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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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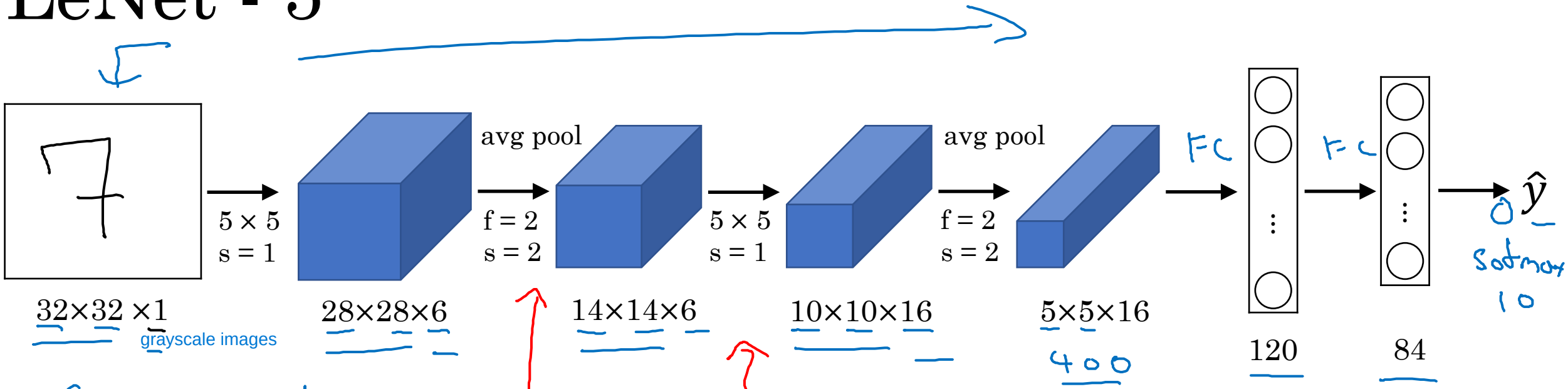
Case Studies

Classic networks

LeNet - 5



60k parameters.

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

Non-linearity after pooling

$n_{H} \times n_{w} \times n_c$ $f \times f \times n_c$

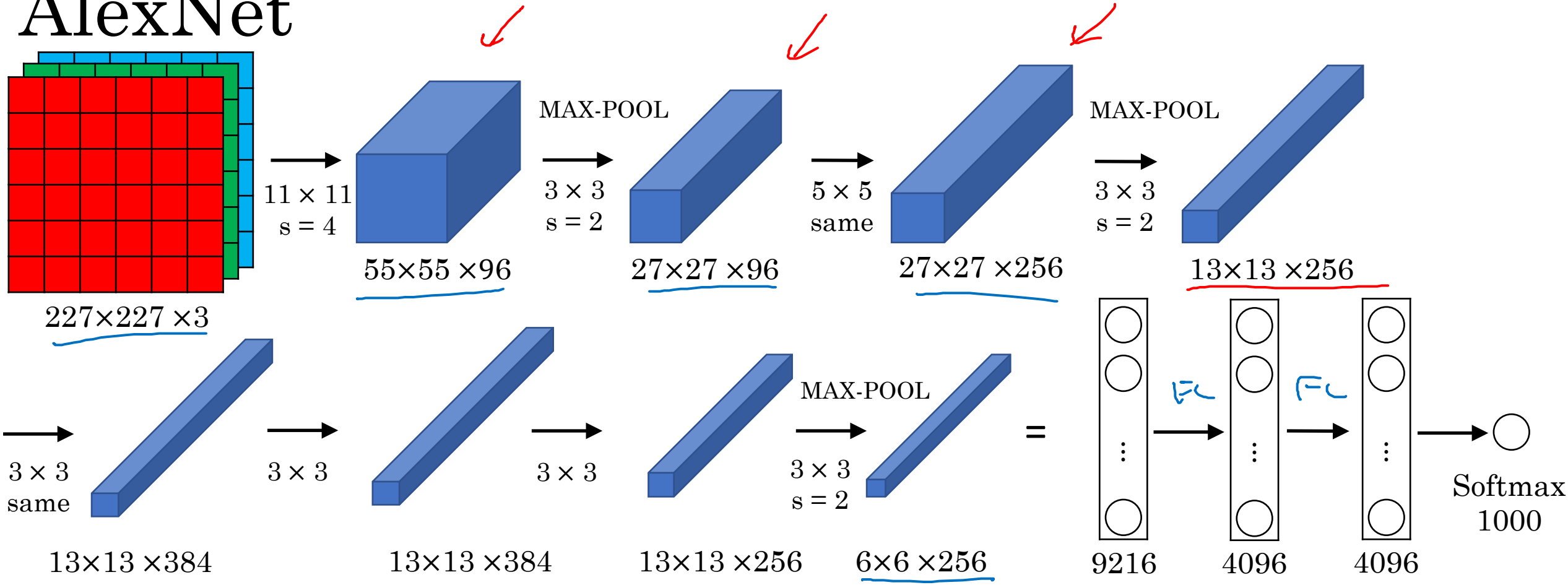
conv pool conv pool fc fc output

Activation: sigmoid/tanh ReLU

II III

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

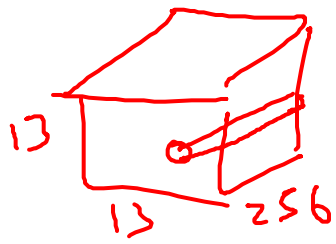
AlexNet



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

9216

60M parameters



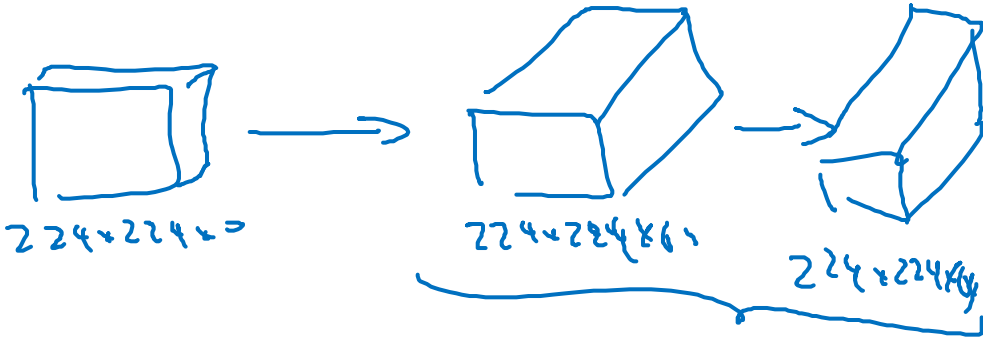
[Krizhevsky et al., 2012. ImageNet classification with deep convolutional neural networks]

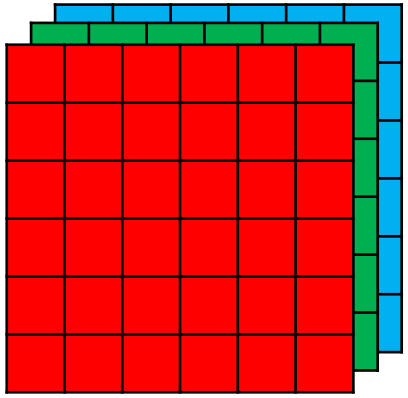
VGG - 16

16 layers that has weight

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

a lot of hyperparameter

VGG-19 -> bigger but work similar with VGG-16

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

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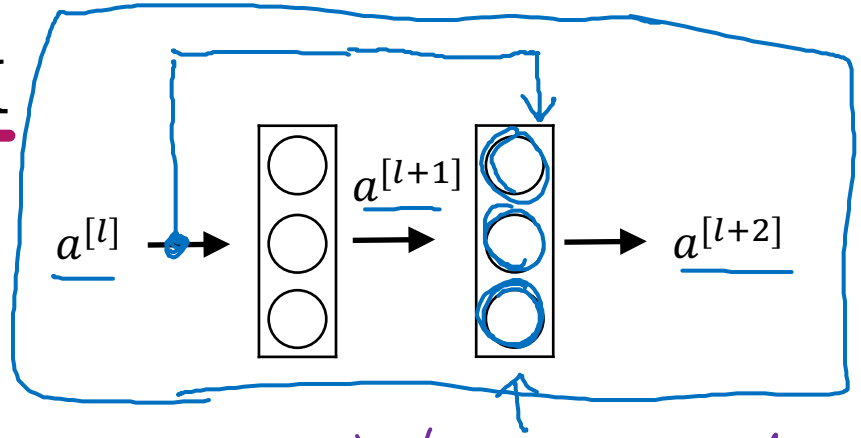
Case Studies

Residual Networks (ResNets)

Residual block



residual blocks take shortcut instead of main path

"short cut" / skip connection

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

"main pain"

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

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

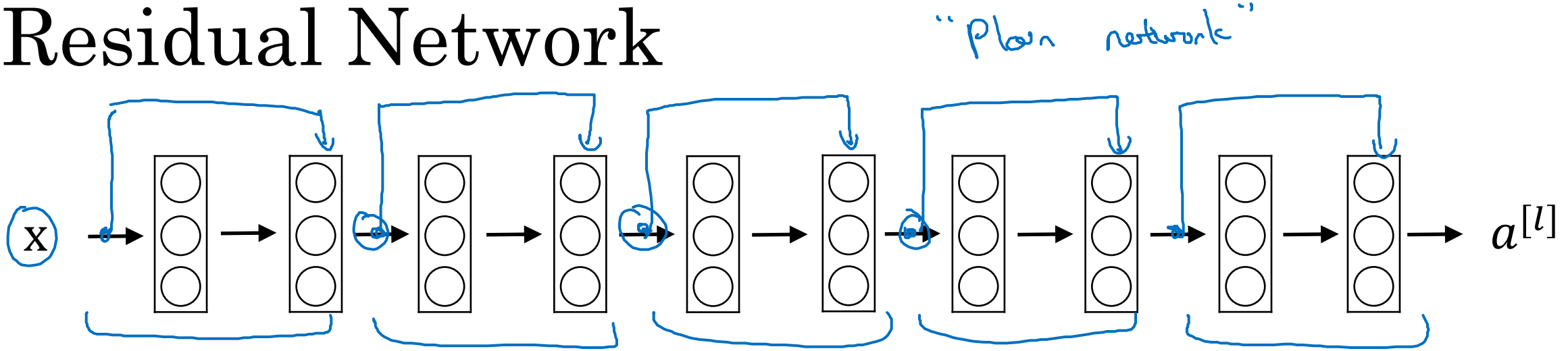
$$z^{[l+2]} = W^{[l+2]} a^{[l+1]} + b^{[l+2]}$$

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

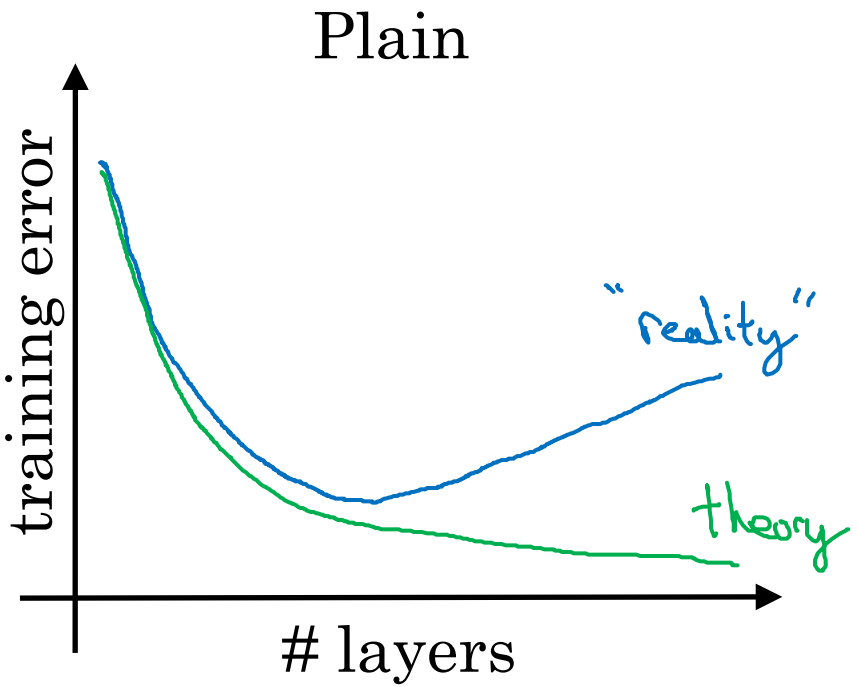
$$a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$$

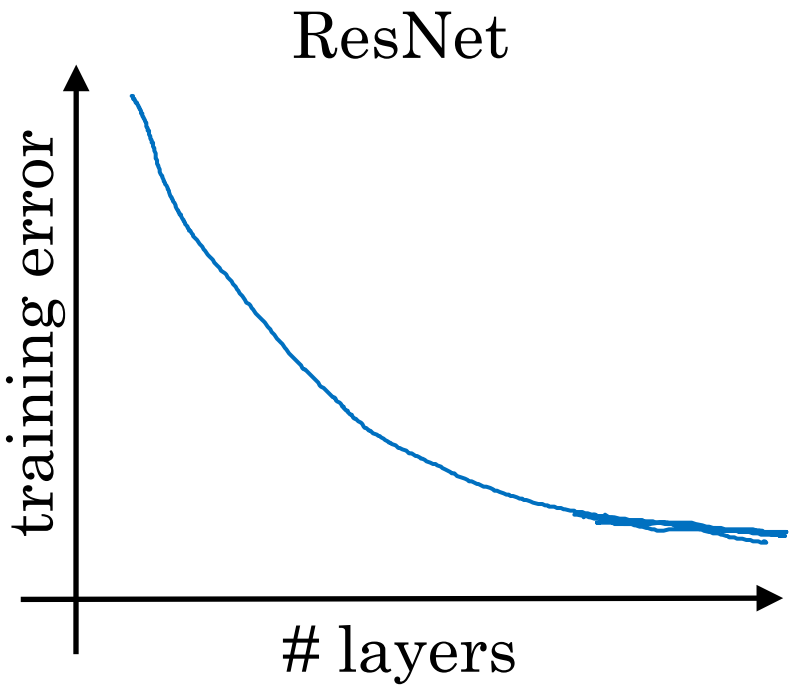
[He et al., 2015. Deep residual networks for image recognition]

Residual Network



5 residual block here





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

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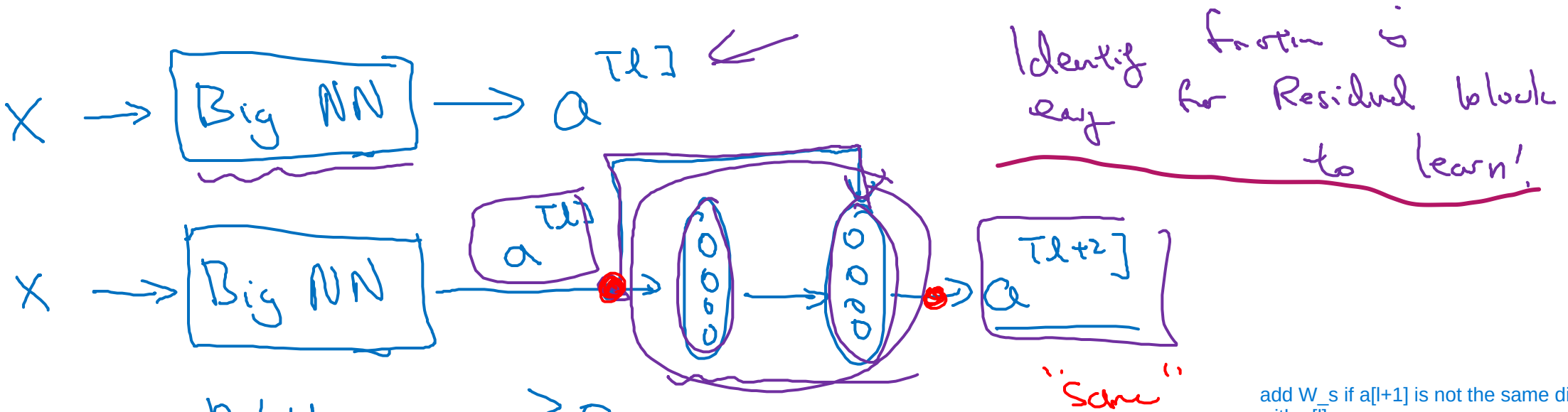
Case Studies

Why ResNets work

Why do residual networks work?



add W_s if a[l+1] is not the same dim with a[l]

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

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

256

If $W^{[l+2]} = 0$, $b^{[l+2]} = 0$

$$= g(W_s a^{[l]}) \quad (W_s \in \mathbb{R}^{256 \times 128})$$

128

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

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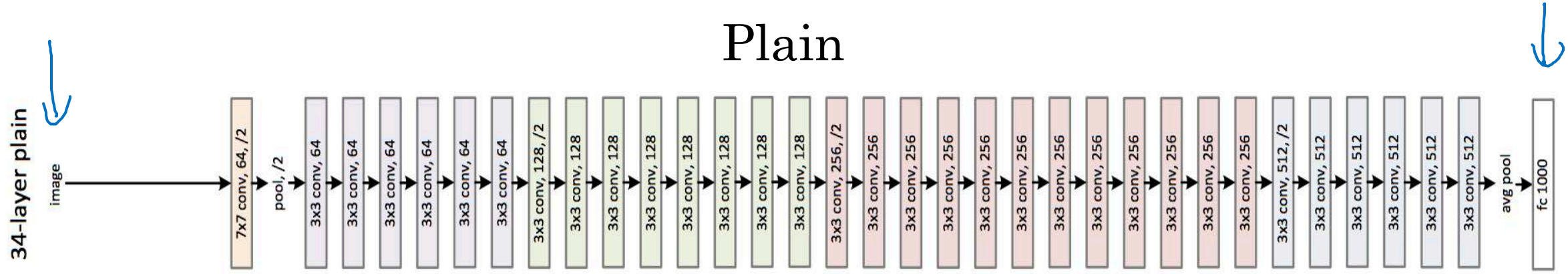
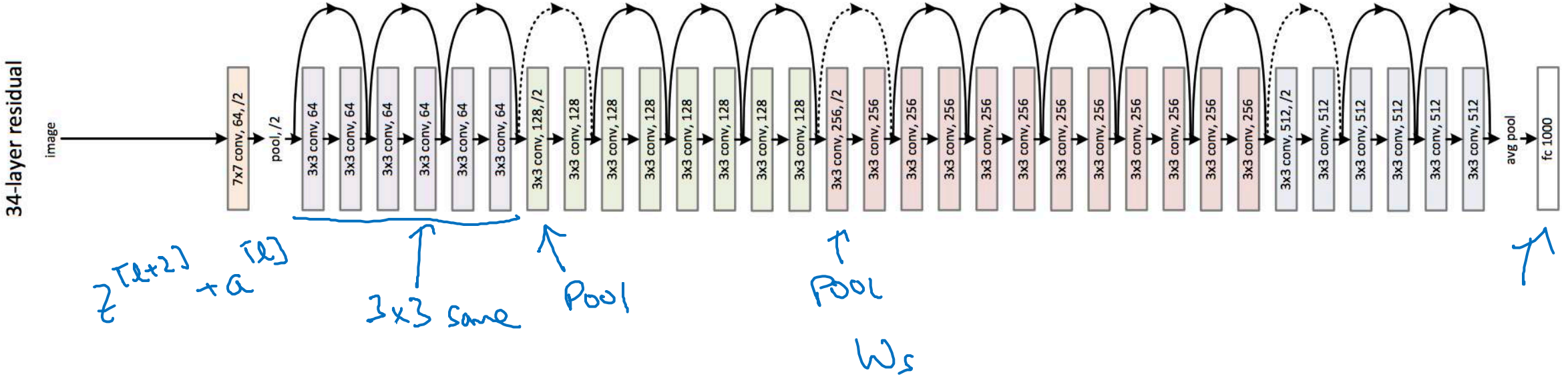
ResNet

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

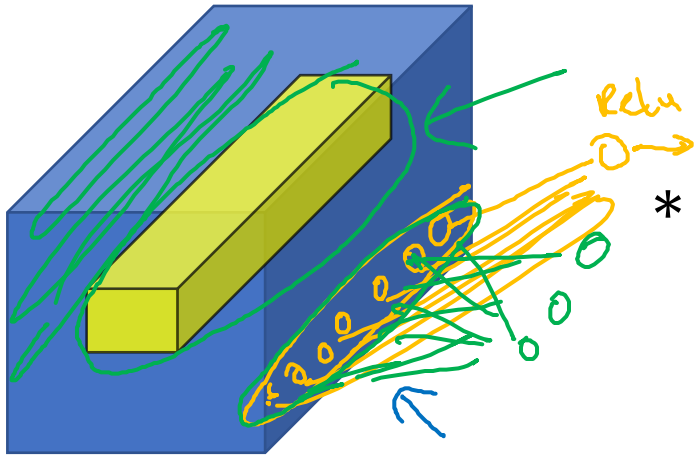
6 × 6 × 1

* 2 =

2	4	6	...		

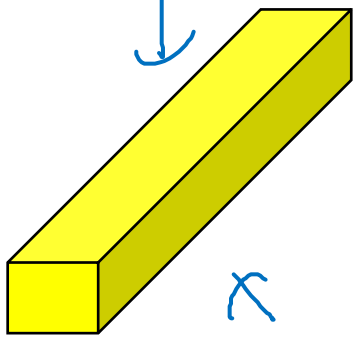
like for each "bar"
input 32 value -> output 1 value

32 → # filters. $n_c^{[l+1]}$



6 × 6 × 32

*

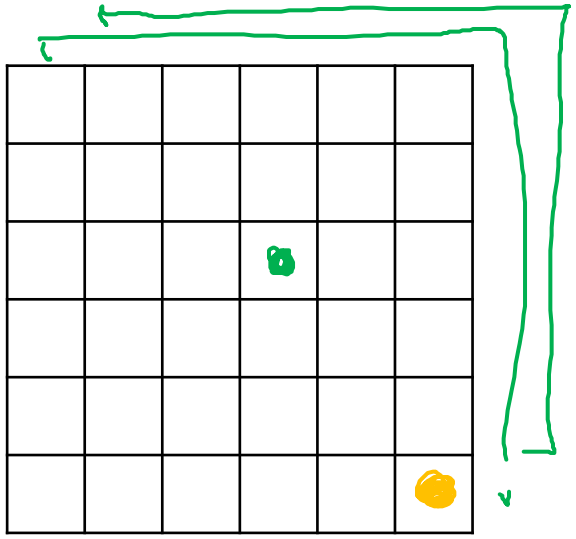


1 × 1 × 32

=

ReLU

Network in Network



6 × 6 × # filters

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

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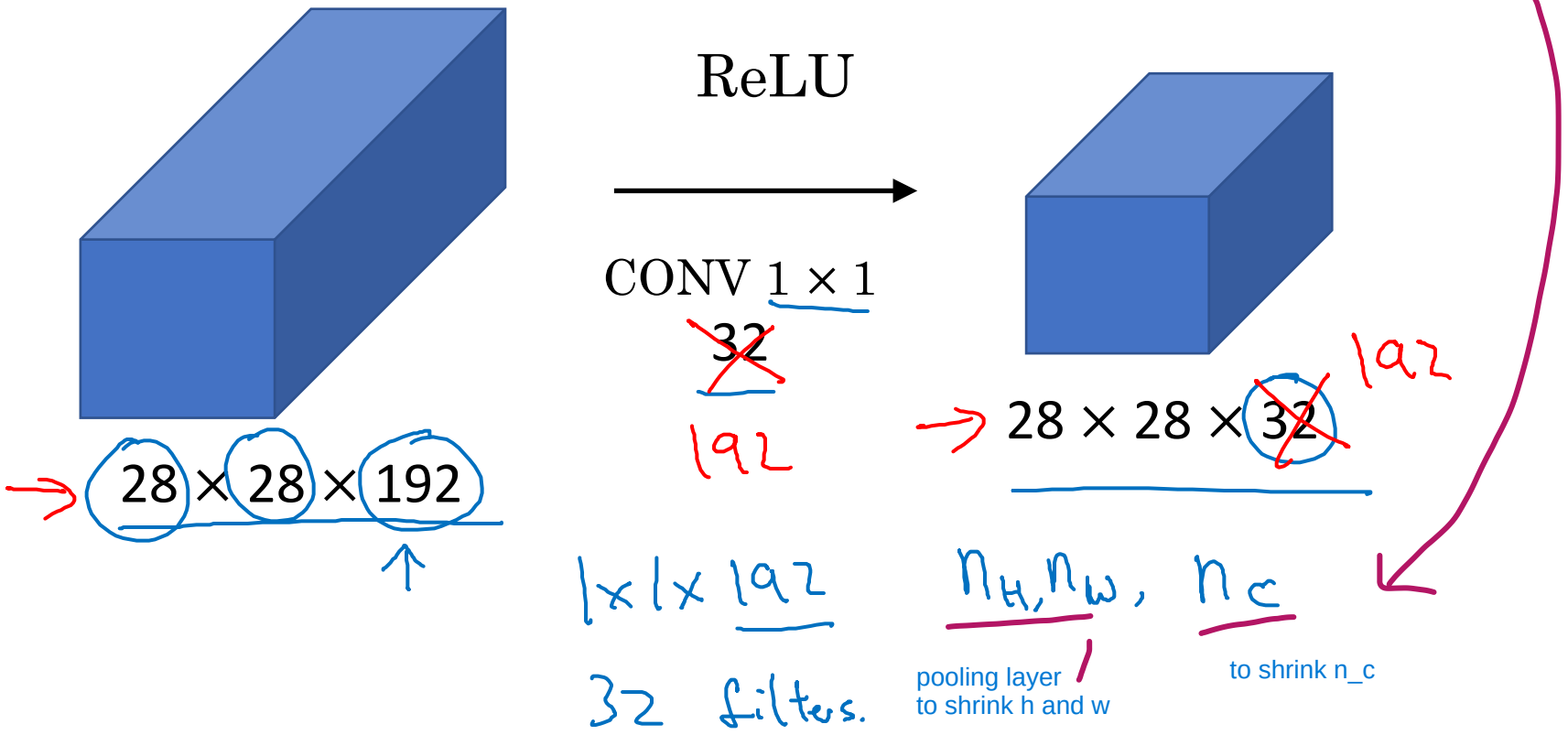
Using 1×1 convolutions



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

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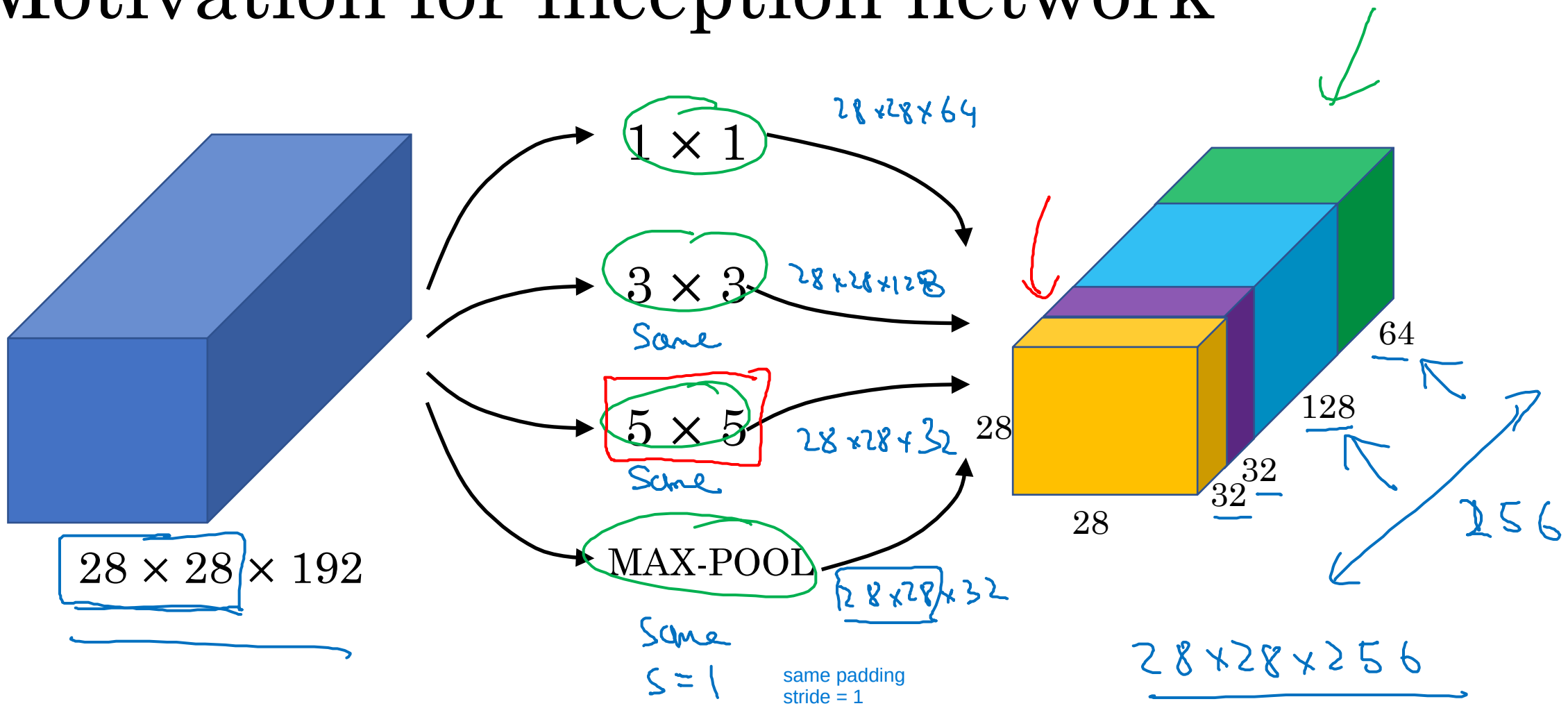
Case Studies

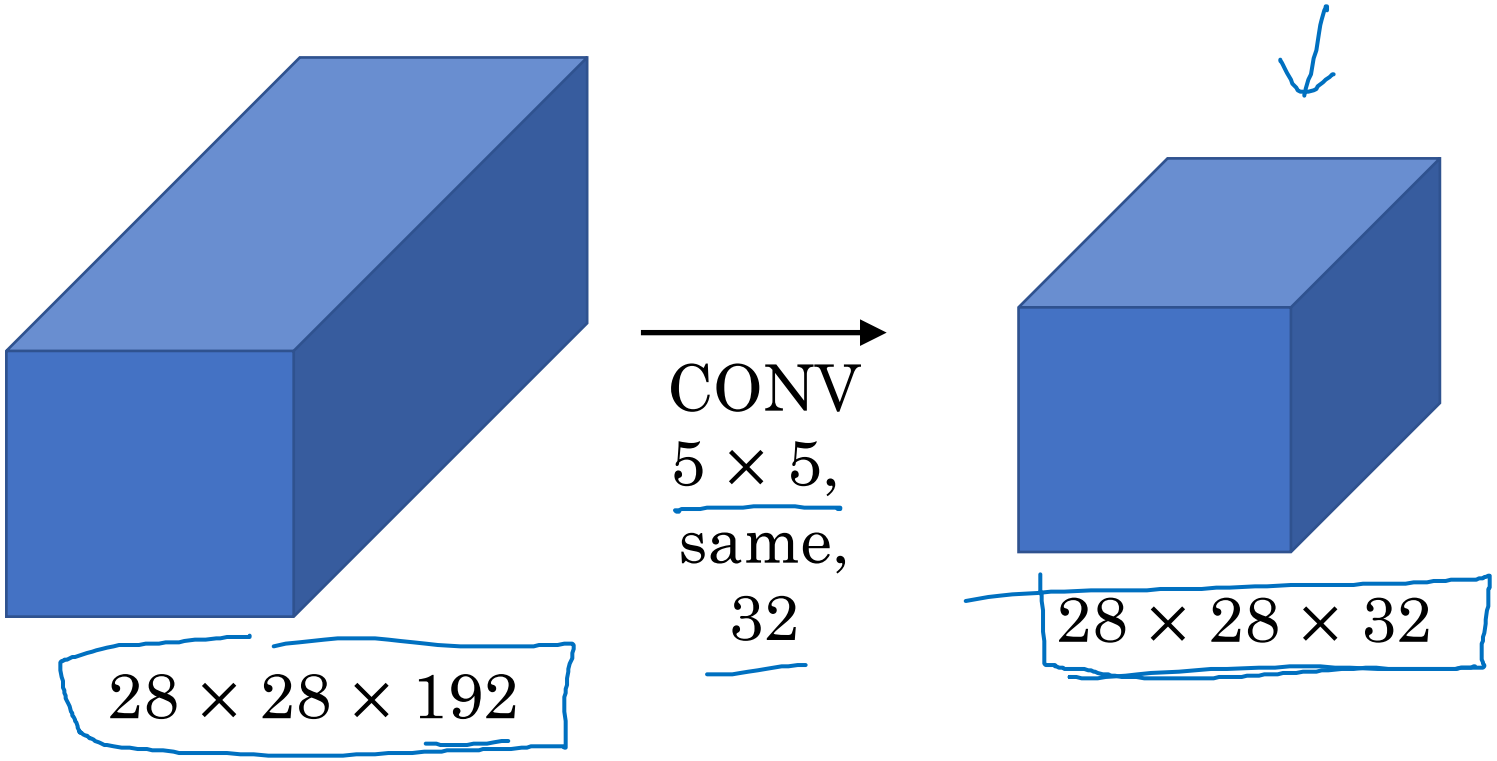
Inception network motivation

Motivation for inception network



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

The problem of computational cost

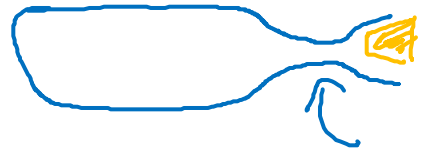


32 filters. filter one 5×5×192.

28×28×32 × 5×5×192 = 120M.

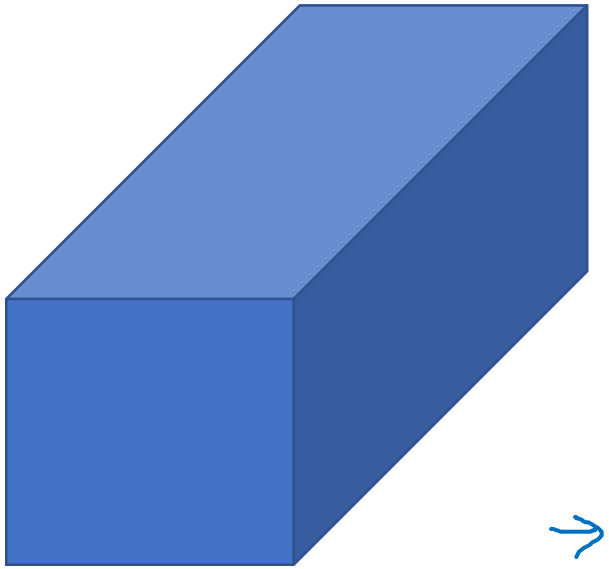
huge, costly

Using 1×1 convolution



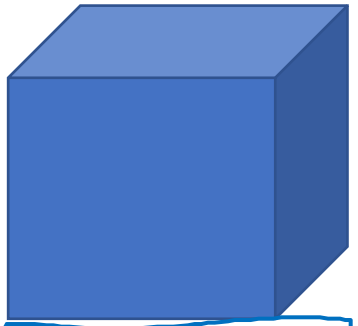
"bottleneck layer"

smaller intermediate layer
bottleneck layer



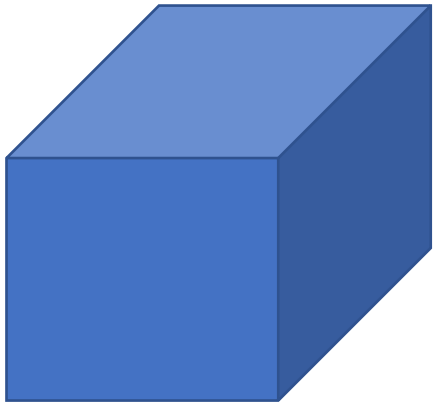
28 × 28 × 192

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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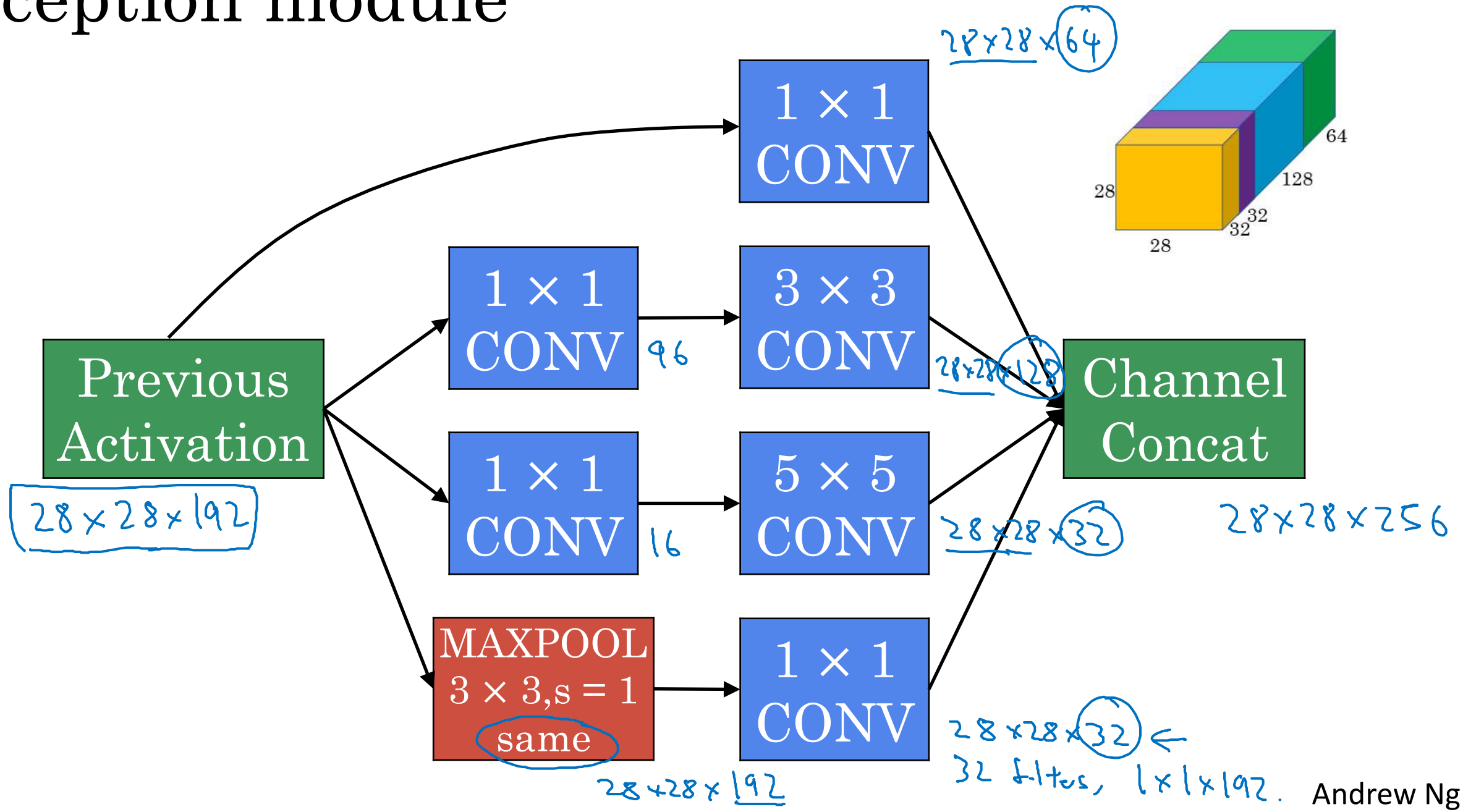
Case Studies

Inception network

Inception module



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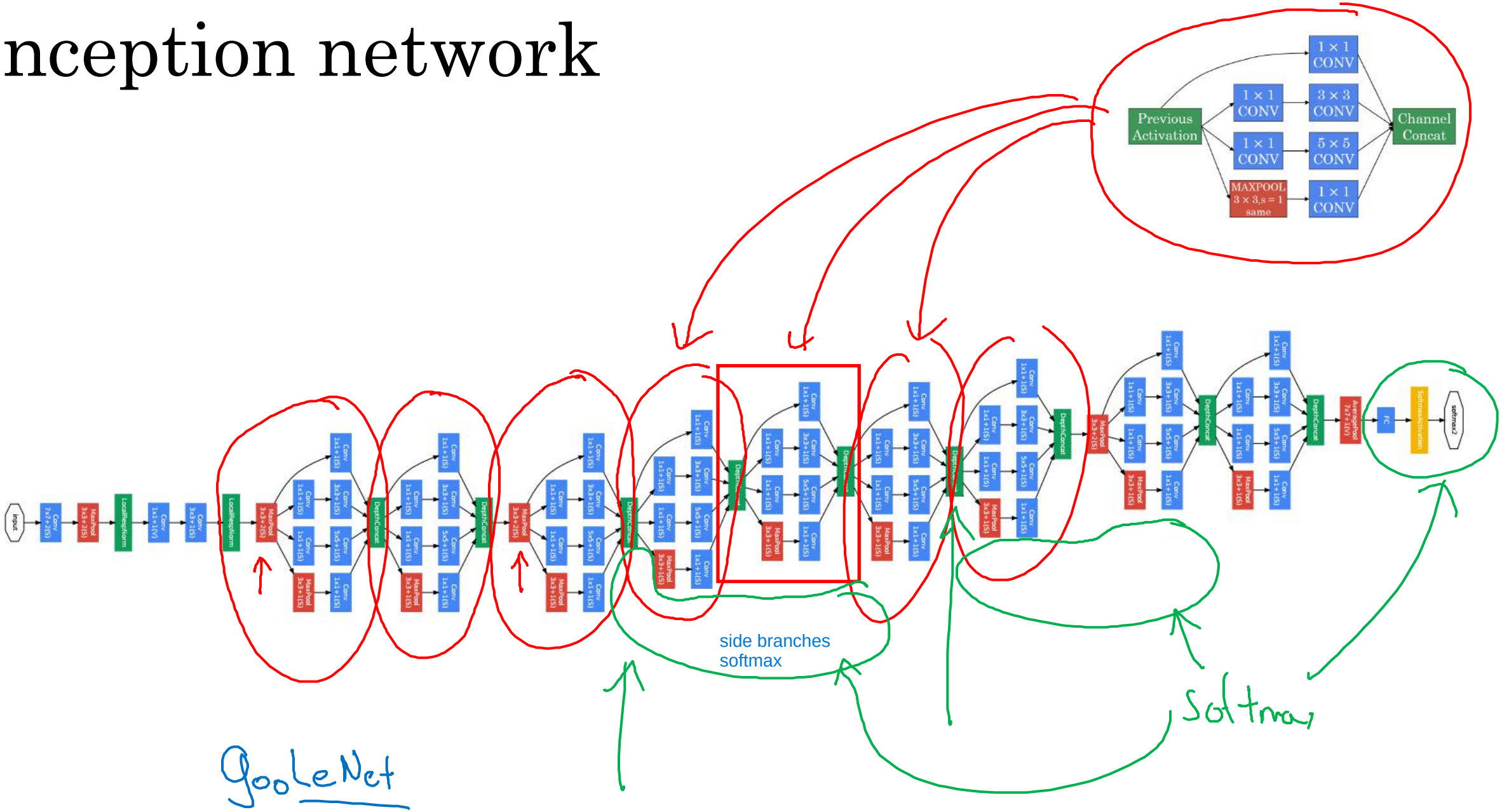
Inception network



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

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

Convolutional Neural Networks

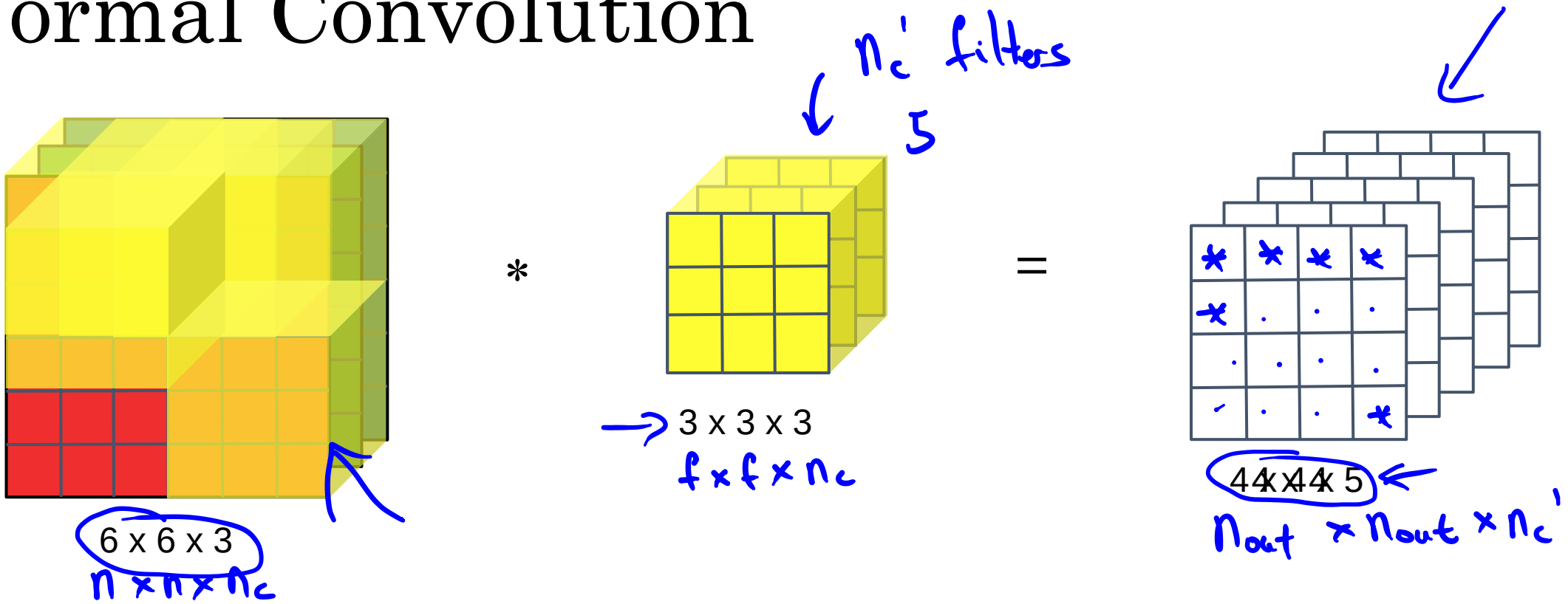
MobileNet

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

num of multiplication needed

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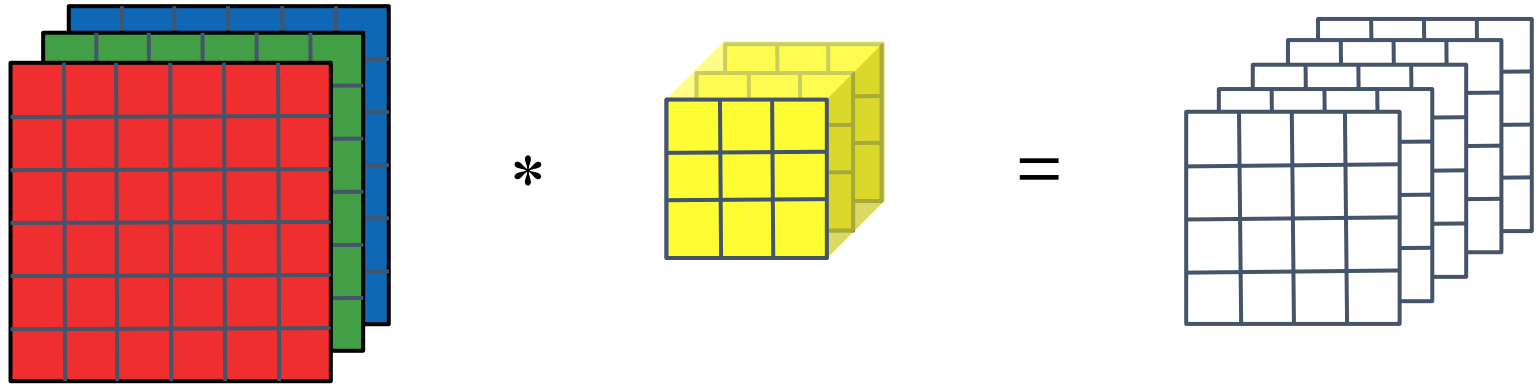
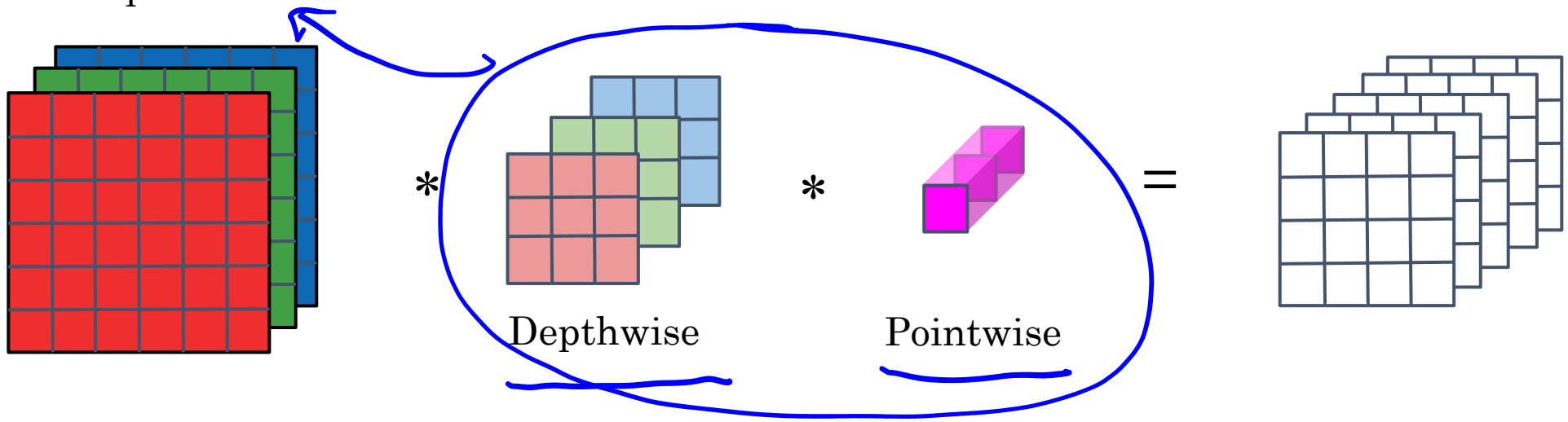
Depthwise Separable Convolution

Normal Convolution



Depthwise Separable Convolution



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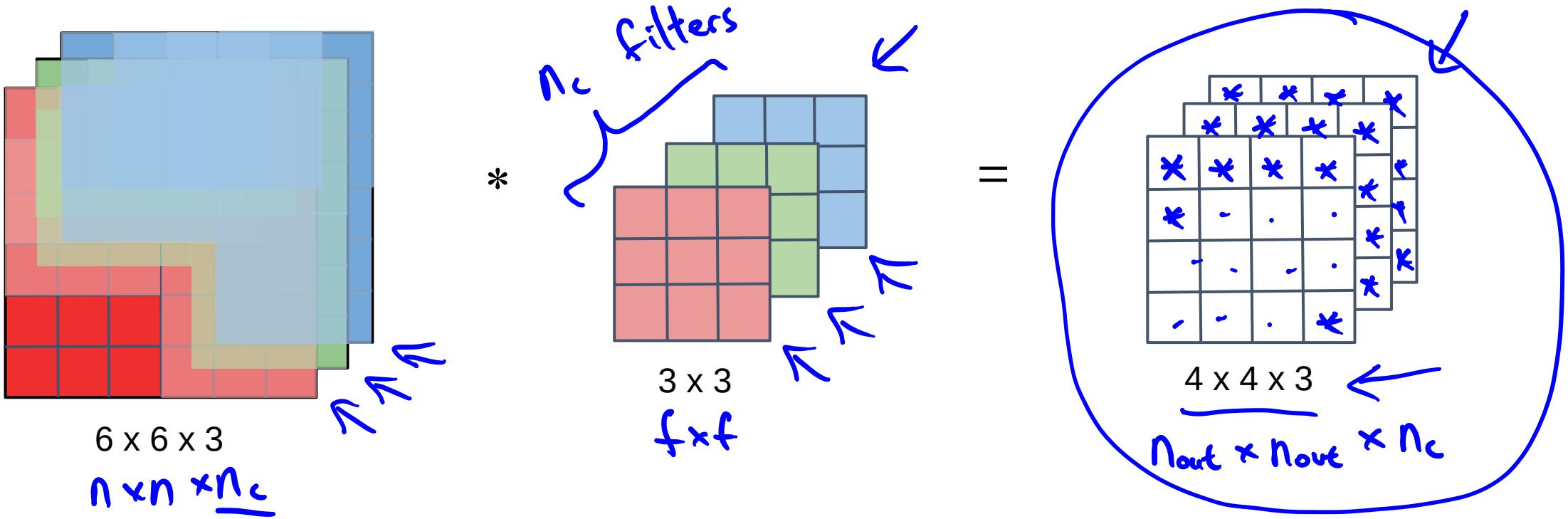
Depthwise Convolution



Computational cost	=	#filter params	x	# filter positions	x	# of filters
432	=	3x3	x	4x4	x	3

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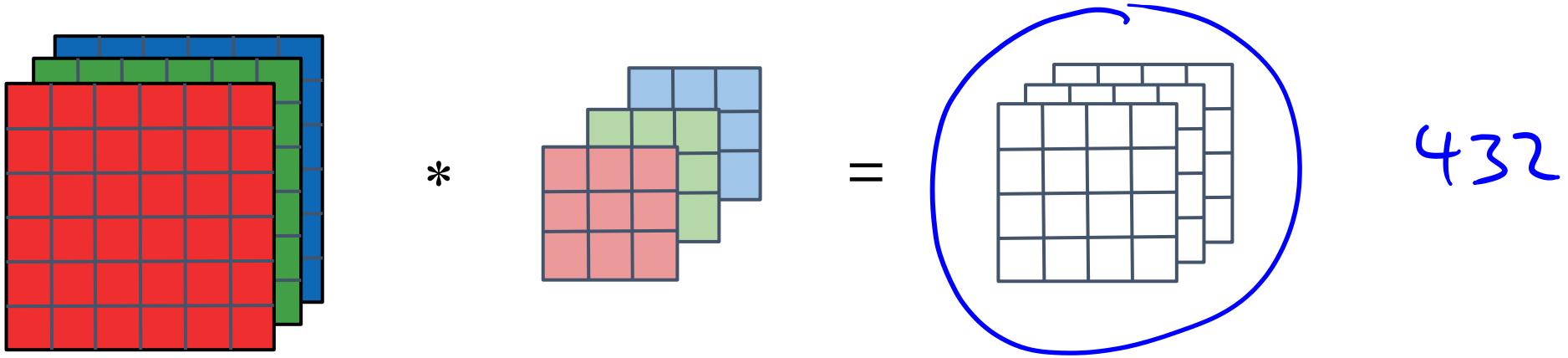
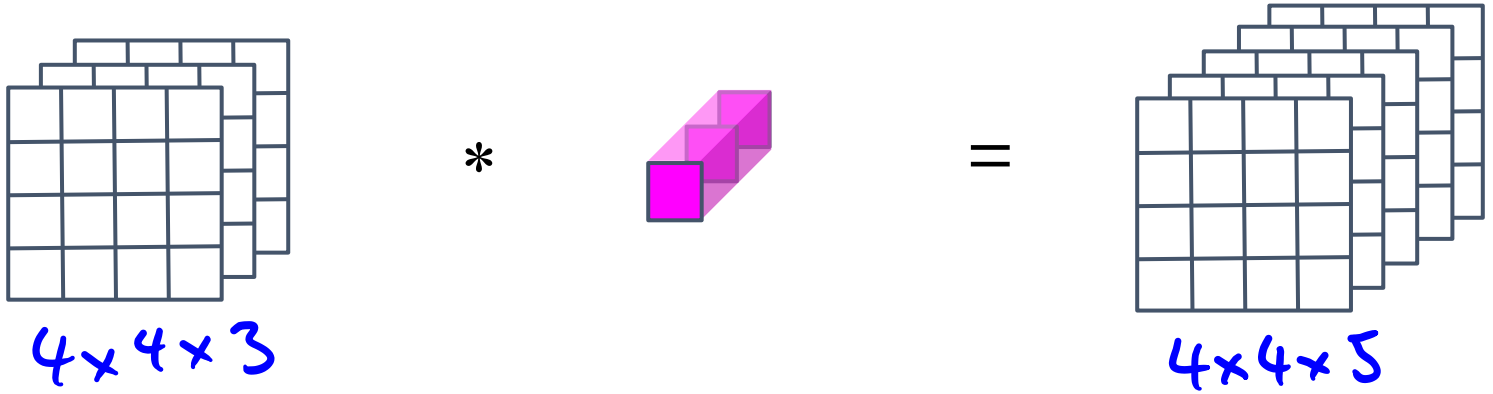
Depthwise Separable Convolution

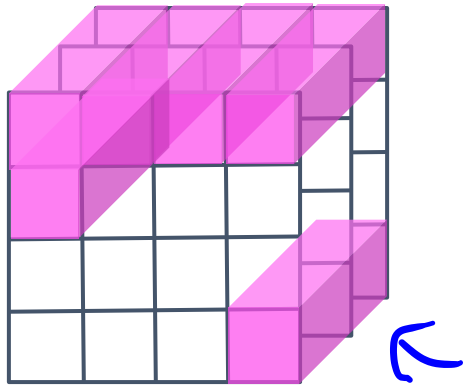
Depthwise Convolution



Pointwise Convolution



Pointwise Convolution



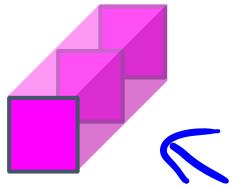
4 x 4 x 3

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

*

n_c' filters

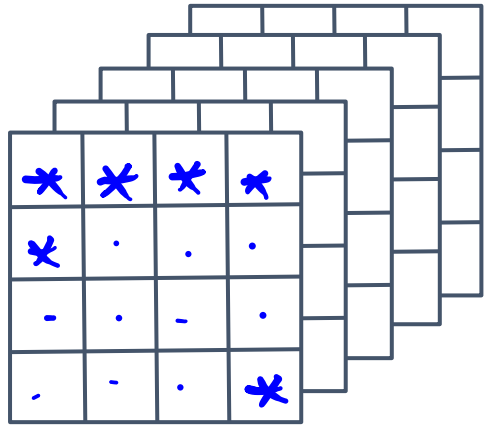
5



1 x 1 x 3

$1 \times 1 \times n_c$

=



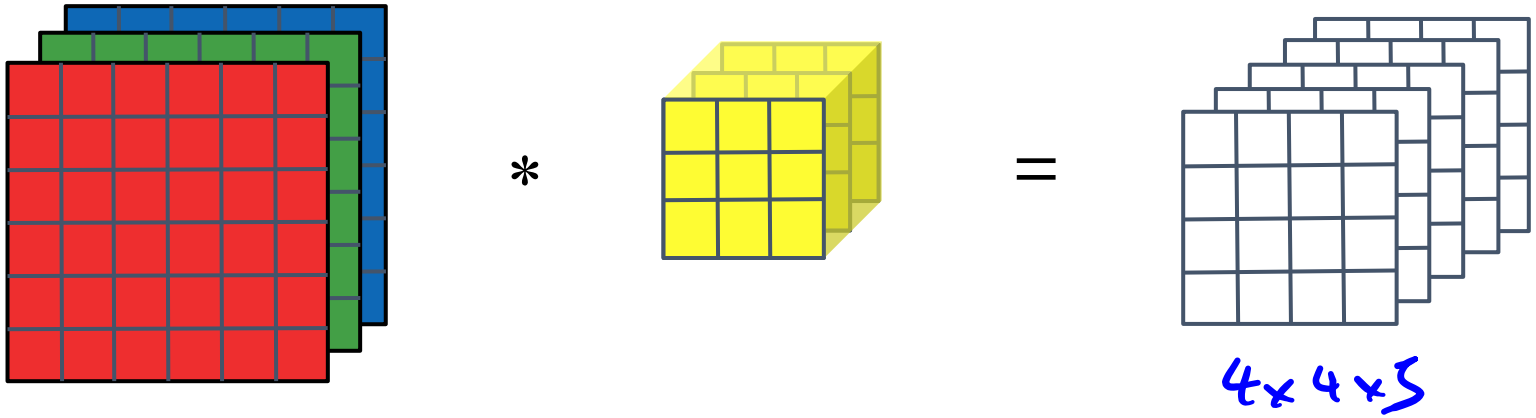
4 x 4 x 5

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

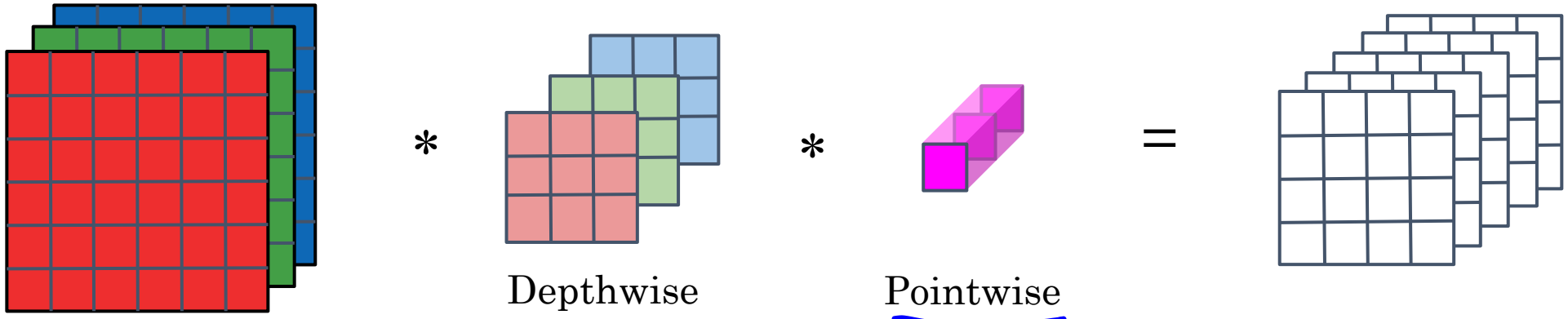
Computational cost	=	#filter params	x	# filter positions	x	# of filters
240	=	$1 \times 1 \times 3$	x	4×4	x	5

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

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

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

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

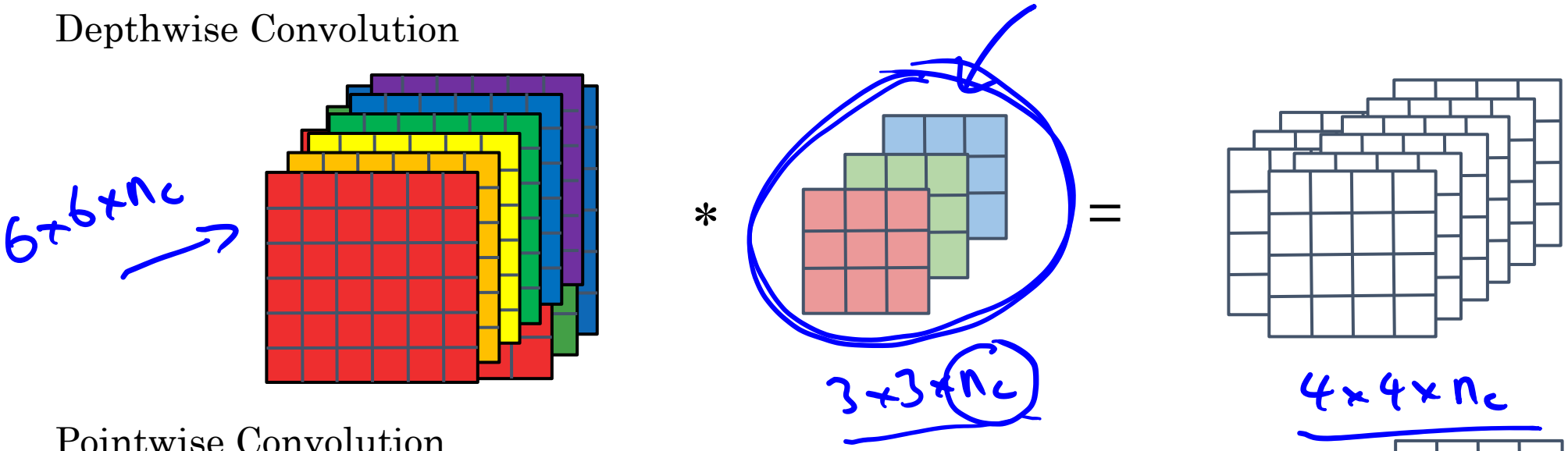
$$= \frac{1}{512} + \frac{1}{3^2}$$

$\sim$10 times cheaper

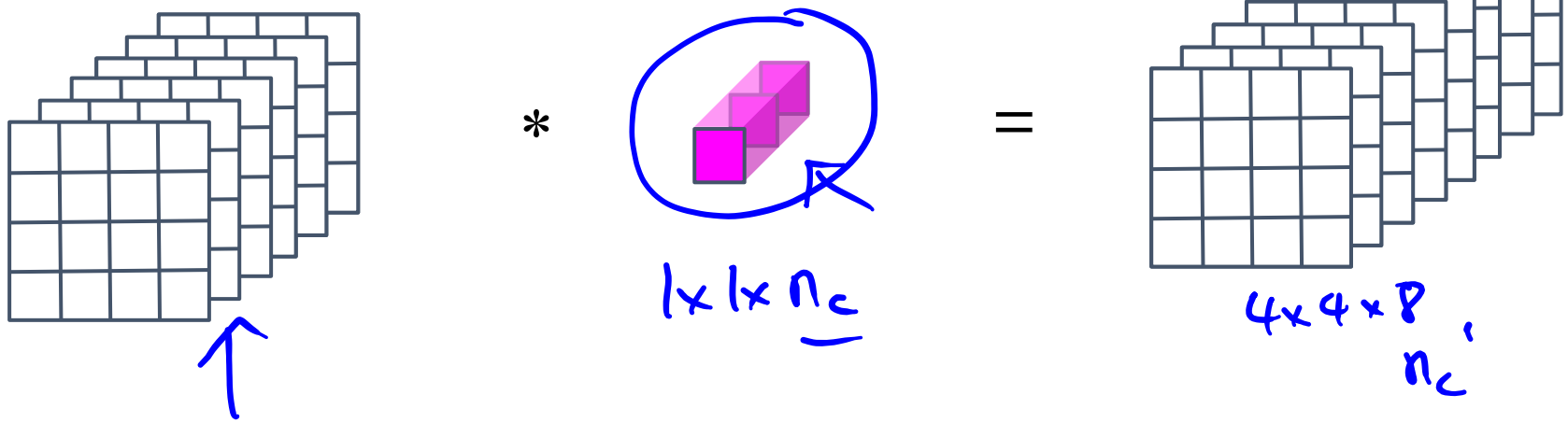
[Howard et al. 2017, MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications]

Depthwise Separable Convolution

Depthwise Convolution



Pointwise Convolution



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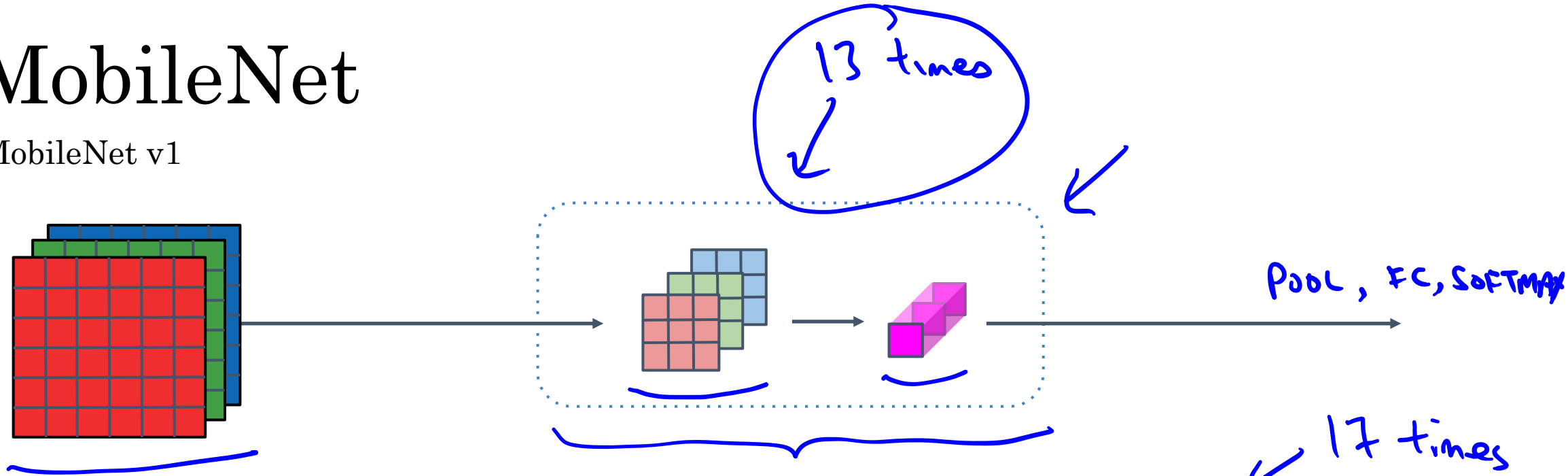
Convolutional Neural Networks

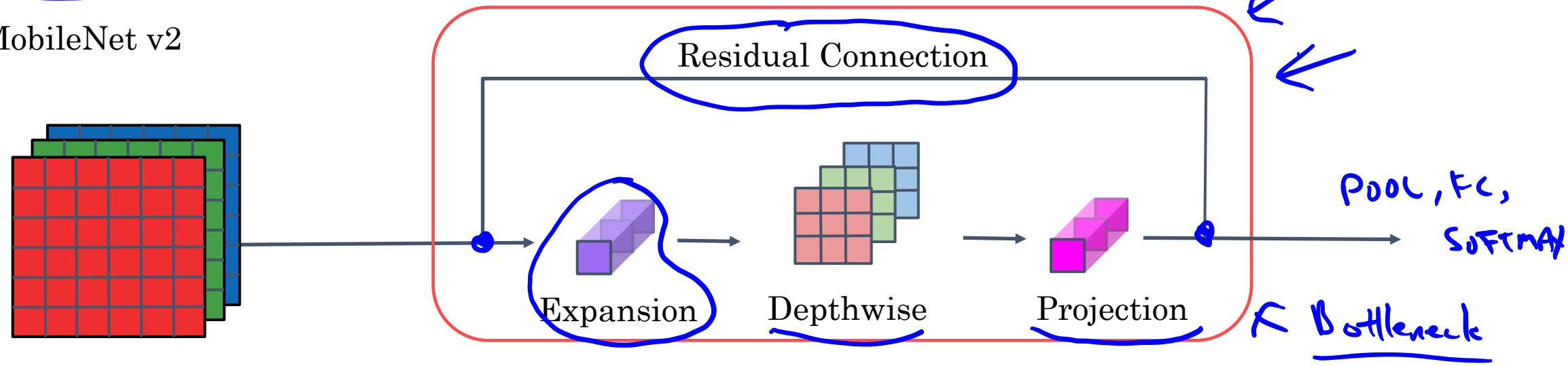
MobileNet Architecture

MobileNet

MobileNet v1

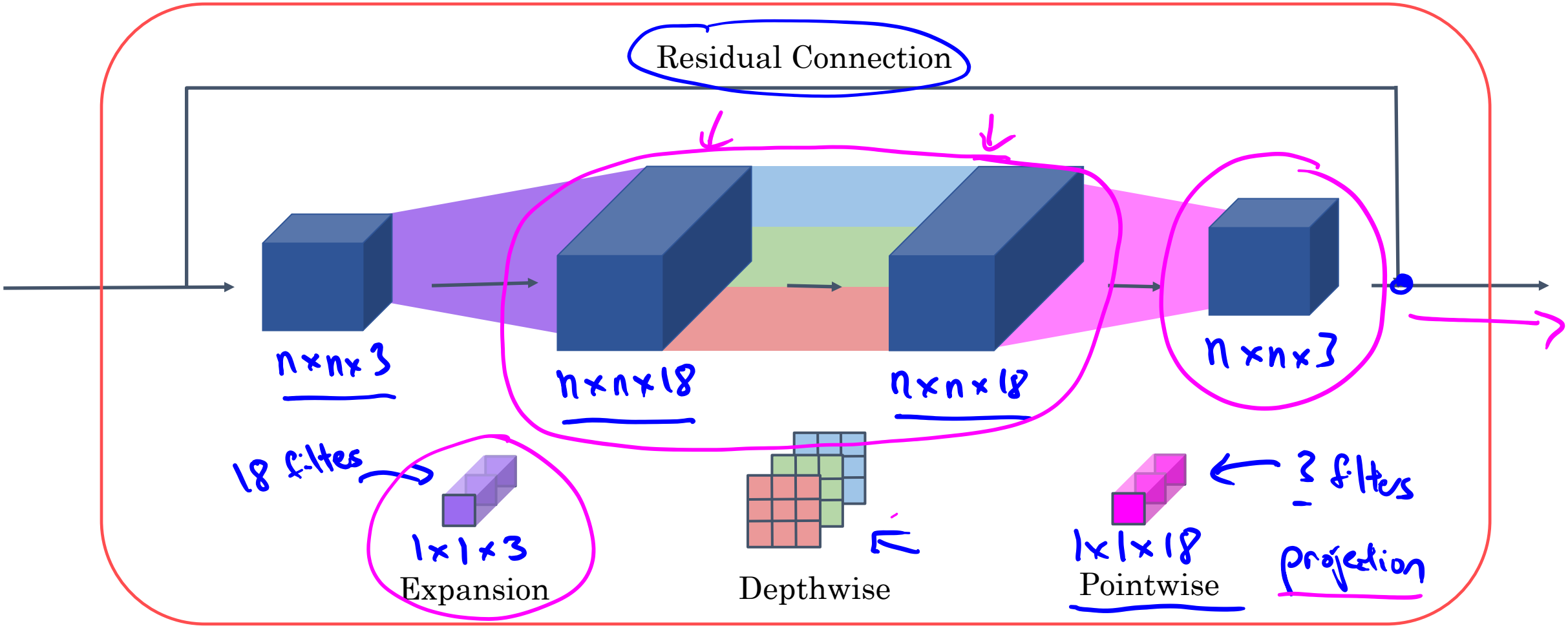


MobileNet v2



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

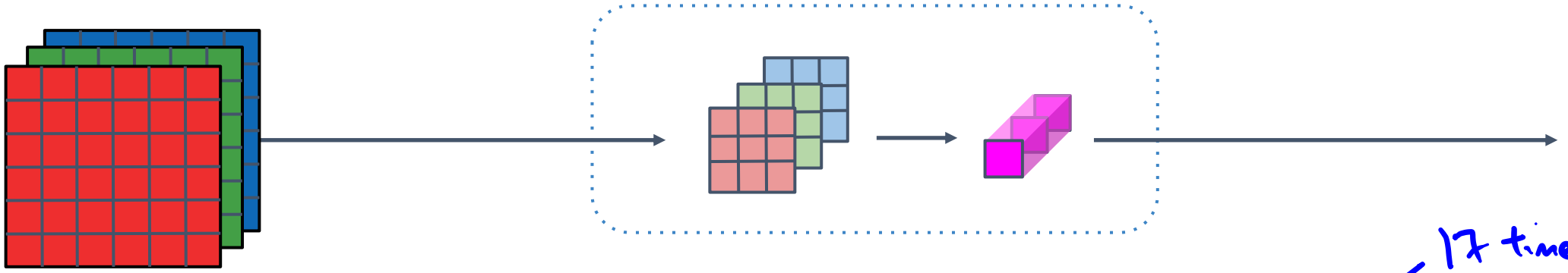
MobileNet v2 Bottleneck



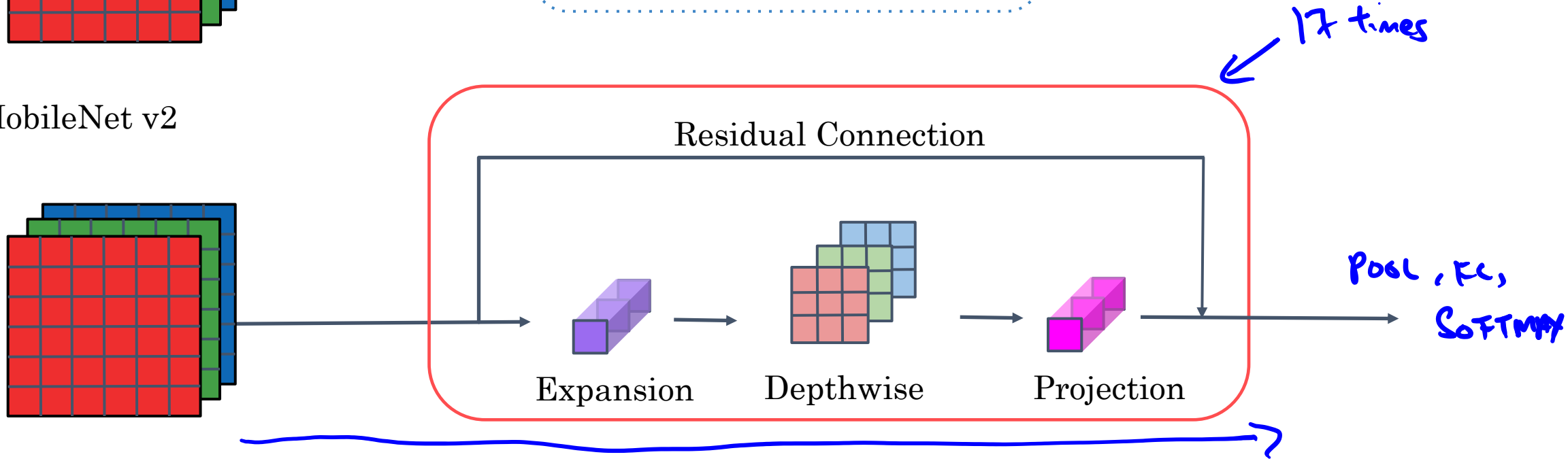
[Sandler et al. 2019, MobileNetV2: Inverted Residuals and Linear Bottlenecks]

MobileNet

MobileNet v1

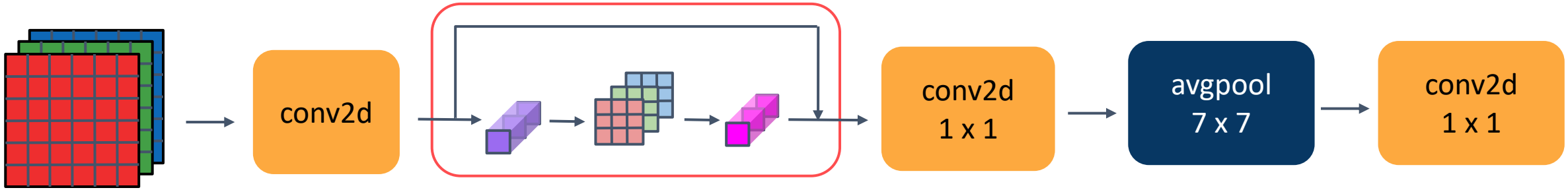


MobileNet v2



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

MobileNet v2 Full Architecture



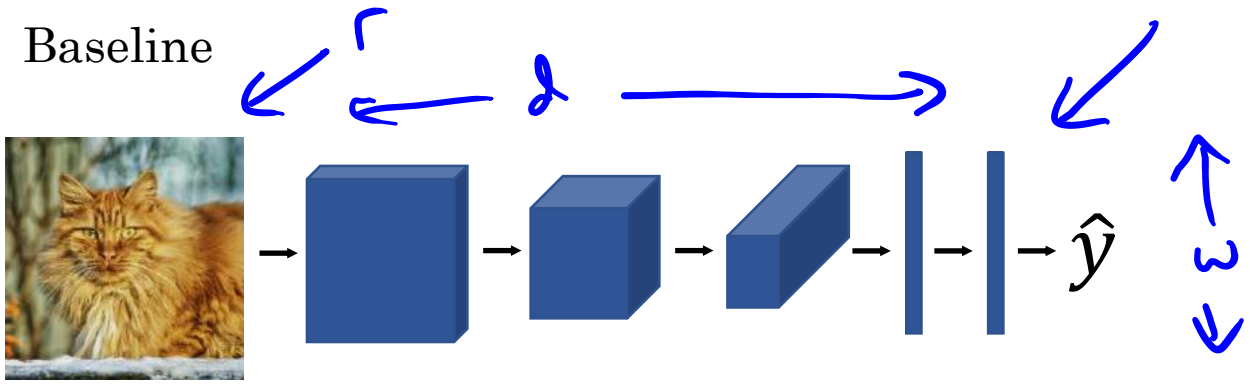
[Sandler et al. 2019, MobileNetV2: Inverted Residuals and Linear Bottlenecks]

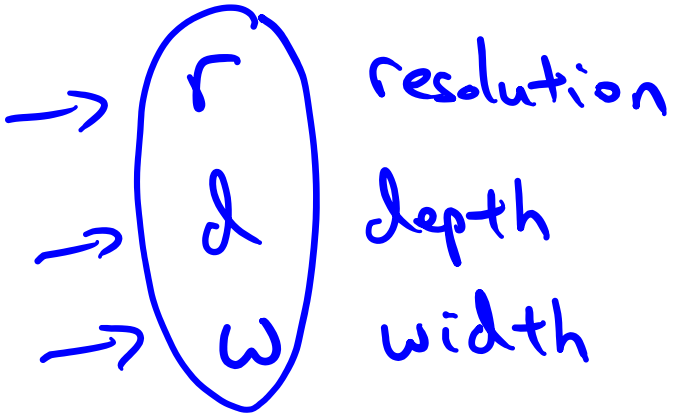
Convolutional Neural Networks

EfficientNet

EfficientNet

Baseline



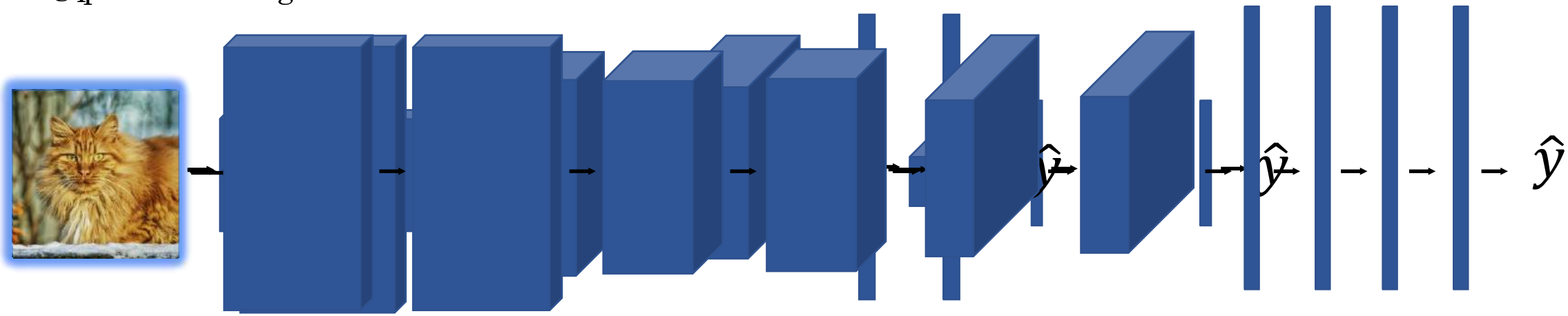


Bigger Resolution

Deeper

Wider

Compound scaling



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

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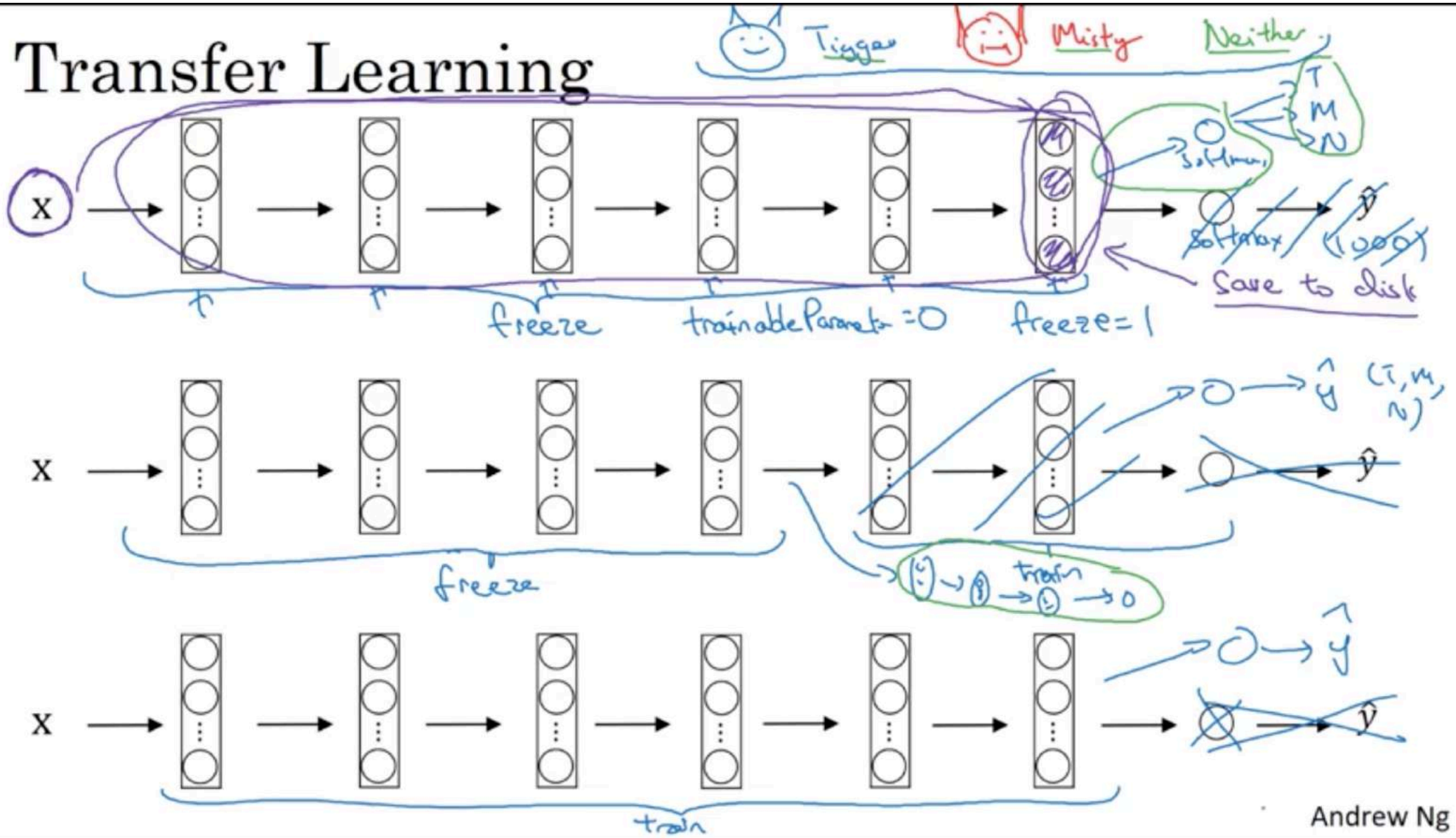
Transfer Learning

Transfer Learning



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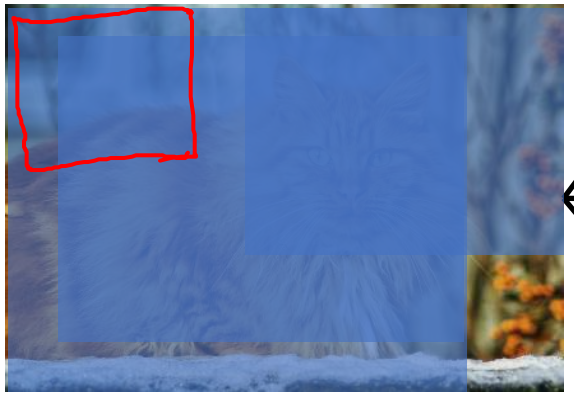
Data augmentation

Common augmentation method

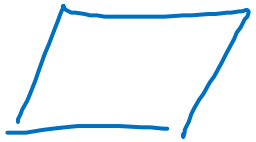
Mirroring

y

Random Cropping



- Rotation
- Shearing
- Local warping
- ...



Color shifting

R G B

+20,-20,+20

-20,+20,+20

+5,0,+50

Advanced:

PCA

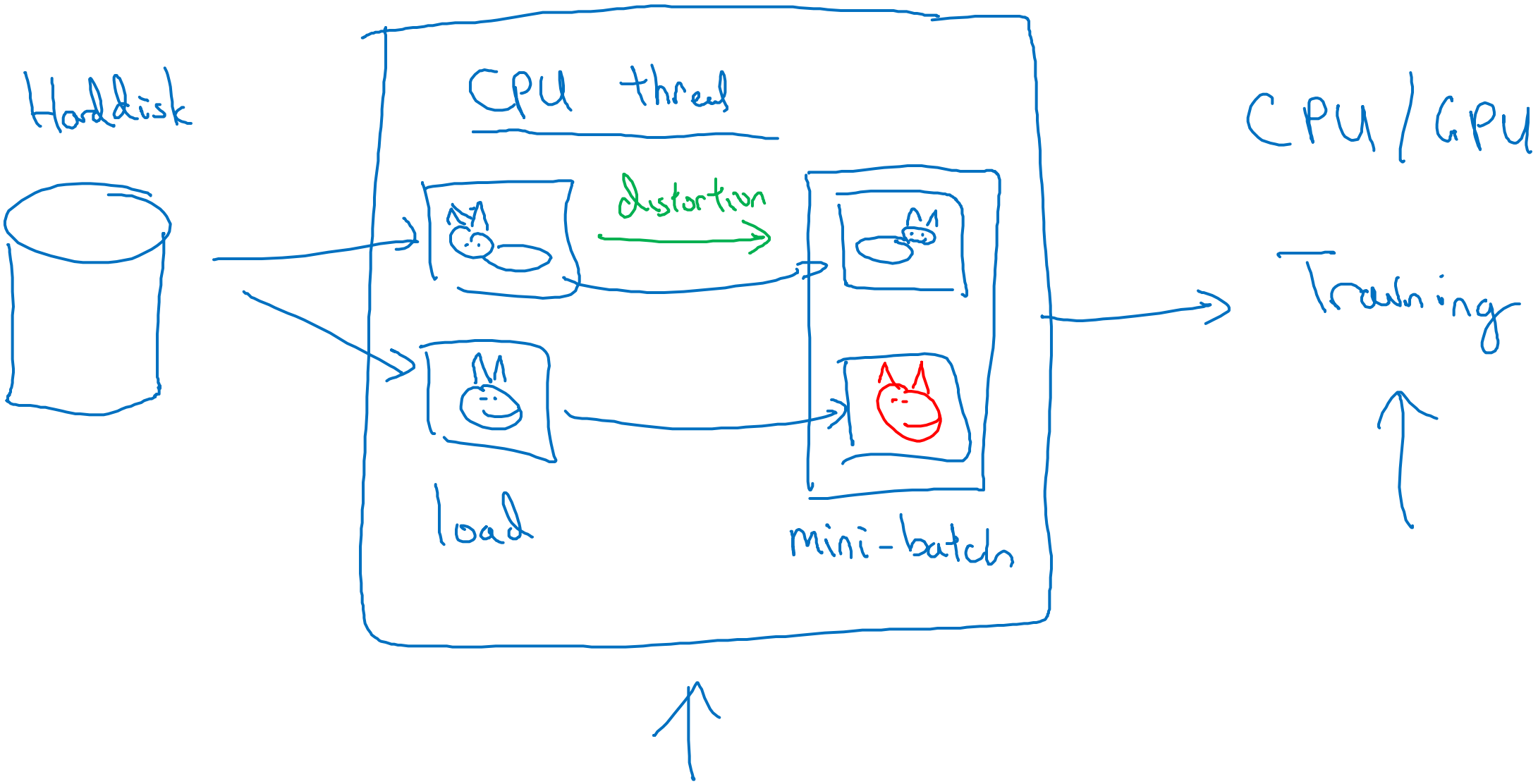
ml-class.org

[AlexNet paper

["PCA color augmentation."

R B G

Implementing distortions during training



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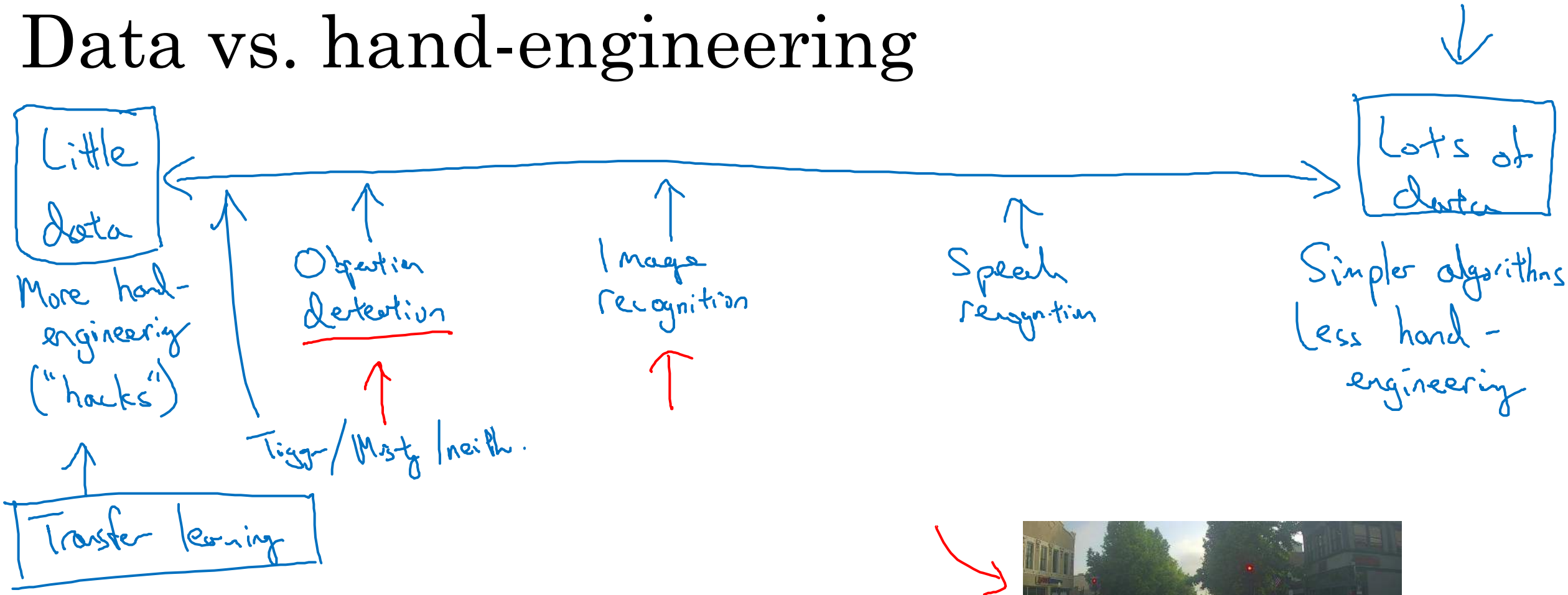
The state of computer vision

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