CNN Case Studies

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Slides are based on Fei Fei Li and colleagues lectures, cs231n, Stanford 2017,
and some are adopted from Kaiming He, ICML tutorial 2016.

AlexNet

[Krizhevsky, Sutskever, Hinton, 2012]

- ImageNet Classification with Deep Convolutional Neural Networks

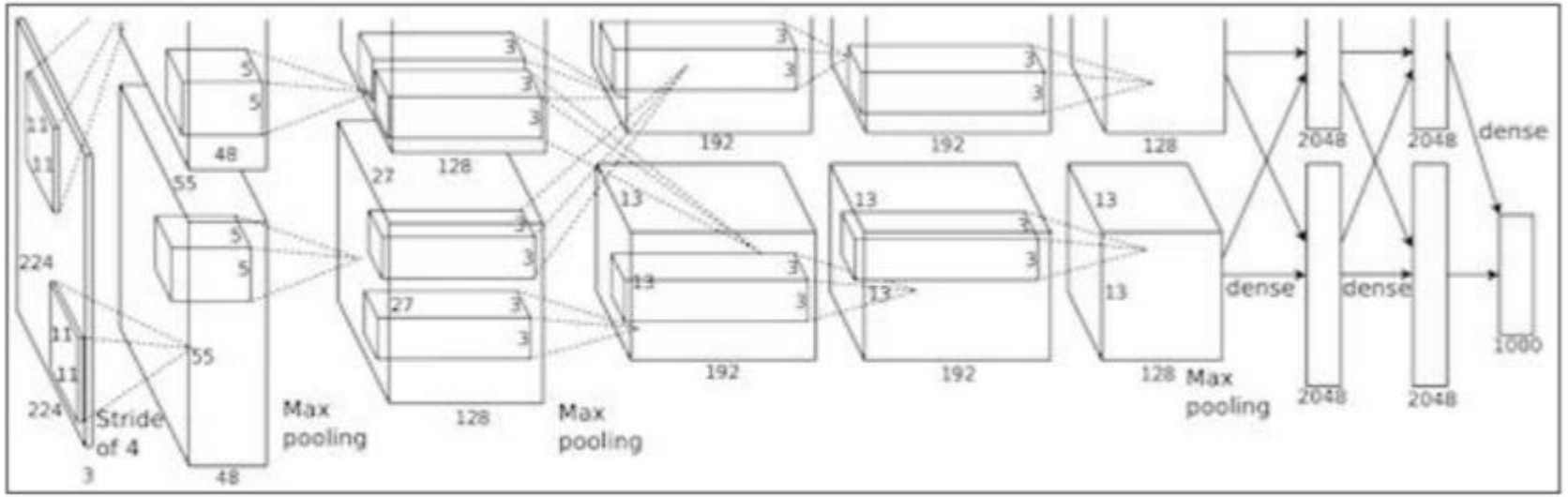


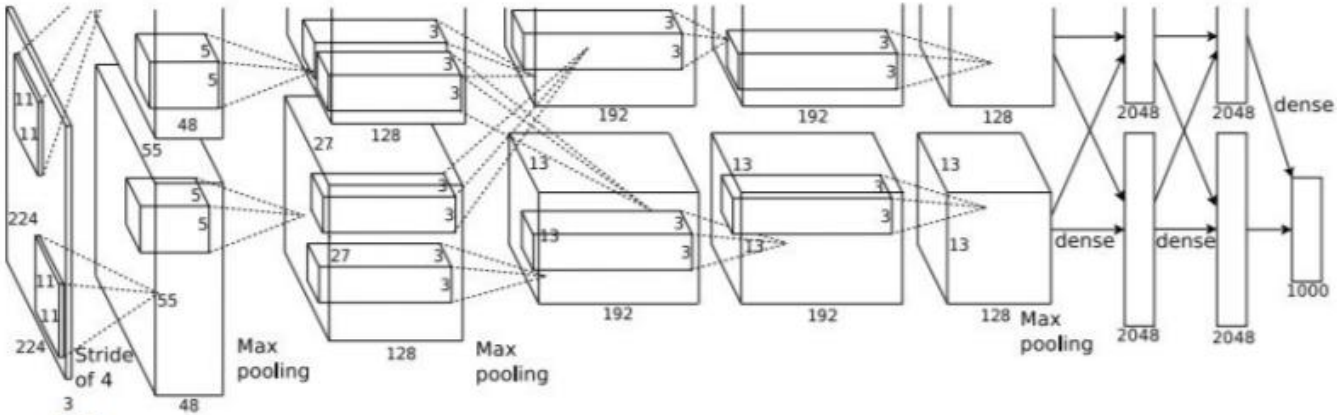
Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

CNN Architectures

- Case Studies
  - AlexNet
  - VGG
  - GoogLeNet
  - ResNet

- Also....
  - Wide ResNet
  - ResNeXT
  - Stochastic Depth
  - FractalNet
  - DenseNet
  - SqueezeNet

Case Study: AlexNet

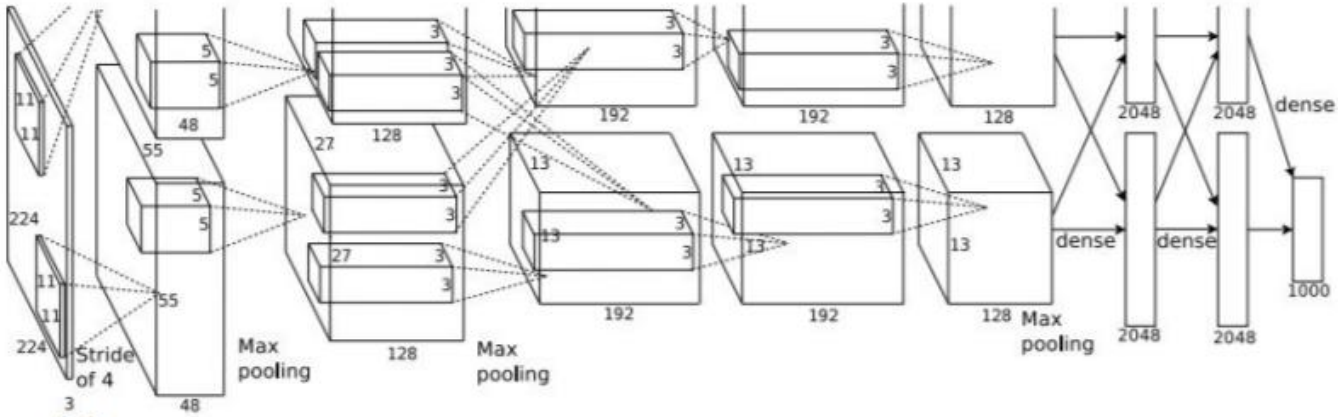


Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256]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

Input: 227x227x3
First layer (CONV1): 11x11x3 stride 4
=>
Output: (227-11)/4+1 = 55

Parameters: (11*11*3)*96 = 35K

Case Study: AlexNet



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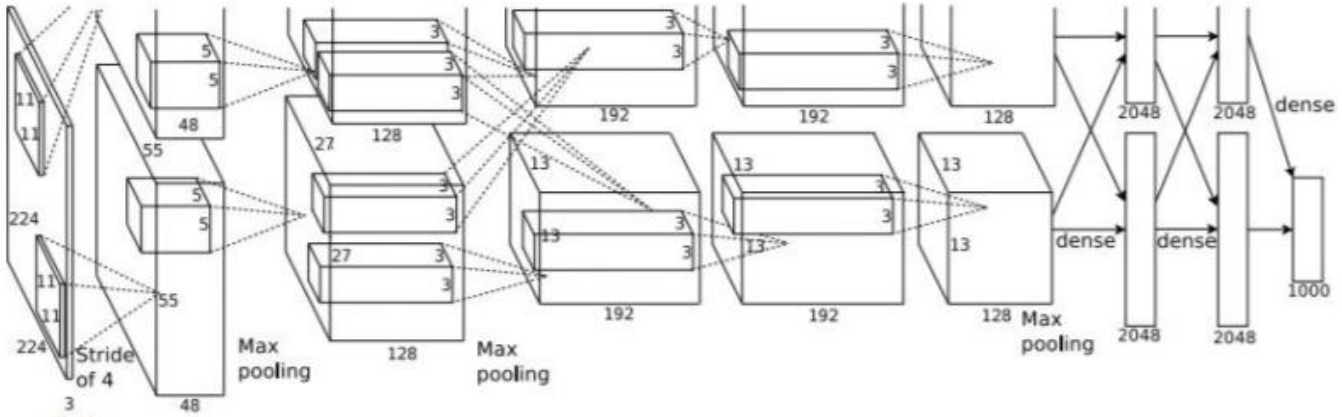
Second layer (POOL1): 3x3 filters stride 2
Output volume: 27x27x96
#Parameters: 0!

Case Study: AlexNet



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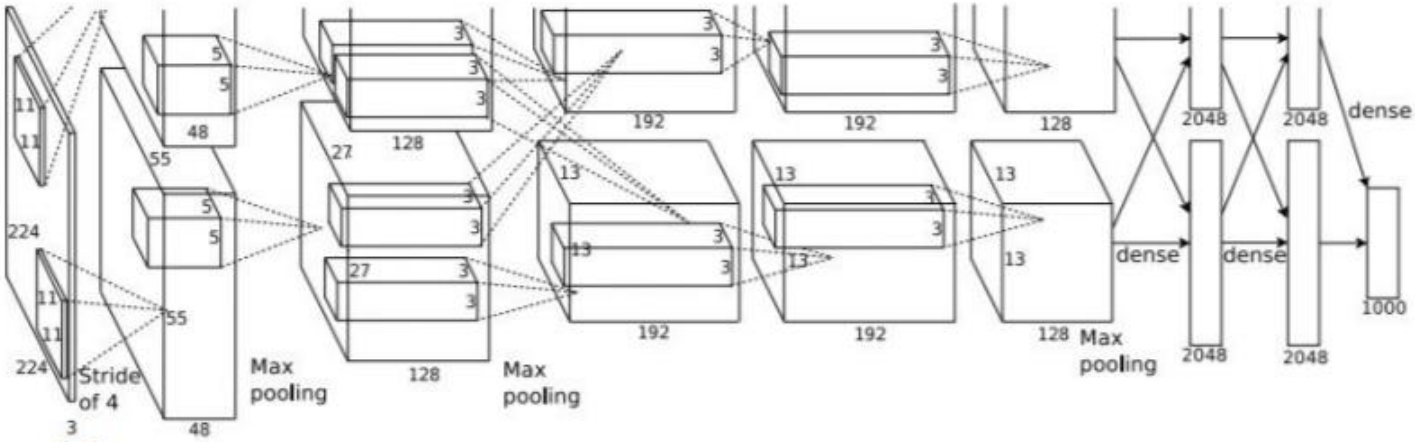
Input: 227x227x3
After CONV1: 55x55x96
After POOL1: 27x27x96

Case Study: AlexNet



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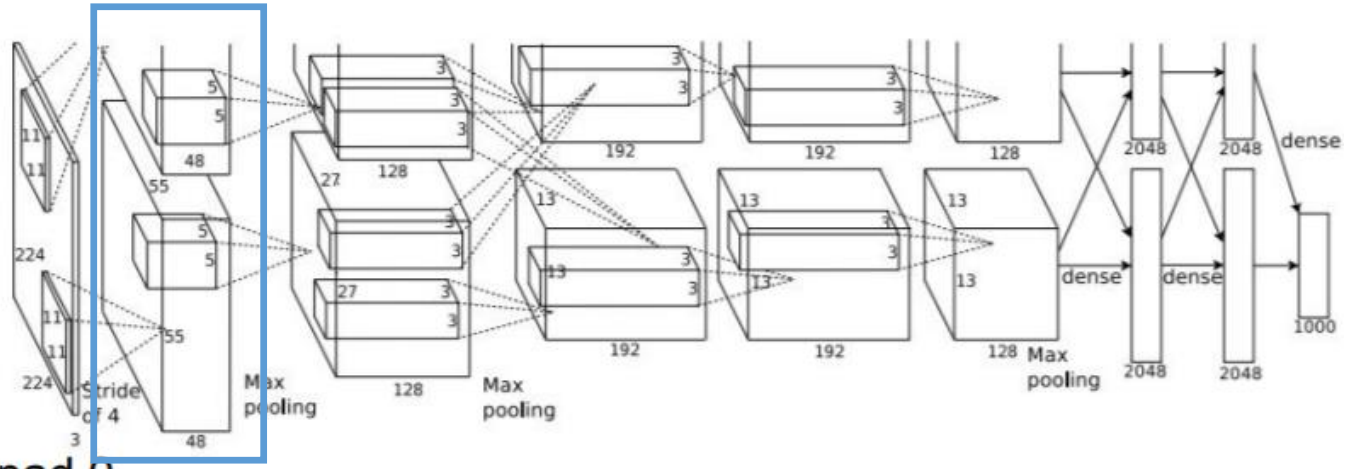
Details/Retrospectives:

- 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%

Case Study: AlexNet



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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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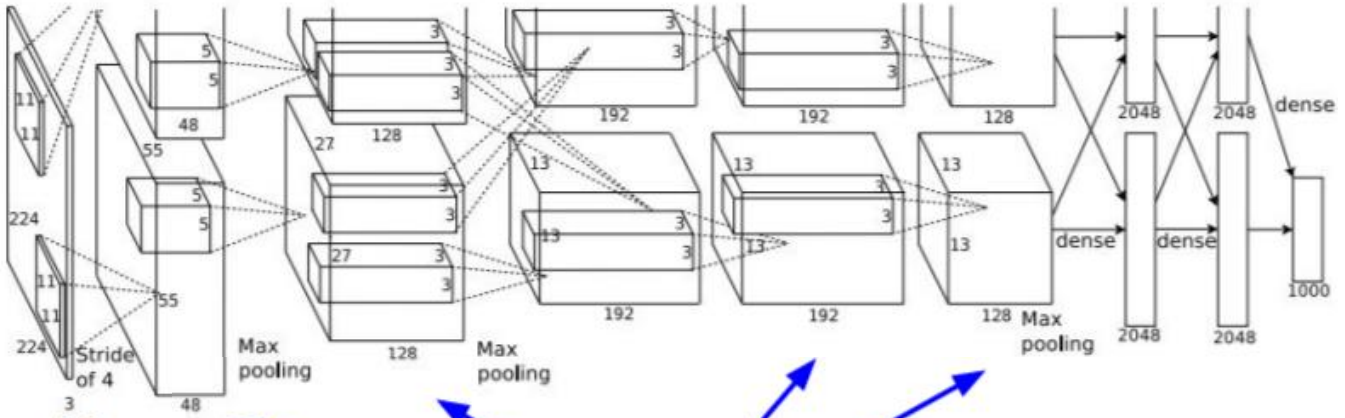
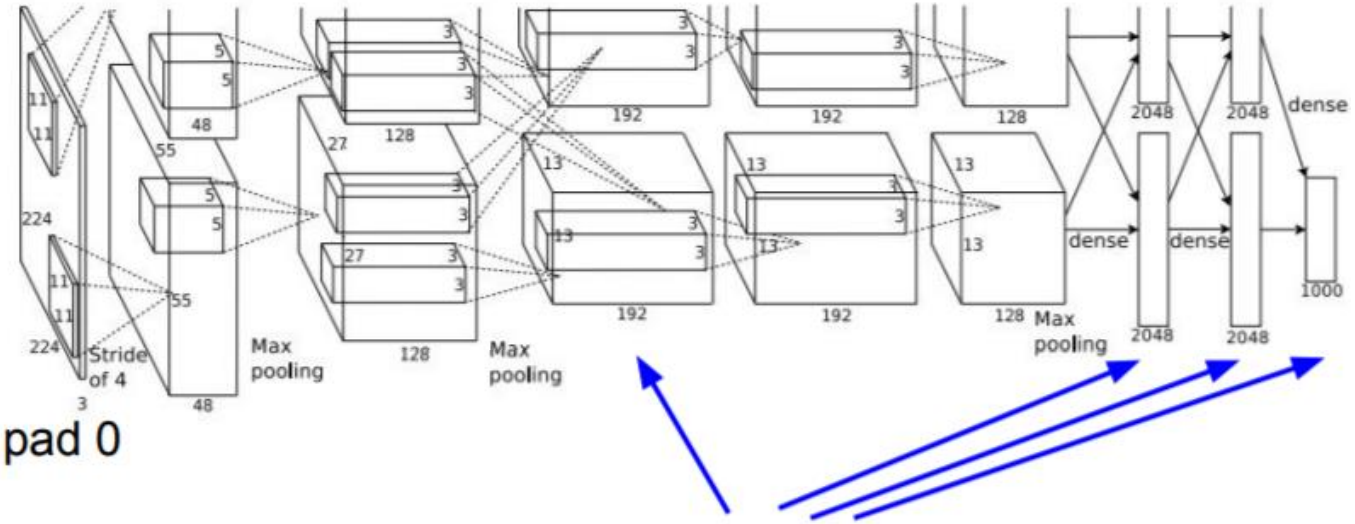


CONV1, CONV2, CONV4, CONV5:
Connections only with feature maps on same GPU

Case Study: AlexNet



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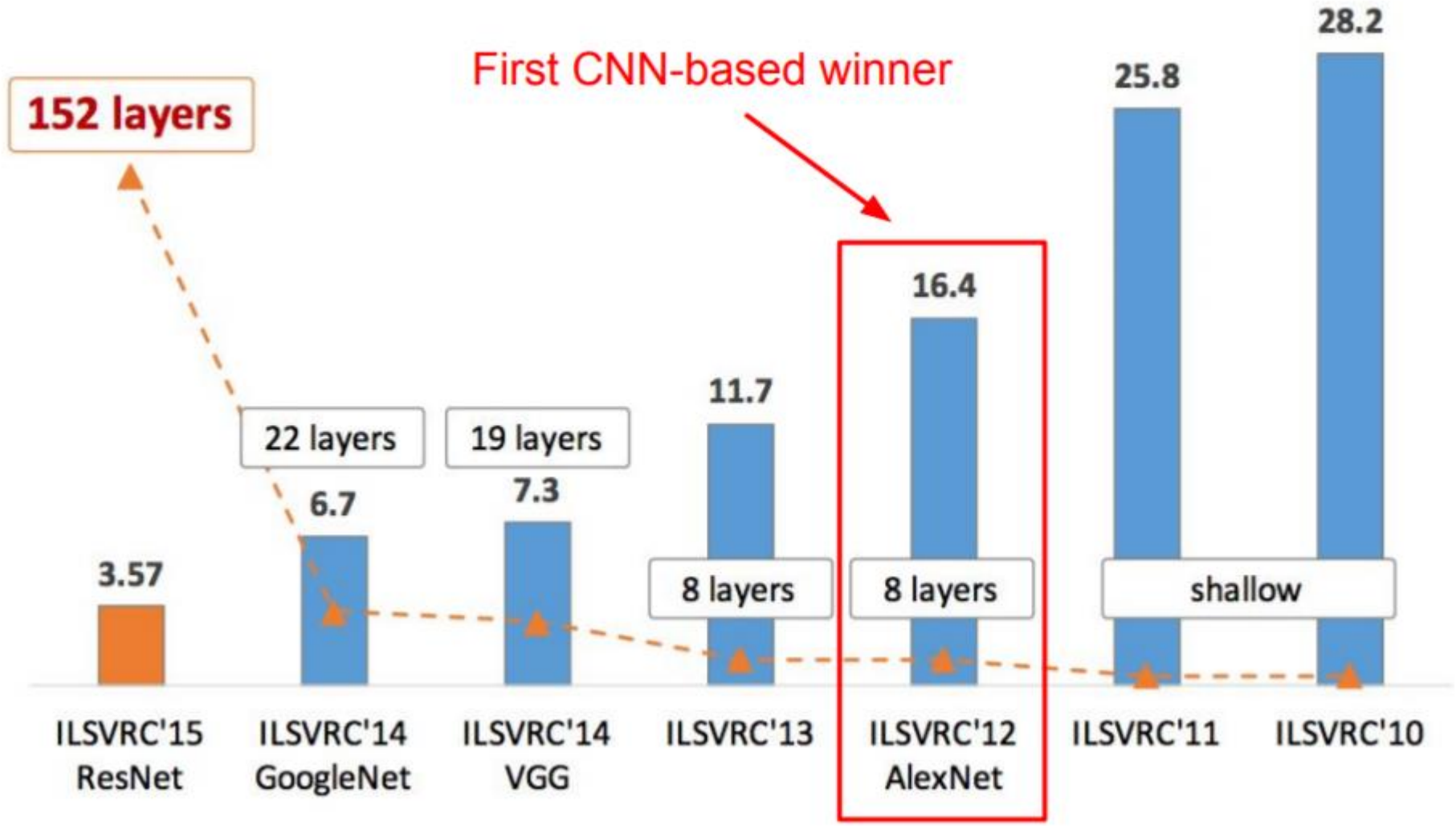
CONV3, FC6, FC7, FC8:
Connections with all feature maps in preceding layer, communication across GPUs

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)



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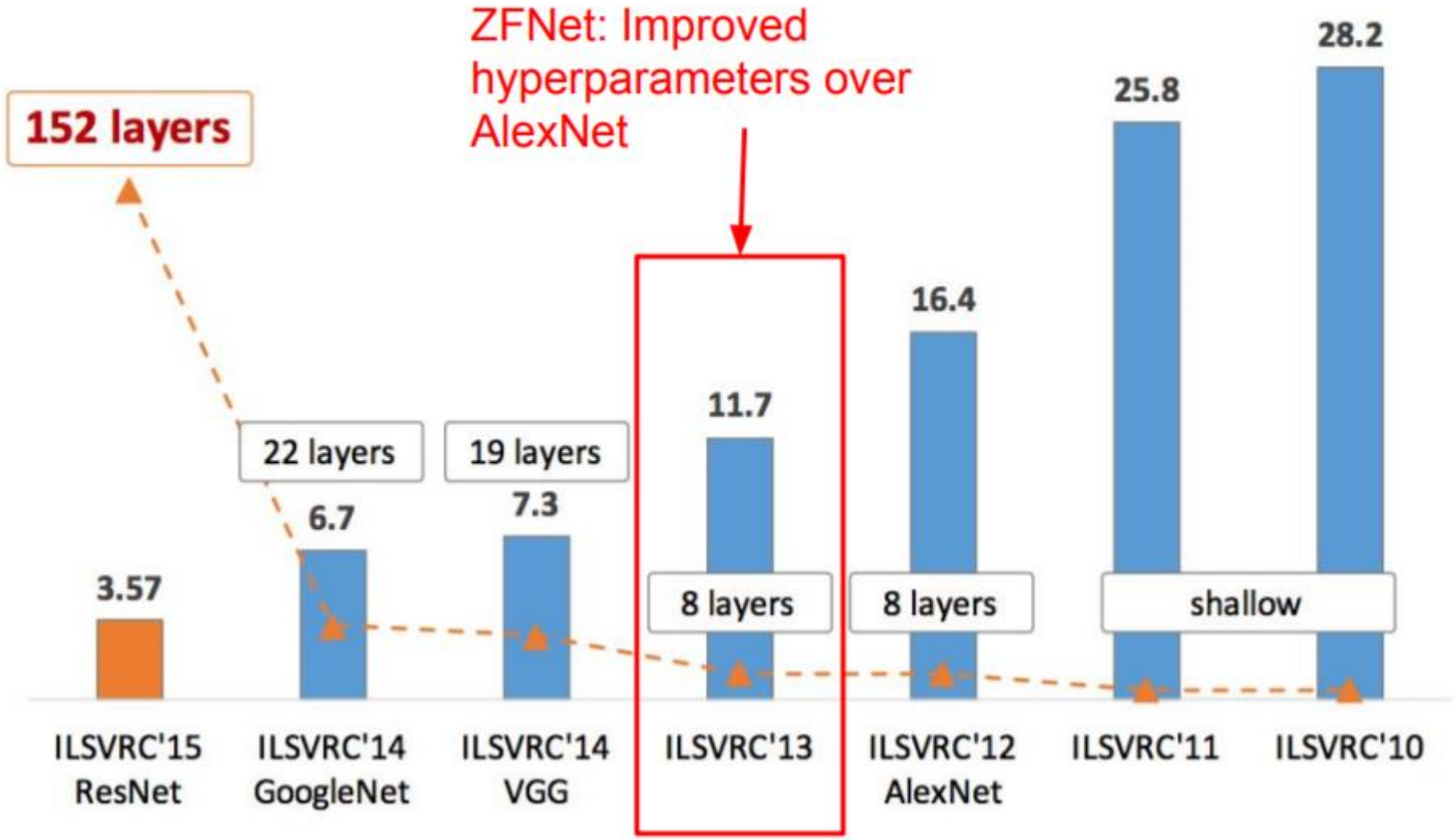
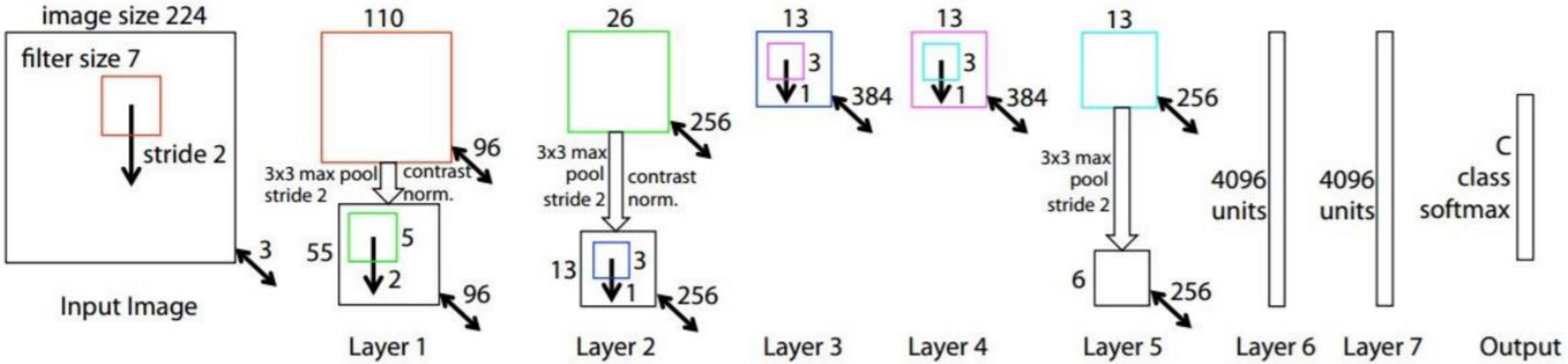


ZFNet

[Zeiler and Fergus, 2013]



TODO: remake figure

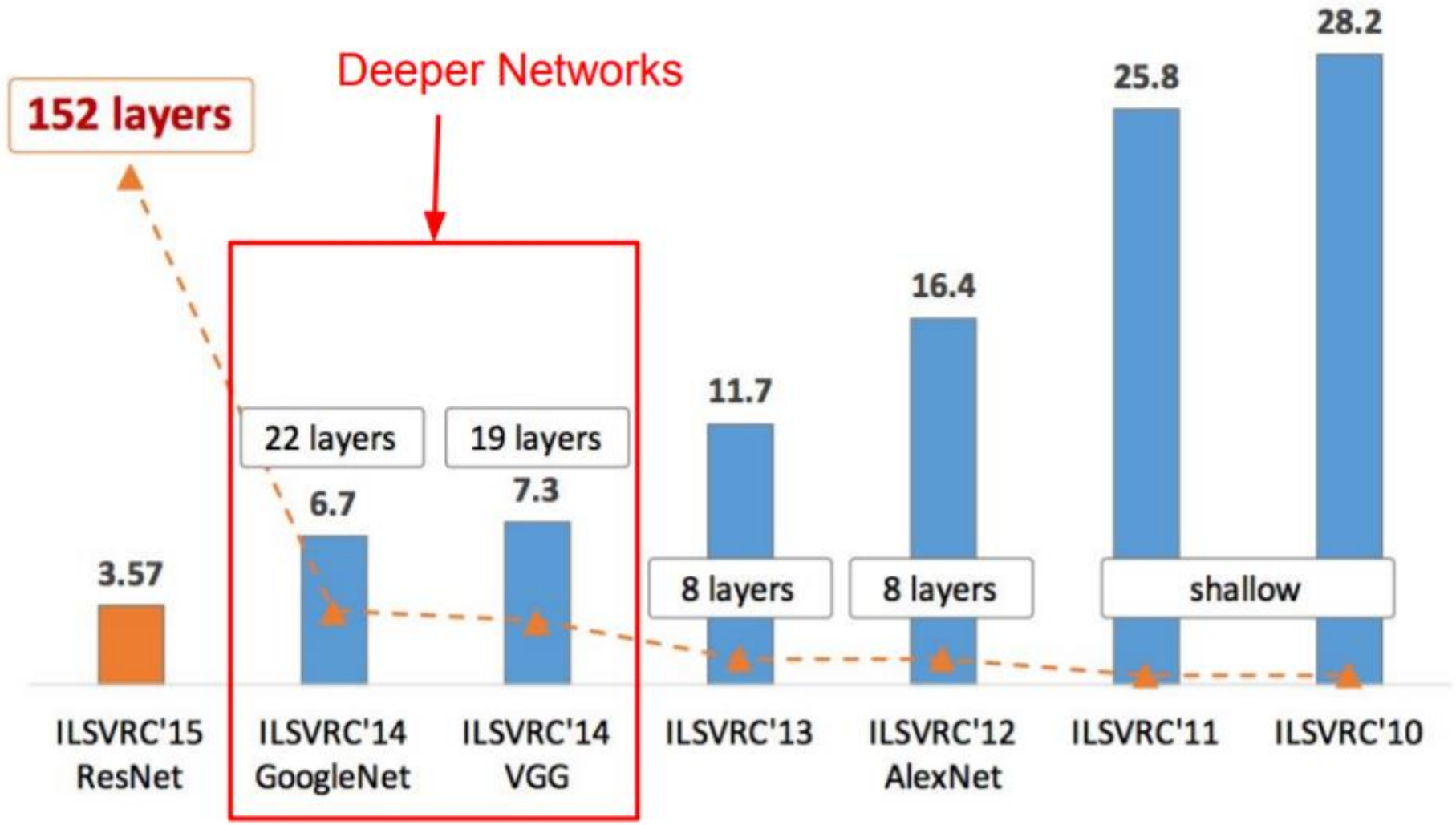
AlexNet but:

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%

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

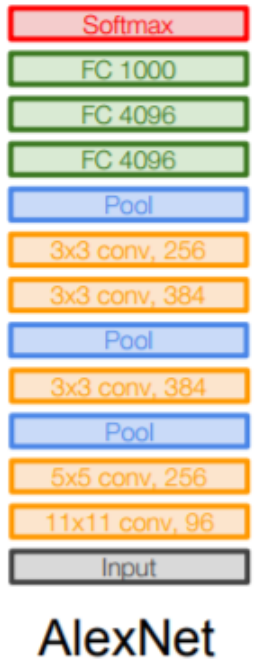


Case Study: VGGNet

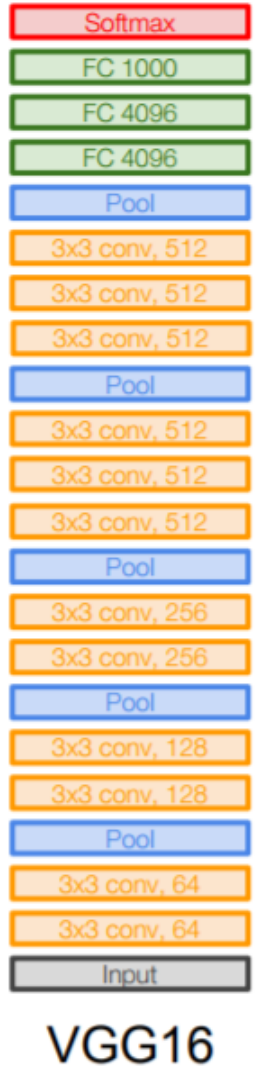
[Simonyan and Zisserman, 2014]

- Small filters
- Deeper networks
  - 8 layers (AlexNet) -> 16 - 19 layers (VGG16Net)
- Only 3x3 CONV
  - stride 1, pad 1
- 2x2 MAX POOL stride 2
- **11.7**% top 5 error in ILSVRC'13 (ZFNet)

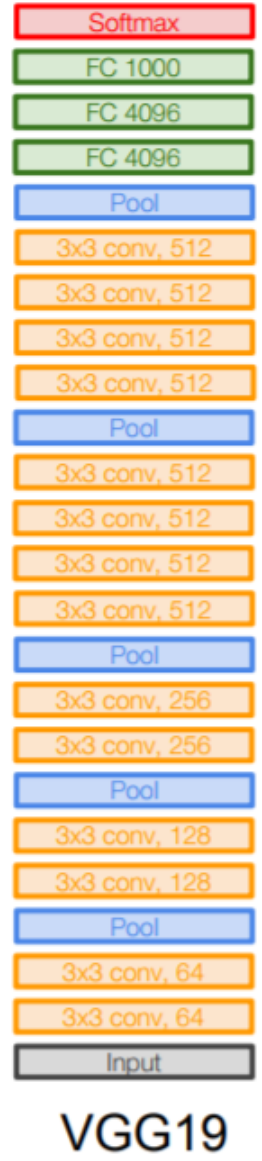
  -> **7.3**% top 5 error in ILSVRC'14



AlexNet



VGG16

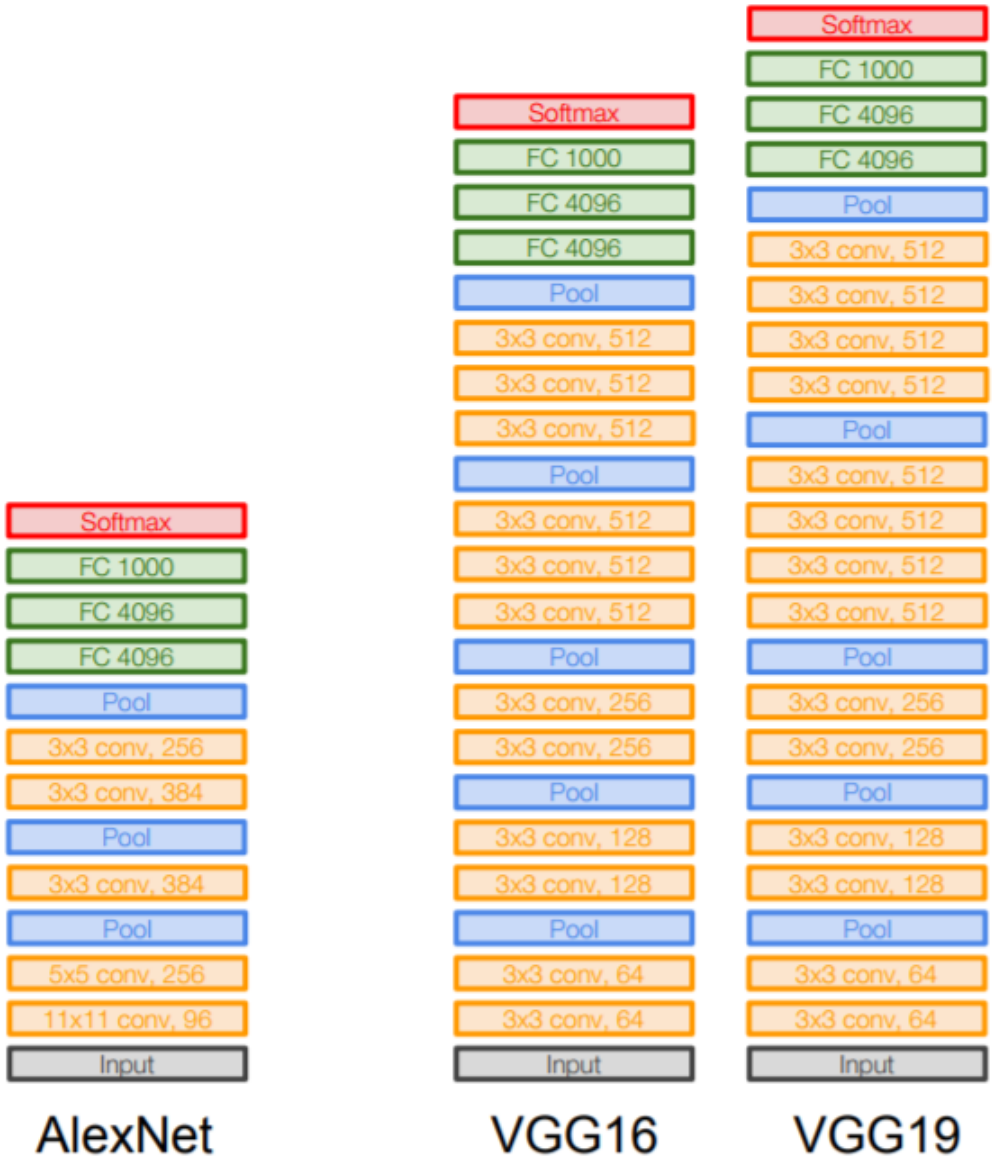


VGG19

Case Study: VGGNet

[Simonyan and Zisserman, 2014]

- 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



Case Study: VGGNet

(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
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POOL2: [14x14x512] memory: 14*14*512=100K params: 0
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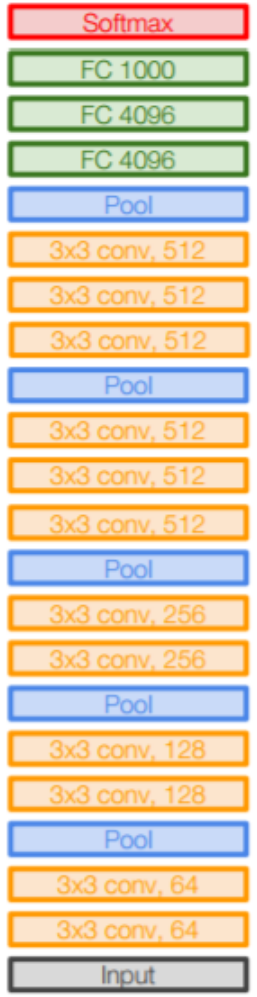
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000



VGG16

Case Study: VGGNet

(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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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

Case Study: VGGNet

(not counting biases)

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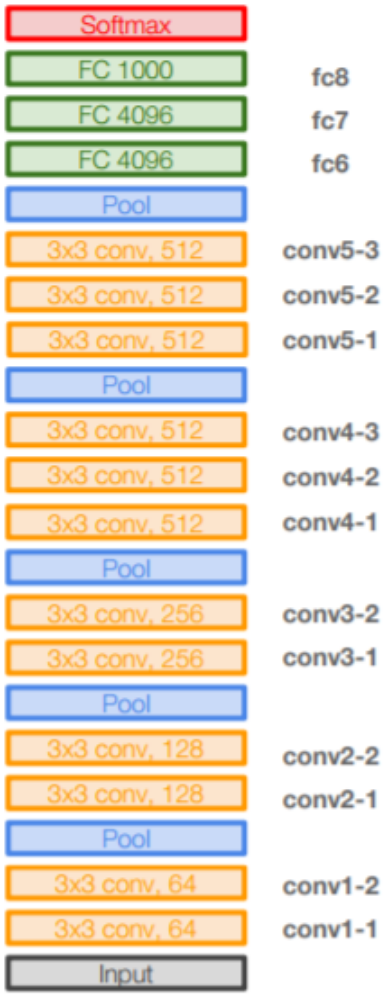
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000



VGG16

Common names

Case Study: VGGNet

(not counting biases)

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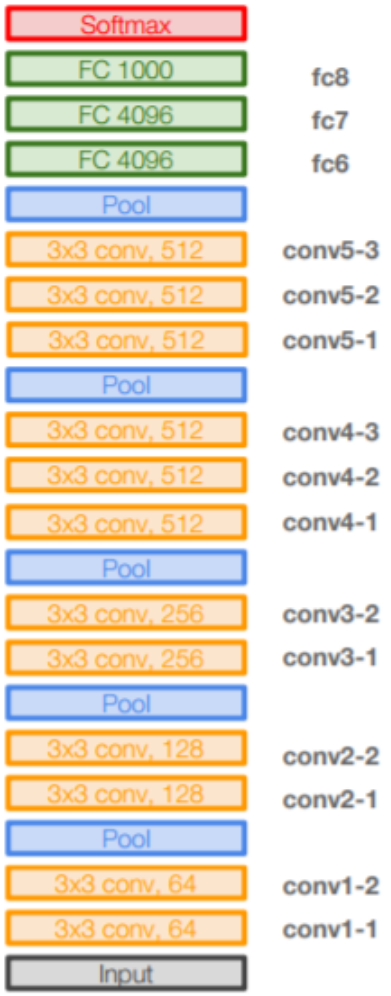
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] 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

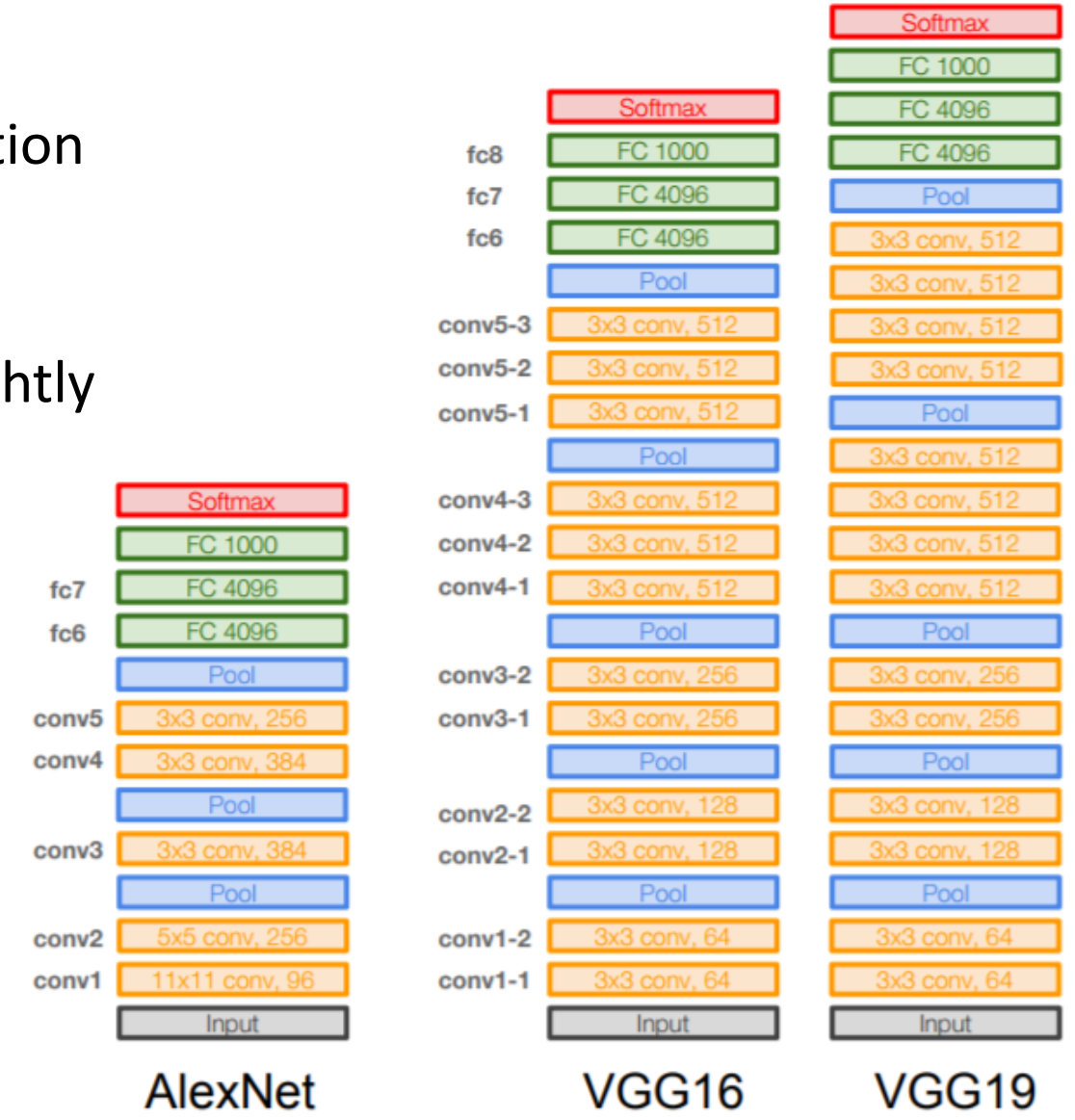


VGG16

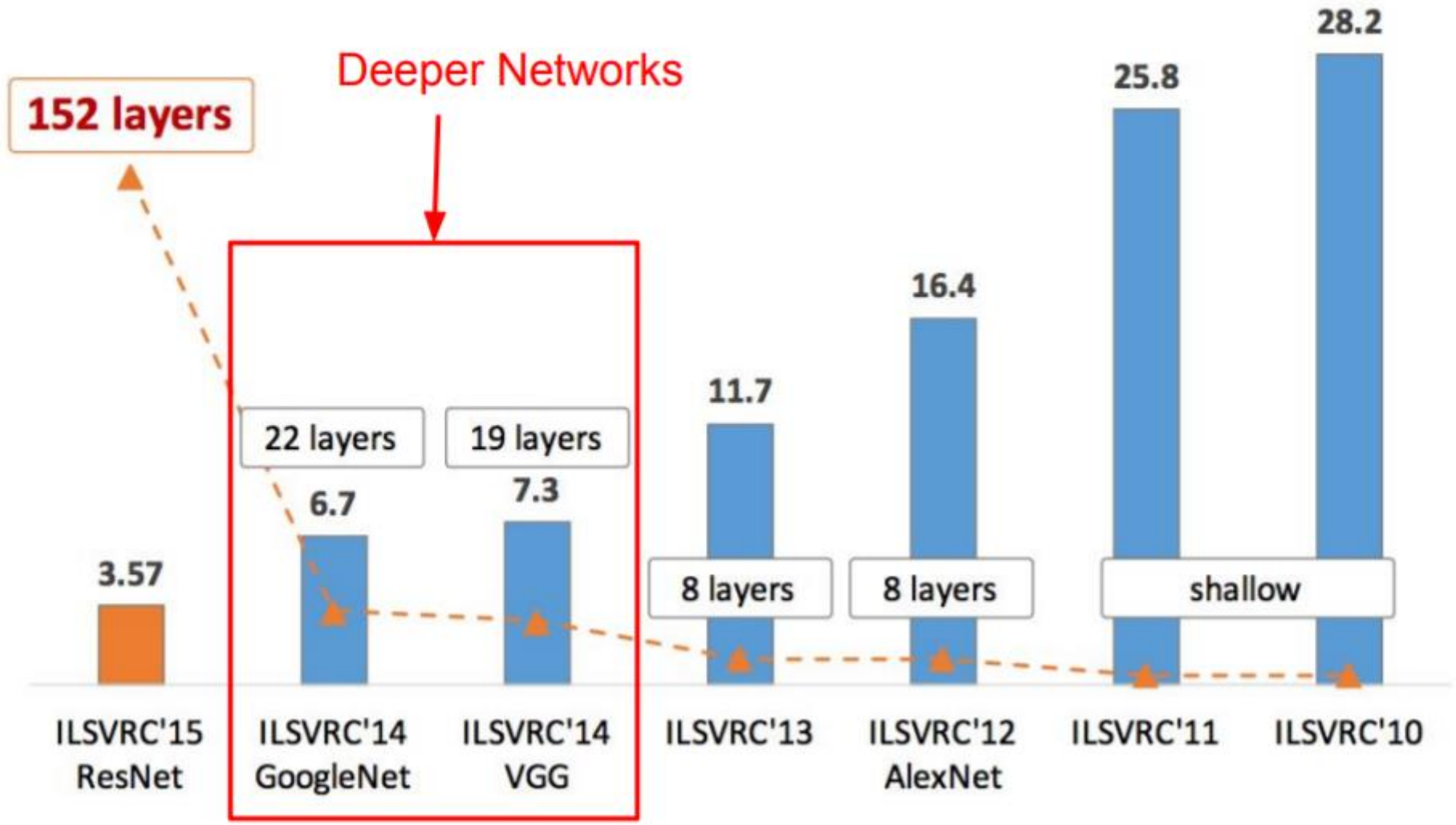
Common names

Case Study: VGGNet

- 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



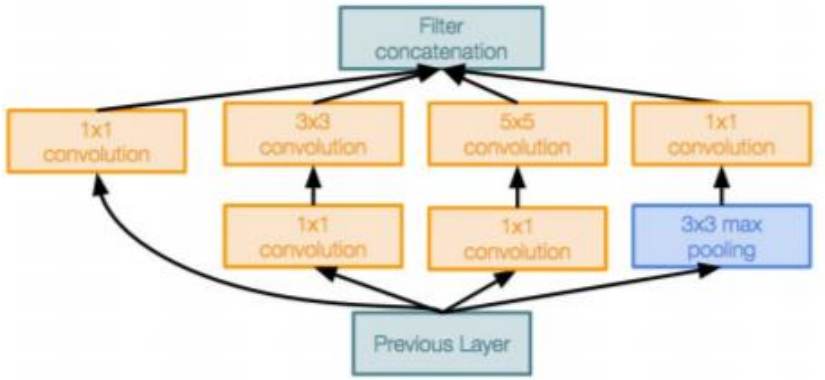
ImageNet Large Scale Visual Recognition Challenge (ILSVRC)



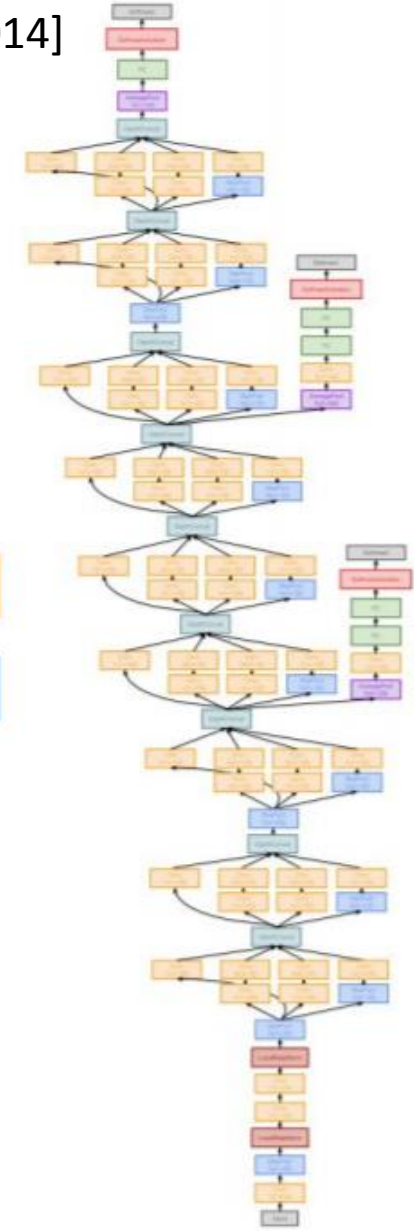
Case Study: GoogLeNet

[Szegedy et al., 2014]

- Deeper networks, with computation
  - 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



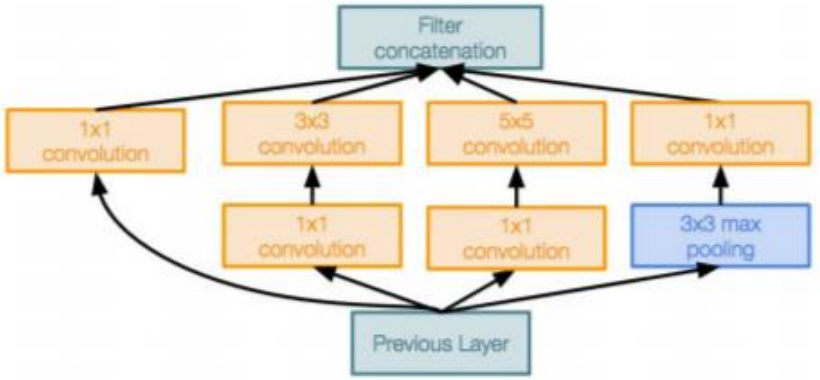
Case Study: GoogLeNet

[Szegedy et al., 2014]

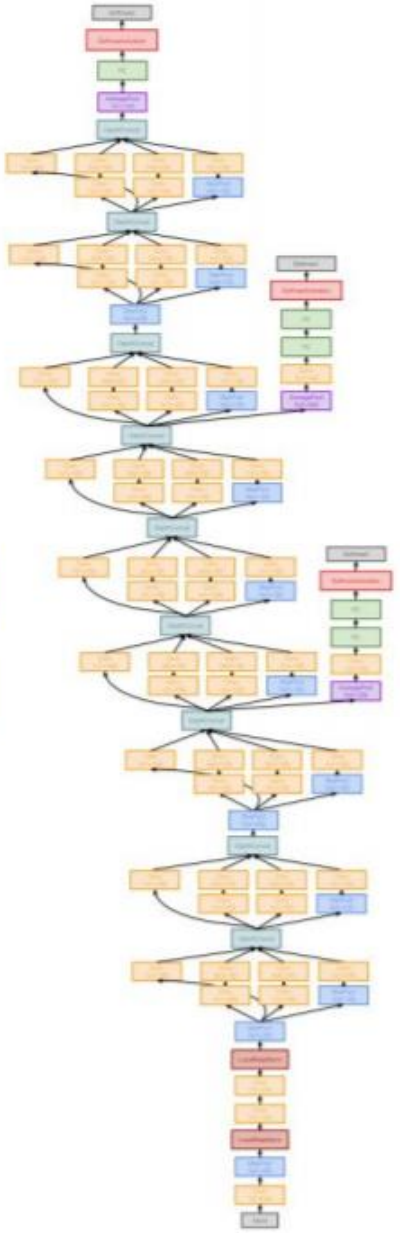
Inception module: a good local network topology

(network within a network)

GoogLeNet stack these modules on top of each other

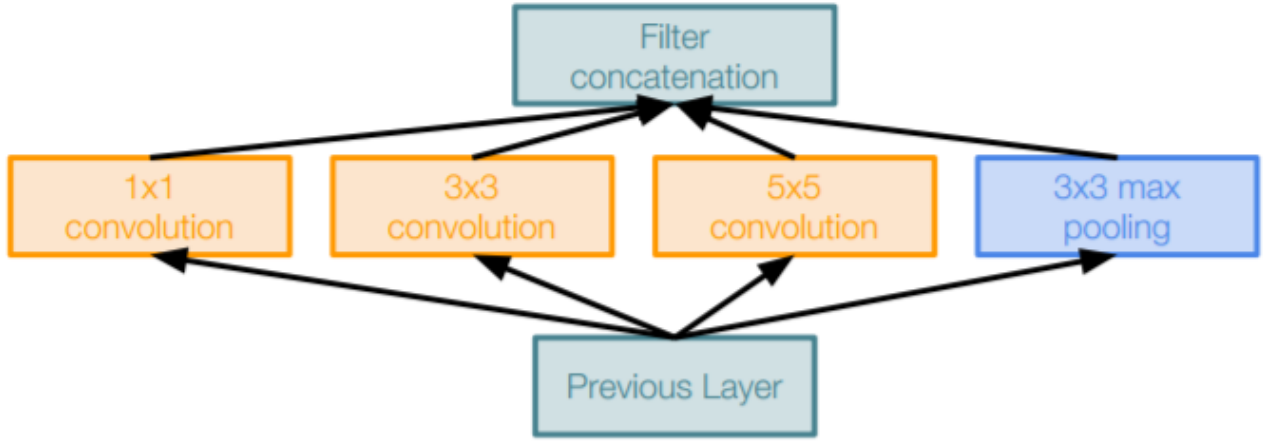


Inception module



Case Study: GoogLeNet

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

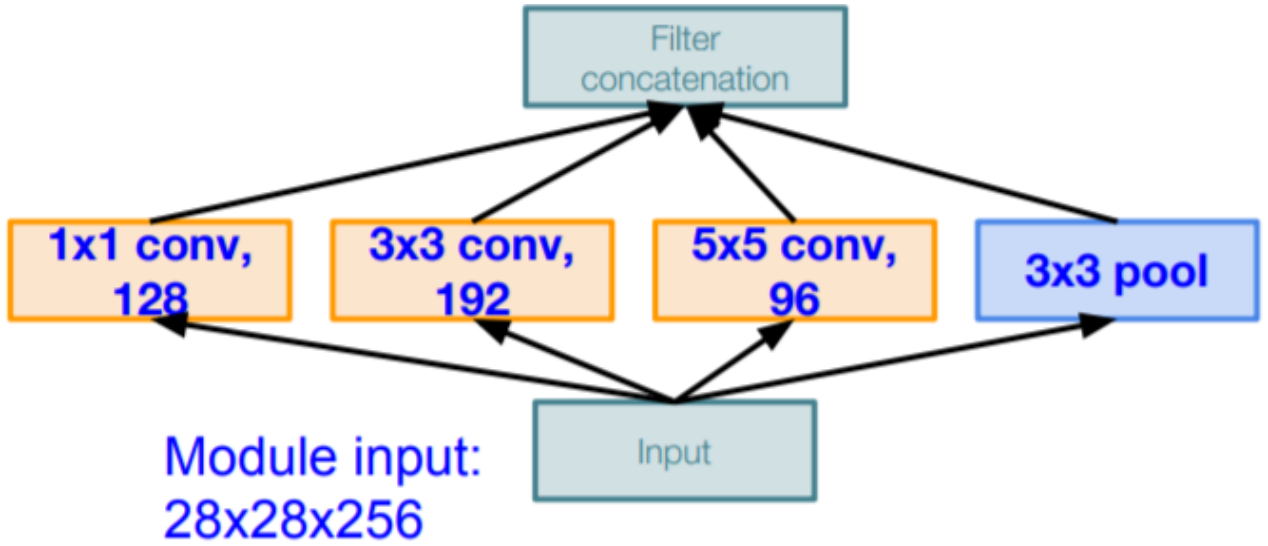


Naive Inception module

Case Study: GoogLeNet

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

Example



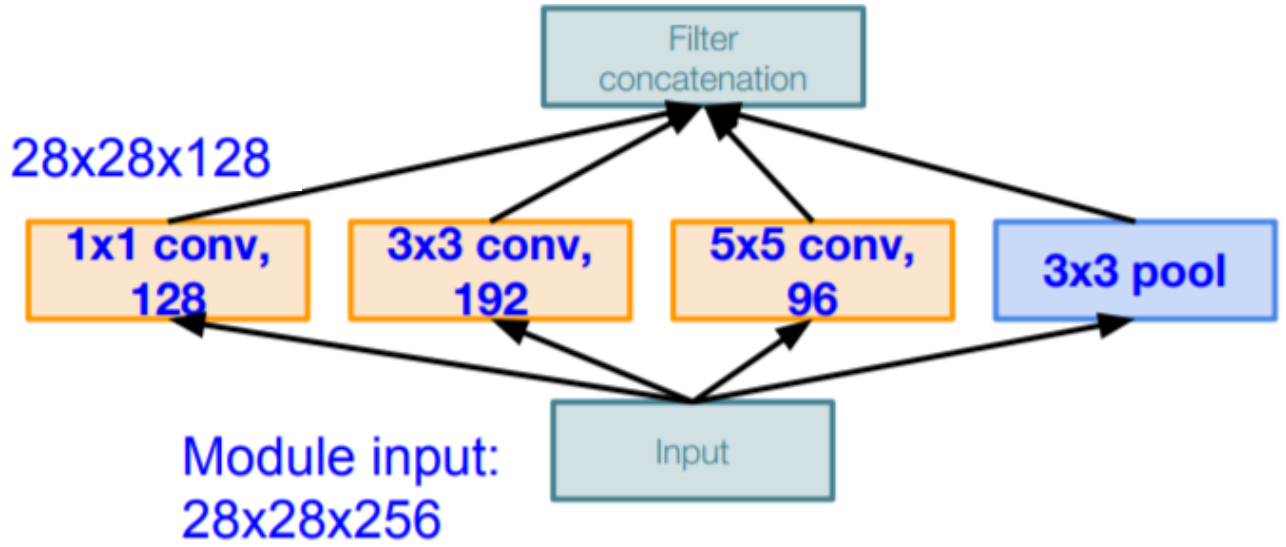
Naive Inception module

Case Study: GoogLeNet

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

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

Example



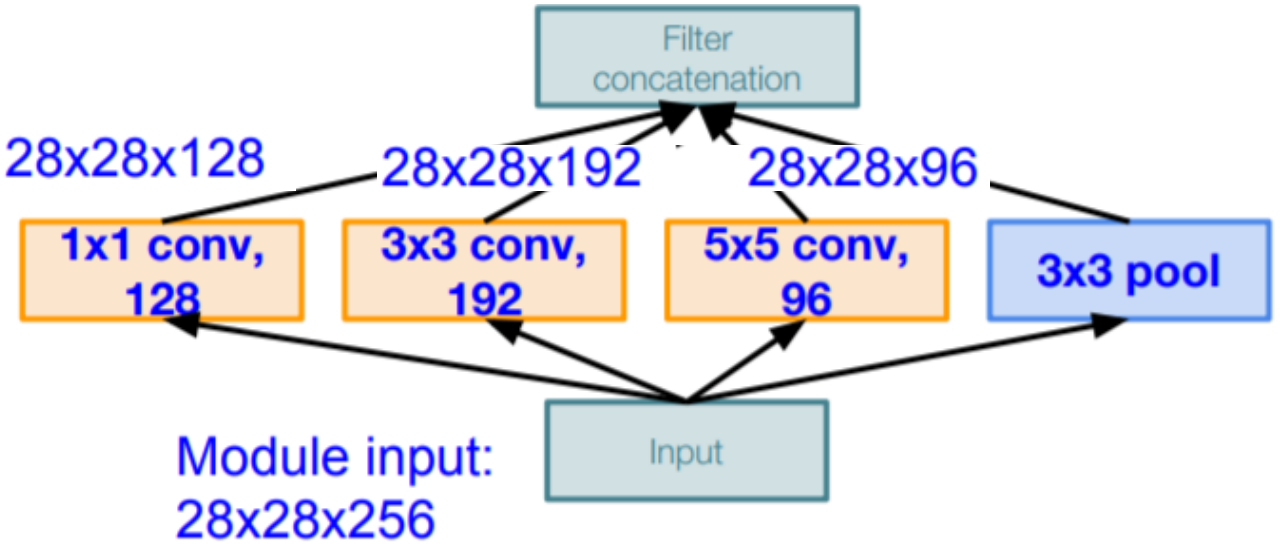
Naive Inception module

Case Study: GoogLeNet

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

- Example:
  - Q1: What is the output size of the 1x1 conv, with 128 filters?
  - Q2: What are the output sizes of all different filter operations?

Example



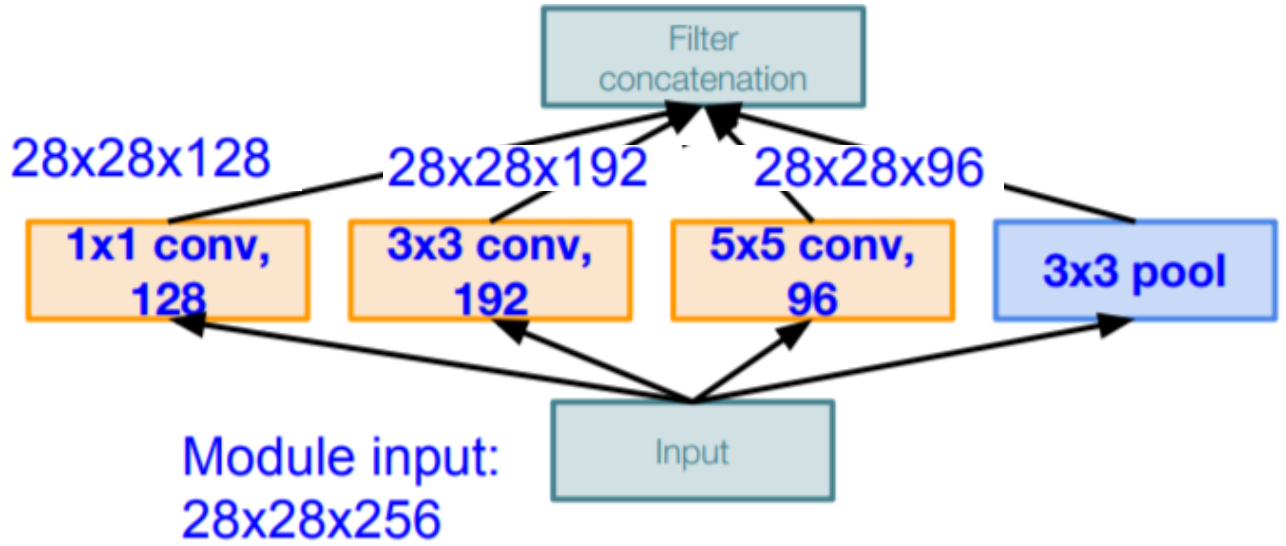
Naive Inception module

Case Study: GoogLeNet

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

- Example:
  - Q1: What is the output size of the 1x1 conv, with 128 filters?
  - Q2: What are the output sizes of all different filter operations?
  - Q3:What is output size after filter concatenation?

Example

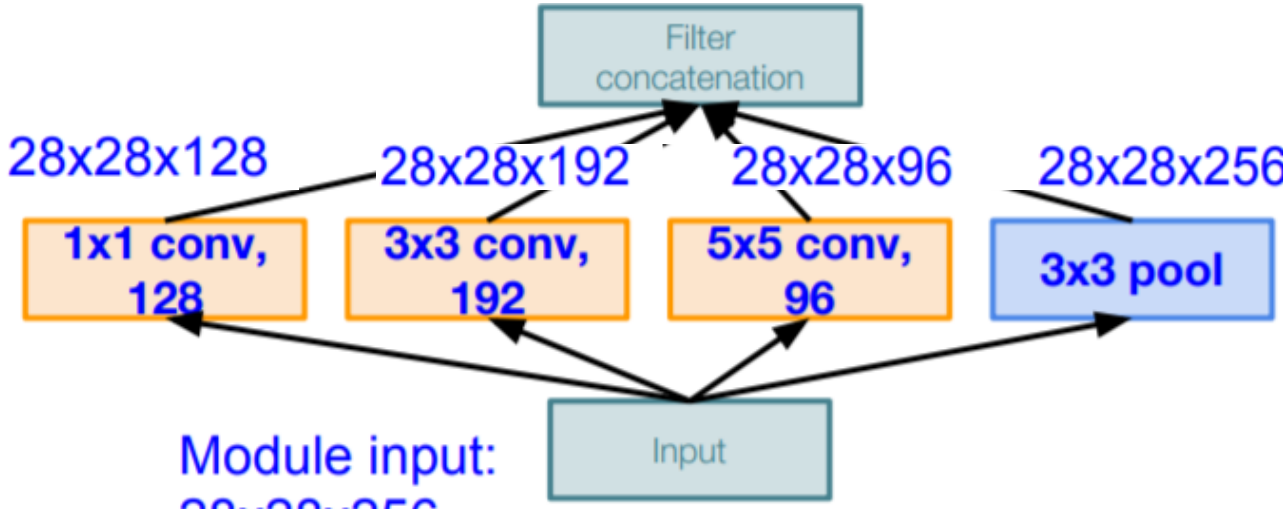


Naive Inception module

Case Study: GoogLeNet

- Conv Ops:
  - [1x1 conv, 128] 28x28x128x1x1x256
  - [3x3 conv, 192] 28x28x192x3x3x256
  - [5x5 conv, 96] 28x28x96x5x5x256
  - Total: **854M** ops
    - Very expensive computations
  - Pooling layer also preserves feature depth, which means total depth after concatenation can only grow at every layer!

Example

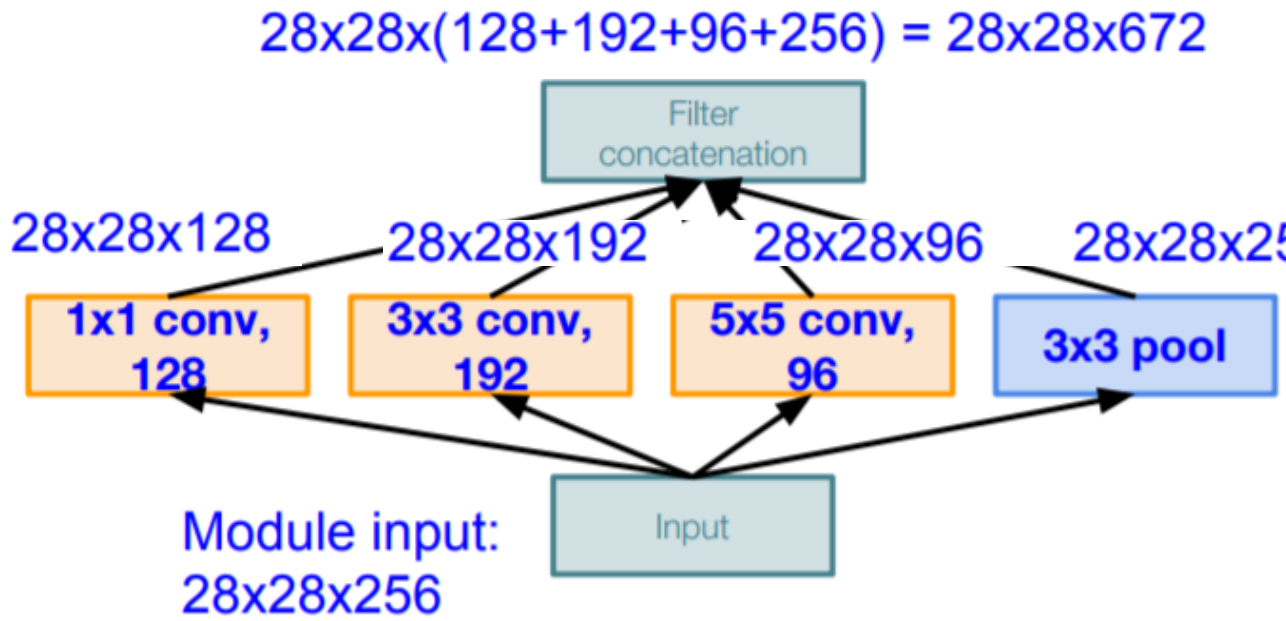


Naive Inception module

Case Study: GoogLeNet

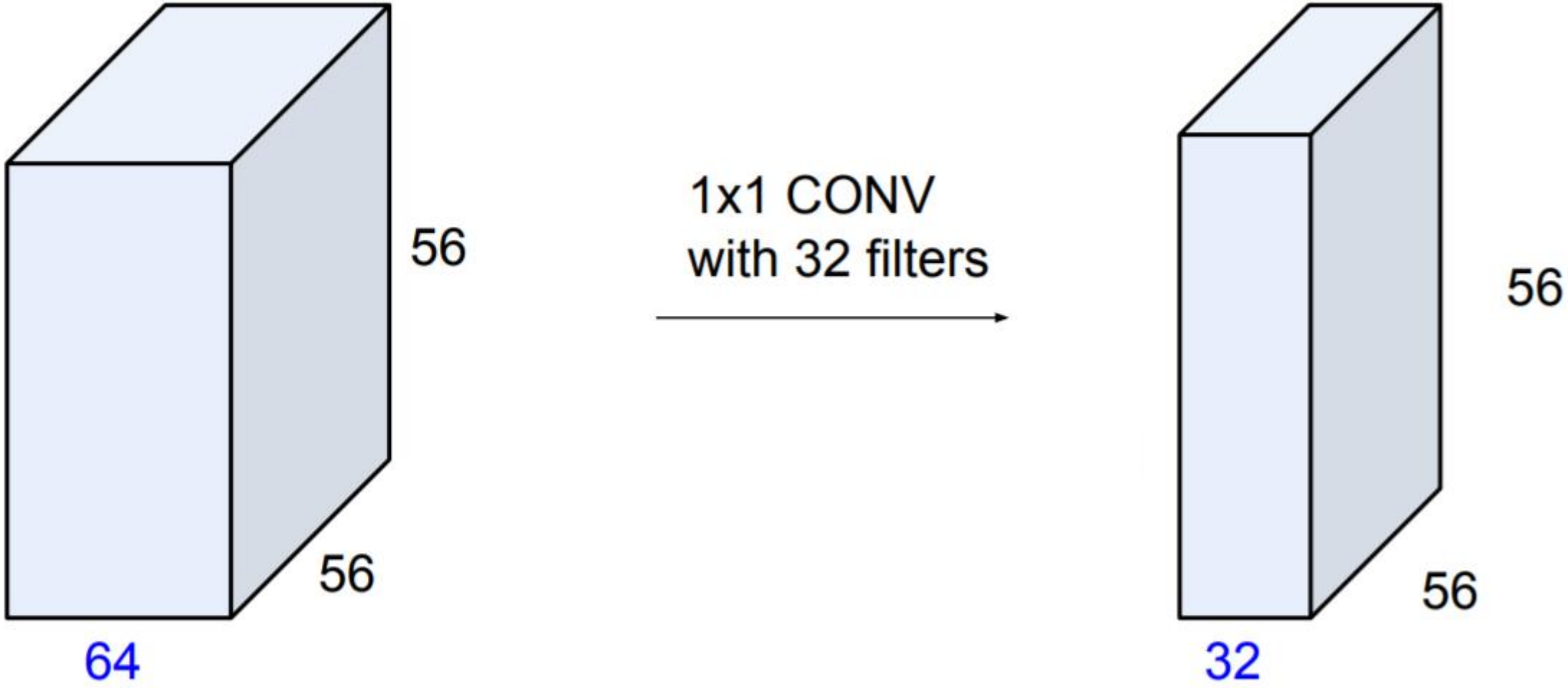
- Solution: “bottleneck” layers that use 1x1 convolutions to reduce feature depth

Example

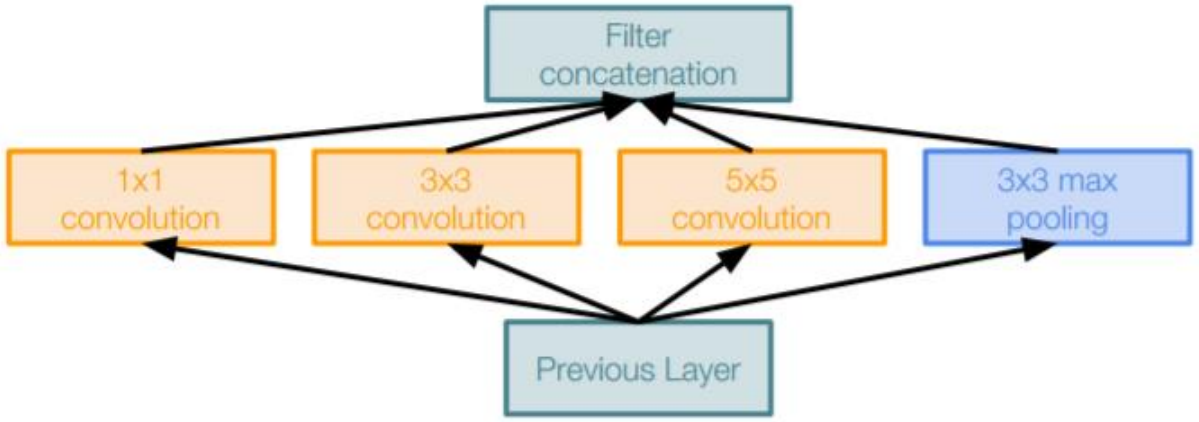


Naive Inception module

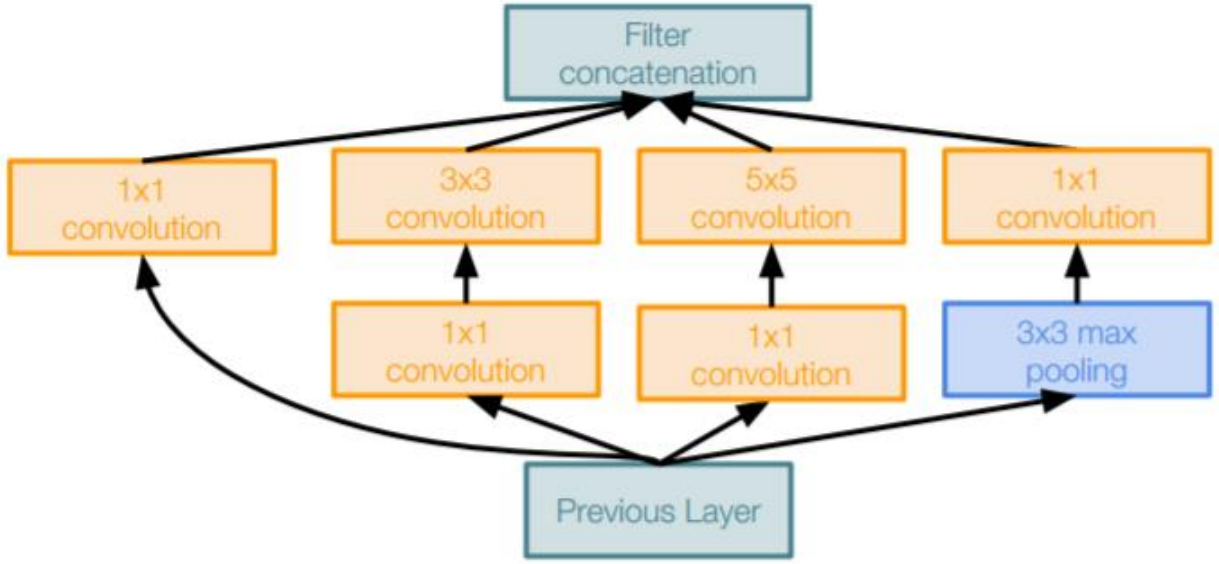
Reminder: 1x1 convolutions



Case Study: GoogLeNet

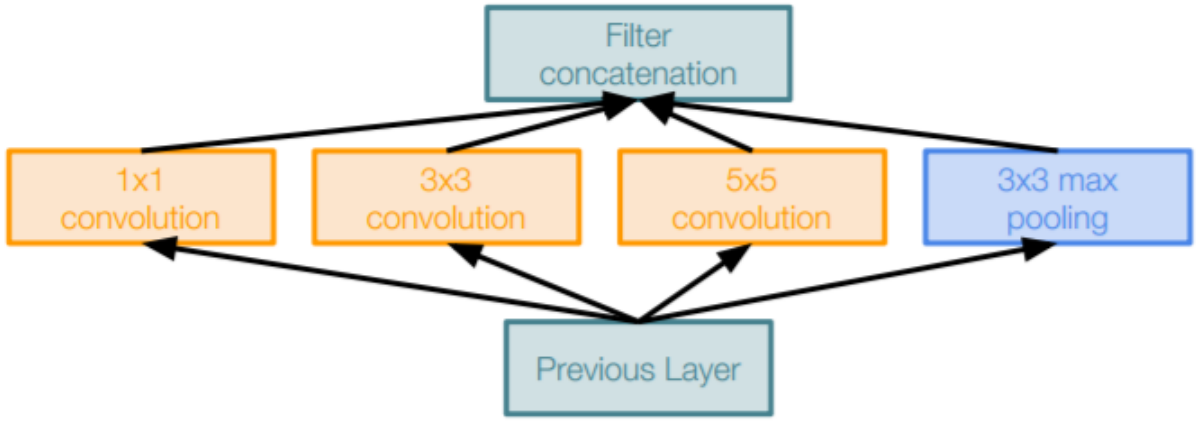


Naive Inception module



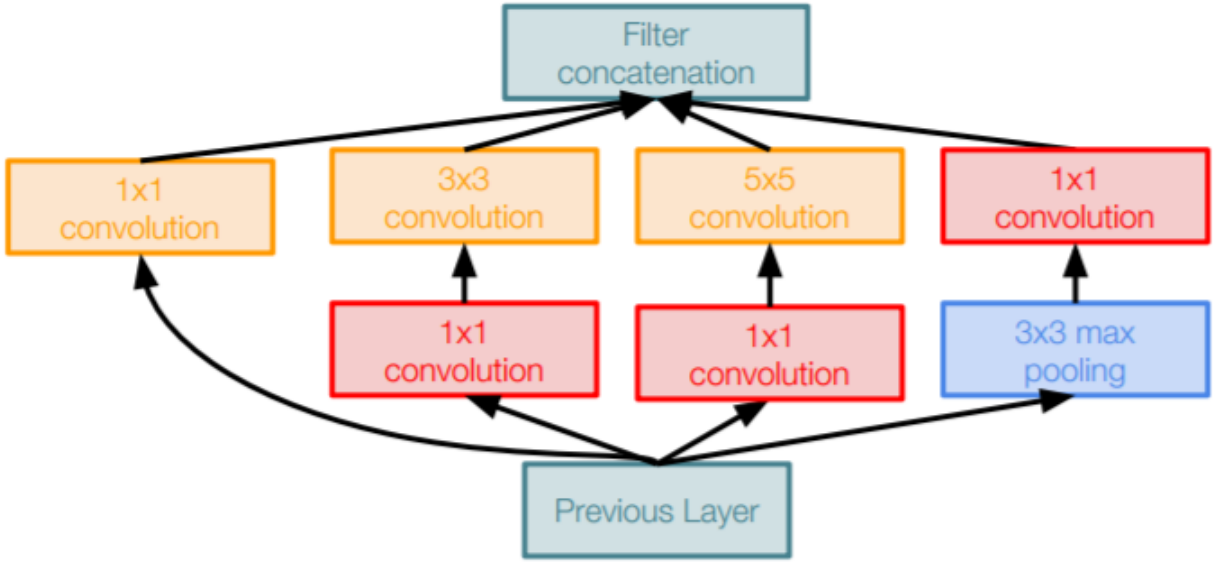
Inception module with dimension reduction

Case Study: GoogLeNet



Naive Inception module

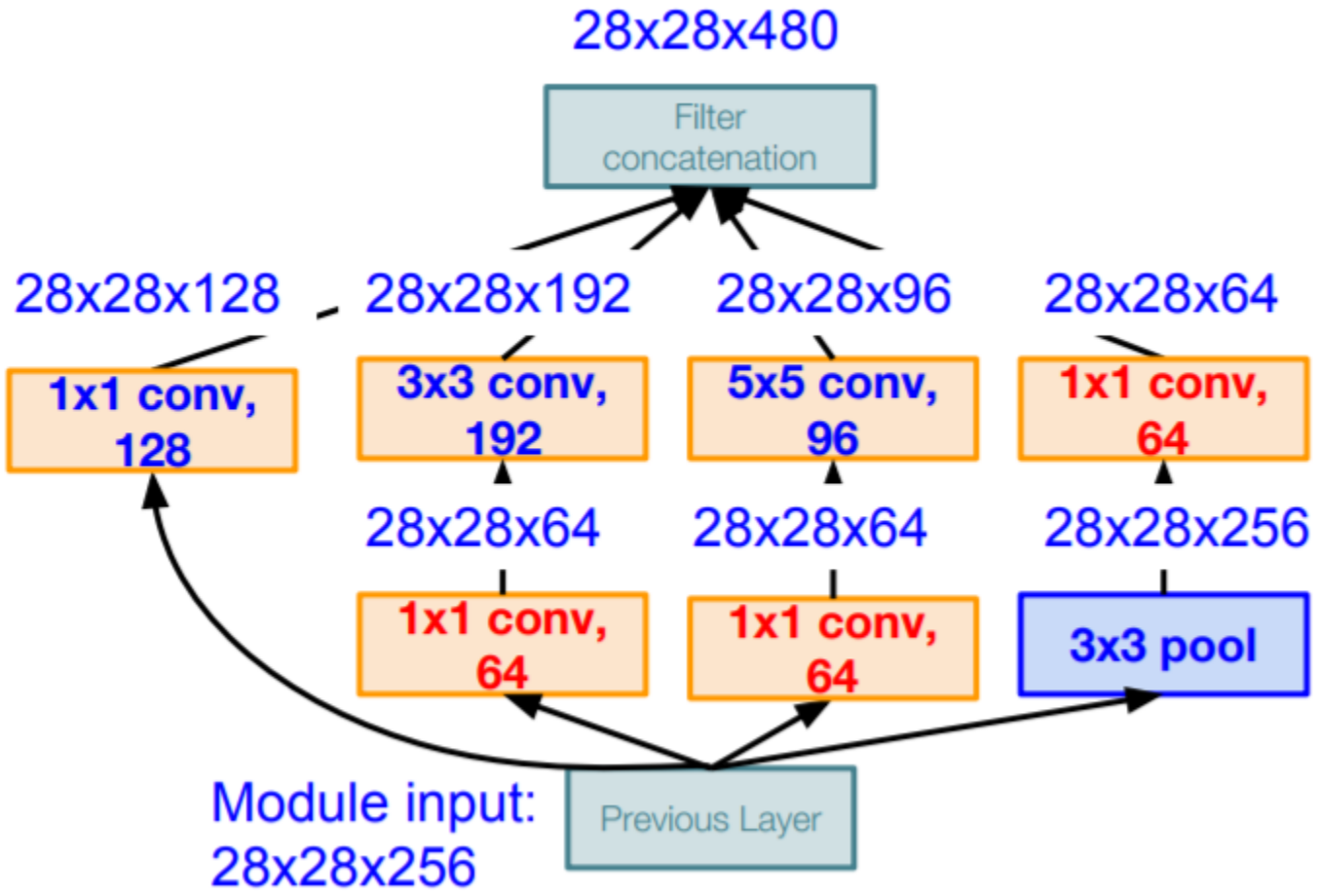
1x1 conv "bottleneck" layers



Inception module with dimension reduction

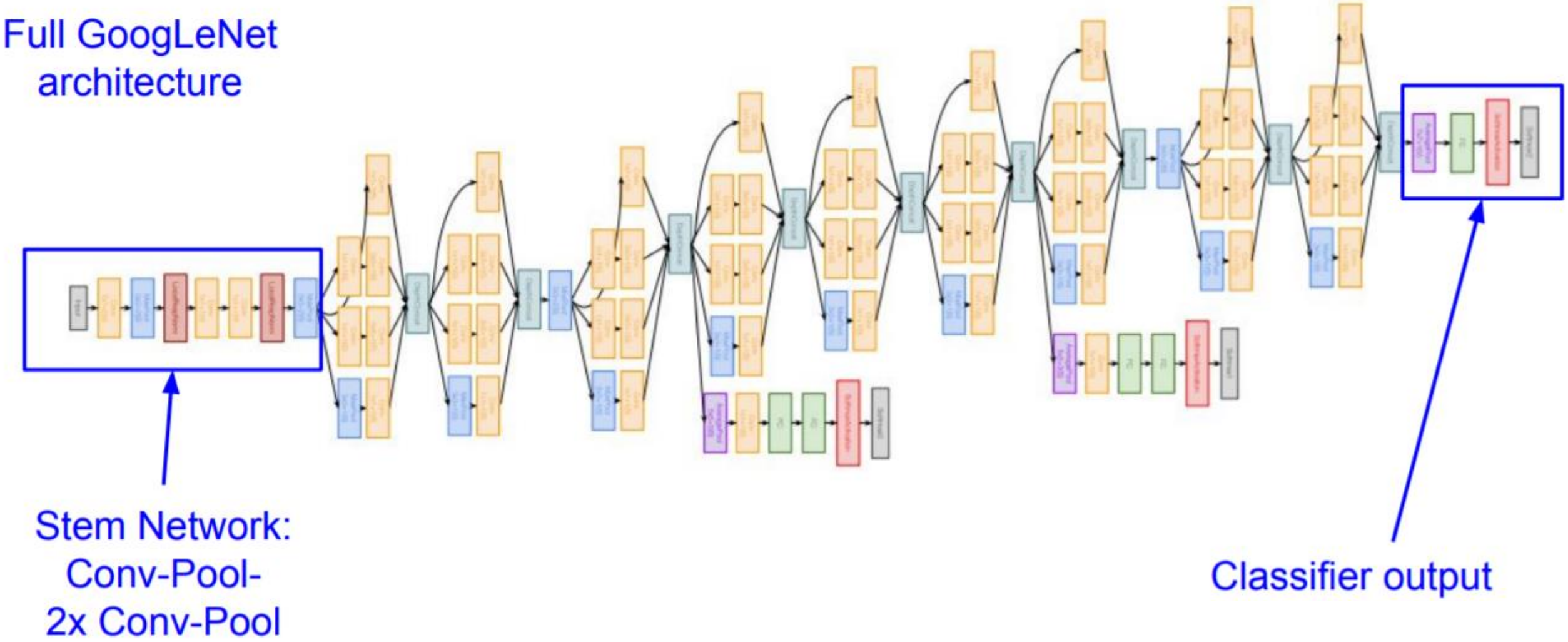
Case Study: GoogLeNet

- 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



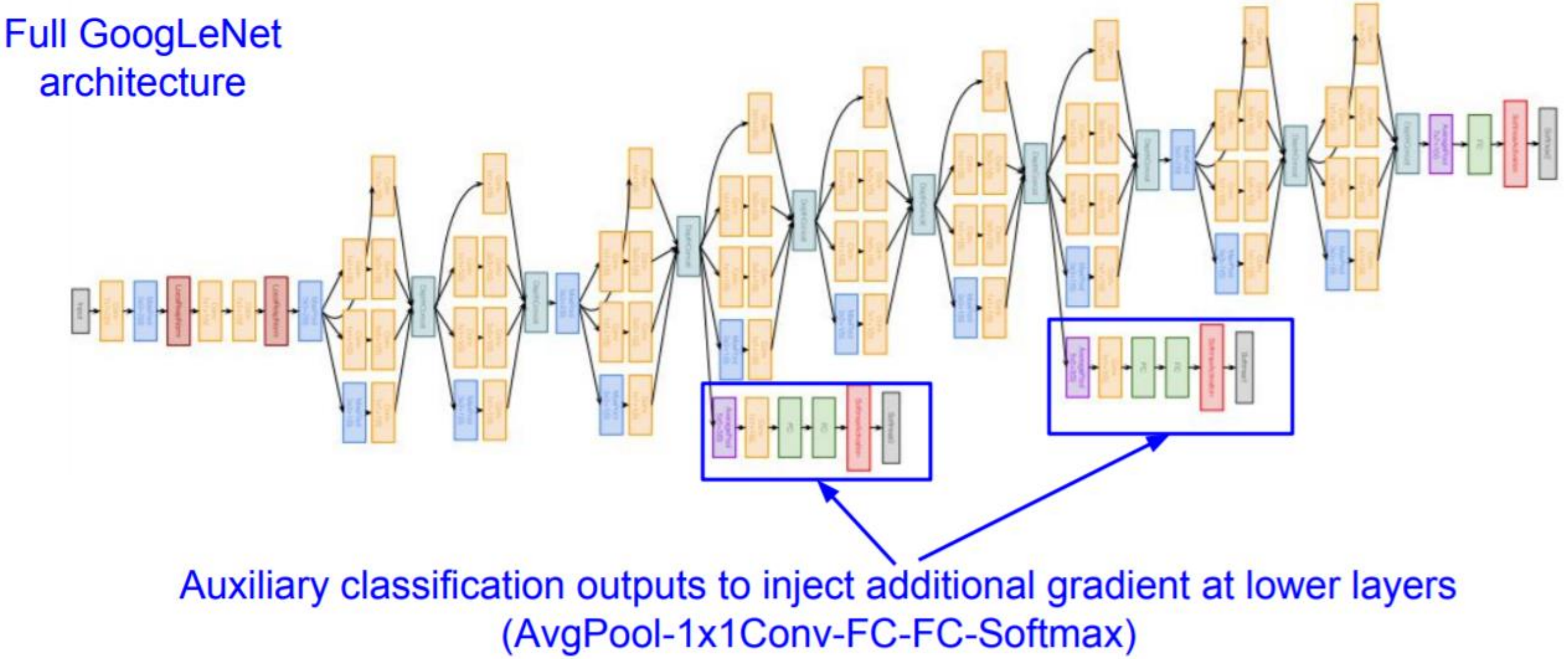
Case Study: GoogLeNet

[Szegedy et al., 2014]



Case Study: GoogLeNet

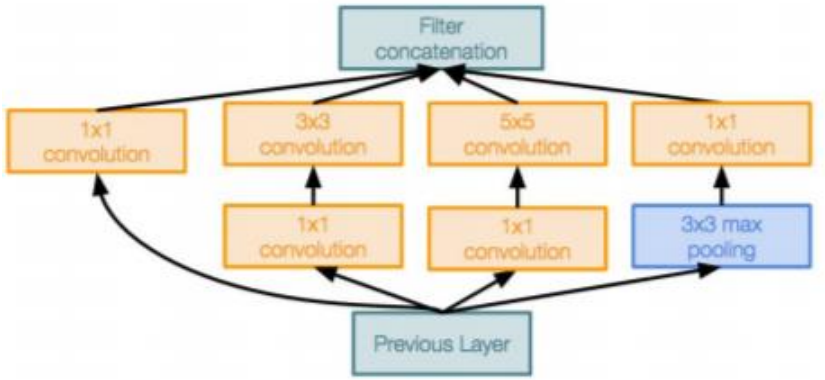
[Szegedy et al., 2014]



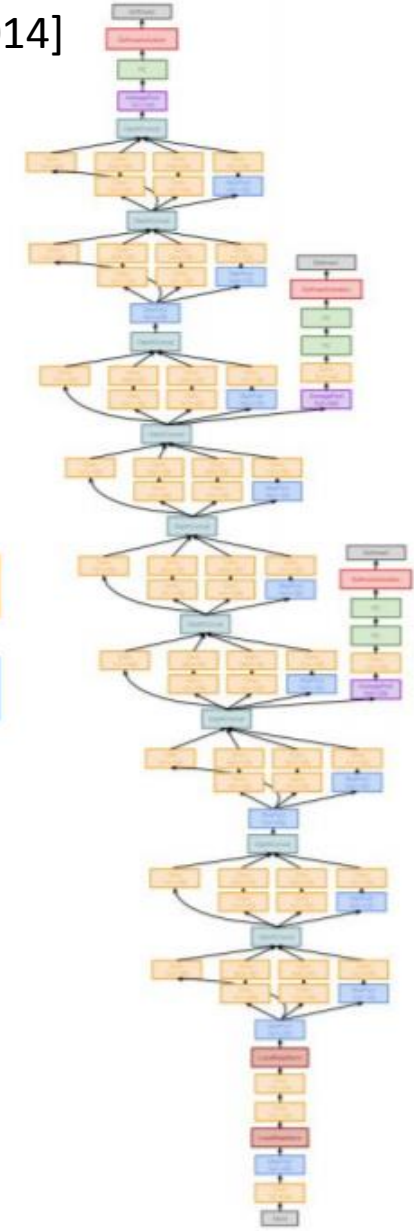
Case Study: GoogLeNet

[Szegedy et al., 2014]

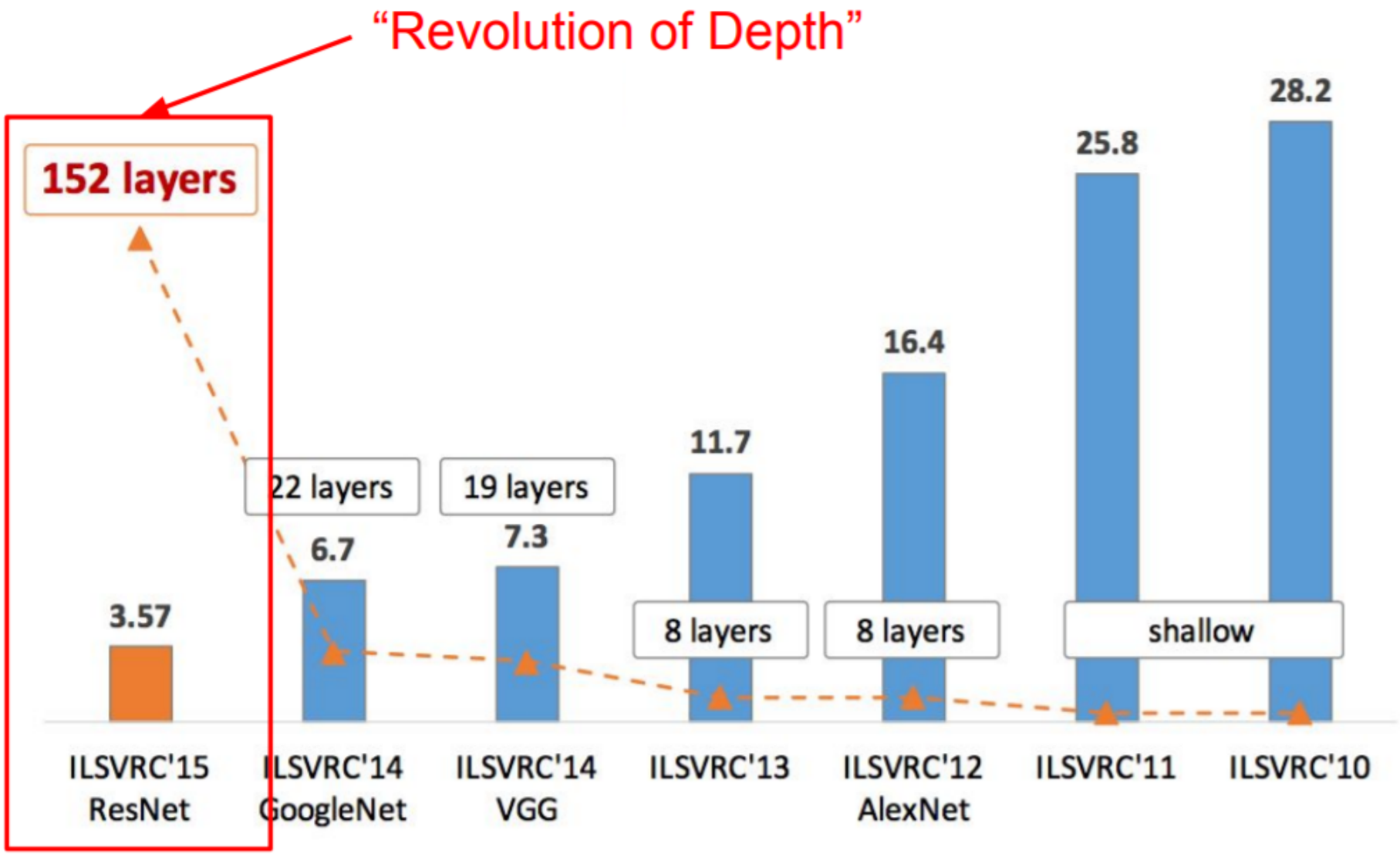
- Deeper networks, with computation
  - 22 layers
  - Efficient “Inception” module
  - No FC layers
  - Only 5 million parameters!
    - 12x less than AlexNet
  - ILSVRC’14 classification winner (6.7% top 5 error)



Inception module



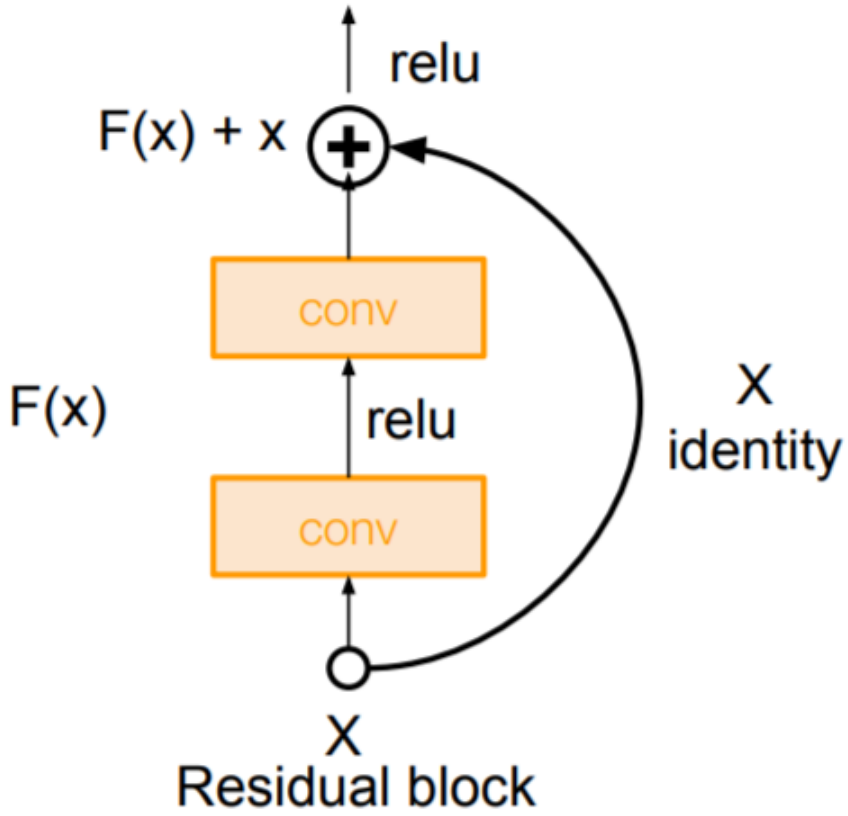
ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

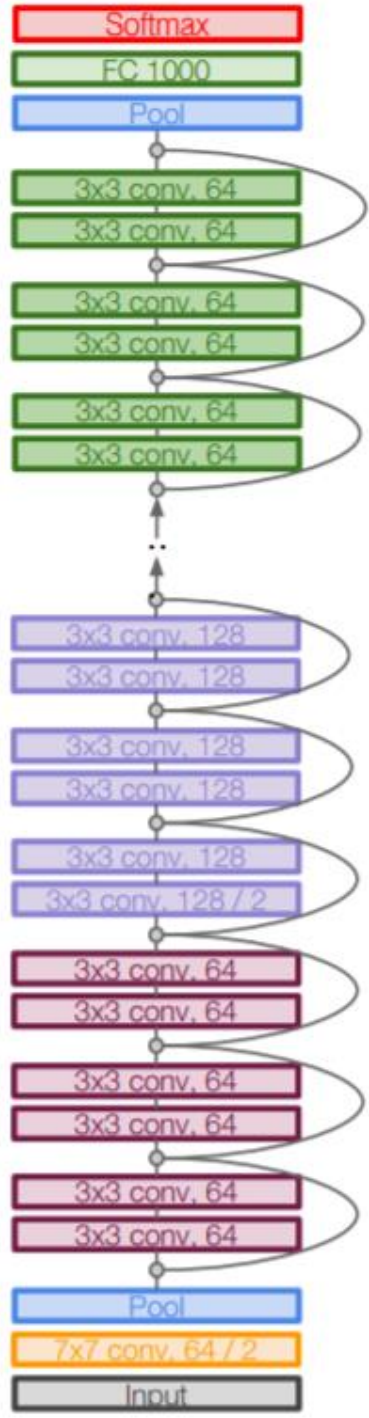


Case Study: ResNet

[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!

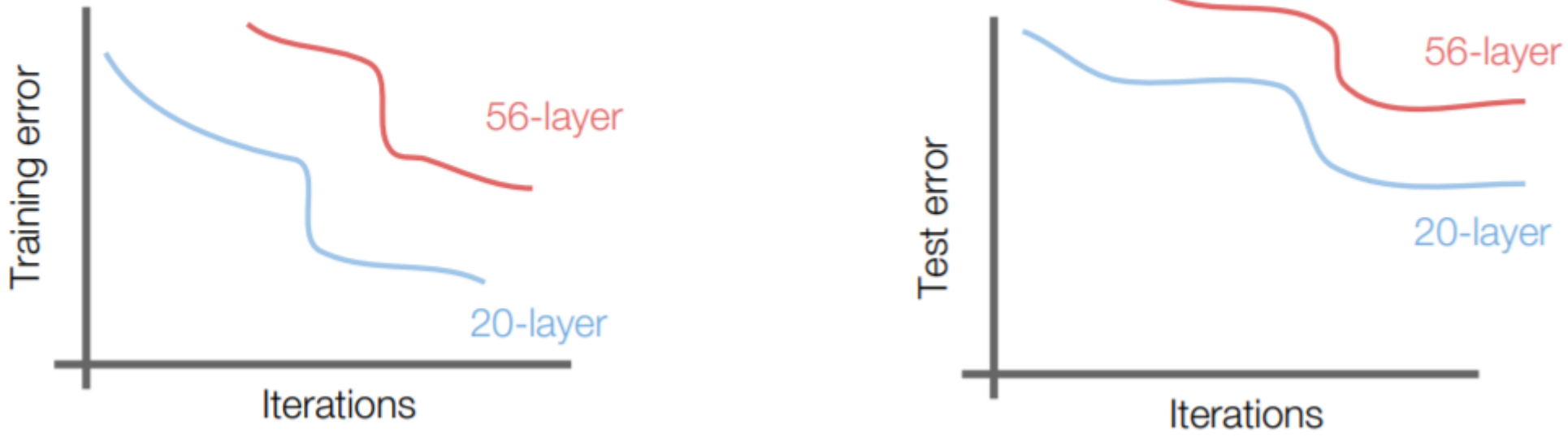




Case Study: ResNet

[He et al., 2015]

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

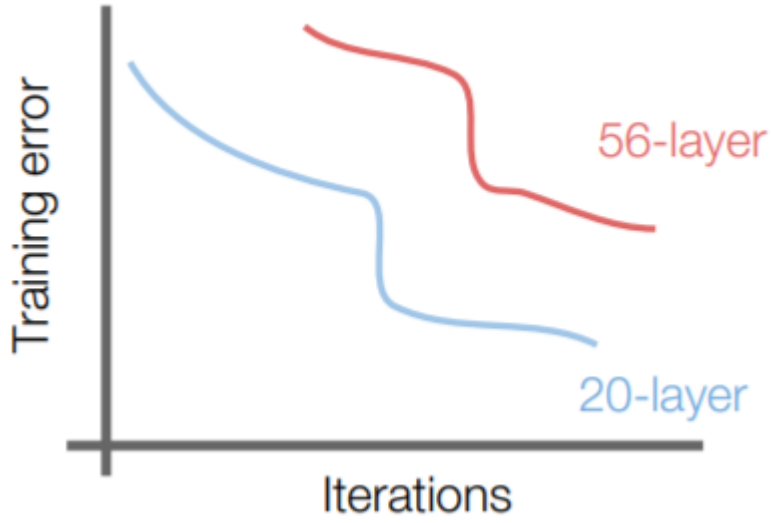


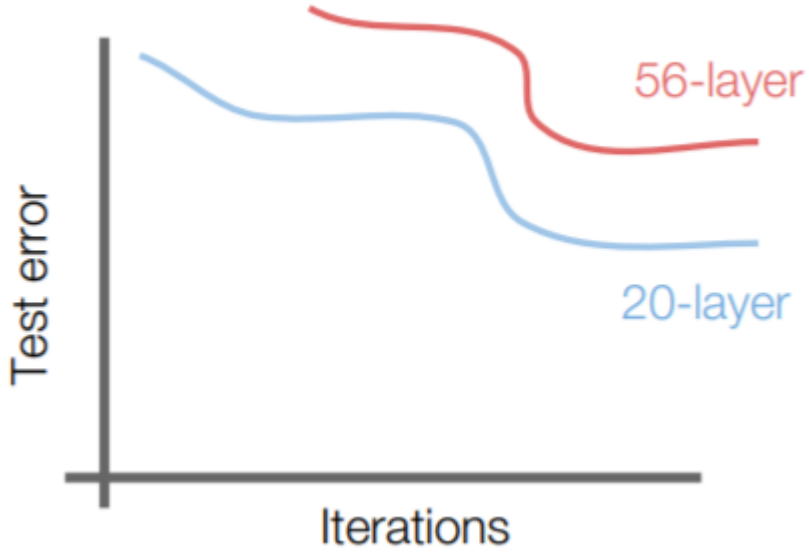
- Q: What’s strange about these training and test curves?

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
  - A deeper model should not have higher training error
  - The deeper model performs worse, but it's not caused by overfitting!

Case Study: ResNet

[He et al., 2015]

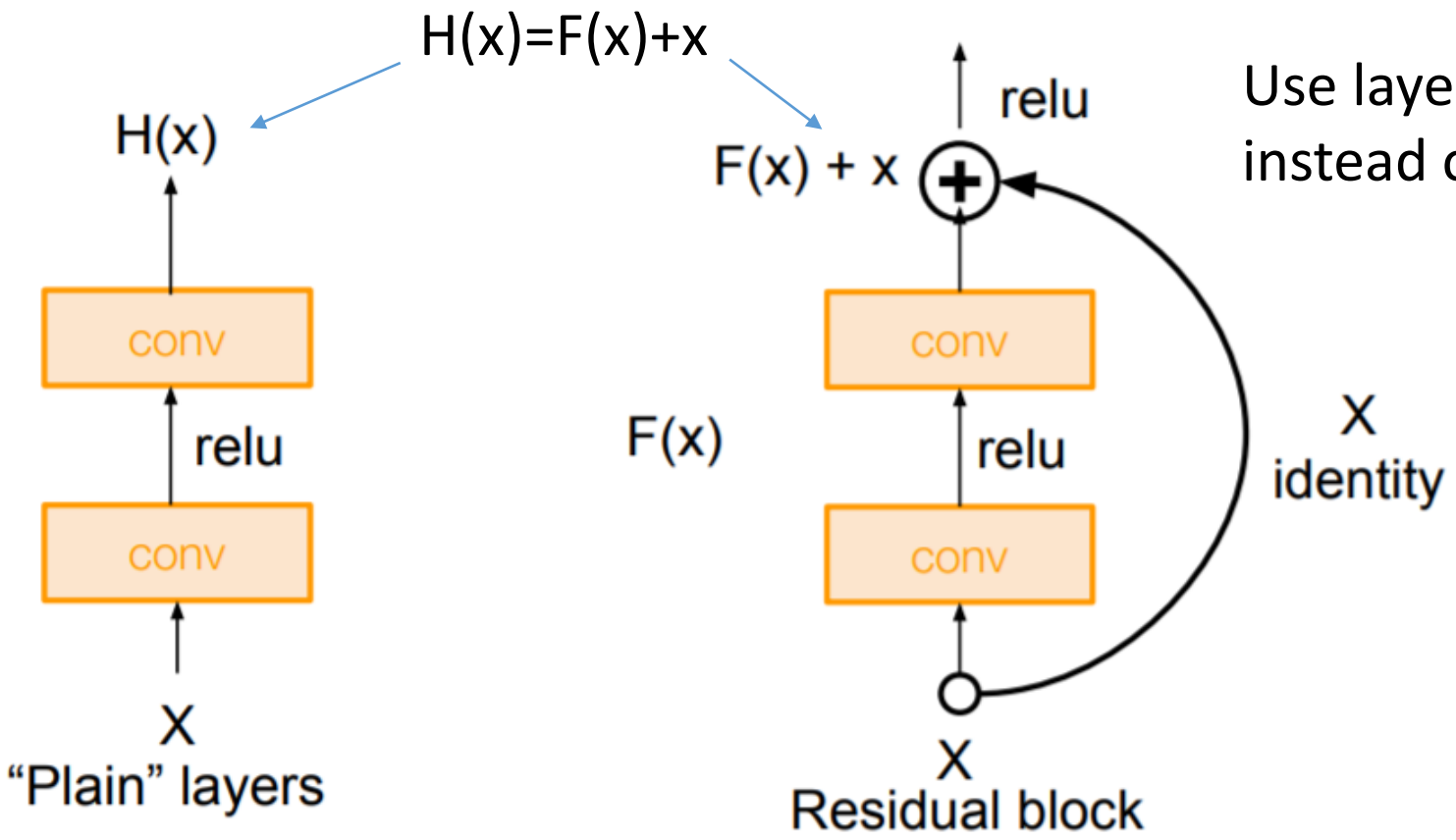
- Hypothesis: the problem is an optimization problem, deeper models are harder to optimize

- 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 et al., 2015]

- Solution: Use network layers to fit a residual mapping F(x) instead of directly trying to fit a desired underlying mapping H(x)

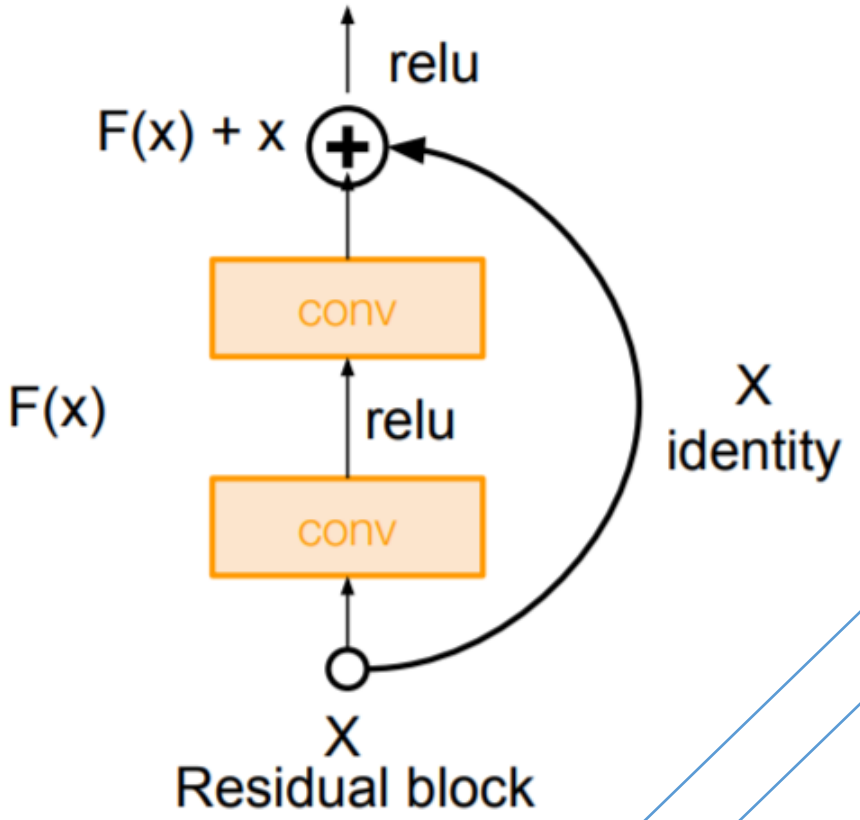


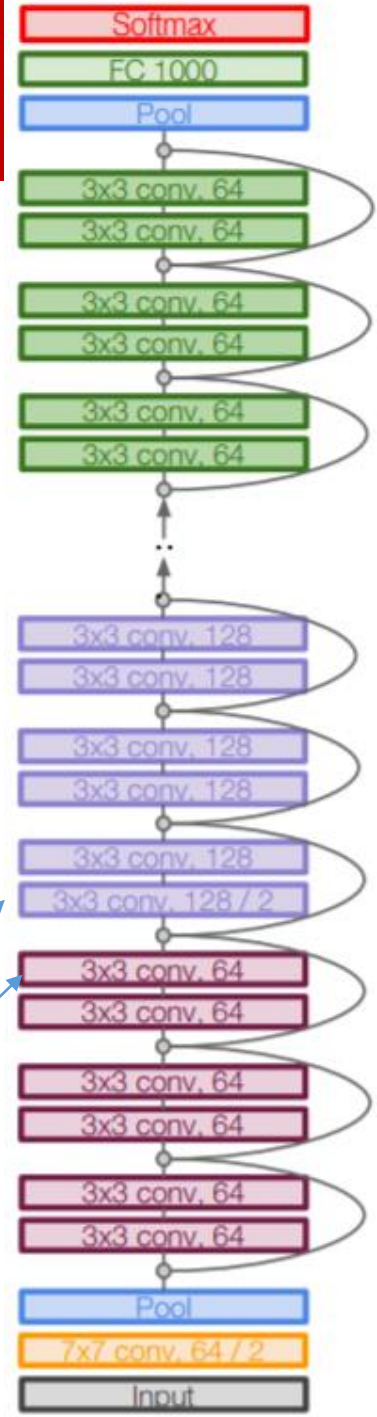
Use layers to fit residual F(x) = H(x) - x instead of H(x) directly

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)





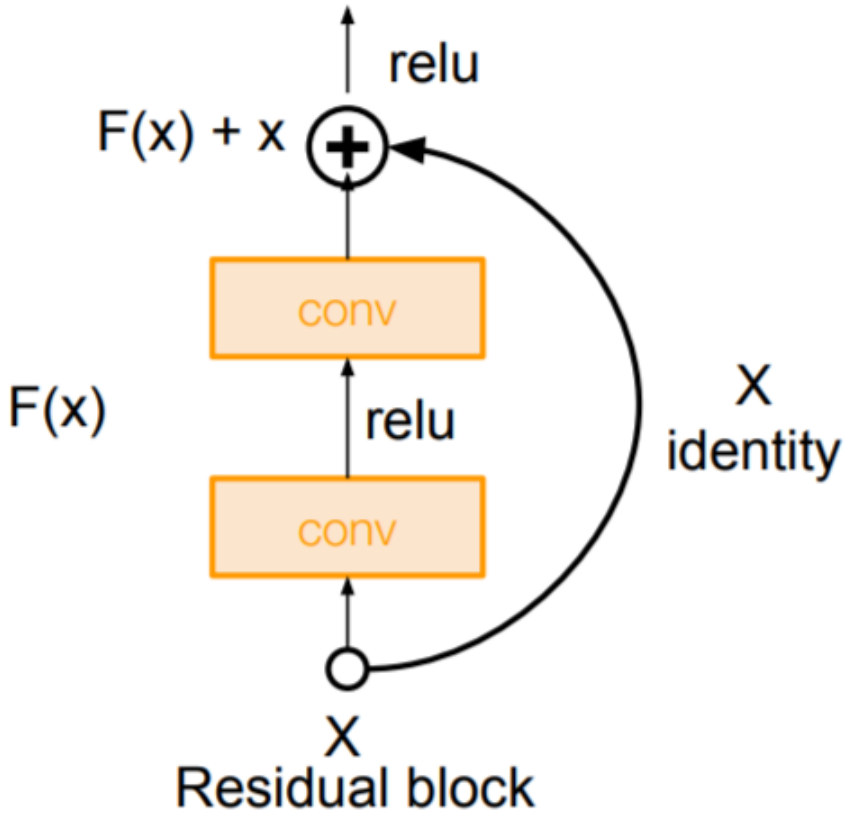
128 filters, spatially with stride 2

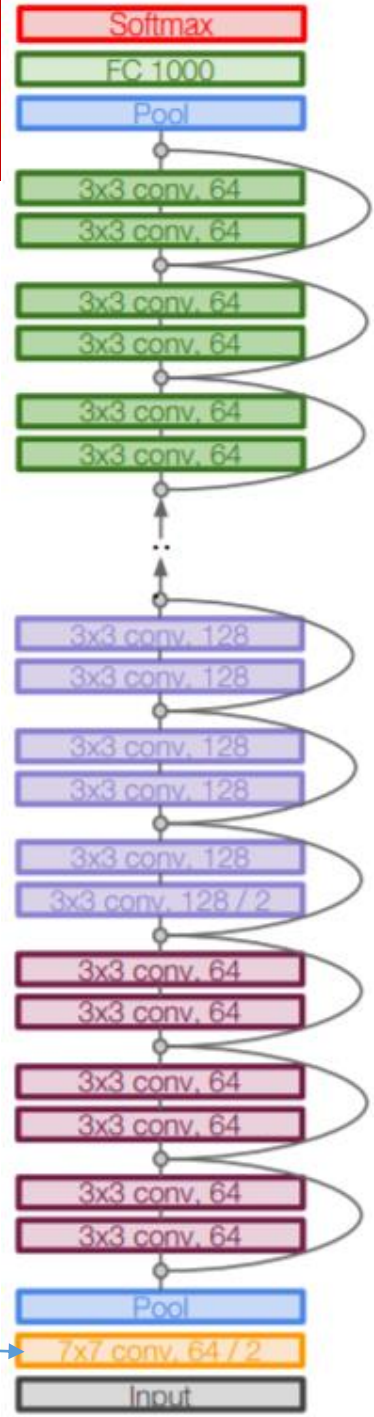
64 filters, spatially with stride 1

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





Beginning conv layer

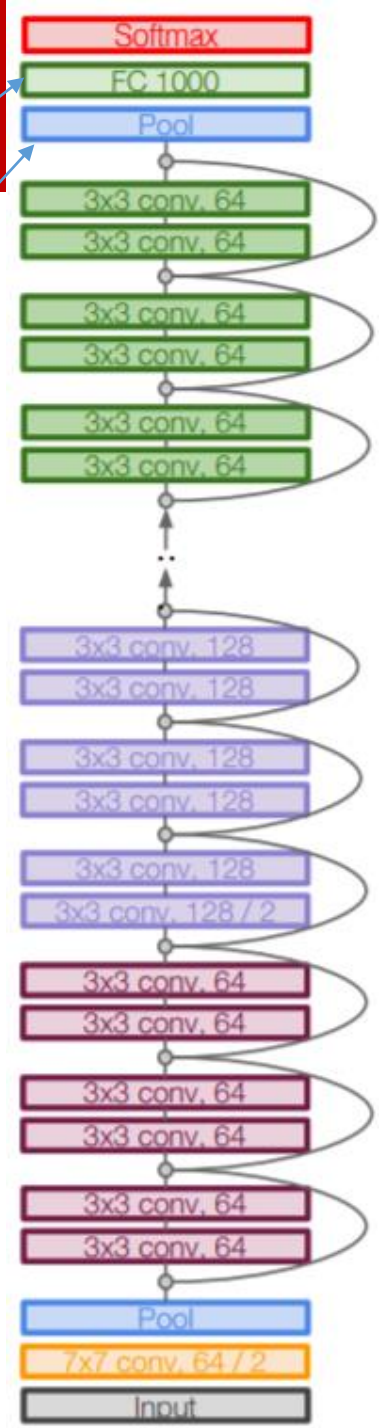
Case Study: ResNet

- 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)

[He et al., 2015]

No FC layers besides
FC 1000 to output classes

Global average pooling
layer after last conv layer

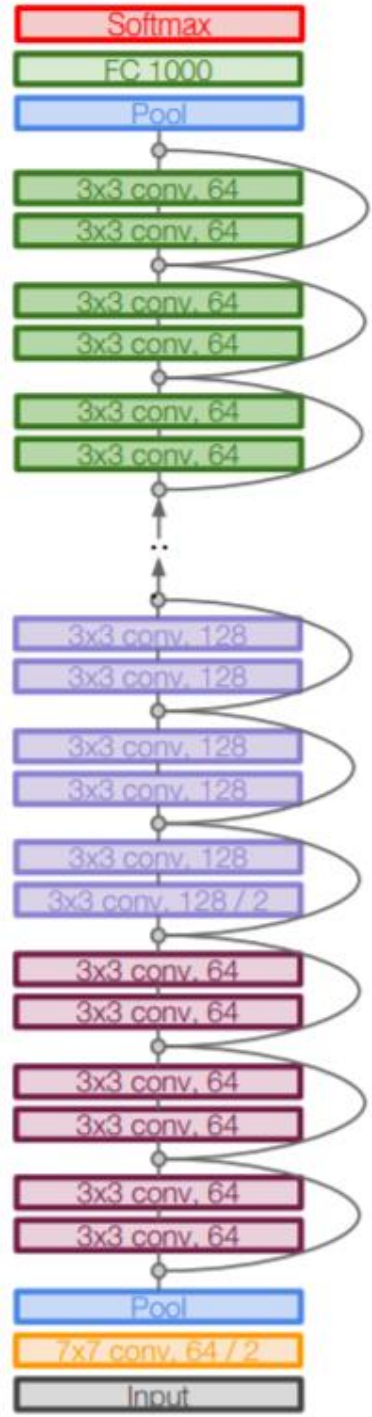


Case Study: ResNet

[He et al., 2015]

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

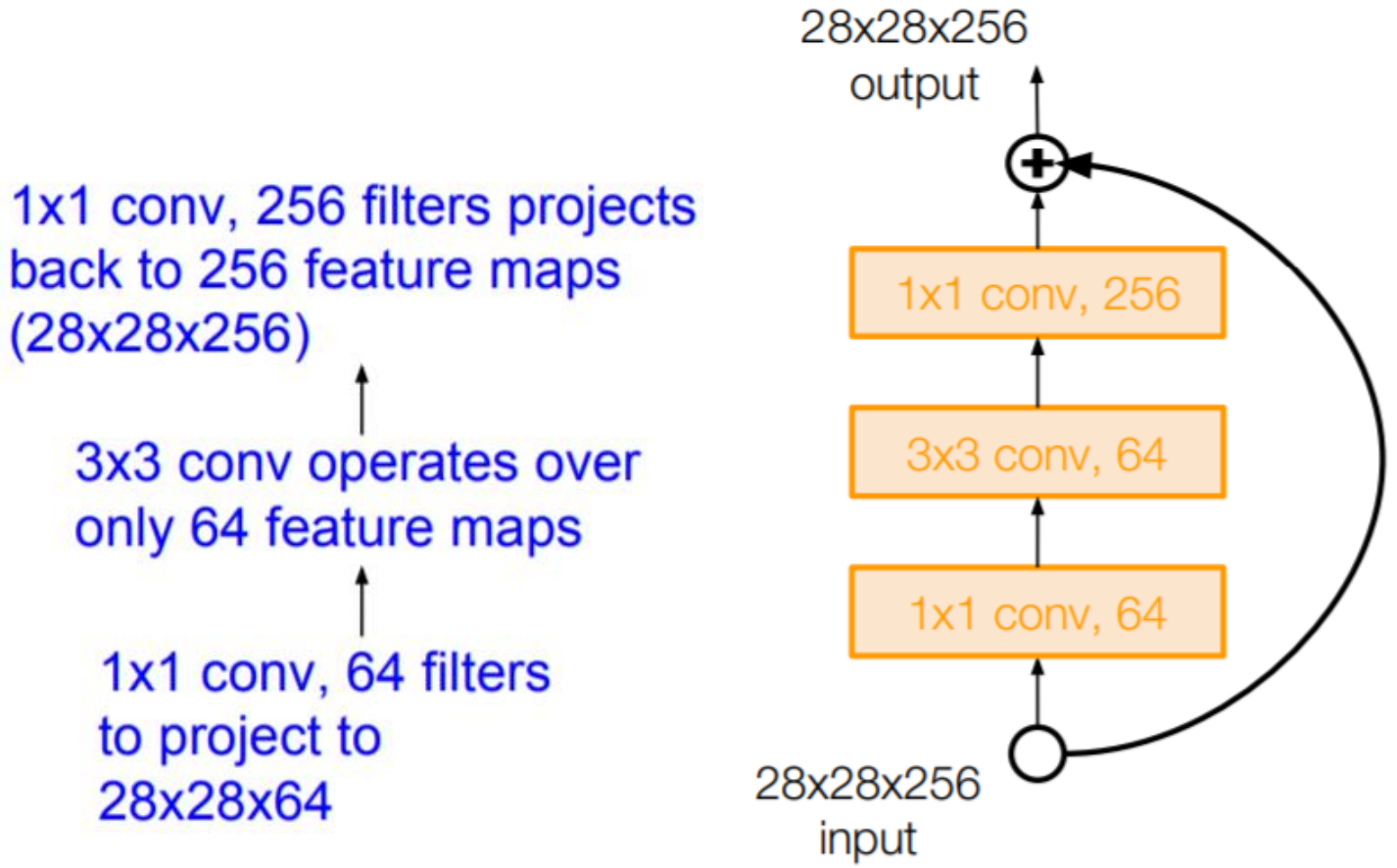
Total depths of 34, 50, 101, or 152 layers for ImageNet



Case Study: ResNet

[He et al., 2015]

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

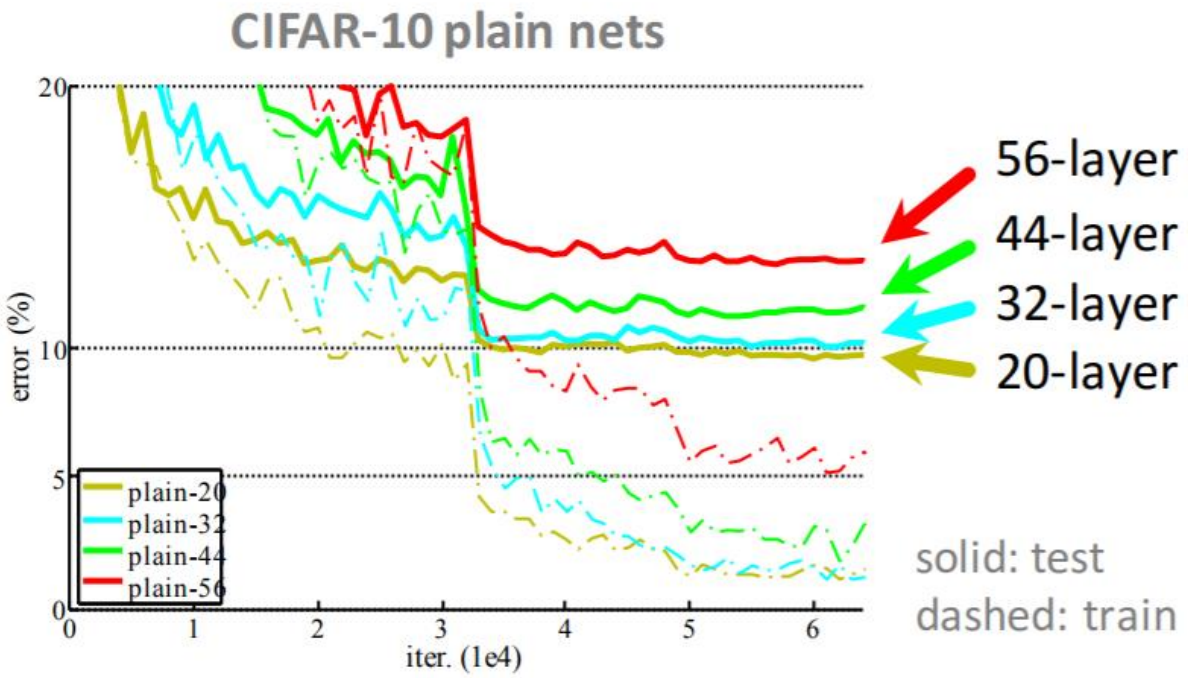


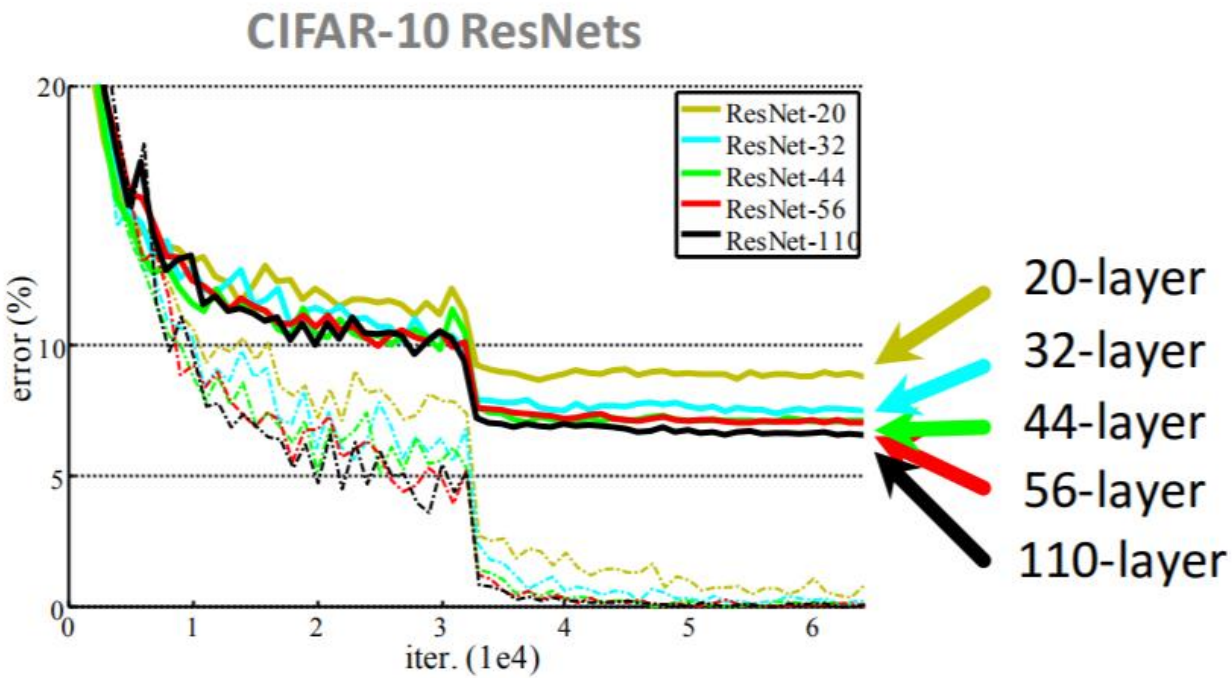
Case Study: ResNet

[He et al., 2015]

- 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

ResNet: CIFAR-10 experiments

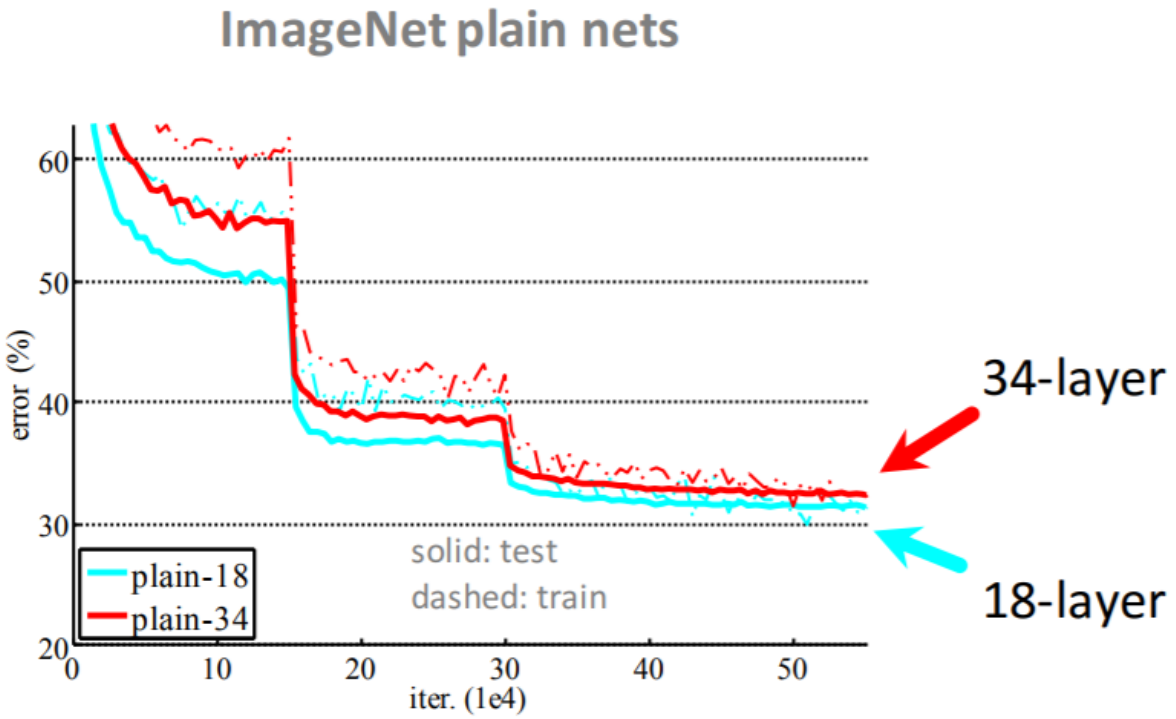


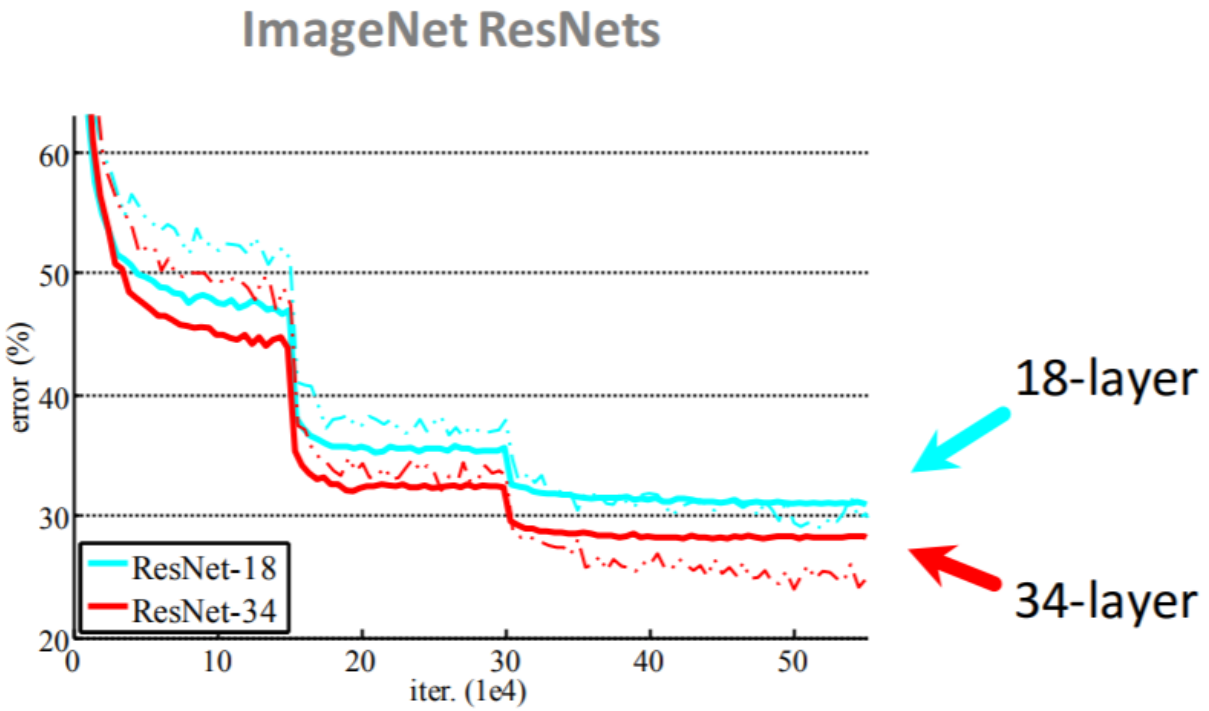


- Deeper ResNets have lower training error, and also lower test error
  - Not explicitly address generalization, but deeper+thinner shows good generalization

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

ResNet: ImageNet experiments





Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Case Study: ResNet

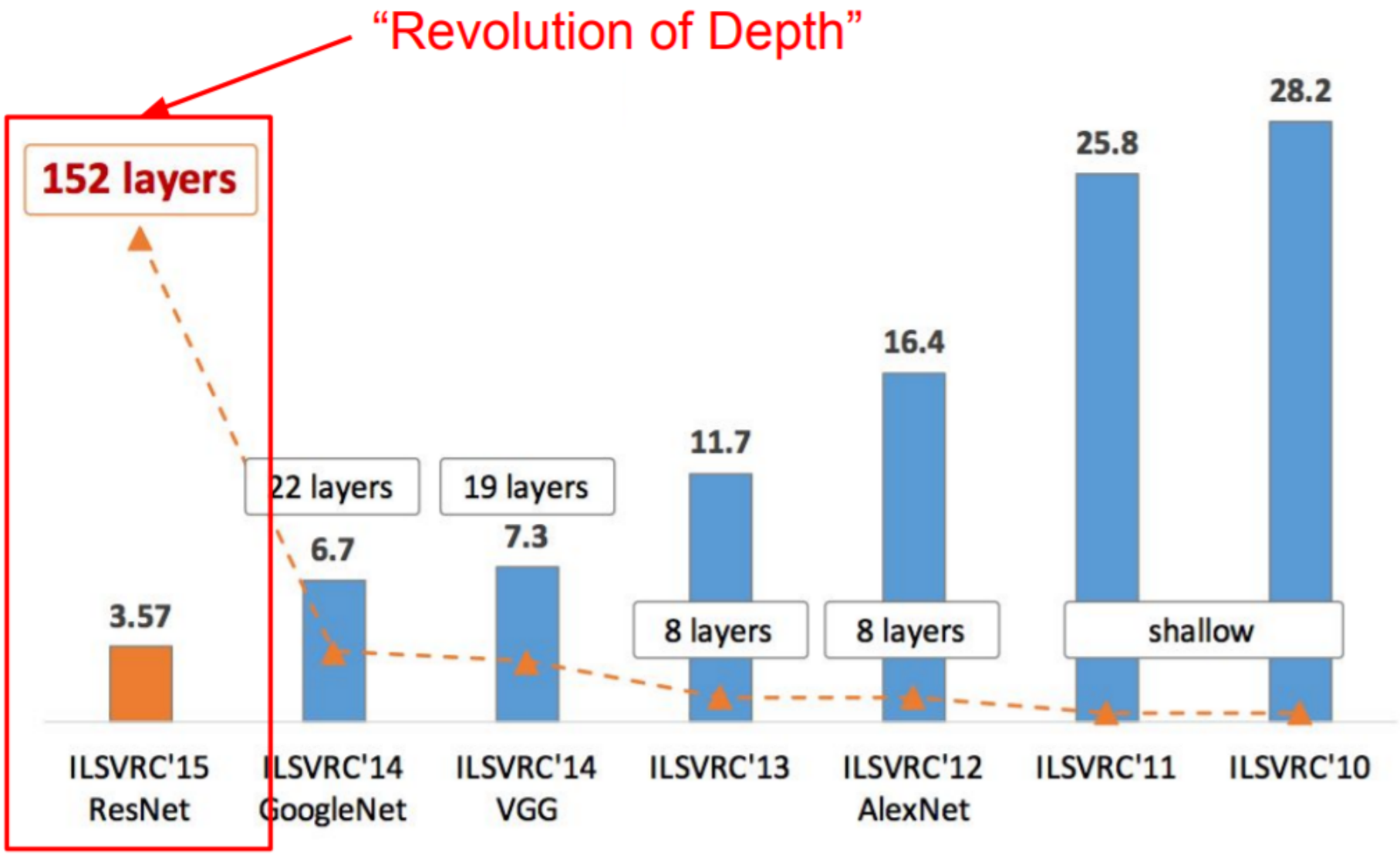
[He et al., 2015]

- 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

ILSVRC 2015 classification winner (3.6% top 5 error)

better than "human performance"! (Russakovsky 2014)

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

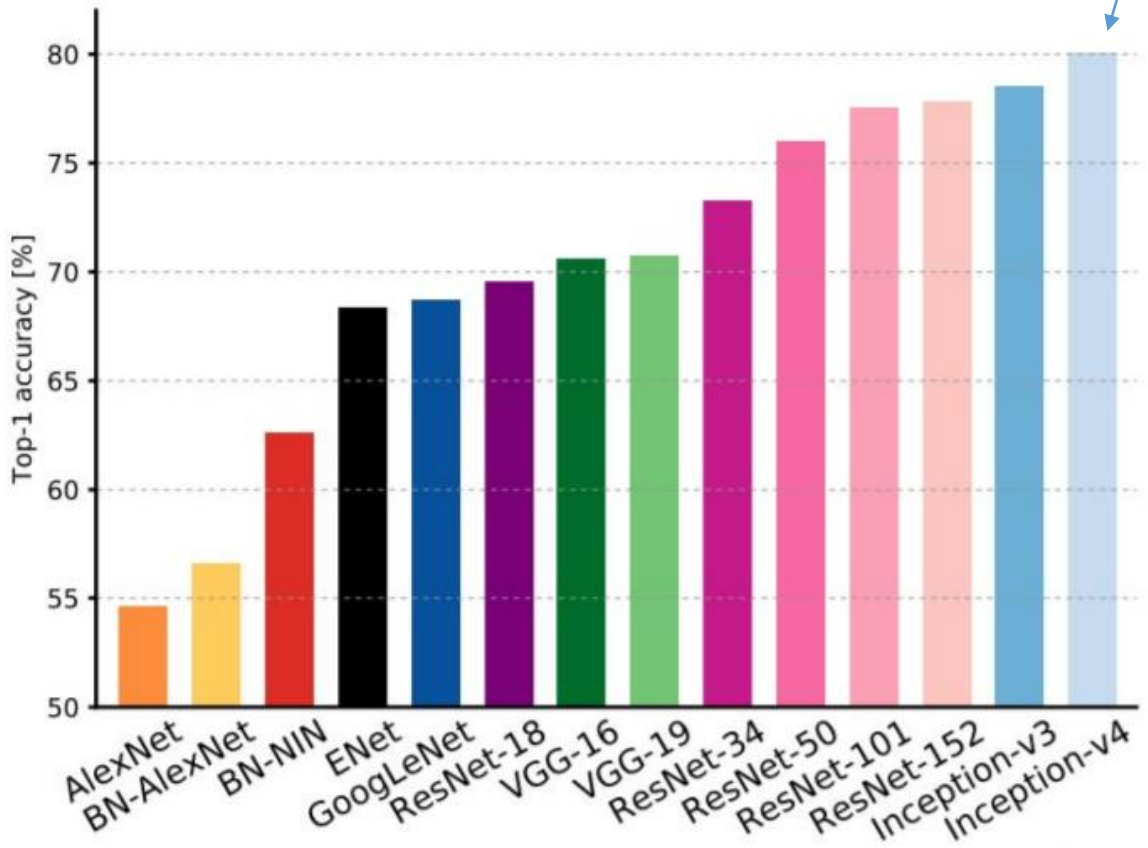


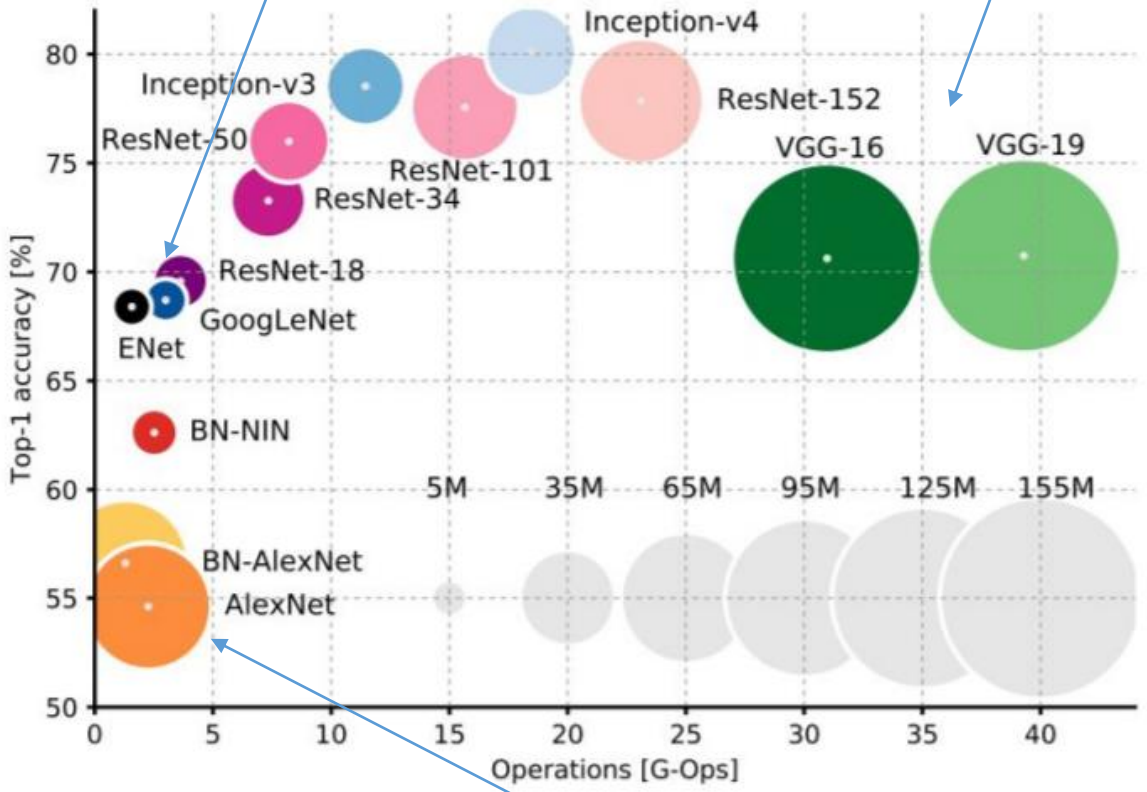
Comparing complexity

Inception-v4: Resnet + Inception!

GoogLeNet: most efficient

VGG: Highest memory, most operations





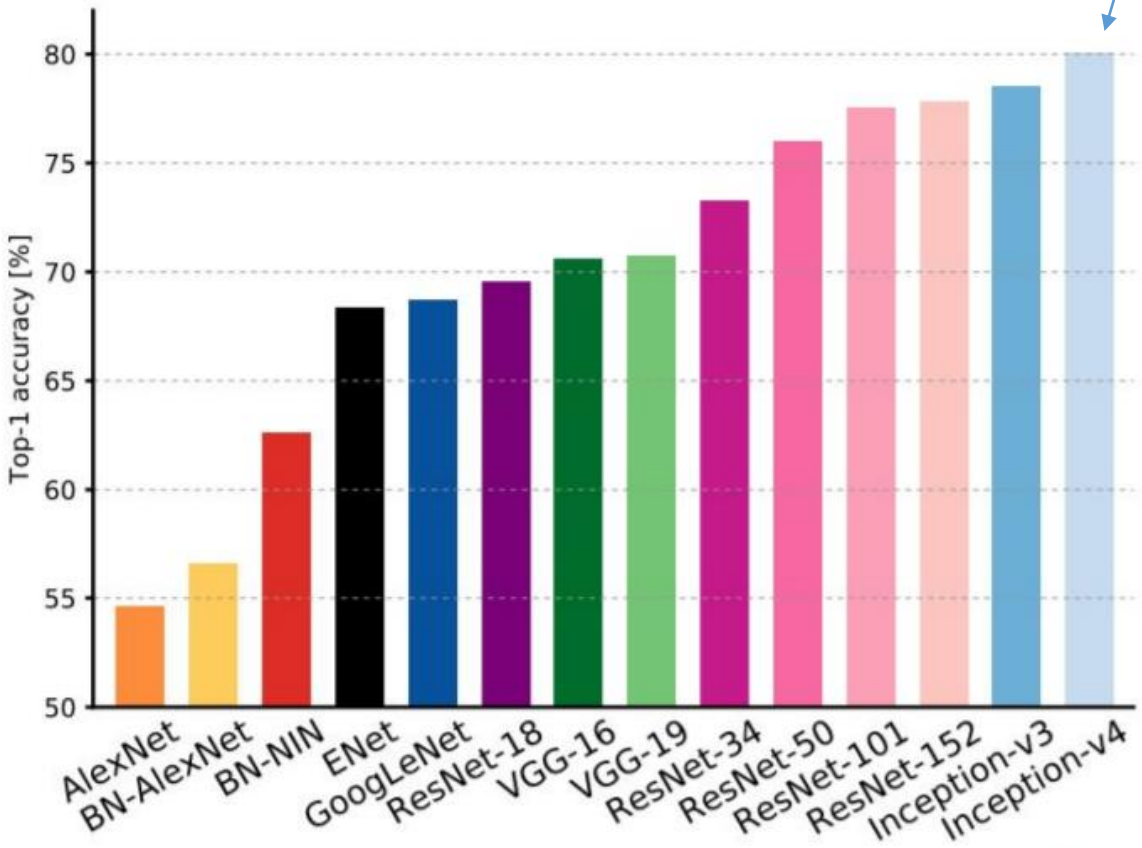
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

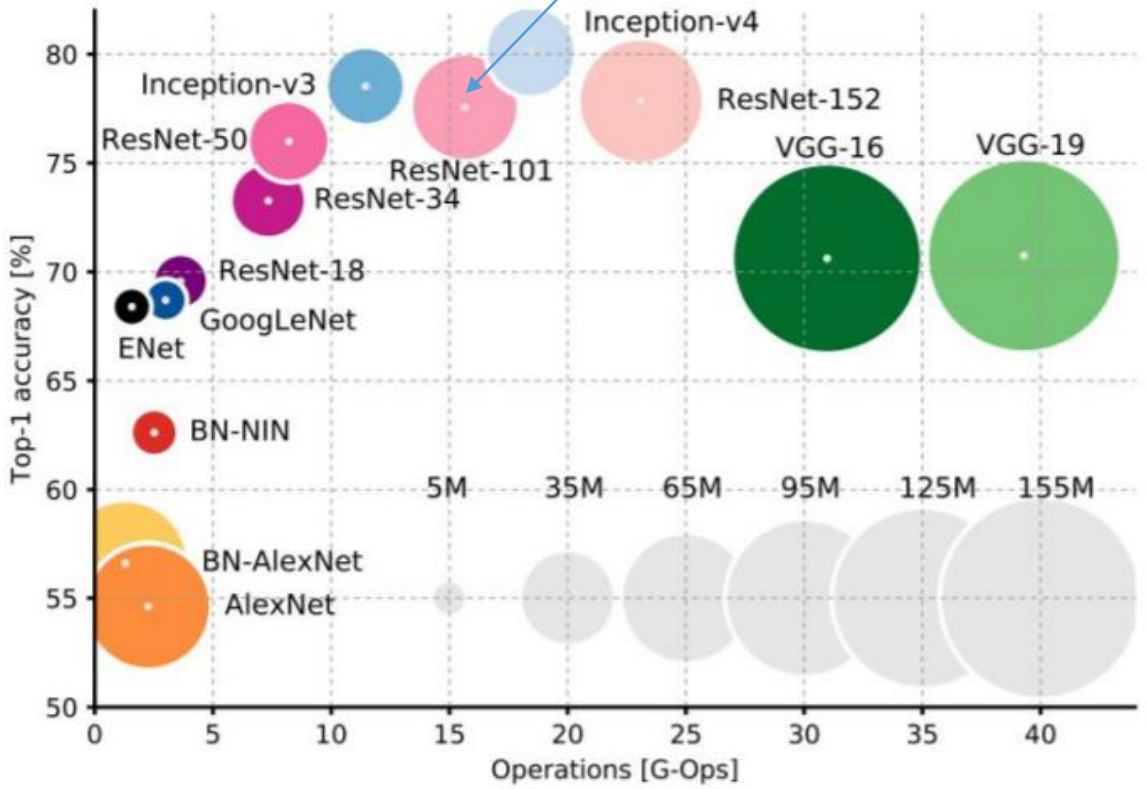
AlexNet: Smaller ops, still memory heavy, lower accuracy

Comparing complexity

Inception-v4: Resnet + Inception!

ResNet: Moderate efficiency depending on model, highest accuracy





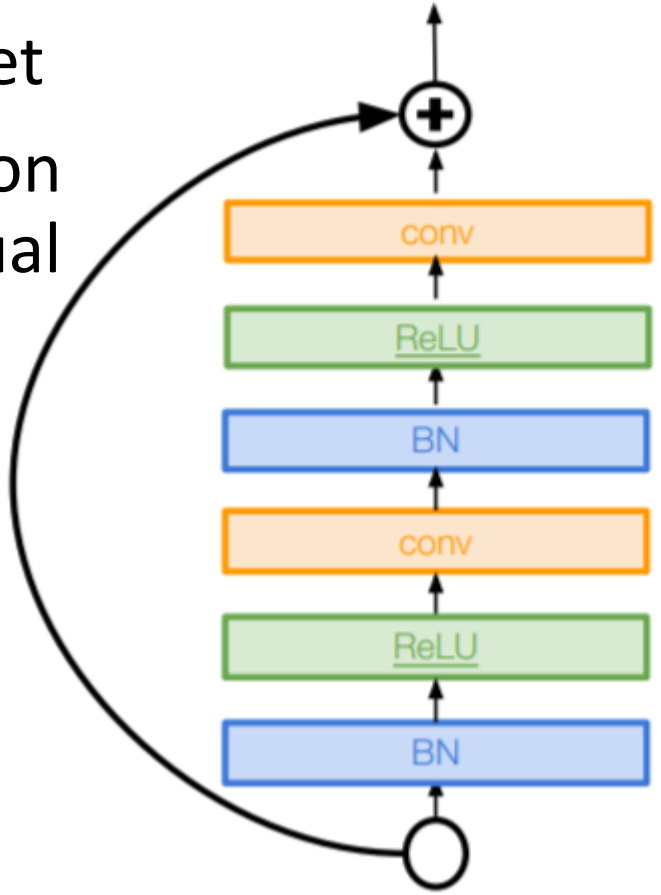
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Improving ResNets...

[He et al. 2016]

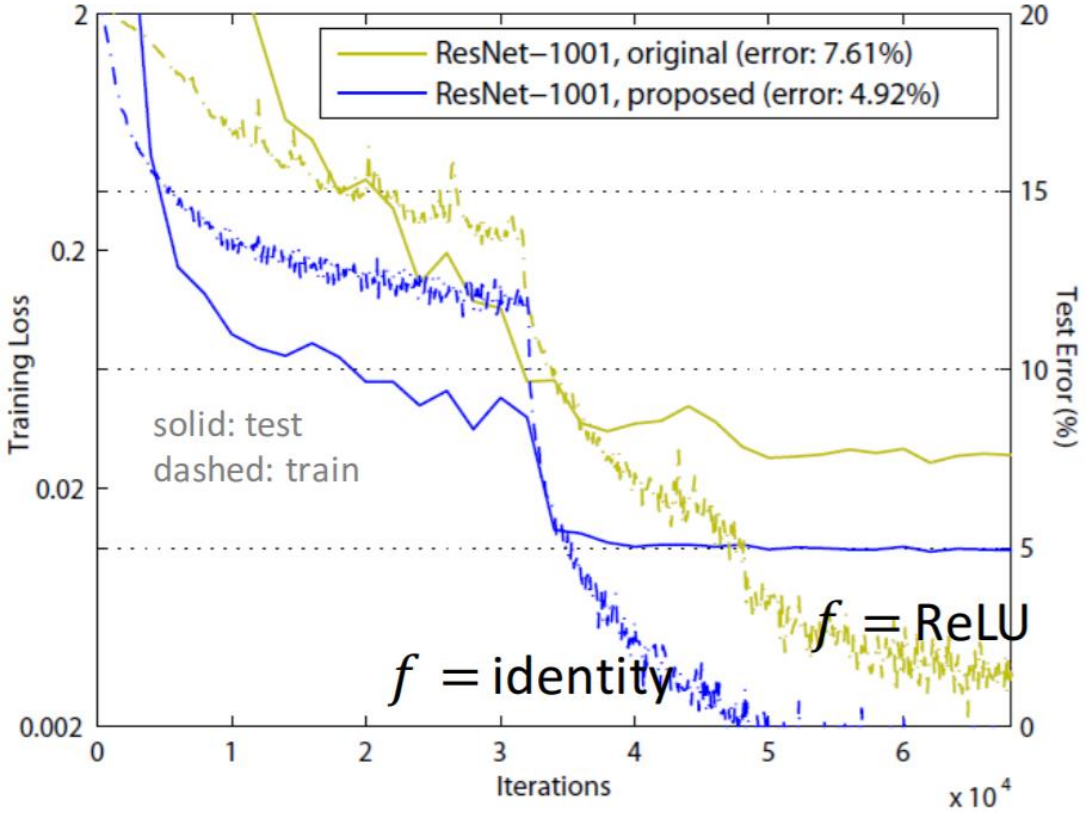
Identity Mappings in Deep Residual Networks

- 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

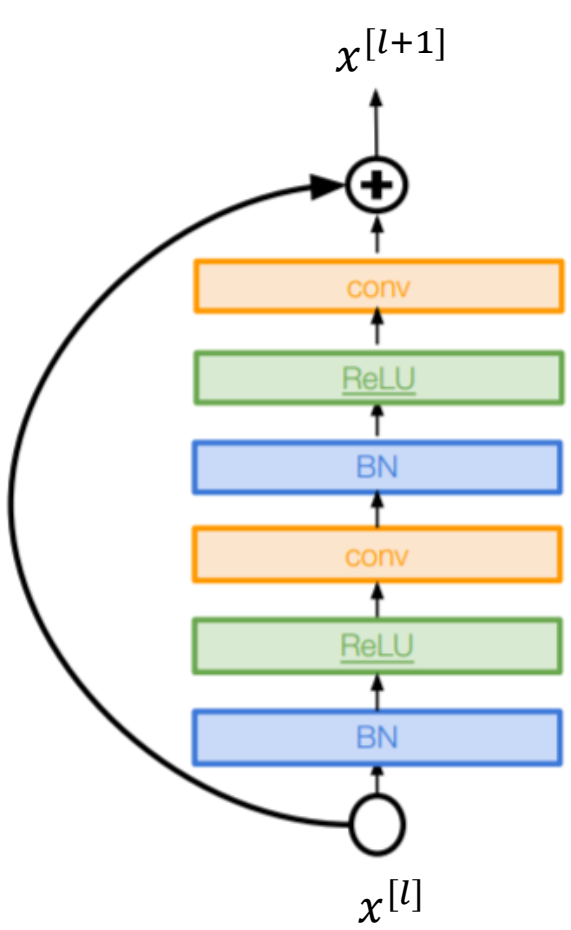


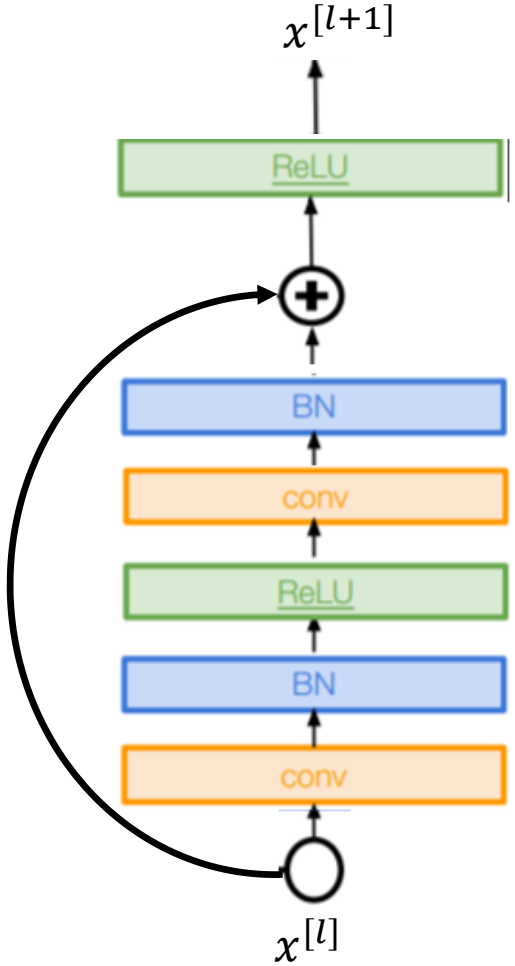
Improving ResNets...

- **Identity Mappings in Deep Residual Networks**



ReLU could block back prop for very deep networks



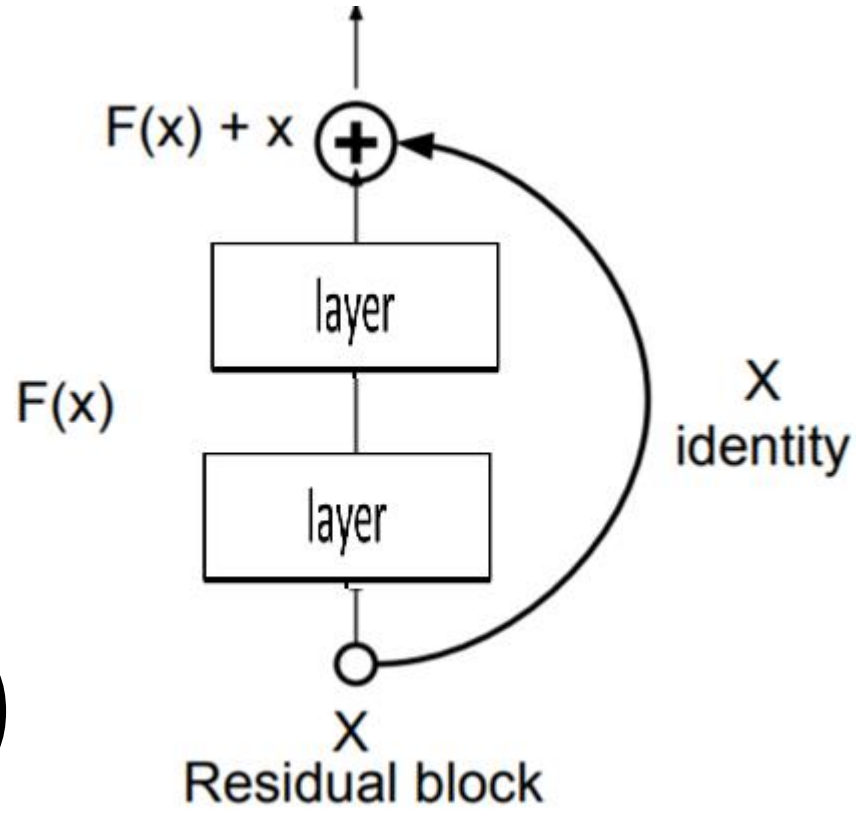


Pre-activation ResNet

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Backprop on ResNet

$$x^{[l+1]} = x^{[l]} + F\left(x^{[l]}\right)$$
$$x^{[l+2]} = x^{[l+1]} + F\left(x^{[l+1]}\right)$$
$$x^{[l+2]} = x^{[l]} + F\left(x^{[l]}\right) + F\left(x^{[l+1]}\right)$$
$$x^{[L]} = x^{[l]} + \sum_{i=l}^{L-1} F\left(x^{[i]}\right)$$



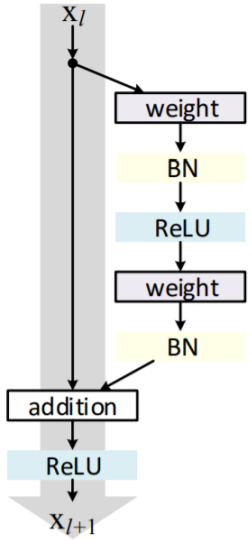
$$\frac{\partial E}{\partial x^{[l]}} = \frac{\partial E}{\partial x^{[L]}}\frac{\partial x^{[L]}}{\partial x^{[l]}} = \frac{\partial E}{\partial x^{[L]}}\left(1 + \frac{\partial}{\partial x^{[l]}}\sum_{i=l}^{L-1} F\left(x^{[i]}\right)\right)$$

Any $\frac{\partial E}{\partial x^{[L]}}$ is **directly back-prop** to any $\frac{\partial E}{\partial x^{[l]}}$, plus residual.

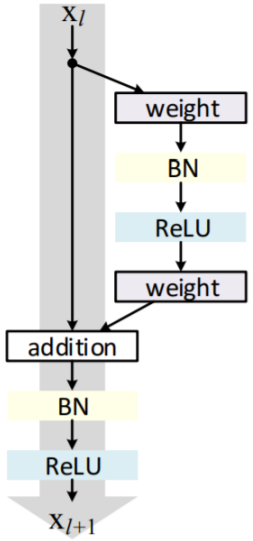
Any $\frac{\partial E}{\partial x^{[l]}}$ is **additive**; unlikely to vanish.

Pre-activation ResNet outperforms other ones

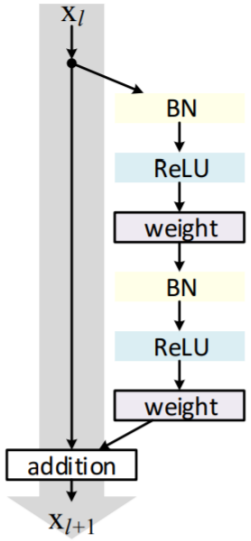
- Keep the shortcut path as smooth as possible



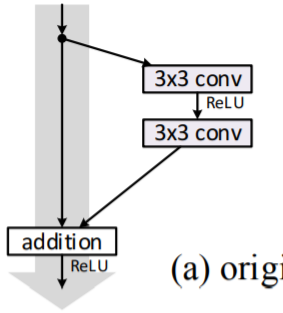
f is ReLU
(original ResNet)



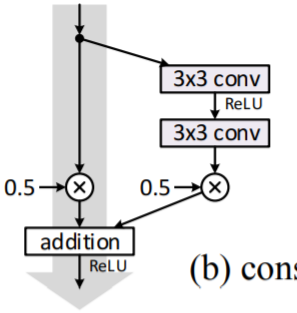
f is BN+ReLU



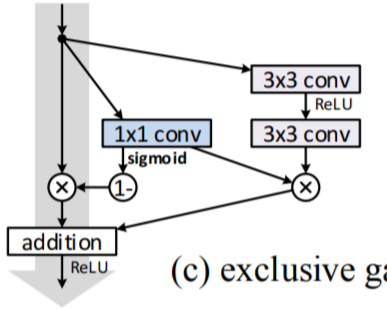
f is identity
(**pre-activation** ResNet)



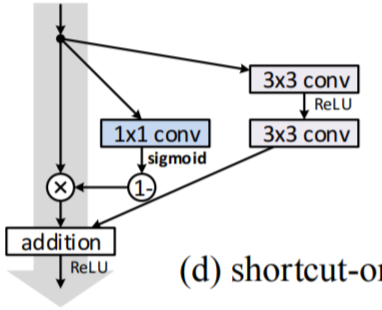
(a) original



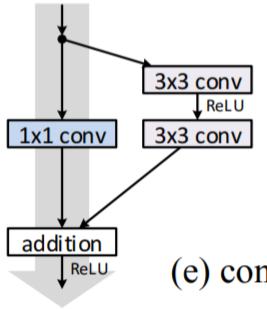
(b) constant scaling



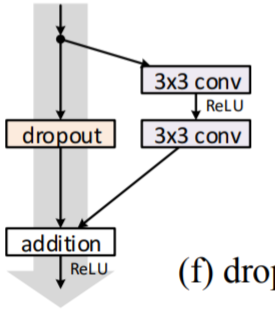
(c) exclusive gating



(d) shortcut-only gating



(e) conv shortcut



(f) dropout shortcut

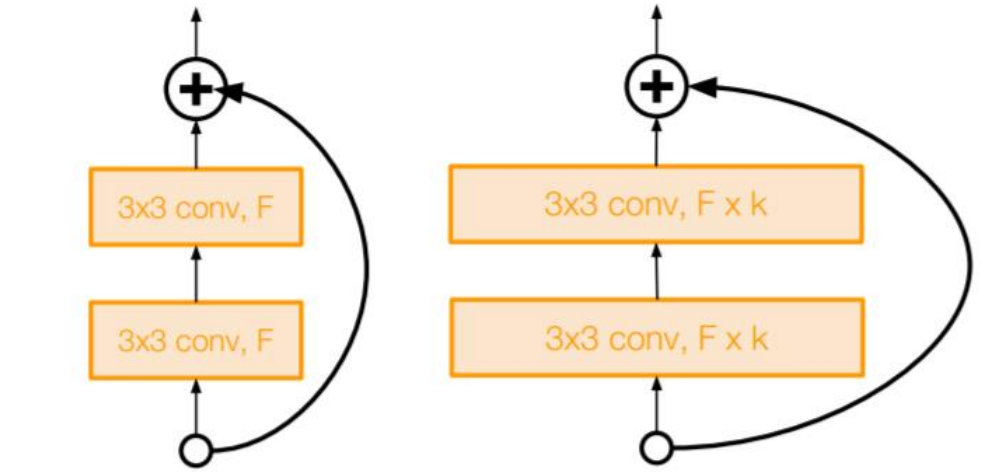
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Improving ResNets...

[Zagoruyko et al. 2016]

Wide Residual Networks

- Argues that residuals are the important factor, not depth
- Uses 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)



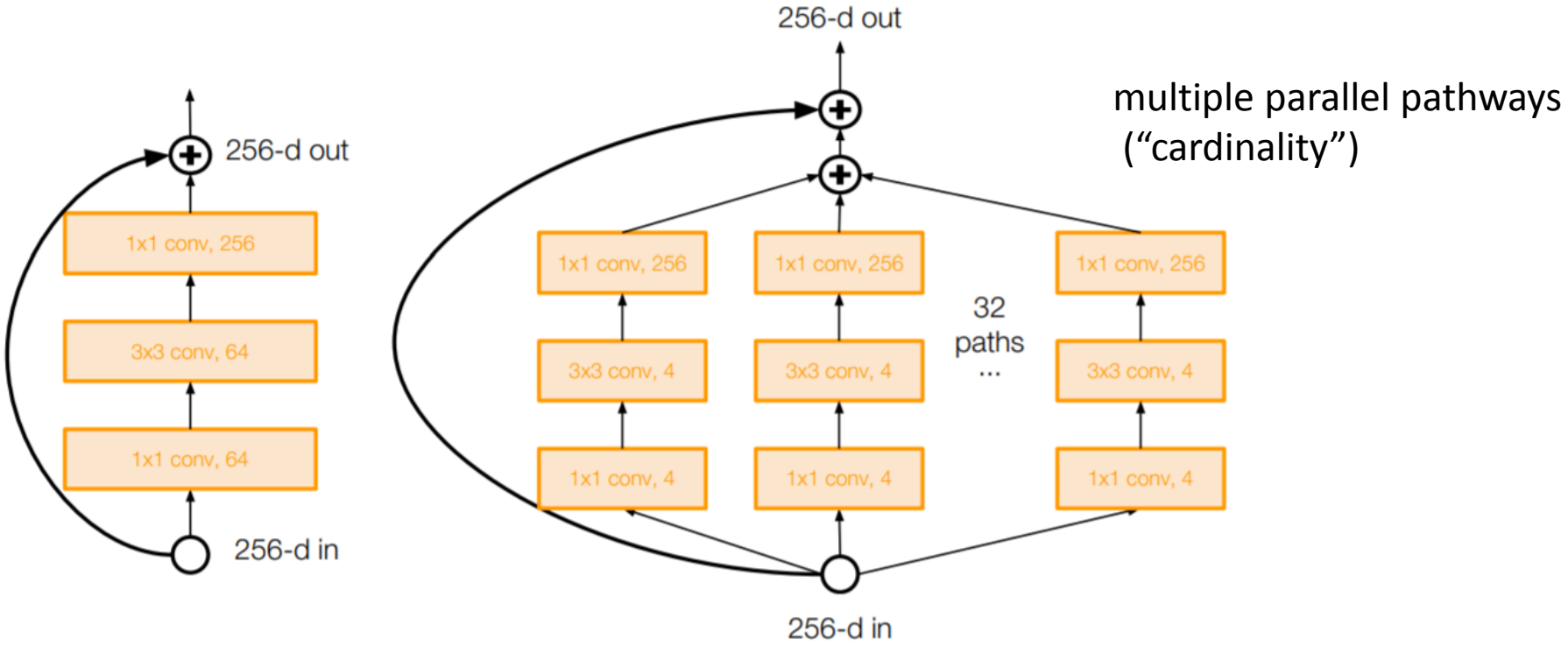
Basic residual block Wide residual block

Improving ResNets...

[Xie et al. 2016]

Aggregated Residual Transformations for Deep Neural Networks (ResNeXt)

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

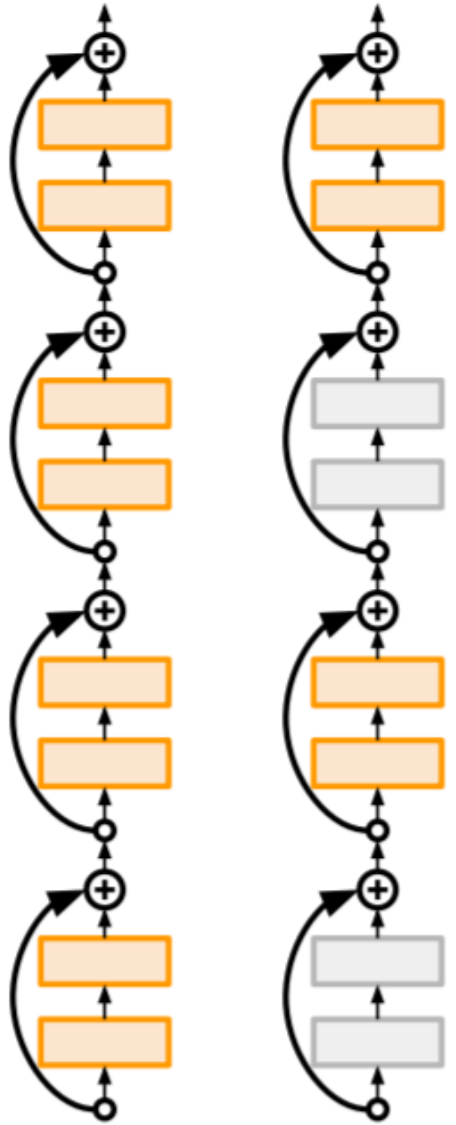


Improving ResNets...

Deep Networks with Stochastic Depth

- 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

[Huang et al. 2016]

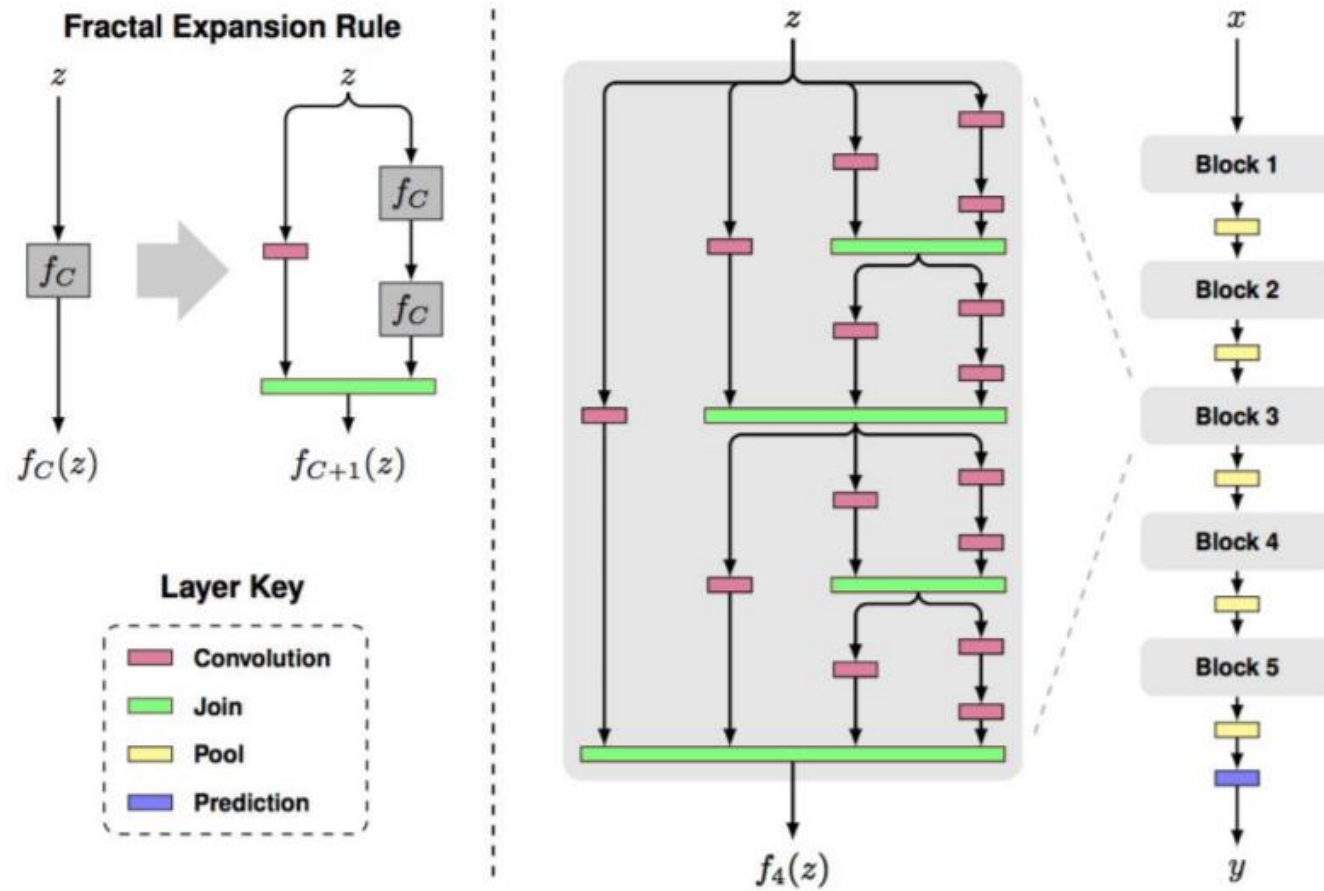


Improving ResNets...

[Larsson et al. 2017]

FractalNet: Ultra-Deep Neural Networks without Residuals

- key is transitioning effectively from shallow to deep
  - 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

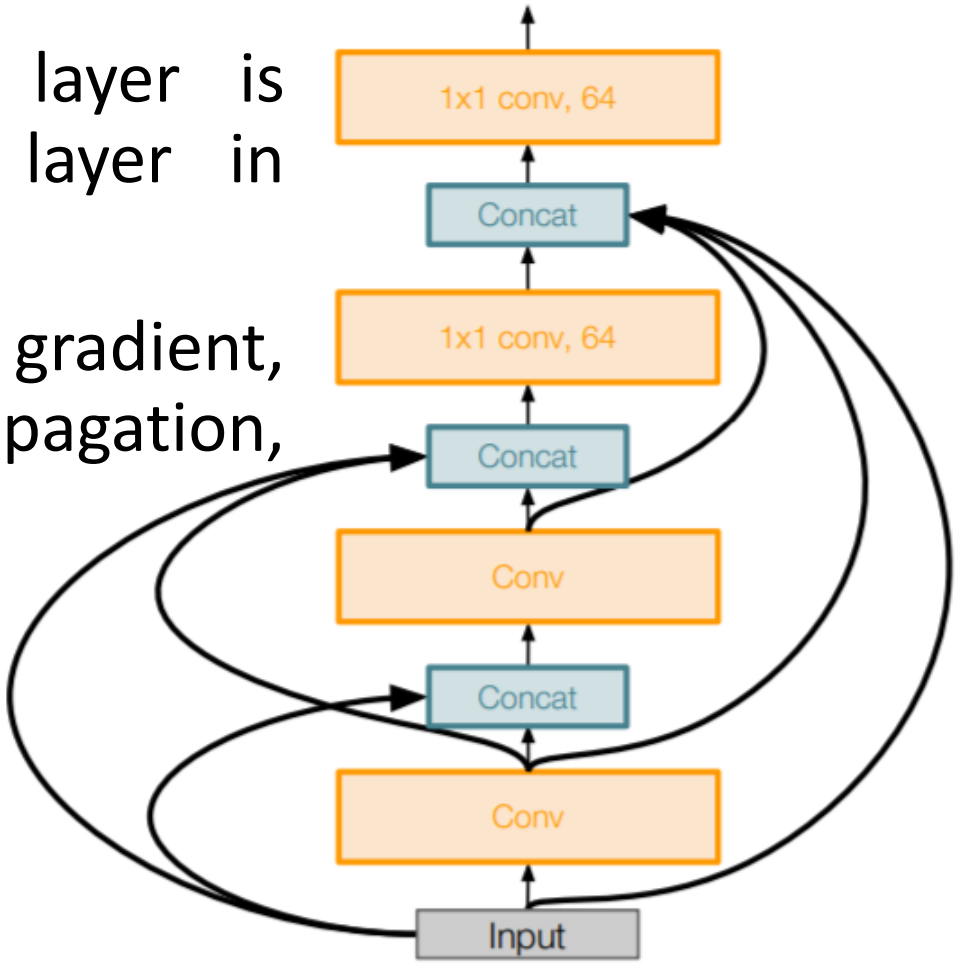


Beyond ResNets...

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

Efficient networks…

[Iandola et al. 2017]

SqueezeNet:

- 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 model size)

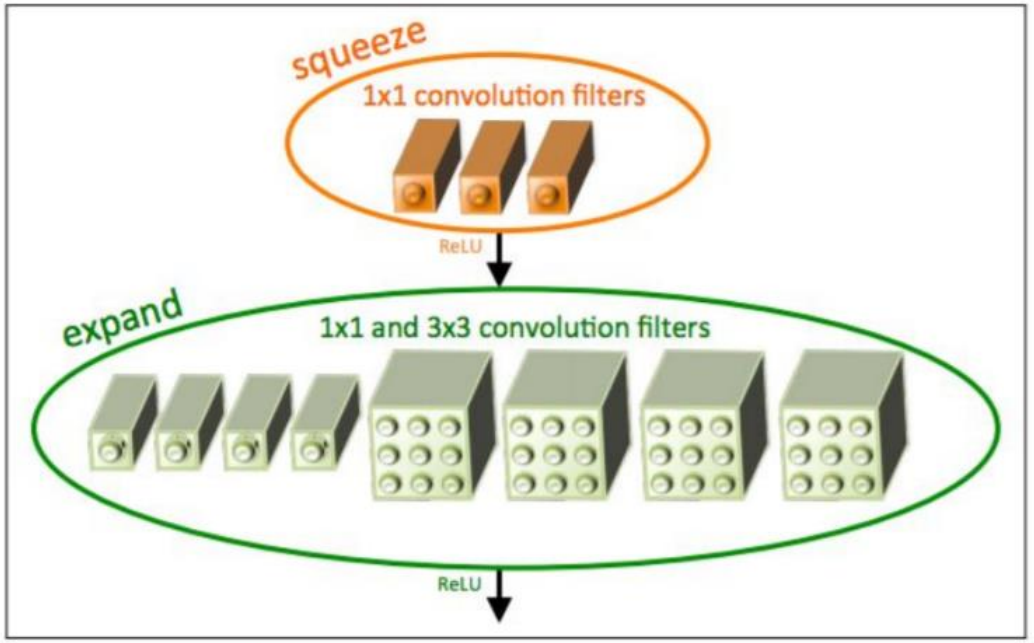


Figure copyright Iandola, Han, Moskewicz, Ashraf, Dally, Keutzer, 2017. Reproduced with permission.

Summary: CNN Architectures

- Case Studies
  - AlexNet
  - VGG
  - GoogLeNet
  - ResNet
- Also....
  - Improvement of ResNet
    - Wide ResNet
    - ResNeXT
    - Stochastic Depth
    - FractalNet
  - DenseNet
  - SqueezeNet

Summary: CNN Architectures

- VGG, GoogLeNet, ResNet all in wide use, available in model zoos
- ResNet current best default
- Trend towards extremely deep networks
- Significant research centers around design of layer / skip connections and improving gradient flow
- Even more recent trend towards examining necessity of depth vs. width and residual connections

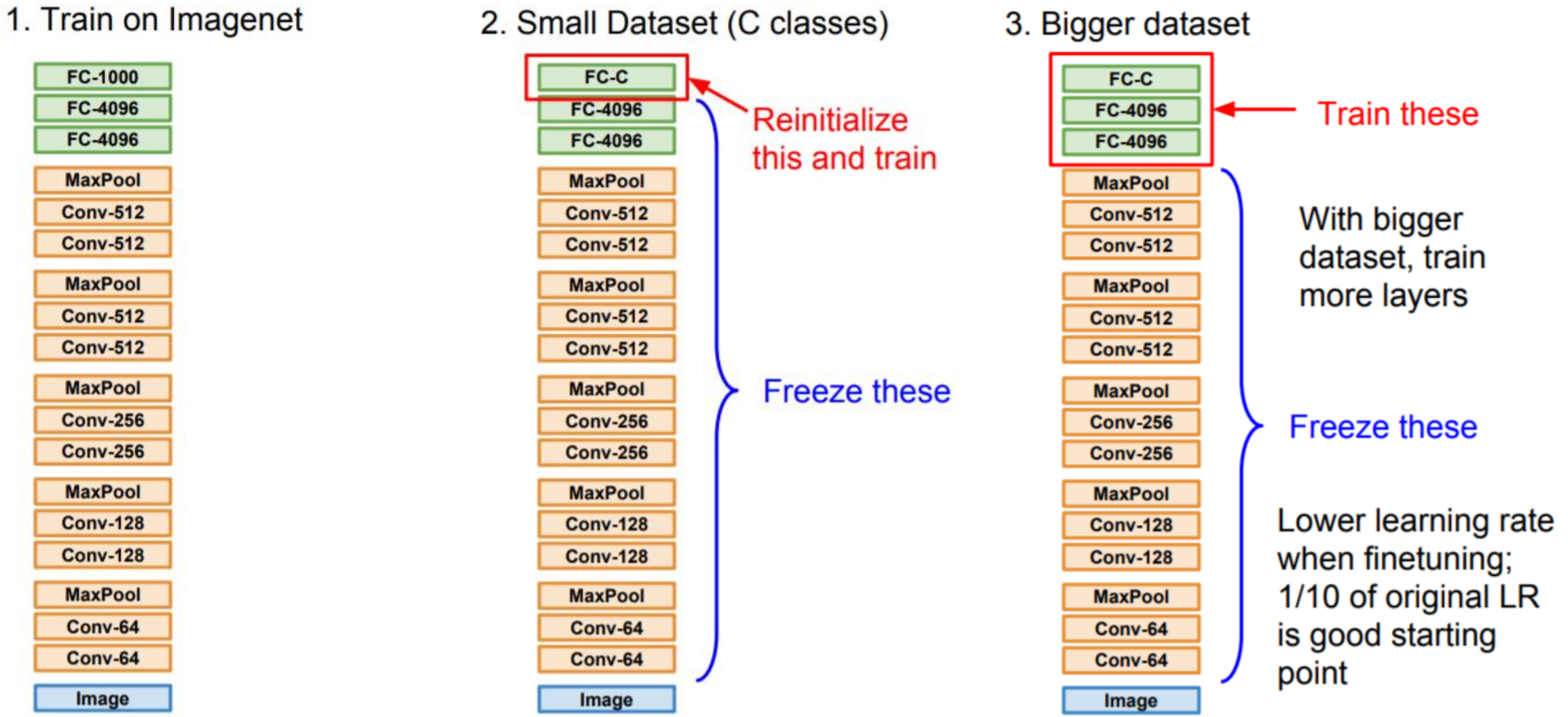
Transfer Learning

- “You need a lot of a data if you want to train/use CNNs”

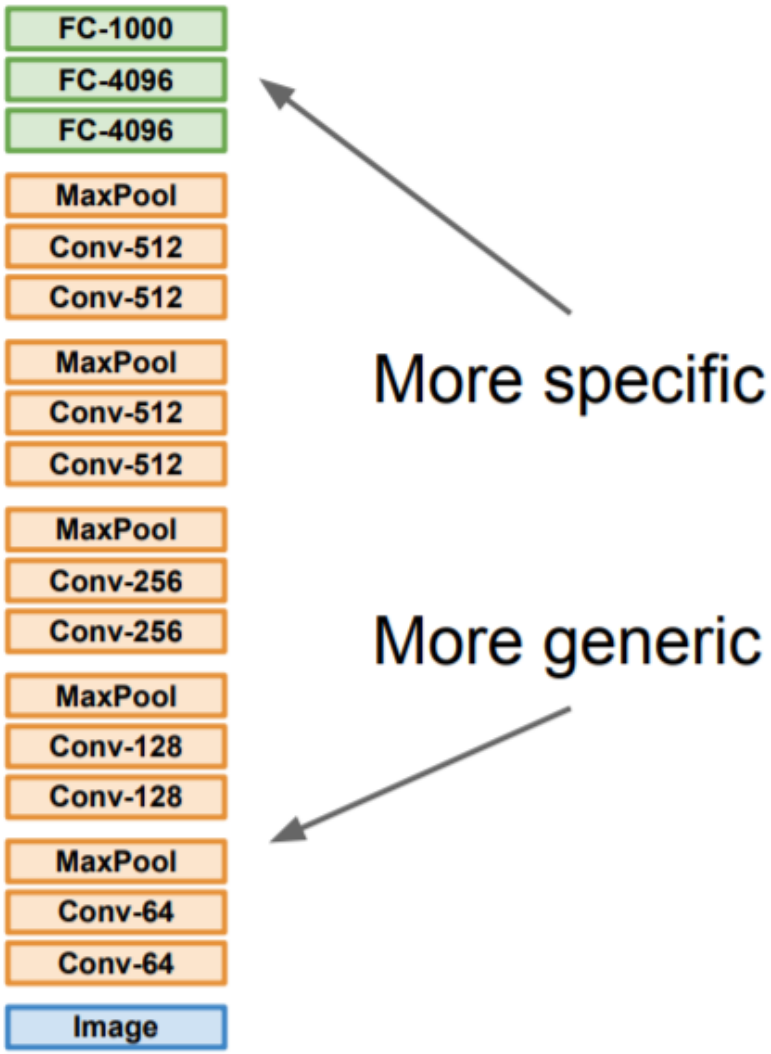
- However, by transfer learning you can use the learned features for a task (using a large amount of data) in another related task (for which you don’t have enough data)

Transfer Learning with CNNs

Donahue et al, “DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition”, ICML 2014.
Razavian et al, “CNN Features Off-the-Shelf: An Astounding Baseline for Recognition”, CVPR Workshops 2014.

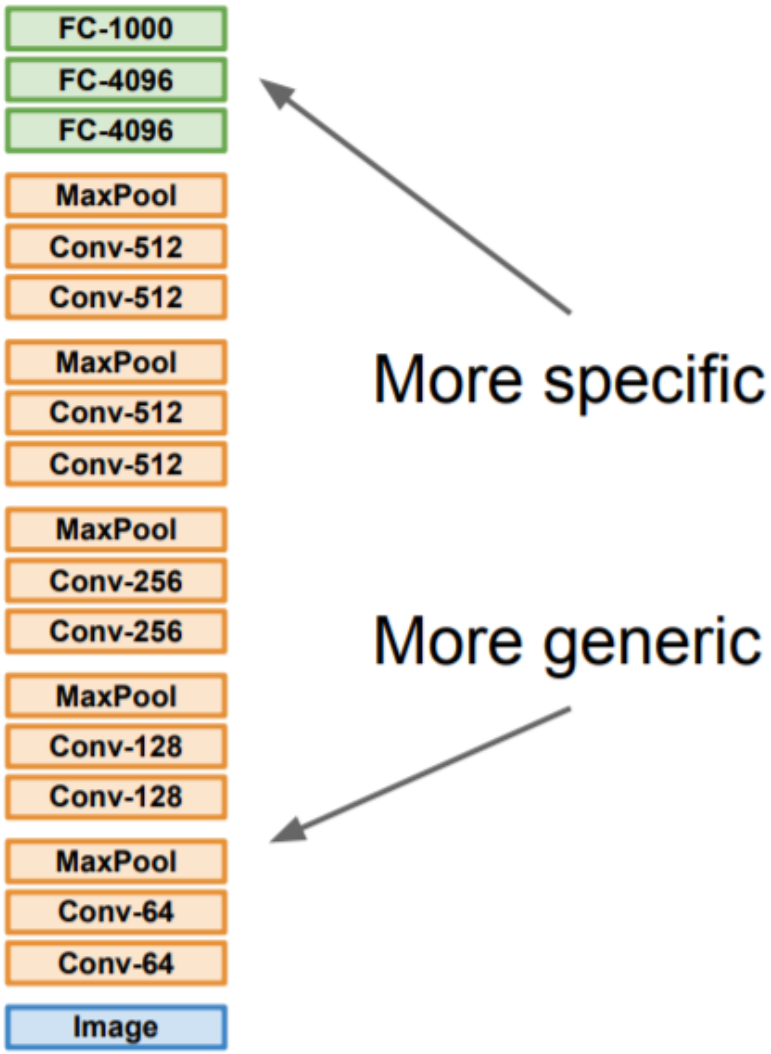


Transfer learning with CNNs



	very similar dataset	very different dataset
very little data		
quite a lot of data		

Transfer learning with CNNs



	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Resources

- Deep Learning Book, Chapter 9.
- Kaming He et al., Deep Residual Learning for Image Recognition, CVPR, 2016.