High Level Computer Vision

CNN Architectures

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https://www.mpi-inf.mpg.de/hlcv

Exam dates

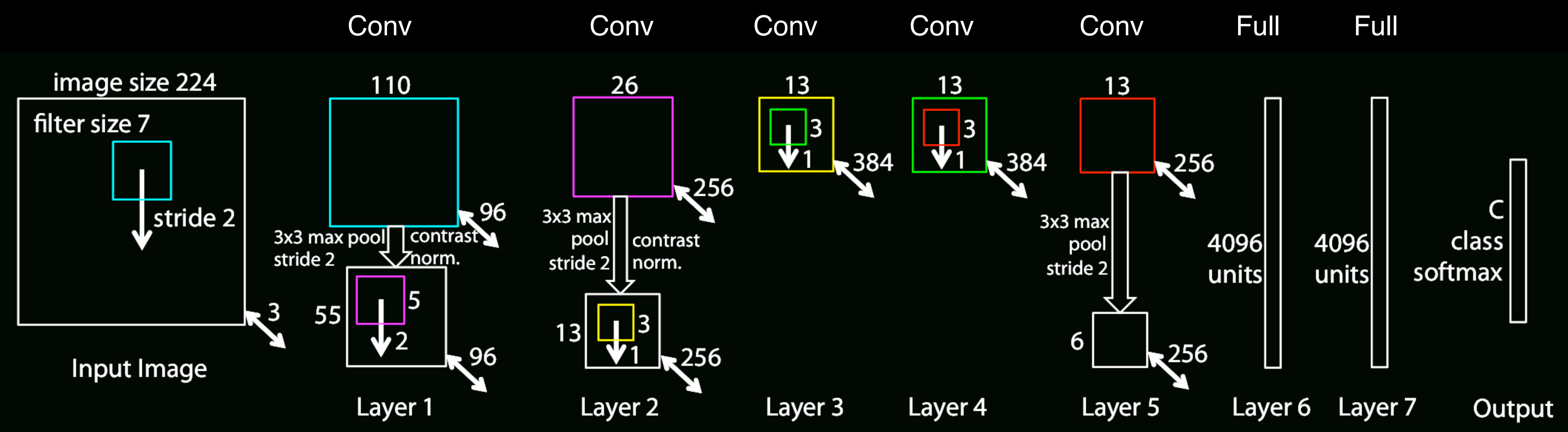
- Exam dates - 3 batches
  - 18/19 July
  - 20/21 August
  - 1/2 October

- Please fill in doodle poll
  - https://doodle.com/poll/6q3uq2pqwhpwbixe

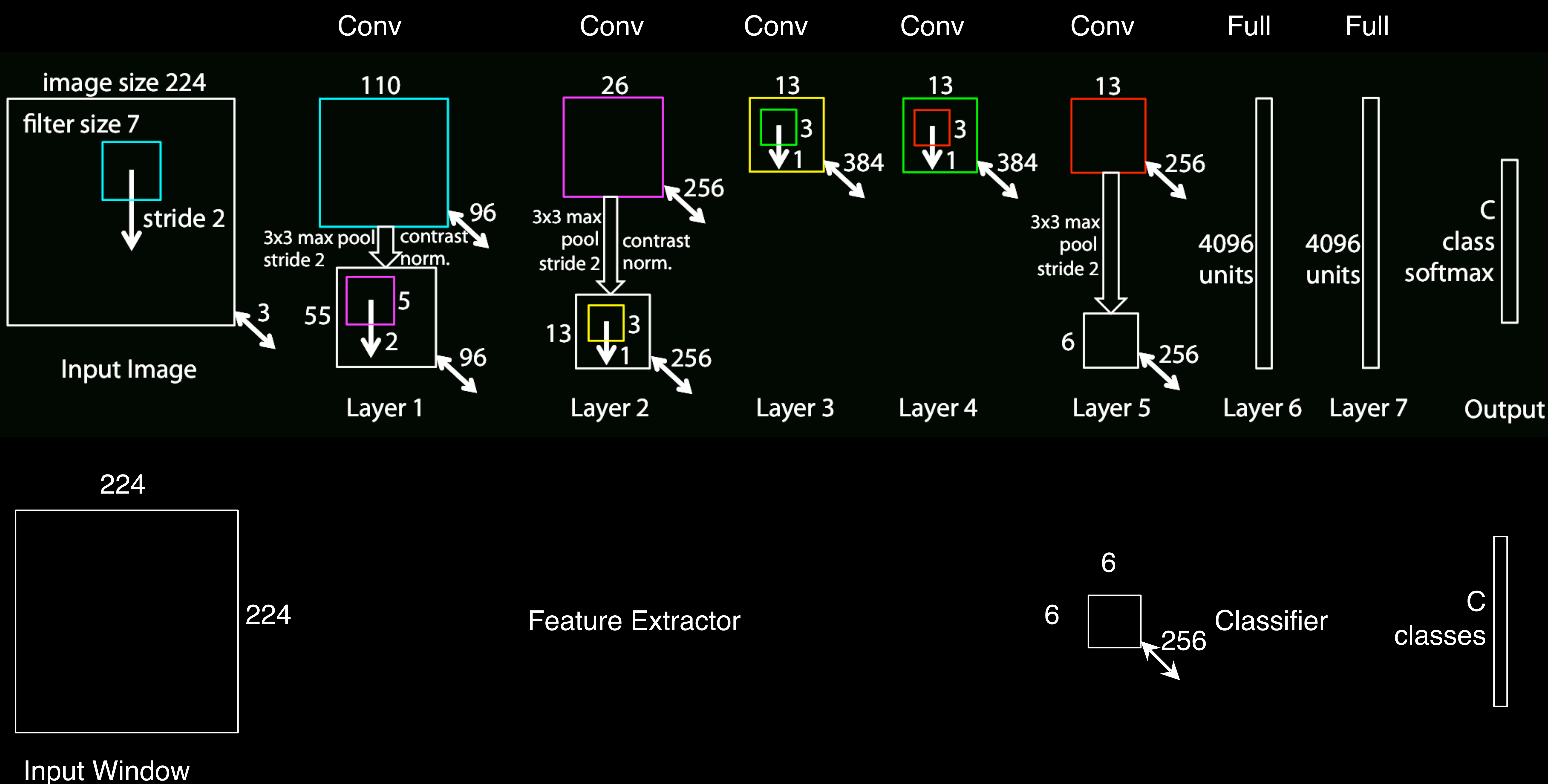
- We will assign exact dates

Some more illustrations on detection …

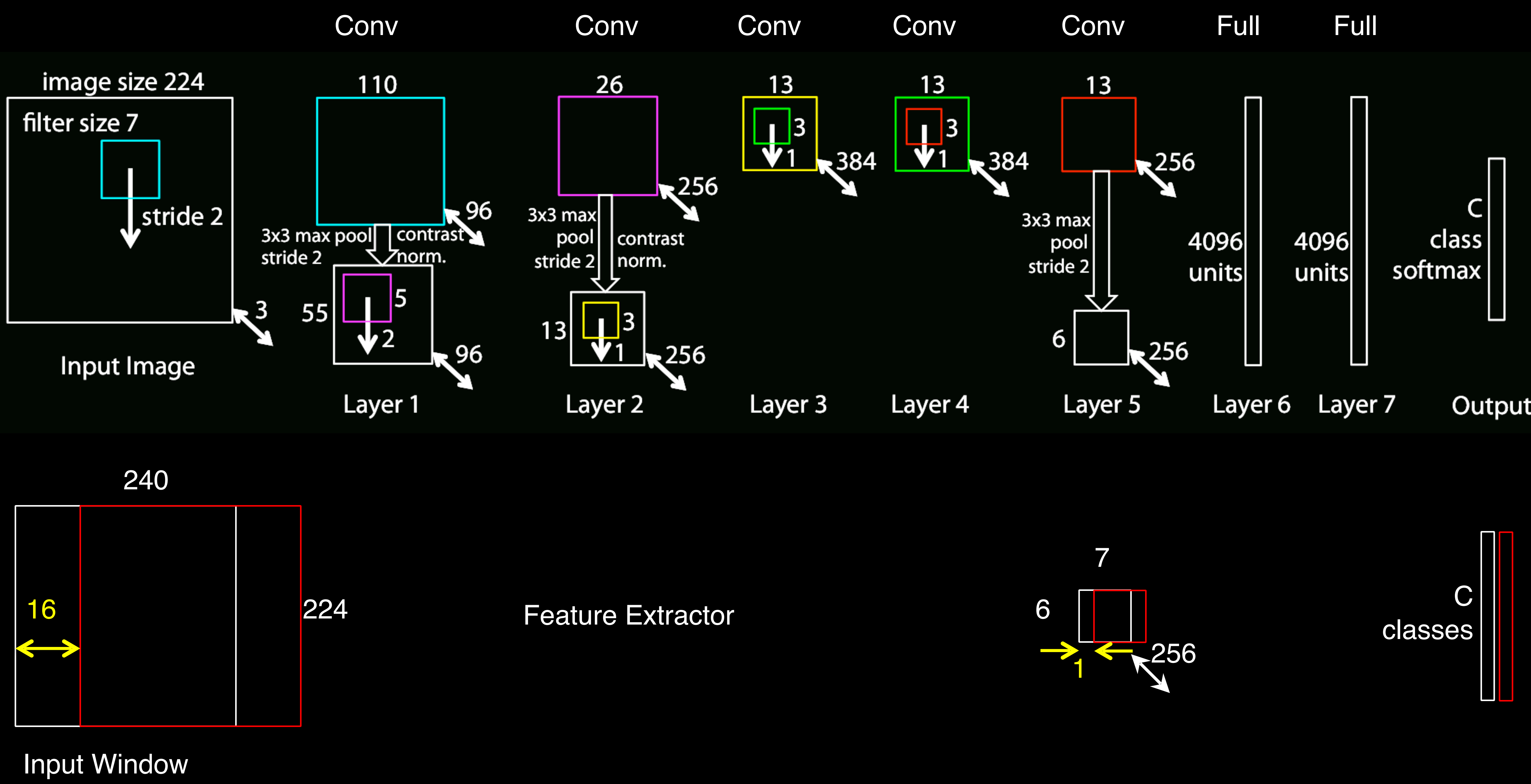
Sliding Window with ConvNet



Sliding Window with ConvNet

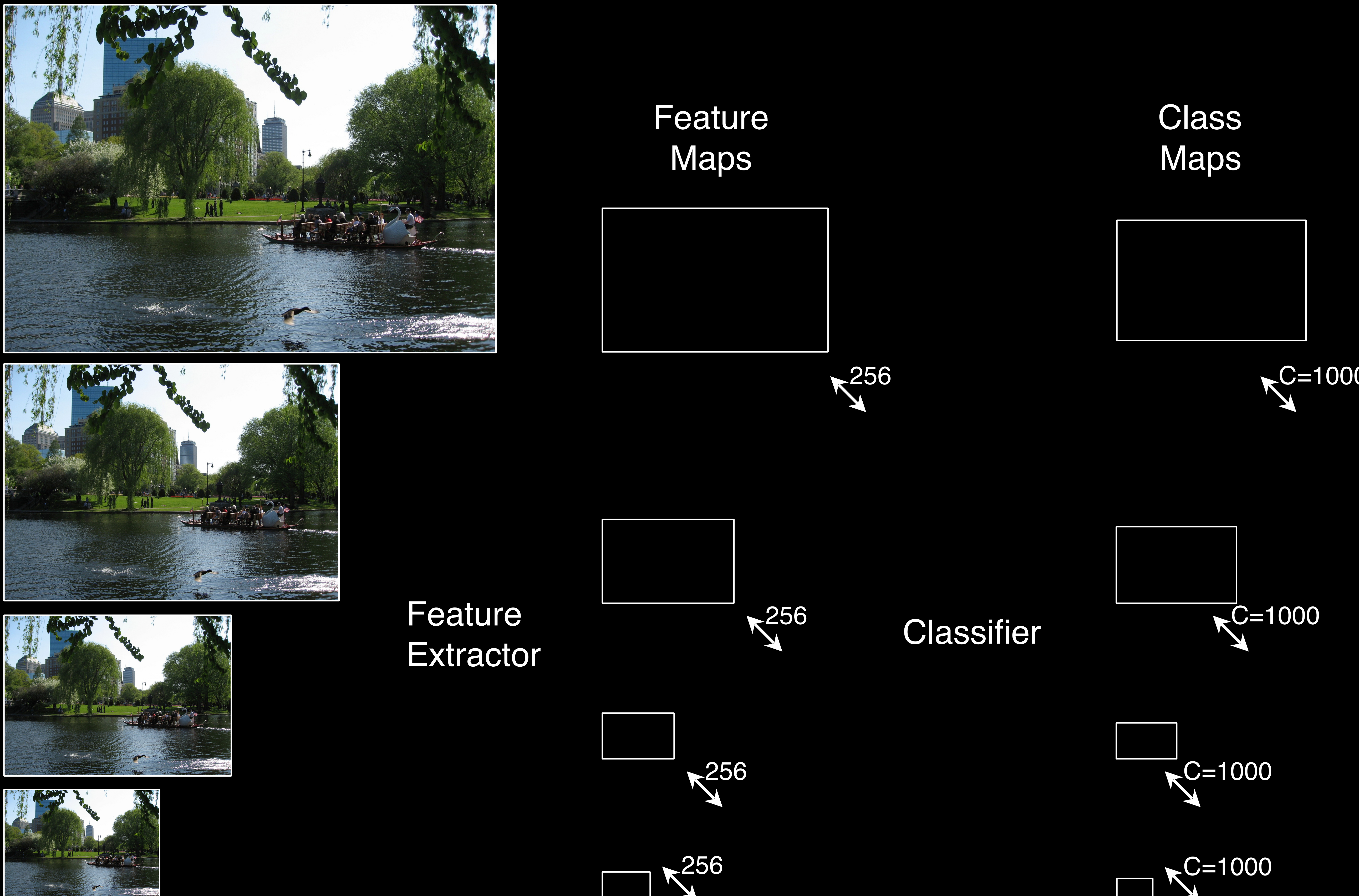


Sliding Window with ConvNet

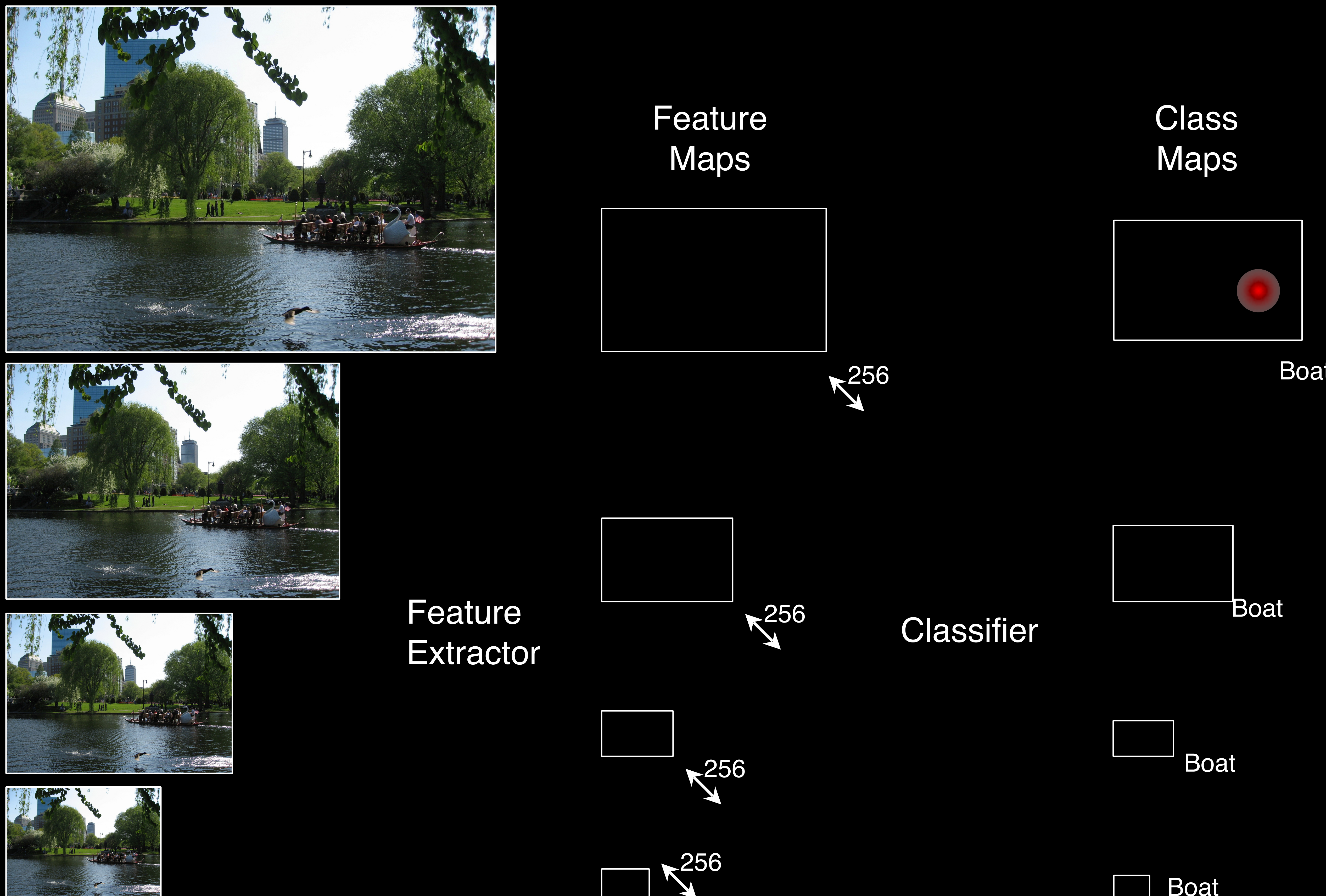


No need to compute two separate windows
Just one big input window, computed in a single pass

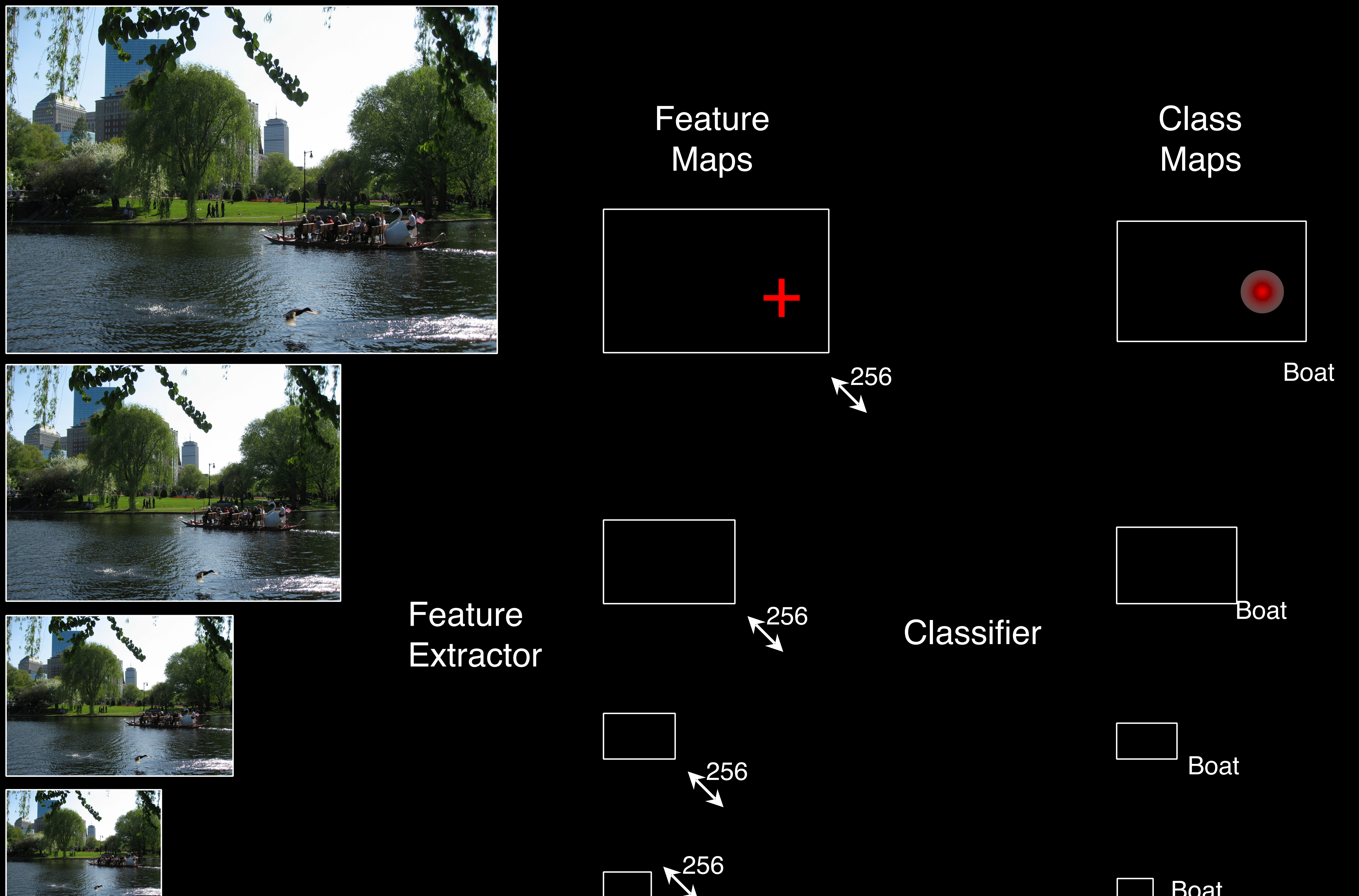
ConvNets for Detection



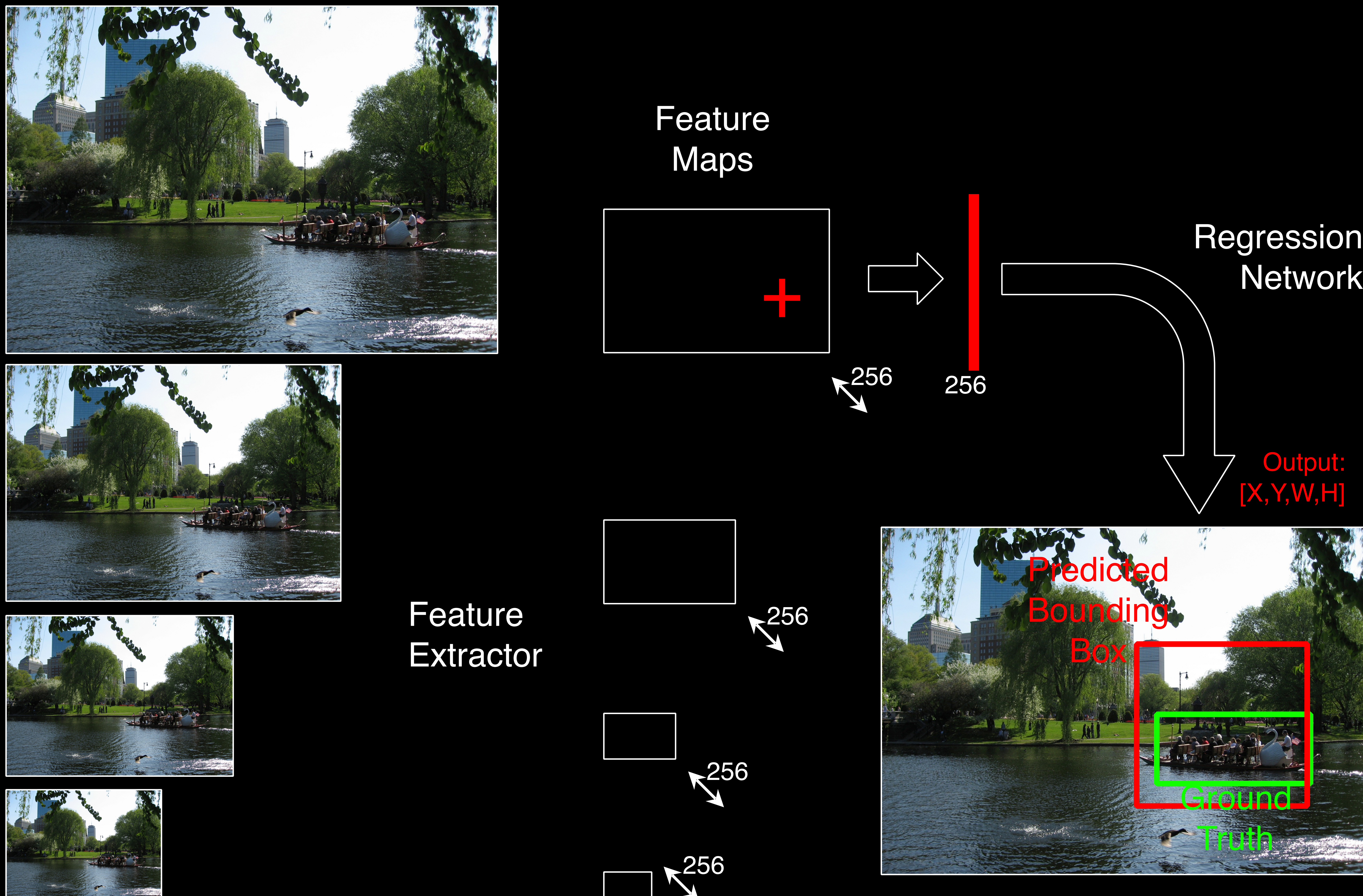
ConvNets for Detection



ConvNets for Detection

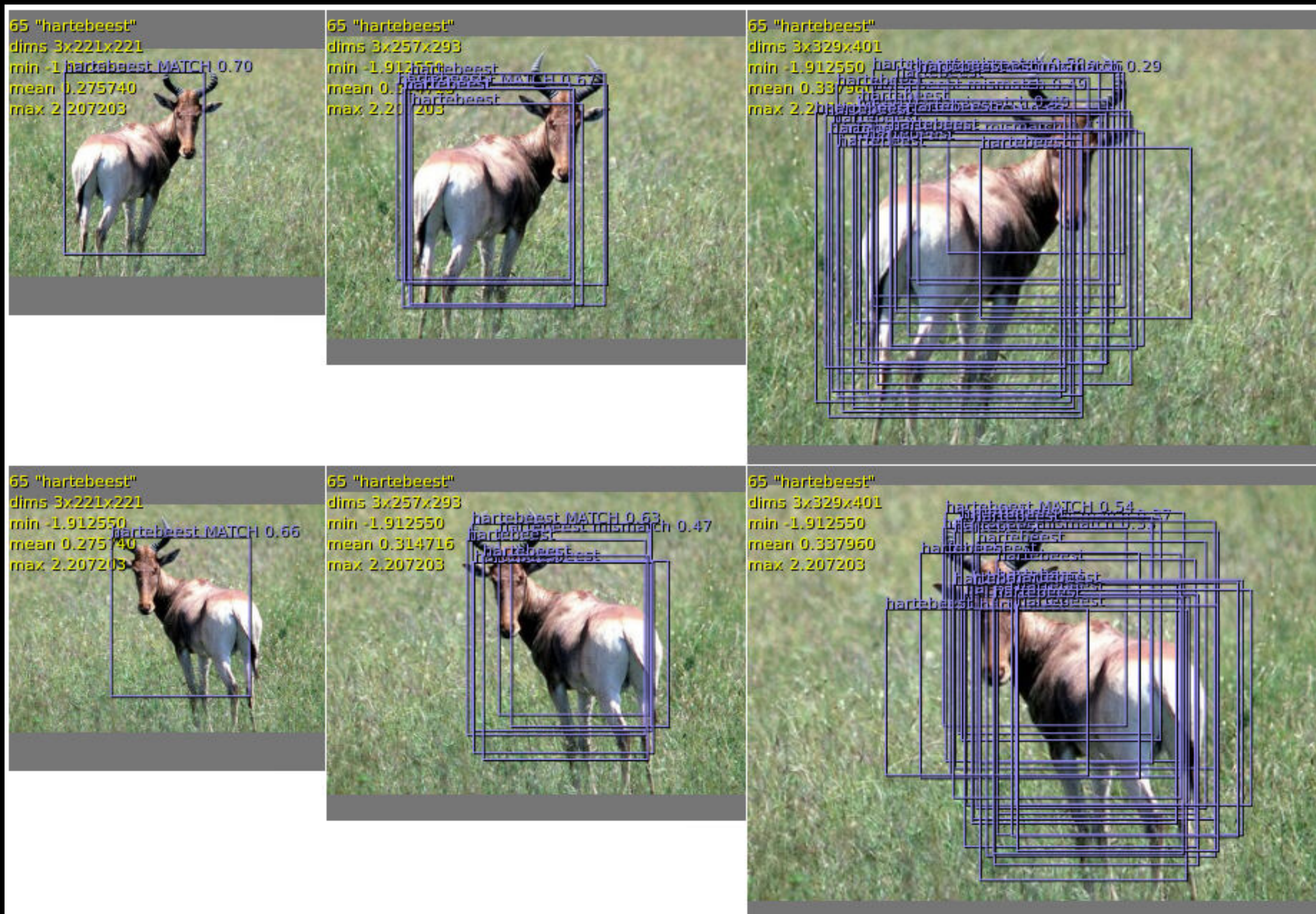


ConvNets for Detection



Bounding Box prediction example

[Sermanet et al. CVPR'14]



Today: CNN Architectures

Case Studies

- AlexNet
- VGG
- GoogLeNet
- ResNet

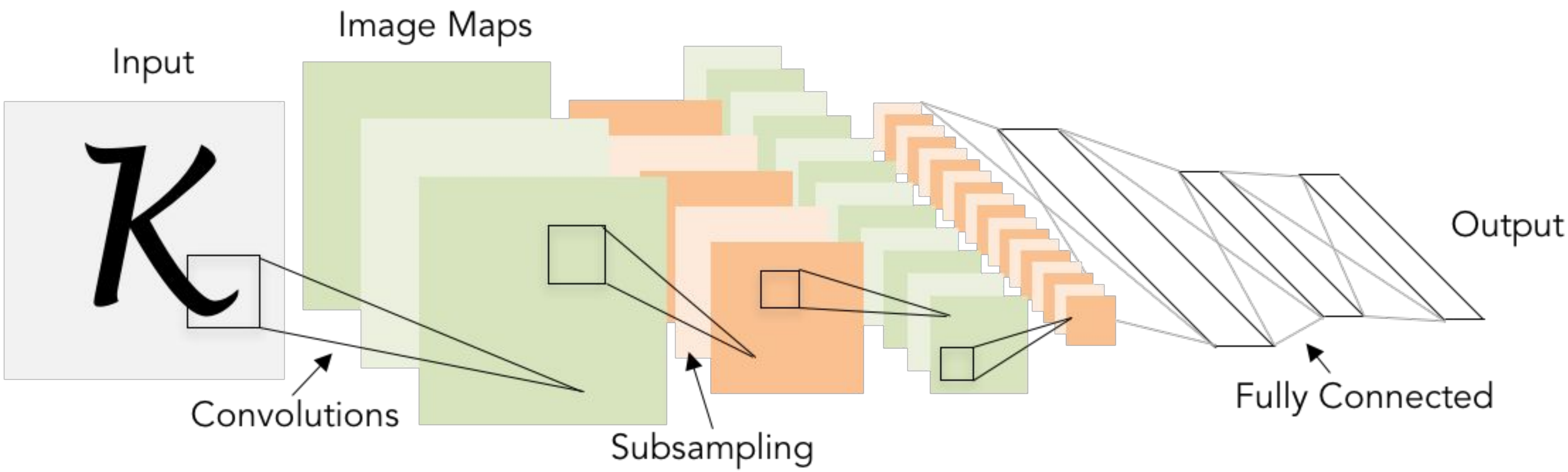
Also....

- NiN (Network in Network)
- Wide ResNet
- ResNeXT
- Stochastic Depth
- Squeeze-and-Excitation Network
- DenseNet
- FractalNet
- SqueezeNet
- NASNet

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Review: LeNet-5

[LeCun et al., 1998]

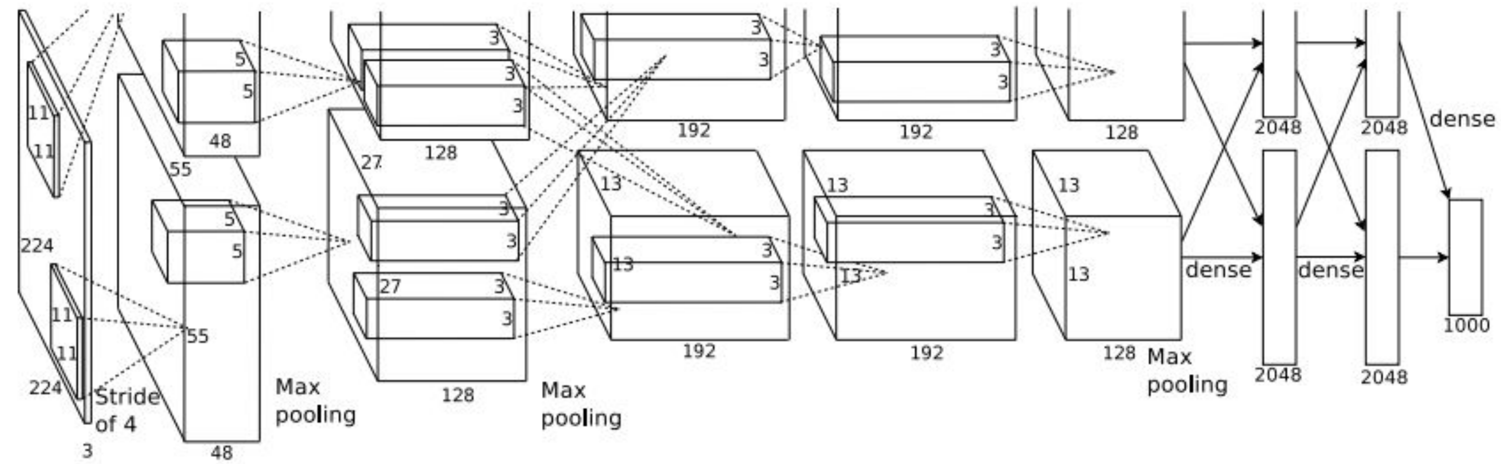


Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-FC-FC]

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]

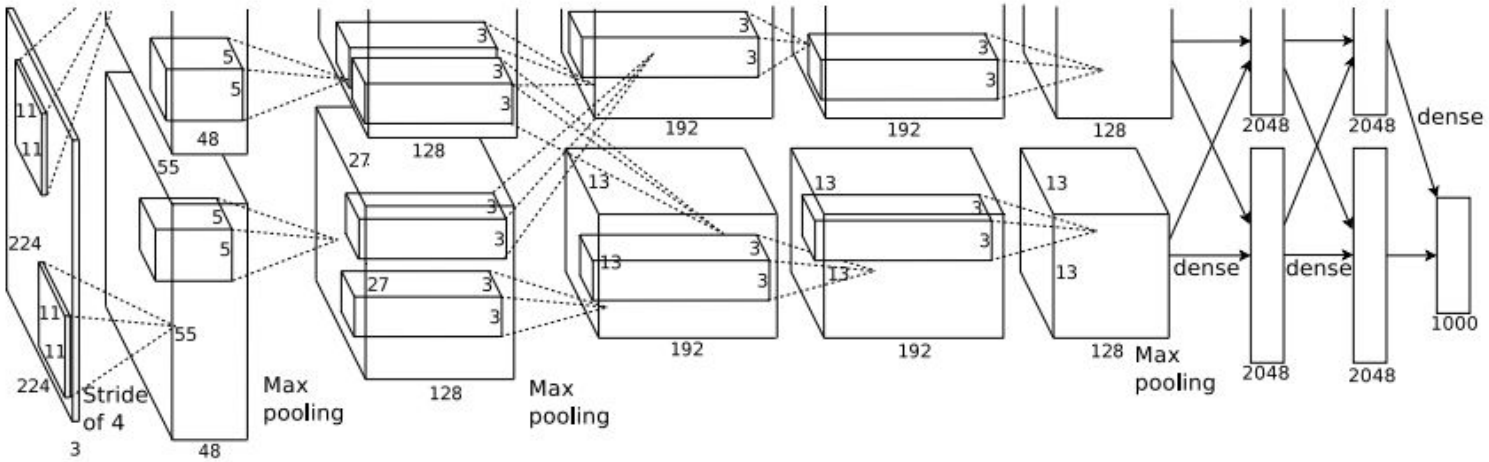


Architecture:
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]



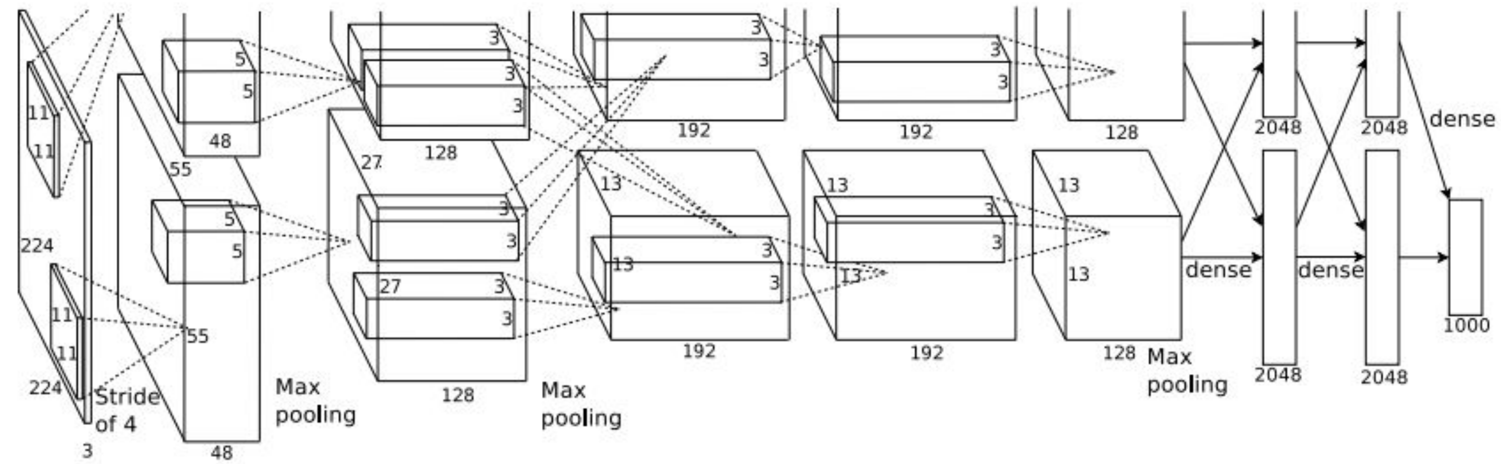
Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Q: what is the output volume size? Hint: (227-11)/4+1 = 55

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

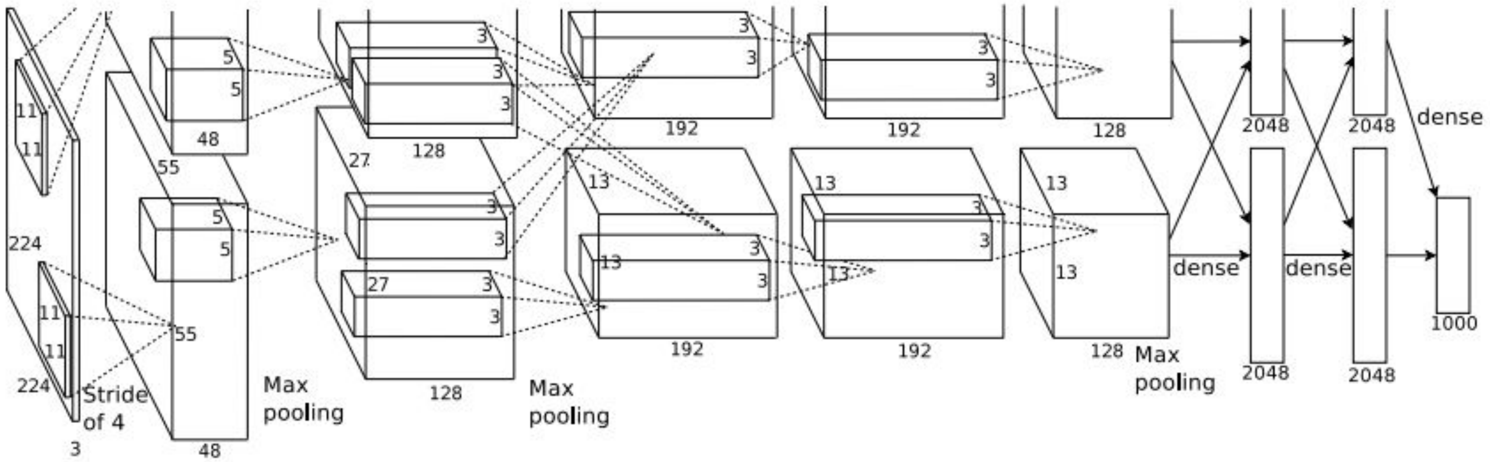
First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**

Q: What is the total number of parameters in this layer?

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]



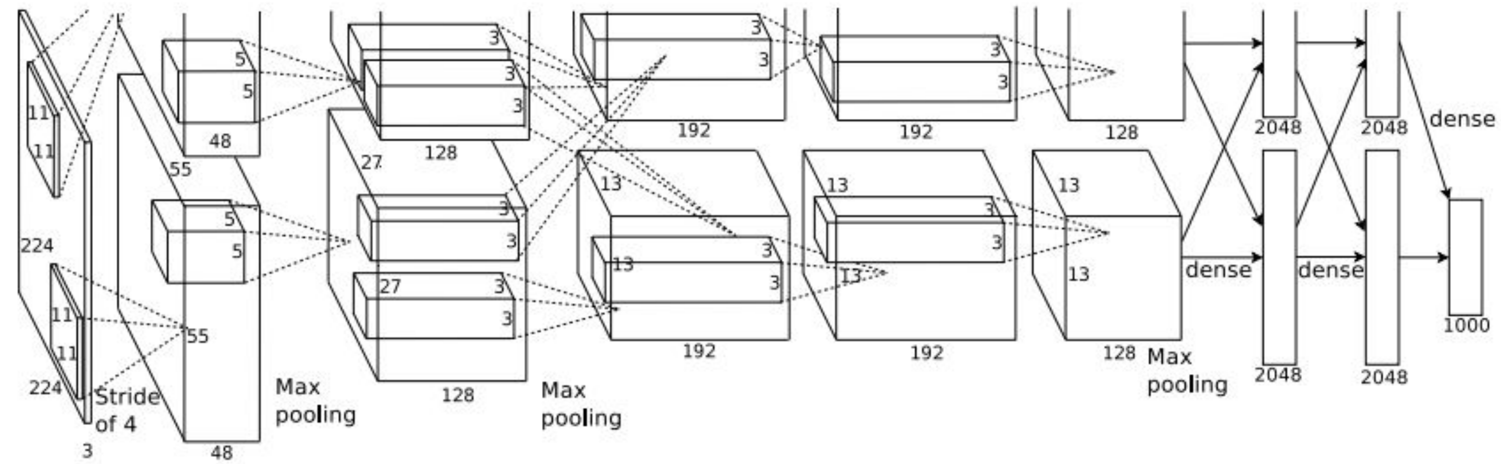
Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**
Parameters: (11*11*3)*96 = **35K**

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images
After CONV1: 55x55x96

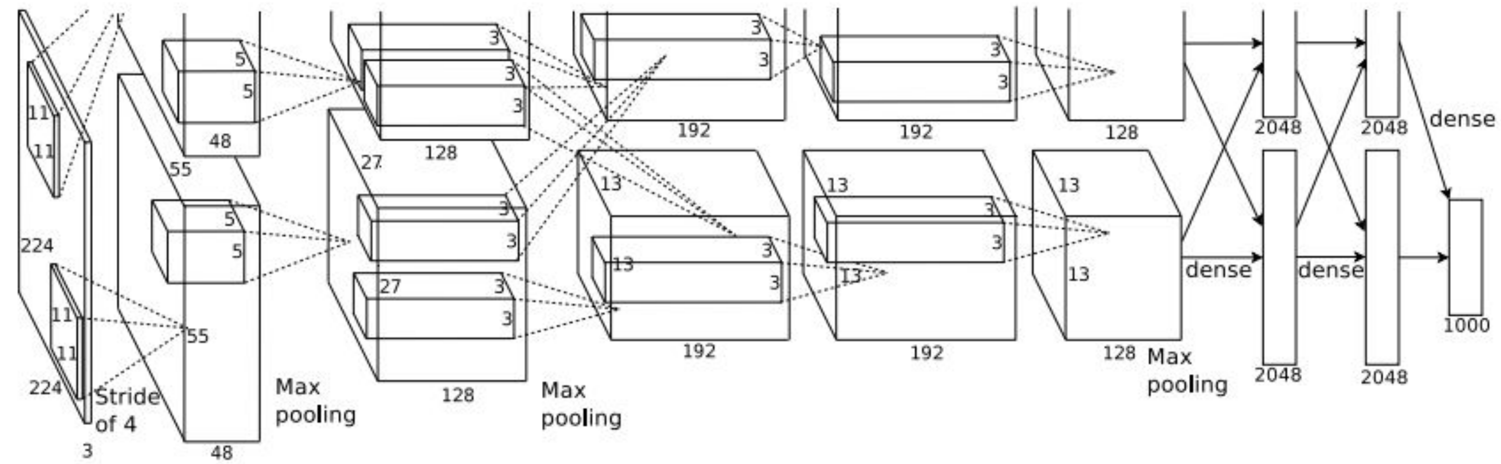
Second layer (POOL1): 3x3 filters applied at stride 2

Q: what is the output volume size? Hint: (55-3)/2+1 = 27

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images
After CONV1: 55x55x96

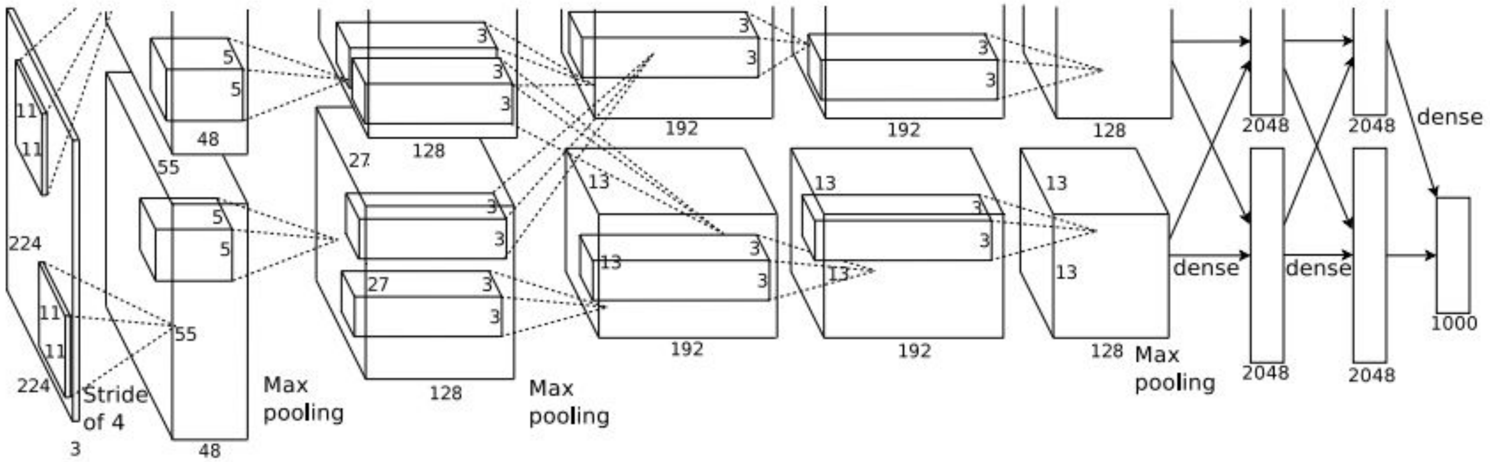
Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96

Q: what is the number of parameters in this layer?

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]



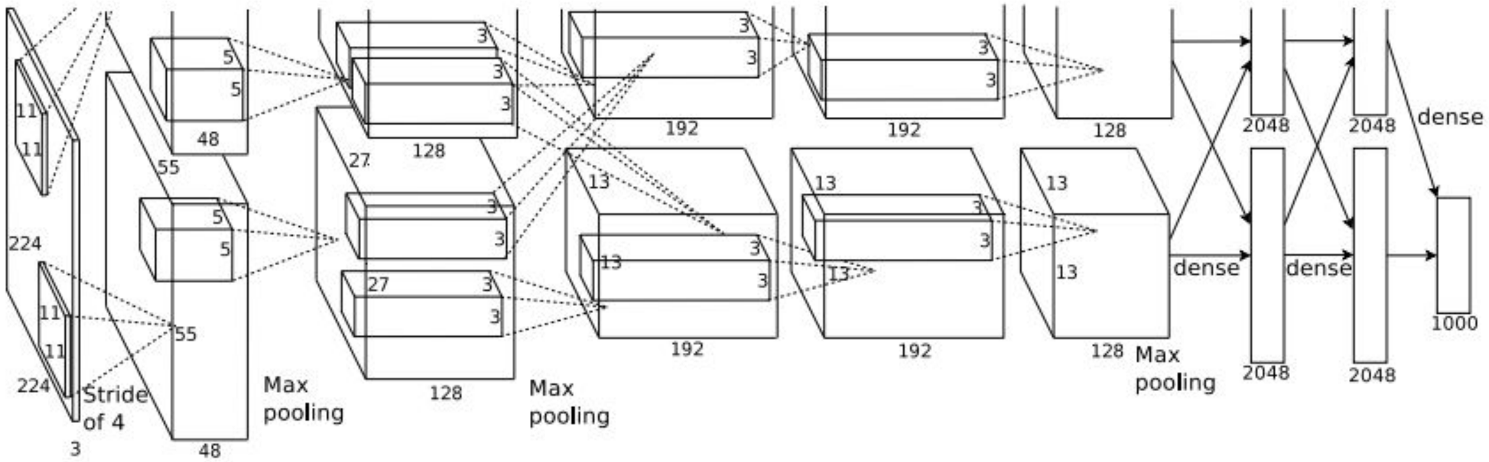
Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96
Parameters: 0!

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]

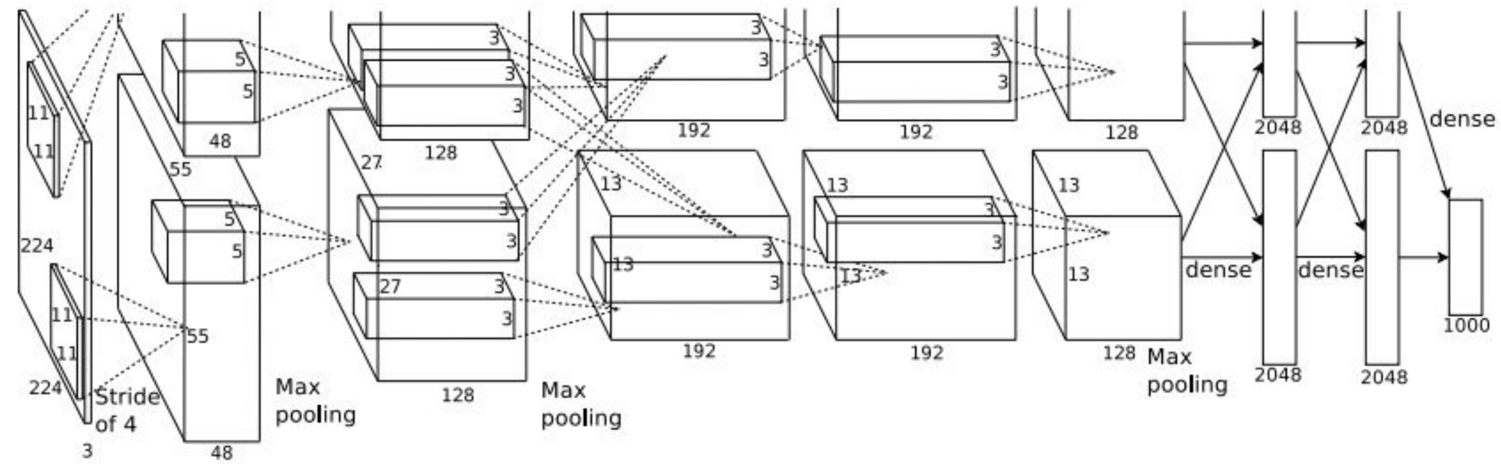


Input: 227x227x3 images
After CONV1: 55x55x96
After POOL1: 27x27x96
...

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]

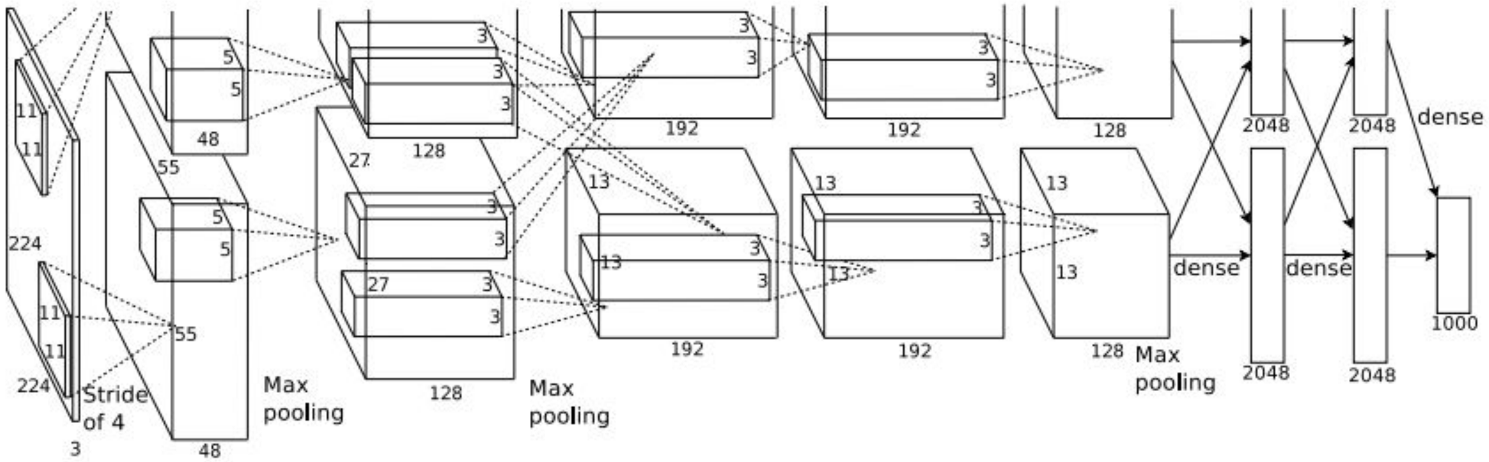


Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]



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[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
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[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
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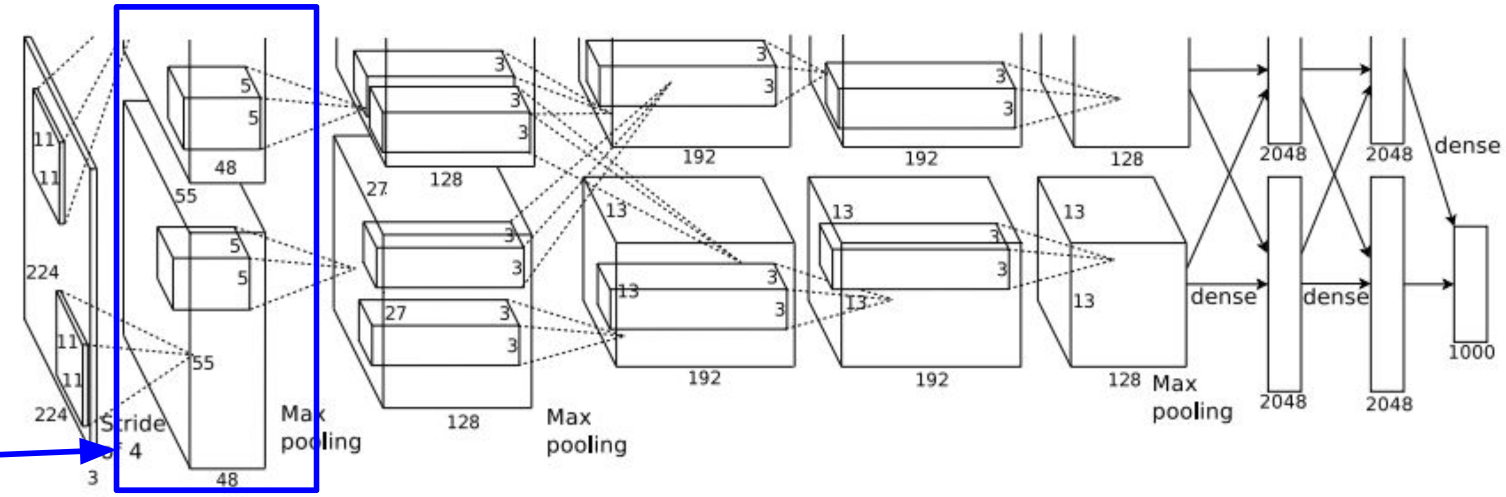
Details/Retrospectives:
- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]



[55x55x48] x 2

Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
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[4096] FC6: 4096 neurons
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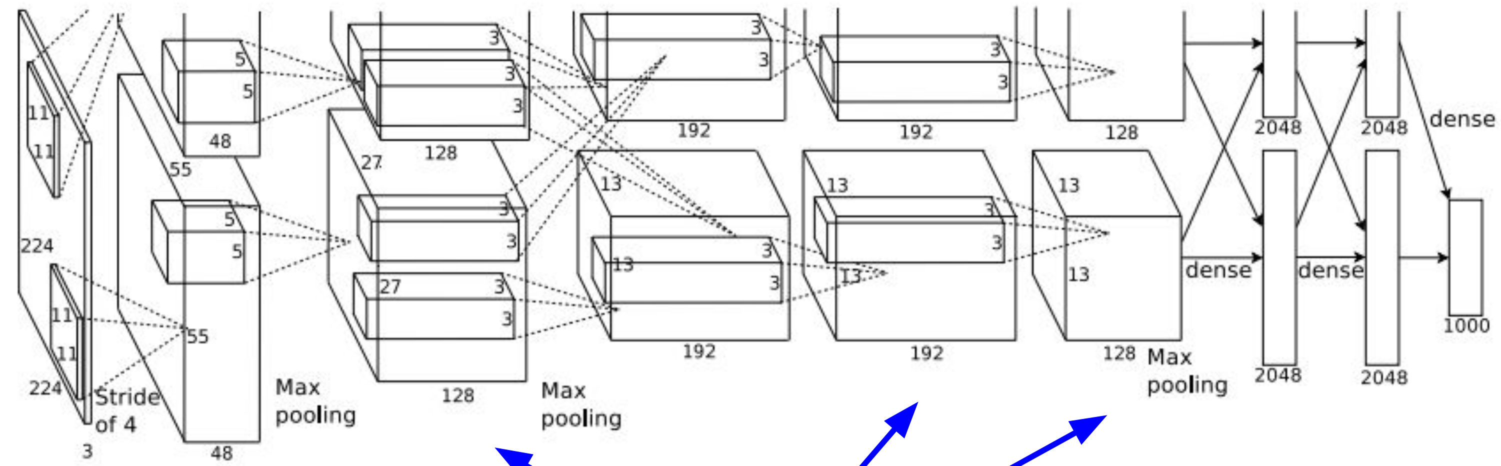
[1000] FC8: 1000 neurons (class scores)

Historical note: Trained on GTX 580 GPU with only 3 GB of memory. Network spread across 2 GPUs, half the neurons (feature maps) on each GPU.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]



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[4096] FC6: 4096 neurons
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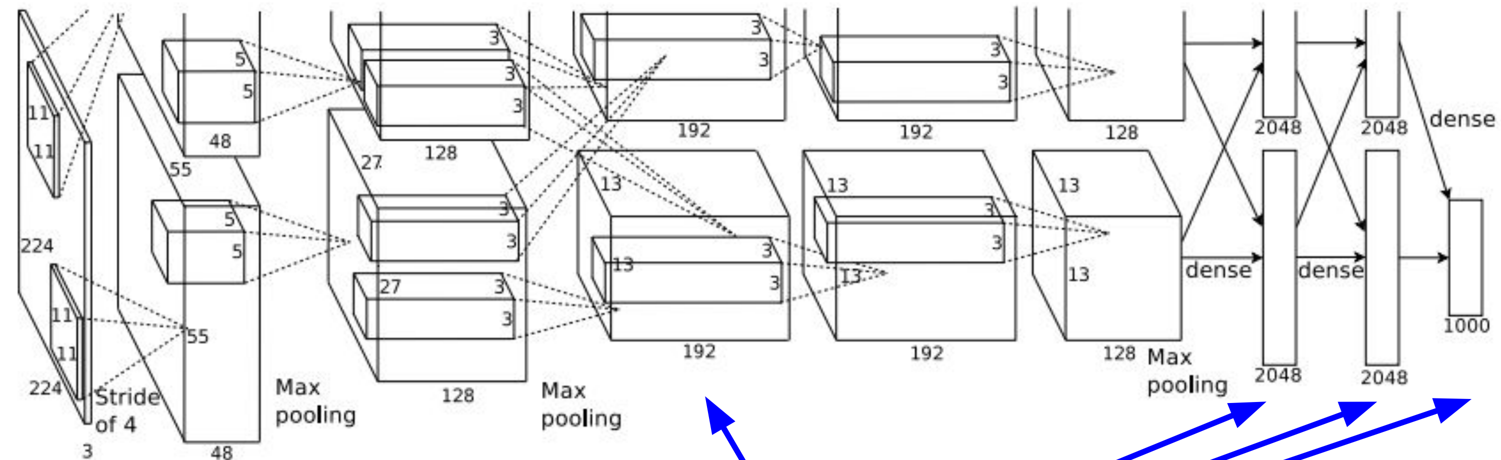
[1000] FC8: 1000 neurons (class scores)

CONV1, CONV2, CONV4, CONV5:
Connections only with feature maps on same GPU

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: AlexNet

[Krizhevsky et al. 2012]



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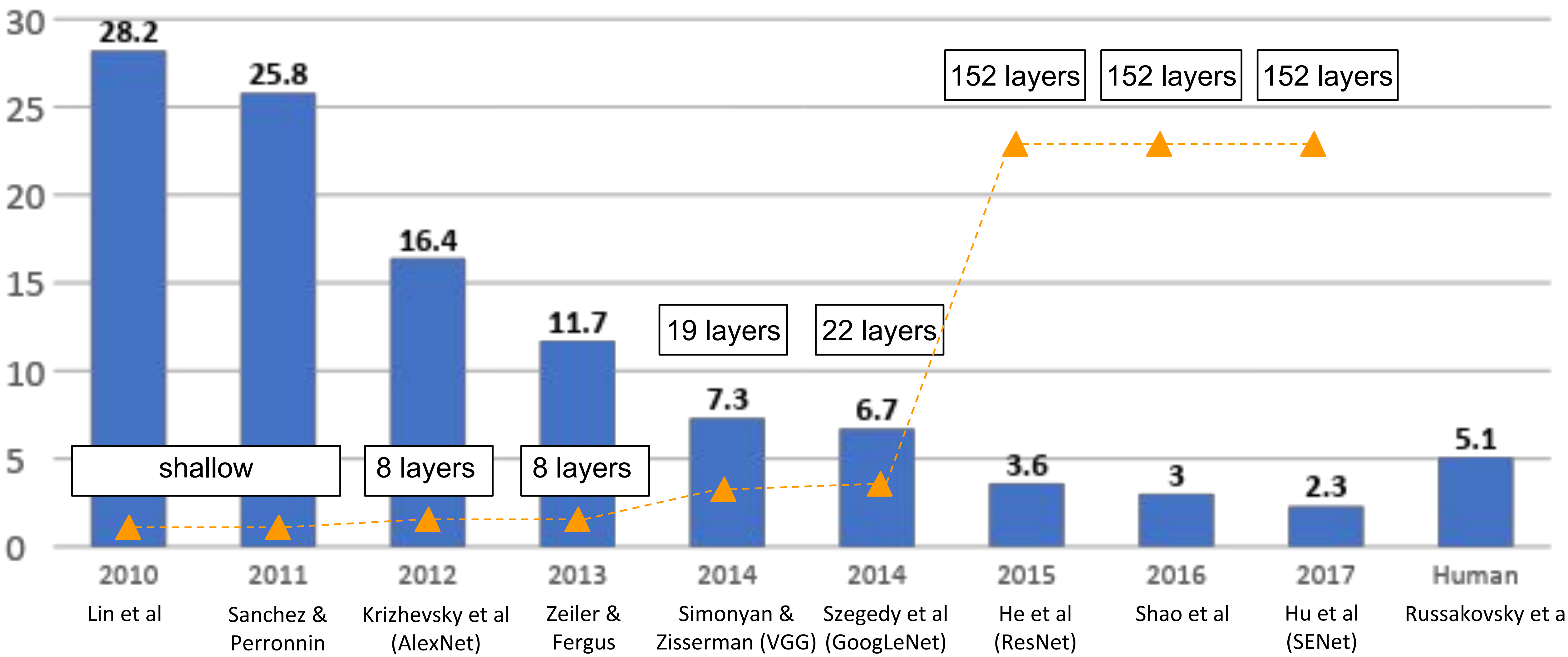
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

CONV3, FC6, FC7, FC8:
Connections with all feature maps in preceding layer, communication across GPUs

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



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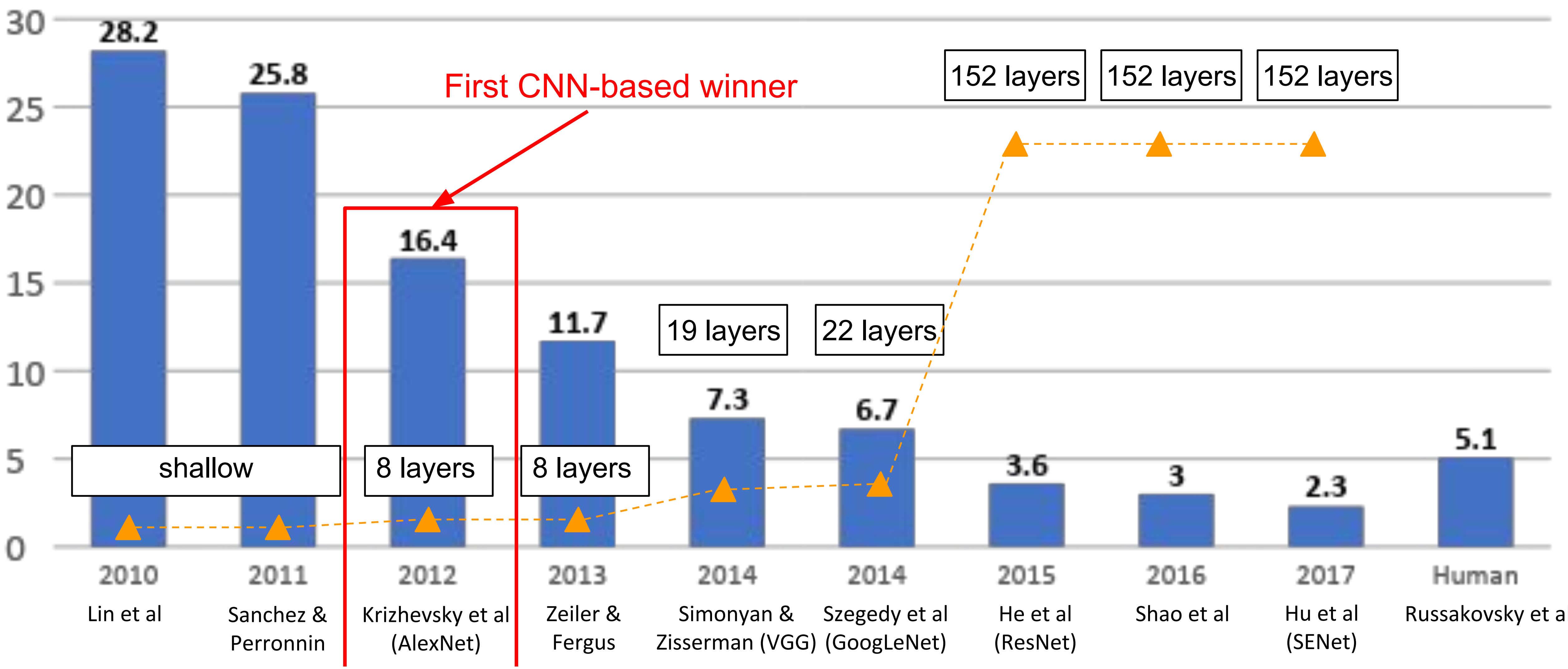

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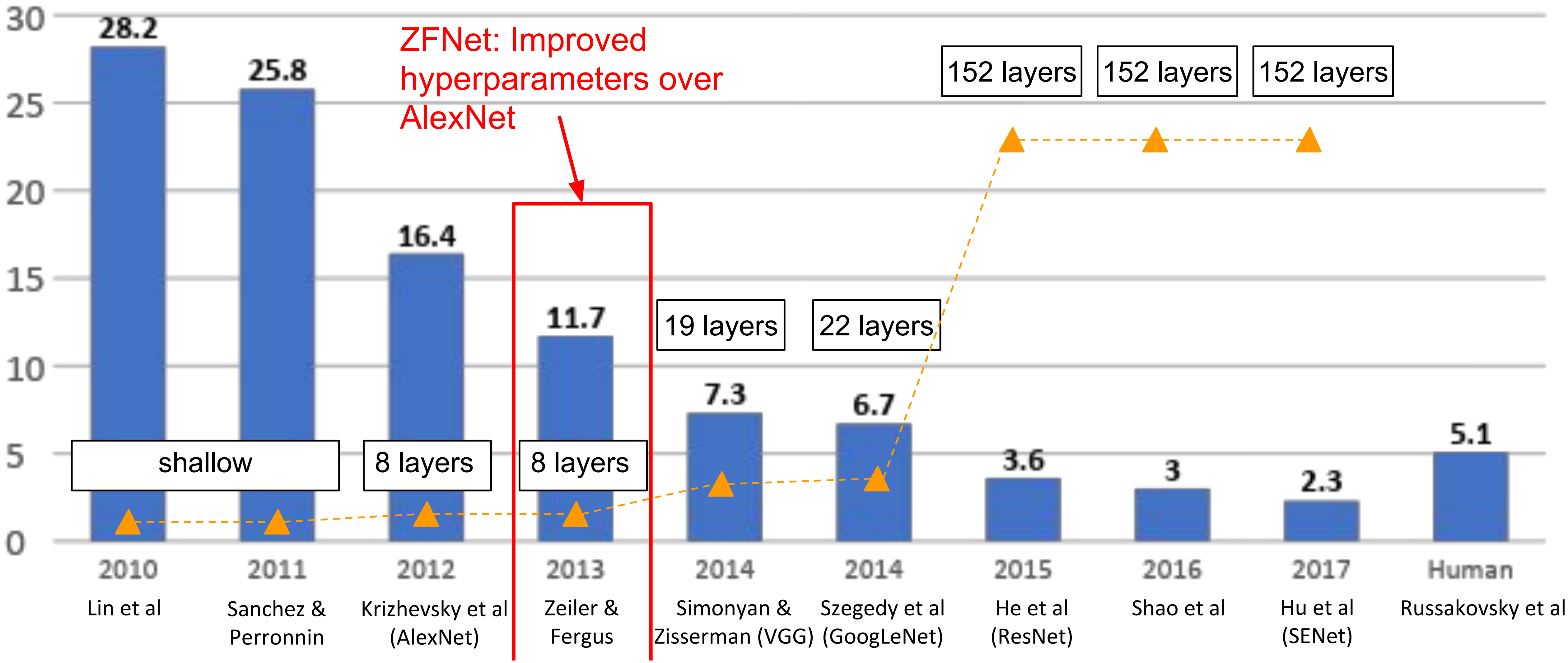

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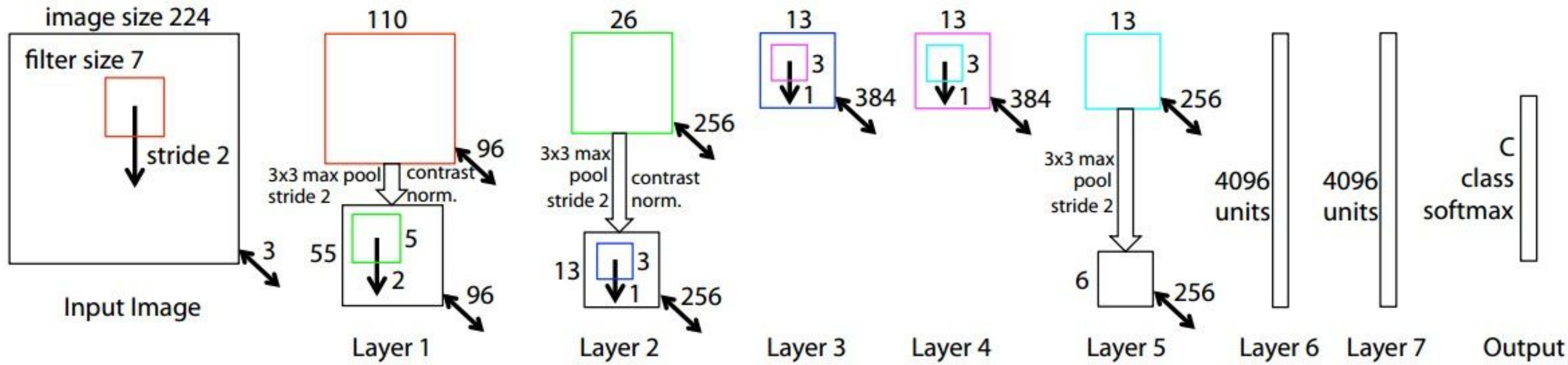
ZFNet

[Zeiler and Fergus, 2013]

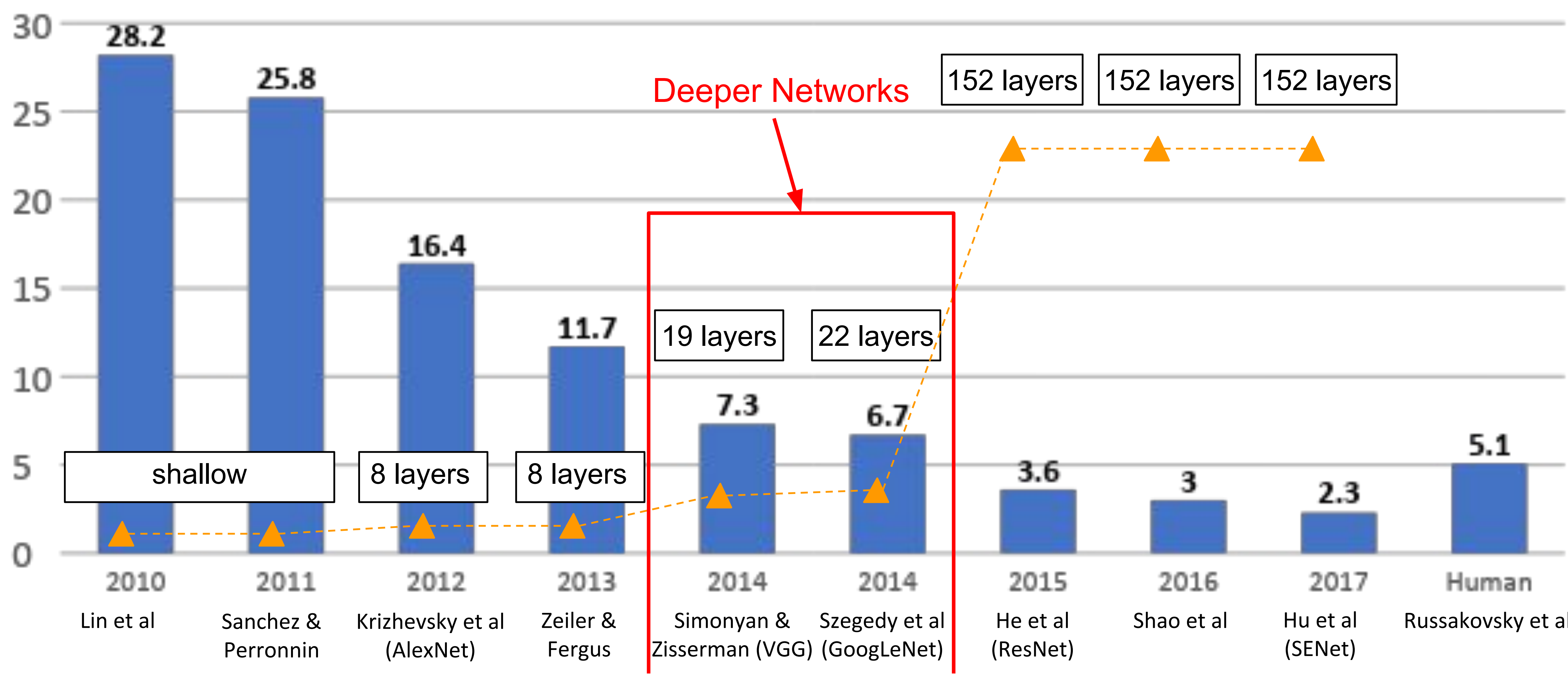


AlexNet but:
CONV1: change from (11x11 stride 4) to (7x7 stride 2)
CONV3,4,5: instead of 384, 384, 256 filters use 512, 1024, 512

ImageNet top 5 error: 16.4% -> 11.7%

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: VGGNet

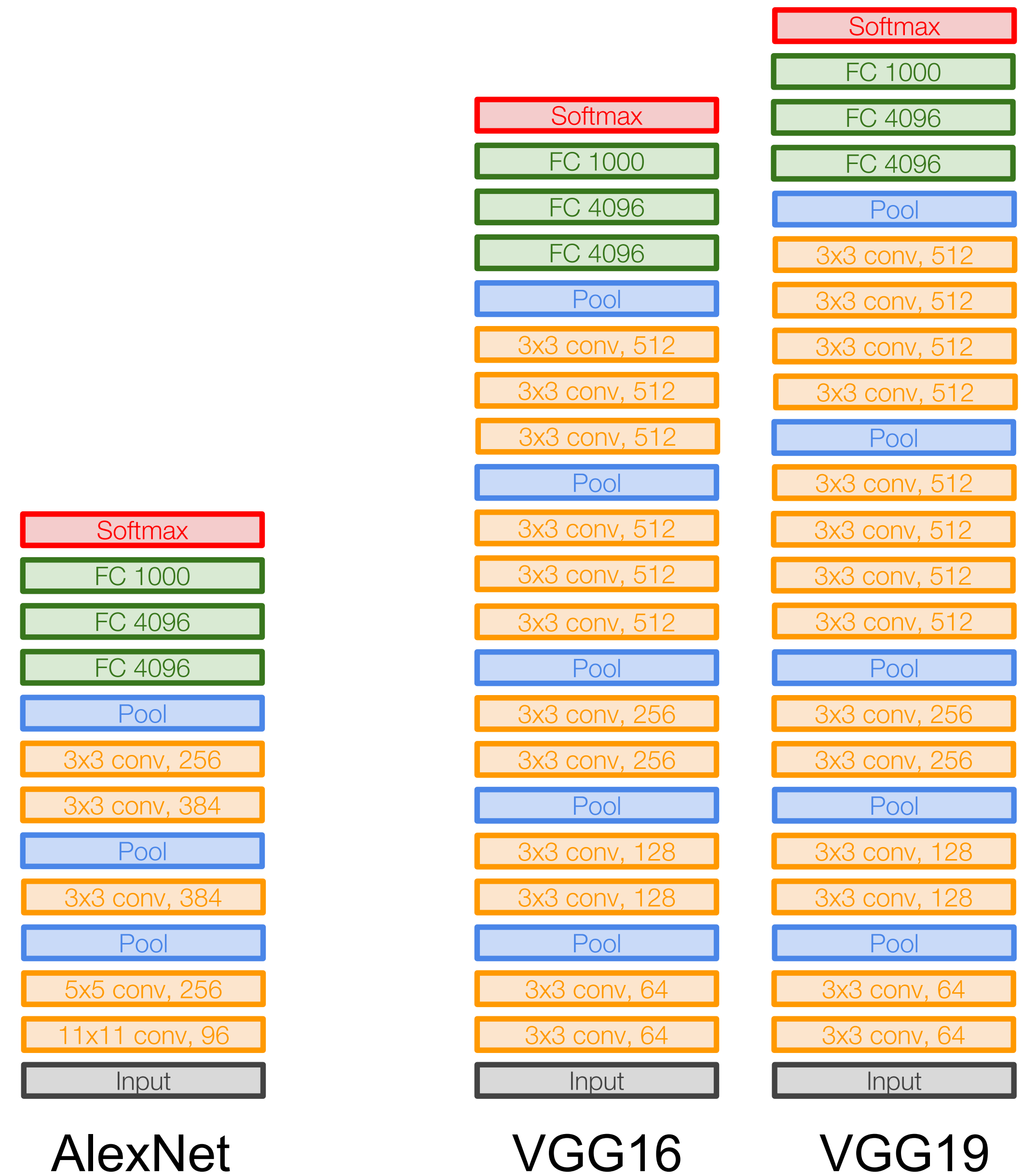
[Simonyan and Zisserman, 2014]

Small filters, Deeper networks

8 layers (AlexNet)
-> 16 - 19 layers (VGG16Net)

Only 3x3 CONV stride 1, pad 1
and 2x2 MAX POOL stride 2

11.7% top 5 error in ILSVRC'13
(ZFNet)
-> 7.3% top 5 error in ILSVRC'14



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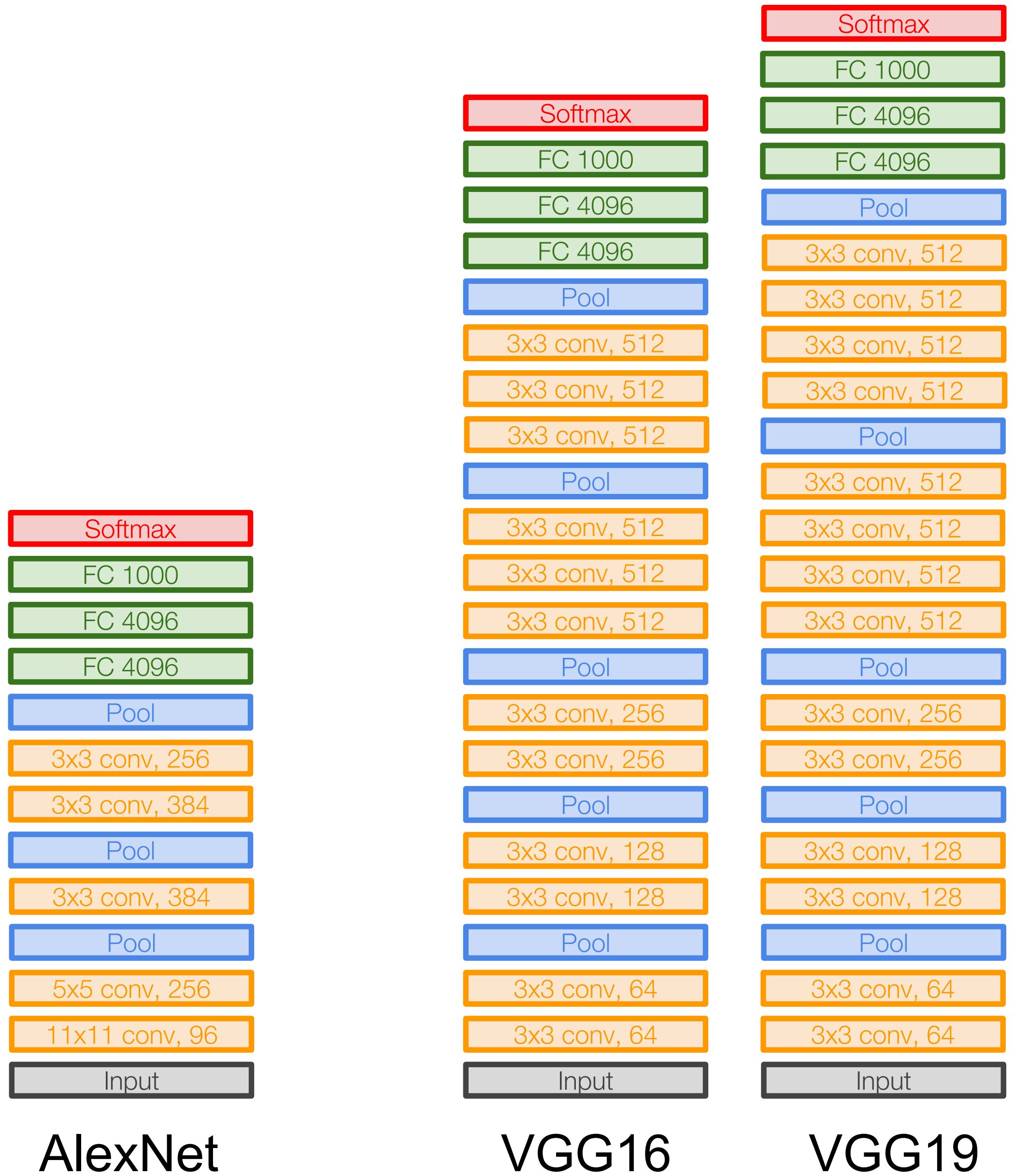
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

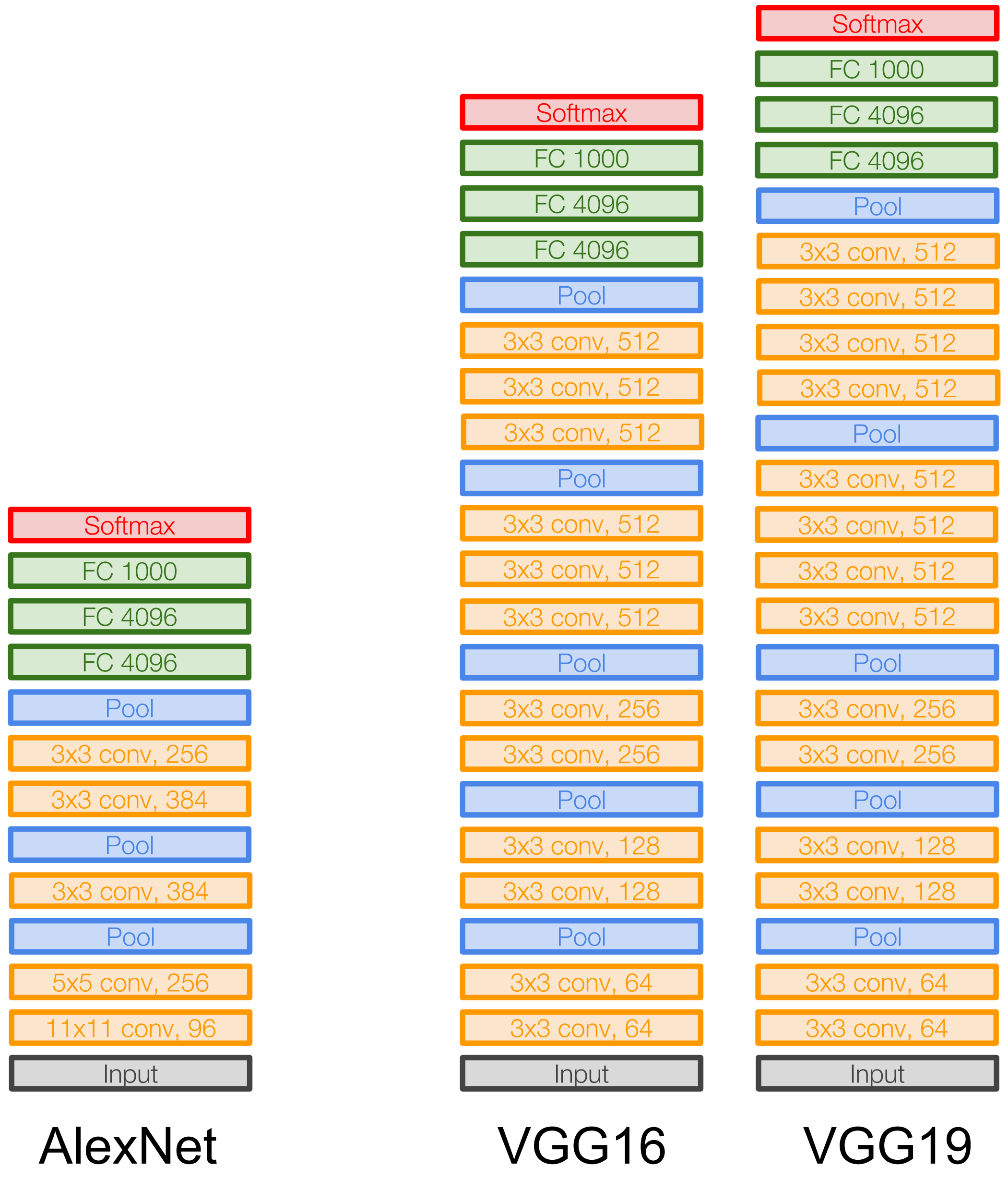
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)

Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

Q: What is the effective receptive field of three 3x3 conv (stride 1) layers?



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

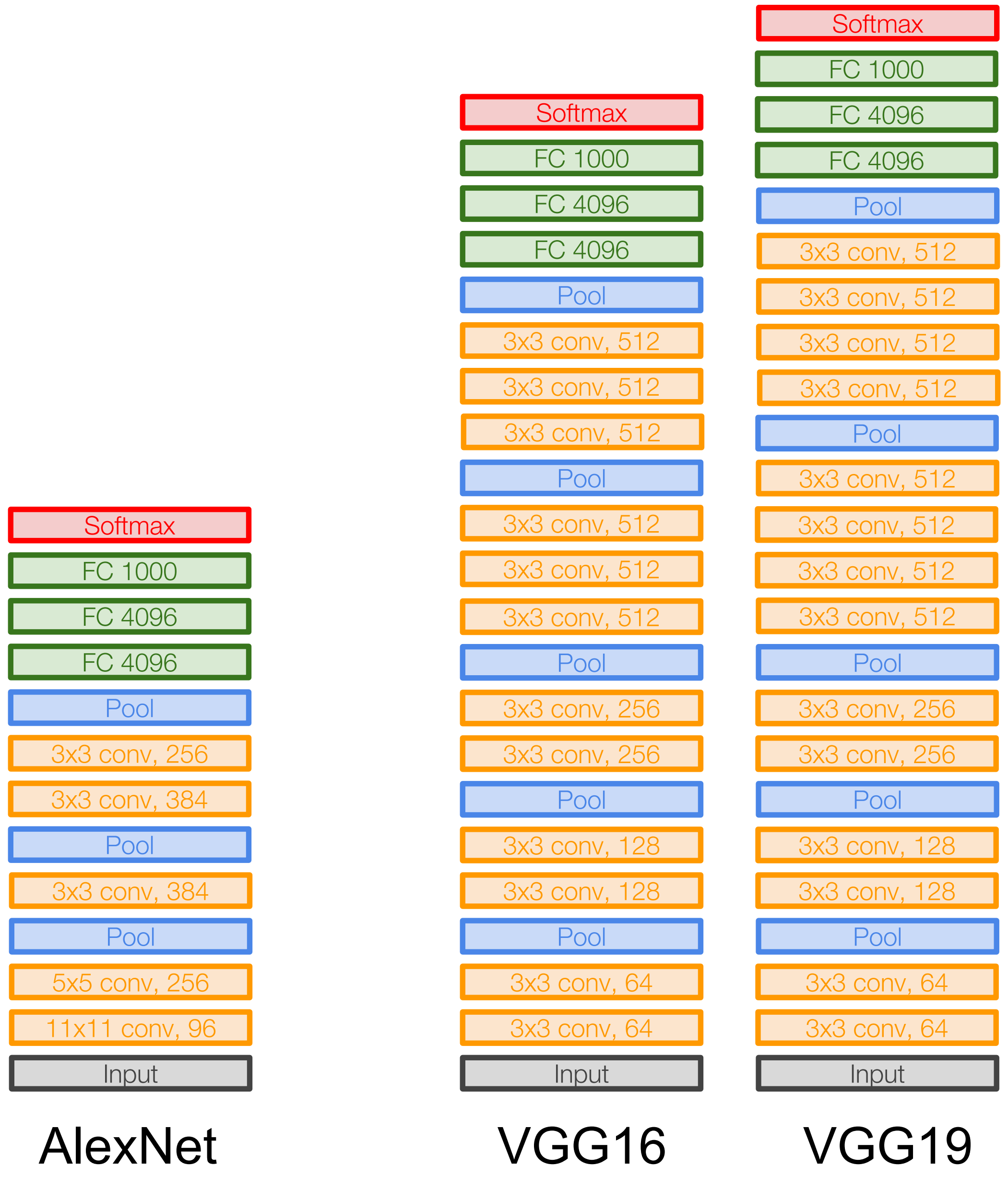
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)

Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

[7x7]



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: VGGNet

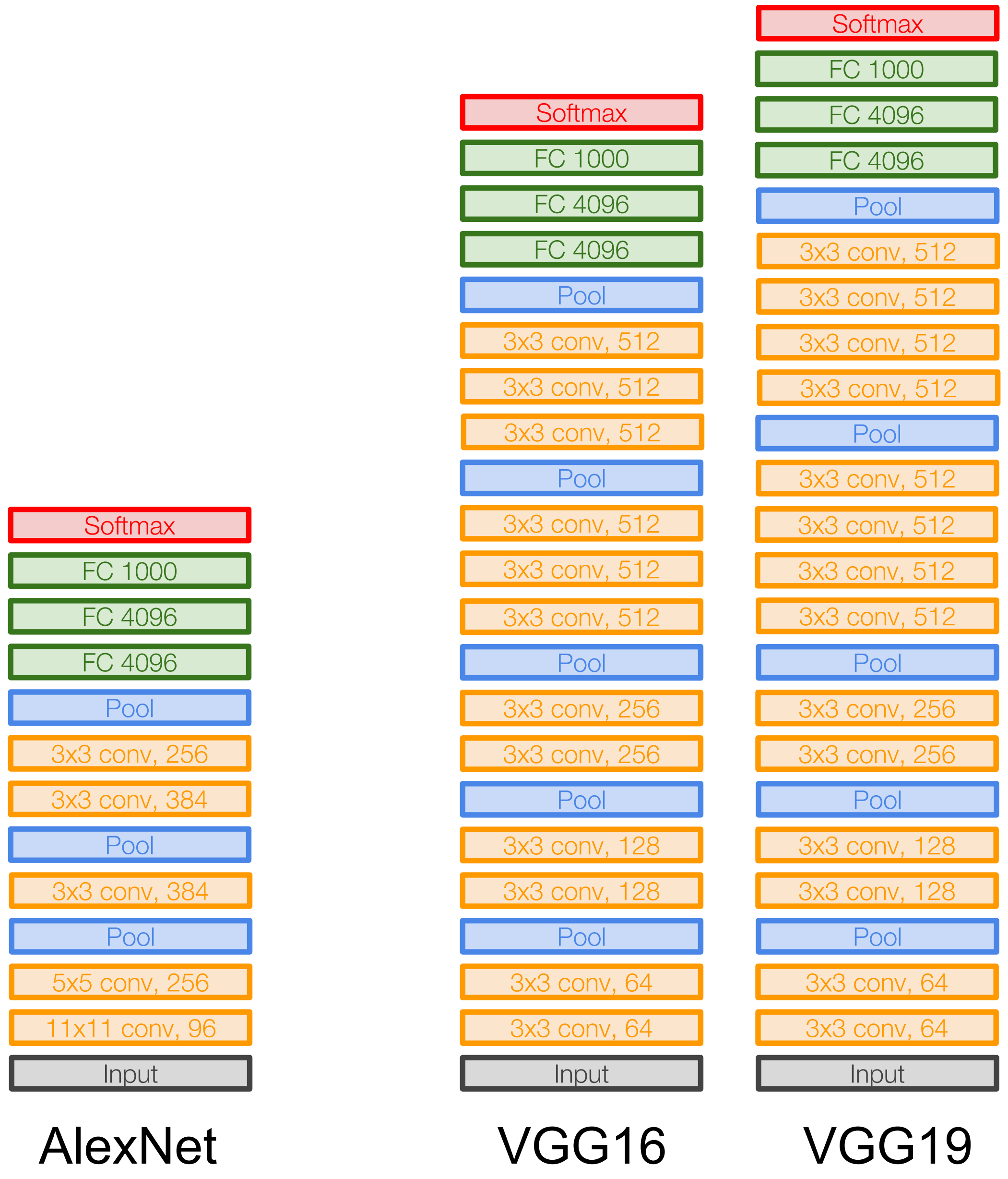
[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)

Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

But deeper, more non-linearities

And fewer parameters: $3 * (3^2C^2)$ vs. 7^2C^2 for C channels per layer



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

VGG16

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
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CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
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POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
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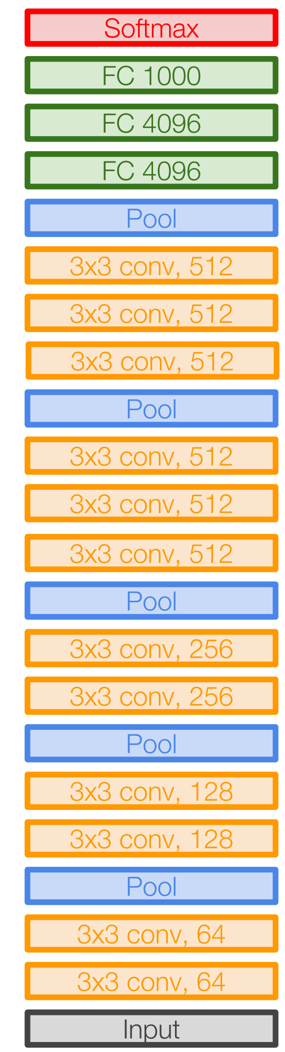
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 96MB / image (for a forward pass)
TOTAL params: 138M parameters



VGG16

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: **224*224*64=3.2M** params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: **224*224*64=3.2M** params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
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CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = **102,760,448**
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

Note:

Most memory is in early CONV

Most params are in late FC

TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

(not counting biases)

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CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
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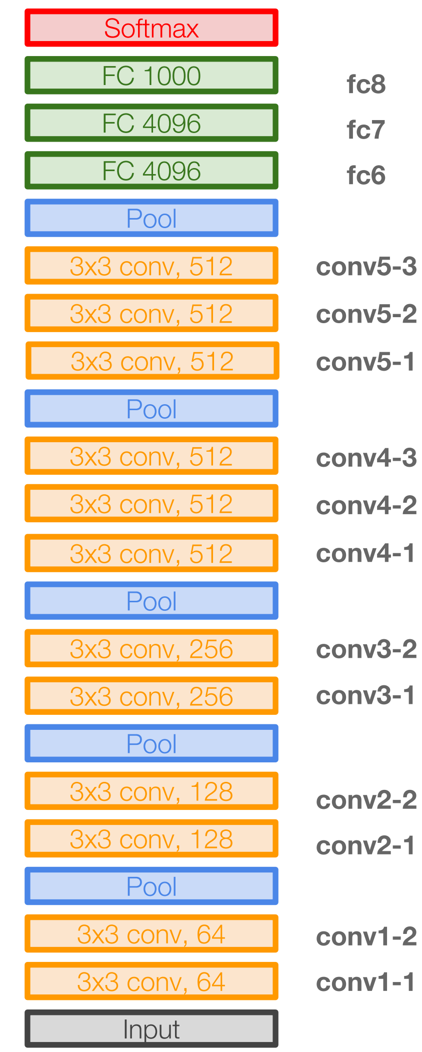
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters



VGG16

Common names

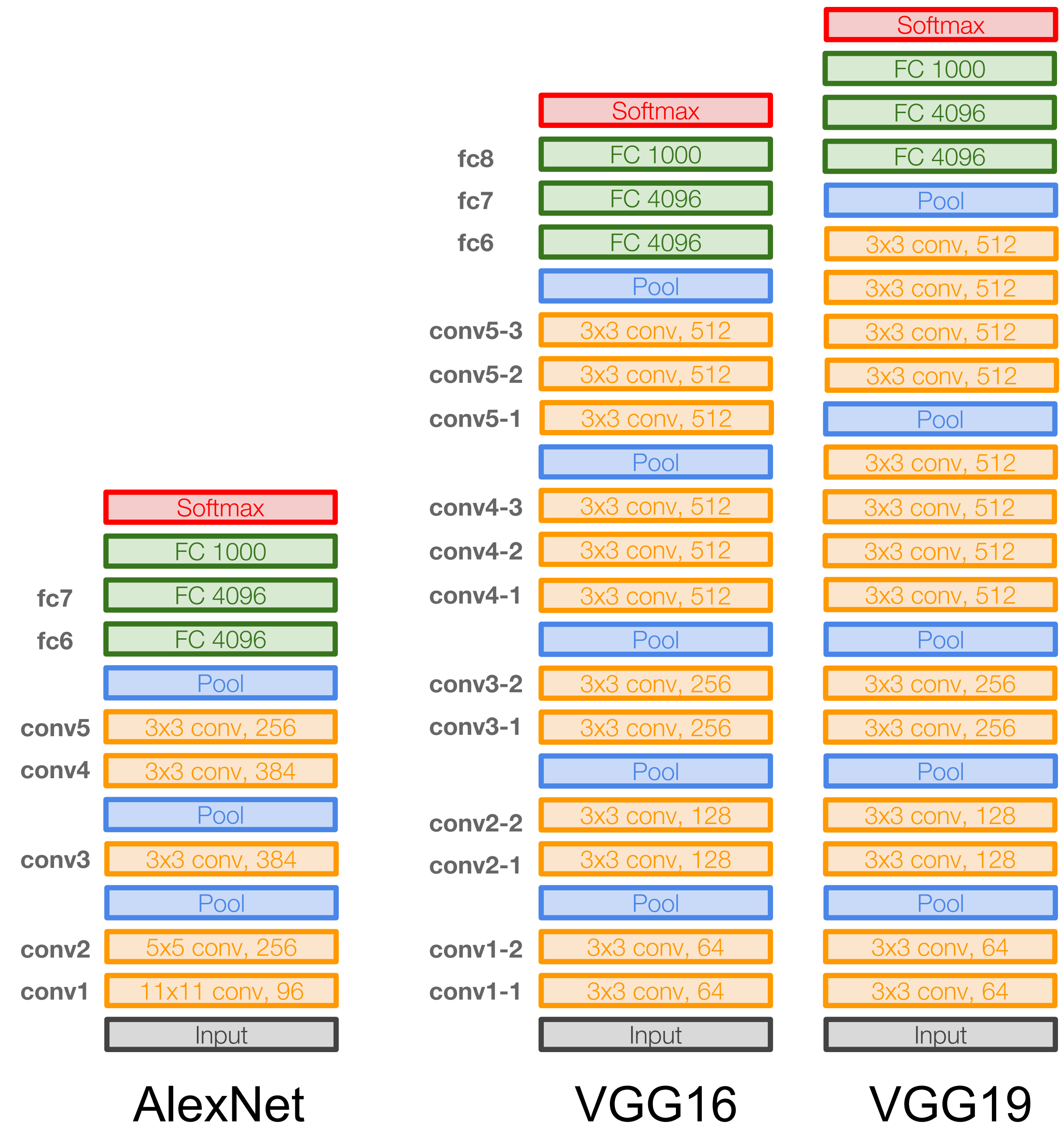
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: VGGNet

[Simonyan and Zisserman, 2014]

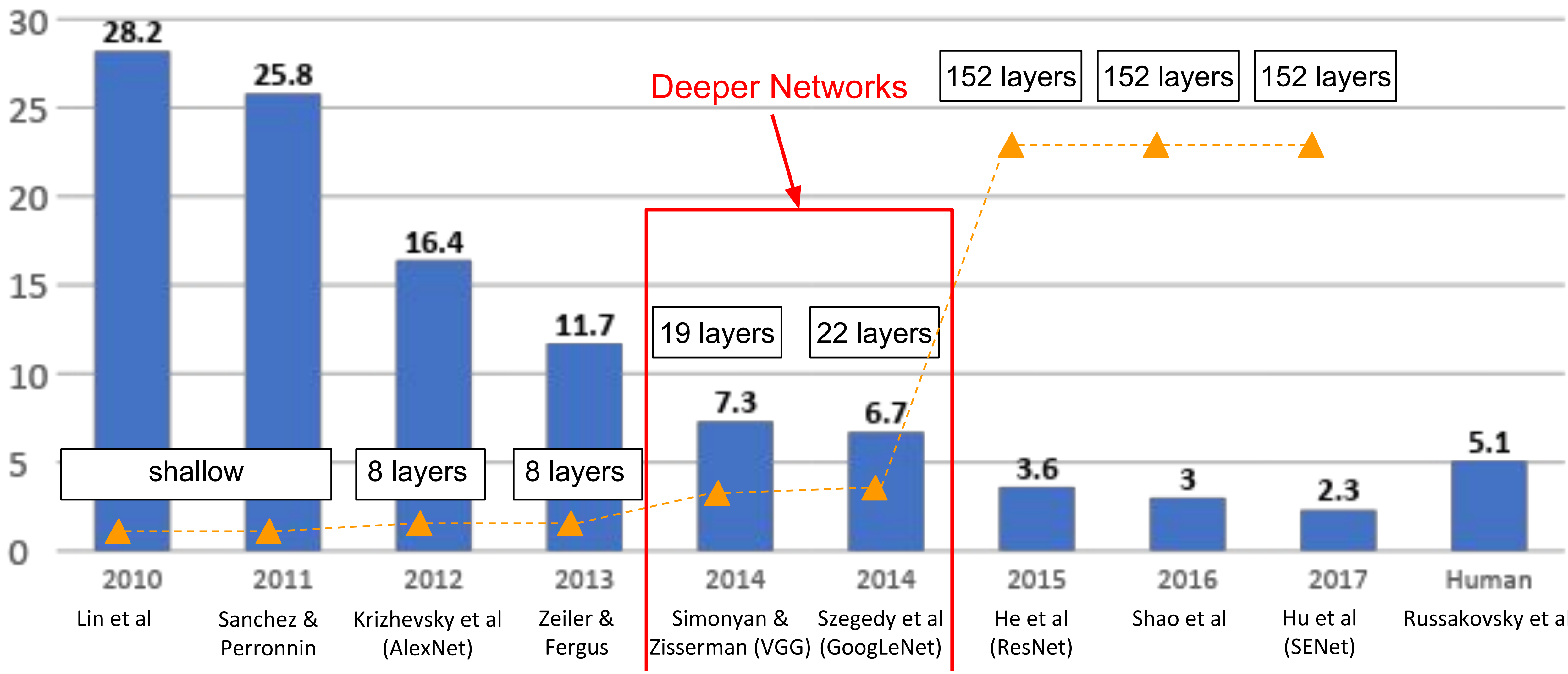
Details:

- ILSVRC’14 2nd in classification, 1st in localization
- Similar training procedure as Krizhevsky 2012
- No Local Response Normalisation (LRN)
- Use VGG16 or VGG19 (VGG19 only slightly better, more memory)
- Use ensembles for best results
- FC7 features generalize well to other tasks



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



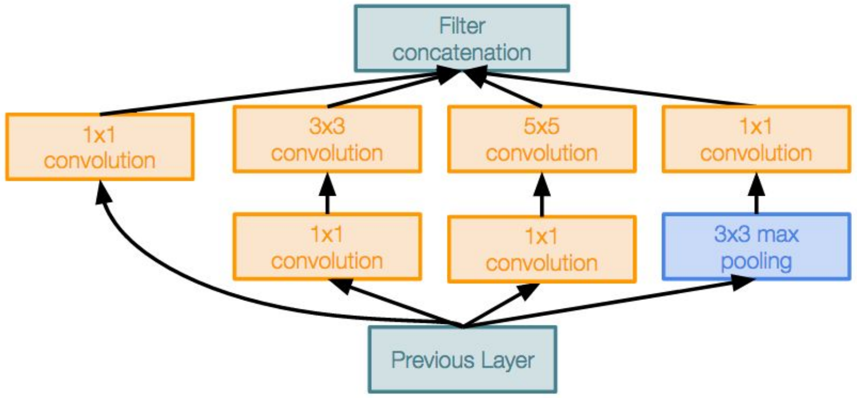
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

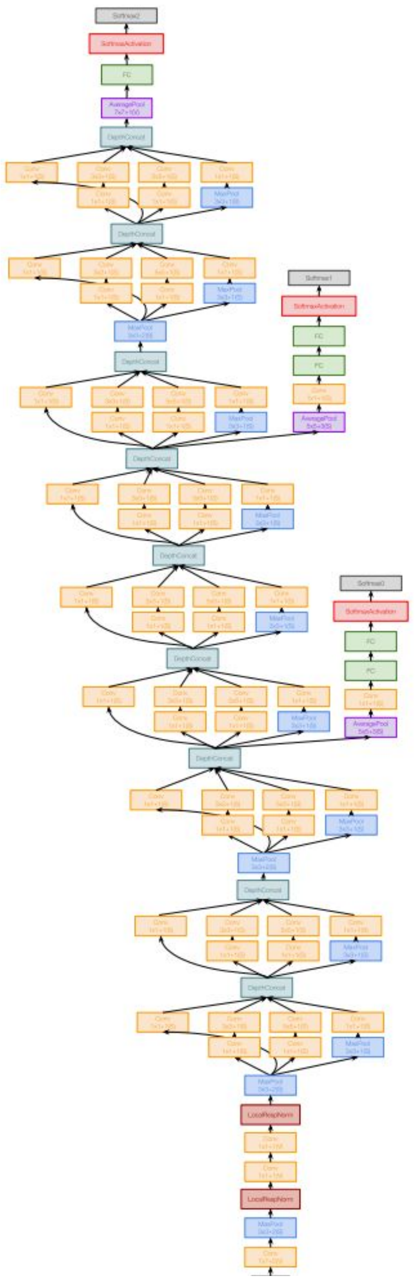
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

- 22 layers
- Efficient “Inception” module
- No FC layers
- Only 5 million parameters!
  12x less than AlexNet
- ILSVRC’14 classification winner
  (6.7% top 5 error)



Inception module

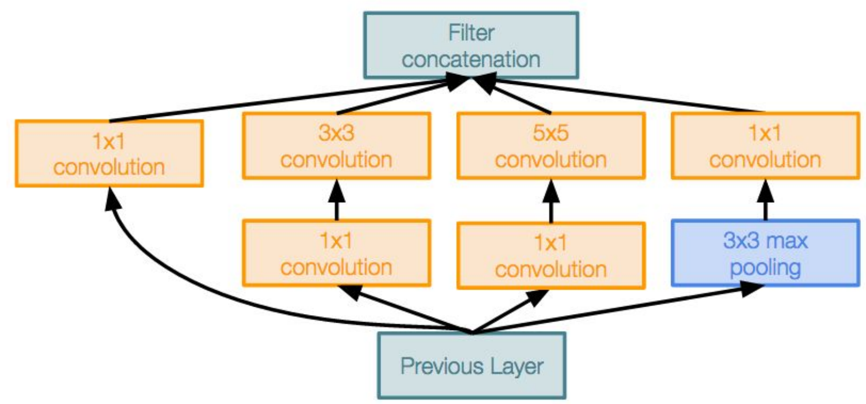


slide credit: Fei-Fei, Justin Johnson, Serena Yeung

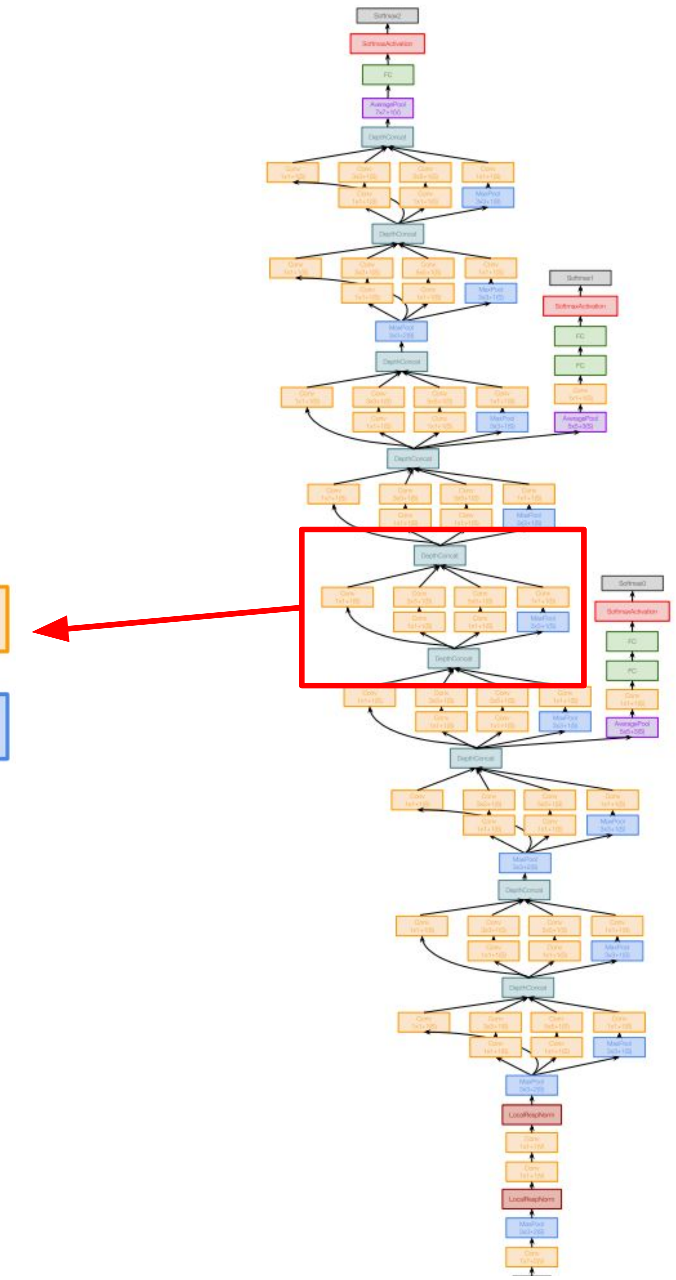
Case Study: GoogLeNet

[Szegedy et al., 2014]

"Inception module": design a good local network topology (network within a network) and then stack these modules on top of each other



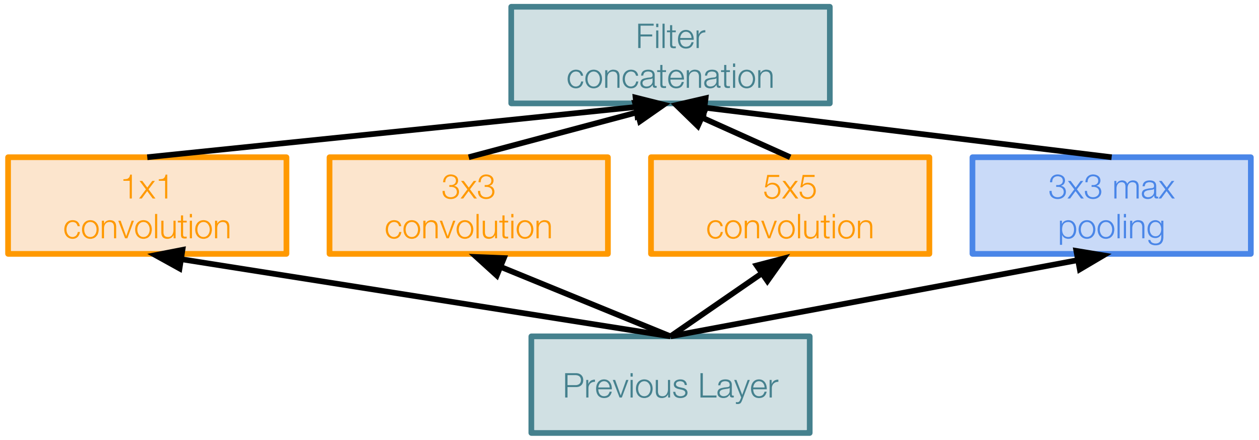
Inception module



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

Apply parallel filter operations on the input from previous layer:

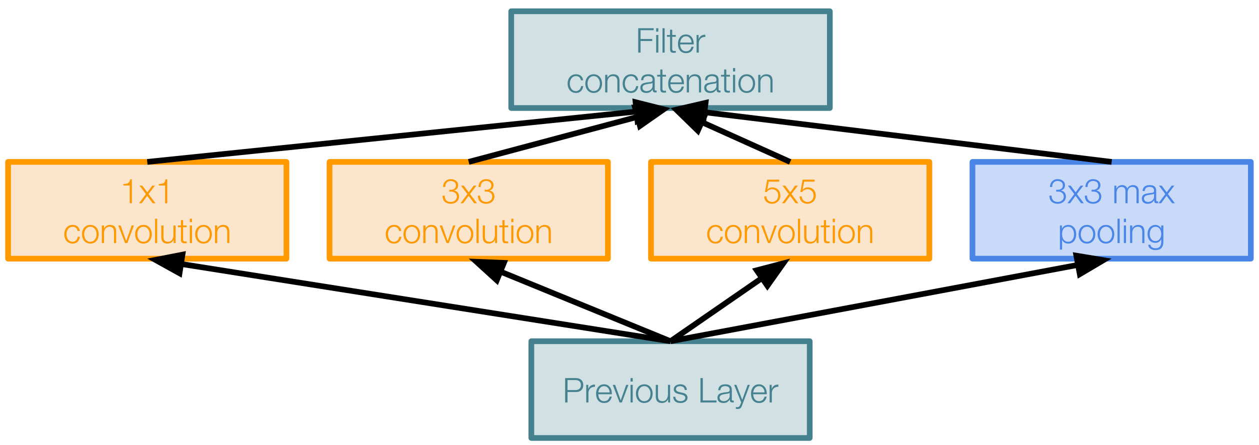
- Multiple receptive field sizes for convolution (1x1, 3x3, 5x5)
- Pooling operation (3x3)

Concatenate all filter outputs together depth-wise

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

Apply parallel filter operations on the input from previous layer:
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Concatenate all filter outputs together depth-wise

Q: What is the problem with this?
[Hint: Computational complexity]

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]

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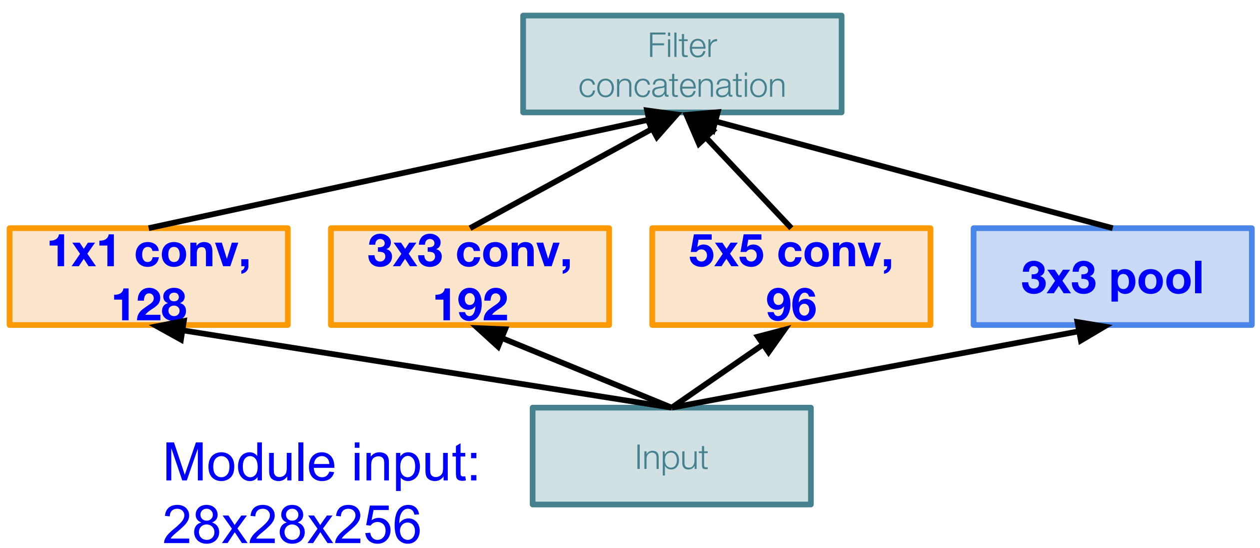
Example:



Naive Inception module

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

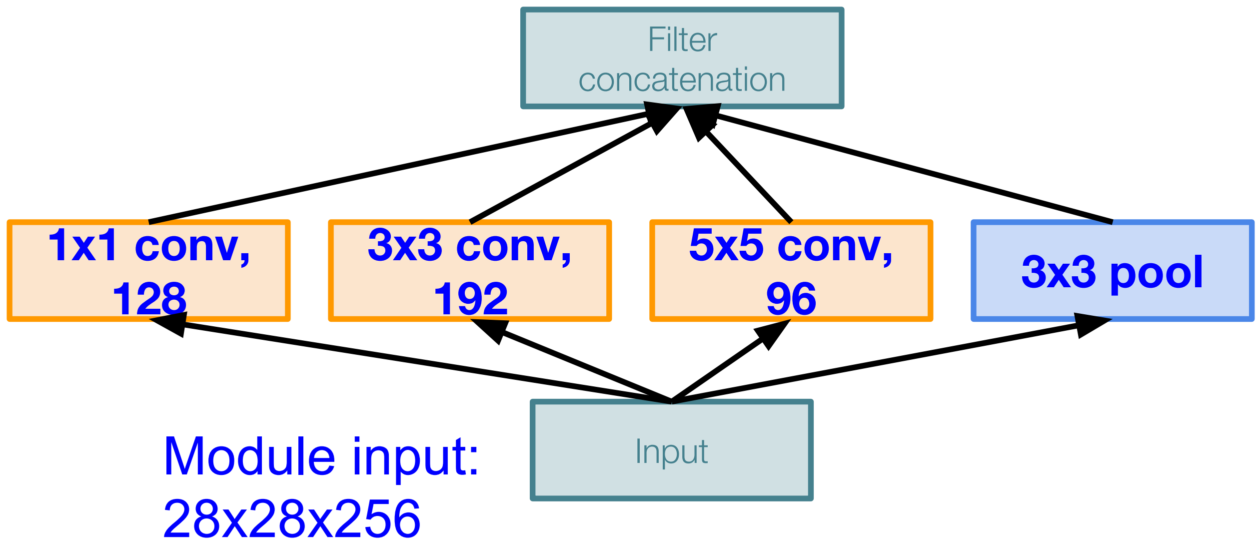
Case Study: GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q1: What is the output size of the 1x1 conv, with 128 filters?



Naive Inception module

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]

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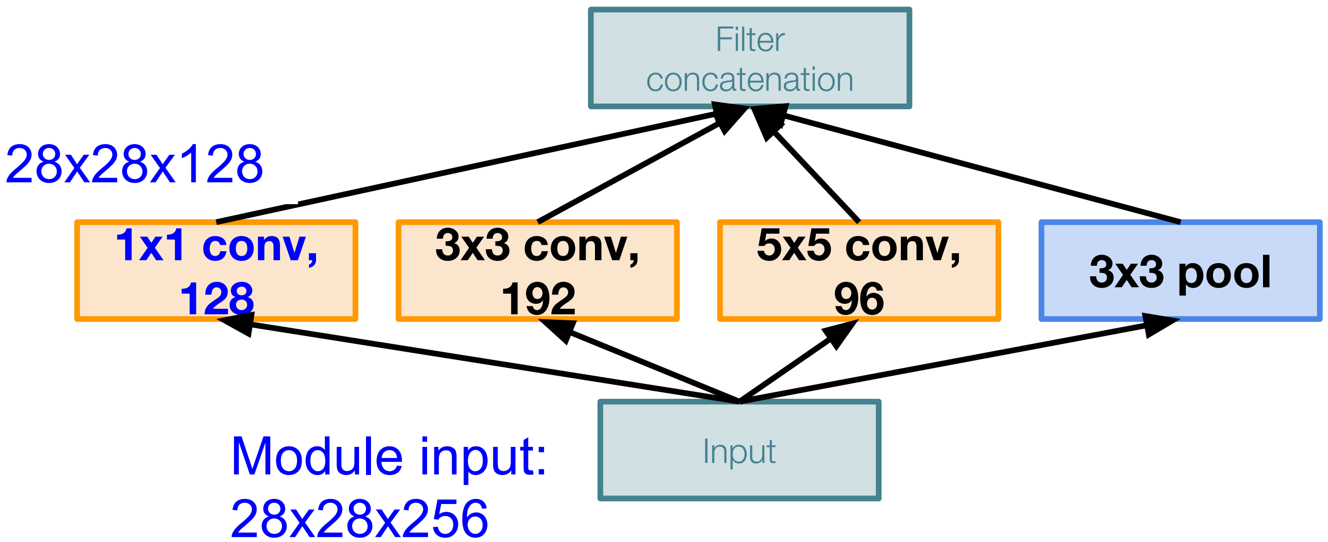


Naive Inception module

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

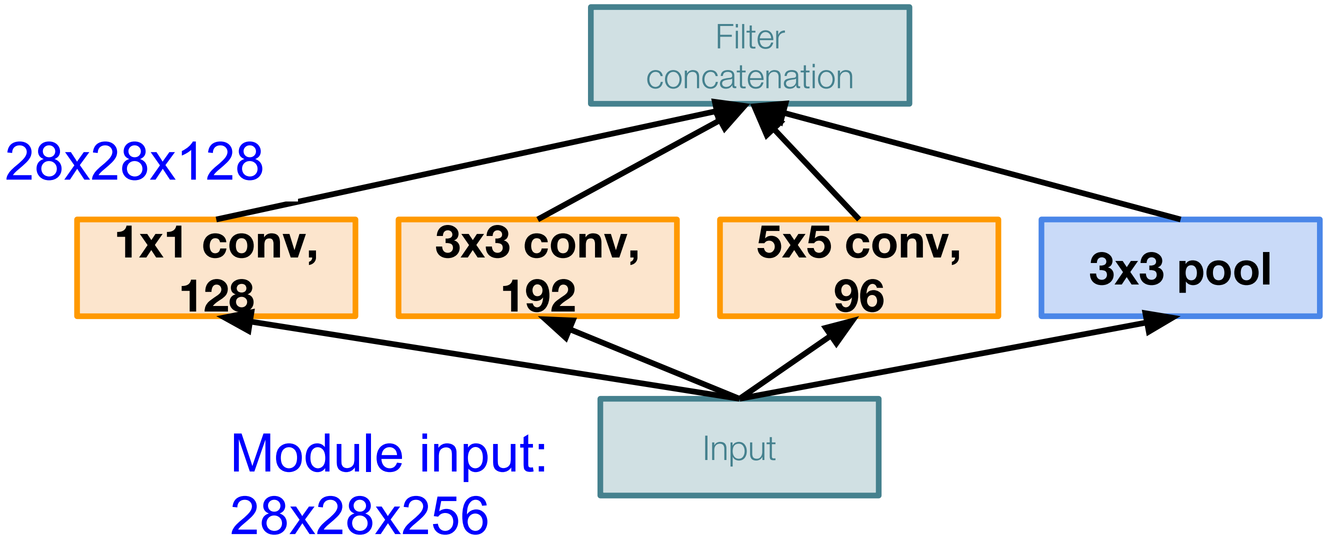
Case Study: GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q2: What are the output sizes of all different filter operations?



Naive Inception module

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]

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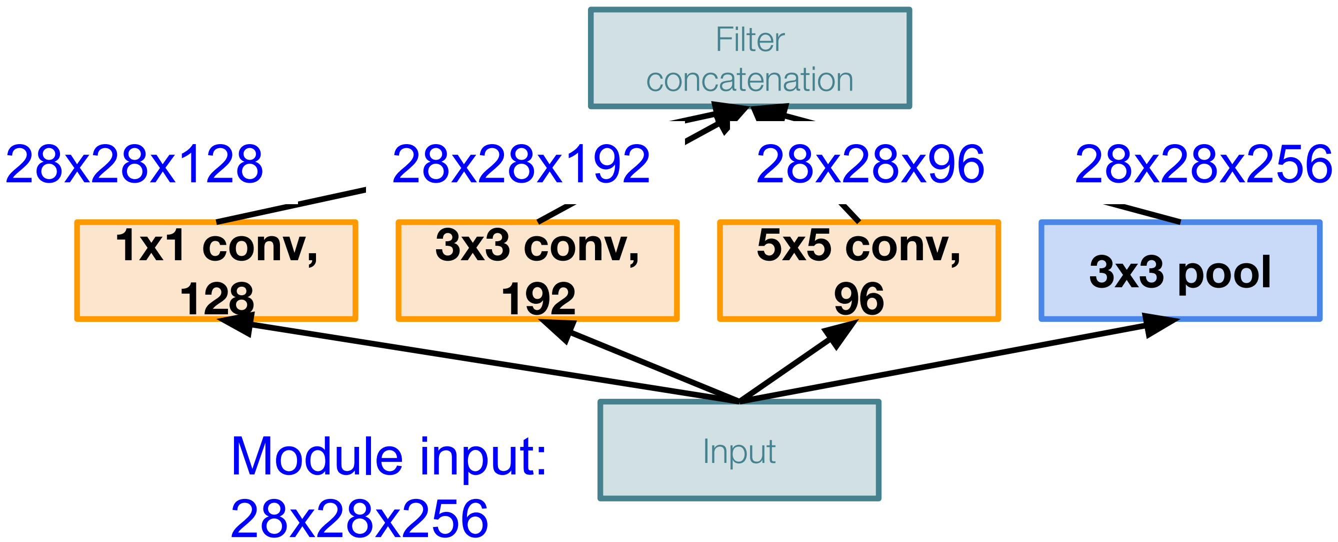


Naive Inception module

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

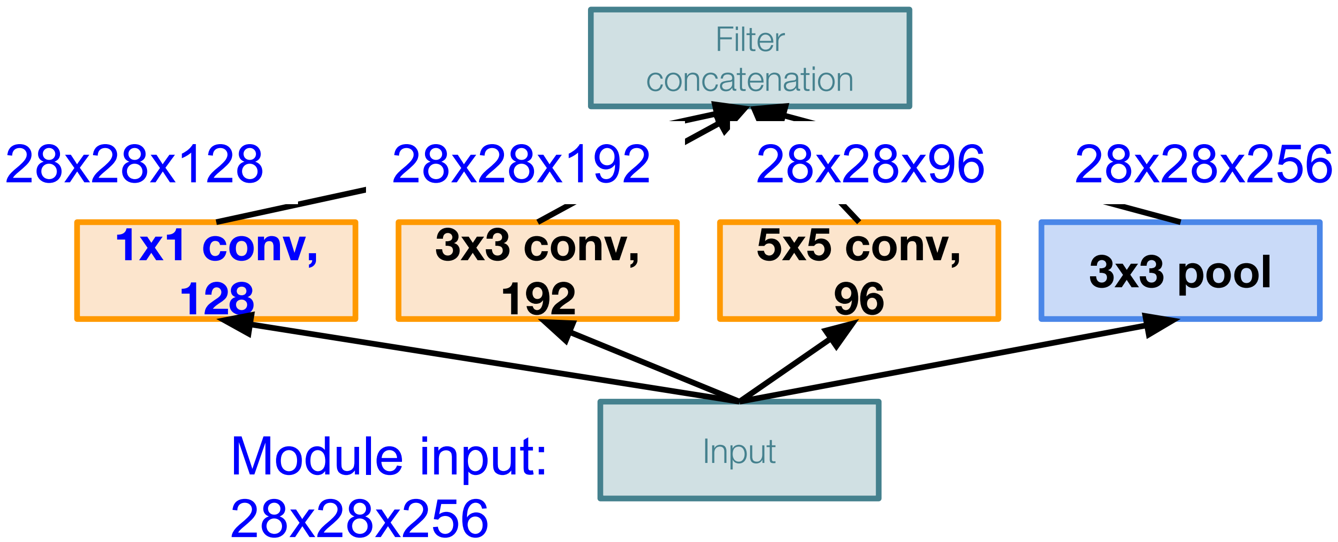
Case Study: GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q3:What is output size after filter concatenation?



Naive Inception module

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]

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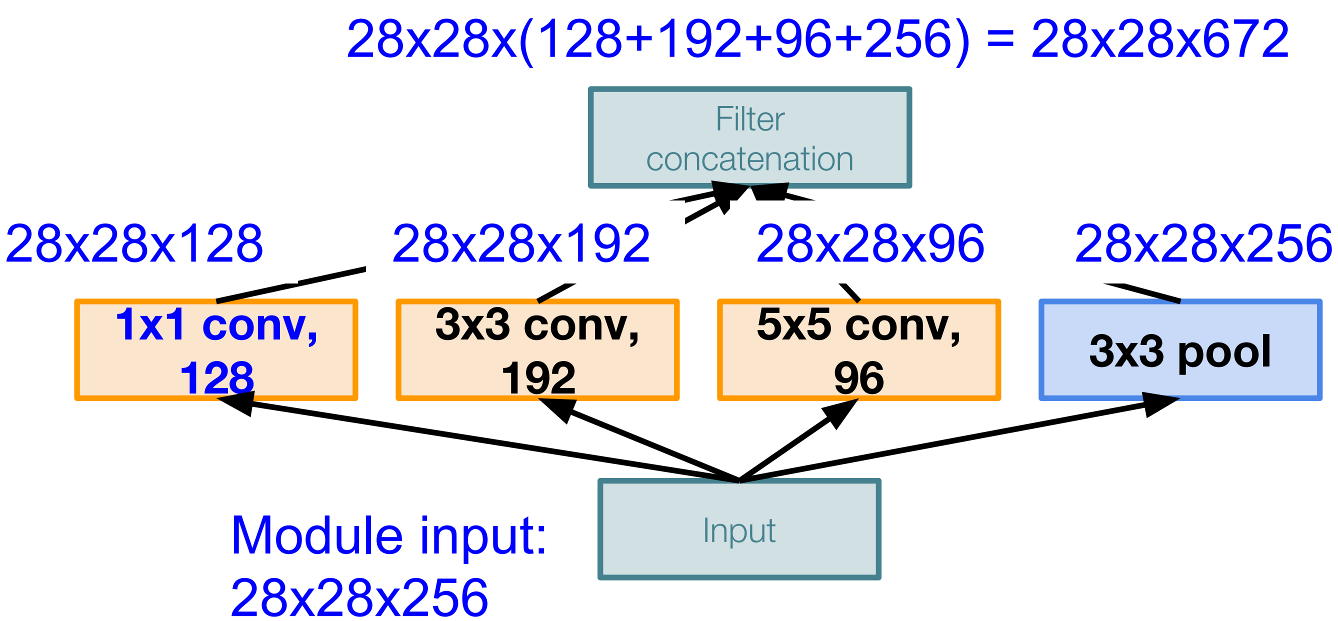


Naive Inception module

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

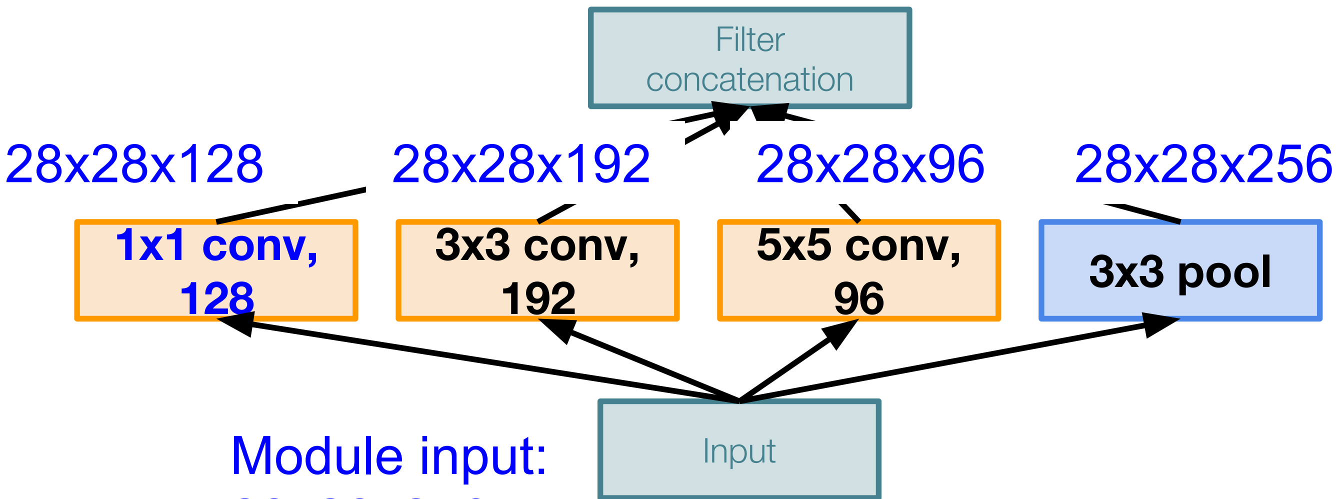
[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q3:What is output size after filter concatenation?

28x28x(128+192+96+256) = 28x28x672



Module input: 28x28x256

Naive Inception module

Conv Ops:

[1x1 conv, 128] 28x28x128x1x1x256

[3x3 conv, 192] 28x28x192x3x3x256

[5x5 conv, 96] 28x28x96x5x5x256

Total: 854M ops

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]

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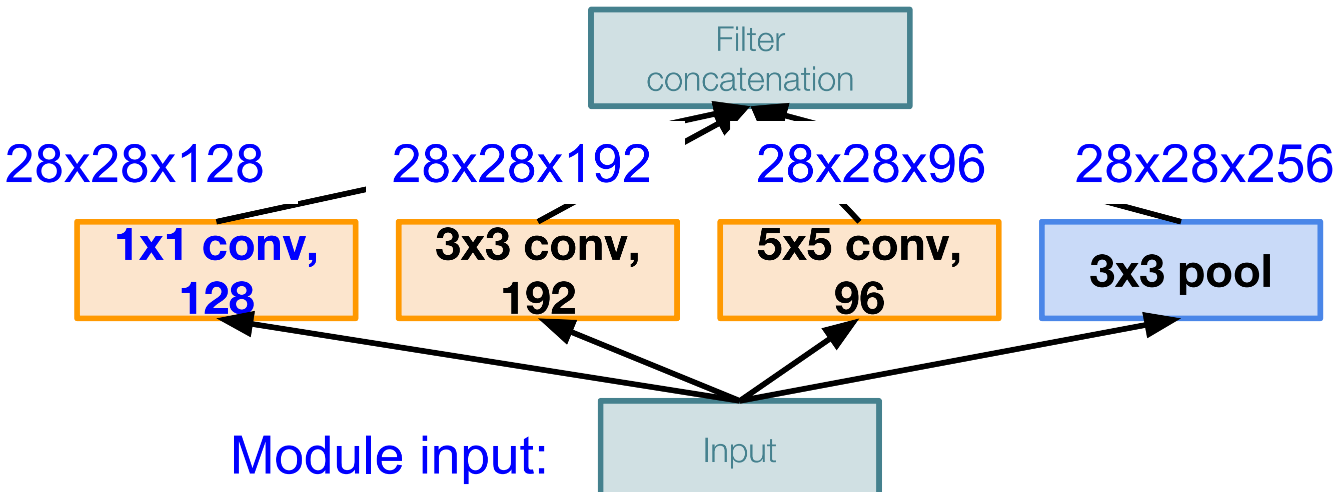
Q3:What is output size after filter concatenation?

28x28x(128+192+96+256) = 28x28x672



Module input: 28x28x256

Naive Inception module

Q: What is the problem with this?
[Hint: Computational complexity]

Conv Ops:
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x256
[5x5 conv, 96] 28x28x96x5x5x256
Total: 854M ops

Very expensive compute

Pooling layer also preserves feature depth, which means total depth after concatenation can only grow at every layer!

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]

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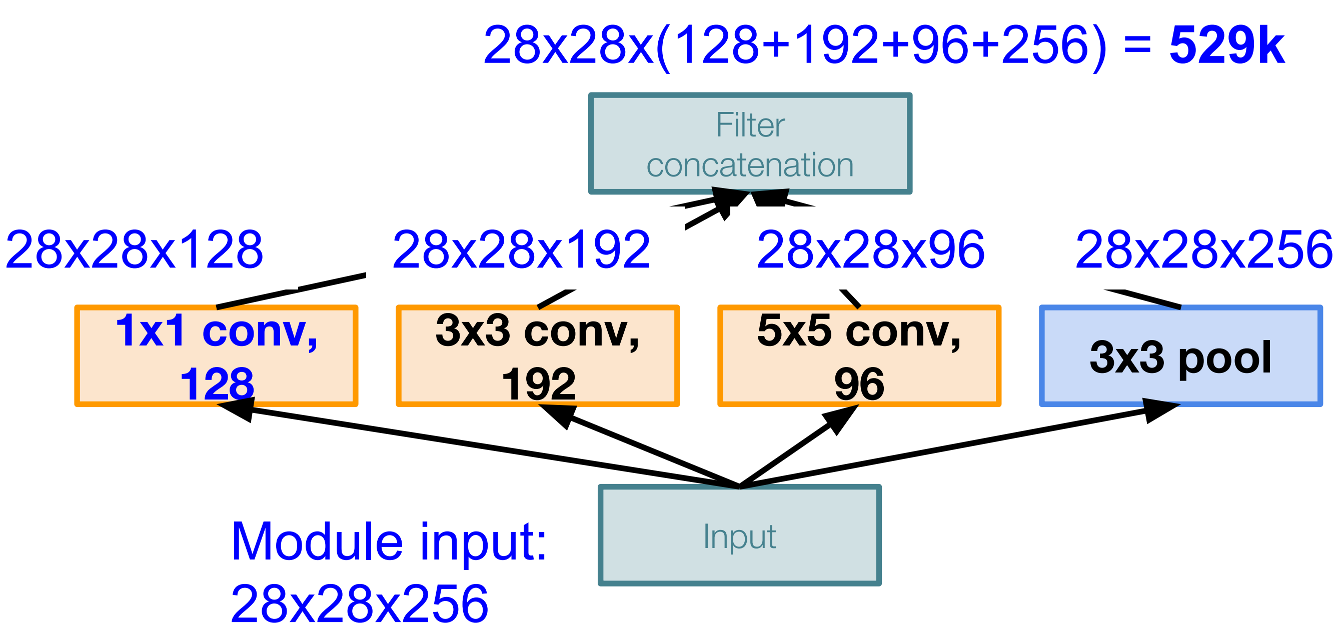
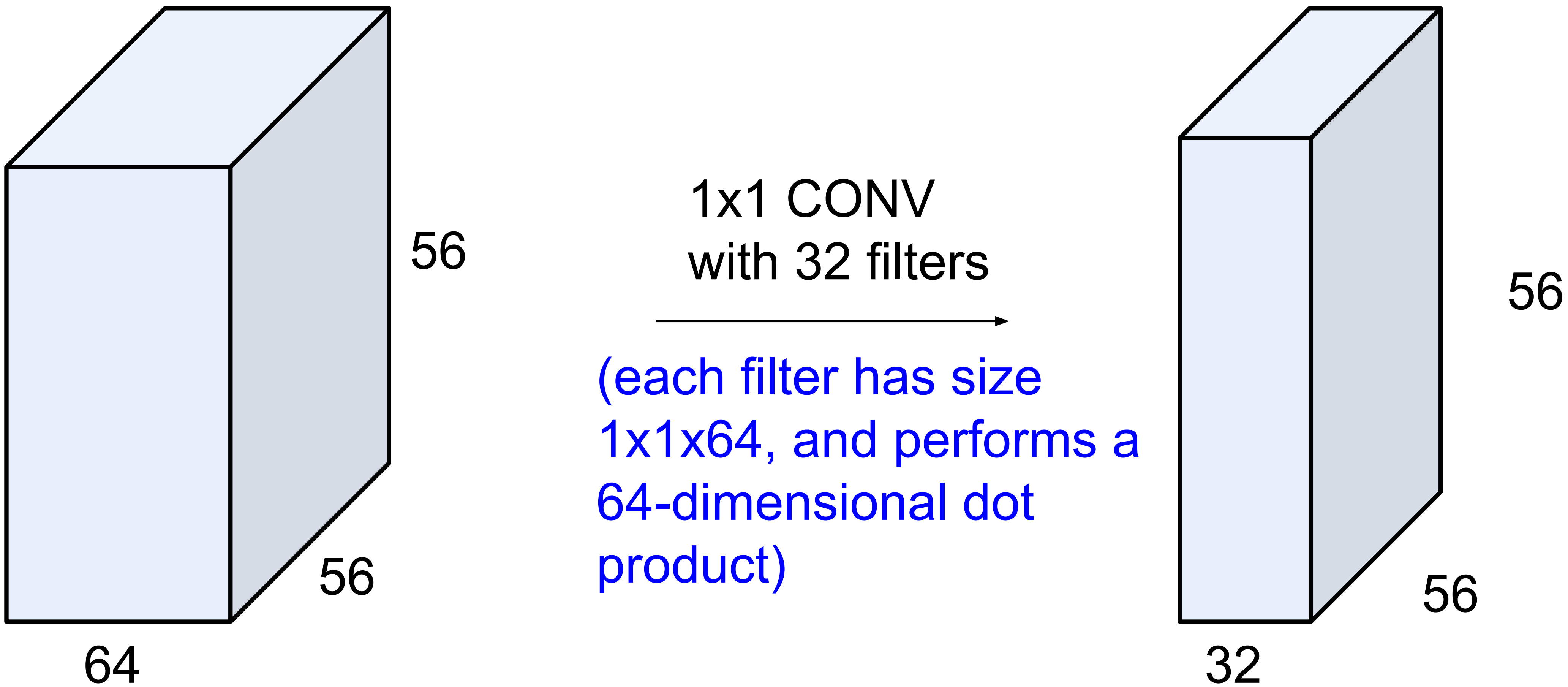


Naive Inception module

Solution: “bottleneck” layers that use 1x1 convolutions to reduce feature depth

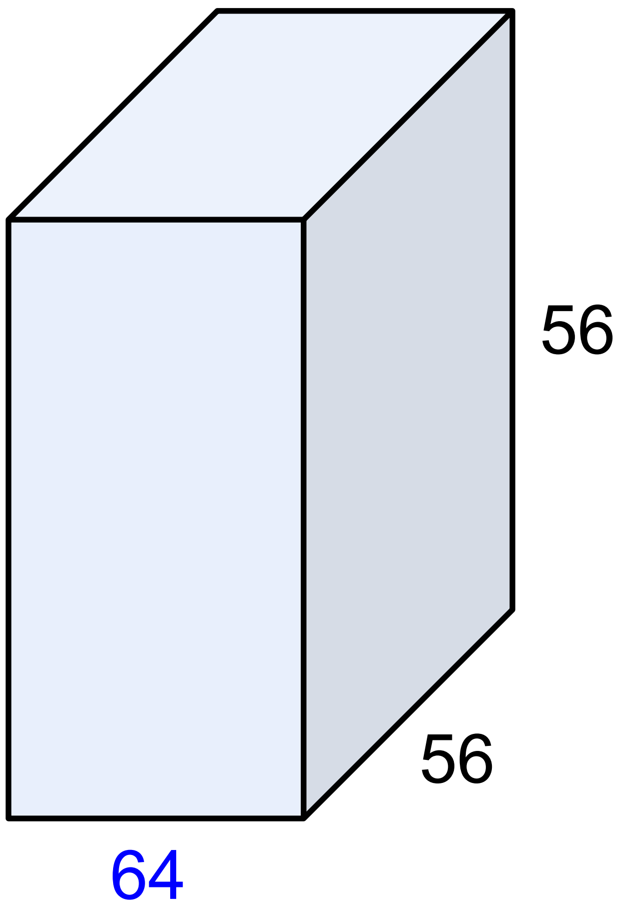
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Reminder: 1x1 convolutions



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

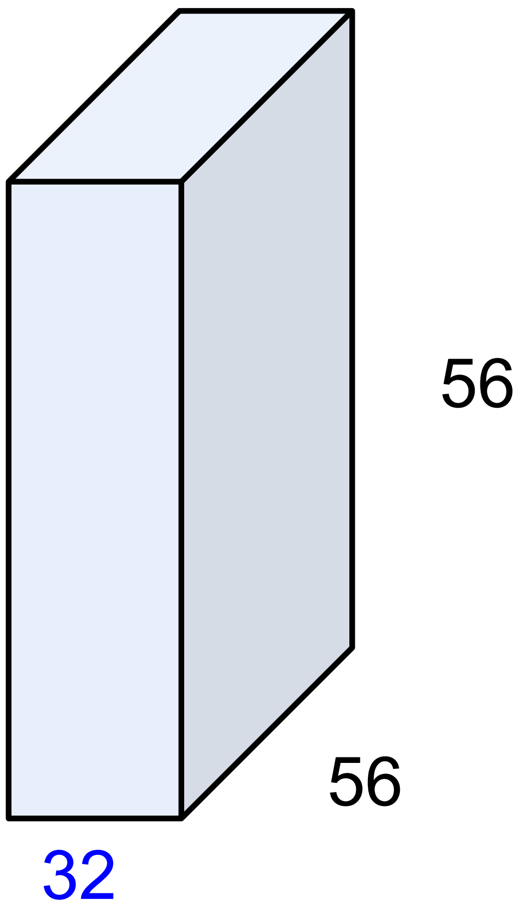
Reminder: 1x1 convolutions



1x1 CONV
with 32 filters

preserves spatial dimensions, reduces depth!

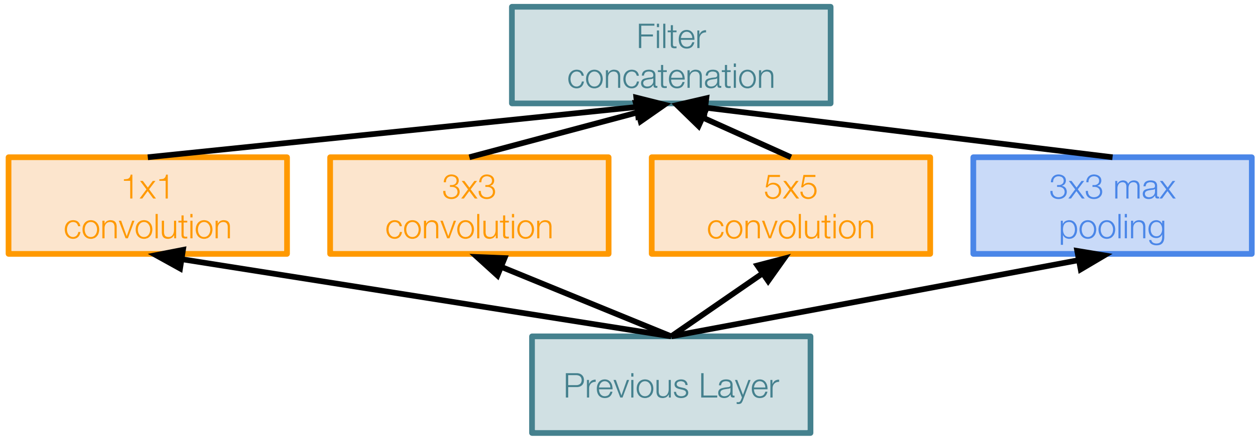
Projects depth to lower dimension (combination of feature maps)



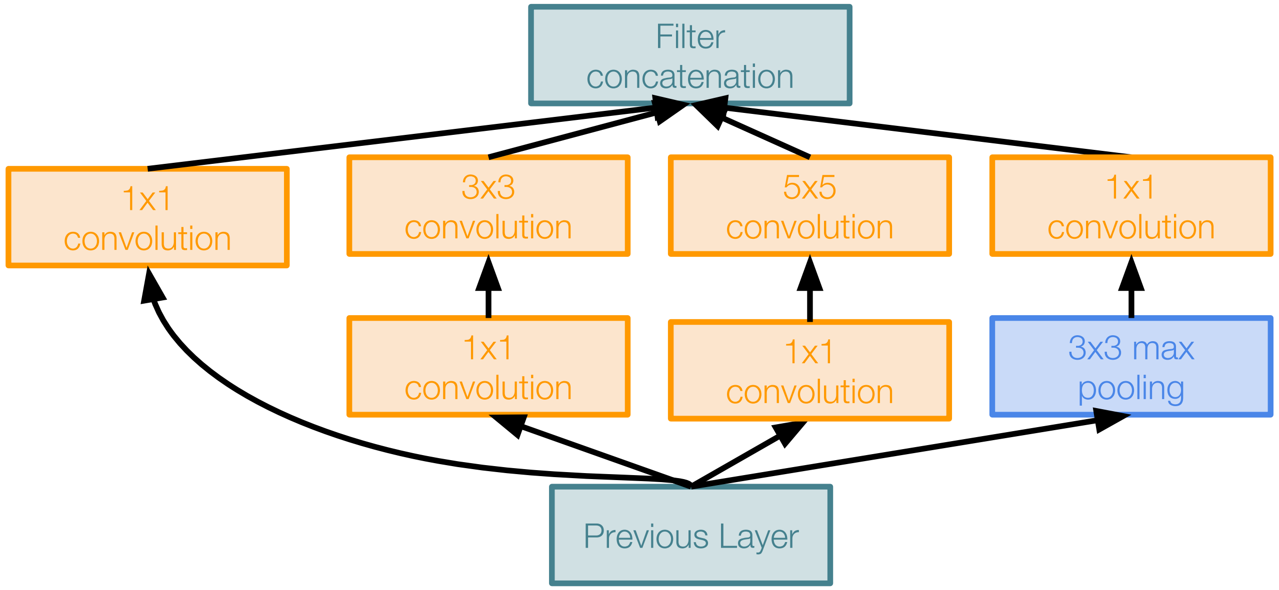
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

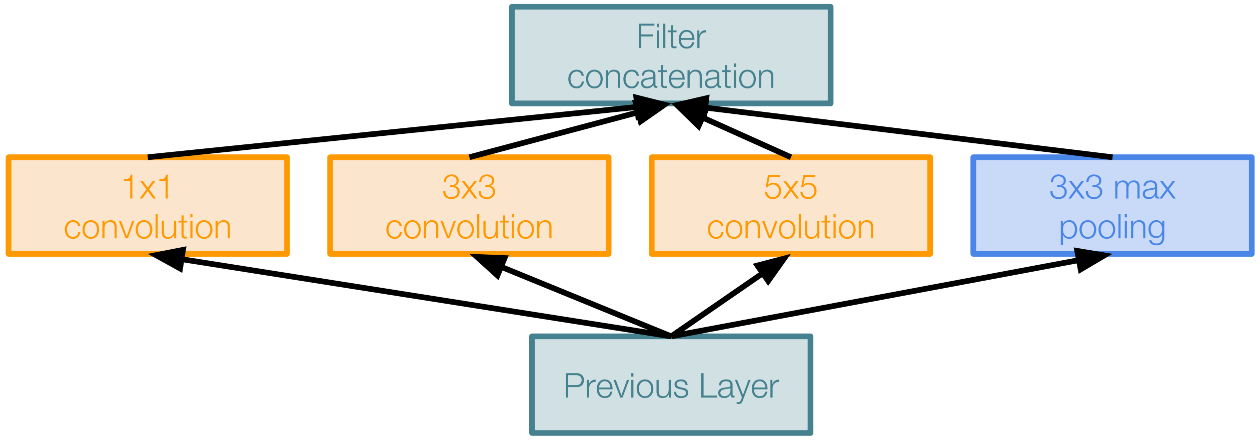


Inception module with dimension reduction

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

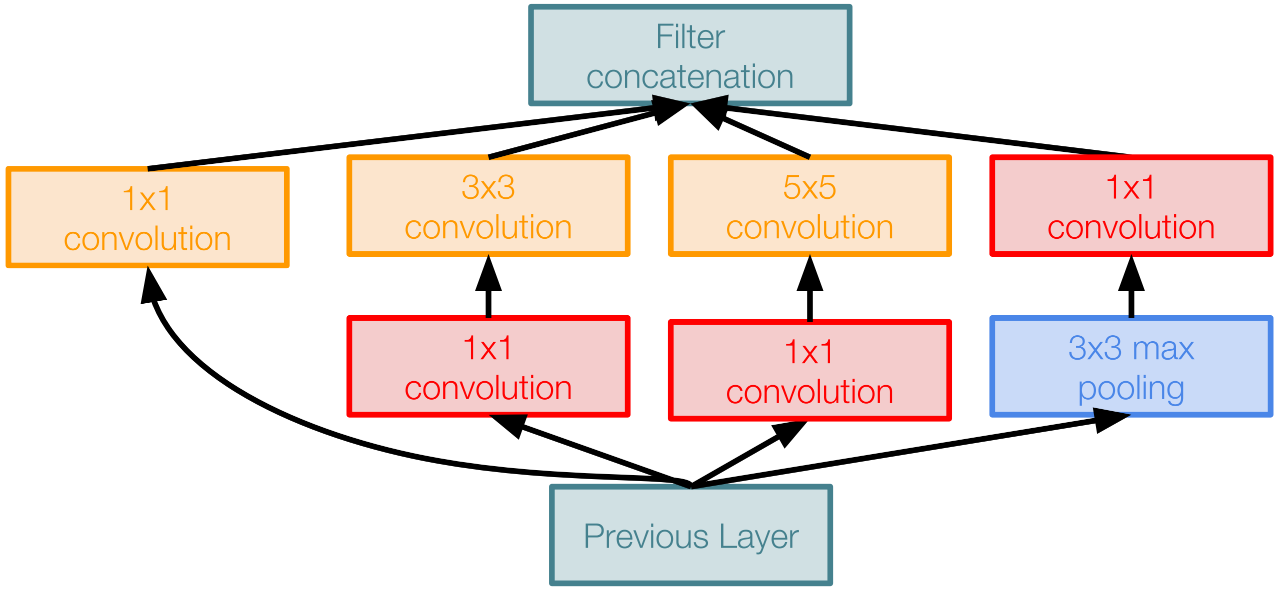
Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

1x1 conv "bottleneck" layers



Inception module with dimension reduction

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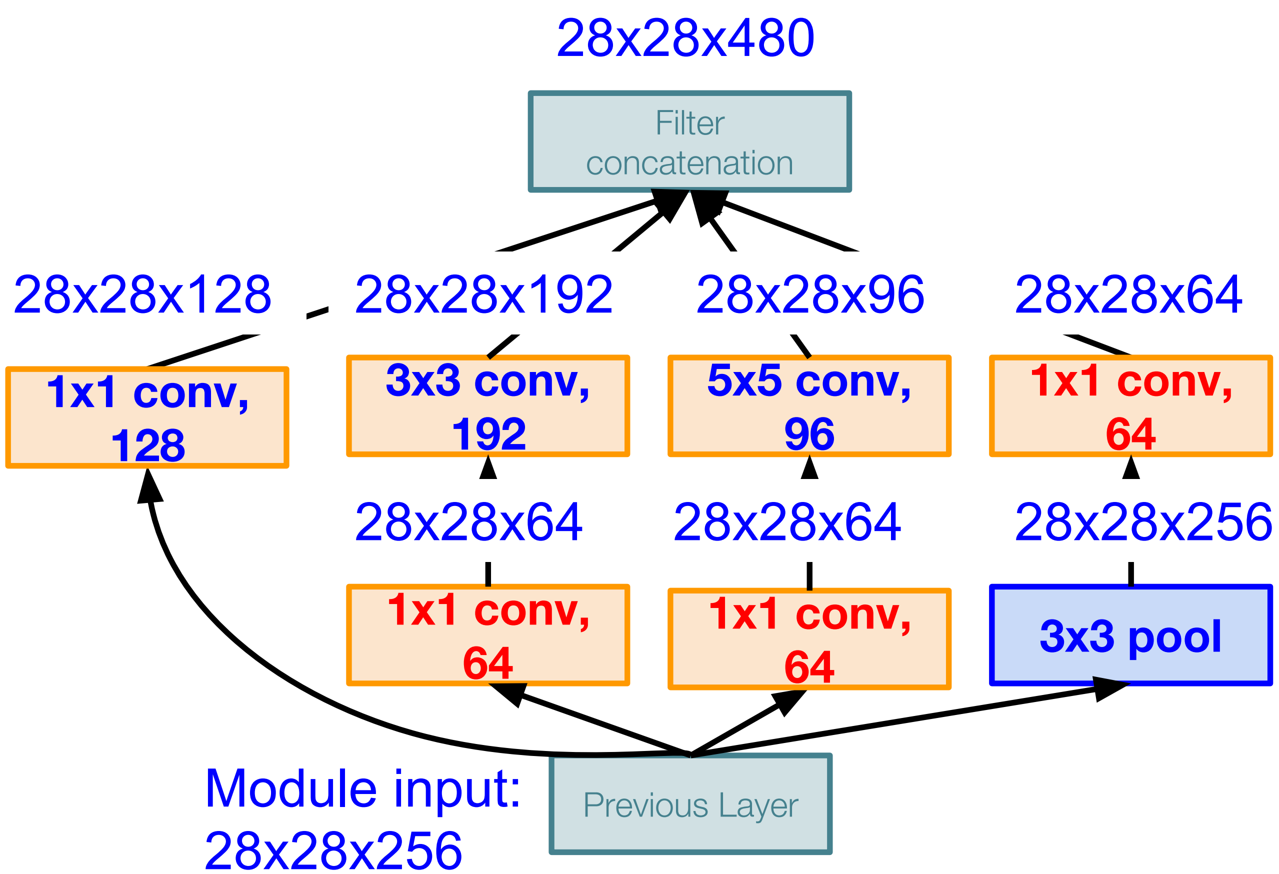
Case Study: GoogLeNet

[Szegedy et al., 2014]



Inception module with dimension reduction

Using same parallel layers as naive example, and adding "1x1 conv, 64 filter" bottlenecks:

Conv Ops:

[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x64
[5x5 conv, 96] 28x28x96x5x5x64
[1x1 conv, 64] 28x28x64x1x1x256

Total: 358M ops

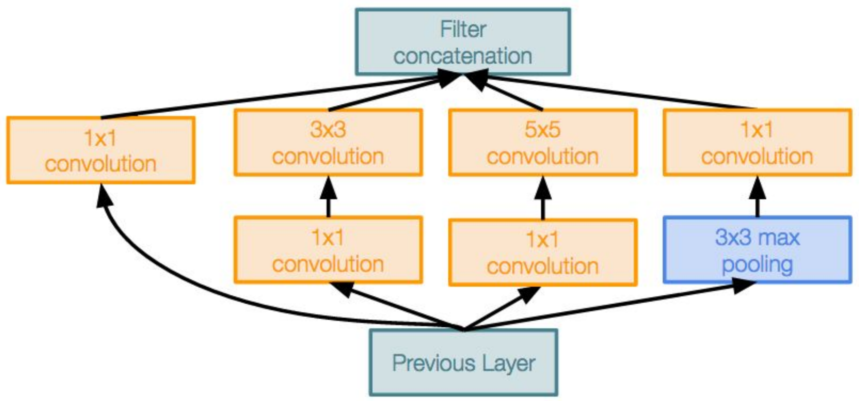
Compared to 854M ops for naive version
Bottleneck can also reduce depth after pooling layer

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

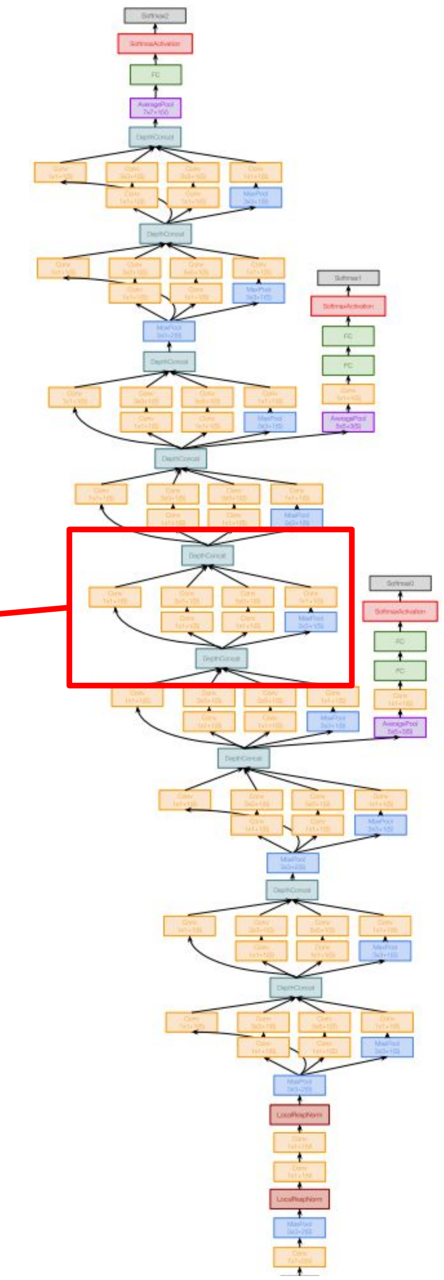
Case Study: GoogLeNet

[Szegedy et al., 2014]

Stack Inception modules with dimension reduction on top of each other



Inception module

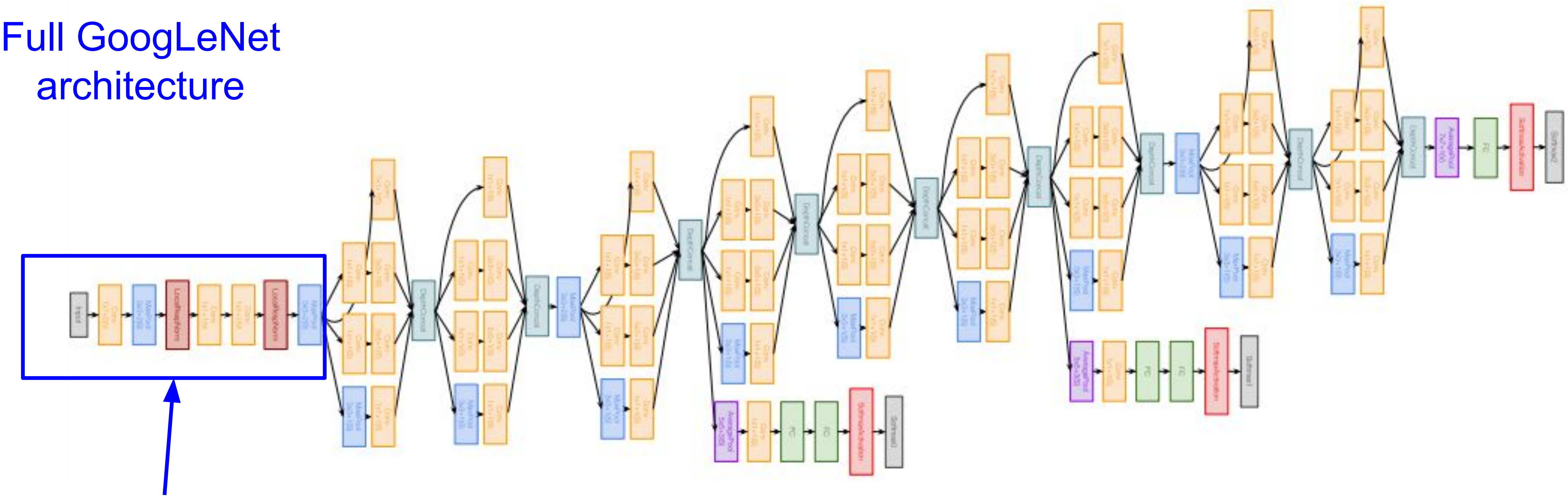


slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



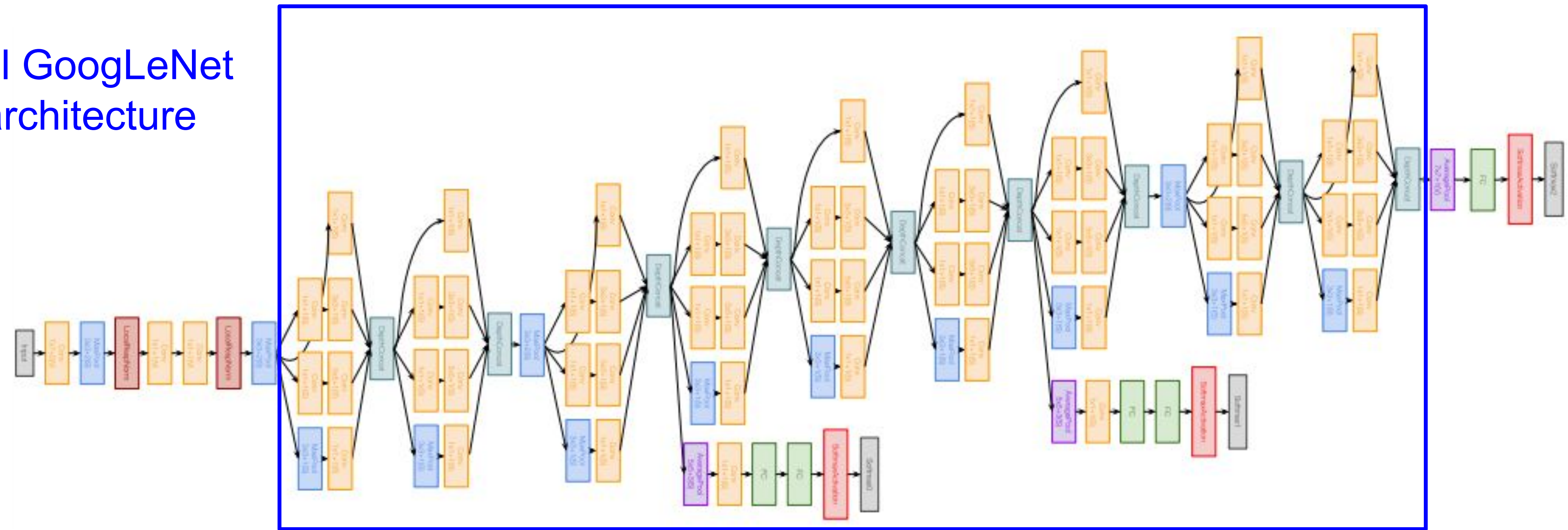
Stem Network:
Conv-Pool-
2x Conv-Pool

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



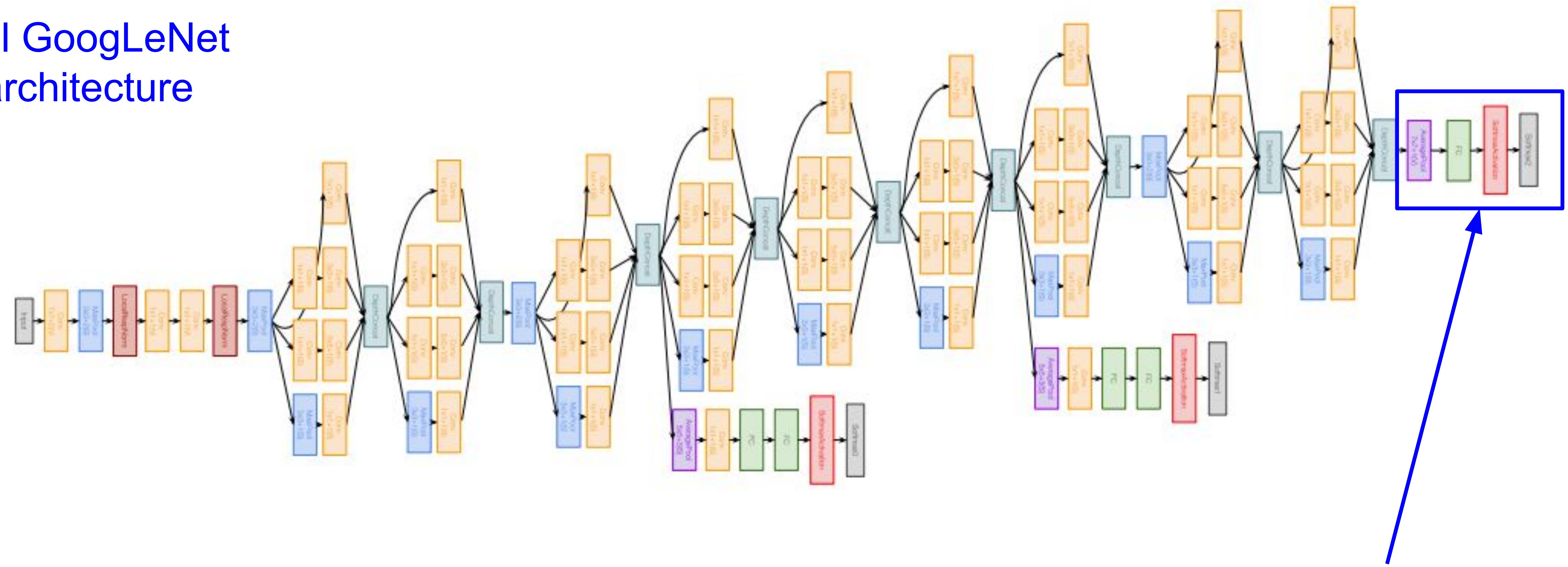
Stacked Inception Modules

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



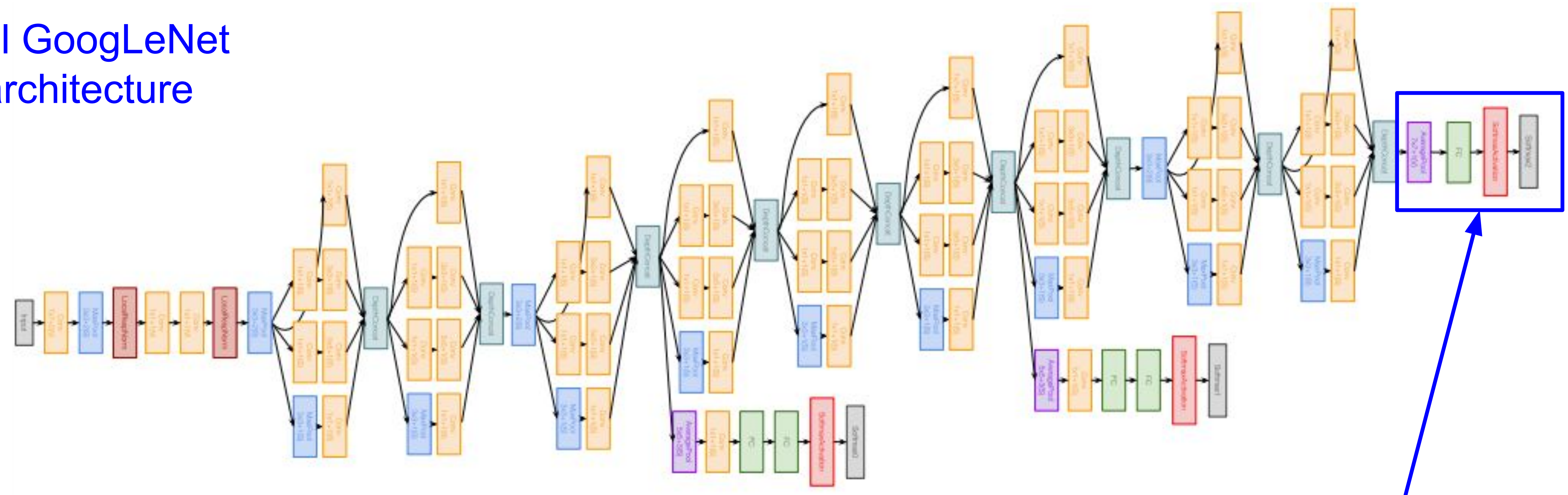
Classifier output

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



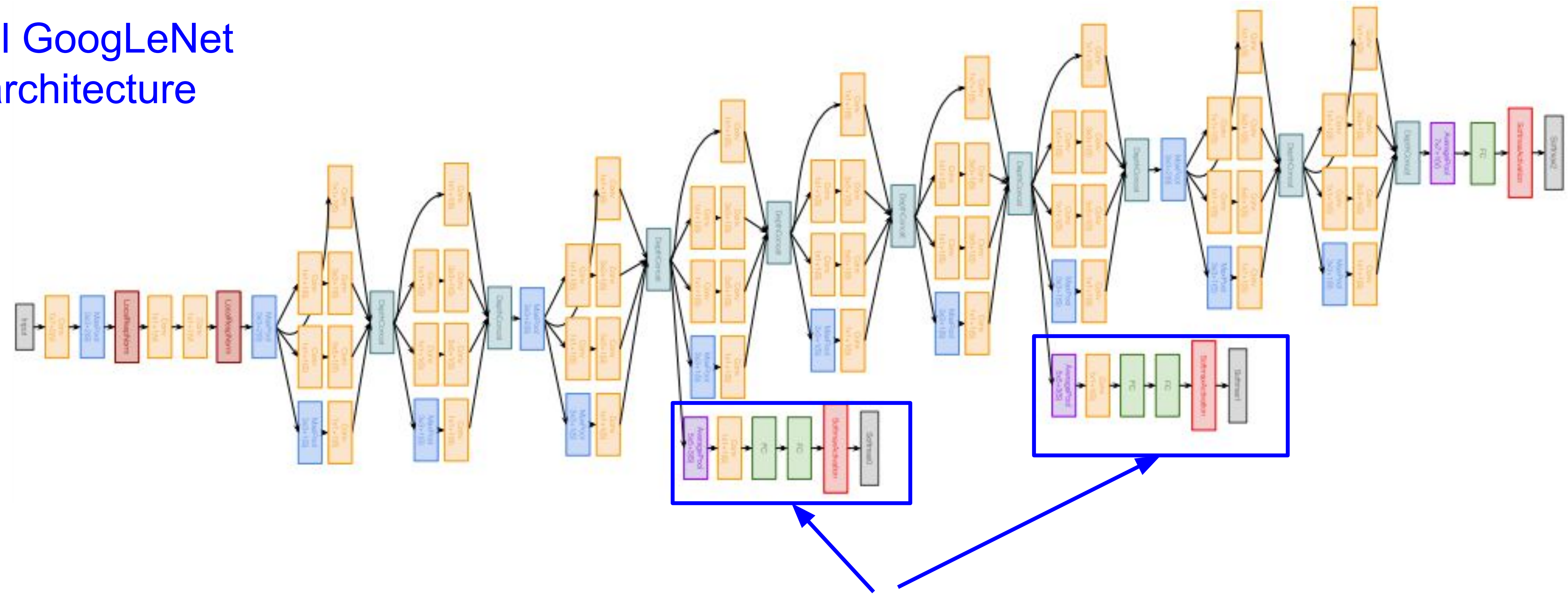
Classifier output
(removed expensive FC layers!)

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



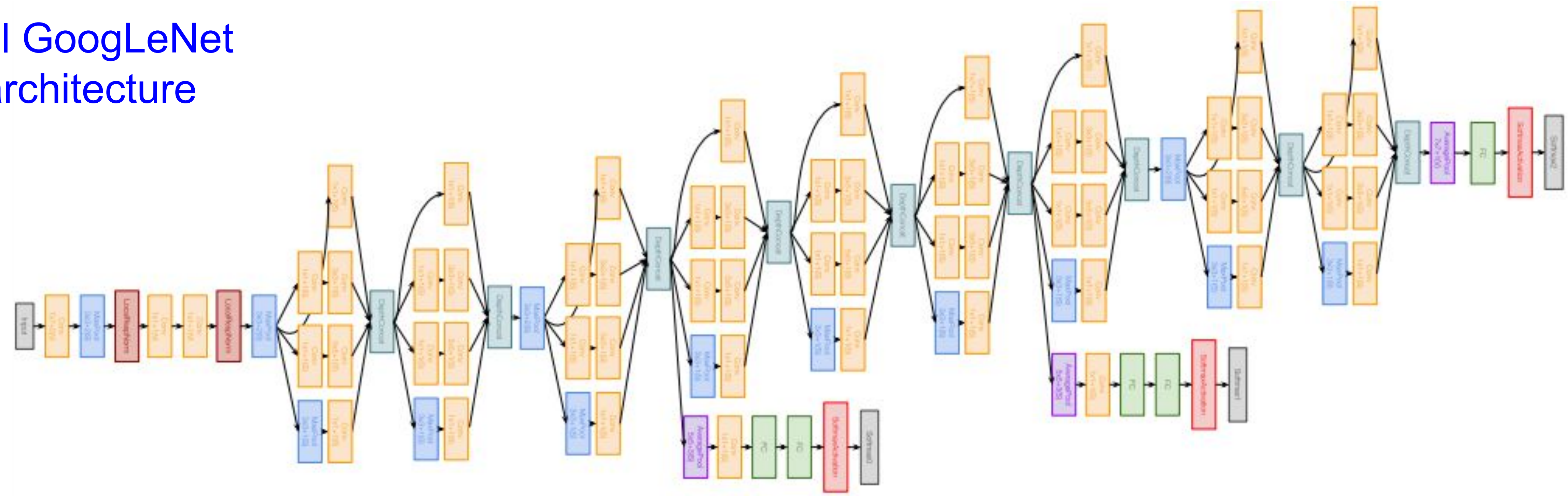
Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



22 total layers with weights
(parallel layers count as 1 layer => 2 layers per Inception module. Don't count auxiliary output layers)

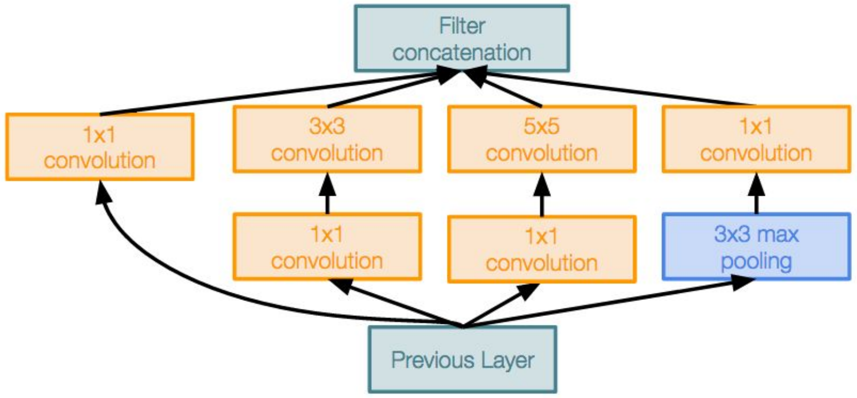
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: GoogLeNet

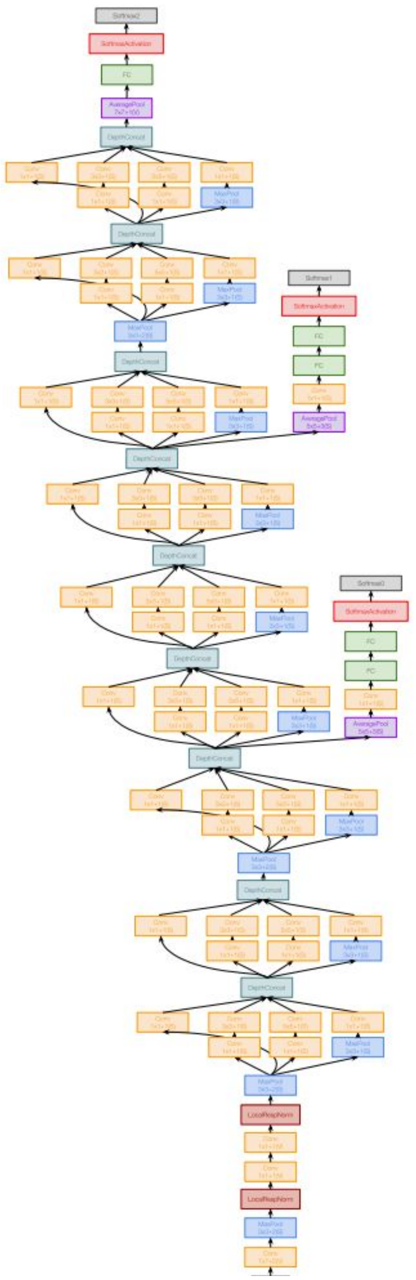
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

- 22 layers
- Efficient "Inception" module
- No FC layers
- 12x less params than AlexNet
- ILSVRC'14 classification winner (6.7% top 5 error)



Inception module



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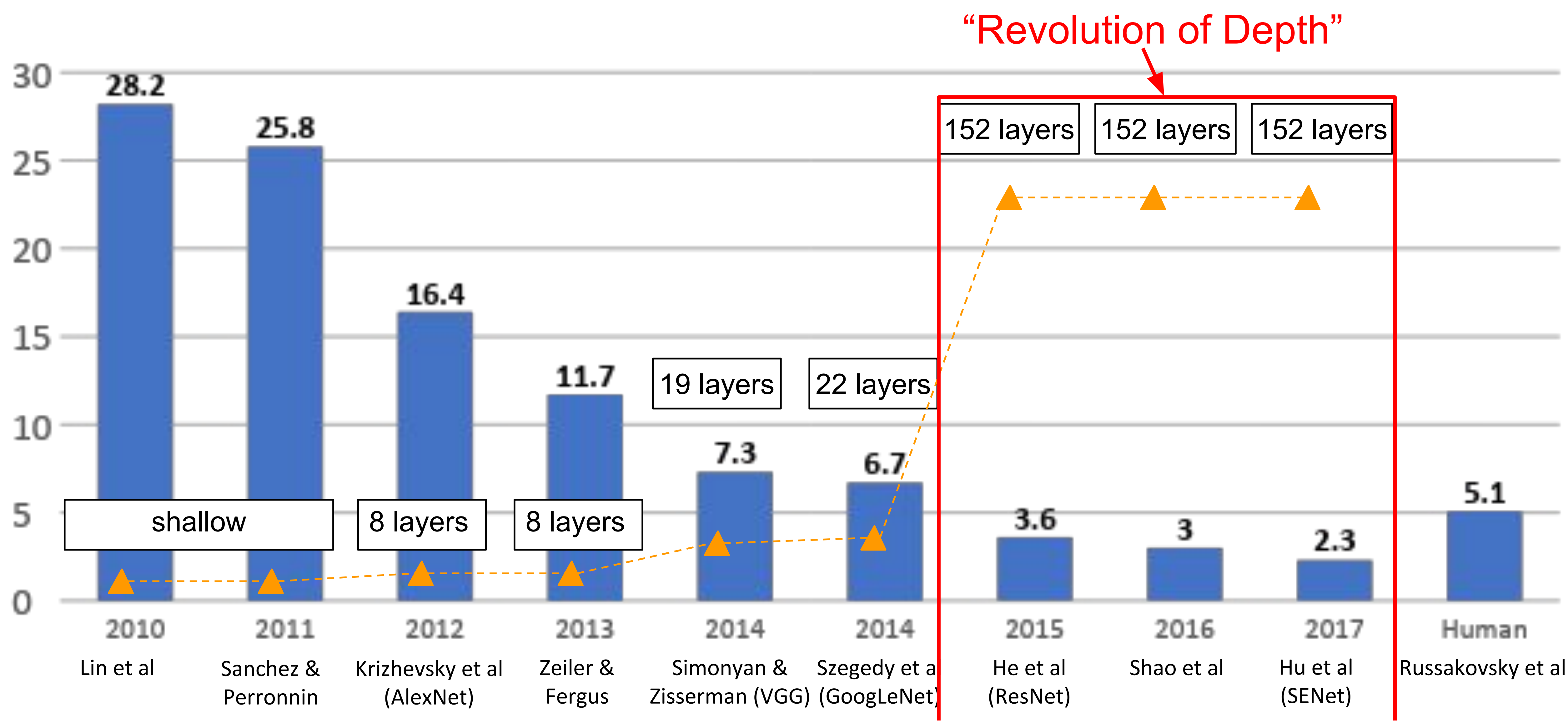
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



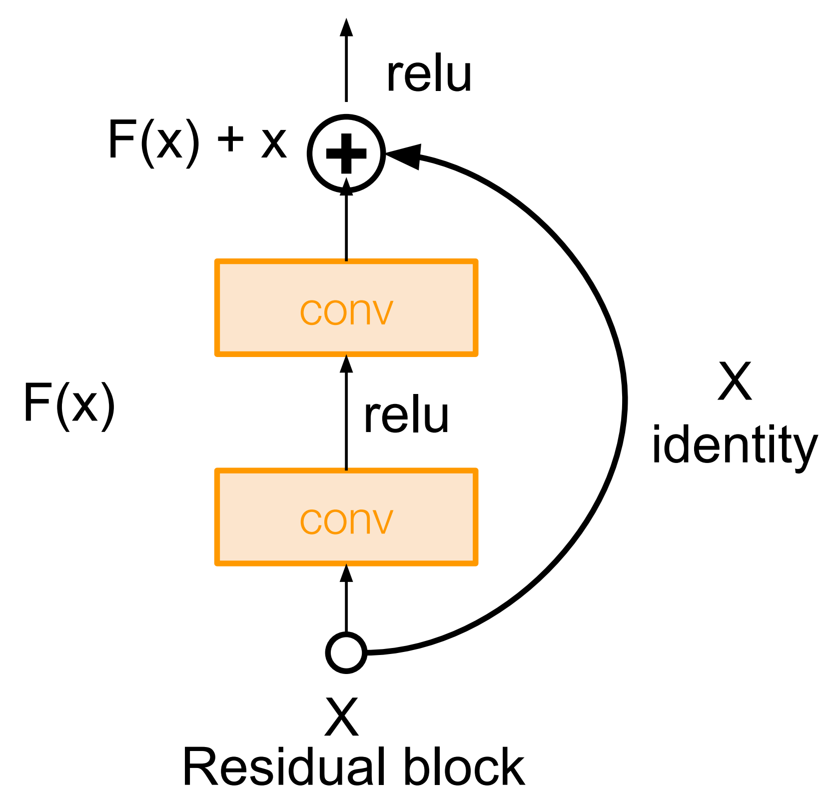
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

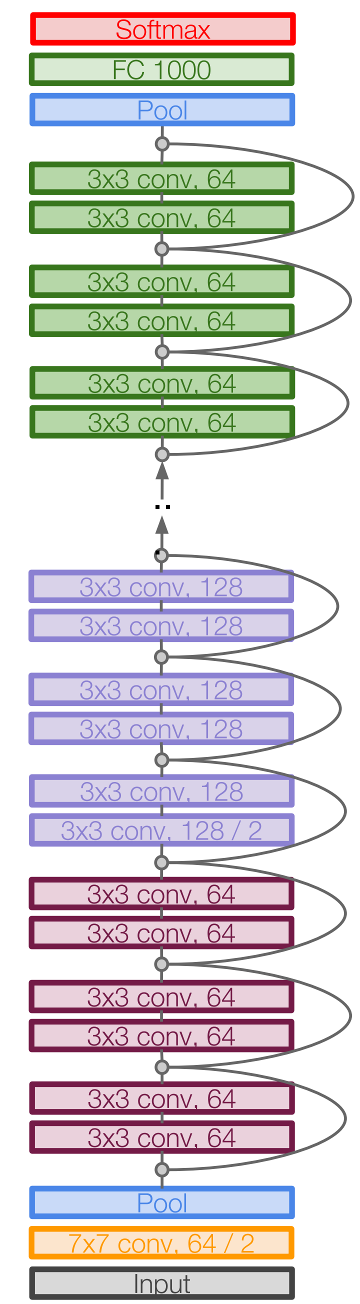
Case Study: ResNet

[He et al., 2015]

Very deep networks using residual connections

- 152-layer model for ImageNet
- ILSVRC'15 classification winner (3.57% top 5 error)
- Swept all classification and detection competitions in ILSVRC'15 and COCO'15!





slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

[He et al., 2015]

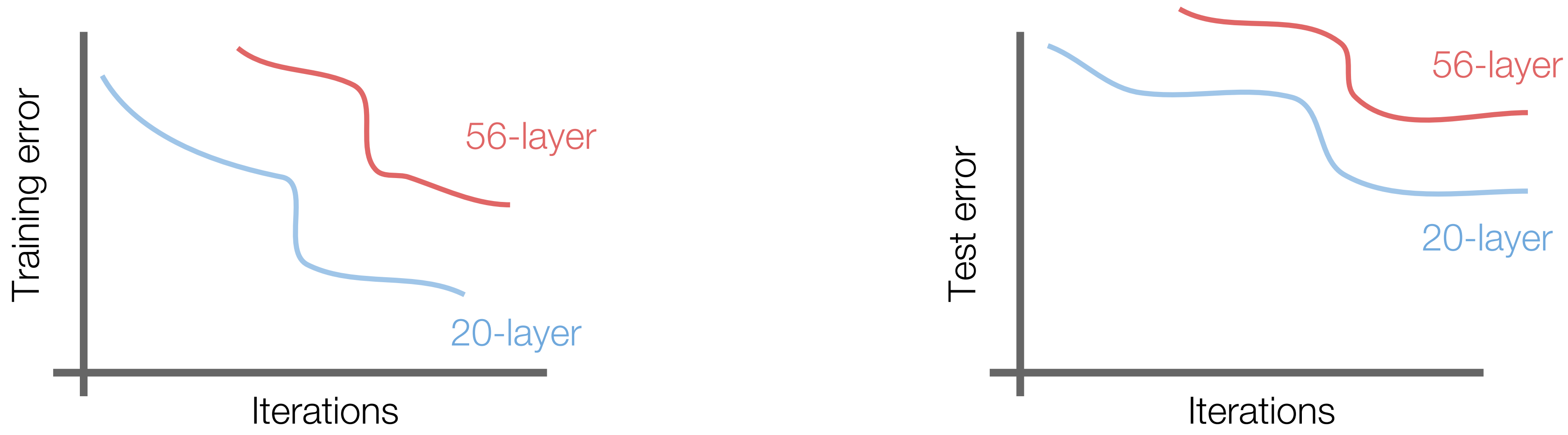
What happens when we continue stacking deeper layers on a “plain” convolutional neural network?

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

[He et al., 2015]

What happens when we continue stacking deeper layers on a “plain” convolutional neural network?



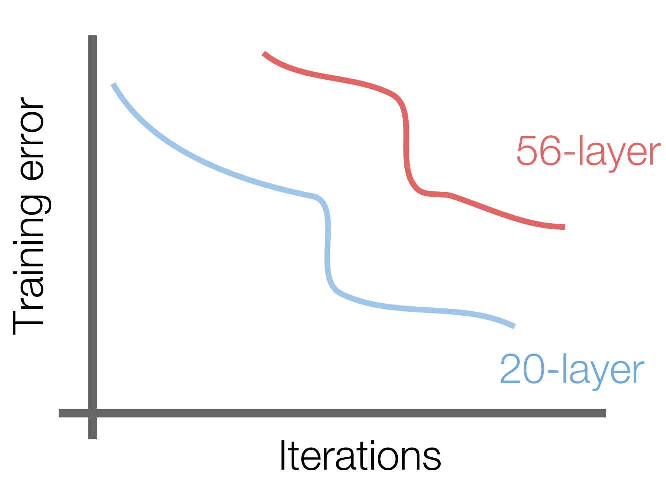
Q: What’s strange about these training and test curves?
[Hint: look at the order of the curves]

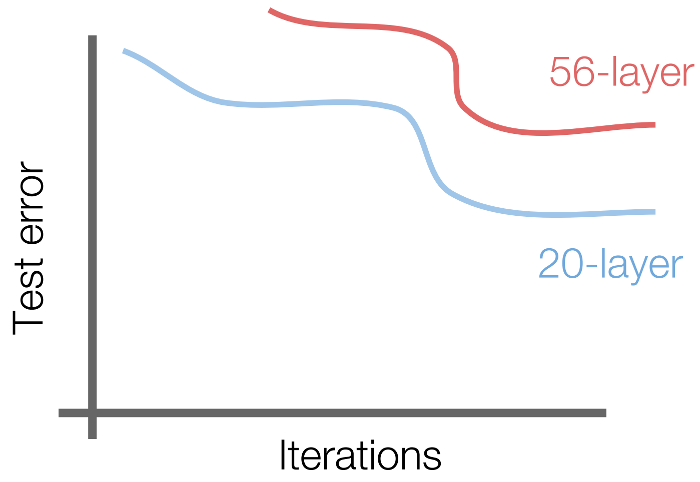
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

[He et al., 2015]

What happens when we continue stacking deeper layers on a "plain" convolutional neural network?





56-layer model performs worse on both training and test error
-> The deeper model performs worse, but it's not caused by overfitting!

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

[He et al., 2015]

Hypothesis: the problem is an *optimization* problem, deeper models are harder to optimize

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

[He et al., 2015]

Hypothesis: the problem is an *optimization* problem, deeper models are harder to optimize

The deeper model should be able to perform at least as well as the shallower model.

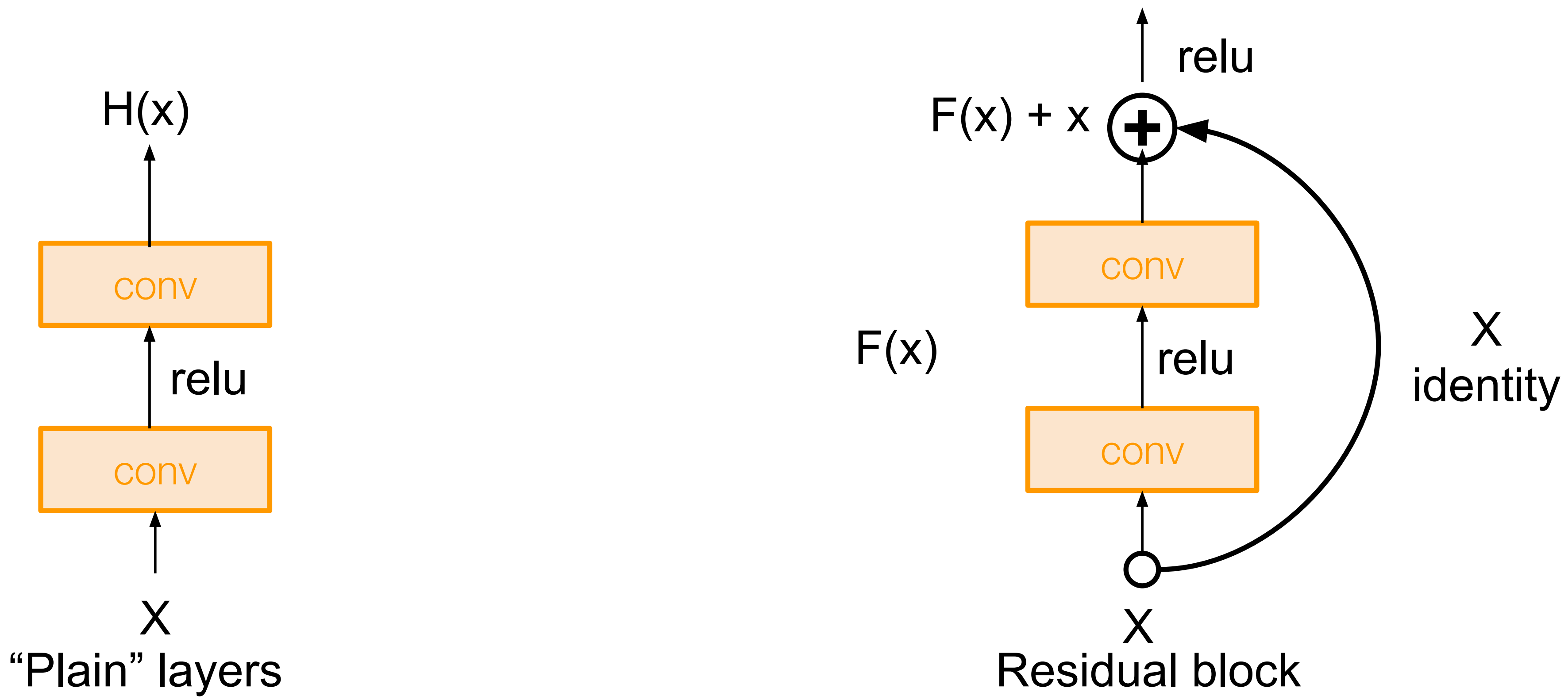
A solution by construction is copying the learned layers from the shallower model and setting additional layers to identity mapping.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

[He et al., 2015]

Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping



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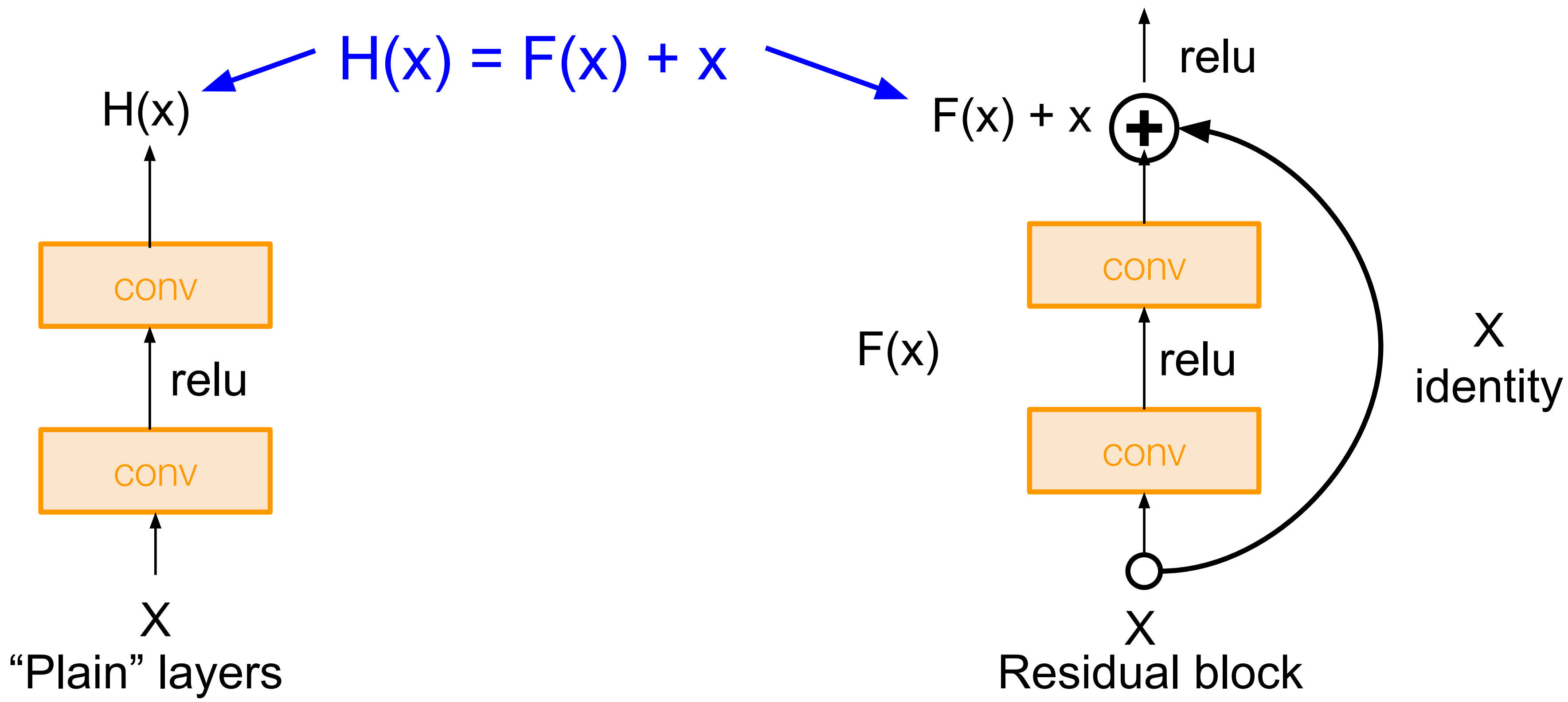


Use layers to fit residual $F(x) = H(x) - x$ instead of $H(x)$ directly

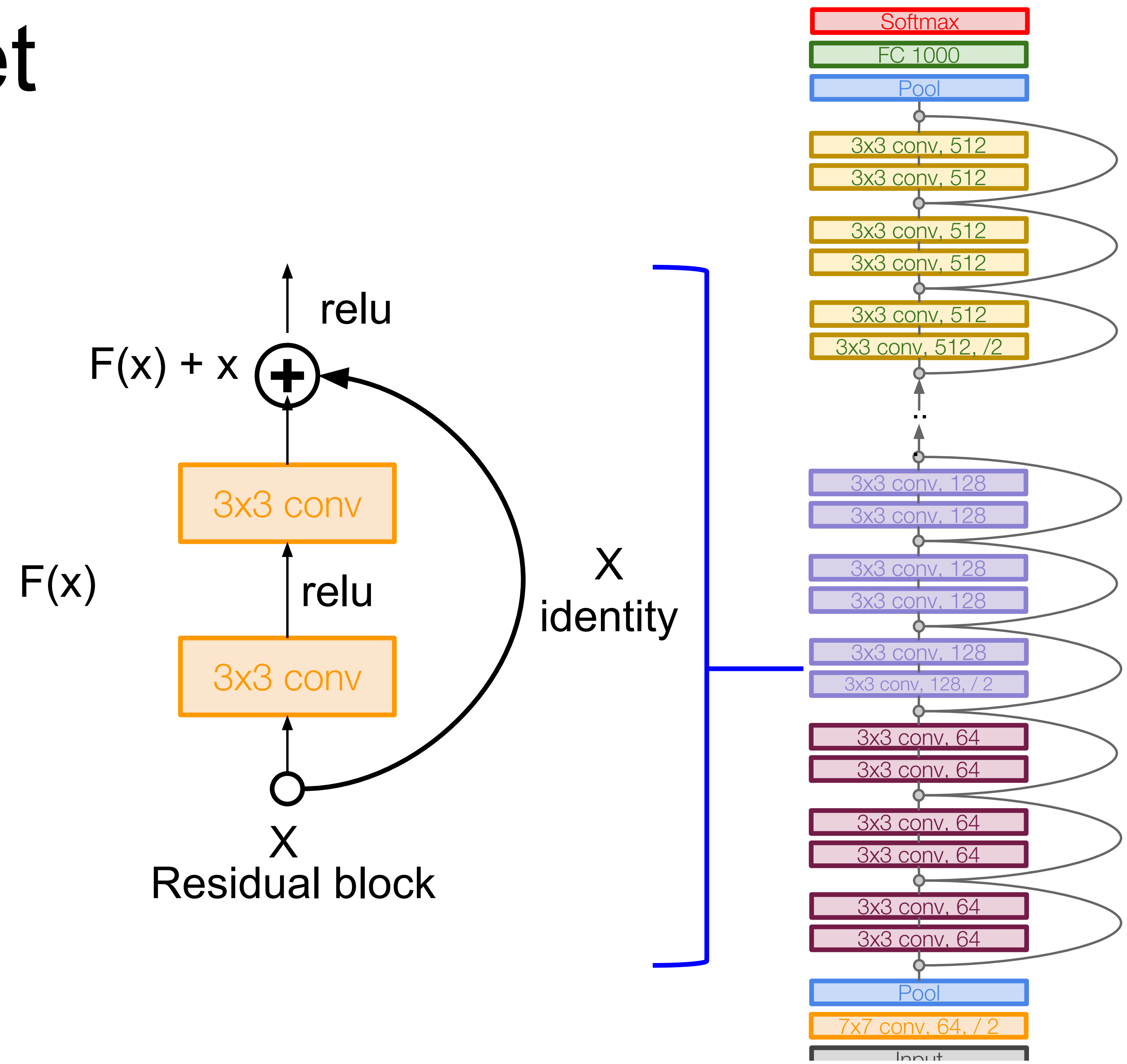
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:

- Stack residual blocks
- Every residual block has two 3x3 conv layers



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

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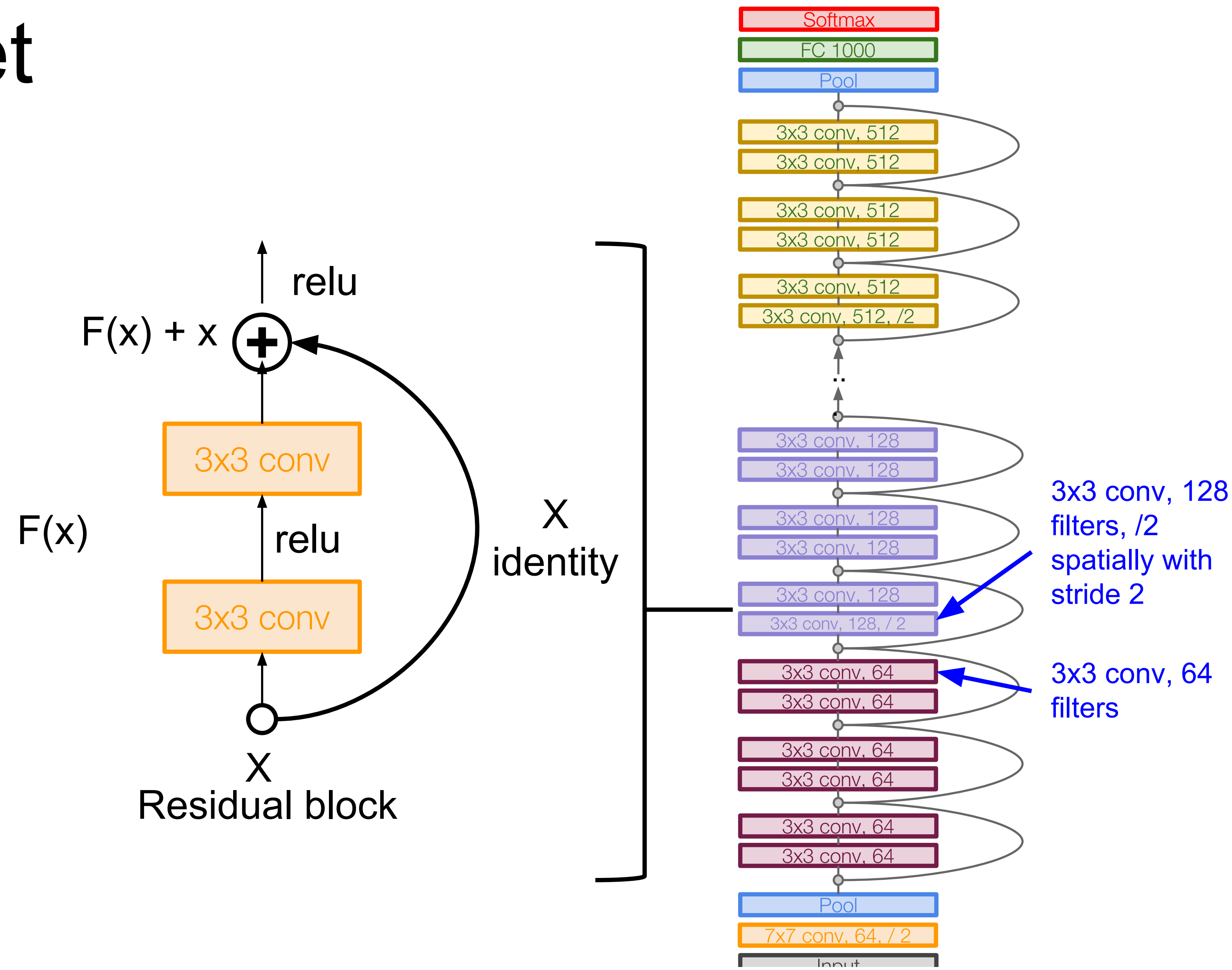
Full ResNet architecture:
- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)



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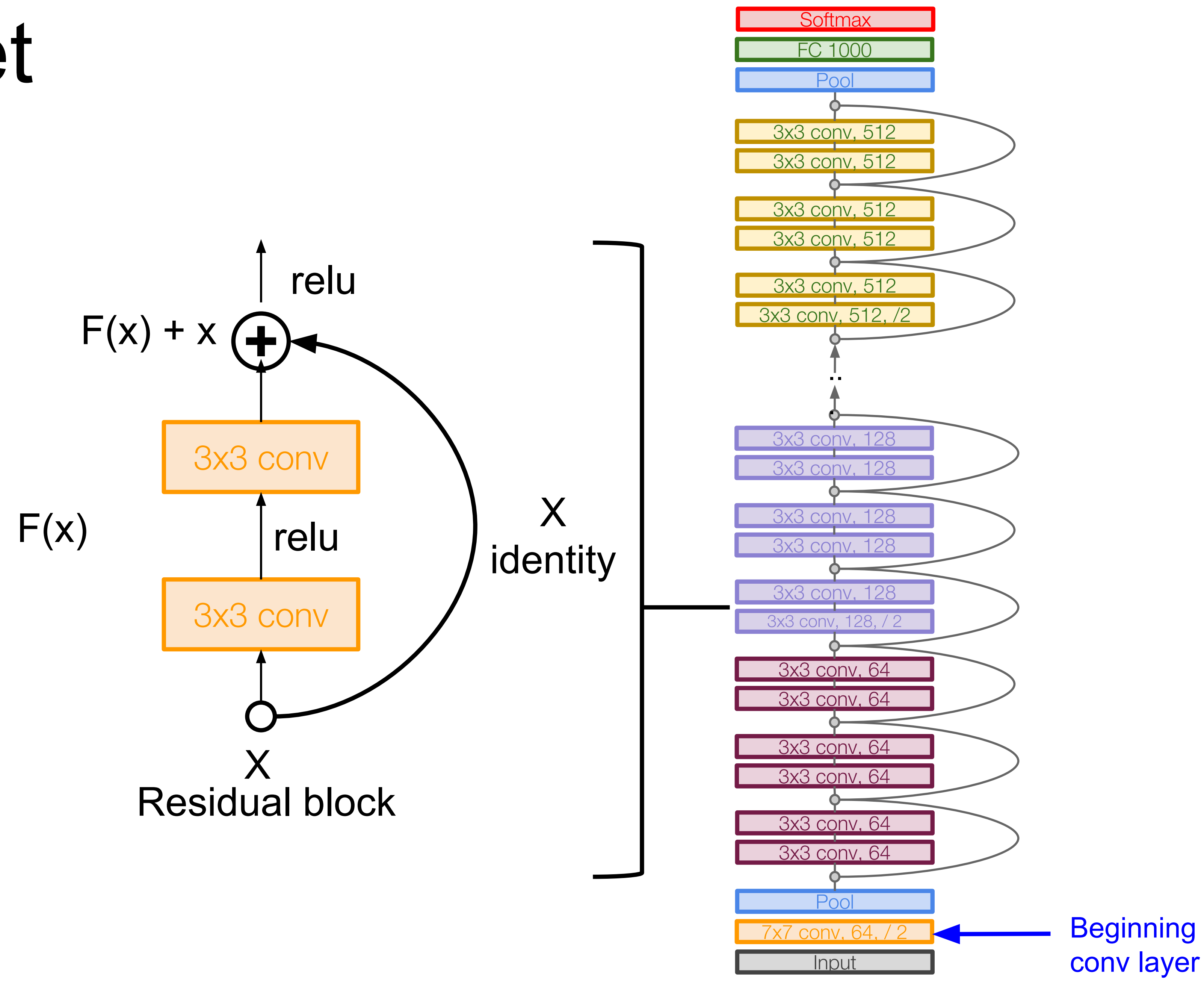

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Case Study: ResNet

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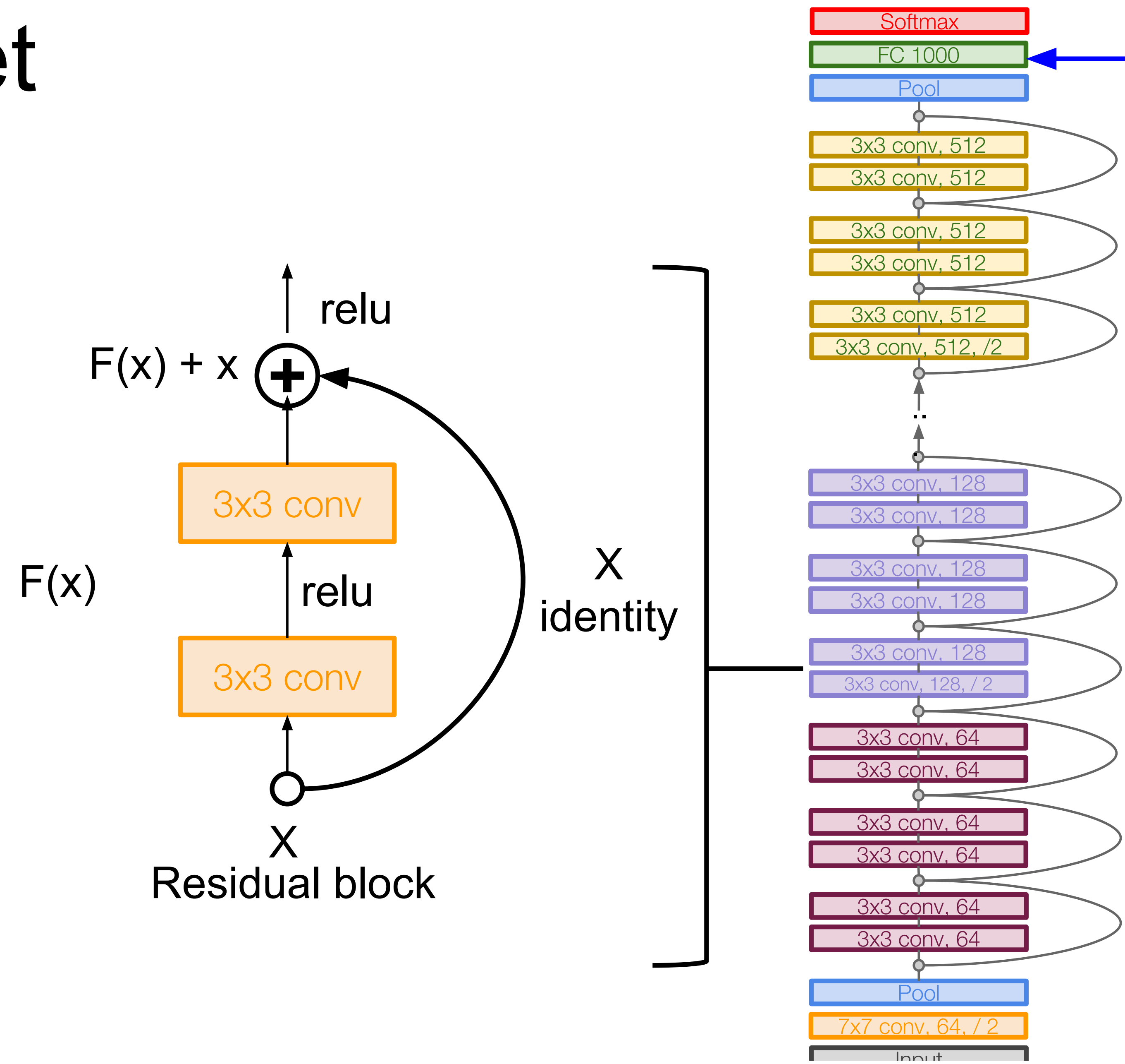
- Additional conv layer at the beginning
- No FC layers at the end (only FC 1000 to output classes)



No FC layers besides FC 1000 to output classes

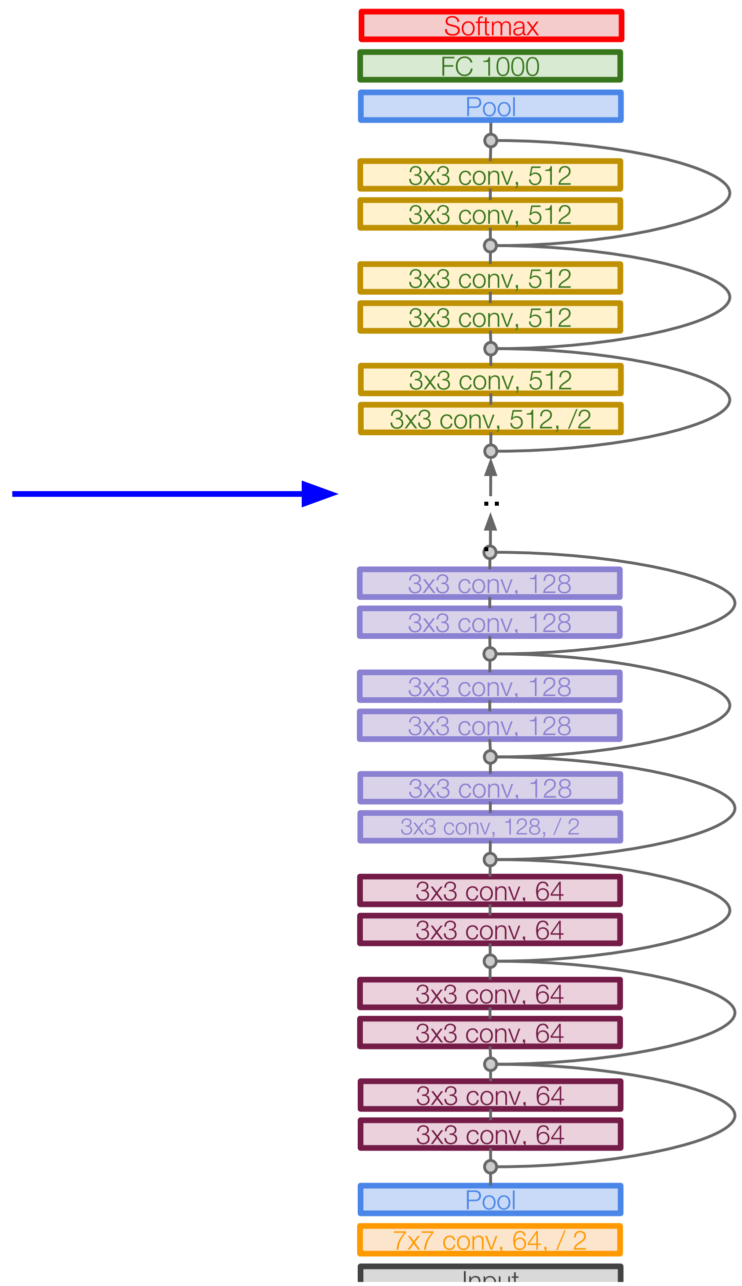
Global average pooling layer after last conv layer

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

[He et al., 2015]

Total depths of 34, 50, 101, or 152 layers for ImageNet

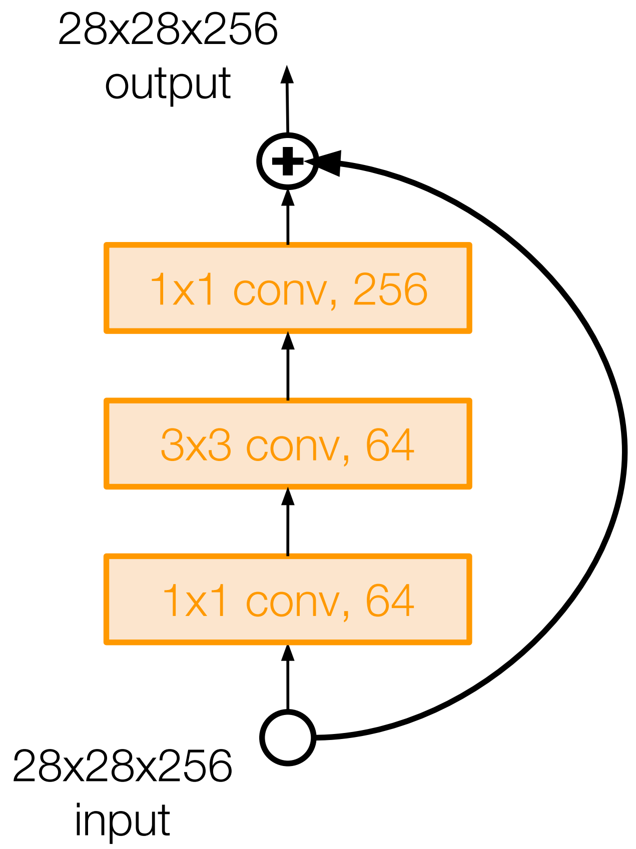


slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

[He et al., 2015]

For deeper networks (ResNet-50+), use "bottleneck" layer to improve efficiency (similar to GoogLeNet)



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

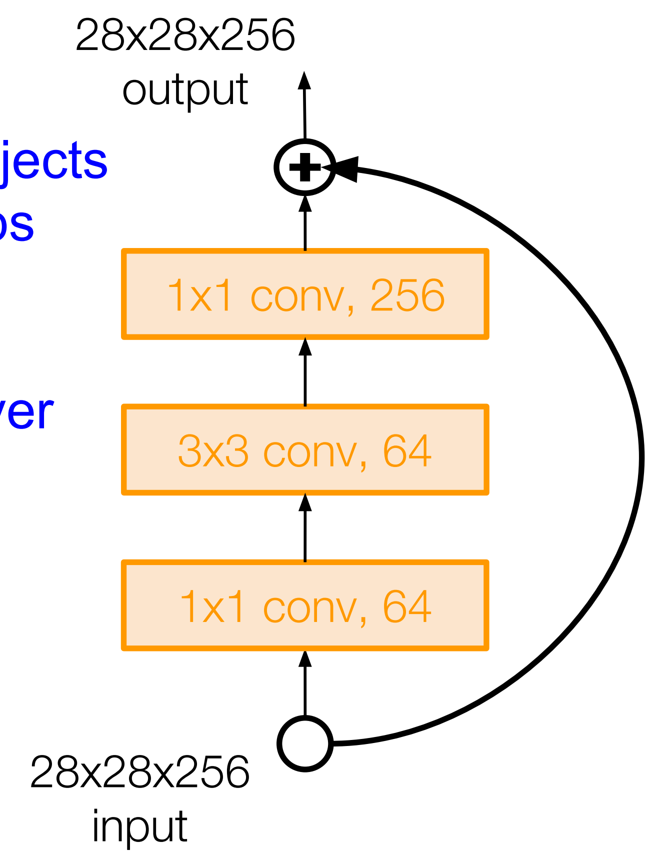
[He et al., 2015]

For deeper networks (ResNet-50+), use "bottleneck" layer to improve efficiency (similar to GoogLeNet)

1x1 conv, 256 filters projects back to 256 feature maps (28x28x256)

3x3 conv operates over only 64 feature maps

1x1 conv, 64 filters to project to 28x28x64



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

[He et al., 2015]

Training ResNet in practice:

- Batch Normalization after every CONV layer
- Xavier 2/ initialization from He et al.
- SGD + Momentum (0.9)
- Learning rate: 0.1, divided by 10 when validation error plateaus
- Mini-batch size 256
- Weight decay of 1e-5
- No dropout used

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

[He et al., 2015]

Experimental Results

- Able to train very deep networks without degrading (152 layers on ImageNet, 1202 on Cifar)
- Deeper networks now achieve lowing training error as expected
- Swept 1st place in all ILSVRC and COCO 2015 competitions

MSRA @ ILSVRC & COCO 2015 Competitions

- **1st places in all five main tracks**
  - ImageNet Classification: *"Ultra-deep"* (quote Yann) 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Case Study: ResNet

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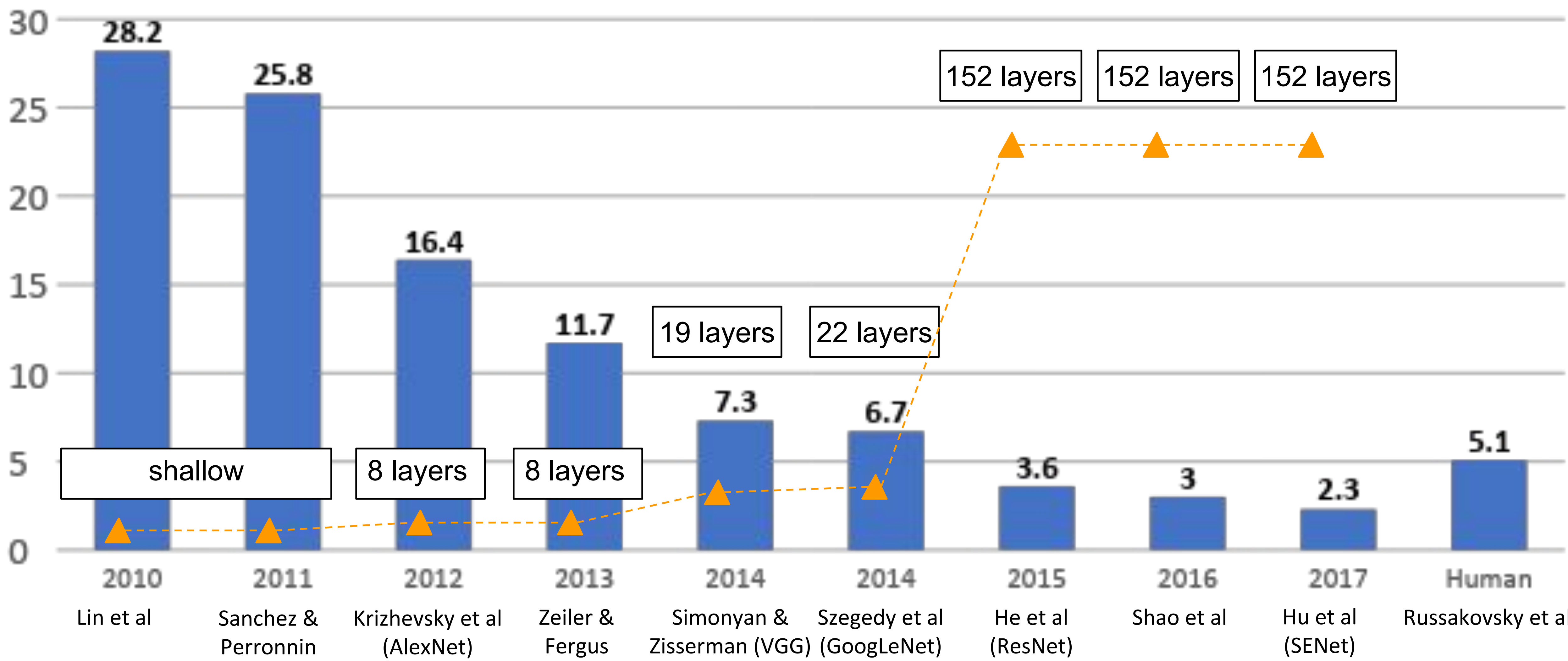
ILSVRC 2015 classification winner (3.6% top 5 error) -- better than "human performance"! (Russakovsky 2014)

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



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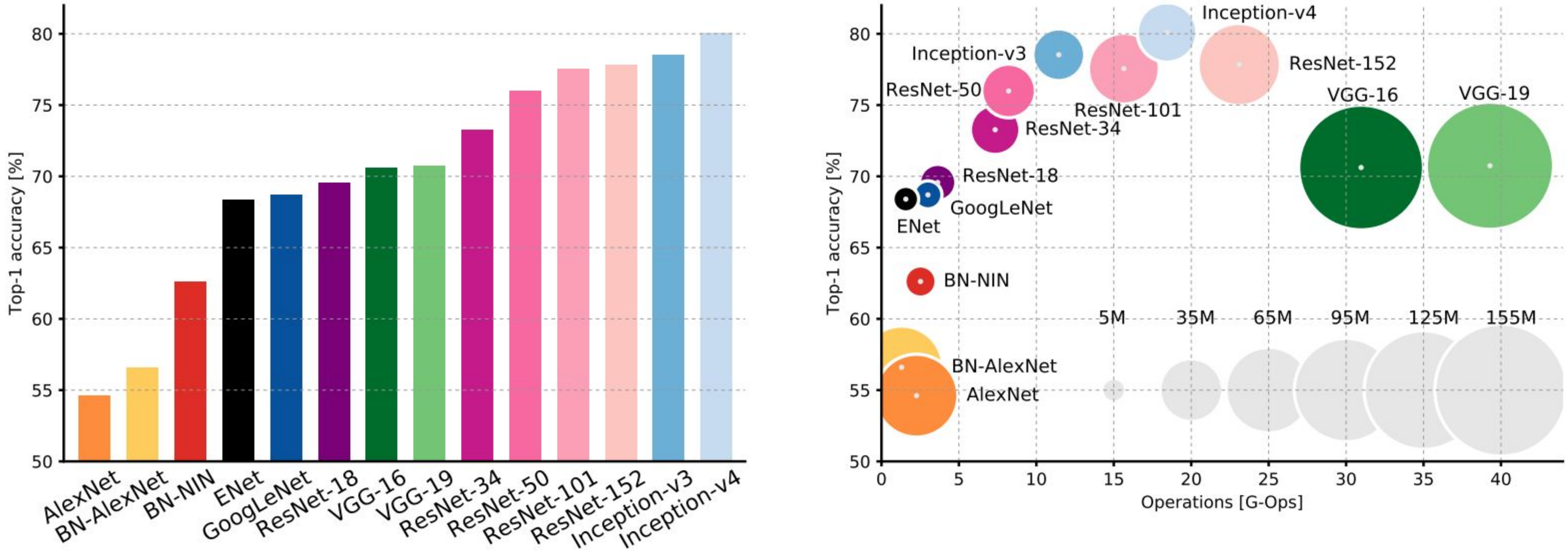
Comparing complexity...

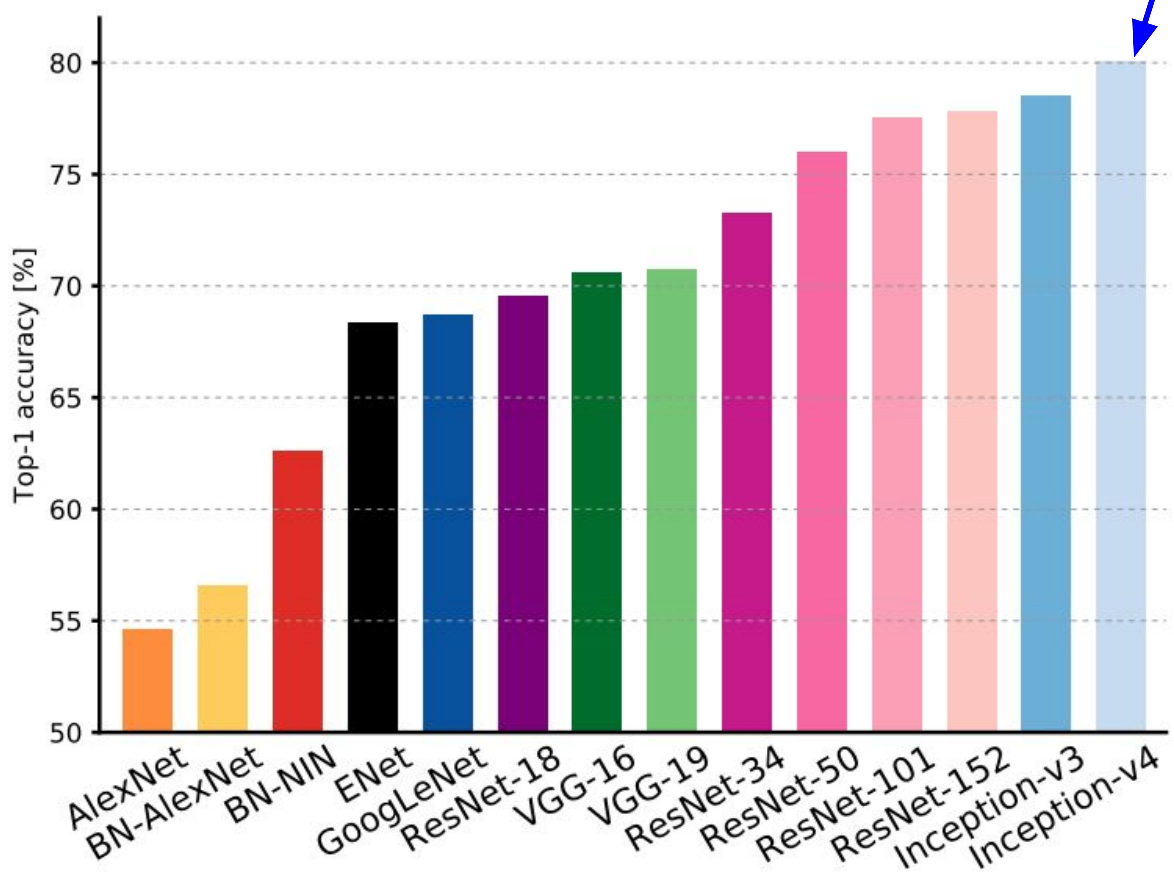


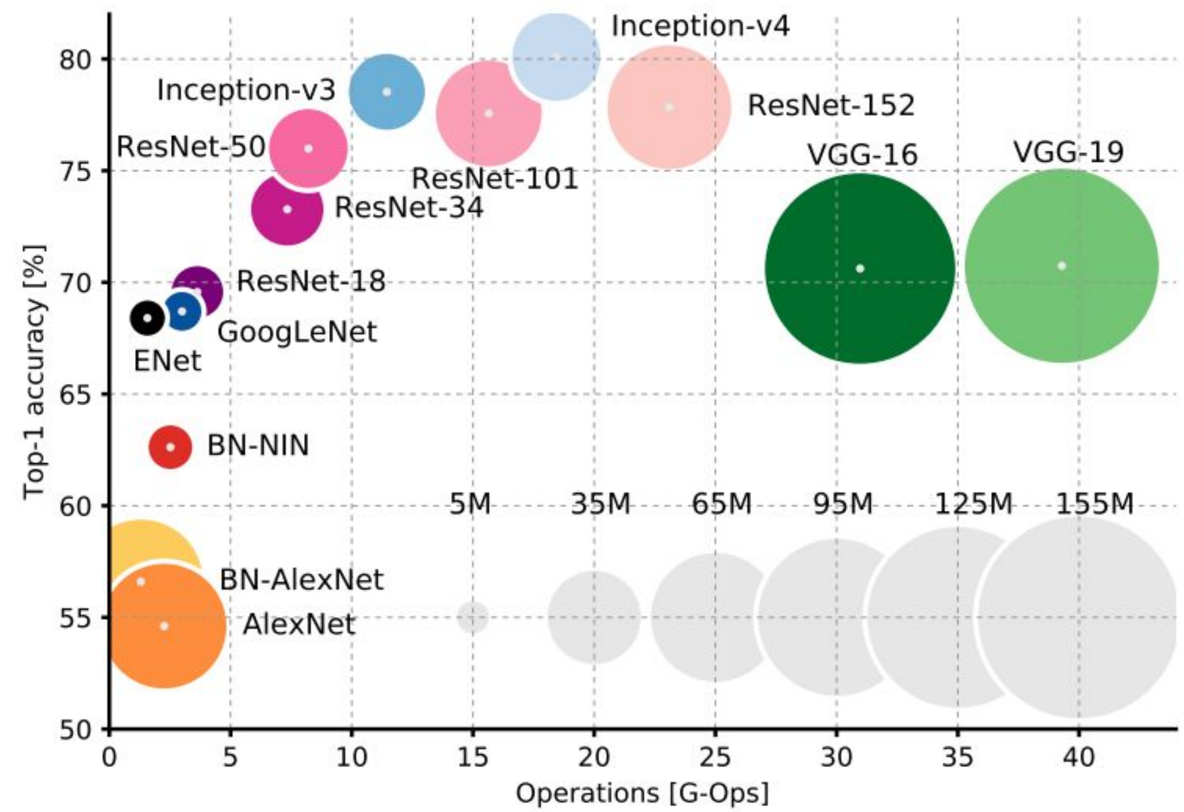
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Comparing complexity...

Inception-v4: Resnet + Inception!





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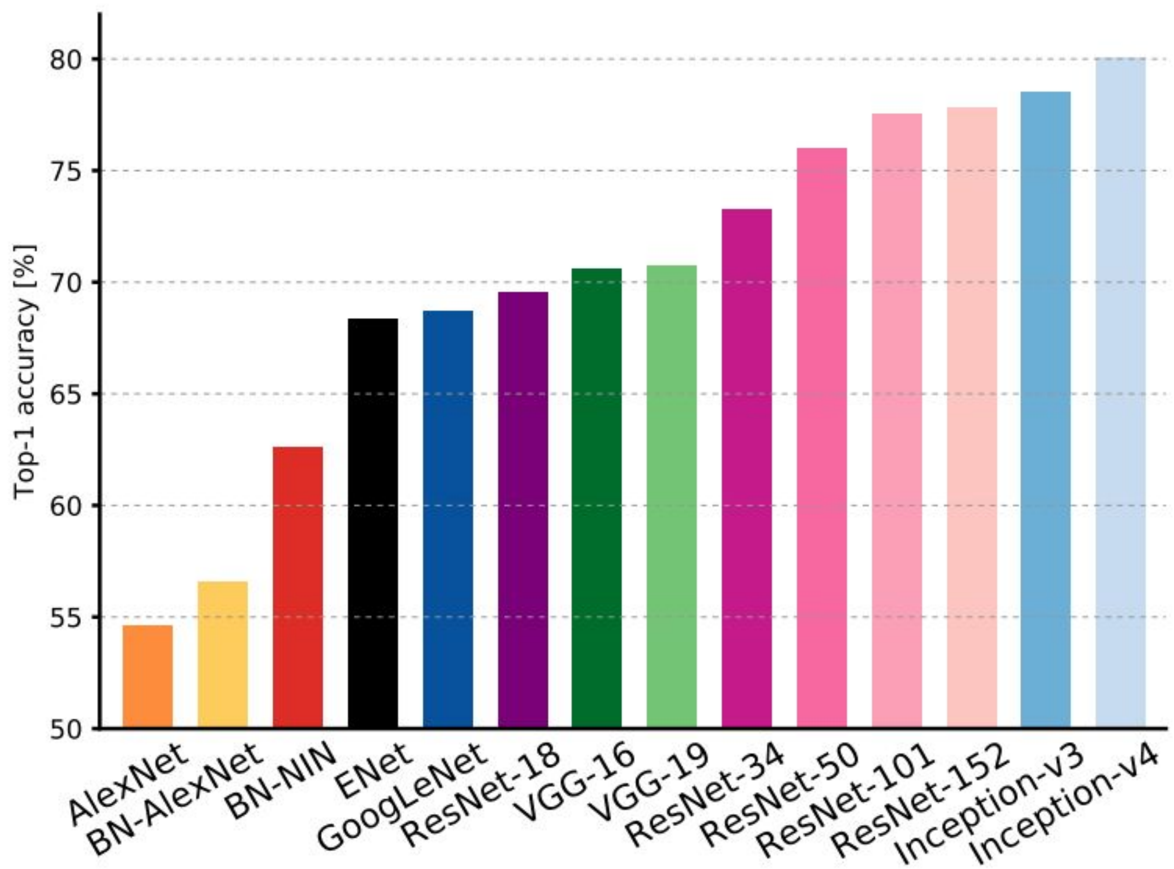
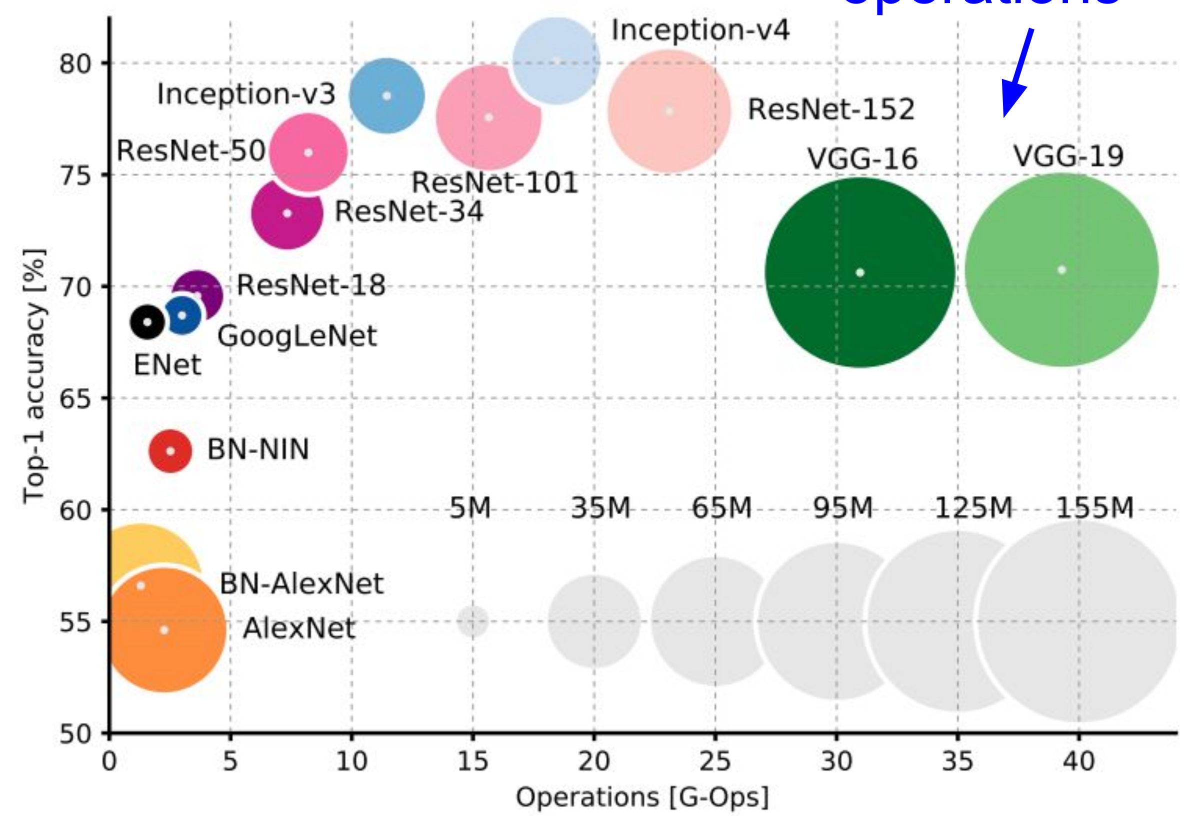
Comparing complexity...

VGG: Highest memory, most operations





An Analysis of Deep Neural Network Models for Practical Applications, 2017.

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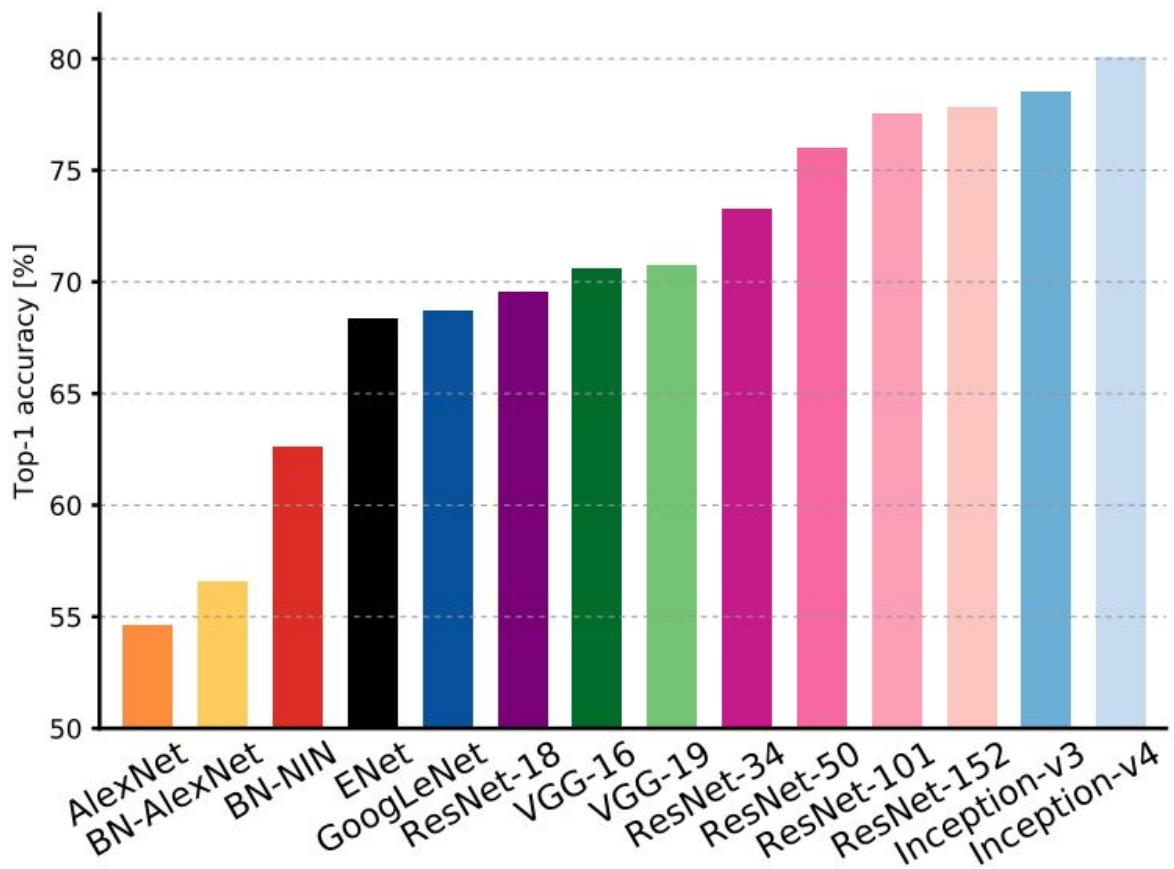
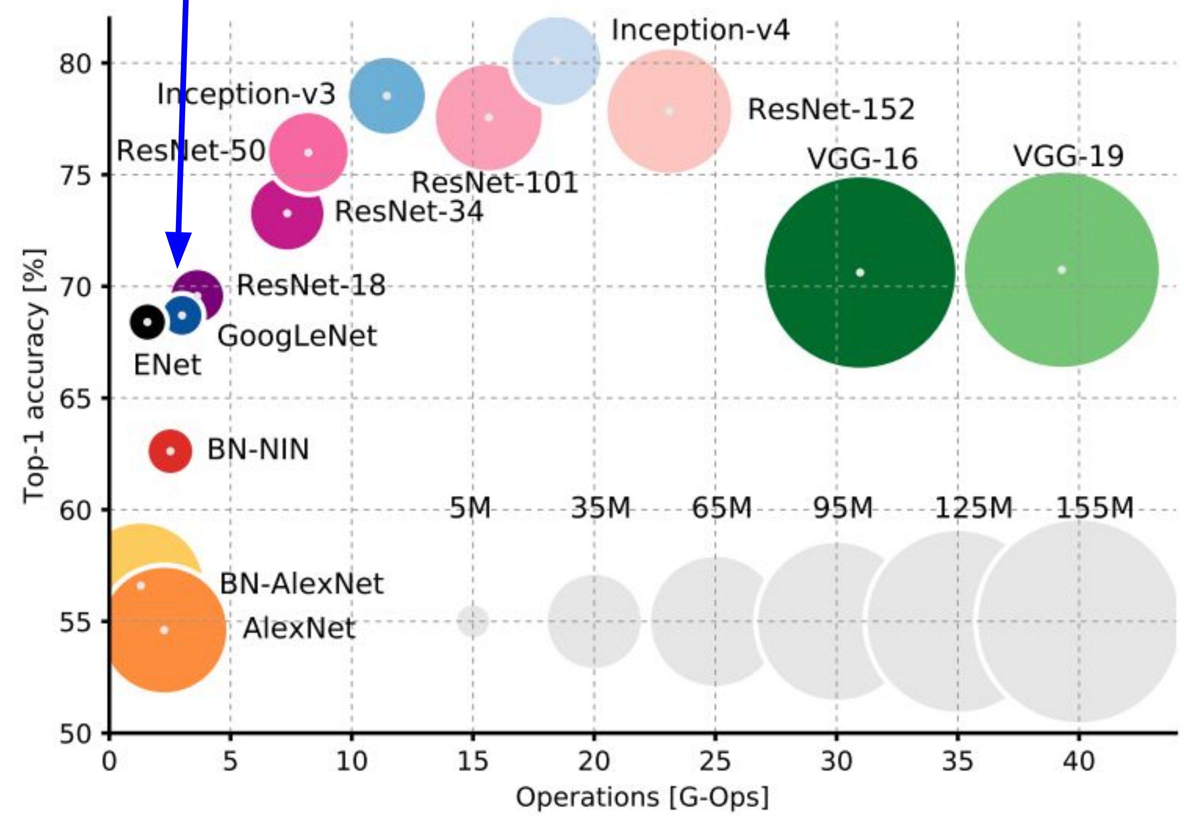
Comparing complexity...

GoogLeNet:
most efficient





An Analysis of Deep Neural Network Models for Practical Applications, 2017.

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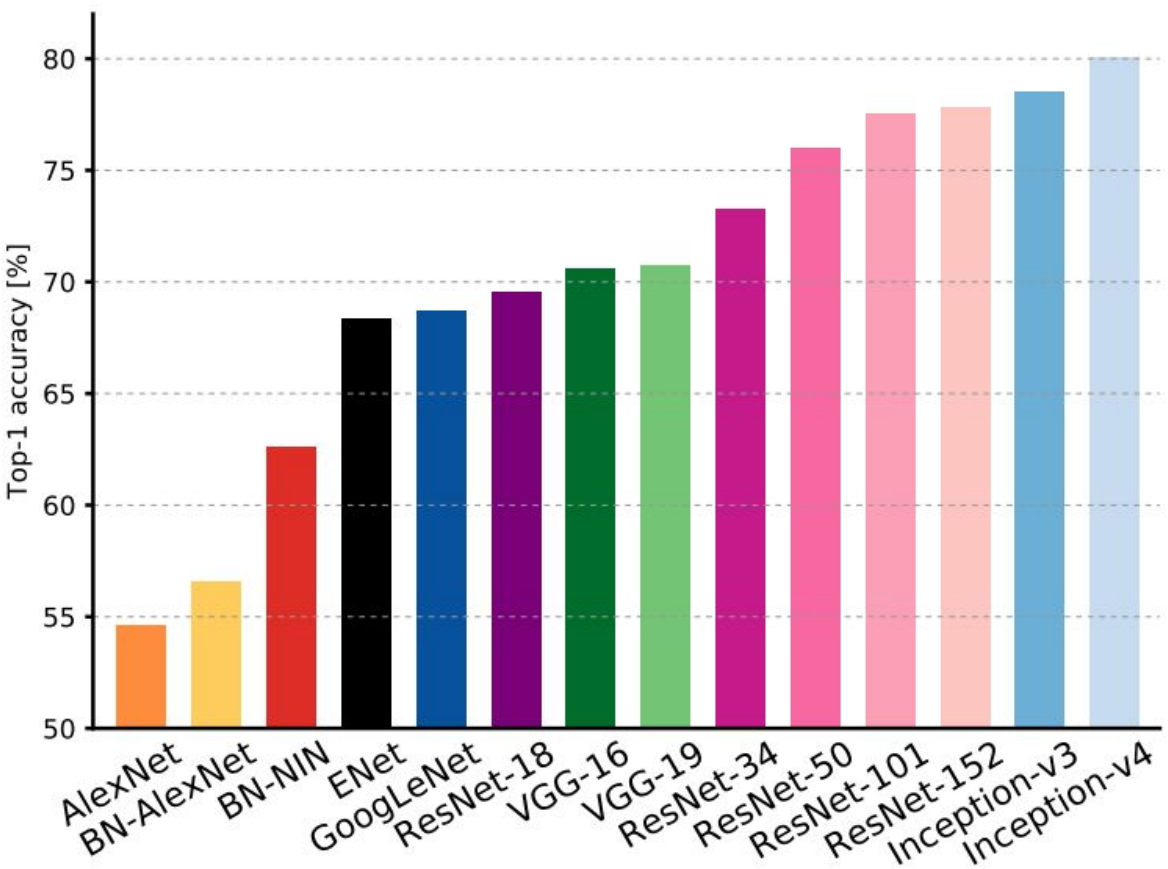
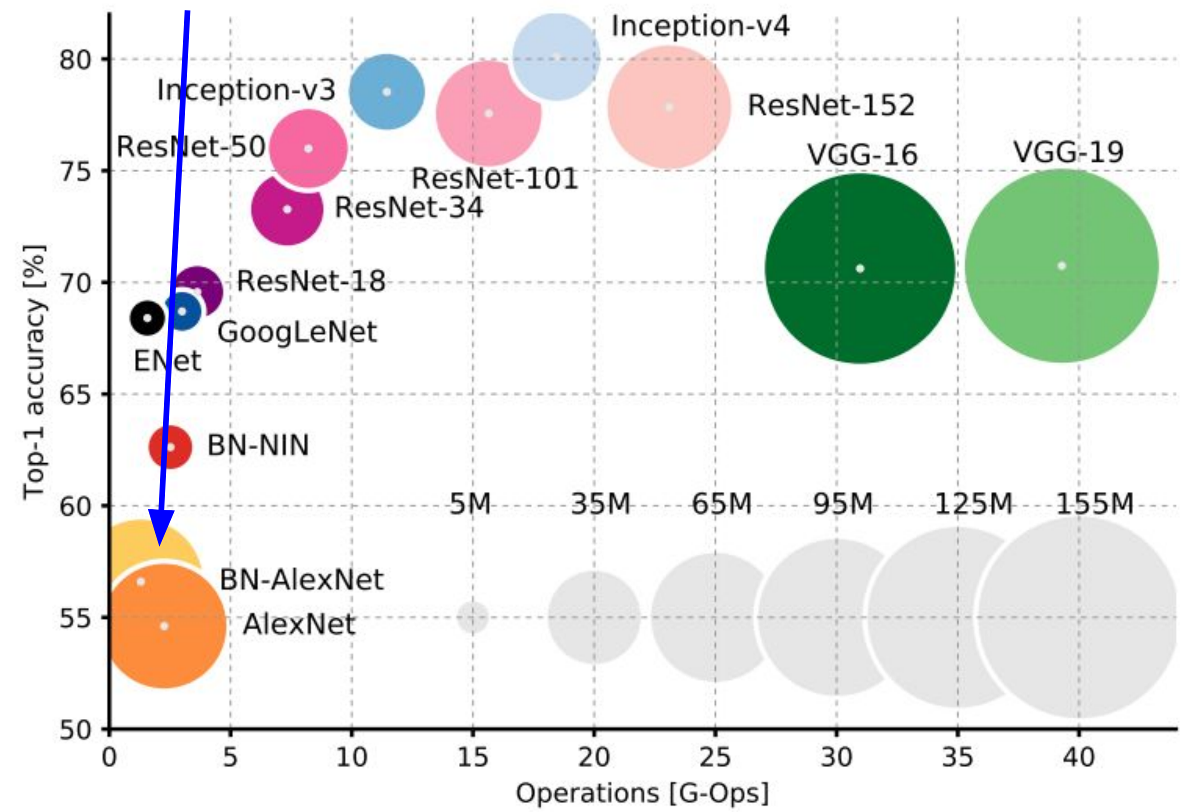
Comparing complexity...

AlexNet:
Smaller compute, still memory heavy, lower accuracy



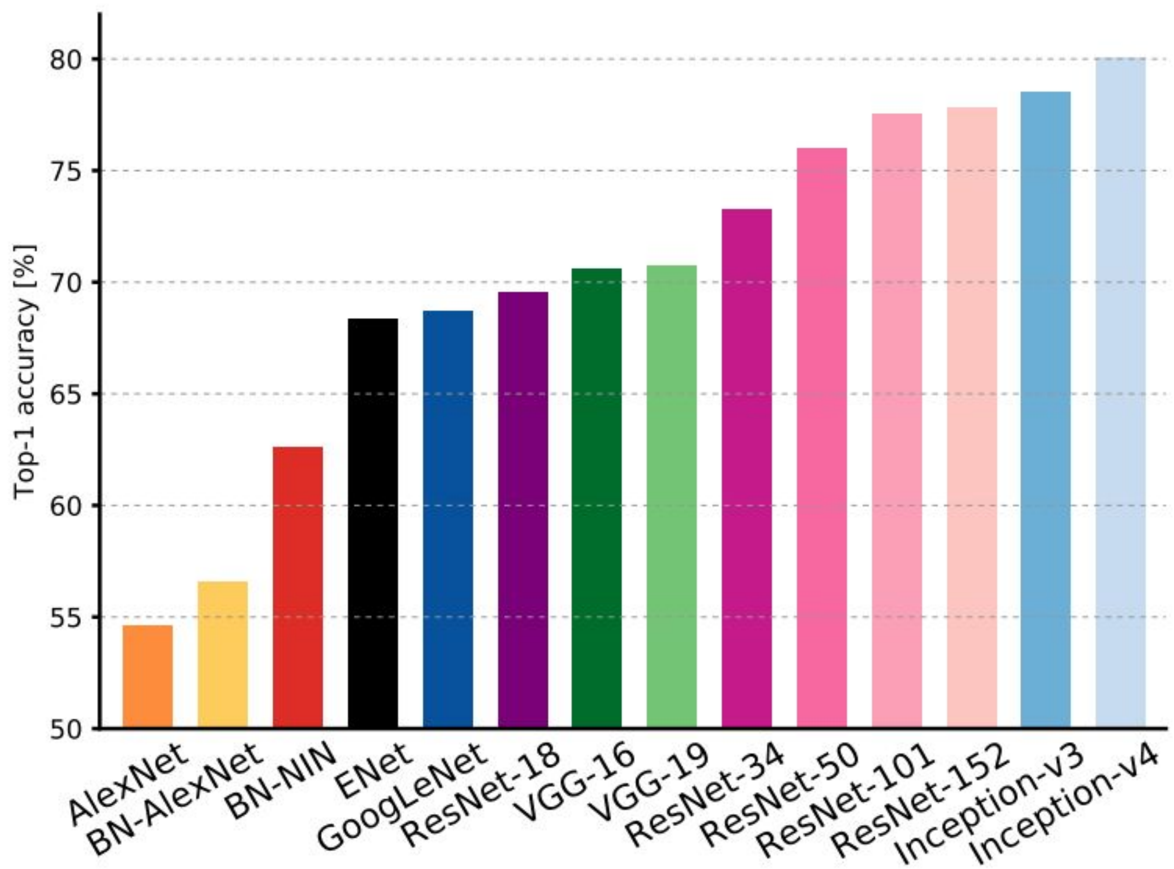


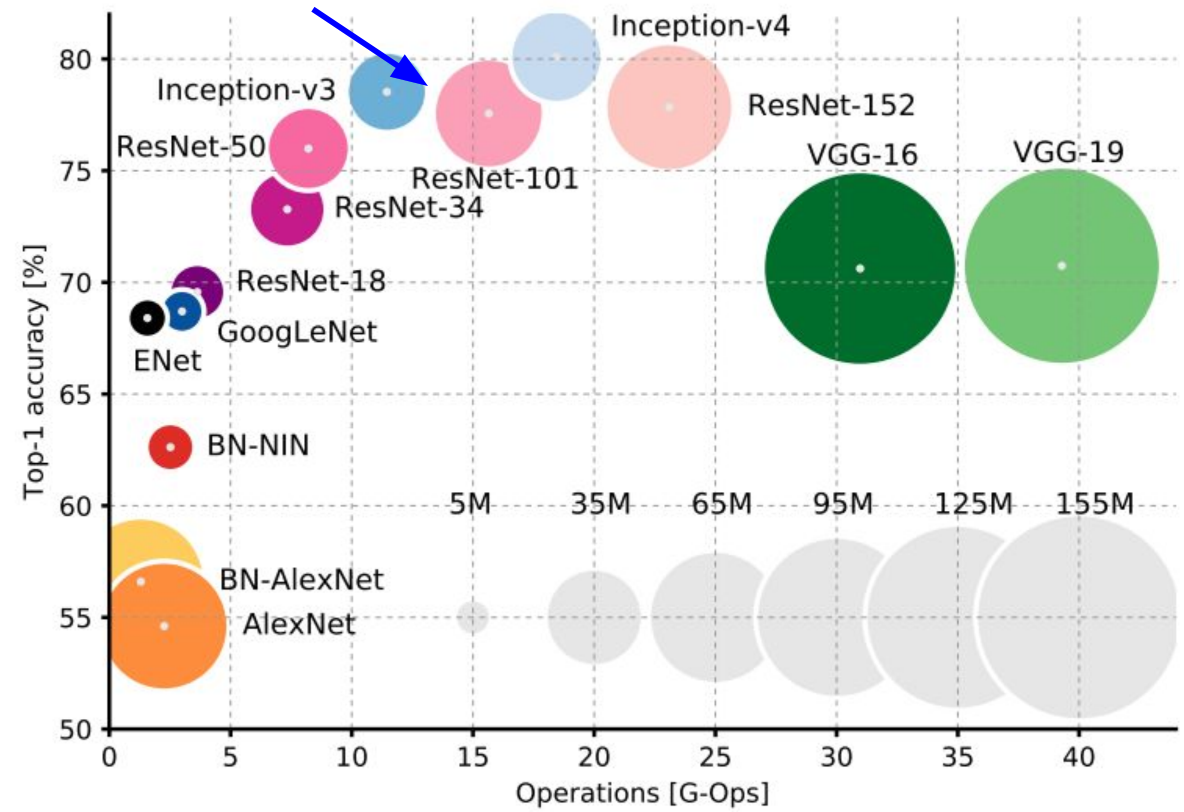
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Comparing complexity...

ResNet:
Moderate efficiency depending on model, highest accuracy





An Analysis of Deep Neural Network Models for Practical Applications, 2017.

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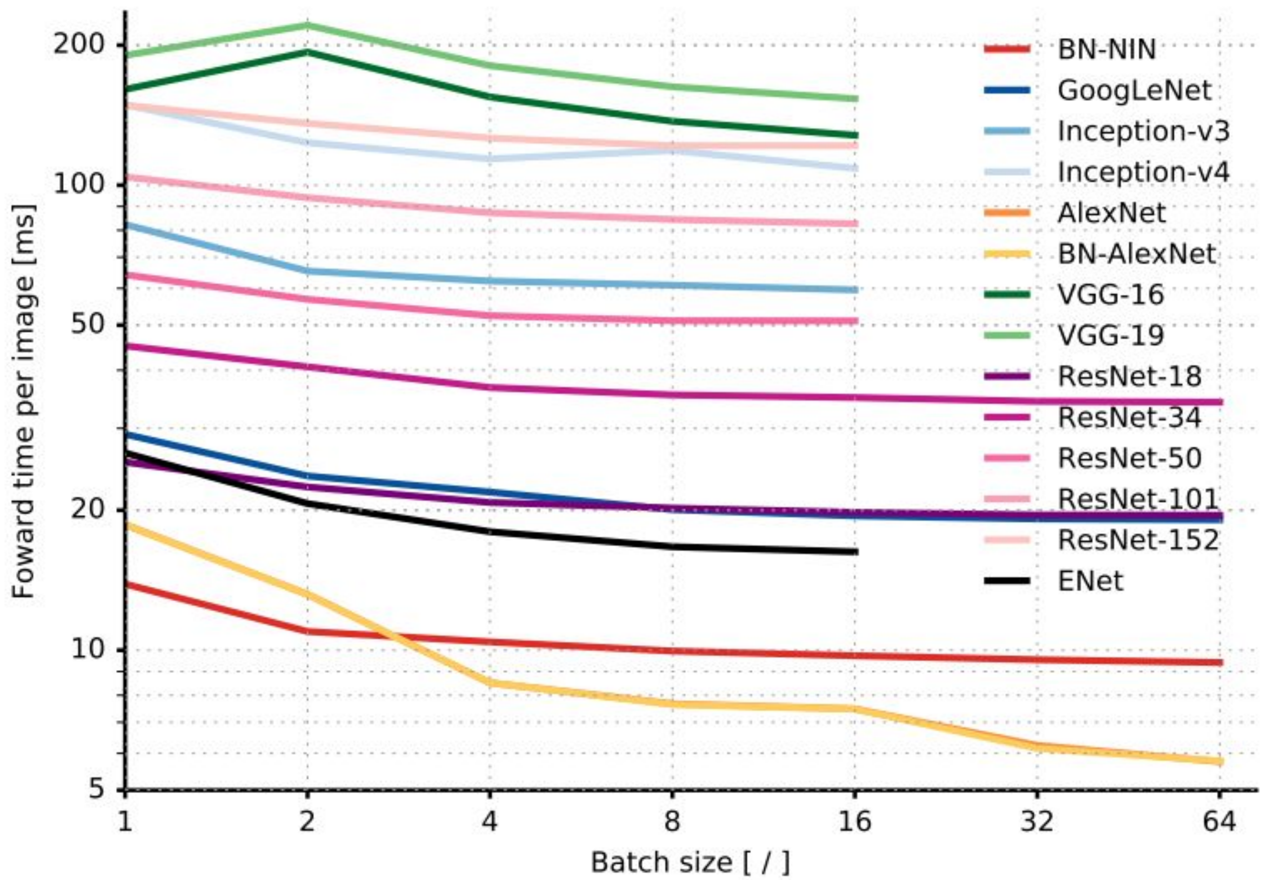
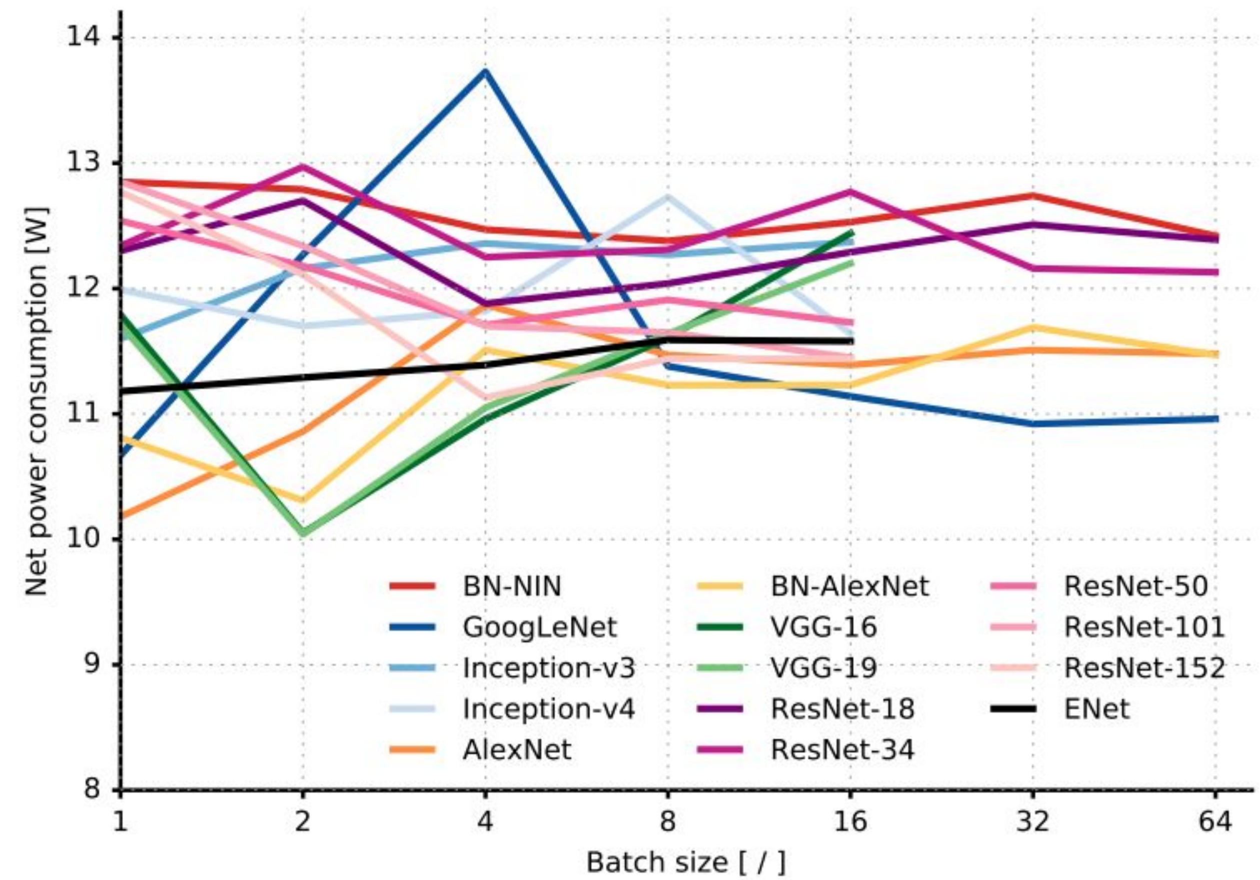
Forward pass time and power consumption





An Analysis of Deep Neural Network Models for Practical Applications, 2017.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

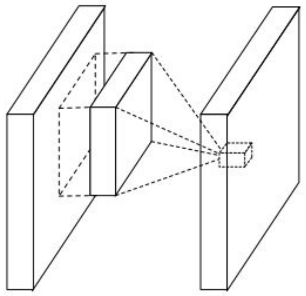
Other architectures to know...

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

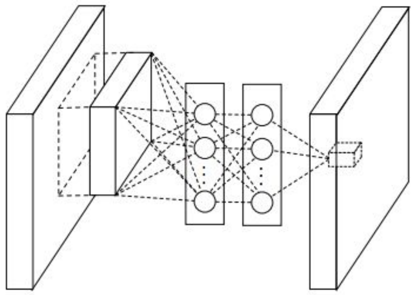
Network in Network (NiN)

[Lin et al. 2014]

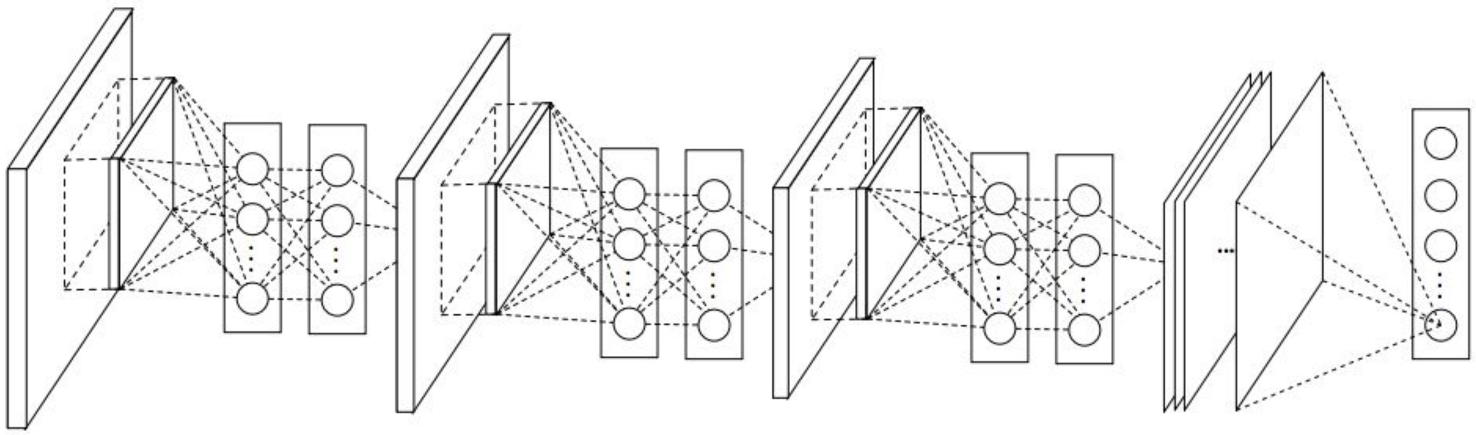
- Mlpconv layer with "micronetwork" within each conv layer to compute more abstract features for local patches
- Micronetwork uses multilayer perceptron (FC, i.e. 1x1 conv layers)
- Precursor to GoogLeNet and ResNet "bottleneck" layers
- Philosophical inspiration for GoogLeNet



(a) Linear convolution layer



(b) Mlpconv layer



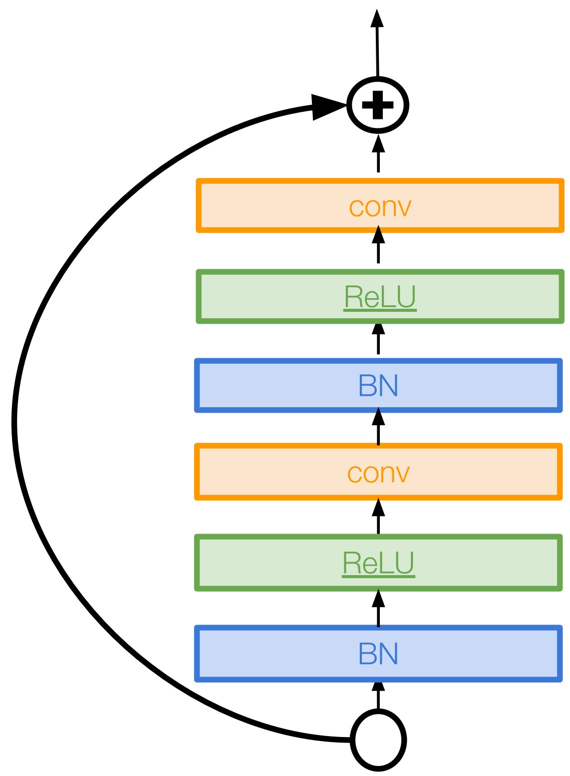
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Improving ResNets...

Identity Mappings in Deep Residual Networks

[He et al. 2016]

- Improved ResNet block design from creators of ResNet
- Creates a more direct path for propagating information throughout network (moves activation to residual mapping pathway)
- Gives better performance



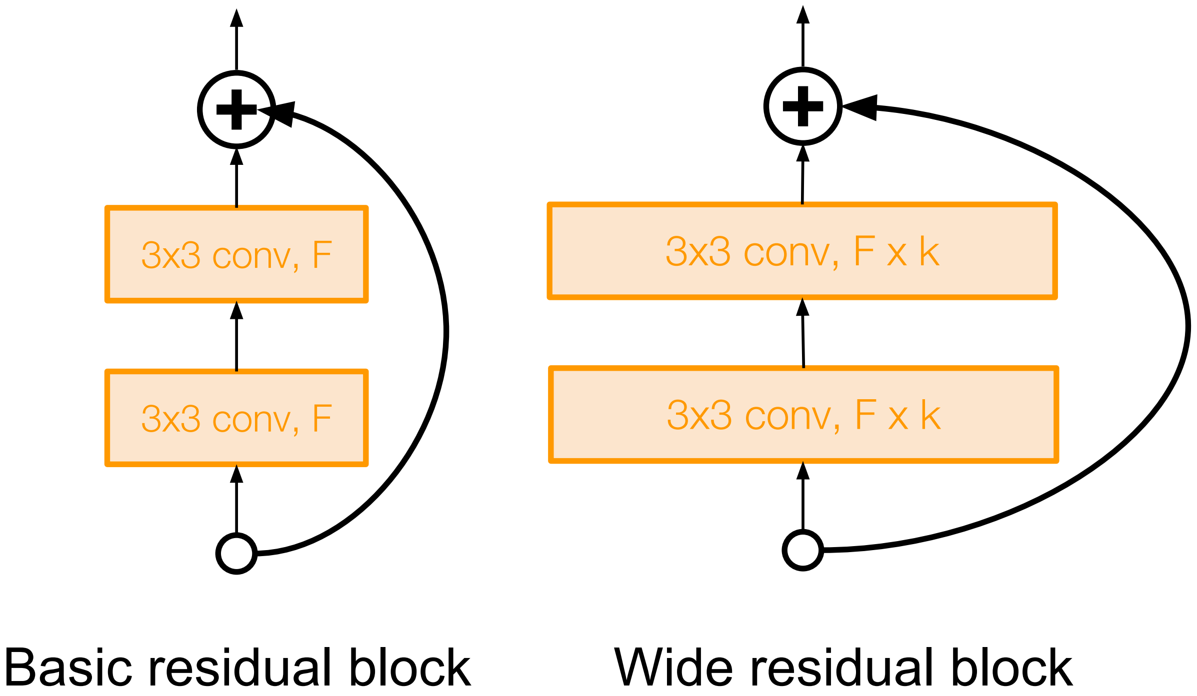
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Improving ResNets...

Wide Residual Networks

[Zagoruyko et al. 2016]

- Argues that residuals are the important factor, not depth
- User wider residual blocks (F x k filters instead of F filters in each layer)
- 50-layer wide ResNet outperforms 152-layer original ResNet
- Increasing width instead of depth more computationally efficient (parallelizable)



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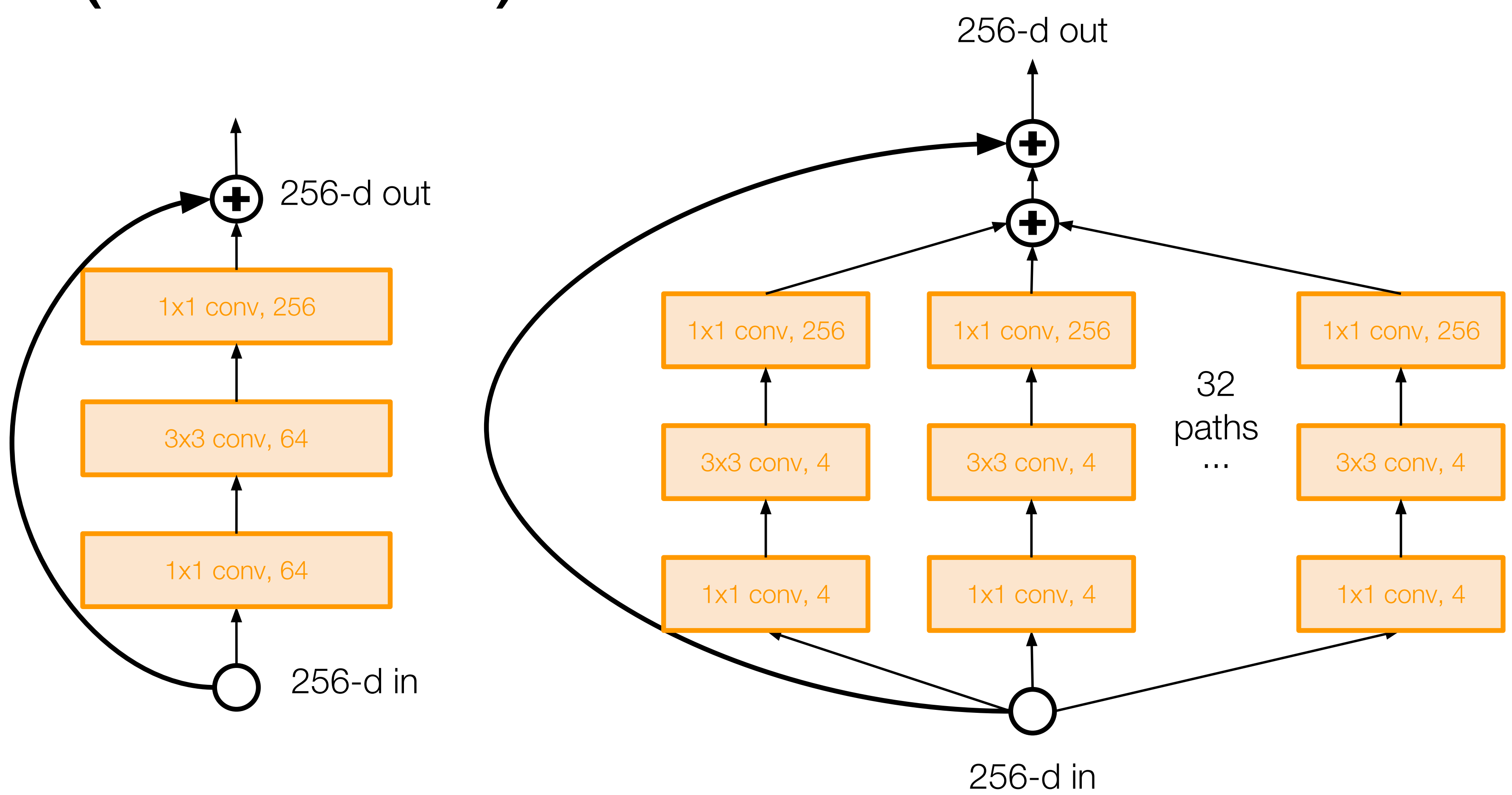
Improving ResNets...

Aggregated Residual Transformations for Deep Neural Networks (ResNeXt)

[Xie et al. 2016]

- Also from creators of ResNet
- Increases width of residual block through multiple parallel pathways ("cardinality")
- Parallel pathways similar in spirit to Inception module



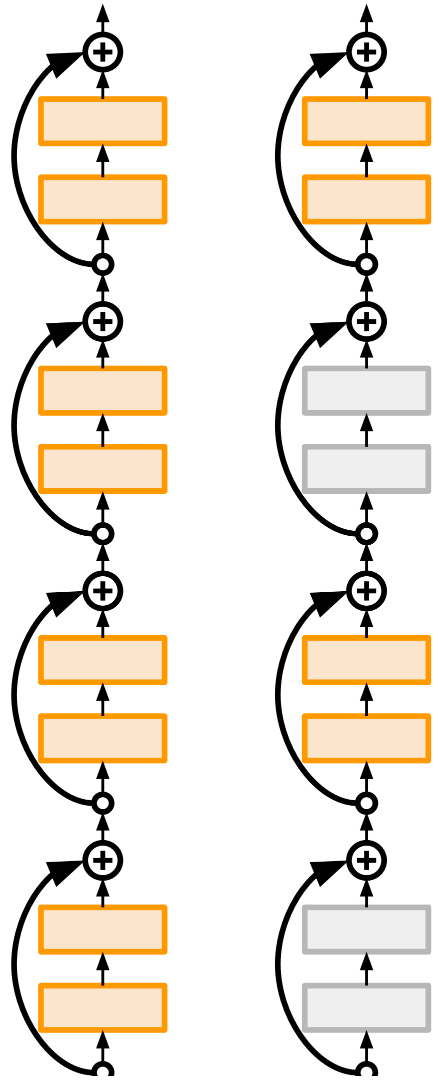
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Improving ResNets...

Deep Networks with Stochastic Depth

[Huang et al. 2016]

- Motivation: reduce vanishing gradients and training time through short networks during training
- Randomly drop a subset of layers during each training pass
- Bypass with identity function
- Use full deep network at test time



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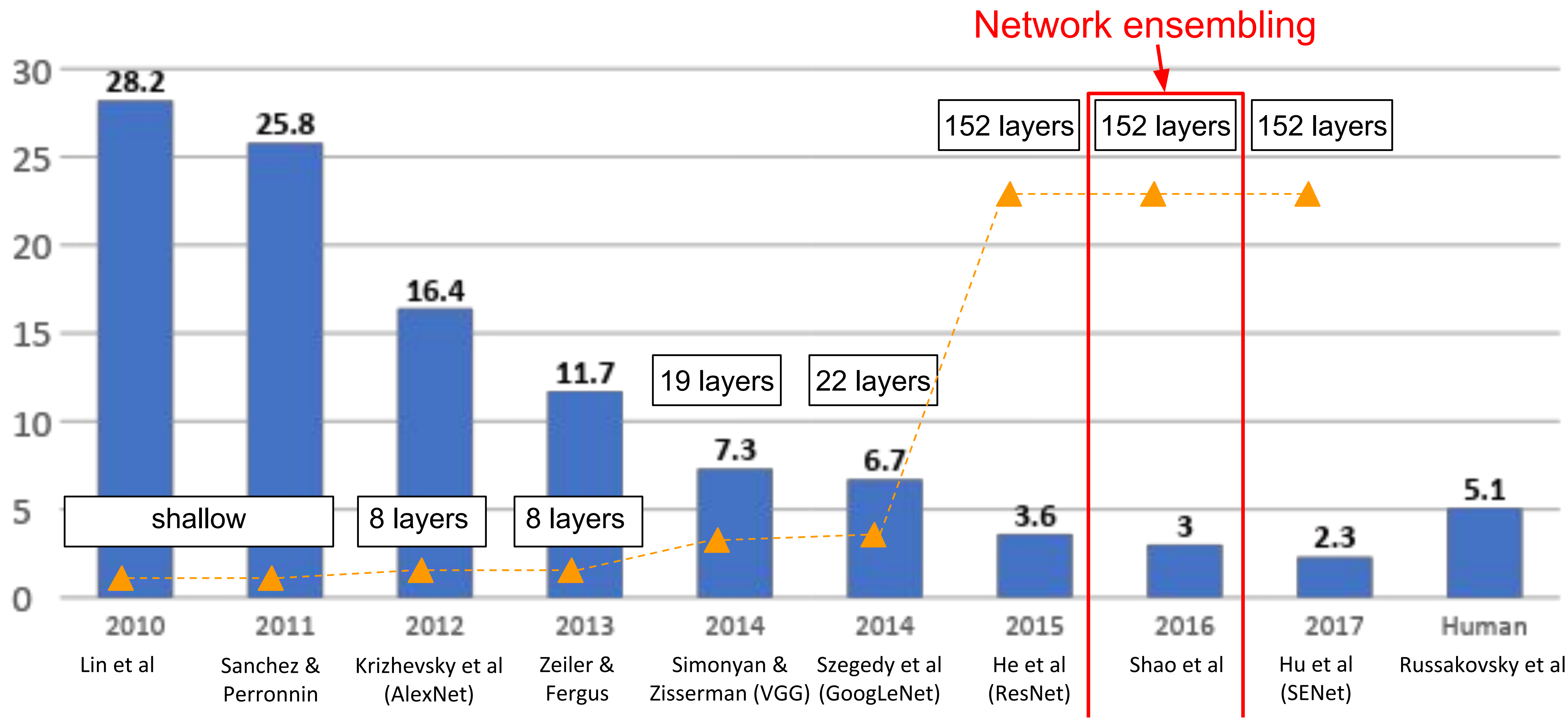
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Improving ResNets...

"Good Practices for Deep Feature Fusion"

[Shao et al. 2016]

- Multi-scale ensembling of Inception, Inception-Resnet, Resnet, Wide Resnet models
- ILSVRC'16 classification winner

	Inception-v3	Inception-v4	Inception-Resnet-v2	Resnet-200	Wrn-68-3	Fusion（Val.）	Fusion（Test）
Err. (%)	4.20	4.01	3.52	4.26	4.65	2.92 (-0.6)	2.99

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

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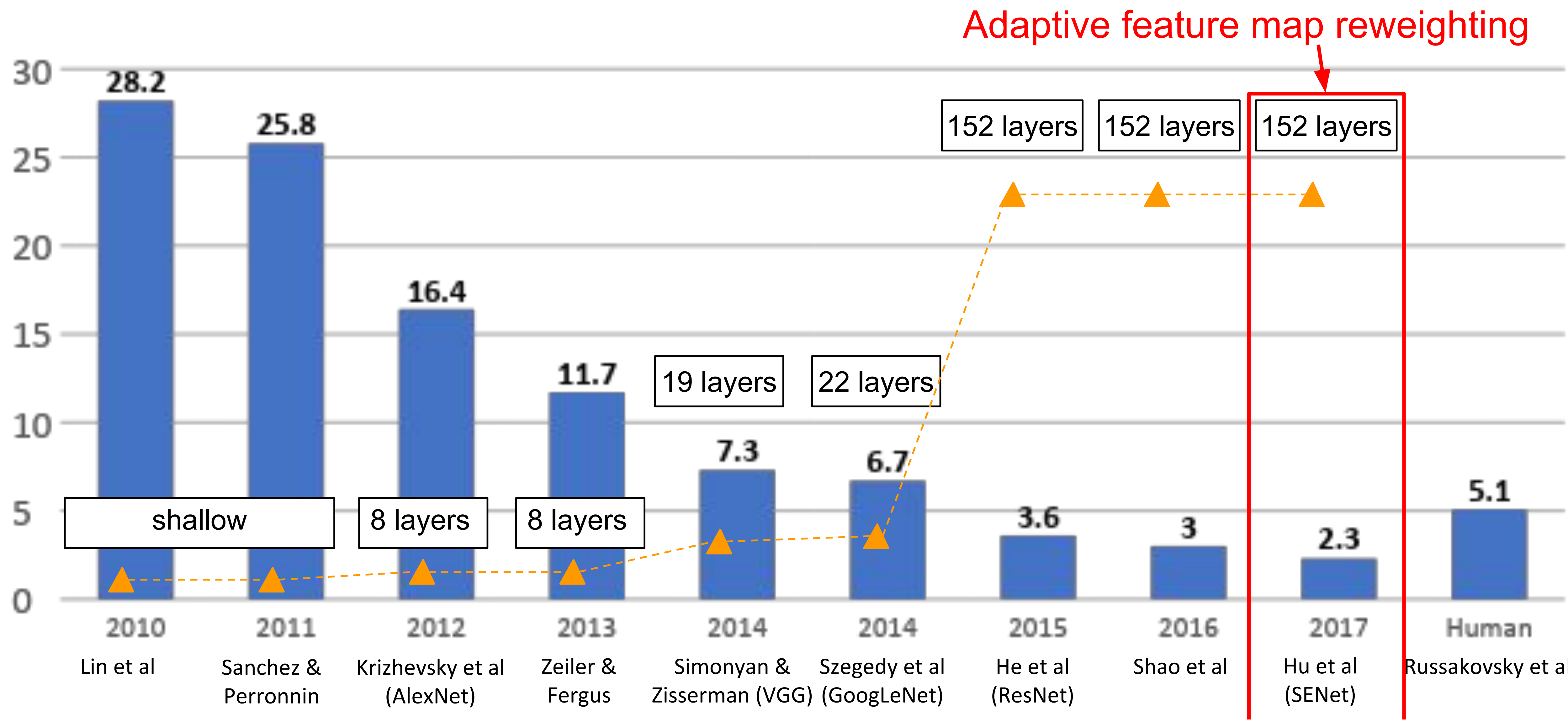


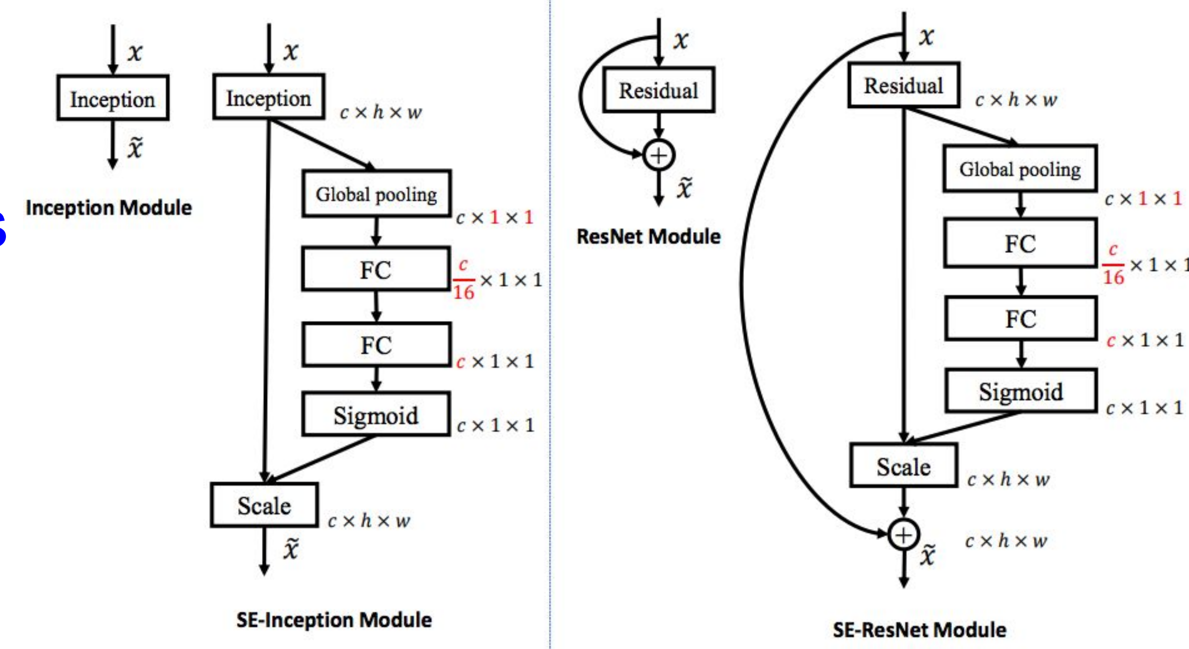
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

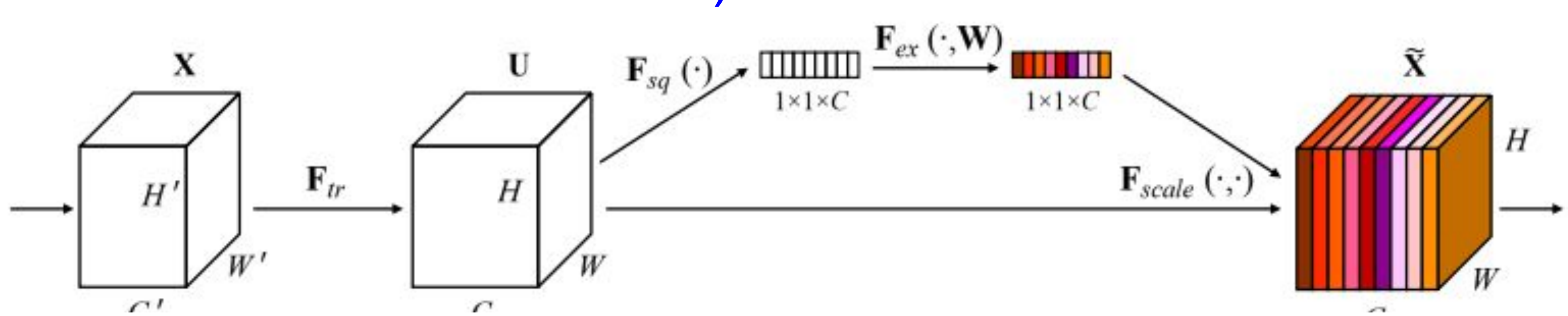
Improving ResNets...

Squeeze-and-Excitation Networks (SENet)

[Hu et al. 2017]

- Add a "feature recalibration" module that learns to adaptively reweight feature maps
- Global information (global avg. pooling layer) + 2 FC layers used to determine feature map weights
- ILSVRC'17 classification winner (using ResNeXt-152 as a base architecture)





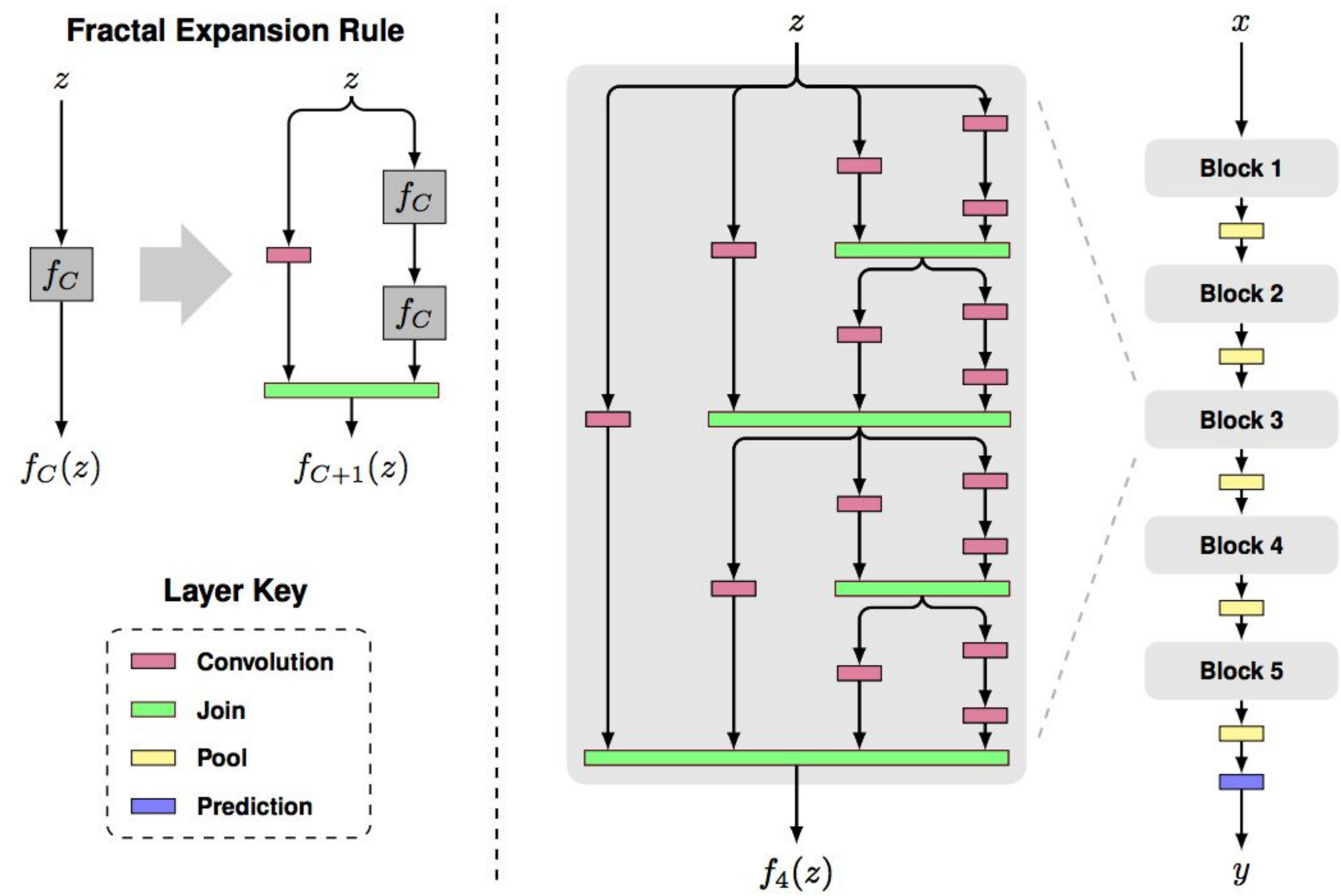
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Beyond ResNets...

FractalNet: Ultra-Deep Neural Networks without Residuals

[Larsson et al. 2017]

- Argues that key is transitioning effectively from shallow to deep and residual representations are not necessary
- Fractal architecture with both shallow and deep paths to output
- Trained with dropping out sub-paths
- Full network at test time



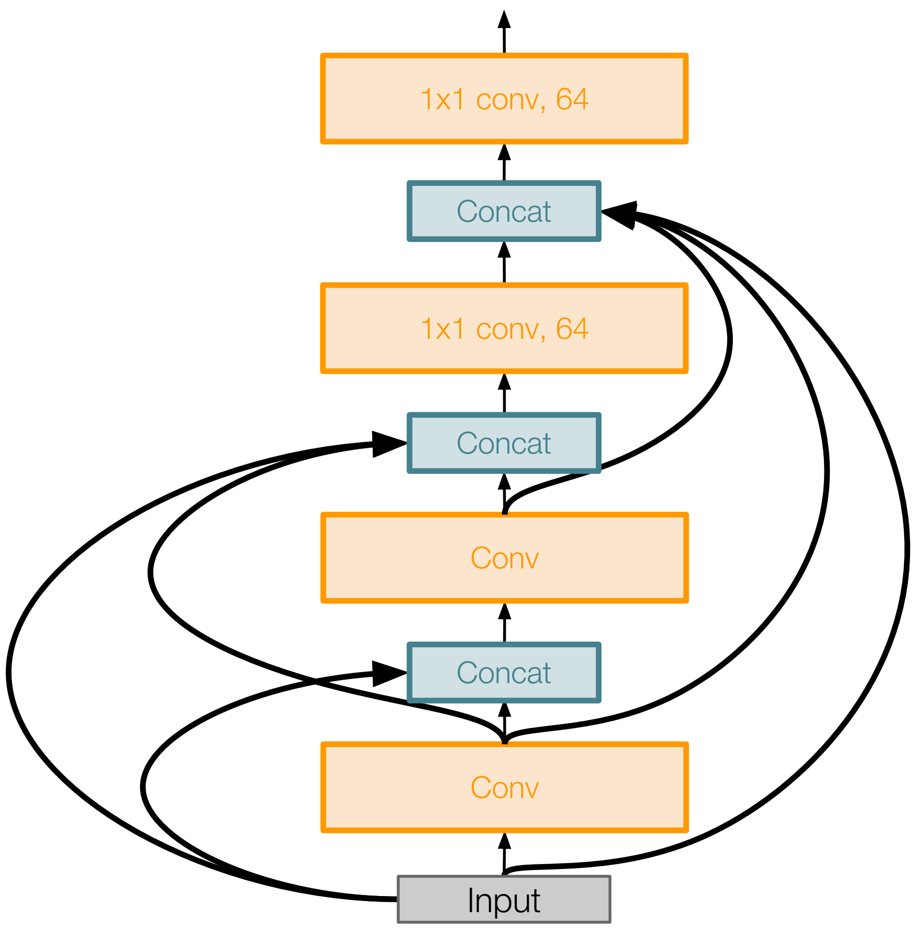
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Beyond ResNets...

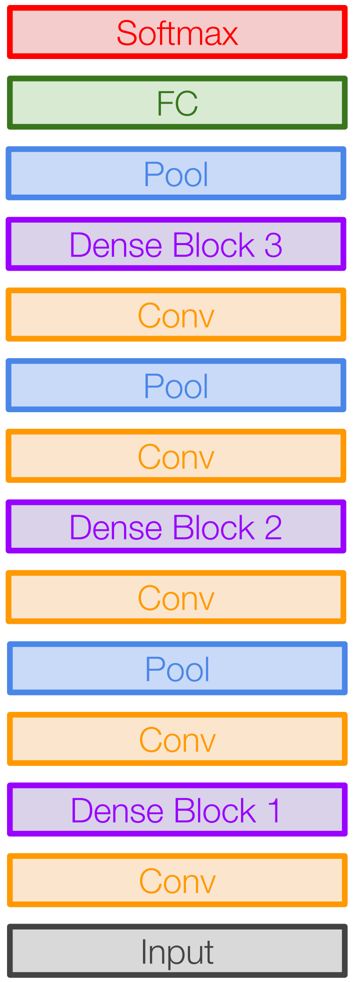
Densely Connected Convolutional Networks

[Huang et al. 2017]

- Dense blocks where each layer is connected to every other layer in feedforward fashion
- Alleviates vanishing gradient, strengthens feature propagation, encourages feature reuse



Dense Block



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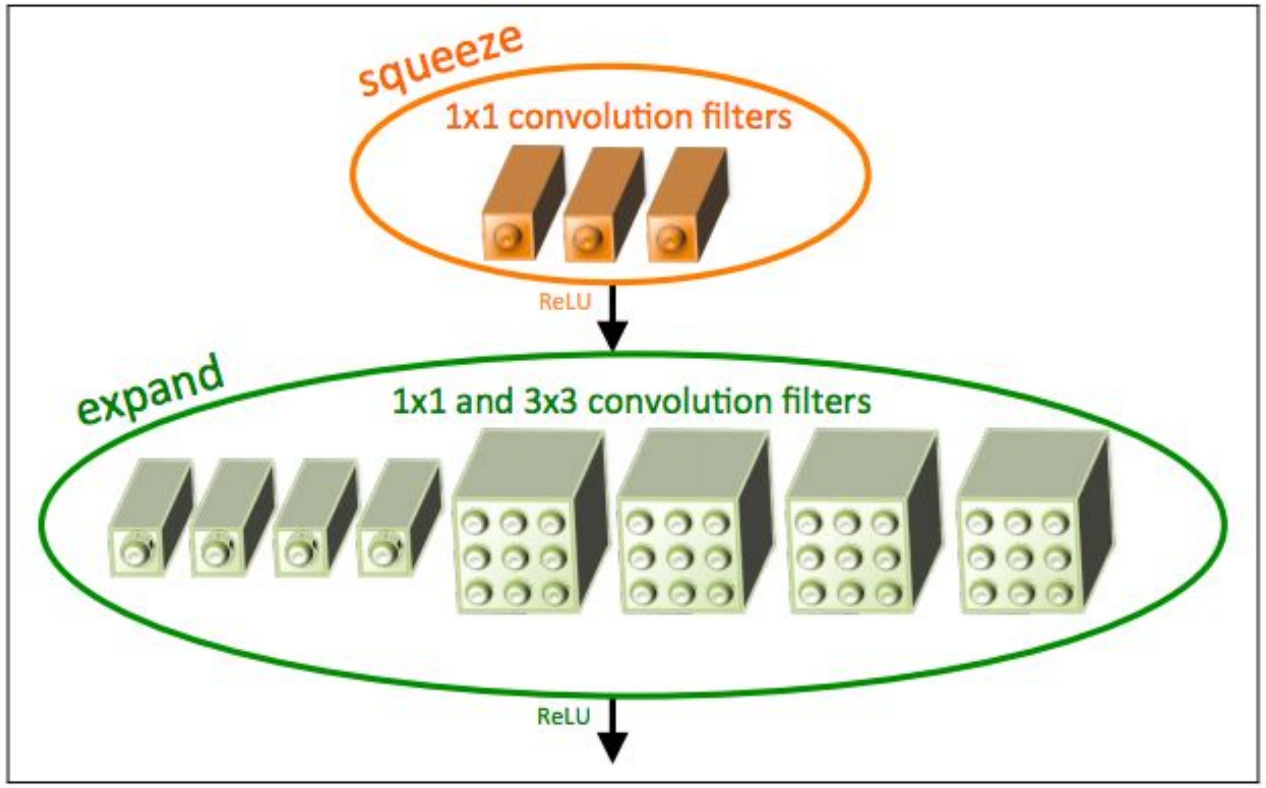
Efficient networks...

SqueezeNet: AlexNet-level Accuracy With 50x Fewer Parameters and <0.5Mb Model Size

[Iandola et al. 2017]

- Fire modules consisting of a 'squeeze' layer with 1x1 filters feeding an 'expand' layer with 1x1 and 3x3 filters
- AlexNet level accuracy on ImageNet with 50x fewer parameters
- Can compress to 510x smaller than AlexNet (0.5Mb)



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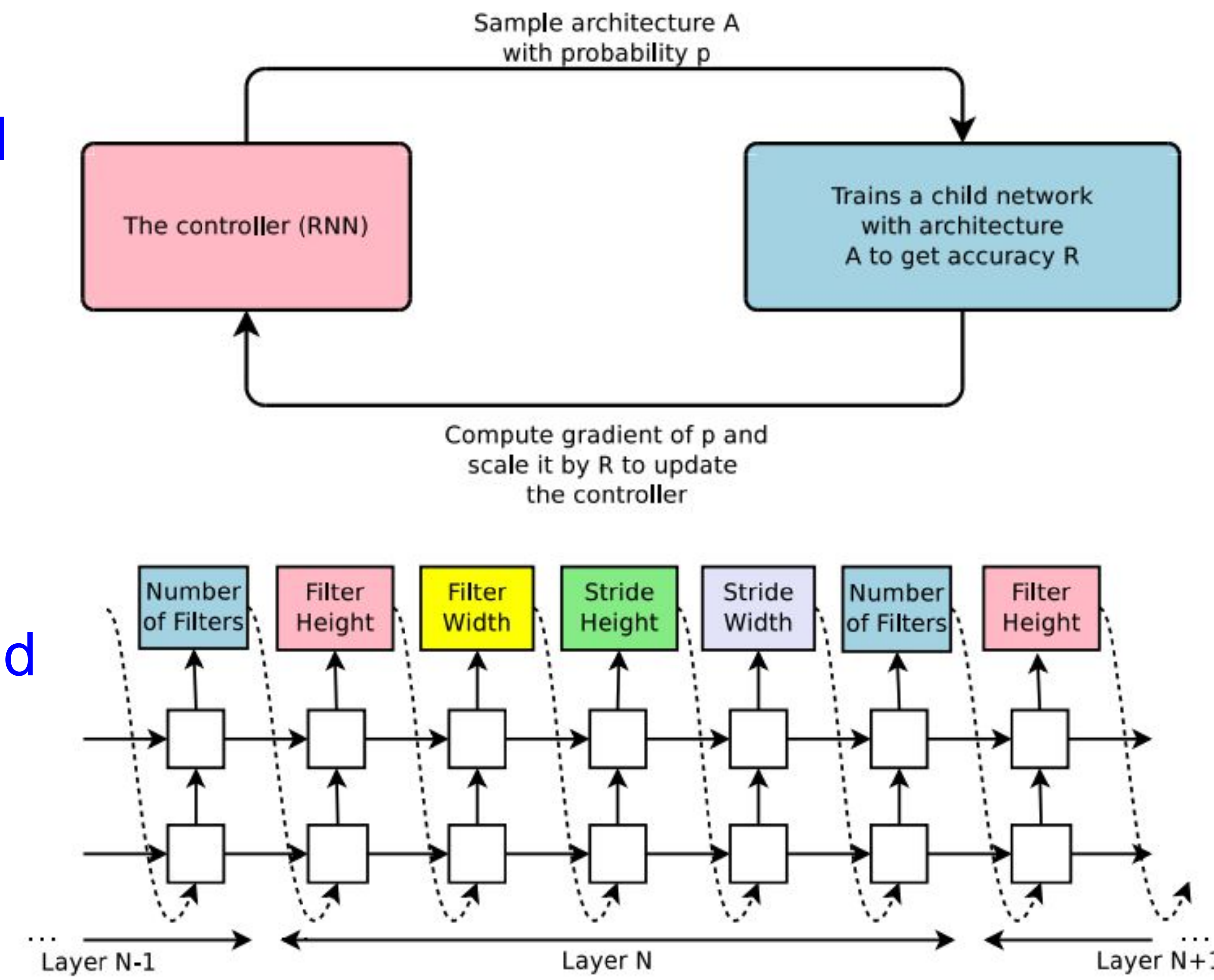
Meta-learning: Learning to learn network architectures...

Neural Architecture Search with Reinforcement Learning (NAS)

[Zoph et al. 2016]

- “Controller” network that learns to design a good network architecture (output a string corresponding to network design)
- Iterate:
  1) Sample an architecture from search space
  2) Train the architecture to get a “reward” R corresponding to accuracy
  3) Compute gradient of sample probability, and scale by R to perform controller parameter update (i.e. increase likelihood of good architecture being sampled, decrease likelihood of bad architecture)



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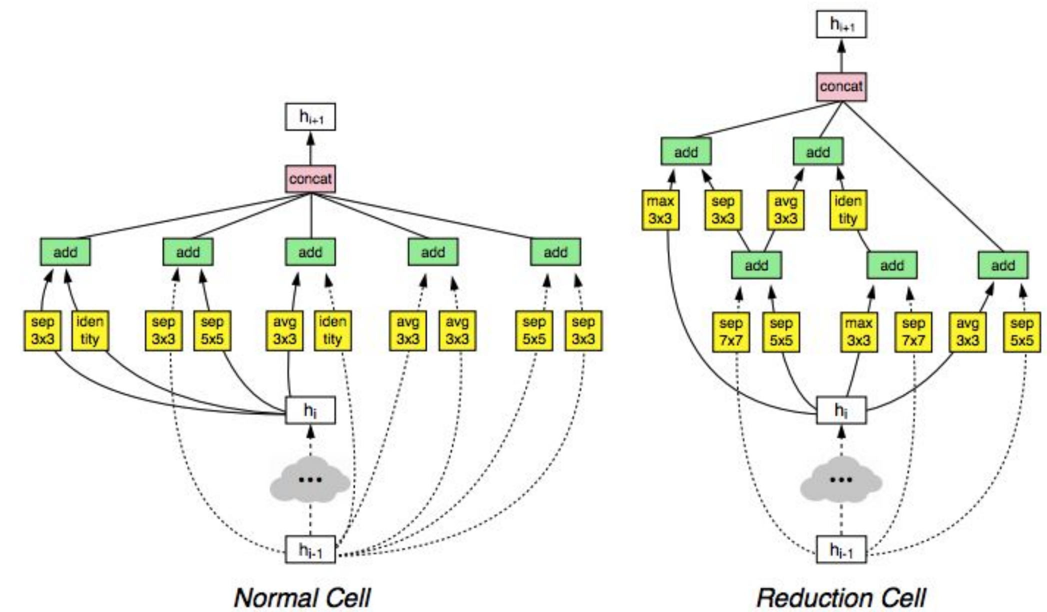
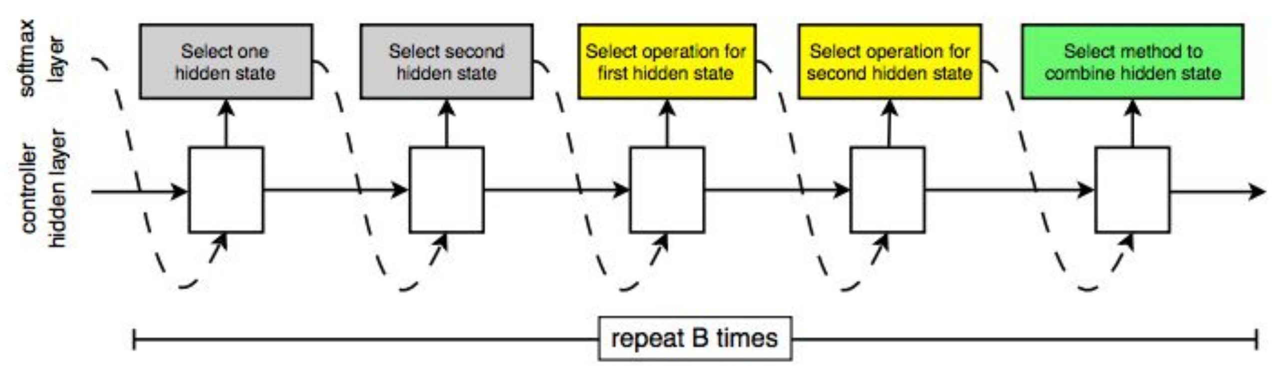
Meta-learning: Learning to learn network architectures...

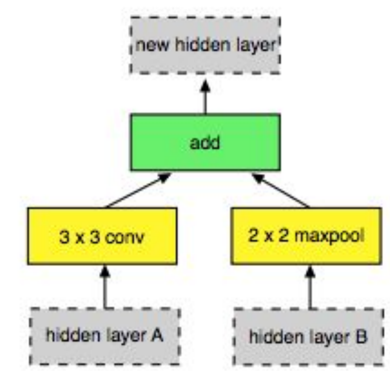
Learning Transferable Architectures for Scalable Image Recognition

[Zoph et al. 2017]

- Applying neural architecture search (NAS) to a large dataset like ImageNet is expensive
- Design a search space of building blocks (“cells”) that can be flexibly stacked
- NASNet: Use NAS to find best cell structure on smaller CIFAR-10 dataset, then transfer architecture to ImageNet







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Summary: CNN Architectures

Case Studies

- AlexNet
- VGG
- GoogLeNet
- ResNet

Also....

- NiN (Network in Network)
- Wide ResNet
- ResNeXT
- Stochastic Depth
- Squeeze-and-Excitation Network
- DenseNet
- FractalNet
- SqueezeNet
- NASNet

slide credit: Fei-Fei, Justin Johnson, Serena Yeung