CNN Architectures

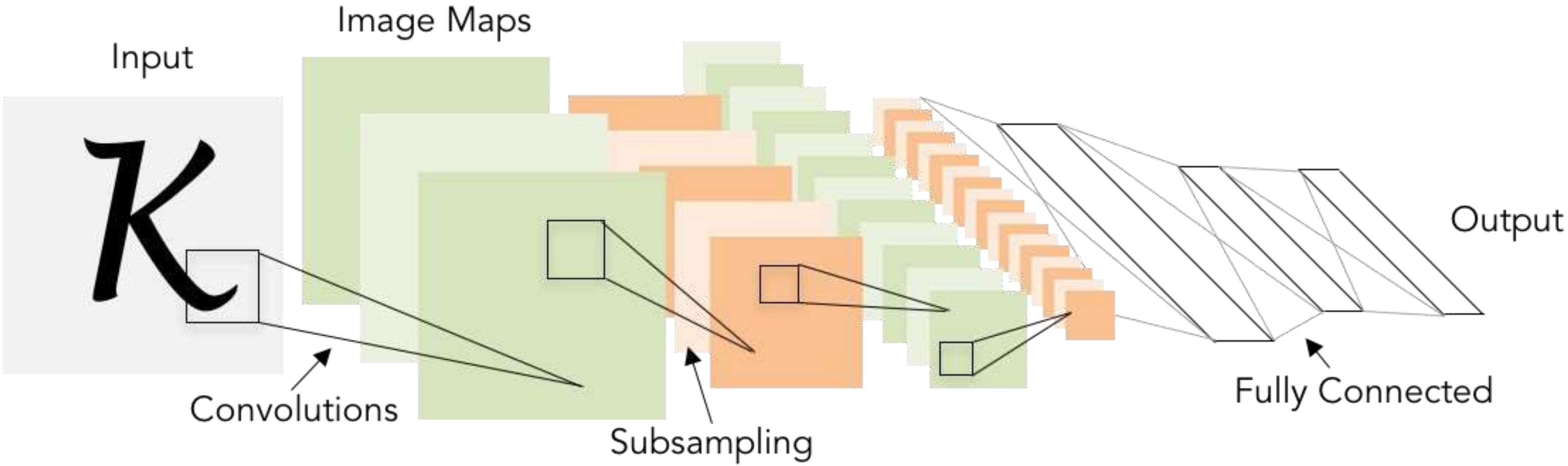
Today: CNN Architectures

Case Studies

- AlexNet
- VGG
- GoogLeNet
- ResNet

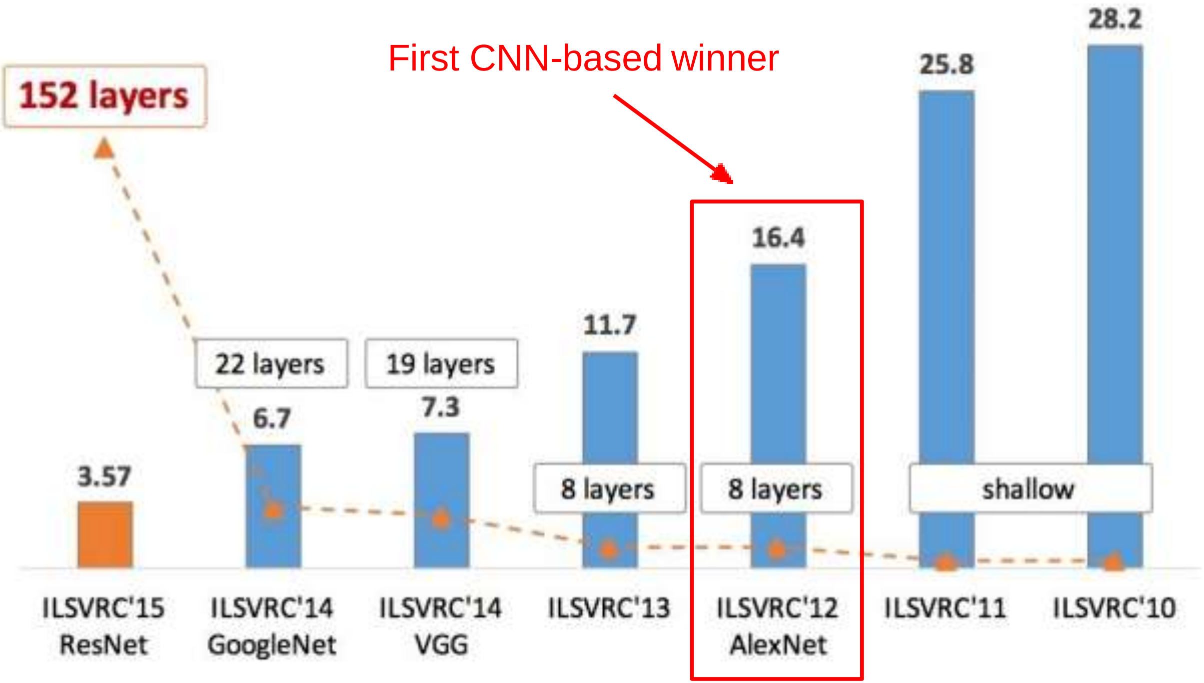
Review: LeNet-5

[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]

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Case Study: AlexNet

[Krizhevsky et al. 2012]

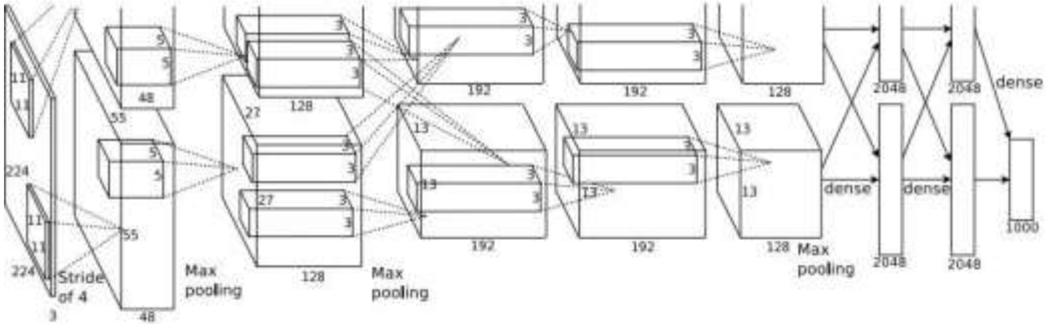
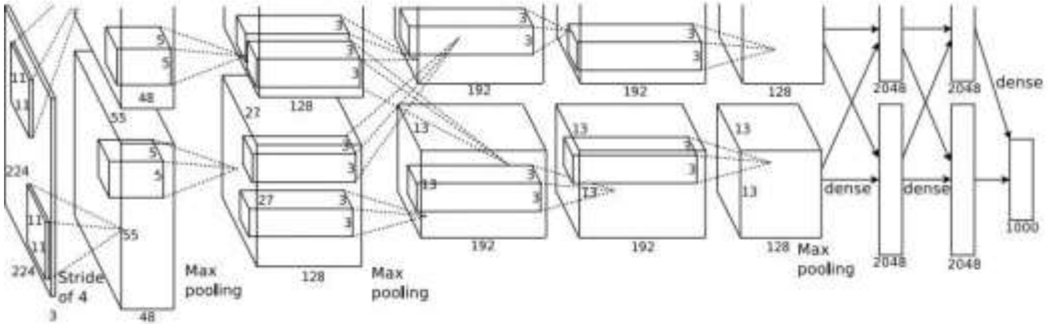


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

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

[Krizhevsky et al. 2012]



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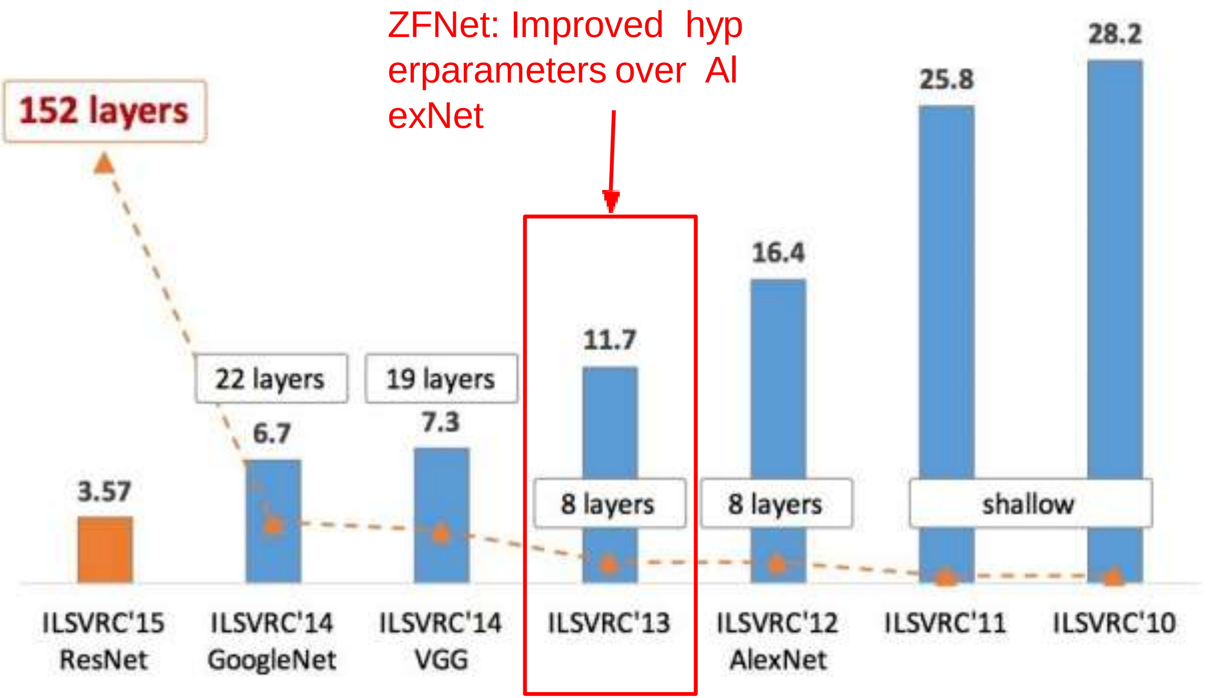
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

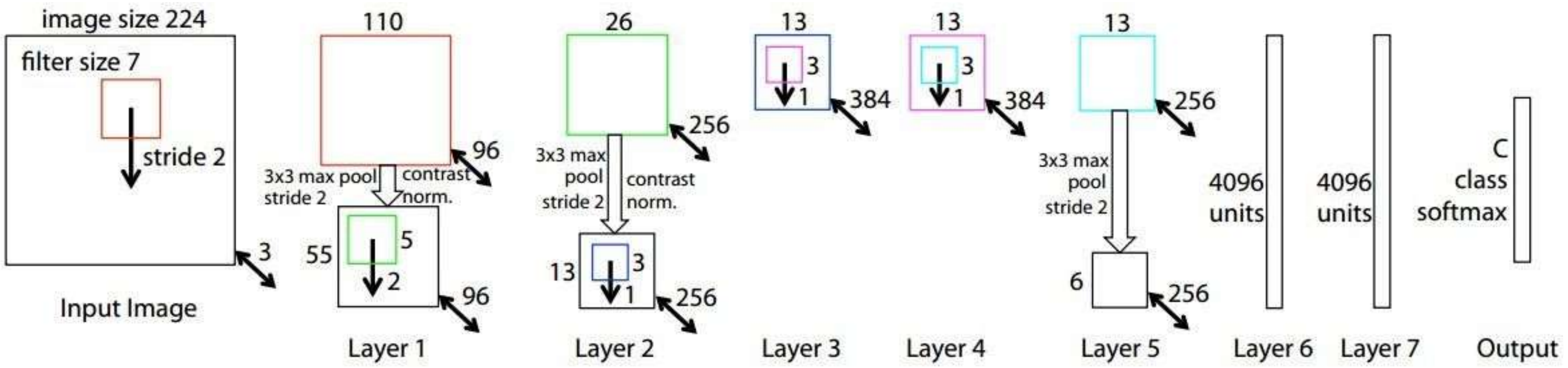
Details/Retrospectives:
-first use of ReLU
-used Norm layers (not common anymore)
-heavy data augmentation
-dropout 0.5
-batch size 128
-SGD Momentum 0.9
-Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
-L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



ZFNet

[Zeiler and Fergus, 2013]

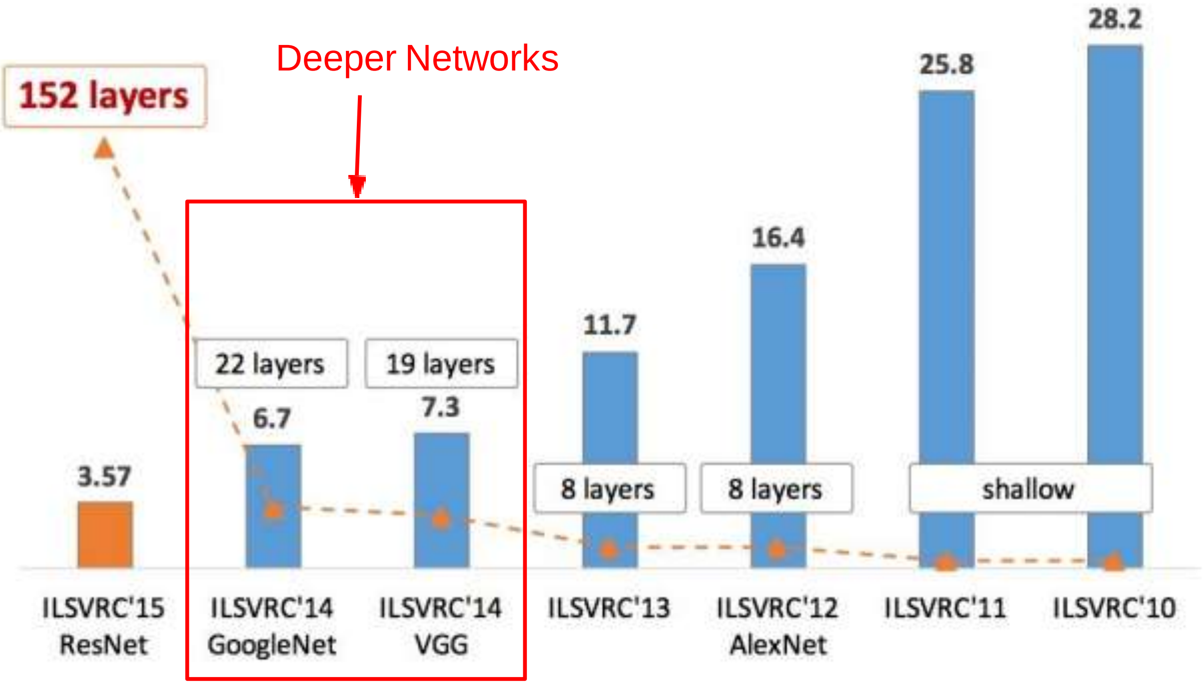


TODO: remake figure

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) winners



Case Study: VGGNet

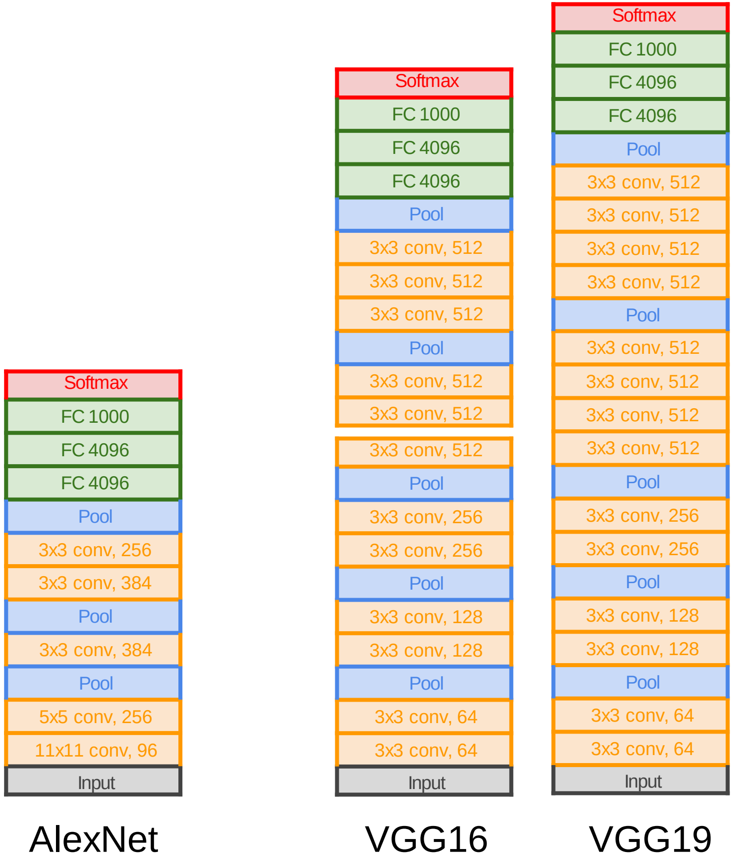
[Simonyan and Zisserman, 2014]

Small filters, Deeper networks

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

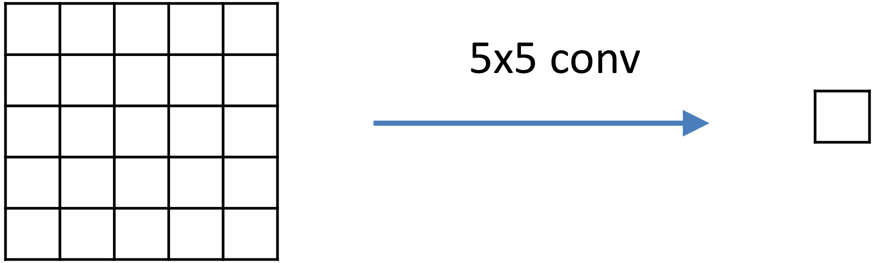
Only 3x3 CONV stride 1, pad 1
and 2x2 MAX POOL stride 2

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



Case Study: VGGNet

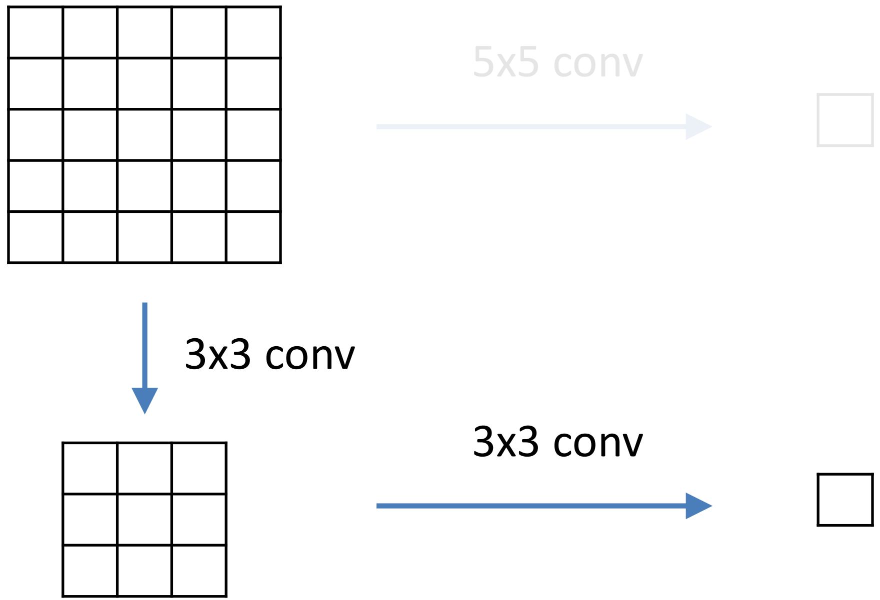
[Simonyan and Zisserman, 2014]



25 params

Case Study: VGGNet

[Simonyan and Zisserman, 2014]



25 params

9+9 prams
More linearity

Case Study: VGGNet

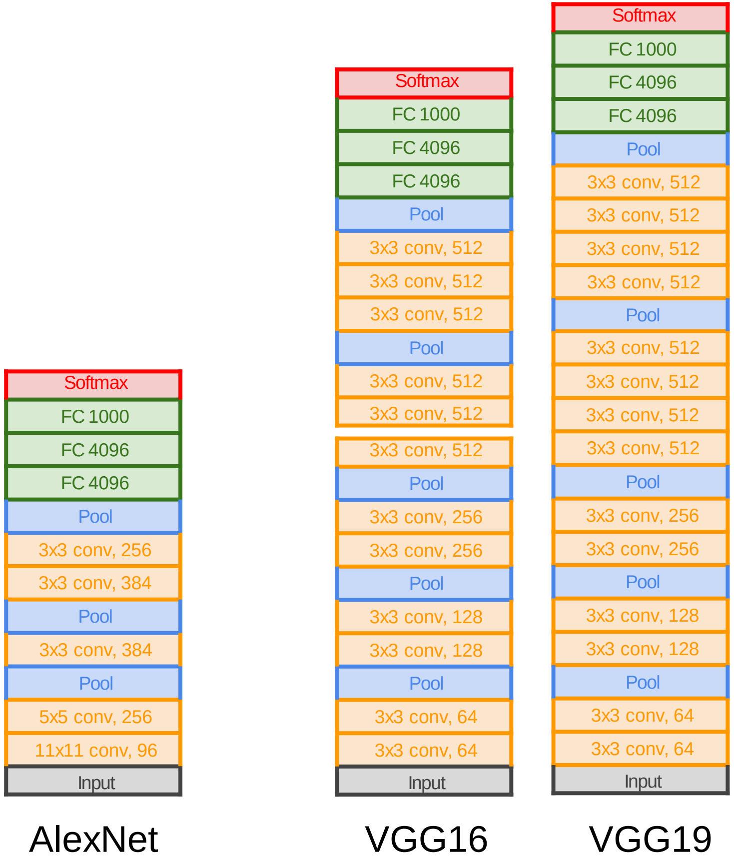
[Simonyan and Zisserman, 2014]

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

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

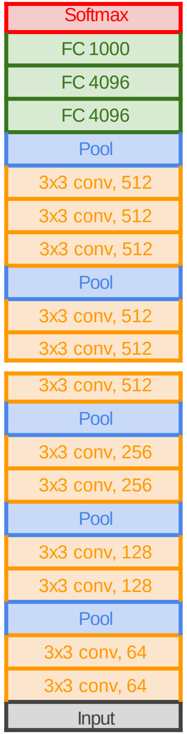
But deeper, more non-linearities

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



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 C
ONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824 CO
NV3-256: [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 C
ONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296 CO
NV3-512: [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 C
ONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296 CO
NV3-512: [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 F
C: [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



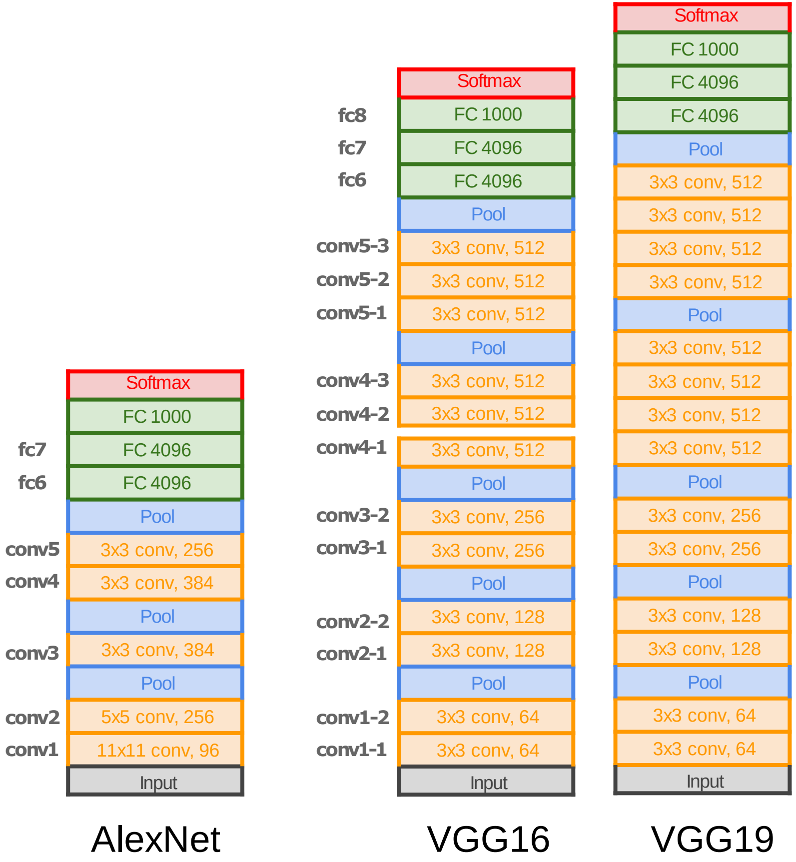
VGG16

Case Study: VGGNet

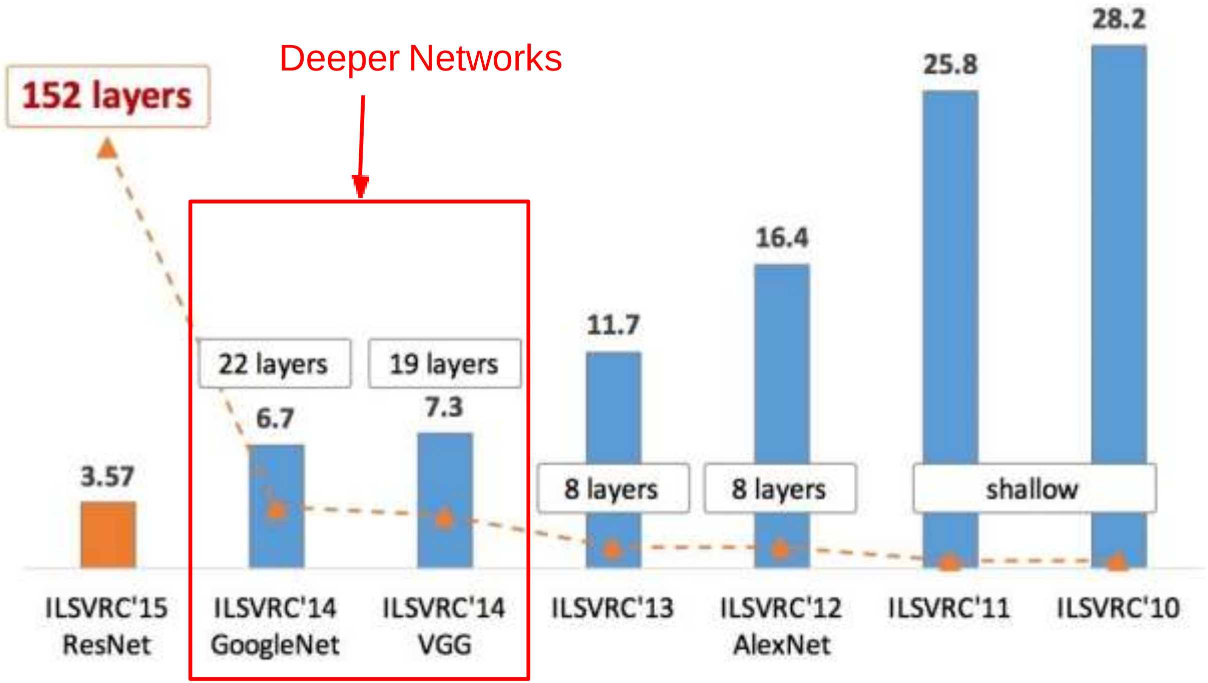
[Simonyan and Zisserman, 2014]

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



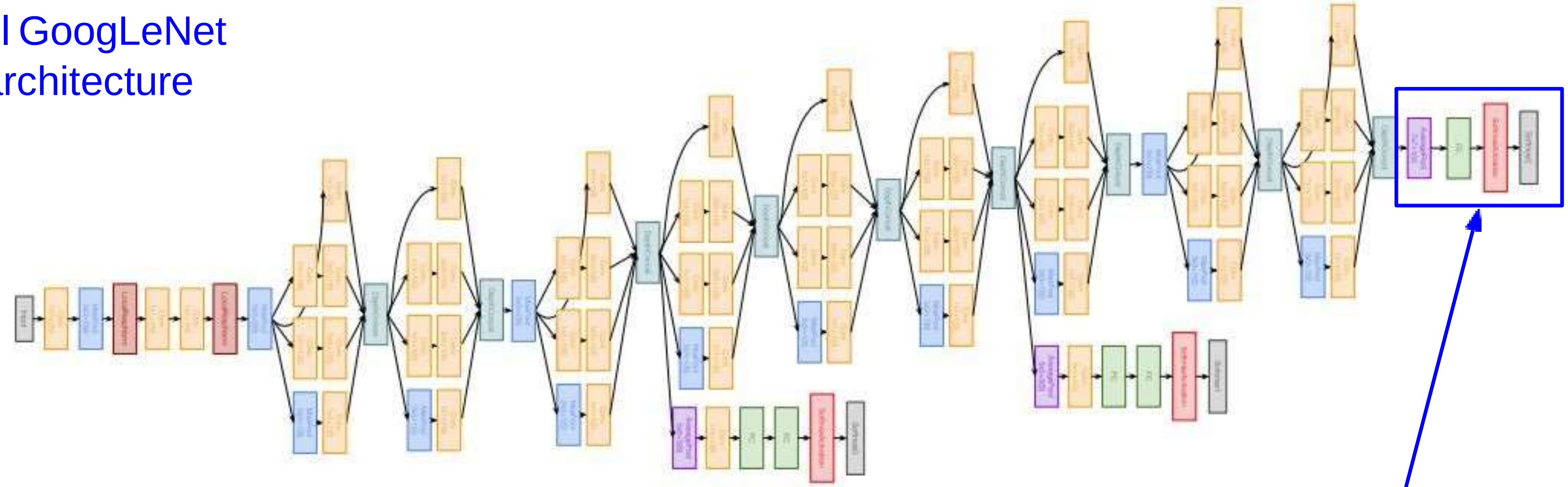
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

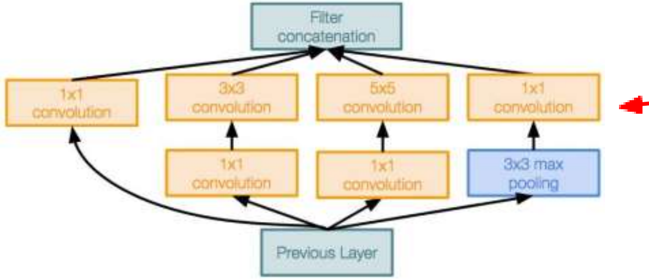


Classifier output

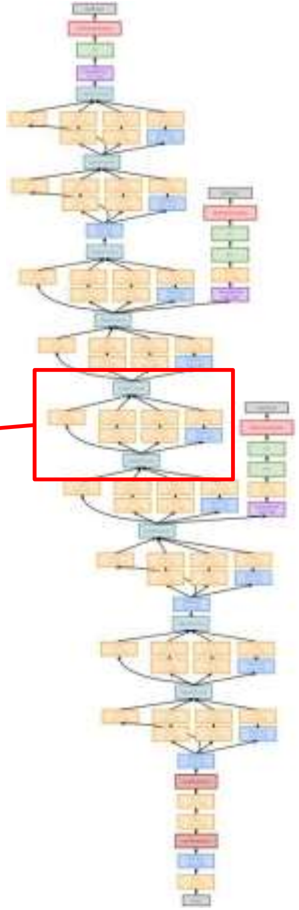
Case Study: GoogLeNet

[Szegedy et al., 2014]

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

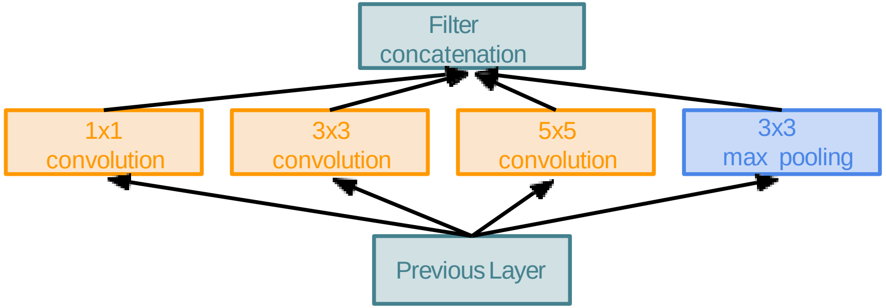


Inception module

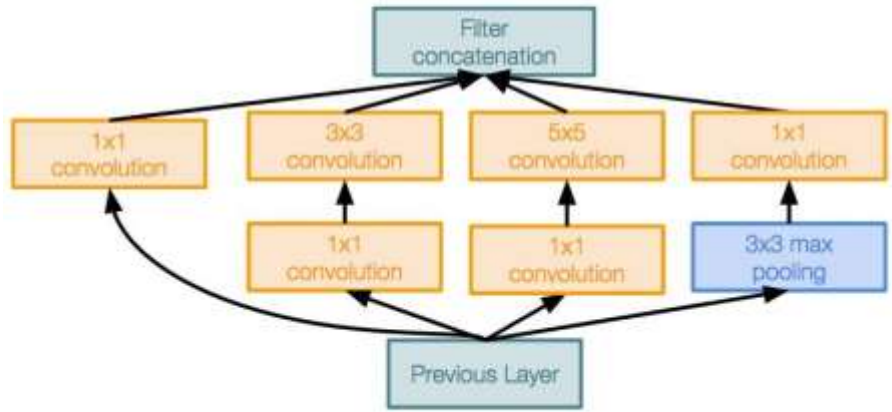


Case Study: GoogLeNet

[Szegedy et al., 2014]



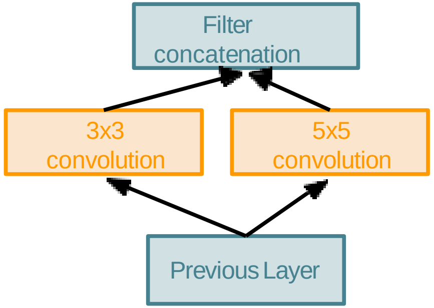
Naive Inception module



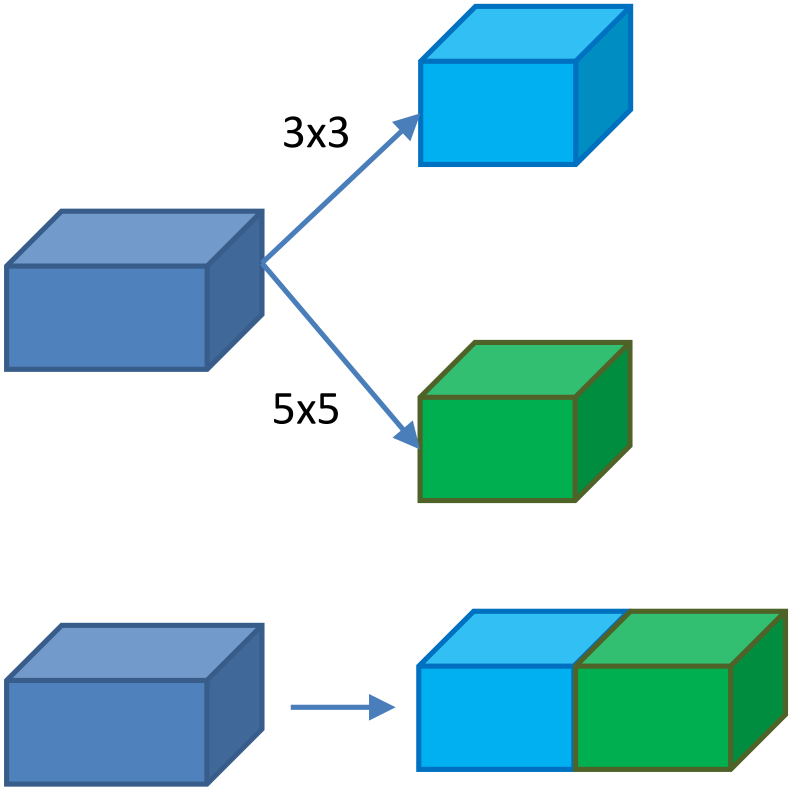
Inception module with dimension reduction

Case Study: GoogLeNet

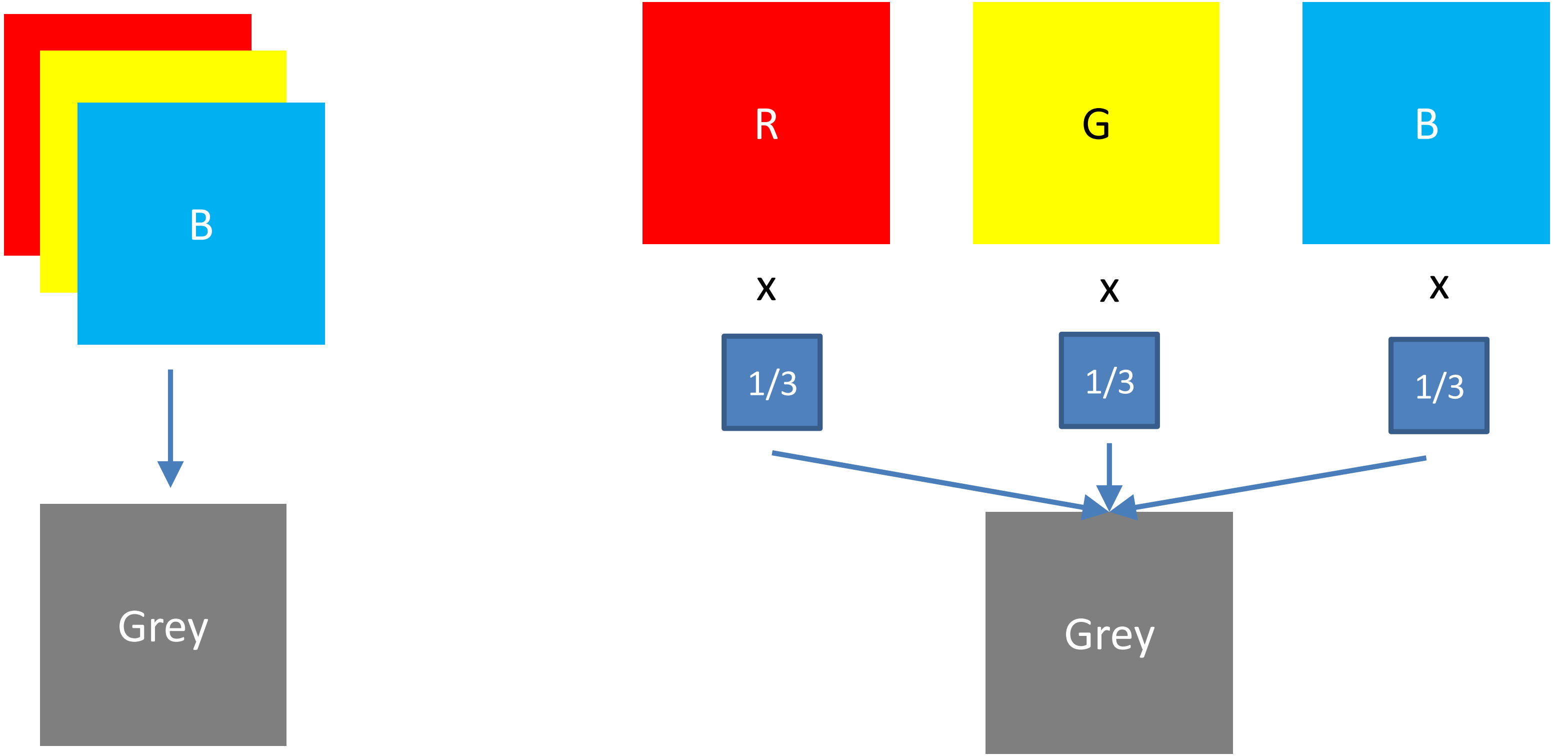
[Szegedy et al., 2014]



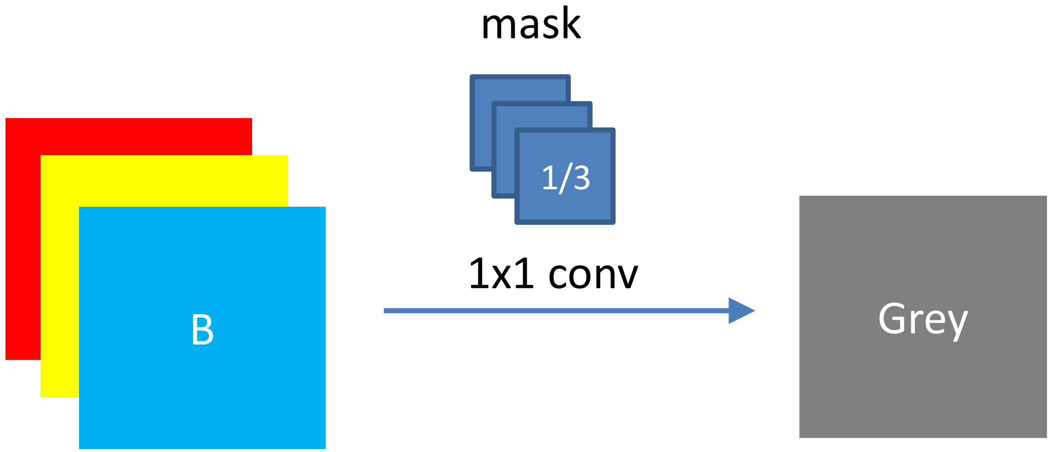
Naive Inception module



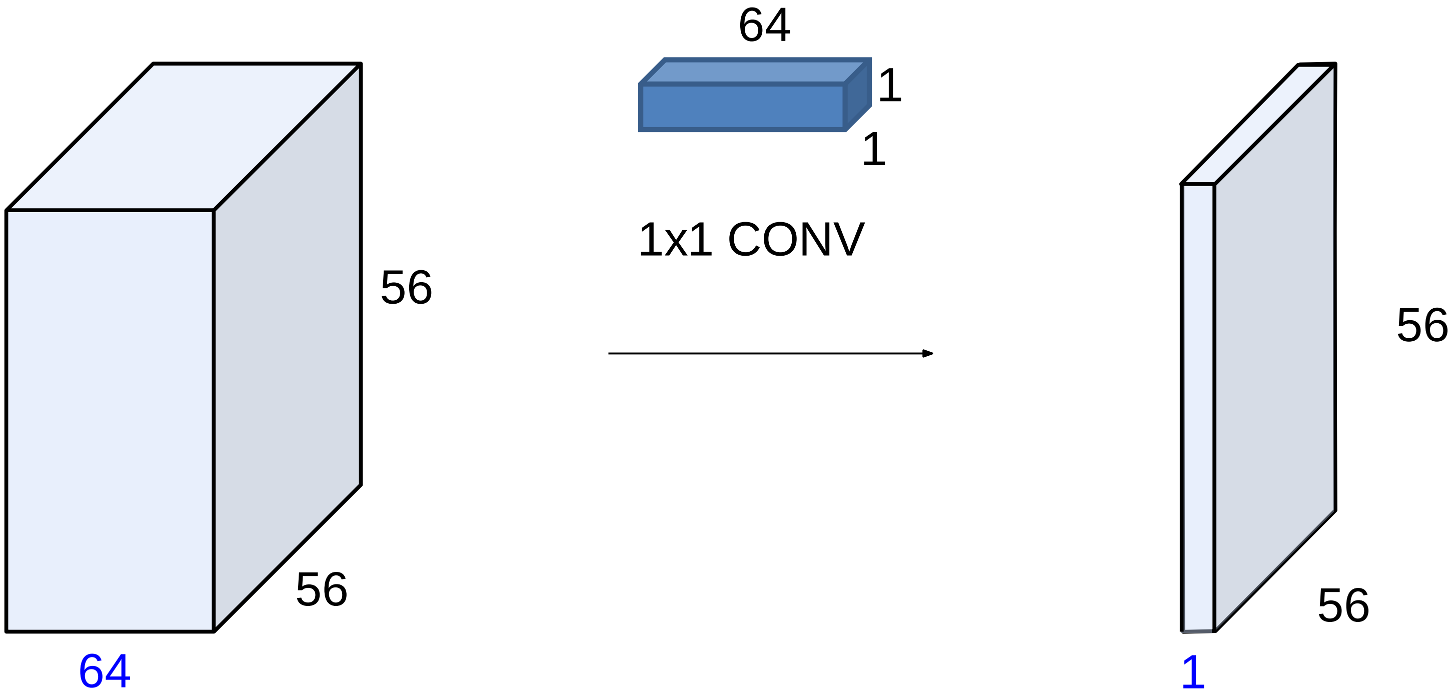
Reminder: 1x1 convolutions



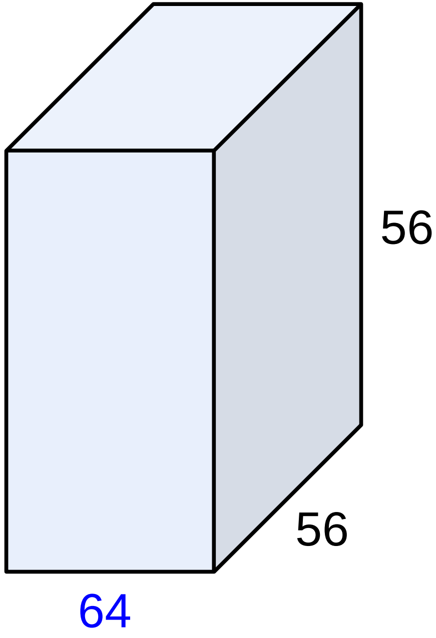
Reminder: 1x1 convolutions



Reminder: 1x1 convolutions



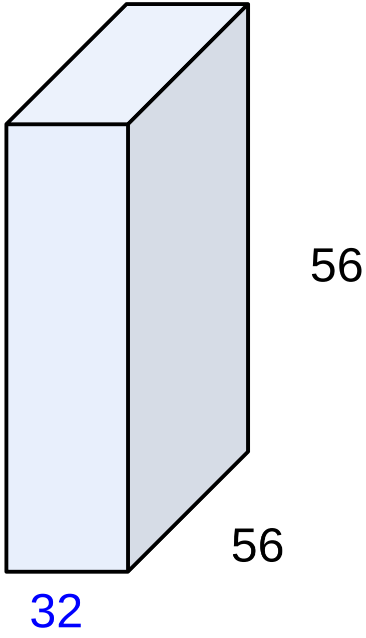
Reminder: 1x1 convolutions



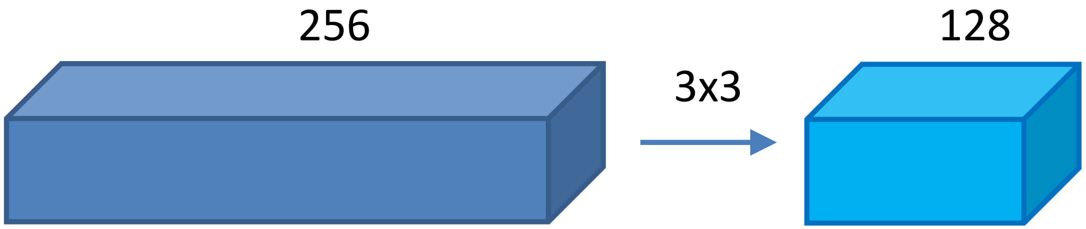
1x1 CONV
with 32 filters

preserves spatial dimensions,
reduces depth!

Projects depth to lower dimension (combination of feature maps)

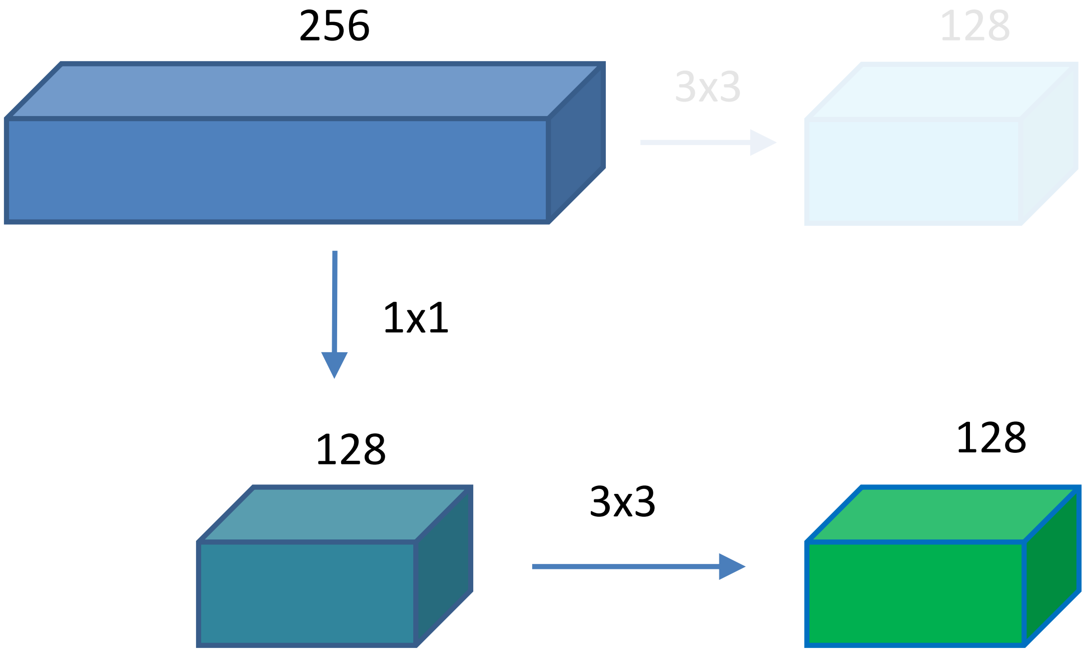


Case Study: GoogLeNet



256 X 3X3 X 128
= 294,912

Case Study: GoogLeNet

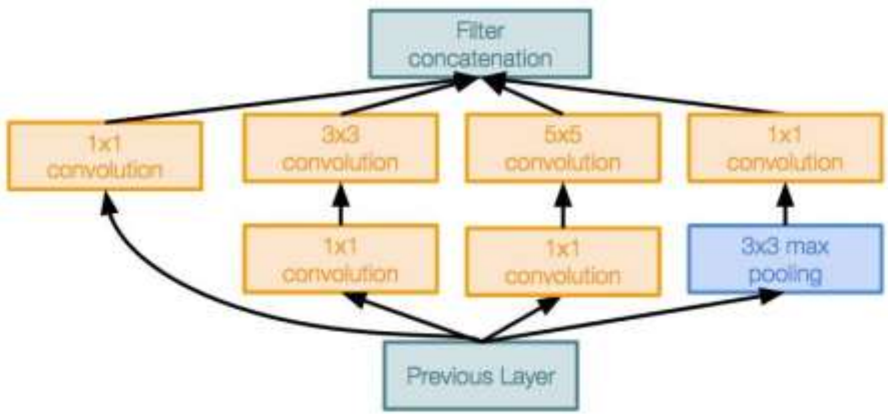


256 X 3X3 X 128
= 294,912

256 X 1X1 X 128
+ 128 X 3X3 X 128
= 189,224

Case Study: GoogLeNet

[Szegedy et al., 2014]



Inception module with dimension reduction

3x3 max pooling, stride=1

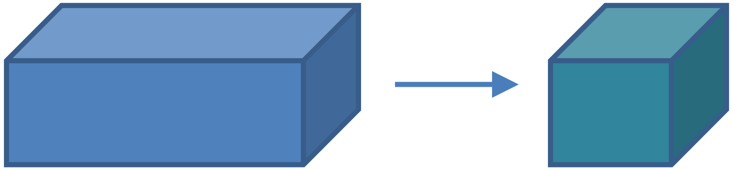
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	3	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Feature map

0	0	0	0	0	0	0
0	3	3	3	0	0	0
0	3	3	3	0	0	0
0	3	3	3	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Enhanced feature map

1x1 Convolution



Case Study: GoogLeNet

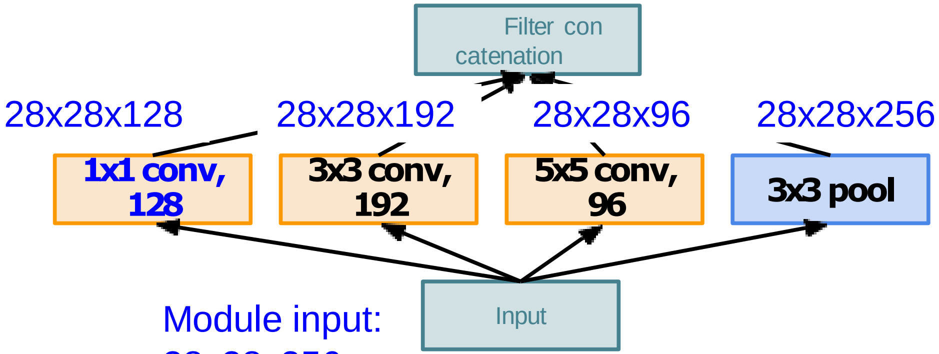
[Szegedy et al., 2014]

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

Example:

Q3:What is output size after filter concatenation?

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



Module input:
28x28x256

Naive Inception module

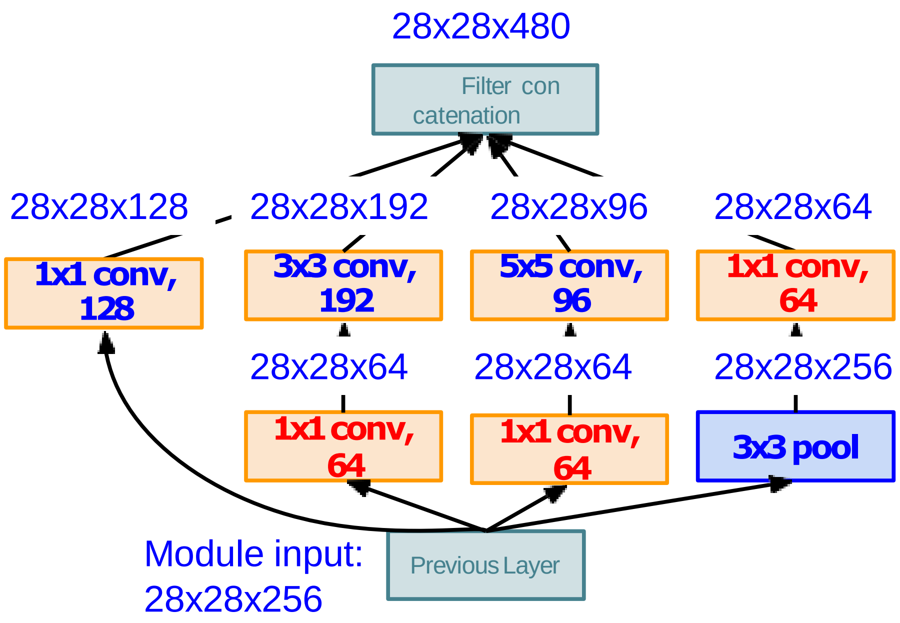
Conv Ops:
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x256
[5x5 conv, 96] 28x28x96x5x5x256
Total: 854M ops

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]



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

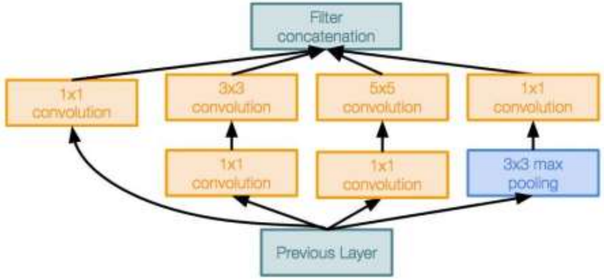
Compared to 854M ops for naive version
Bottleneck can also reduce depth after pooling layer

Case Study: GoogLeNet

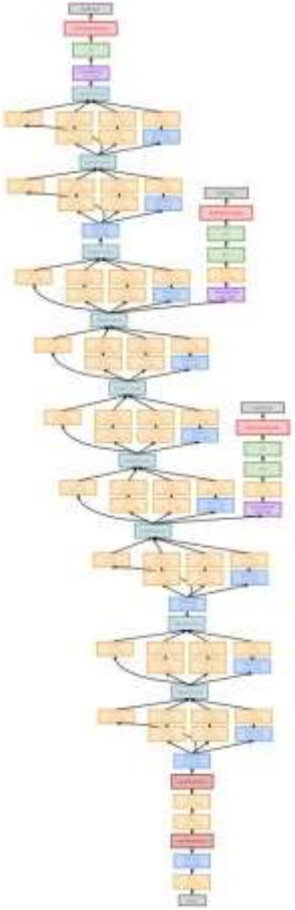
[Szegedy et al., 2014]

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)



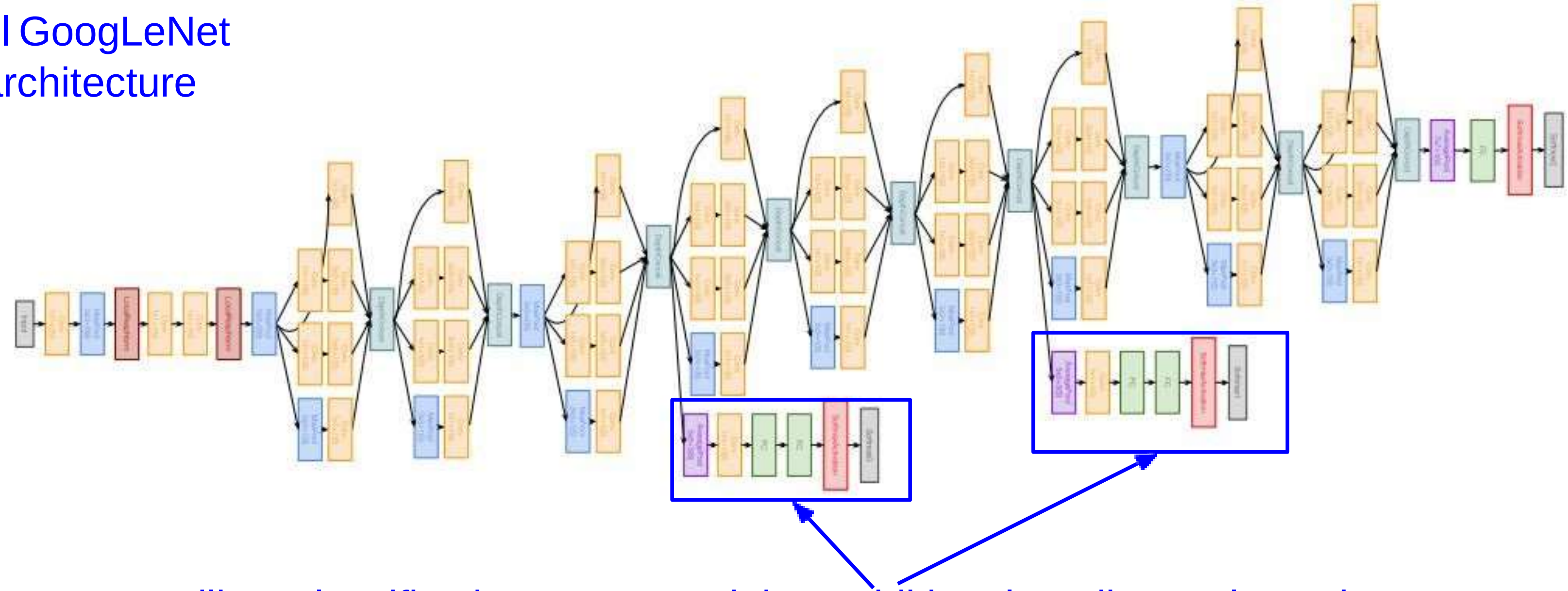
Inception module



Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

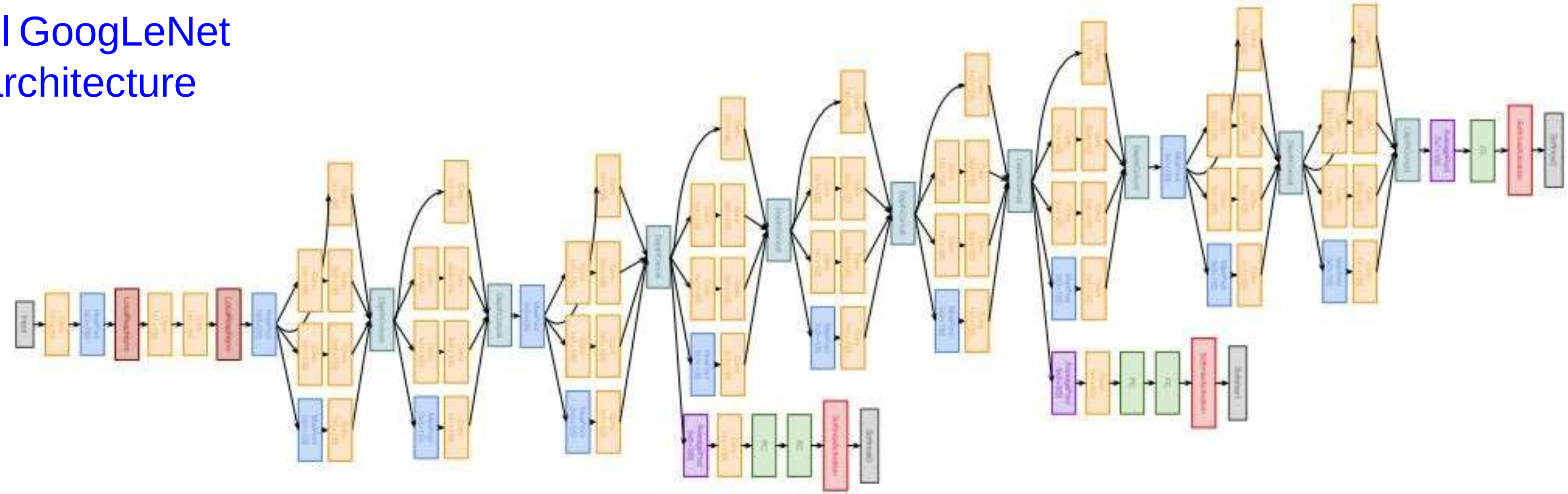


Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

Case Study: GoogLeNet

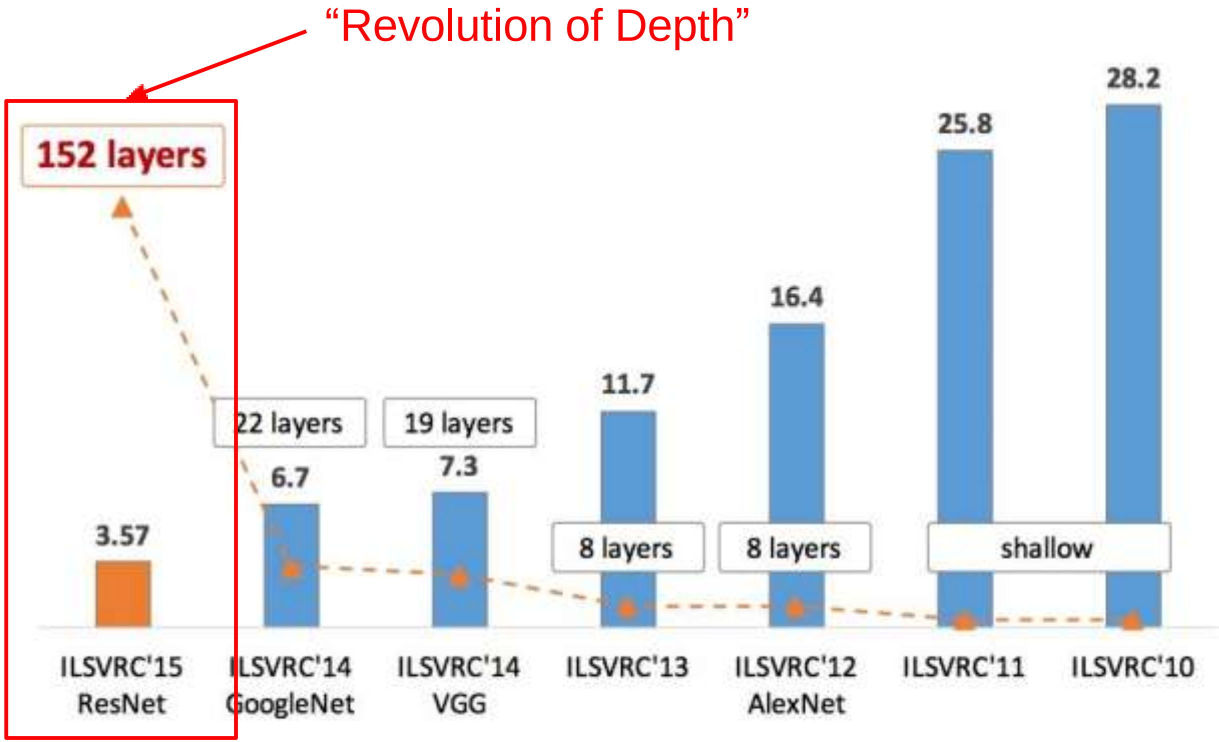
[Szegedy et al., 2014]

Full GoogLeNet architecture



22 total layers with weights (including each parallel layer in an Inception module)

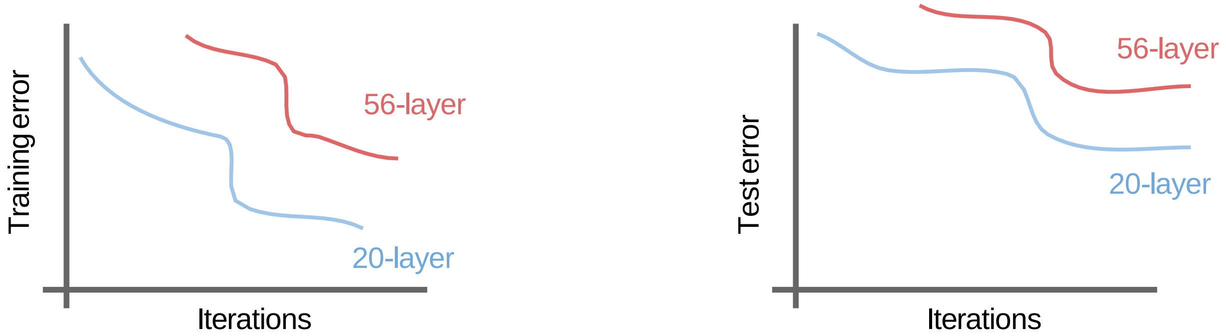
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Case Study: ResNet

[He et al., 2015]

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



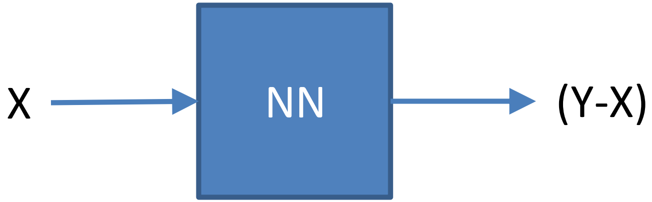
56-layer model performs worse on both training and test error
-> The deeper model performs worse, but it's not caused by overfitting!

Case Study: ResNet

X	Y
1	0.9
2	2.1
3	3.0
4	4.2

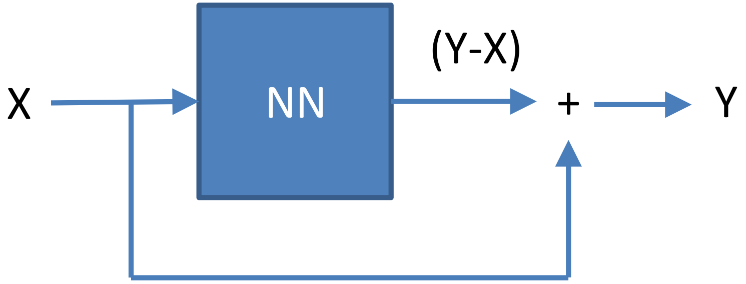
Case Study: ResNet

X	Y	Y-X
1	0.9	-0.1
2	2.1	0.1
3	3.0	0.0
4	4.2	0.2



Case Study: ResNet

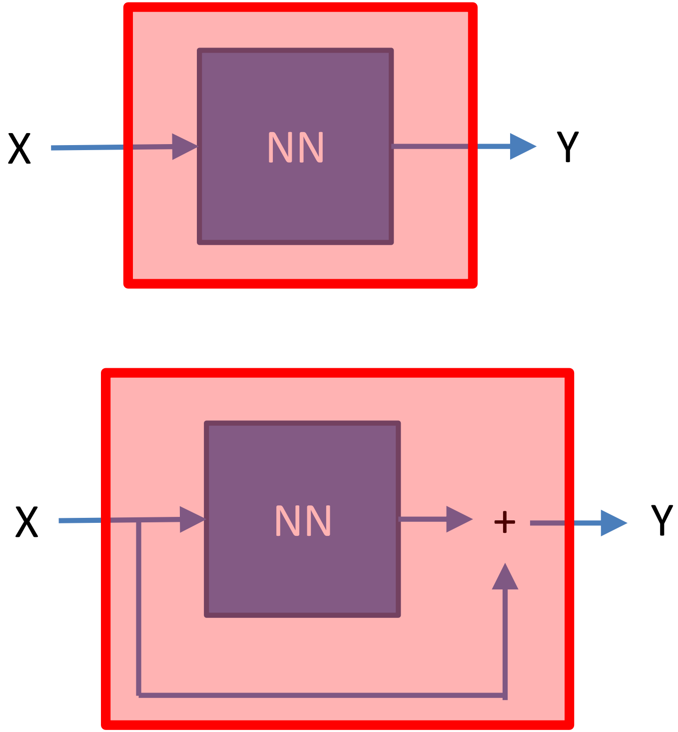
X	Y	Y-X
1	0.9	-0.1
2	2.1	0.1
3	3.0	0.0
4	4.2	0.2



Case Study: ResNet

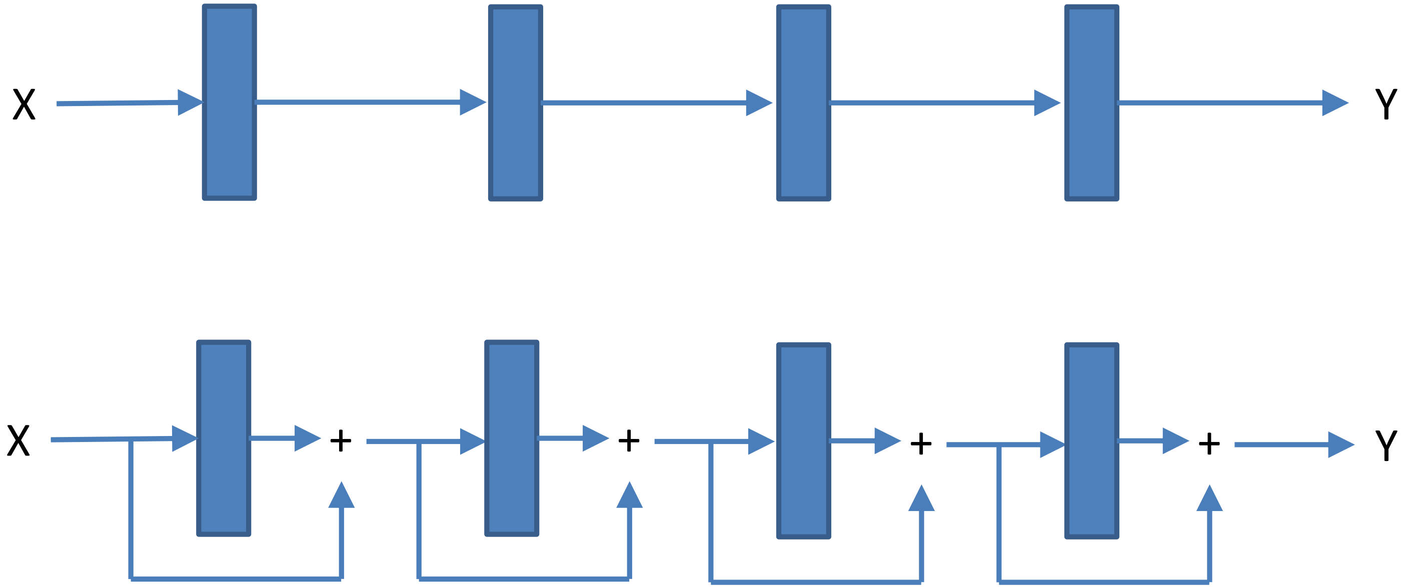
[He et al., 2015]

X	Y
1	0.9
2	2.1
3	3.0
4	4.2



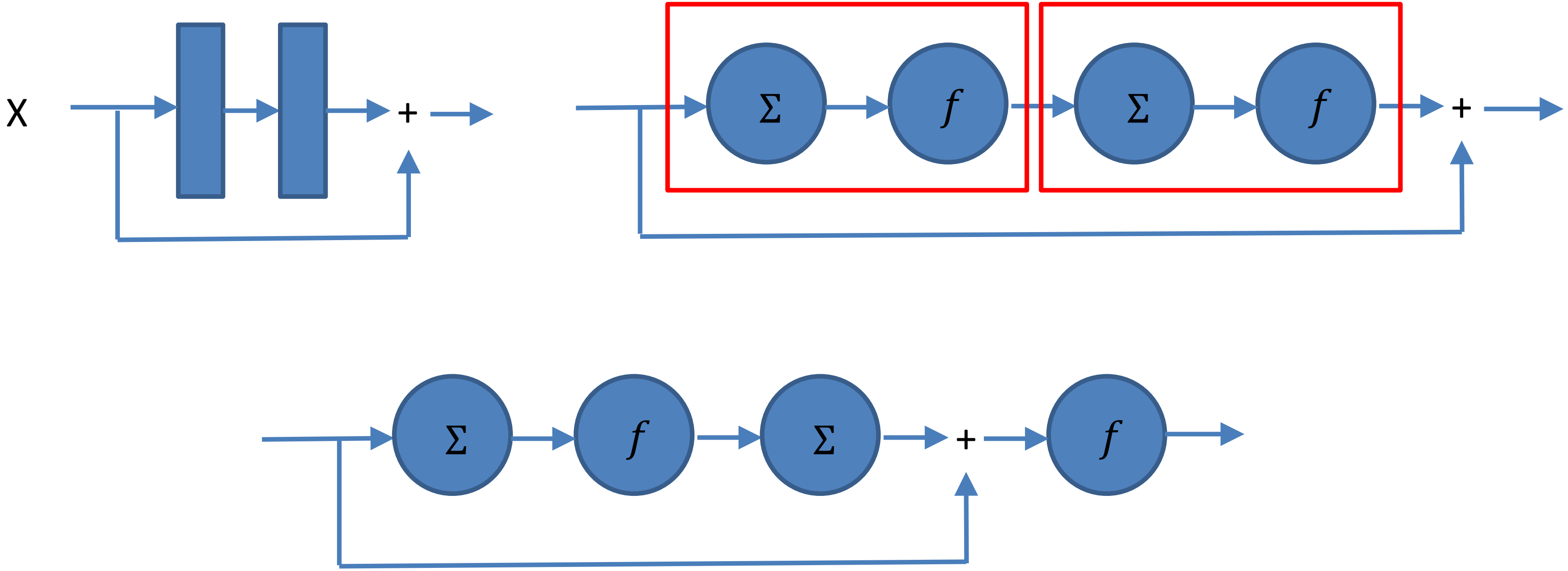
Case Study: ResNet

[He et al., 2015]

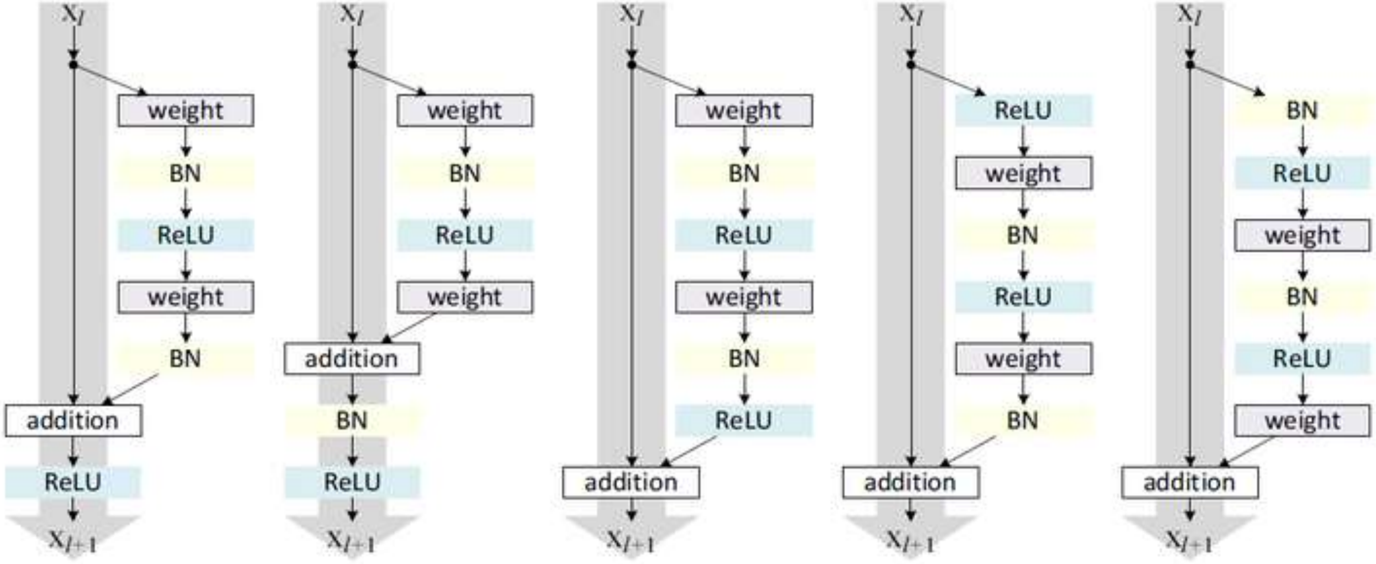


Case Study: ResNet

[He et al., 2015]



Case Study: ResNet



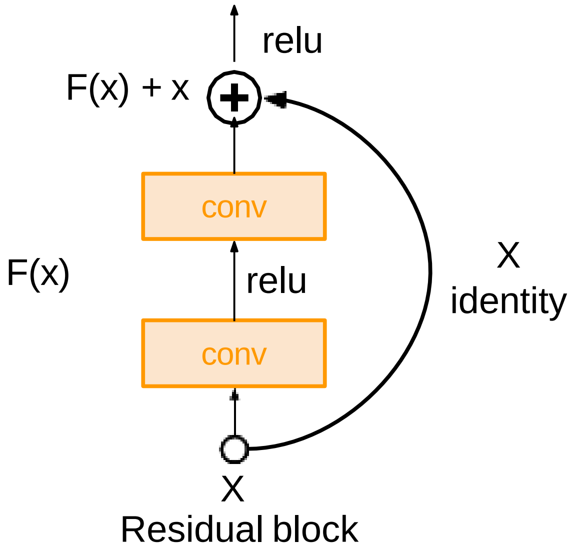
(a) original (b) BN after addition (c) ReLU before addition (d) ReLU-only pre-activation (e) **full pre-activation**

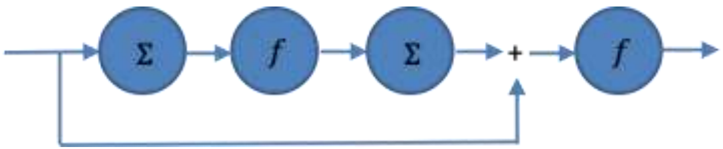
Case Study: ResNet

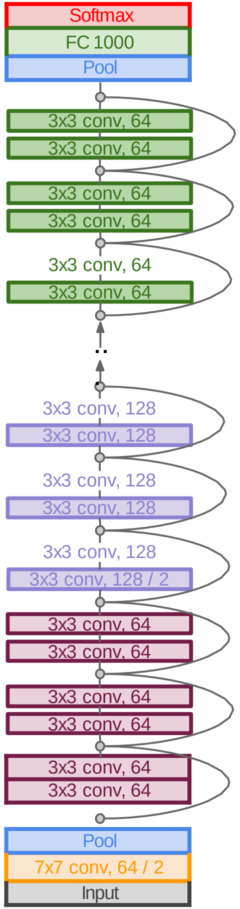
[He et al., 2015]

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 I LSVRC'15 and COCO'15!





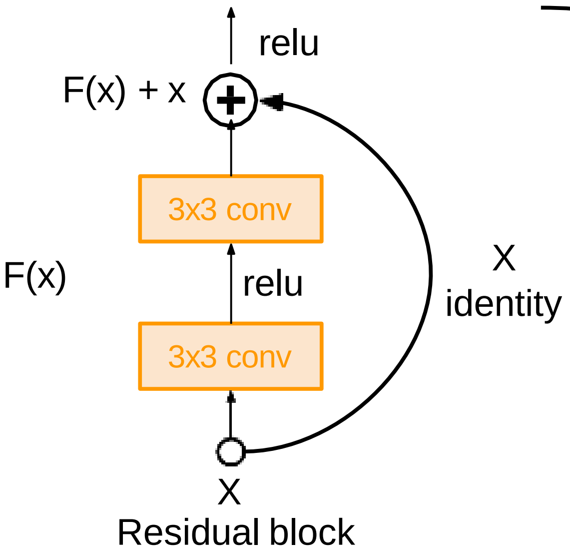


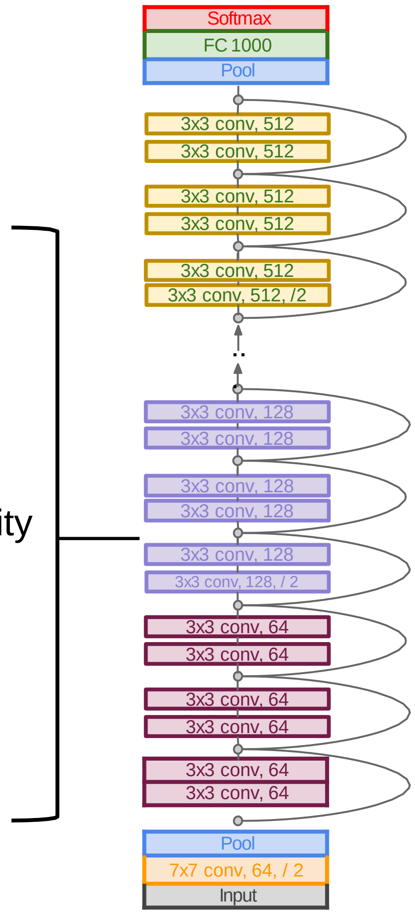
Case Study: ResNet

[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)
- Global average pooling layer after last conv. layer





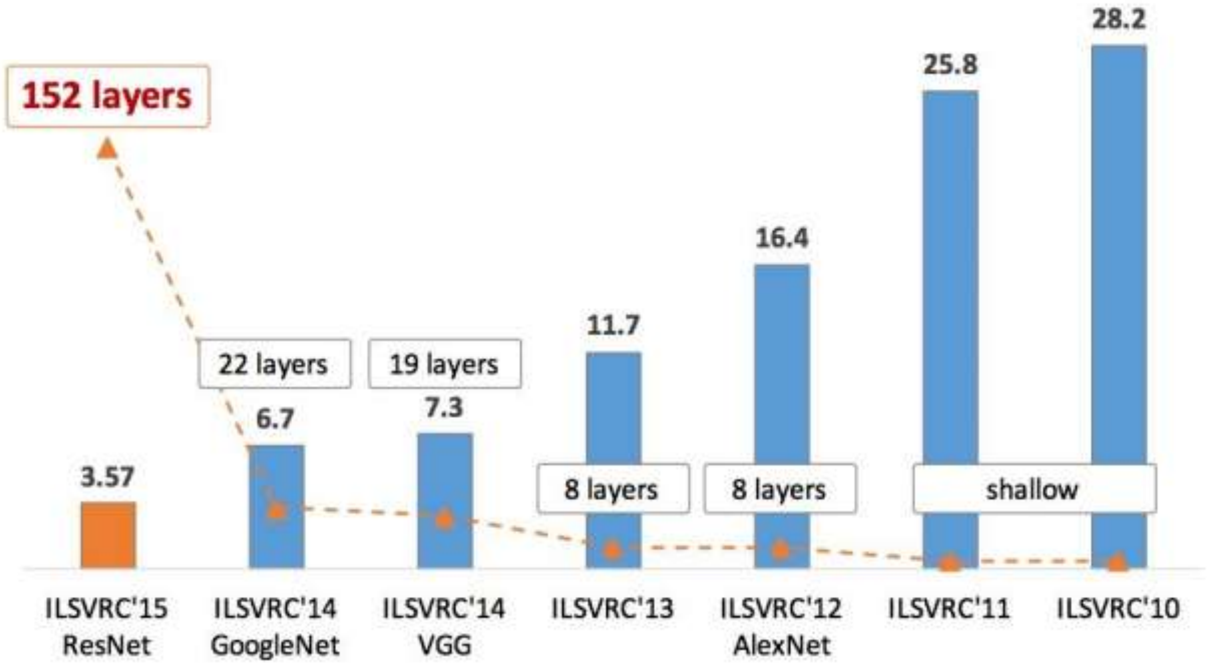
Case Study: ResNet

[He et al., 2015]

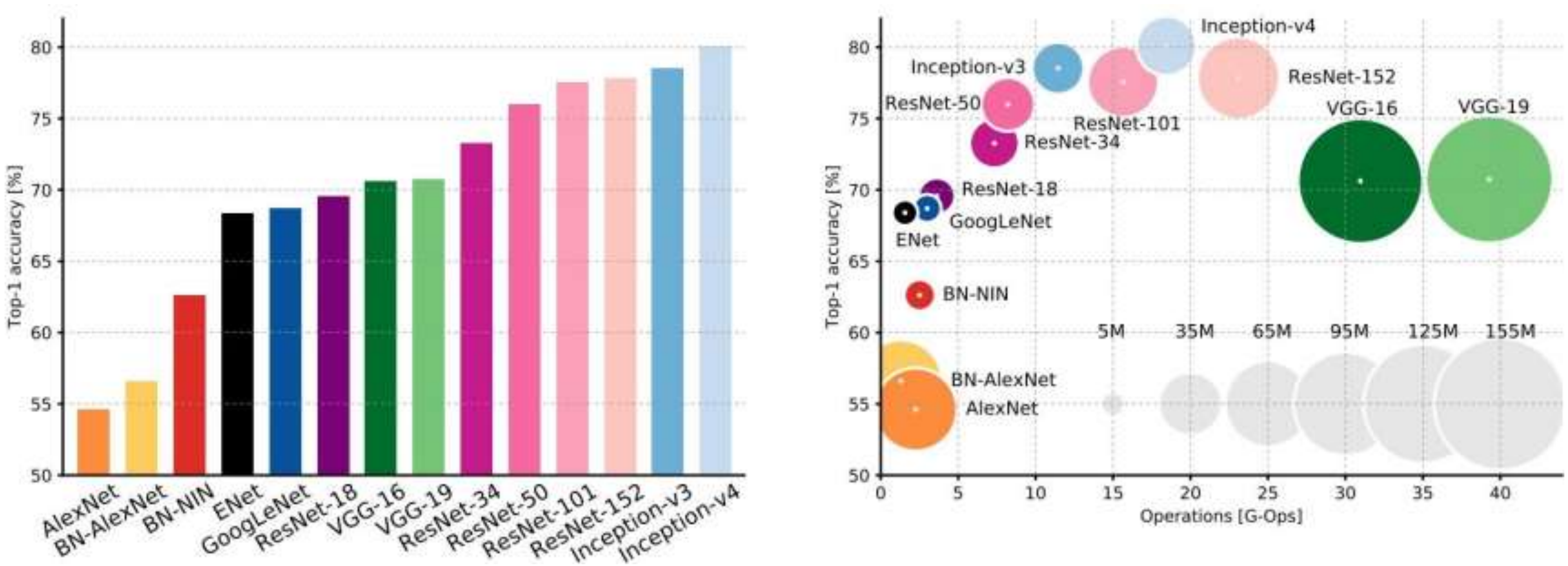
Training ResNet in practice:

- 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

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



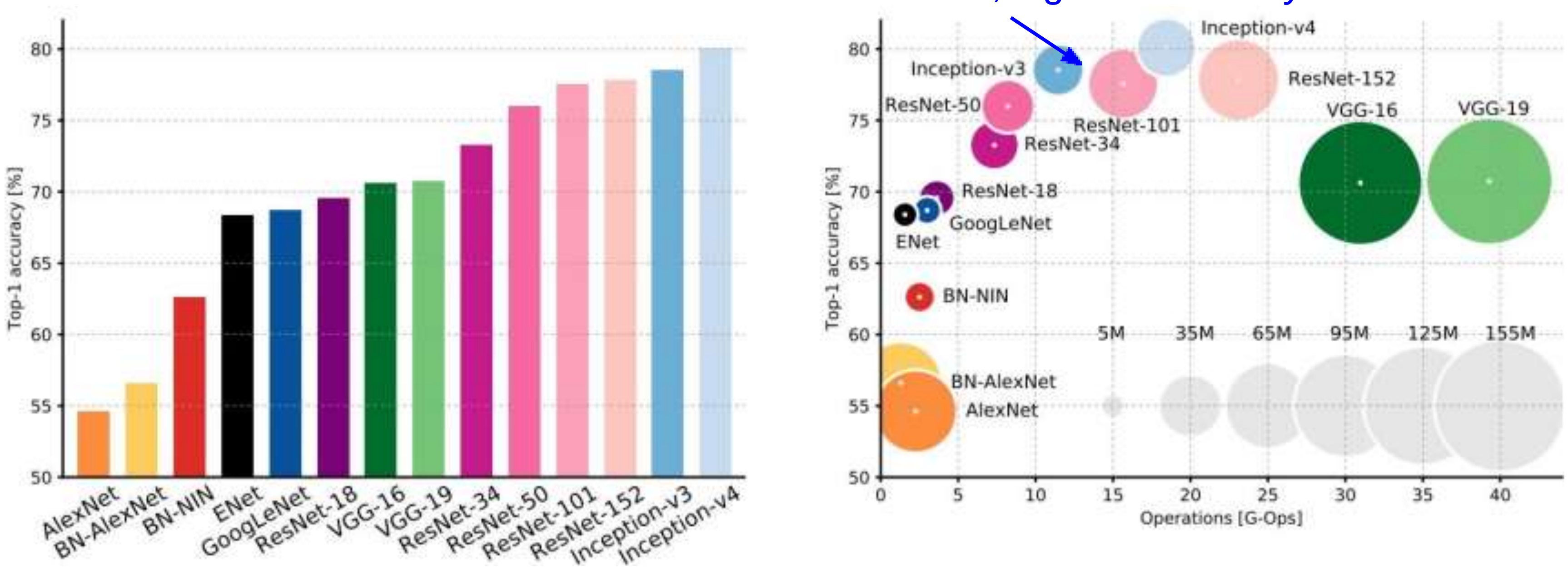
Comparing complexity...



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

Comparing complexity...

ResNet:
Moderate efficiency depending on model, highest accuracy



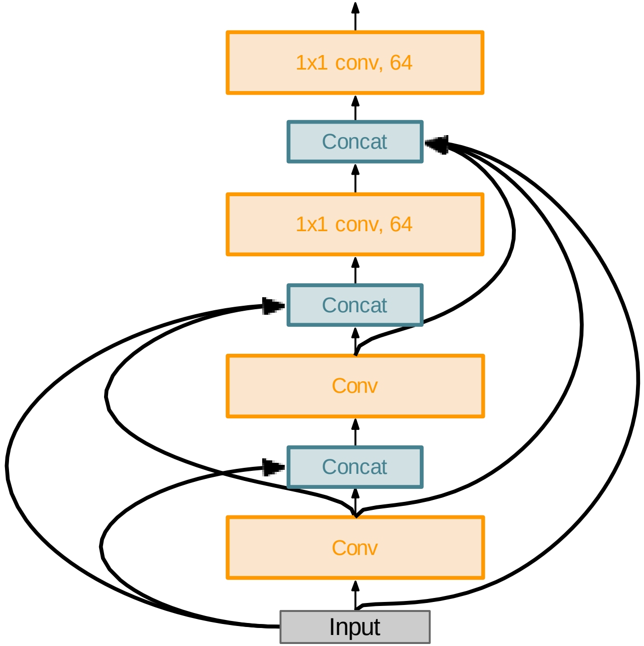
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Beyond ResNets...

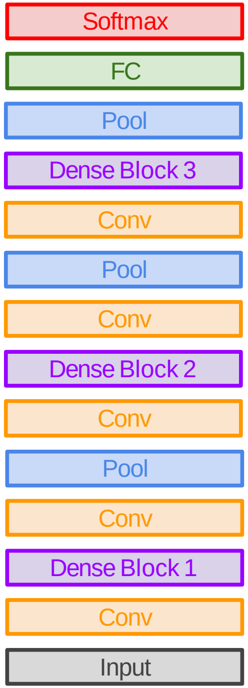
Densely Connected Convolutional Networks

[Huang et al. 2017]

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



Dense Block

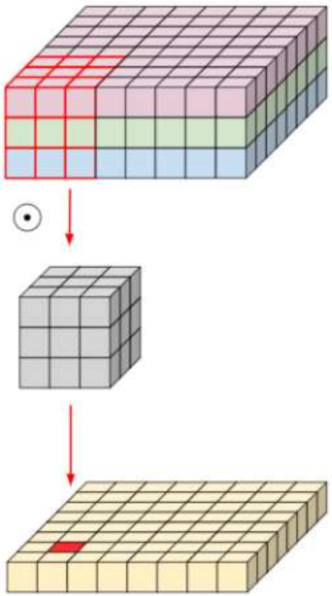


Summary: CNN Architectures

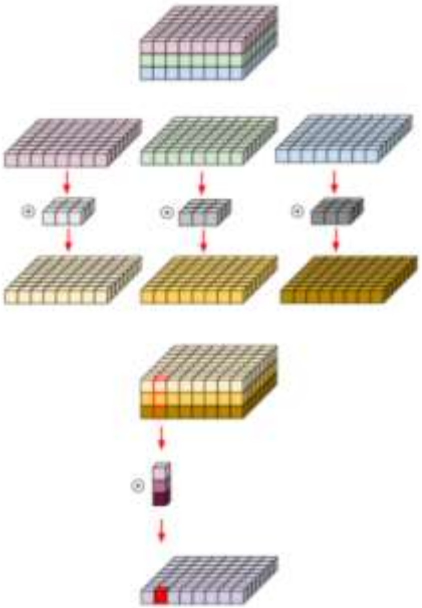
- VGG, GoogLeNet, ResNet all in wide use, available in model zoos
- ResNet current best default
- Trend towards extremely deep networks
- Significant research centers around design of layer / skip connections and improving gradient flow
- Even more recent trend towards examining necessity of depth vs.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

Depthwise Separable Convolution

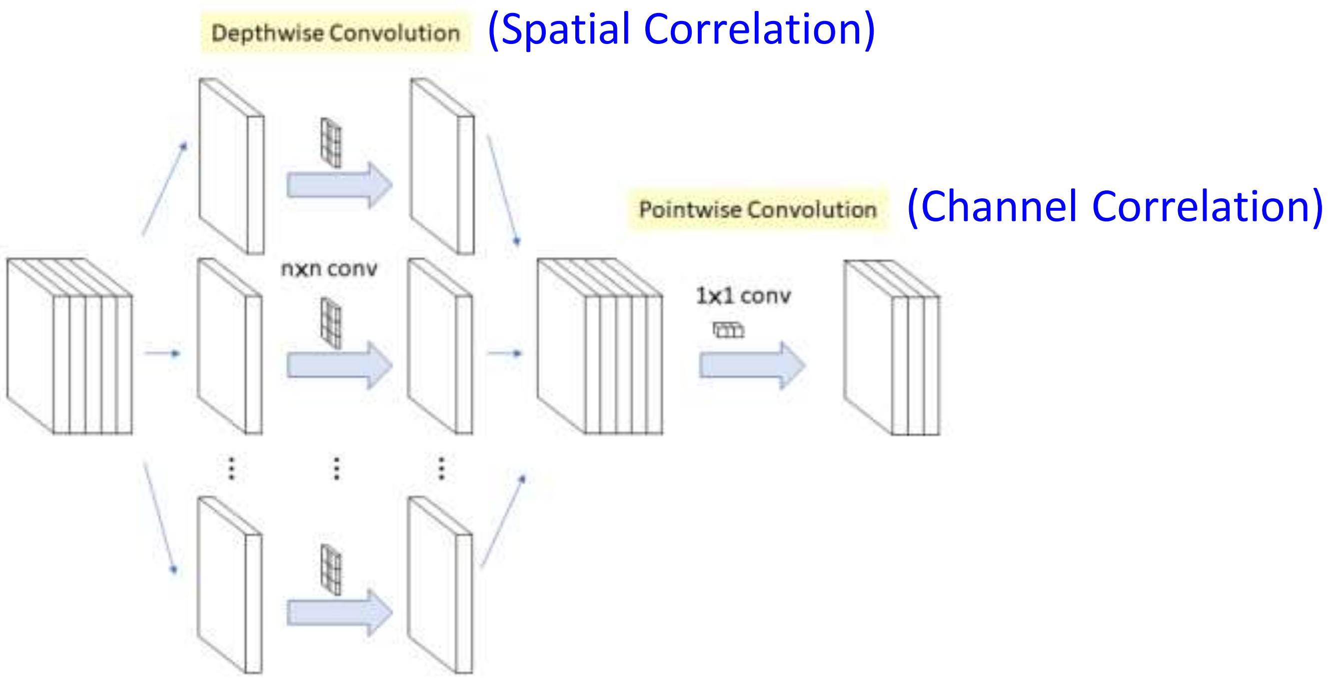
Regular Conv



Depthwise Separable Conv

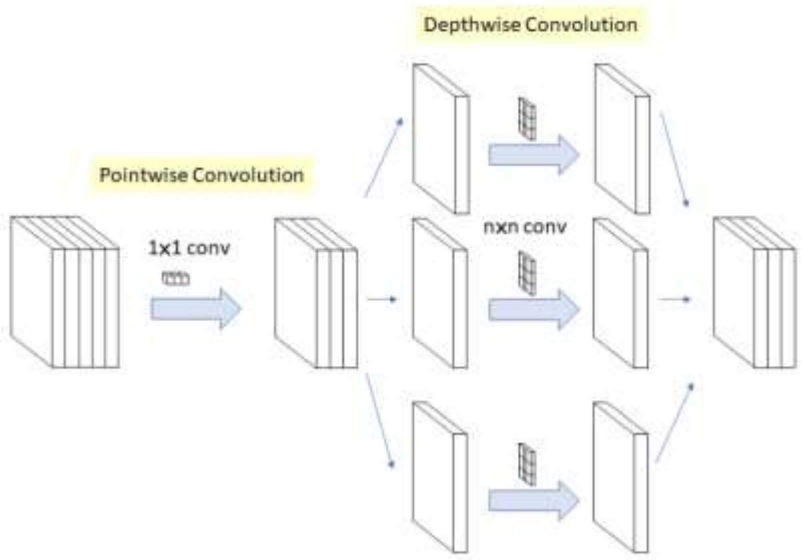


Depthwise Separable Convolution



Depthwise Separable Convolution

Xception



Depthwise Separable Convolution