Copyright Notice

deeplearning.ai

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)

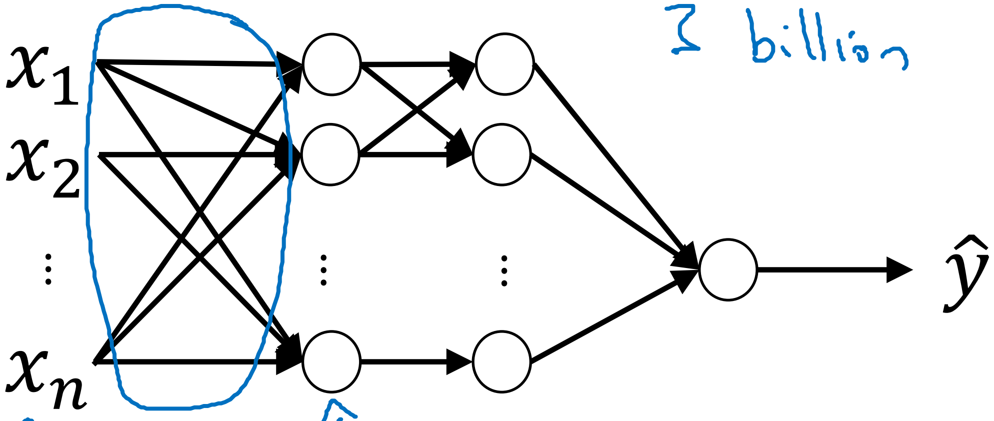
12288

1000 × 1000 × 3
= 3 million

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

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

3 billion



3M

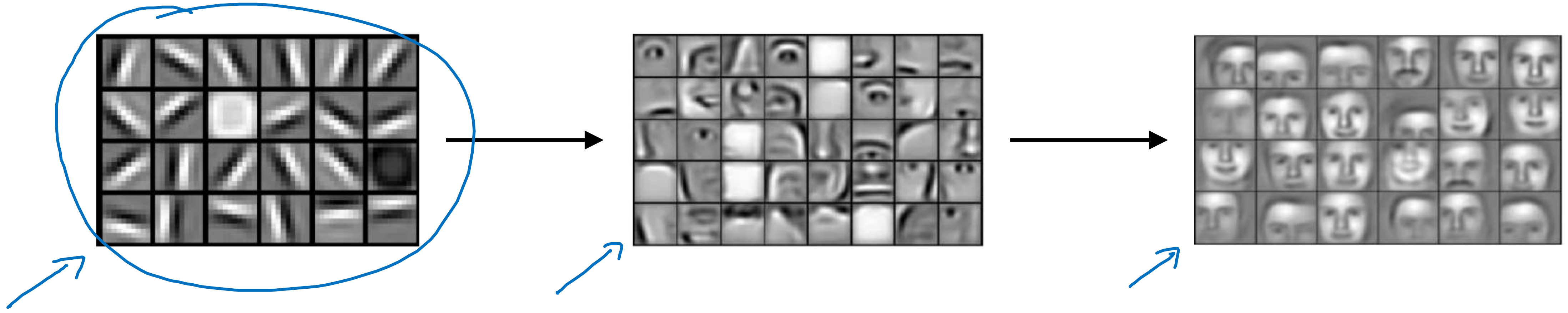
1000

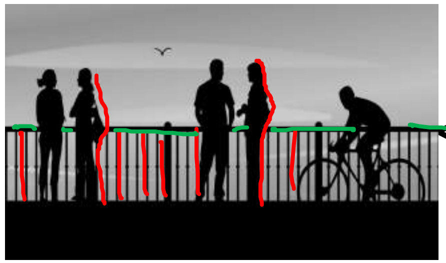
deeplearning.ai

Convolutional Neural Networks

Edge detection example

Computer Vision Problem





vertical edges

horizontal edges

Andrew Ng

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

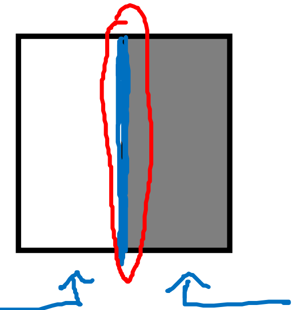
=

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

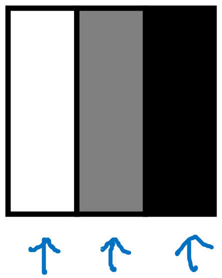
4×4

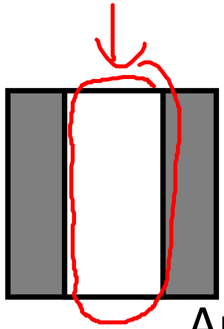
Vertical edge detection

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



*





Andrew Ng

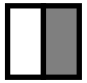
deeplearning.ai

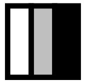
Convolutional Neural Networks

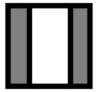
More edge detection

Vertical edge detection examples

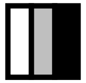
$$\begin{bmatrix} 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \end{bmatrix} * \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} = \boxed{\begin{bmatrix} 0 & 30 &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







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



Andrew Ng

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

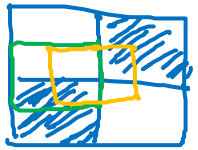
6x6

*

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



Andrew Ng

Learning to detect edges

Giviing more wts to central row.

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°

Andrew Ng

deeplearning.ai

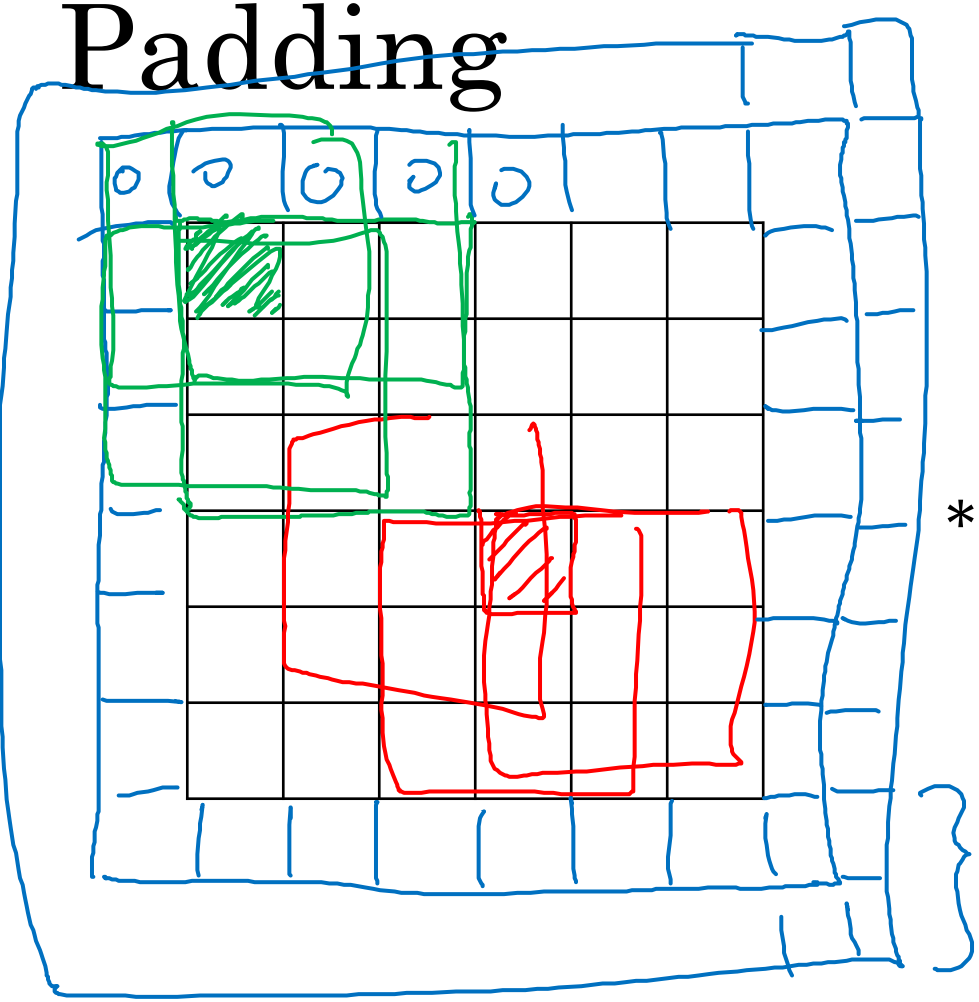
Convolutional Neural Networks

Padding

Padding is done to make convolve out image to be of the same size as that of the input imag. We pad

Padding

- shrinky output
- throw away info from edge

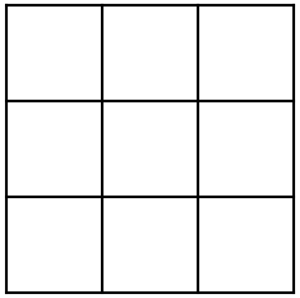


p=2

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

$n \times n$

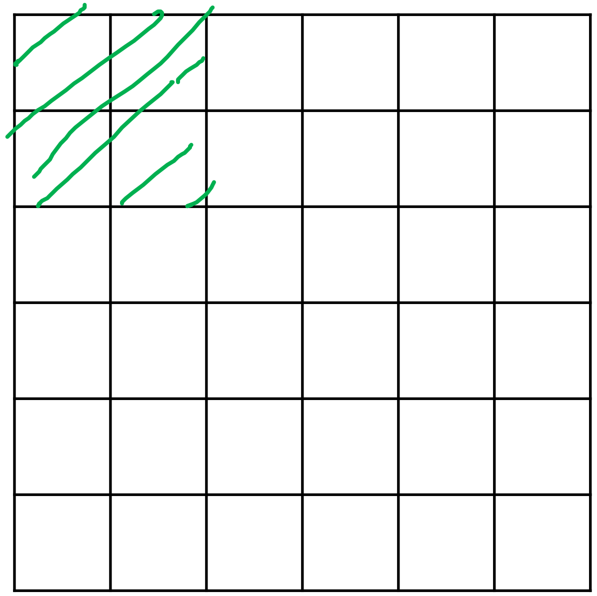
$*$



3×3

f×f

$=$



6×6

~~4×4~~

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

$6-3+1=4$

$p = \text{padding} = 1$

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

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

Andrew Ng

Valid and Same convolutions

→ no padding

"Valid": $n \times n \quad * \quad f \times f \longrightarrow \underline{n-f+1} \times n-f+1$

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

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

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

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

$3 \times 3 \quad p = \frac{3-1}{2} = 1 \quad \Big| \quad 5 \times 5 \quad p=2$

$f=5$

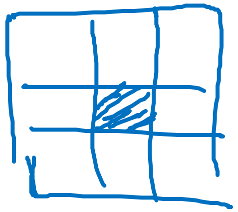
f is usually odd

1×1

3×3

5×5

7×7



Andrew Ng

final ouput image start ((n+2p-f)/s + 1)

deeplearning.ai

Convolutional Neural Networks

Strided convolutions

Strided convolution

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

7×7

*

3	4	4
1	0	2
-1	0	3

3×3

=

91	100	83
69	91	127
44	72	74

3×3

stride = 2

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

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

padding p stride s

$s = 2$

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

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

Andrew Ng

Summary of convolutions

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

padding $p \quad\quad$ stride s

Output size:

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

Technical note on cross-correlation vs. convolution

Convolution in math textbook:

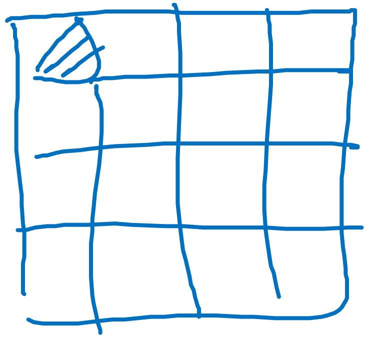
2 7	3 2	7 5	4	6	2
6 9	6 0	9 4	8	7	4
3 -1	4 1	8 3	3	8	9
7	8	3	6	6	3
4	2	1	8	3	4
3	2	4	1	9	8

*

3	4	5
1	0	2
-1	9	7

7	2	5
9	0	4
-1	1	3

=



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

Andrew Ng

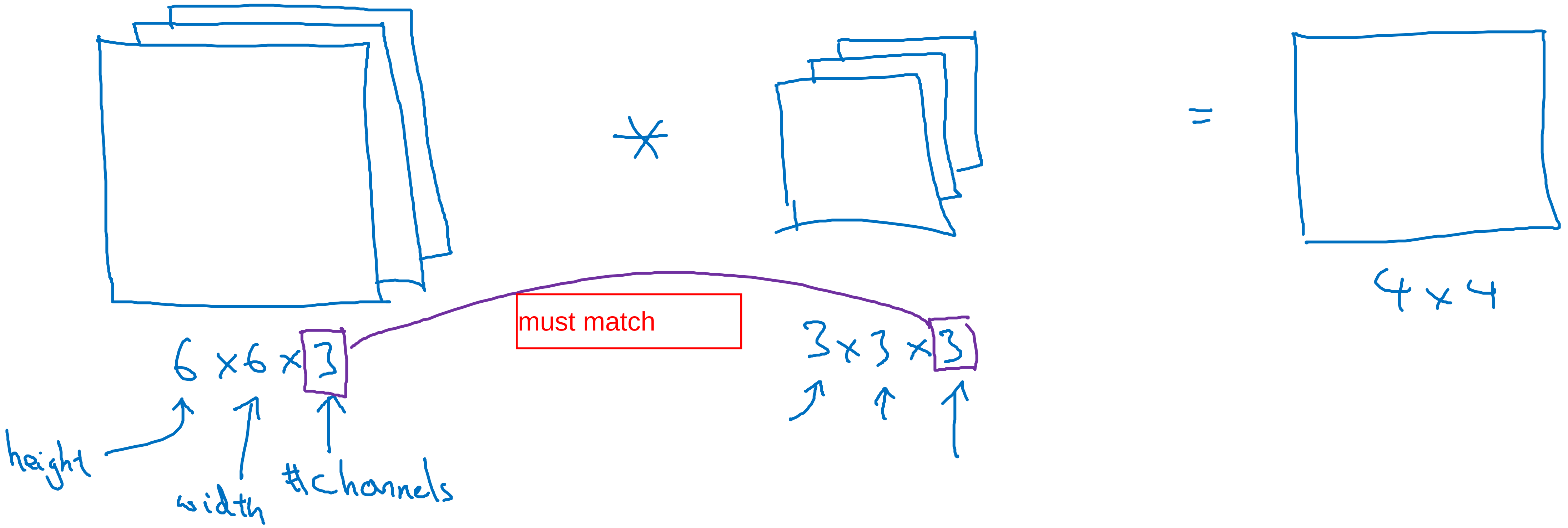
convolving volume with a 3D filter , but we get only a 2D result volume as th

Convolutional Neural Networks

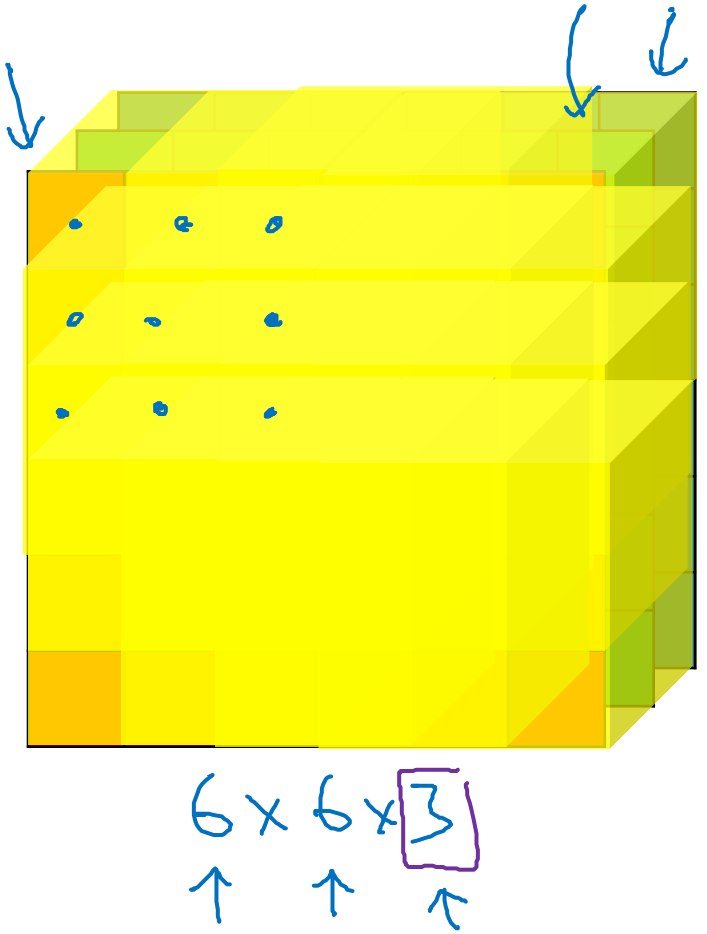
deeplearning.ai

Convolutions over volumes

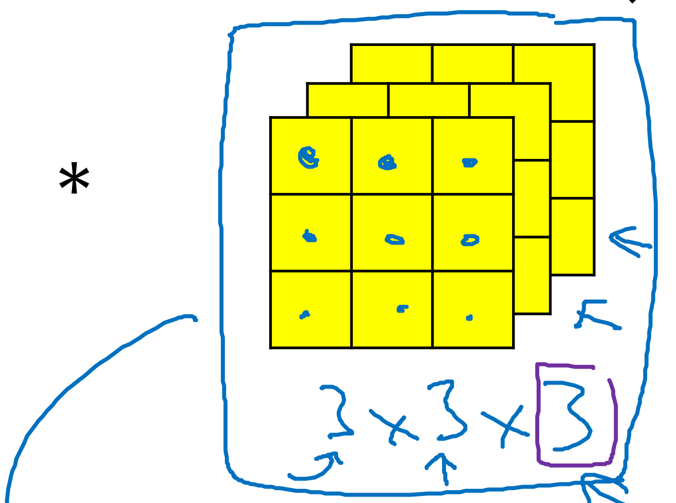
Convolutions on RGB images



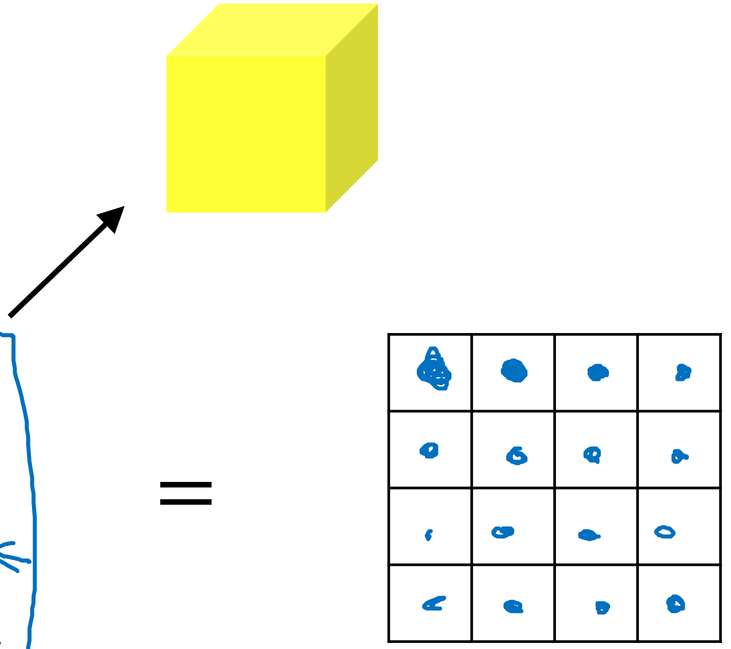
Convolutions on RGB image

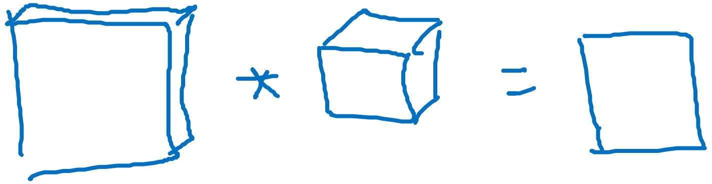


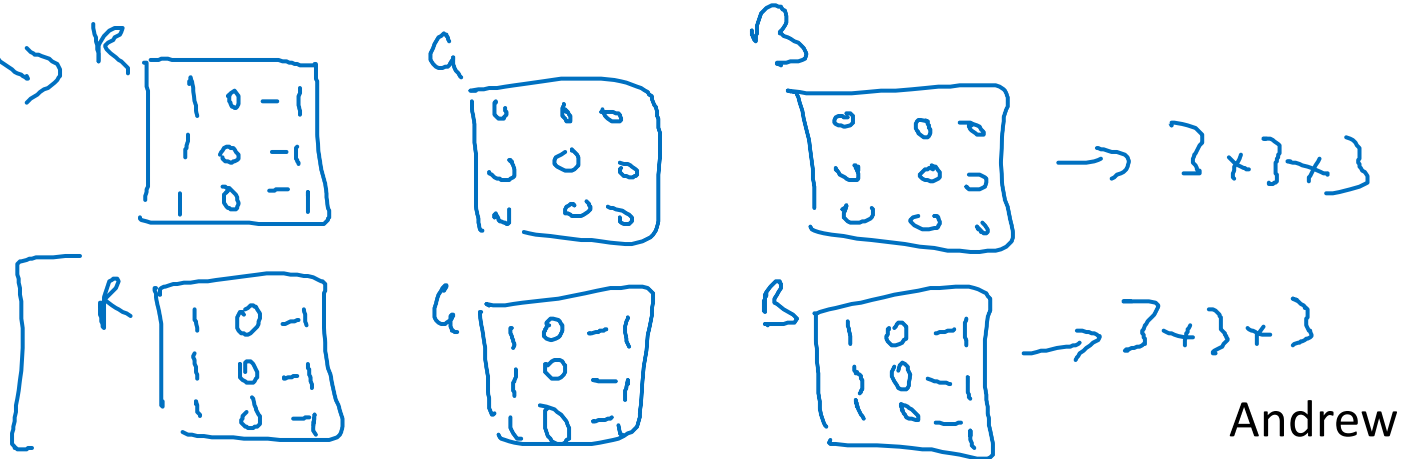
*



=

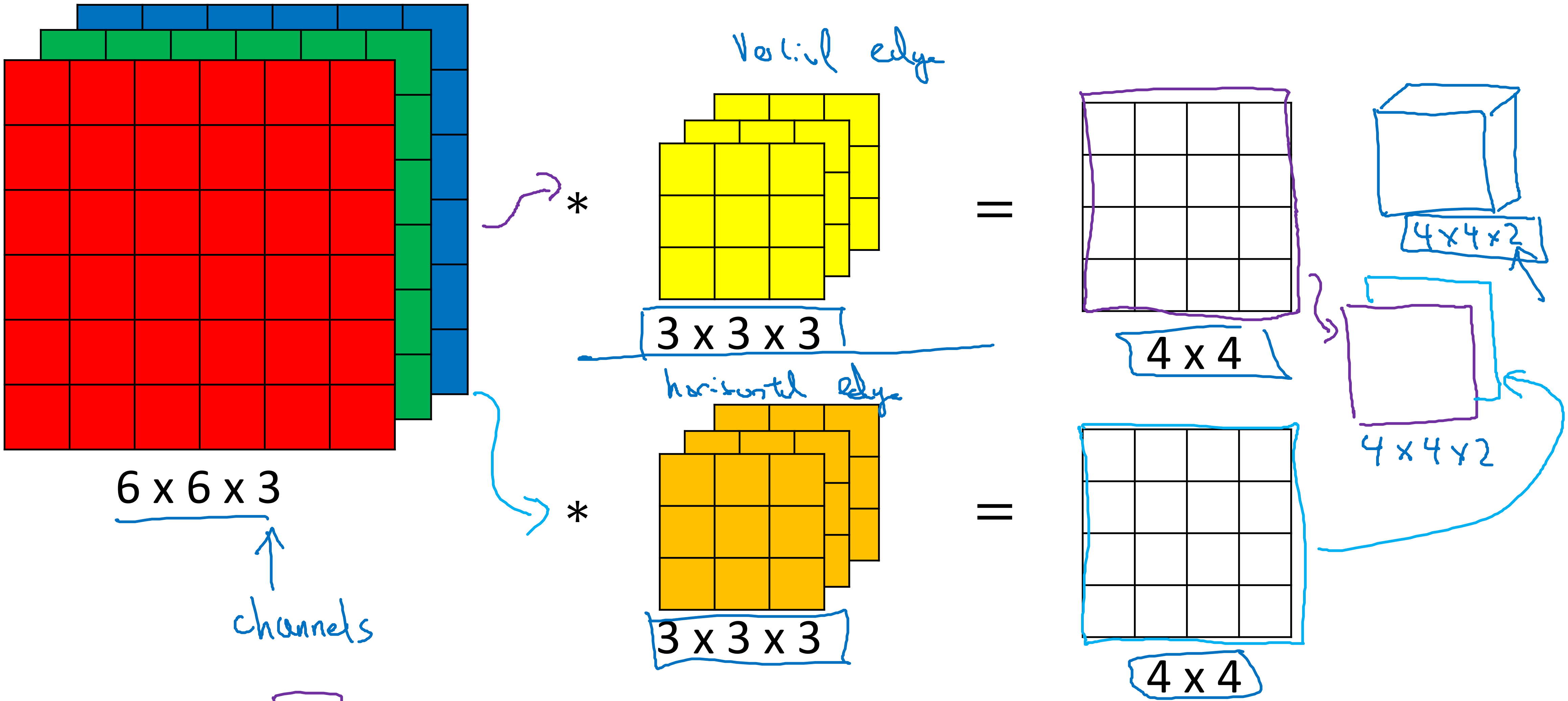






Andrew Ng

Multiple filters



Summary: $n \times n \times \boxed{n_c} \quad * \quad f \times f \times \boxed{n_c} \quad \longrightarrow \quad n-f+1 \times n-f+1 \times n_c'$

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

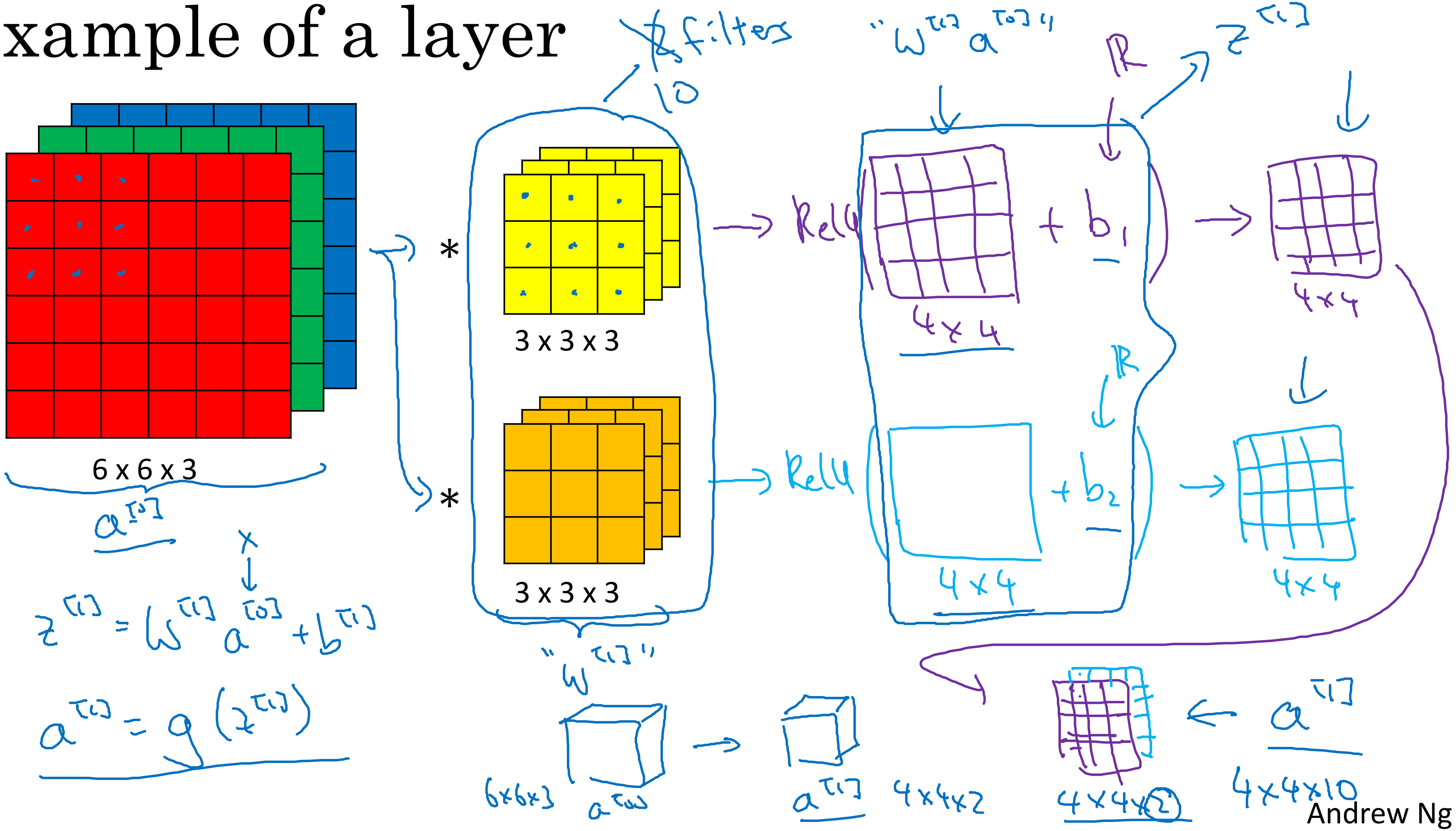
You see below in 280 waala example that no matter what the size of the input is , as long as long we are using a 10 filters , we willl only ne

Convolutional Neural Networks

deeplearning.ai

One layer of a convolutional network

Example of a layer

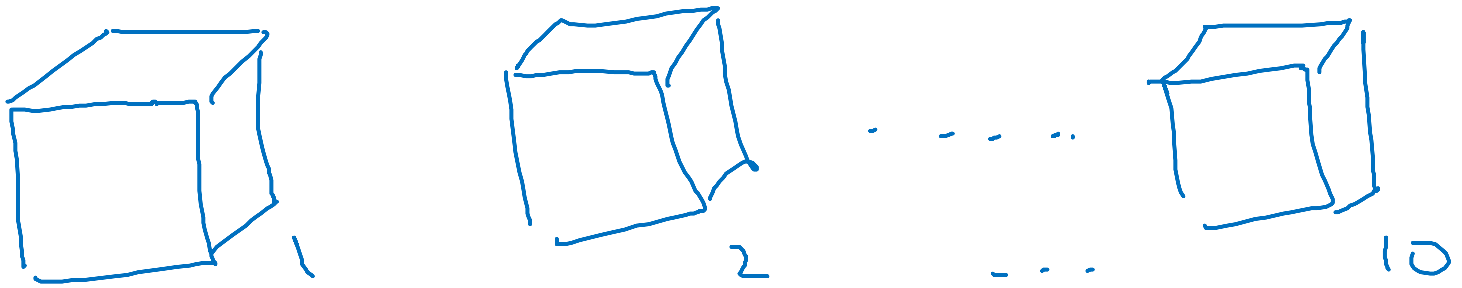


$$z^{[1]} = W^{[1]} a^{[0]} + b^{[1]}$$

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

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?



$3 \times 3 \times 3$

27 parameters.

+ bias

→ 28 parameters.

$\boxed{\text{280 parameters.}}$

Andrew Ng

Summary of notation

If layer l is a convolution layer:

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

f x f filter

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

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

bias: $n_c^{[l]}$ — $(1,1,1,n_c^{[l]})$ ← #filters in layer l.

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

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

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

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

$n_c \times n_H \times n_W$

nc is number of filters and wts and etc are for whole filters collective

Andrew Ng

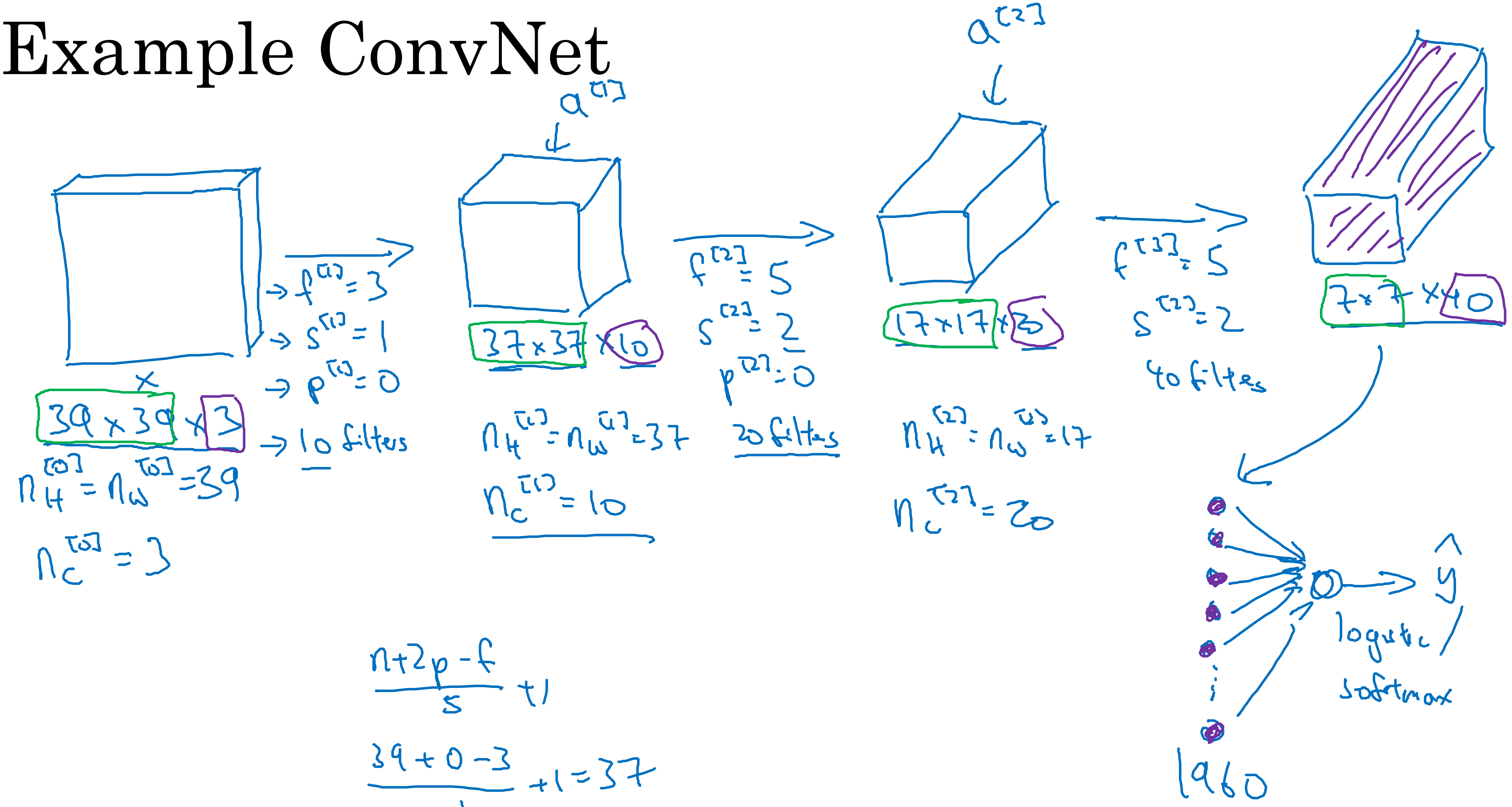
So what we did below is we took 39 x 39 x 3 image and ckomputed 1960 featurs of it

deeplearning.ai

Convolutional Neural Networks

A simple convolution network example

Example ConvNet



$$\frac{n+2p-f}{s}+1$$

$$\frac{39+0-3}{1}+1=37$$

Andrew Ng

Types of layer in a convolutional network:

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

deeplearning.ai

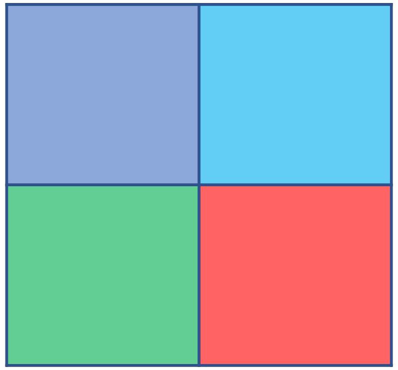
Convolutional Neural Networks

Pooling layers

DEon eto reduce size of t, to reduce the fompurtatiriion and to spped up the process of thrr

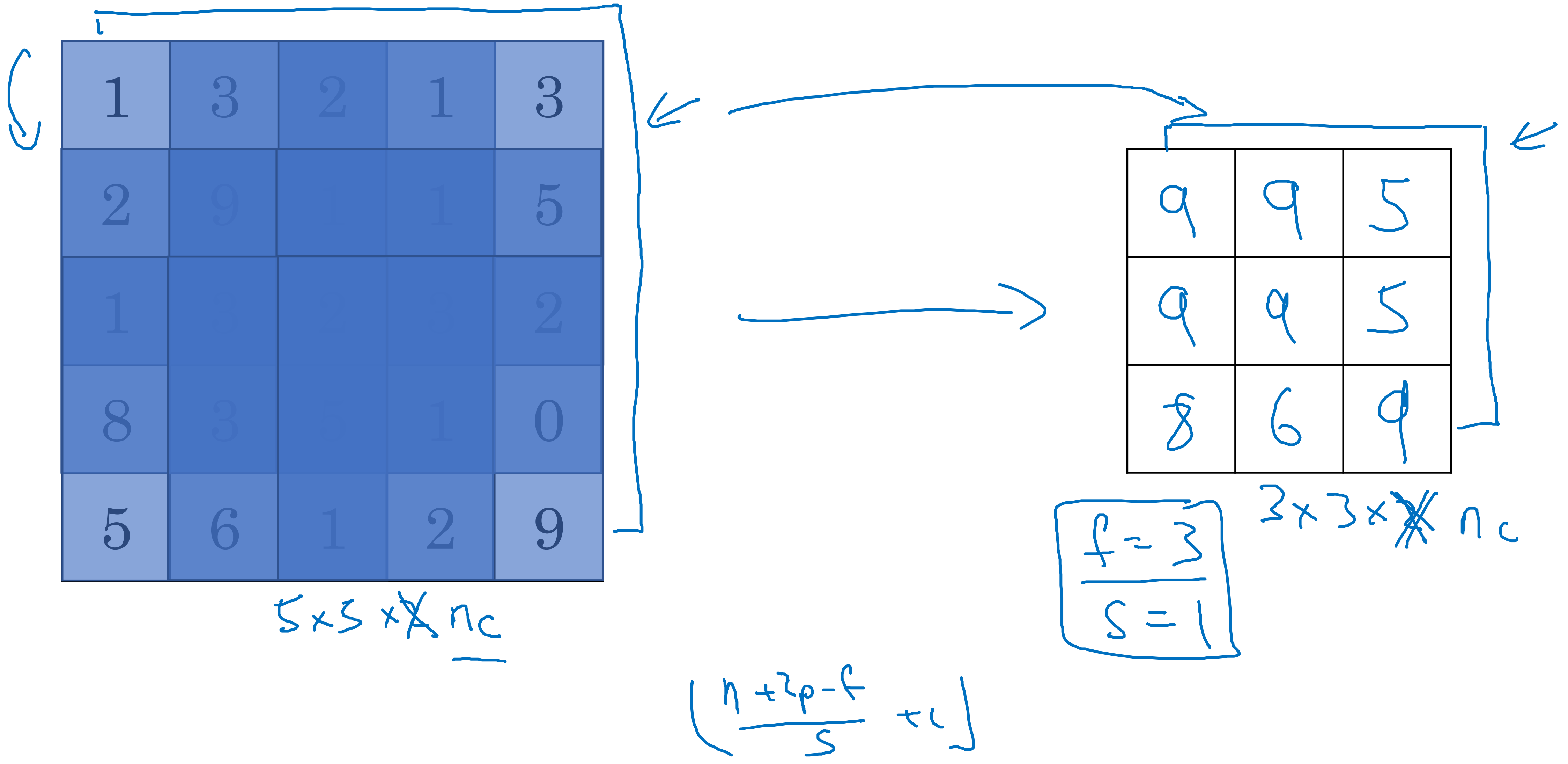
Pooling layer: Max pooling

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



Andrew Ng

Pooling layer: Max pooling



Pooling layer: Average pooling

$$\begin{bmatrix} 1 & 3 & 2 & 1 \\ 2 & 9 & 1 & 1 \\ 1 & 4 & 2 & 3 \\ 5 & 6 & 1 & 2 \end{bmatrix} \longrightarrow \begin{bmatrix} 3.75 & 1.25 \\ 4 & 2 \end{bmatrix}$$

$f = 2$

$s = 2$

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

Summary of pooling

Hyperparameters:

f : filter size

s : stride

Max or average pooling

$\boxed{\begin{array}{l} f=2, s=2 \\ f=3, s=2 \end{array}}$

$\rightarrow$ ~~p: padding.~~

No parameters to learn!

$$n_H \times n_W \times n_C$$

$$\downarrow$$

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

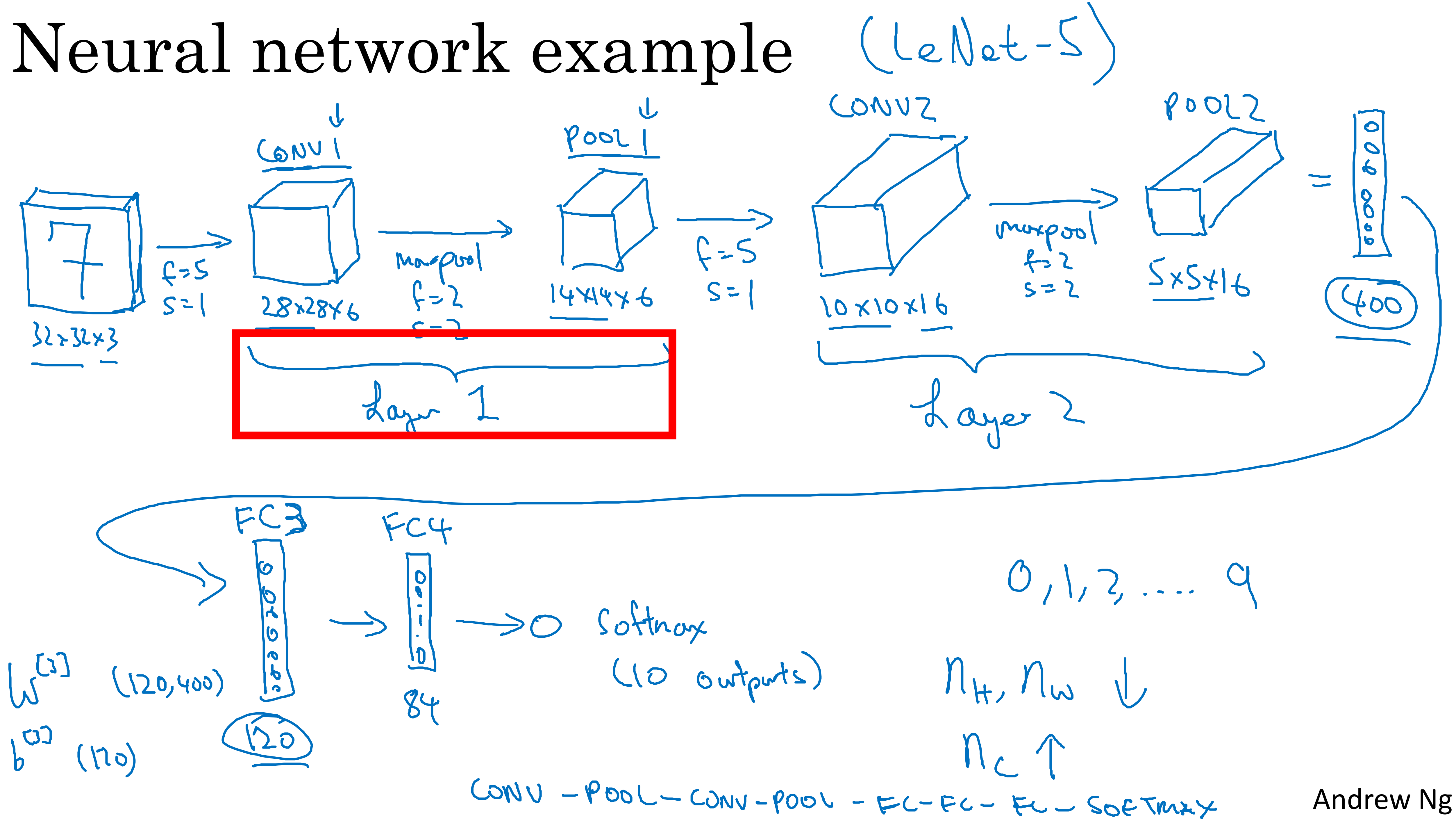
Andrew Ng

deeplearning.ai

Convolutional Neural Networks

Convolutional neural network example

Neural network example



Andrew Ng

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

Andrew Ng

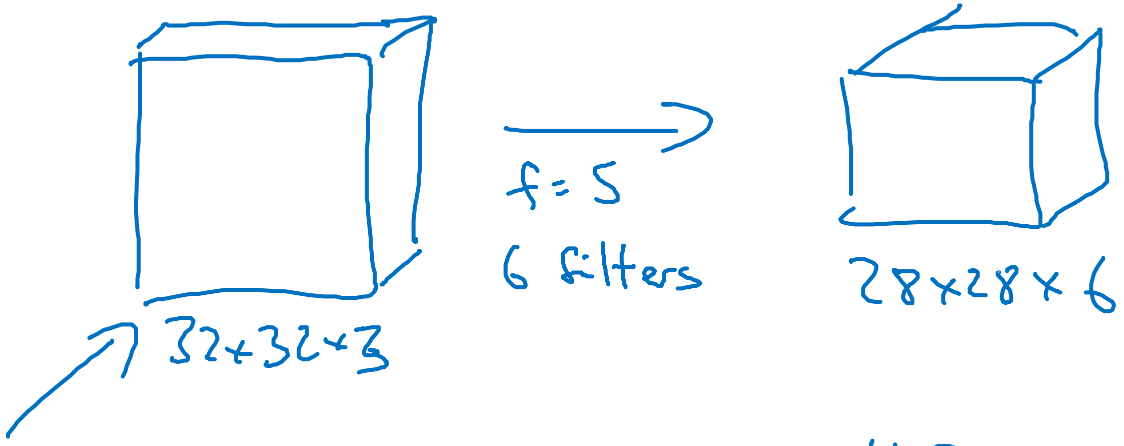
Advantages are : Parameterer sharing and sparsity of connections. Very le

Convolutional Neural Networks

deeplearning.ai

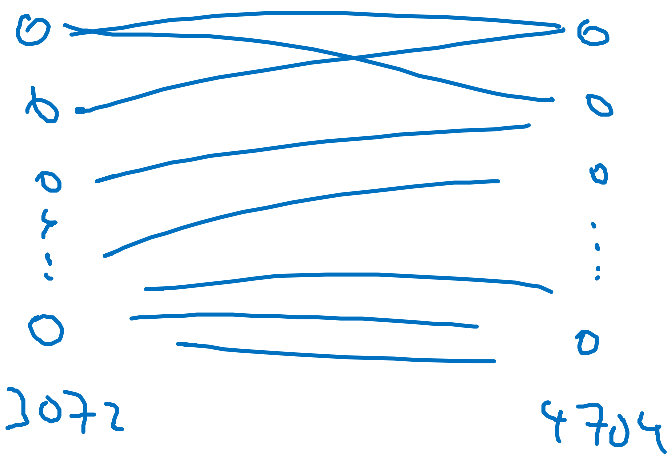
Why convolutions?

Why convolutions



3,072

4,704



$5 \times 5 - 25$

26

$6 \times 26 = 156$ parameters

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

Why convolutions

translation invariance

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

3×3

=

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

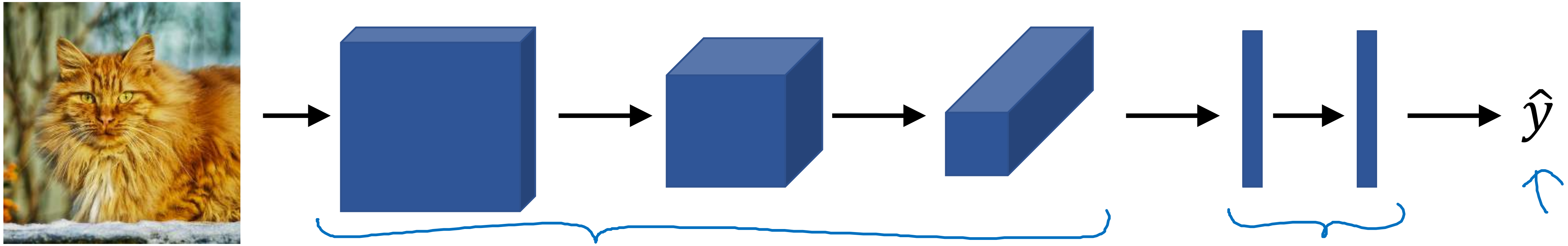
Parameter sharing: A feature detector (such as a vertical edge detector) that's useful in one part of the image is probably useful in another part of the image.

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

Putting it together

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

$\boxed{w, b}$



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