2019
怪兽
学堂

CNN分类专题

虾米

2019-4

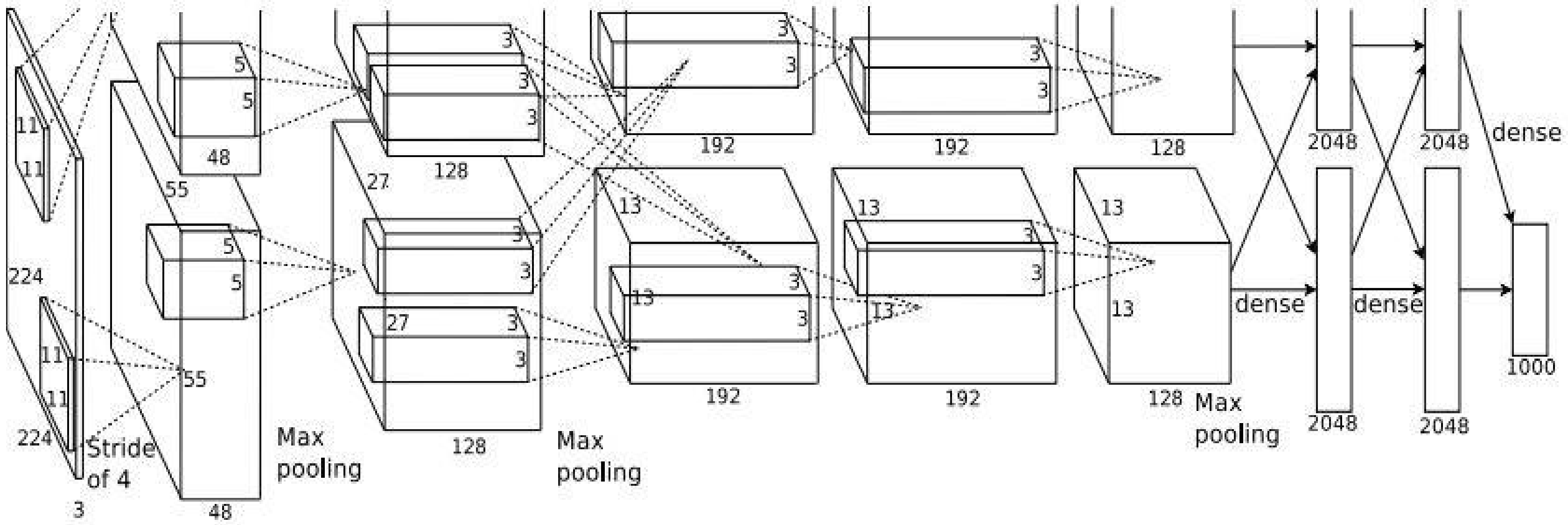
CNN Architectures

Case Studies

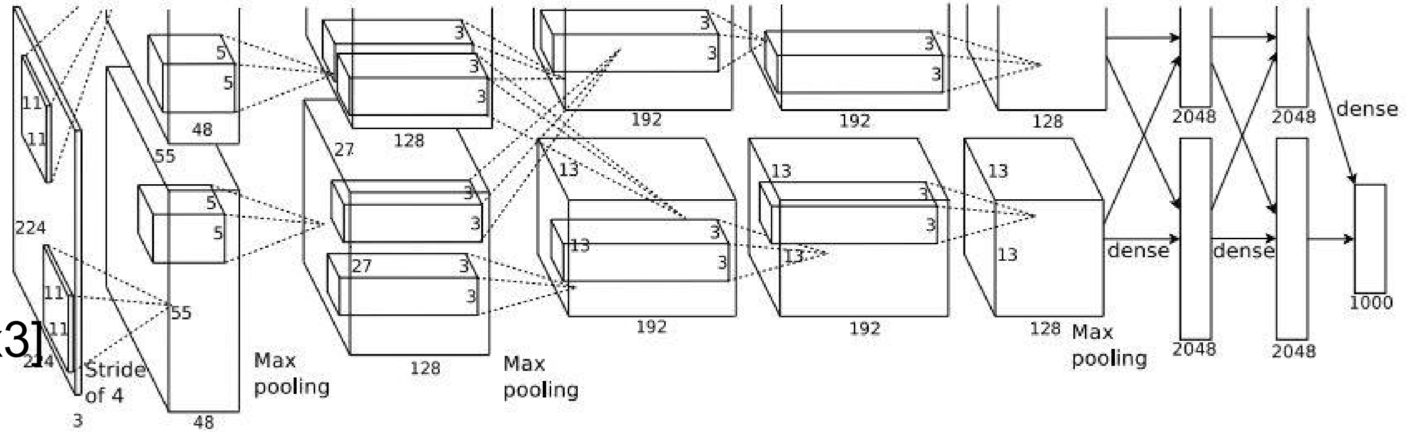
- AlexNet
- VGG
- GoogLeNet
- ResNet
- ResNeXT

Case Study: AlexNet

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

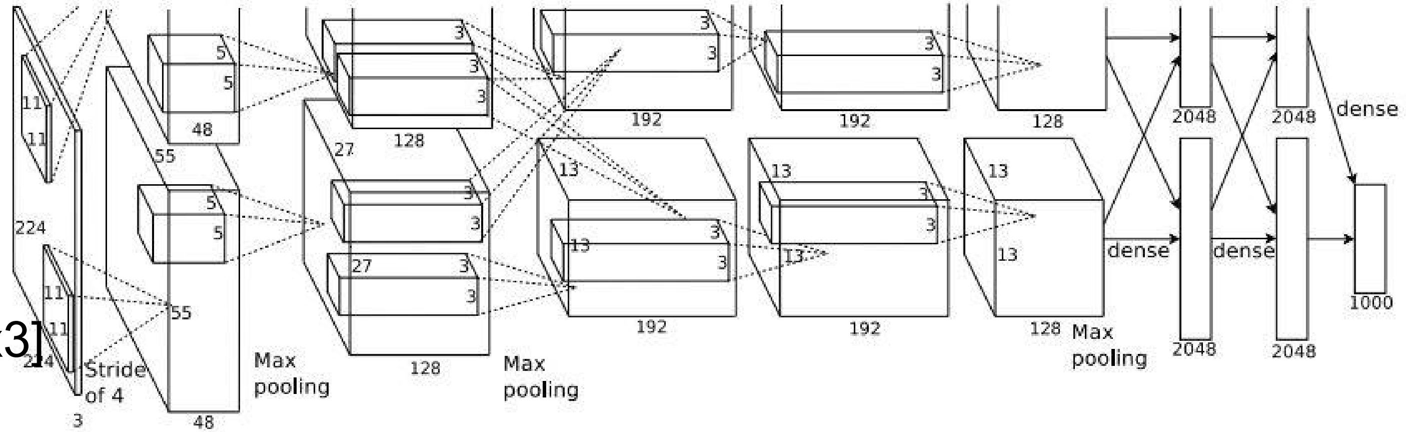


Case Study: AlexNet



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)

Case Study: AlexNet



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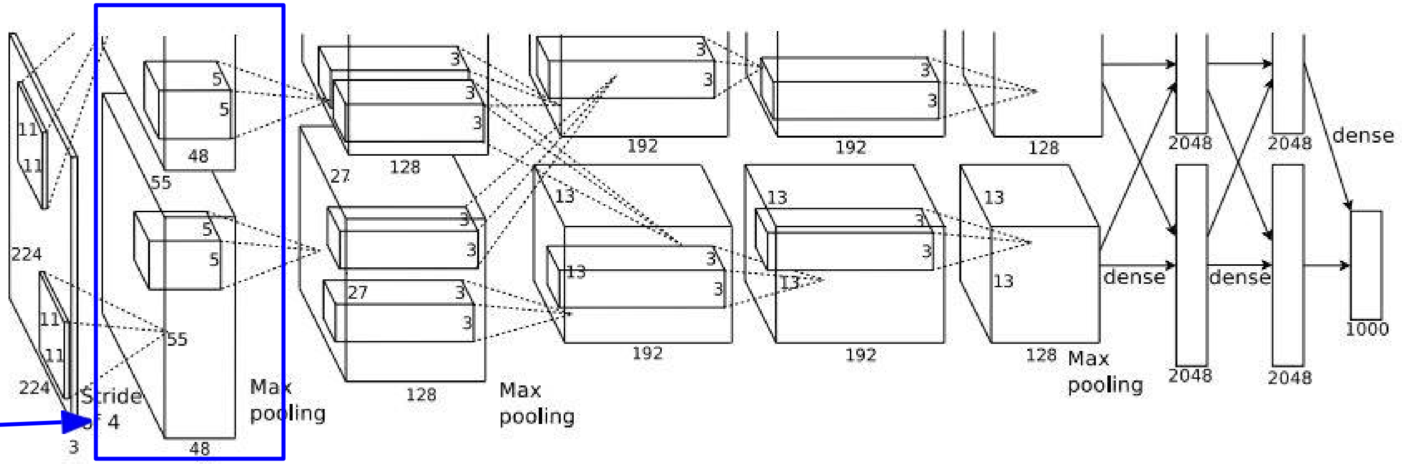
Details/Retrospectives:

- 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



[55x55x48] x 2

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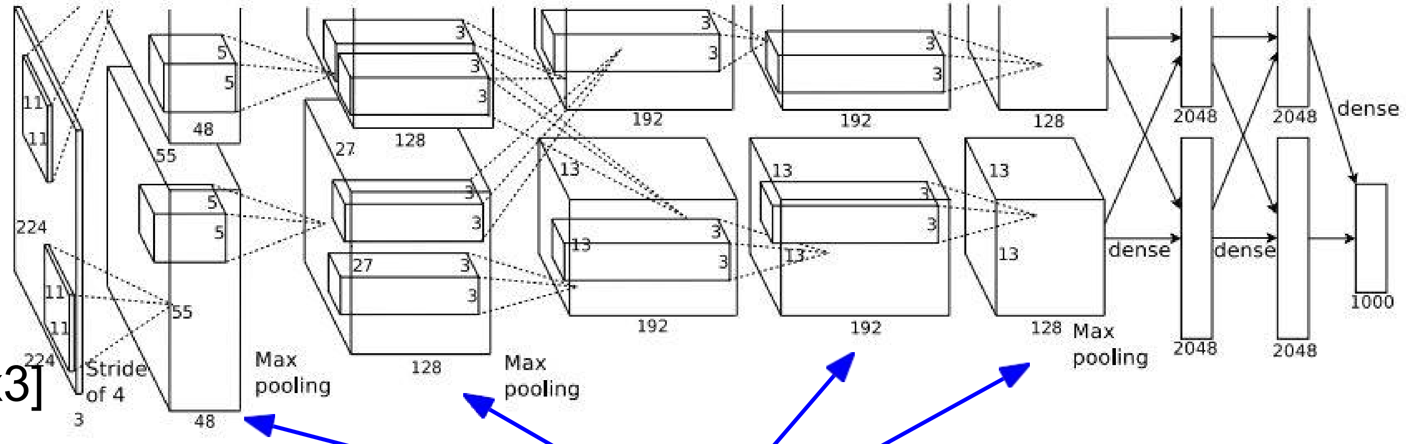
Historical note: Trained on GTX 580 GPU with only 3 GB of memory. Network spread across 2 GPUs, half the neurons (feature maps) on each GPU.

Case Study: AlexNet



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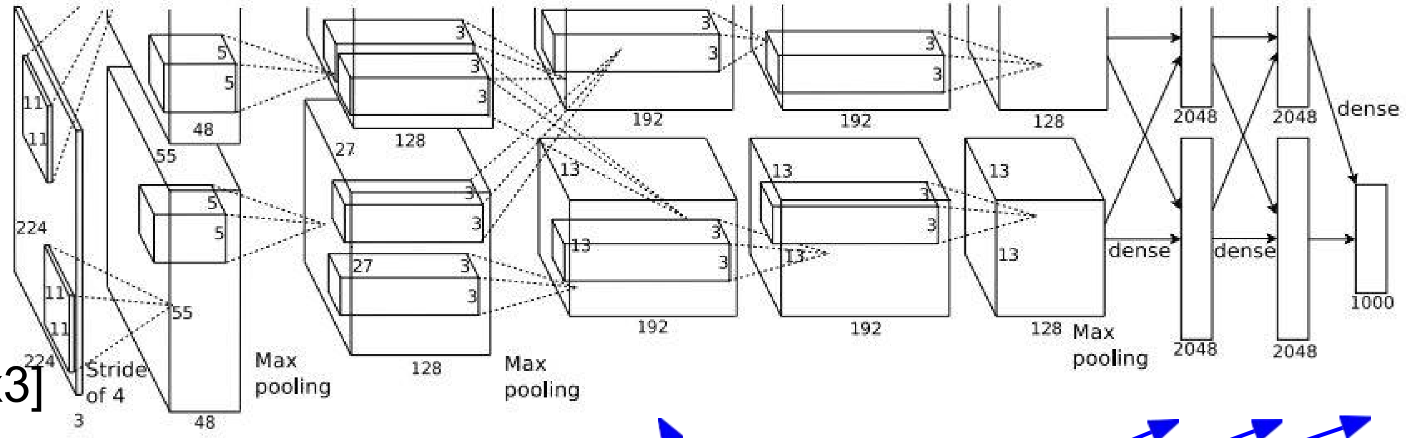
CONV1, CONV2, CONV4, CONV5:
Connections only with feature maps on same GPU

Case Study: AlexNet



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[4096] FC6: 4096 neurons
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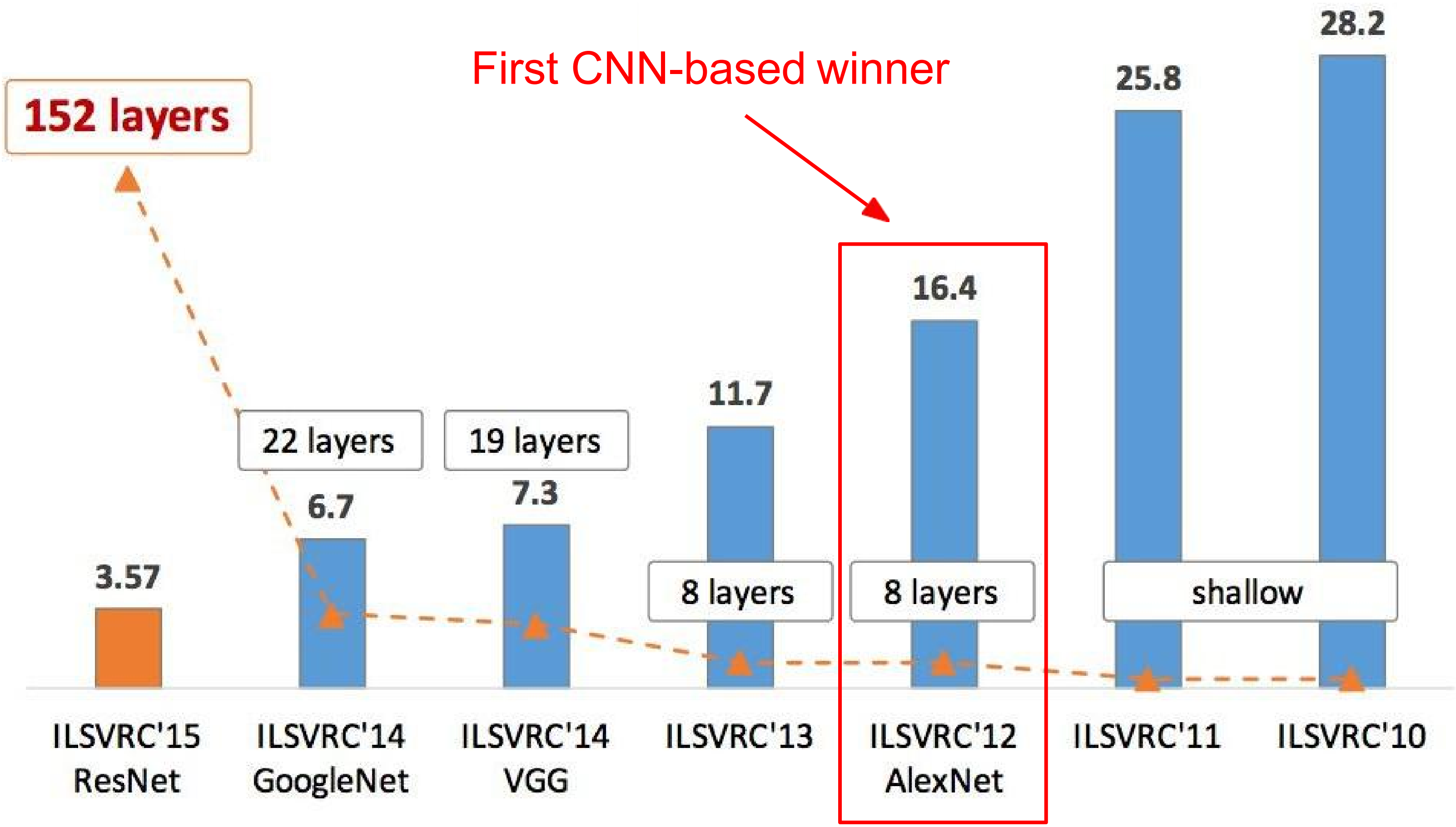
CONV3, FC6, FC7, FC8:
Connections with all feature maps in preceding layer, communication across GPUs

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



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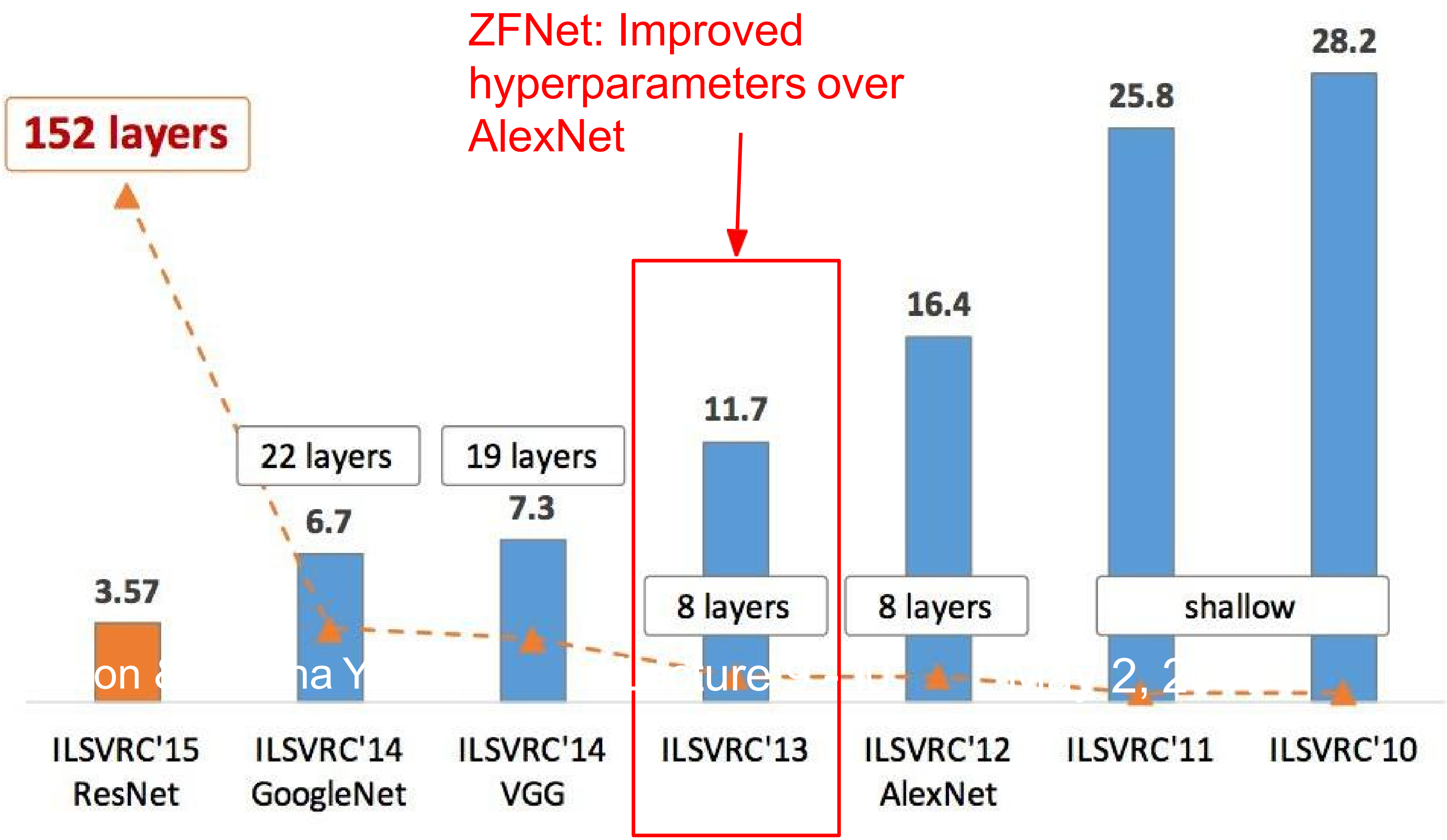
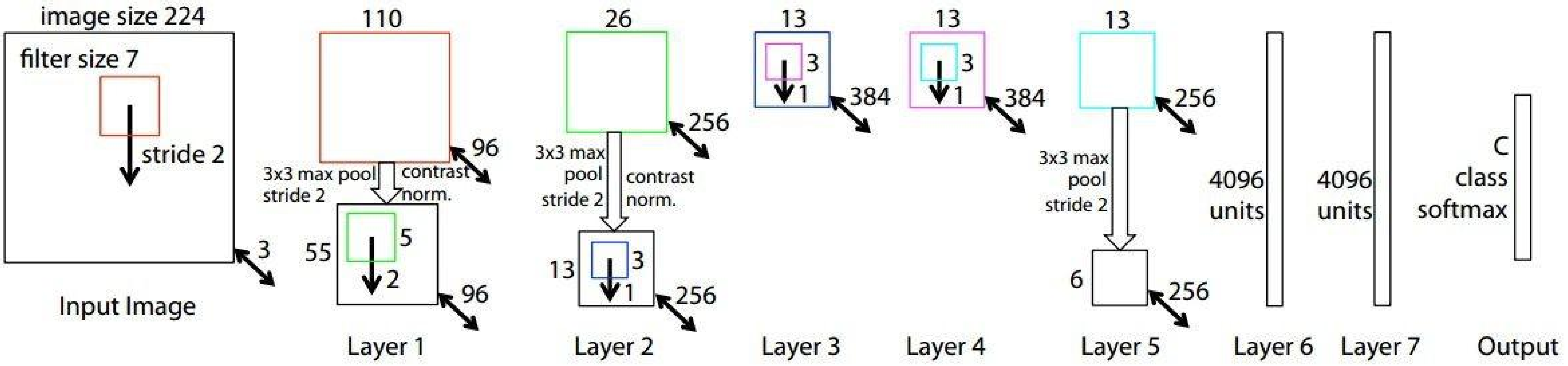


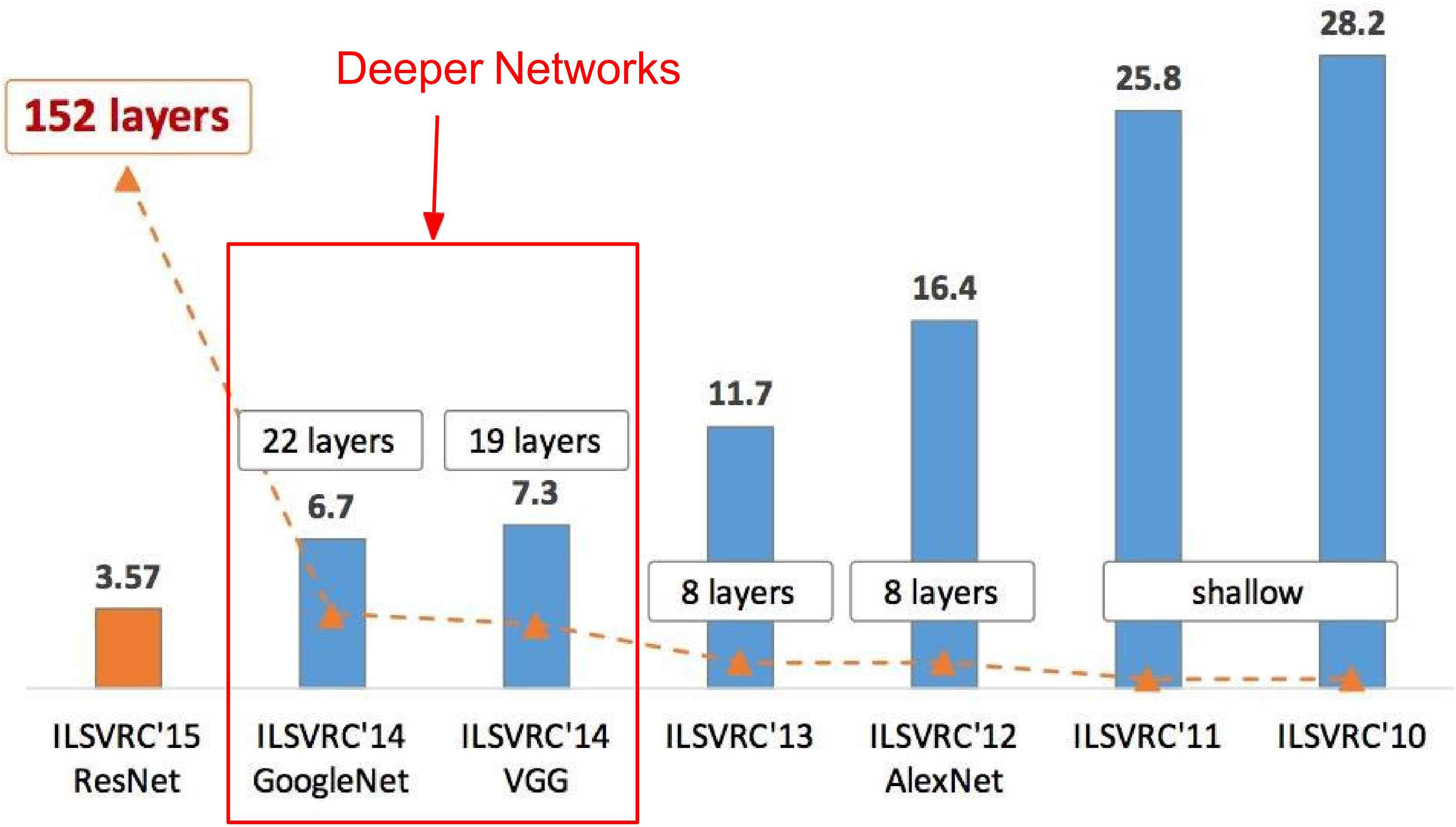
ZFNet



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) winners



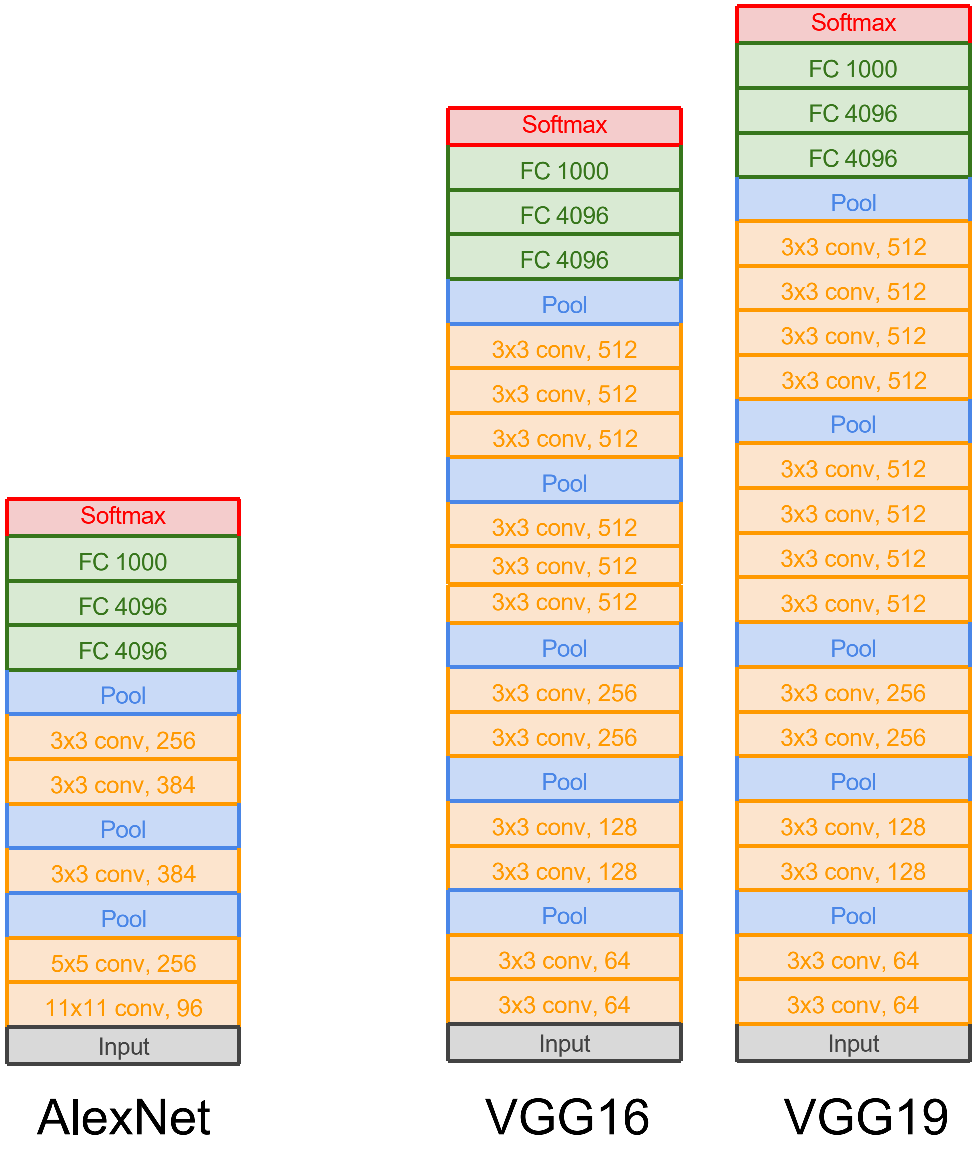
Case Study: VGGNet

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



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

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

Note:

Most memory is in early CONV

Most params are in late FC

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
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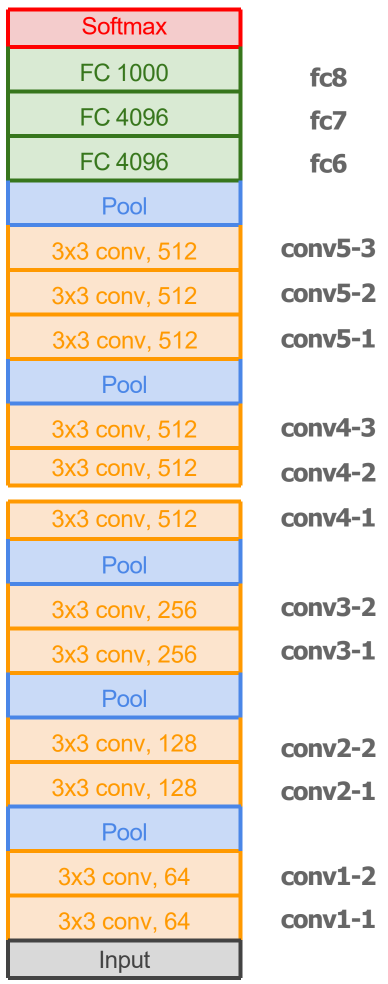


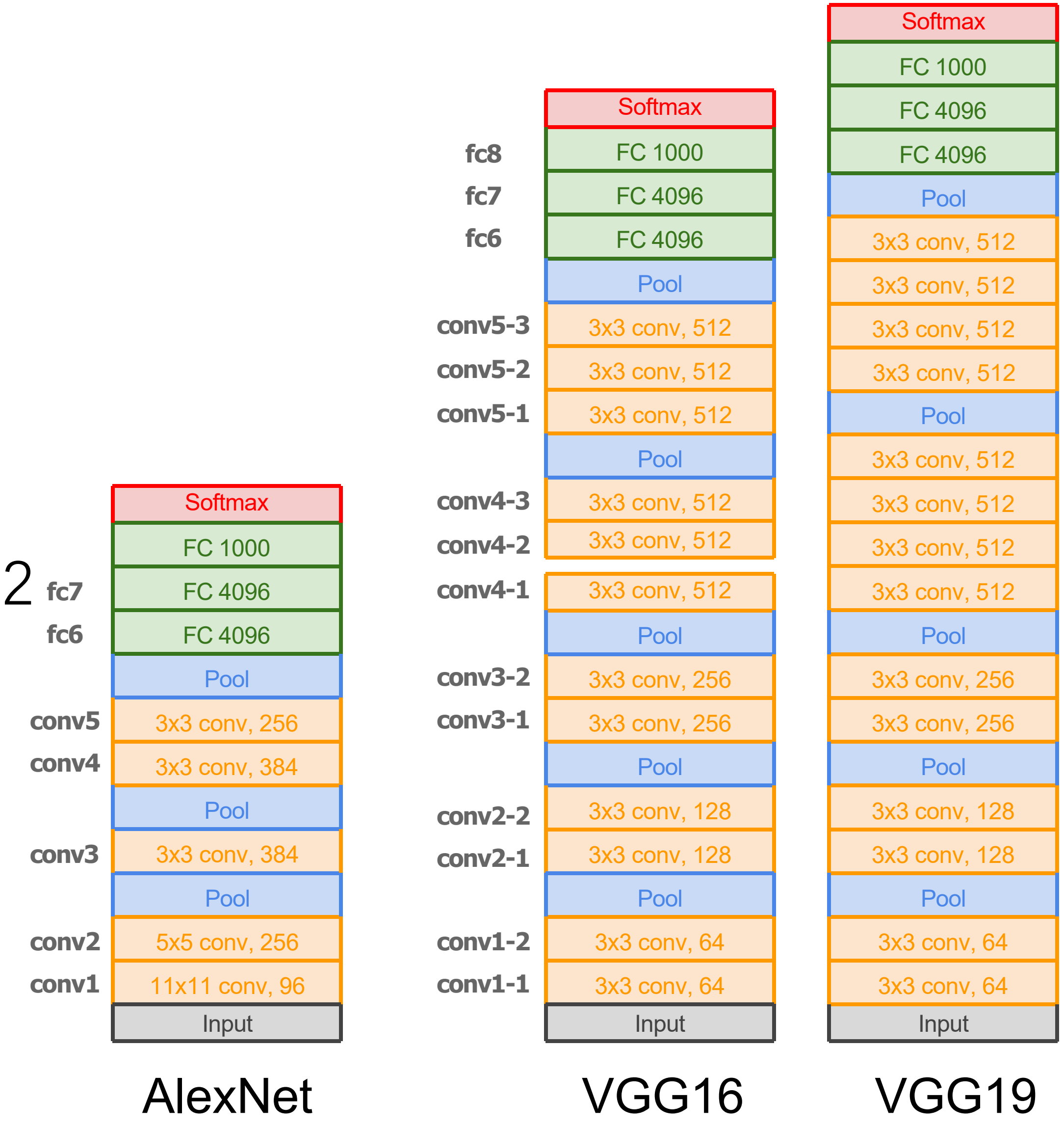
VGG16

Common names

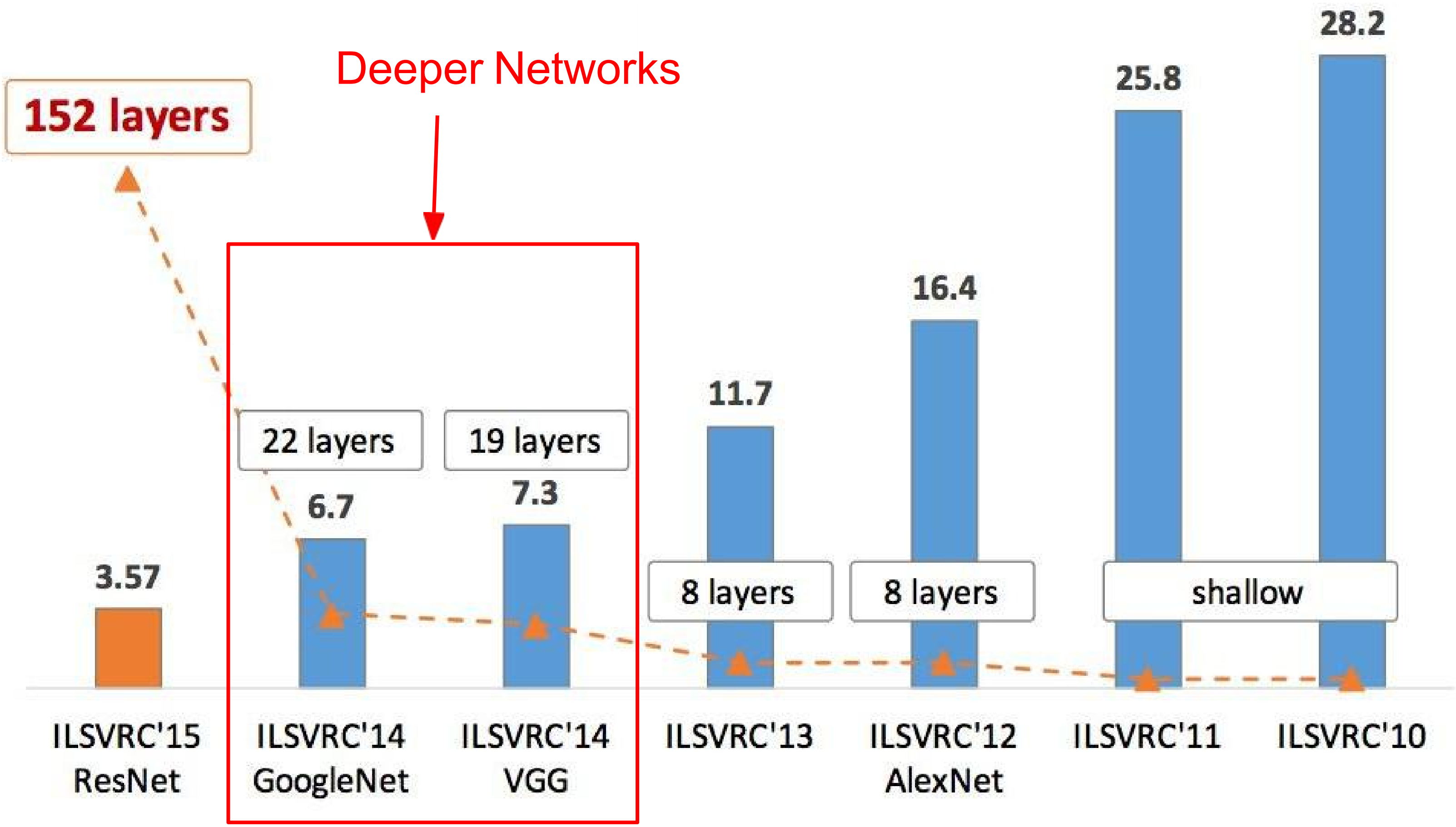
Case Study: VGGNet

Details:

- ILSVRC14 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



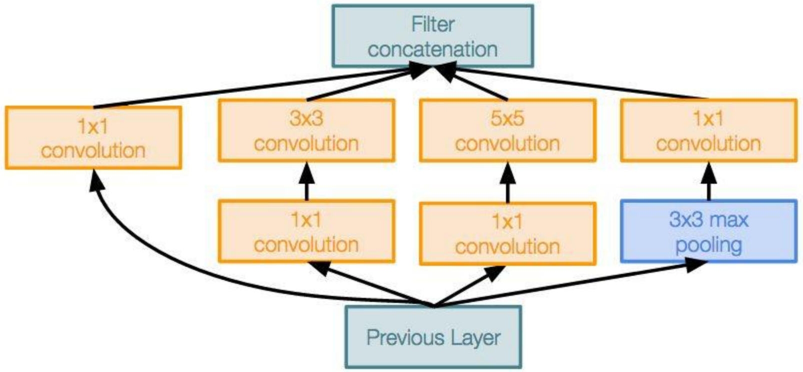
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



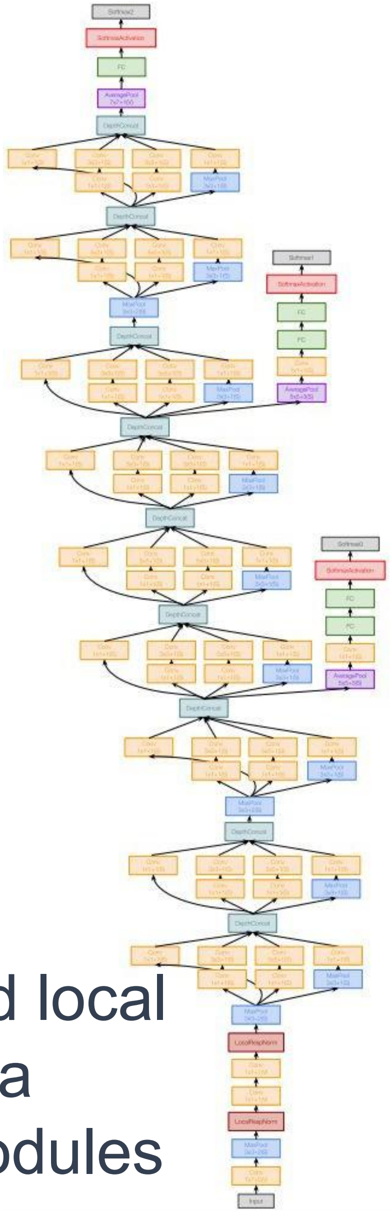
Case Study: GoogLeNet

Deeper networks, with computational efficiency

- 22 layers
- Efficient “Inception” module
- No FC layers
- Only 5 million parameters!12x less than AlexNet
- ILSVRC14 classification winner (6.7% top 5 error)

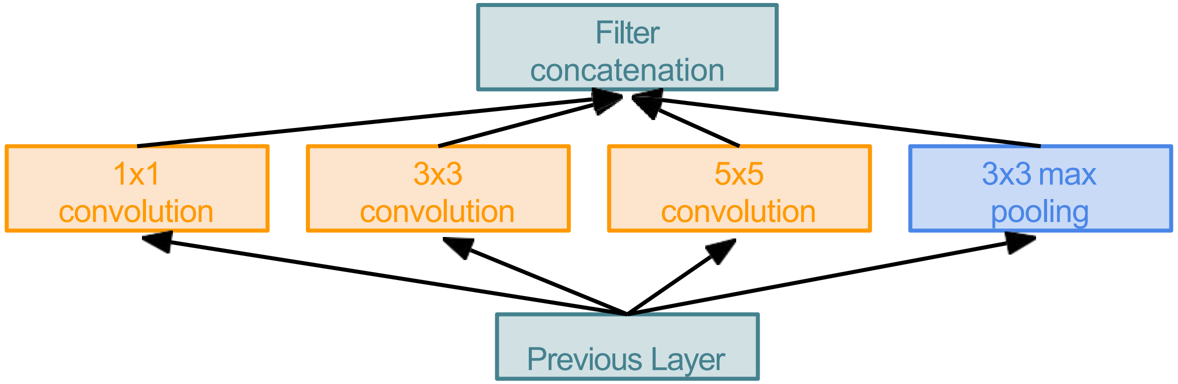


Inception module



“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



Naive Inception module

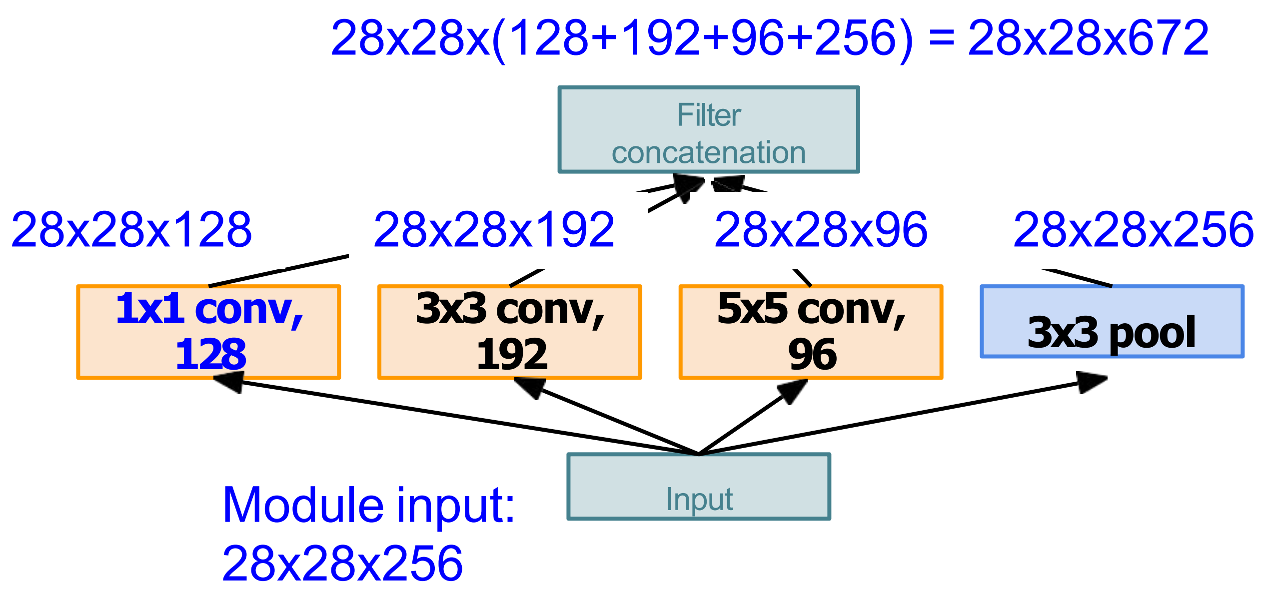
Apply parallel filter operations on the input from previous layer:

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

Concatenate all filter outputs together depth-wise

Case Study: GoogLeNet

Example:



Naive Inception module

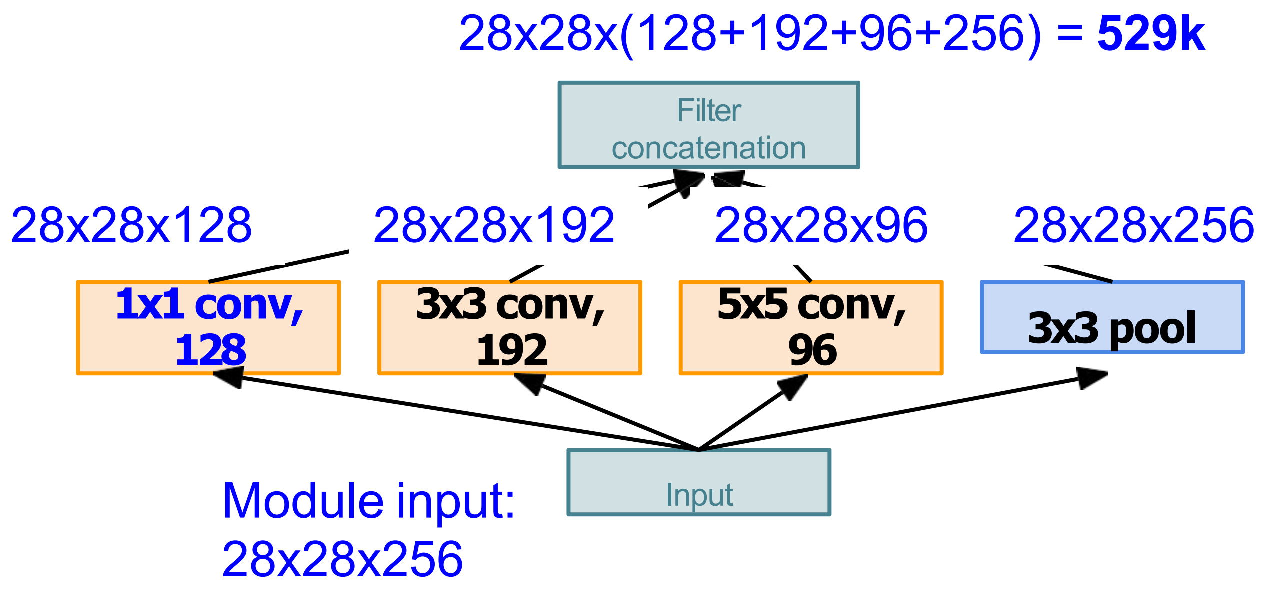
Conv Ops:
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x256
[5x5 conv, 96] 28x28x96x5x5x256
Total: 854M ops

Very expensive compute

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

Case Study: GoogLeNet

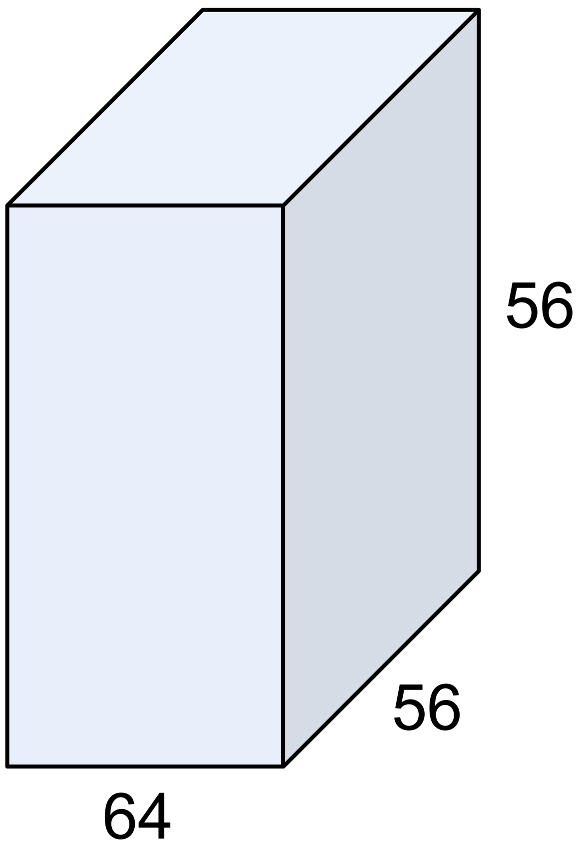
Example:



Naive Inception module

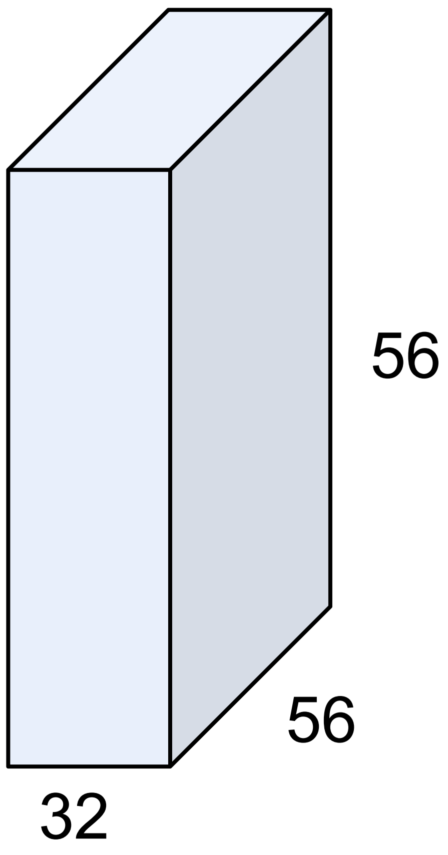
Solution: “bottleneck” layers that use 1x1 convolutions to reduce feature depth

Reminder: 1x1 convolutions



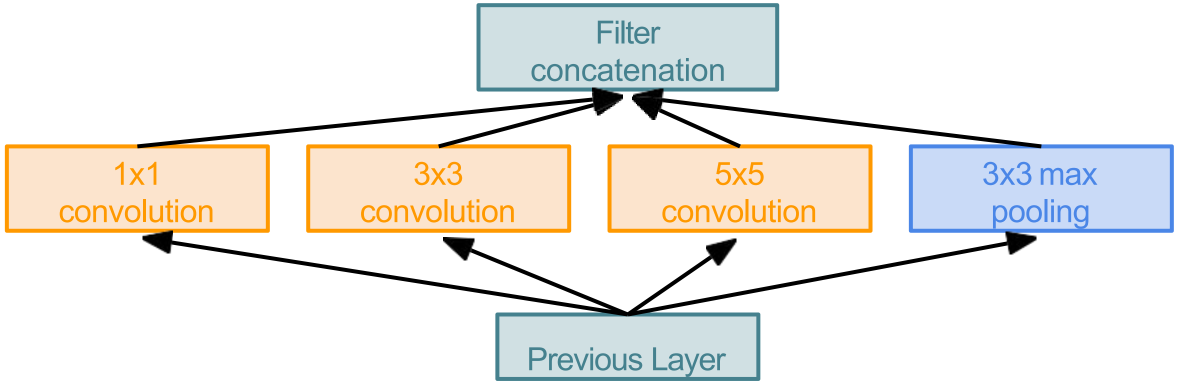
1x1 CONV
with 32 filters

- (each filter has size 1x1x64, and performs a 64-dimensional dot product)
- preserves spatial dimensions, reduces depth!
- Projects depth to lower dimension (combination of feature maps)

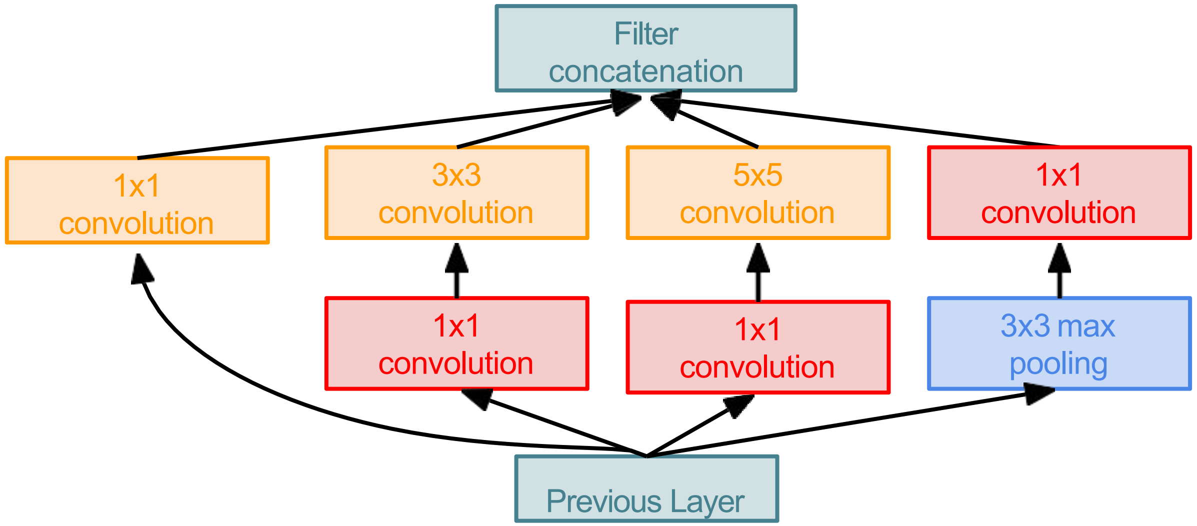


Case Study: GoogLeNet

1x1 conv “bottleneck”
layers

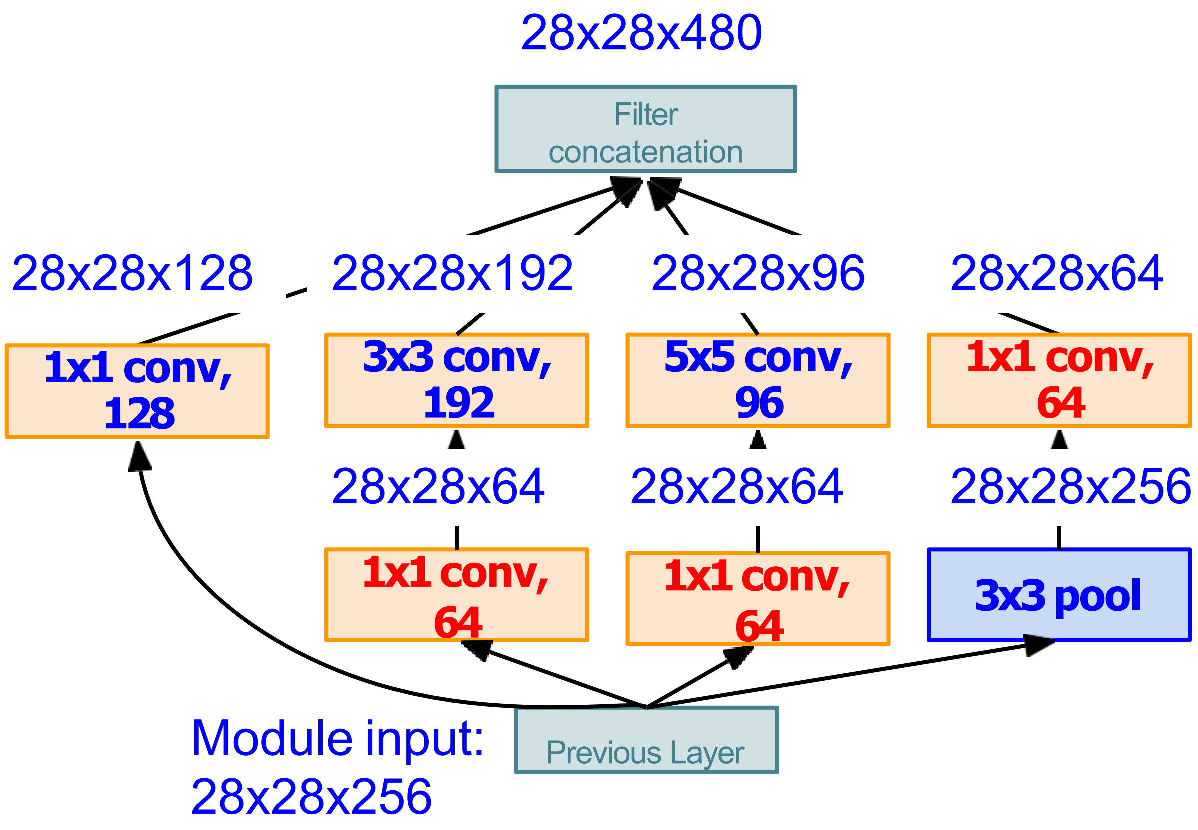


Naive Inception module



Inception module with dimension reduction

Case Study: GoogLeNet



Inception module with dimension reduction

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

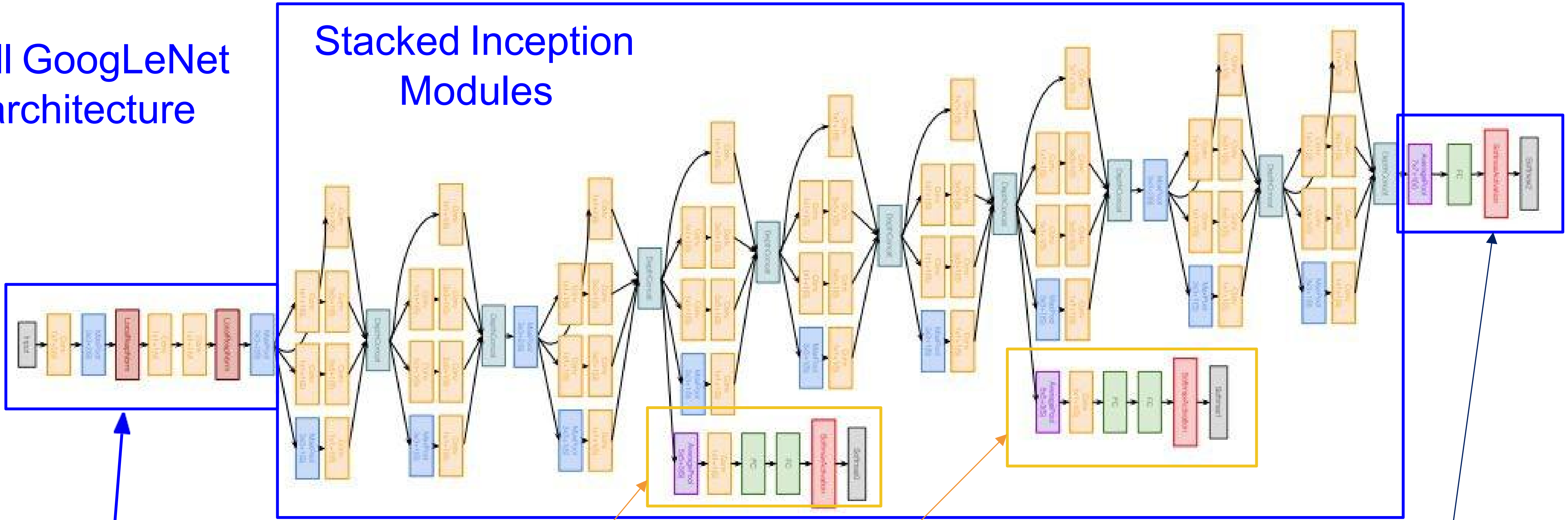
Conv Ops:

[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x64
[5x5 conv, 96] 28x28x96x5x5x64
[1x1 conv, 64] 28x28x64x1x1x256
Total: 358M ops

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

Case Study: GoogLeNet

Full GoogLeNet architecture

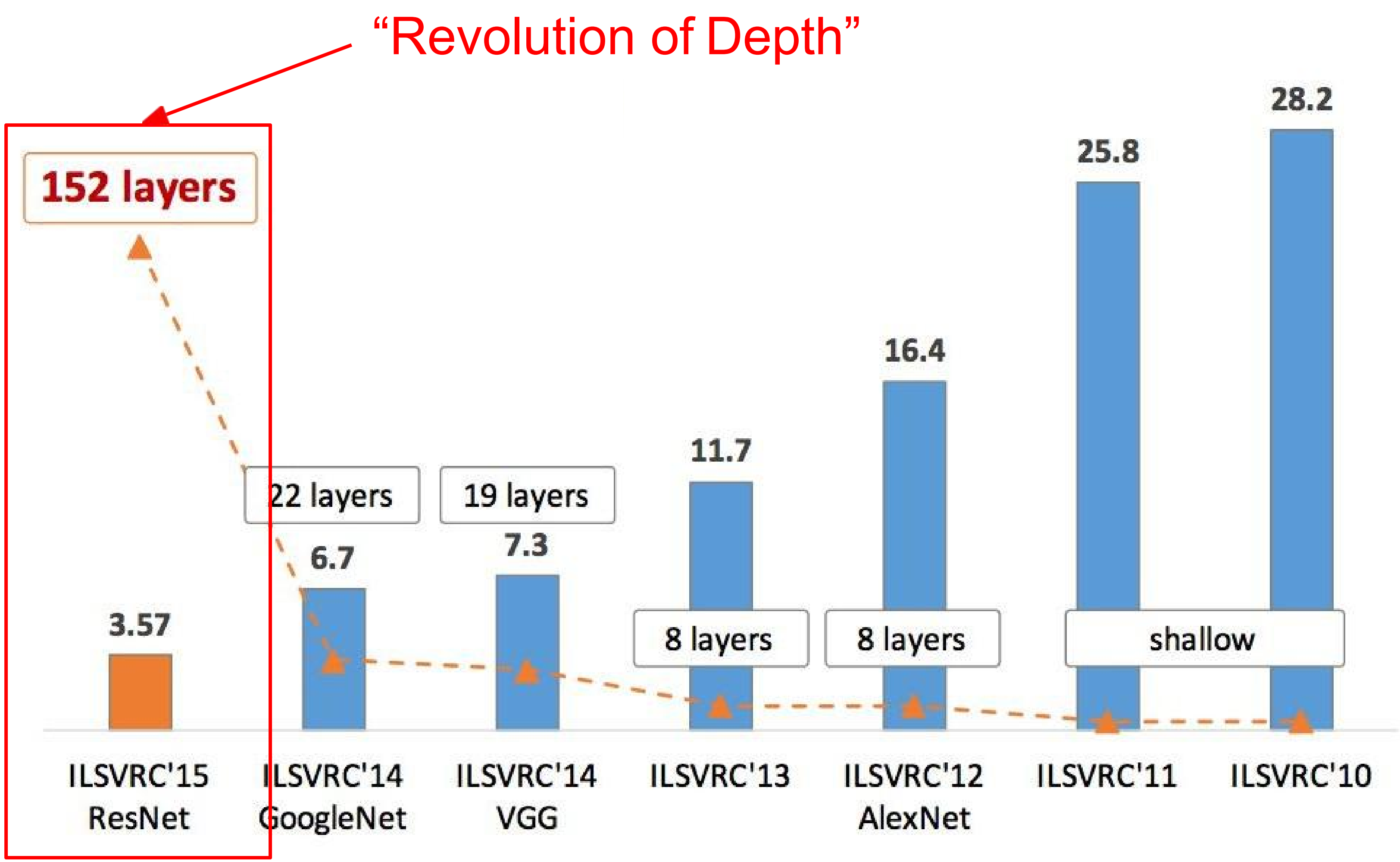


Stem Network:
Conv-Pool-
2x Conv-Pool

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

Classifier output
(removed expensive FC layers!)

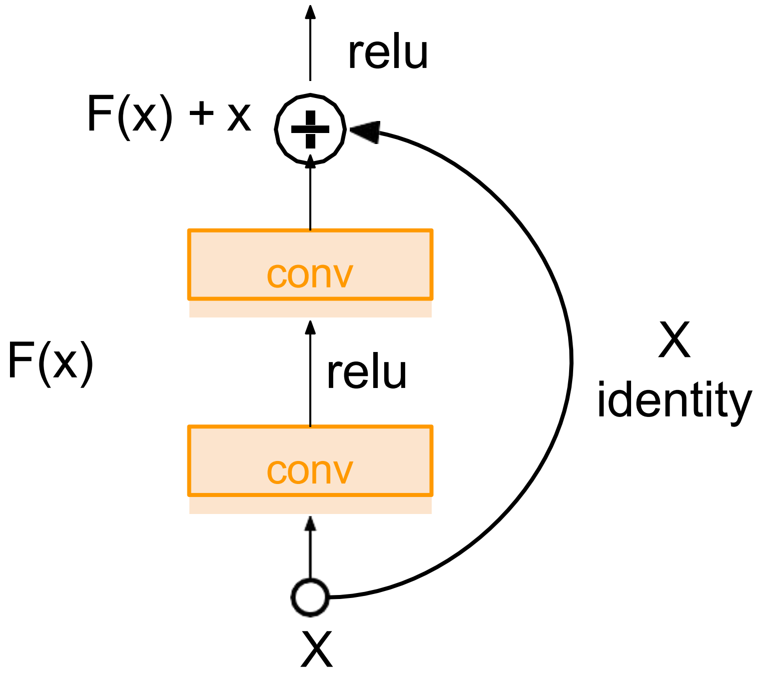
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



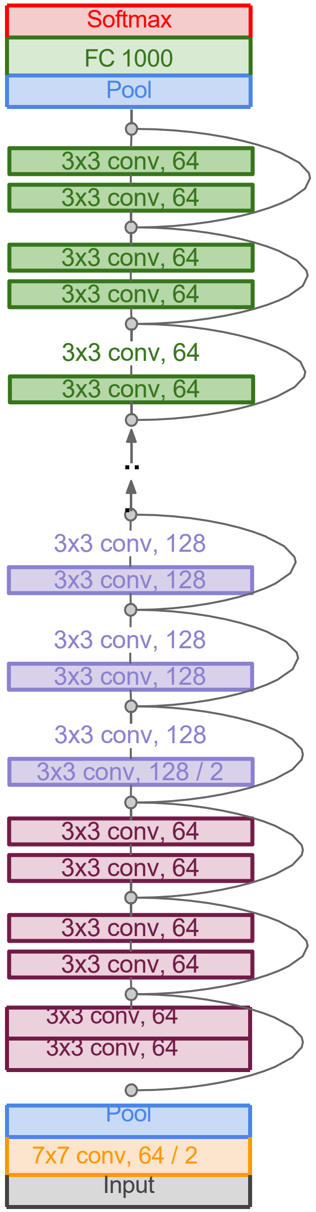
Case Study: ResNet

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 ILSVRC15 and COCO15!

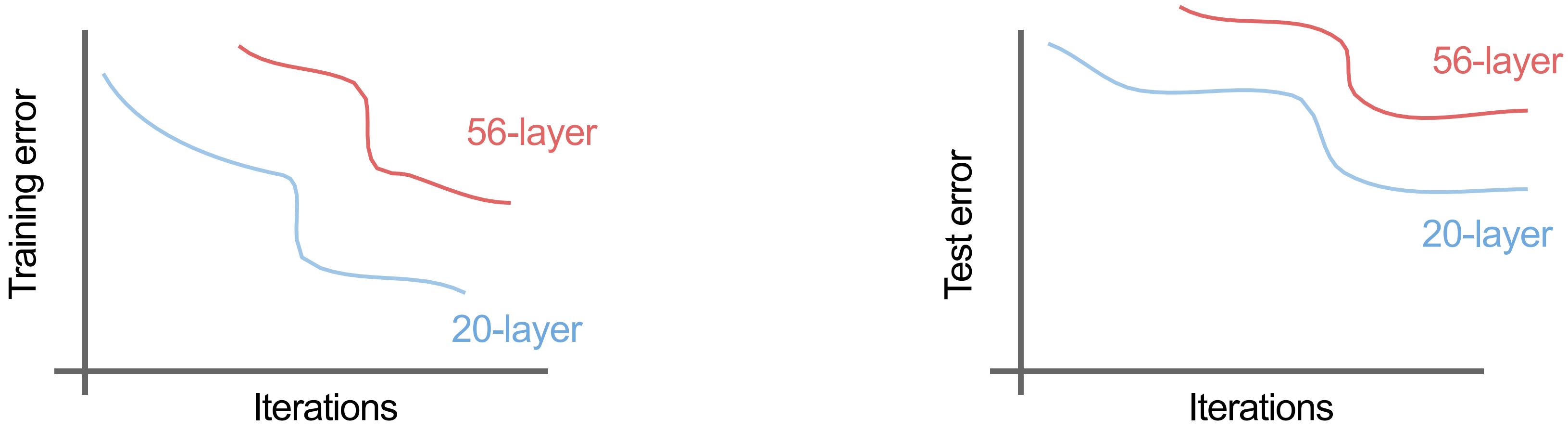


Residual block



Case Study: ResNet

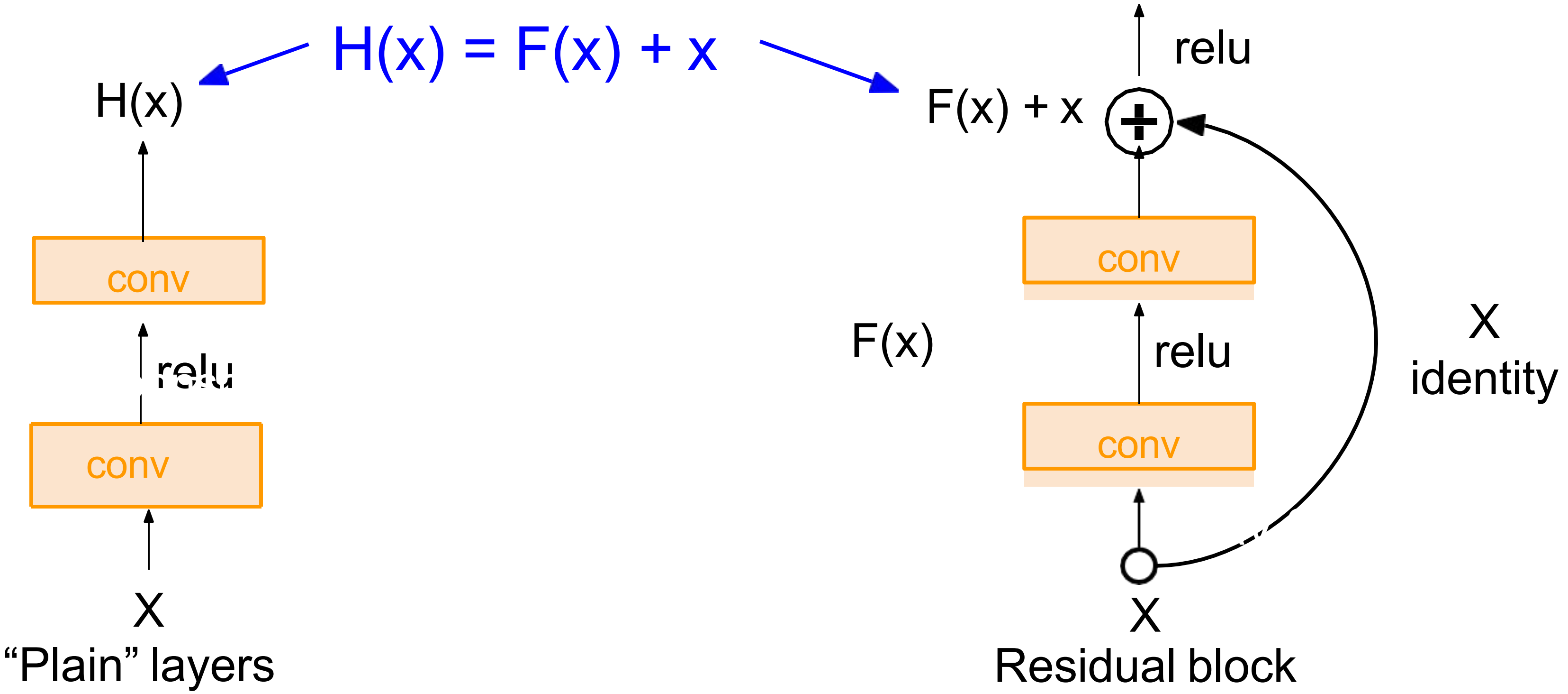
What happens when we continue stacking deeper layers on a “plain” convolutional neural network?



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

- Hypothesis: the problem is an *optimization* problem, deeper models are harder to optimize
- Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping

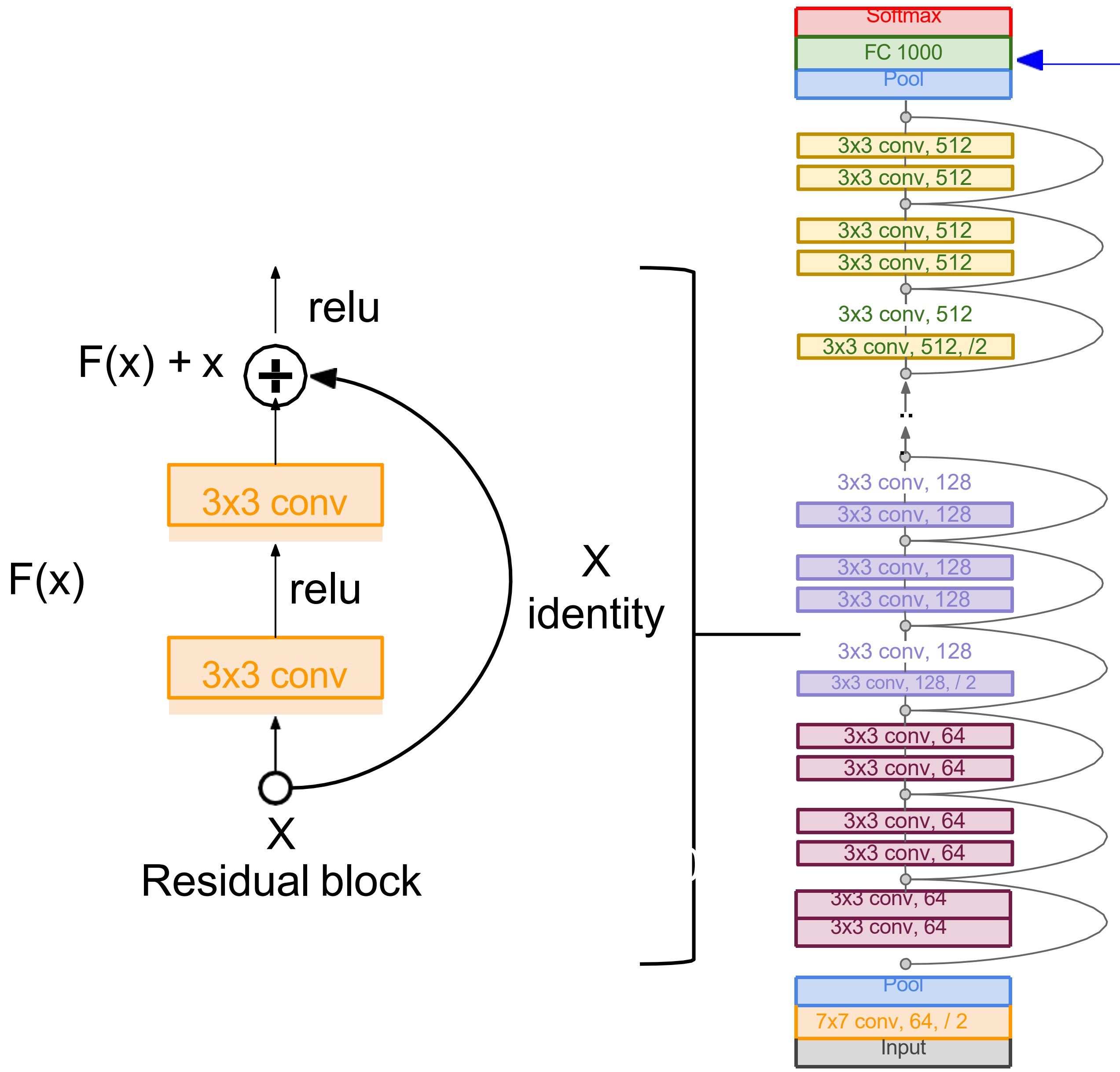


Use layers to fit residual $F(x) = H(x) - x$ instead of $H(x)$ directly

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)



No FC layers besides FC 1000 to output classes

Global average pooling layer after last conv layer

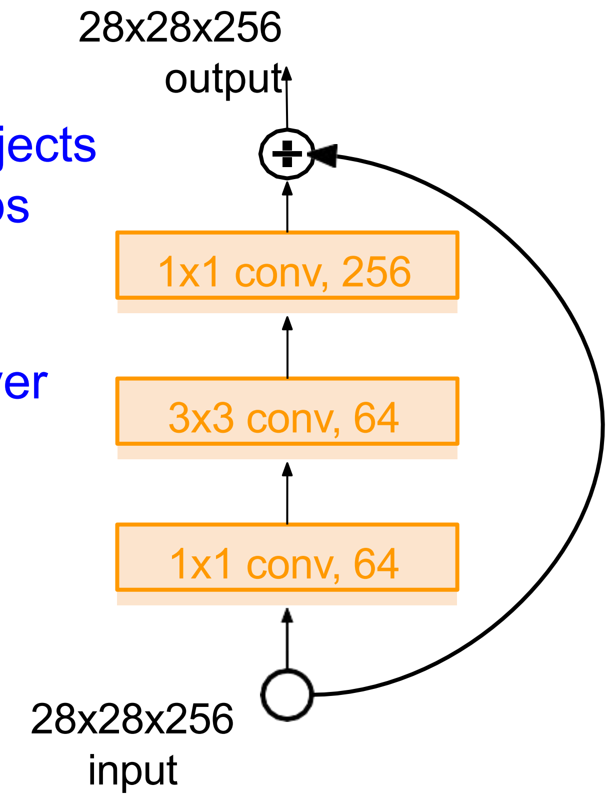
Case Study: ResNet

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

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

Experimental Results

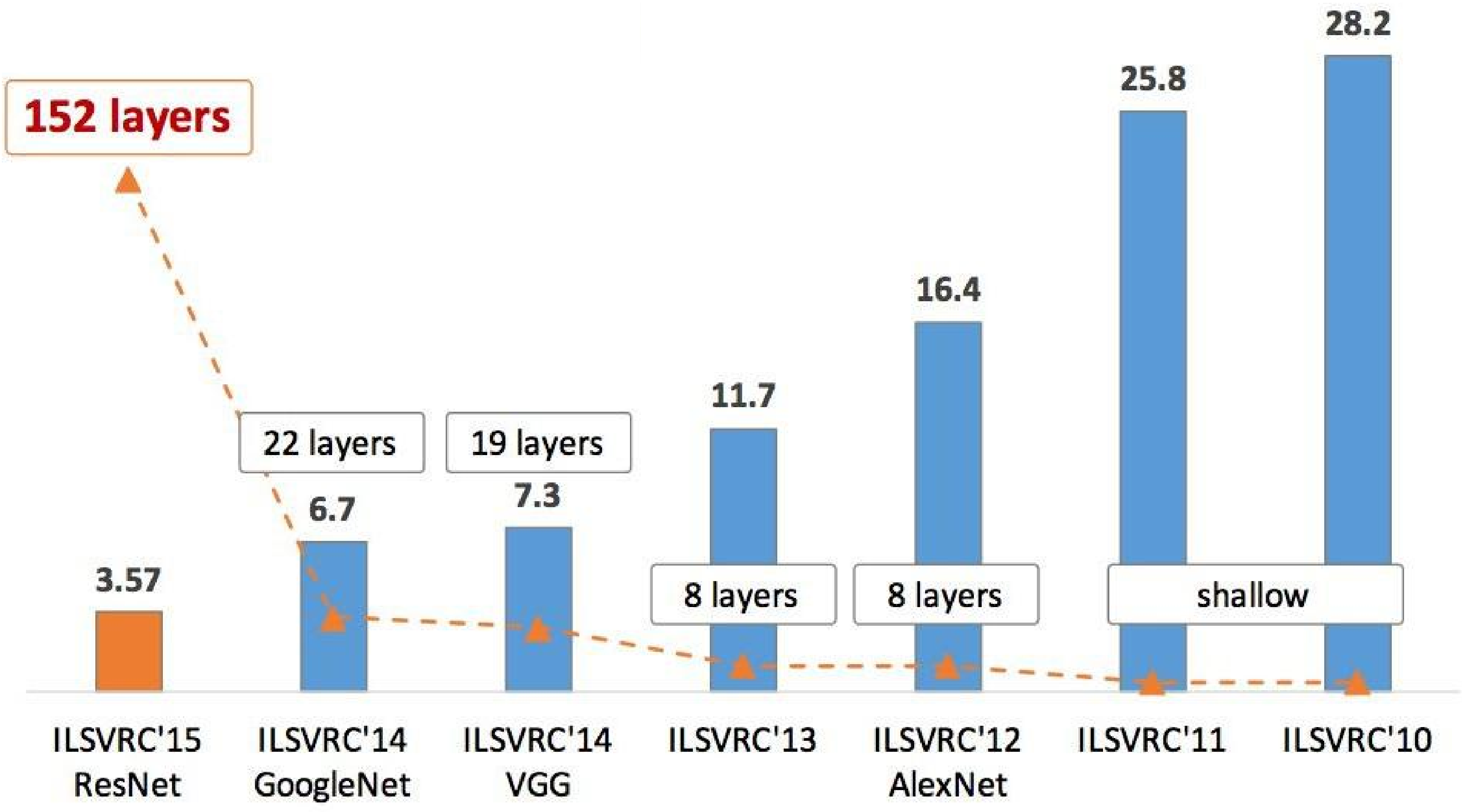
- Able to train very deep networks without degrading (152 layers on ImageNet, 1202 on Cifar)
- Deeper networks now achieve lowing training error as expected
- Swept 1st place in all ILSVRC and COCO 2015 competitions

MSRA @ ILSVRC & COCO 2015 Competitions

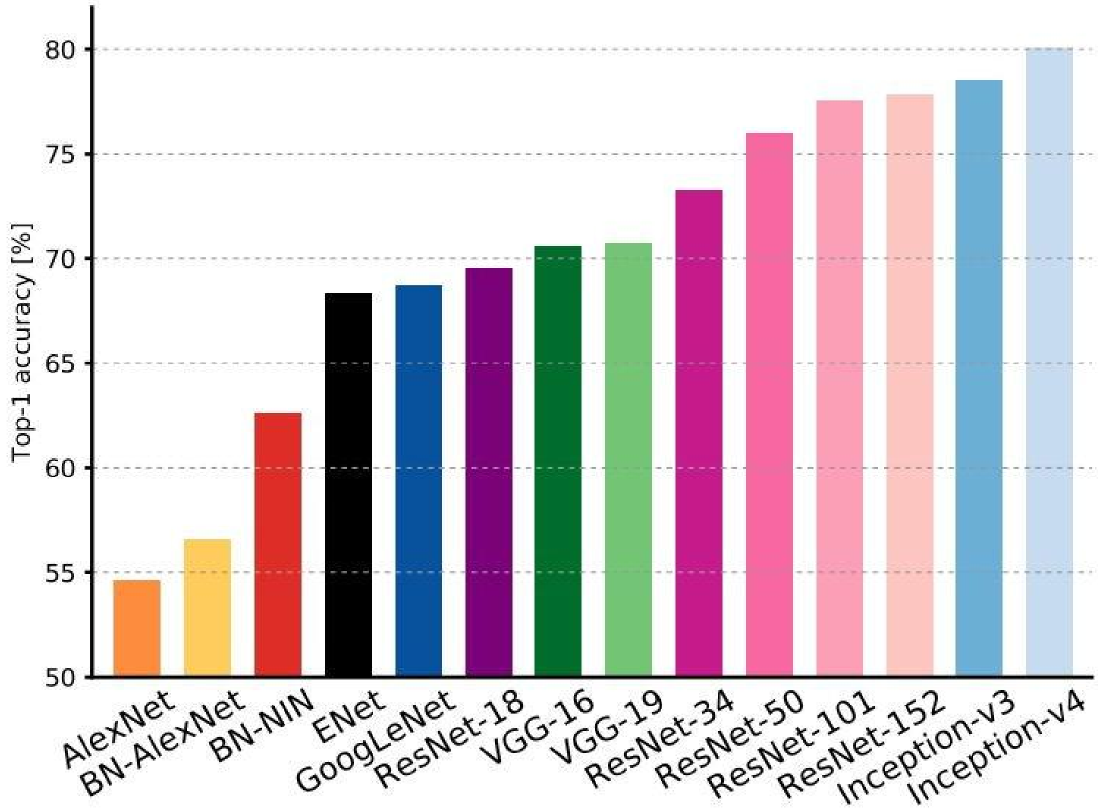
- **1st places in all five main tracks**
  - ImageNet Classification: *"Ultra-deep"* (quote Yann) 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

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

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

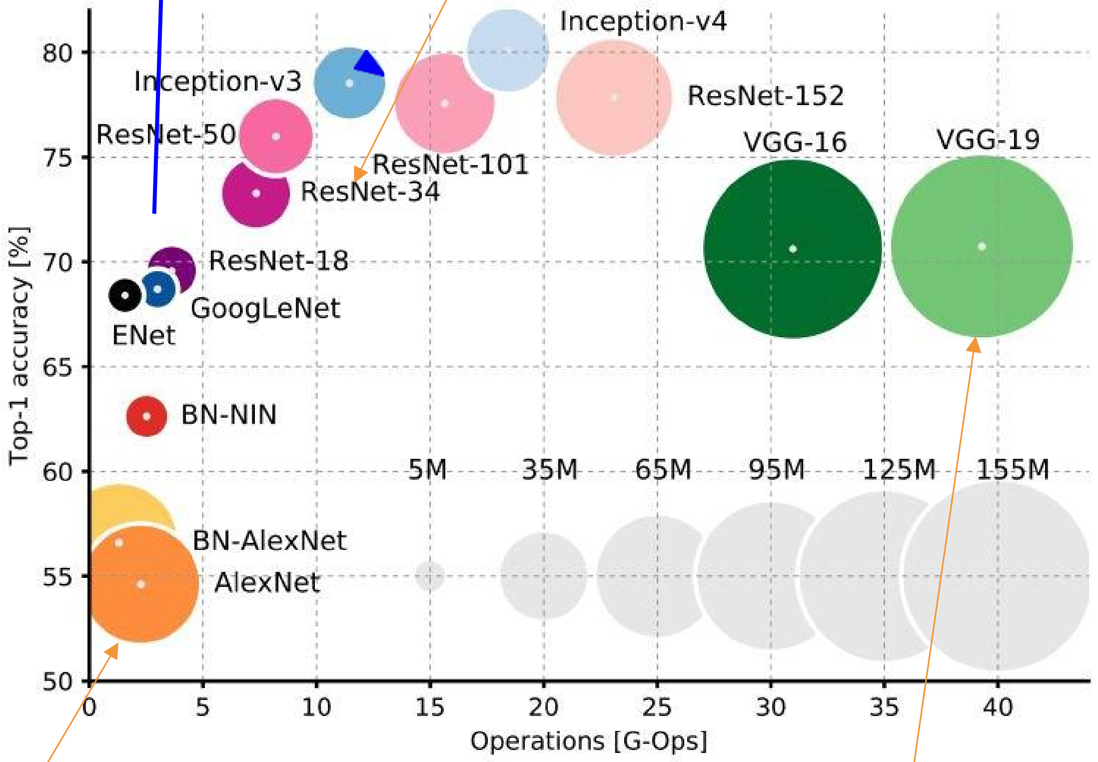


Comparing complexity...



GoogLeNet:
most efficient

ResNet : Moderate efficiency depending on model, highest accuracy



AlexNet:
Smaller compute, still memory heavy, lower accuracy

VGG: Highest memory, most operations

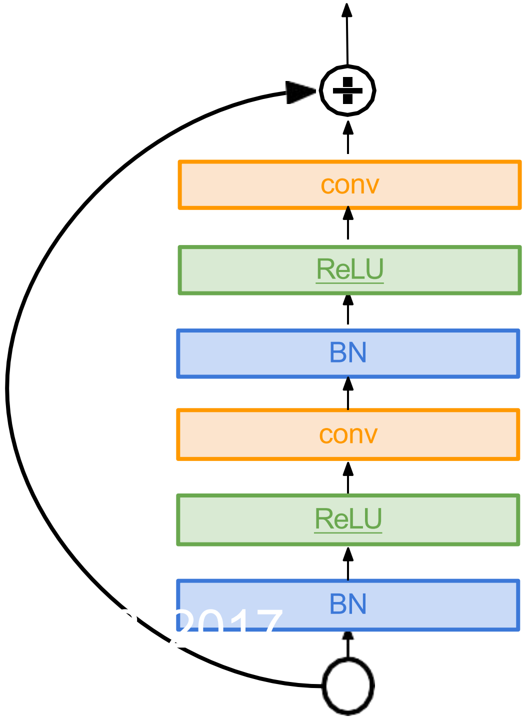
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Other architectures to know...

Identity Mappings in Deep Residual Networks

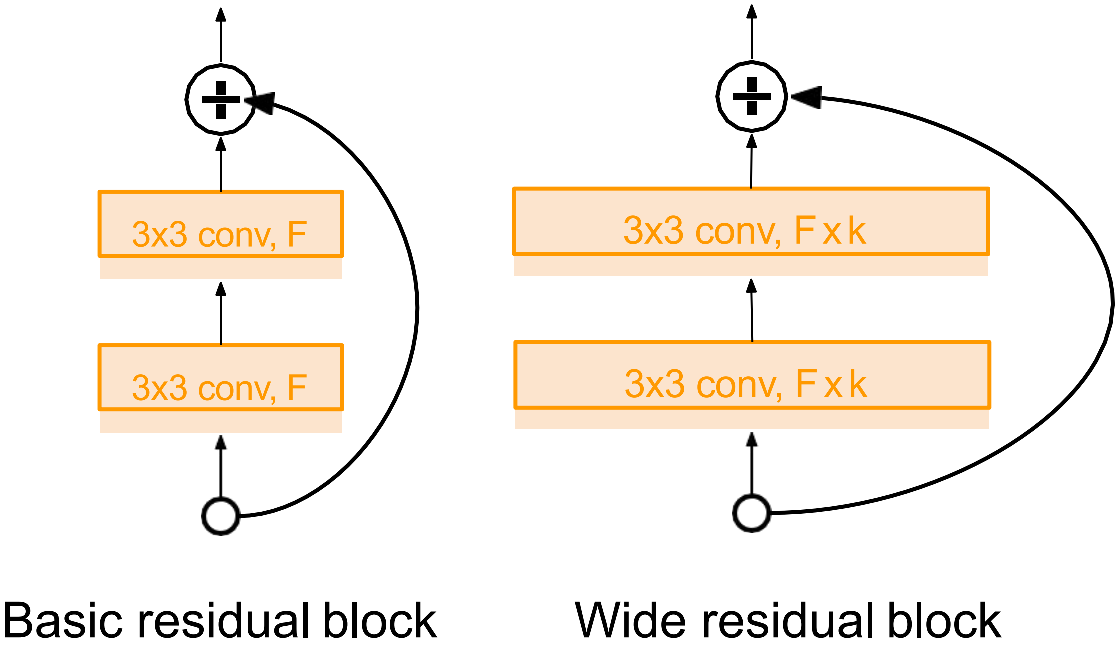
[He et al. 2016]

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



Wide Residual Networks

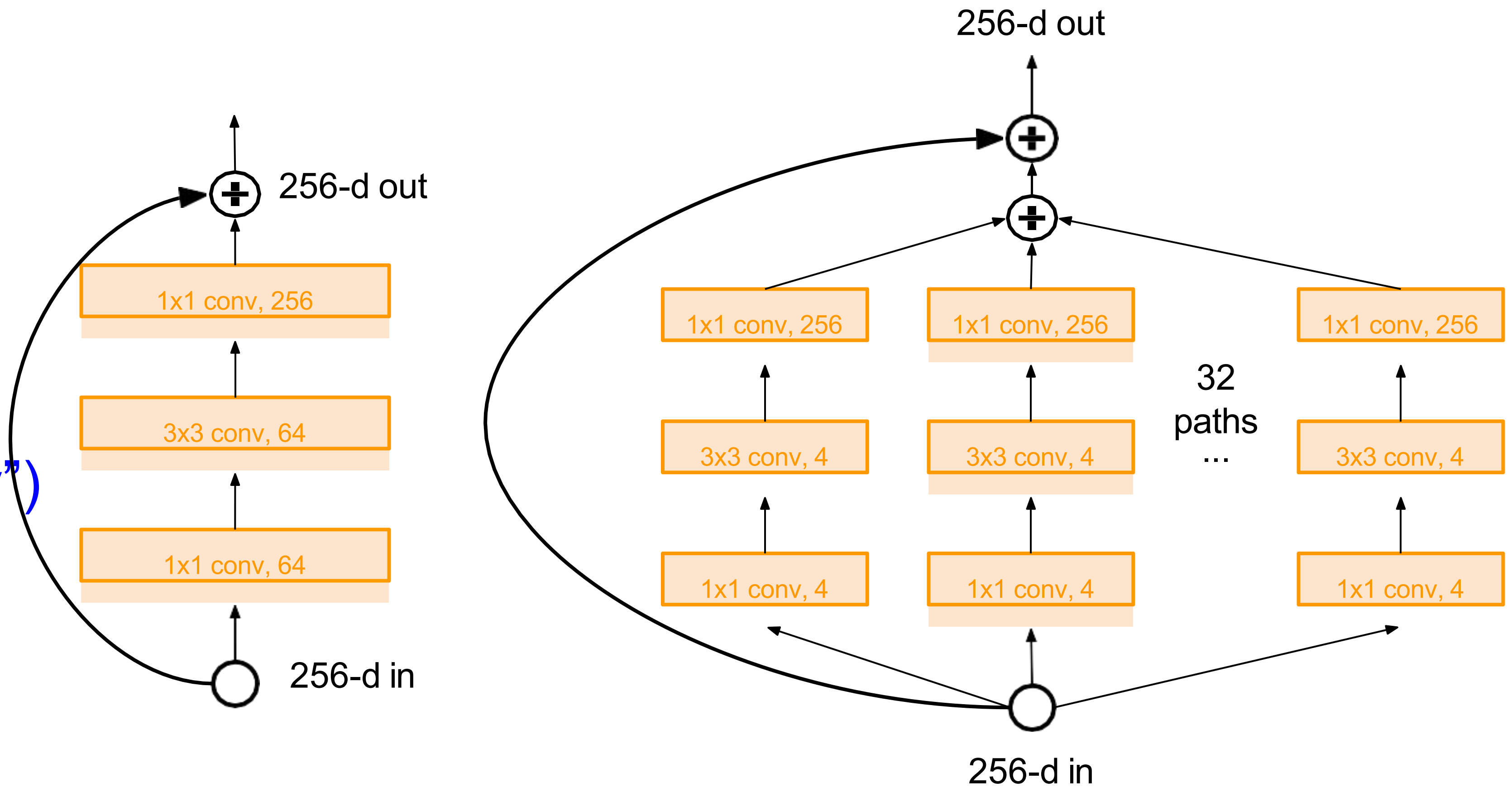
- Argues that residuals are the important factor, not depth
- User wider residual blocks (F x k filters instead of F filters in each layer)
- 50-layer wide ResNet outperforms 152-layer original ResNet
- Increasing width instead of depth more computationally efficient (parallelizable)



Improving ResNets...

Aggregated Residual Transformations for Deep Neural Networks (ResNeXt)

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



2019
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THANKS