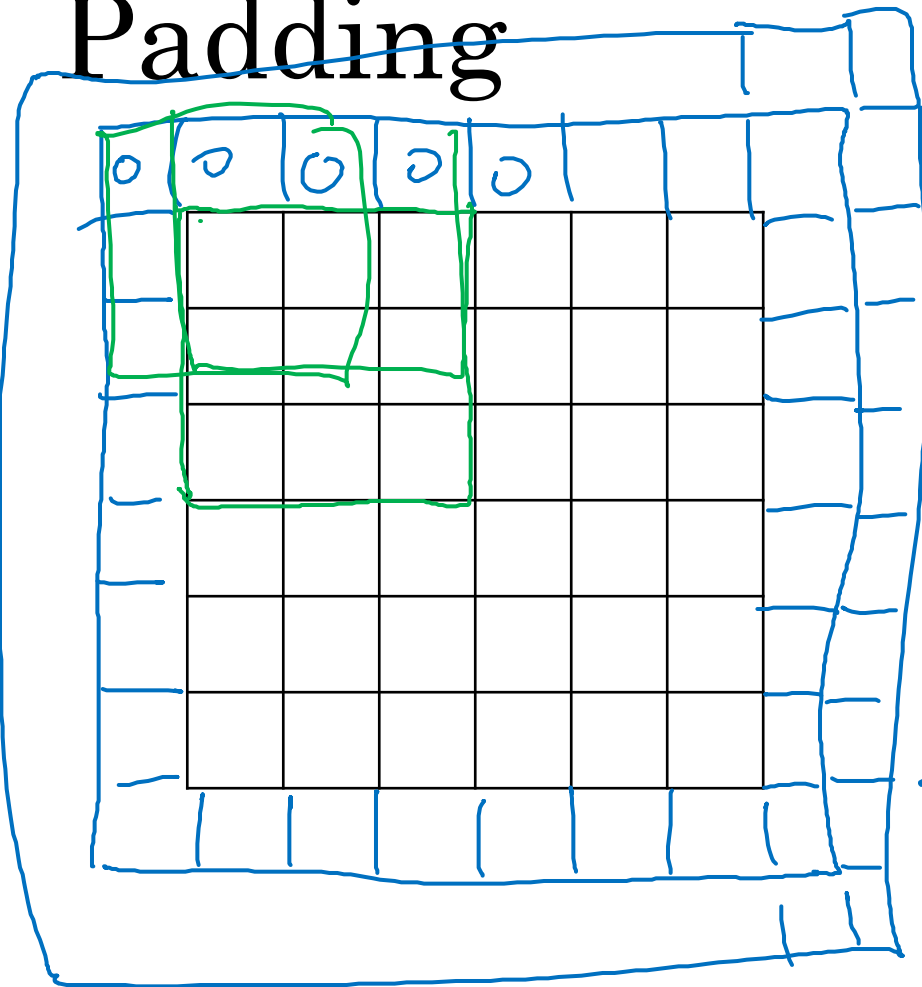


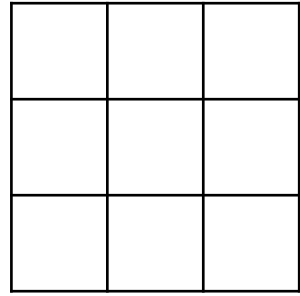
Convolutional Neural Networks

Padding

Padding

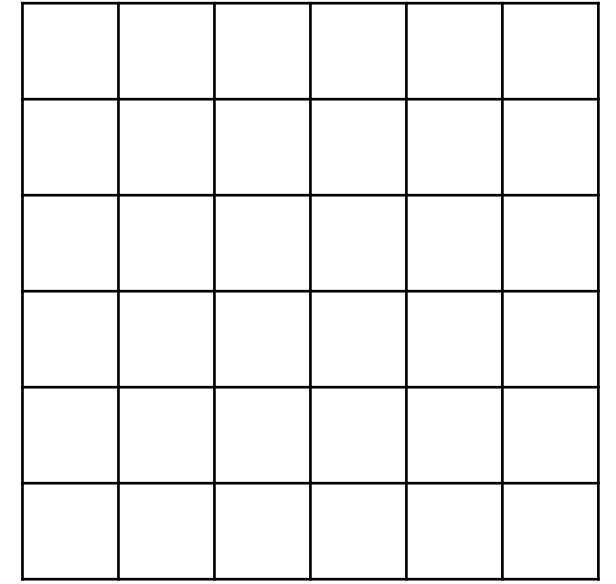


*



3x3
f x f

=



6x6

6x6 → 8x8
n x n

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

p = padding = 1

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

→ ~~4x4~~

Valid and Same convolutions

→ no padding

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

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

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

$$3 \times 3$$

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

$$\left| \begin{array}{c} 5 \times 5 \\ f=5 \end{array} \right.$$

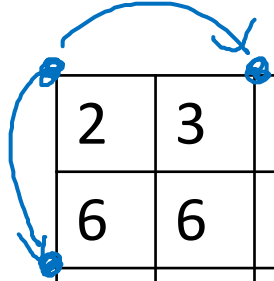
$$p=2$$

f is usually odd
 1×1
 3×3
 5×5
 7×7

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

7x7

3	4	4
1	0	2
-1	0	3

3x3

stride = 2

=

91	100	83
69	91	127
44	72	74

3x3

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

$n \times n$ * $f \times f$
 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:

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

Technical note on cross-correlation vs. convolution

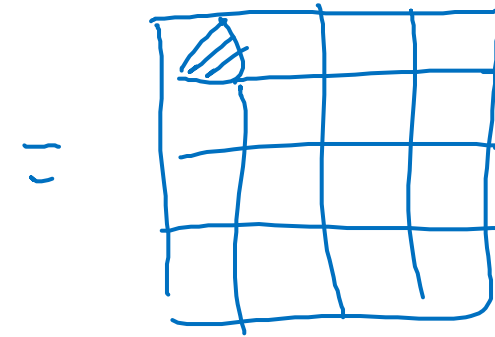
Convolution in math textbook:

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

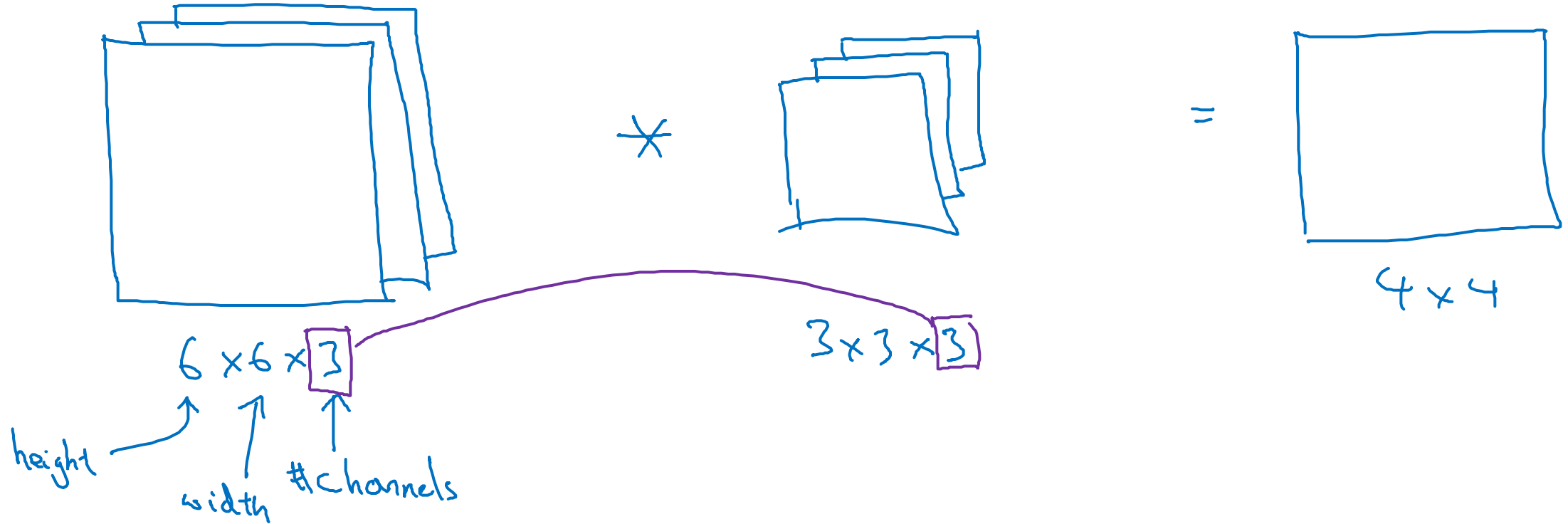


$$(A * B) * C = A * (B * C)$$

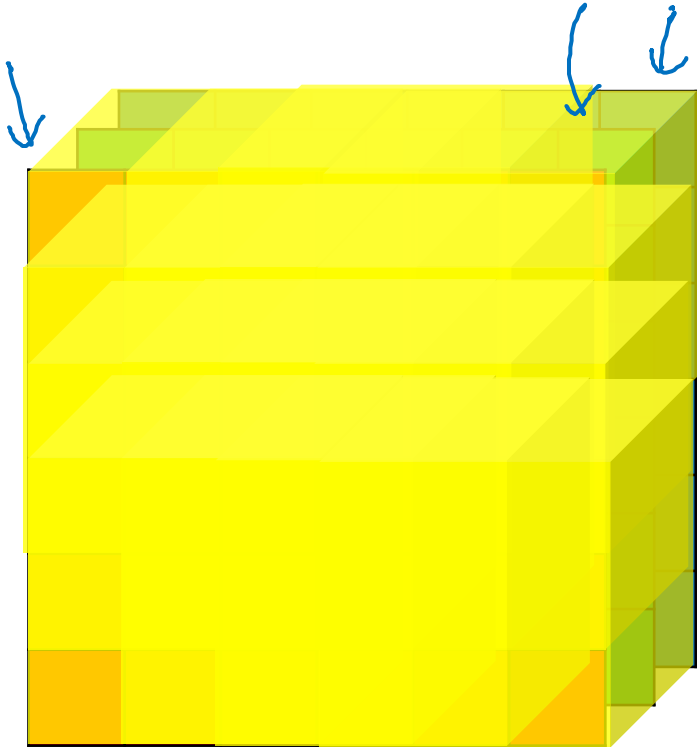
Convolutional Neural Networks

Convolutions over
volumes

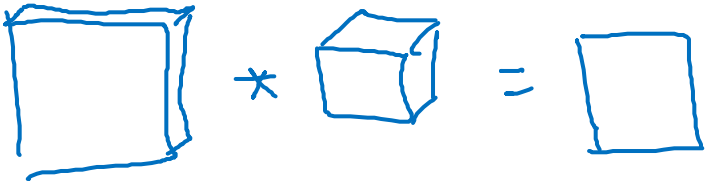
Convolutions on RGB images



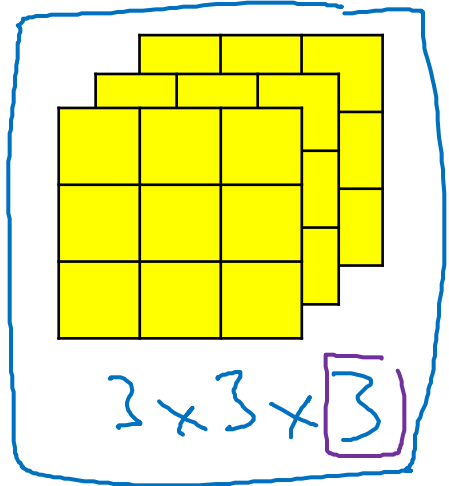
Convolutions on RGB image



$6 \times 6 \times 3$
↑ ↑ ↑

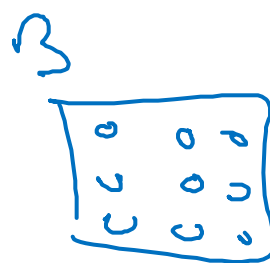
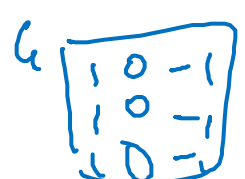
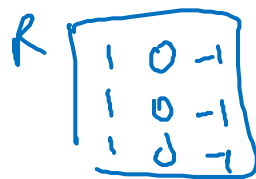
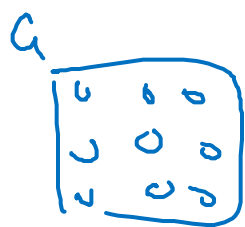
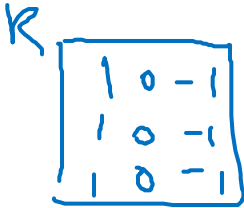


*

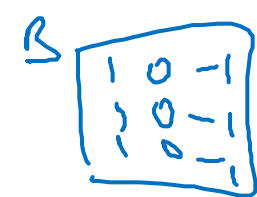


$3 \times 3 \times 3$

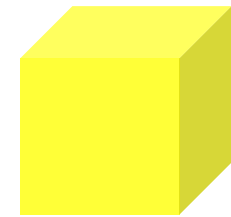
27 numbers



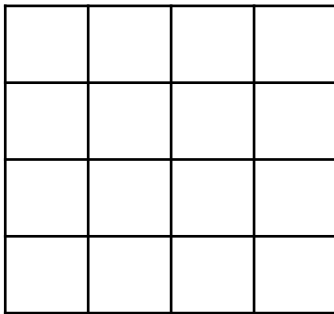
$\rightarrow 3 \times 3 \times 3$



$\rightarrow 3 \times 3 \times 3$

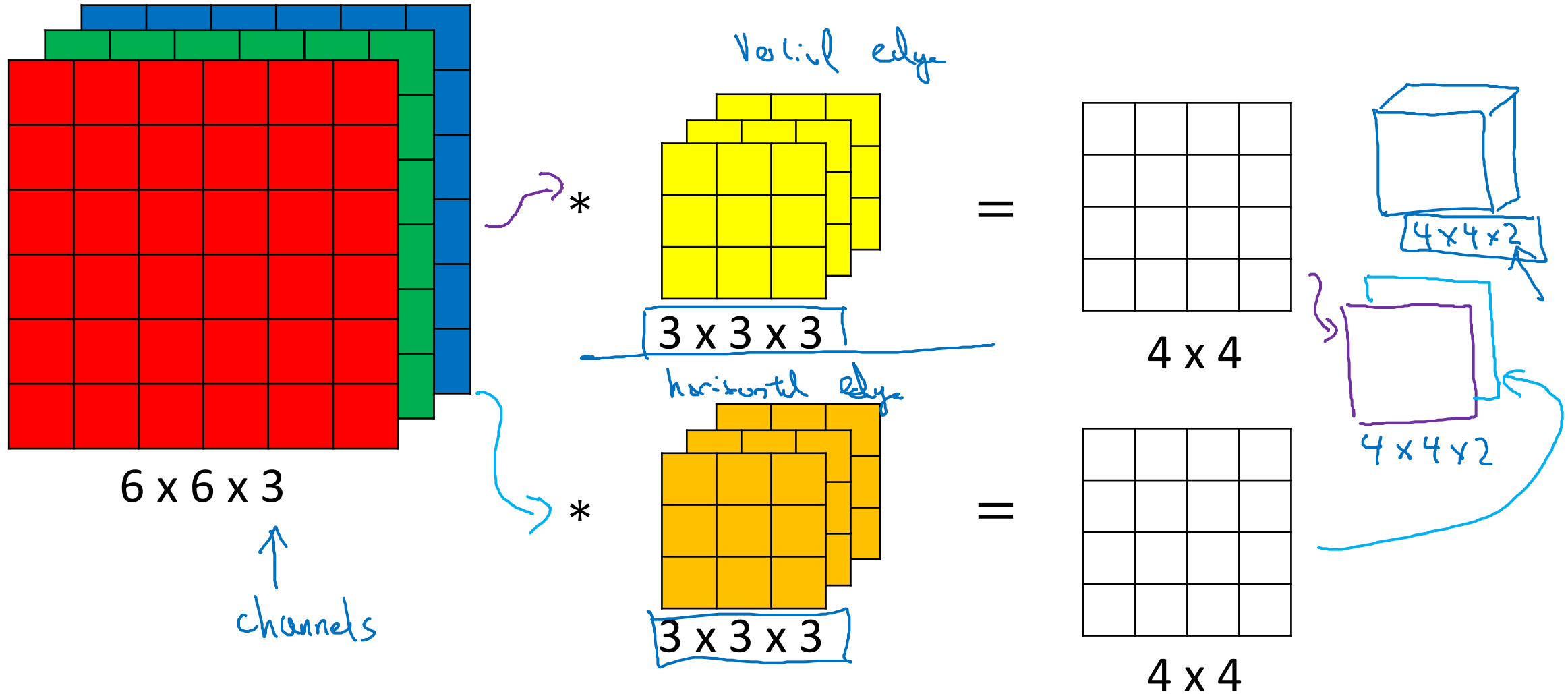


=



4×4

Multiple filters



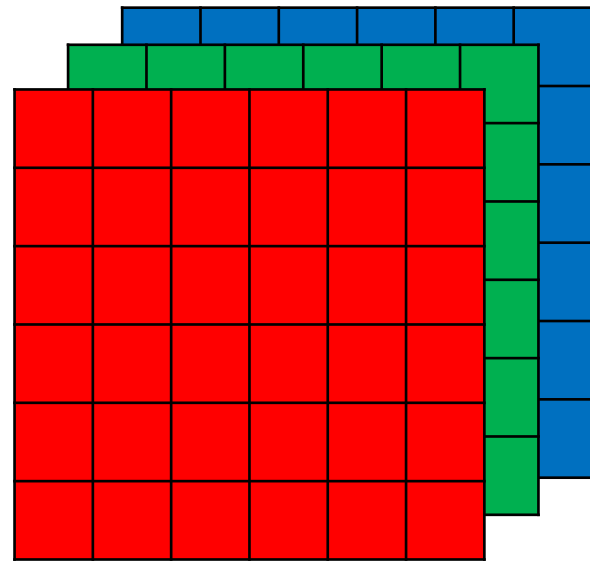
Summary: $n \times n \times n_c$ $\times$ $f \times f \times n_c$ $\rightarrow$ $\frac{n-f+1}{4} \times \frac{n-f+1}{4} \times \frac{n_c}{2}$ $\uparrow$ #filters

$6 \times 6 \times 3$ $3 \times 3 \times 3$ $4 \times 4 \times 2$

Convolutional Neural Networks

One layer of a
convolutional
network

Example of a layer



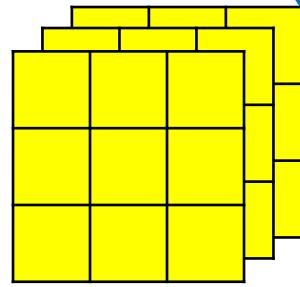
6 x 6 x 3

$a^{[0]}$

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

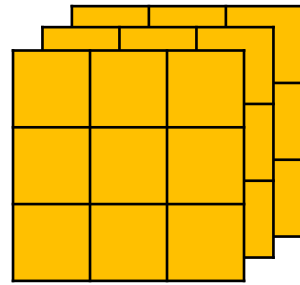
$$a^{[1]} = g(z^{[1]})$$

*



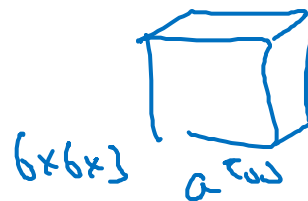
3 x 3 x 3

*



3 x 3 x 3

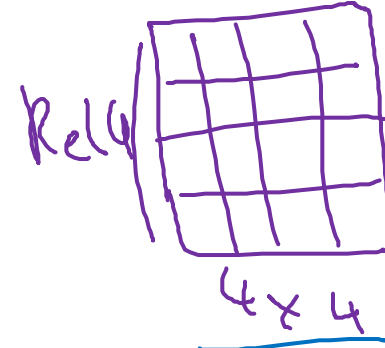
" $W^{[1]}$ "



6 x 6 x 3

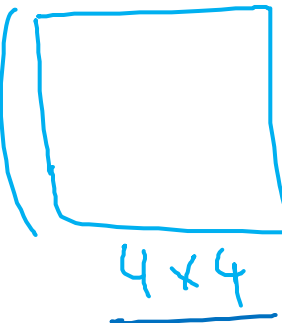
$a^{[0]}$

→



4 x 4

→



4 x 4



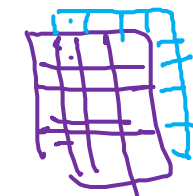
4 x 4 x 2

+ b_1

↓ R

+ b_2

↓ R



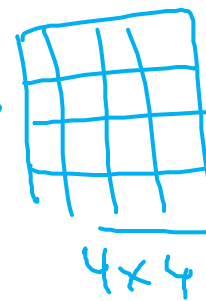
4 x 4 x 2

→



4 x 4

→



4 x 4

←

$a^{[1]}$

4 x 4 x 10

2 filters
10

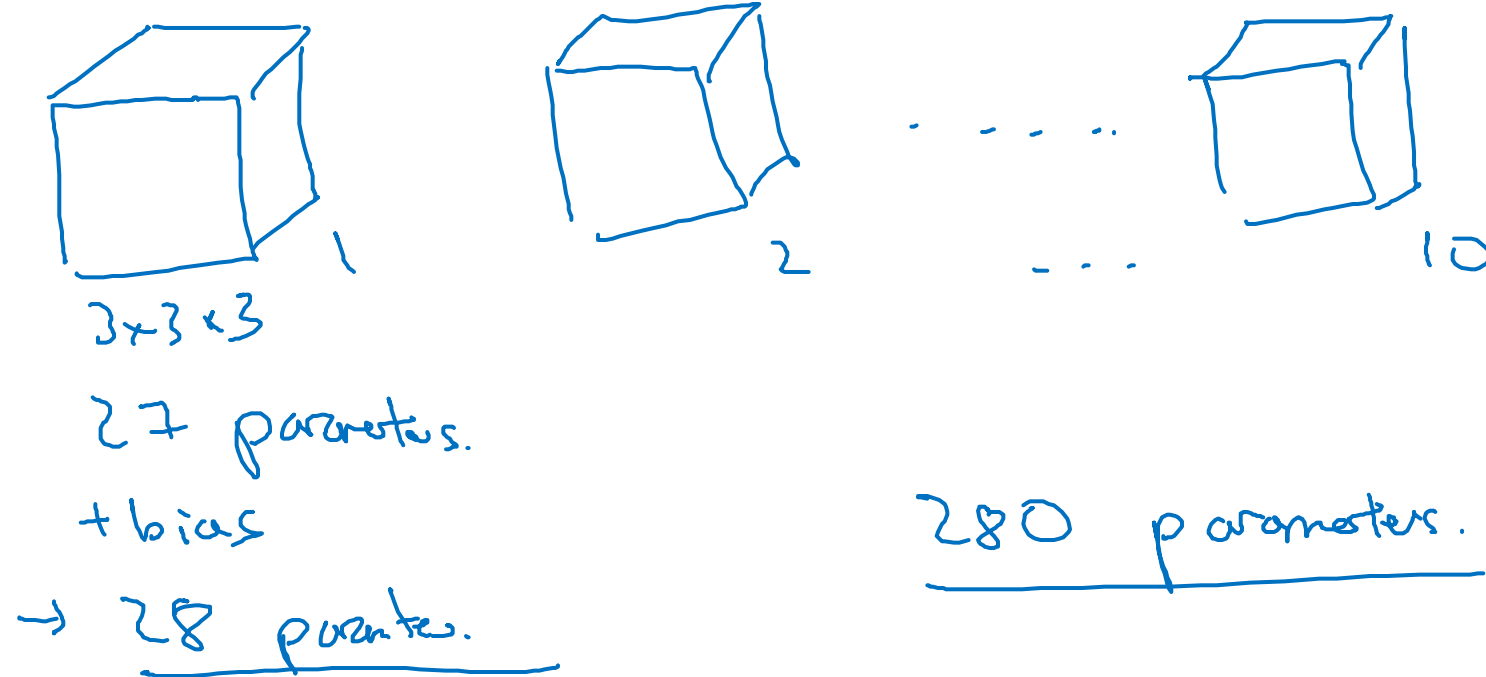
" $W^{[1]} a^{[0]}$ "

R

$z^{[1]}$

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: $n_c^{[l]}$

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

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

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

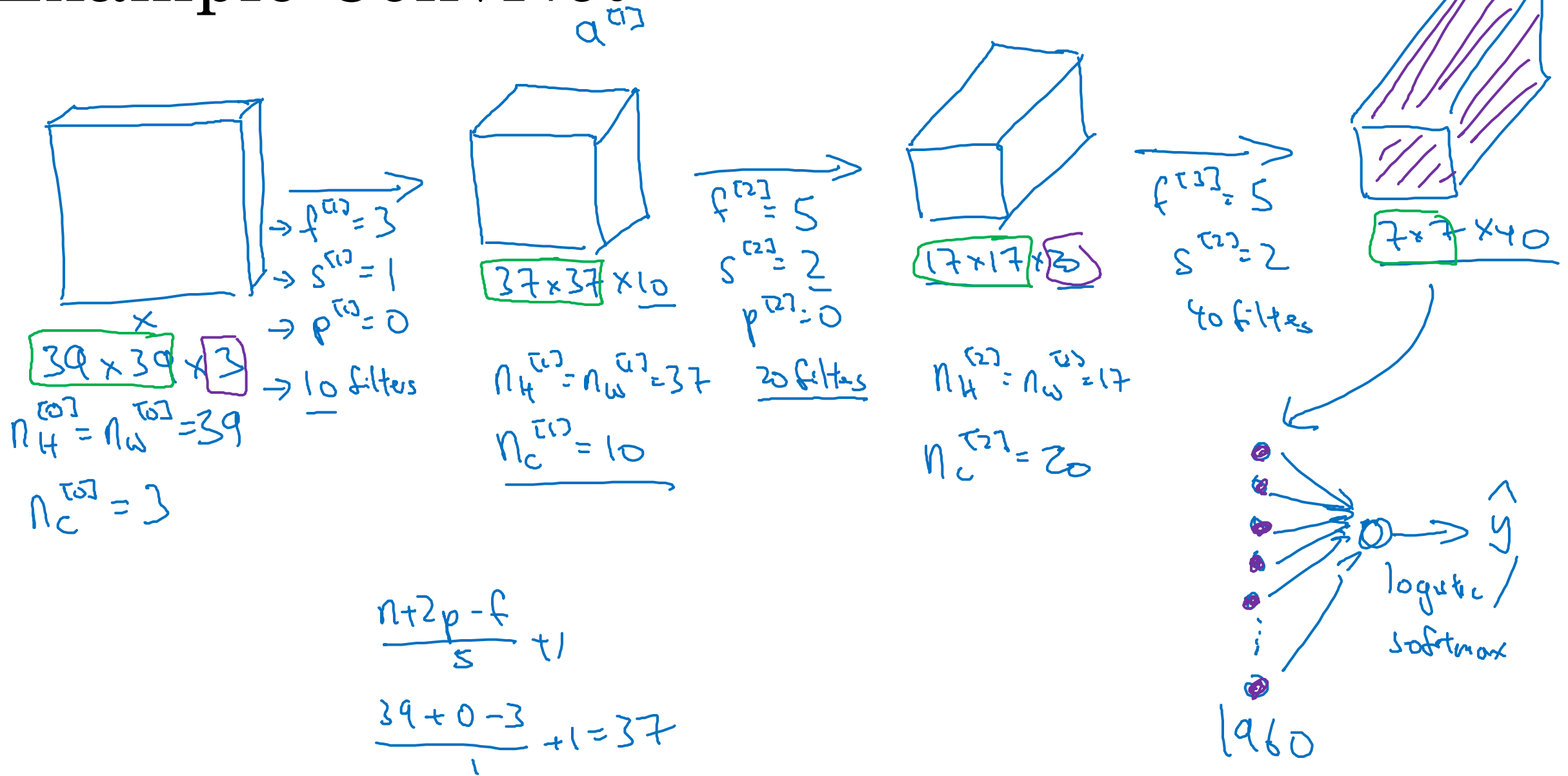
← #filters in layer l.

$n_c \times n_H \times n_W$

Convolutional Neural Networks

A simple convolution
network example

Example ConvNet



Types of layer in a convolutional network:

- Convolution
- Pooling
- Fully connected

Convolutional Neural Networks

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

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

$5 \times 5 \times 2$ n_c



9	9	5
9	9	5
8	6	9

$f=3$
 $s=1$
 $3 \times 3 \times 2$ n_c

$$\left(\frac{n + 2p - f}{s} + 1 \right)$$

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

s : stride

Max or average pooling

~~$\Rightarrow p$: padding.~~

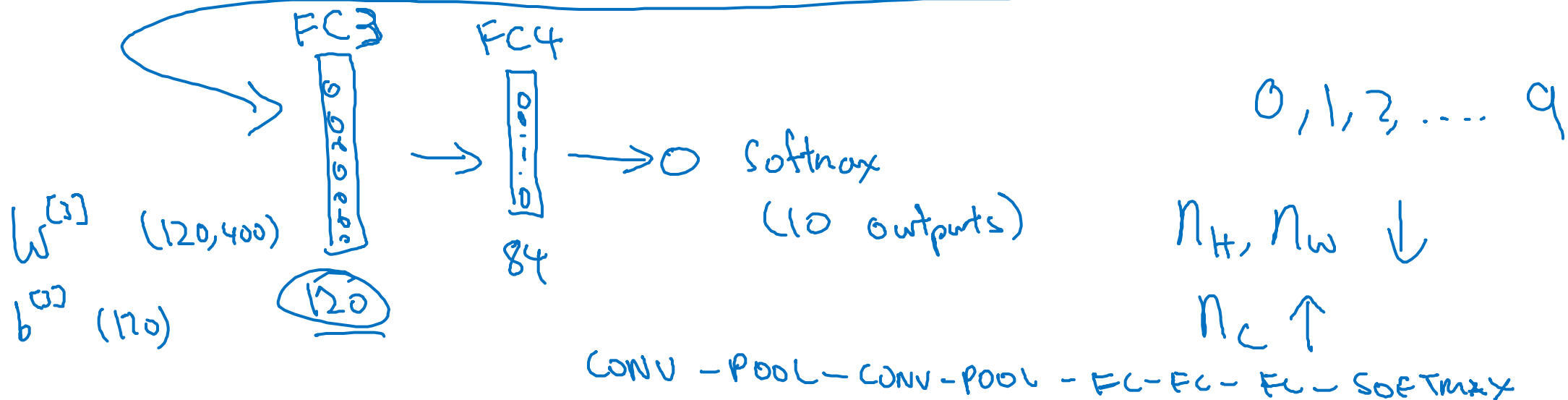
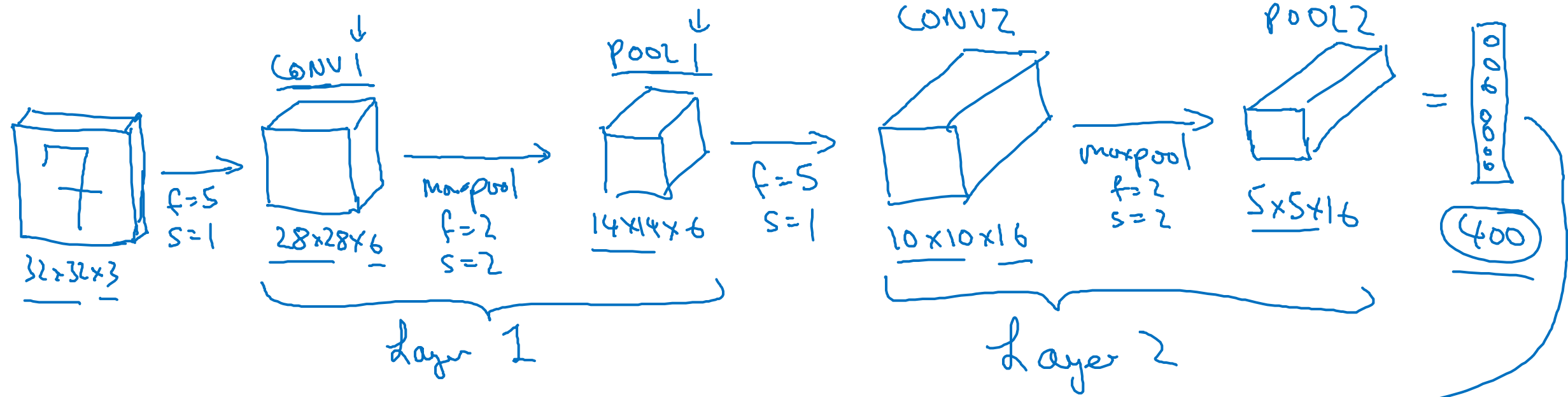
No parameters to learn!

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

Convolutional Neural Networks

Convolutional neural
network example

Neural network example (LeNet-5)



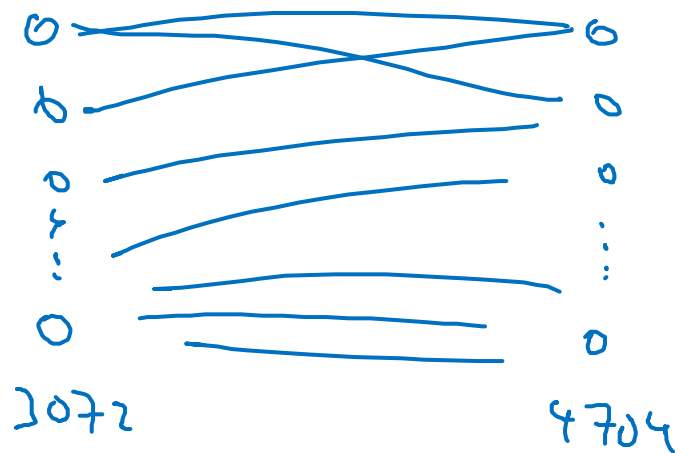
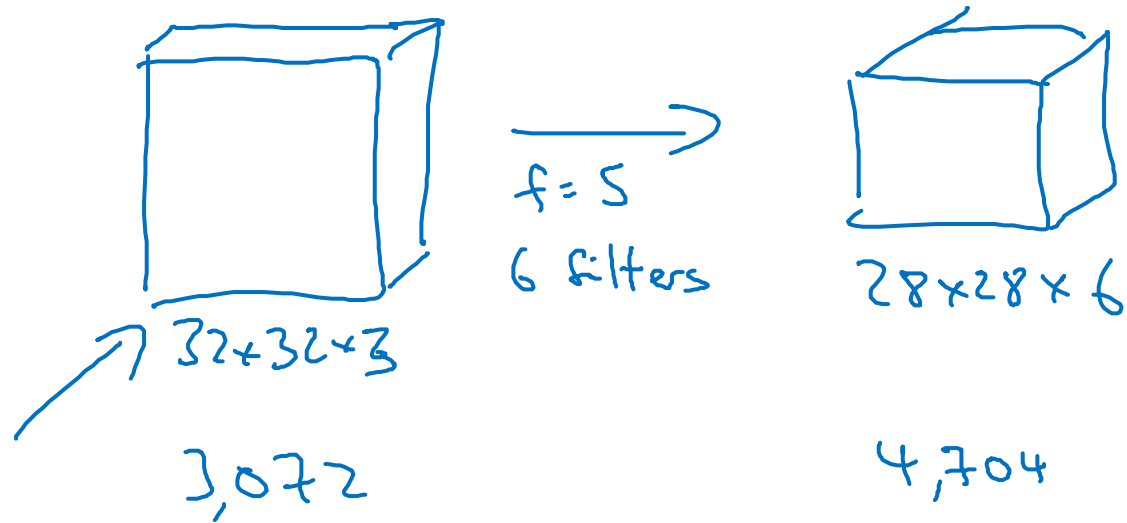
Neural network example

	Activation shape	Activation Size	# parameters
Input:	(32,32,3)	3,072 $a^{[0]}$	0
CONV1 (f=5, s=1)	(28,28,8)	<u>6,272</u>	456 ←
POOL1	(14,14,8)	<u>1,568</u>	0 ←
CONV2 (f=5, s=1)	(10,10,16)	<u>1,600</u>	1516 ←
POOL2	(5,5,16)	<u>400</u>	0 ←
FC3	(120,1)	<u>120</u>	48120 }
FC4	(84,1)	<u>84</u>	10164 }
Softmax	(10,1)	<u>10</u>	850

Convolutional Neural Networks

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

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

 $=$

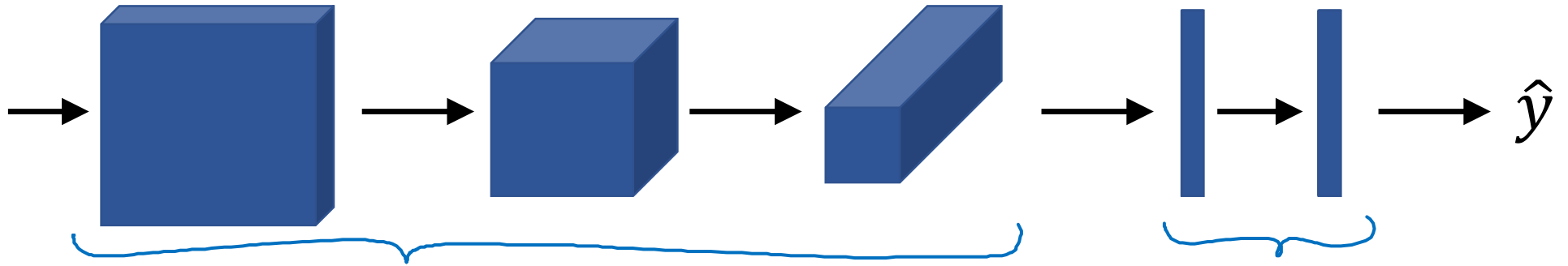
0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0

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



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

Use gradient descent to optimize parameters to reduce J