We are starting at 14:00!

Grab a seat and get ready

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#7 Modern CNNs

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Agenda

14:00 - 14:15: Recap: convolution

14:15 - 14:45: AlexNet & VGG

14:45 - 15:15: Going deeper

15:15 - 15:30: Improving efficiency: part 1

15:30 - 16:00: Improving efficiency: part 2

16:00 - 16:30: Break

16:30 - 17:00: Transfer learning

17:30 - 18:00: Challenges & Next steps

Last week: You learned to build a CNN

- Convolution
- Pooling/downsampling
- Training

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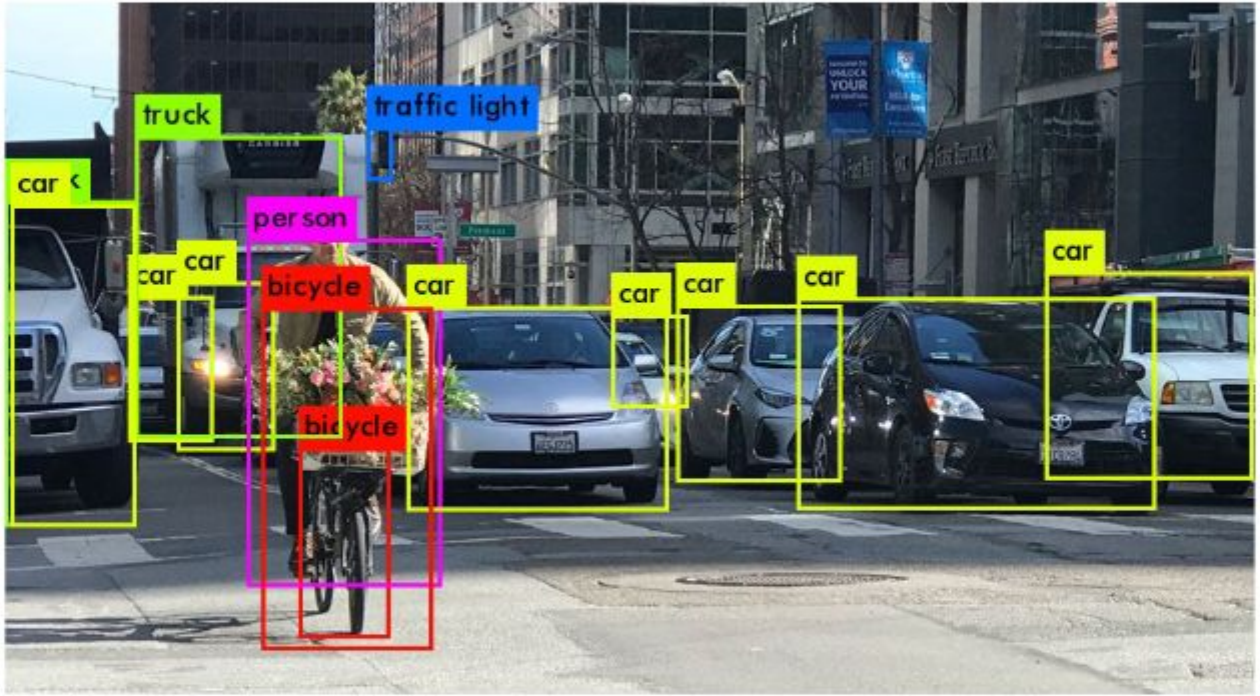
Today: CNNs “in the real world”



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CNNs are everywhere: image segmentation

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CNNs are everywhere: pose estimation

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CNNs are everywhere: image style transfer

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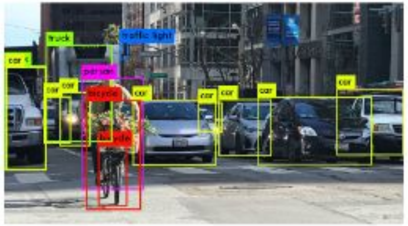
Today: Large-scale CNNs & transfer learning

The success of deep learning for image recognition has been driven by two key factors:

1. Large-scale CNNs
2. Transfer learning



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Recap: convolution

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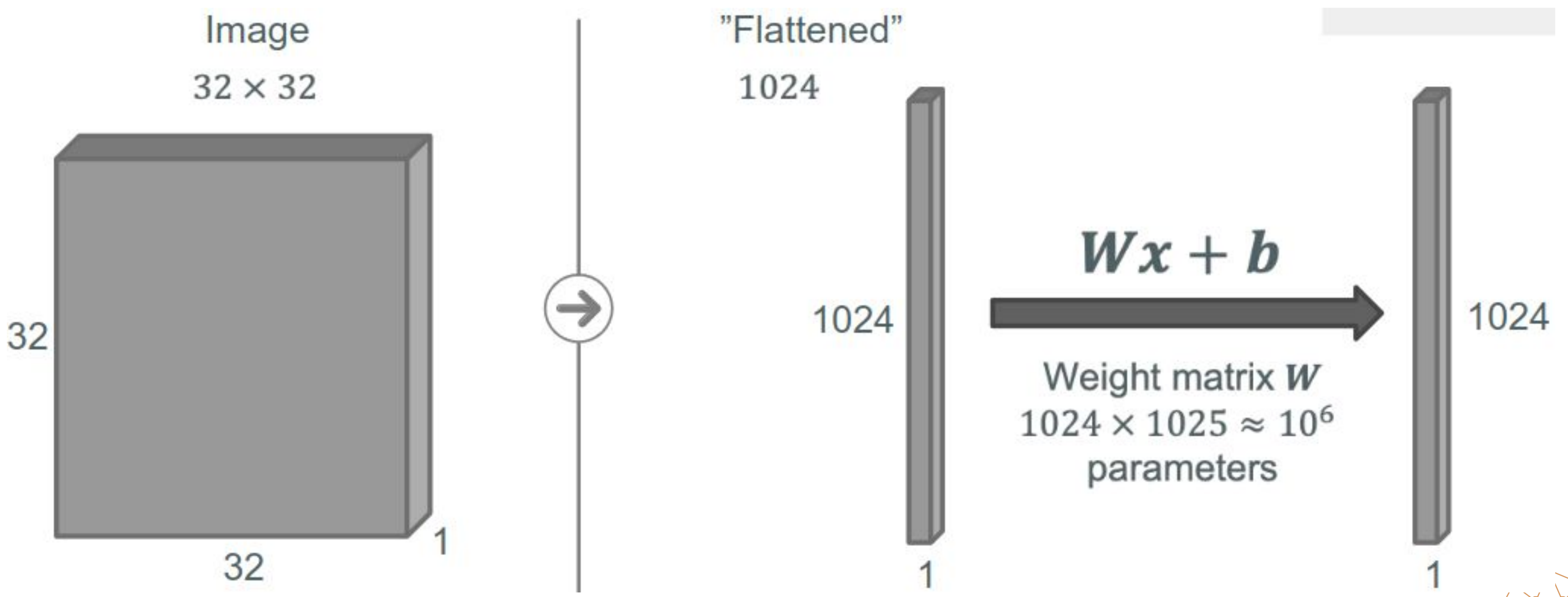
32 x 32 grayscale image: fully-connected layer



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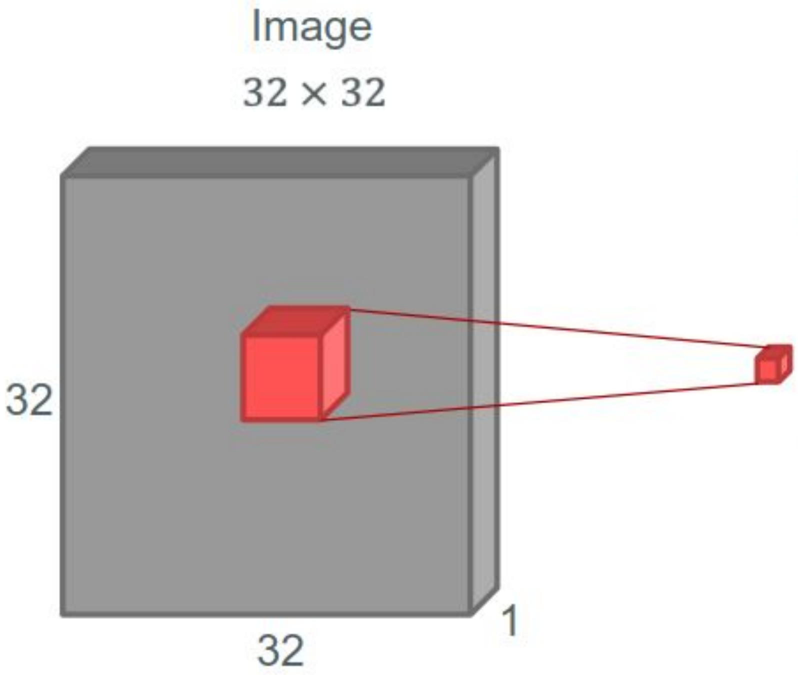
Convolution



Convolve the filter with the image:
Slide over the image, computing dot products

1 number: $\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x} + b$

The result is the inner product of

- a local 3×3 chunk $\boldsymbol{x}$ of the image
- a 3×3 filter $\boldsymbol{w}$
- plus a bias b

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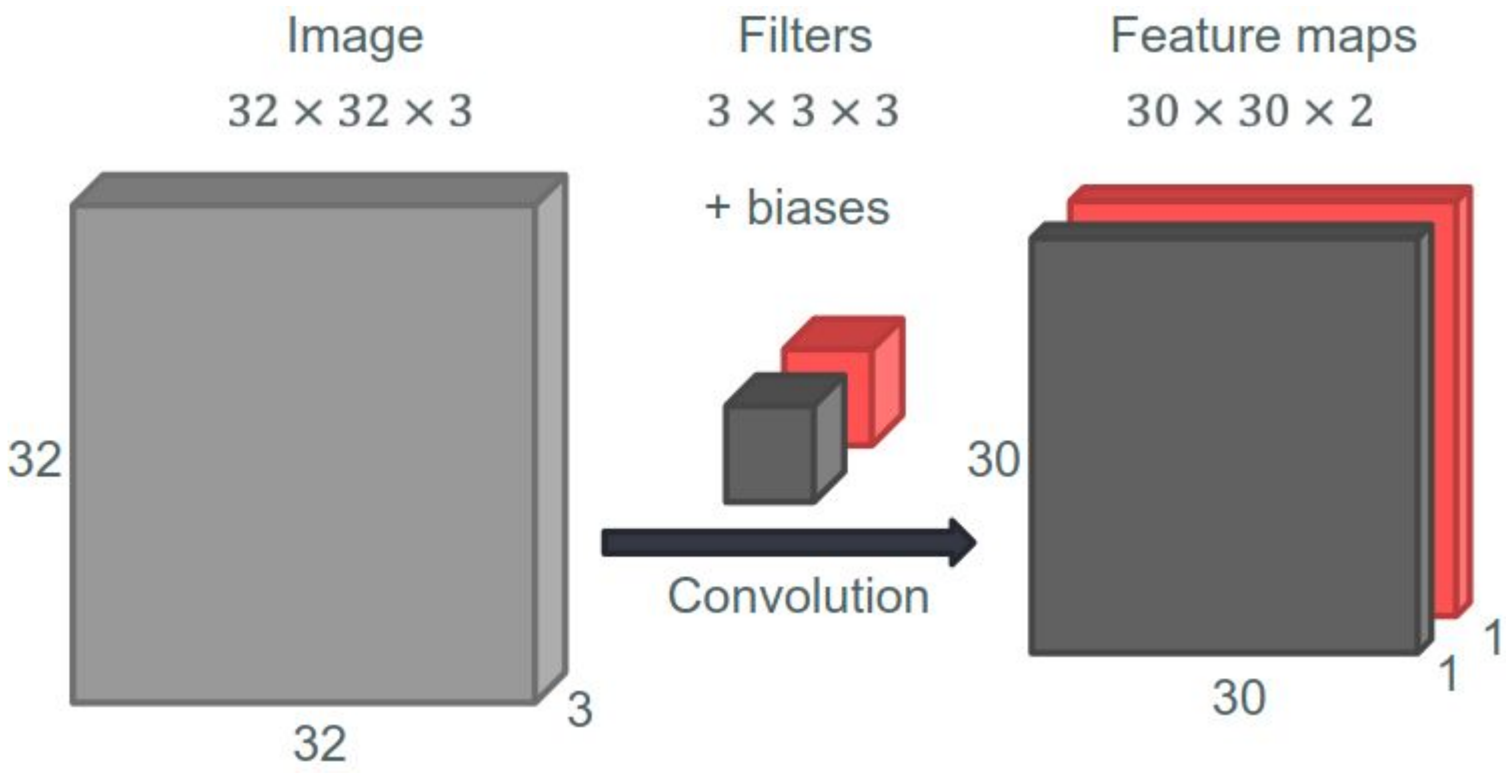
Convolution: color image



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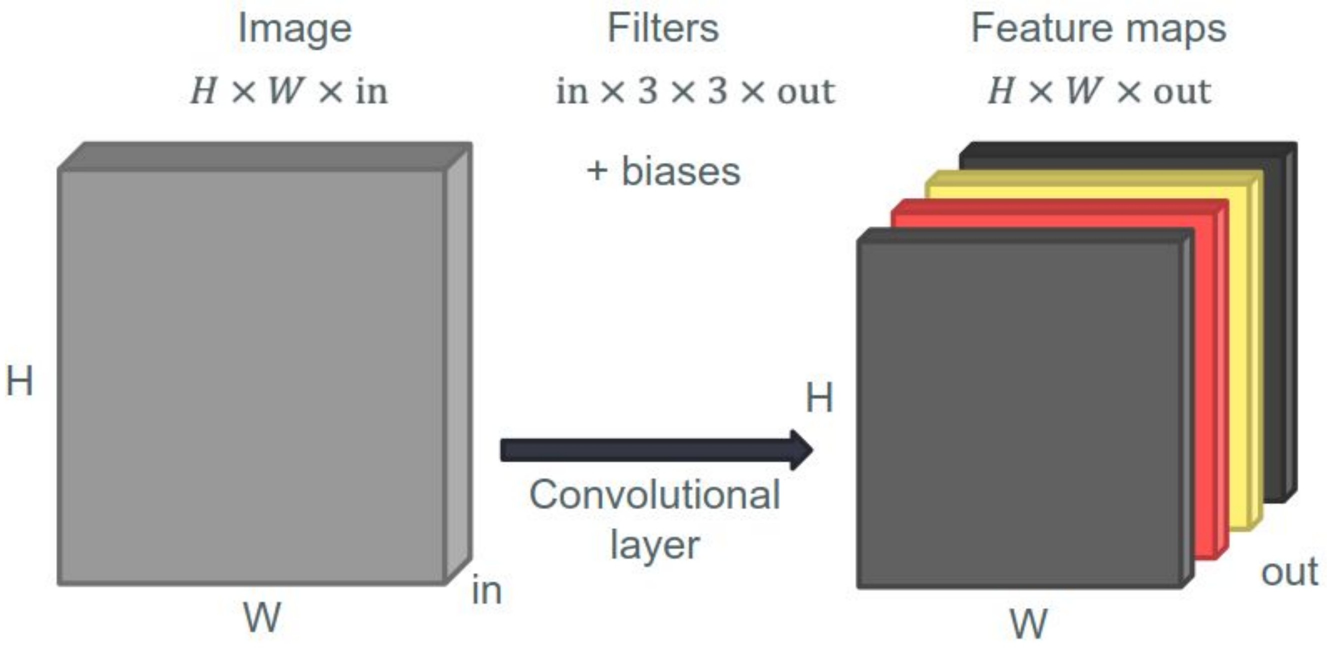
Convolution: in general



"Stack up" feature maps to get a new $H \times W \times \mathrm{out}$ "image"

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Practice

Recap: Recap how much convolutions reduce the number of parameters. Count parameters of a fully-connected and a convnet

Coding Exercise 1

AlexNet & VGG

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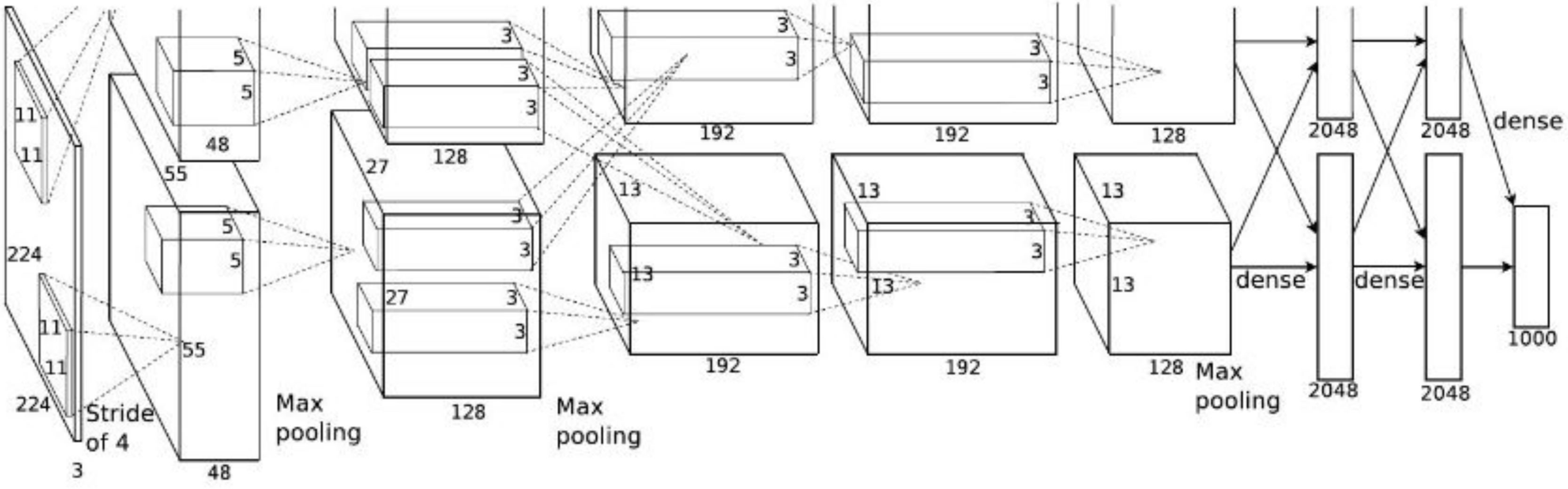
AlexNet (2012)

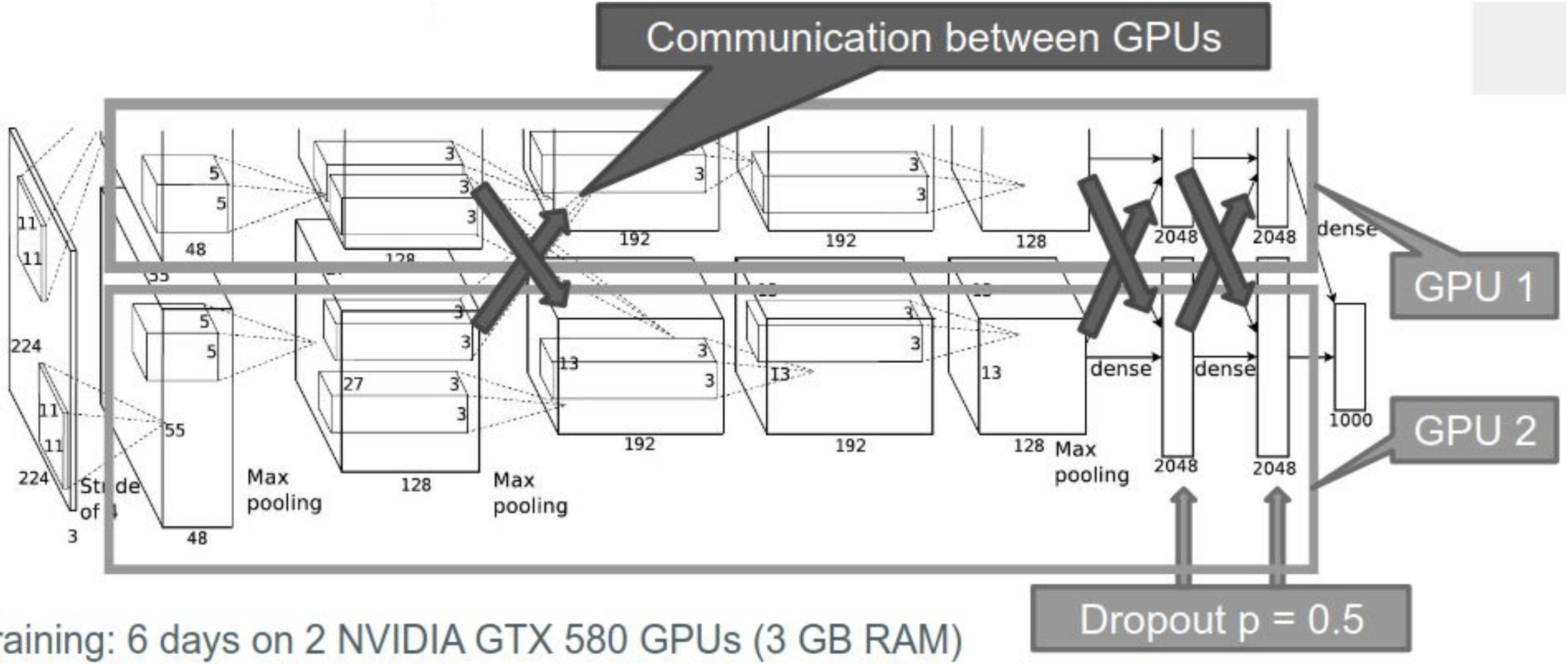


Alex Krizhevsky, Ilya Sutskeever, Geoffrey Hinton

“ImageNet classification with deep convolutional neural networks.” NeurIPS 2012

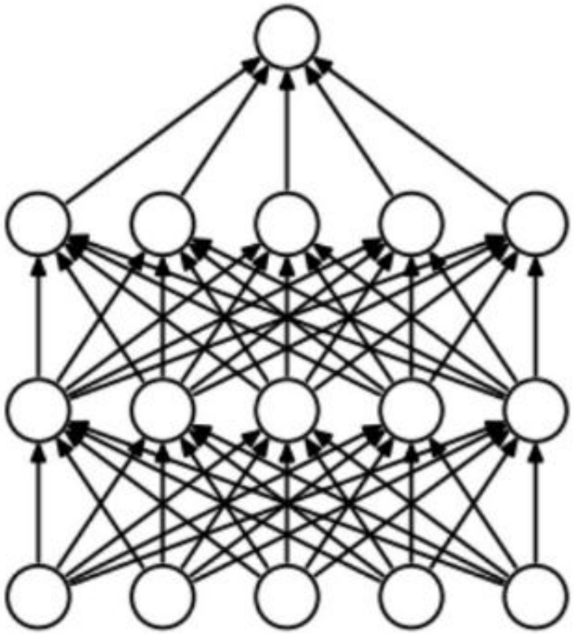
AlexNet (2012)

```
torchvision.models.alexnet()
```

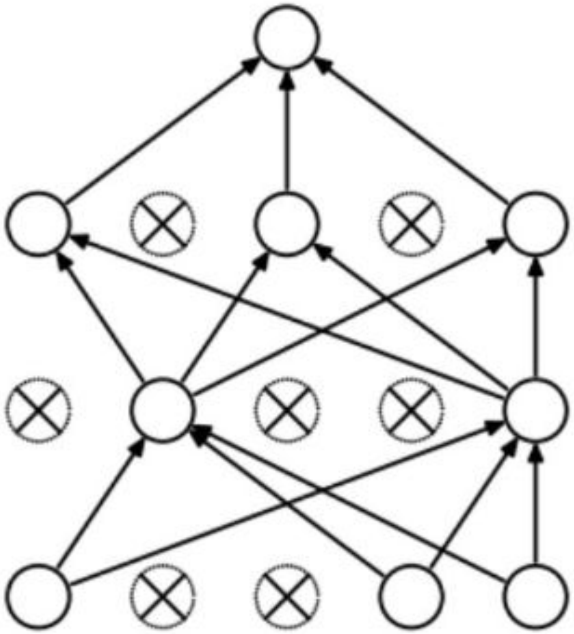


Training: 6 days on 2 NVIDIA GTX 580 GPUs (3 GB RAM)
8 layers / 60 million parameters

Dropout stochastically deactivates neurons



(a) Standard Neural Net



(b) After applying dropout.

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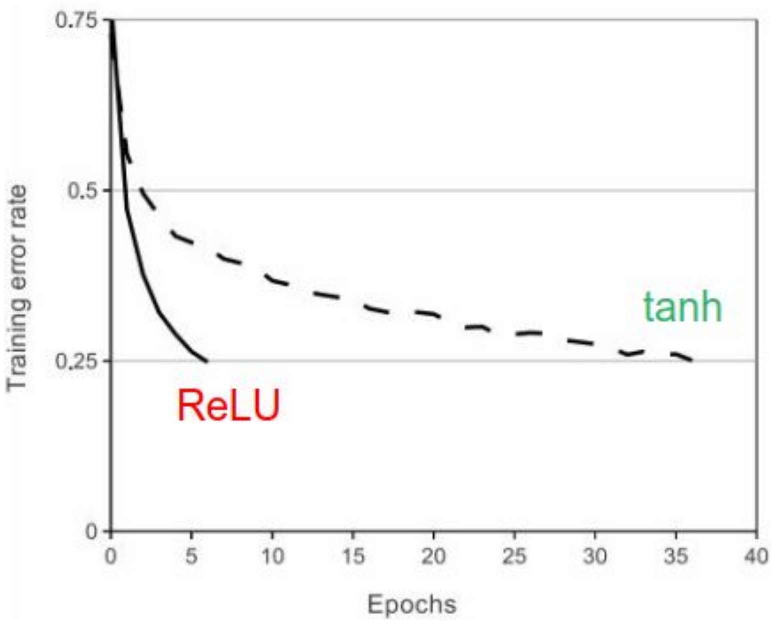
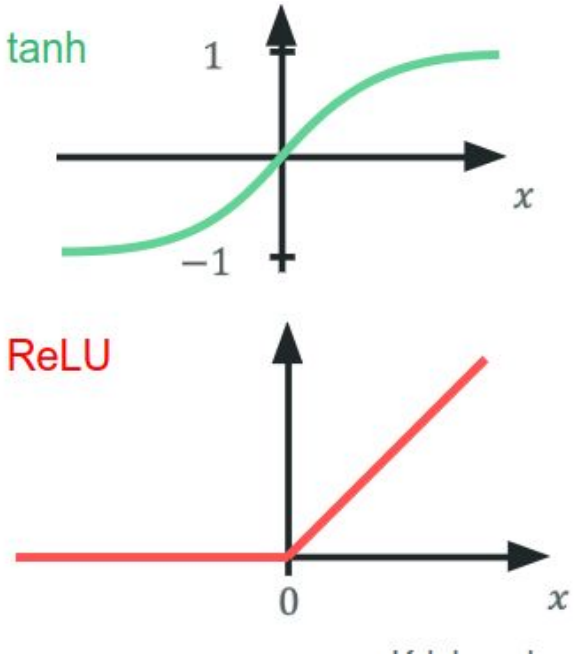
ReLU trains faster than tanh





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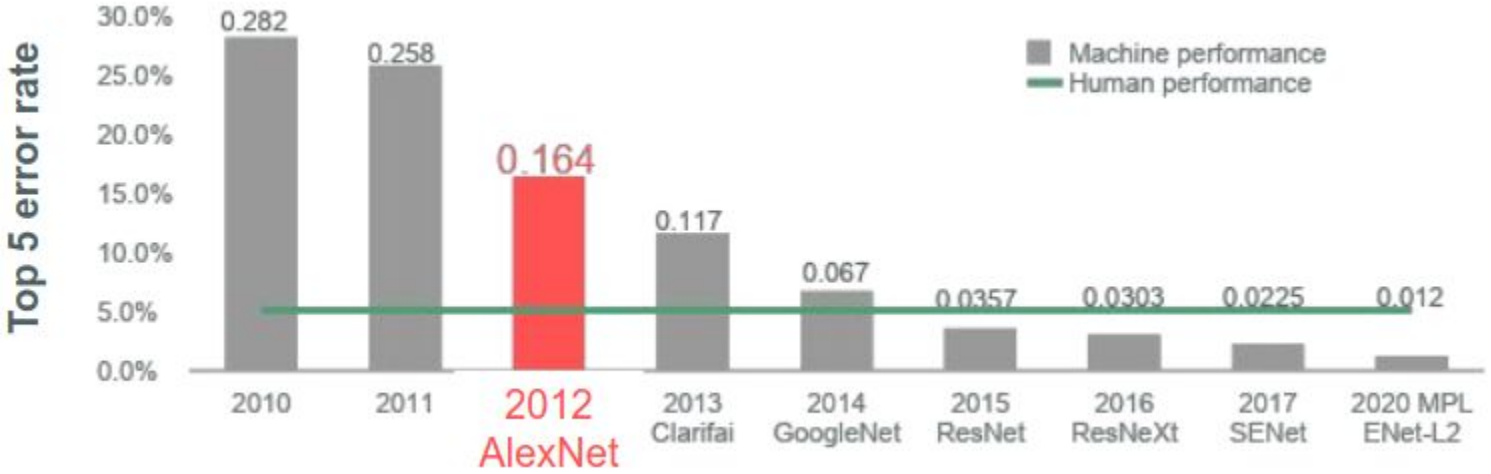
AlexNet (2012): Results

Smoked the competition with 16% top-5 error (runner-up had 26%)

One of the first neural nets trained on a GPU with CUDA.

Paper cited over 80,000 times



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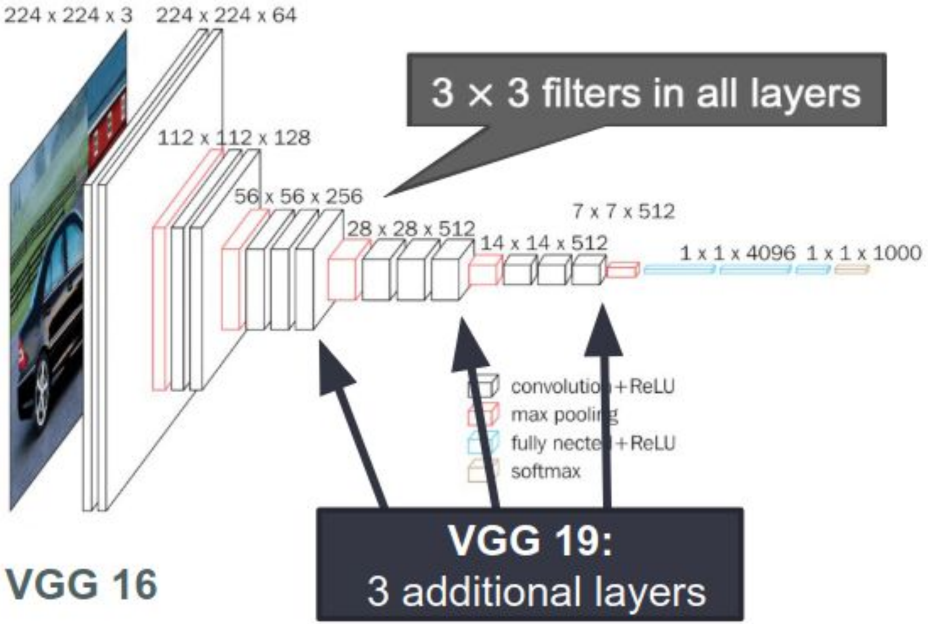
VGG (2014)

```
torchvision.models.vgg16()
torchvision.models.vgg19()
torchvision.models.vgg19_bn()
...
```



By the Vision Geometry Group at Oxford

Only 3 × 3 filters and max pooling

Training: 3 weeks on 4 NVIDIA Titan Black GPUs, 6 GB RAM

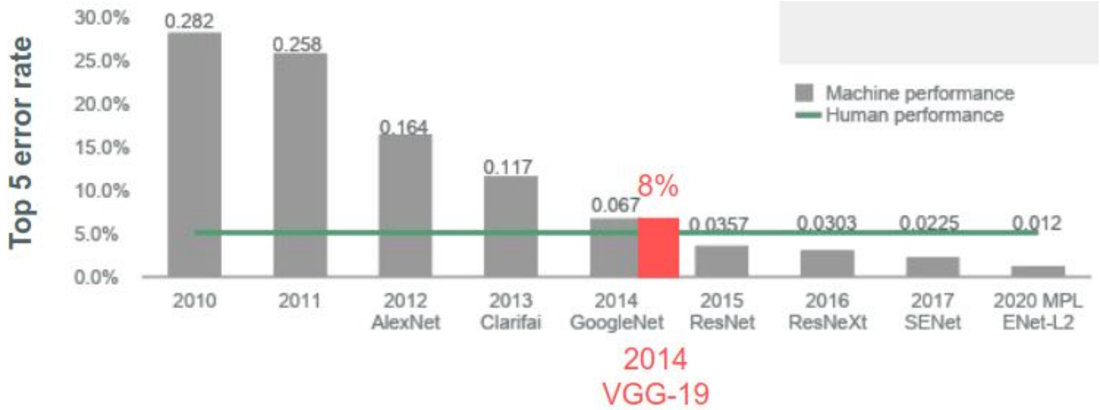
First train smaller configurations, then inject layers in between:
11 □ 13 □ 16 □ 19 layers

VGG-19: 138 million parameters / 500 MB

VGG (2014)

Has been very popular
for a long time

- Particularly simple architecture
- Half the error rate of AlexNet
- Pre-trained net available



A couple of drawbacks:

- Slow and complex to train. Started with 11-layer version, then add additional layers, iterate until at 19
- Weights themselves are large: over 530 MB, which makes deploying it a tiresome task
- First couple of layers are very expensive to compute as they operate at full resolution

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Practice

Inspect what AlexNet has learned: filters and feature maps

[Interactive Demo 3.2]()

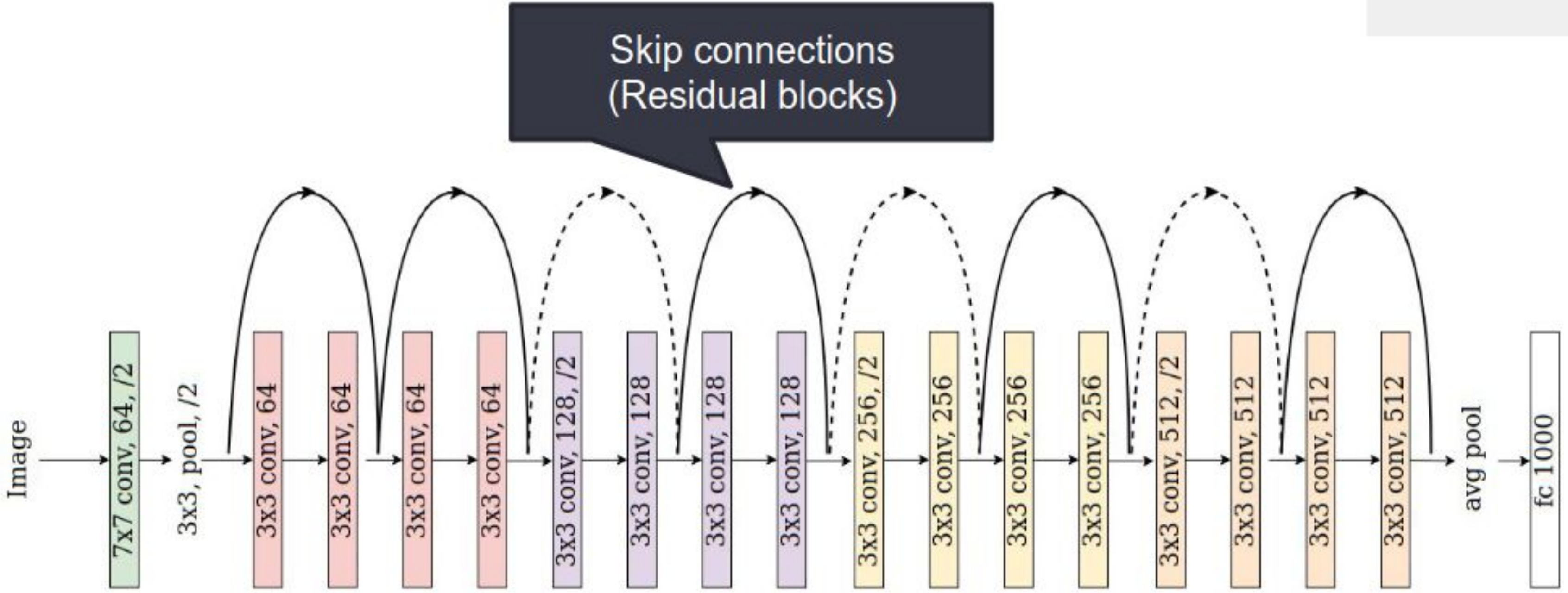
Going deeper

Residual Networks (ResNets)

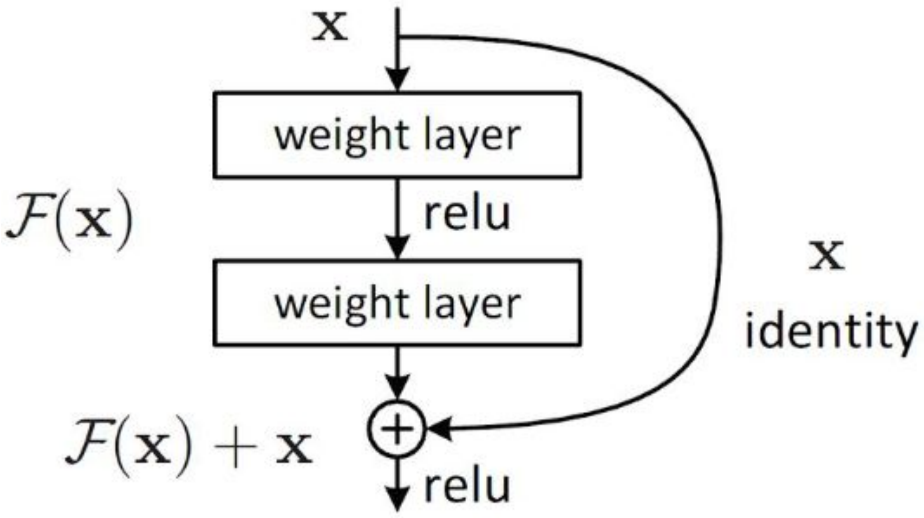

WE NEED TO GO
DEEPER
troll-face.ru

ResNet (2015)

```
torchvision.models.resnet18()
...
torchvision.models.resnet152()
```



Residual blocks ("skip connections")



Each block learns to approximate a residual function

Better gradient flow because of skip connections

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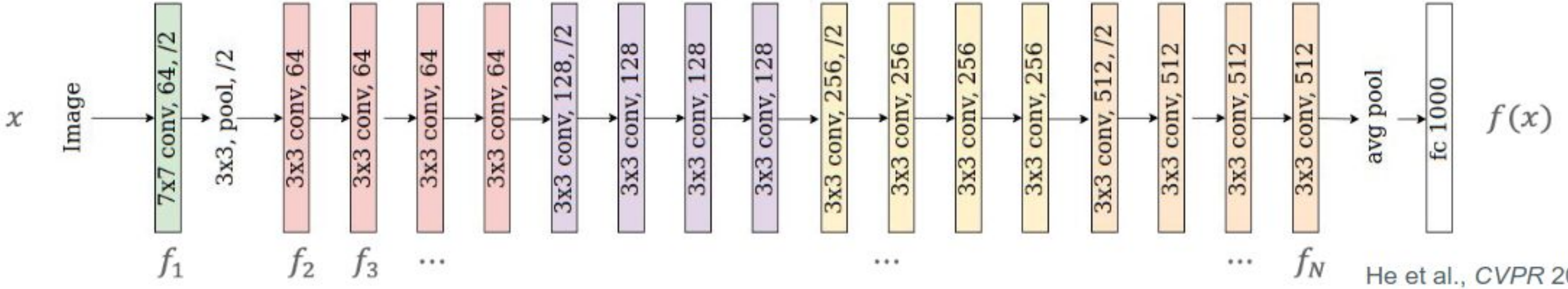
Skip connections avoid vanishing gradients

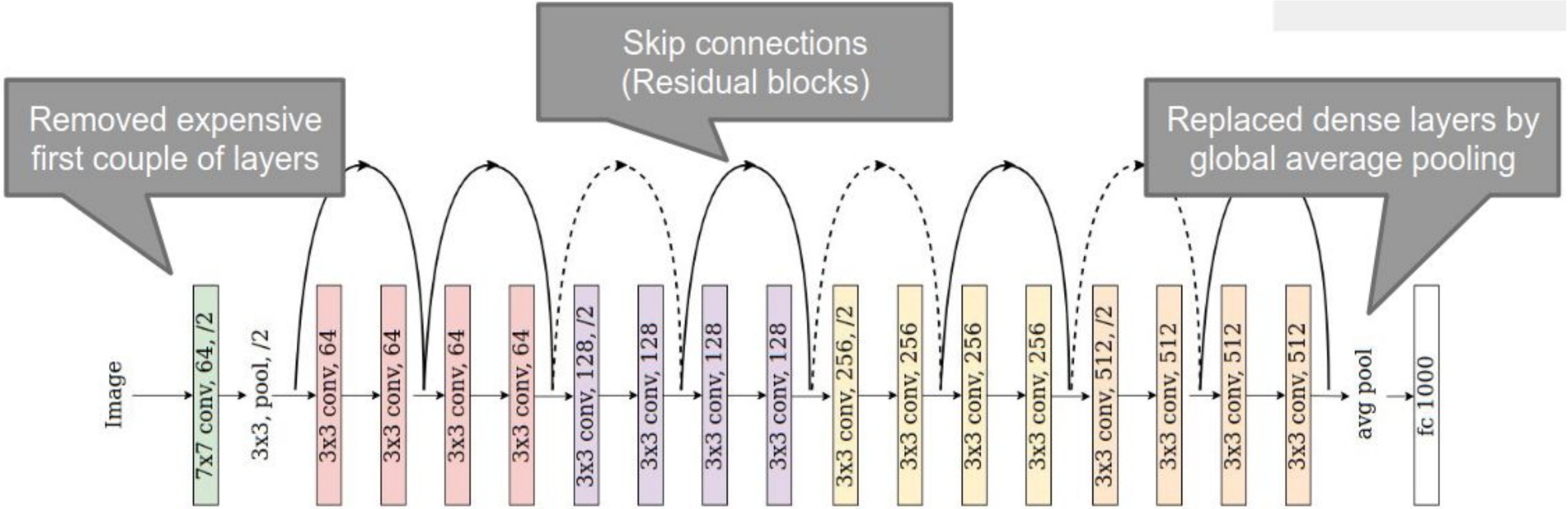
$$f(x) = f_1\left(f_2(\cdots f_N(x))\right) \quad \Rightarrow \quad f'(x) = f_1'(f_2(\cdots)) \cdot f_2'(\cdots) \cdot \ldots \cdot f_N'(x) \qquad \textit{(chain rule)}$$



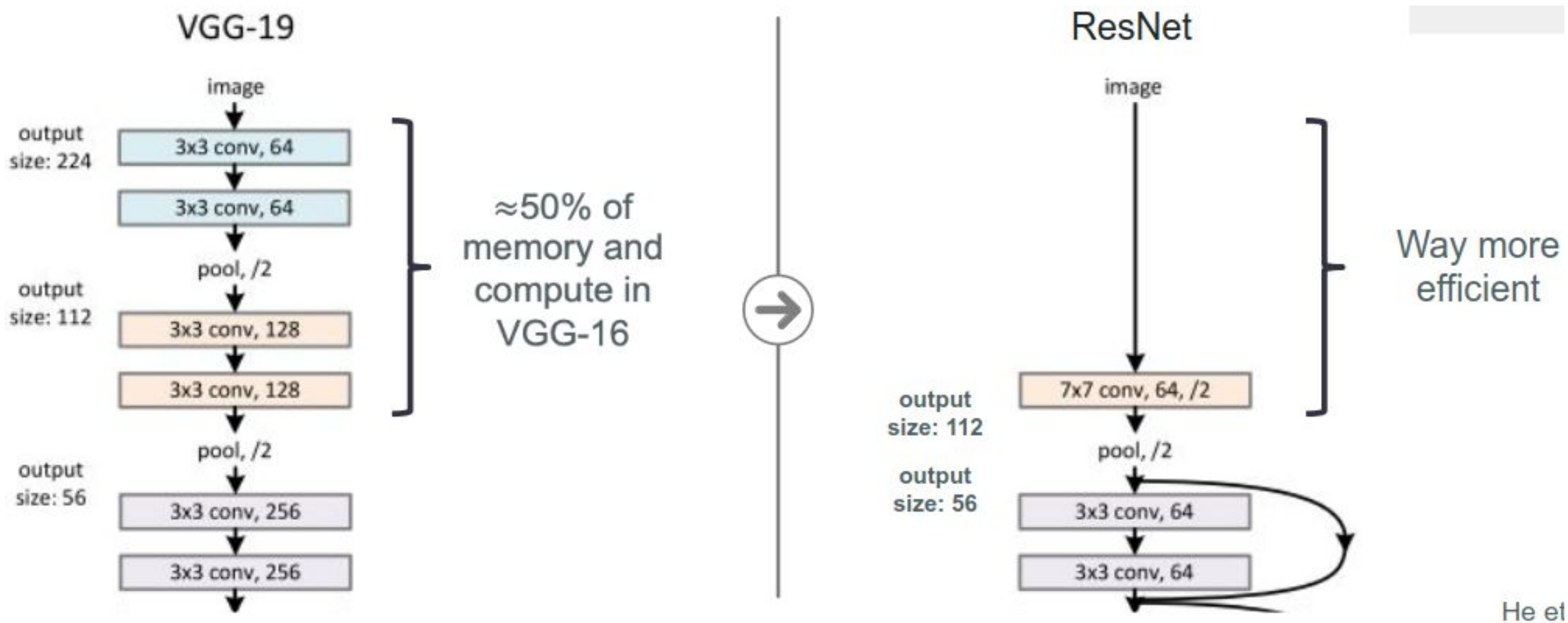
He et al., *CVPR* 2016

ResNet (2015)

```
torchvision.models.resnet18()
...
torchvision.models.resnet152()
```



ResNet: Remove expensive early layers



He et

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Practice

- Load a pre-trained ResNet-18
- Run a couple of images through the net
- Inspect its predictions

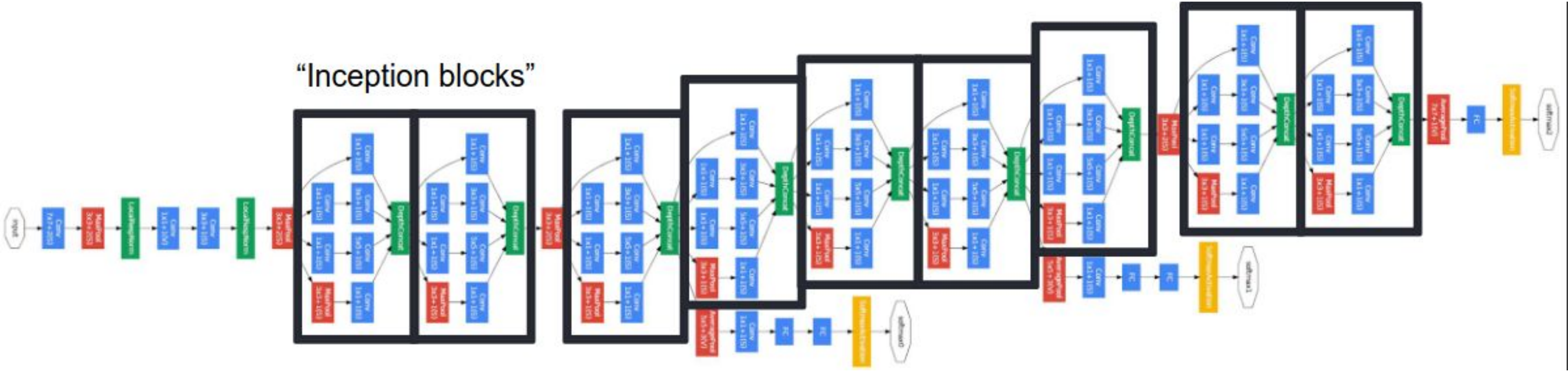
How does it fare with non-photographic images?

[Coding Exercise 4.1]

Improving efficiency

Part 1: Inception + ResNeXt

Inception / GoogLeNet (2014/15)



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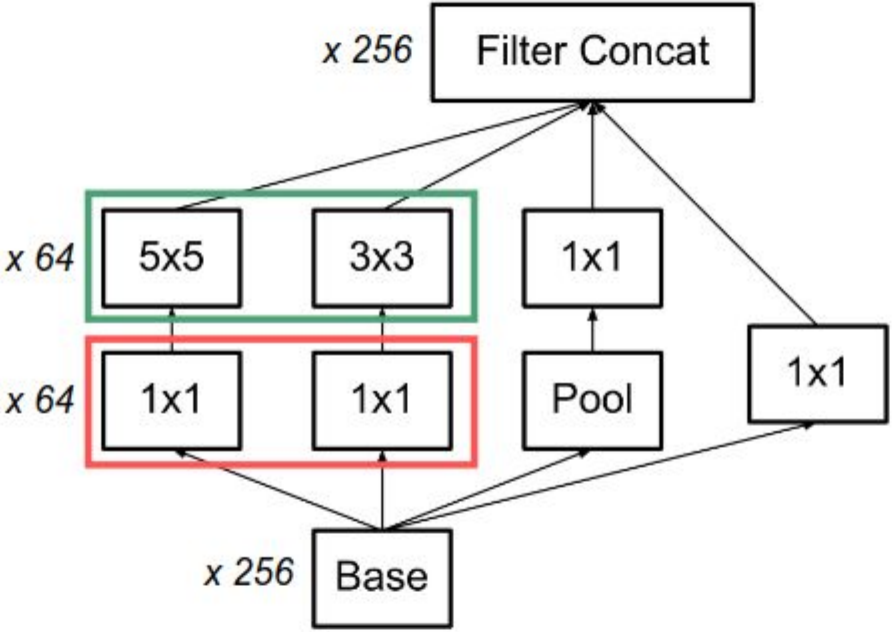
Inception v1: efficiency by 1 x 1 convolutions

```
torchvision.models.googlenet()
```

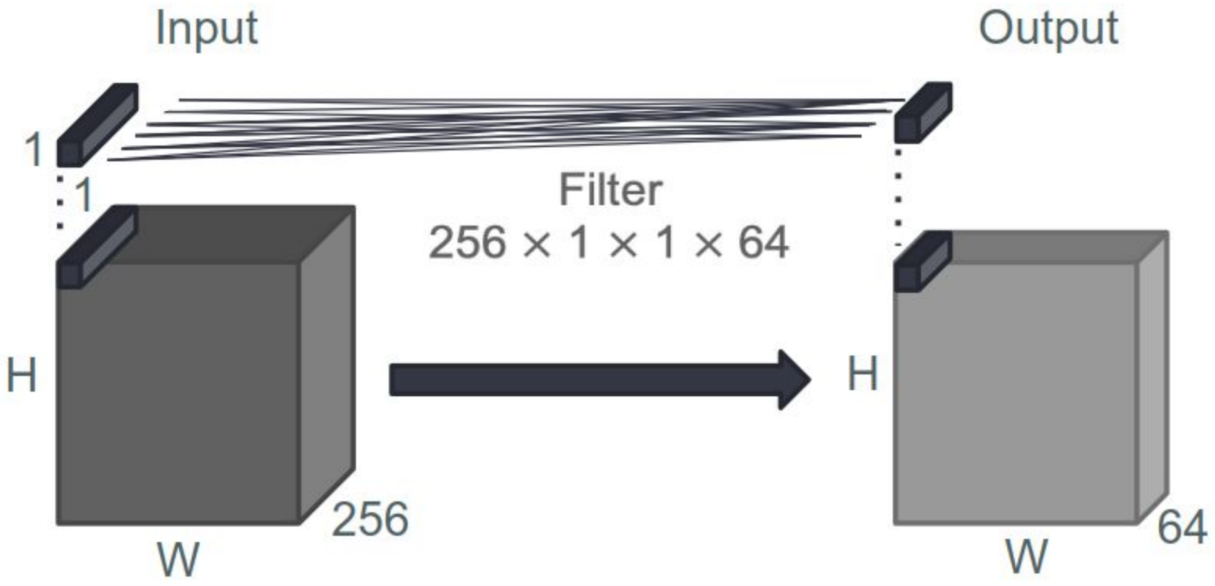
A single "Inception Module"

Spatial Processing

Reducing number of feature maps



1 x 1 convolutions



No spatial processing

Reduces number of channels

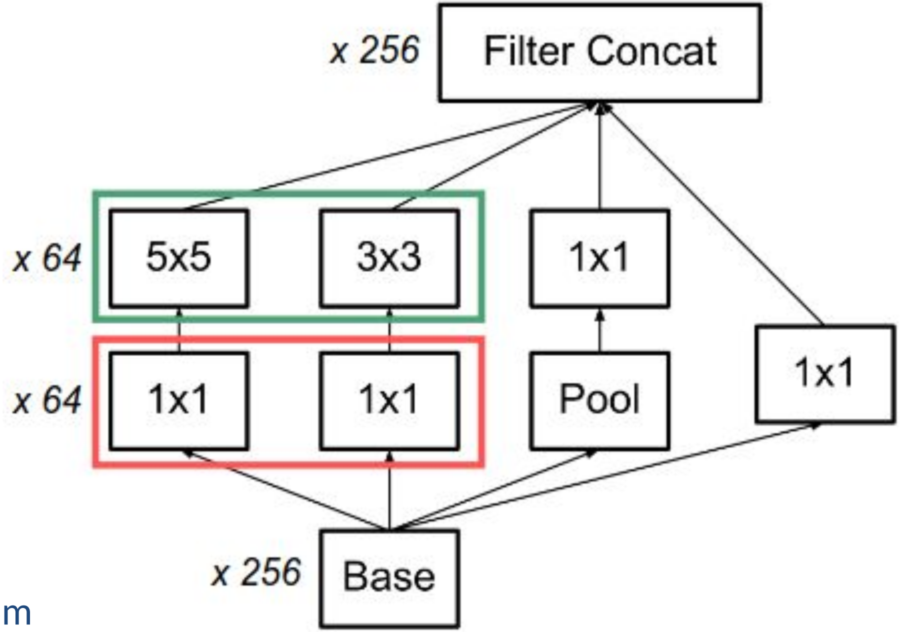
Inception v1: efficiency by 1 x 1 convolutions

```
torchvision.models.googlenet()
```

A single "Inception Module"

Spatial Processing

Reducing number of feature maps



 # parameters

Standard convolution: 256 x 5 x 5 x 256 = 1.6m

Inception branch: 256 x 64 + 64 x 5 x 5 x 64 = 120k

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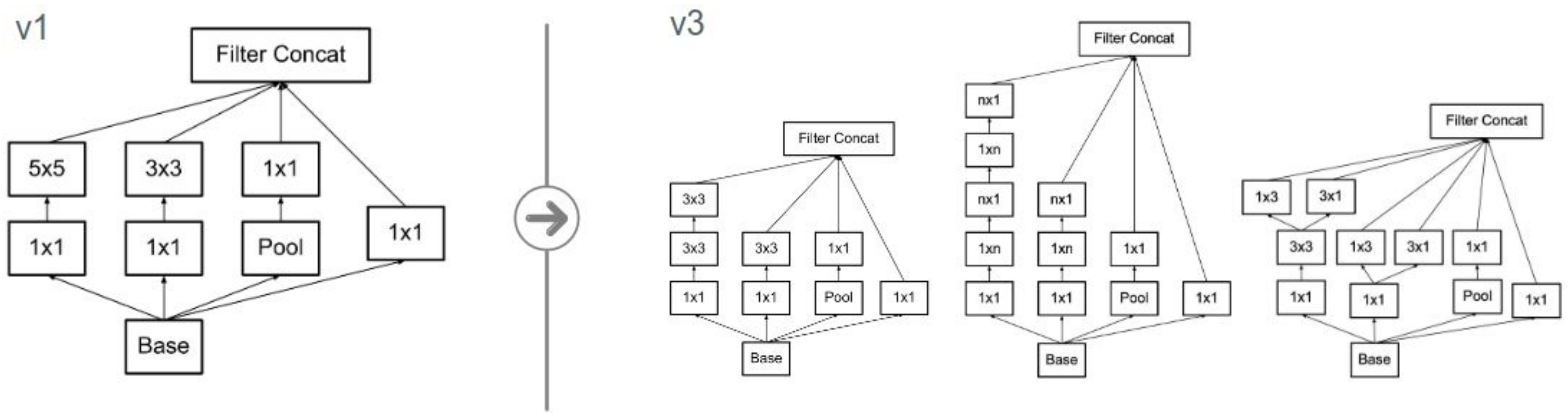
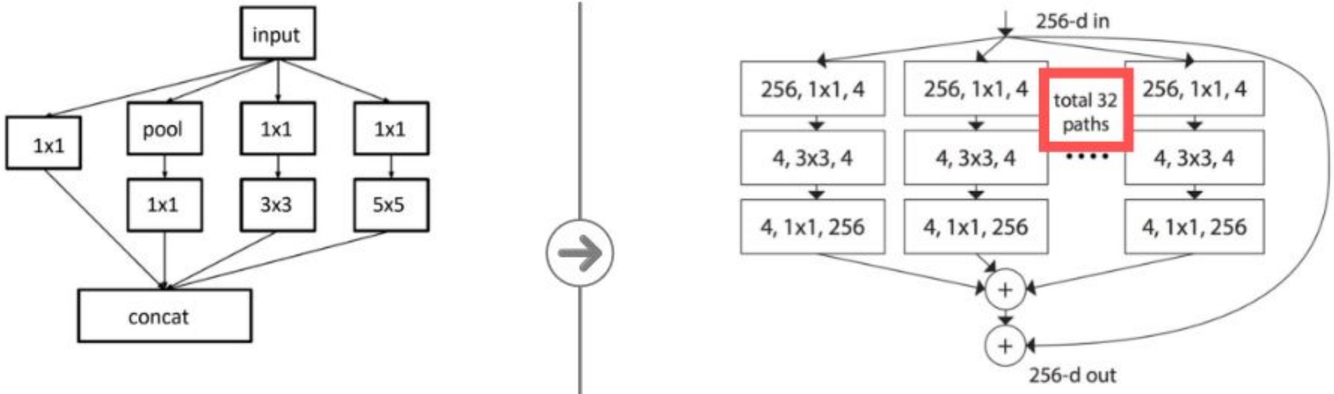
Inception v3: efficiency and bottlenecks

```
torchvision.models.inception_v3()
```



ResNeXt: combining Inception and ResNet

```
torchvision.models. models.resnext50_32x4d()
```



Inception:
heterogeneous multi-branch

ResNeXt:
uniform multi-branch

Compression

Spatial processing

Channel mixing

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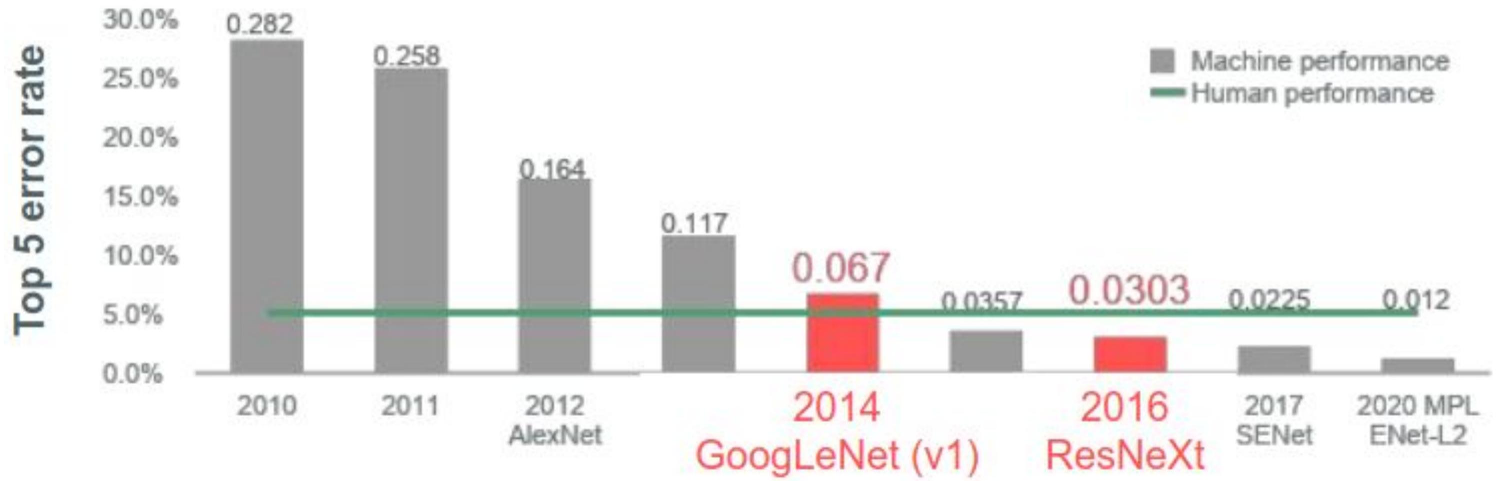
Inception-v1 (2014) + ResNeXt (2016): Results

6.7% top-5 error rate in 2014, 3.0% in 2016!

Top-5 error rate of human expert (Andrej Karpathy) was ~5%



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Improving efficiency

Part 2: MobileNet / depthwise separable convolutions

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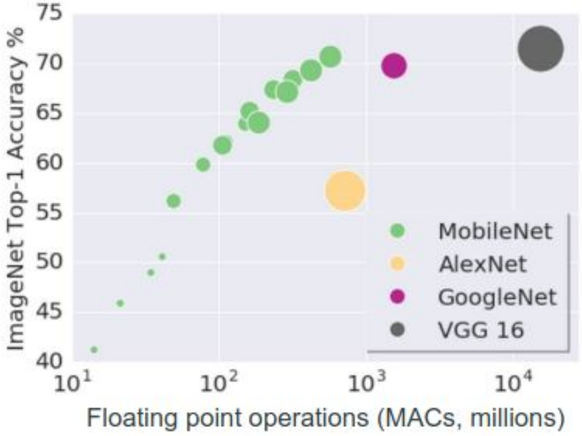
MobileNet (2017): pushing efficiency

```
torchvision.models.mobilenet_v2()
```



Same accuracy as VGG, >100 frames/sec on iPhone 7

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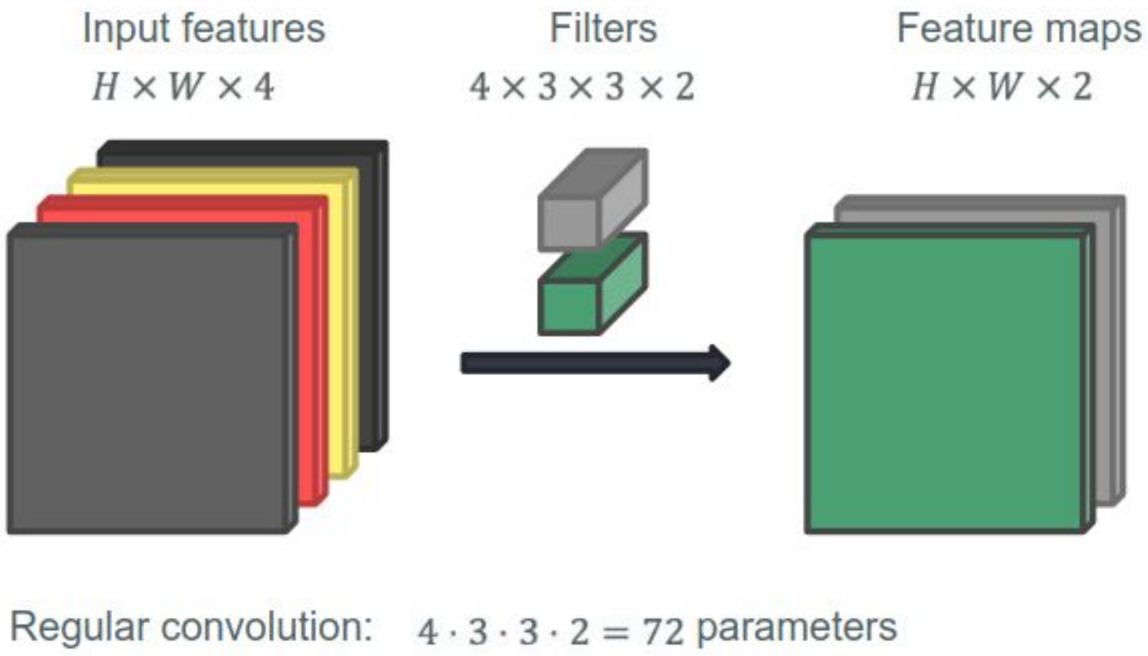
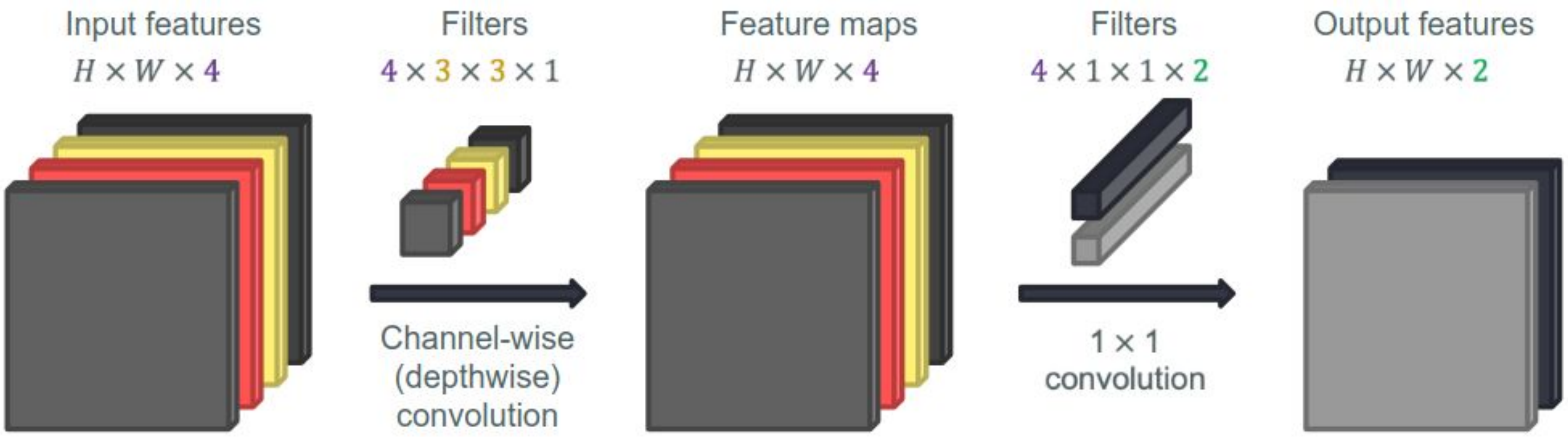
Recap: regular convolution layer



Depthwise separable convolution



Depthwise separable: $4 \cdot 3 \cdot 3 + 4 \cdot 2 = 44$ parameters $\quad O(MK^2 + MN)$ parameters

Regular convolution: $4 \cdot 3 \cdot 3 \cdot 2 = 72$ parameters $\quad O(MK^2N)$ parameters

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Depthwise separable convolution

Depthwise separable: $512 \cdot 3 \cdot 3 + 512 \cdot 512 = 267\text{k parameters}$

Regular convolution: $512 \cdot 3 \cdot 3 \cdot 512 = 2.4\text{m parameters}$

Practice

Understand how depthwise separable convolutions improve efficiency and save parameters in CNNs.

Coding Exercise 6.1

Break

Transfer learning

Building upon pre-trained CNNs

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Standing on the shoulders of giants

Image source: https://www.cgtrader.com/3d-models/character/man/cartoon-giant

Transfer learning: motivation

Suppose you want to build an app to recognize flowers…

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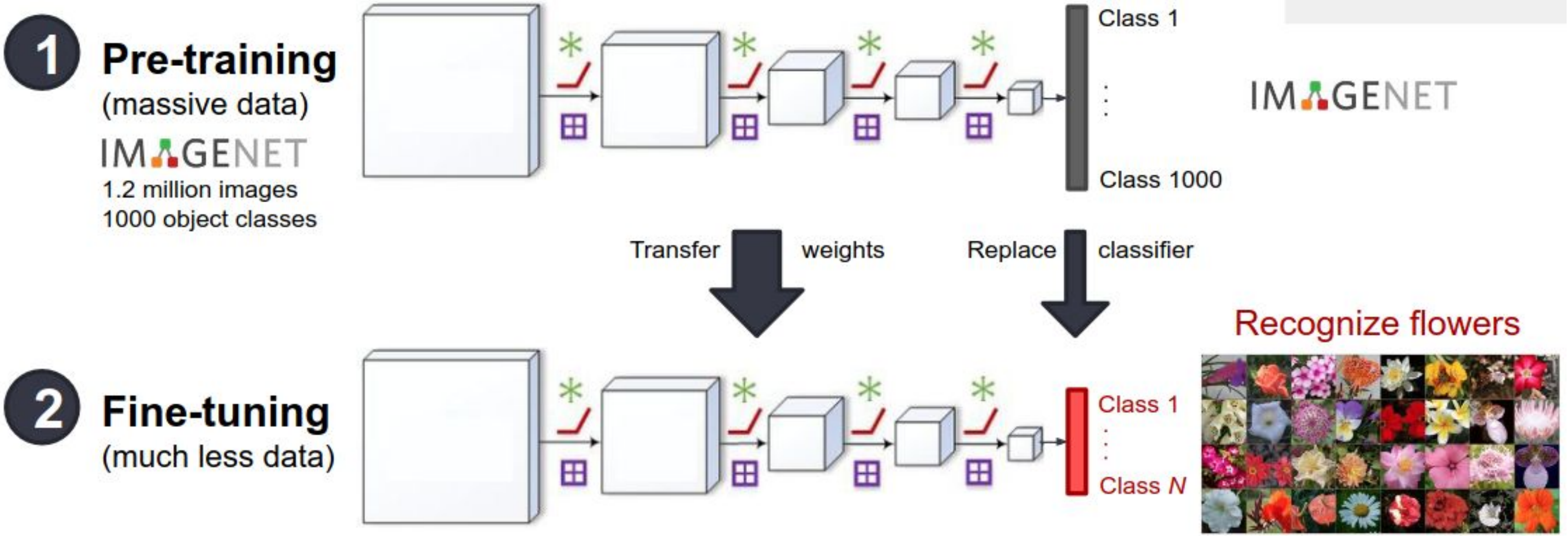
Transfer learning: the idea



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Transfer learning: what should we train?

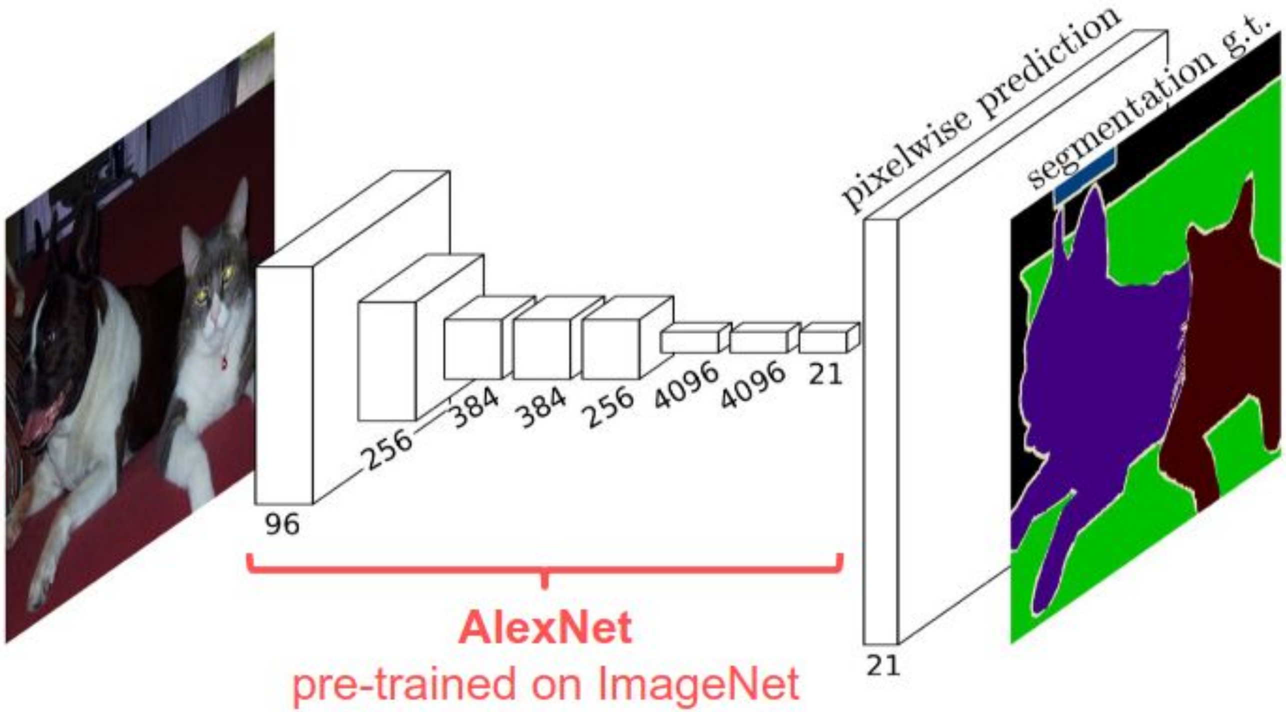
Option 1: Train only classification layer, freeze backbone
(sometimes referred to as the “linear evaluation protocol”)

- Fast & simple

Option 2: Train classification layer, fine-tune backbone at the same time

- Slower, but can adapt feature extraction to dataset statistics

Example: semantic segmentation



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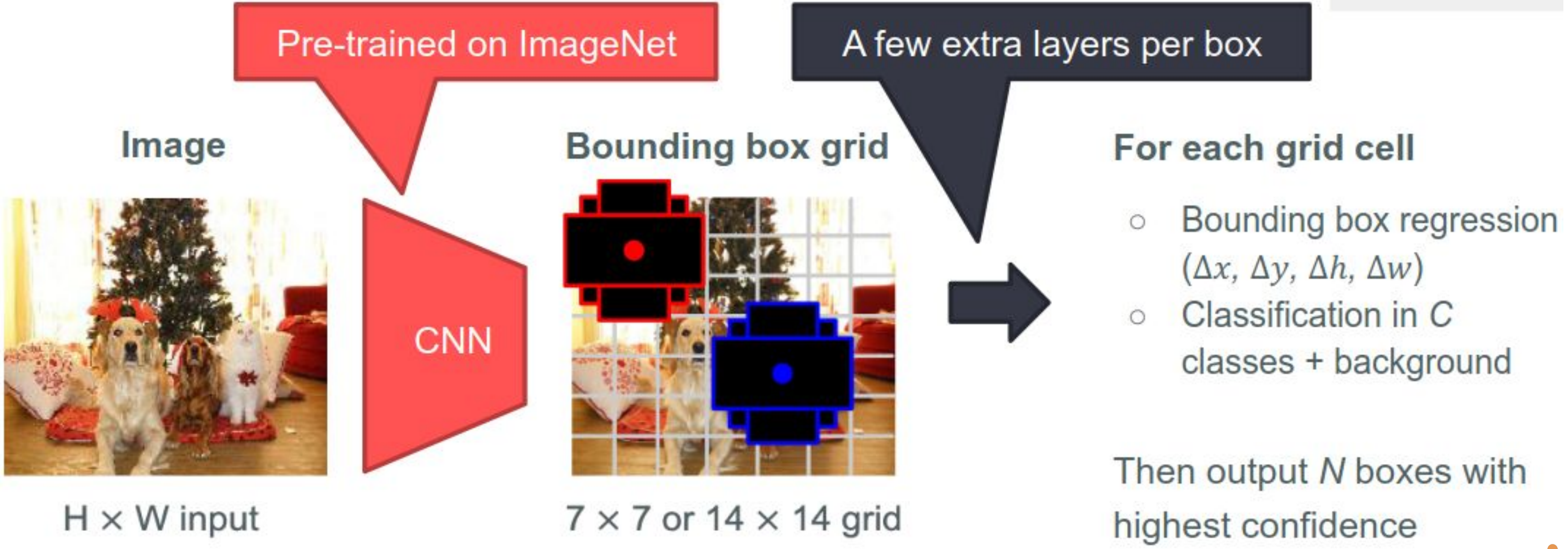
Single-stage object detectors: SSD, YOLO, …



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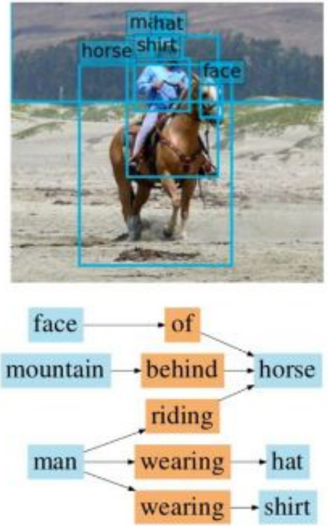
Pre-training on ImageNet is everywhere ...

Pose estimation

Image captioning

"two young girls are playing with lego toy."

Scene graph prediction



...

Many, many more

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Practice

Implement transfer learning for Pokemon classification

Which approach do you think will perform best?

- Training from scratch
- Training only the classification layer
- Fine-tuning entire network

Section 7.4

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TYU: Convolution

Assume that the number of filters is less than number of input channel, Which of the following will reduce the number of dimensions of input X

A. 1x1 CONV, 3 filters, no padding
B. 3x3 CONV, 3 filters, no padding
C. 3x3 POOL, 3 filters, no padding
D. All of the above

Challenges & Next steps!

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Any questions?

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THANKS

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coming soon
coming soon