

# WEEK 2 CNN COURSE

## WHY LOOK AT CASE STUDIES?

### Outline

#### Classic networks:

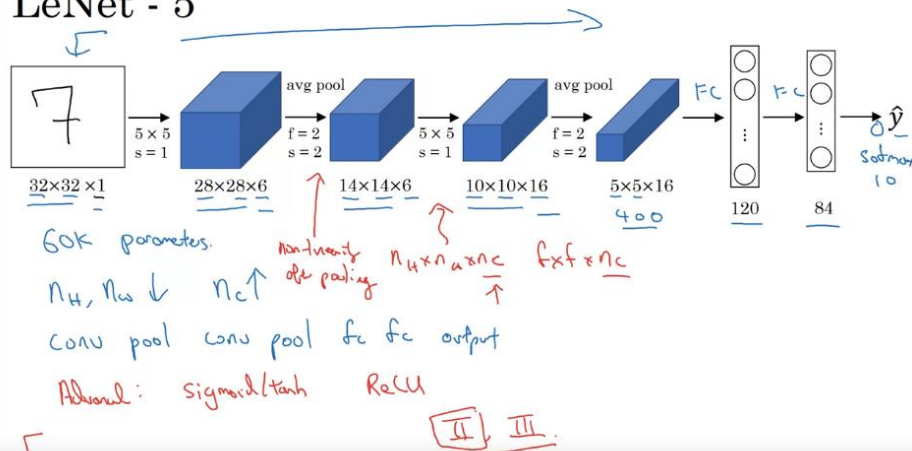
- LeNet-5 ←
- AlexNet ←
- VGG ←

ResNet (152)

Inception

## CLASSIC NETWORKS:

## LeNet - 5

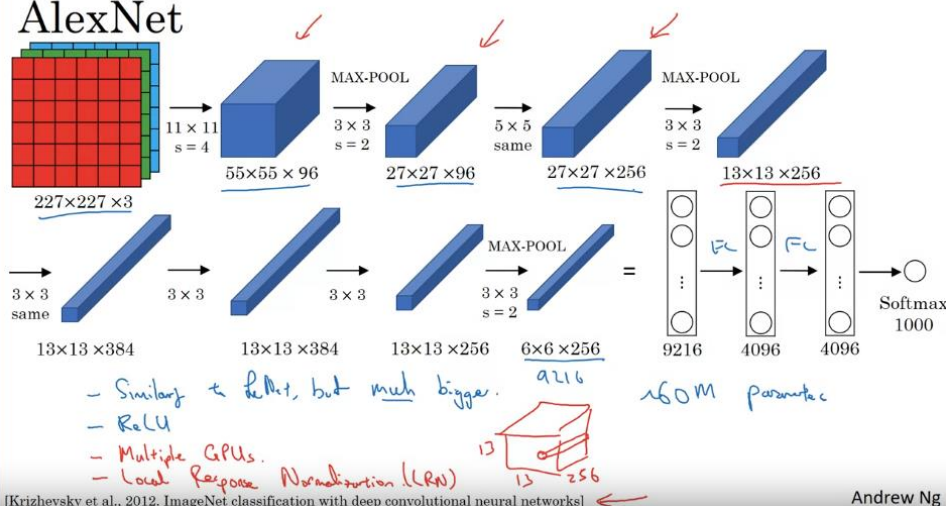


[LeCun et al., 1998. Gradient-based learning applied to document recognition]

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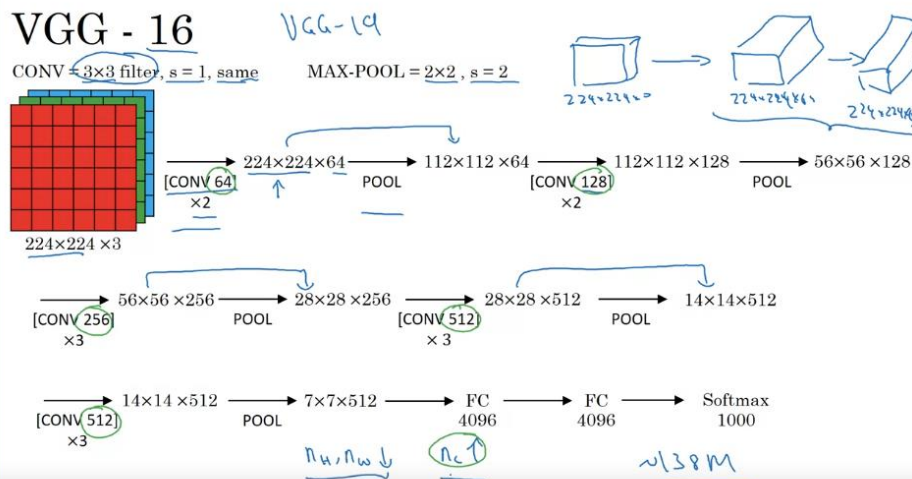
**Red part can be skipped its optional. ↑↑↑**

## AlexNet



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## VGG - 16

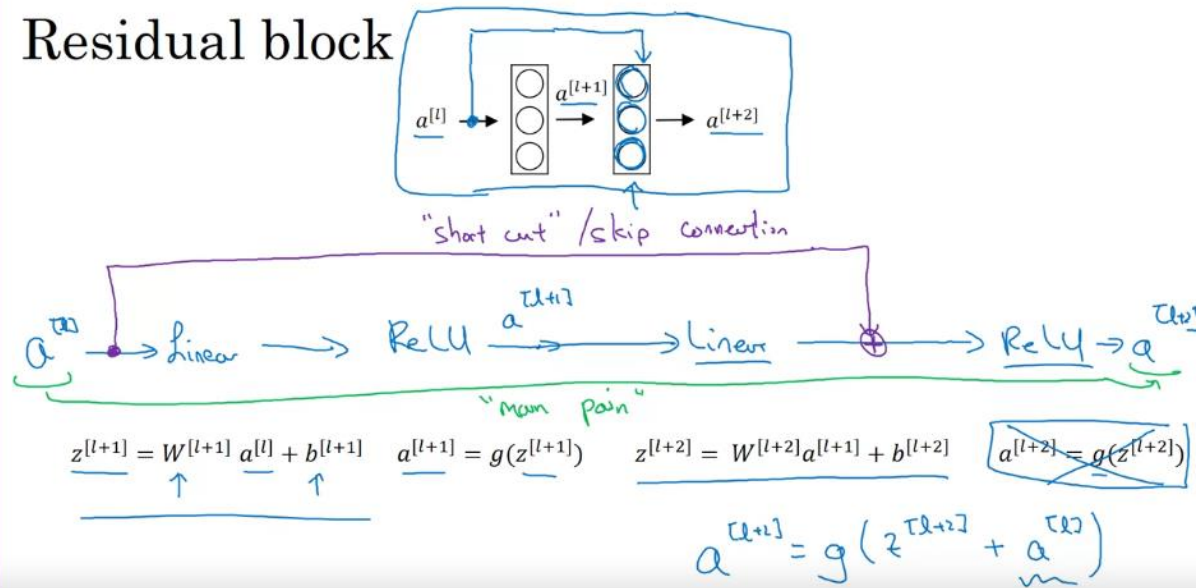


[Simonyan & Zisserman 2015. Very deep convolutional networks for large-scale image recognition]

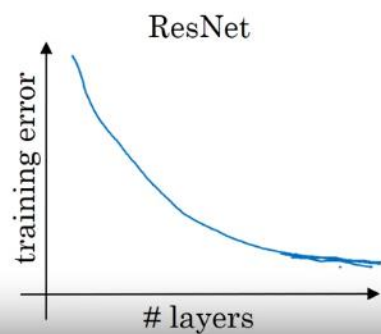
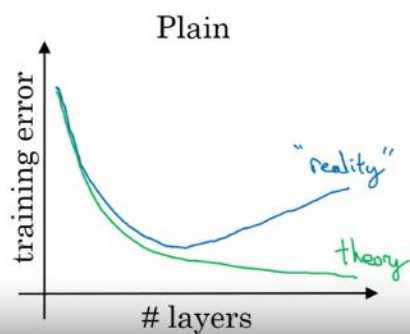
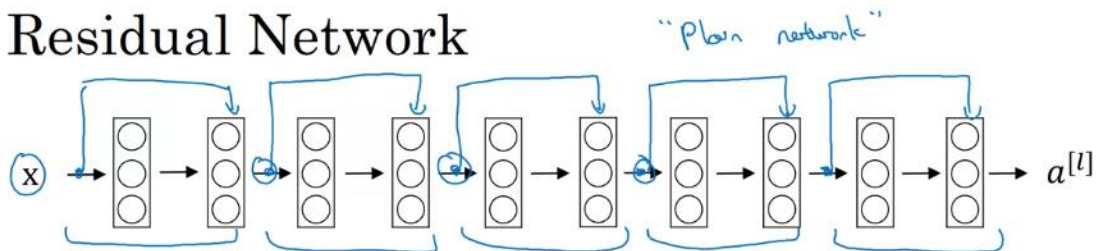
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# RESNETS ( RESIDUAL NETWORKS)

## Residual block

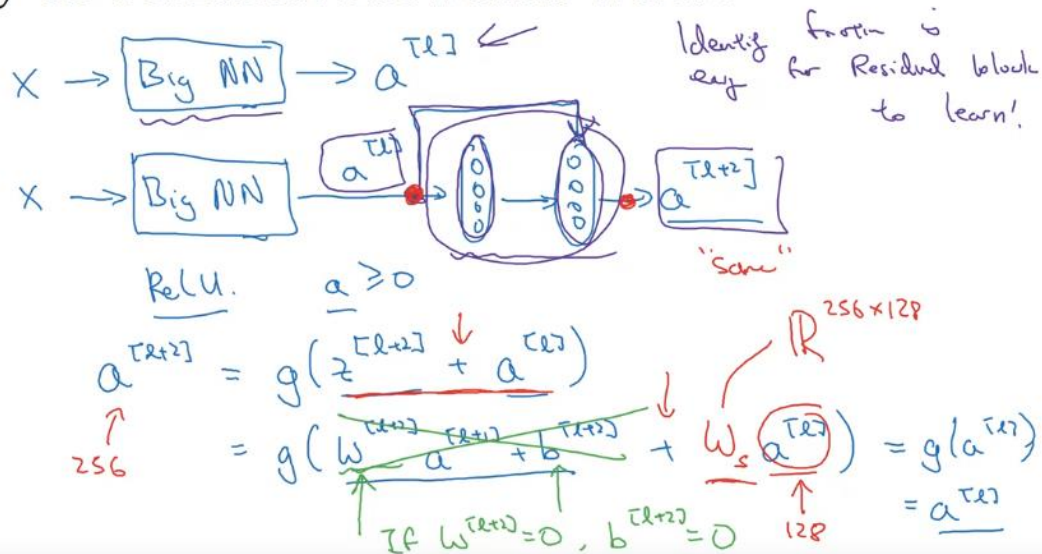


## Residual Network



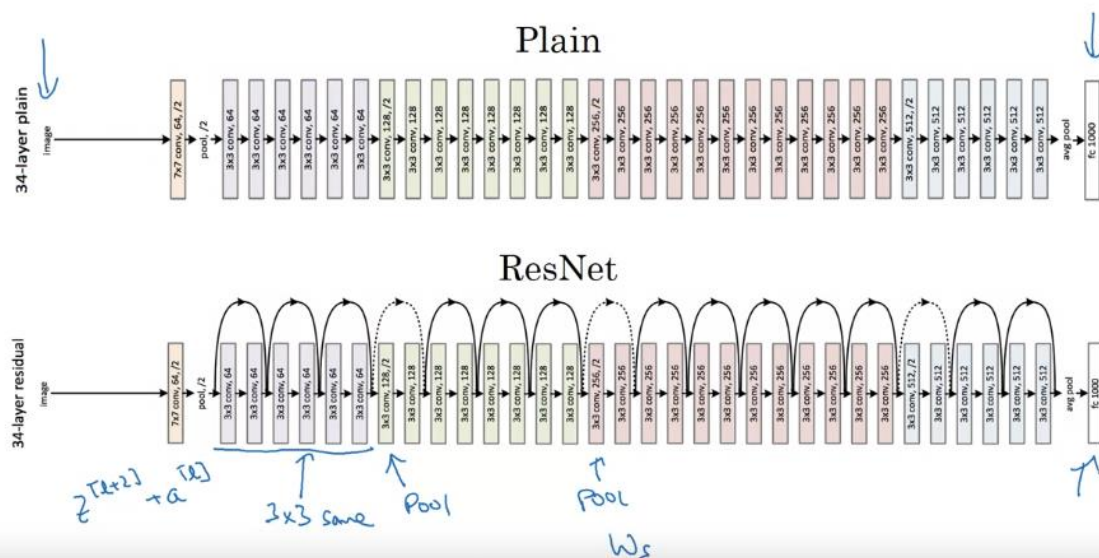
# WHY DO RESNETS WORK?

## Why do residual networks work?



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## ResNet

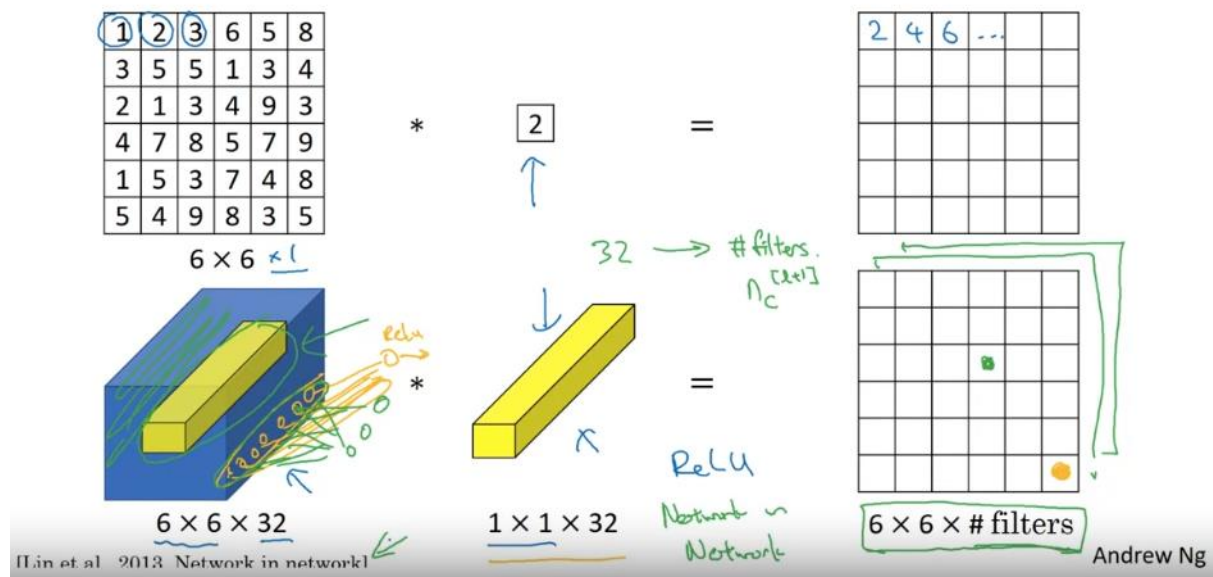


[He et al., 2015. Deep residual networks for image recognition]

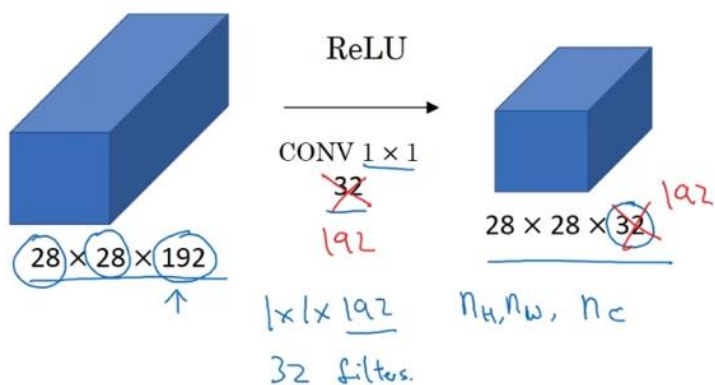
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## NETWORKS IN NETWORKS AND 1x1 CONVOLUTIONS:

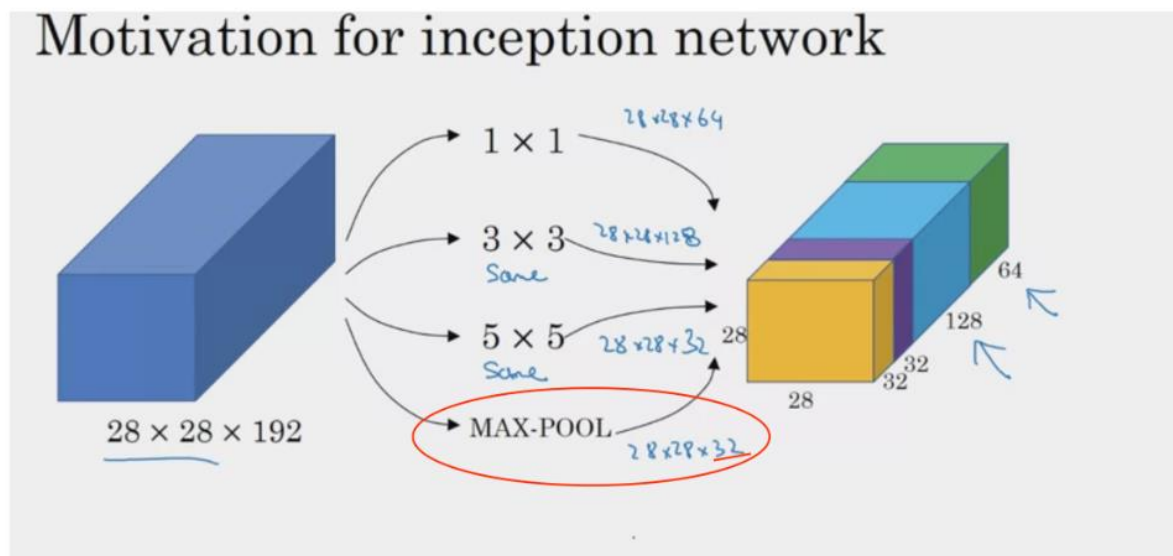
Why does a  $1 \times 1$  convolution do?



Using  $1 \times 1$  convolutions



# Clarifications about Upcoming Inception Network Motivation Video



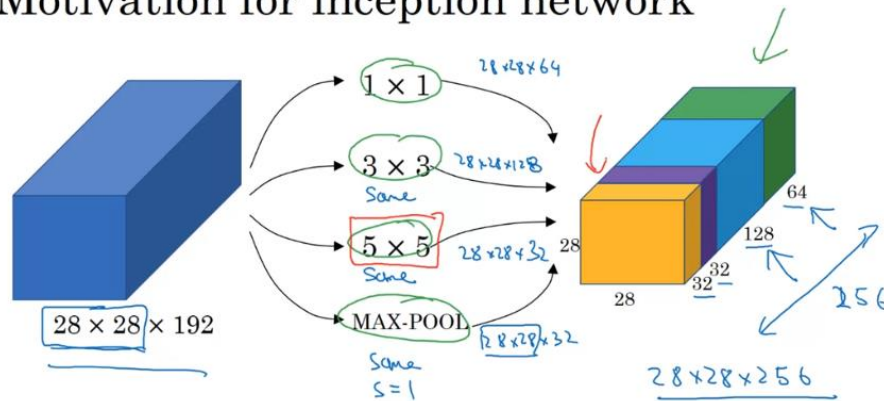
**Note 1:** If at 2:03 you get confused why after applying max pooling you get  $28 \times 28 \times 32$  output, please know Andrew mentions to talk about this in detail later, which he does in the following lecture video, [Inception Network](#) and explains why it got shrunk down from 192 to 32.

**Note 2:** At 3:00, Andrew should have said  $28 \times 28 \times 192$  instead of  $28 \times 28 \times 129$ . The subtitles have been corrected.



# INCEPTION NETWORK MOTIVATION

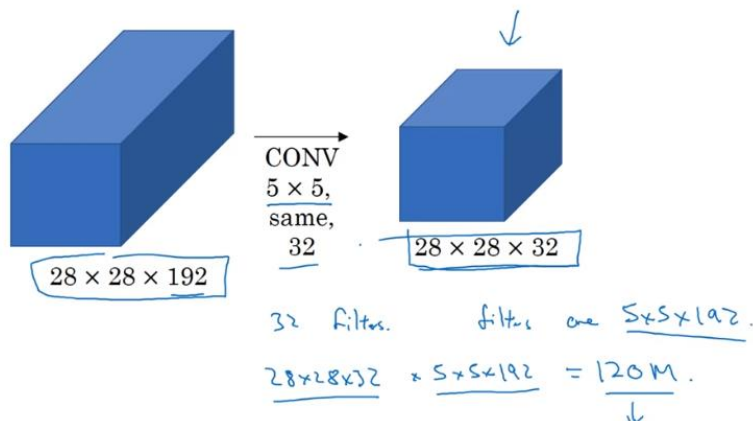
## Motivation for inception network



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

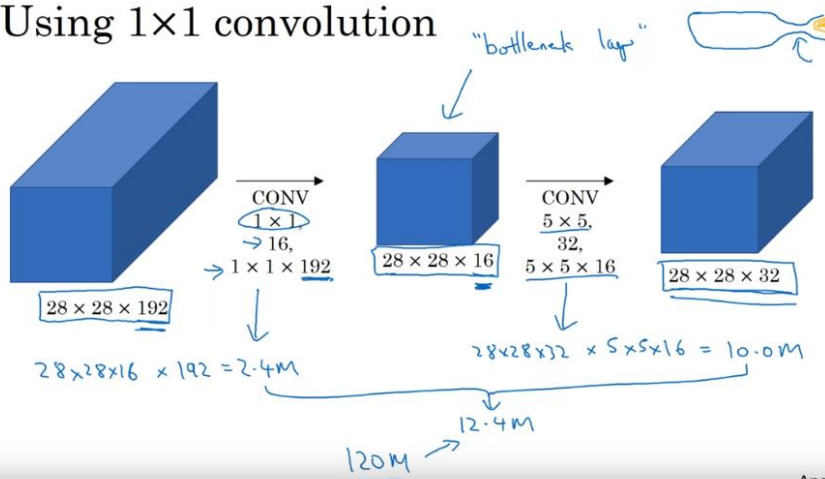
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## The problem of computational cost



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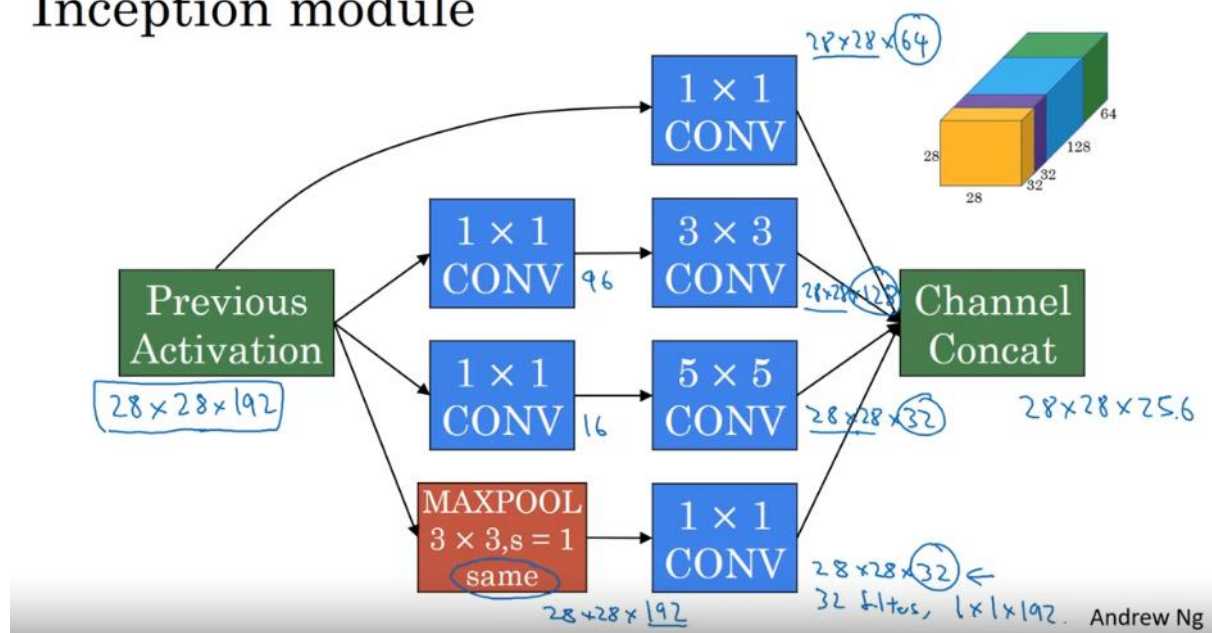
## Using 1x1 convolution



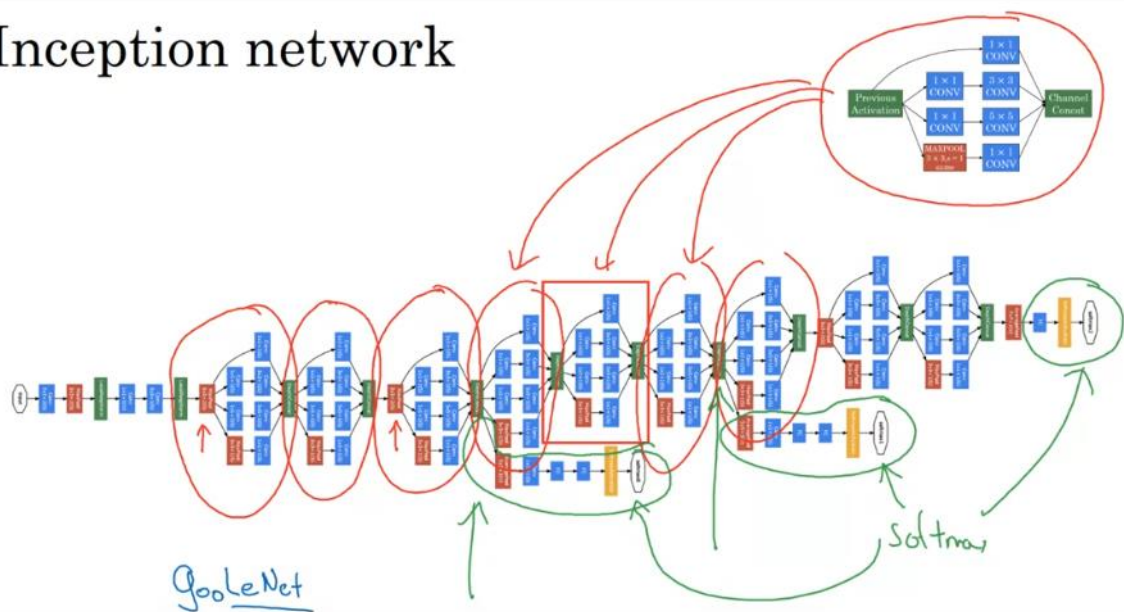
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# INCEPTION NETWORK

## Inception module



## Inception network





# MOBILE NET

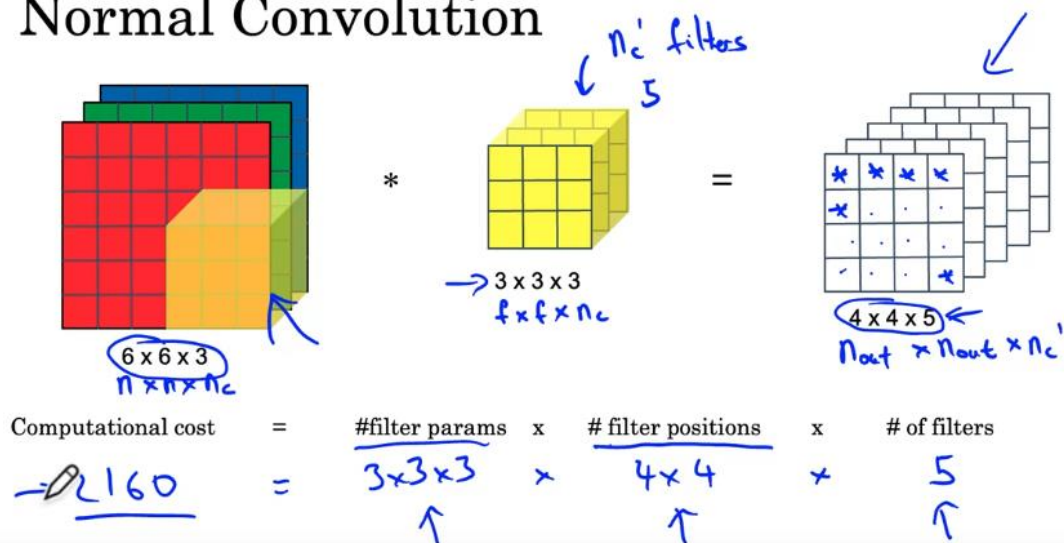
## Motivation for MobileNets

- 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] Andrew Ng

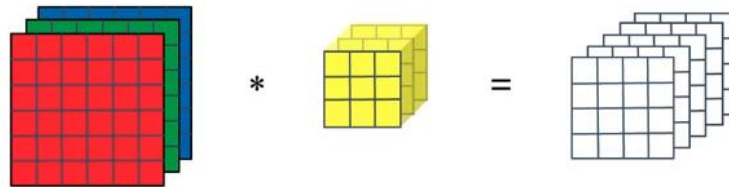
## Normal Convolution



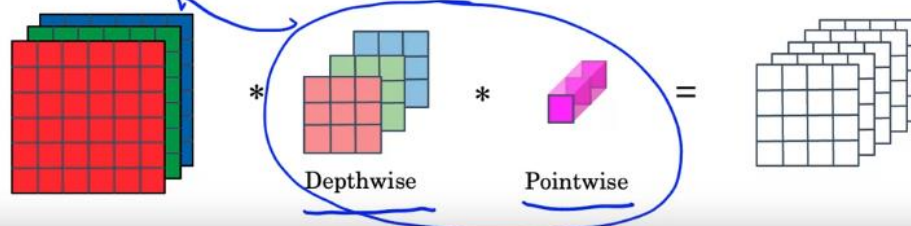
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# Depthwise Separable Convolution

Normal Convolution

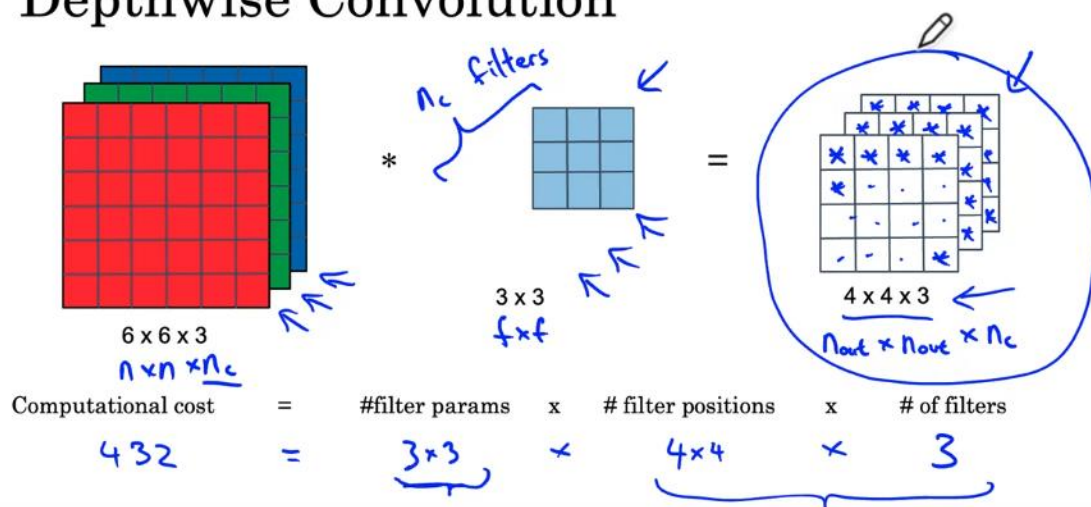


Depthwise Separable Convolution



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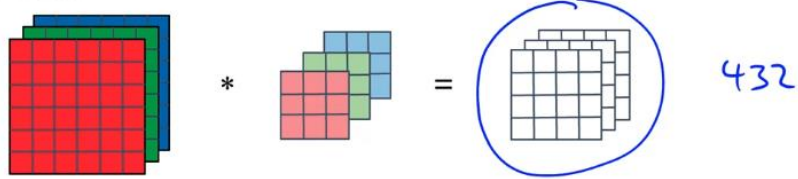
## Depthwise Convolution



Andrew Ng

# Depthwise Separable Convolution

Depthwise Convolution

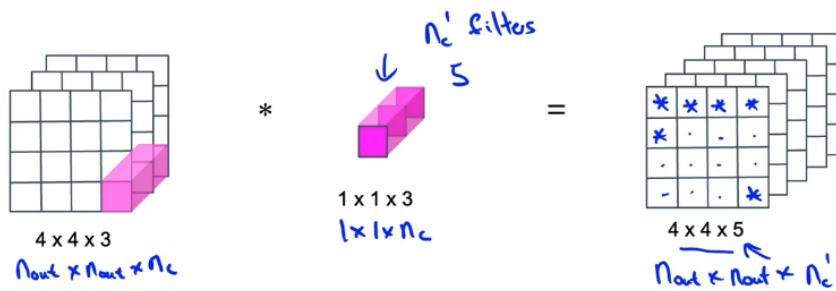


Pointwise Convolution



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## Pointwise Convolution



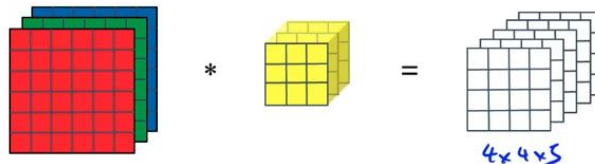
Computational cost = #filter params x #filter positions x # of filters

$1 \times 1 \times 3$  x  $4 \times 4$  x  $5$

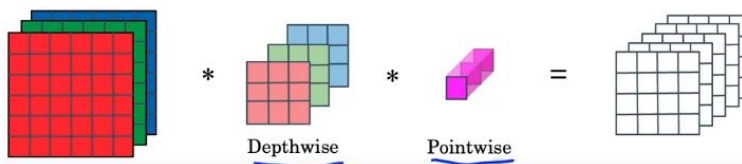
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## Depthwise Separable Convolution

Normal Convolution



Depthwise Separable Convolution



Andrew Ng

## Cost Summary

Cost of normal convolution  $\swarrow$  2160

Cost of depthwise separable convolution  $\swarrow$

$$\begin{array}{cc} \text{depthwise} & + & \text{pointwise} \\ 432 & + & 240 = 672 \end{array}$$

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

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

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

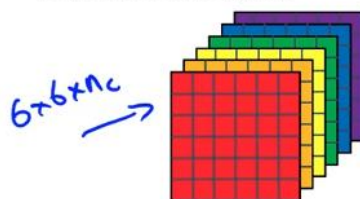
$$= \frac{1}{512} + \frac{1}{3^2}$$

$\sim 10$  times cheaper 

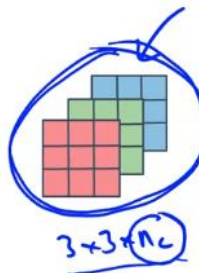
[Howard et al. 2017, MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications] Andrew Ng

## Depthwise Separable Convolution

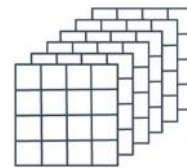
Depthwise Convolution



\*

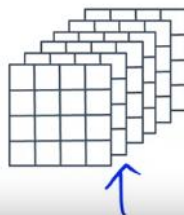


=

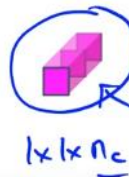


$$4 \times 4 \times n_c$$

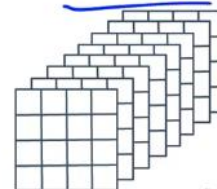
Pointwise Convolution



\*



=



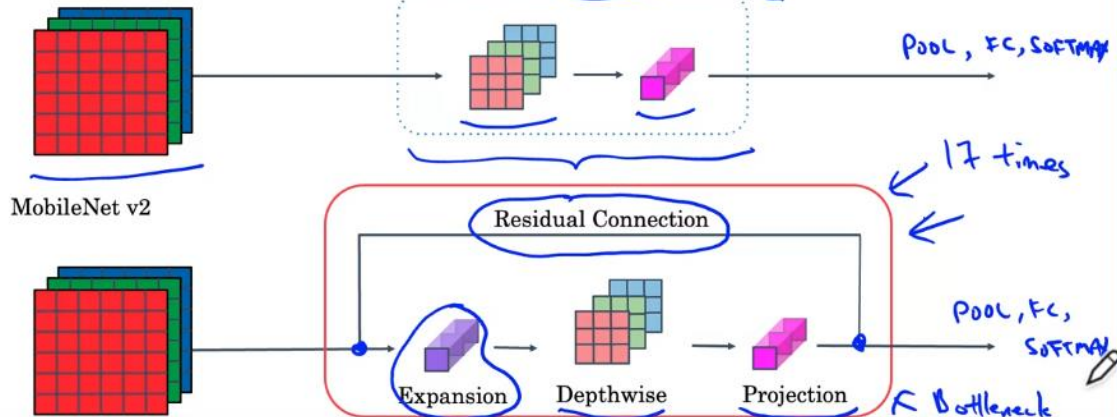
$$4 \times 4 \times 8 \quad \text{nc}$$

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# MOBILE NET ARCHITECTURE

## MobileNet

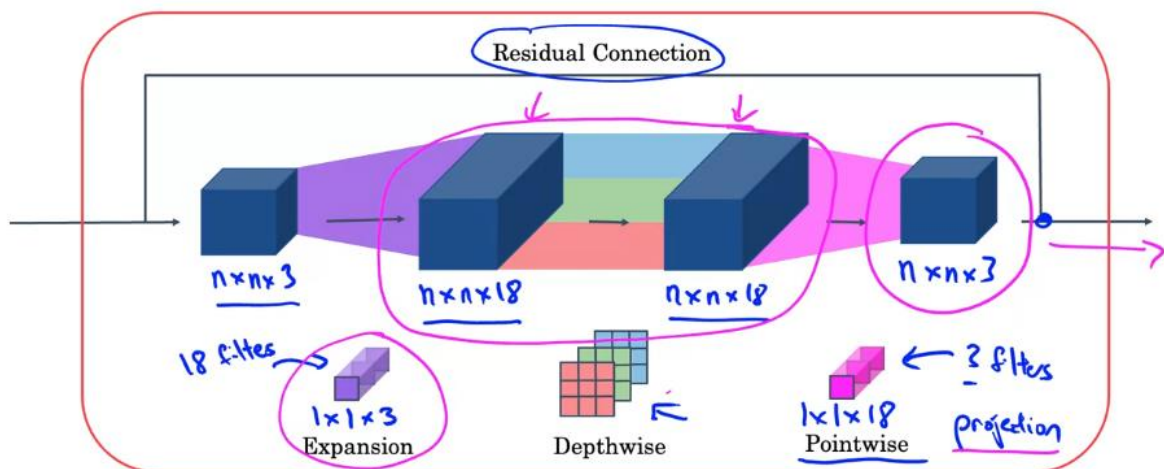
MobileNet v1



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

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## MobileNet v2 Bottleneck



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

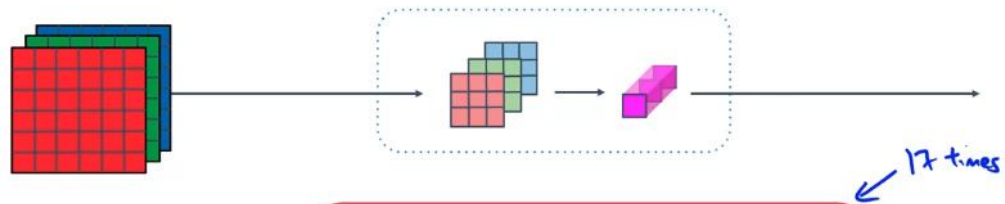


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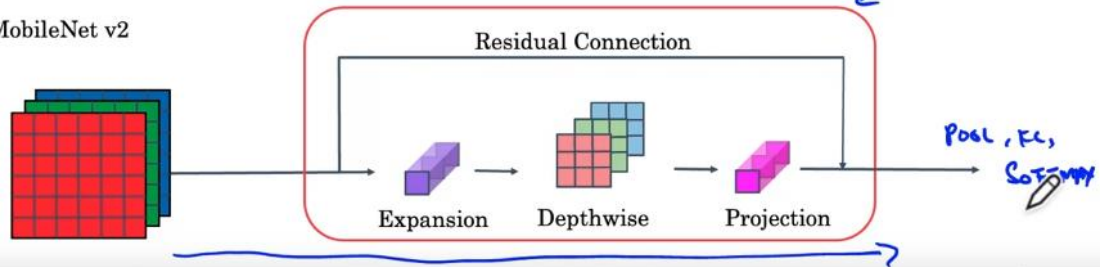


# MobileNet

MobileNet v1



MobileNet v2

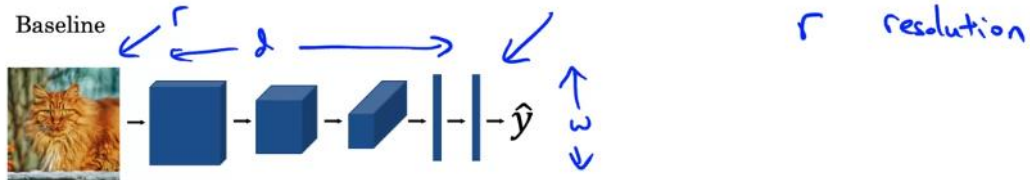


[Sandler et al. 2019, MobileNetV2: Inverted Residuals and Linear Bottlenecks]

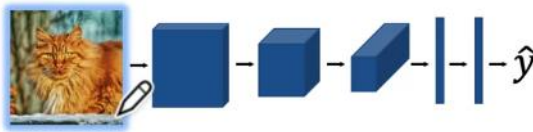
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# EFFICIENT NET

## EfficientNet



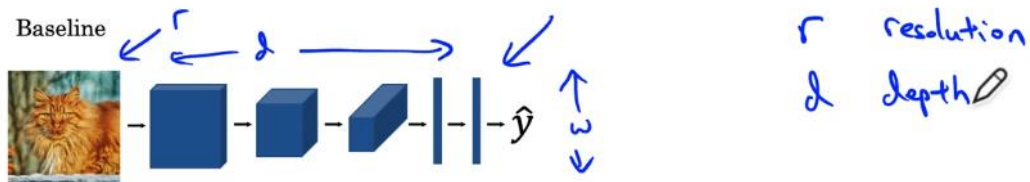
Higher Resolution



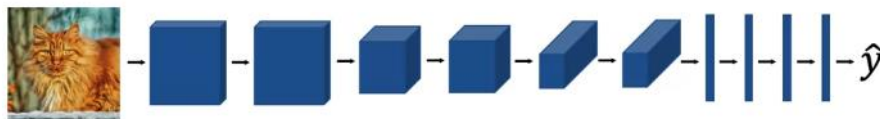
[Tan and Le, 2019, EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks]

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## EfficientNet



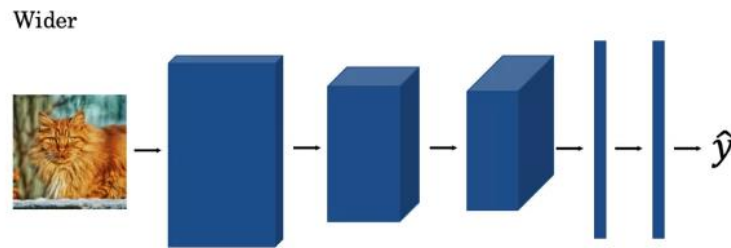
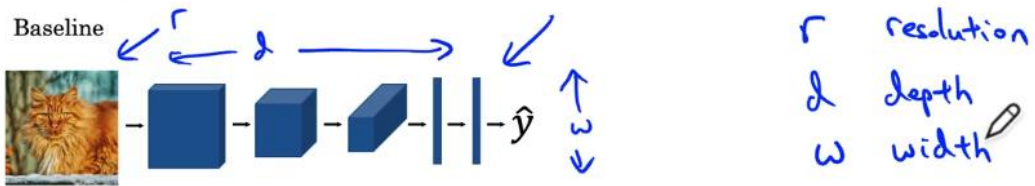
Deeper



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

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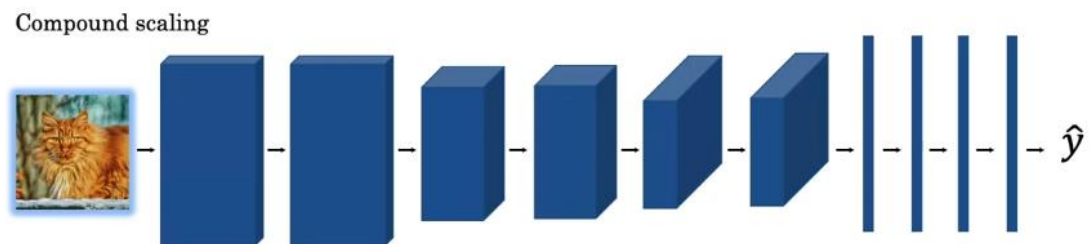
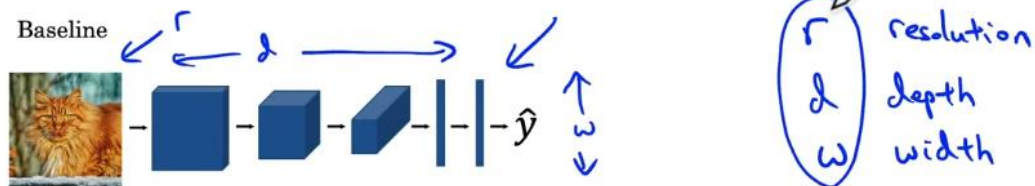
# EfficientNet



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

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# EfficientNet



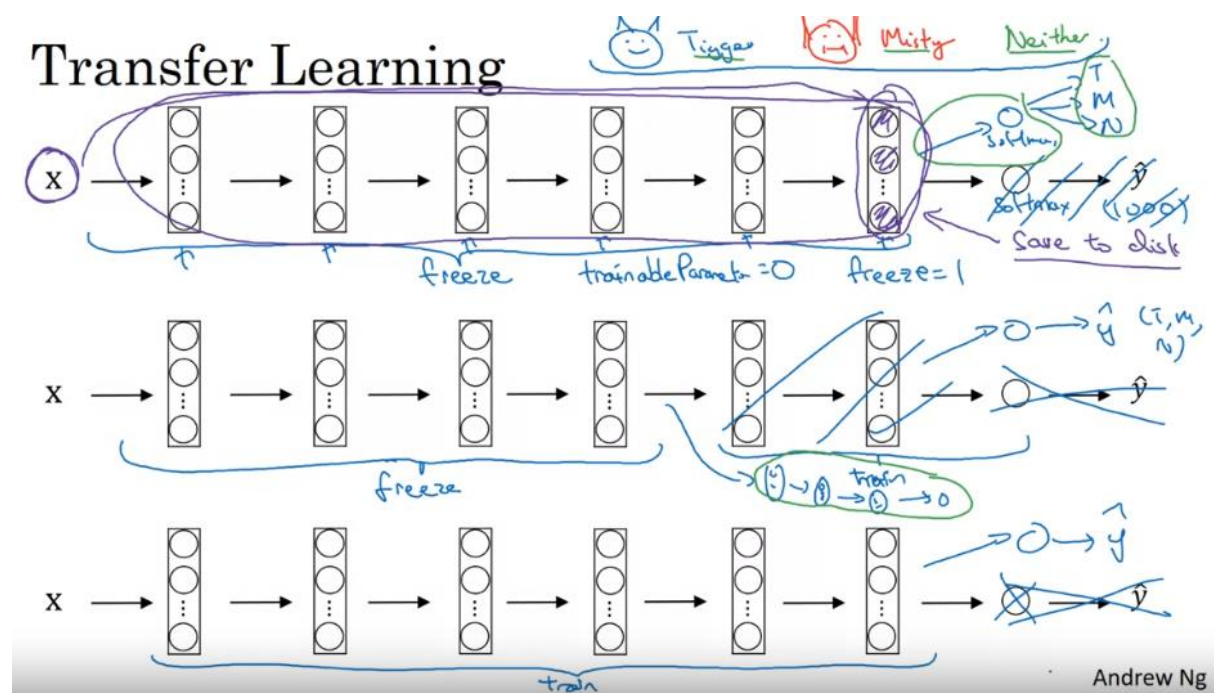
[Tan and Le, 2019, EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks]

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# USING OPEN SOURCE IMPLEMENTATIONS

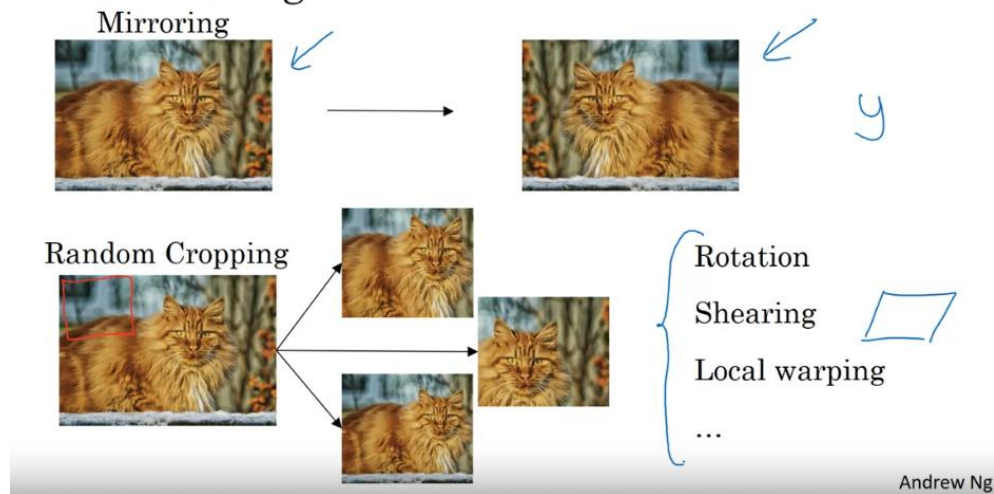
- About git giithub

## TRANSFER LEARNING

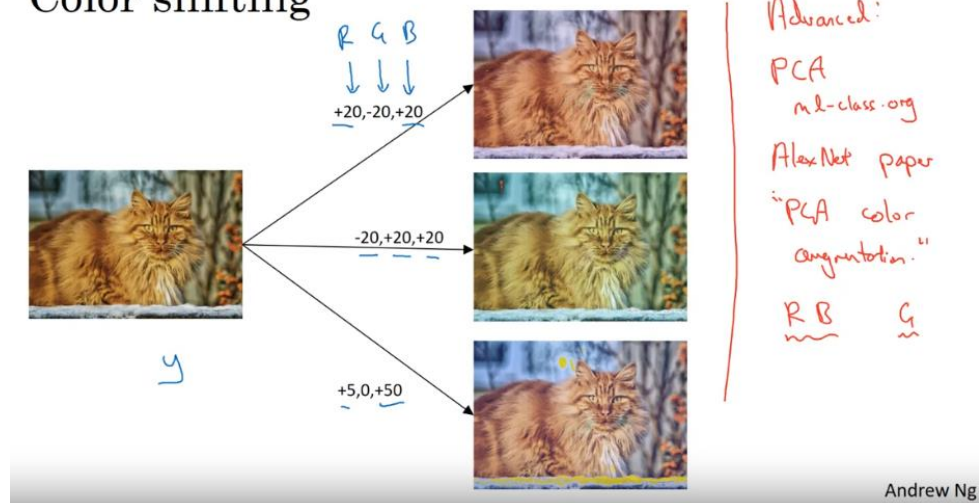


# DATA AUGMENTATION

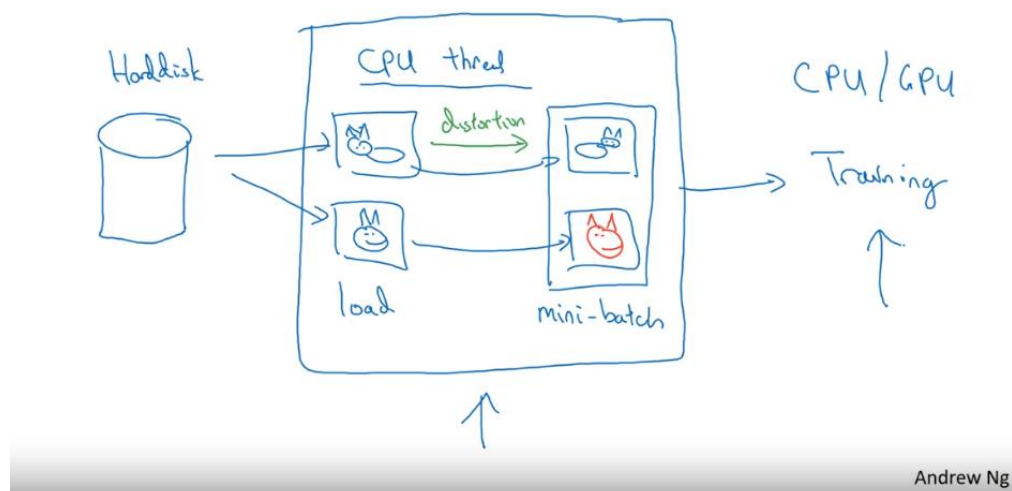
## Common augmentation method



## Color shifting



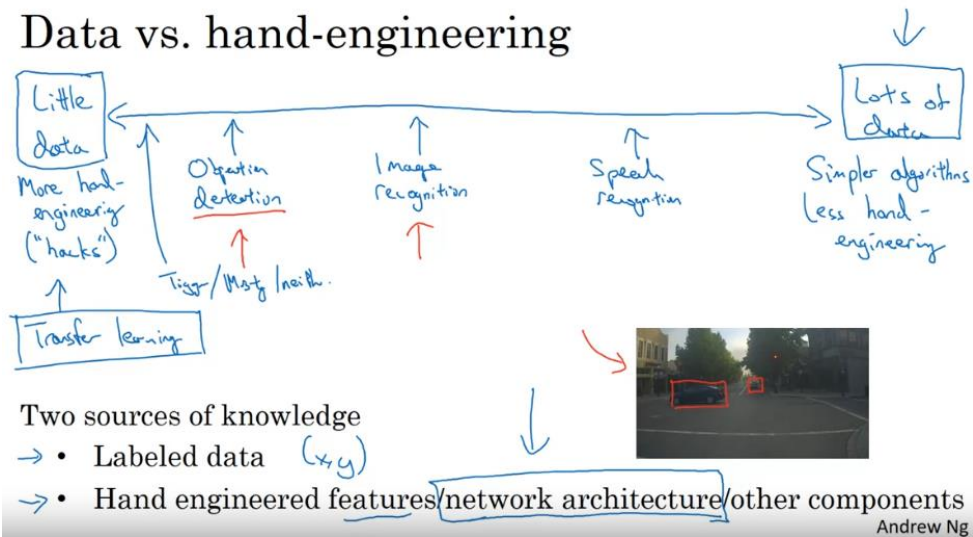
## Implementing distortions during training





# STATE OF COMPUTER VISION

## Data vs. hand-engineering



## Tips for doing well on benchmarks/winning competitions

### Ensembling

- Train several networks independently and average their outputs

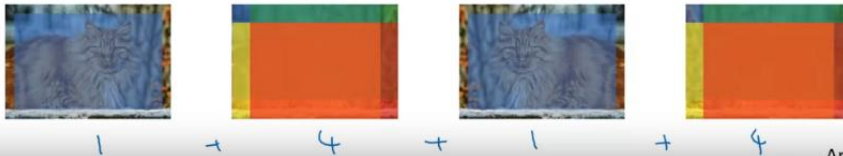
3-15 networks

$\rightarrow \hat{y}$

### 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