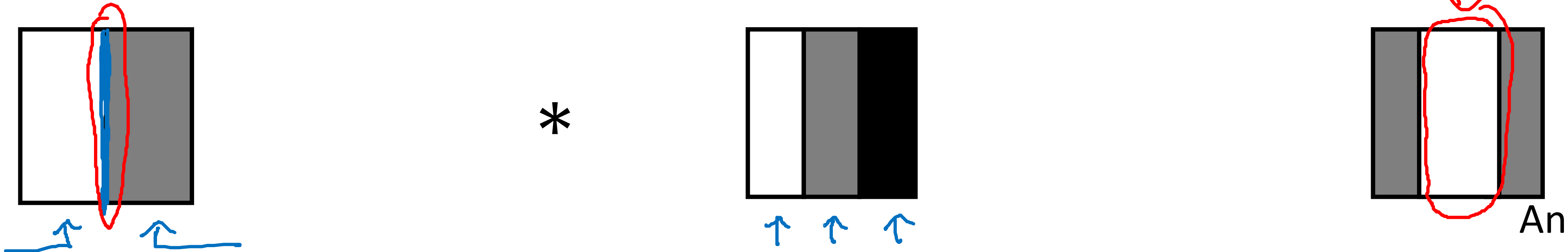
-5	-4	0	8
-10	-2	2	3
0	-2	-4	-7
-3	-2	-3	-16

4×4

Andrew Ng

Vertical edge detection

$$\underbrace{\begin{bmatrix} 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \end{bmatrix}}_{6 \times 6} * \underbrace{\begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}}_{3 \times 3} = \underbrace{\begin{bmatrix} 0 & 30 & 30 & 0 \\ 0 & 30 & 30 & 0 \\ 0 & 30 & 30 & 0 \\ 0 & 30 & 30 & 0 \end{bmatrix}}_{4 \times 4}$$



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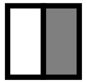
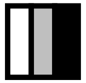
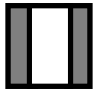
Convolutional Neural Networks

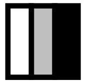
More edge detection

Vertical edge detection examples

$$
\begin{bmatrix}
10 & 10 & 10 & 0 & 0 & 0 \\
10 & 10 & 10 & 0 & 0 & 0 \\
10 & 10 & 10 & 0 & 0 & 0 \\
10 & 10 & 10 & 0 & 0 & 0 \\
10 & 10 & 10 & 0 & 0 & 0 \\
10 & 10 & 10 & 0 & 0 & 0
\end{bmatrix}
*
\begin{bmatrix}
1 & 0 & -1 \\
1 & 0 & -1 \\
1 & 0 & -1
\end{bmatrix}
=
\begin{bmatrix}
0 & 30 & 30 & 0 \\
0 & 30 & 30 & 0 \\
0 & 30 & 30 & 0 \\
0 & 30 & 30 & 0
\end{bmatrix}
$$

$$
\begin{bmatrix}
0 & 0 & 0 & 10 & 10 & 10 \\
0 & 0 & 0 & 10 & 10 & 10 \\
0 & 0 & 0 & 10 & 10 & 10 \\
0 & 0 & 0 & 10 & 10 & 10 \\
0 & 0 & 0 & 10 & 10 & 10 \\
0 & 0 & 0 & 10 & 10 & 10
\end{bmatrix}
*
\begin{bmatrix}
1 & 0 & -1 \\
1 & 0 & -1 \\
1 & 0 & -1
\end{bmatrix}
=
\begin{bmatrix}
0 & -30 & -30 & 0 \\
0 & -30 & -30 & 0 \\
0 & -30 & -30 & 0 \\
0 & -30 & -30 & 0
\end{bmatrix}
$$

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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

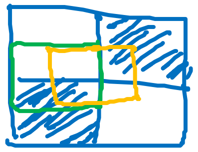
6 x 6

$*$

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

3×3

$=$

45°
70°
73°

Convolutional Neural Networks

Padding

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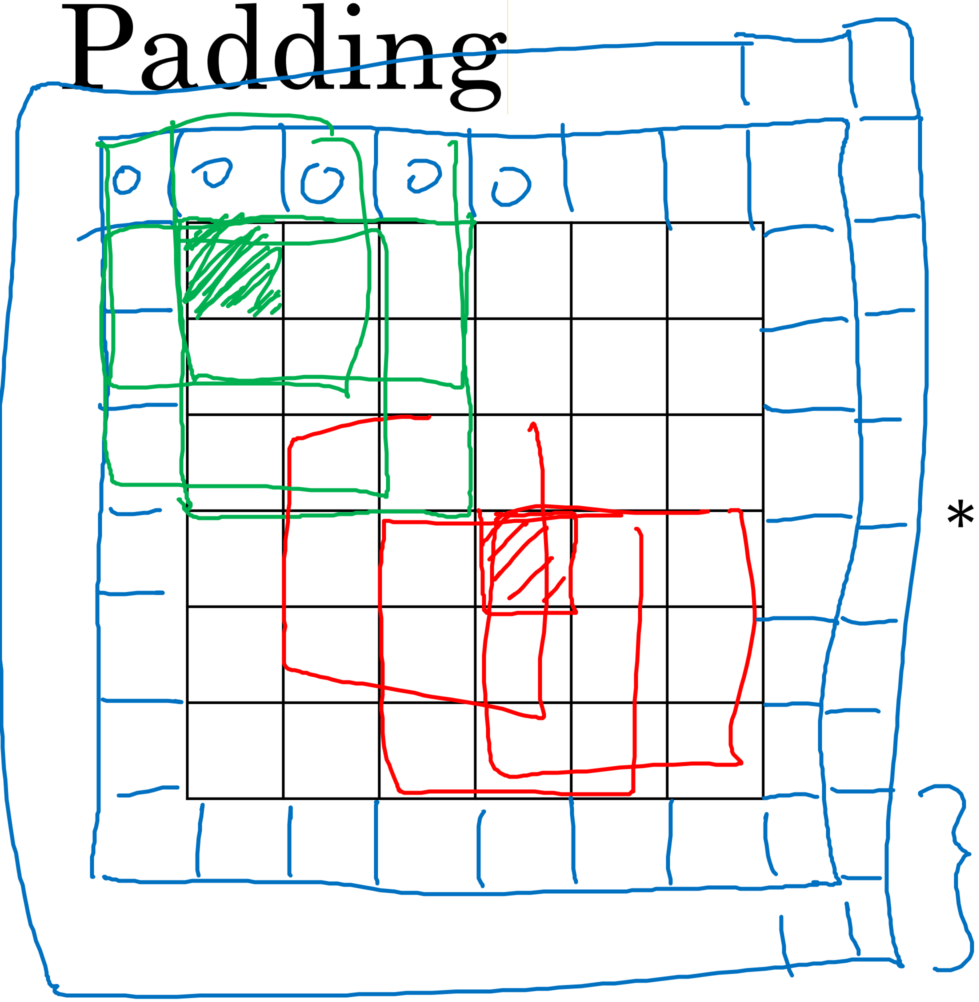
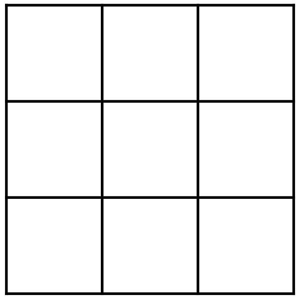
Padding

- shrinky output
- throw away info from edge



p=2

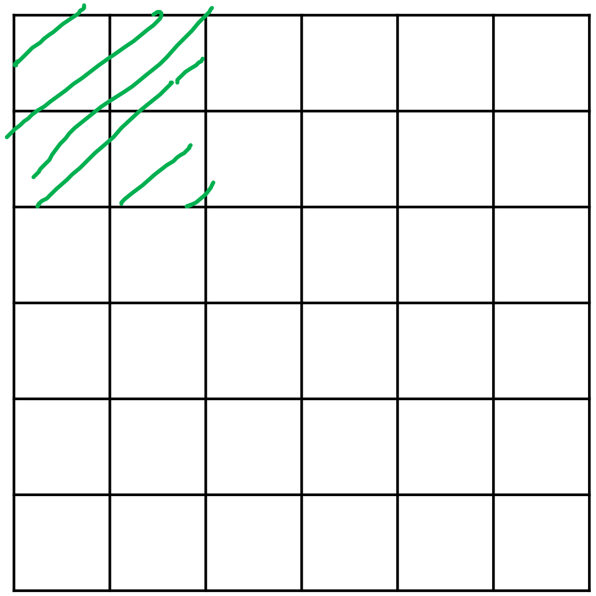
$*$



3×3

$f \times f$

$=$



6×6

~~4×4~~

$6 \times 6 \rightarrow 8 \times 8$

$n \times n$

$n - f + 1 \times n - f + 1$

$6 - 3 + 1 = 4$

$n + 2p - f + 1 \times n + 2p - f + 1$

$6 + 2 - 3 + 1 \times \_\_ = 6 \times 6$

p = padding size
f = filter size
n = final dimension

P = padding = 1

Andrew Ng

Valid and Same convolutions

→ no padding

"Valid": $n \times n \quad * \quad f \times f \quad \rightarrow \quad n-f+1 \times n-f+1$

$6 \times 6 \quad * \quad 3 \times 3 \quad \rightarrow \quad 4 \times 4$

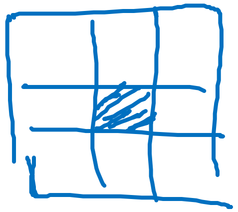
"Same": Pad so that output size is the same as the input size.

$n+2p-f+1 \times n+2p-f+1$

$\cancel{n}+2p-f+1 = \cancel{n} \Rightarrow \boxed{p = \frac{f-1}{2}}$

$3 \times 3 \qquad p = \frac{3-1}{2} = 1$ | 5×5 $\;f=5 \qquad p=2$

f is usually odd



1×1

3×3

5×5

7×7

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Convolutional Neural Networks

Strided convolutions

跨步

Strided convolution

$$\underbrace{\begin{bmatrix} 2 & 3 & 7 & 4 & 6 & 2 & 9 \\ 6 & 6 & 9 & 8 & 7 & 4 & 3 \\ 3 & 4 & 8 & 3 & 8 & 9 & 7 \\ 7 & 8 & 3 & 6 & 6 & 3 & 4 \\ 4 & 2 & 1 & 8 & 3 & 4 & 6 \\ 3 & 2 & 4 & 1 & 9 & 8 & 3 \\ 0 & 1 & 3 & 9 & 2 & 1 & 4 \end{bmatrix}}_{7\times 7} * \underbrace{\begin{bmatrix} 3 & 4 & 4 \\ 1 & 0 & 2 \\ -1 & 0 & 3 \end{bmatrix}}_{3\times 3} = \underbrace{\begin{bmatrix} 91 & 100 & 83 \\ 69 & 91 & 127 \\ 44 & 72 & 74 \end{bmatrix}}_{3\times 3}$$

stride = 2

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

$n \times n \quad * \quad f \times f$

padding p $\qquad$ stride s

$s = 2$

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

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

Andrew Ng

Summary of convolutions

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

padding $p \qquad$ stride s

Output size:

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

Andrew Ng

Technical note on cross-correlation vs. convolution

Convolution in math textbook:

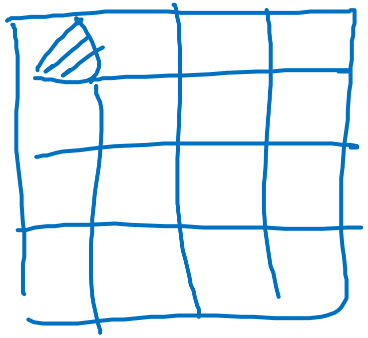
2^{7}	3^{2}	7^{5}	4	6	2
6^{9}	6^{0}	9^{4}	8	7	4
3^{-1}	4^{1}	8^{3}	3	8	9
7	8	3	6	6	3
4	2	1	8	3	4
3	2	4	1	9	8

*

3	4	5
1	0	2
-1	9	7

7	2	5
9	0	4
-1	1	3

=



DL -> skip the flipping

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

convolves

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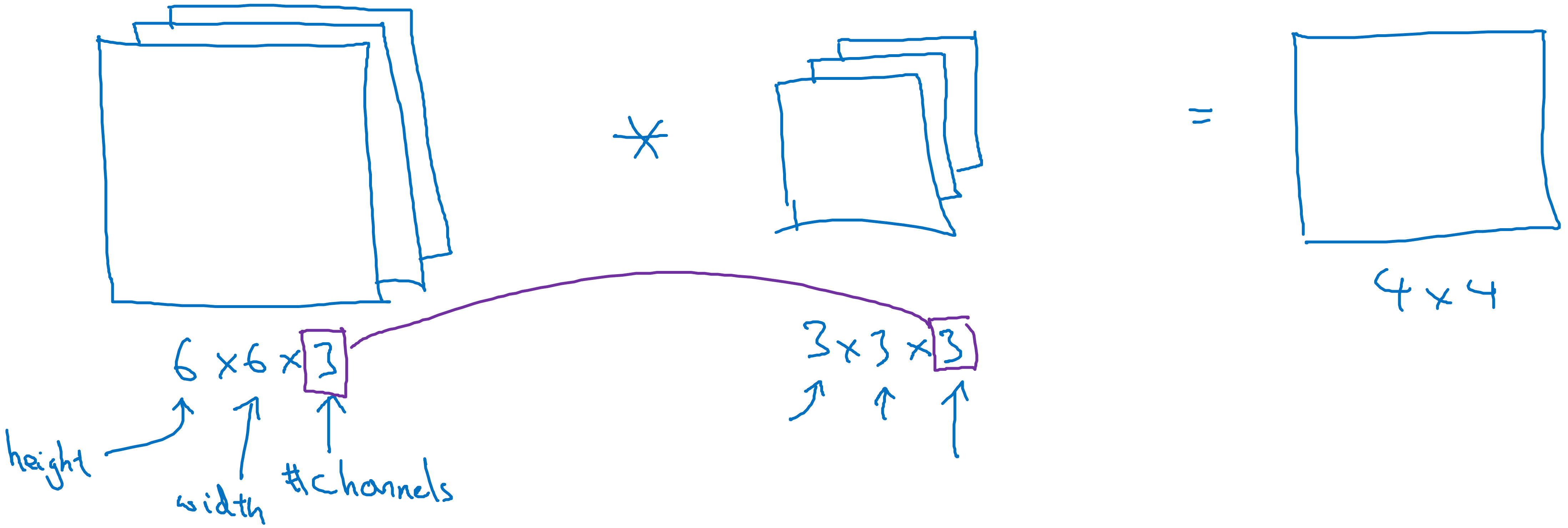
Convolutional Neural Networks

Convolutions over volumes

Convolutions on RGB images



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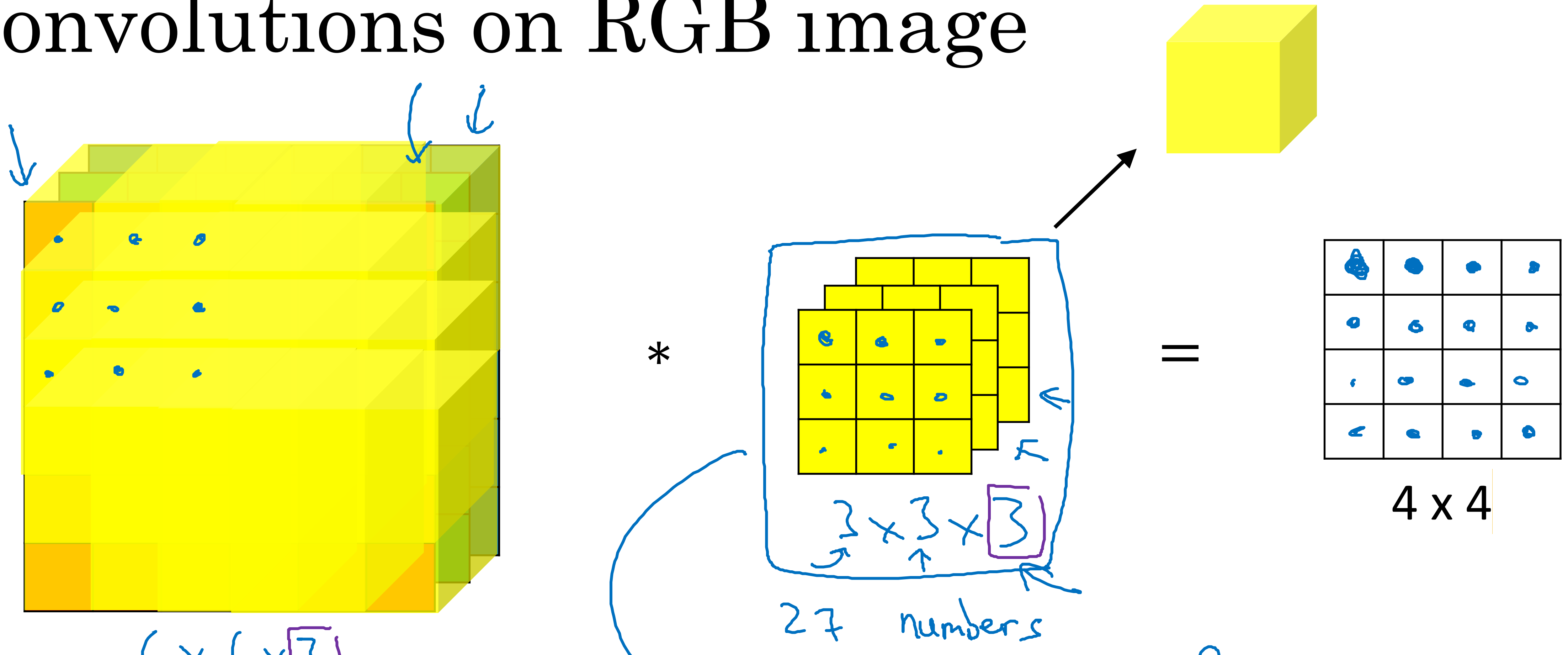
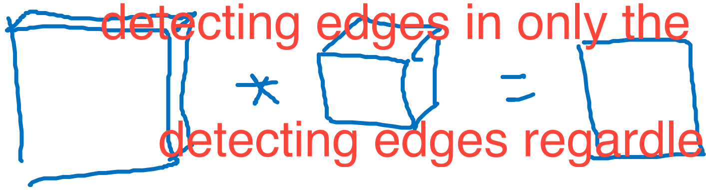
Convolutions on RGB image



6 x 6 x 3



detecting edges in only the red channels

R $\begin{bmatrix}1&0&-1\\1&0&-1\\1&0&-1\end{bmatrix}$ G $\begin{bmatrix}0&0&0\\0&0&0\\0&0&0\end{bmatrix}$ B $\begin{bmatrix}0&0&0\\0&0&0\\0&0&0\end{bmatrix}$ → 3x3x3

detecting edges regardless of color

R $\begin{bmatrix}1&0&-1\\1&0&-1\\1&0&-1\end{bmatrix}$ G $\begin{bmatrix}1&0&-1\\1&0&-1\\1&0&-1\end{bmatrix}$ B $\begin{bmatrix}1&0&-1\\1&0&-1\\1&0&-1\end{bmatrix}$ → 3x3x3

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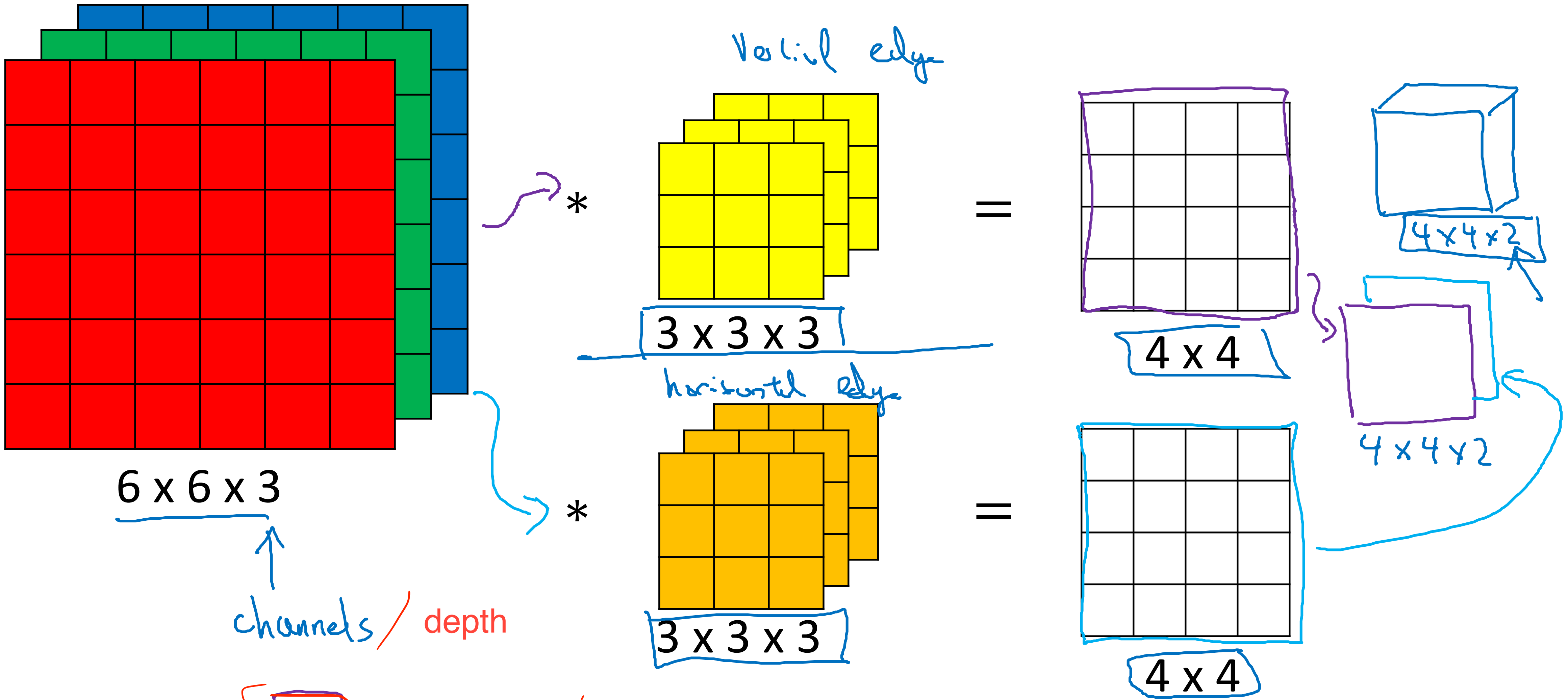
Multiple filters



Summary: $n \times n \times n_c \ * \ f \times f \times n_c \rightarrow n-f+1 \times n-f+1 \times n_c'$

$6 \times 6 \times 3 \qquad 3 \times 3 \times 3 \qquad 4 \times 4 \times 2$ ← #filters

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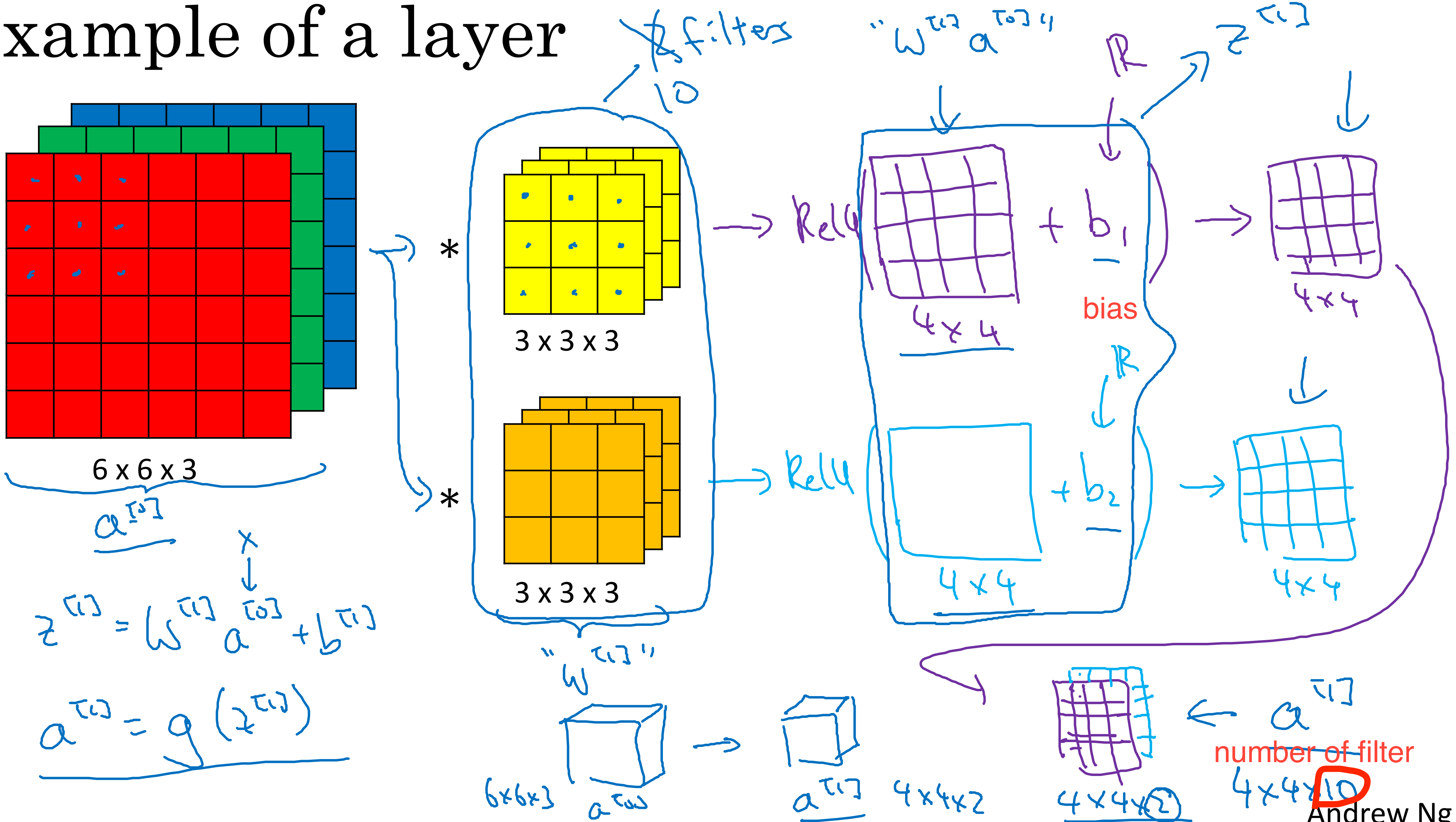
Convolutional Neural Networks

One layer of a convolutional network

Example of a layer



$$z^{[1]} = W^{[1]} a^{[0]} + b^{[1]}$$

$$a^{[1]} = g(z^{[1]})$$

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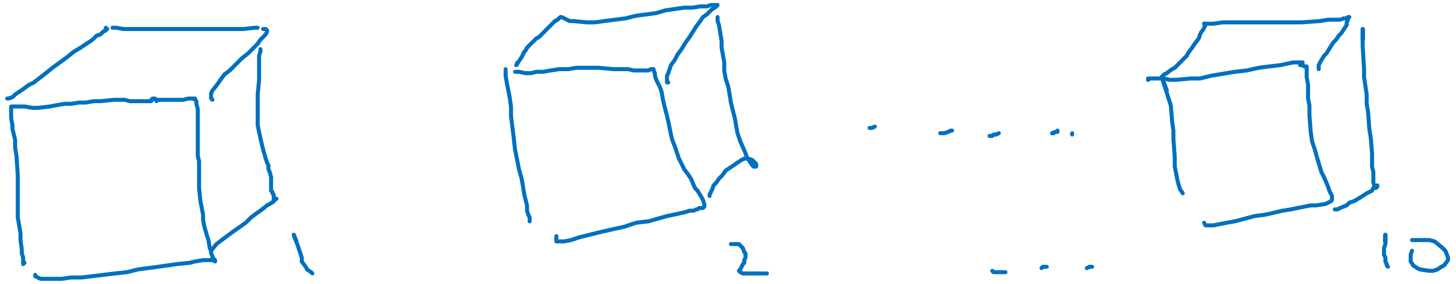
Number of parameters in one layer

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



3x3x3

27 parameters.

+bias

→ 28 parameters.

280 parameters.

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Summary of notation

If layer l is a convolution layer:

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

$p^{[l]}$ = padding

$s^{[l]}$ = stride

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

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

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

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

sample

$n_c \times n_H \times n_W$

Weights: $f^{[l]} \times f^{[l]} \times n_c^{[l-1]} \times n_c^{[l]}$ ← #filters in layer l.

bias: $n_c^{[l]}$ – $(1,1,1,n_c^{[l]})$

Input: $n_H^{[l-1]} \times n_W^{[l-1]} \times \boxed{n_c^{[l-1]}}$

Output: $n_H^{[l]} \times n_W^{[l]} \times \boxed{n_c^{[l]}}$

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

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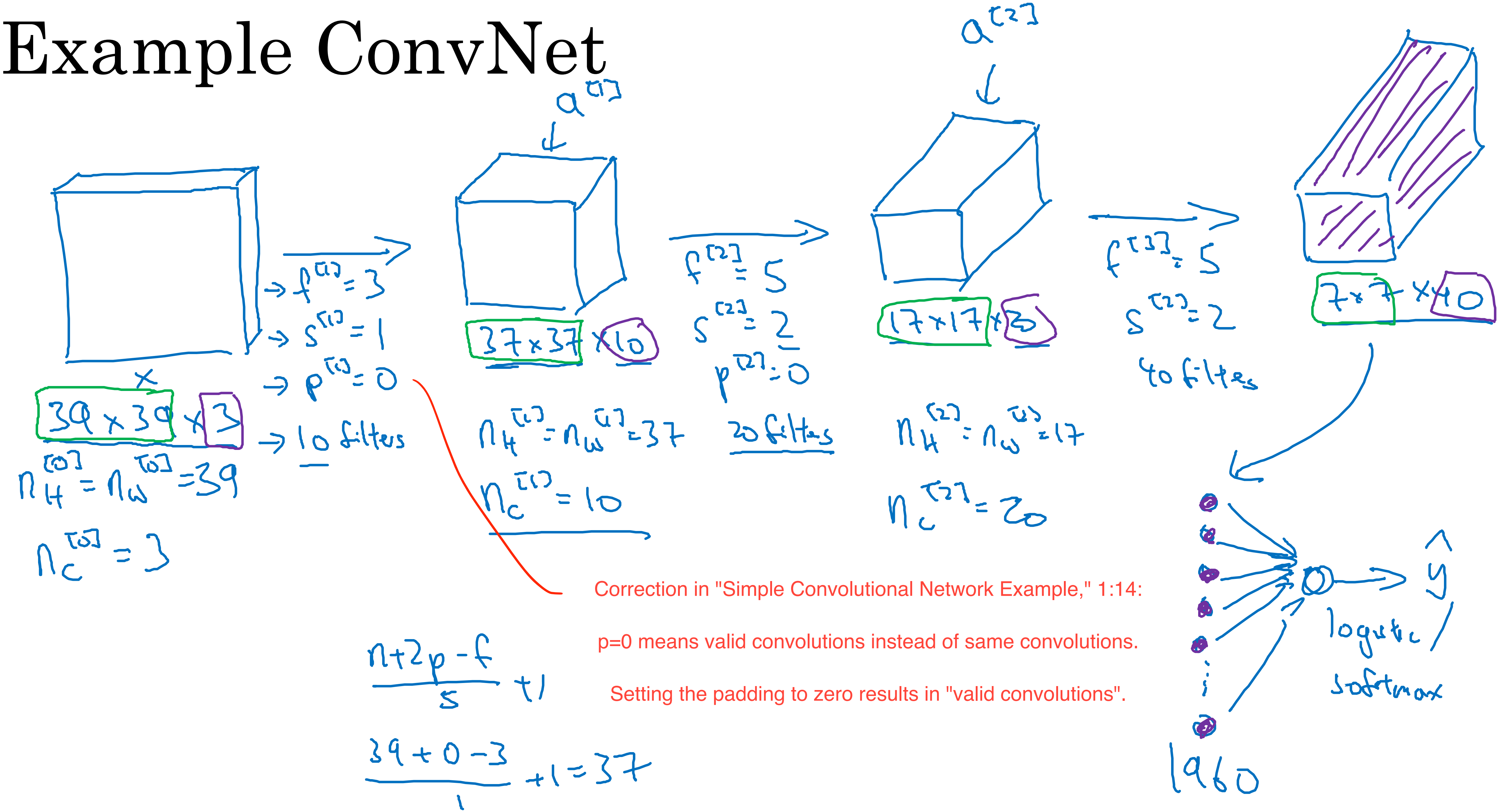
Convolutional Neural Networks

A simple convolution network example

Example ConvNet



Correction in "Simple Convolutional Network Example," 1:14:

p=0 means valid convolutions instead of same convolutions.

Setting the padding to zero results in "valid convolutions".

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Types of layer in a convolutional network:

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

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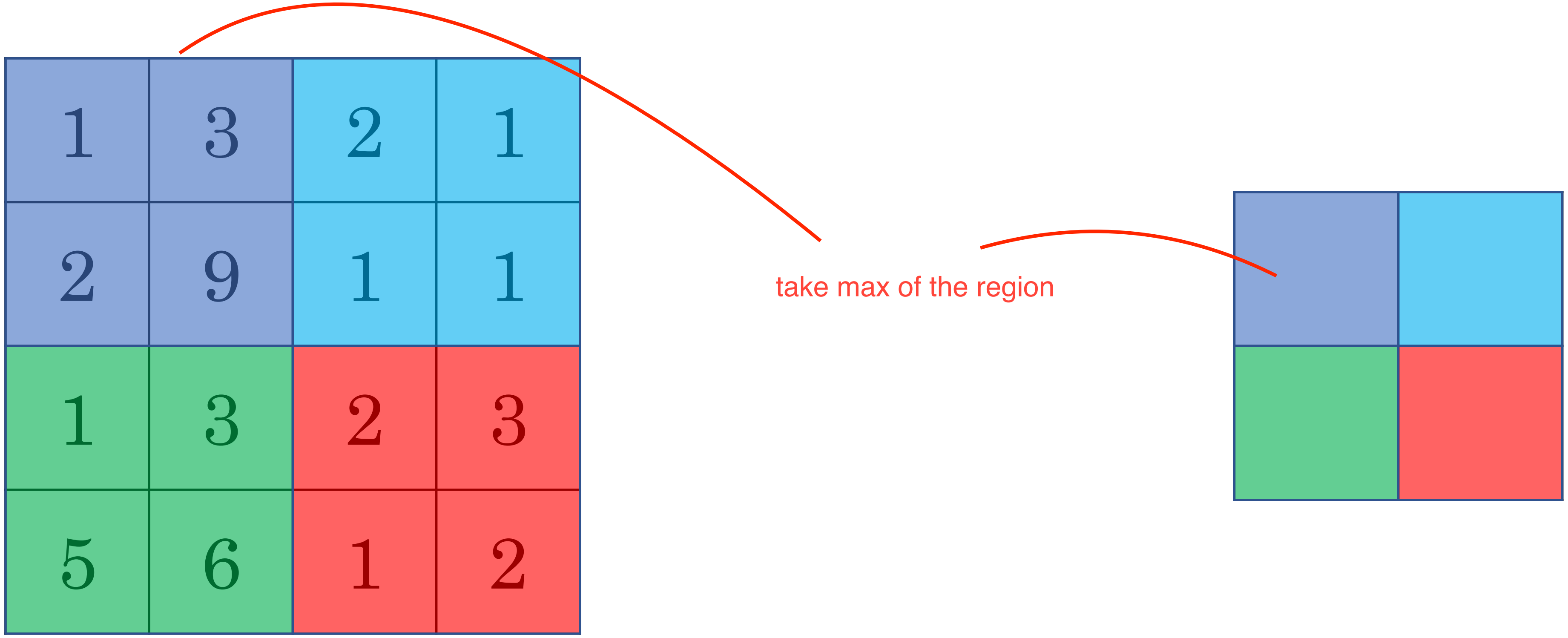
Convolutional Neural Networks

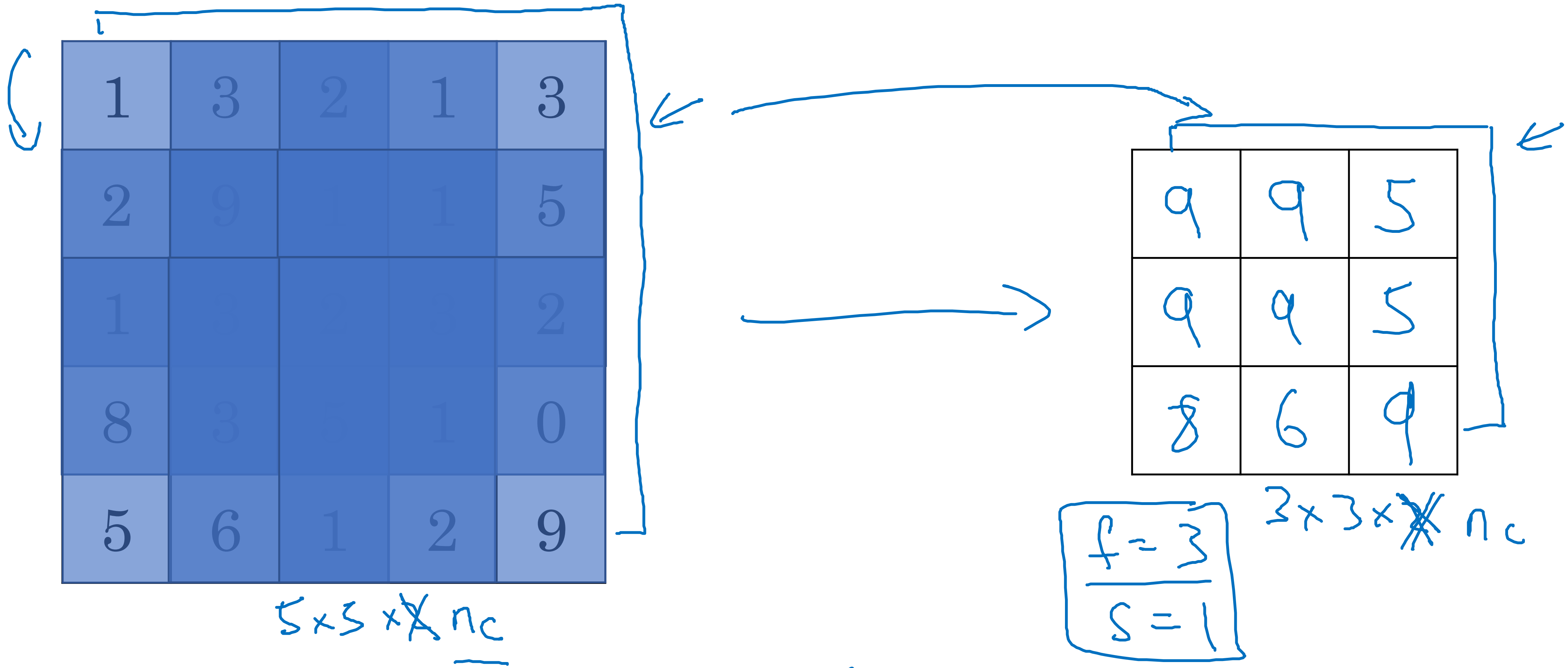
Pooling layers

Pooling layer: Max pooling

max pooling is used much more than avg pooling



Pooling layer: Max pooling



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

Pooling layer: Average pooling

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

$\longrightarrow$

3.75	1.25
4	2

hyperparameter

$f=2$

$s=2$

no parameter to learn for pooling layer

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

Andrew Ng

Summary of pooling

Hyperparameters:

f : filter size

s : stride

Max or average pooling

$f=2, s=2$

$f=3, s=2$

→ ~~p: padding.~~

No parameters to learn!

$$n_H \times n_W \times n_C$$

$$\downarrow$$

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

$$\times\ n_C$$

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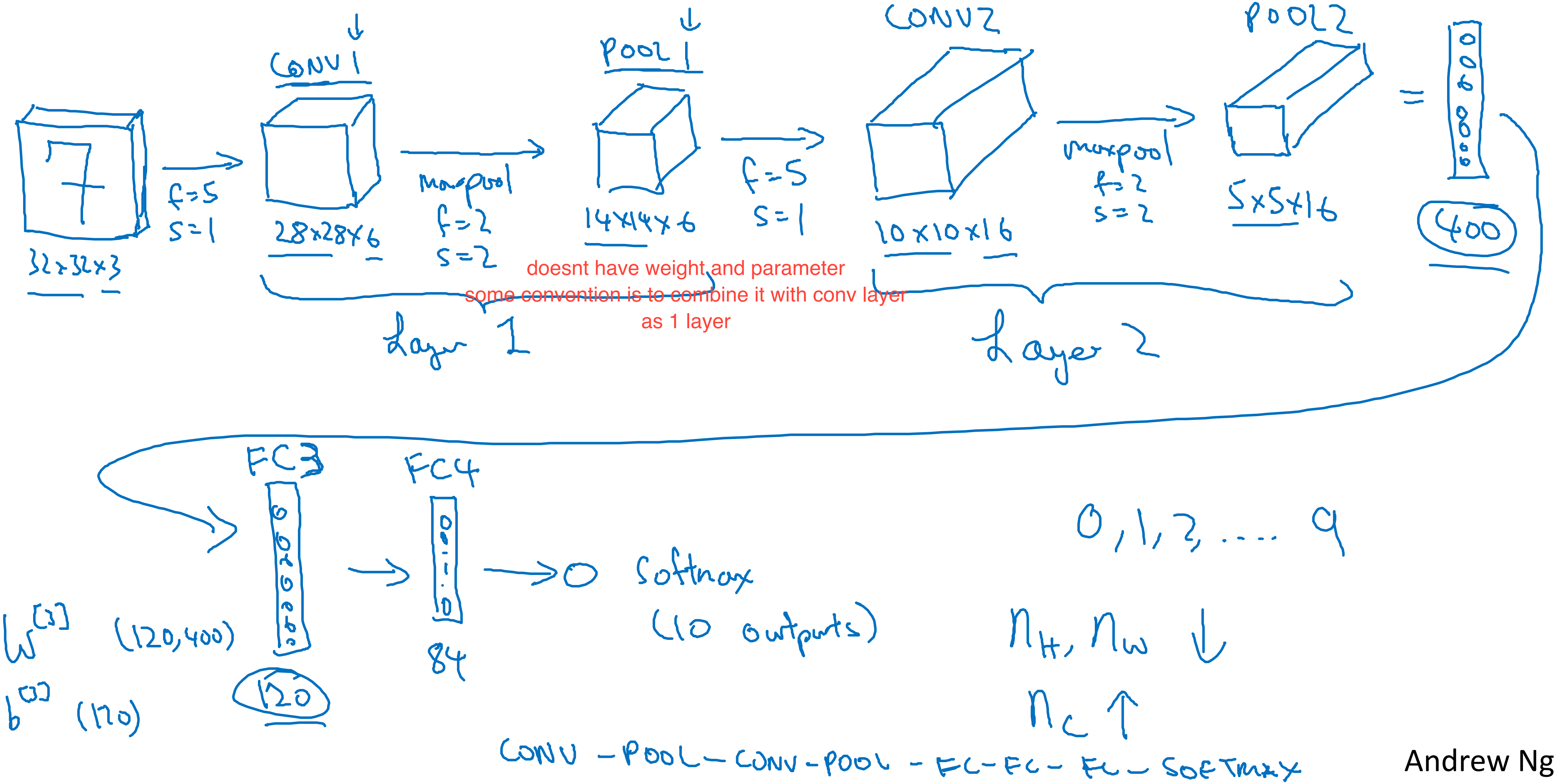
Convolutional Neural Networks

Convolutional neural network example

Neural network example (LeNet-5)



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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	608
POOL1	(14,14,8)	1,568	0
CONV2 (f=5, s=1)	(10,10,16)	1,600	3216
POOL2	(5,5,16)	400	0
FC3	(120,1)	120	48120
FC4	(84,1)	84	10164
Softmax	(10,1)	10	850

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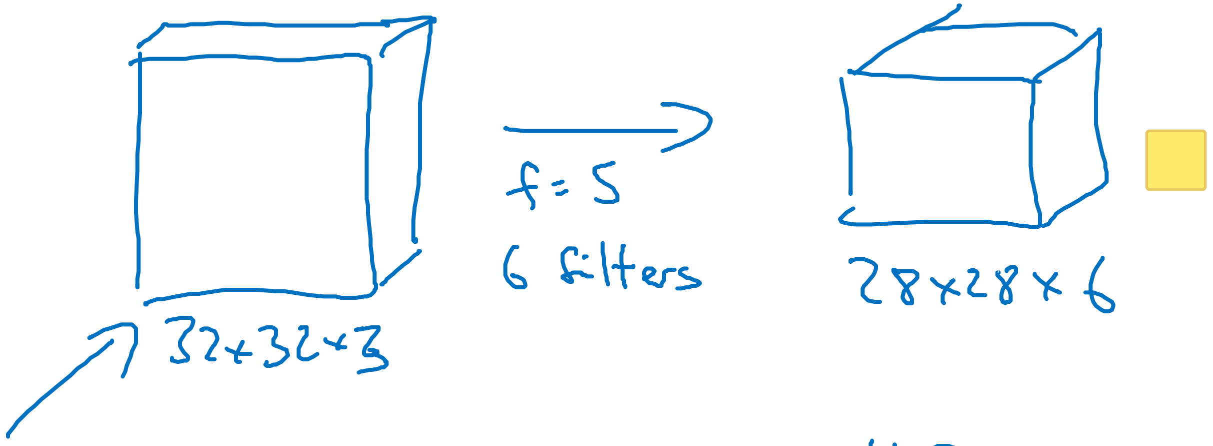
Convolutional Neural Networks

Why convolutions?

Why convolutions



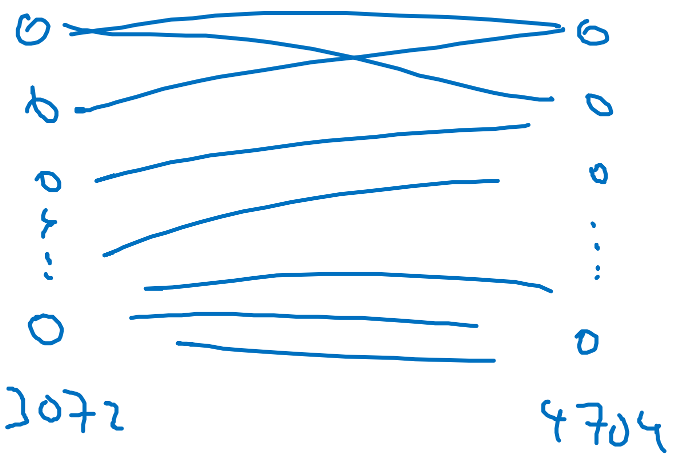
3,072 4,704

$5 \times 5 = 25$

26

$6 \times 26 = 156$ parameters

correction: (5*5*3+1)*6 = 456



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

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Why convolutions

translation invariance

$$\begin{array}{|c|c|c|c|c|c|}\hline 10 & 10 & 10 & 0 & 0 & 0 \\ \hline 10 & 10 & 10 & 0 & 0 & 0 \\ \hline 10 & 10 & 10 & 0 & 0 & 0 \\ \hline 10 & 10 & 10 & 0 & 0 & 0 \\ \hline 10 & 10 & 10 & 0 & 0 & 0 \\ \hline 10 & 10 & 10 & 0 & 0 & 0 \\ \hline \end{array} * \underbrace{\begin{array}{|c|c|c|}\hline 1 & 0 & -1 \\ \hline 1 & 0 & -1 \\ \hline 1 & 0 & -1 \\ \hline \end{array}}_{3\times 3} = \begin{array}{|c|c|c|c|}\hline 0 & 30 & 30 & 0 \\ \hline 0 & 30 & 30 & 0 \\ \hline 0 & 30 & 30 & 0 \\ \hline 0 & 30 & 30 & 0 \\ \hline \end{array}$$

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.

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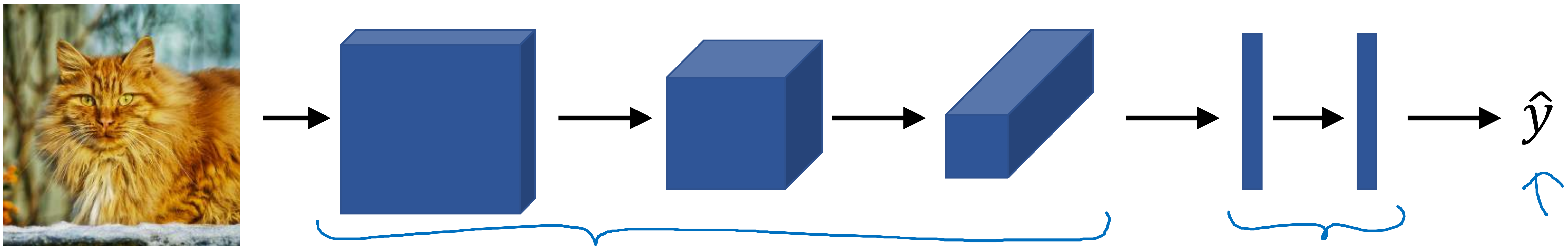
Putting it together

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

$\boxed{w, b}$



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