deeplearning.ai

Convolutional Neural Networks

Computer vision

Computer Vision Problems

Image Classification

64x64

Cat? (0/1)

Neural Style Transfer

Object detection

Deep Learning on large images

64x64 x 3

Cat? (0/1)

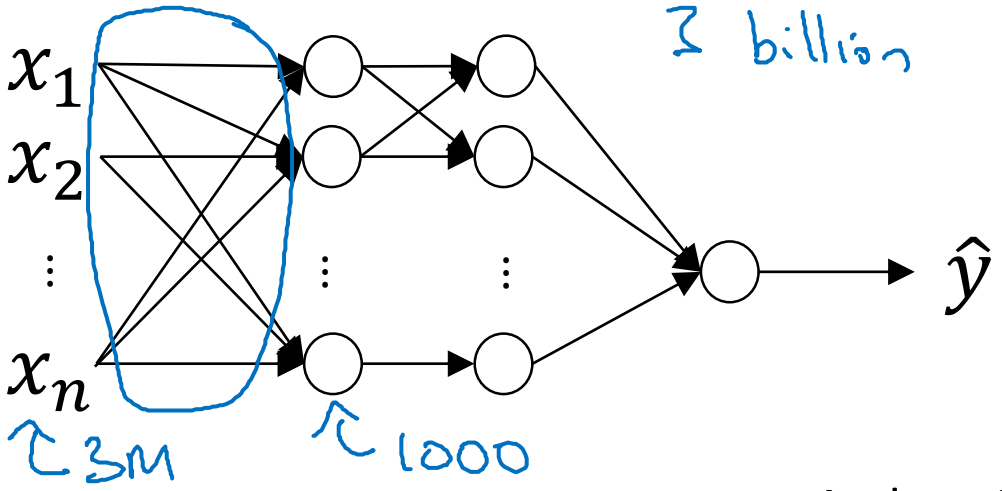
12288

1000 x 1000 x 3
= 3 million

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

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

3 billion



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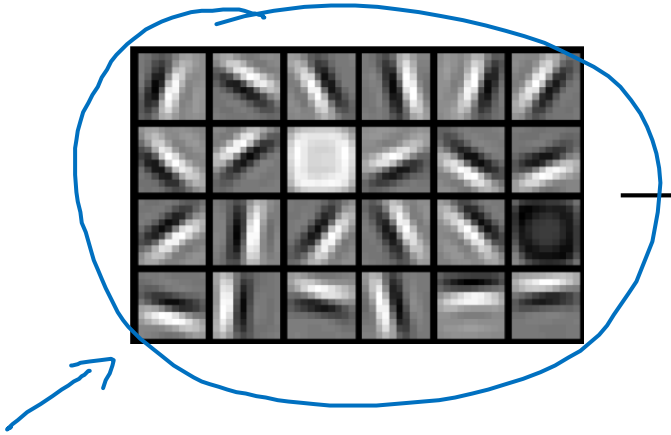
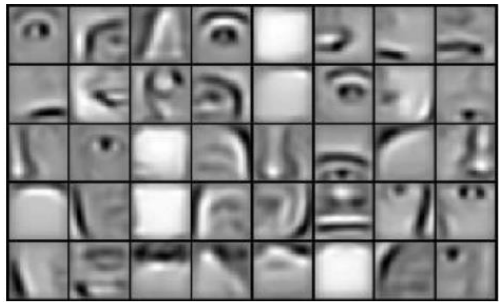
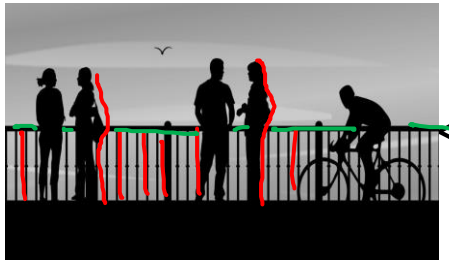
Convolutional Neural Networks

Edge detection example

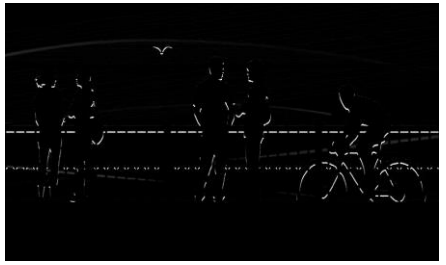
Computer Vision Problem







vertical edges



horizontal edges

Vertical edge detection

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

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 x 6

"convolution"

*

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

3 x 3

→ filter kernel

=

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

4 x 4

Vertical edge detection

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

6 x 6

*

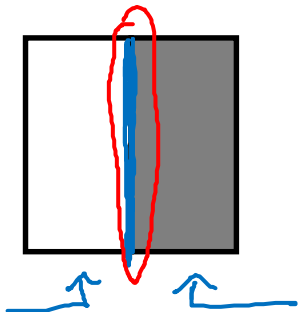
1	0	-1
1	0	-1
1	0	-1

3 x 3

=

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

4 x 4



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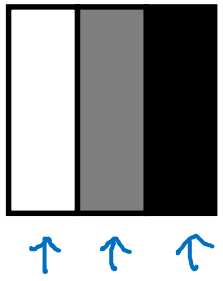

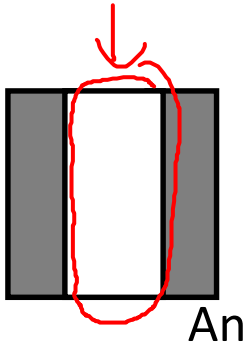

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Convolutional Neural Networks

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

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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

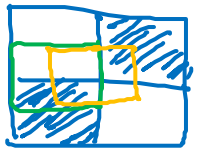
Horizontal

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

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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°

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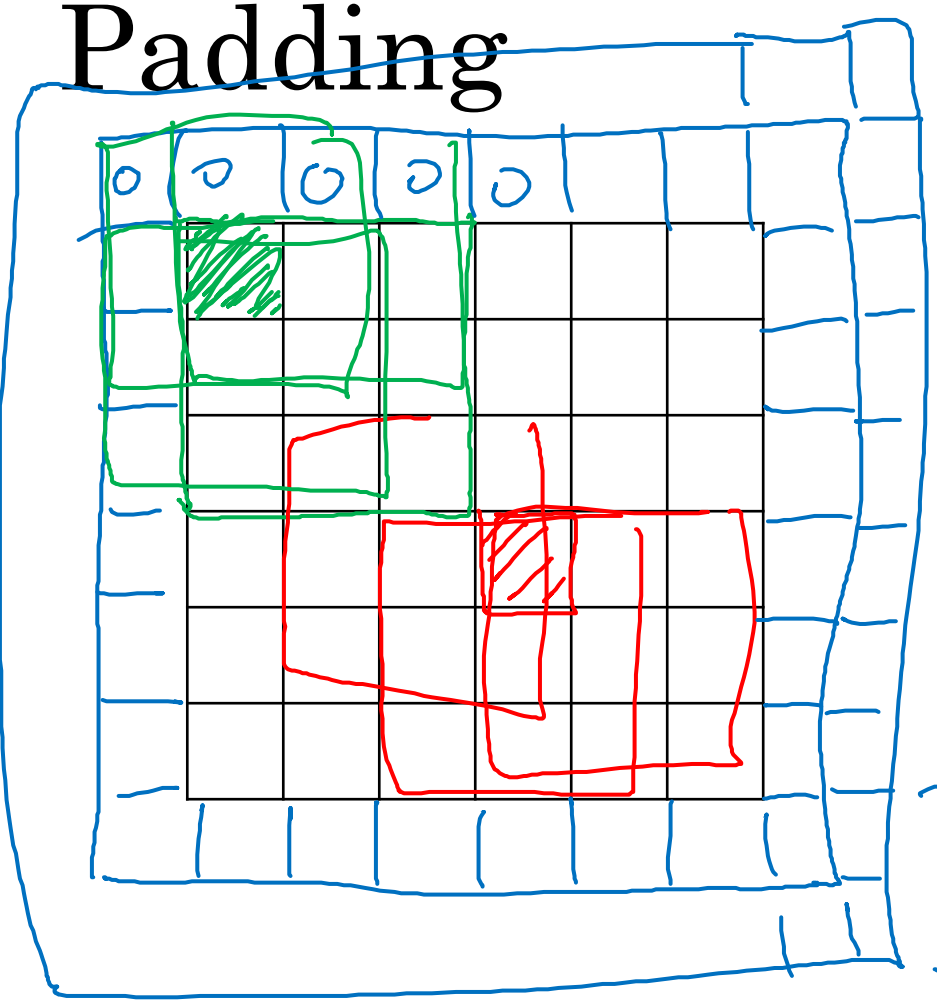
Convolutional Neural Networks

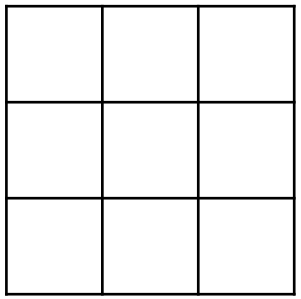
Padding

Padding

- shrinky output
- throw away info from edge

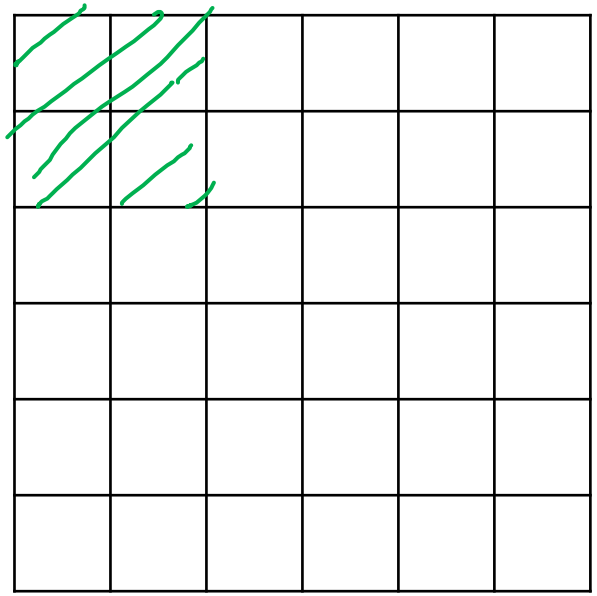


*



3×3
f×f

=



6×6

p=2

6×6 → 8×8
n×n

n-f+1 × n-f+1

6-3+1=4

→ ~~4×4~~

p = padding = 1

n+2p-f+1 × n+2p-f+1

6+2-3+1 × ___ = 6×6

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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.

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

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

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

$5 \times 5 \quad f=5 \quad p=2$

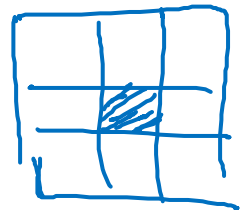
f is usually odd

1x1

3x3

5x5

7x7



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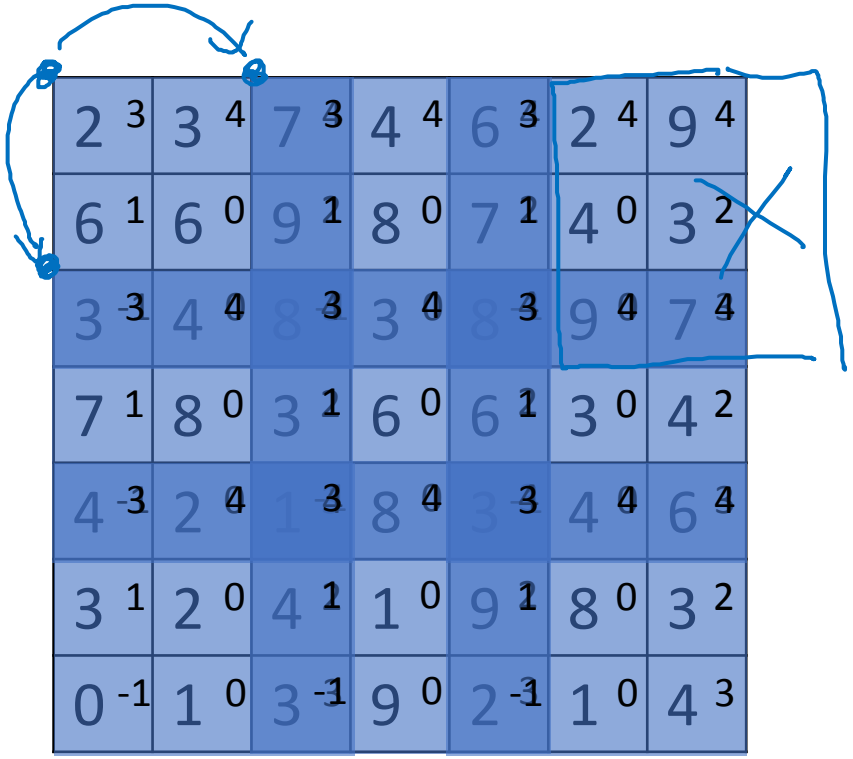
Convolutional Neural Networks

Strided convolutions

Strided convolution



7×7

*

3	4	4
1	0	2
-1	0	3

3×3

stride = 2

=

91	100	83
69	91	127
44	72	74

3×3

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

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

padding p stride s

$s = 2$

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

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

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Summary of convolutions

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

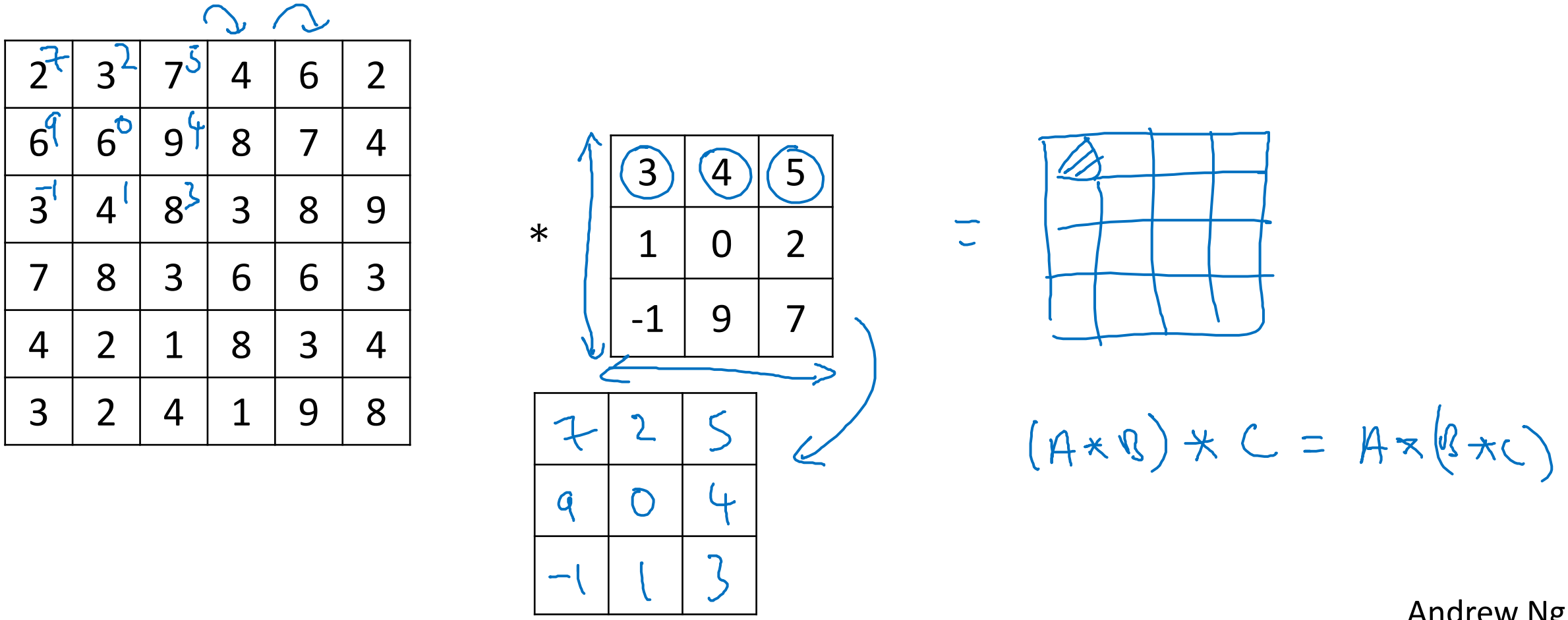
padding p $\quad$ stride s

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:



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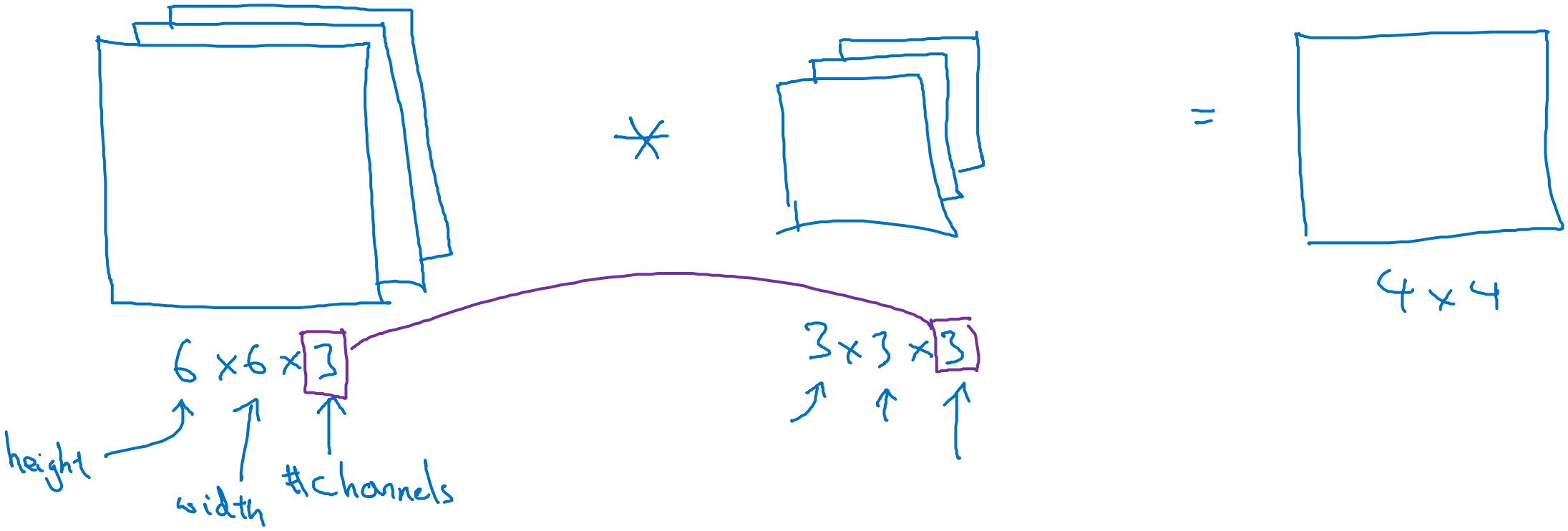
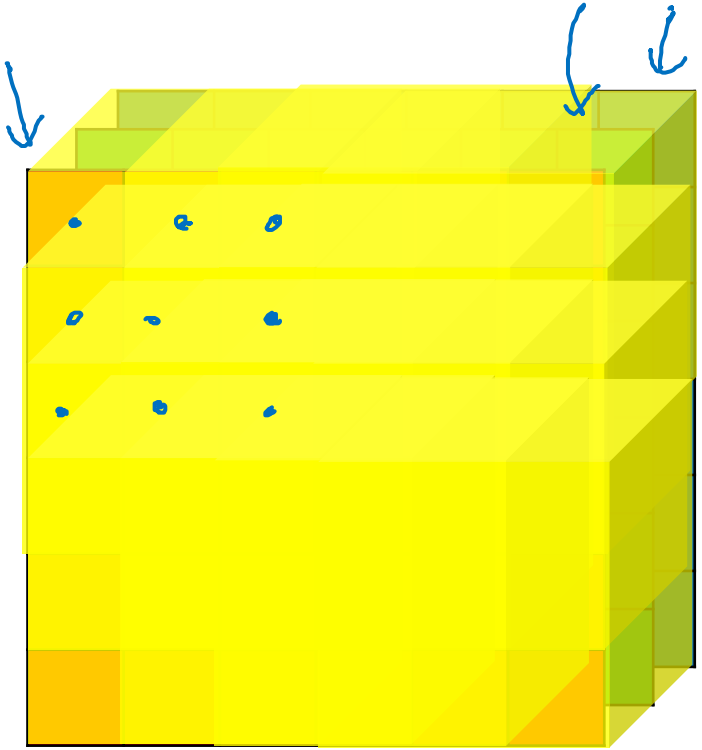
Convolutional Neural Networks

Convolutions over volumes

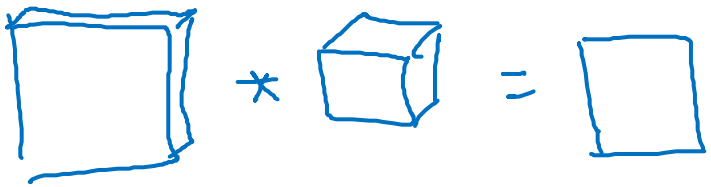
Convolutions on RGB images

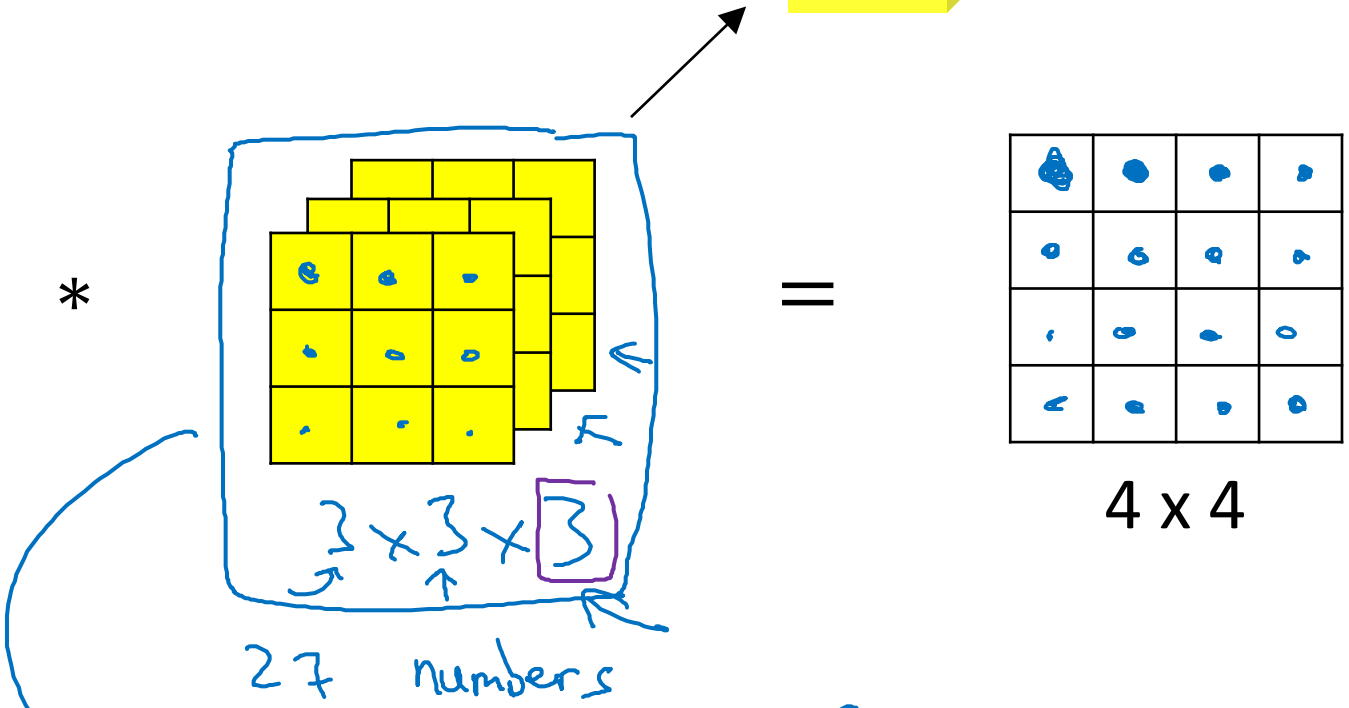


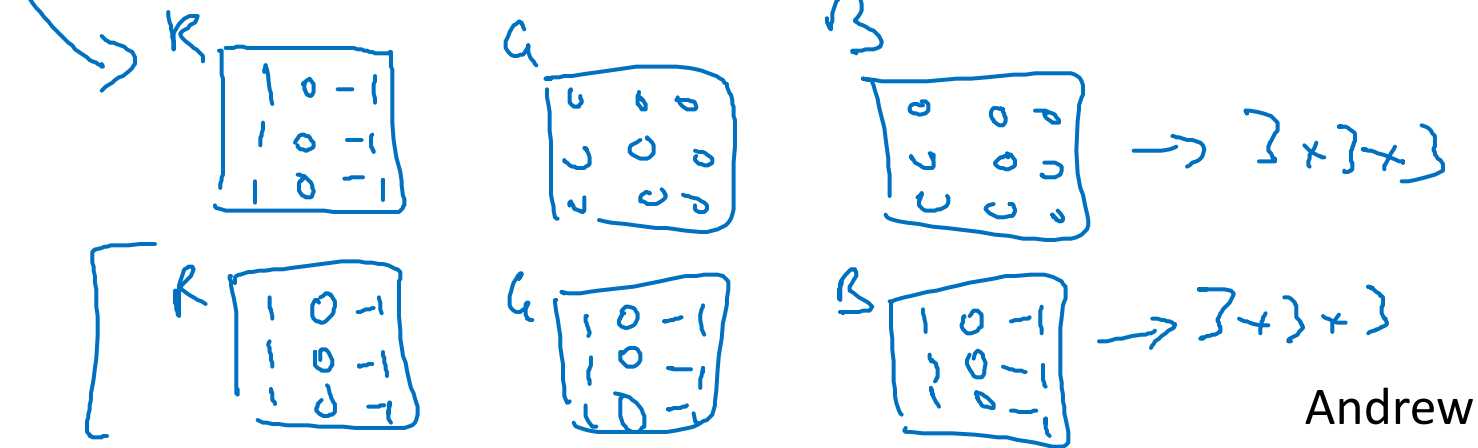
Convolutions on RGB image



6 x 6 x 3







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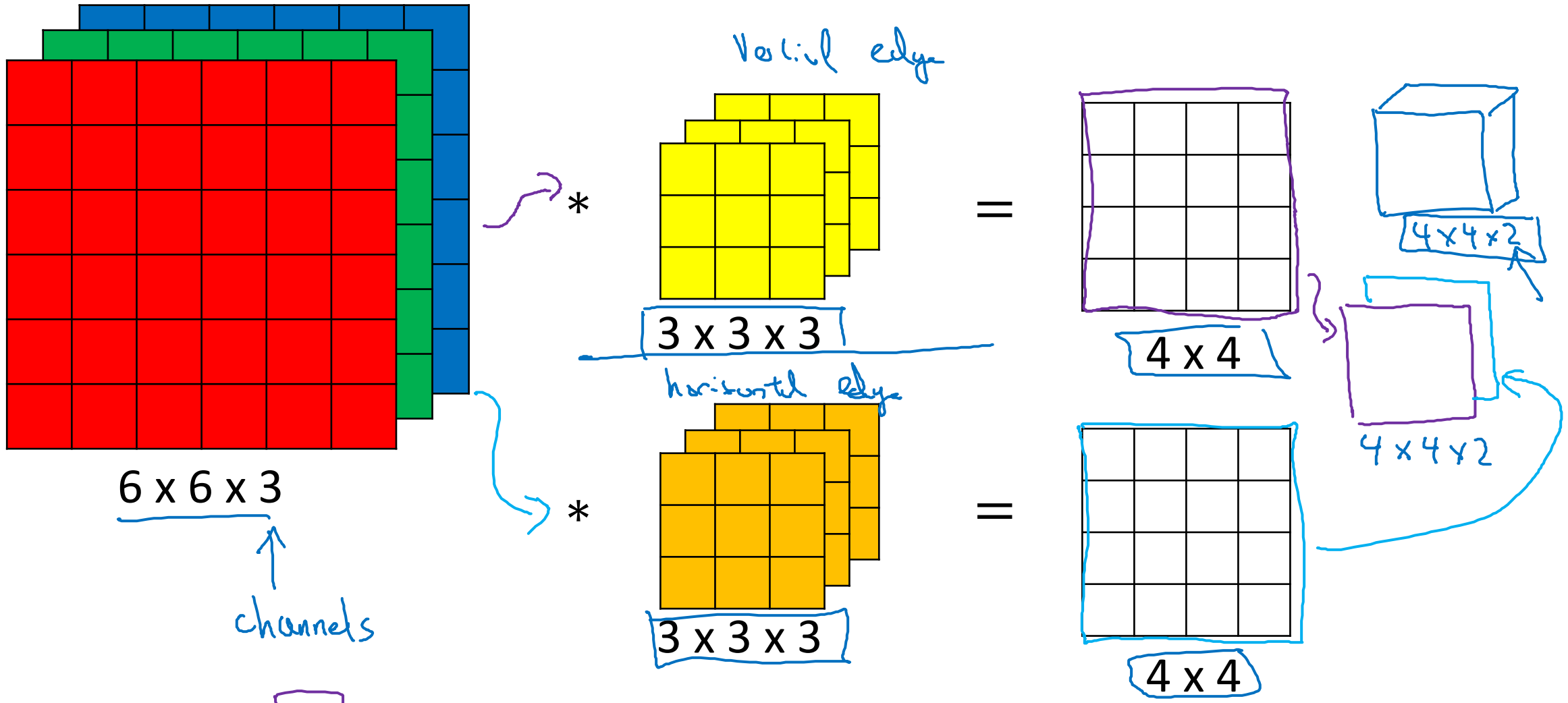
Multiple filters



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

$6 \times 6 \times 3$ * $3 \times 3 \times 3$ → $4 \times 4 \times 2$ (# filters)

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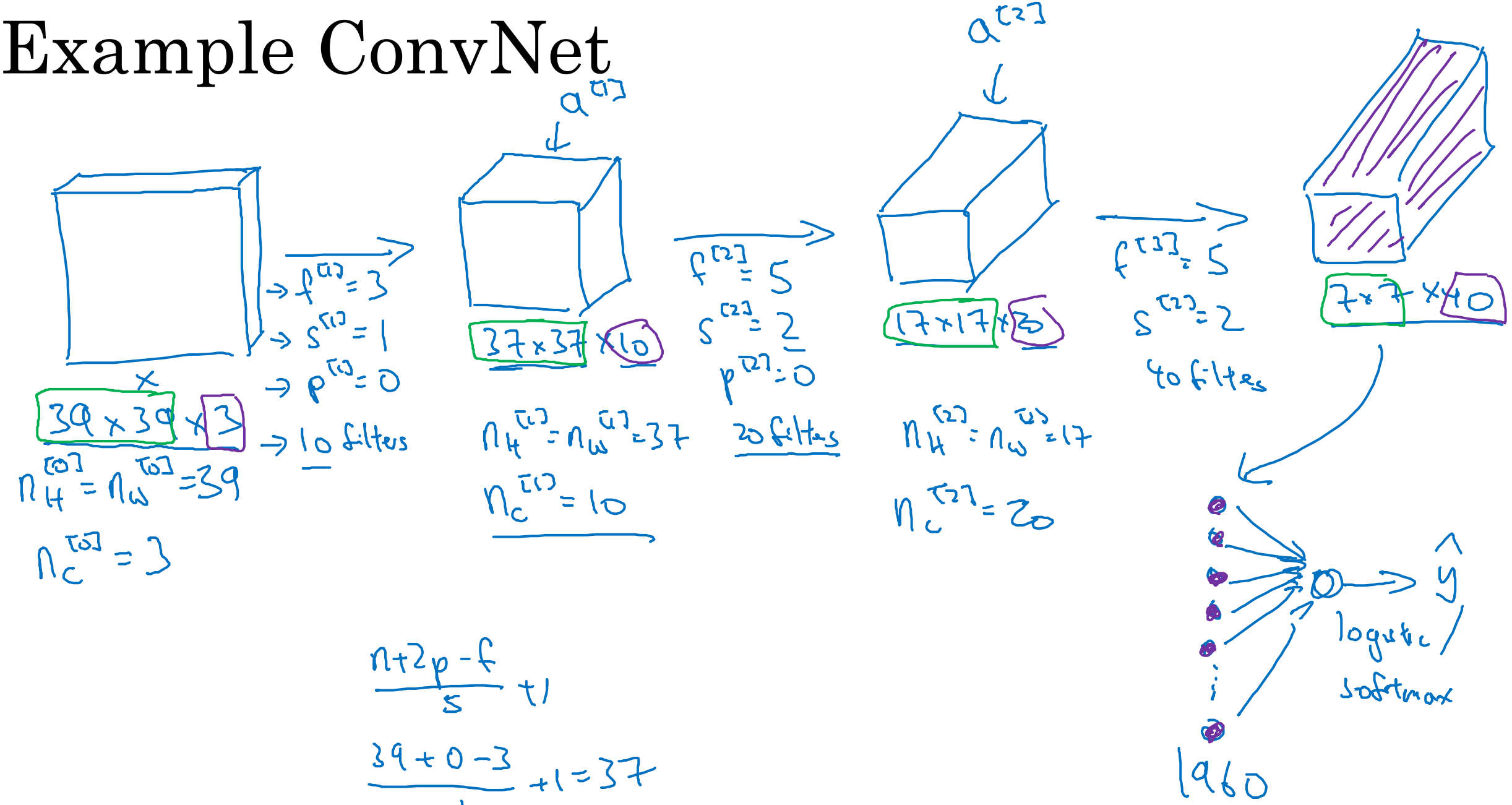
Convolutional Neural Networks

A simple convolution network example

Example ConvNet



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

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

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Types of layer in a convolutional network:

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

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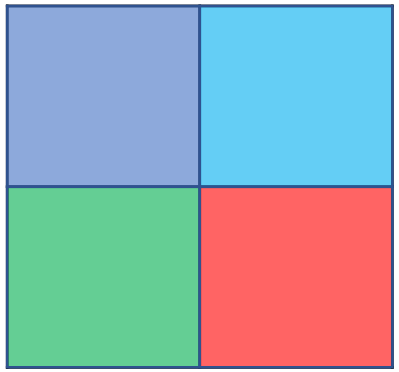
Convolutional Neural Networks

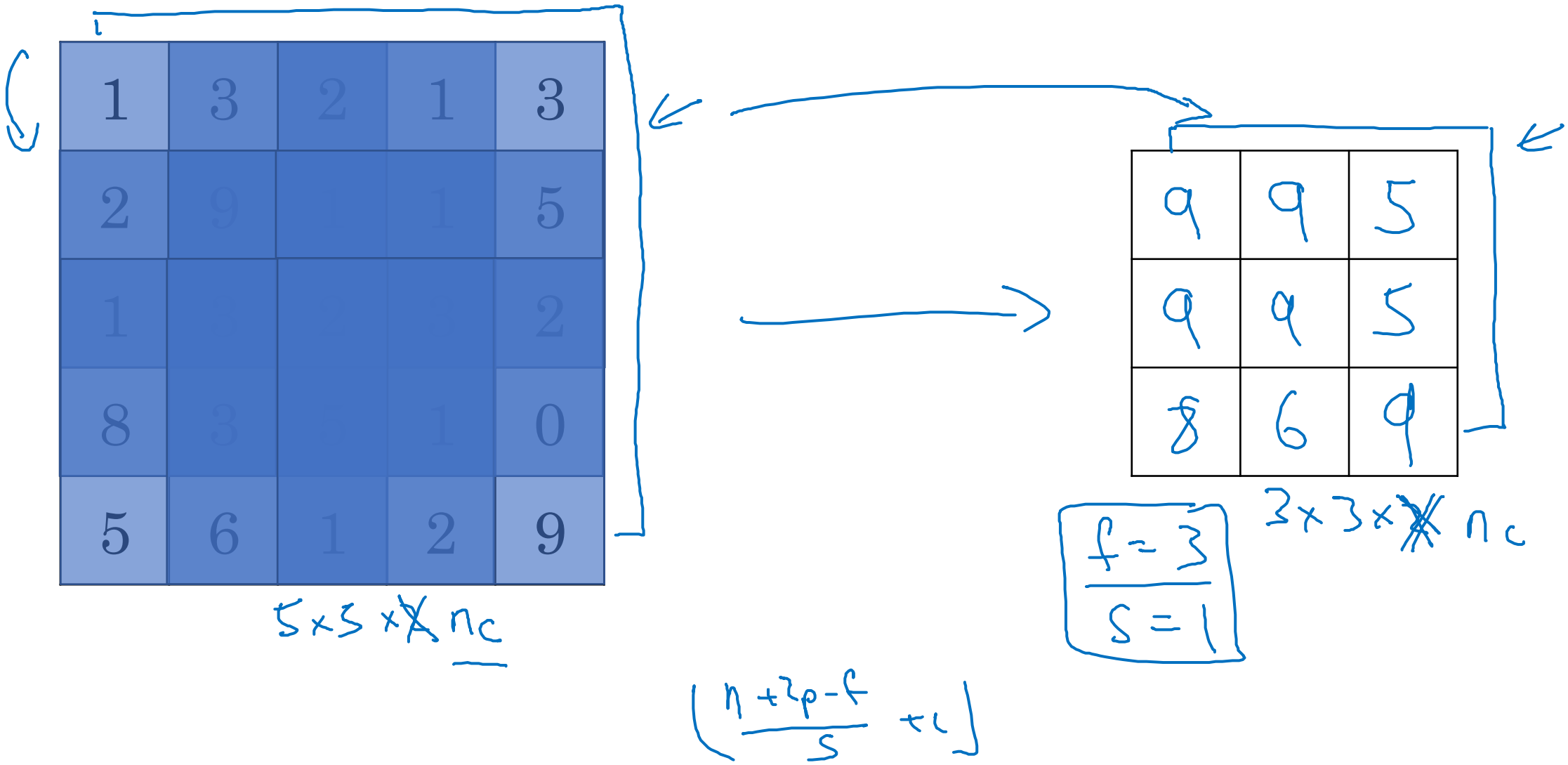
Pooling layers

Pooling layer: Max pooling

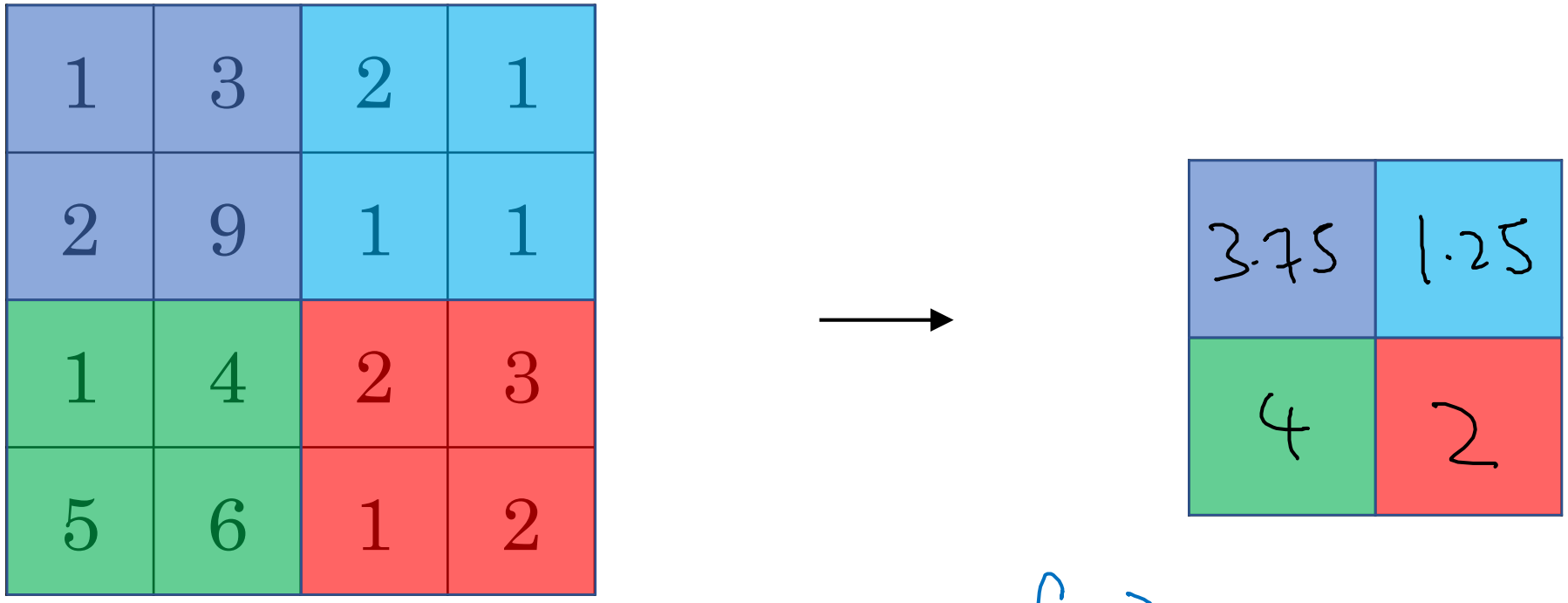
1	3	2	1
2	9	1	1
1	3	2	3
5	6	1	2



Pooling layer: Max pooling



Pooling layer: Average pooling



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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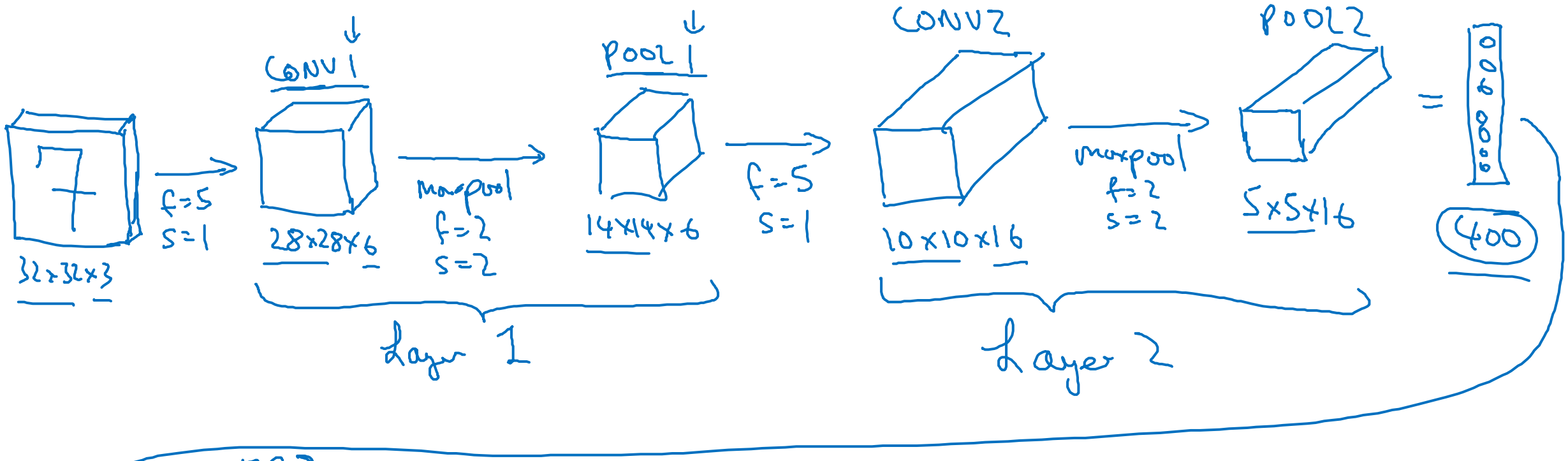
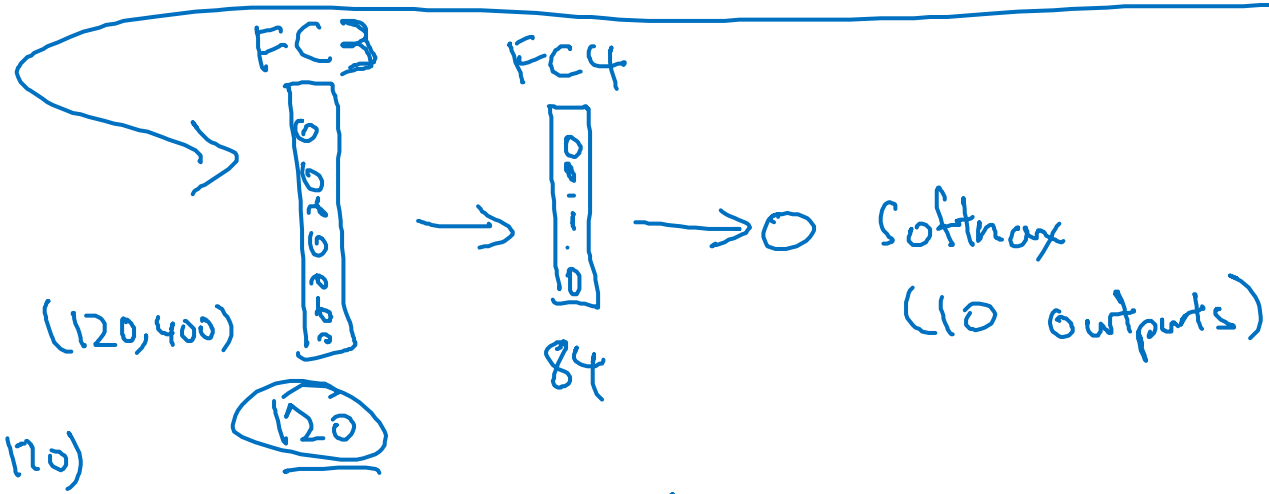
Convolutional Neural Networks

Convolutional neural network example

Neural network example (LeNet-5)





0, 1, 2, ... 9

$n_H, n_W \downarrow$

$n_C \uparrow$

CONV – POOL – CONV – POOL – FC – FC – FC – SOFTMAX

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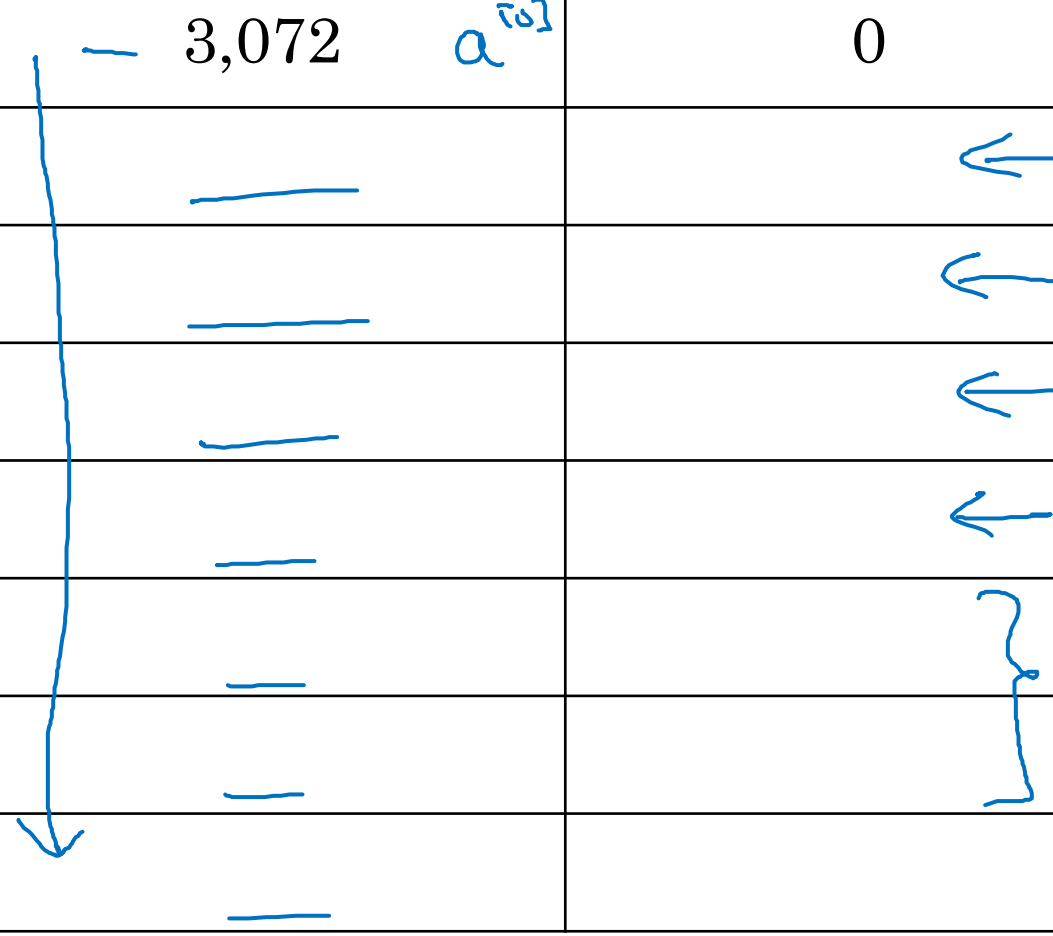
Neural network example

	Activation shape	Activation Size	# parameters
Input:	(32,32,3)	3,072	0



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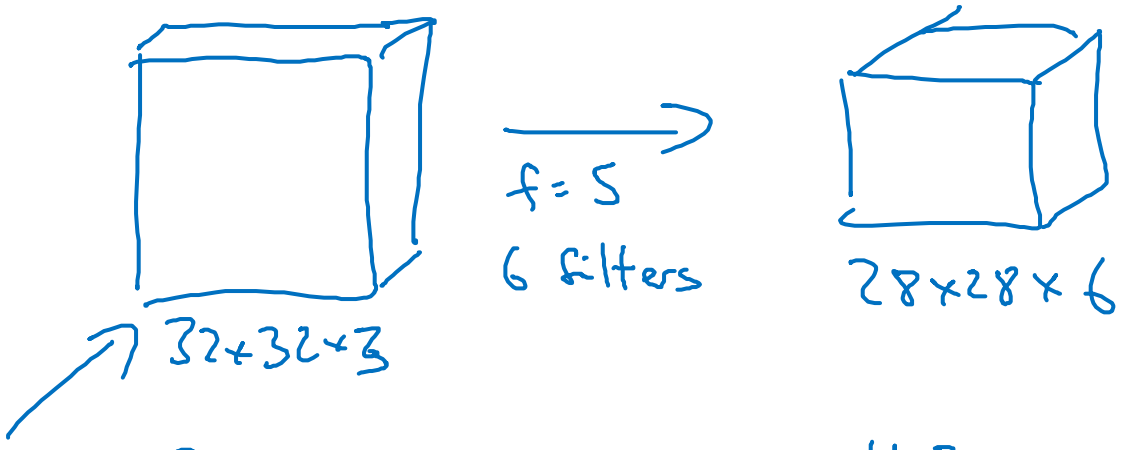
Convolutional Neural Networks

Why convolutions?

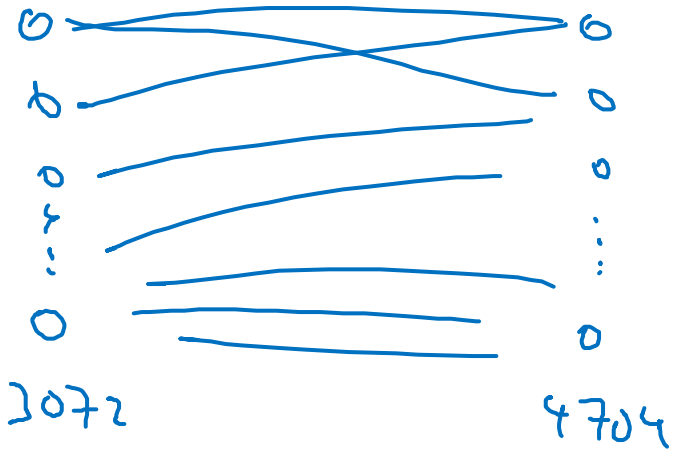
Why convolutions



5x5 — 25

26

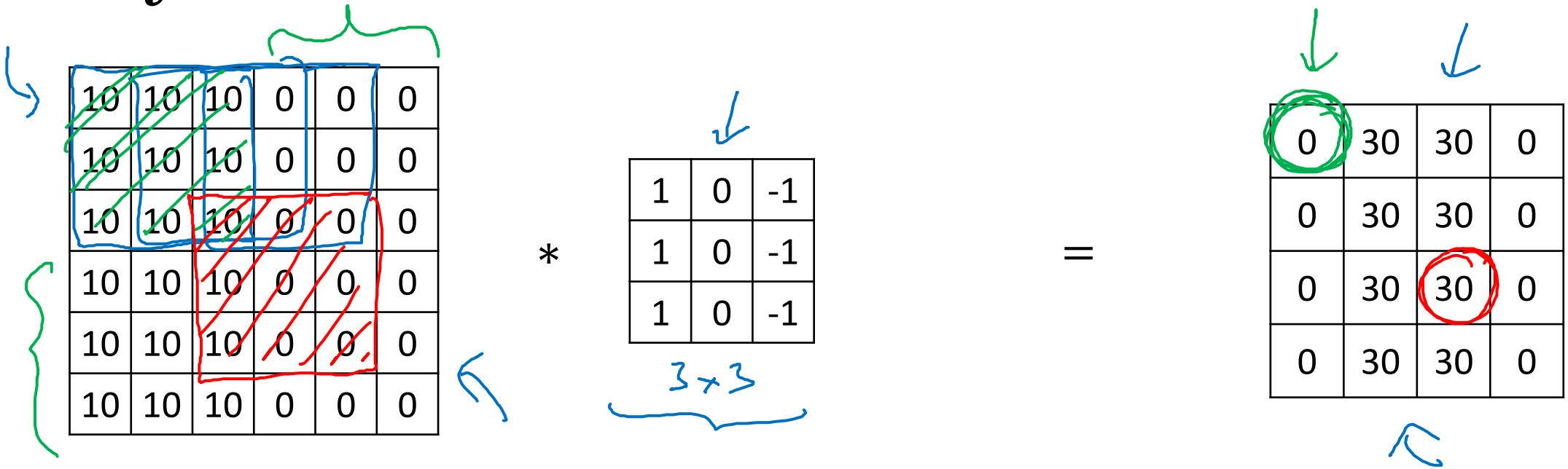
6 x 26 = 156 parameters



3,072 x 4,704 ≈ 14M

Why convolutions

translation invariance

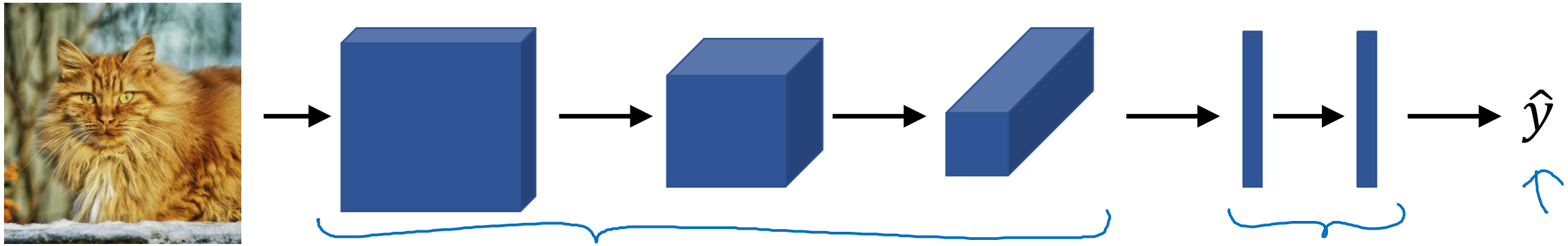


Parameter sharing: A feature detector (such as a vertical edge detector) that's useful in one part of the image is probably useful in another part of the image.

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

Putting it together

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



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