

Convolutional Neural Networks

Part I

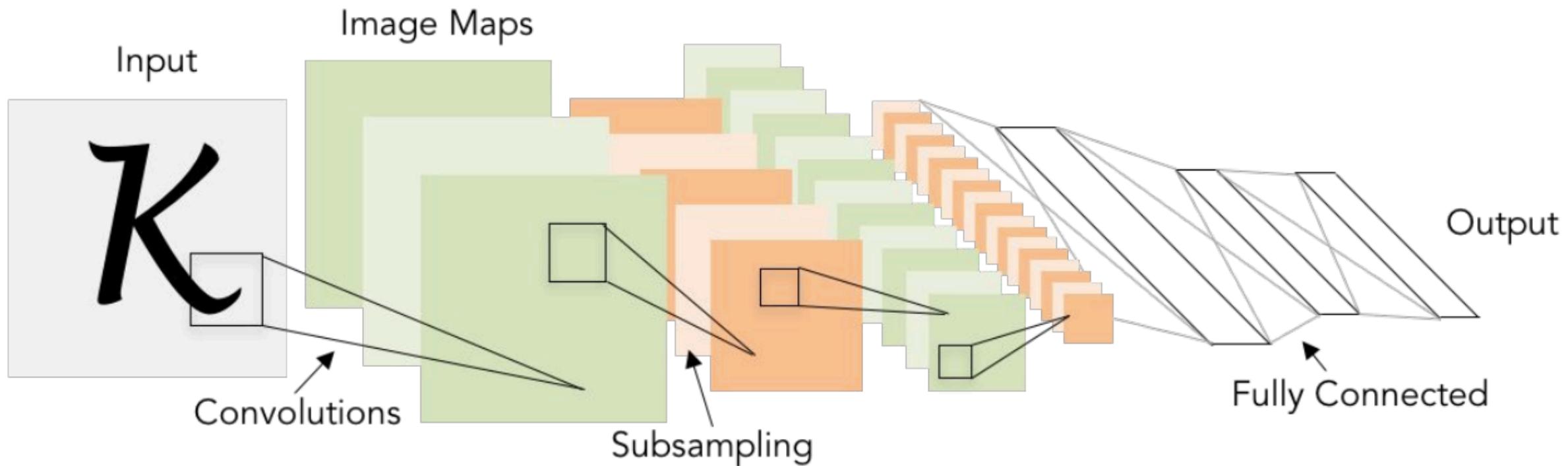
Suleyman Demirel University

CSS634: Deep Learning

PhD Abay Nussipbekov

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]

Case Study: AlexNet

[Krizhevsky et al. 2012]

Architecture:

CONV1

MAX POOL1

NORM1

CONV2

MAX POOL2

NORM2

CONV3

CONV4

CONV5

Max POOL3

FC6

FC7

FC8

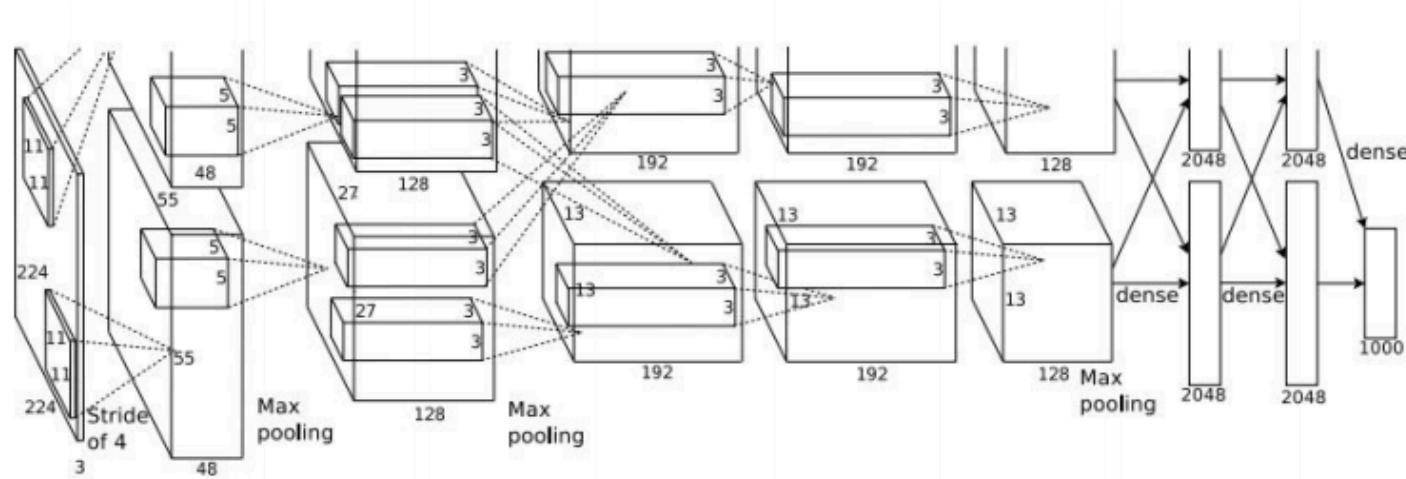
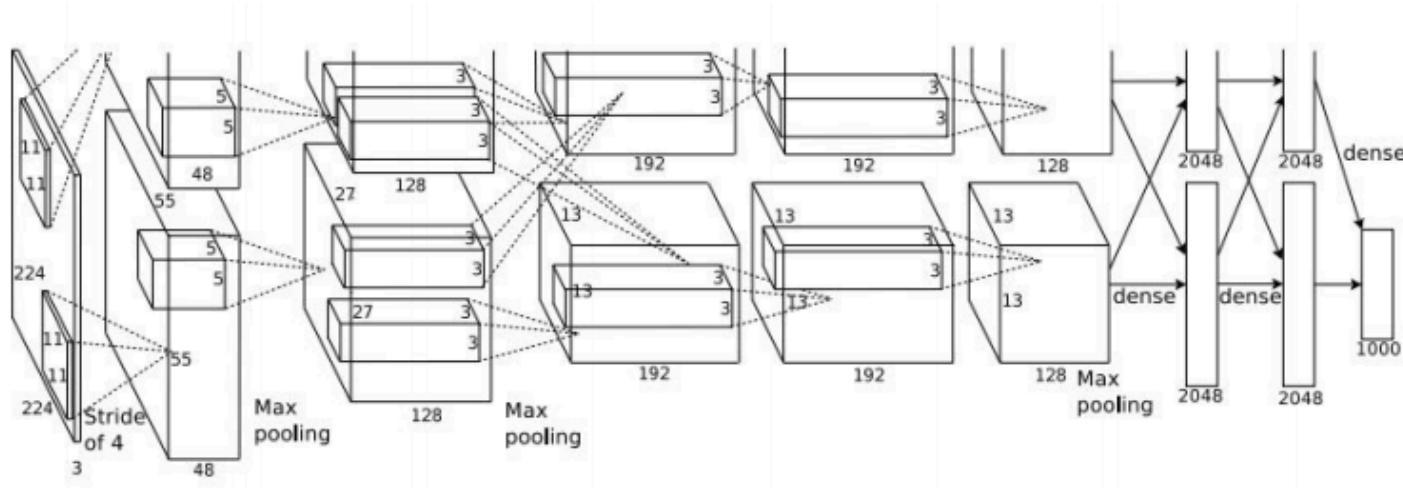


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Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4

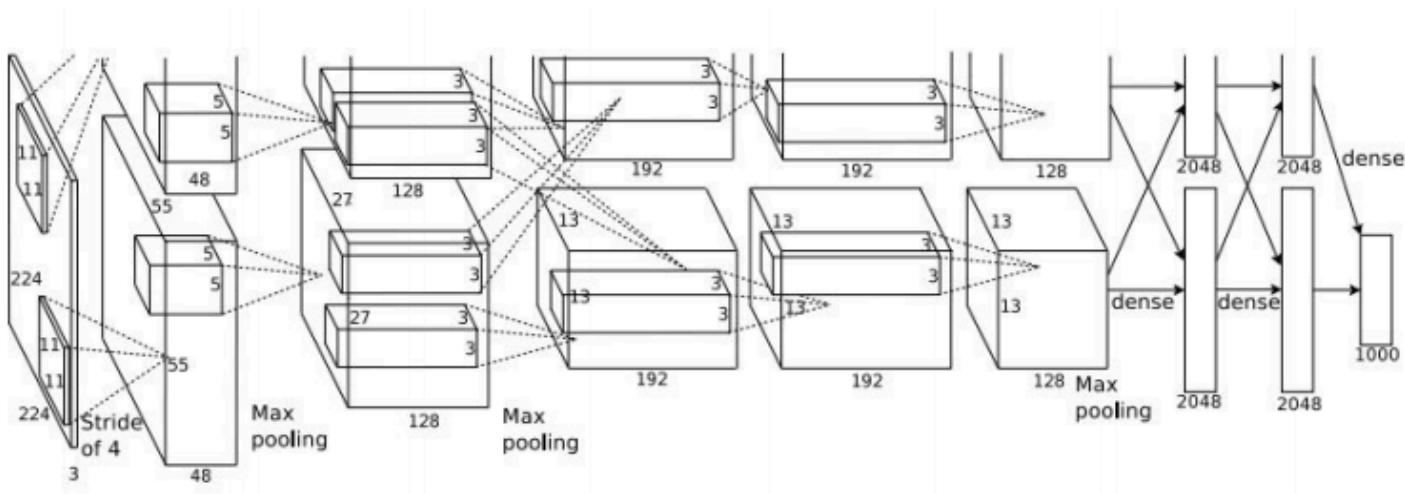
=>

Q: what is the output volume size? Hint: $(227-11)/4+1 = 55$

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Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4

=>

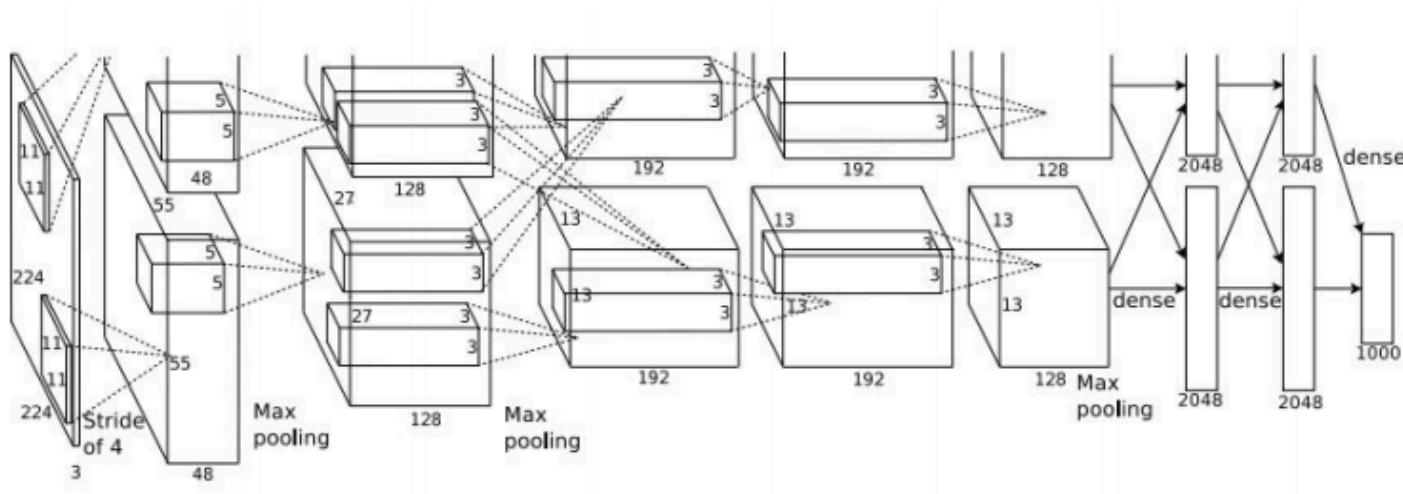
Output volume **[55x55x96]**

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

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Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4

=>

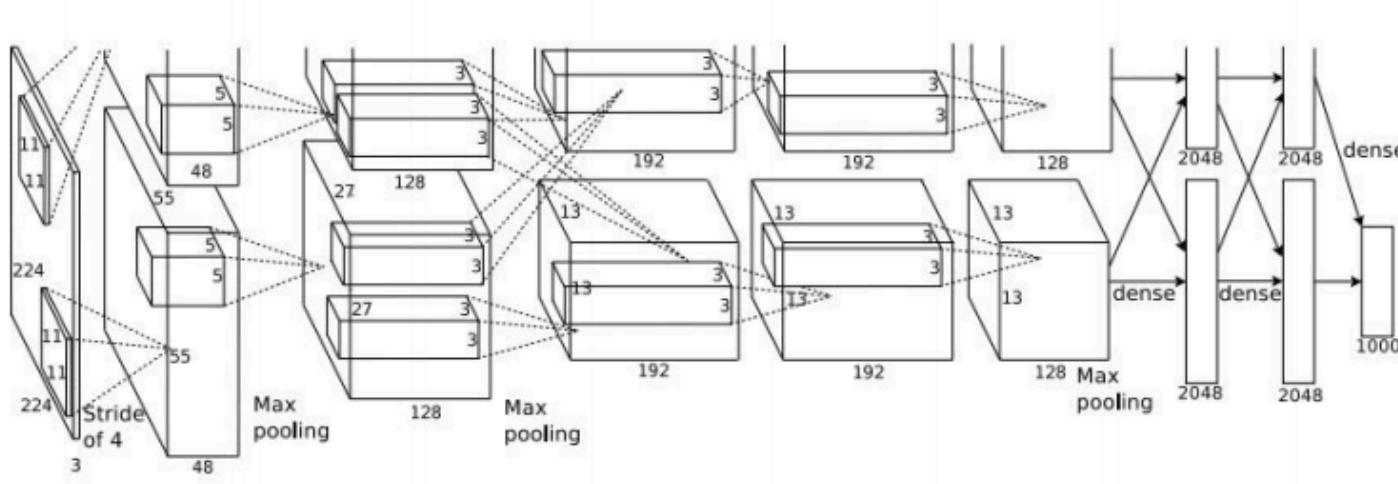
Output volume **[55x55x96]**

Parameters: $(11 \times 11 \times 3) \times 96 = 35\text{K}$

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Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

After CONV1: 55x55x96

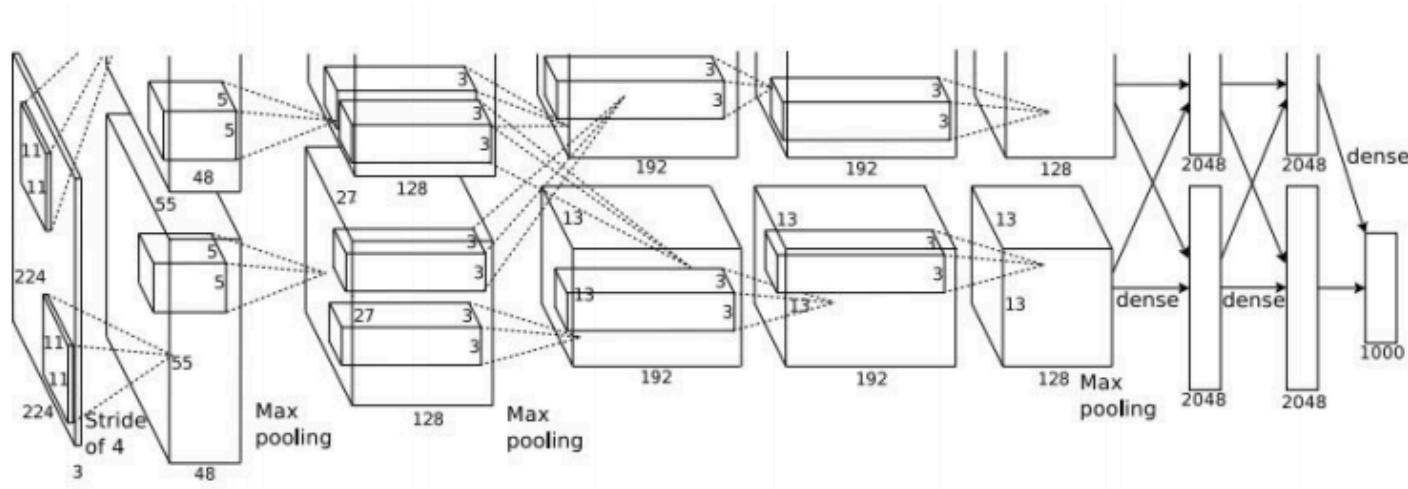
Second layer (POOL1): 3x3 filters applied at stride 2

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

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Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

After CONV1: 55x55x96

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

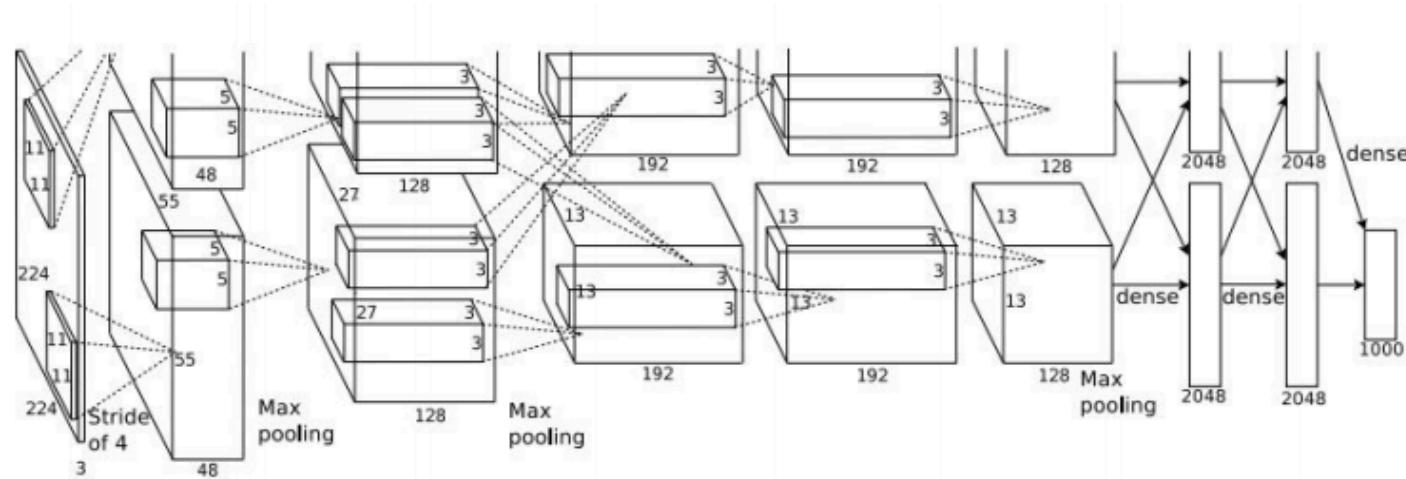
Output volume: 27x27x96

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

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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!

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Case Study: AlexNet

[Krizhevsky et al. 2012]

Input: 227x227x3 images

After CONV1: 55x55x96

After POOL1: 27x27x96

...

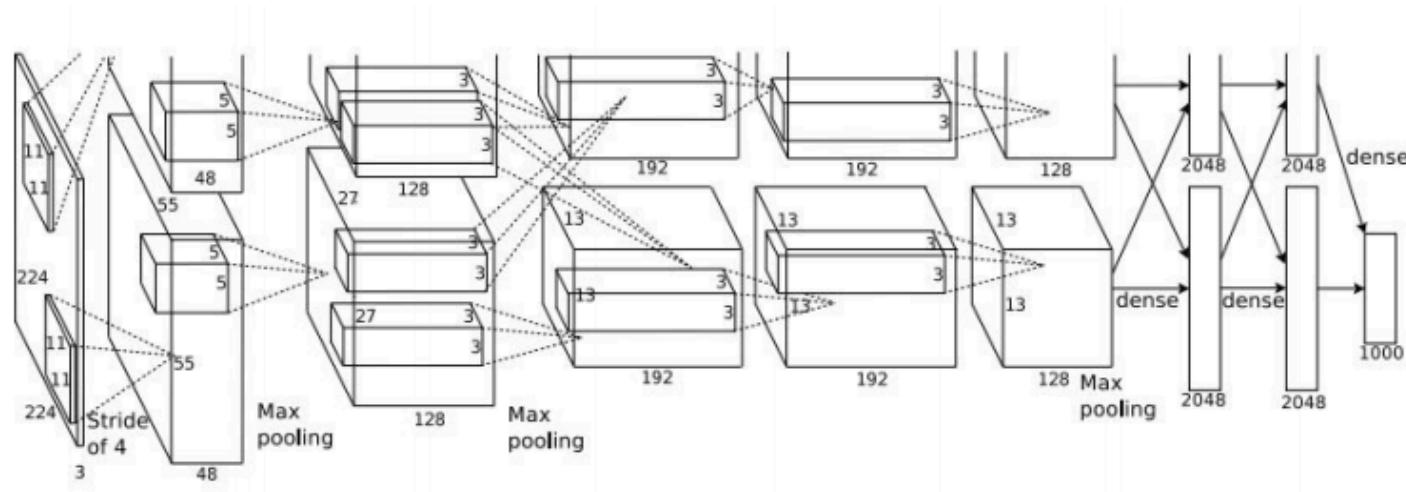


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Case Study: AlexNet

[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)

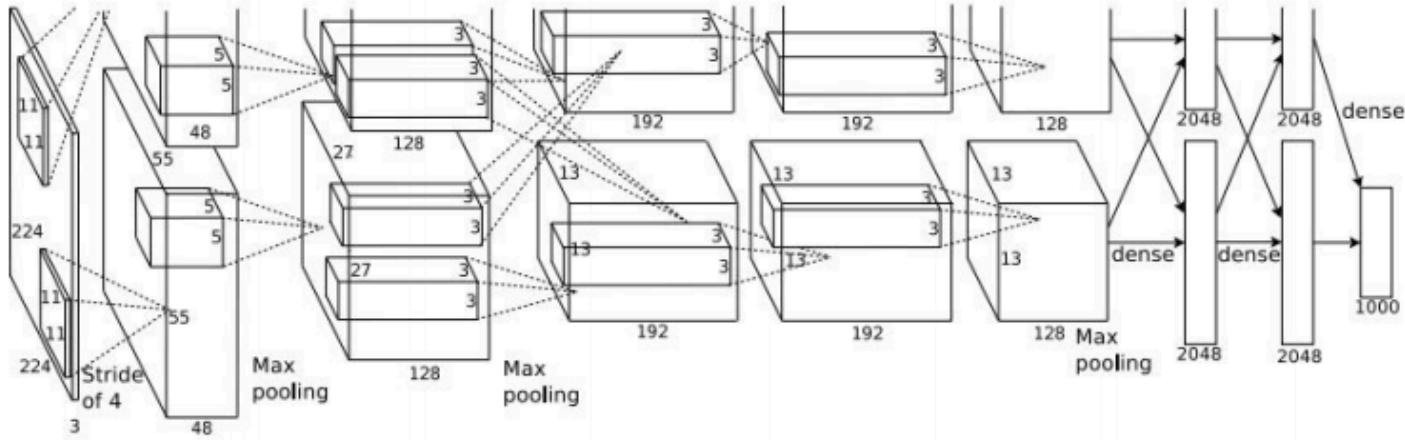


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Case Study: AlexNet

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[13x13x256] MAX POOL2: 3x3 filters at stride 2

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[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1

[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1

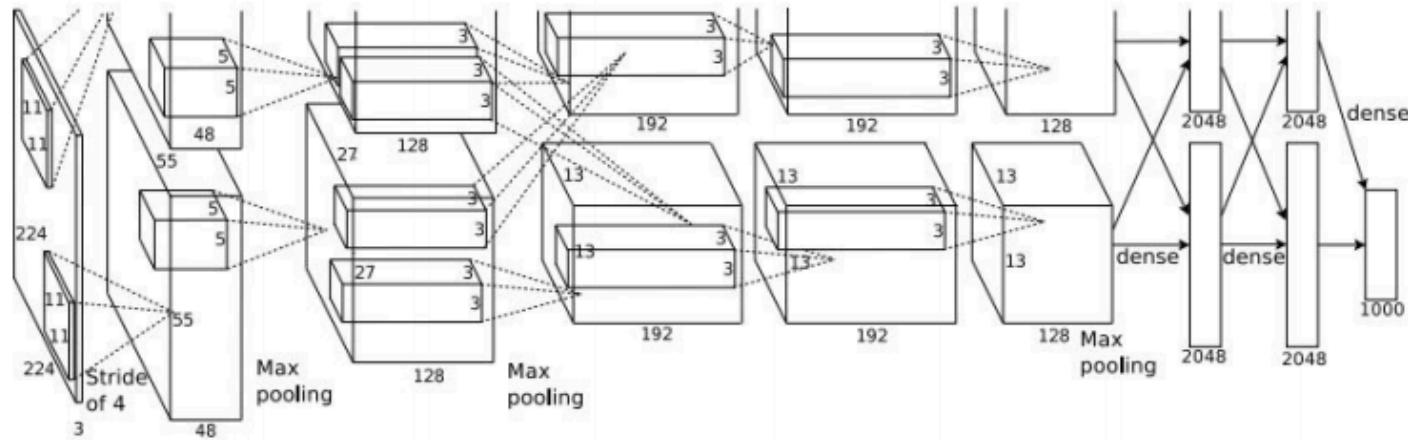
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[4096] FC6: 4096 neurons

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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%

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Case Study: AlexNet

[Krizhevsky et al. 2012]

Full (simplified) AlexNet architecture:

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[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1

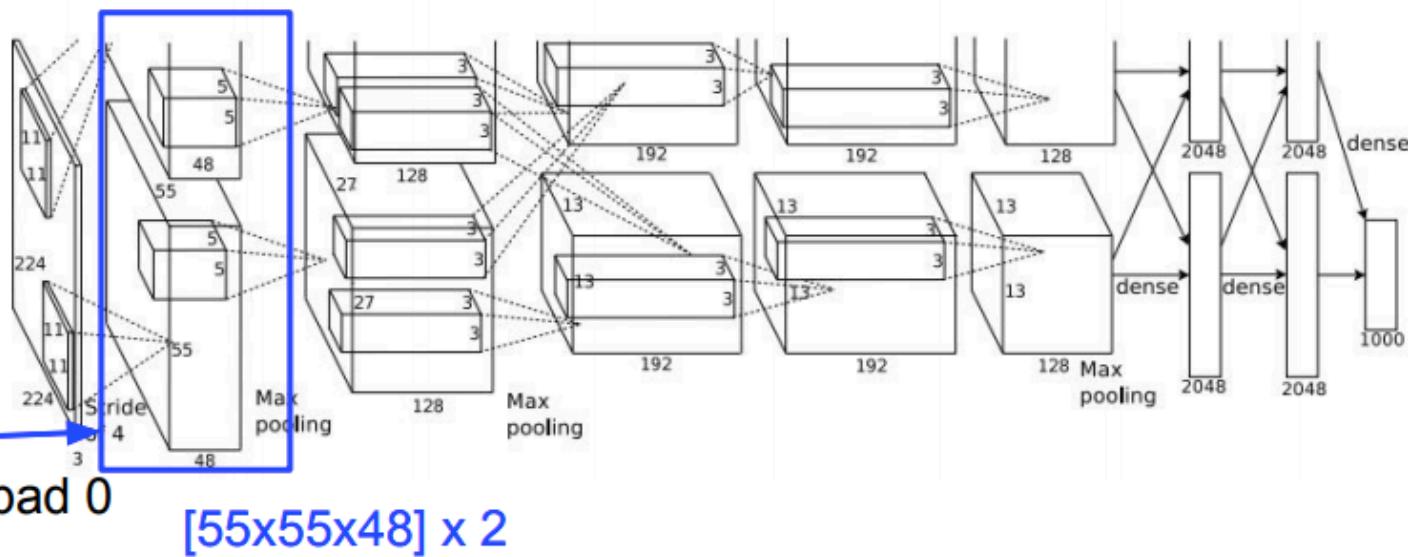
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[4096] FC6: 4096 neurons

[4096] FC7: 4096 neurons

[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.

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Case Study: AlexNet

[Krizhevsky et al. 2012]

Full (simplified) AlexNet architecture:

[227x227x3] INPUT

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[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1

[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1

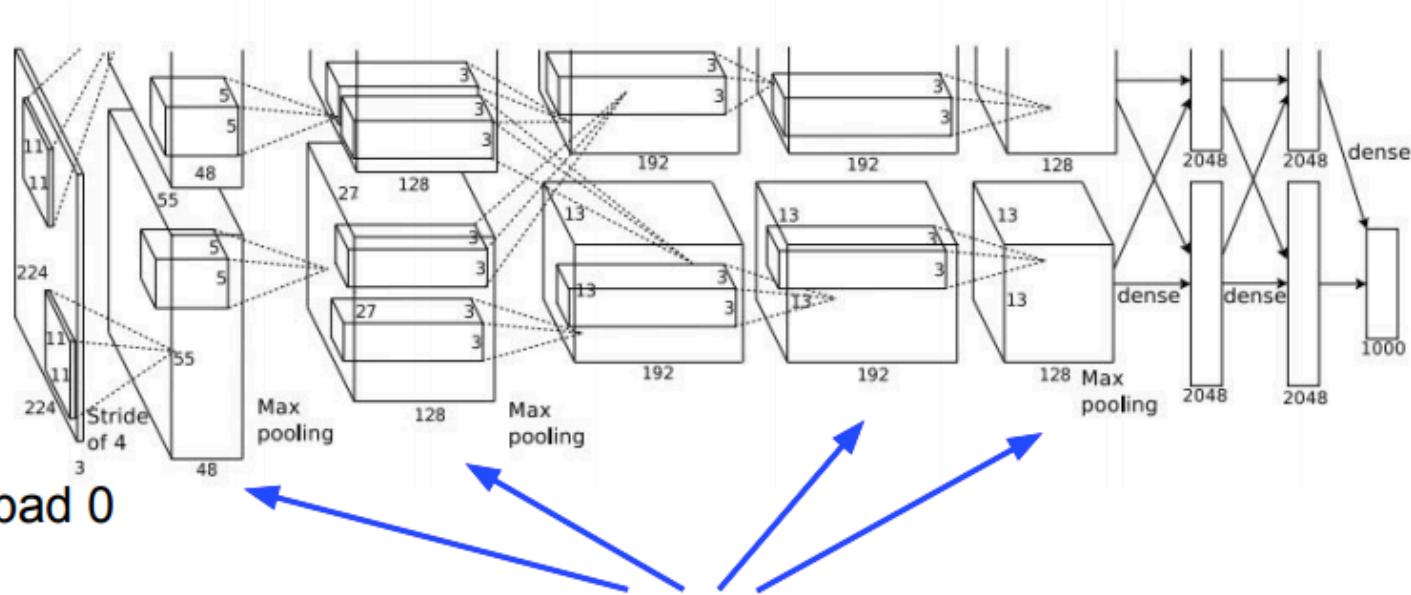
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1

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[4096] FC6: 4096 neurons

[4096] FC7: 4096 neurons

[1000] FC8: 1000 neurons (class scores)



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

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Case Study: AlexNet

[Krizhevsky et al. 2012]

Full (simplified) AlexNet architecture:

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[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1

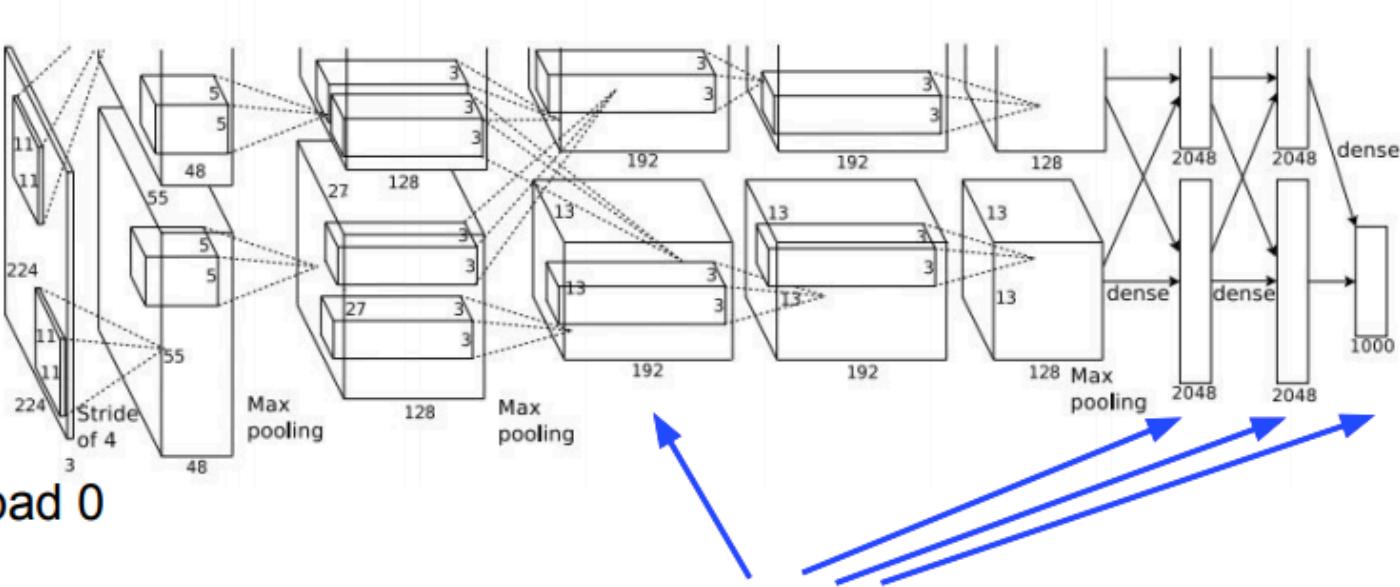
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1

[6x6x256] MAX POOL3: 3x3 filters at stride 2

[4096] FC6: 4096 neurons

[4096] FC7: 4096 neurons

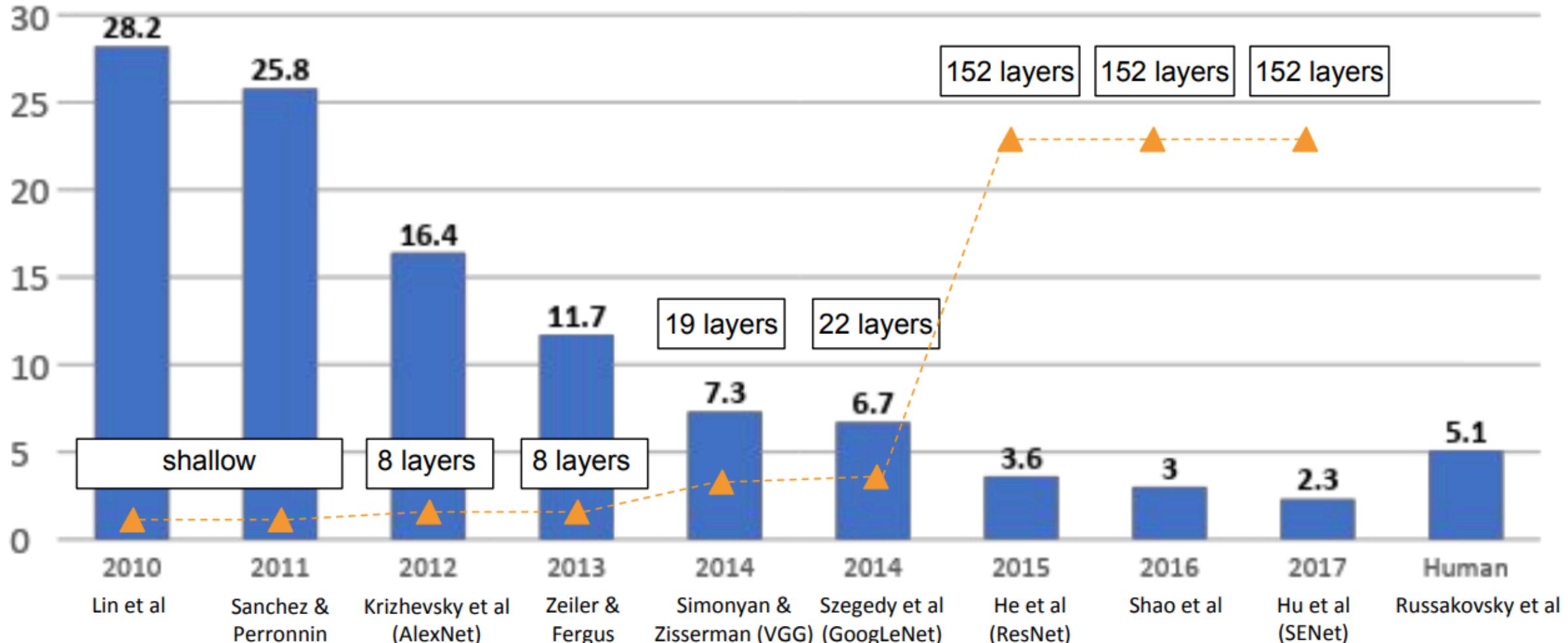
[1000] FC8: 1000 neurons (class scores)



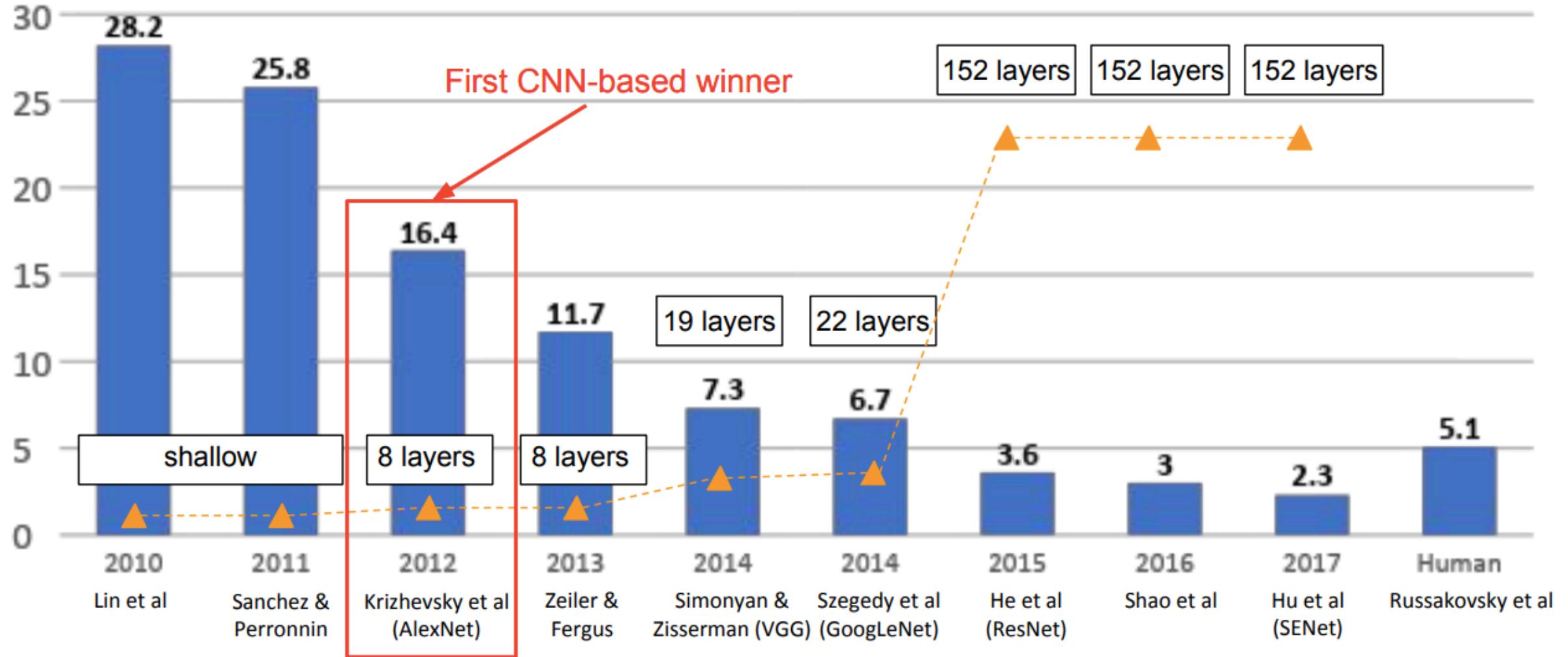
CONV3, FC6, FC7, FC8:
Connections with all feature maps in
preceding layer, communication
across GPUs

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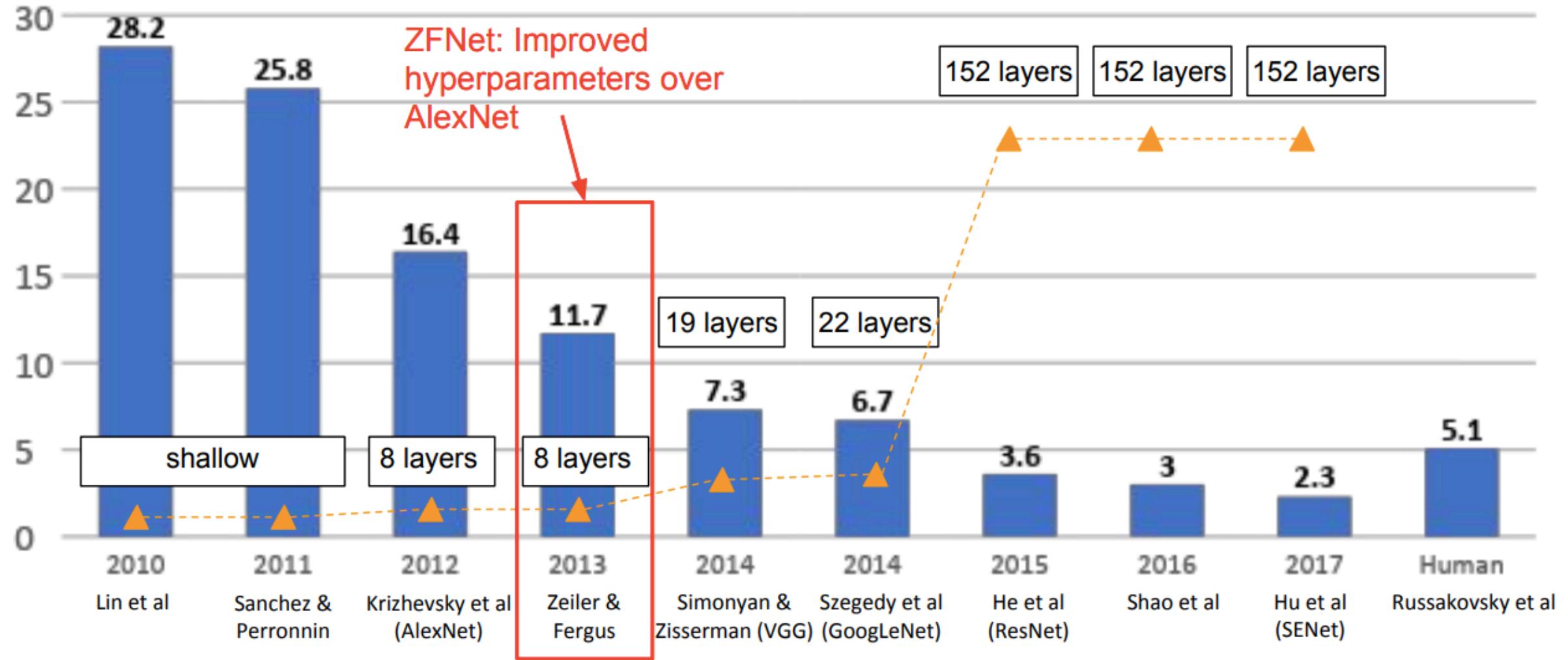
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

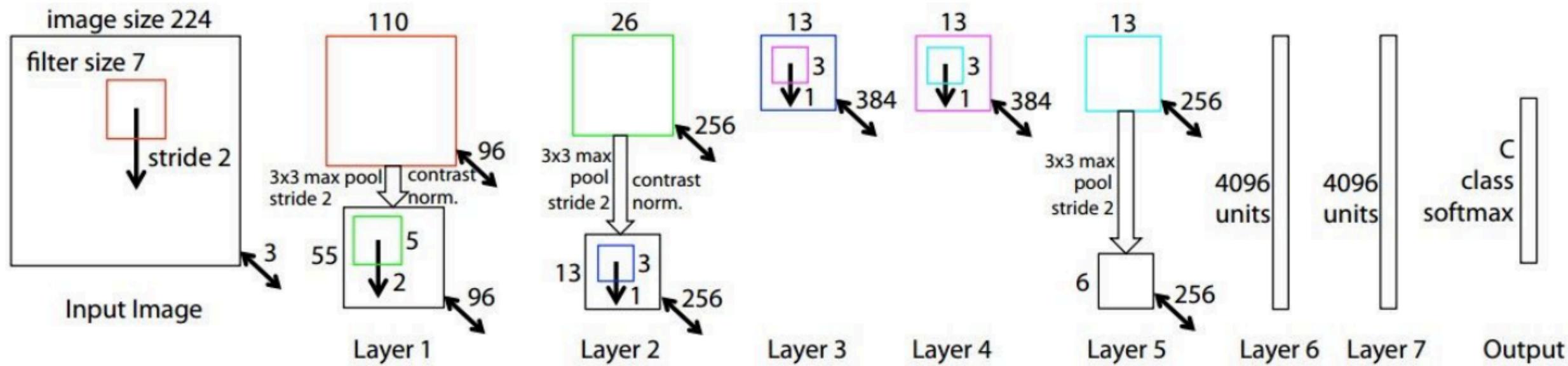


ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



ZFNet

[Zeiler and Fergus, 2013]



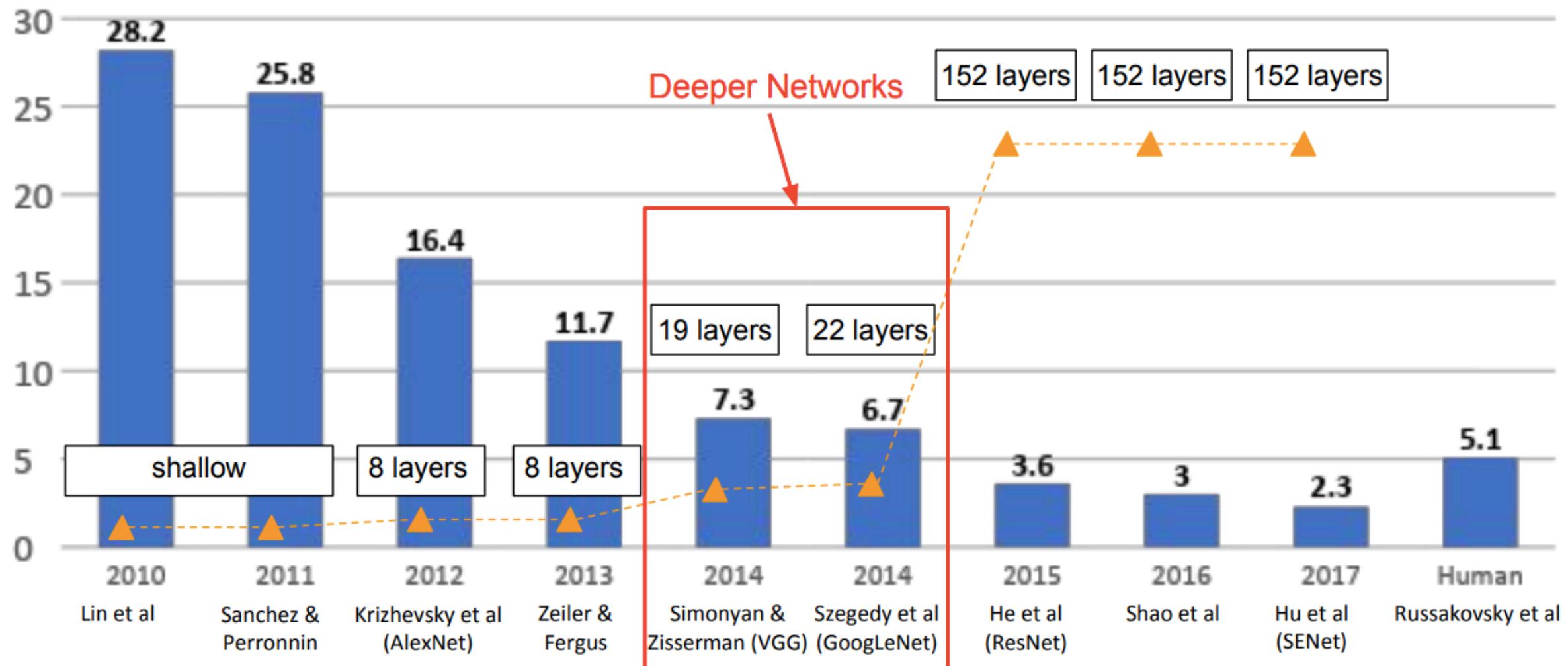
AlexNet but:

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% \rightarrow 11.7%

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Small filters, Deeper networks

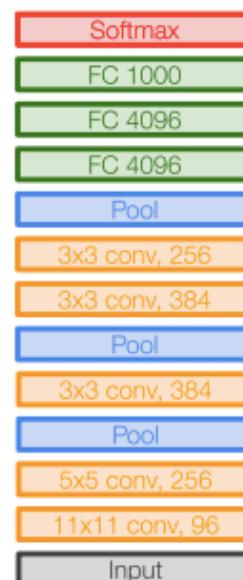
8 layers (AlexNet)

-> 16 - 19 layers (VGG16Net)

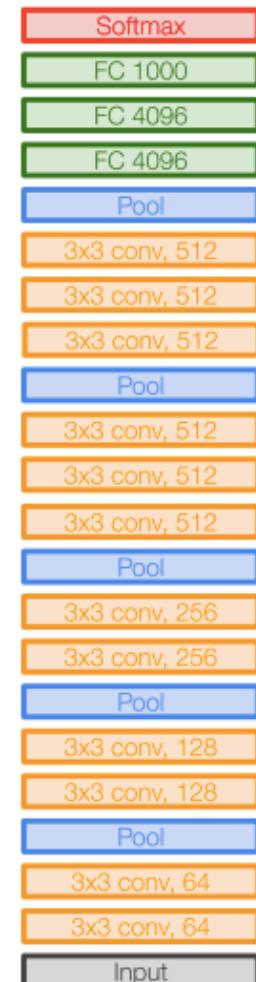
Only 3x3 CONV stride 1, pad 1
and 2x2 MAX POOL stride 2

11.7% top 5 error in ILSVRC'13 (ZFNet)

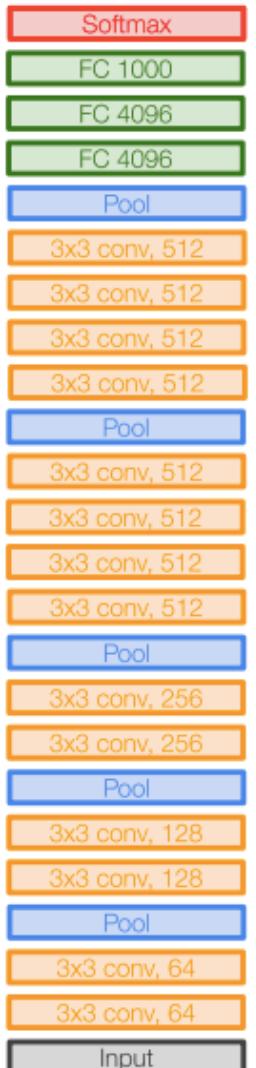
-> 7.3% top 5 error in ILSVRC'14



AlexNet



VGG16

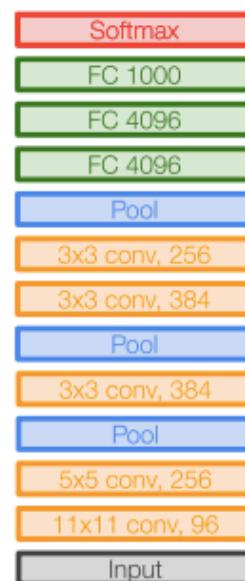


VGG19

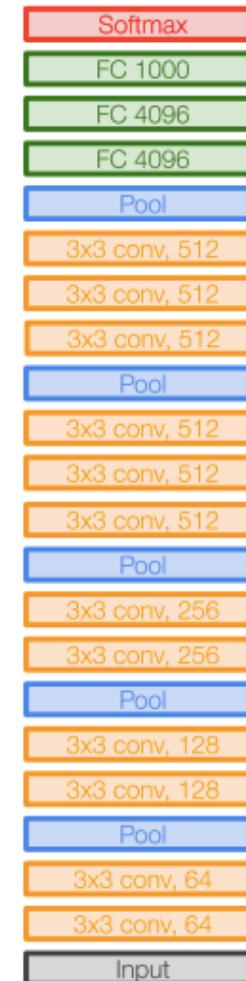
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

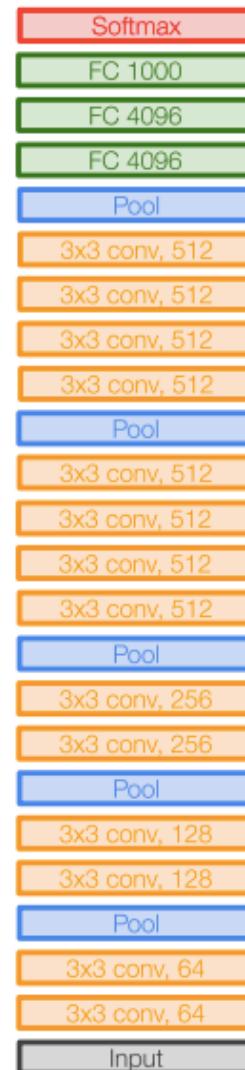
Q: Why use smaller filters? (3x3 conv)



AlexNet



VGG16



VGG19

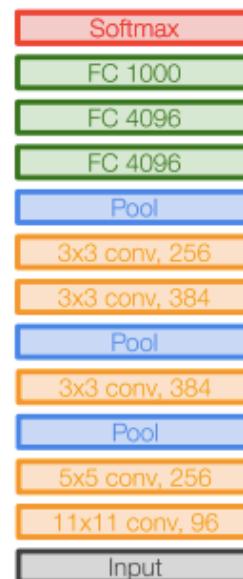
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

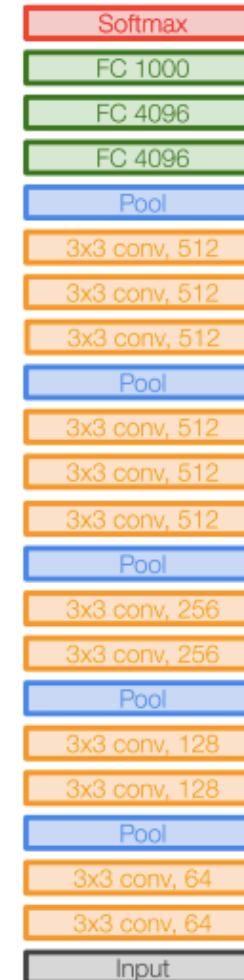
Q: Why use smaller filters? (3x3 conv)

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

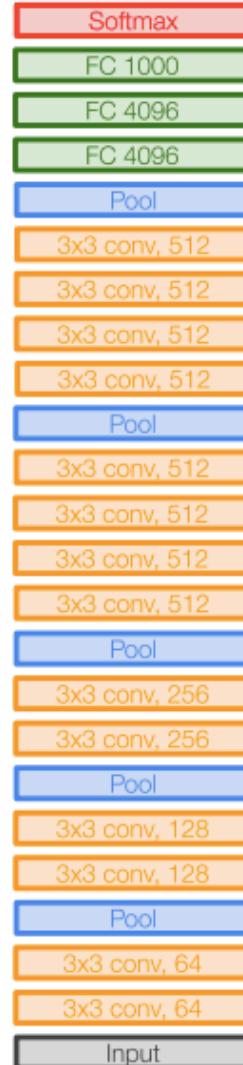
Q: What is the effective receptive field of three 3×3 conv (stride 1) layers?



AlexNet



VGG16



VGG19

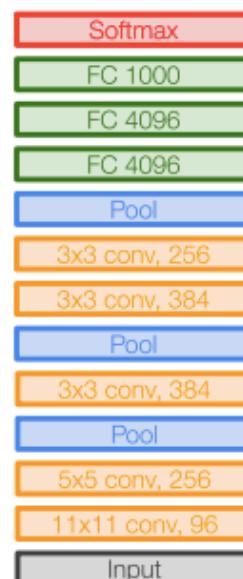
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

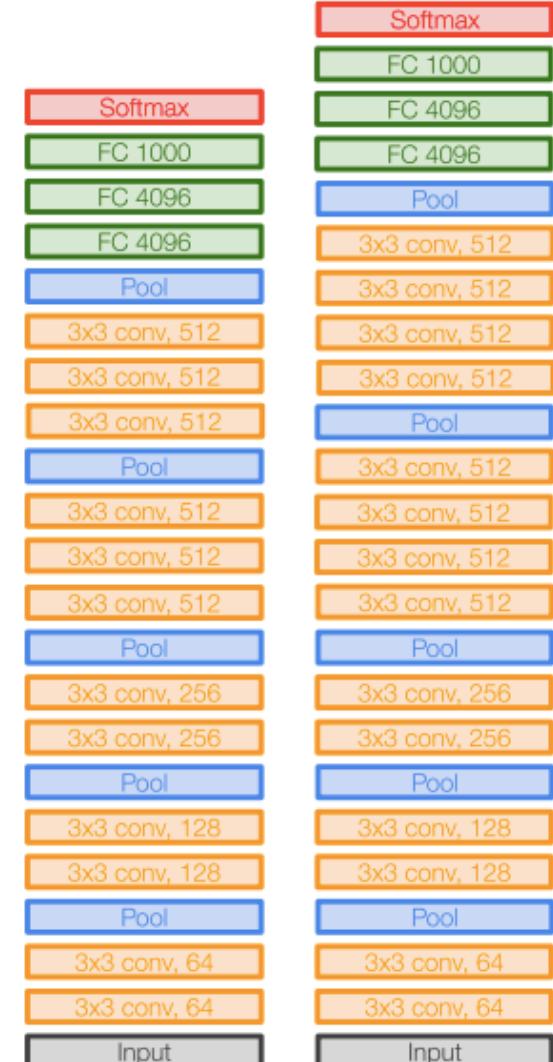
Q: Why use smaller filters? (3x3 conv)

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

[7x7]



AlexNet



VGG16

VGG19

Case Study: VGGNet

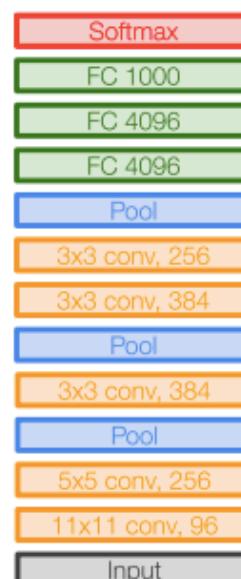
[Simonyan and Zisserman, 2014]

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

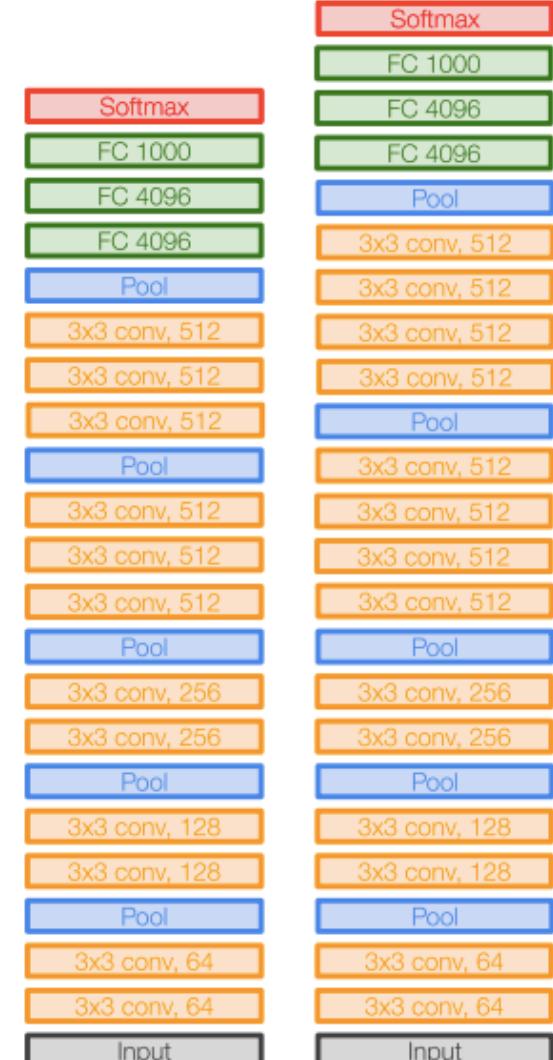
Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

But deeper, more non-linearities

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



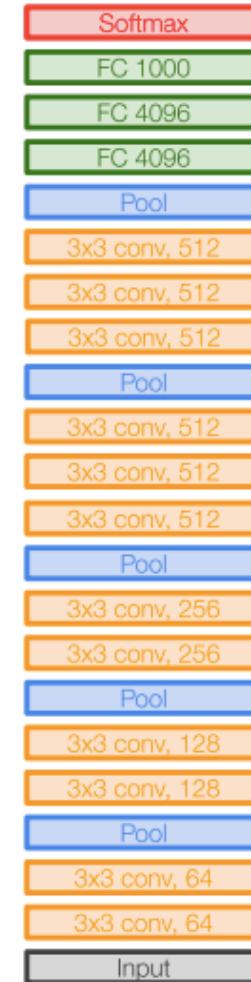
AlexNet



VGG16

VGG19

INPUT: [224x224x3] memory: 224*224*3=150K params: 0 (not counting biases)
 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

INPUT: [224x224x3] memory: $224 \times 224 \times 3 = 150K$ params: 0 (not counting biases)

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 3) \times 64 = 1,728$

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 64) \times 64 = 36,864$

POOL2: [112x112x64] memory: $112 \times 112 \times 64 = 800K$ params: 0

CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 64) \times 128 = 73,728$

CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 128) \times 128 = 147,456$

POOL2: [56x56x128] memory: $56 \times 56 \times 128 = 400K$ params: 0

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 128) \times 256 = 294,912$

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 256) \times 256 = 589,824$

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 256) \times 256 = 589,824$

POOL2: [28x28x256] memory: $28 \times 28 \times 256 = 200K$ params: 0

CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 256) \times 512 = 1,179,648$

CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

POOL2: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: 0

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

POOL2: [7x7x512] memory: $7 \times 7 \times 512 = 25K$ params: 0

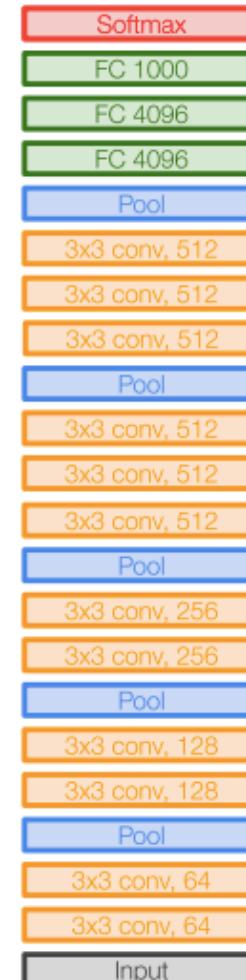
FC: [1x1x4096] memory: 4096 params: $7 \times 7 \times 512 \times 4096 = 102,760,448$

FC: [1x1x4096] memory: 4096 params: $4096 \times 4096 = 16,777,216$

FC: [1x1x1000] memory: 1000 params: $4096 \times 1000 = 4,096,000$

TOTAL memory: $24M * 4 \text{ bytes} \approx 96\text{MB / image}$ (for a forward pass)

TOTAL params: 138M parameters



VGG16

INPUT: [224x224x3] memory: $224 \times 224 \times 3 = 150K$ params: 0 (not counting biases)

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 3) \times 64 = 1,728$

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 64) \times 64 = 36,864$

POOL2: [112x112x64] memory: $112 \times 112 \times 64 = 800K$ params: 0

CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 64) \times 128 = 73,728$

CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 128) \times 128 = 147,456$

POOL2: [56x56x128] memory: $56 \times 56 \times 128 = 400K$ params: 0

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 128) \times 256 = 294,912$

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 256) \times 256 = 589,824$

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 256) \times 256 = 589,824$

POOL2: [28x28x256] memory: $28 \times 28 \times 256 = 200K$ params: 0

CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 256) \times 512 = 1,179,648$

CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

POOL2: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: 0

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

POOL2: [7x7x512] memory: $7 \times 7 \times 512 = 25K$ params: 0

FC: [1x1x4096] memory: 4096 params: $7 \times 7 \times 512 \times 4096 = 102,760,448$

FC: [1x1x4096] memory: 4096 params: $4096 \times 4096 = 16,777,216$

FC: [1x1x1000] memory: 1000 params: $4096 \times 1000 = 4,096,000$

Note:

Most memory is in early CONV

Most params are in late FC

TOTAL memory: $24M * 4 \text{ bytes} \approx 96\text{MB} / \text{image}$ (only forward! ~ 2 for bwd)

TOTAL params: 138M parameters

INPUT: [224x224x3] memory: $224 \times 224 \times 3 = 150K$ params: 0 (not counting biases)

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 3) \times 64 = 1,728$

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 64) \times 64 = 36,864$

POOL2: [112x112x64] memory: $112 \times 112 \times 64 = 800K$ params: 0

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CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 128) \times 128 = 147,456$

POOL2: [56x56x128] memory: $56 \times 56 \times 128 = 400K$ params: 0

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 128) \times 256 = 294,912$

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POOL2: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: 0

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

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POOL2: [7x7x512] memory: $7 \times 7 \times 512 = 25K$ params: 0

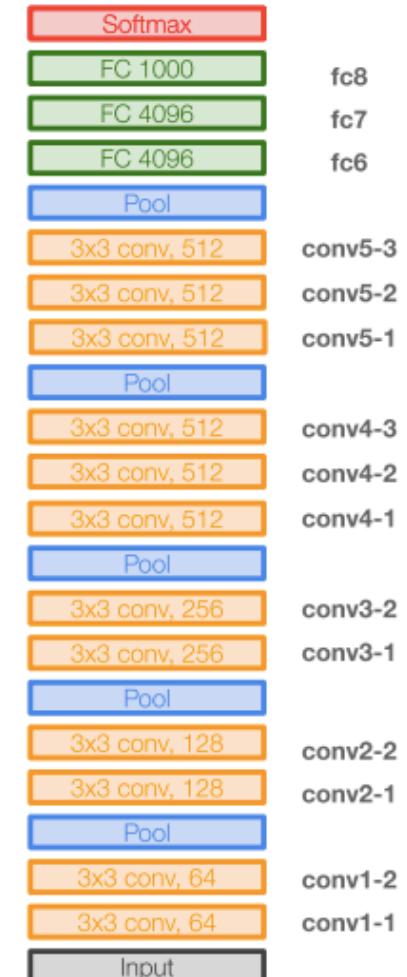
FC: [1x1x4096] memory: 4096 params: $7 \times 7 \times 512 \times 4096 = 102,760,448$

FC: [1x1x4096] memory: 4096 params: $4096 \times 4096 = 16,777,216$

FC: [1x1x1000] memory: 1000 params: $4096 \times 1000 = 4,096,000$

TOTAL memory: $24M * 4 \text{ bytes} \approx 96\text{MB} / \text{image}$ (only forward! ~ 2 for bwd)

TOTAL params: 138M parameters



VGG16

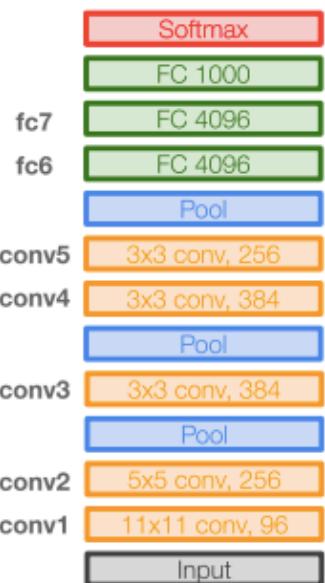
Common names

Case Study: VGGNet

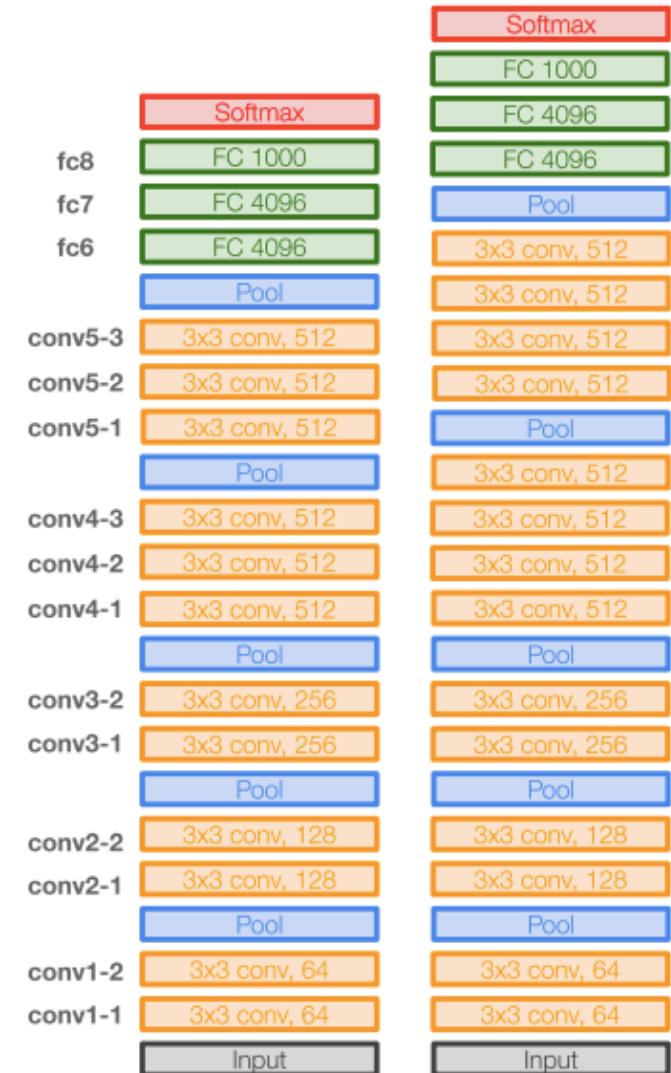
[Simonyan and Zisserman, 2014]

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



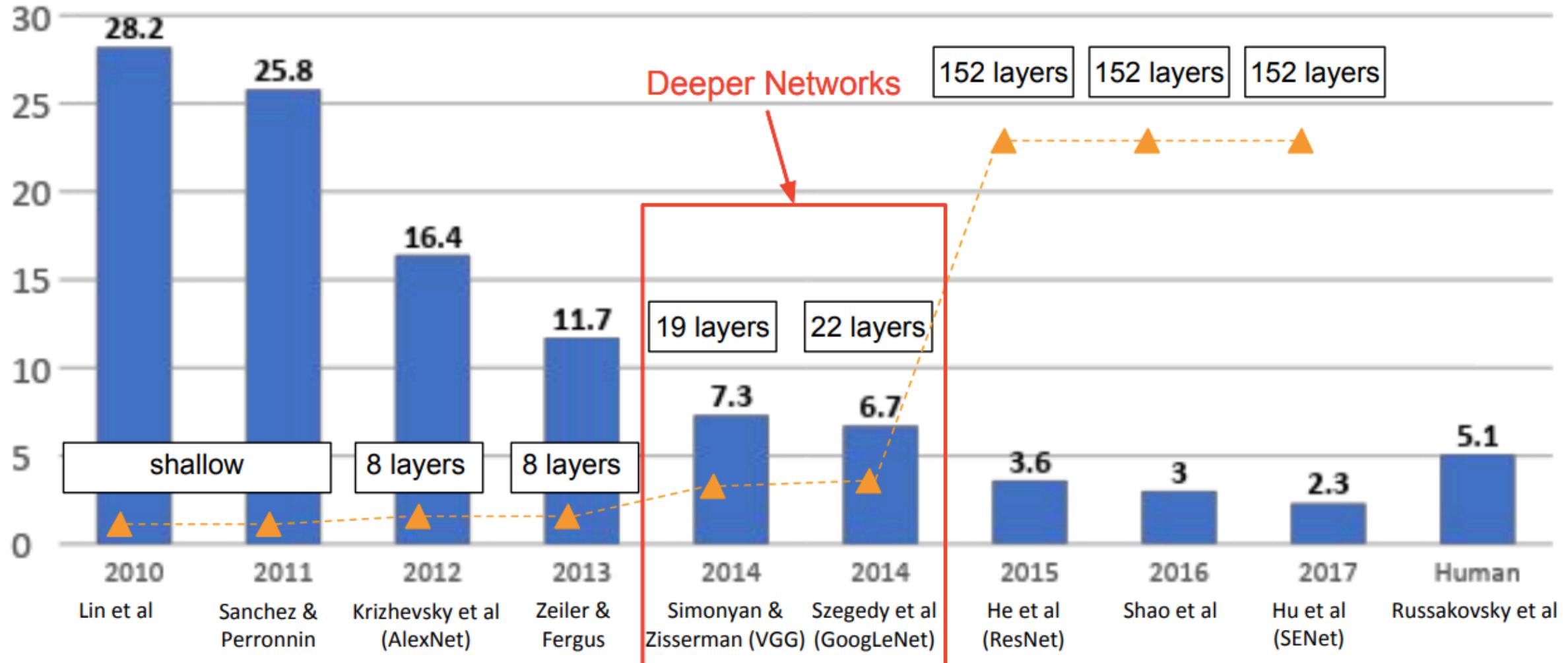
AlexNet



VGG16

VGG19

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

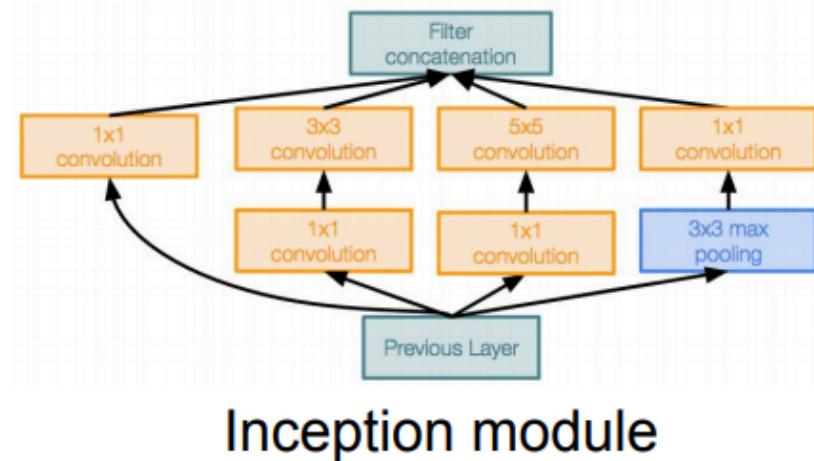


Case Study: GoogLeNet

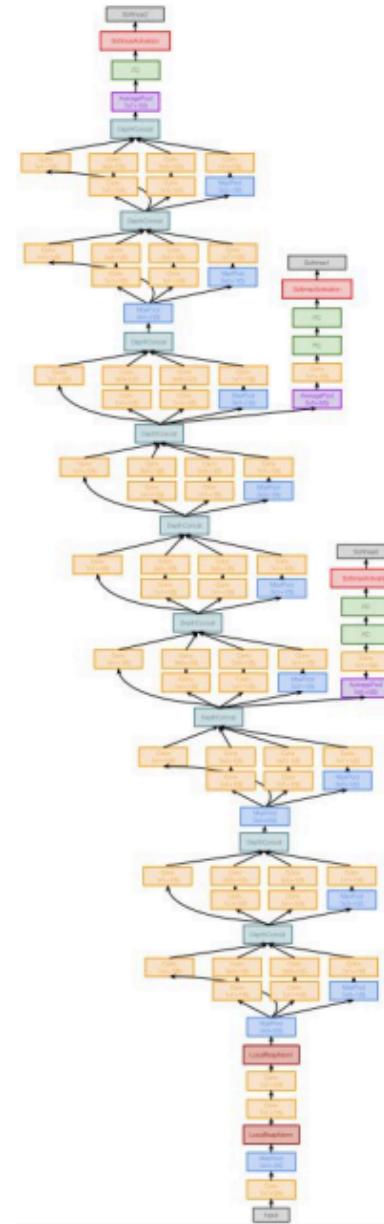
[Szegedy et al., 2014]

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



GoogLeNet / Inception v1

Szegedy, Christian, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. "[Going deeper with convolutions.](#)" In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1-9. 2015.

3 key ideas:

1. 1x1 in the middle of the network
2. global average pooling instead of fully connected layers
3. inception module

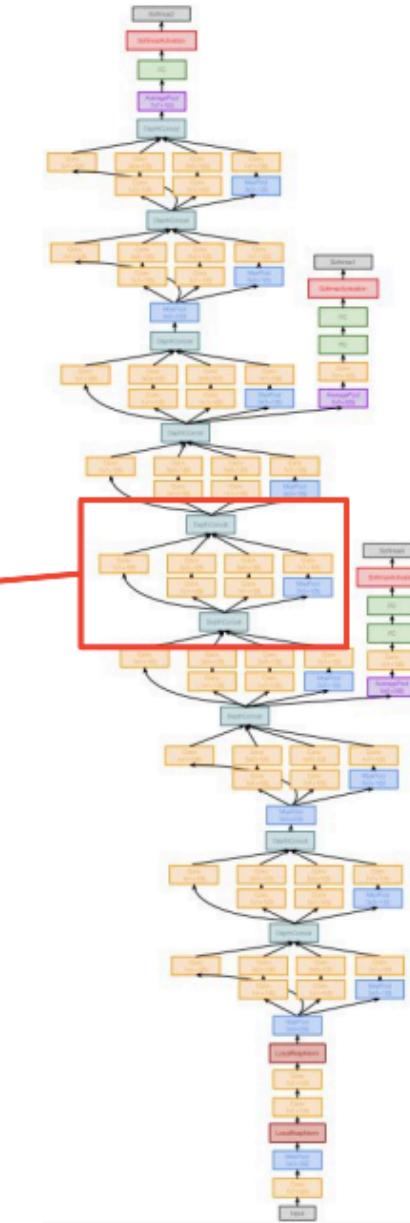
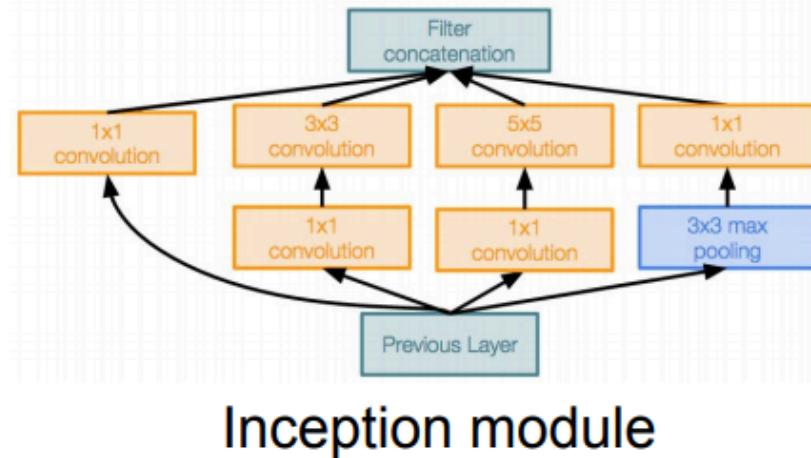


Note that the name inception doesn't have to make sense and is unrelated to the main concept; according to the authors, it comes from an internet meme that is in turn based on a movie called "Inception"

Case Study: GoogLeNet

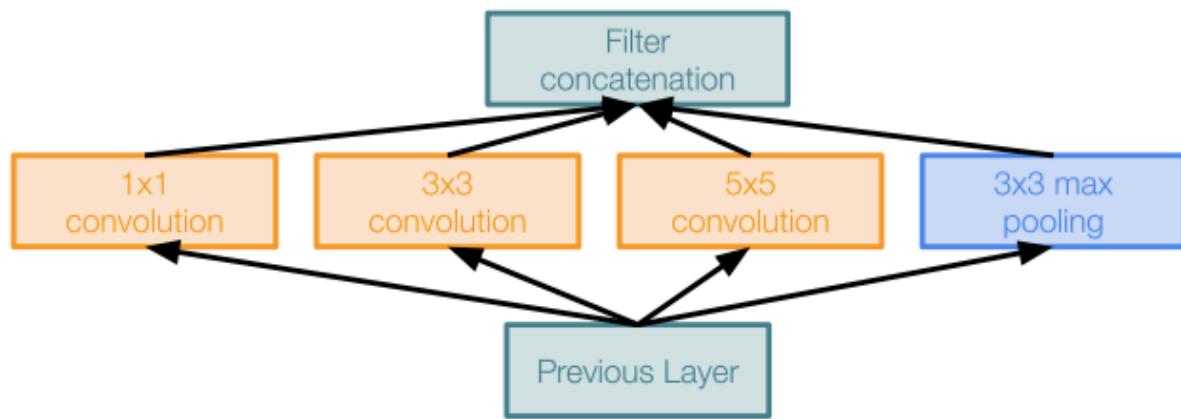
[Szegedy et al., 2014]

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



Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

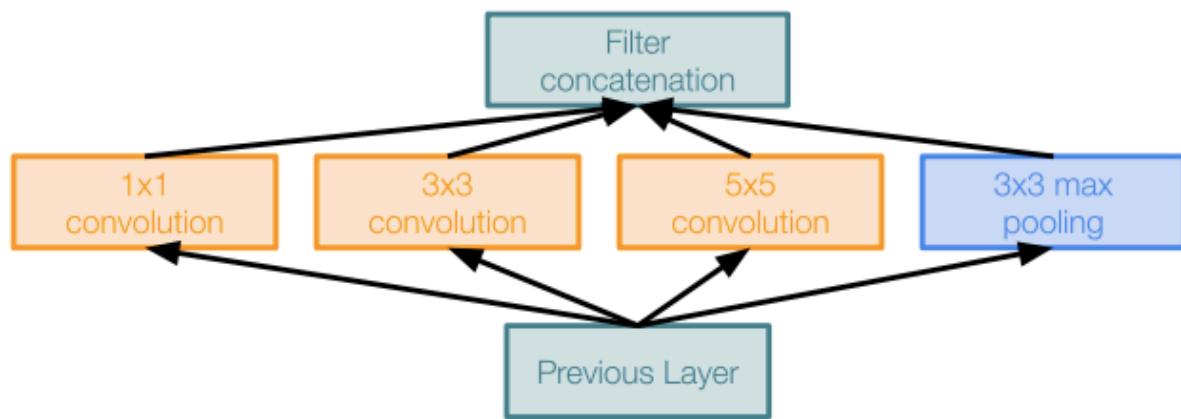
Apply parallel filter operations on the input from previous layer:

- Multiple receptive field sizes for convolution (1×1 , 3×3 , 5×5)
- Pooling operation (3×3)

Concatenate all filter outputs together depth-wise

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 (1×1 , 3×3 , 5×5)
- Pooling operation (3×3)

Concatenate all filter outputs together depth-wise

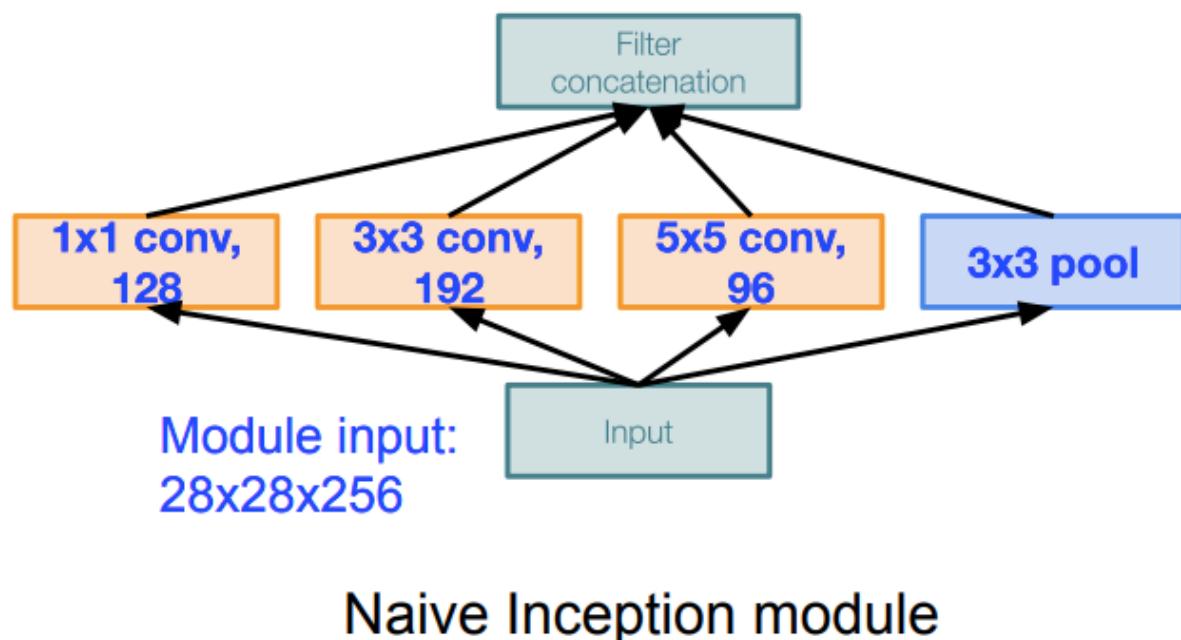
Q: What is the problem with this?
[Hint: Computational complexity]

Case Study: GoogLeNet

[Szegedy et al., 2014]

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

Example:



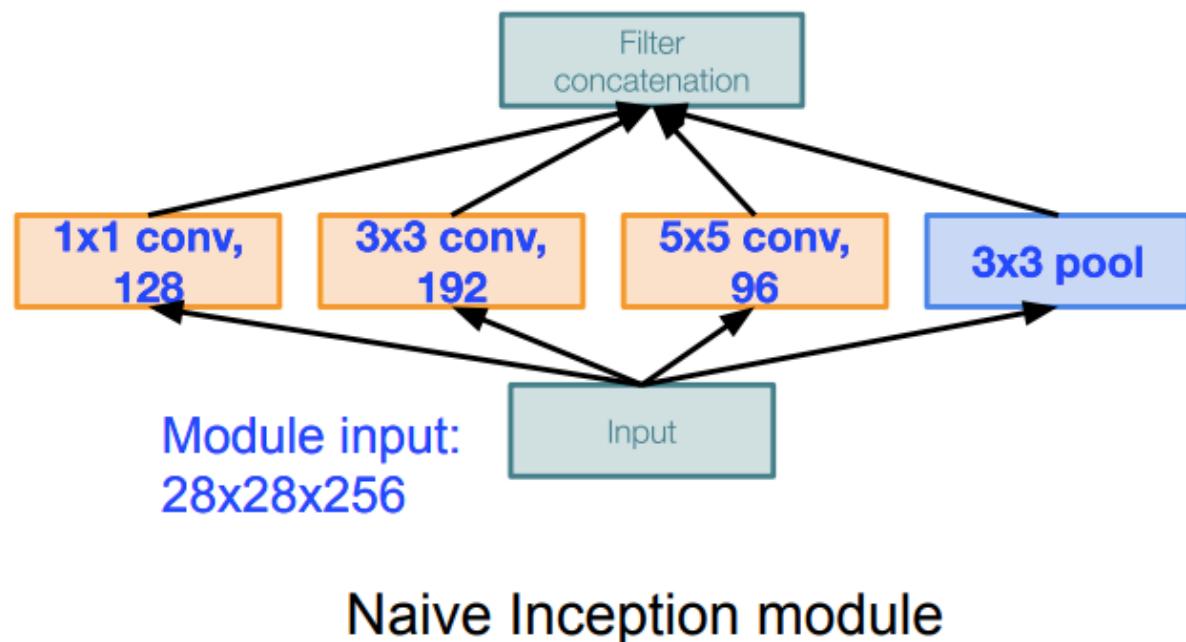
Case Study: GoogLeNet

[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?



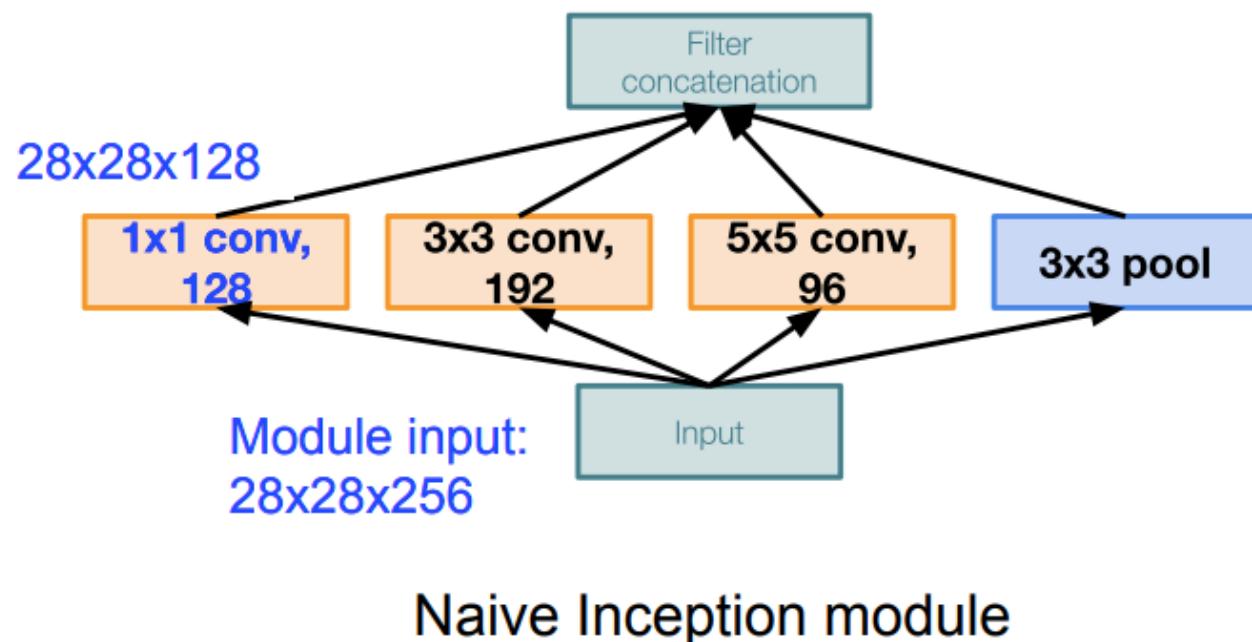
Case Study: GoogLeNet

[Szegedy et al., 2014]

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

Example:

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Naive Inception module

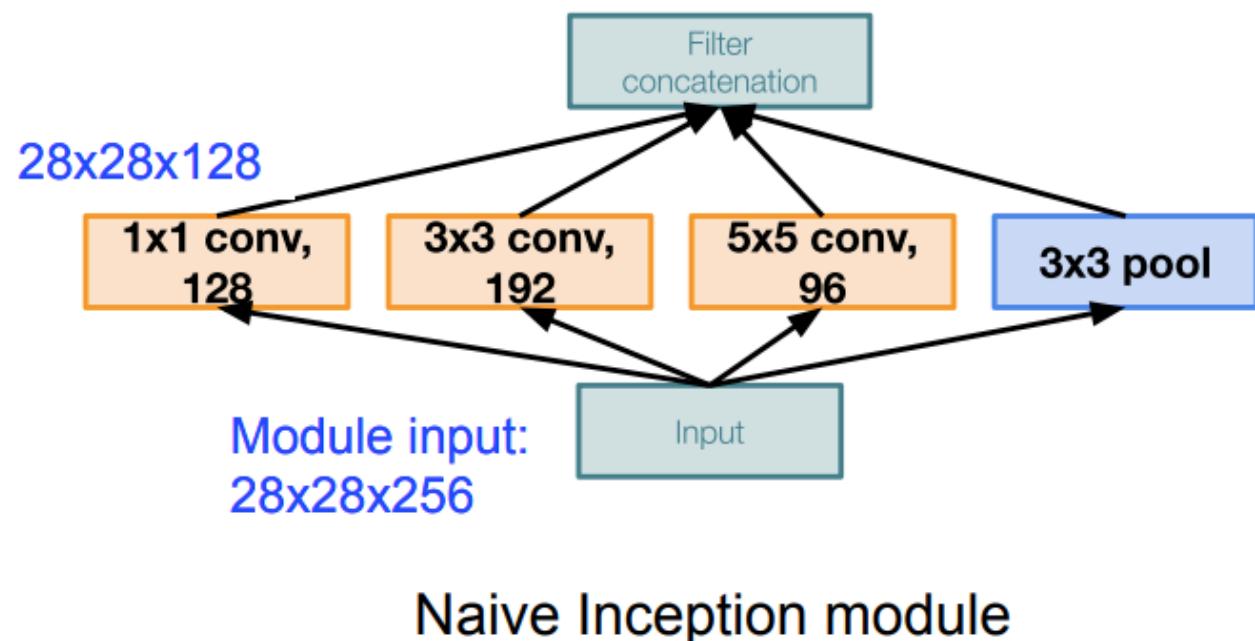
Case Study: GoogLeNet

[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

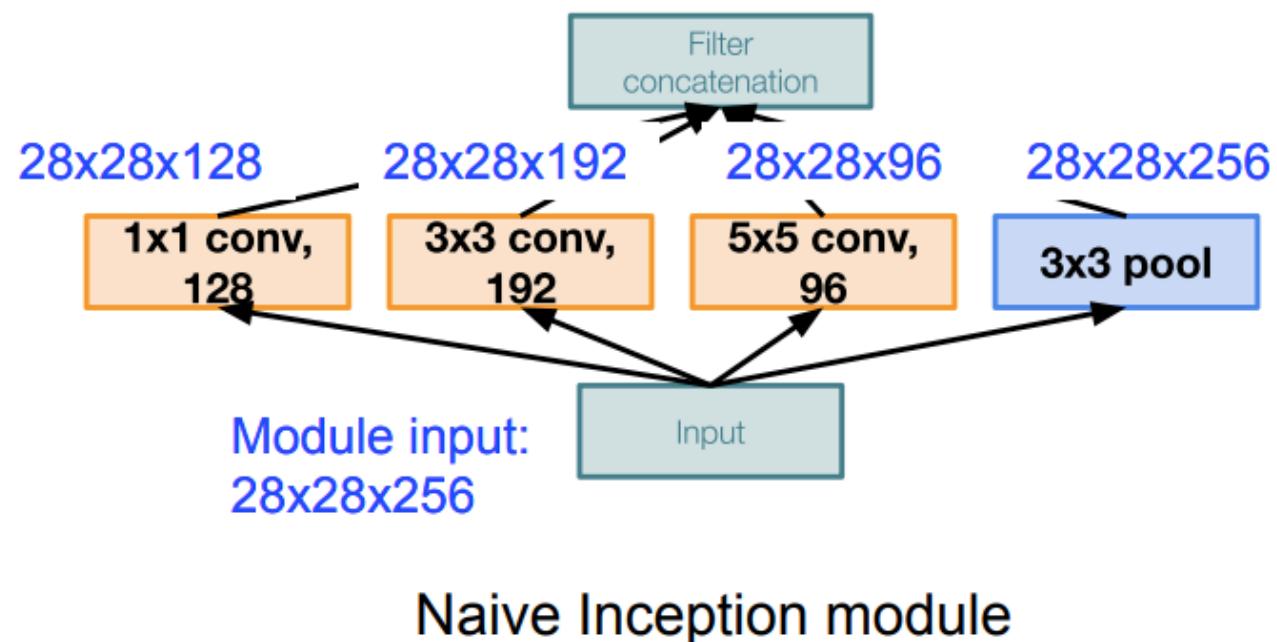
Case Study: GoogLeNet

[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

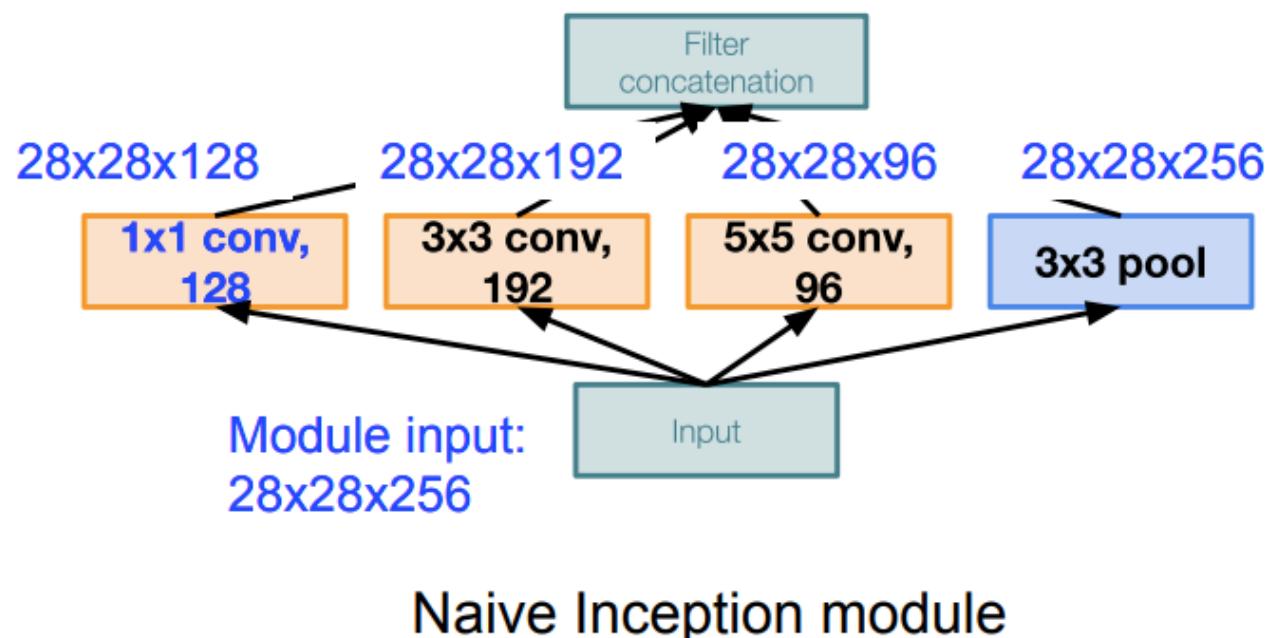
Case Study: GoogLeNet

[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

Case Study: GoogLeNet

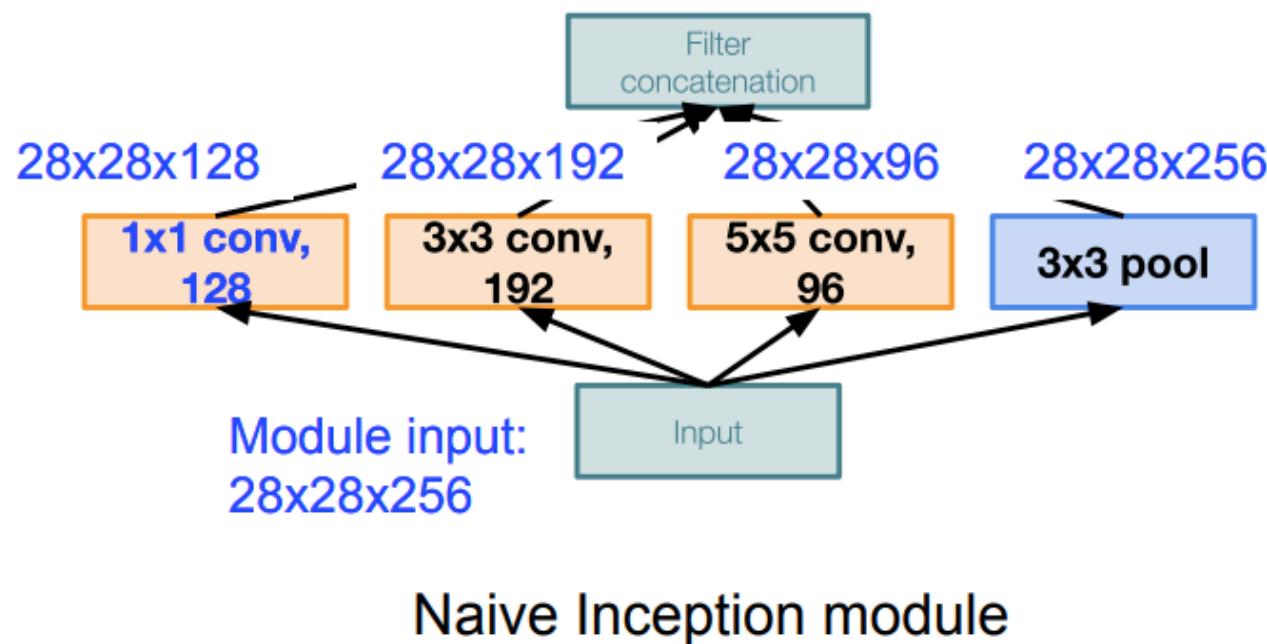
[Szegedy et al., 2014]

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

Example:

Q3: What is output size after
filter concatenation?

$$28 \times 28 \times (128 + 192 + 96 + 256) = 28 \times 28 \times 672$$



Naive Inception module

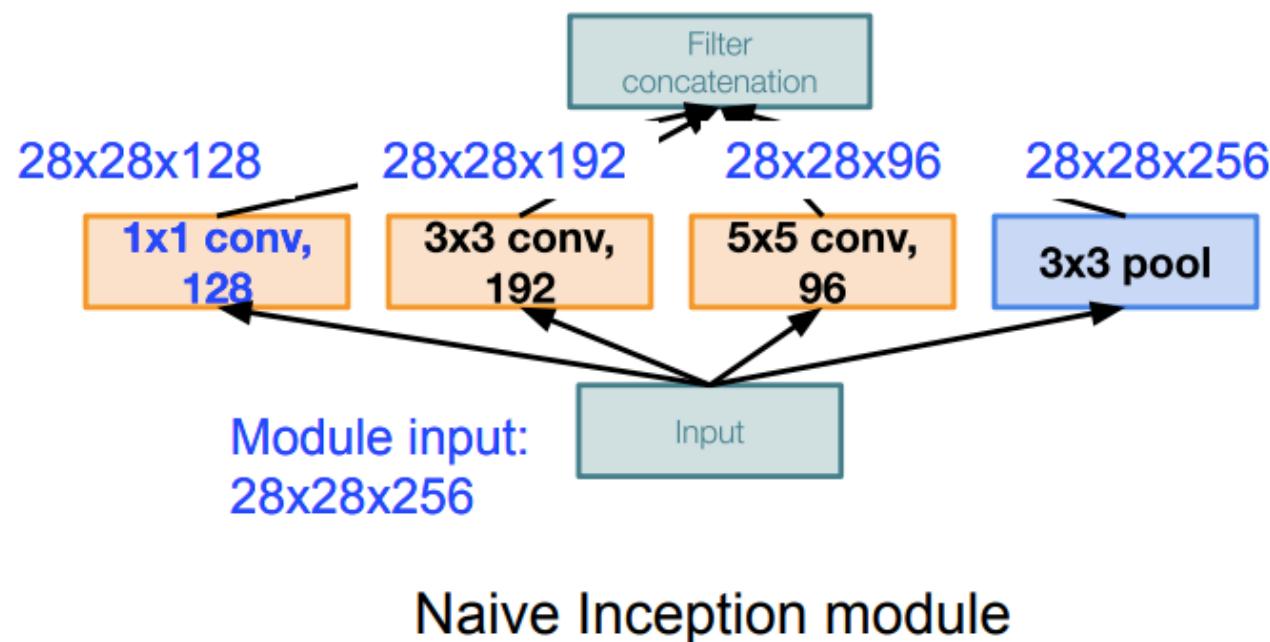
Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3: What is output size after filter concatenation?

$$28 \times 28 \times (128 + 192 + 96 + 256) = 28 \times 28 \times 672$$



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

Conv Ops:

[1x1 conv, 128] $28 \times 28 \times 128 \times 1 \times 1 \times 256$

[3x3 conv, 192] $28 \times 28 \times 192 \times 3 \times 3 \times 256$

[5x5 conv, 96] $28 \times 28 \times 96 \times 5 \times 5 \times 256$

Total: 854M ops

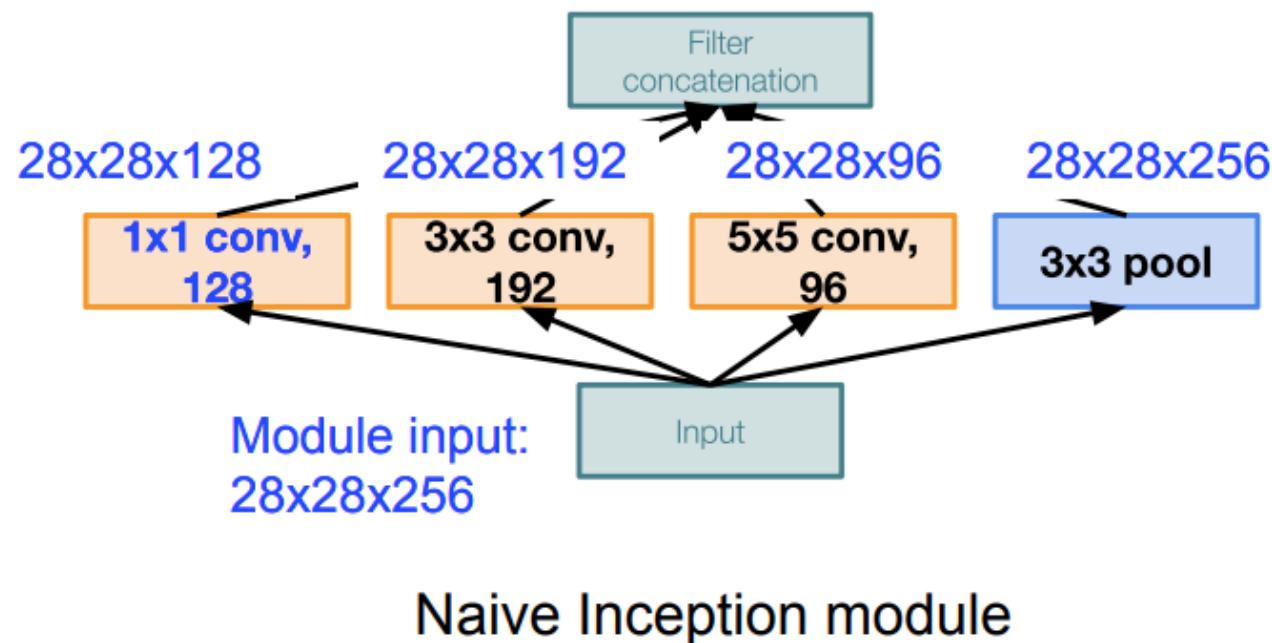
Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3: What is output size after filter concatenation?

$$28 \times 28 \times (128 + 192 + 96 + 256) = 28 \times 28 \times 672$$



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[Hint: Computational complexity]

Conv Ops:

[1x1 conv, 128] $28 \times 28 \times 128 \times 1 \times 1 \times 256$

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[5x5 conv, 96] $28 \times 28 \times 96 \times 5 \times 5 \times 256$

Total: 854M ops

Very expensive compute

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

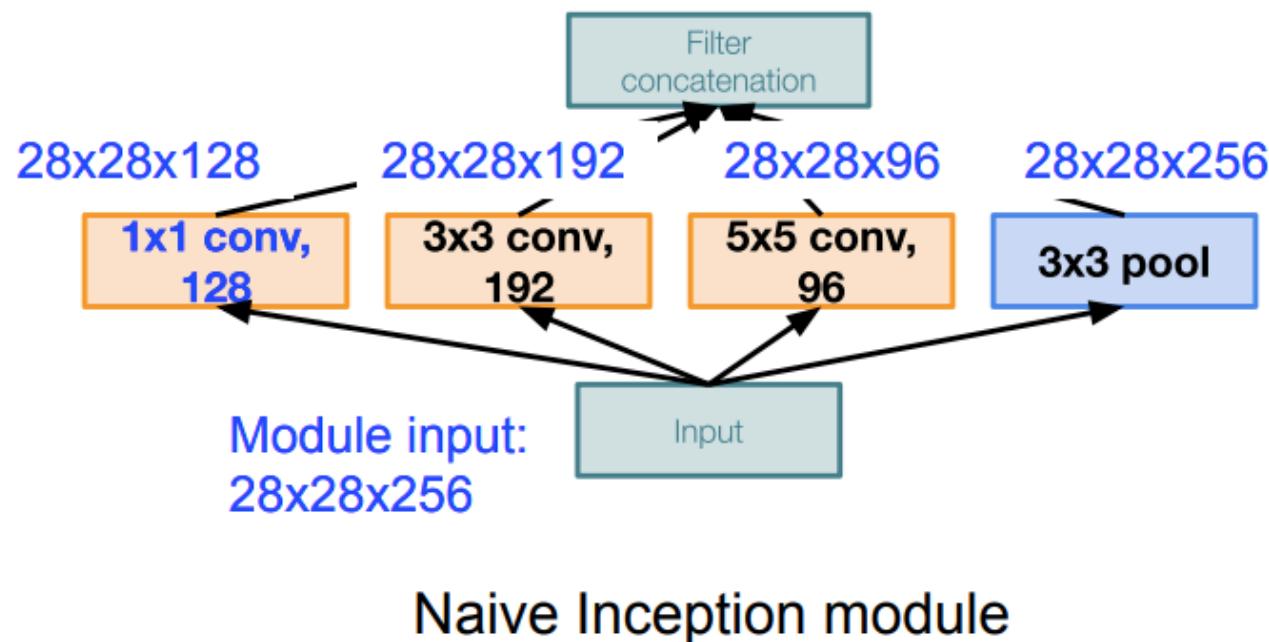
Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3: What is output size after filter concatenation?

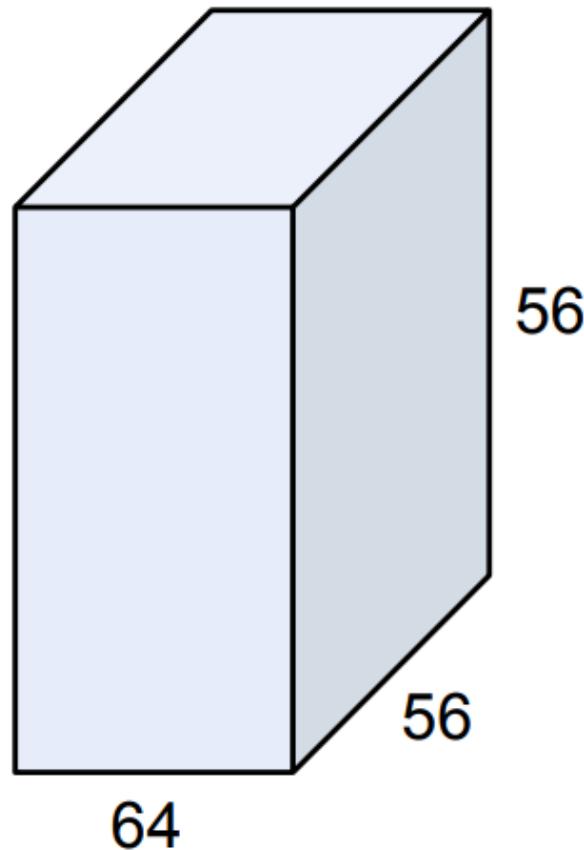
$$28 \times 28 \times (128 + 192 + 96 + 256) = 529k$$



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

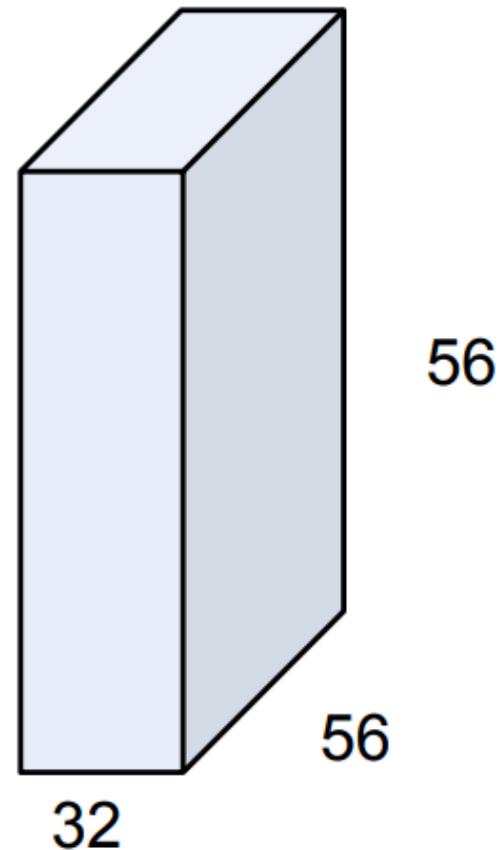
Solution: “bottleneck” layers that use 1×1 convolutions to reduce feature depth

Reminder: 1x1 convolutions

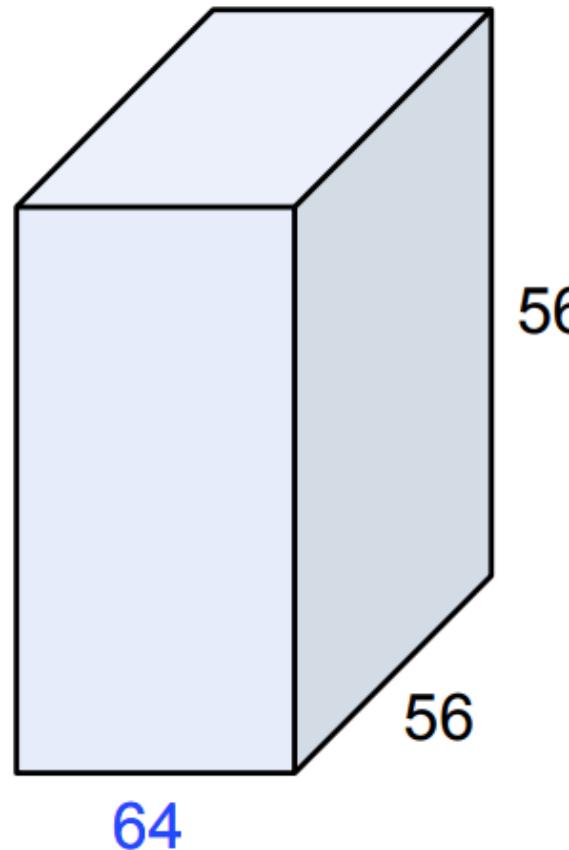


1x1 CONV
with 32 filters

(each filter has size
 $1 \times 1 \times 64$, and performs a
64-dimensional dot
product)



Reminder: 1x1 convolutions

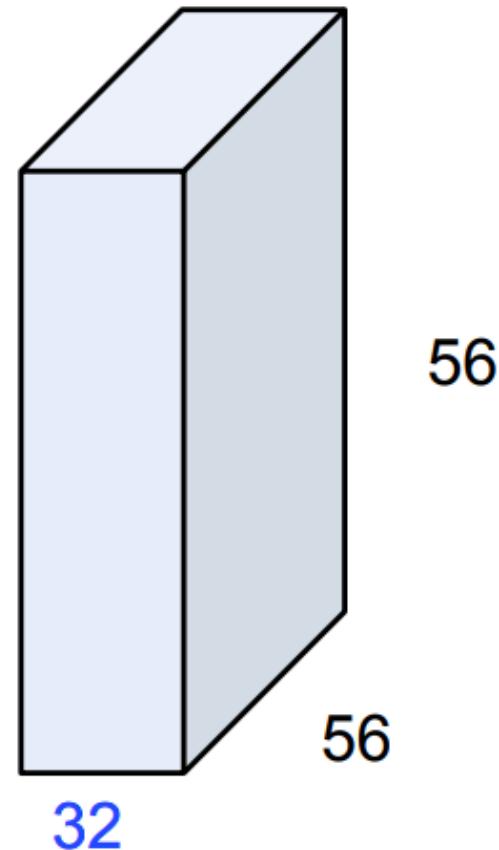


1x1 CONV
with 32 filters



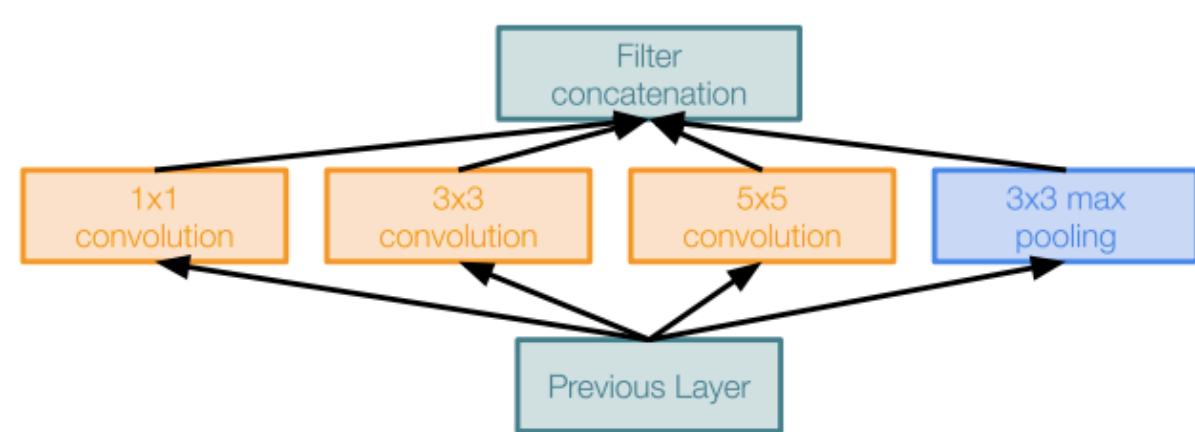
preserves spatial
dimensions, reduces depth!

Projects depth to lower
dimension (combination of
feature maps)

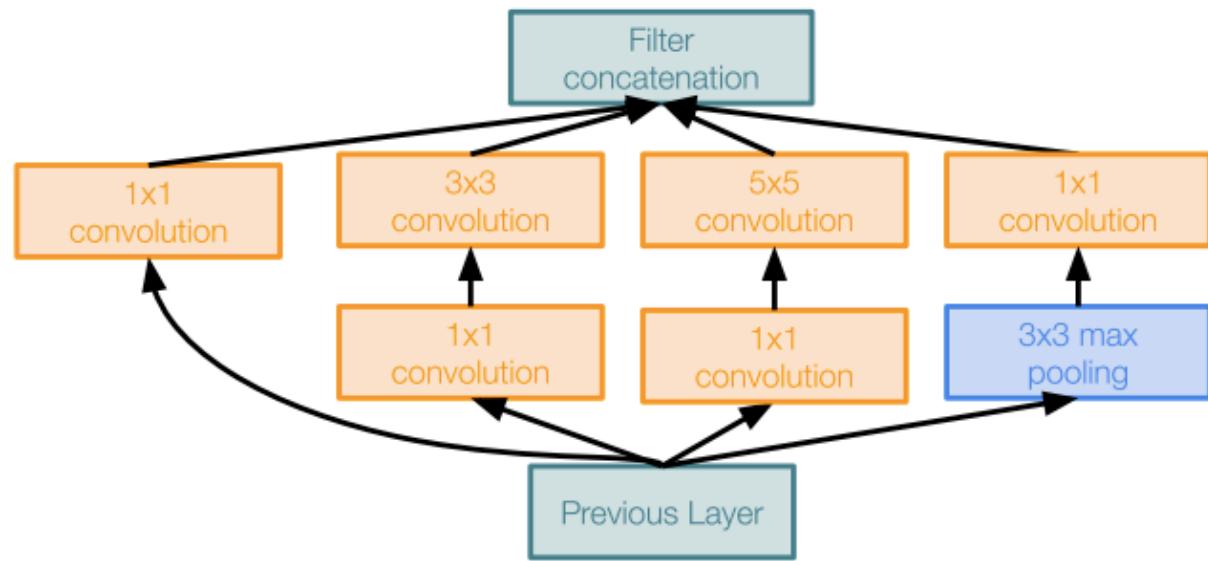


Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

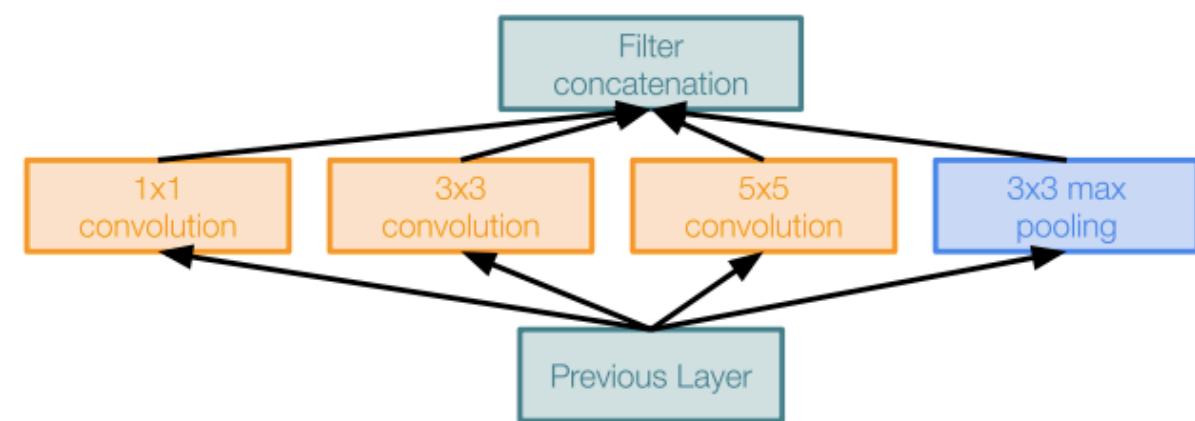


Inception module with dimension reduction

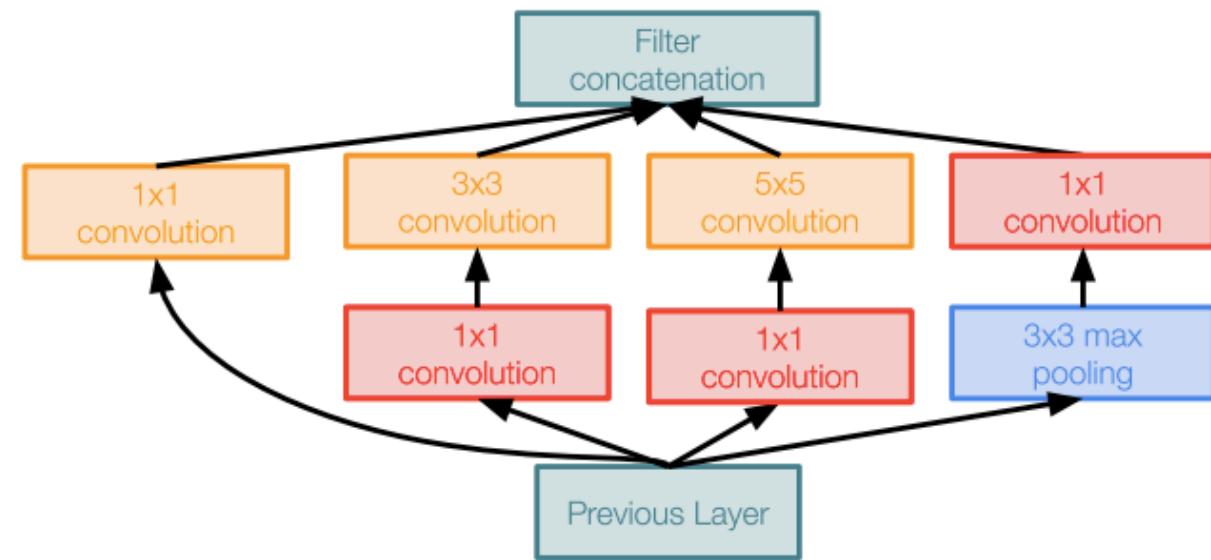
Case Study: GoogLeNet

[Szegedy et al., 2014]

1x1 conv “bottleneck”
layers



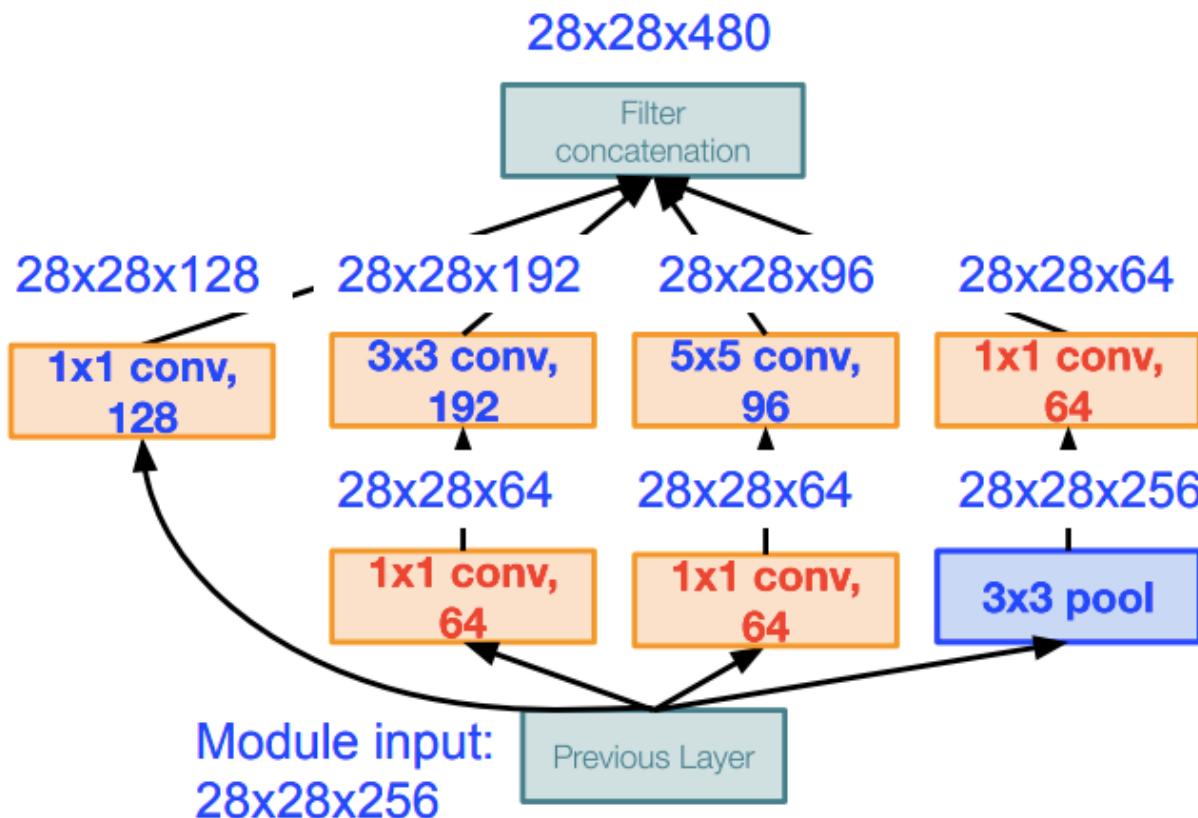
Naive Inception module



Inception module with dimension reduction

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] $28 \times 28 \times 64 \times 1 \times 1 \times 256$
- [1x1 conv, 64] $28 \times 28 \times 64 \times 1 \times 1 \times 256$
- [1x1 conv, 128] $28 \times 28 \times 128 \times 1 \times 1 \times 256$
- [3x3 conv, 192] $28 \times 28 \times 192 \times 3 \times 3 \times 64$
- [5x5 conv, 96] $28 \times 28 \times 96 \times 5 \times 5 \times 64$
- [1x1 conv, 64] $28 \times 28 \times 64 \times 1 \times 1 \times 256$

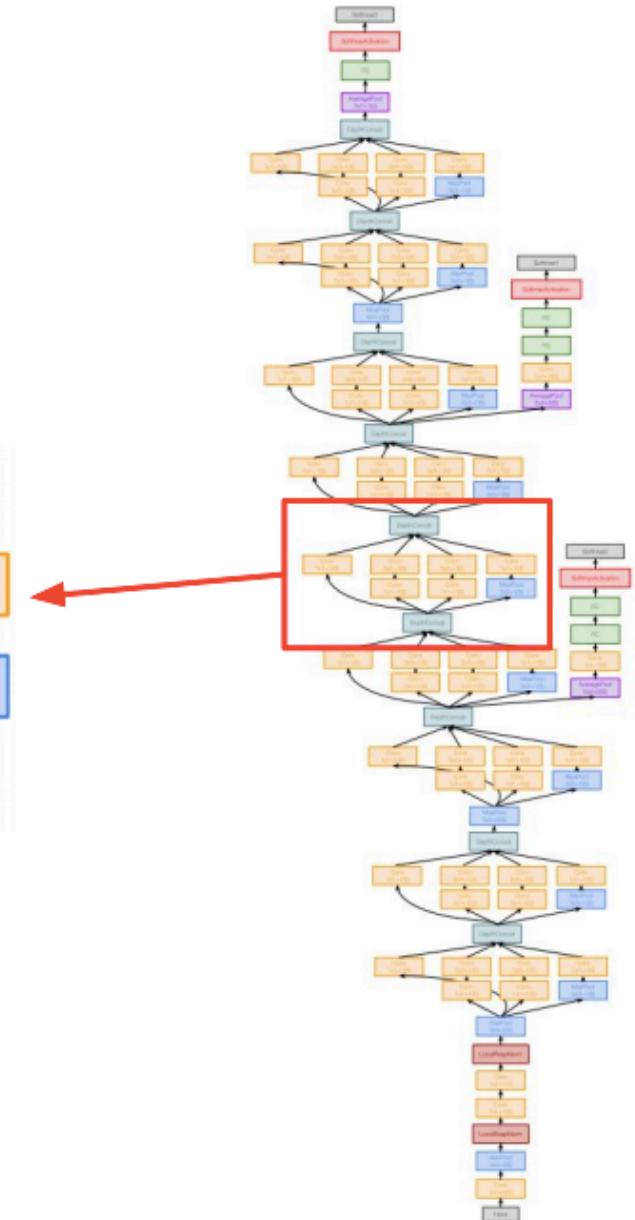
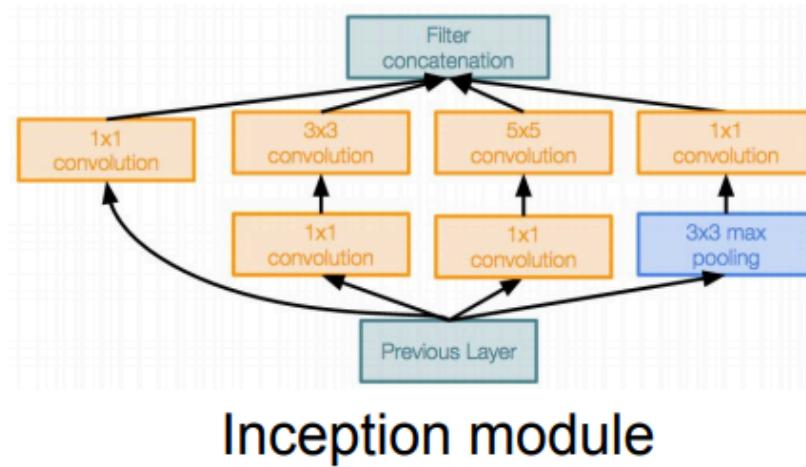
Total: 358M ops

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

Case Study: GoogLeNet

[Szegedy et al., 2014]

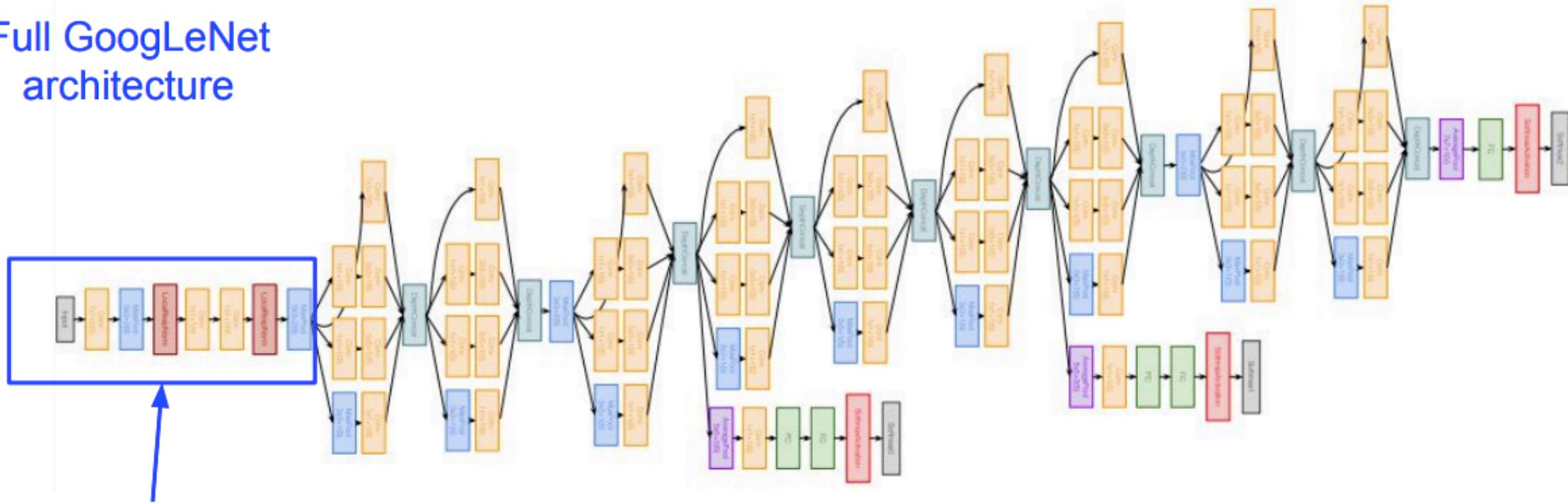
Stack Inception modules
with dimension reduction
on top of each other



Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

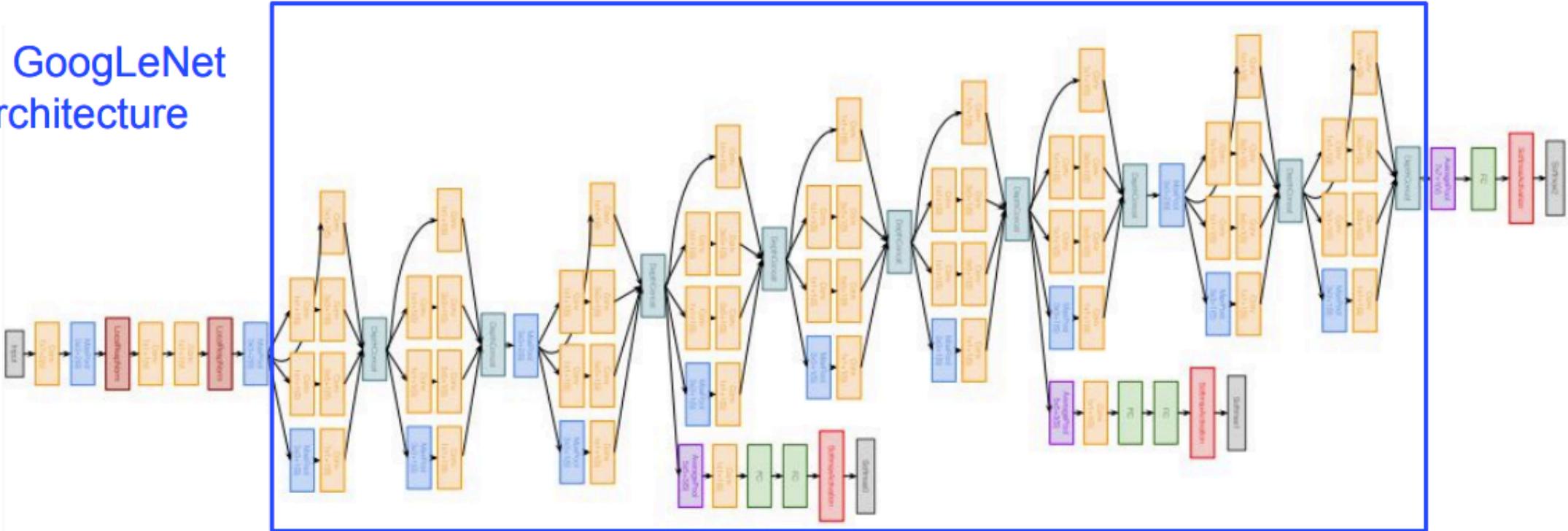


Stem Network:
Conv-Pool-
2x Conv-Pool

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

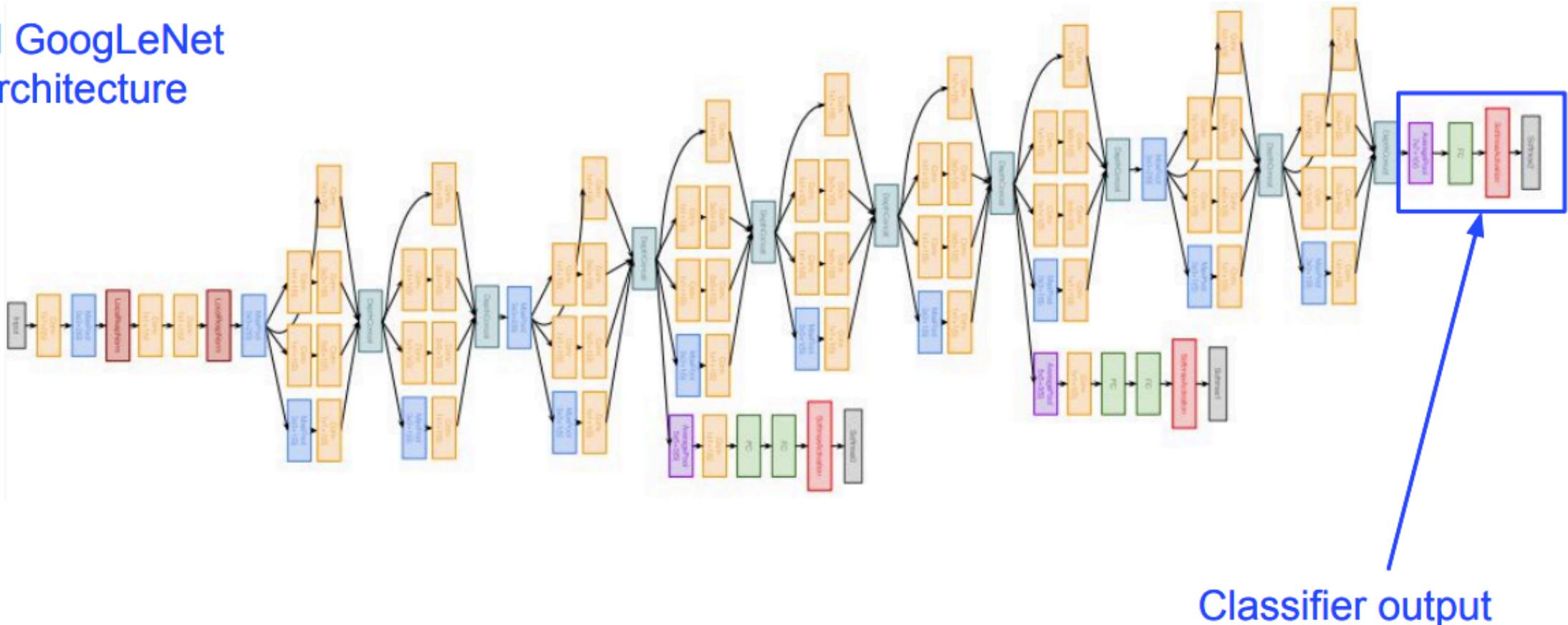


Stacked Inception
Modules

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

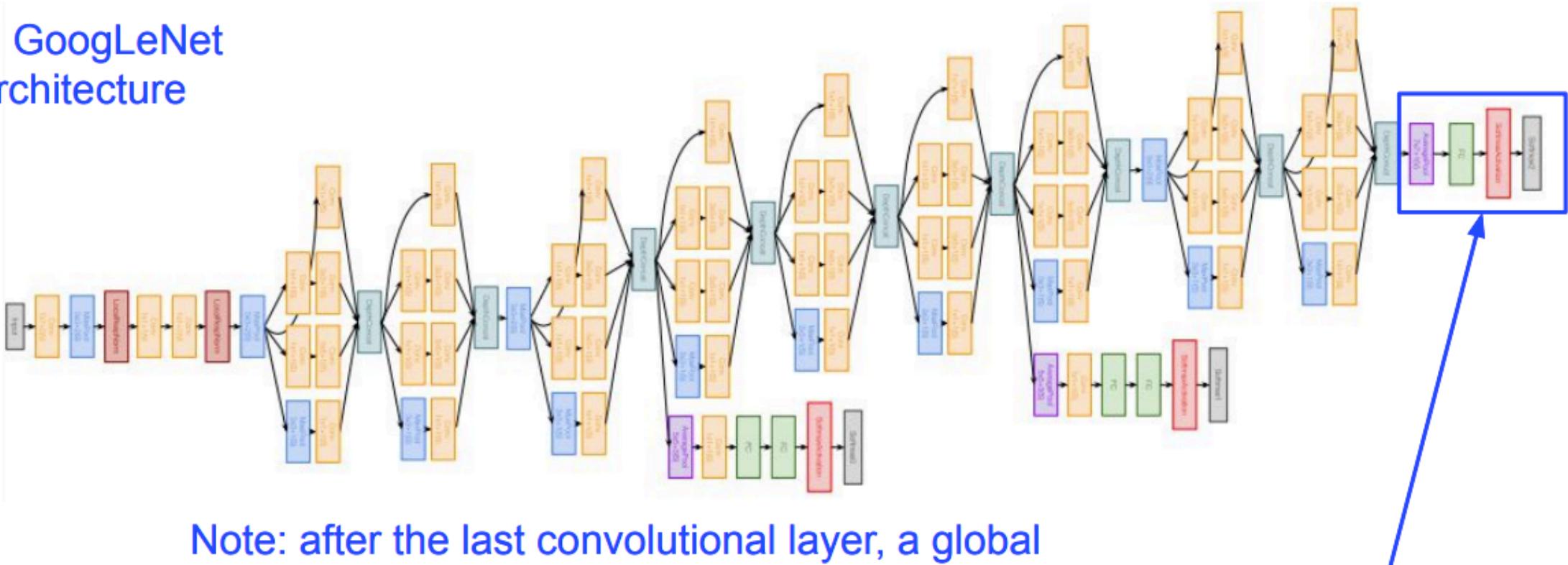


Classifier output

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture



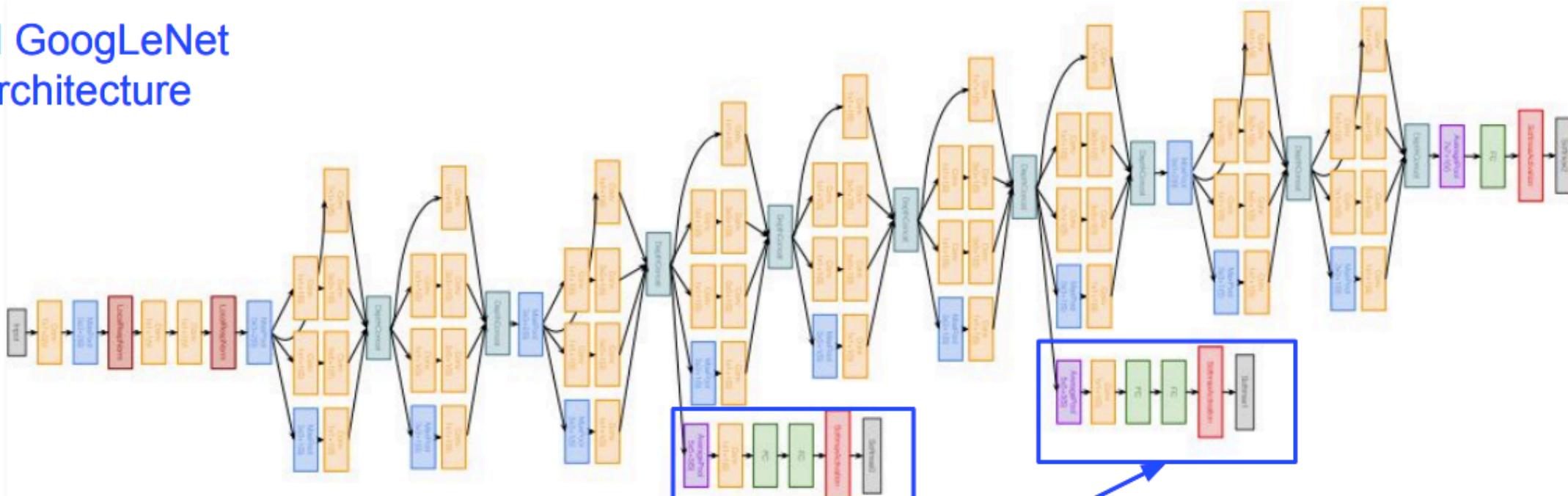
Note: after the last convolutional layer, a global average pooling layer is used that spatially averages across each feature map, before final FC layer. No longer multiple expensive FC layers!

Classifier output

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

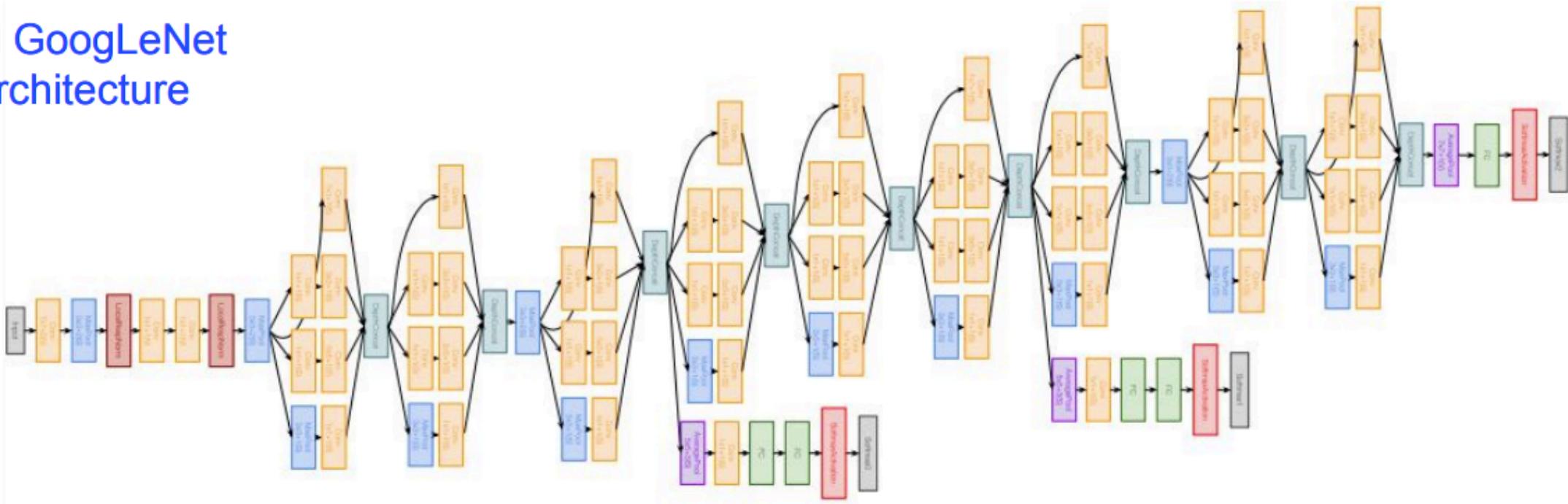


Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



22 total layers with weights

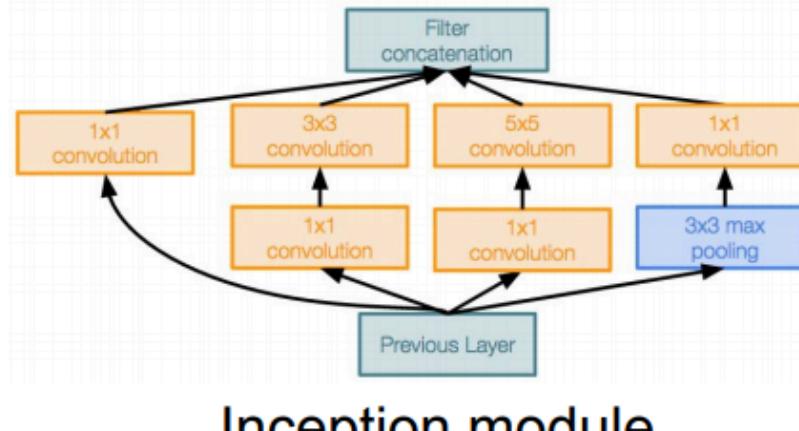
(parallel layers count as 1 layer => 2 layers per Inception module. Don't count auxiliary output layers)

Case Study: GoogLeNet

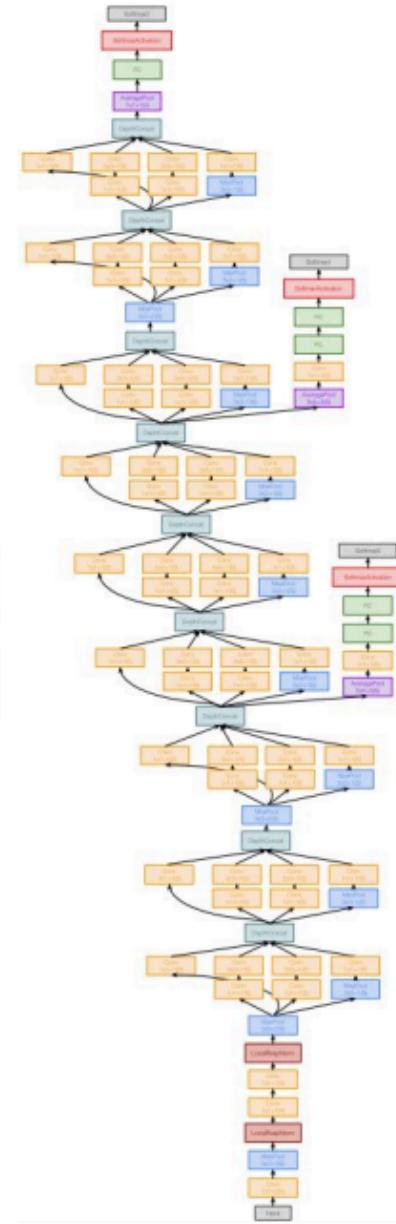
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

- 22 layers
- Efficient “Inception” module
- Avoids expensive FC layers
- 12x less params than AlexNet
- ILSVRC’14 classification winner (6.7% top 5 error)

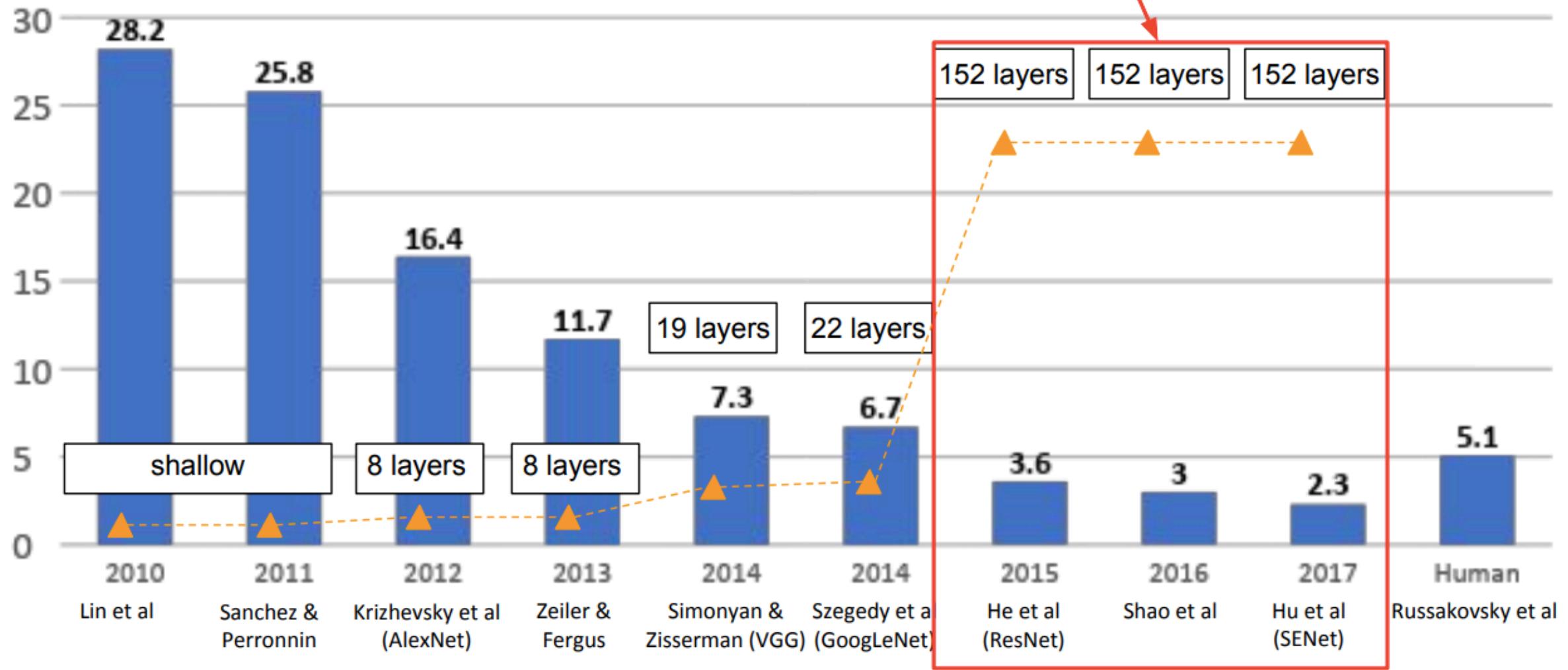


Inception module



ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

“Revolution of Depth”

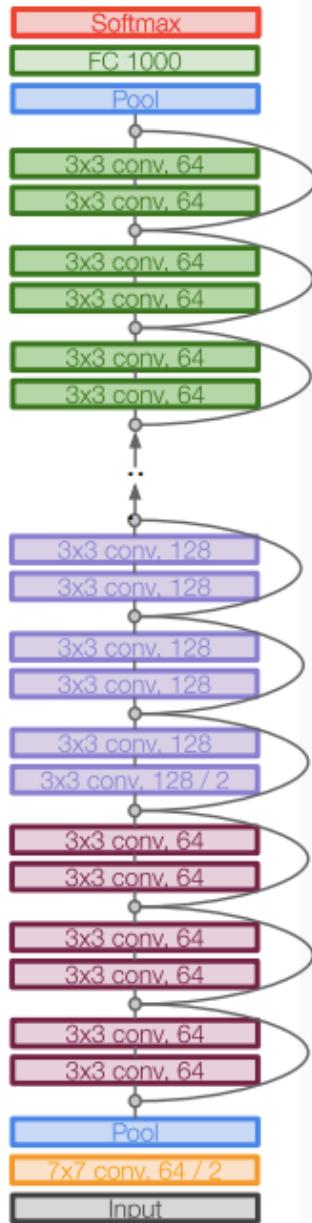
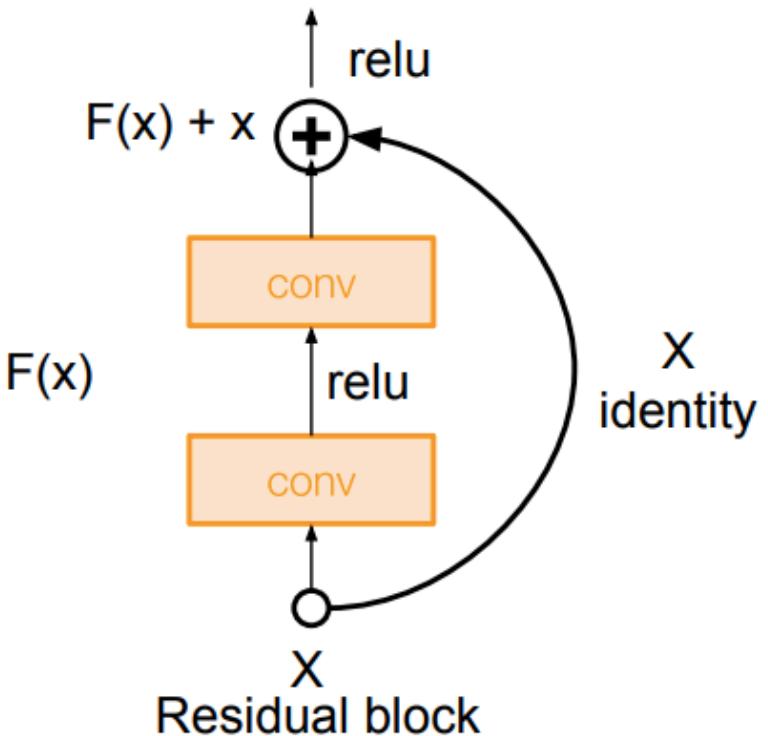


Case Study: ResNet

[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!



Case Study: ResNet

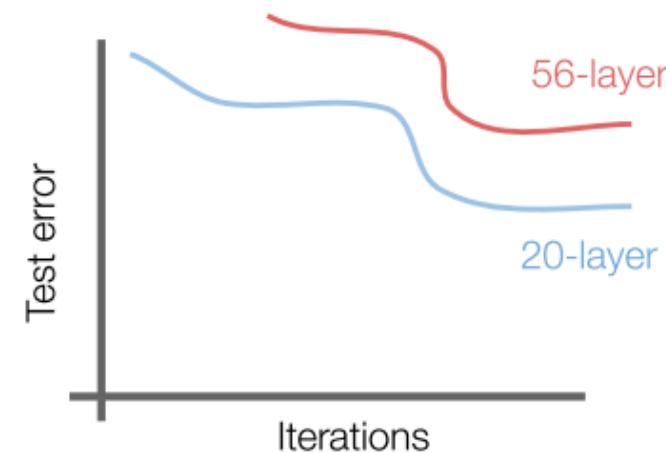
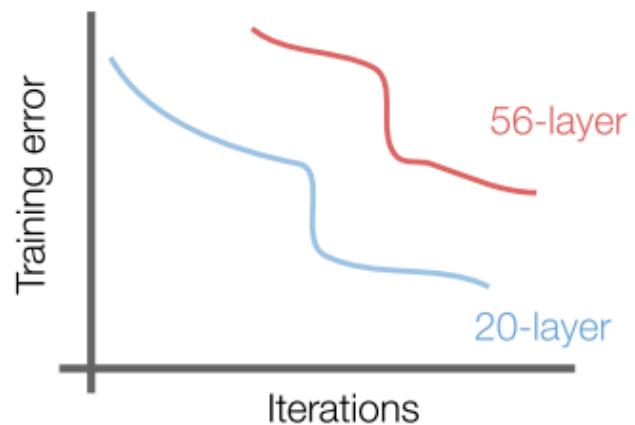
[He et al., 2015]

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

Case Study: ResNet

[He et al., 2015]

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

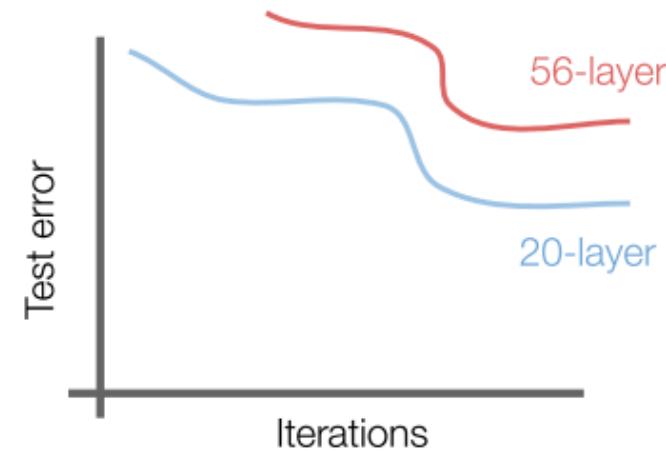
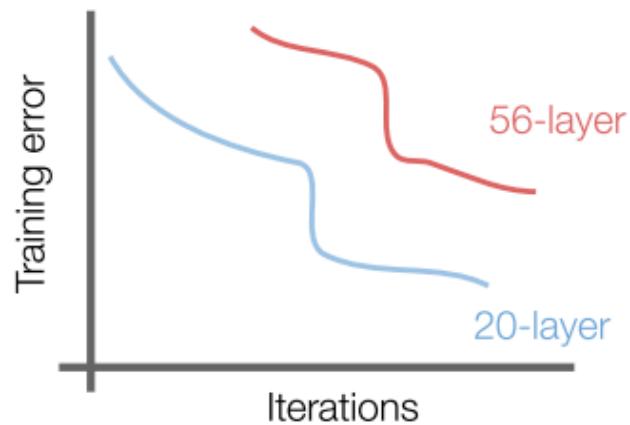


Q: What's strange about these training and test curves?
[Hint: look at the order of the curves]

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!

Case Study: ResNet

[He et al., 2015]

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

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.

Case Study: ResNet

He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "[Deep residual learning for image recognition.](#)" In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770-778. 2016.

With their simple trick of allowing skip connections (the possibility to learn identity functions and skip layers that are not useful), ResNets allow us to implement very, very deep architectures

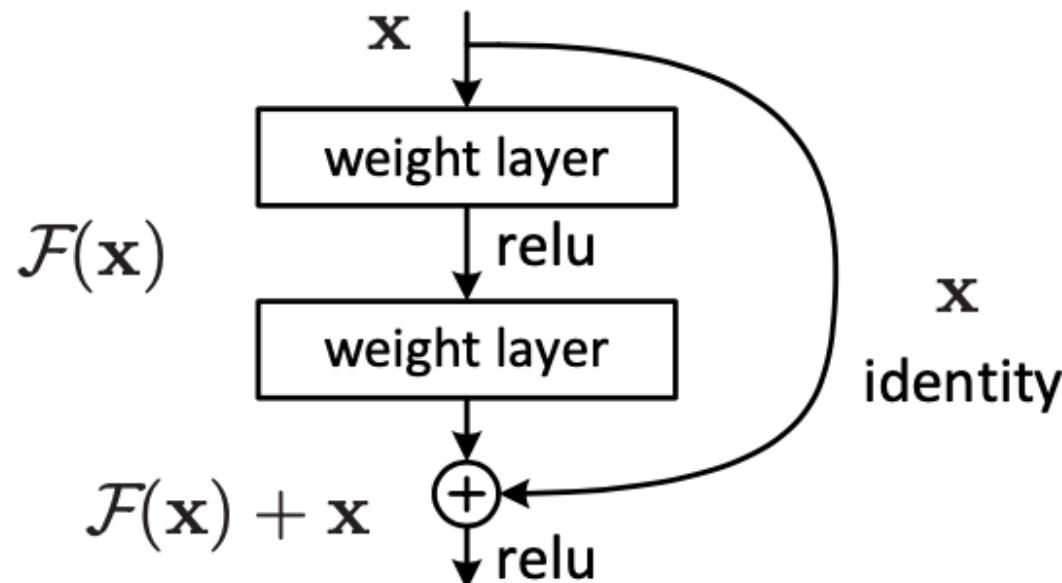
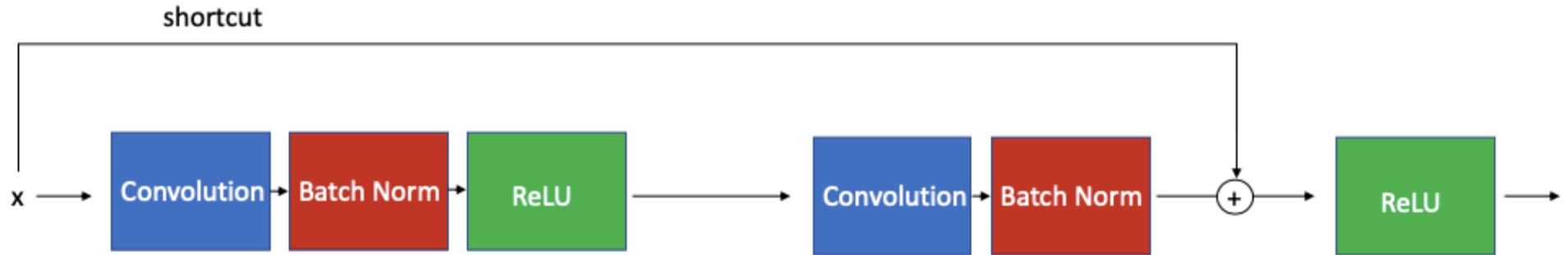


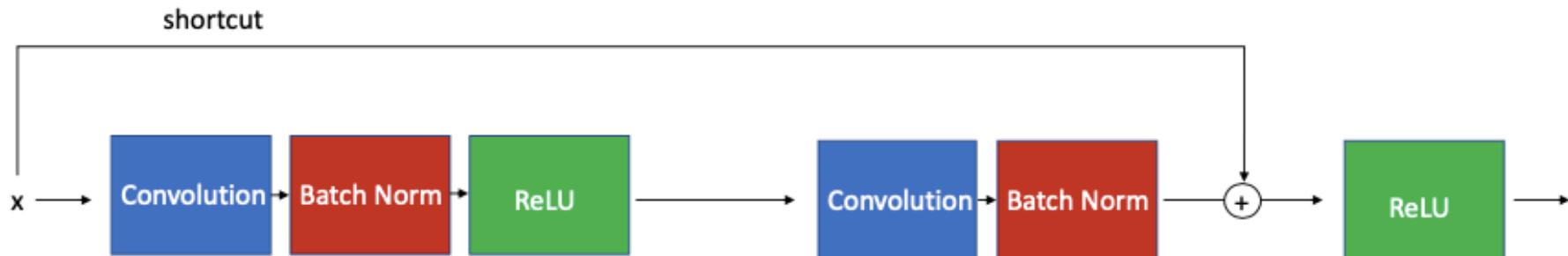
Figure 2. Residual learning: a building block.

Why ResNet Work



In general: $a^{(l+2)} = \sigma(z^{(l+2)} + a^{(l)})$

Why ResNet Work



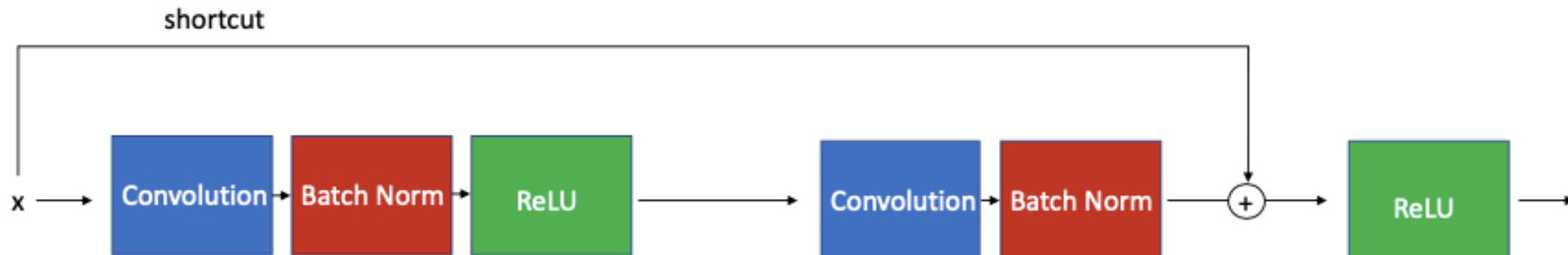
$$\begin{aligned} a^{(l+2)} &= \sigma(z^{(l+2)} + a^{(l)}) \\ &= \sigma(a^{(l+1)}W^{(l+2)} + b^{(l+2)} + a^{(l)}) \end{aligned}$$

If all weights and the bias are zero, then

$$= \sigma(a^{(l)}) = a^{(l)} \quad (\text{identity function})$$

due to ReLU

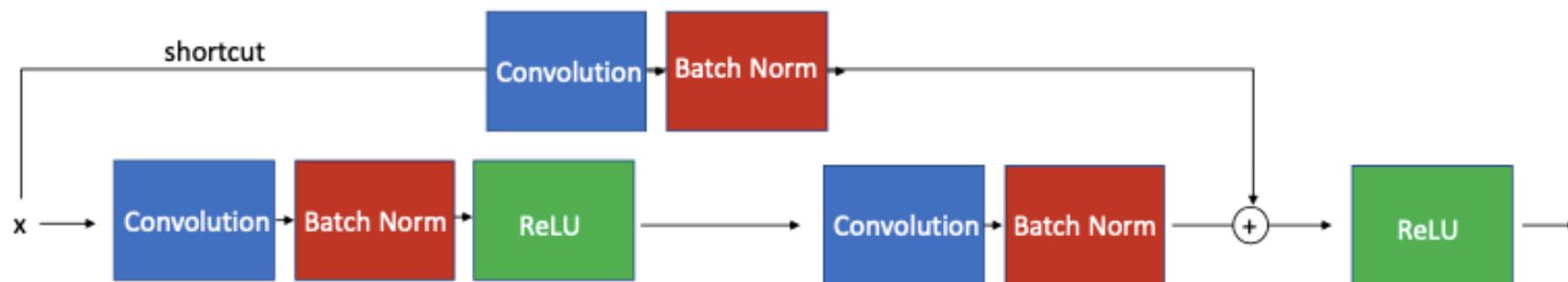
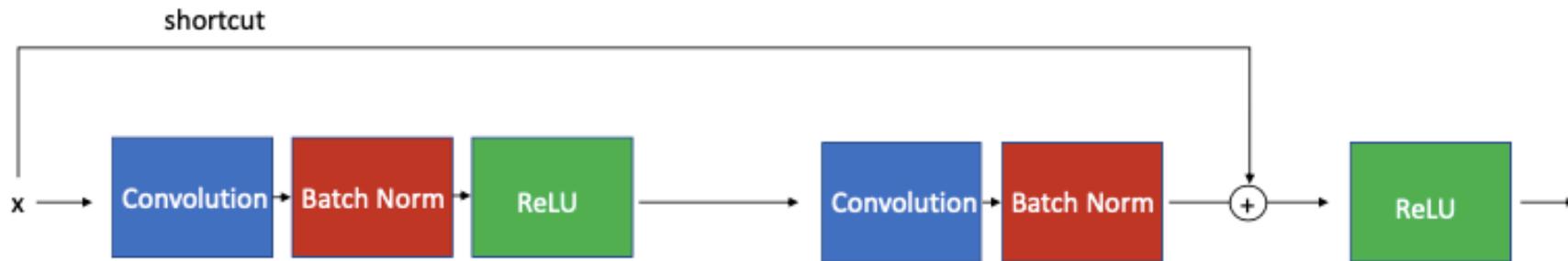
Why ResNet Work



$$a^{(l+2)} = \sigma(z^{(l+2)} + a^{(l)})$$

We assume these have the same dimension
(e.g., via "same" convolution)

Why ResNet Work



alternative residual blocks with skip connections such that the input passed via the shortcut is resized to dimensions of the main path's output

Residual Block in PyTorch

```
class ConvNet(torch.nn.Module):

    def __init__(self, num_classes):
        super(ConvNet, self).__init__()

        #####
        ### 1st residual block
        #####
        # 28x28x1 => 28x28x4
        self.conv_1 = torch.nn.Conv2d(in_channels=1,
                                    out_channels=4,
                                    kernel_size=(1, 1),
                                    stride=(1, 1),
                                    padding=0)
        self.conv_1_bn = torch.nn.BatchNorm2d(4)

        # 28x28x4 => 28x28x1
        self.conv_2 = torch.nn.Conv2d(in_channels=4,
                                    out_channels=1,
                                    kernel_size=(3, 3),
                                    stride=(1, 1),
                                    padding=1)
        self.conv_2_bn = torch.nn.BatchNorm2d(1)

        #####
        ### 2nd residual block
        #####
        # 28x28x1 => 28x28x4
        self.conv_3 = torch.nn.Conv2d(in_channels=1,
                                    out_channels=4,
                                    kernel_size=(1, 1),
                                    stride=(1, 1),
                                    padding=0)
        self.conv_3_bn = torch.nn.BatchNorm2d(4)

        # 28x28x4 => 28x28x1
        self.conv_4 = torch.nn.Conv2d(in_channels=4,
                                    out_channels=1,
                                    kernel_size=(3, 3),
                                    stride=(1, 1),
                                    padding=1)
        self.conv_4_bn = torch.nn.BatchNorm2d(1)

        #####
        ### Fully connected
        #####
        self.linear_1 = torch.nn.Linear(28*28*1, num_classes)
```

Residual Block in PyTorch

```
def forward(self, x):
    #####
    ### 1st residual block
    #####
    shortcut = x

    out = self.conv_1(x)
    out = self.conv_1_bn(out)
    out = F.relu(out)

    out = self.conv_2(out)
    out = self.conv_2_bn(out)

    out += shortcut
    out = F.relu(out)

    #####
    ### 2nd residual block
    #####
    shortcut = out

    out = self.conv_3(out)
    out = self.conv_3_bn(out)
    out = F.relu(out)

    out = self.conv_4(out)
    out = self.conv_4_bn(out)

    out += shortcut
    out = F.relu(out)

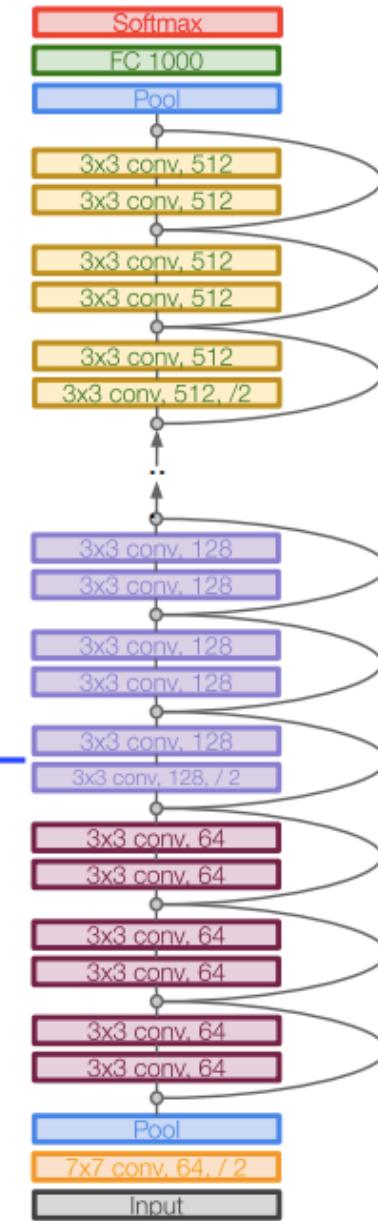
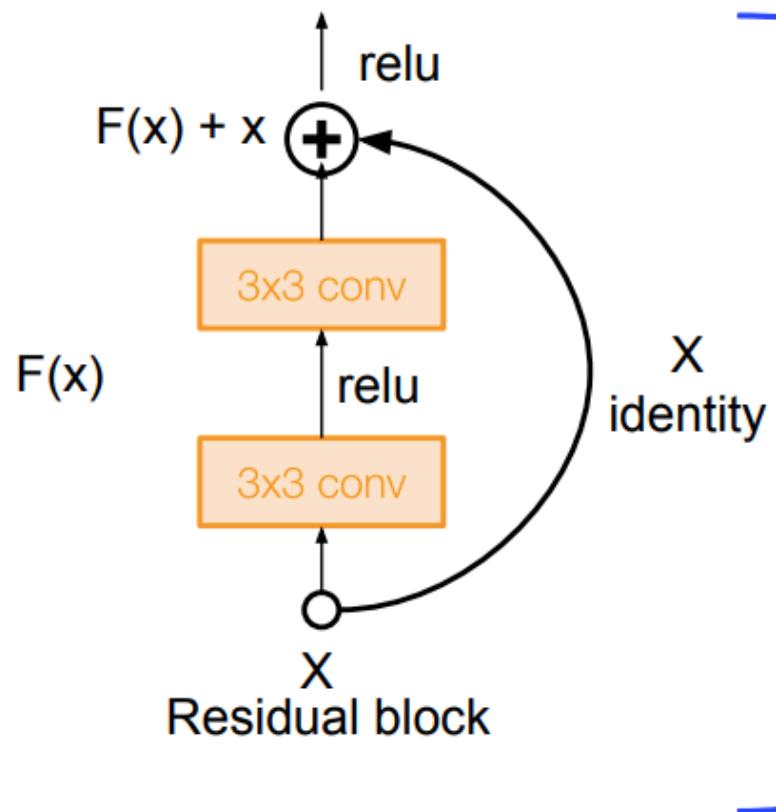
    #####
    ### Fully connected
    #####
    logits = self.linear_1(out.view(-1, 28*28*1))
    probas = F.softmax(logits, dim=1)
    return logits, probas
```

Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:

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

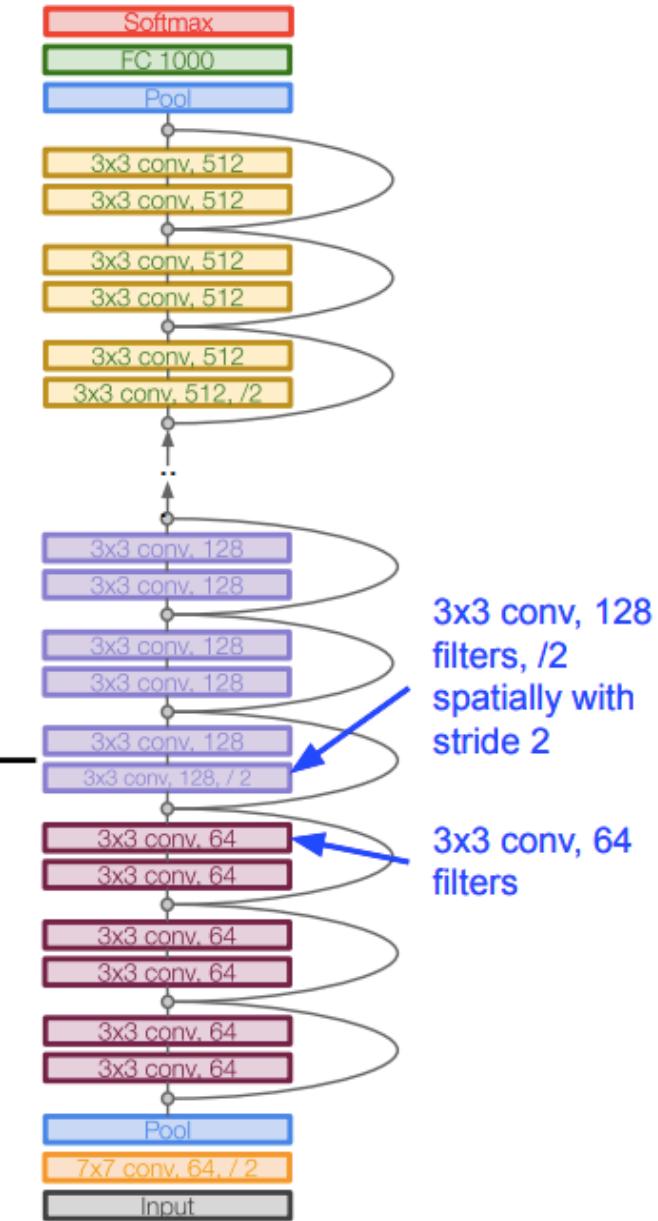
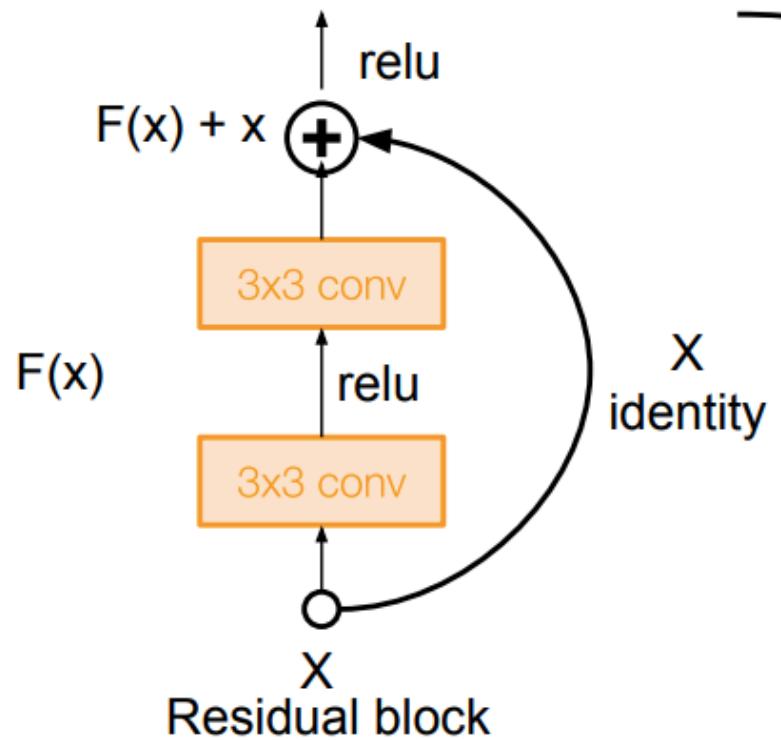


Case Study: ResNet

[He et al., 2015]

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)

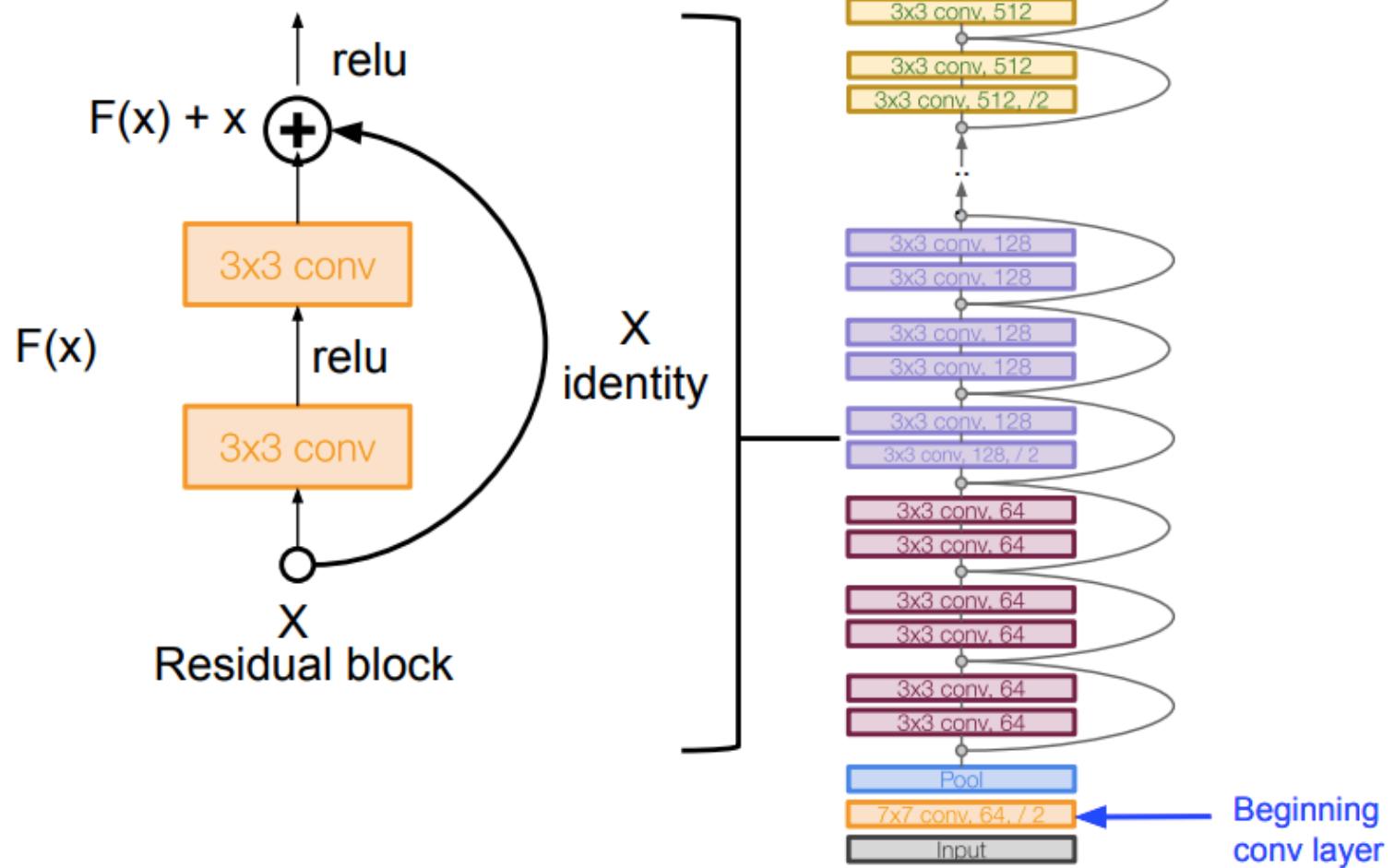


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- Additional conv layer at the beginning

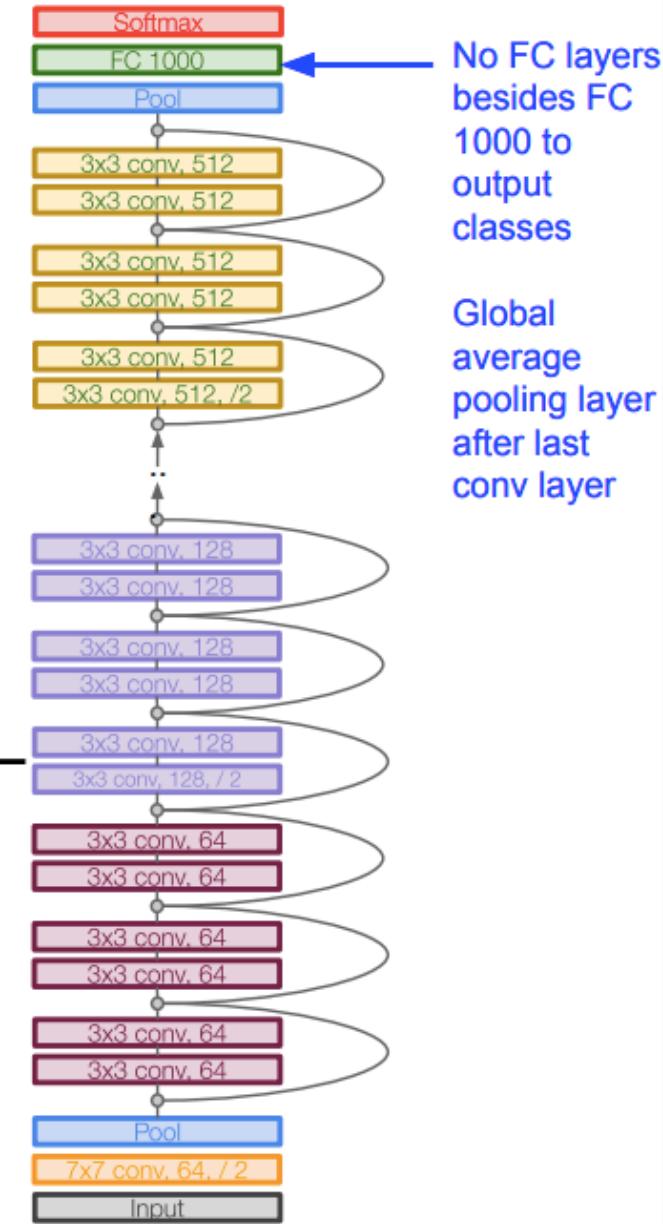
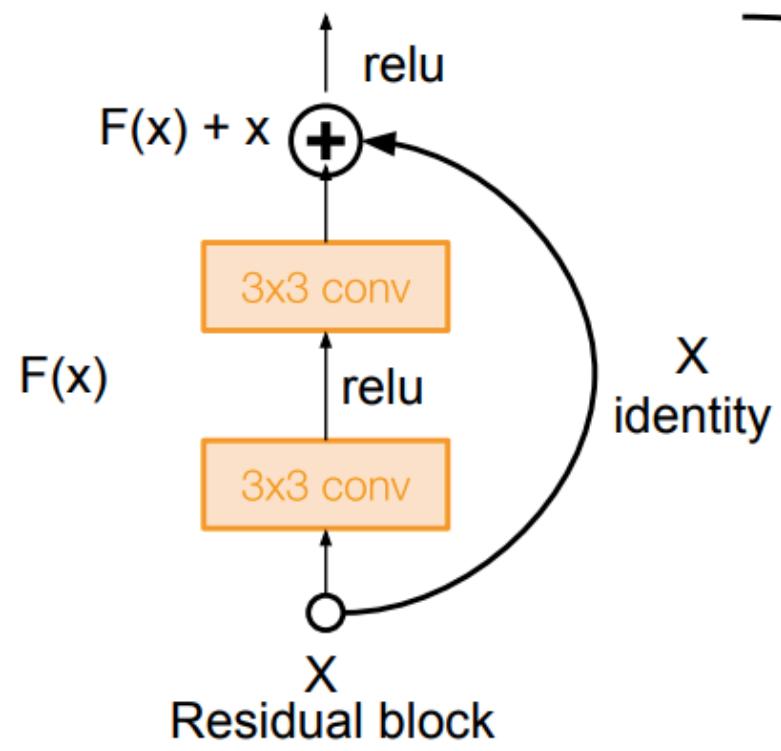


Case Study: ResNet

[He et al., 2015]

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



Case Study: ResNet

[He et al., 2015]

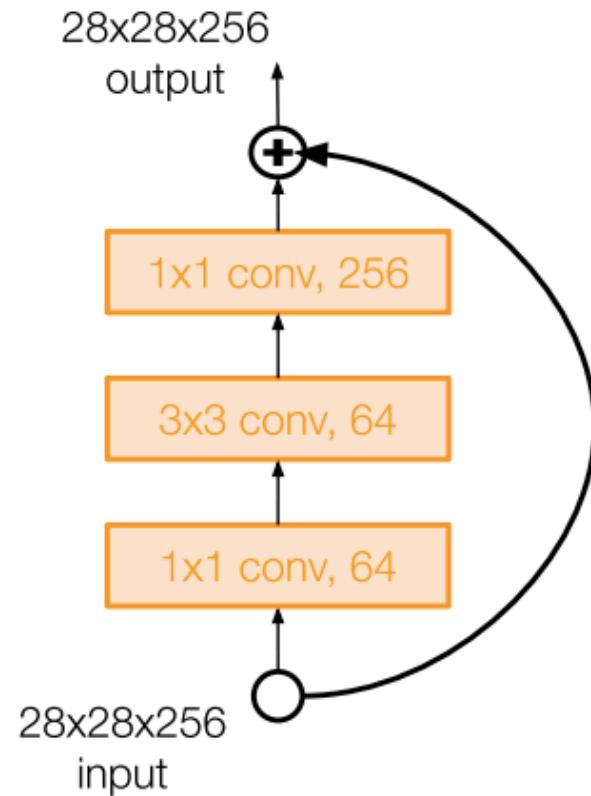
Total depths of 34, 50, 101, or
152 layers for ImageNet



Case Study: ResNet

[He et al., 2015]

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



Case Study: ResNet

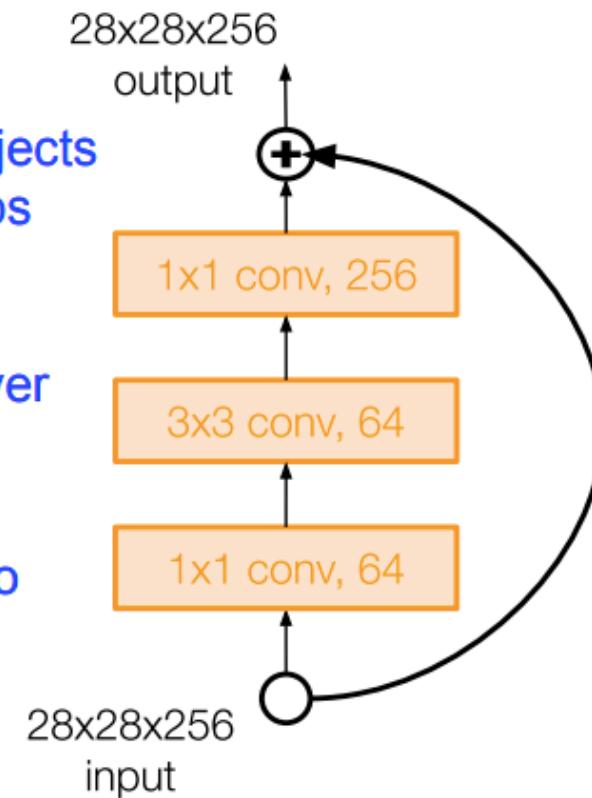
[He et al., 2015]

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



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

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

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Experimental Results

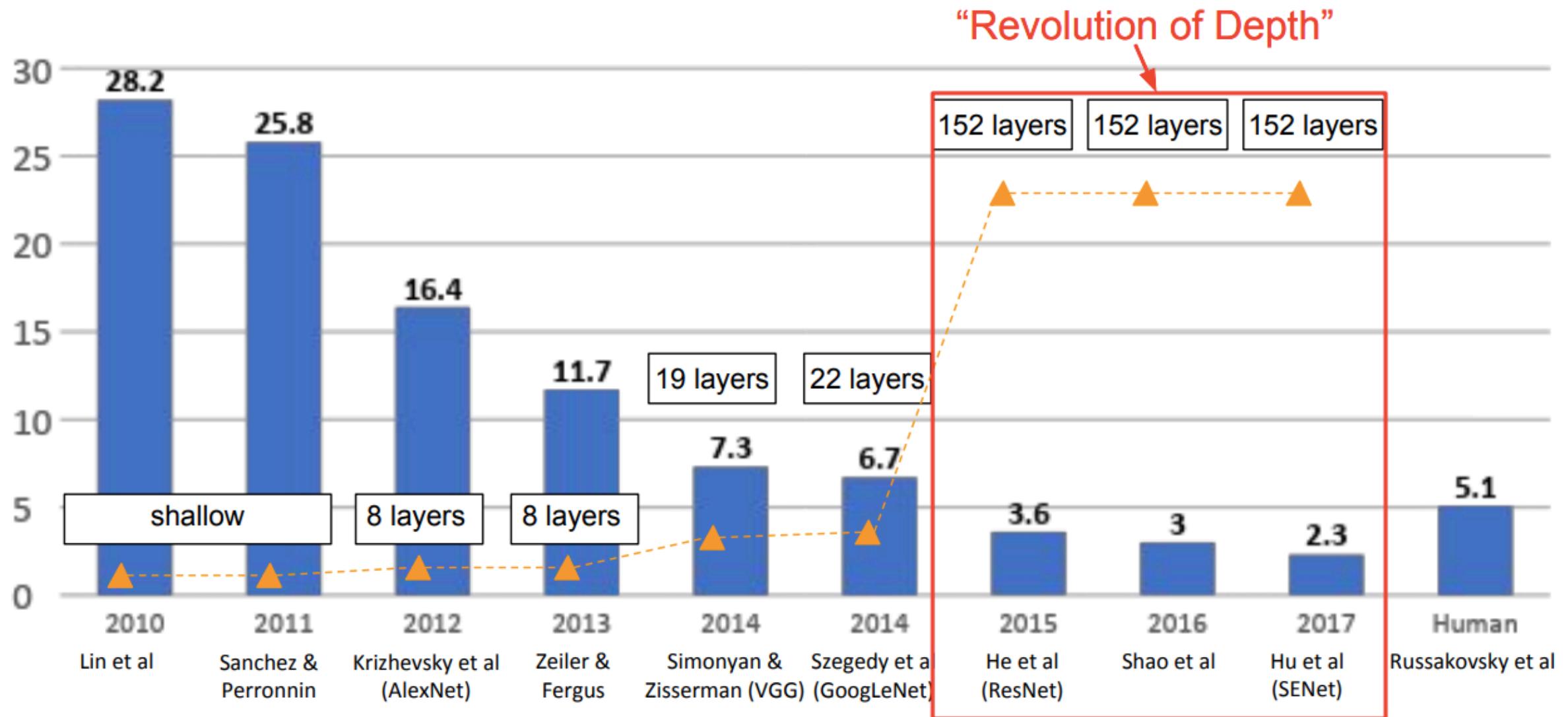
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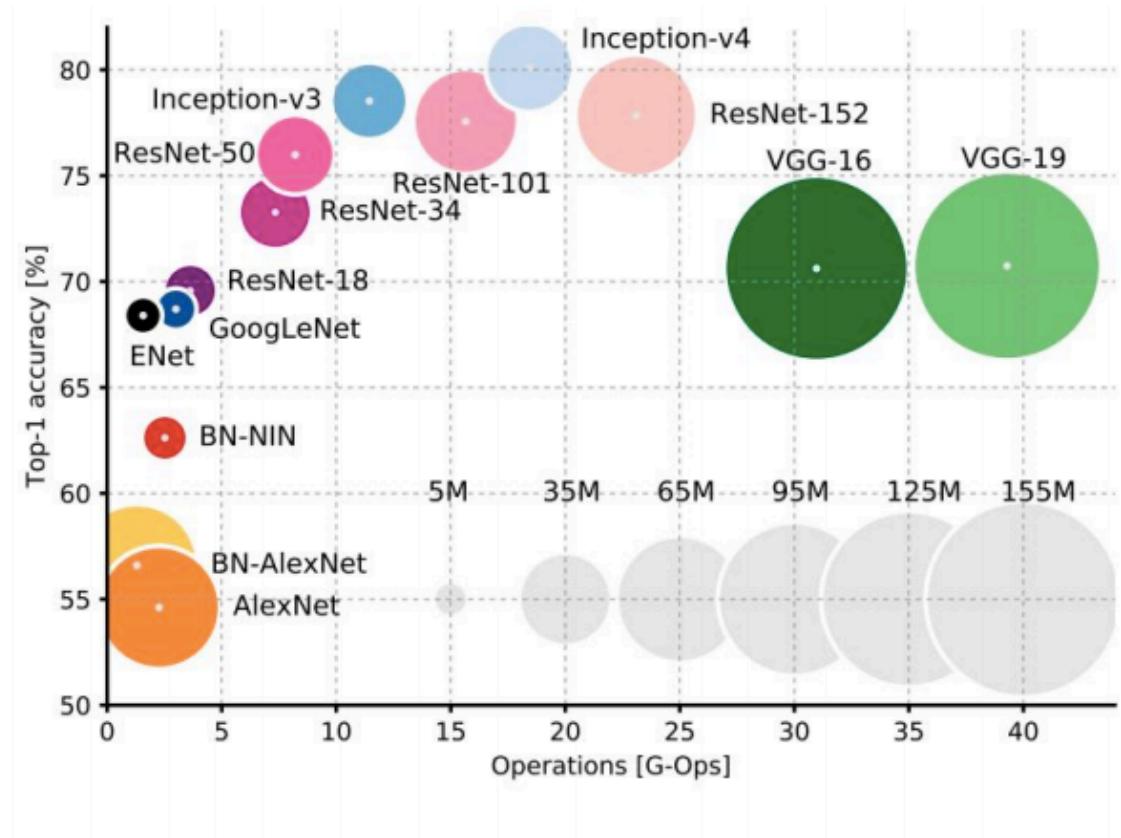
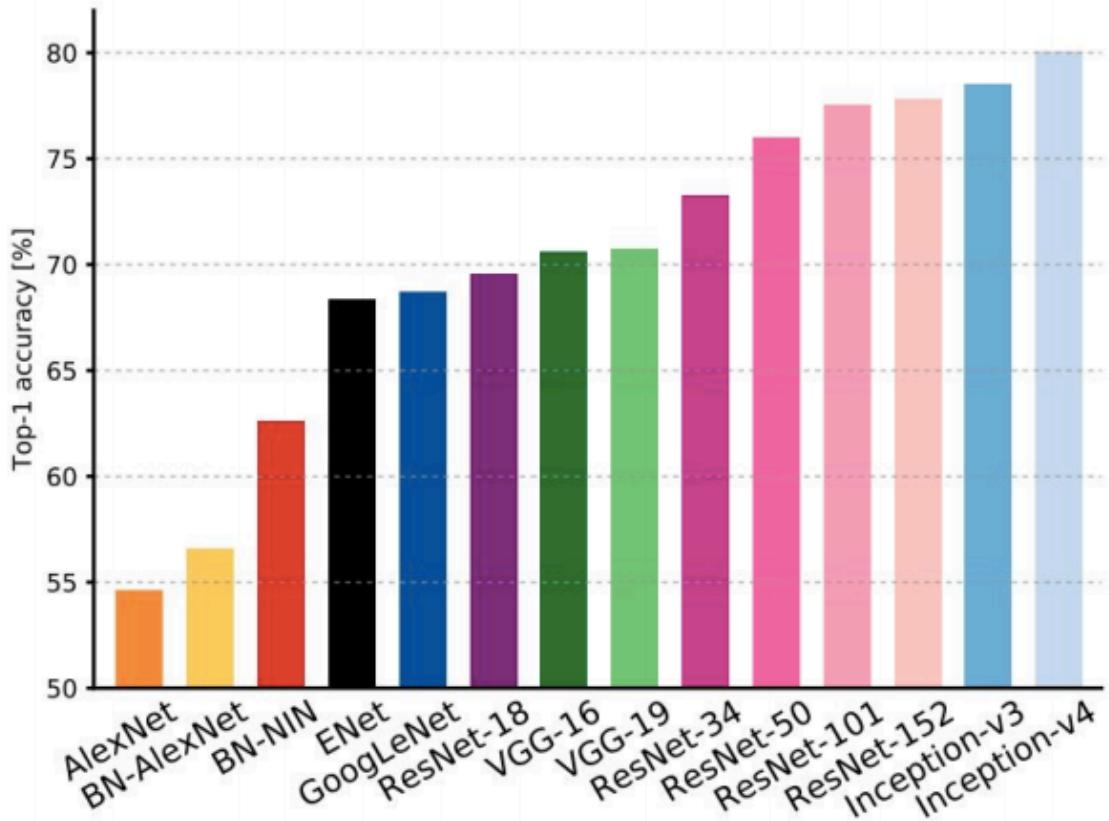
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ILSVRC 2015 classification winner (3.6% top 5 error) -- better than “human performance”! (Russakovsky 2014)

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Comparing complexity...



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

State of the Art Results

RANK	METHOD	TOP 1 ACCURACY	TOP 5 ACCURACY	NUMBER OF PARAMS	EXTRA TRAINING DATA	PAPER TITLE	YEAR
1	FixResNeXt-101 32x48d	86.4%	98.0%	829M	✓	Fixing the train-test resolution discrepancy	2019
2	ResNeXt-101 32x48d	85.4%	97.6%	829M	✓	Exploring the Limits of Weakly Supervised Pretraining	2018
3	ResNeXt-101 32x32d	85.1%	97.5%	466M	✓	Exploring the Limits of Weakly Supervised Pretraining	2018

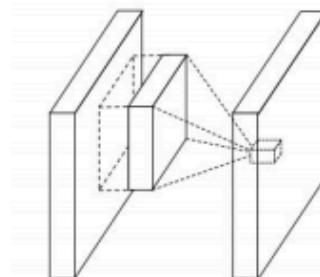
But research into CNN architectures is still flourishing

Of historical note...

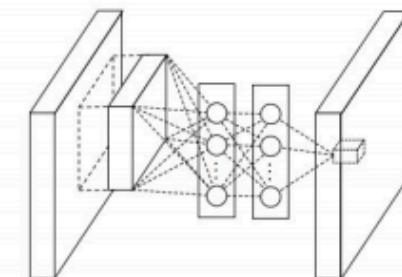
Network in Network (NiN)

[Lin et al. 2014]

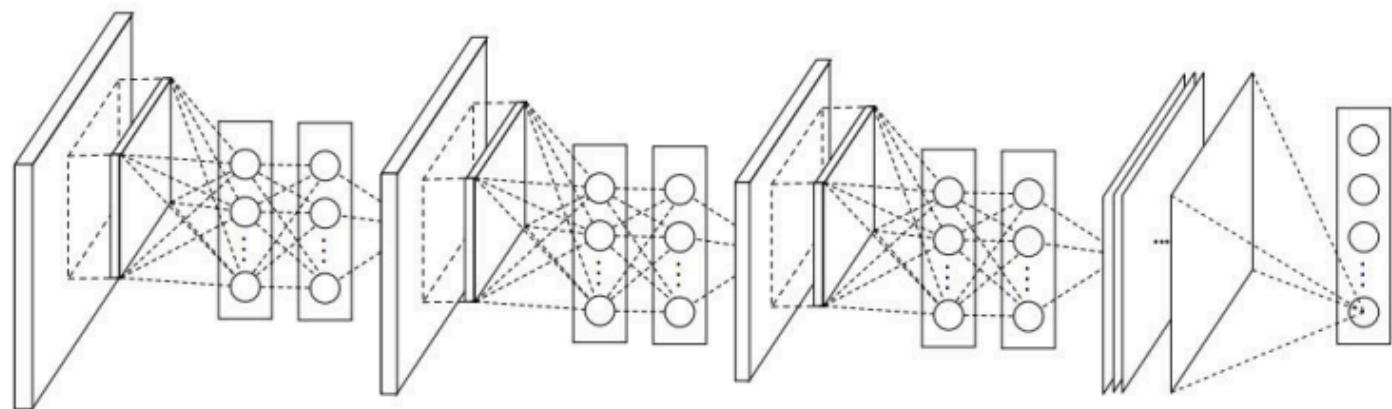
- Mlpconv layer with “micronetwork” within each conv layer to compute more abstract features for local patches
- Micronetwork uses multilayer perceptron
- Precursor to GoogLeNet and ResNet “bottleneck” layers
- Philosophical inspiration for GoogLeNet



(a) Linear convolution layer



(b) Mlpconv layer



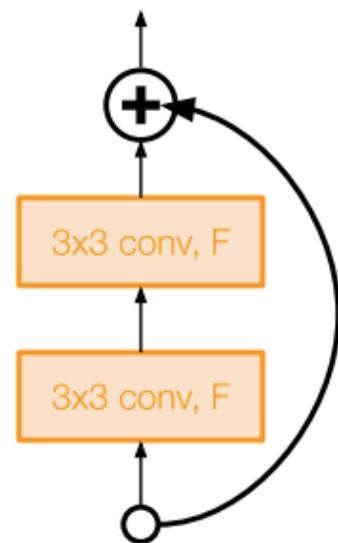
Figures copyright Lin et al., 2014. Reproduced with permission.

Improving ResNets...

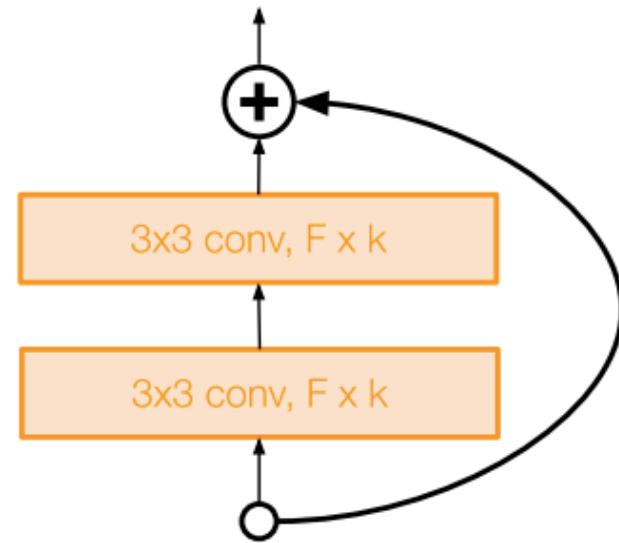
Wide Residual Networks

[Zagoruyko et al. 2016]

- Argues that residuals are the important factor, not depth
- Use wider residual blocks ($F \times k$ 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)



Basic residual block



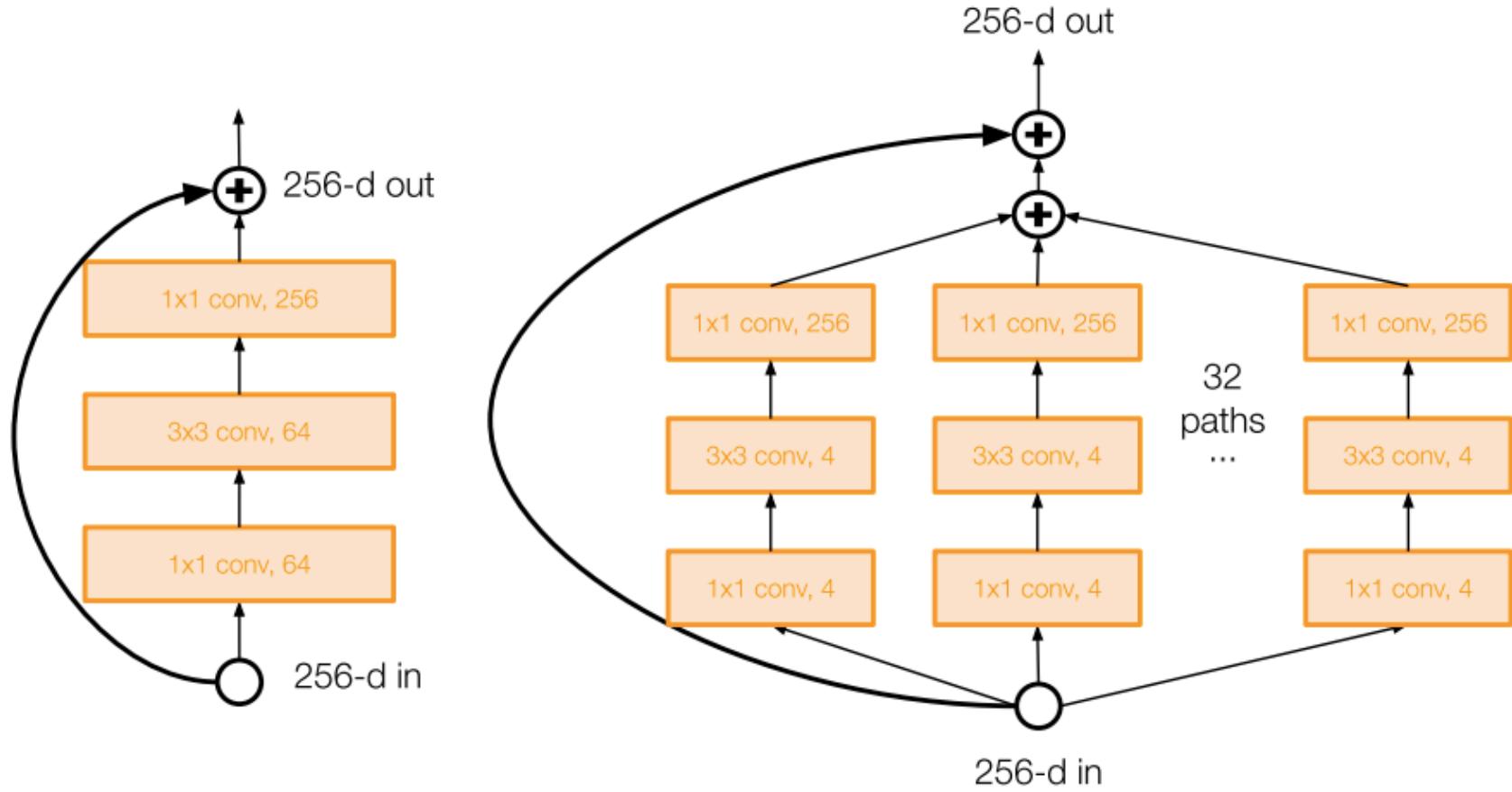
Wide residual block

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



Resources Used

- CS231n Convolutional Neural Networks for Visual Recognition by Fei-Fei Li, Justin Johnson, Seran Yeung
- STAT 479: Deep Learning by Sebastian Raschka