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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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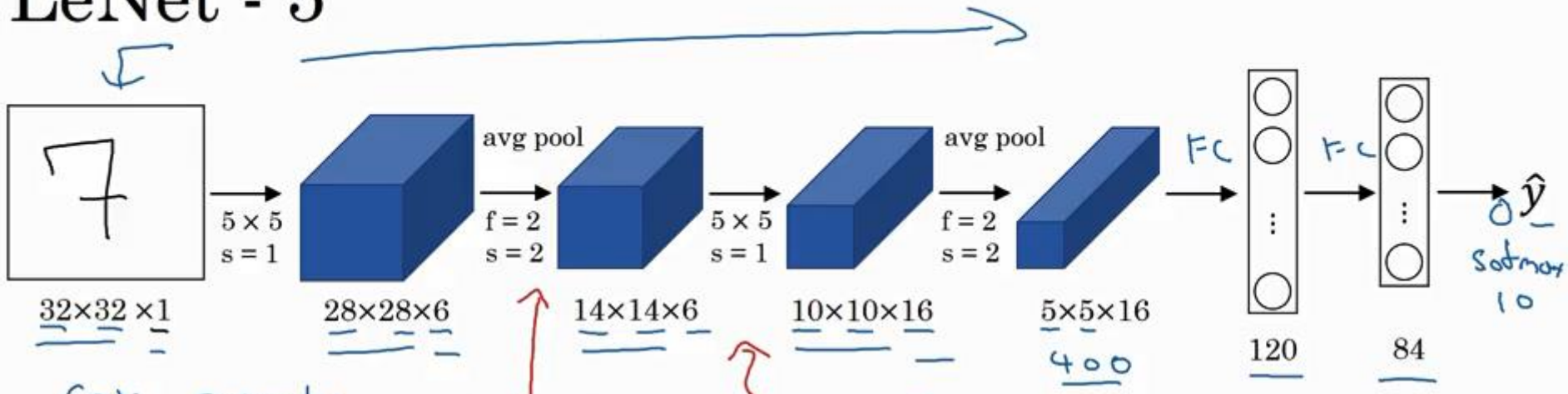
# Case Studies

## Classic networks

# LeNet - 5




60k parameters.

$n_H, n_W \downarrow$ $n_C \uparrow$

Conv pool conv pool fc fc output

Activation: Sigmoid/tanh ReLU

Nonlinearity after pooling

$n_{H} \times n_{W} \times n_C$ $f \times f \times n_C$

II III

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

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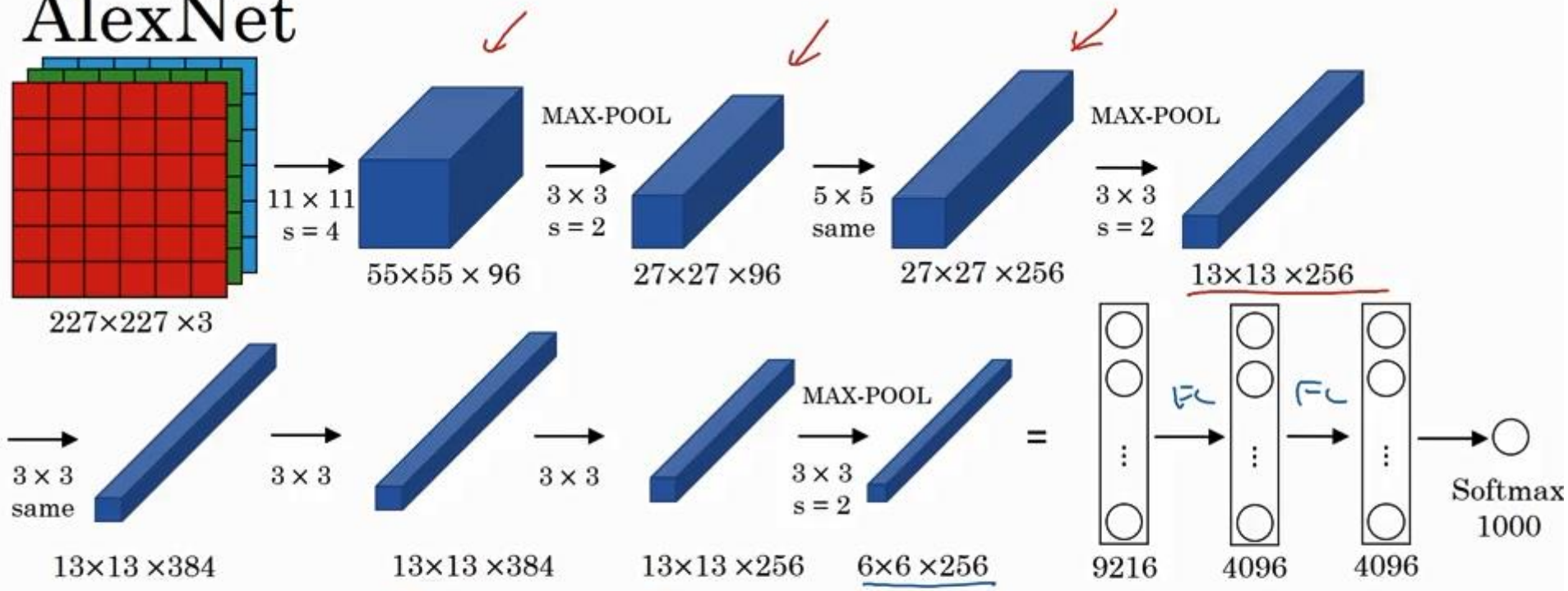
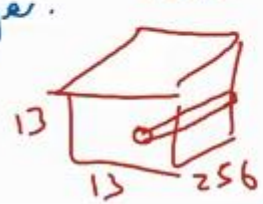
# AlexNet




- 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]

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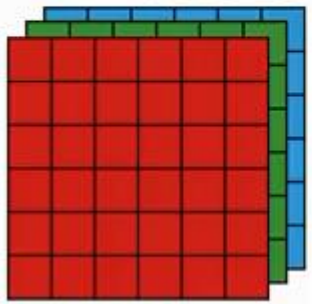
# VGG - 16

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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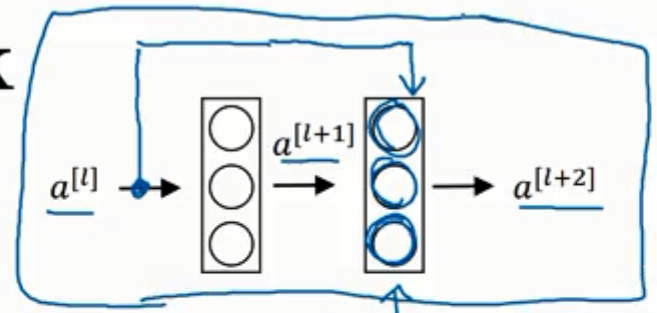
# Case Studies

# Residual Networks (ResNets)

# Residual block




"short cut" / skip connection

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

"main pain"

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

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

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

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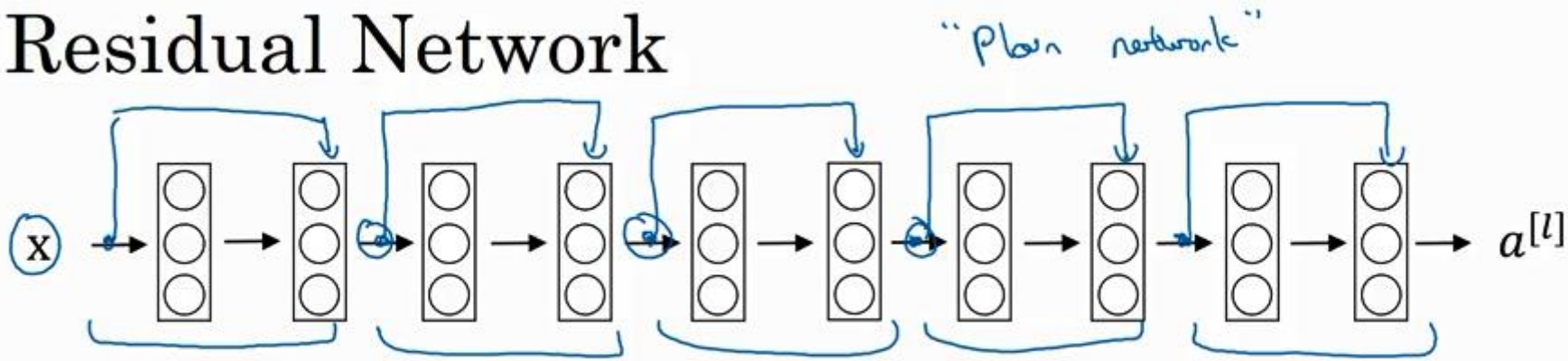
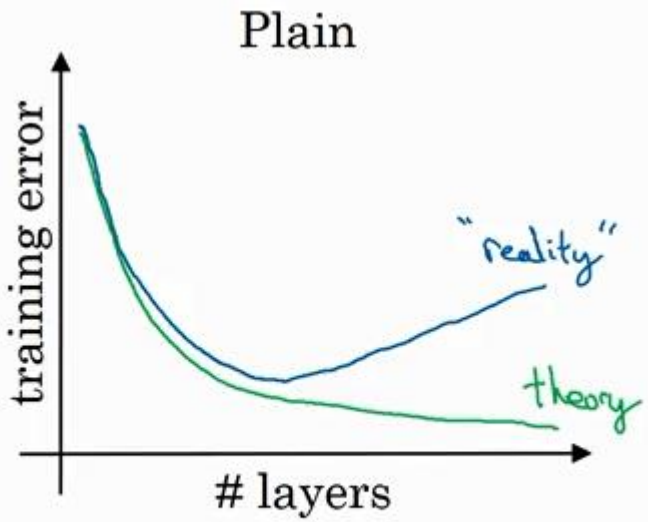
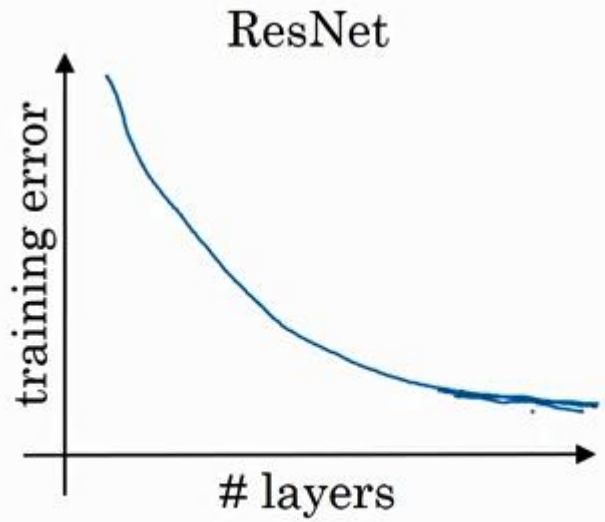
# Residual Network




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

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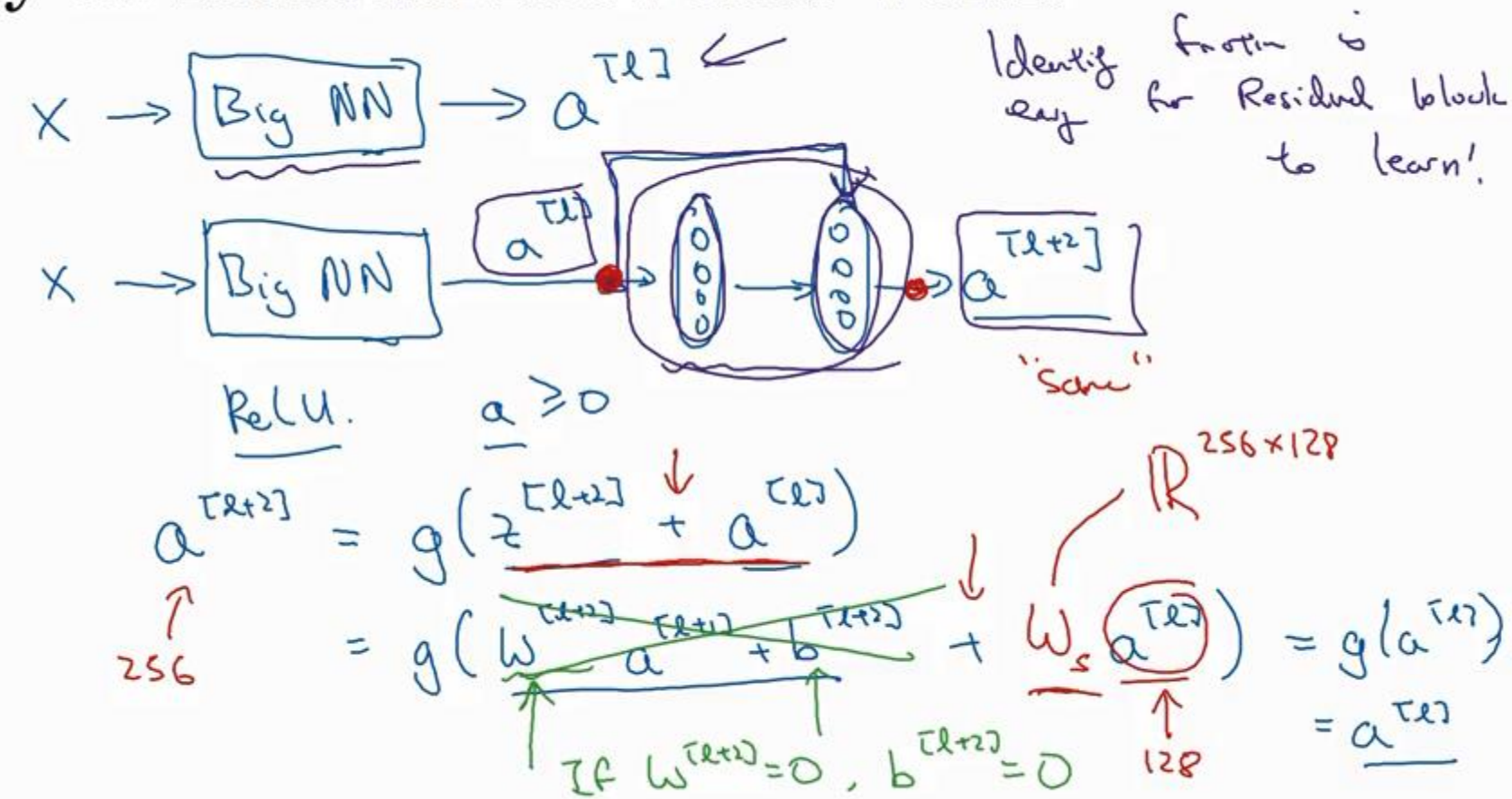
# Why ResNets work

# Why do residual networks work?

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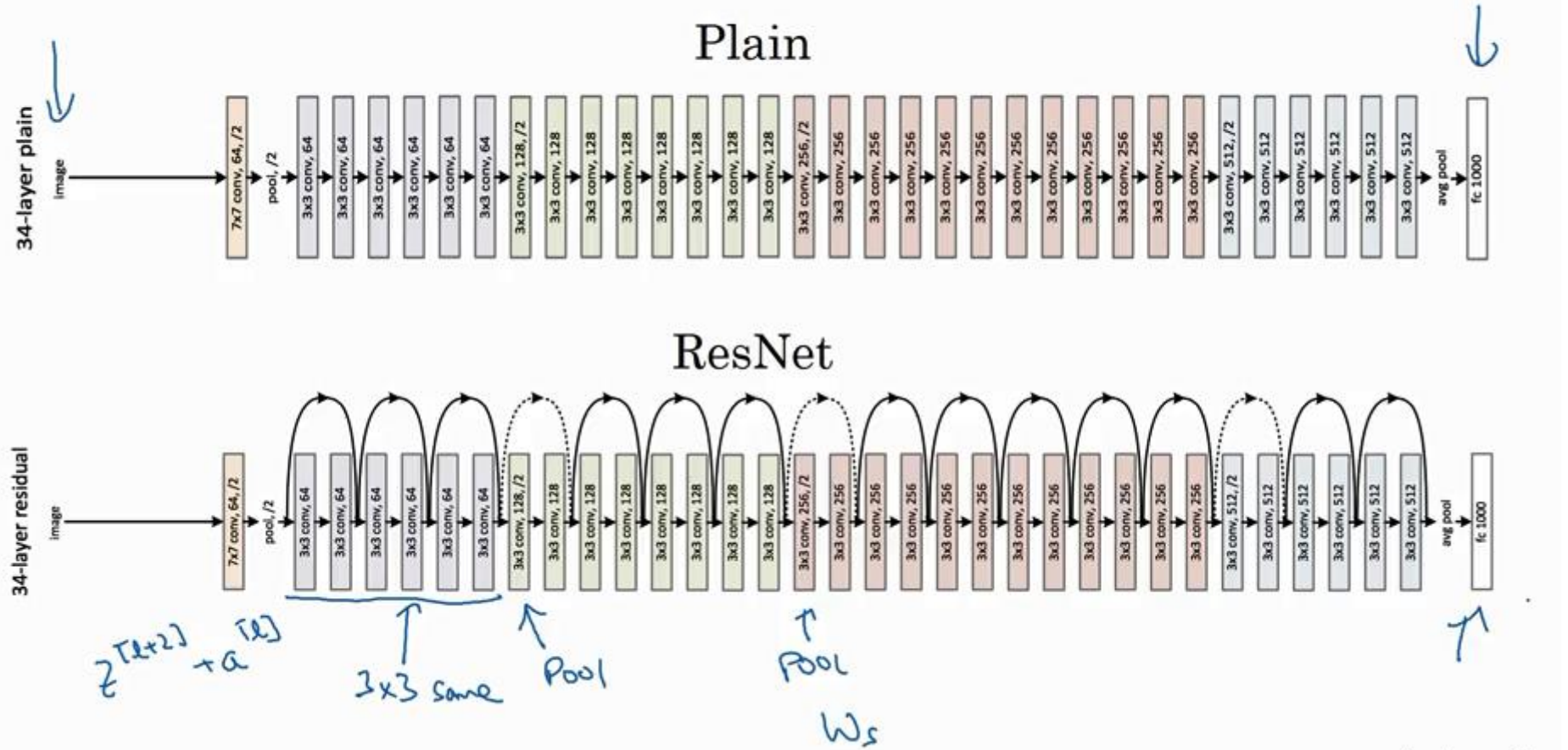
# ResNet




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

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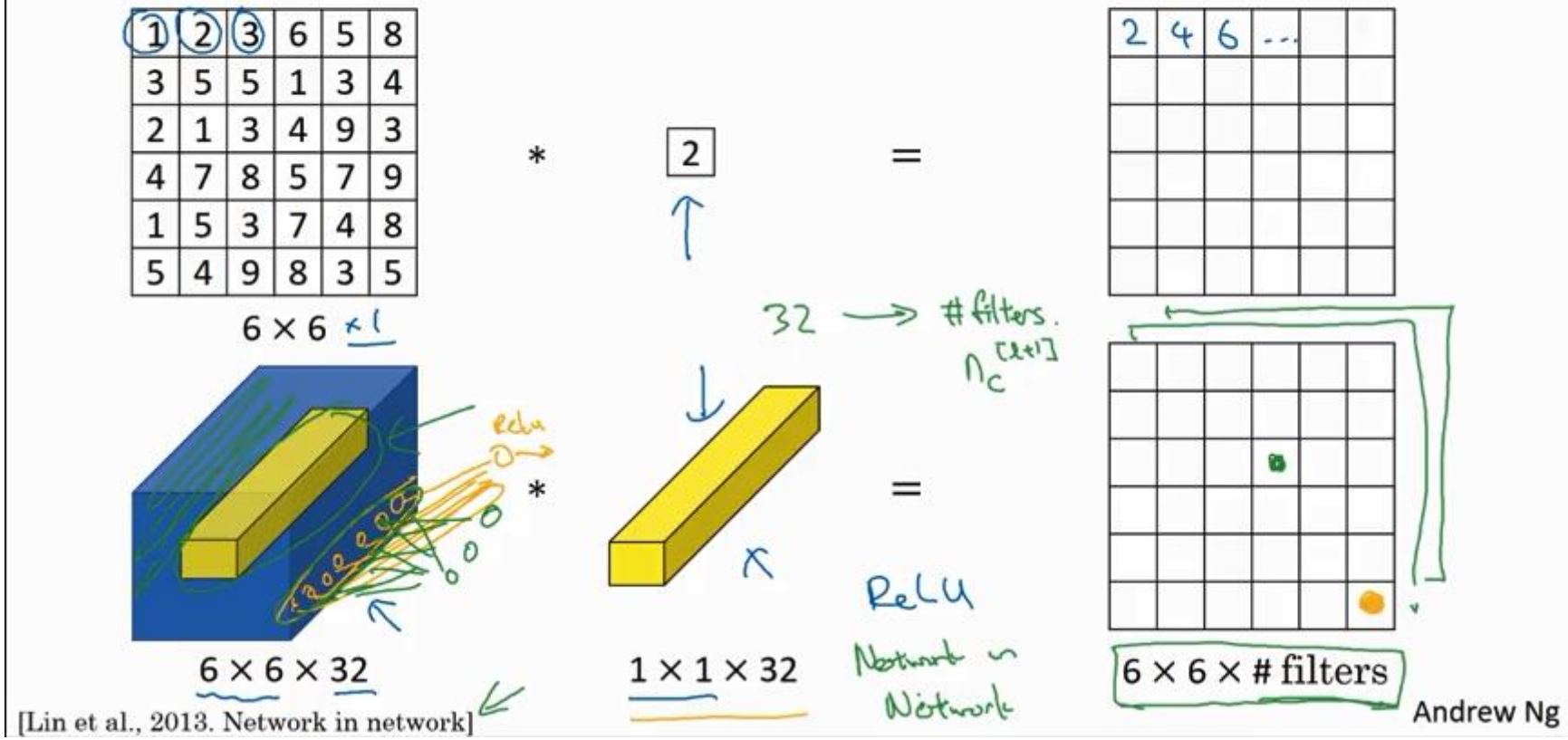
Case Studies

# Network in Network and 1×1 convolutions

# Why does a 1 × 1 convolution do?




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

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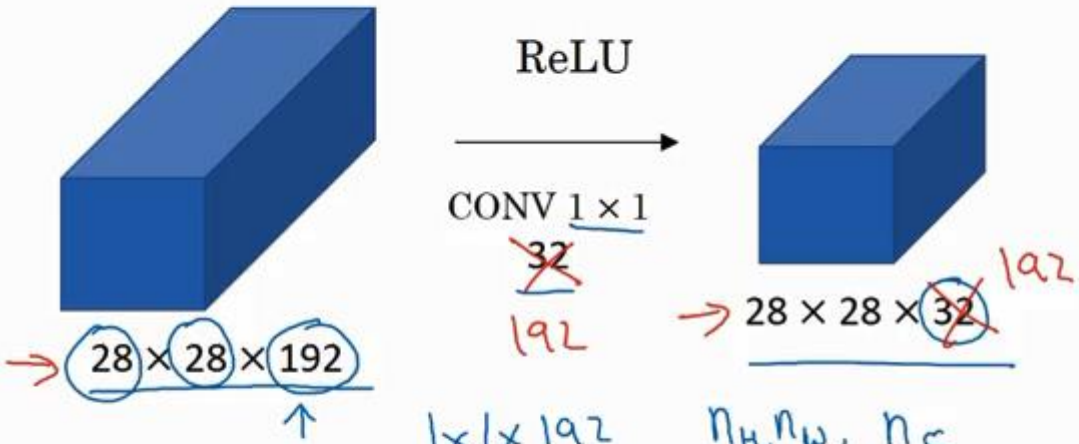
# Using 1×1 convolutions




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

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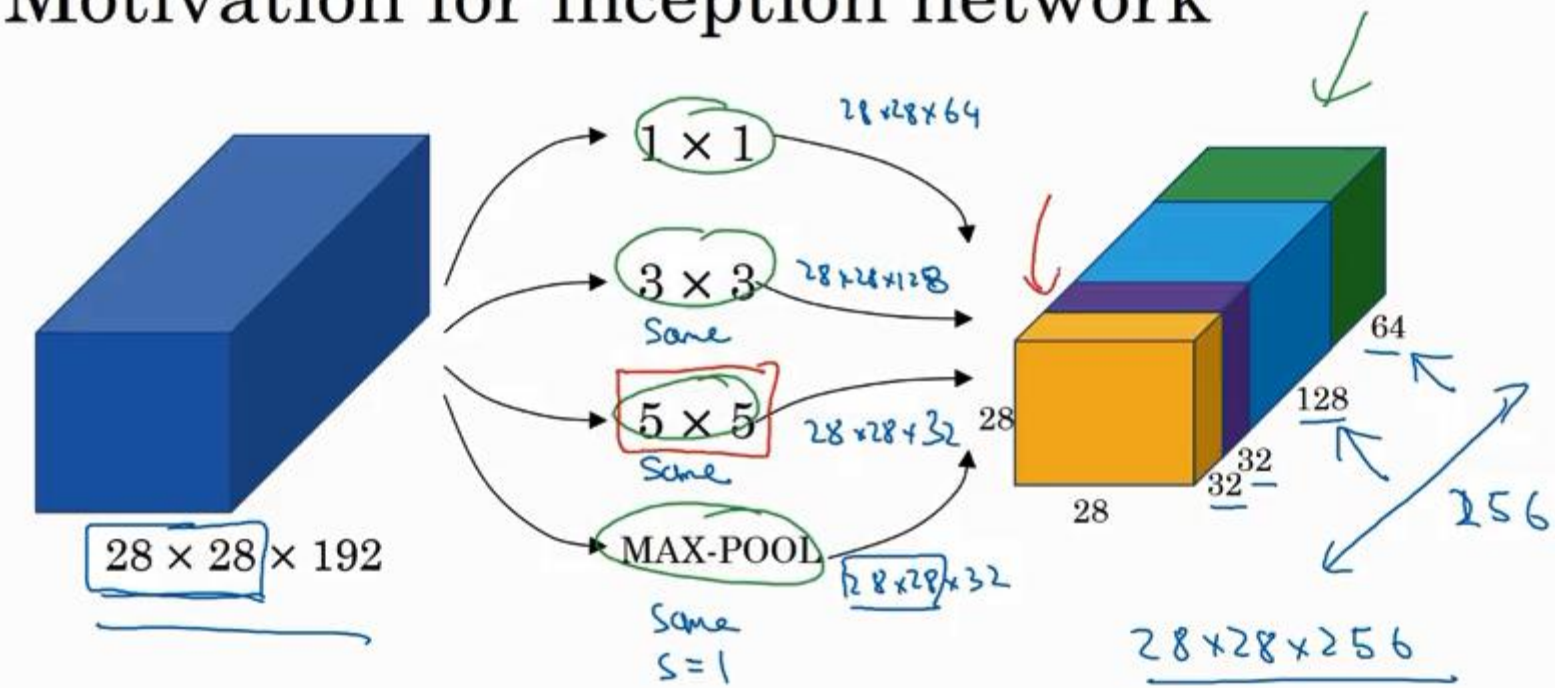
# Inception network motivation

# Motivation for inception network




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

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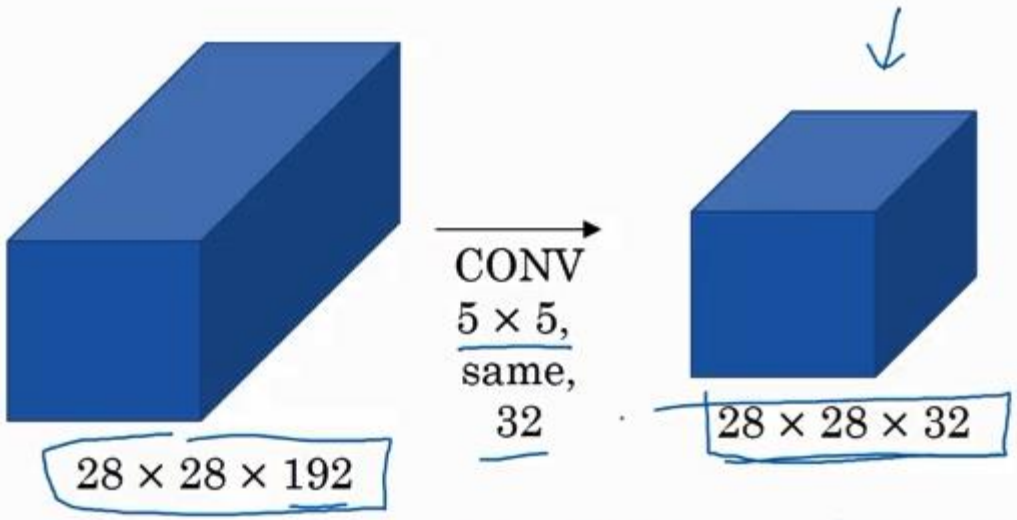
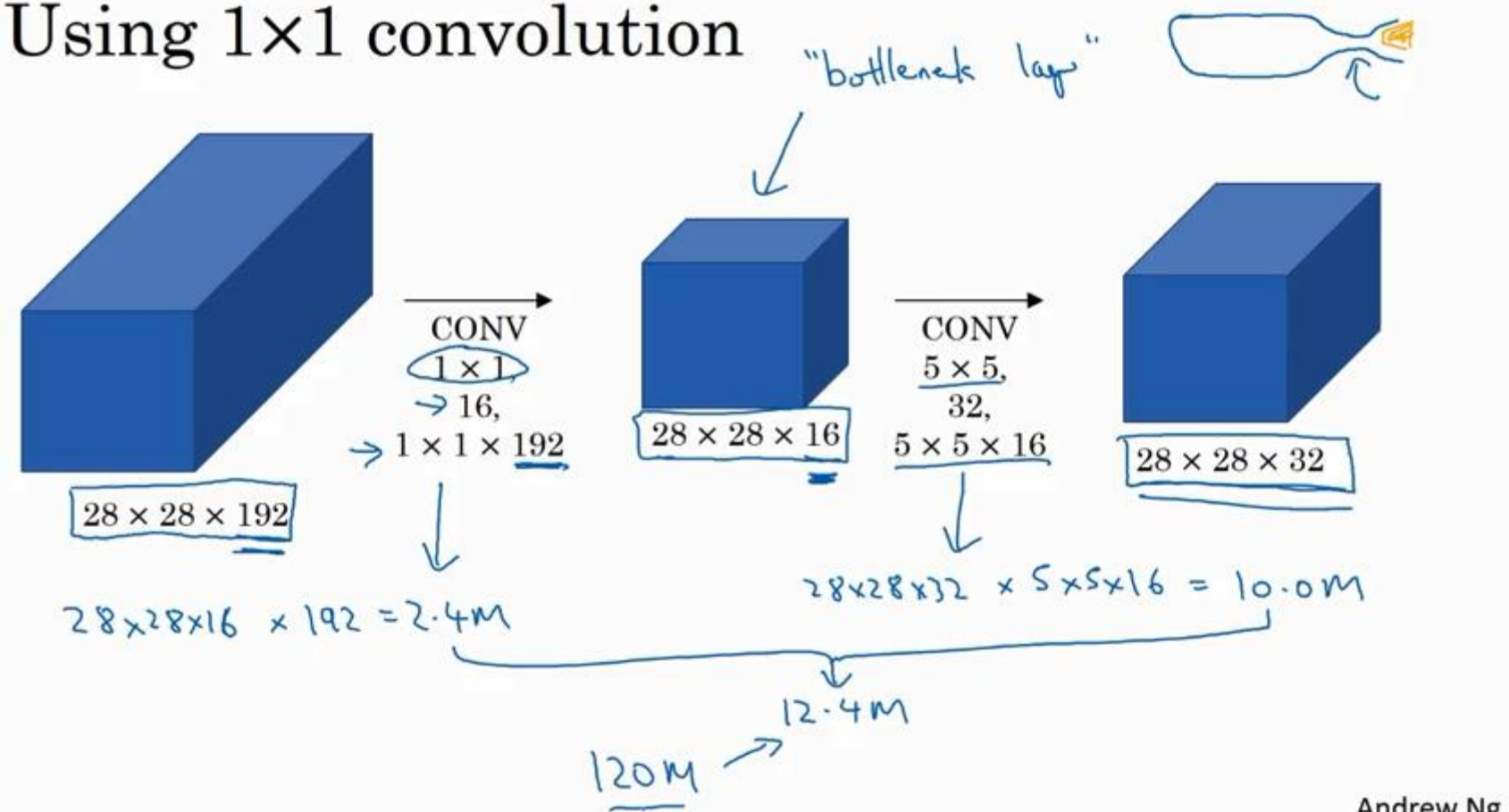
# The problem of computational cost




32 filters. filter one 5×5×192.

28×28×32 × 5×5×192 = 120M.

# Using 1×1 convolution

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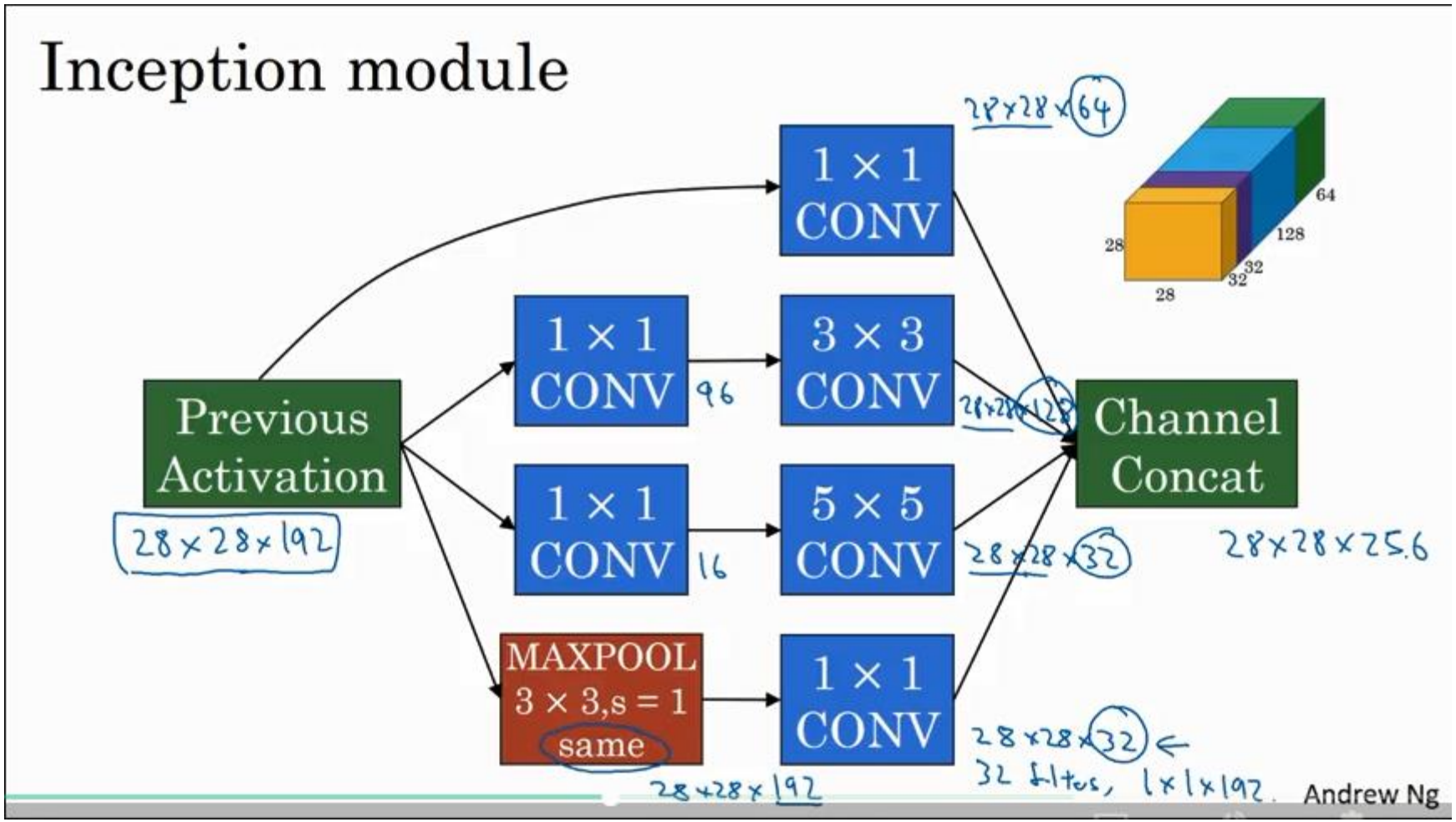
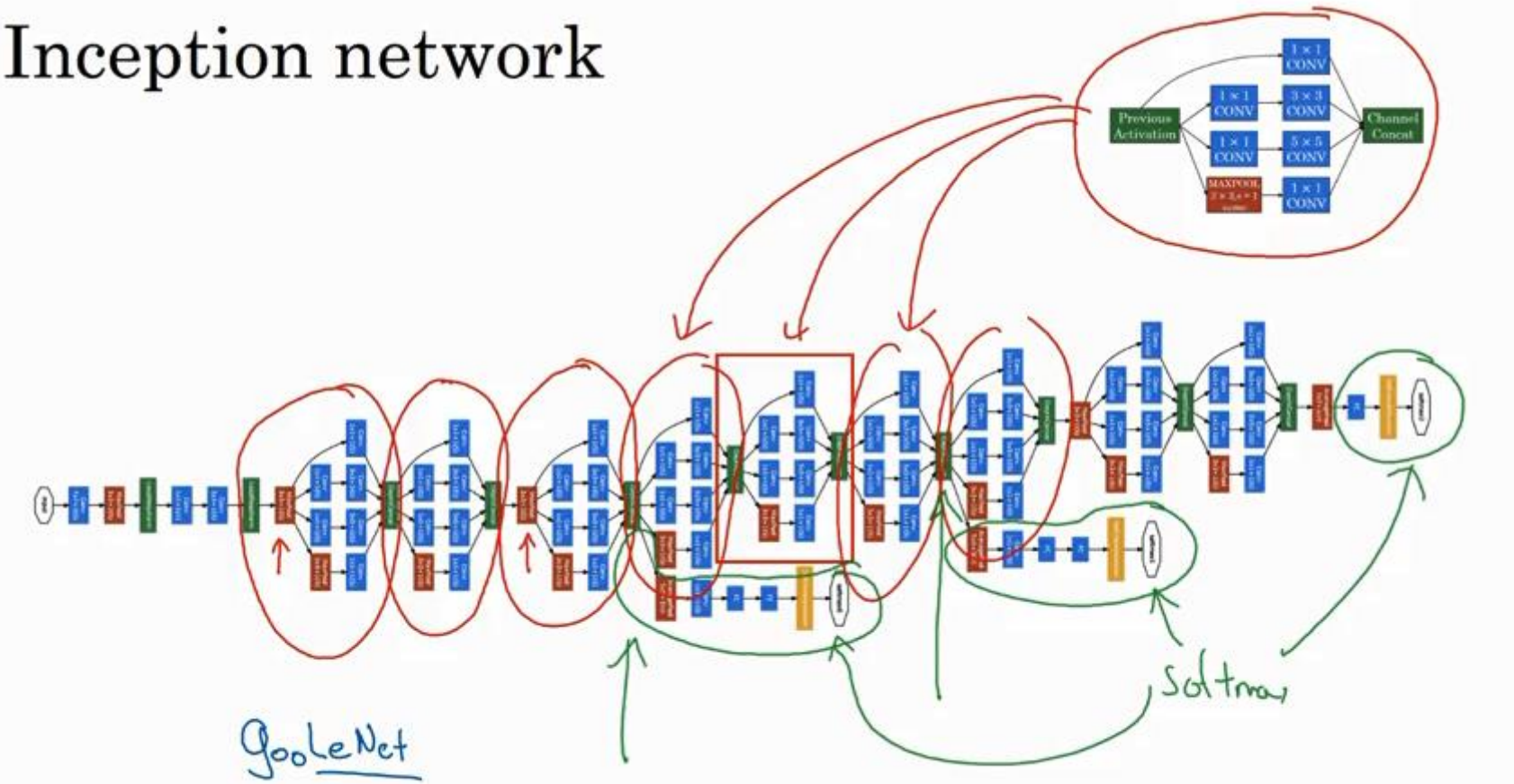
# Inception network

# Inception module



# Inception network




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

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

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# Practical advice for using ConvNets

## Using open-source implementations

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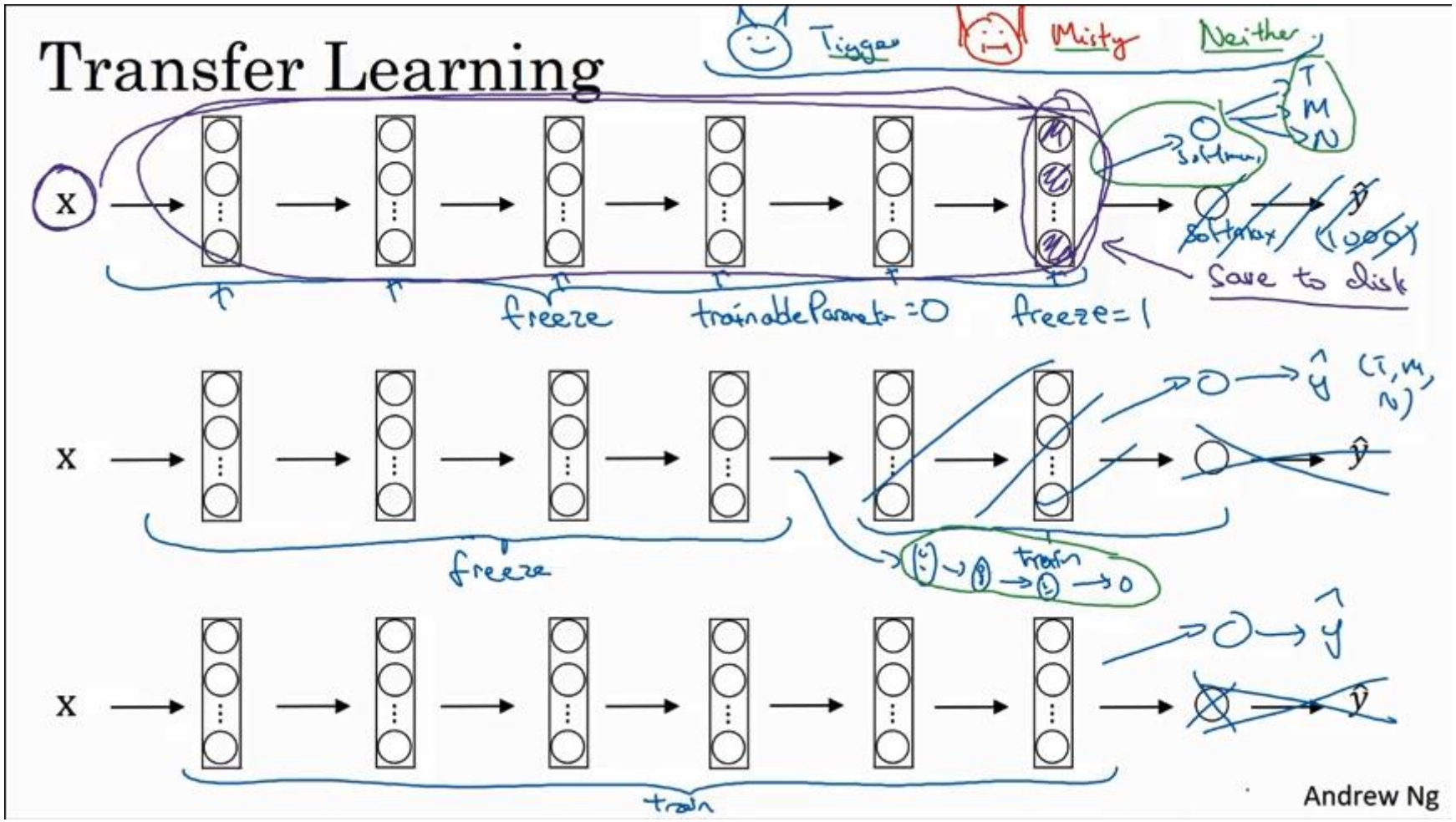
# Practical advice for using ConvNets

## Transfer Learning

# Transfer Learning

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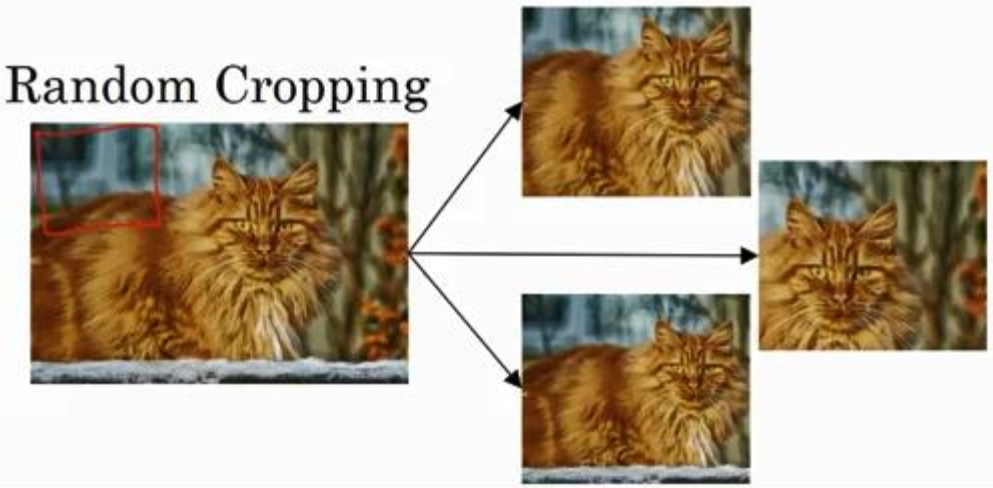
# Practical advice for using ConvNets

## Data augmentation

# Common augmentation method

Mirroring

Random Cropping



- Rotation
- Shearing
- Local warping
- ...

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# Color shifting

R G B

+20,-20,+20

-20,+20,+20

+5,0,+50

y

Advanced:

PCA

ml-class.org

[AlexNet paper

["PCA color augmentation."

R B G

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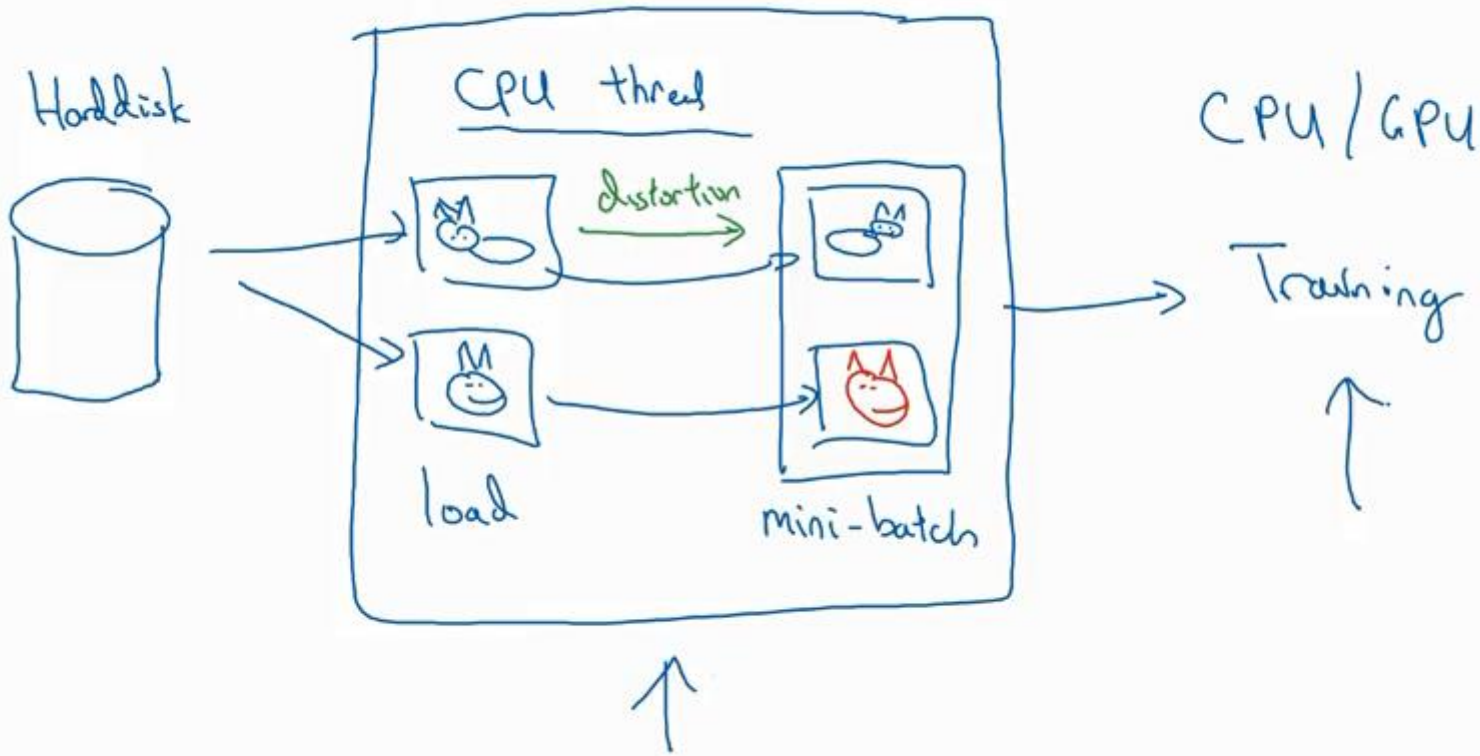
# Implementing distortions during training

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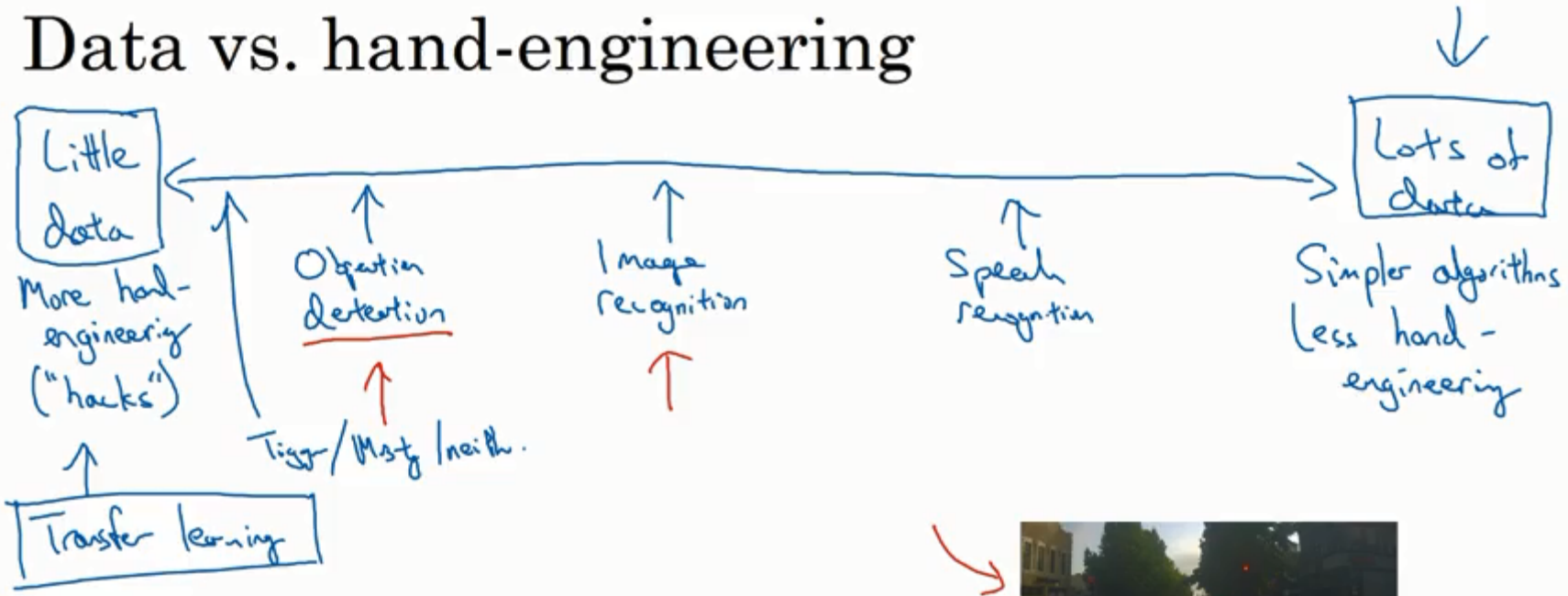
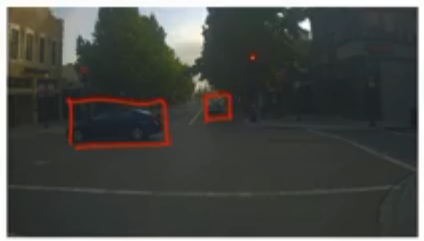
# Practical advice for using ConvNets

## 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

网易云课堂

Ensembling

3-15 networks

→ $\hat{y}$

- 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

1 + 4 + 1 + 4

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# Use open source code

网易云课堂

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