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 × 3

Cat? (0/1)

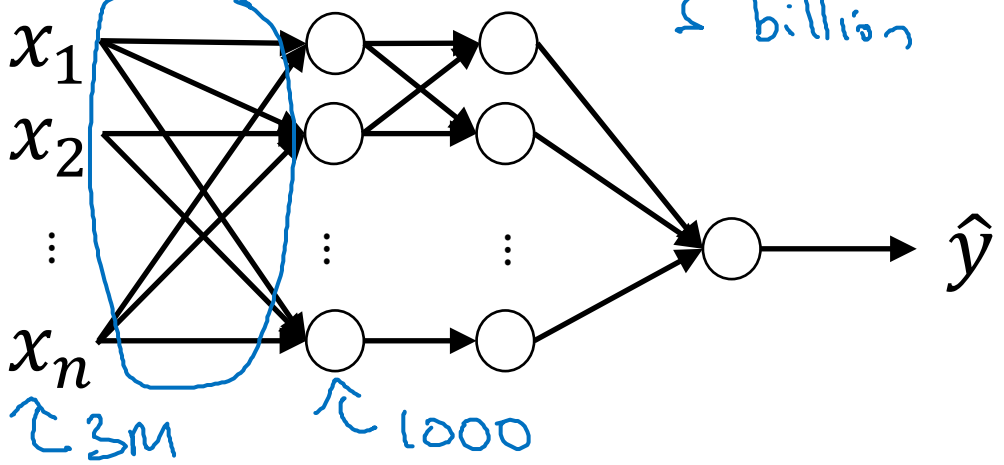
12288

1000 × 1000 × 3
= 3 million

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

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

3 billion



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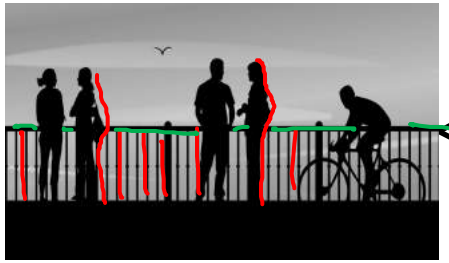
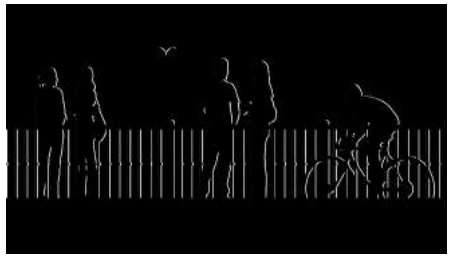
Convolutional Neural Networks

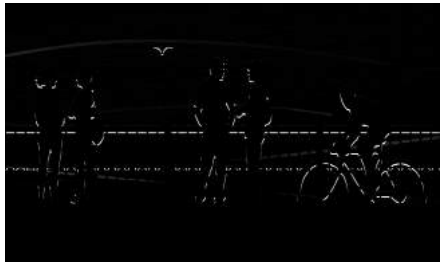
Edge detection example

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

*

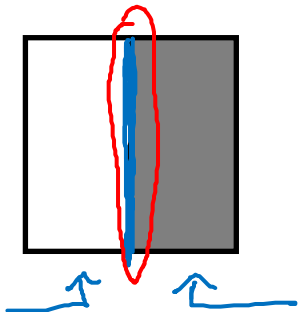
1	0	-1
1	0	-1
1	0	-1

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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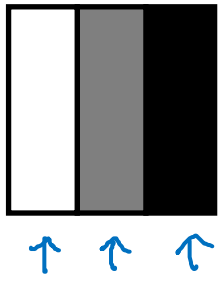

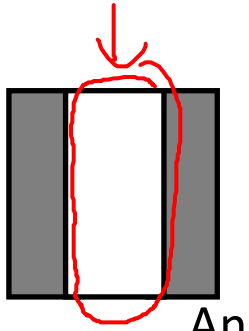

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Convolutional Neural Networks

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

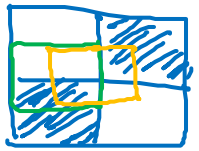
Horizontal

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

=

$\begin{bmatrix} 45° \\ 70° \\ 73° \end{bmatrix}$

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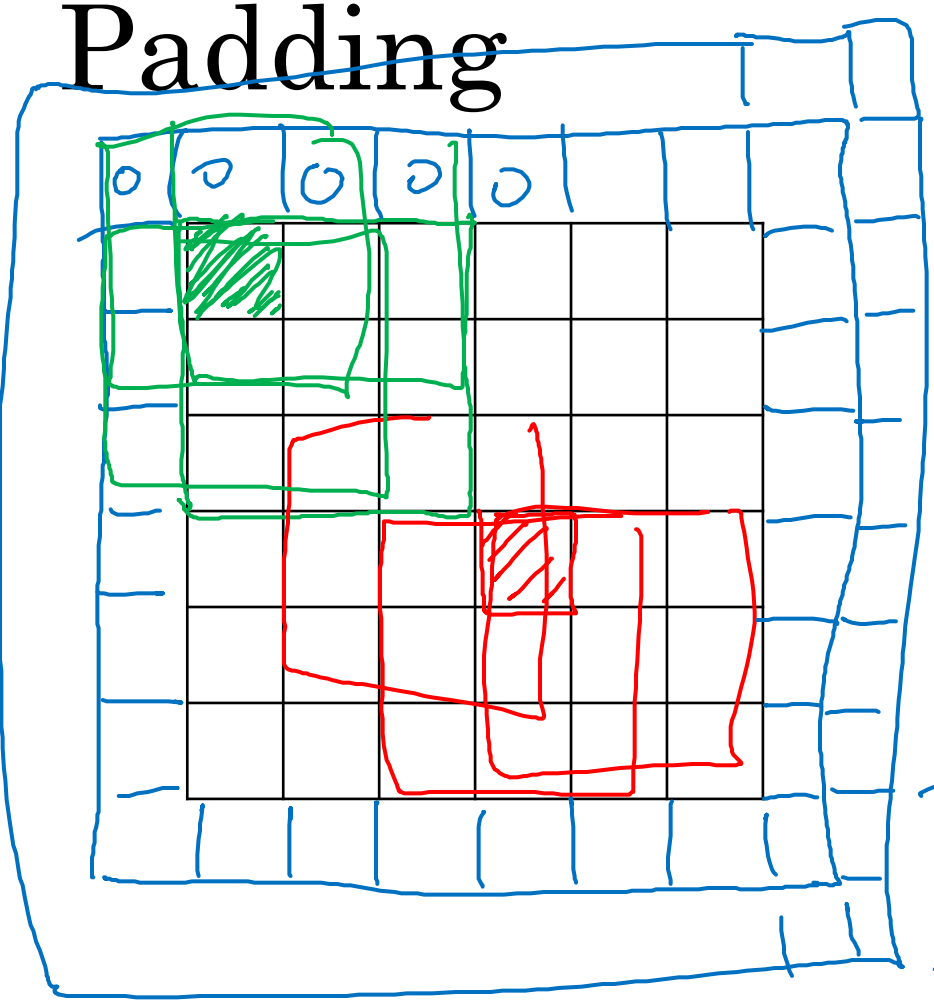
Convolutional Neural Networks

Padding

Padding

- shrinky output
- throw away info from edge



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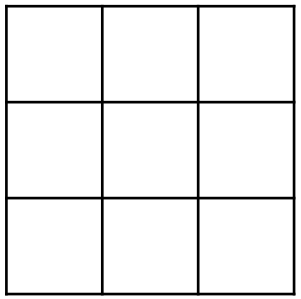
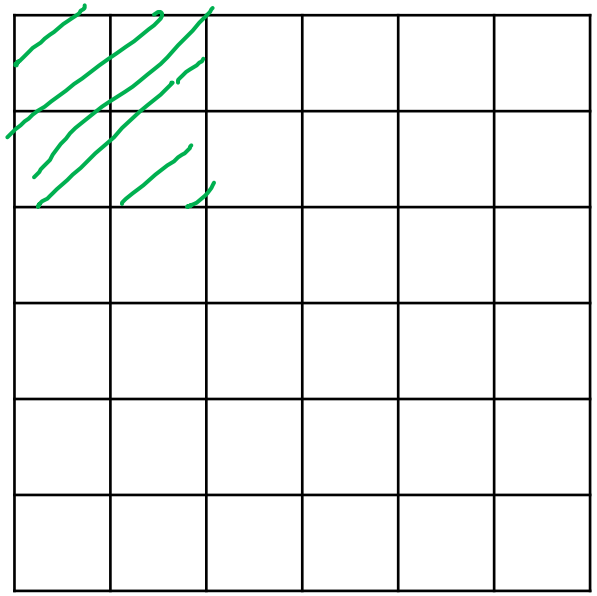


3×3
f×f

=



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.

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

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

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

$5 \times 5 \quad p = 2$

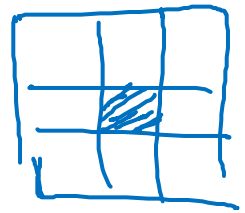
f is usually odd

1×1

3×3

5×5

7×7



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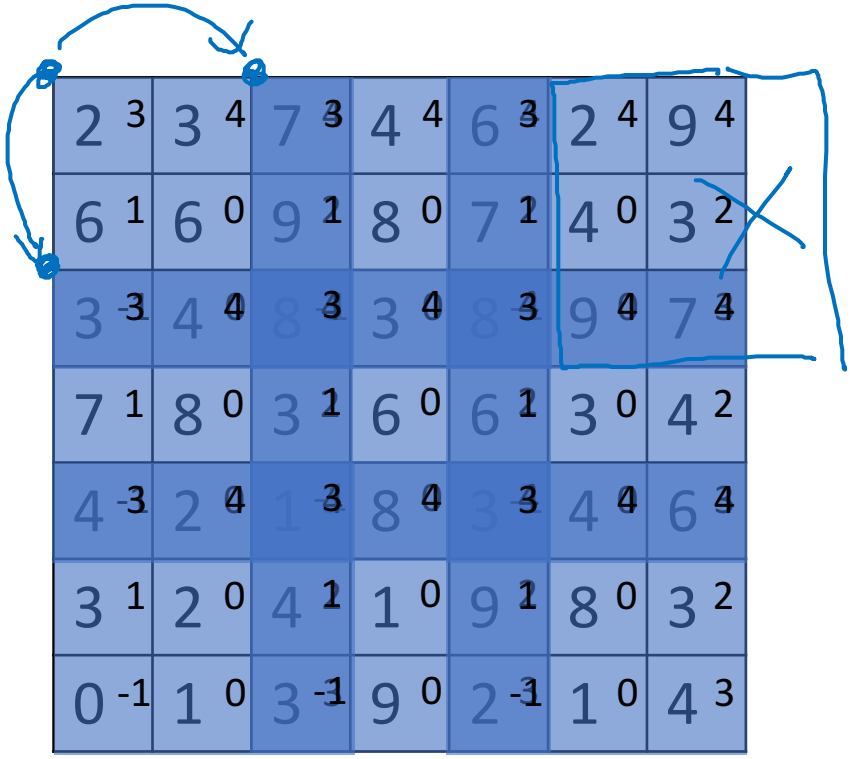
Convolutional Neural Networks

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

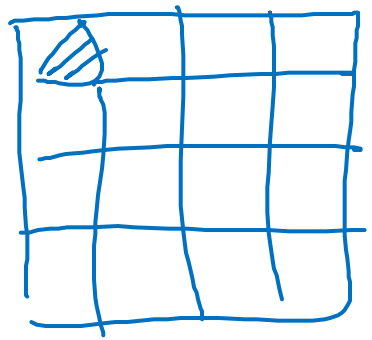
Convolution in math textbook:

2	3	7	4	6	2
6	6	9	8	7	4
3	4	8	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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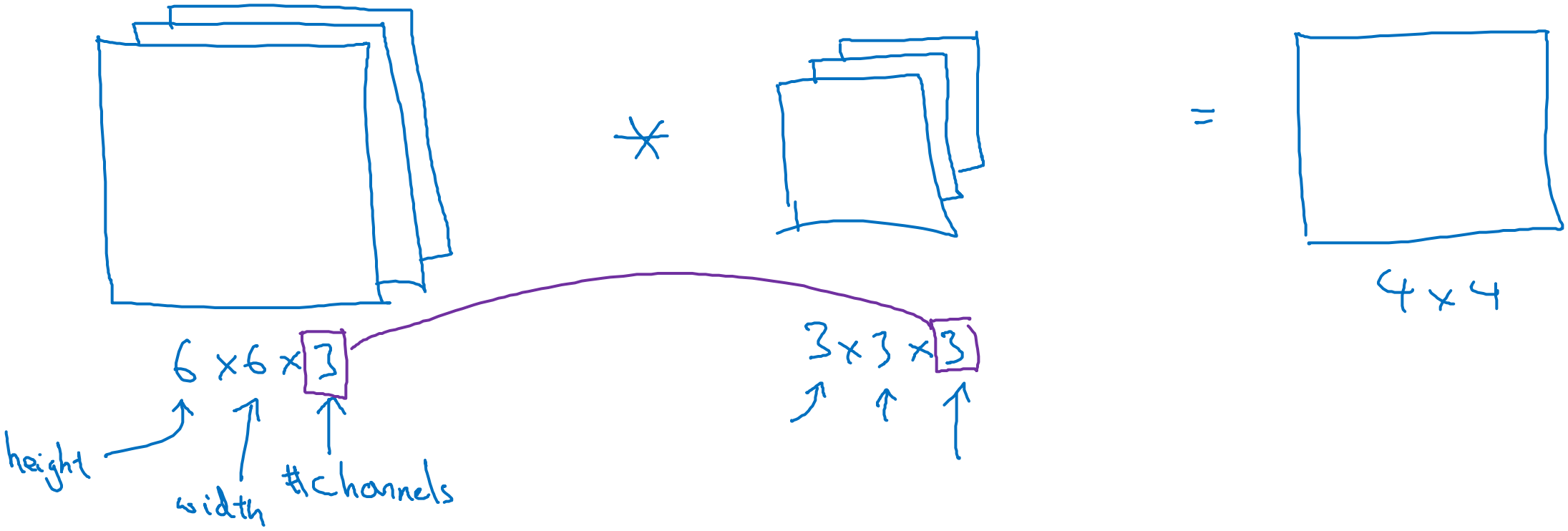
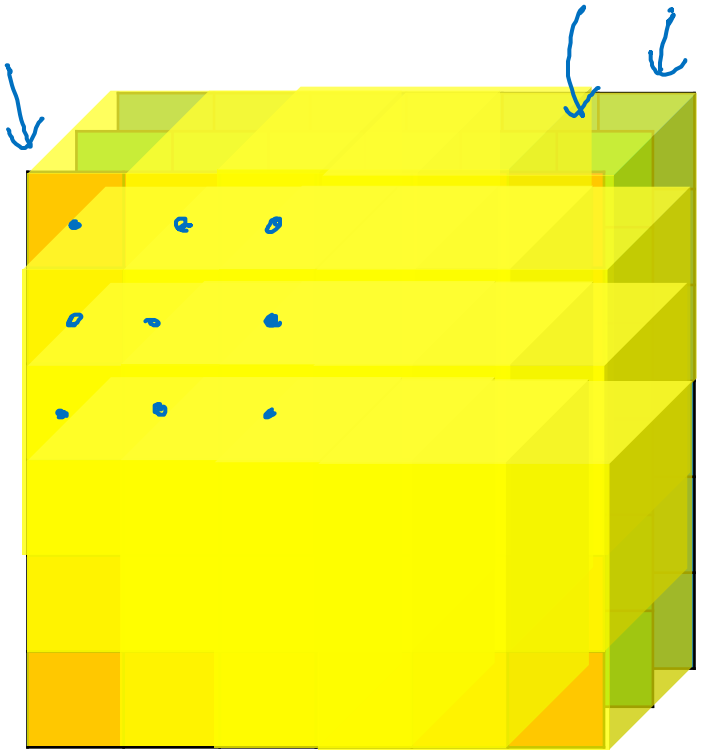
Convolutional Neural Networks

Convolutions over volumes

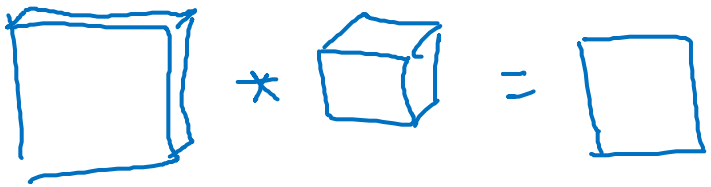
Convolutions on RGB images

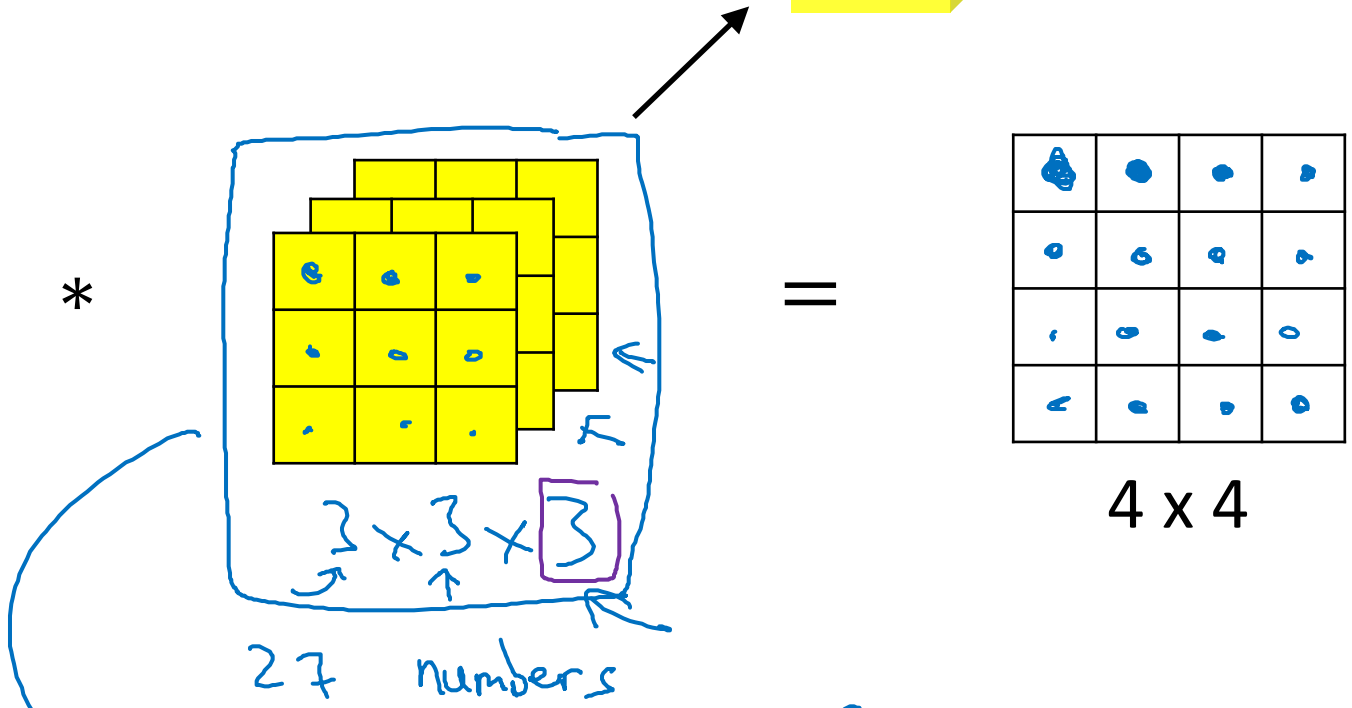


Convolutions on RGB image

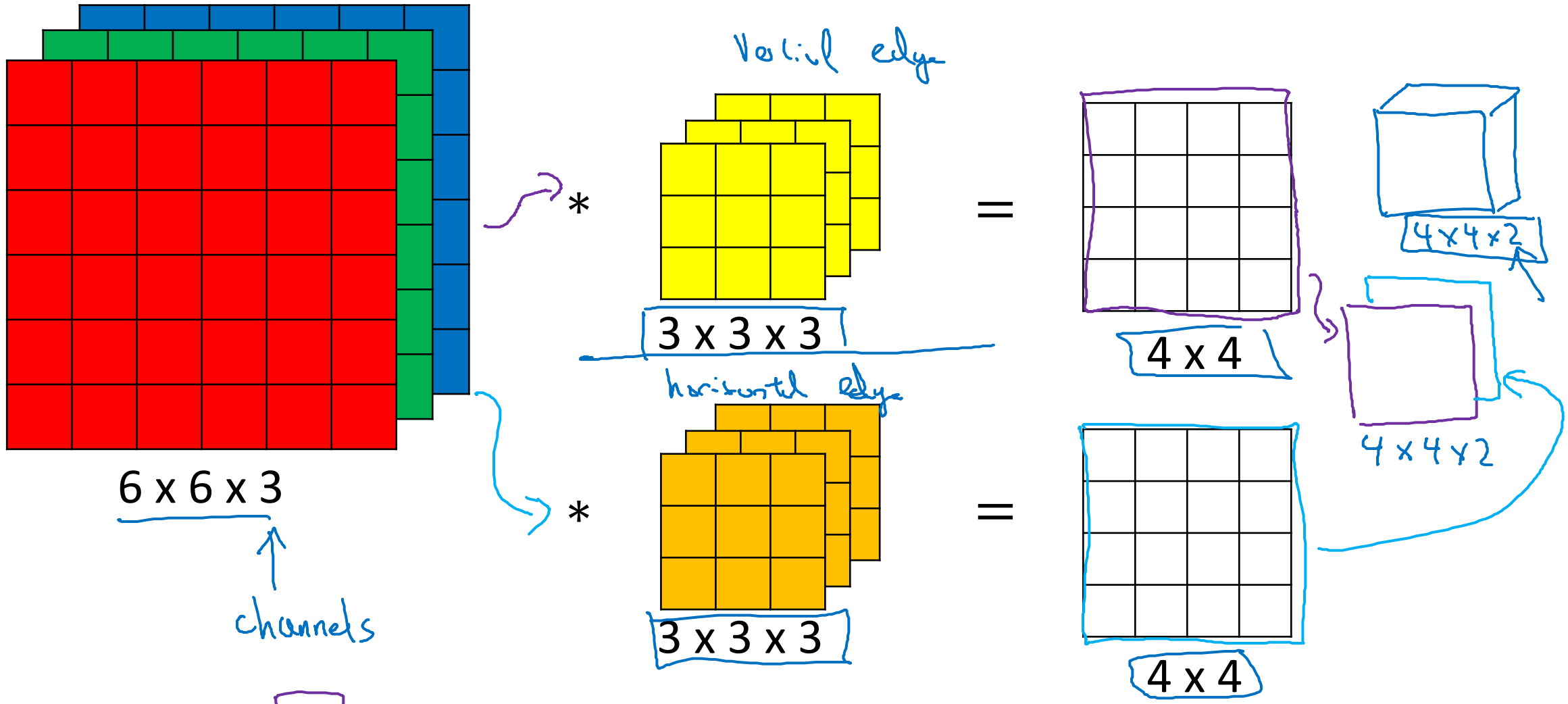


6 x 6 x 3





Multiple filters



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

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

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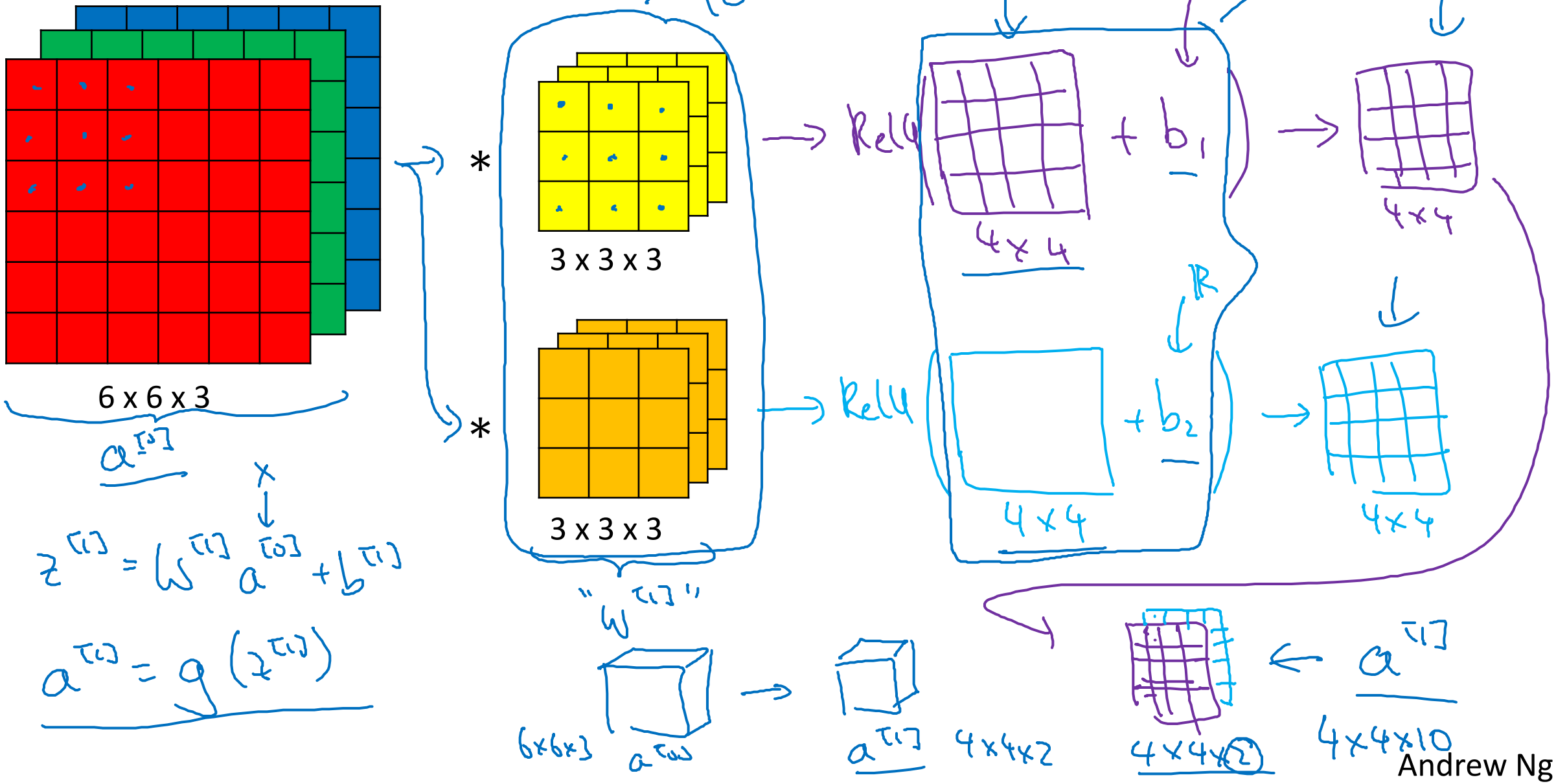
Convolutional Neural Networks

One layer of a convolutional network

Example of a layer



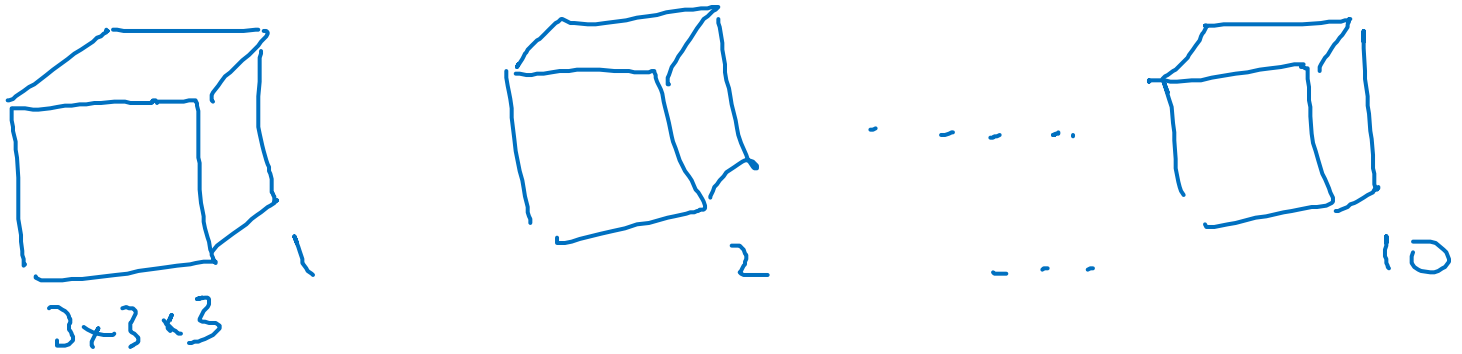
$a^{[0]}$

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

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

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?



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

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

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

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

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

$n_c \times n_H \times n_W$

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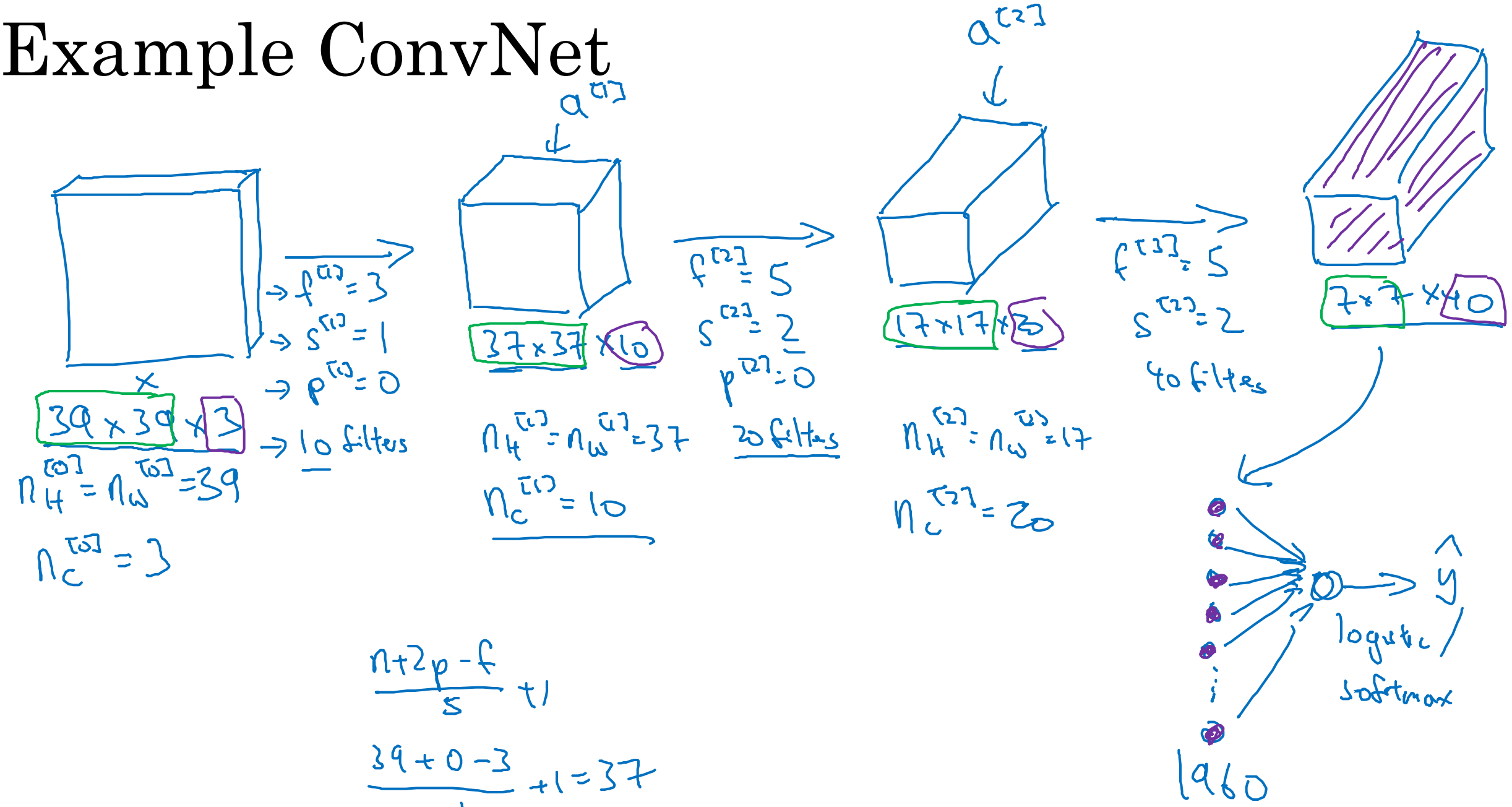
Convolutional Neural Networks

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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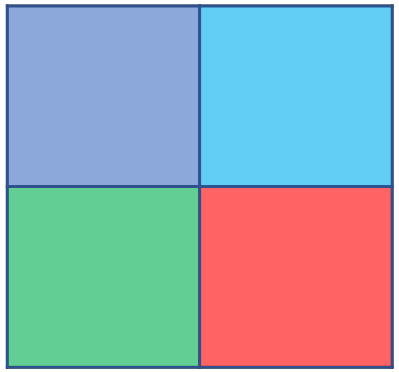
Convolutional Neural Networks

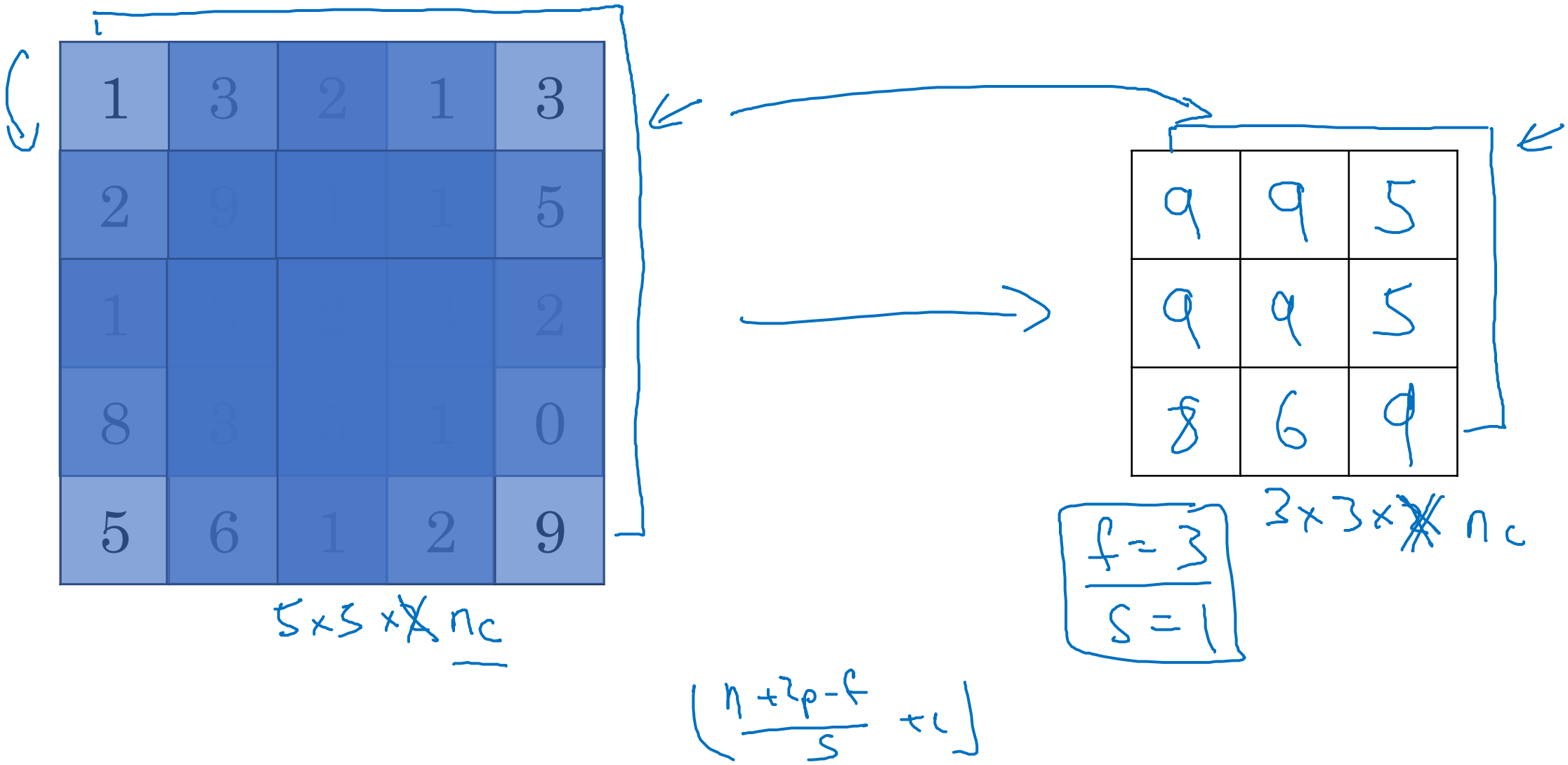
Pooling layers

Pooling layer: Max pooling

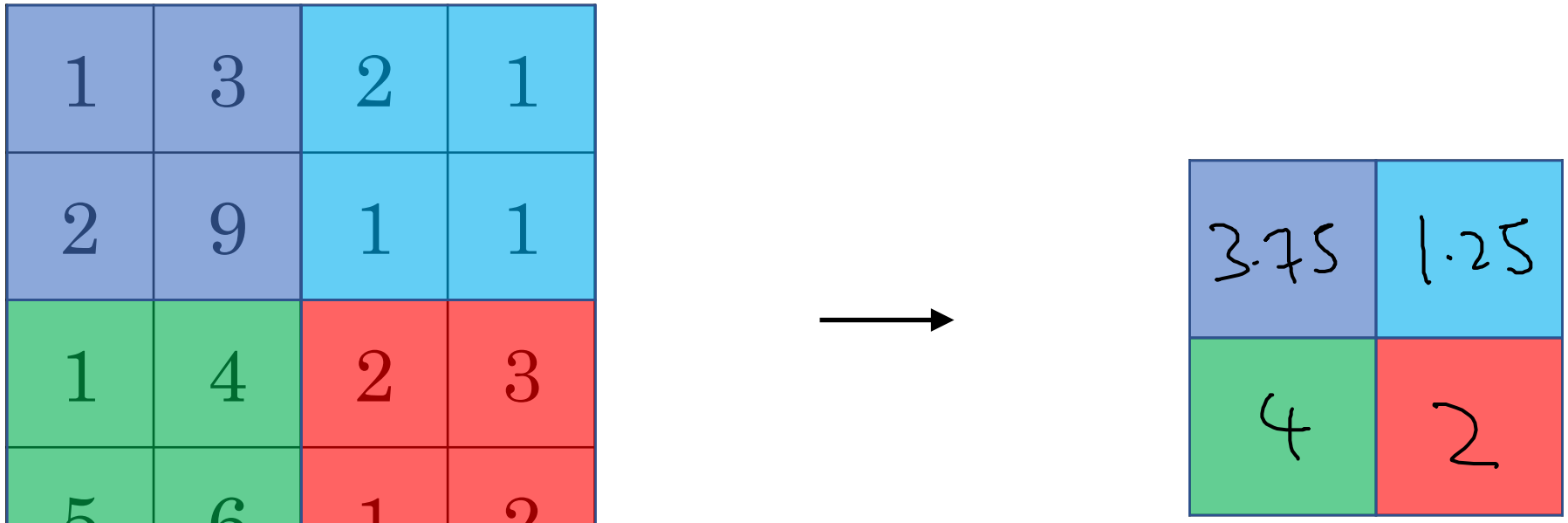
1	3	2	1
2	9	1	1
1	3	2	3
5	6	1	2



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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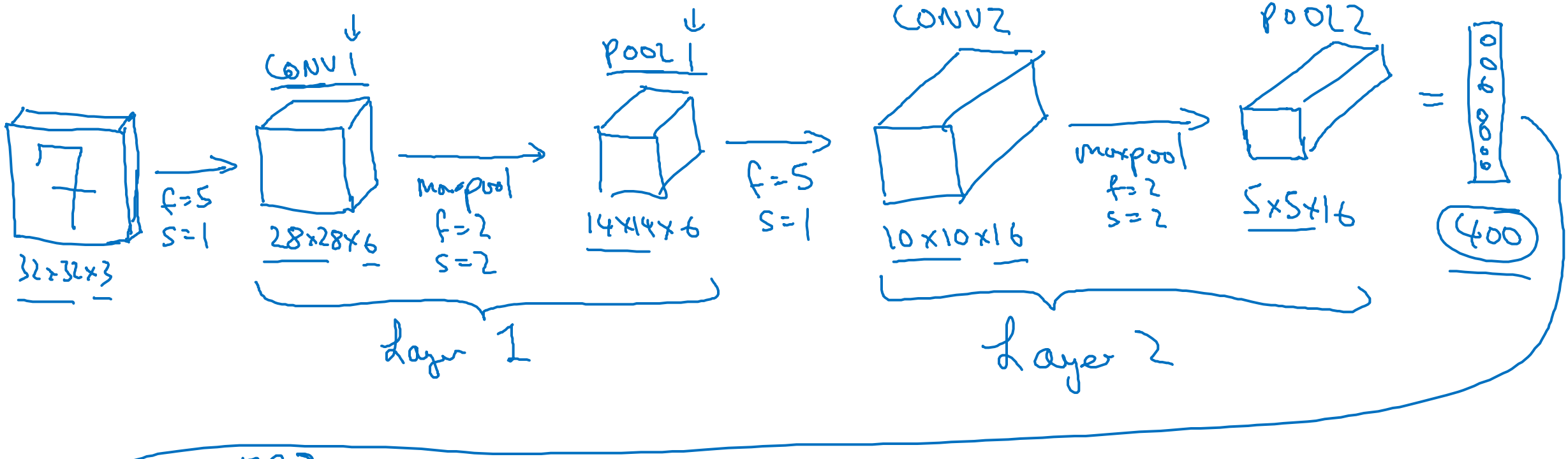
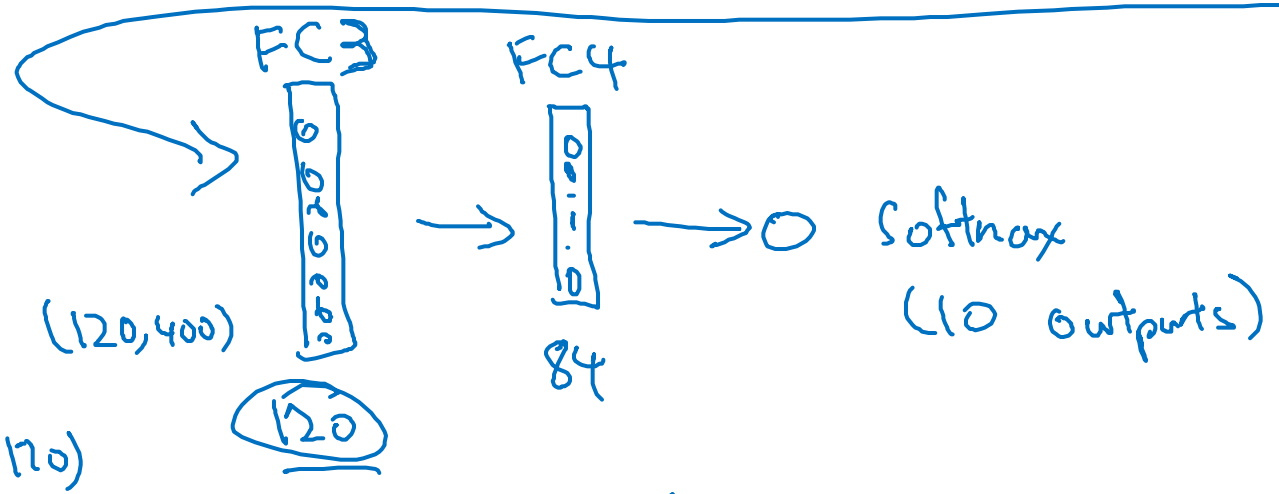
Convolutional Neural Networks

Convolutional neural network example

Neural network example (LeNet-5)





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Neural network example

	Activation shape	Activation Size	# parameters
Input:	(32,32,3)	3,072	0
CONV1 (f=5, s=1)	(28,28,6)	4,704	608
POOL1	(14,14,6)	1,176	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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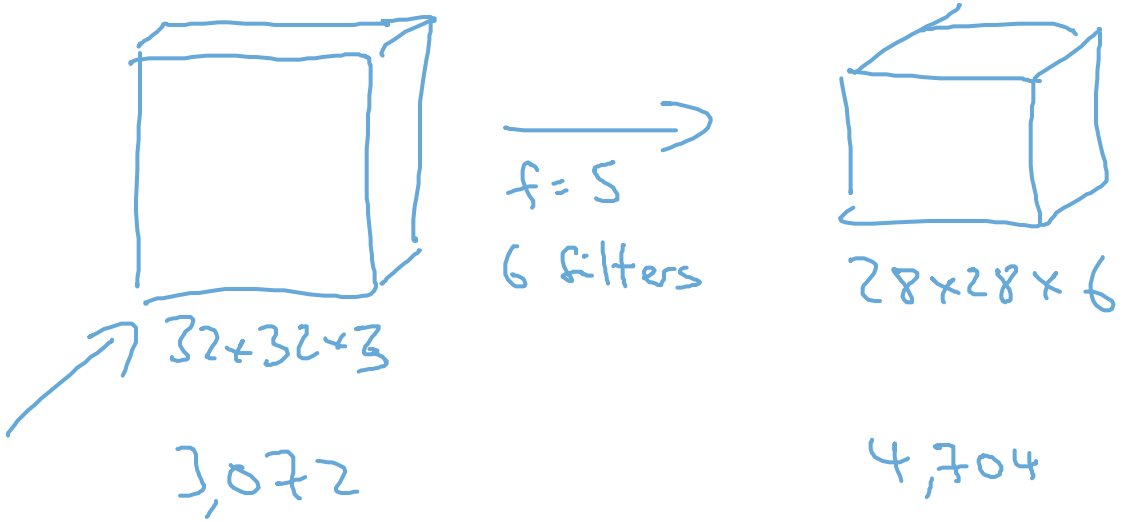
Convolutional Neural Networks

Why convolutions?

Why convolutions



(5*5*3+1)*6 = 456 Parameters

This is based on the equation:

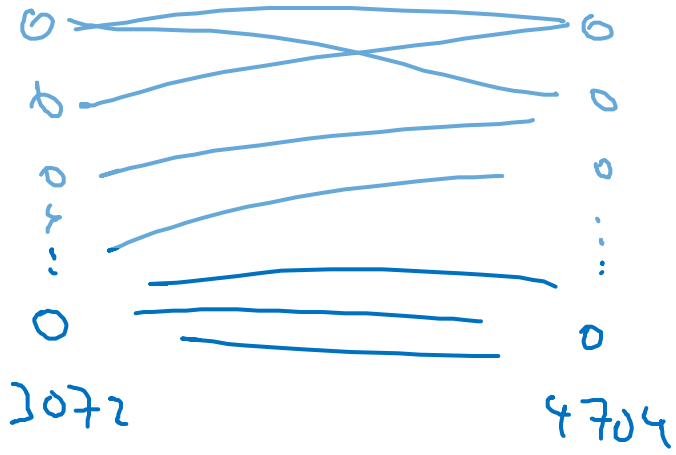
$$(f^{[l]} \times f^{[l]} \times n_c^{[l-1]} + 1) \times n_c^{[l]}.$$

$f^{[l]}$ is the filter height (and width).

$n_c^{[l-1]}$ is the number of channels in the previous layer.

$n_c^{[l]}$ is the number of channels in the current layer.

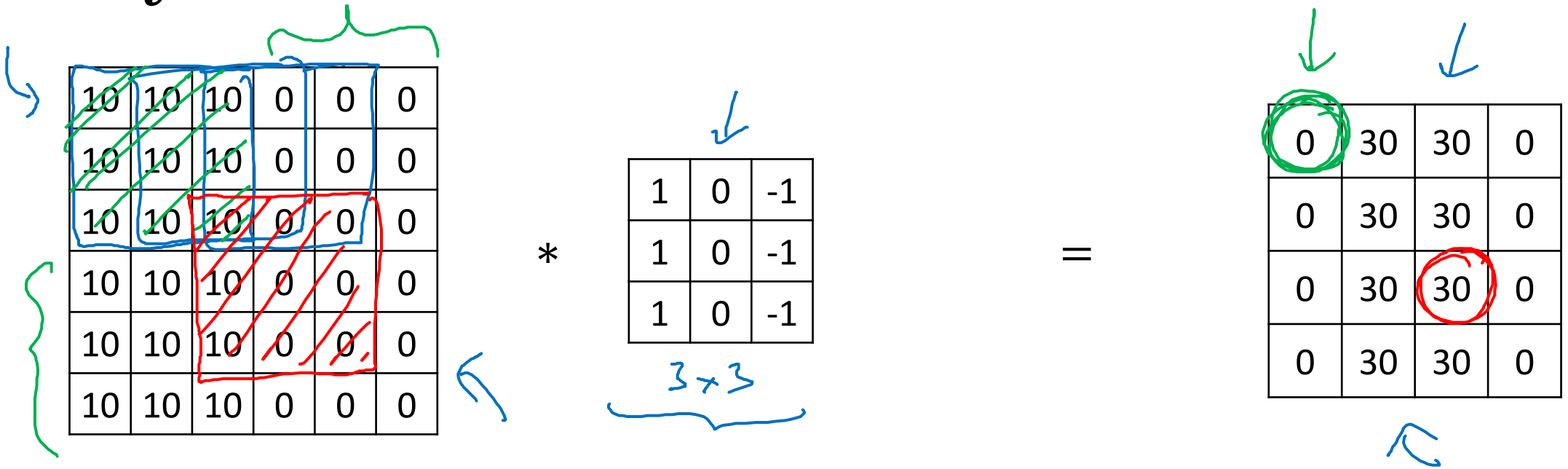
The "1" is the bias term.



3,072 × 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.

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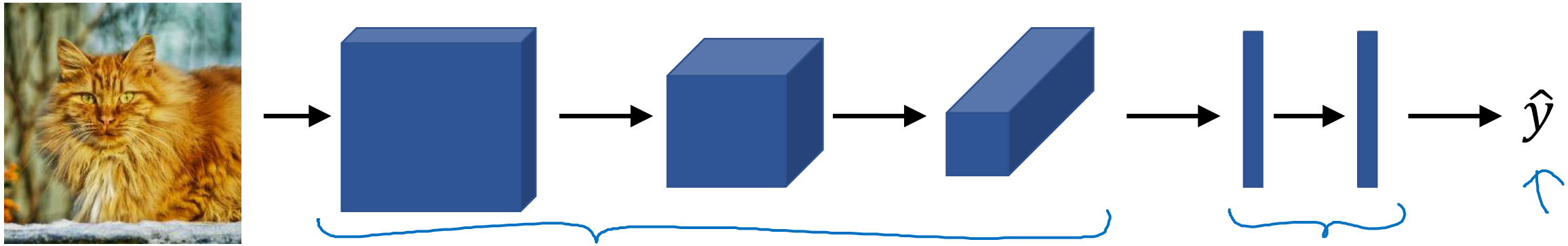
Putting it together

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

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Case Studies

Why look at case studies?

Outline

Classic networks:

- LeNet-5 ←
- AlexNet ←
- VGG ←

ResNet (152)

Inception

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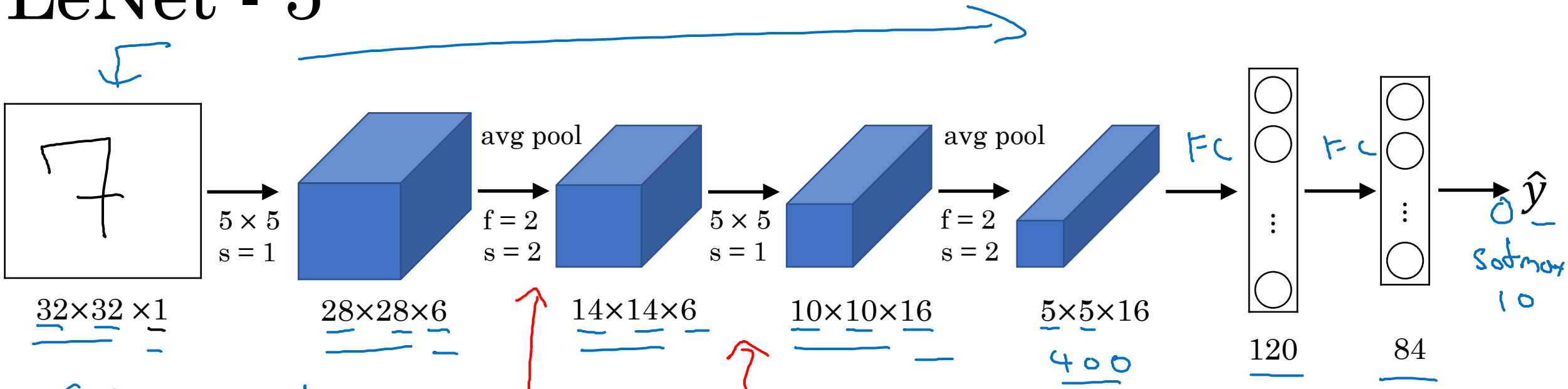
Case Studies

Classic networks

LeNet - 5



60k parameters.

$n_H, n_w \downarrow$ $n_c \uparrow$

Non-linearity after pooling

$n_H \times n_w \times n_c$ $f \times f \times n_c$

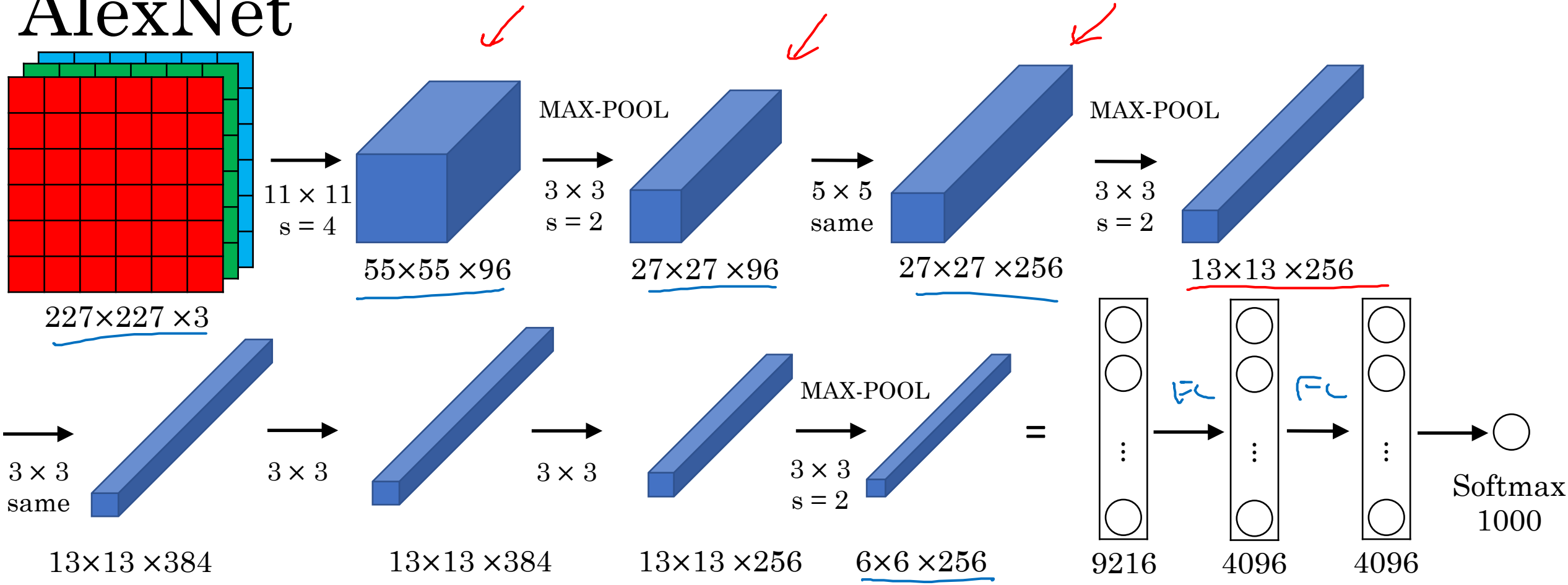
conv pool conv pool fc fc output

Advanced: sigmoid/tanh ReLU

II III

[LeCun et al., 1998. Gradient-based learning applied to document recognition]

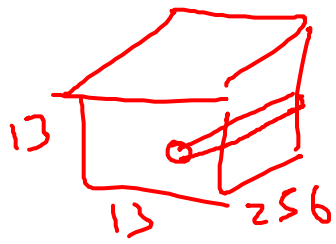
AlexNet



- Similar to LeNet, but much bigger.
- ReLU
- Multiple GPUs.
- Local Response Normalization (LRN)

9216

60M parameters

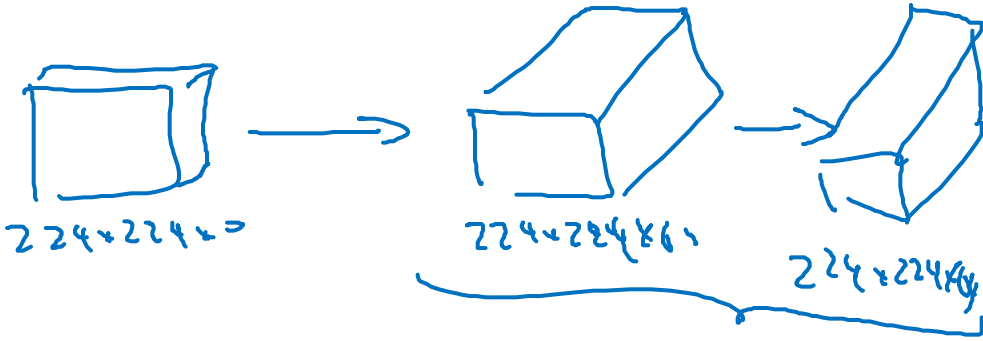


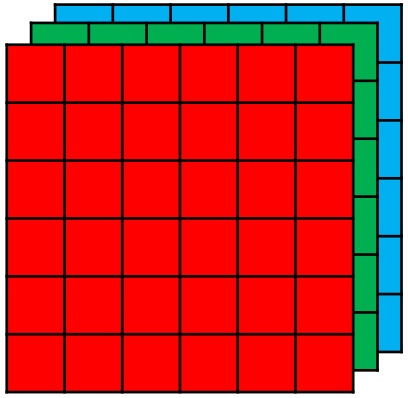
[Krizhevsky et al., 2012. ImageNet classification with deep convolutional neural networks]

VGG - 16

VGG-19

CONV = 3×3 filter, s = 1, same MAX-POOL = 2×2 , s = 2





224×224 ×3

[CONV 64] ×2

224×224×64

POOL

112×112 ×64

[CONV 128] ×2

112×112 ×128

POOL

56×56 ×128

[CONV 256] ×3

56×56 ×256

POOL

28×28 ×256

[CONV 512] ×3

28×28 ×512

POOL

14×14×512

[CONV 512] ×3

14×14 ×512

POOL

7×7×512

FC 4096

FC 4096

Softmax 1000

$n_H, n_W \downarrow$

$n_c \uparrow$

~138M

[Simonyan & Zisserman 2015. Very deep convolutional networks for large-scale image recognition]

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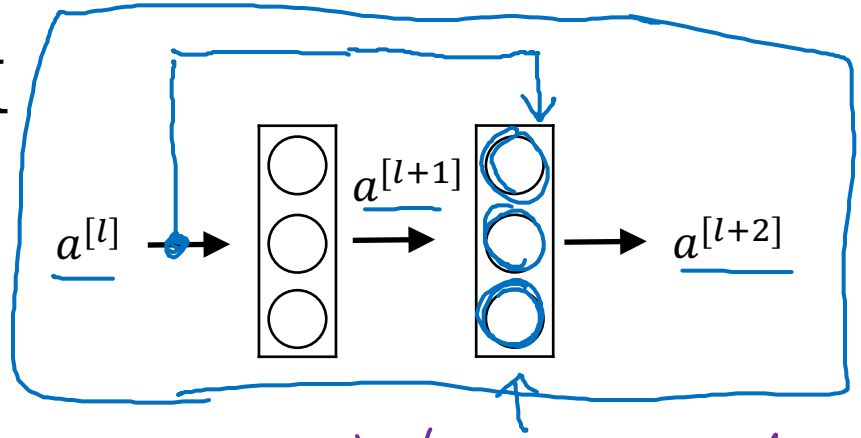
Case Studies

Residual Networks (ResNets)

Residual block



$a^{[l]}$ → Linear → ReLU → $a^{[l+1]}$ → Linear → (+) → ReLU → $a^{[l+2]}$

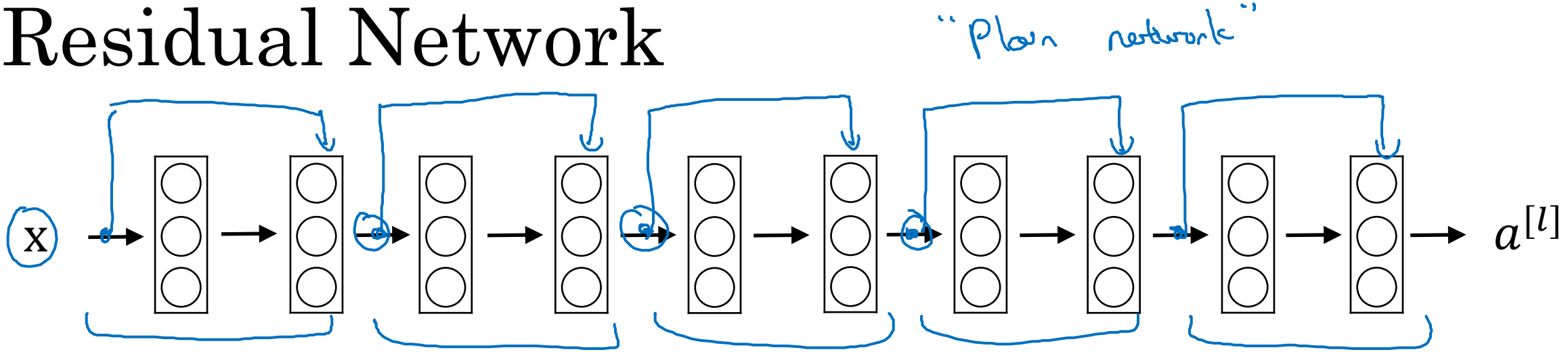
"main pain"

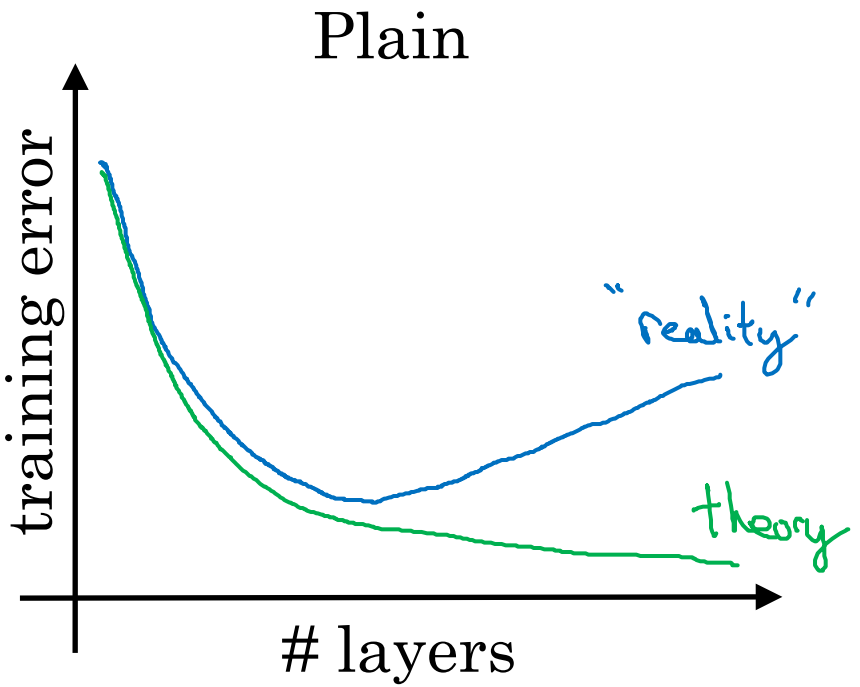
$$z^{[l+1]} = W^{[l+1]} a^{[l]} + b^{[l+1]} \qquad a^{[l+1]} = g(z^{[l+1]}) \qquad z^{[l+2]} = W^{[l+2]} a^{[l+1]} + b^{[l+2]} \qquad \cancel{a^{[l+2]} = g(z^{[l+2]})}$$

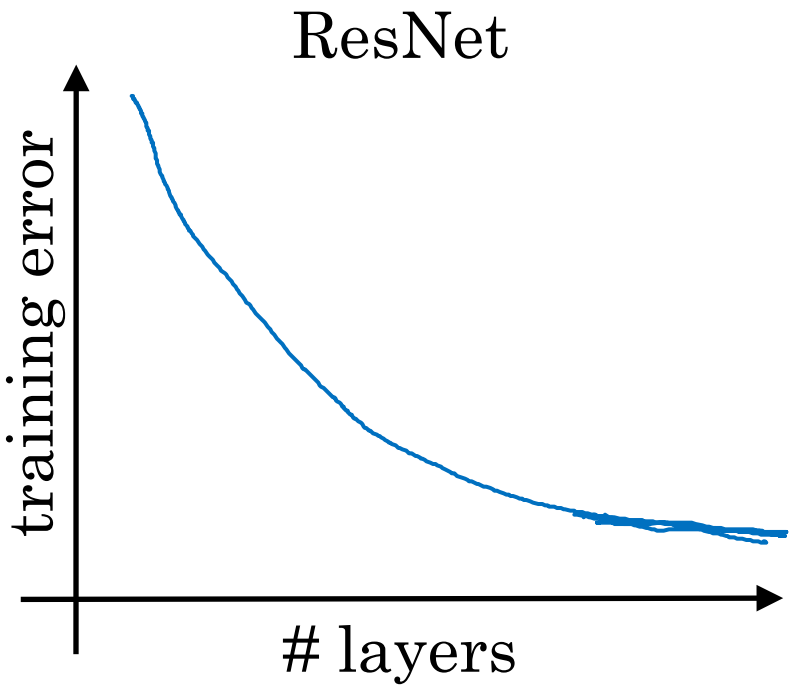
$$a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$$

[He et al., 2015. Deep residual networks for image recognition]

Residual Network







[He et al., 2015. Deep residual networks for image recognition]

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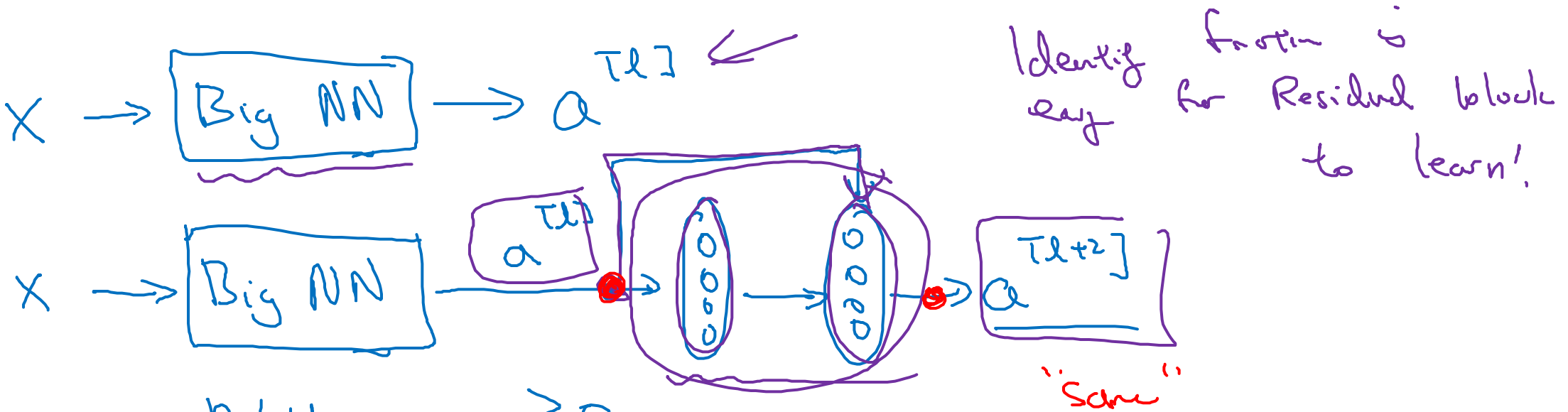
Case Studies

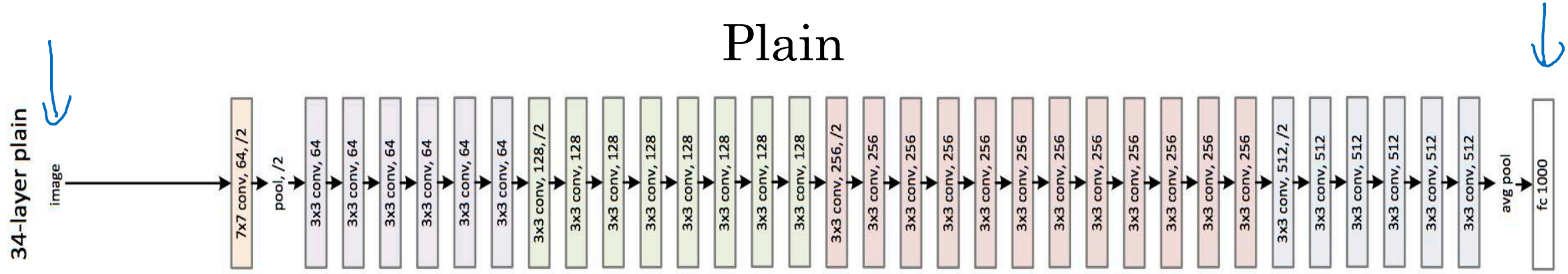
Why ResNets work

Why do residual networks work?

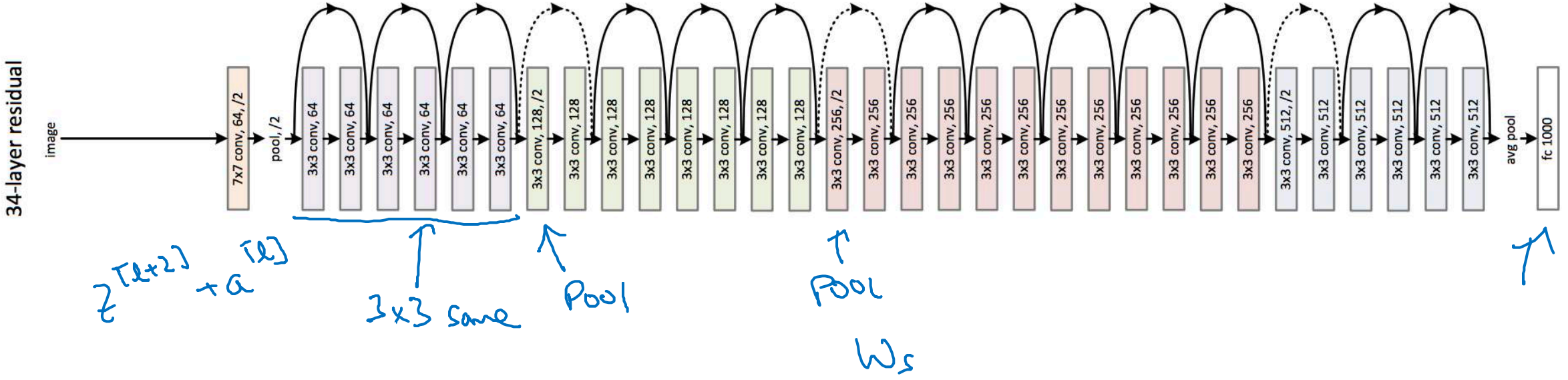


ResNet

Plain



ResNet



[He et al., 2015. Deep residual networks for image recognition]

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Case Studies

Network in Network and 1×1 convolutions

Why does a 1 × 1 convolution do?

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

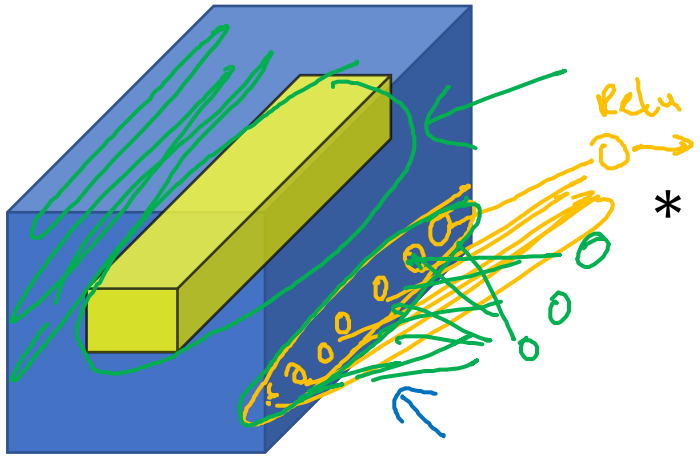
6 × 6 × 1

*

2

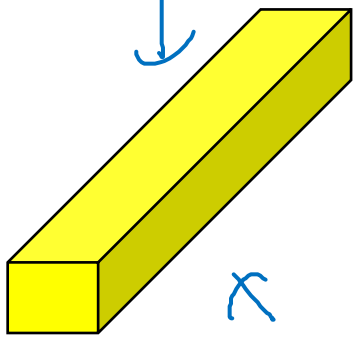
=

2	4	6	…		



6 × 6 × 32

*

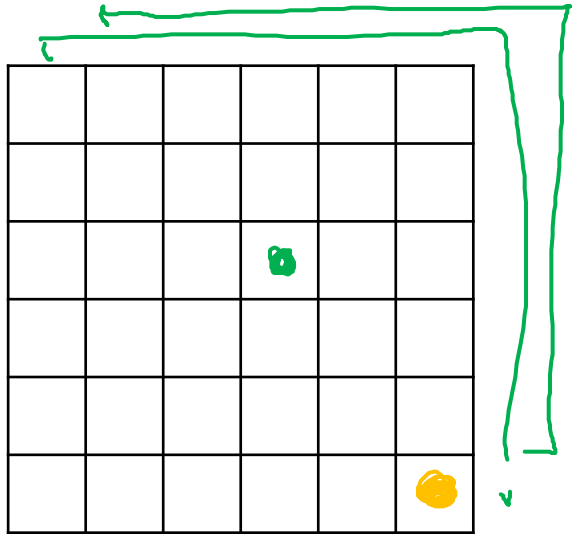


1 × 1 × 32

32 → # filters.

$n_c^{[l+1]}$

=



6 × 6 × # filters

ReLU

Network in Network

[Lin et al., 2013. Network in network]

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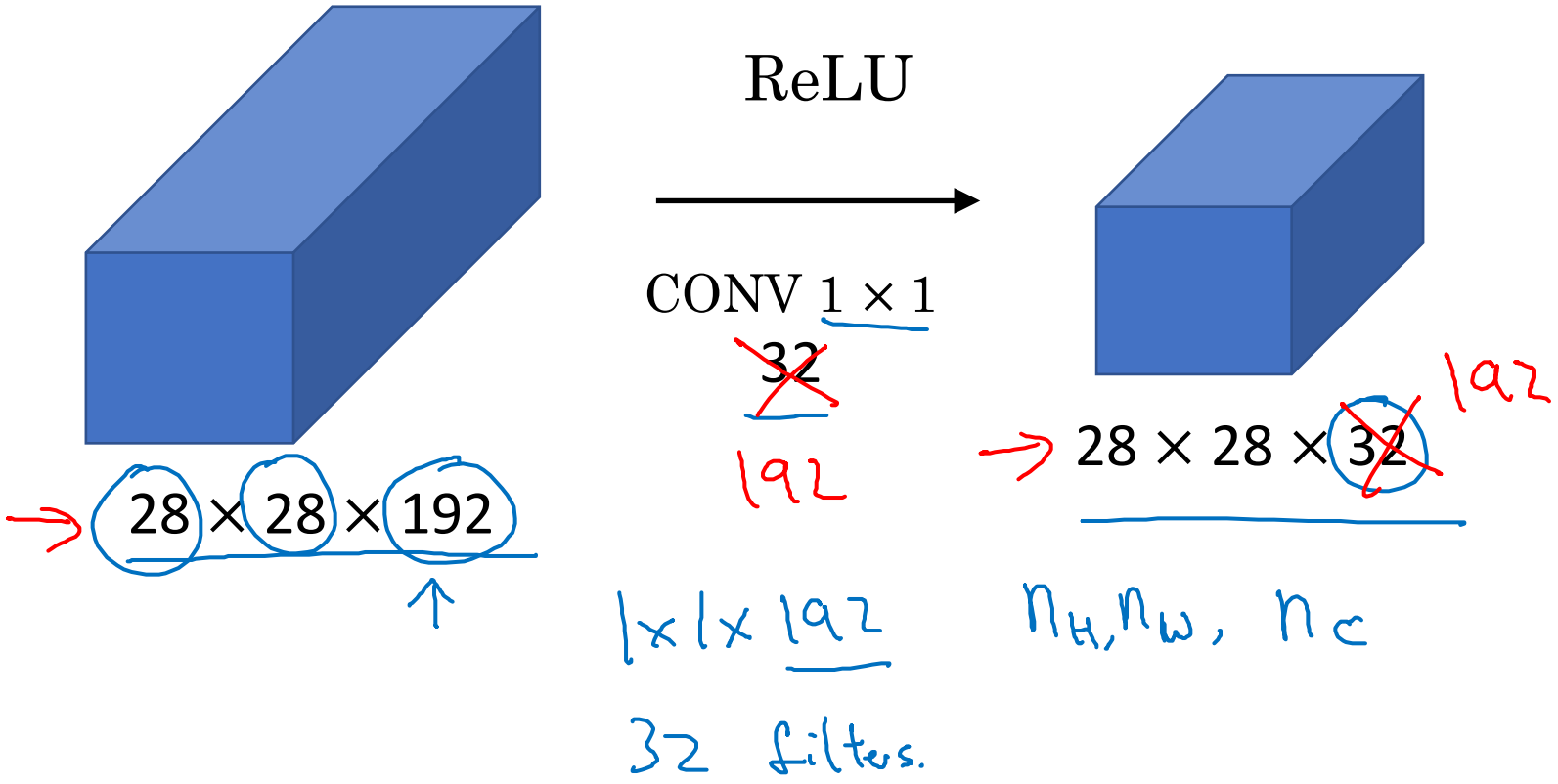
Using 1×1 convolutions



[Lin et al., 2013. Network in network]

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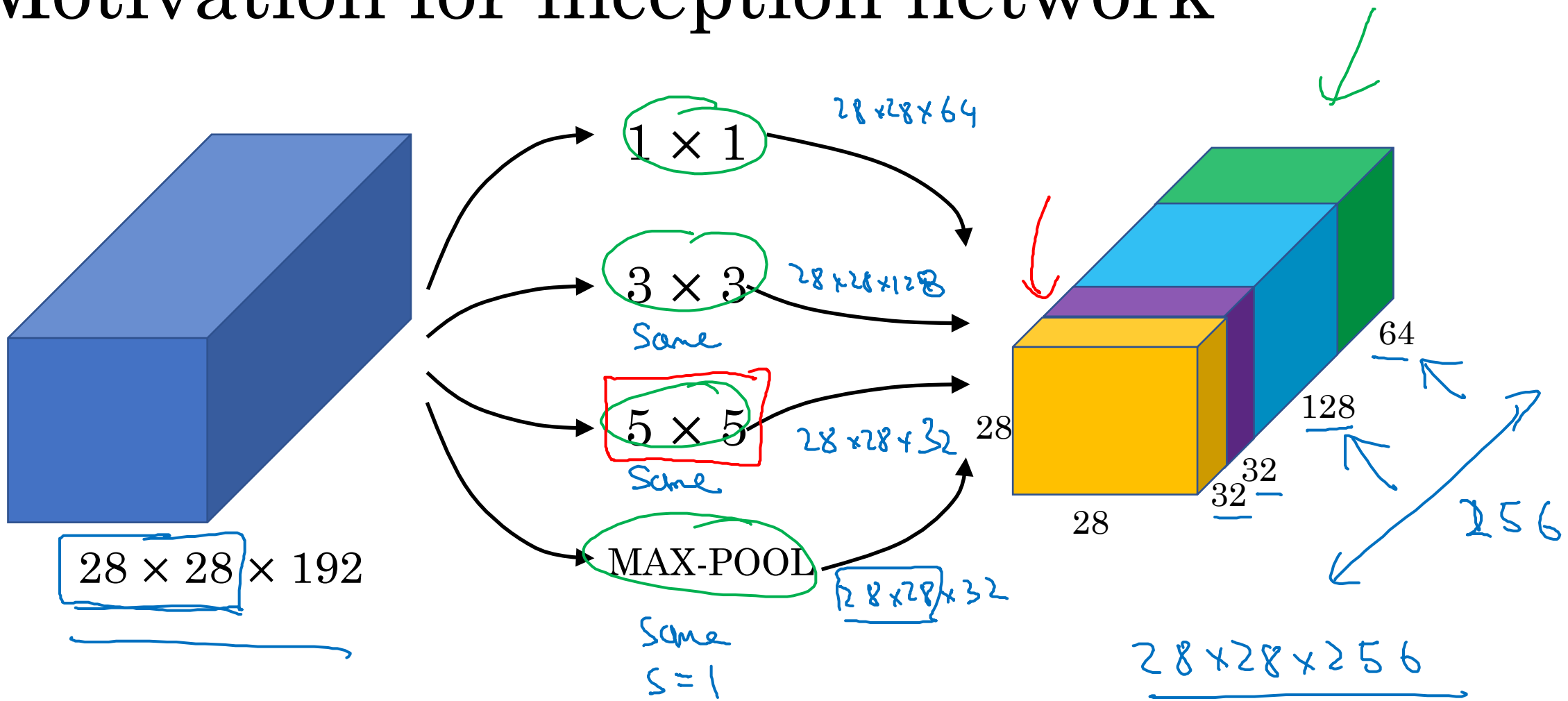
Case Studies

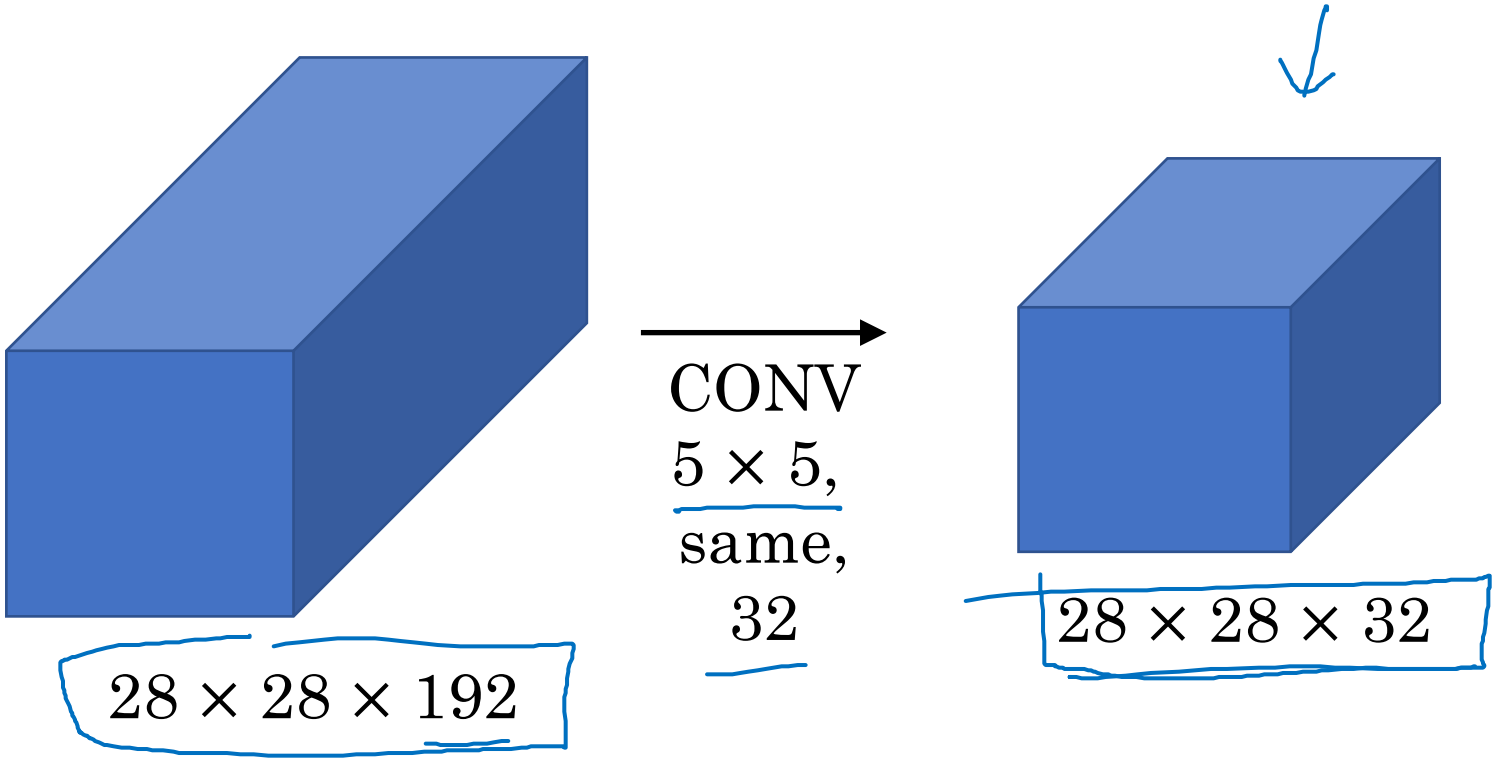
Inception network motivation

Motivation for inception network



[Szegedy et al. 2014. Going deeper with convolutions]

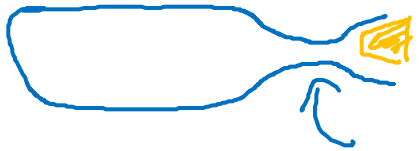
The problem of computational cost



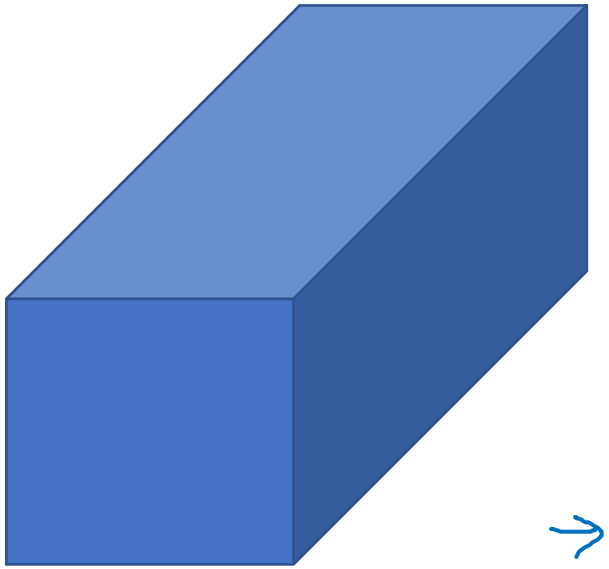
32 filters. filter one 5×5×192.

28×28×32 × 5×5×192 = 120M.

Using 1×1 convolution

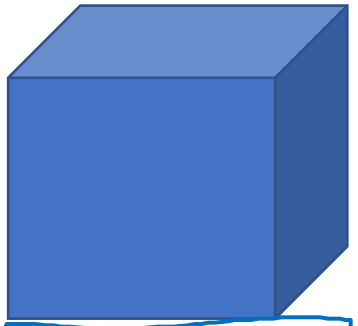


"bottleneck layer"



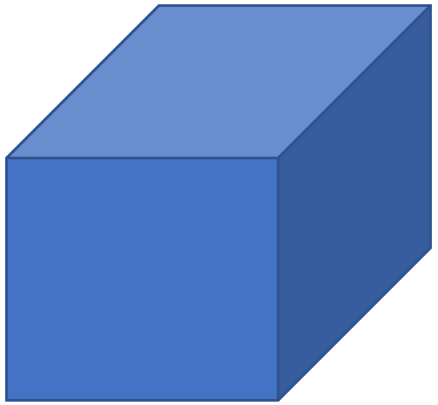
28 × 28 × 192

CONV
1 × 1,
16,
1 × 1 × 192



28 × 28 × 16

CONV
5 × 5,
32,
5 × 5 × 16



28 × 28 × 32

28×28×16 × 192 = 2.4M

28×28×32 × 5×5×16 = 10.0M

12.4M

120M

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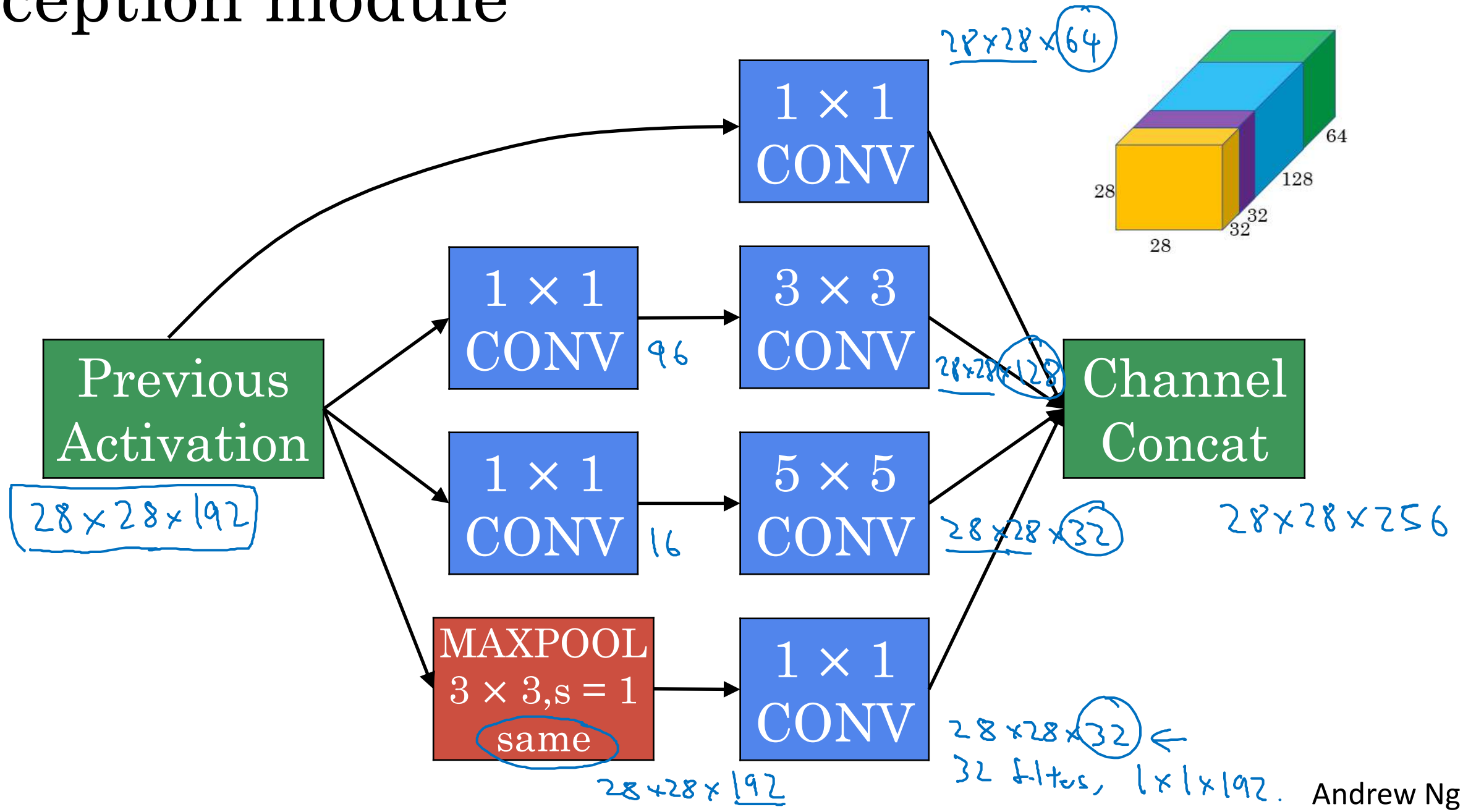
Case Studies

Inception network

Inception module



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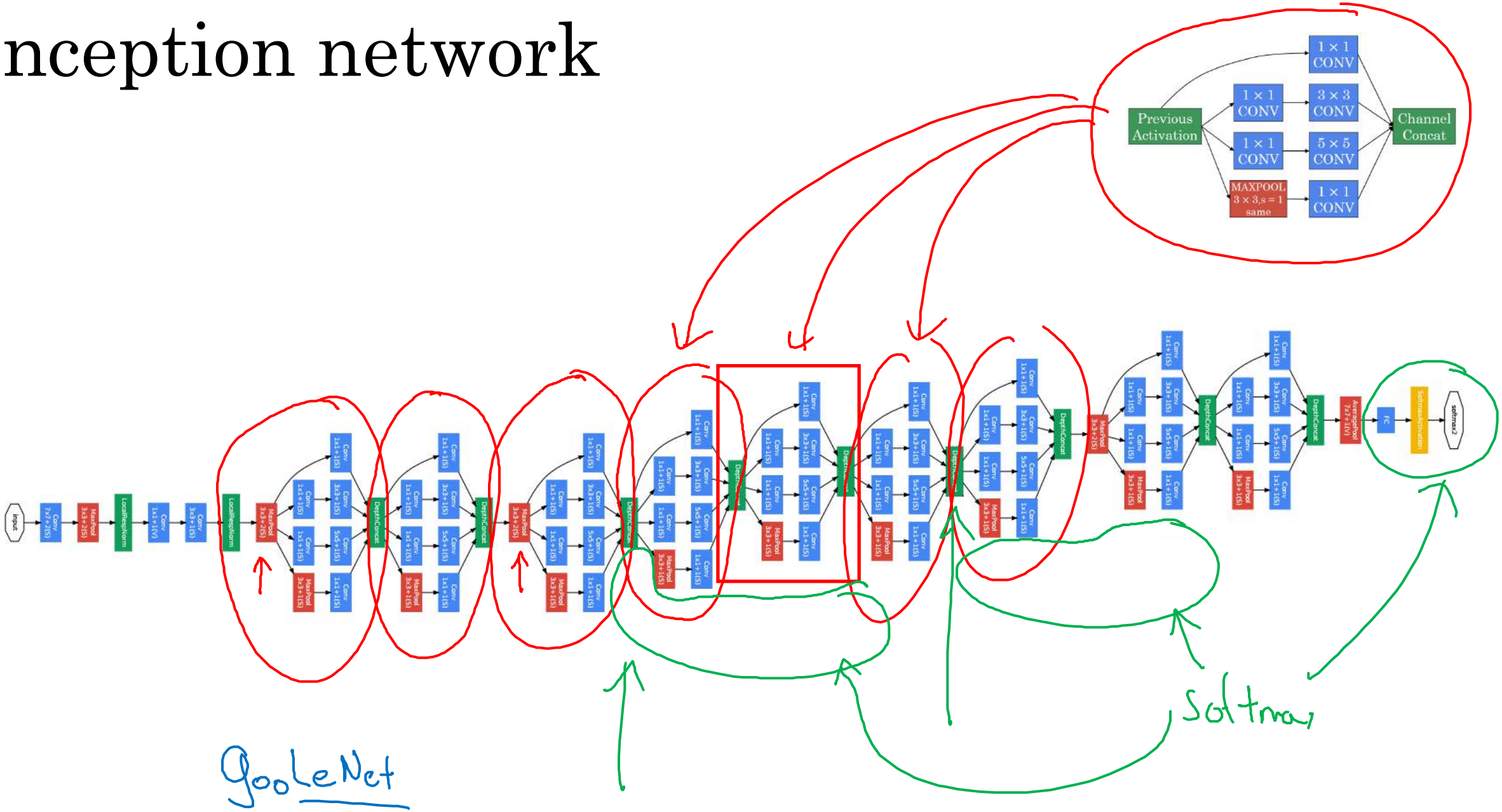
Inception network



[Szegedy et al., 2014, Going Deeper with Convolutions]

http://knowyourmeme.com/memes/we-need-to-go-deeper

Convolutional Neural Networks

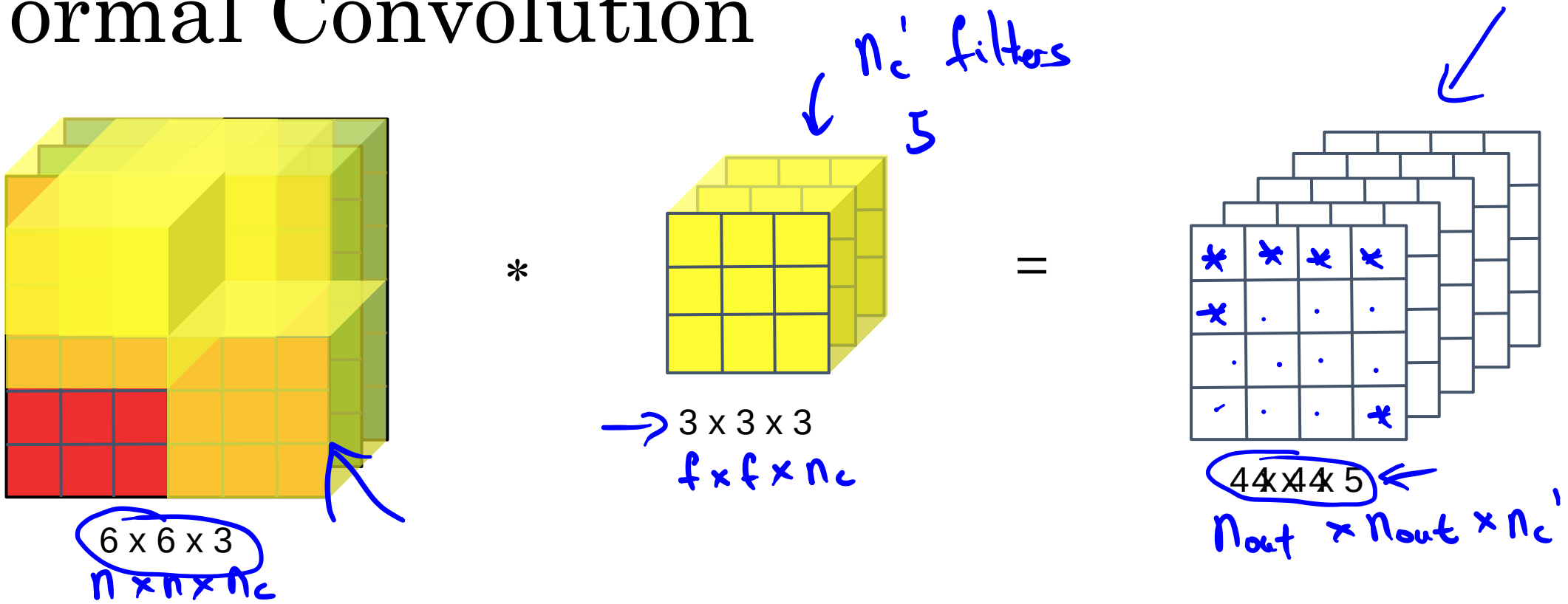
MobileNet

Motivation for MobileNets

- Low computational cost at deployment
- Useful for mobile and embedded vision applications
- Key idea: Normal vs. depthwise-separable convolutions

[Howard et al. 2017, MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications]

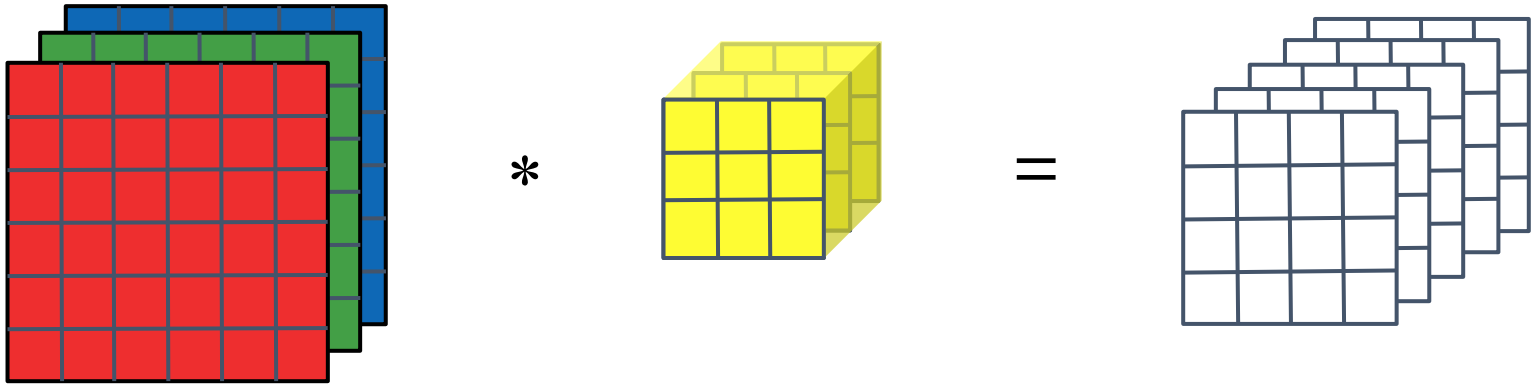
Normal Convolution



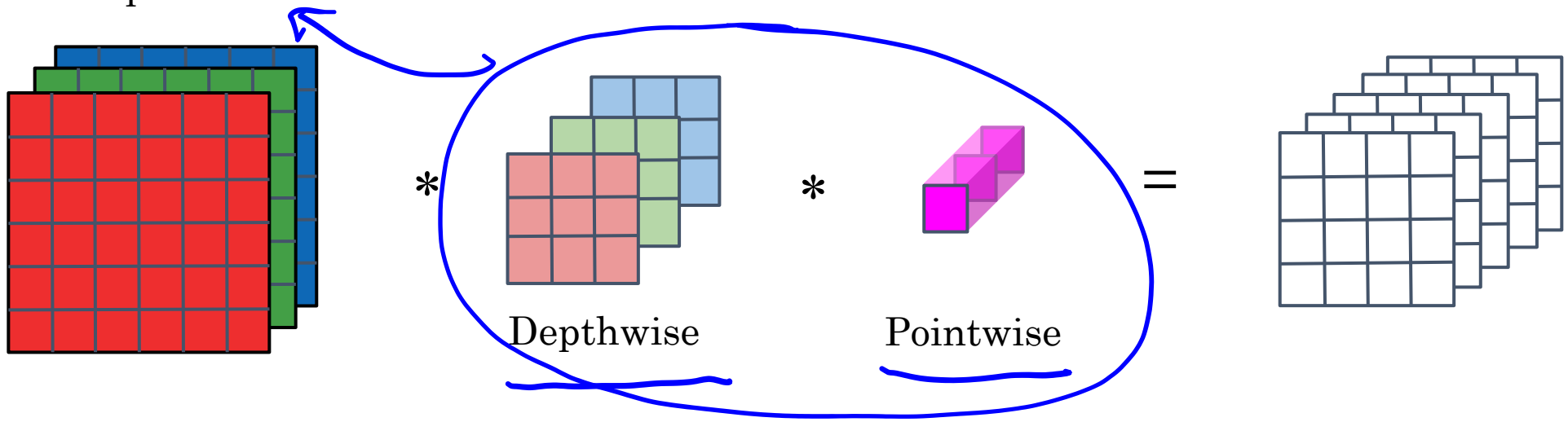
Computational cost	=	#filter params	x	# filter positions	x	# of filters
→ 2160	=	3x3x3	x	4x4	x	5

Depthwise Separable Convolution

Normal Convolution



Depthwise Separable Convolution



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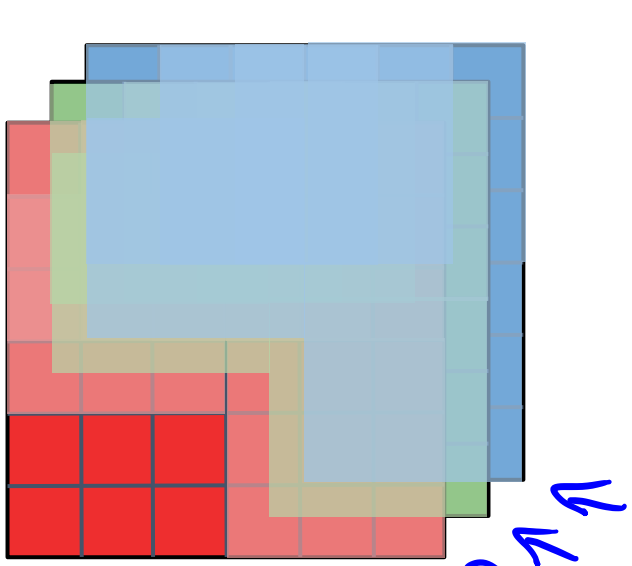
Depthwise Convolution



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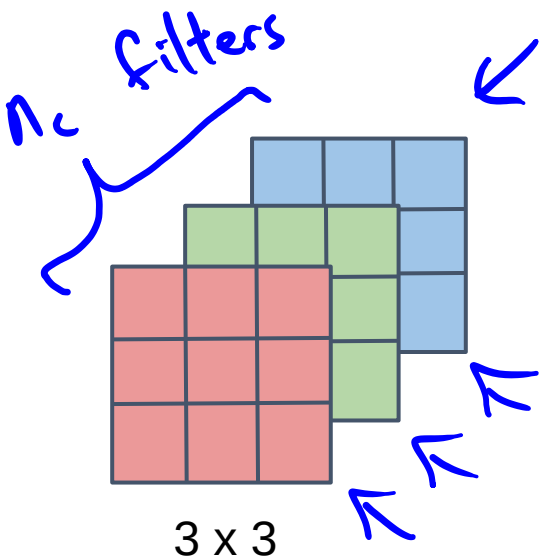

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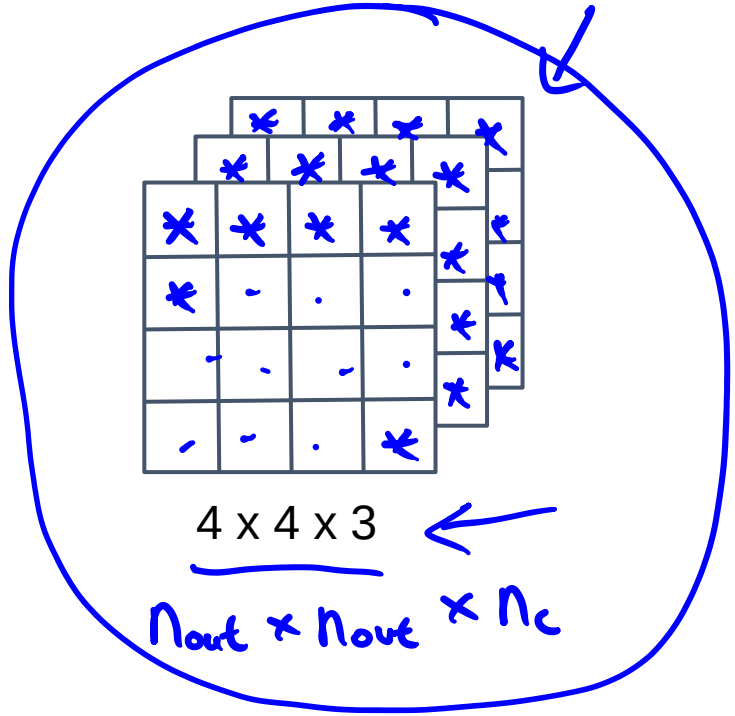

$n \times n \times n_c$

Computational cost	=	#filter params	x	# filter positions	x	# of filters
432	=	3×3	×	4×4	×	3

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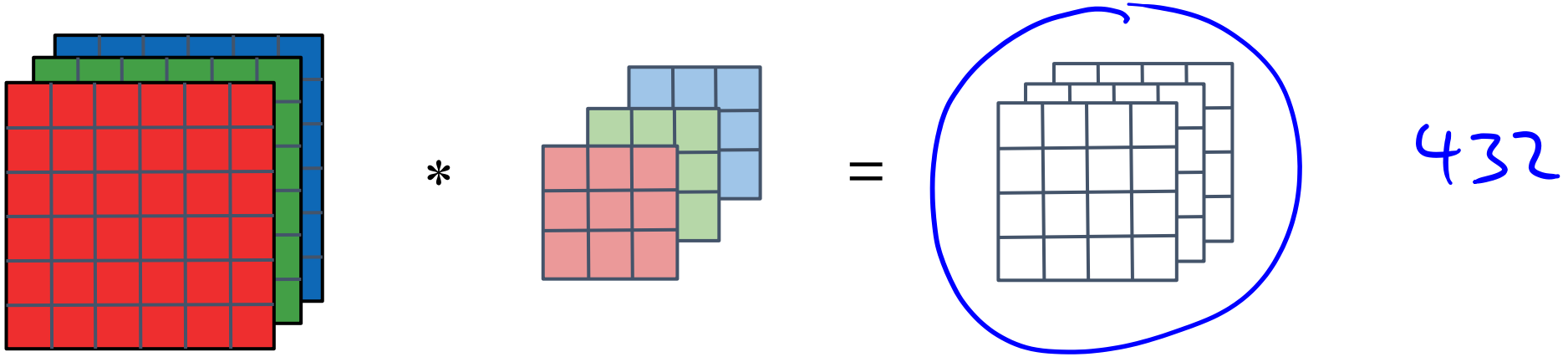
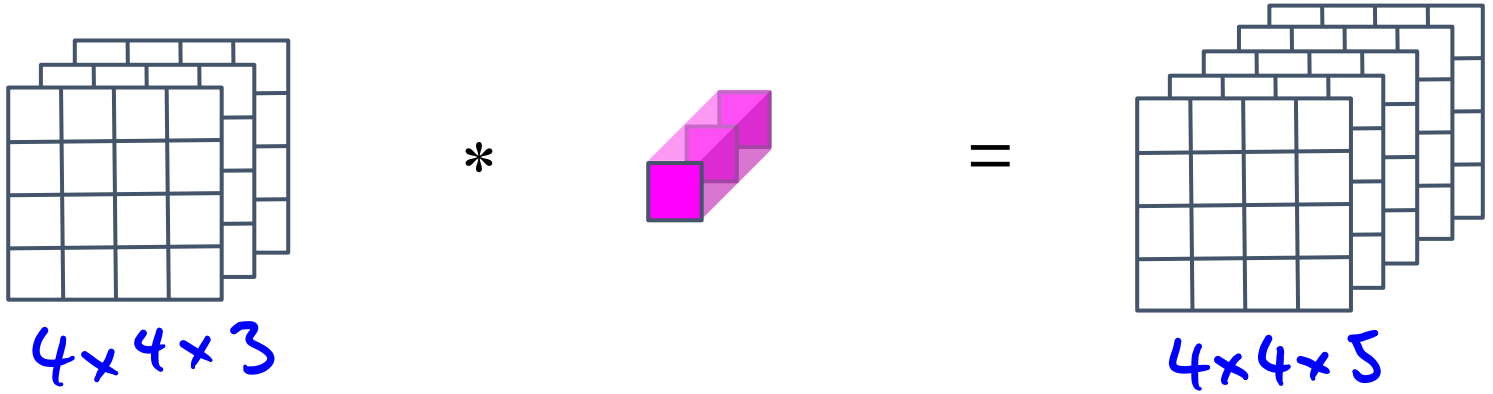
Depthwise Separable Convolution

Depthwise Convolution



Pointwise Convolution



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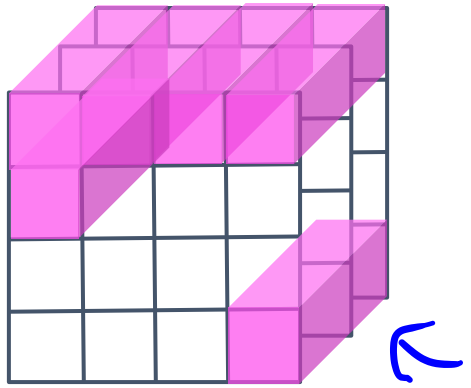
Pointwise Convolution



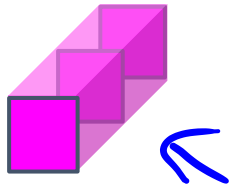
4 x 4 x 3

$n_{out} \times n_{out} \times n_c$

*

n_c' filters

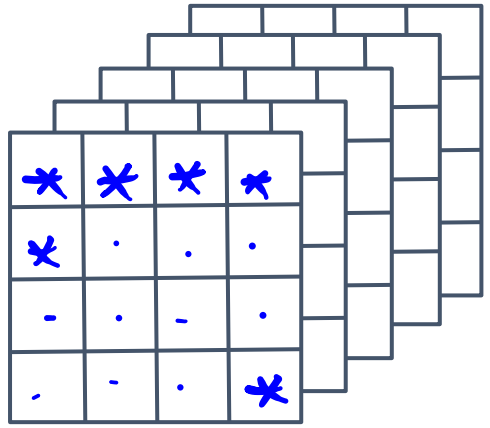
5



1 x 1 x 3

$1 \times 1 \times n_c$

=



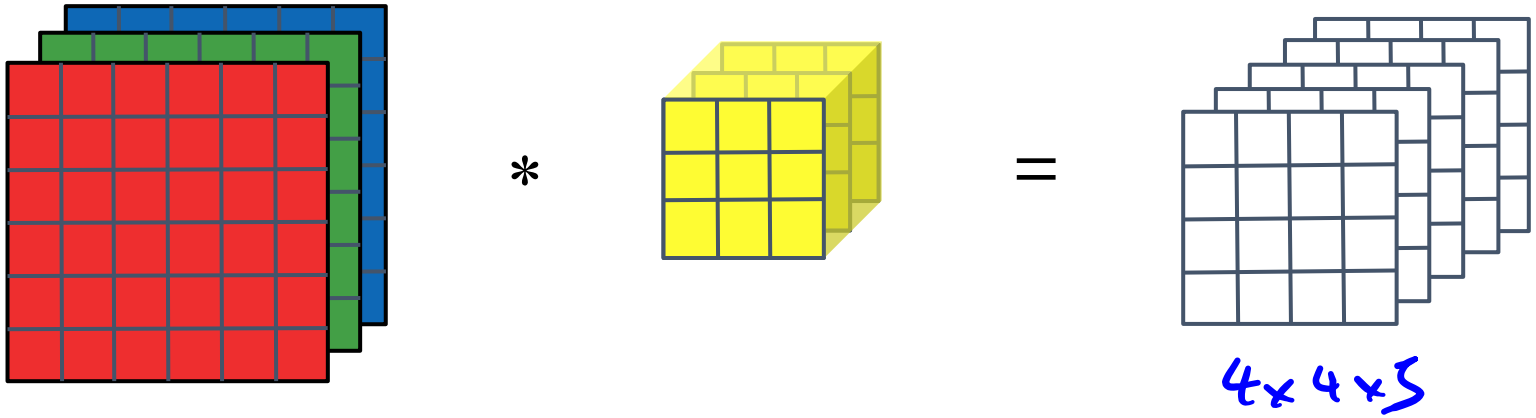
4 x 4 x 5

$n_{out} \times n_{out} \times n_c'$

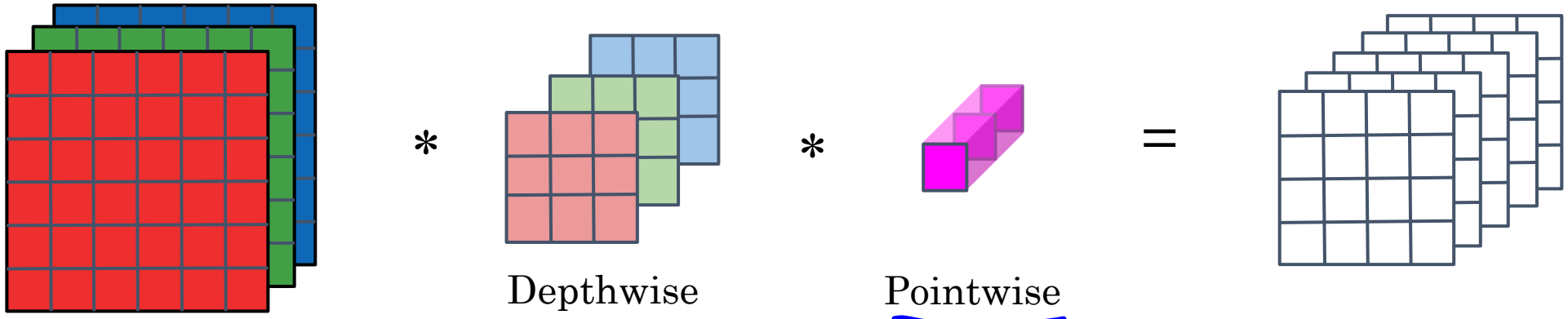
Computational cost	=	#filter params	x	# filter positions	x	# of filters
240	=	$1 \times 1 \times 3$	x	4×4	x	5

Depthwise Separable Convolution

Normal Convolution



Depthwise Separable Convolution



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Cost Summary

Cost of normal convolution 2160

Cost of depthwise separable convolution

depthwise + pointwise

432 + 240 = 672

$$\frac{672}{2160} = 0.31$$

$$= \frac{1}{n_c} + \frac{1}{f^2}$$

$$\frac{1}{5} + \frac{1}{9}$$

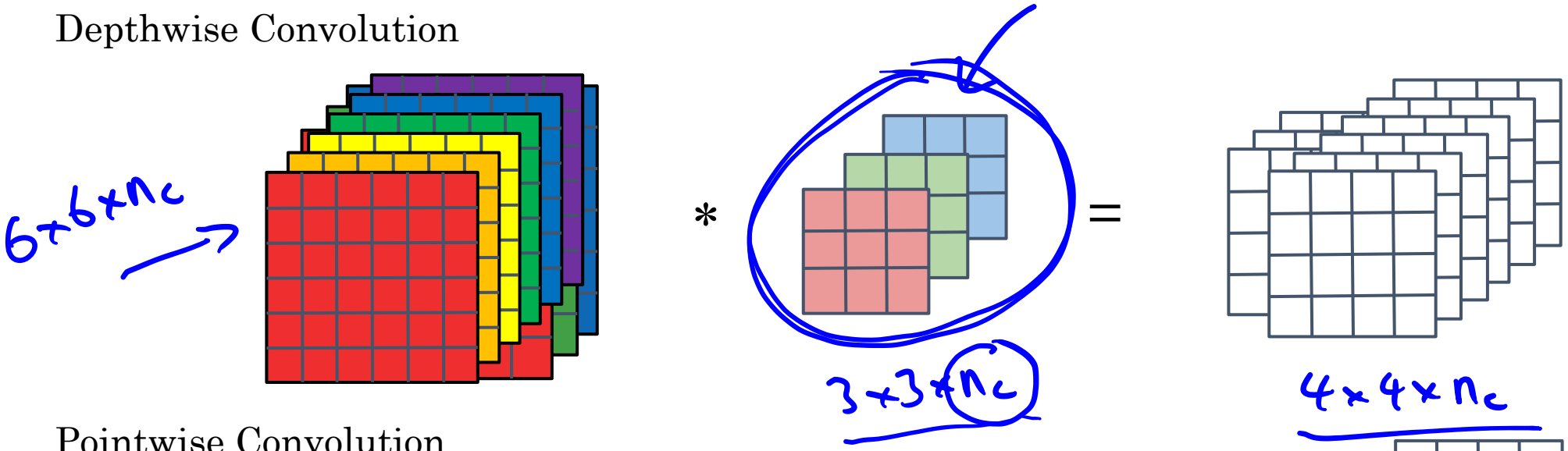
$$= \frac{1}{512} + \frac{1}{3^2}$$

~10 times cheaper

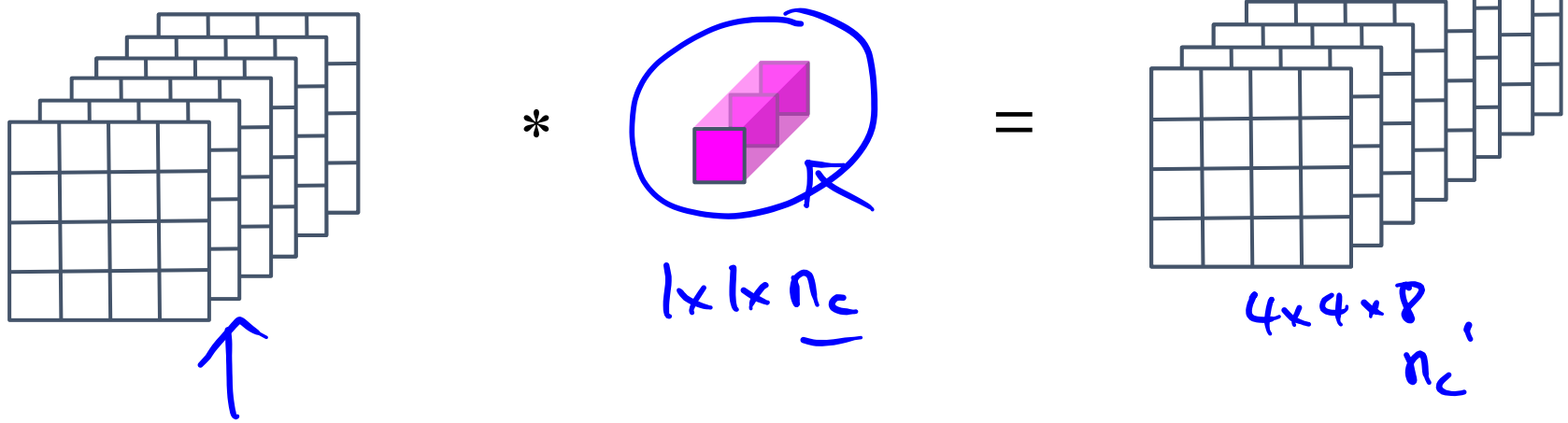
[Howard et al. 2017, MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications]

Depthwise Separable Convolution

Depthwise Convolution



Pointwise Convolution



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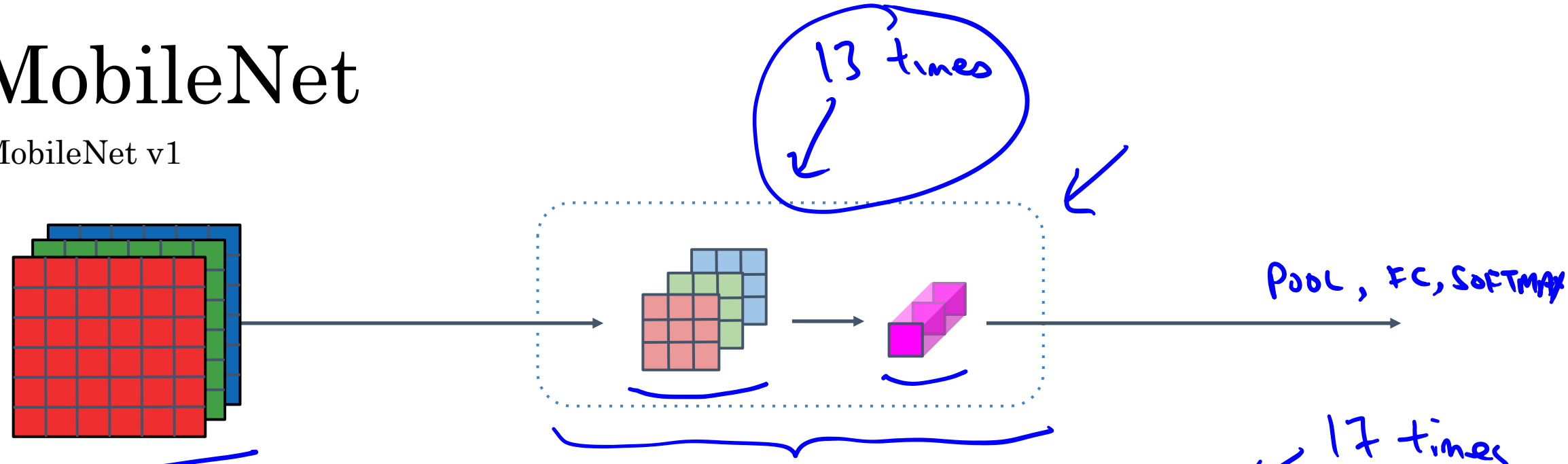
Convolutional Neural Networks

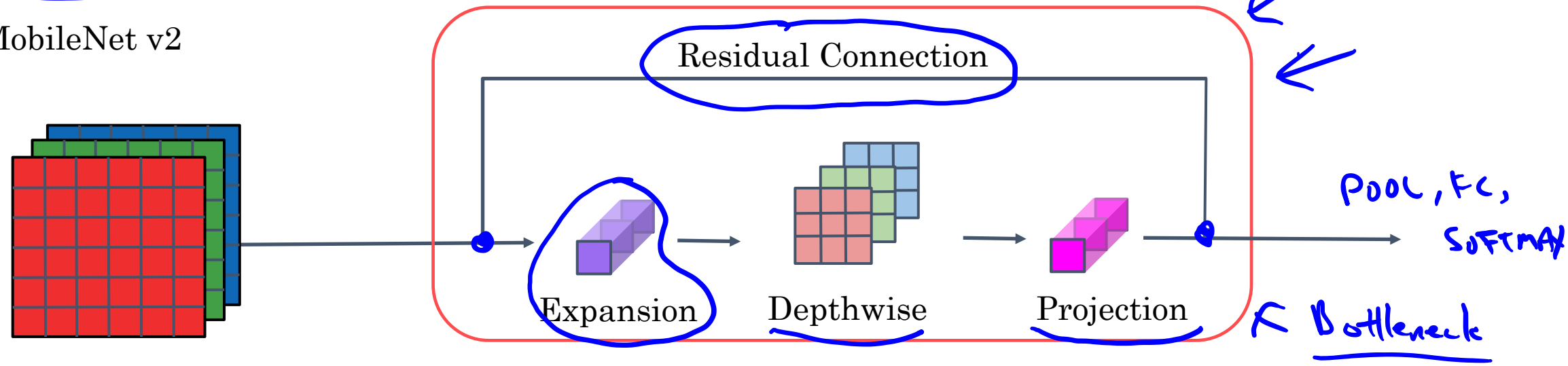
MobileNet Architecture

MobileNet

MobileNet v1

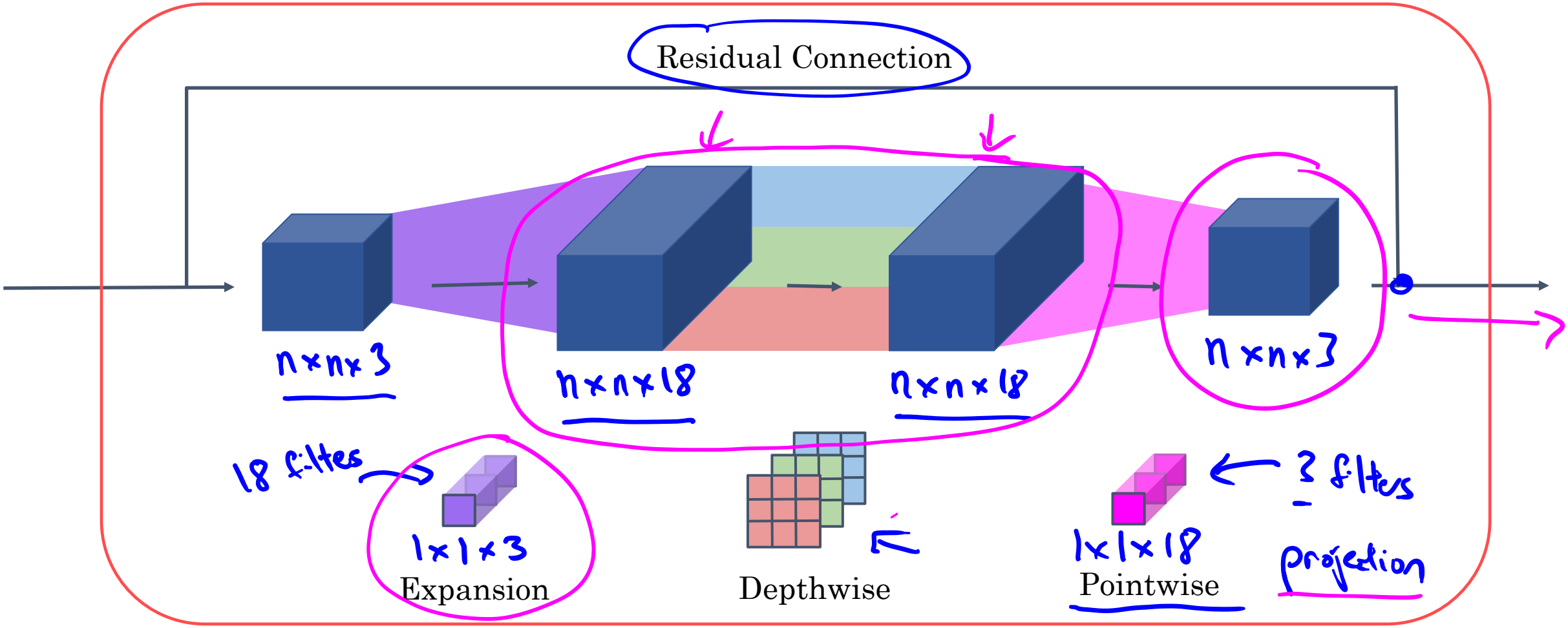


MobileNet v2



[Sandler et al. 2019, MobileNetV2: Inverted Residuals and Linear Bottlenecks]

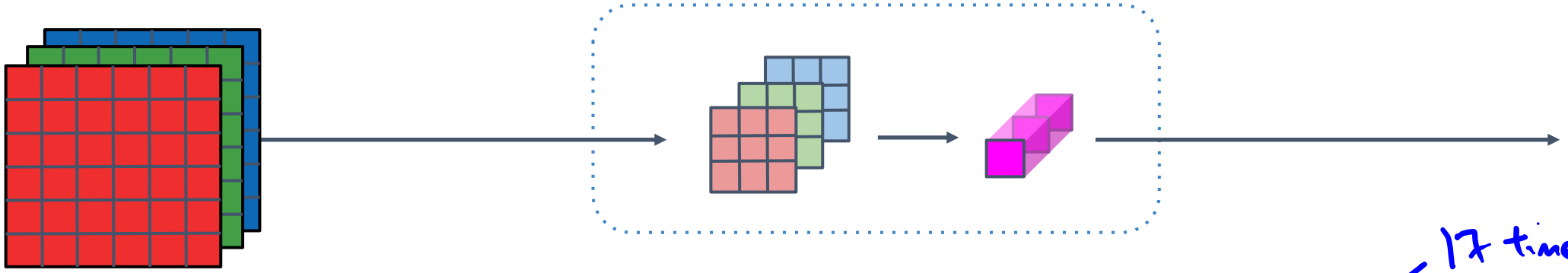
MobileNet v2 Bottleneck



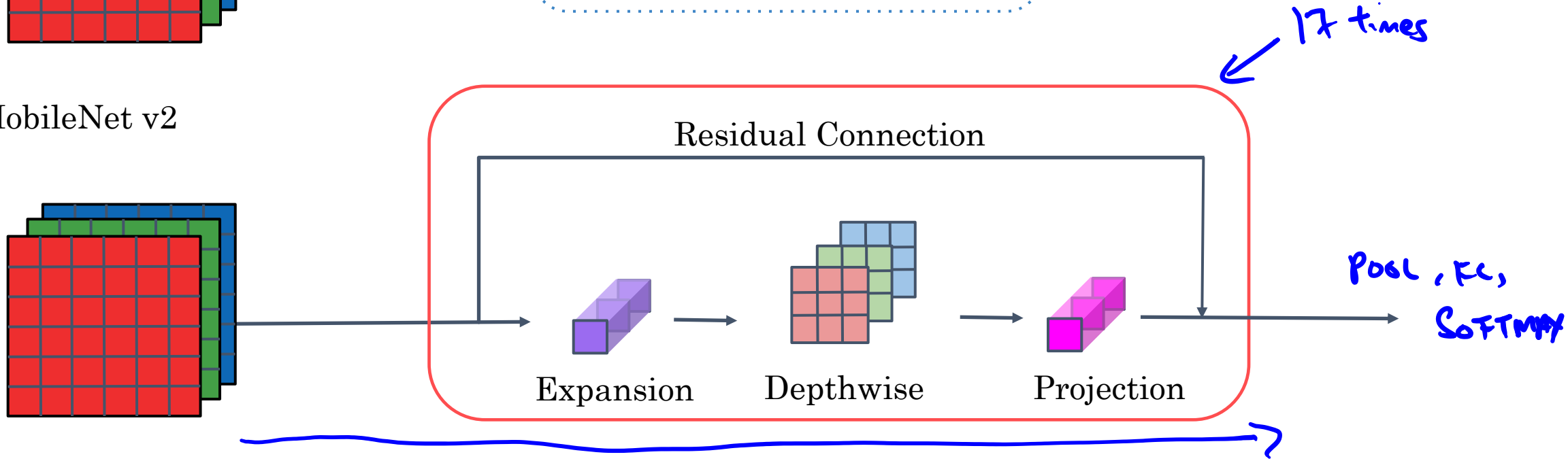
[Sandler et al. 2019, MobileNetV2: Inverted Residuals and Linear Bottlenecks]

MobileNet

MobileNet v1

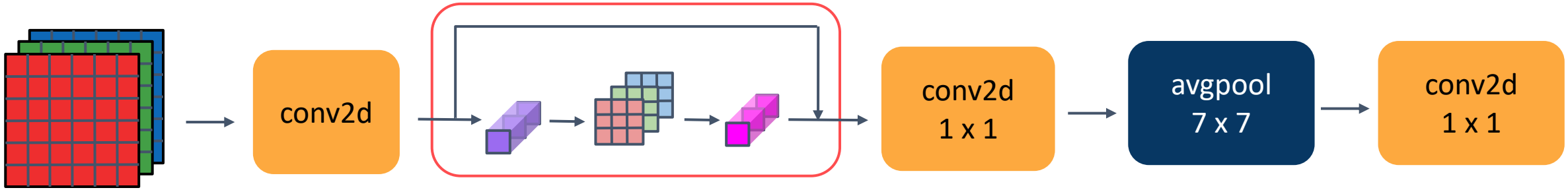


MobileNet v2



[Sandler et al. 2019, MobileNetV2: Inverted Residuals and Linear Bottlenecks]

MobileNet v2 Full Architecture



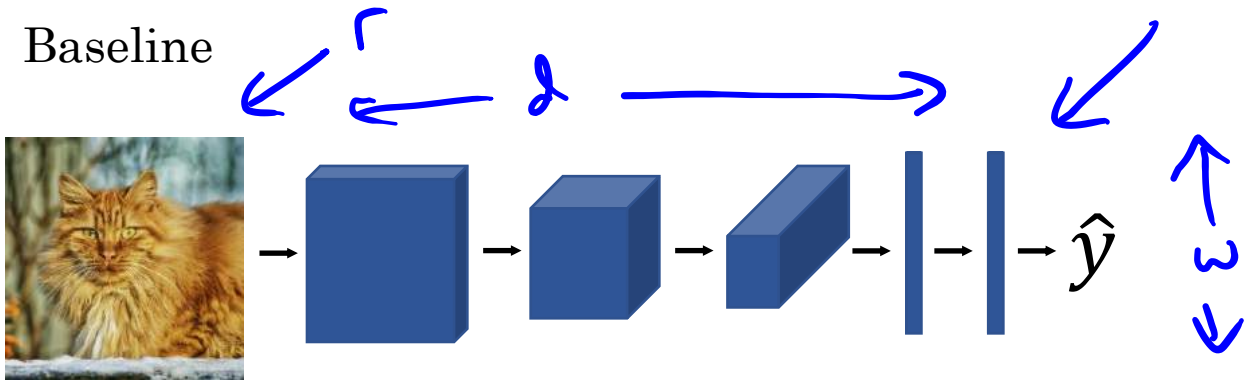
[Sandler et al. 2019, MobileNetV2: Inverted Residuals and Linear Bottlenecks]

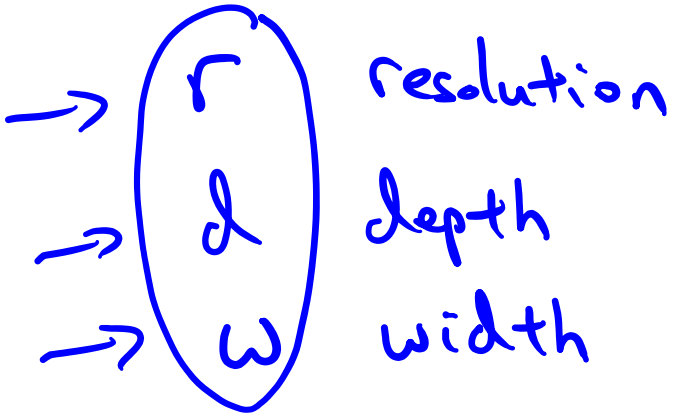
Convolutional Neural Networks

EfficientNet

EfficientNet

Baseline

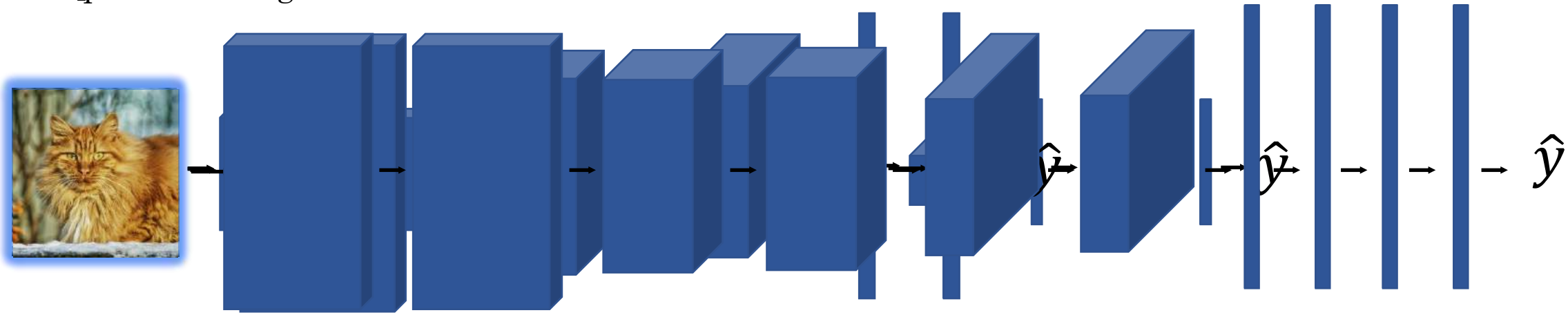




Wider Resolution

Deeper

Compound scaling



[Tan and Le, 2019, EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks]

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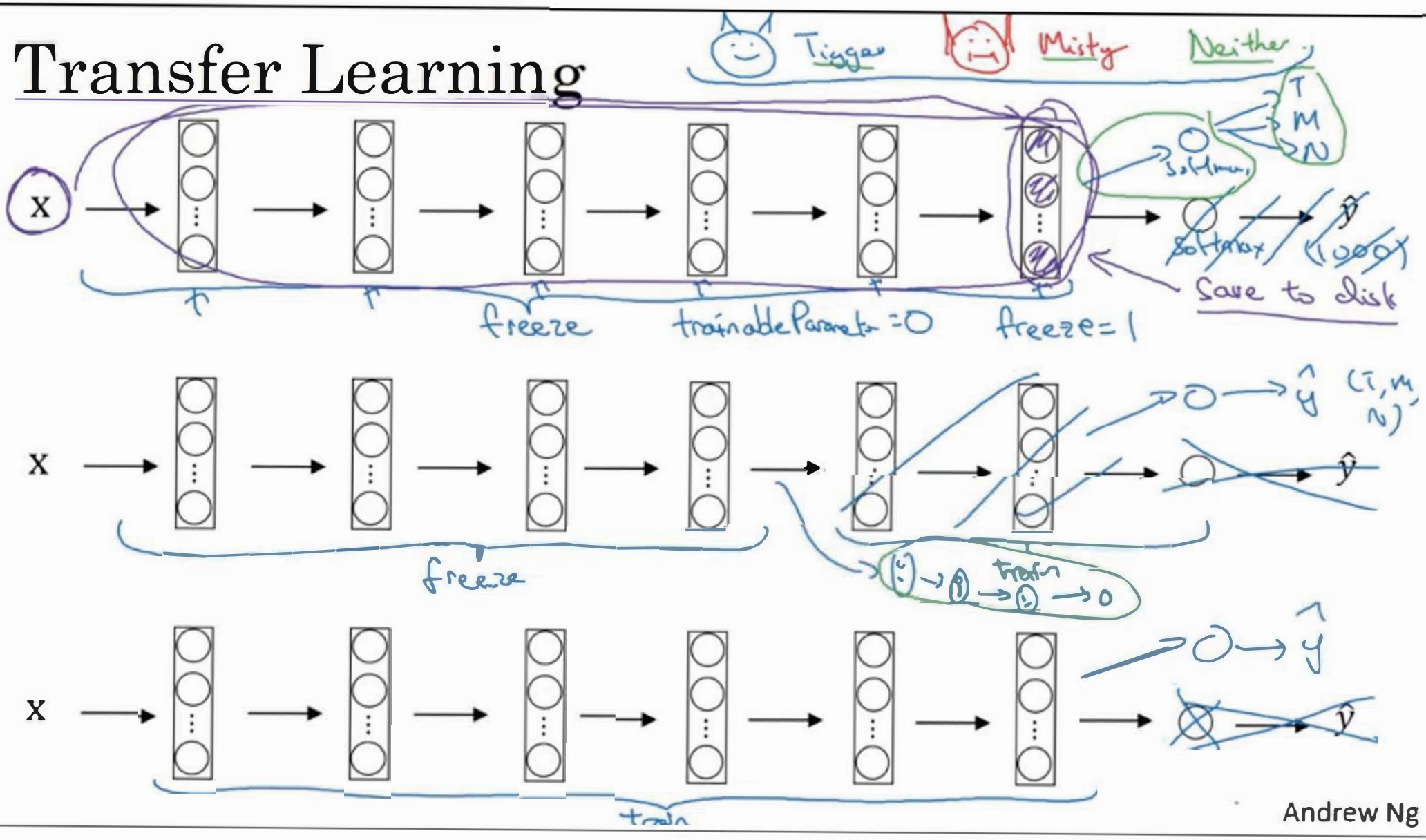
Practical advice for using ConvNets

Transfer Learning

Transfer Learning



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Practical advice for using ConvNets

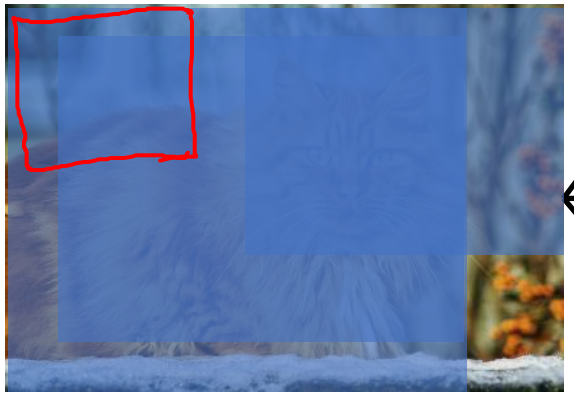
Data augmentation

Common augmentation method

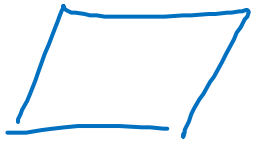
Mirroring

y

Random Cropping



- Rotation
- Shearing
- Local warping
- ...



Color shifting

R G B

+20,-20,+20

-20,+20,+20

+5,0,+50

Advanced:

PCA

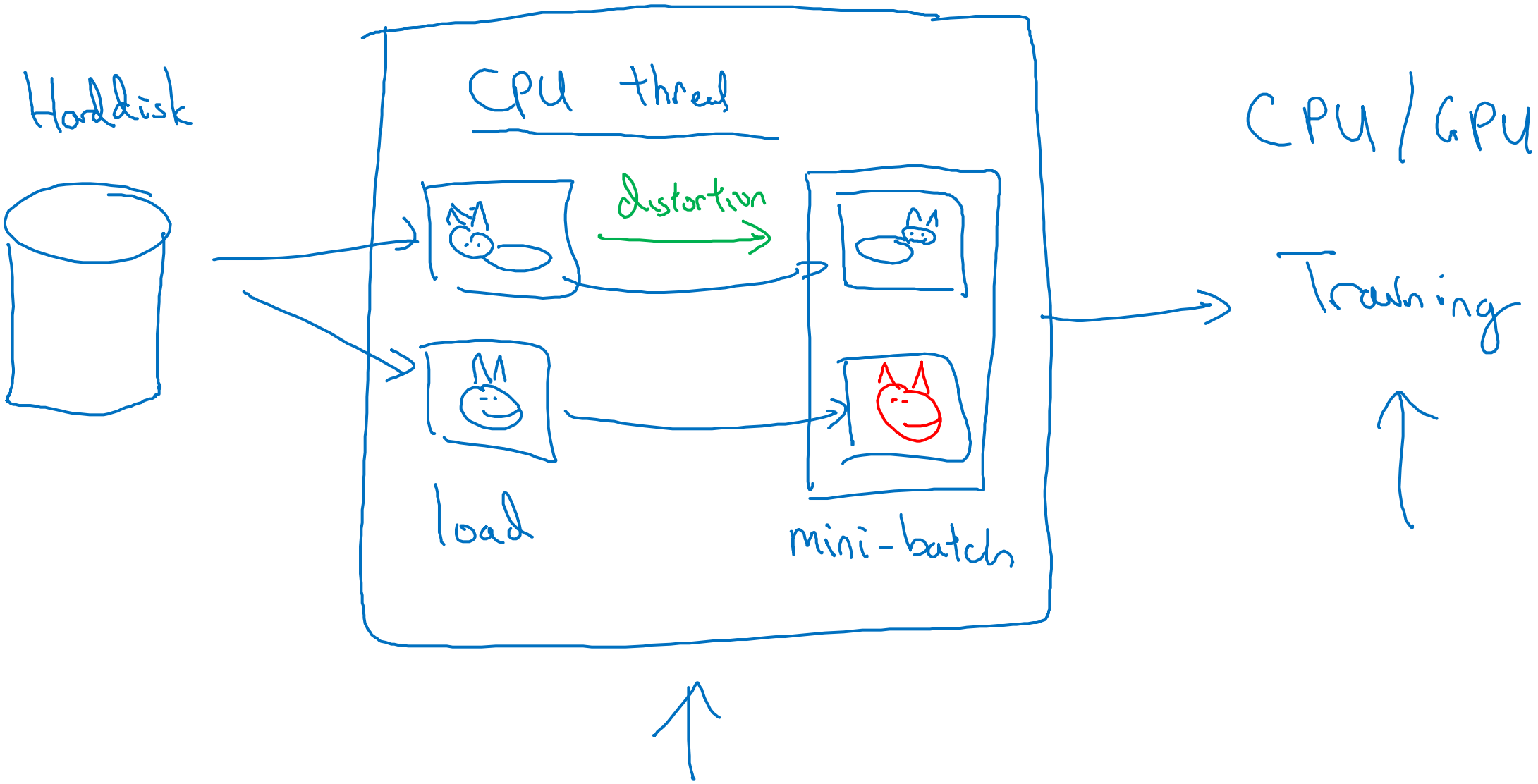
ml-class.org

[AlexNet paper

["PCA color augmentation."

R B G

Implementing distortions during training



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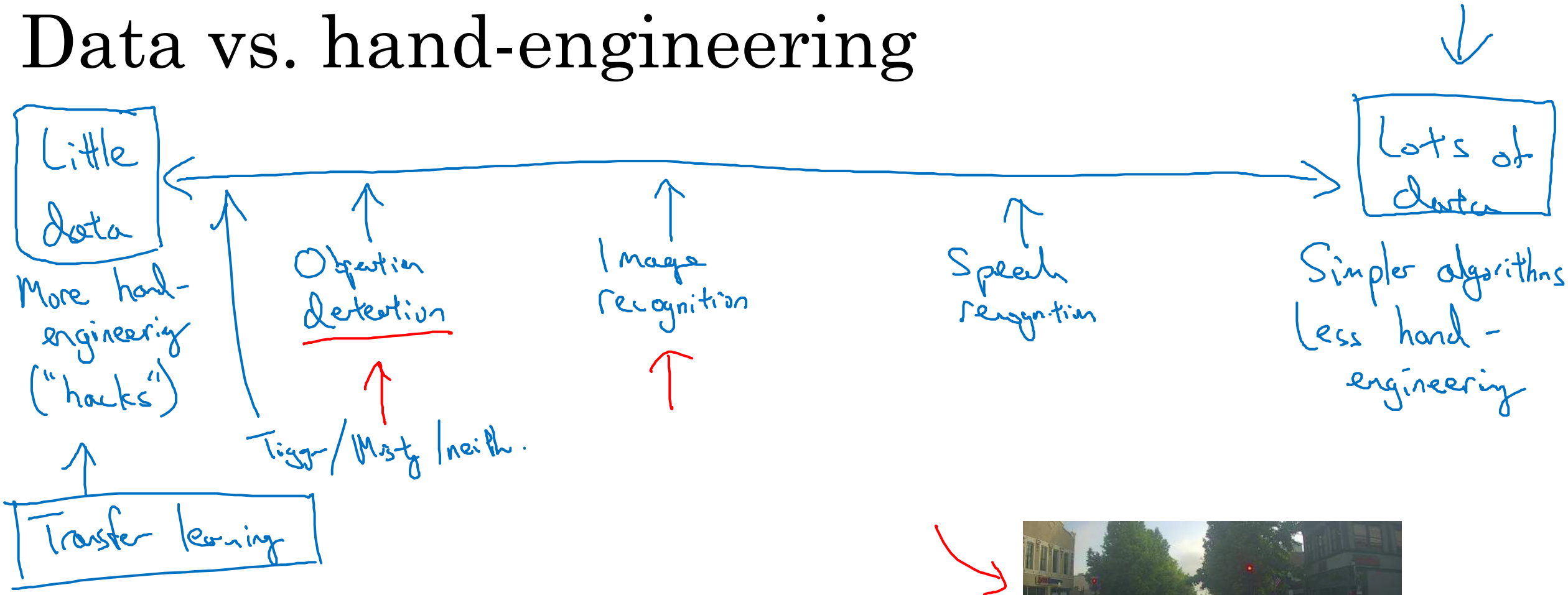
Practical advice for using ConvNets

The state of computer vision

Data vs. hand-engineering



Two sources of knowledge

- Labeled data (x, y)
- Hand engineered features/network architecture/other components

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Tips for doing well on benchmarks/winning competitions

Ensembling

3-15 networks

- Train several networks independently and average their outputs

Multi-crop at test time

- Run classifier on multiple versions of test images and average results

10-crop

Use open source code

- Use architectures of networks published in the literature
- Use open source implementations if possible
- Use pretrained models and fine-tune on your dataset

Copyright Notice

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Object Detection

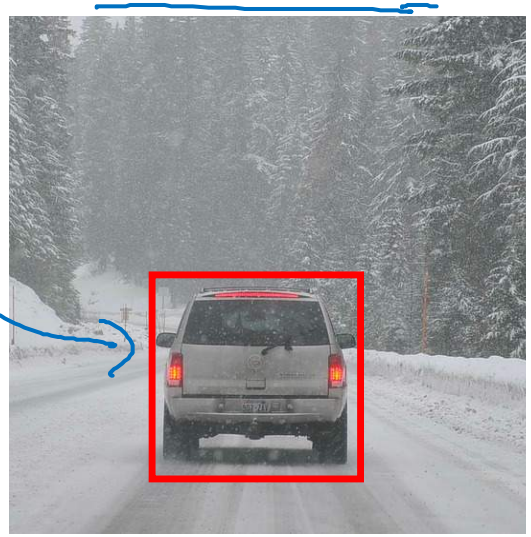
Object localization

What are localization and detection?

Image classification

"Car"

Classification with localization



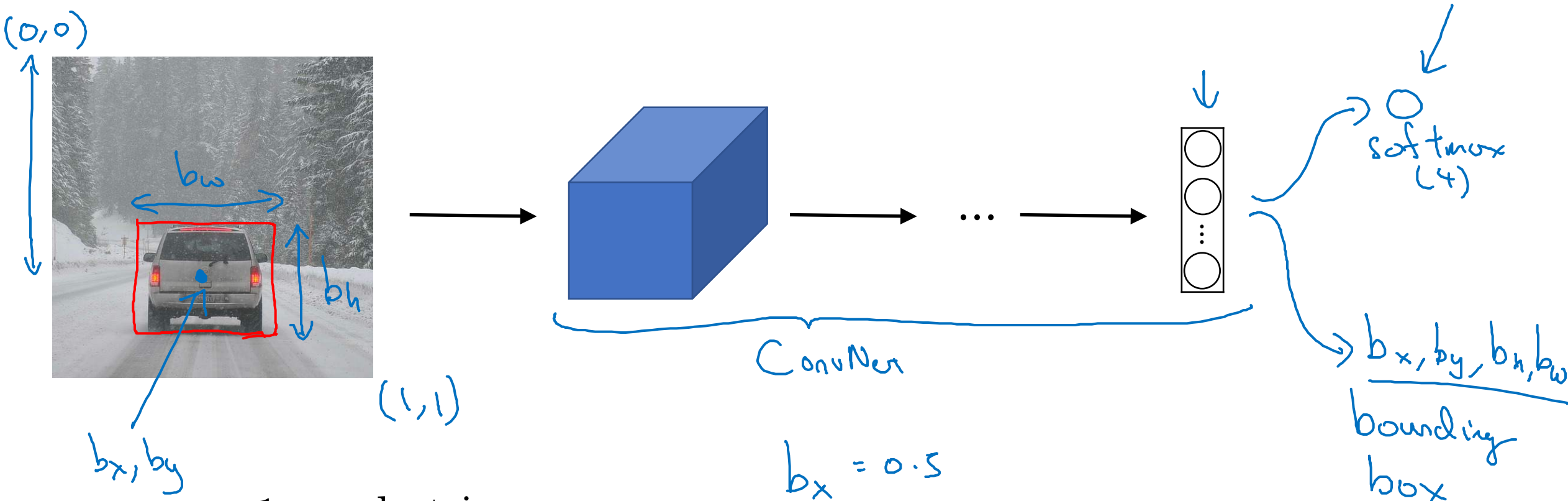
"Car"

1 object

Detection

multiple objects

Classification with localization



1 - pedestrian
2 - car
3 - motorcycle
4 - background

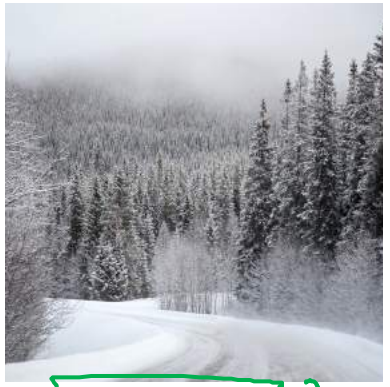
$b_x = 0.5$
$b_y = 0.7$
$b_h = 0.3$
$b_w = 0.4$

Defining the target label y

1 - pedestrian
2 - car
3 - motorcycle
4 - background

Need to output b_x, b_y, b_h, b_w, class label (1-4)

$x =$



$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

p_c: is there an object?

$$(x, y) \begin{bmatrix} 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \end{bmatrix}$$

p_c

← "don't care"

$$\mathcal{L}(\hat{y}, y) = \begin{cases} (\hat{y}_1 - y_1)^2 + (\hat{y}_2 - y_2)^2 + \cdots + (\hat{y}_8 - y_8)^2 & \text{if } y_1 = 1 \\ (\hat{y}_1 - y_1)^2 & \text{if } y_1 = 0 \end{cases}$$

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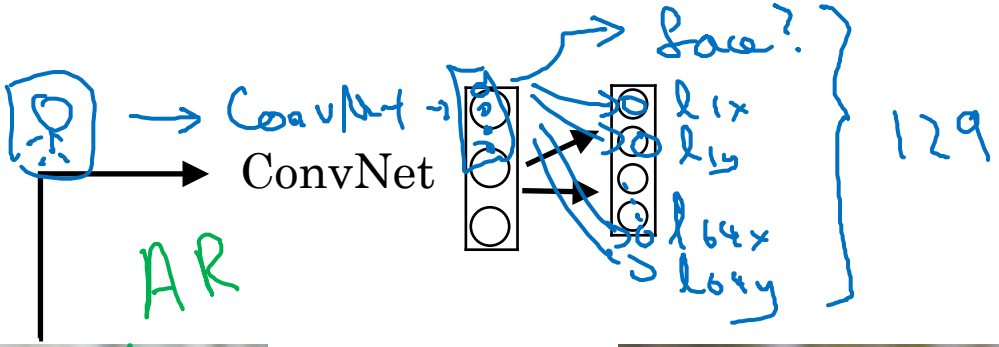
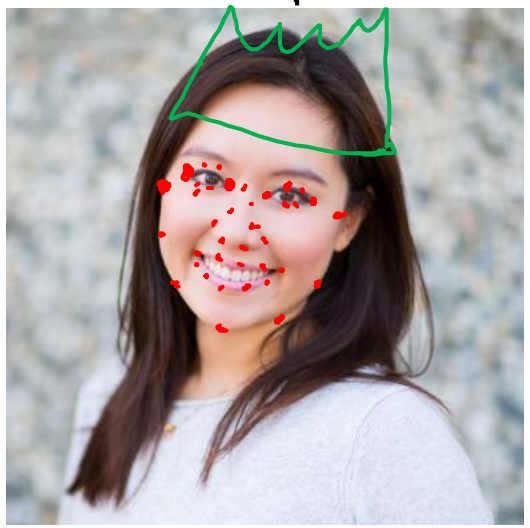
Object Detection

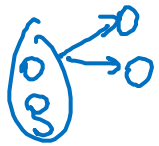
Landmark detection

Landmark detection



b_x, b_y, b_h, b_w





$l_{1x}, l_{1y},$
$l_{2x}, l_{2y},$
$l_{3x}, l_{3y},$
l_{4x}, l_{4y}
$\vdots$
l_{64}, l_{64y}

x, y

$l_{1x}, l_{1y},$
$\vdots$
l_{32x} l_{32y}

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Object Detection

Object detection

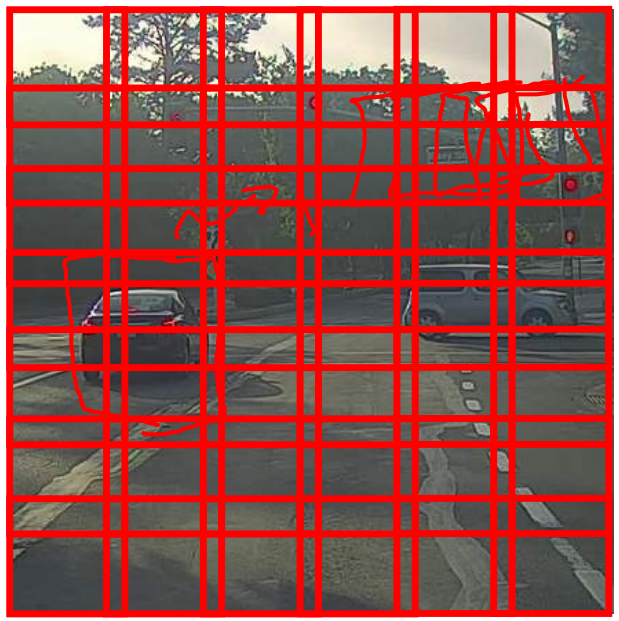
Car detection example

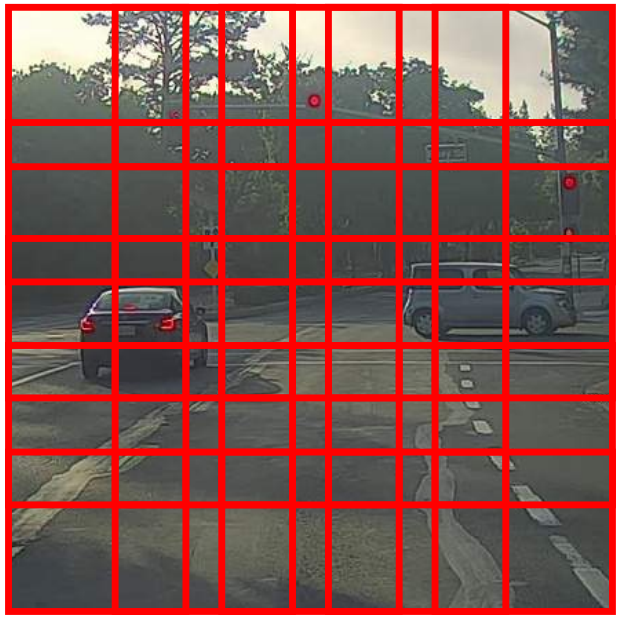
Training set:

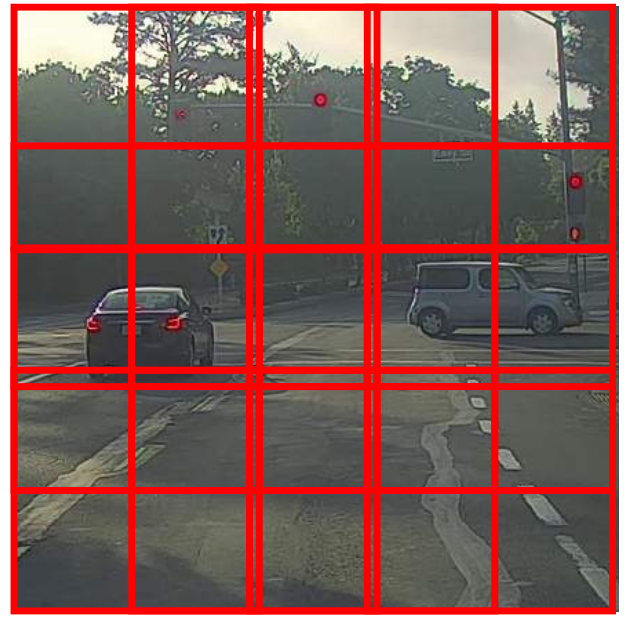
x	y
	1
	1
	1
	0
	0

→ ConvNet → y

Sliding windows detection







Computation cost

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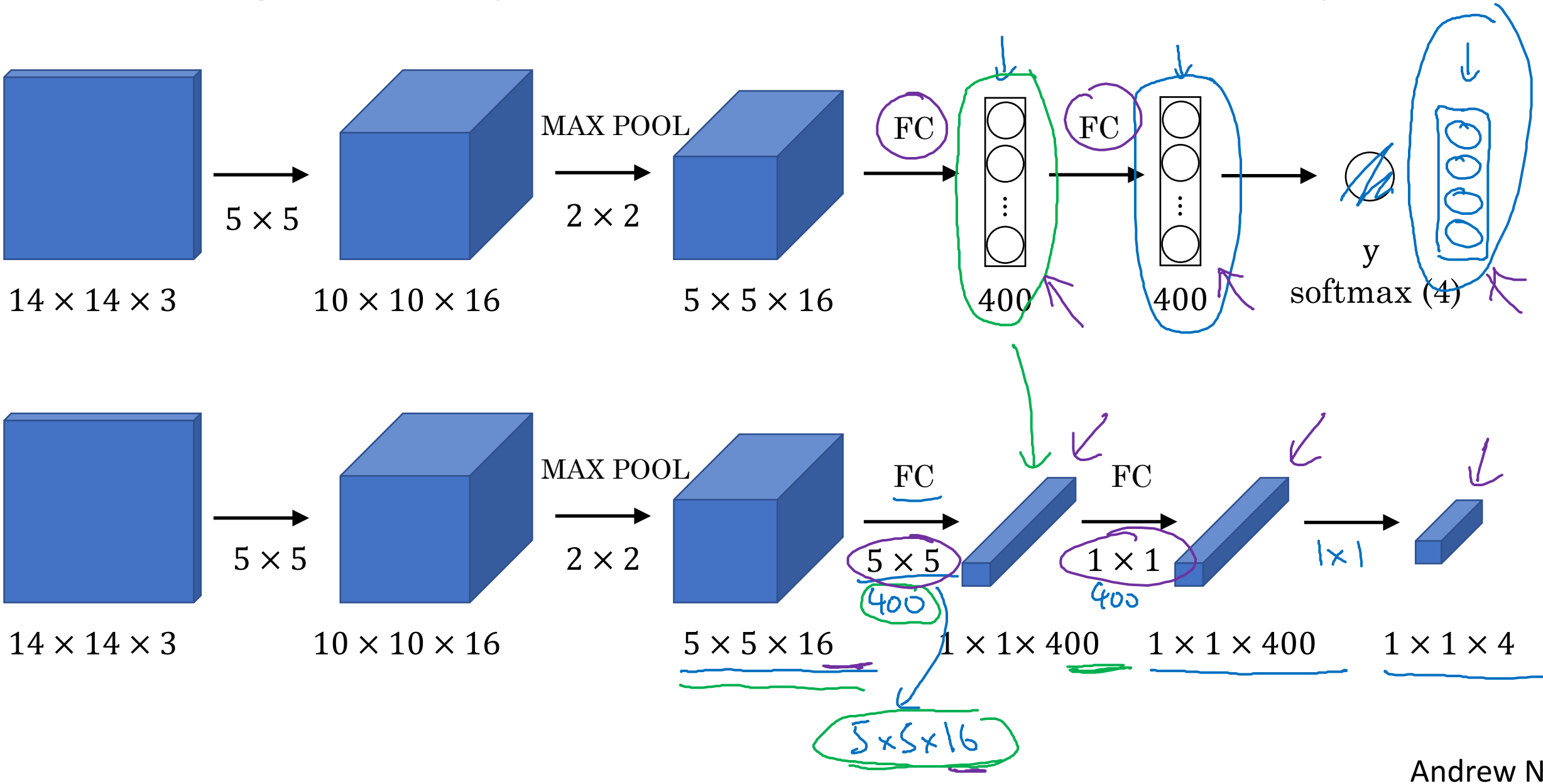
Object Detection

Convolutional implementation of sliding windows

Turning FC layer into convolutional layers



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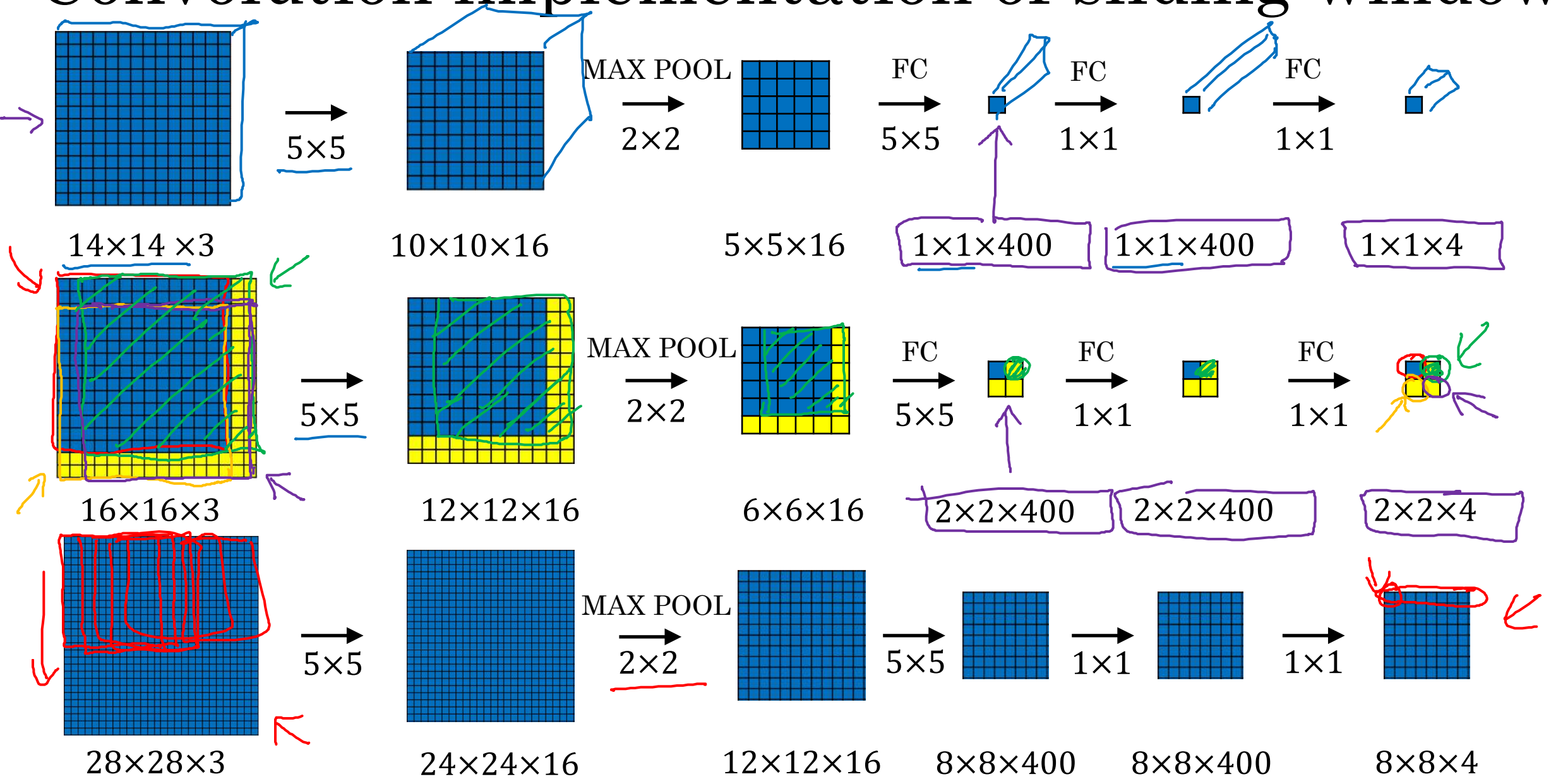
Convolution implementation of sliding windows



[Sermanet et al., 2014, OverFeat: Integrated recognition, localization and detection using convolutional networks]

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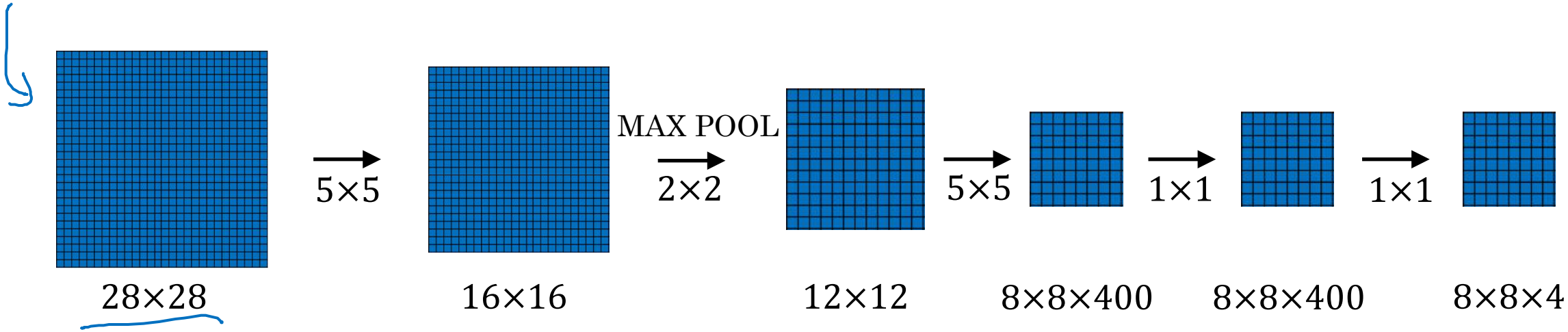
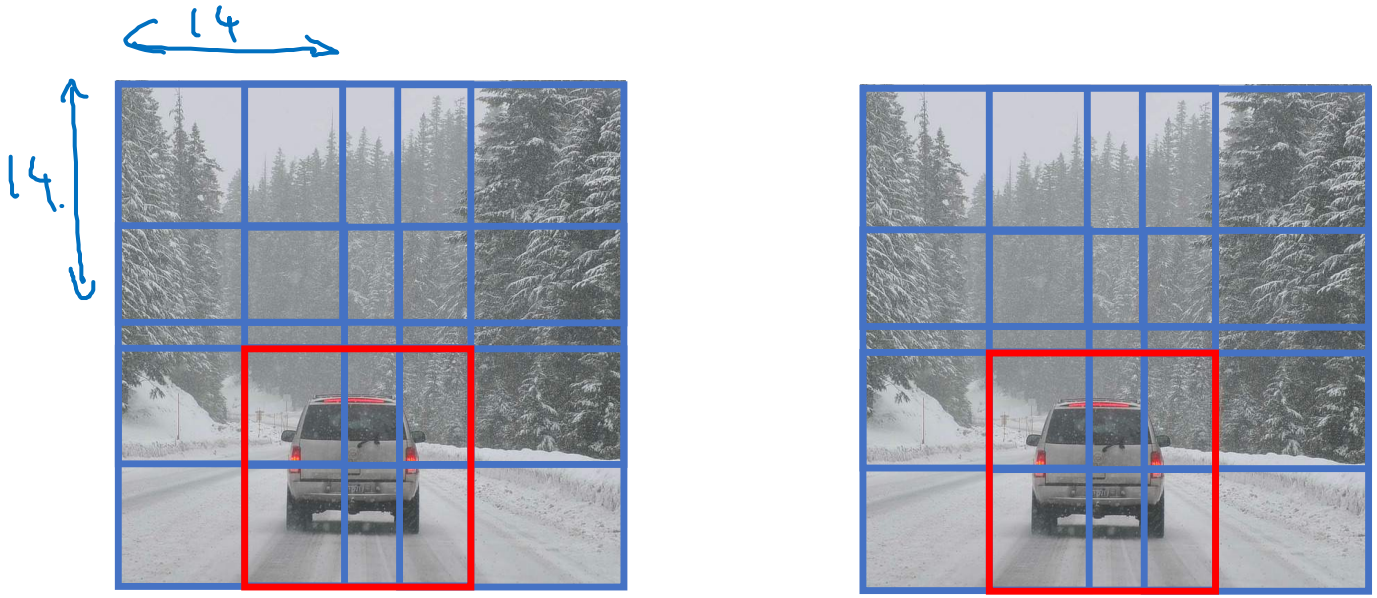
Convolution implementation of sliding windows





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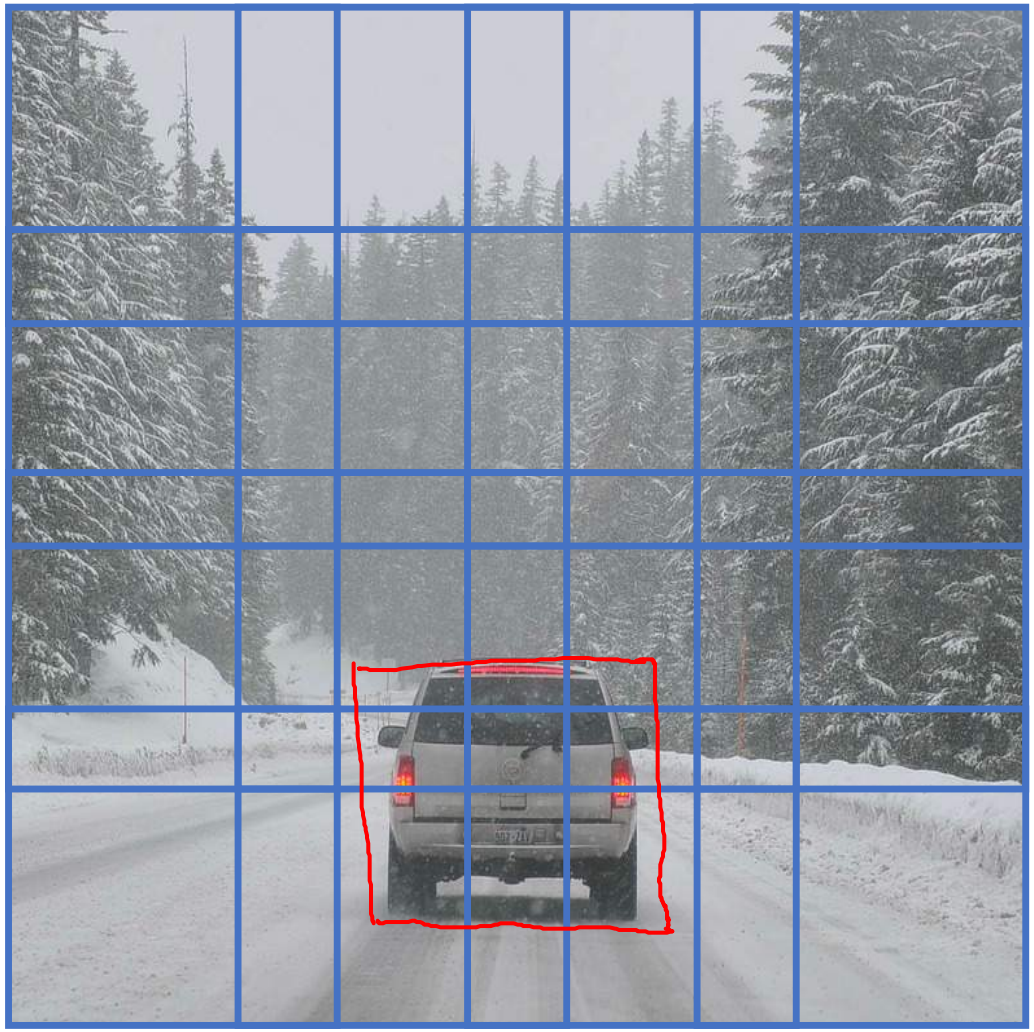
Object Detection

Bounding box predictions

Output accurate bounding boxes



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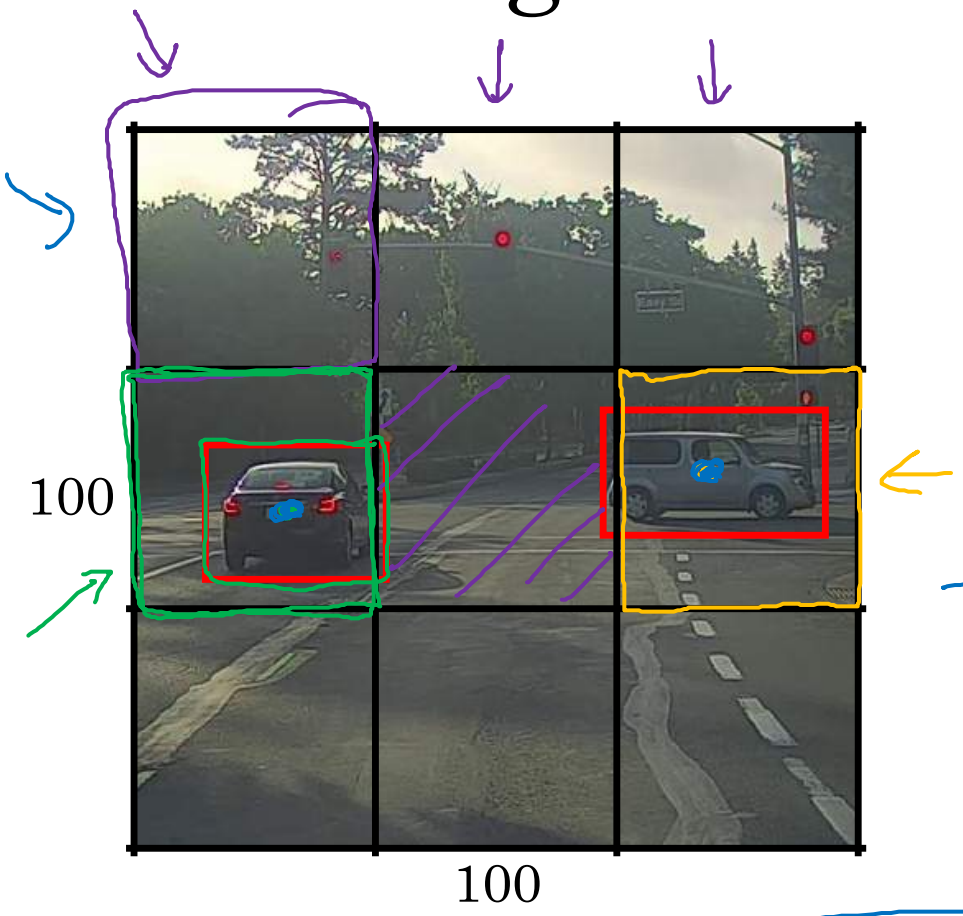
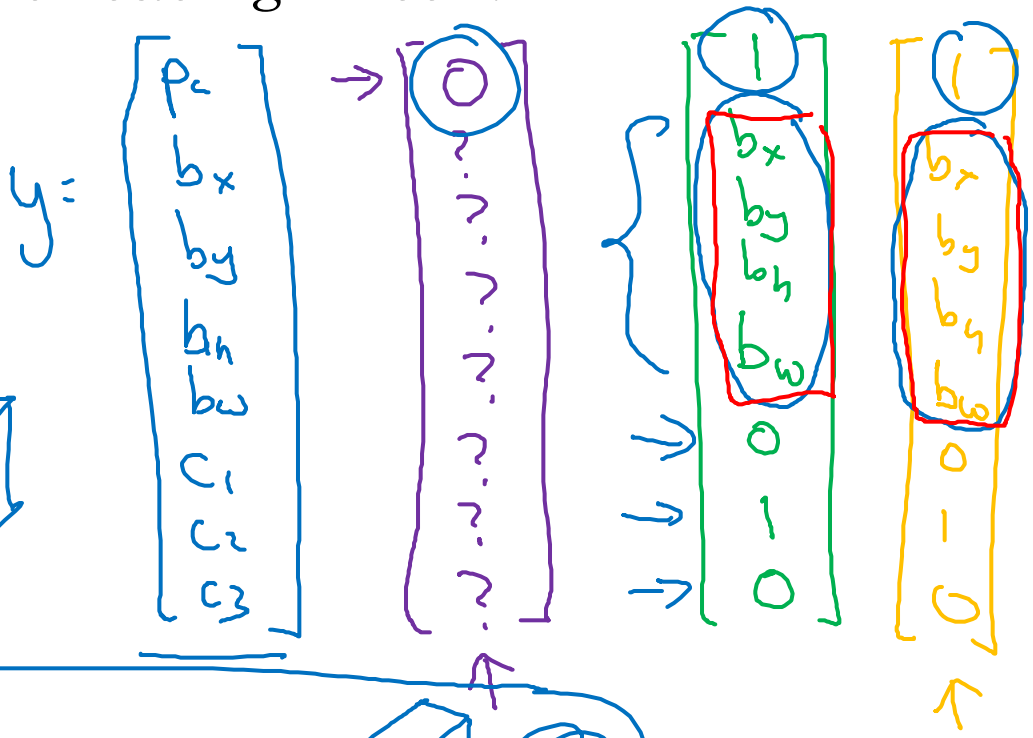
YOLO algorithm



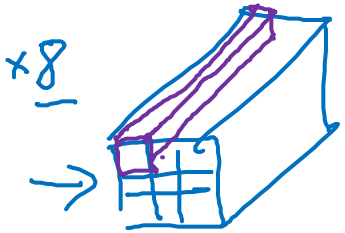
Labels for training

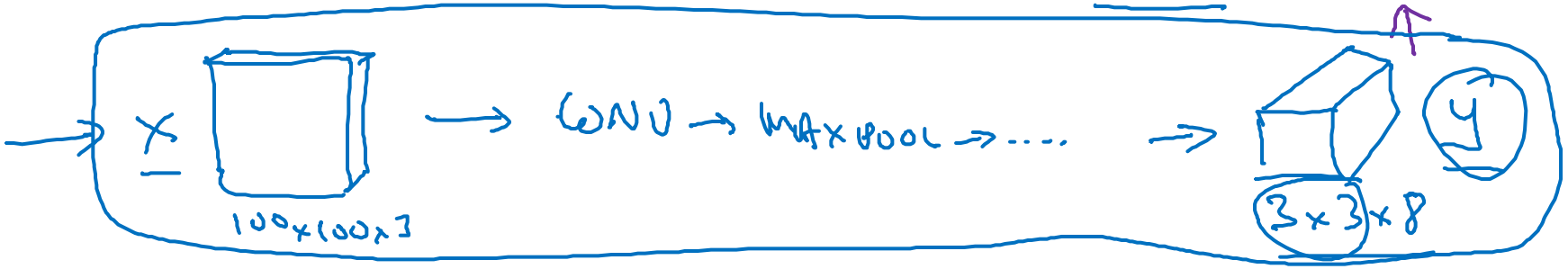
For each grid cell:



Target output:

3 x 3 x 8



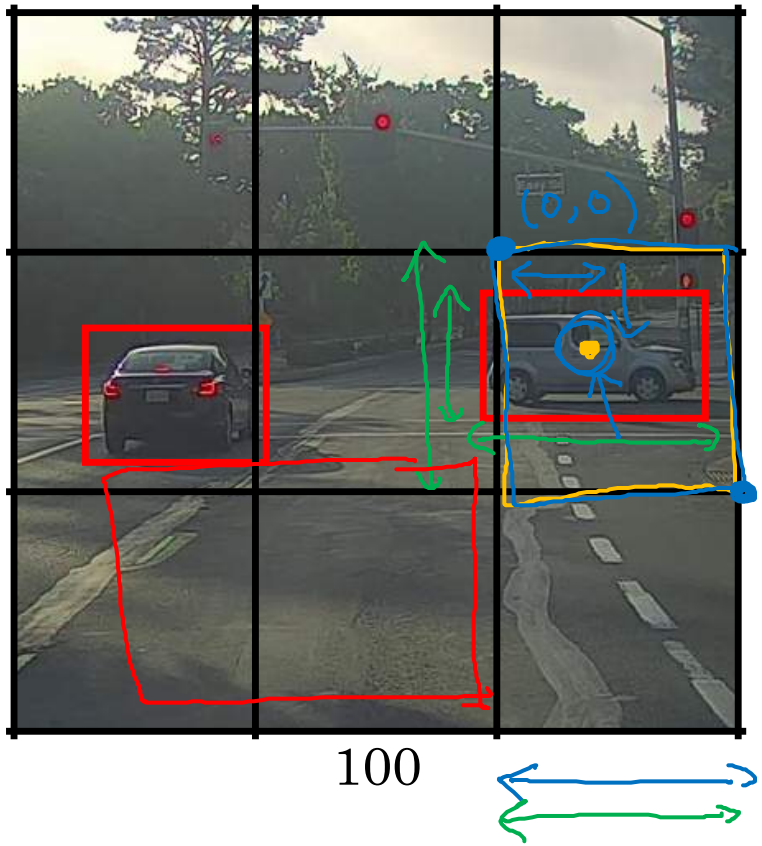


3 6 1

→ 19 x 19 x 8

[Redmon et al., 2015, You Only Look Once: Unified real-time object detection]

Specify the bounding boxes



$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

p_c: 0.4, 0.3 — between 0 and 1

b_x, b_y, b_h, b_w: 0.9, 0.5 — could be > 1

c_1, c_2, c_3: between 0 and 1

[Redmon et al., 2015, You Only Look Once: Unified real-time object detection]

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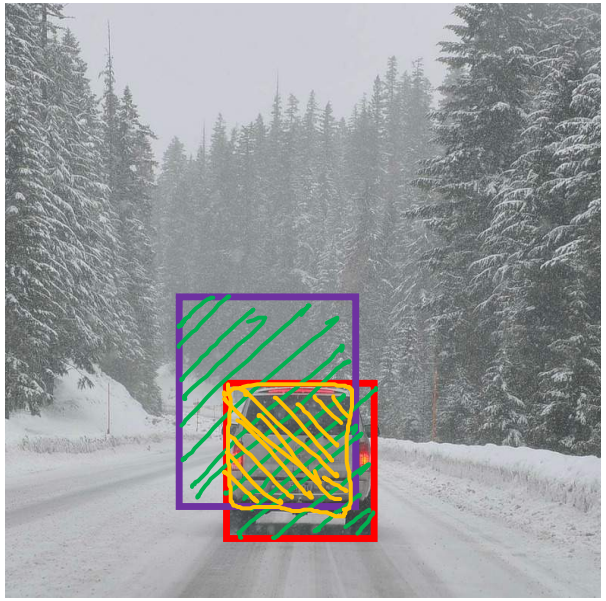
Object Detection

Intersection over union

Evaluating object localization



Intersection over Union (IoU)

$$= \frac{\text{Size of } \square}{\text{Size of } \square}$$

"Correct" if IoU $\geq$ 0.5 ←

0.6 ←

More generally, IoU is a measure of the overlap between two bounding boxes.

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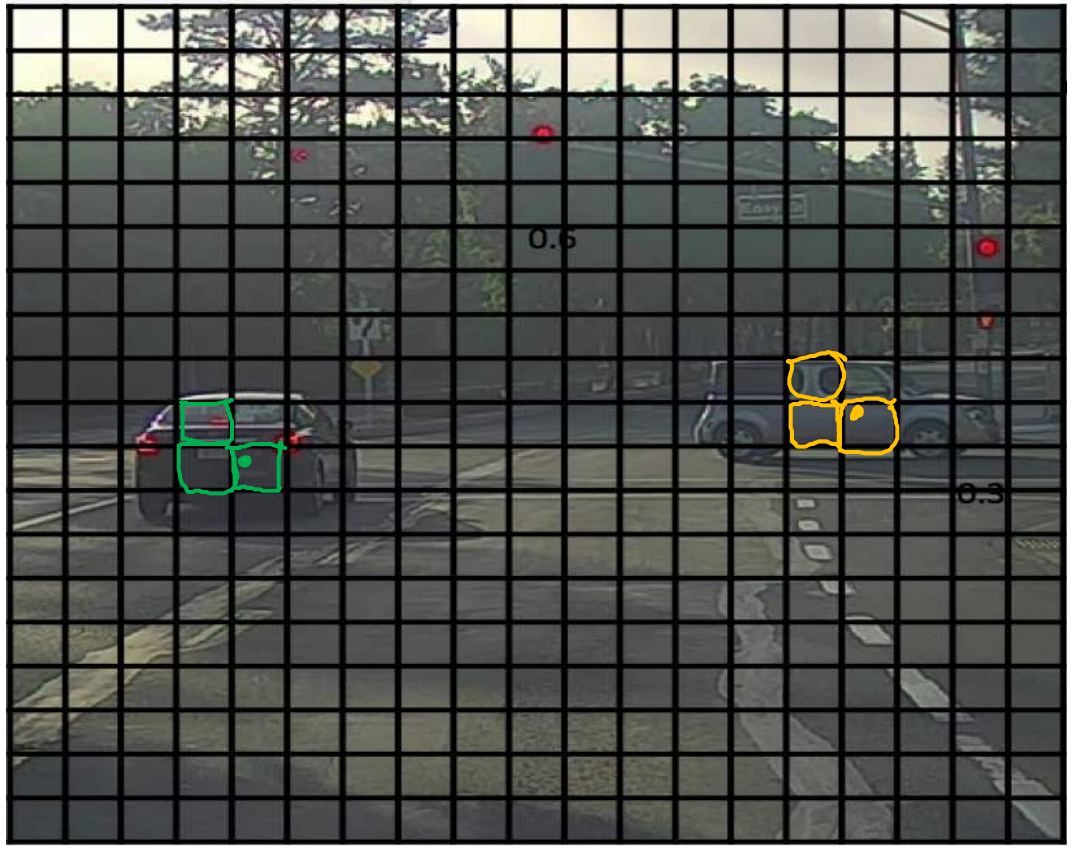
Object Detection

Non-max suppression

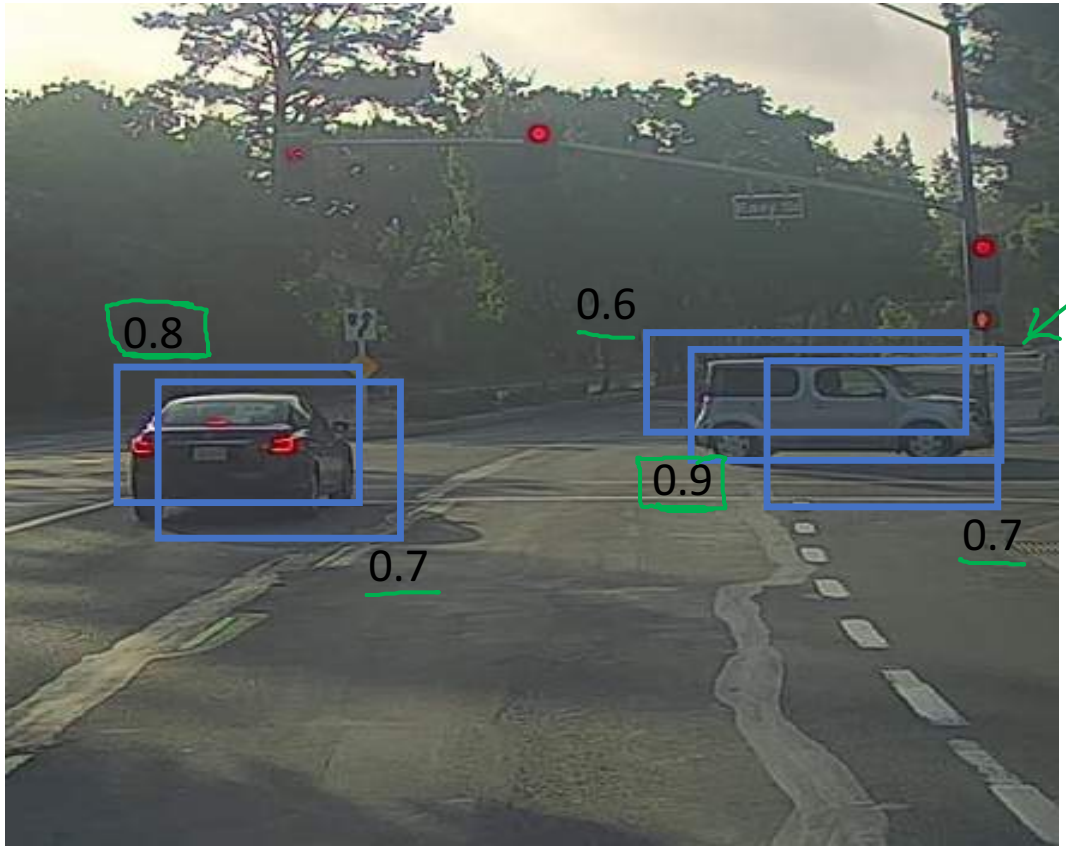
Non-max suppression example

Non-max suppression example



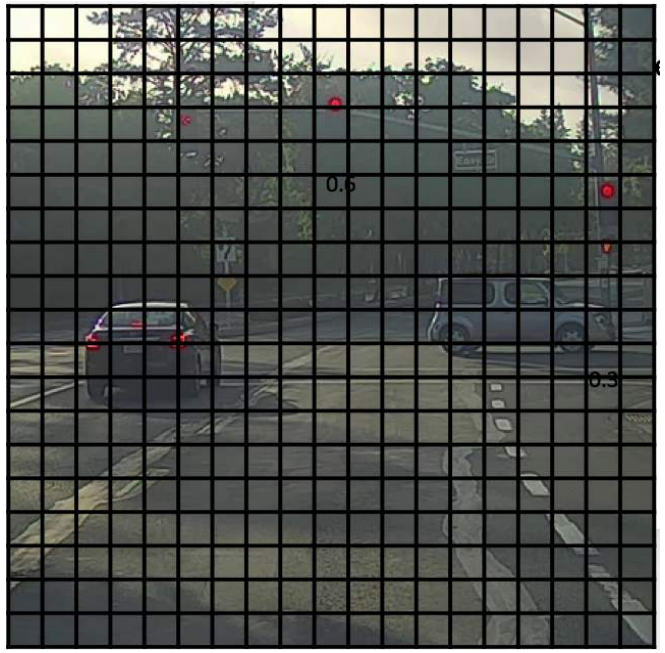
19×19

Non-max suppression example



p_c

Non-max suppression algorithm



19×19

Each output prediction is:

$$\begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \end{bmatrix}$$

Discard all boxes with $p_c \leq 0.6$

While there are any remaining boxes:

- Pick the box with the largest p_c
  Output that as a prediction.
- Discard any remaining box with IoU ≥ 0.5 with the box output in the previous step

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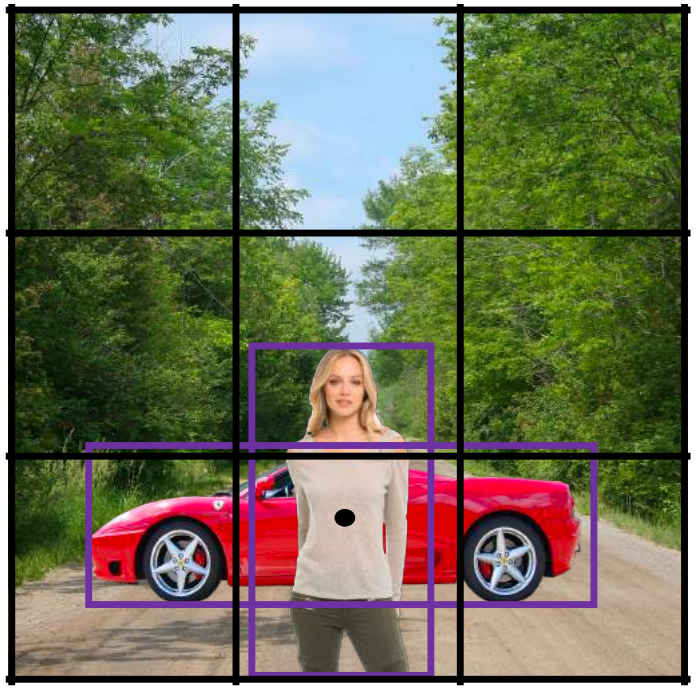
Object Detection

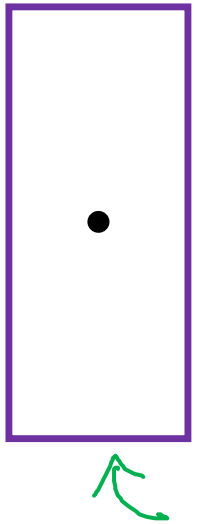
Anchor boxes

Overlapping objects:

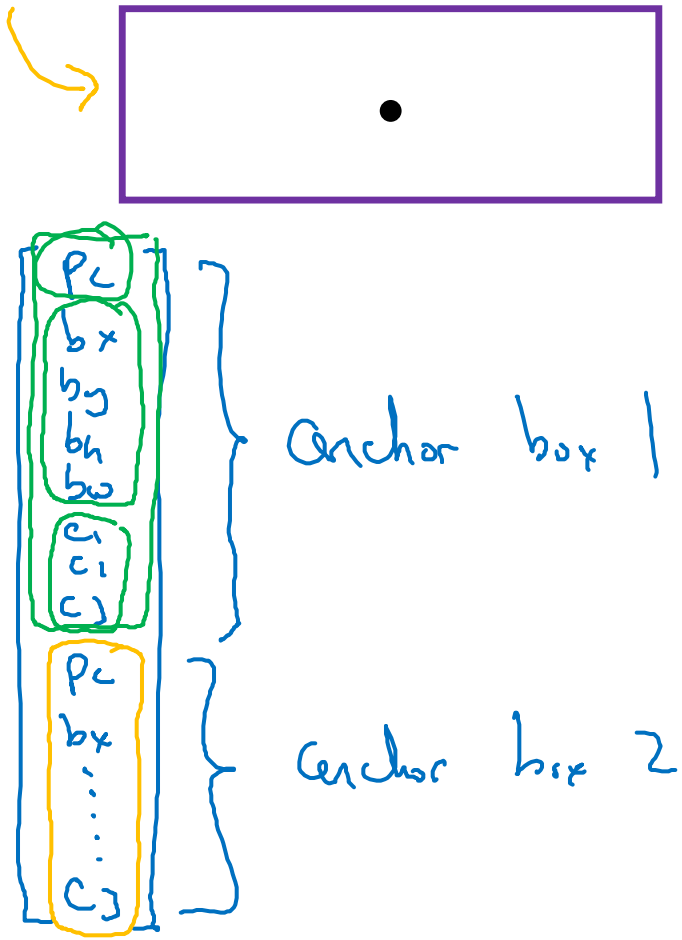


$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

Anchor box 1:



Anchor box 2:



[Redmon et al., 2015, You Only Look Once: Unified real-time object detection]

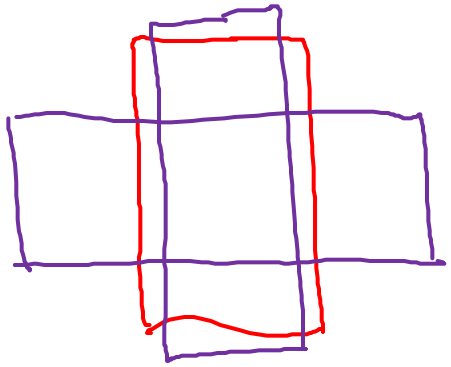
Anchor box algorithm

Previously:

Each object in training image is assigned to grid cell that contains that object's midpoint.

Output y:

$3 \times 3 \times 8$



With two anchor boxes:

Each object in training image is assigned to grid cell that contains object's midpoint and anchor box for the grid cell with highest IoU.

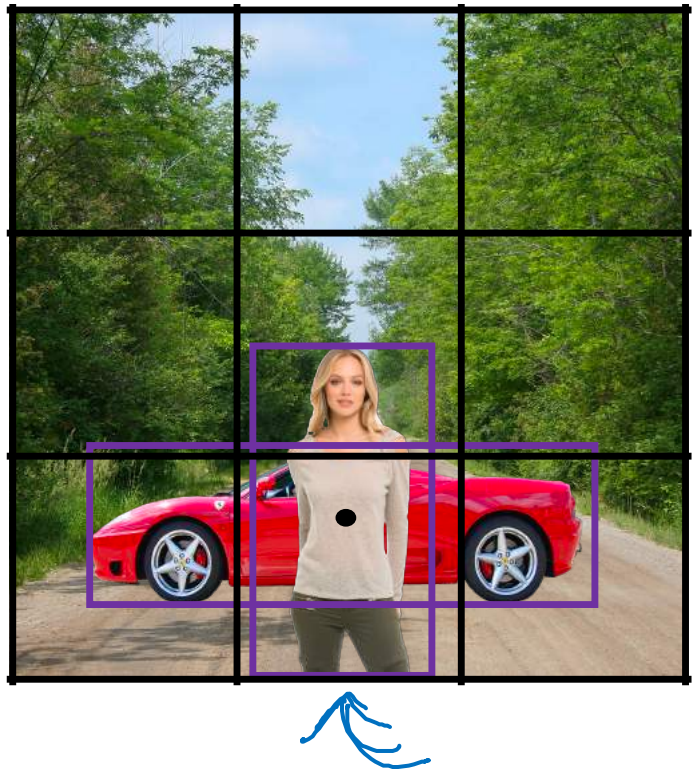
(grid cell, anchor box)

Output y:

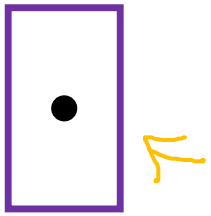
$3 \times 3 \times 16$

$3 \times 3 \times 2 \times 8$

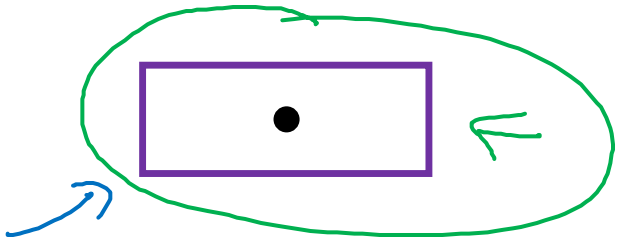
Anchor box example



Anchor box 1:



Anchor box 2:



$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \\ p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

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Object Detection

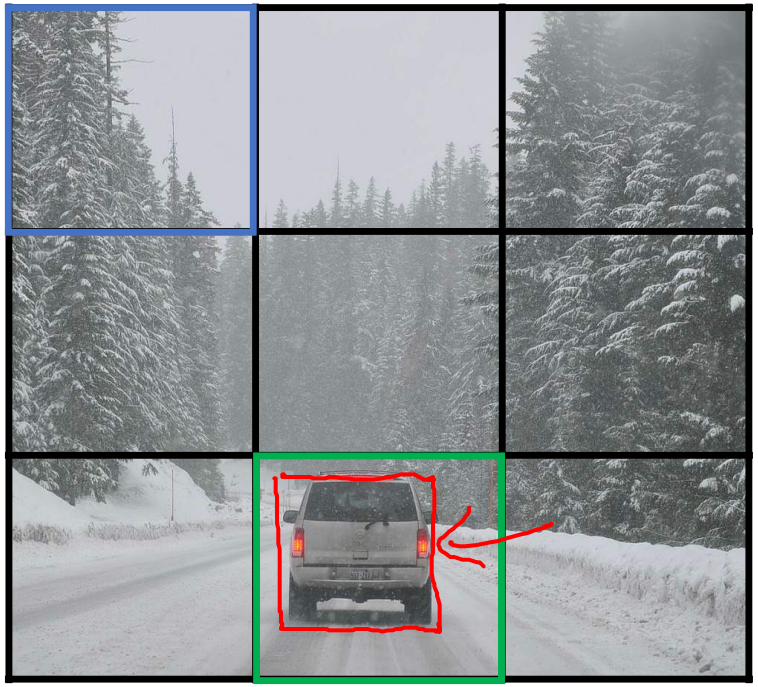
Putting it together: YOLO algorithm

Training

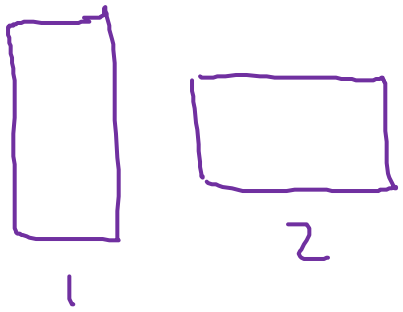
1 - pedestrian

2 - car

3 - motorcycle



$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \\ p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix} \rightarrow \begin{bmatrix} 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \end{bmatrix} \rightarrow \begin{bmatrix} 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 0 \\ 1 \\ 0 \end{bmatrix}$$



3×3×16

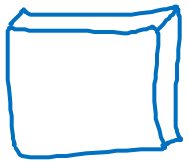
y is 3×3×2×8

19×19×16

19×19×40

#anchors

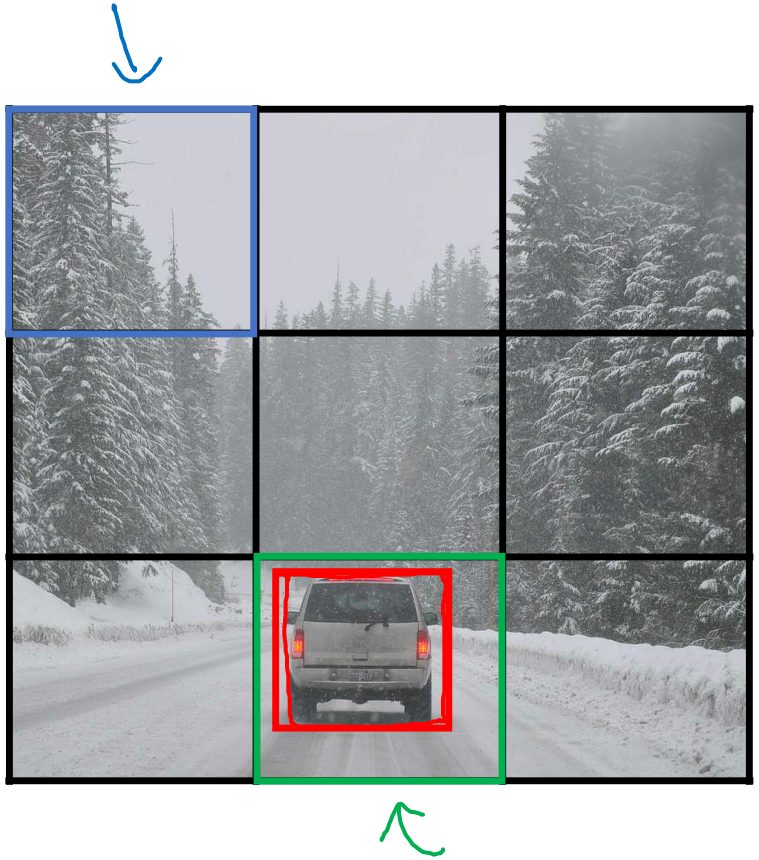
5 + #classes



→ ConvNet →

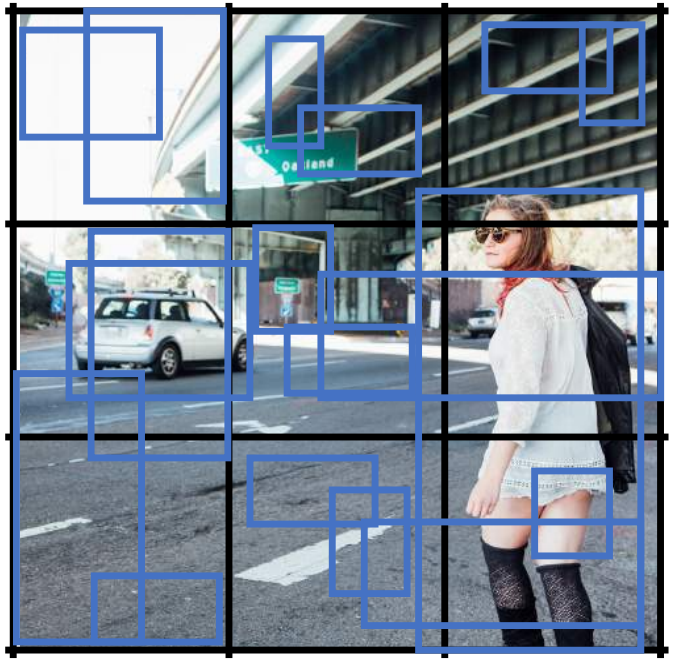
[Redmon et al., 2015, You Only Look Once: Unified real-time object detection]

Making predictions



$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \\ p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

Outputting the non-max supressed outputs



- For each grid call, get 2 predicted bounding boxes.
- Get rid of low probability predictions.
- For each class (pedestrian, car, motorcycle) use non-max suppression to generate final predictions.

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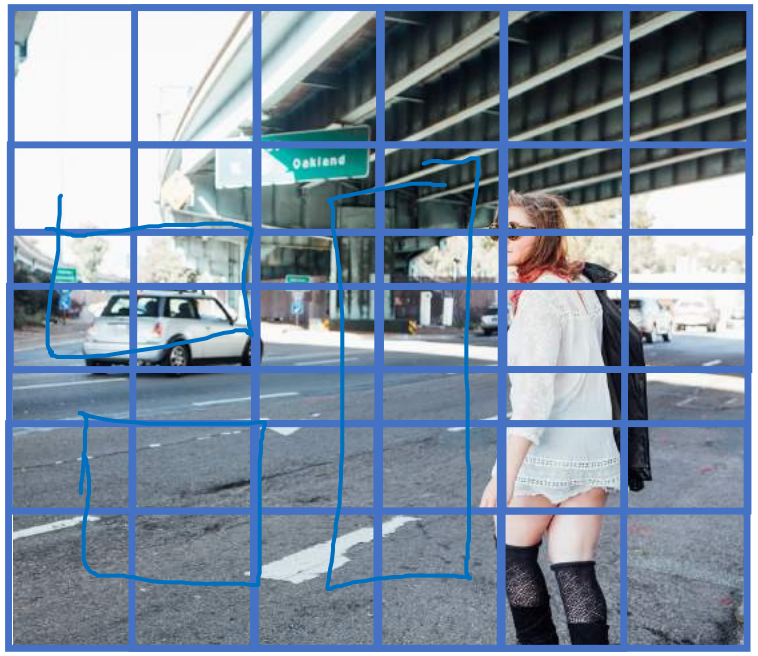
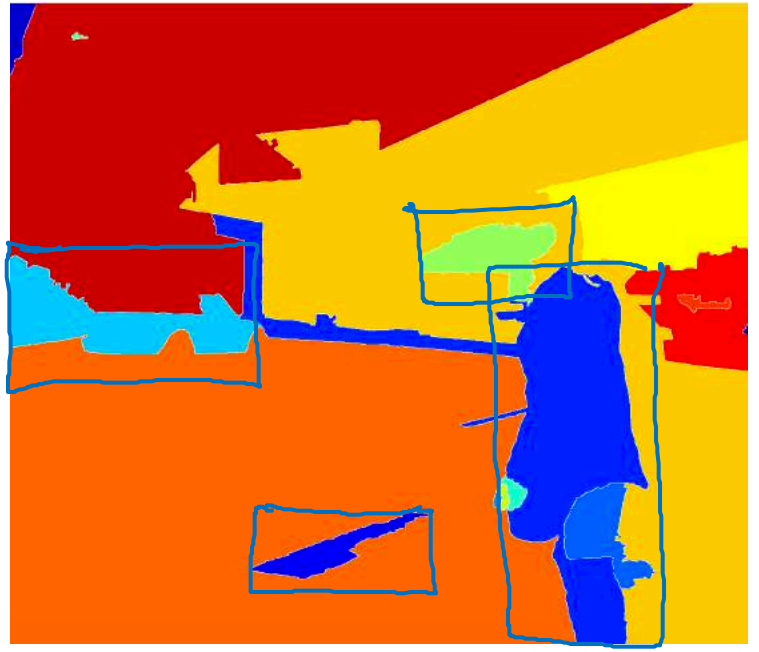
Object Detection

Region proposals (Optional)

Region proposal: R-CNN





Segmentation algorithm

~2,000

[Girshik et. al, 2013, Rich feature hierarchies for accurate object detection and semantic segmentation]

Faster algorithms

R-CNN: Propose regions. Classify proposed regions one at a time. Output label + bounding box.

Fast R-CNN: Propose regions. Use convolution implementation of sliding windows to classify all the proposed regions.

Faster R-CNN: Use convolutional network to propose regions.

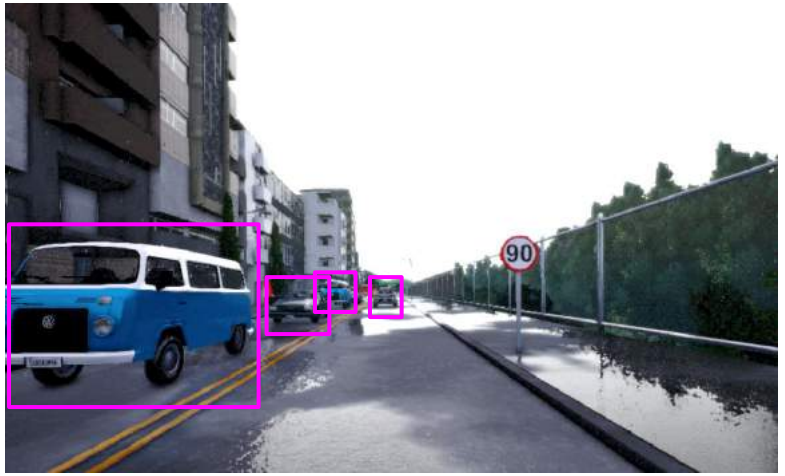
[Girshik et. al, 2013. Rich feature hierarchies for accurate object detection and semantic segmentation]
[Girshik, 2015. Fast R-CNN]
[Ren et. al, 2016. Faster R-CNN: Towards real-time object detection with region proposal networks]

Convolutional Neural Networks

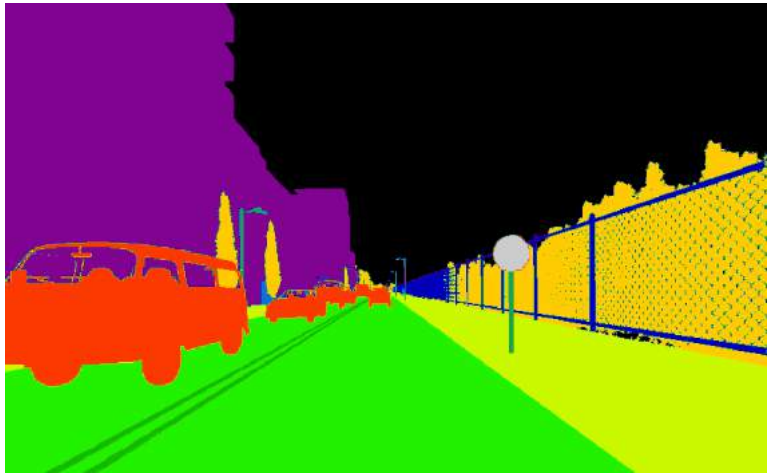
Semantic segmentation with U-Net

Object Detection vs. Semantic Segmentation

Input image

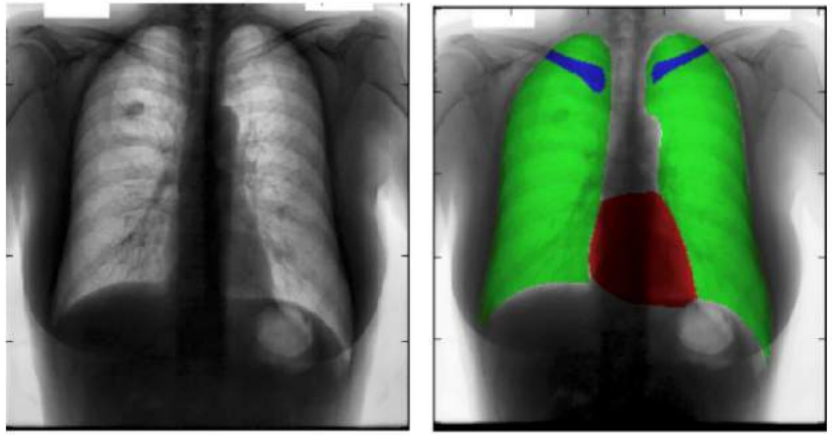


Object Detection

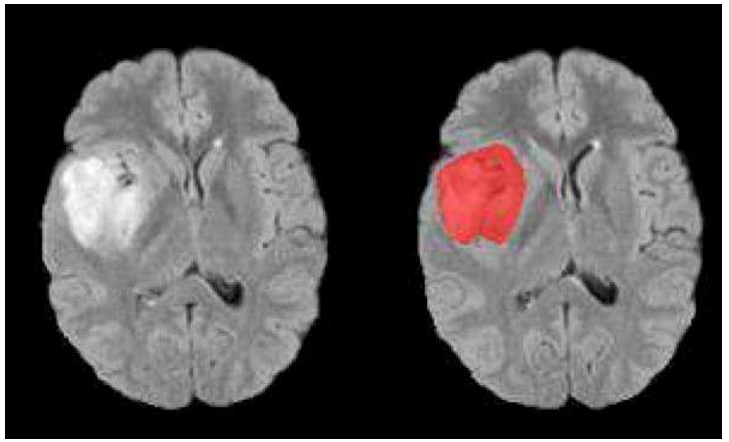


Semantic Segmentation

Motivation for U-Net



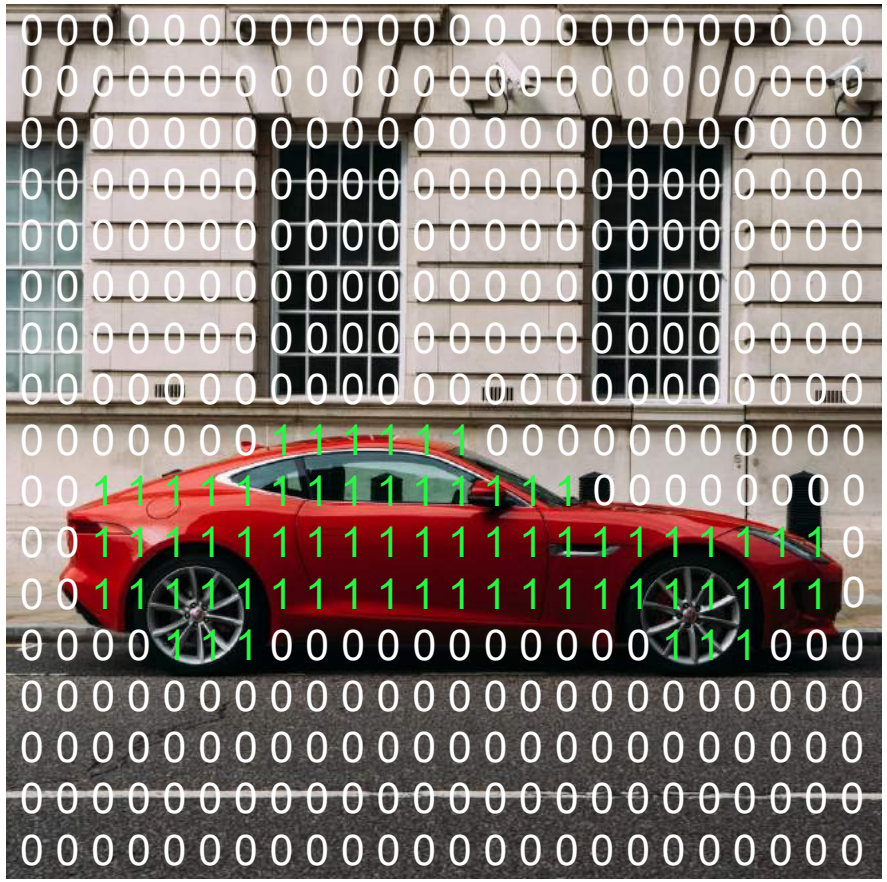
Chest X-Ray



Brain MRI

[Novikov et al., 2017, Fully Convolutional Architectures for Multi-Class Segmentation in Chest Radiographs]
[Dong et al., 2017, Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks]

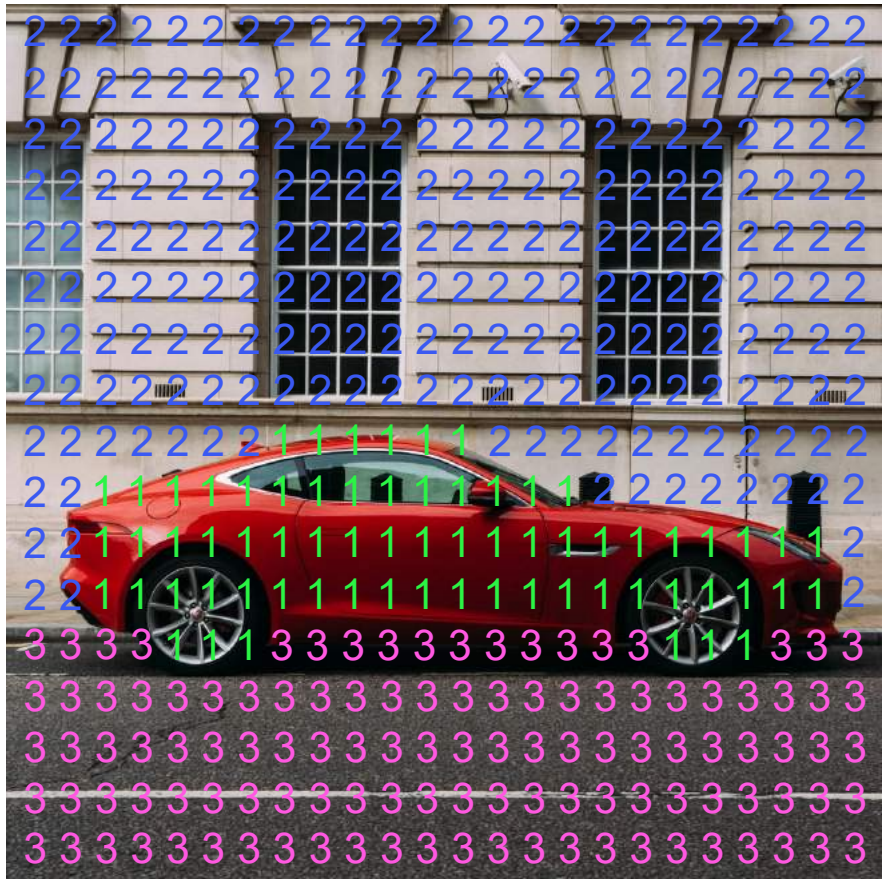
Per-pixel class labels



1. Car
0. Not Car

Andrew Ng

Per-pixel class labels

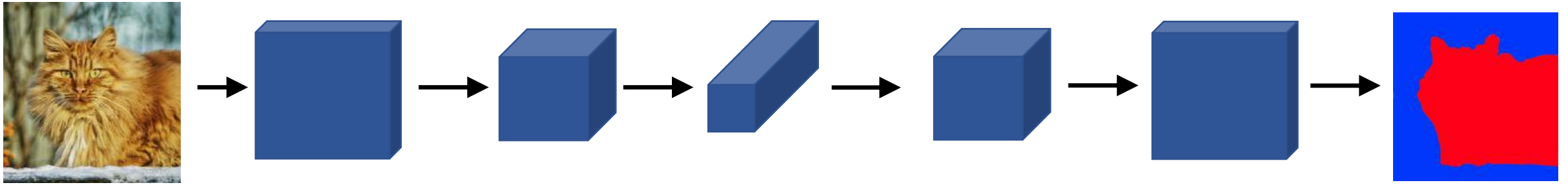


1. Car
2. Building
3. Road

Segmentation Map

Andrew Ng

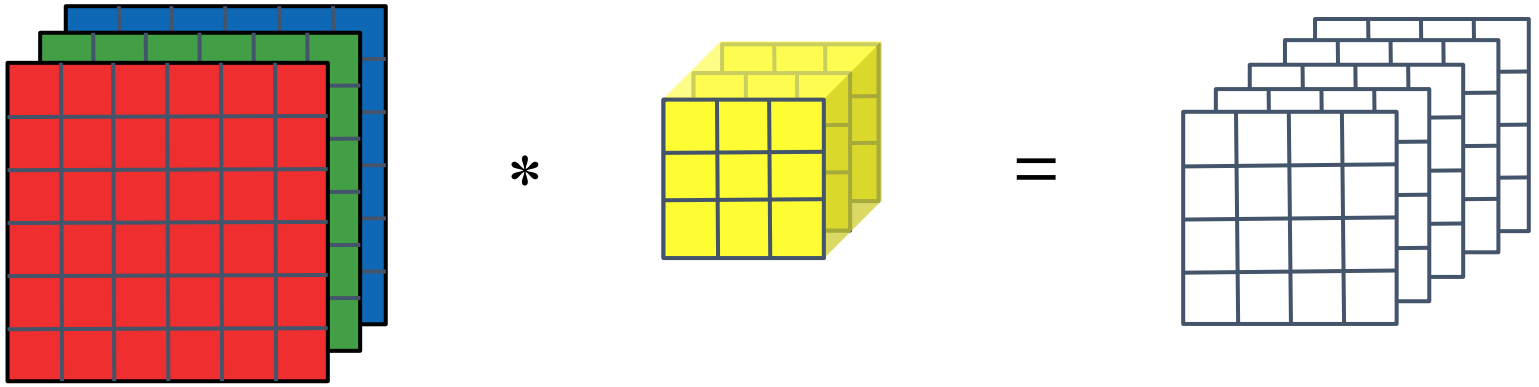
Deep Learning for Semantic Segmentation



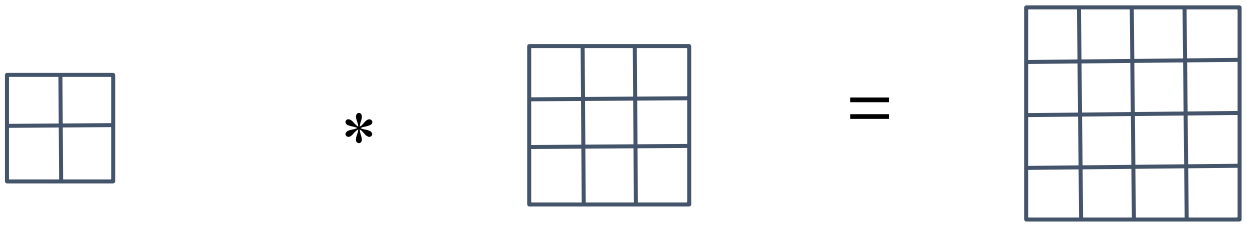
Andrew Ng

Transpose Convolution

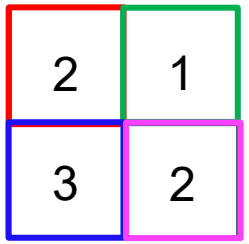
Normal Convolution



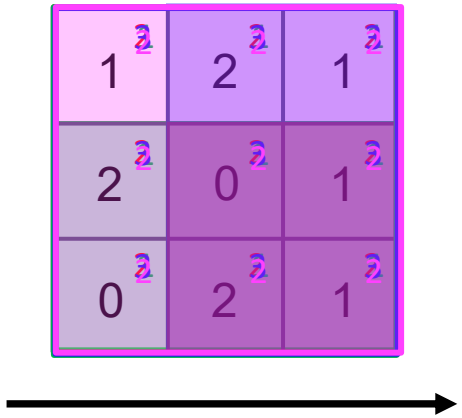
Transpose Convolution



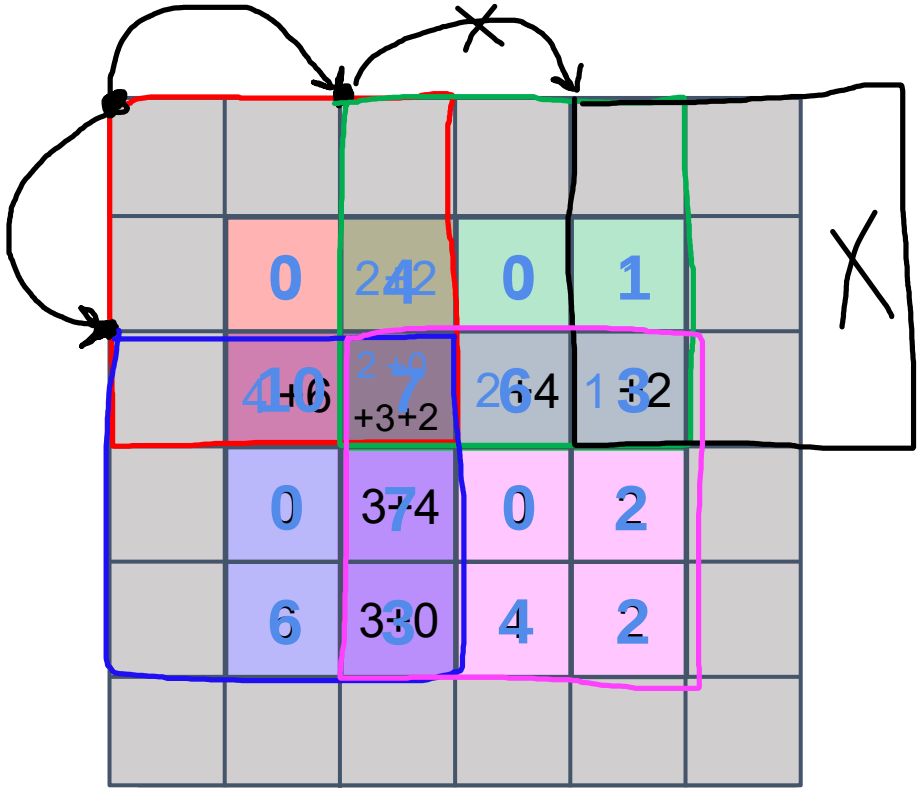
Transpose Convolution



2 x 2



weight filter

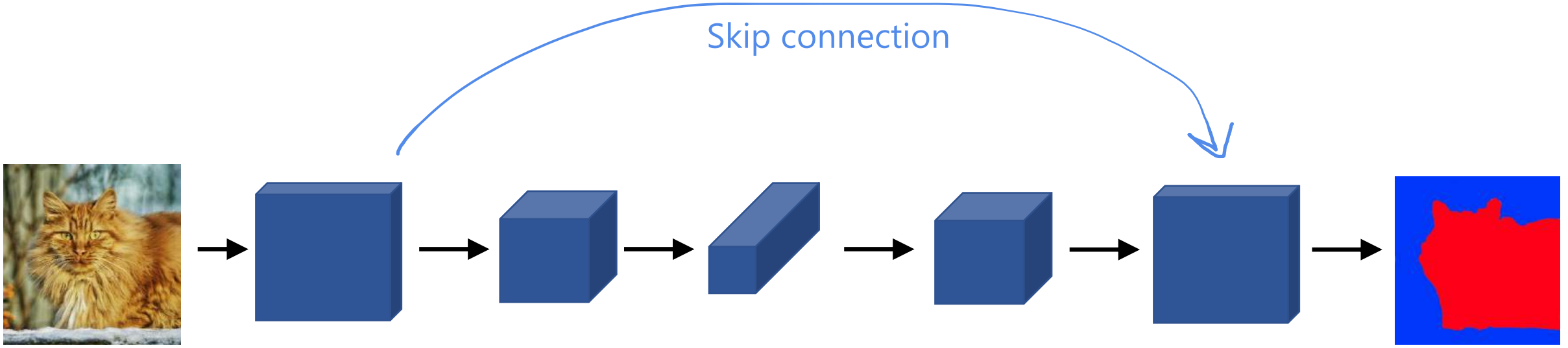


4 x 4

filter f x f = 3 x 3 padding p = 1 stride s = 2

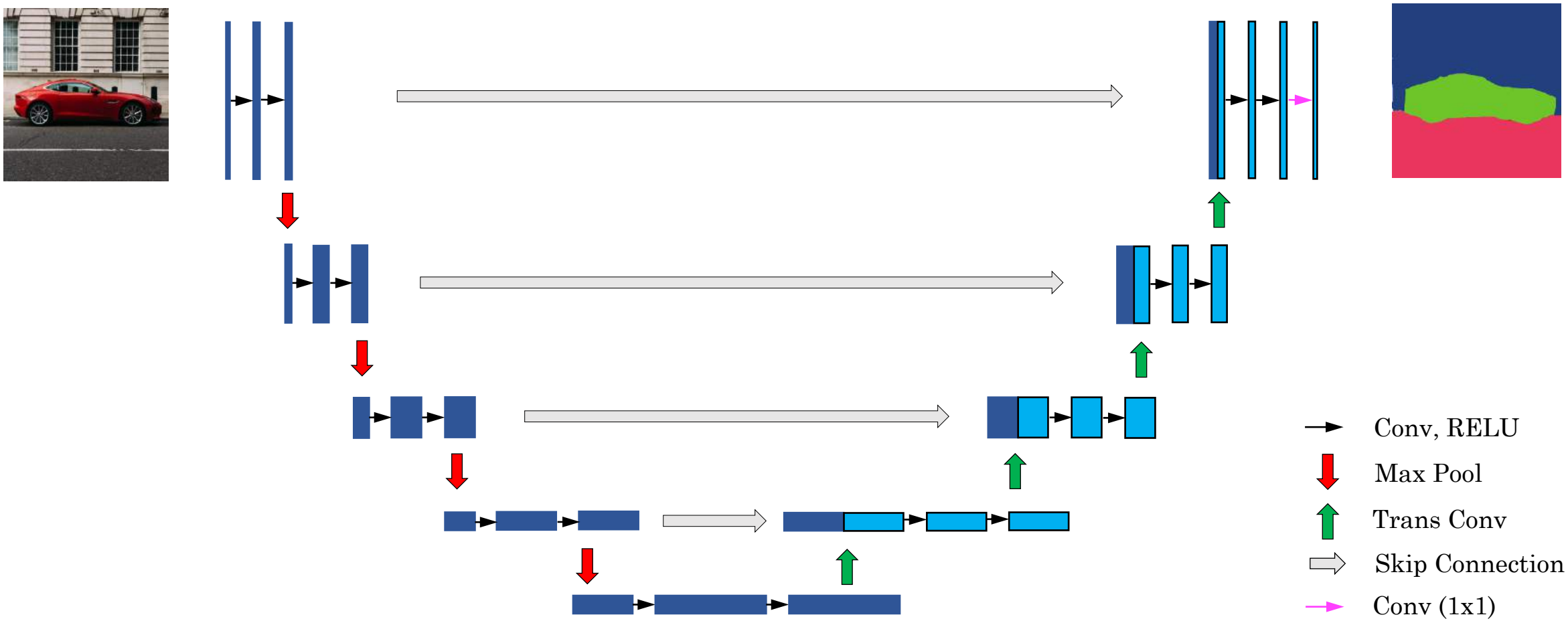
Andrew Ng

Deep Learning for Semantic Segmentation



Andrew Ng

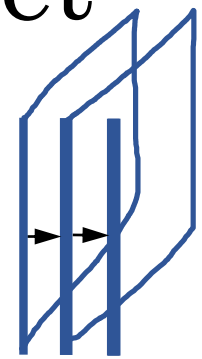
U-Net



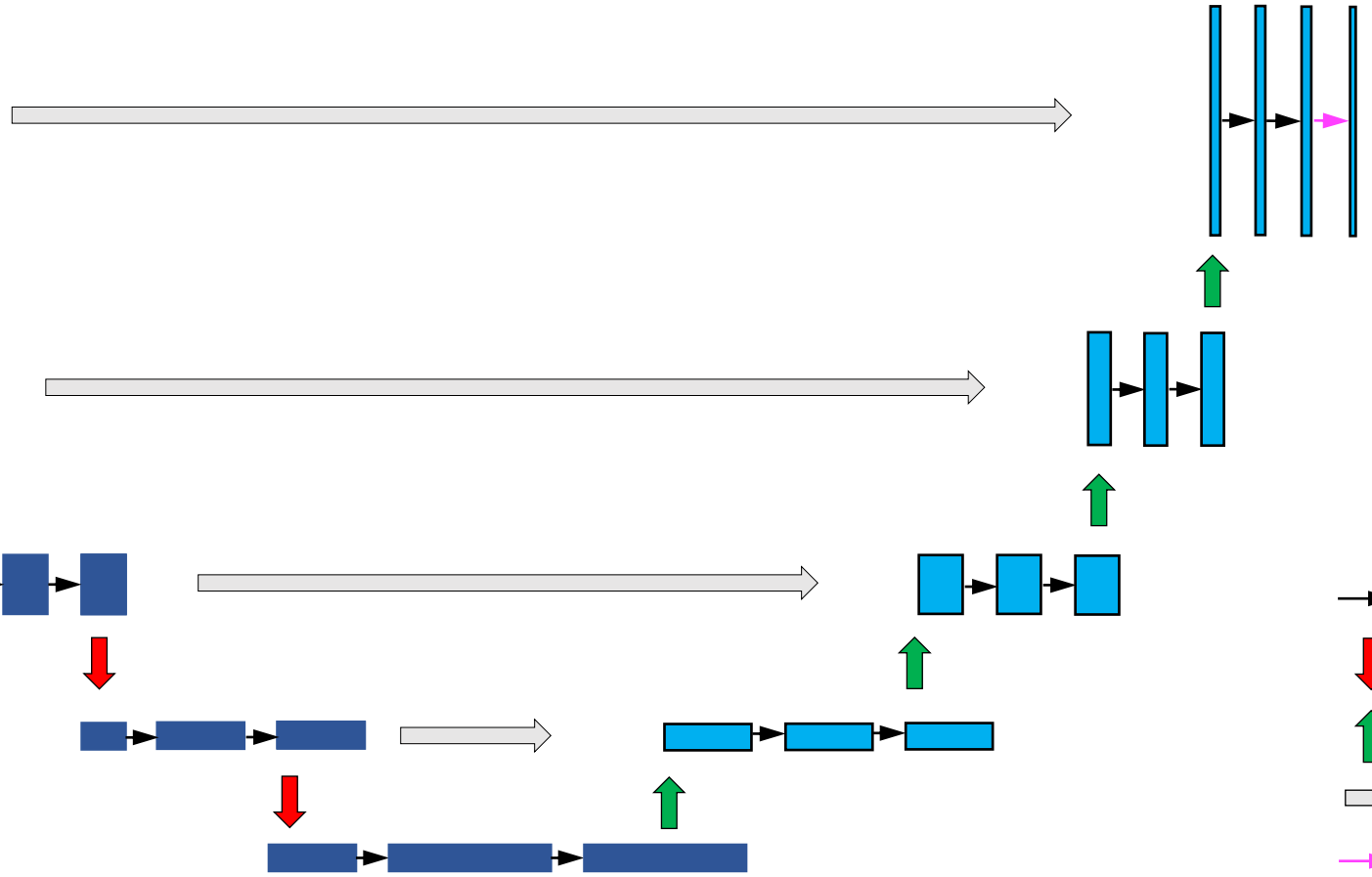
[Ronneberger et al., 2015, U-Net: Convolutional Networks for Biomedical Image Segmentation]

U-Net

h x w x 3



h x w x # classes



Conv, RELU

Max Pool

Trans Conv

Skip Connection

Conv (1x1)

[Ronneberger et al., 2015, U-Net: Convolutional Networks for Biomedical Image Segmentation]

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Face recognition

What is face recognition?

Face recognition

[Courtesy of Baidu]

Face verification vs. face recognition

- Verification
  - Input image, name/ID
  - Output whether the input image is that of the claimed person
- Recognition
  - Has a database of K persons
  - Get an input image
  - Output ID if the image is any of the K persons (or "not recognized")

1:1 99% 99.9

1:K K=100

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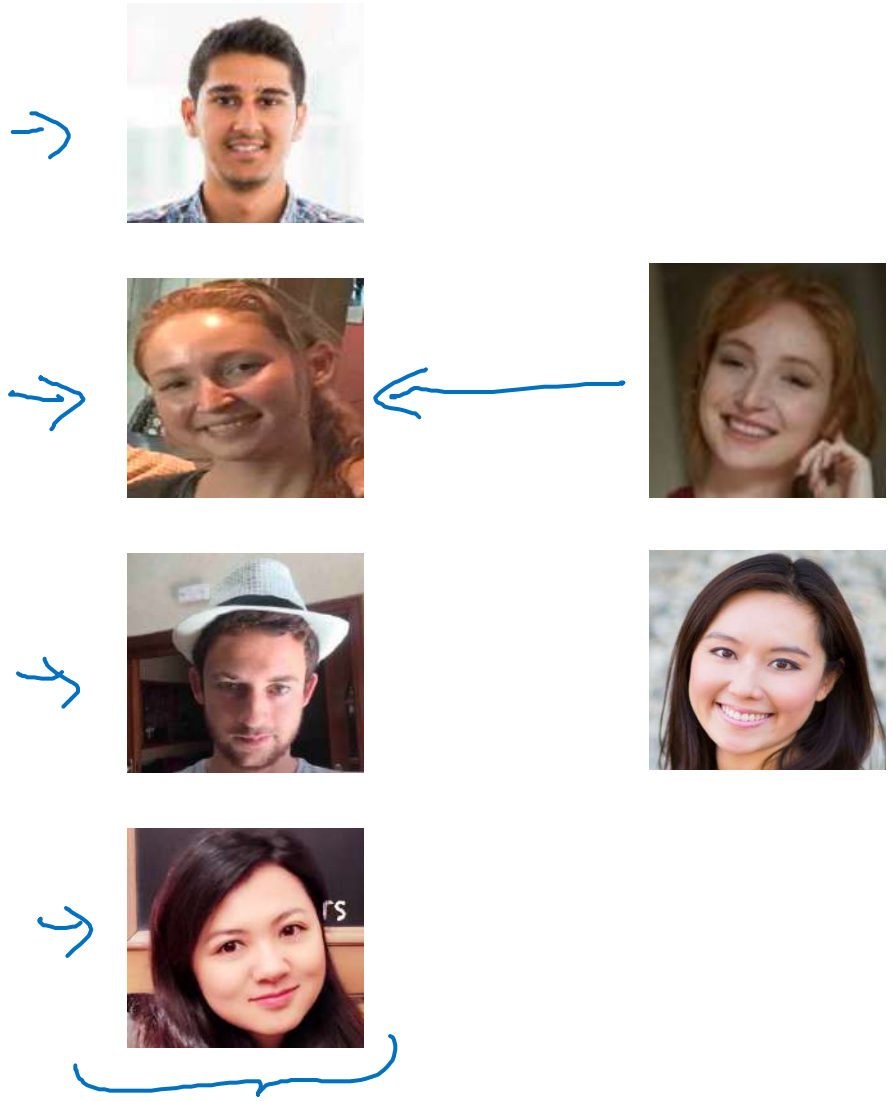
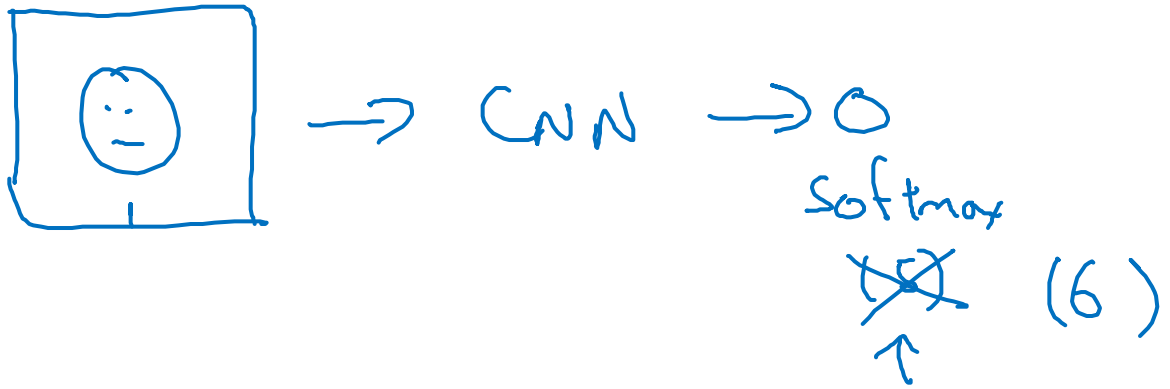
Face recognition

One-shot learning

One-shot learning



Learning from one example to recognize the person again



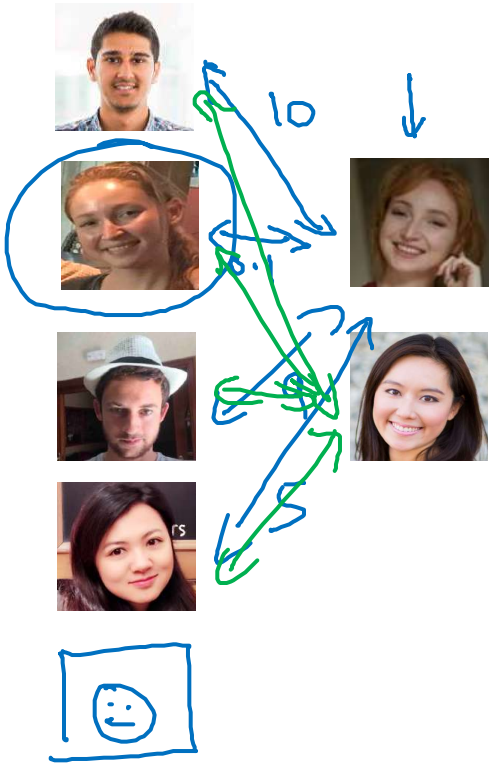
Learning a "similarity" function

→ d(img1,img2) = degree of difference between images

If d(img1,img2) $\leq \tau$ "same"

$> \tau$ "different"

} Verification.



d(img1, img2)

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Face recognition

Siamese network

Siamese network

$x^{(1)}$

"encoding of $x^{(1)}$"

128

$f(x^{(1)})$

128

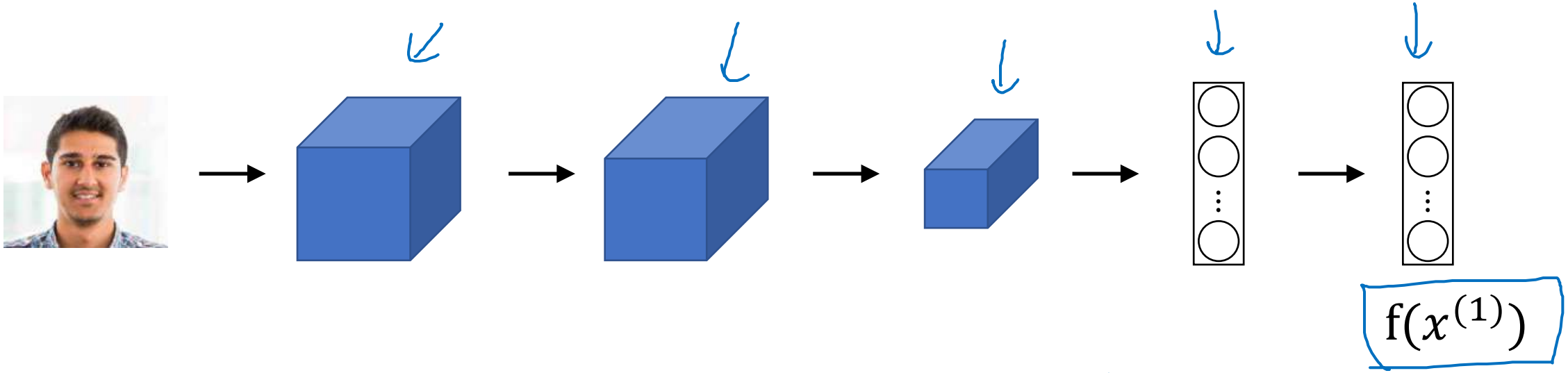
$x^{(2)}$

$f(x^{(2)})$

$$d(x^{(1)}, x^{(2)}) = \| f(x^{(1)}) - f(x^{(2)}) \|_2^2$$

[Taigman et. al., 2014. DeepFace closing the gap to human level performance]

Goal of learning



Parameters of NN define an encoding $f(x^{(i)})$ 128

Learn parameters so that:

If $x^{(i)}, x^{(j)}$ are the same person, $\left\|f(x^{(i)}) - f(x^{(j)})\right\|^2$ is small.

If $x^{(i)}, x^{(j)}$ are different persons, $\left\|f(x^{(i)}) - f(x^{(j)})\right\|^2$ is large.

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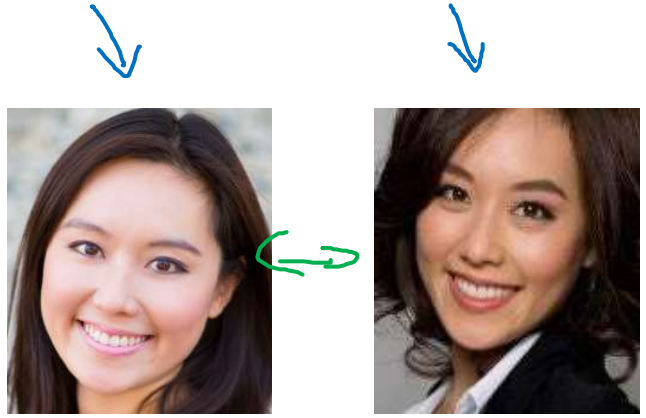
Face recognition

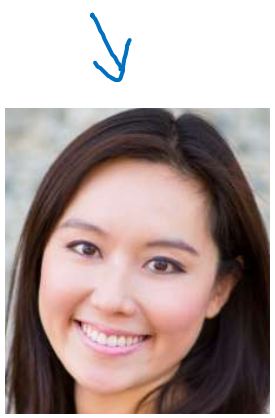
Triplet loss

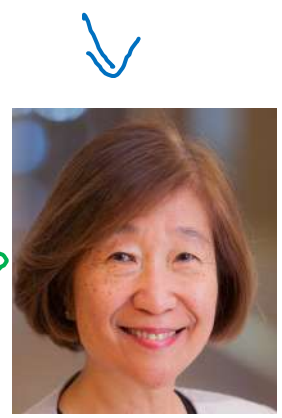
Learning Objective



Anchor

Positive





Anchor

Negative

A

$d(A,P) = 0.5$ P

A

$d(A,N) = 0.5$ N → 0.7

Want: $\|f(A) - f(P)\|^2 + \alpha \leq \|f(A) - f(N)\|^2$ (α → 0.2)

$d(A,P)$ $d(A,N)$

$$\|f(A) - f(P)\|^2 - \|f(A) - f(N)\|^2 + \alpha \leq 0$$

0 0 margin

$f(\text{img}) = \vec{0}$

[Schroff et al.,2015, FaceNet: A unified embedding for face recognition and clustering]

Loss function

Given 3 images A, P, N:

$$\mathcal{L}(A, P, N) = \max\left(\|f(A) - f(P)\|^2 - \|f(A) - f(N)\|^2 + \alpha, 0\right)$$

$$J = \sum_{i=1}^{m} \mathcal{L}(A^{(i)}, P^{(i)}, N^{(i)})$$

A, P

Training set: 10k pictures of 1k persons

[Schroff et al.,2015, FaceNet: A unified embedding for face recognition and clustering]

Choosing the triplets A,P,N

During training, if A,P,N are chosen randomly, $d(A,P) + \alpha \leq d(A,N)$ is easily satisfied.

$\|f(A) - f(P)\|^2 + \alpha \leq \|f(A) - f(N)\|^2$

Choose triplets that're "hard" to train on.

$d(A,P) + \alpha \leq d(A,N)$

$d(A,P) \approx d(A,N)$

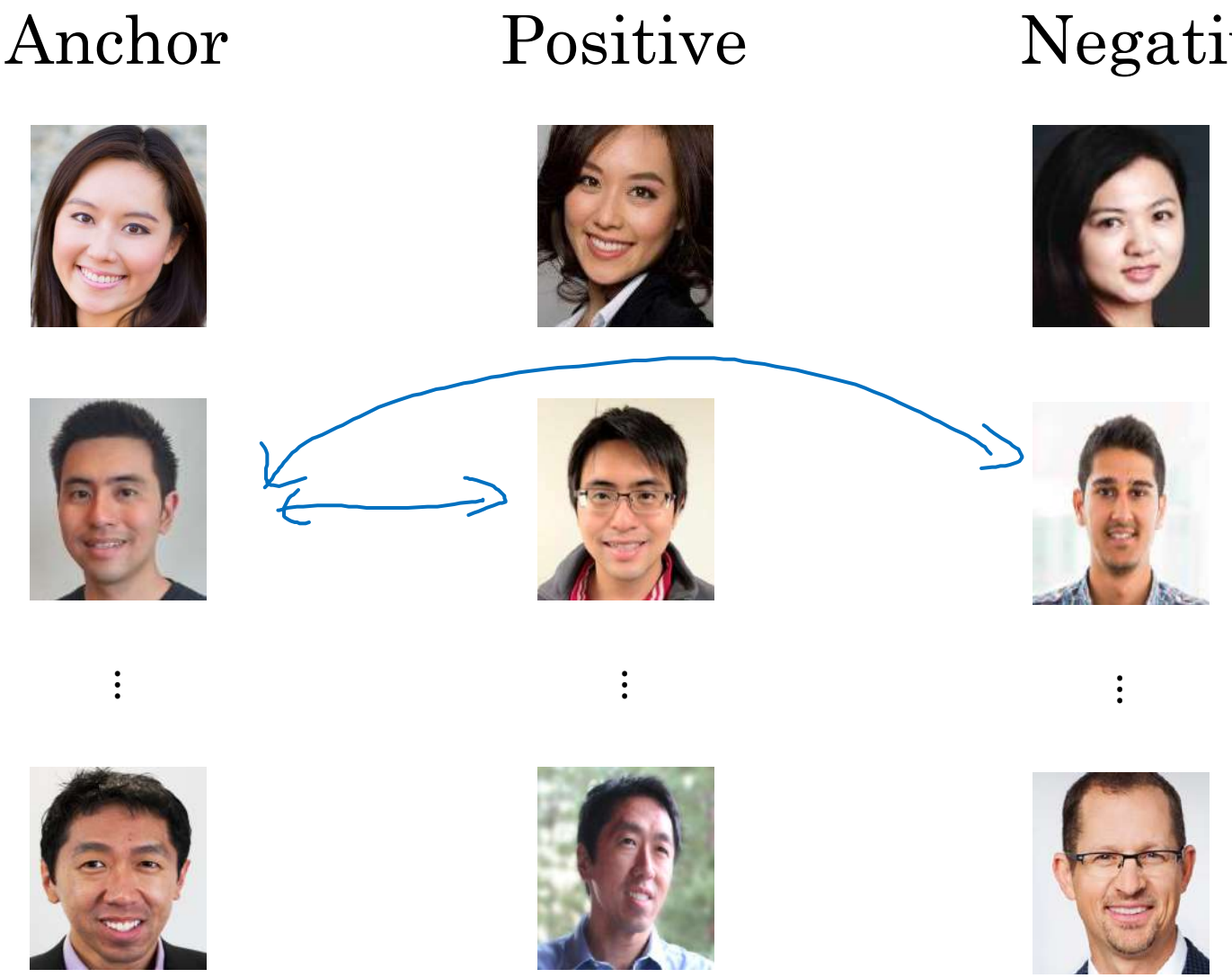
↓ ↑

Face Net

Deep Face

[Schroff et al.,2015, FaceNet: A unified embedding for face recognition and clustering]

Training set using triplet loss



$$J$$

$$d(x^{(i)}, x^{(j)})$$

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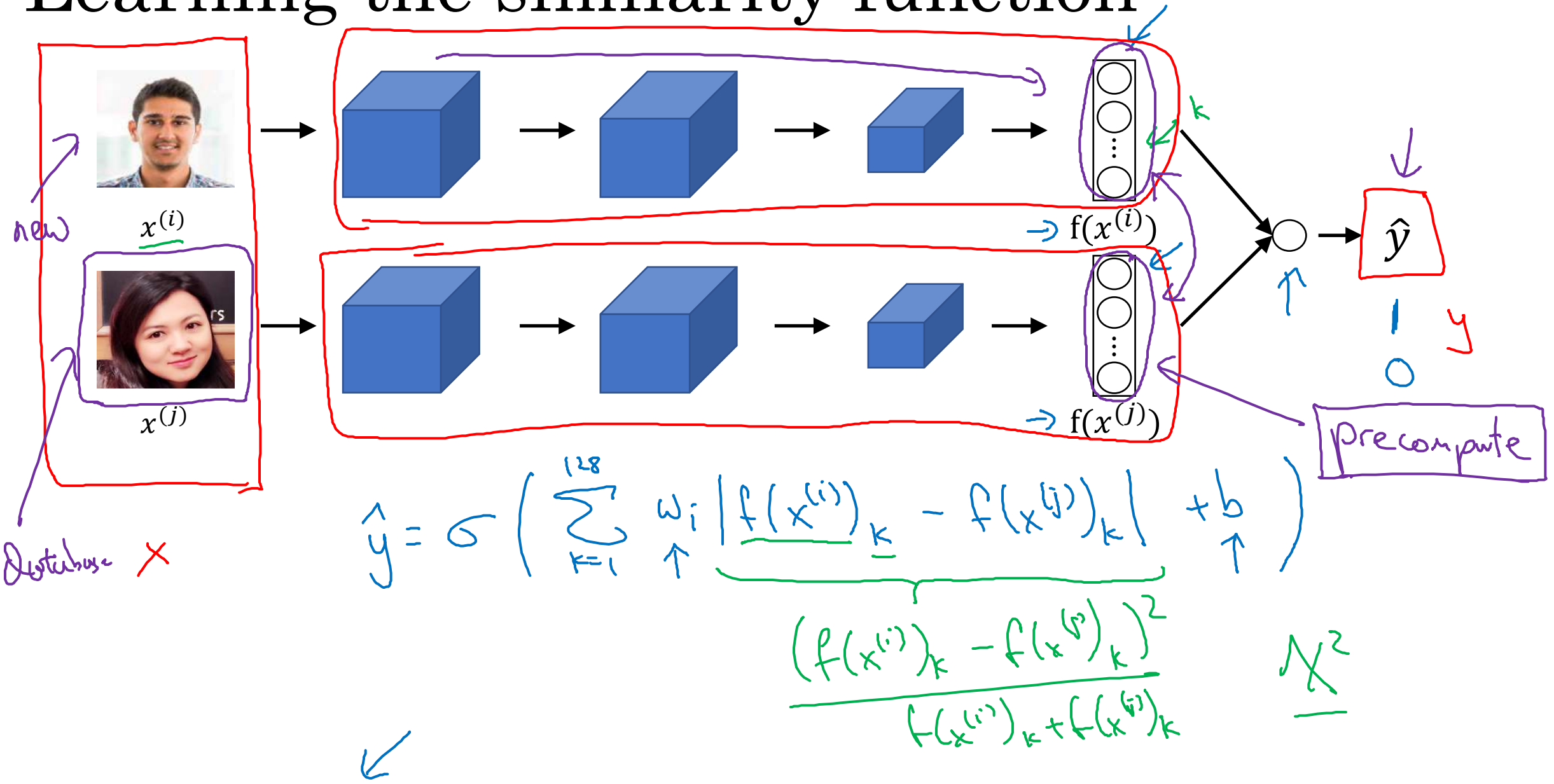
Face recognition

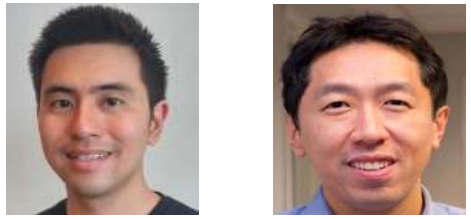
Face verification and binary classification

Learning the similarity function



[Taigman et. al., 2014. DeepFace closing the gap to human level performance]

Face verification supervised learning

x	y	
	1	"Same"
	0	"Albert"
	0	
	1	

[Taigman et. al., 2014. DeepFace closing the gap to human level performance]

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Neural Style Transfer

What is neural style transfer?

Neural style transfer


Content (C) Style (S)

Generated image (G)


Content (C) Style (S)

Generated image (G)

[Images generated by Justin Johnson]

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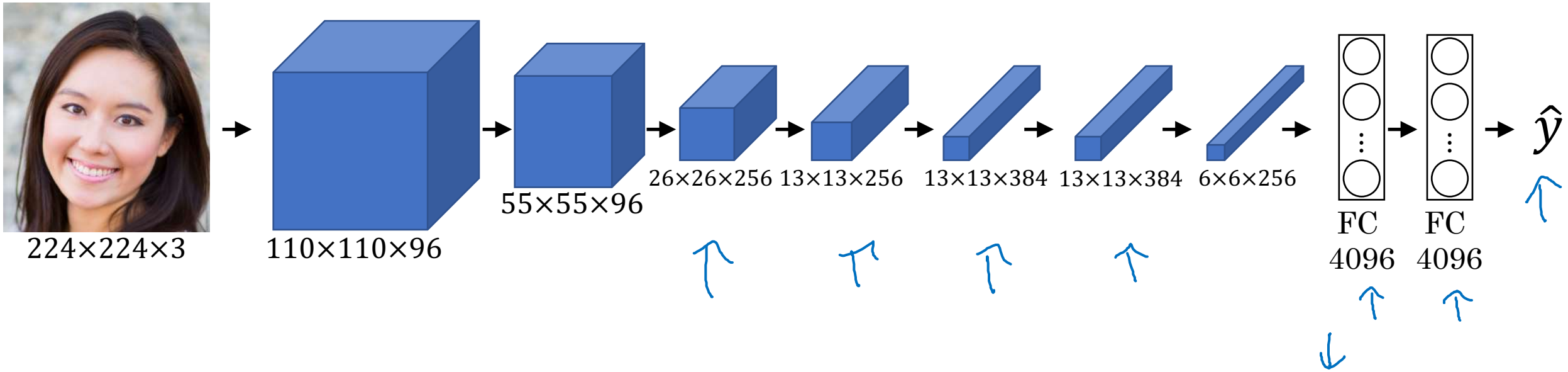
Neural Style Transfer

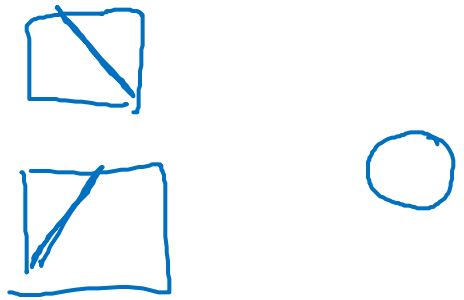
What are deep ConvNets learning?

Visualizing what a deep network is learning



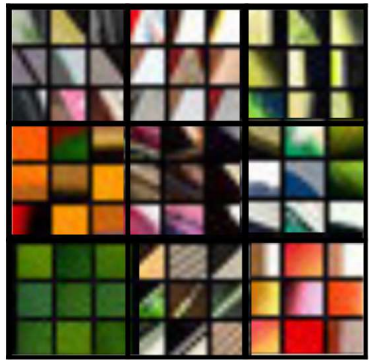
Pick a unit in layer 1. Find the nine image patches that maximize the unit's activation.

Repeat for other units.

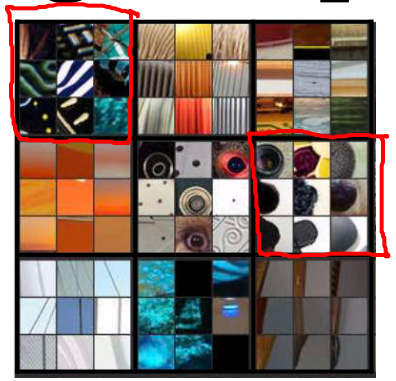


[Zeiler and Fergus., 2013, Visualizing and understanding convolutional networks]

Visualizing deep layers

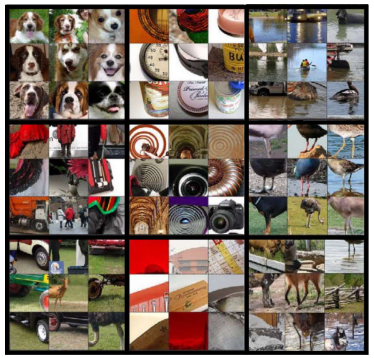


Layer 1

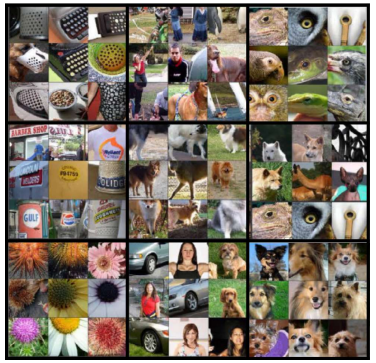


Layer 2

Layer 3

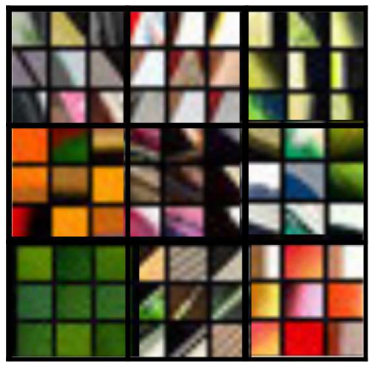


Layer 4



Layer 5

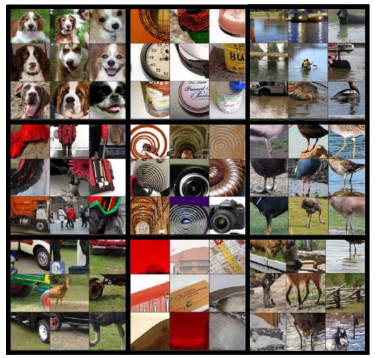
Visualizing deep layers: Layer 1



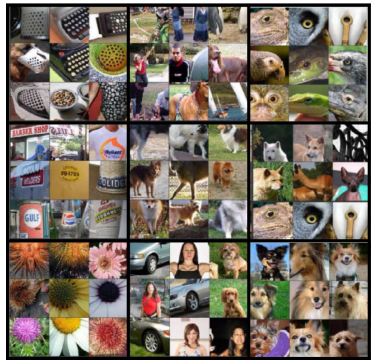
Layer 1

Layer 2

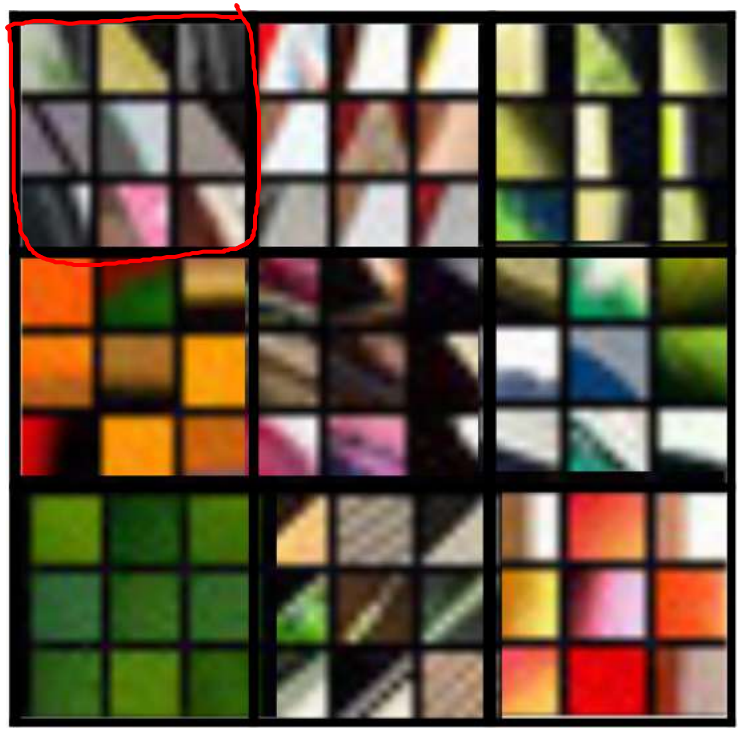
Layer 3



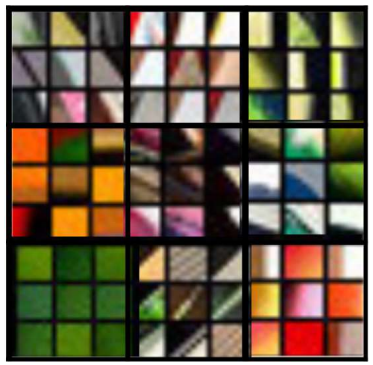
Layer 4



Layer 5



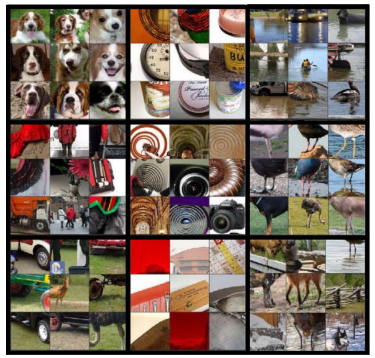
Visualizing deep layers: Layer 2



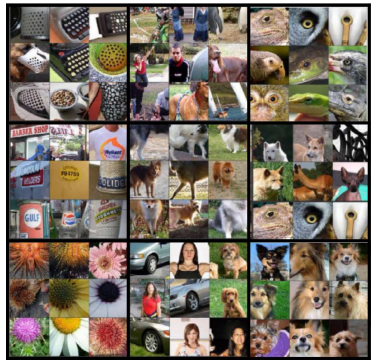
Layer 1

Layer 2

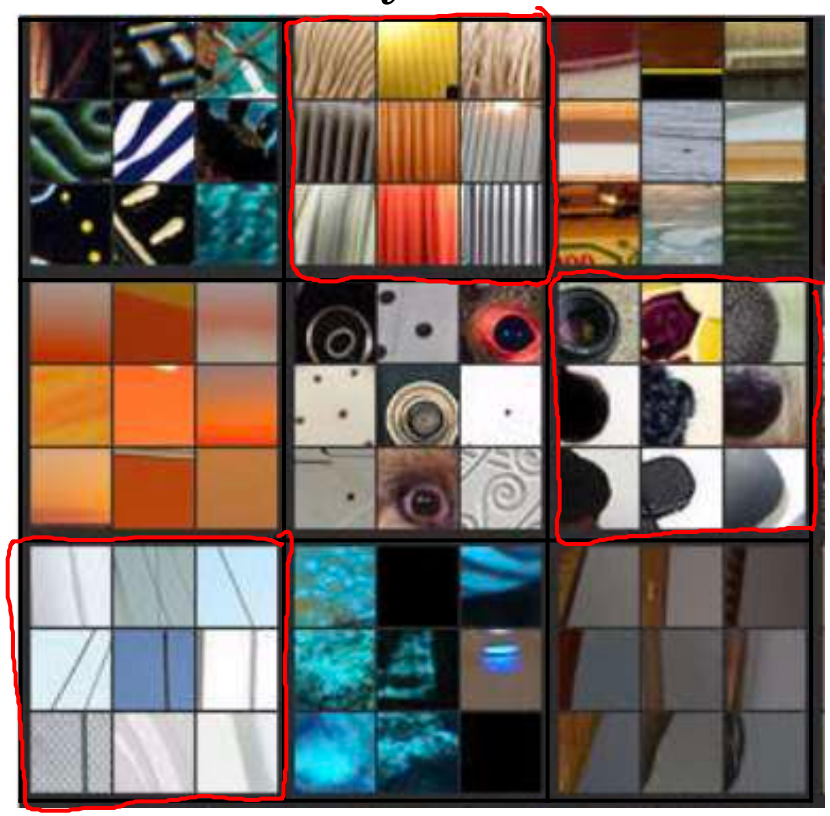
Layer 3



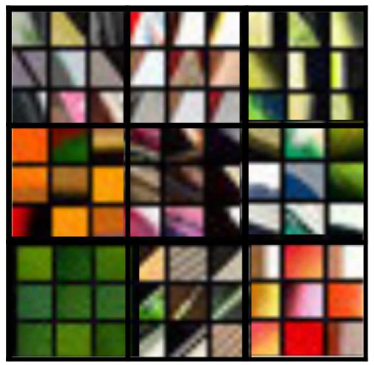
Layer 4



Layer 5



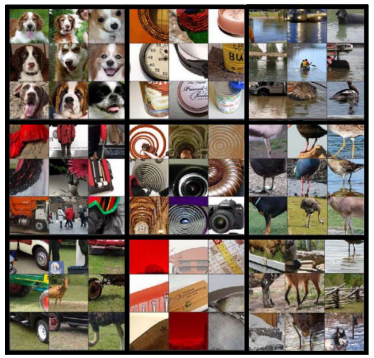
Visualizing deep layers: Layer 3



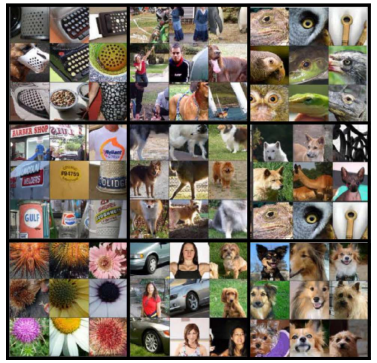
Layer 1

Layer 2

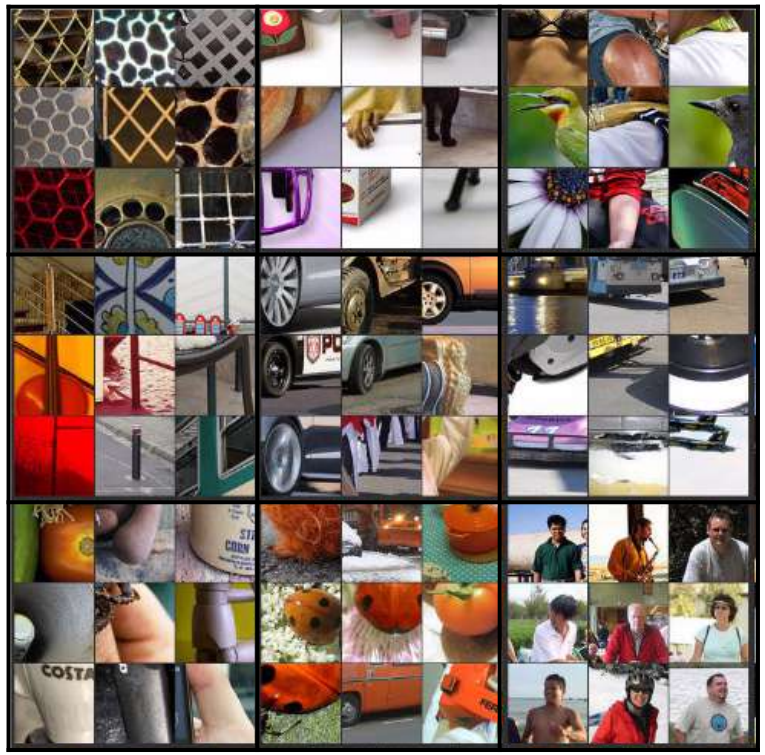
Layer 3



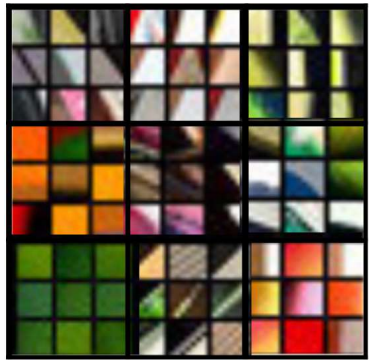
Layer 4



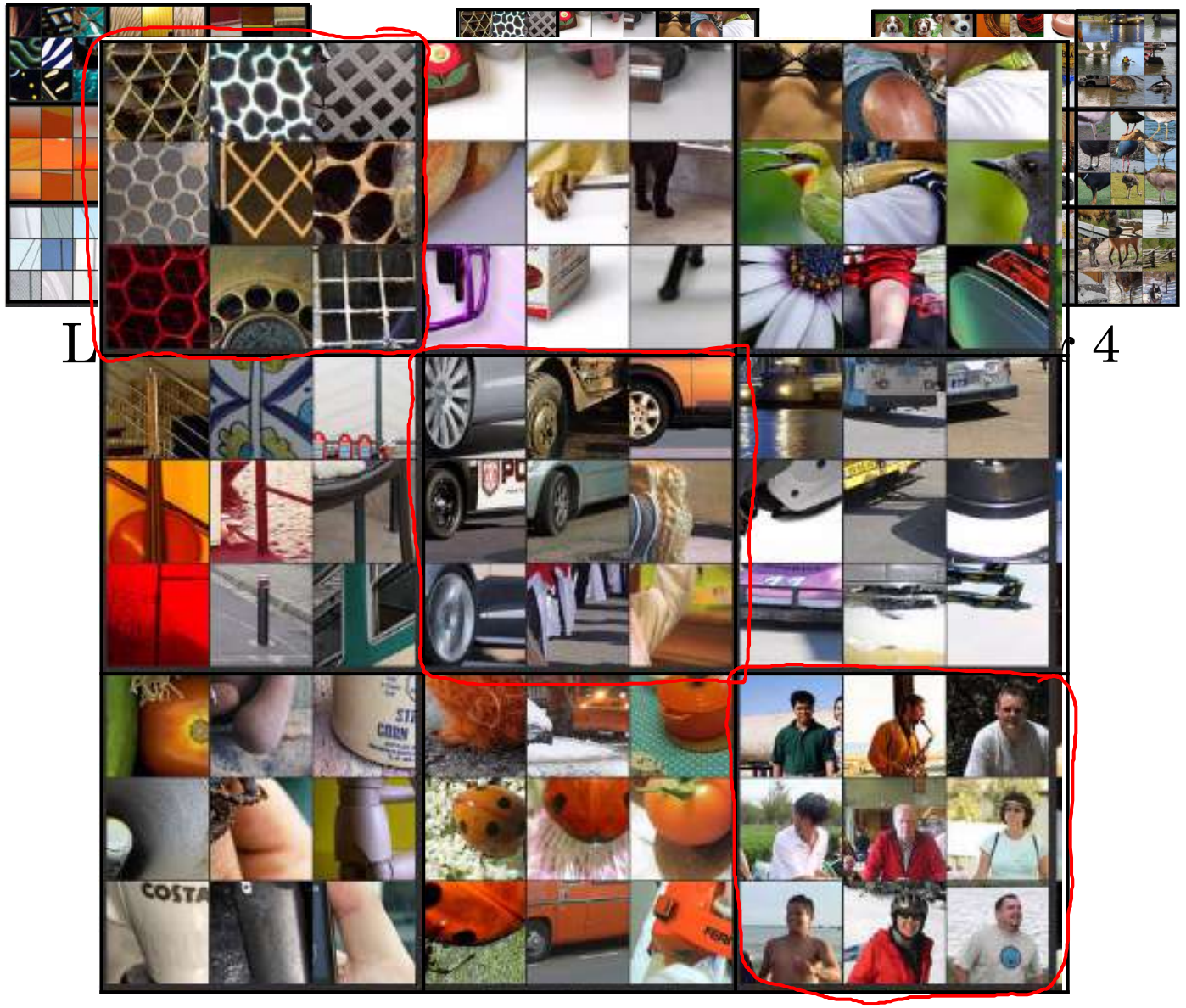
Layer 5

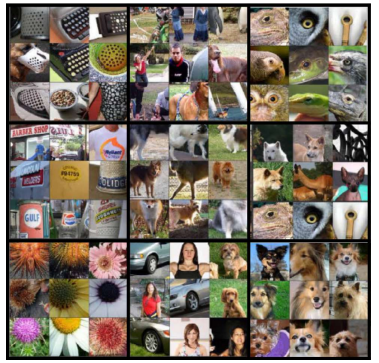


Visualizing deep layers: Layer 3



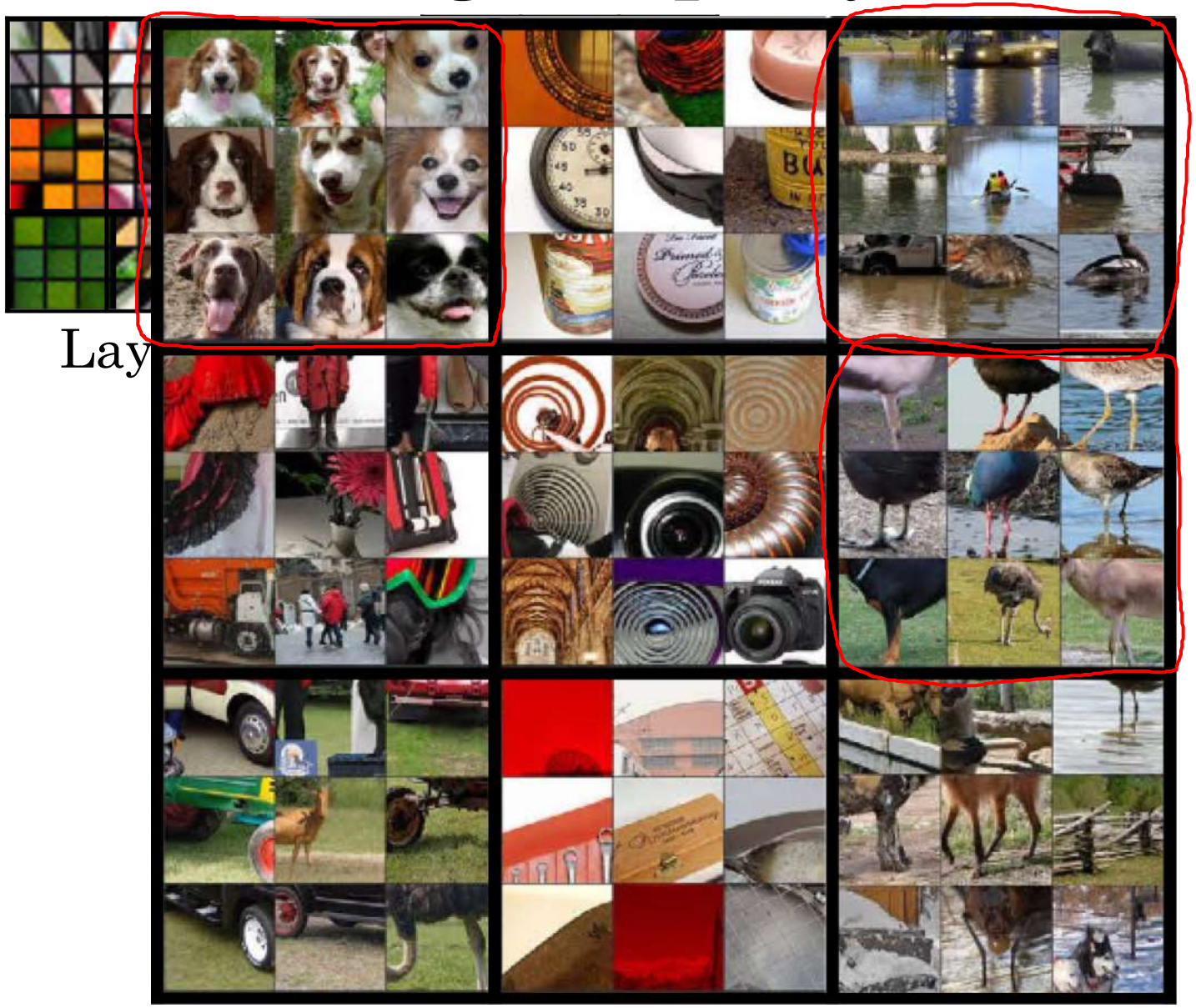
Layer 1



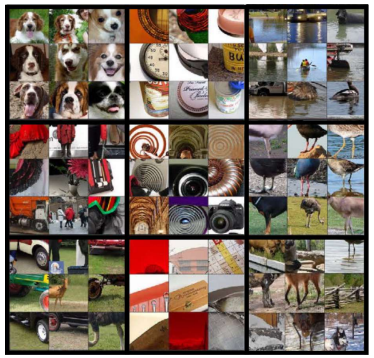


Layer 5

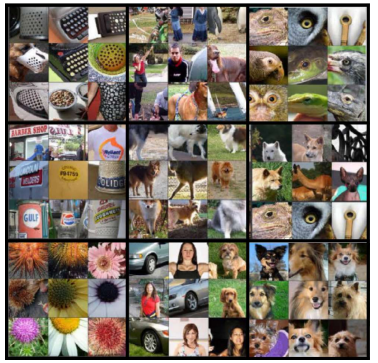
Visualizing deep layers: Layer 4



Lay

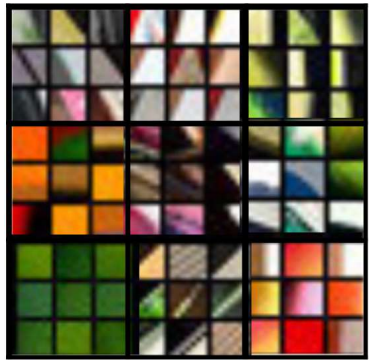


Layer 4

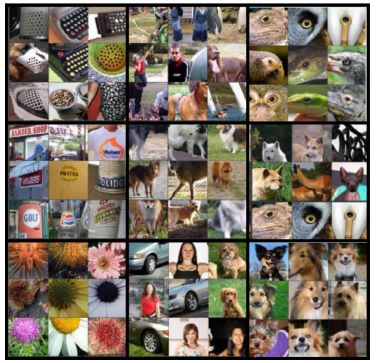


Layer 5

Visualizing deep layers: Layer 5



Layer 1



Layer 5

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Neural Style Transfer

Cost function

Neural style transfer cost function

Content C

Style S

Generated image G

$$J(G) = \alpha J_{content}(C, G) + \beta J_{style}(S, G)$$

[Gatys et al., 2015. A neural algorithm of artistic style. Images on slide generated by Justin Johnson]

Find the generated image G

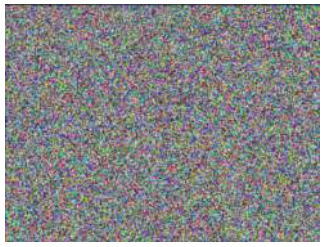
1. Initiate G randomly

   G: 100×100×3

   ↑ RGB

2. Use gradient descent to minimize $J(G)$

$$G := G - \frac{\partial}{\partial G} J(G)$$



[Gatys et al., 2015. A neural algorithm of artistic style]

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Neural Style Transfer

Content cost function

Content cost function

$$J(G) = \alpha J_{content}(C, G) + \beta J_{style}(S, G)$$

- Say you use hidden layer l to compute content cost.
- Use pre-trained ConvNet. (E.g., VGG network)
- Let $a^{[l](C)}$ and $a^{[l](G)}$ be the activation of layer l on the images
- If $a^{[l](C)}$ and $a^{[l](G)}$ are similar, both images have similar content

$$J_{content}(C, G) = \frac{1}{2} \left\| a^{[l](C)} - a^{[l](G)} \right\|^2$$

[Gatys et al., 2015. A neural algorithm of artistic style]

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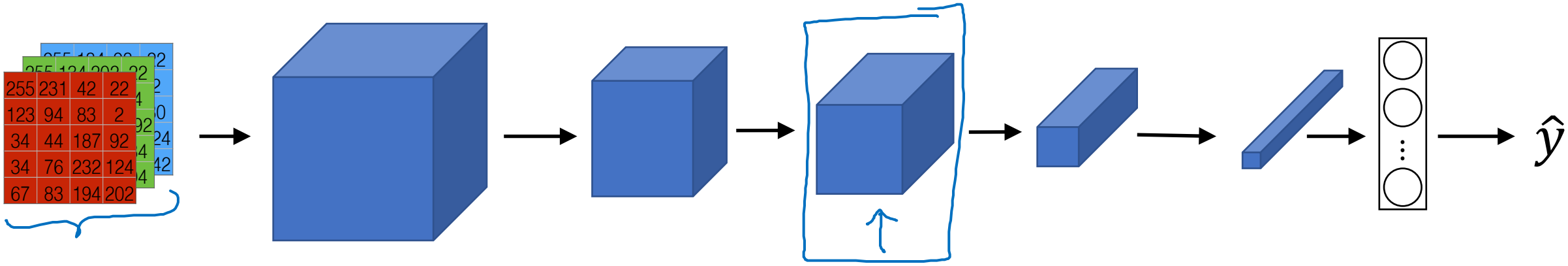
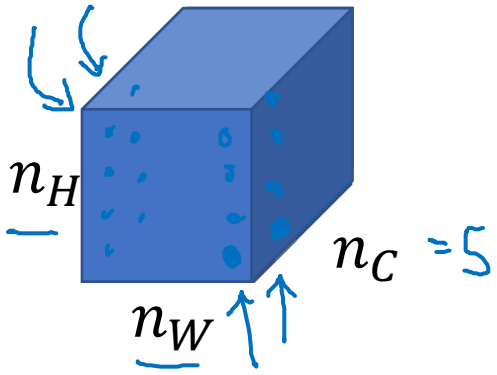
Neural Style Transfer

Style cost function

Meaning of the "style" of an image



Say you are using layer l's activation to measure "style."
Define style as correlation between activations across channels.

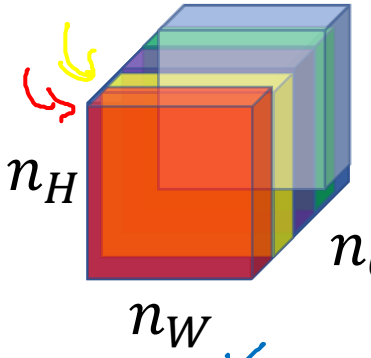


How correlated are the activations across different channels?

[Gatys et al., 2015. A neural algorithm of artistic style]

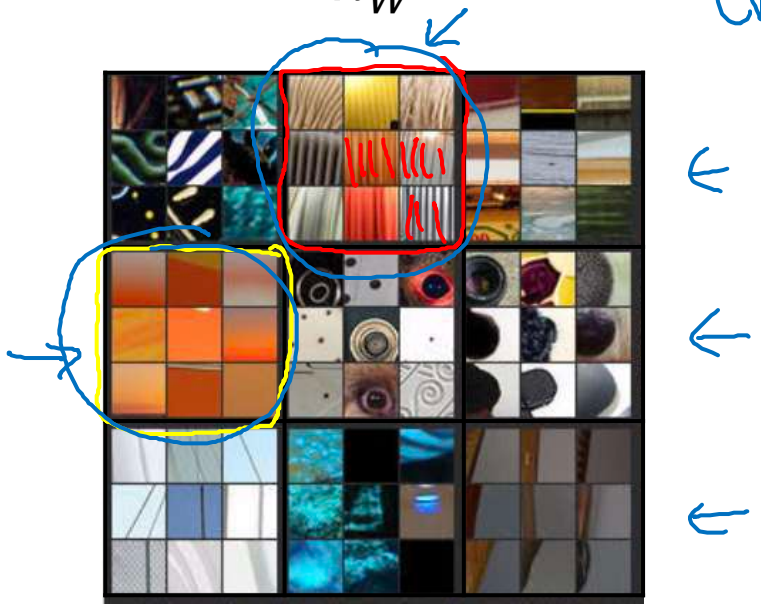
Intuition about style of an image

Style image

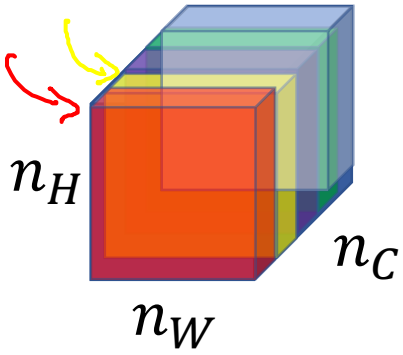


Correlated?

Uncorrelated



Generated Image



[Gatys et al., 2015. A neural algorithm of artistic style]

Style matrix

Let $a^{[l]}_{i,j,k}$ = activation at (i, j, k). $G^{[l]}$ is $n_c^{[l]} \times n_c^{[l]}$

H W C

n_c

$G^{[l]}_{kk'}$

$k = 1, \ldots, n_c^{[l]}$

$$G^{[l](S)}_{kk'} = \sum_{i=1}^{n_H^{[l]}} \sum_{j=1}^{n_W^{[l]}} a^{[l](S)}_{ijk} \, a^{[l](S)}_{ijk'}$$

$$G^{[l](G)}_{kk'} = \sum_{i=1}^{n_H^{[l]}} \sum_{j=1}^{n_W^{[l]}} a^{[l](G)}_{ijk} \, a^{[l](G)}_{ijk}$$

"Gram matrix"

$$J^{[l]}_{style}(S, G) = \frac{1}{(\ldots)} \left\| G^{[l](S)} - G^{[l](G)} \right\|_F^2$$

$$= \frac{1}{(2 n_H^{[l]} n_W^{[l]} n_c^{[l]})^2} \sum_k \sum_{k'} \left(G^{[l](S)}_{kk'} - G^{[l](G)}_{kk'} \right)^2$$

β

[Gatys et al., 2015. A neural algorithm of artistic style]

Style cost function

$$\left\| G^{[l](S)} - G^{[l](G)} \right\|_F^2$$

$$J_{style}^{[l]}(S,G) = \frac{1}{\left(2n_H^{[l]} n_W^{[l]} n_C^{[l]}\right)^2} \sum_k \sum_{k'} \left(G_{kk'}^{[l](S)} - G_{kk'}^{[l](G)}\right)$$

$$J_{style}(S,G) = \sum_l \lambda^{[l]} J_{style}^{[l]}(S,G)$$

$$J(G) = \alpha J_{content}(C,G) + \beta J_{style}(S,G)$$

G

[Gatys et al., 2015. A neural algorithm of artistic style]

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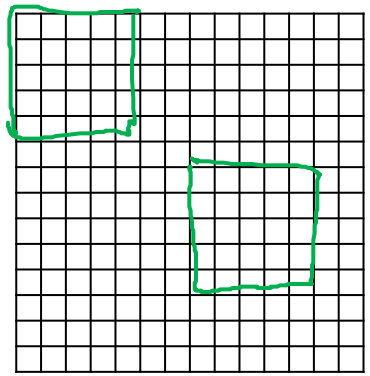
Convolutional Networks in 1D or 3D

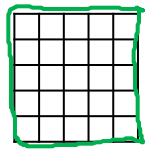
1D and 3D generalizations of models

Convolutions in 2D and 1D

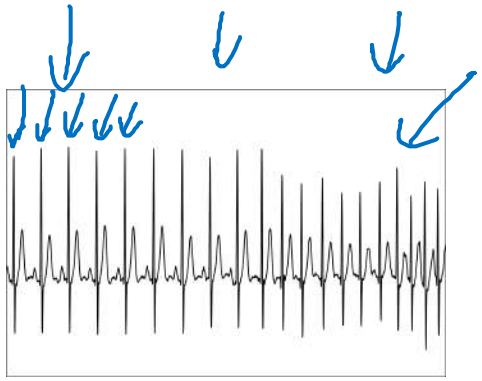


2D input image
14×14

*



2D filter
5×5



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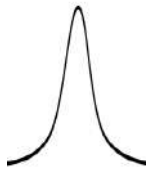
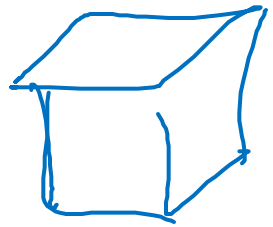


1	20	15	3	18	12	4	17

14

1	3	10	3	1

5



$14 \times 14 \times 3 \quad * \quad 5 \times 5 \times 3$

$\rightarrow 10 \times 10 \times 16$

$10 \times 10 \times 16 \quad * \quad 5 \times 5 \times 16$

$\rightarrow 6 \times 6 \times 32$

$14 \times 1 \quad * \quad 5 \times 1$

$\rightarrow 10 \times 16$

$10 \times 16 \quad * \quad 5 \times 16$

$\rightarrow 6 * 32$

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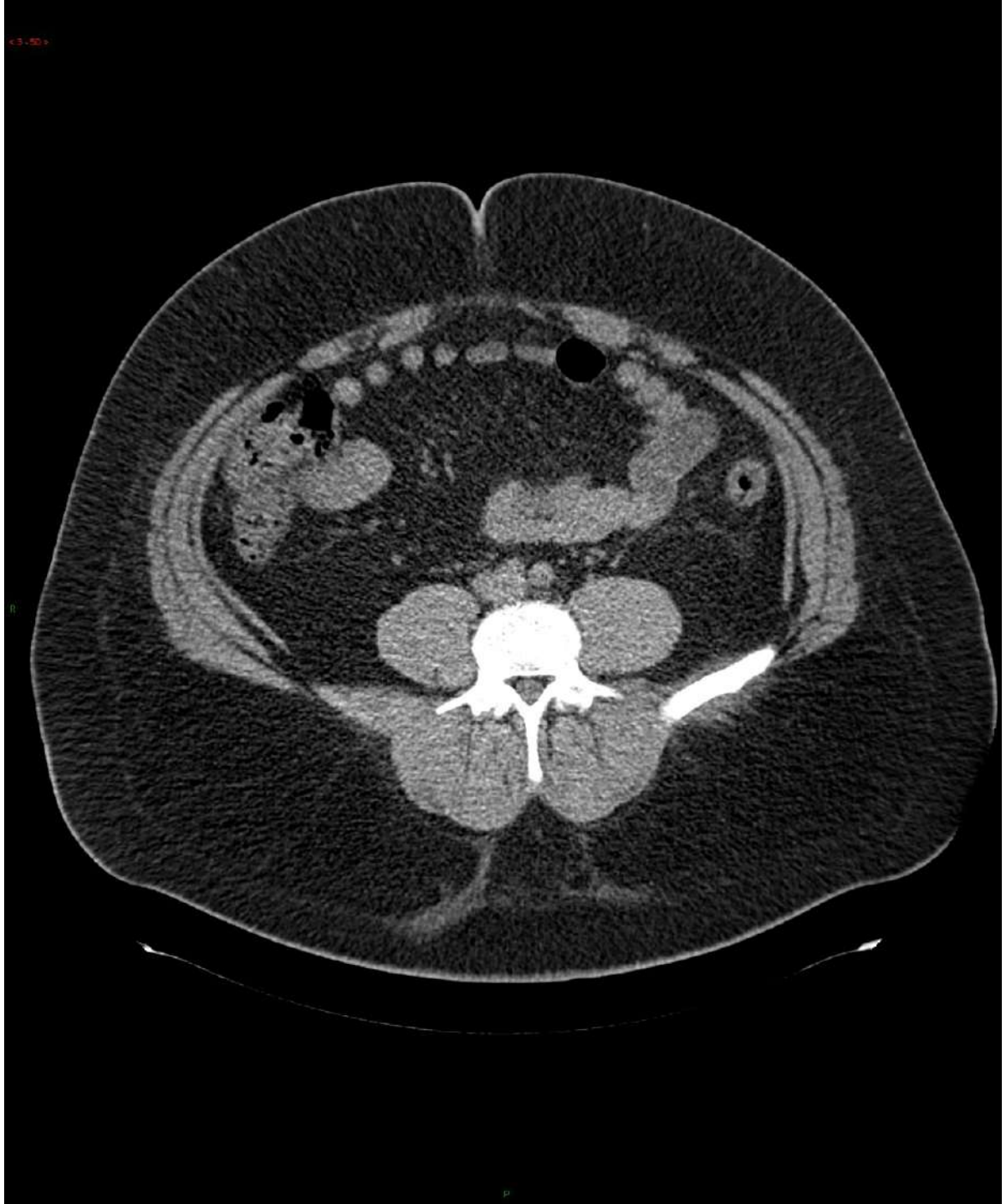
3D data



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3D data

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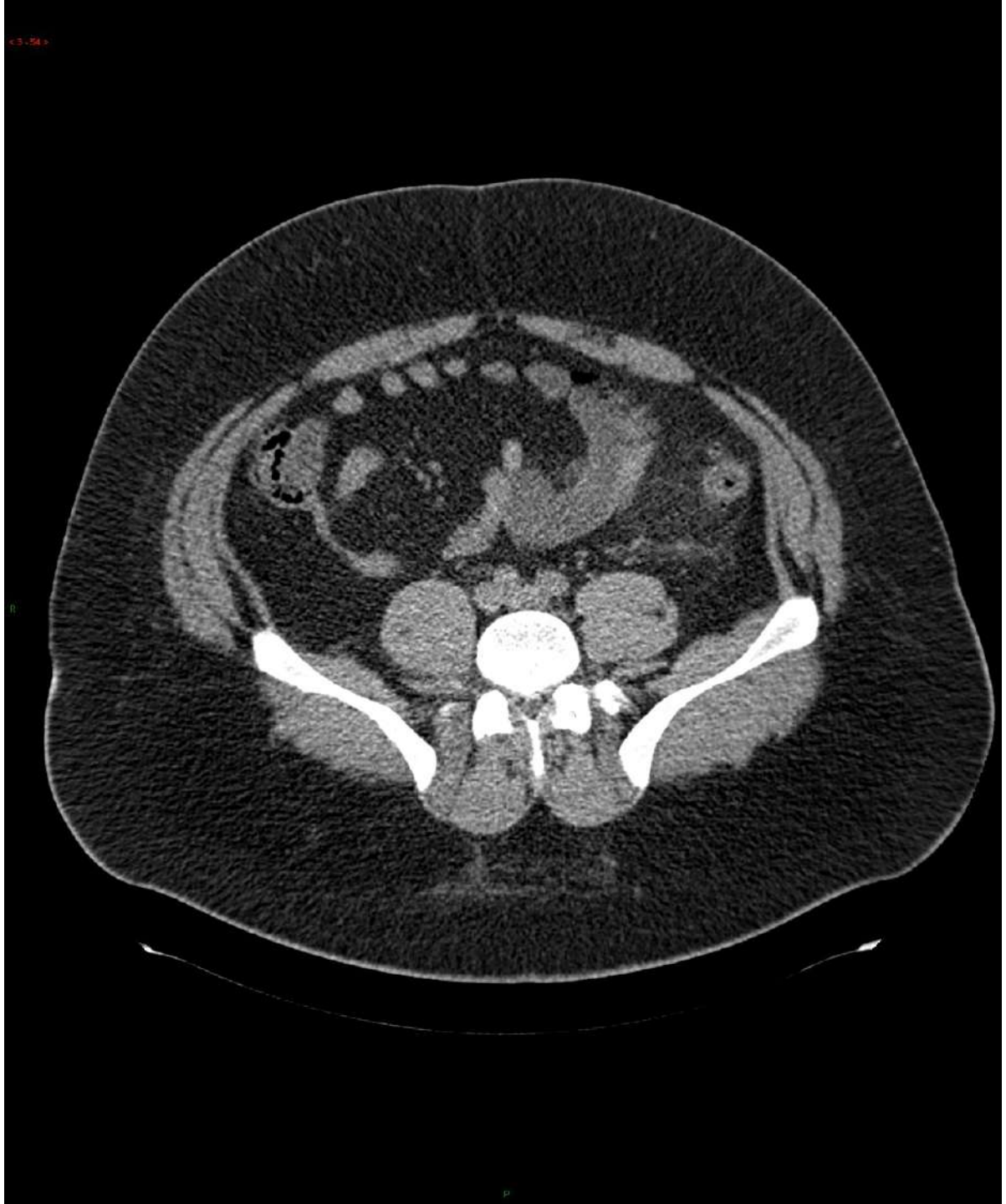
3D data



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3D data

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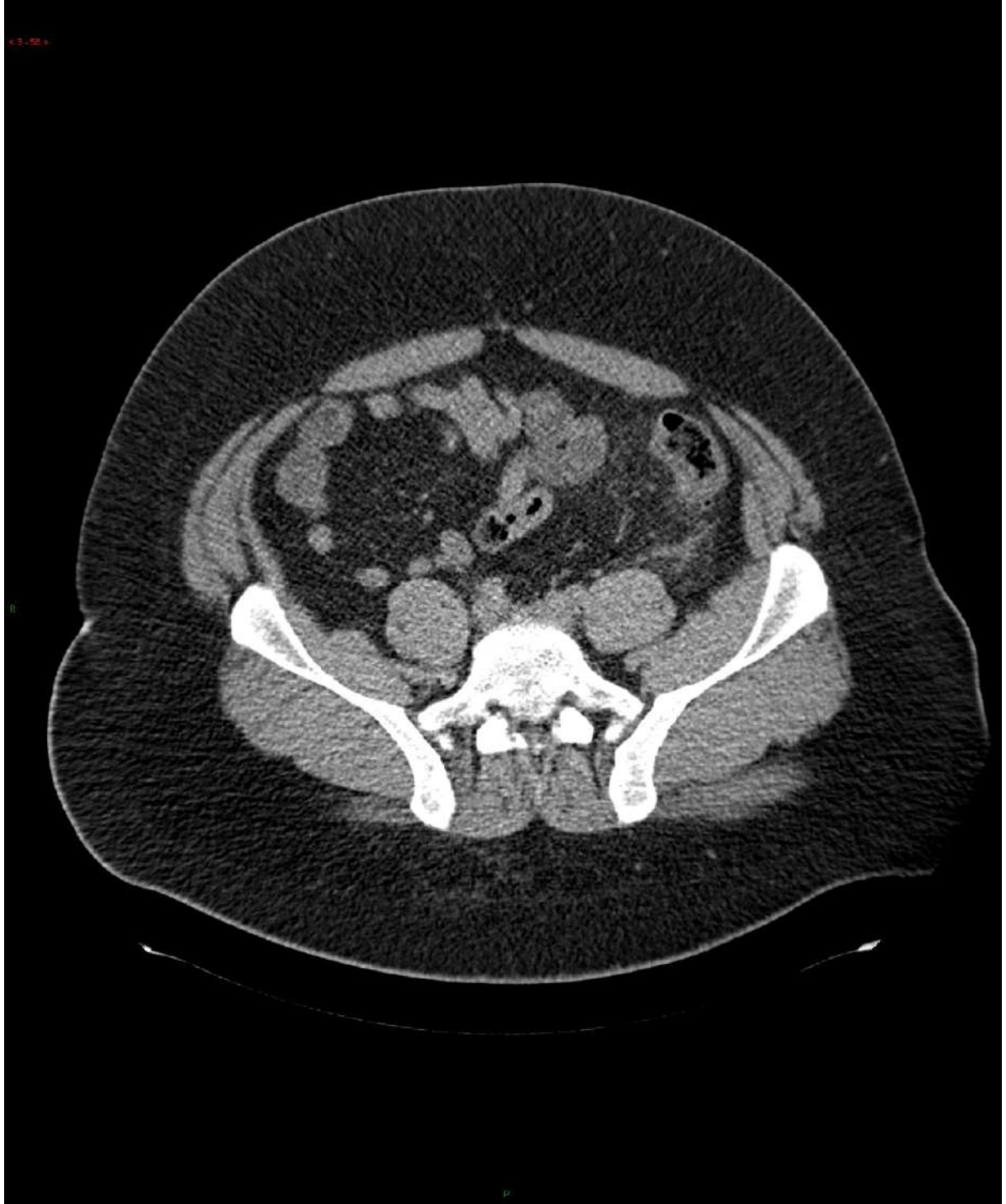
3D data



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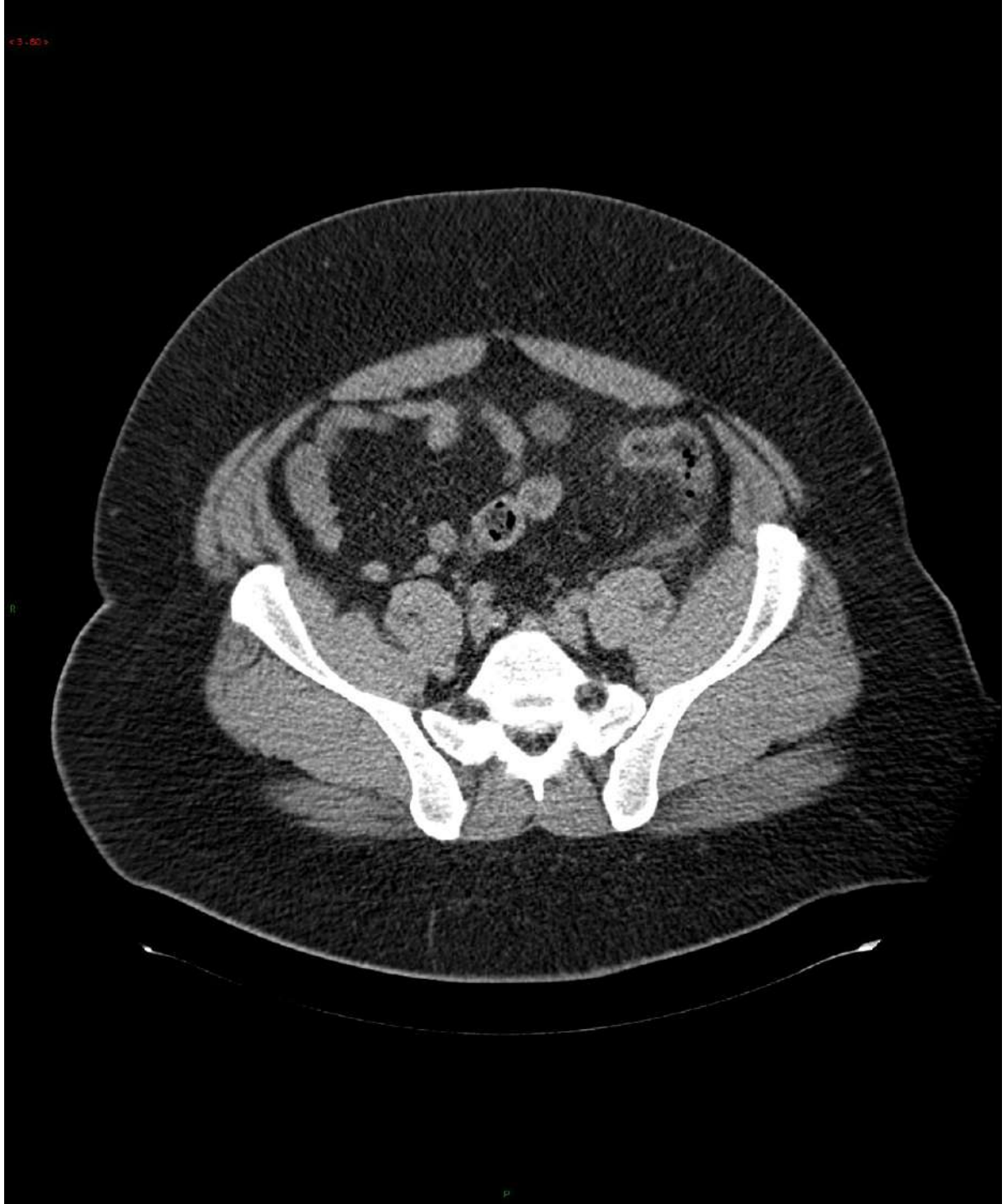
3D data



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3D data

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3D data

Andrew Ng

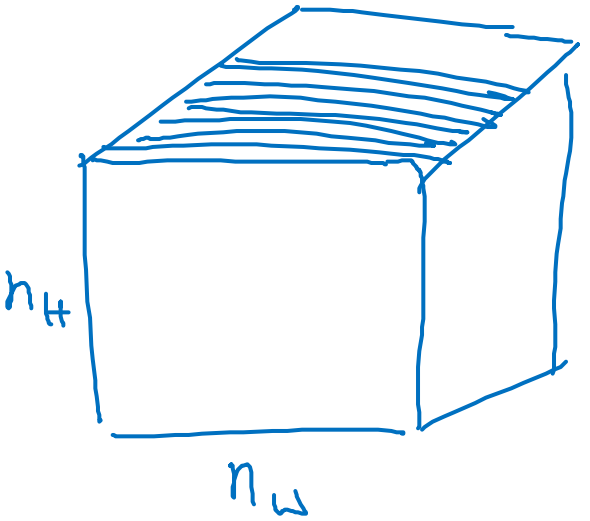
3D data

Andrew Ng

3D data

Andrew Ng

3D data



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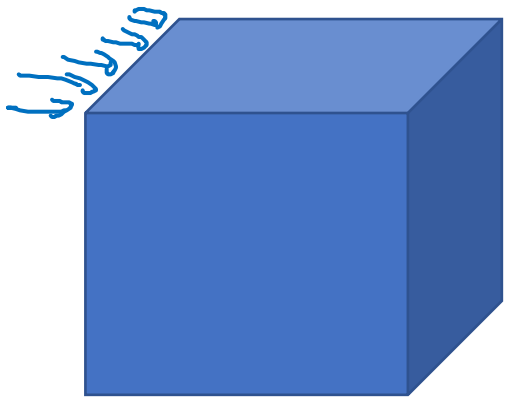
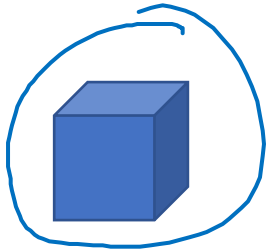
3D convolution



3D volume

*



3D filter

n_c

$14 \times 14 \times 14 \times 1$

$* \quad 5 \times 5 \times 5 \times 1$

16 filters.

$\rightarrow 10 \times 10 \times 10 \times 16$

$* \; 5 \times 5 \times 5 \times 16$

32 filters

$\rightarrow \quad 6 \times 6 \times 6 \times 32$