CNN Architectures

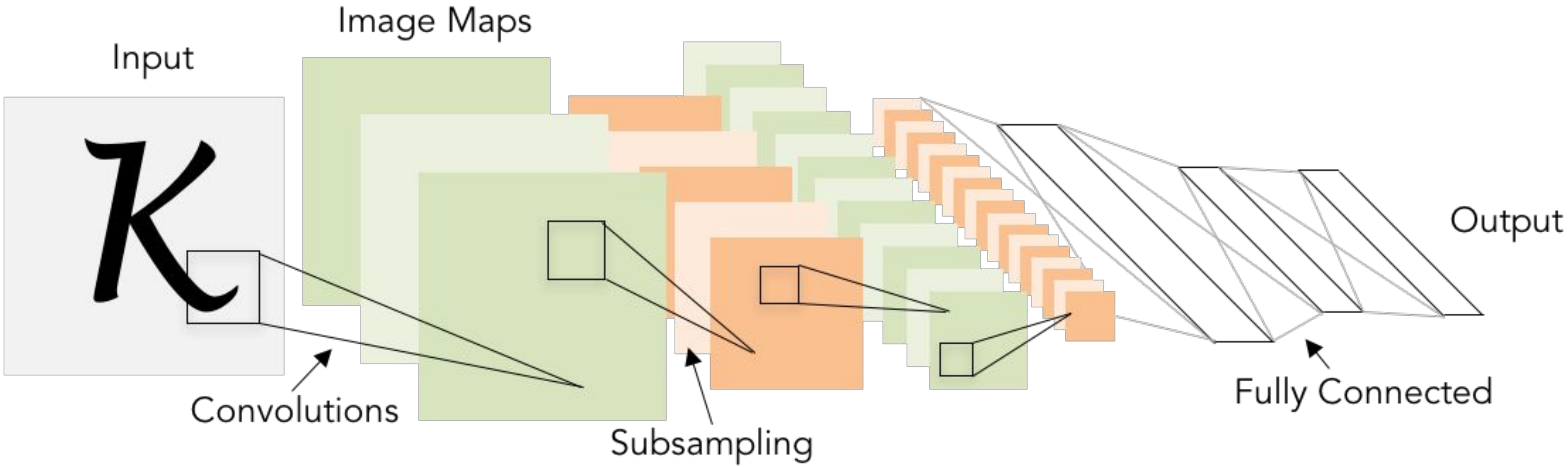
CNN Architectures

- VGG
- GoogLeNet
- ResNet

- Depthwise Convolution

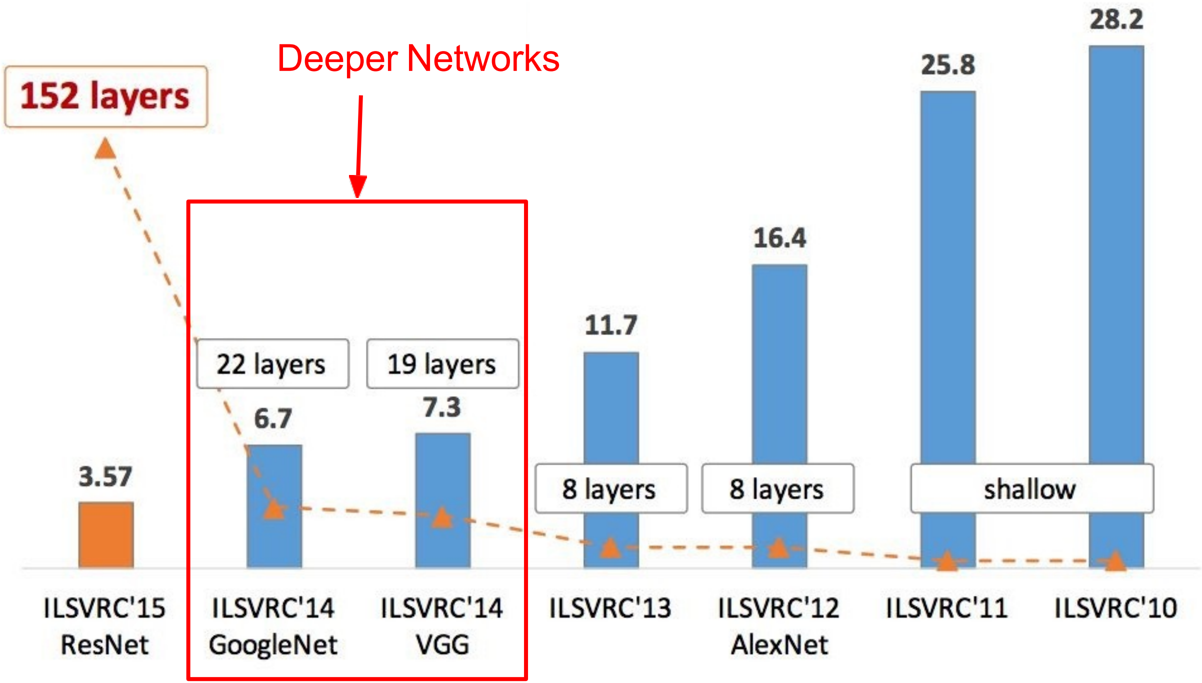
Review: LeNet-5

[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

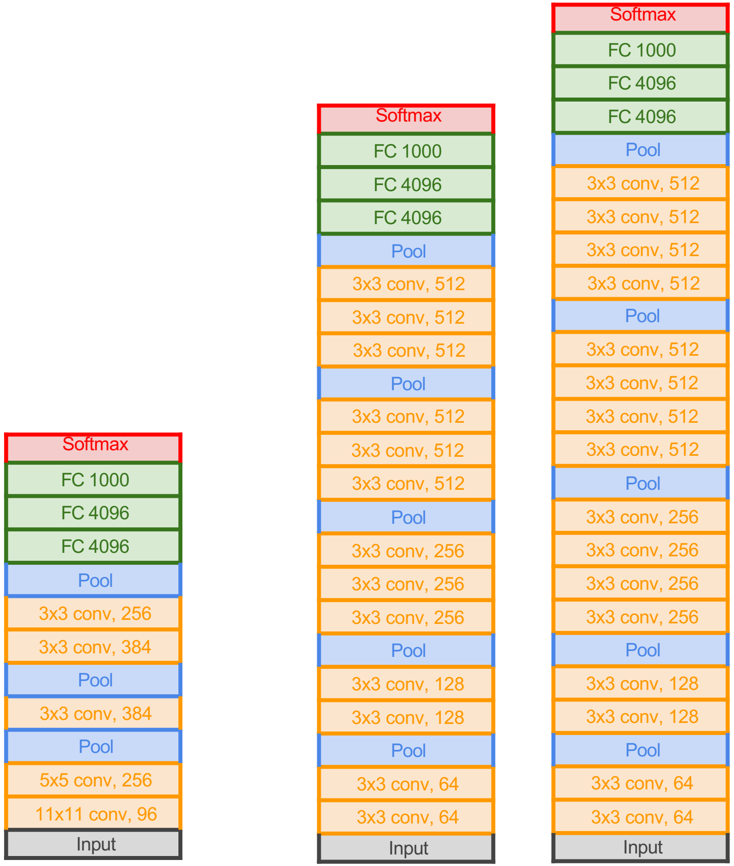


VGGNet

Small filters, Deeper networks

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

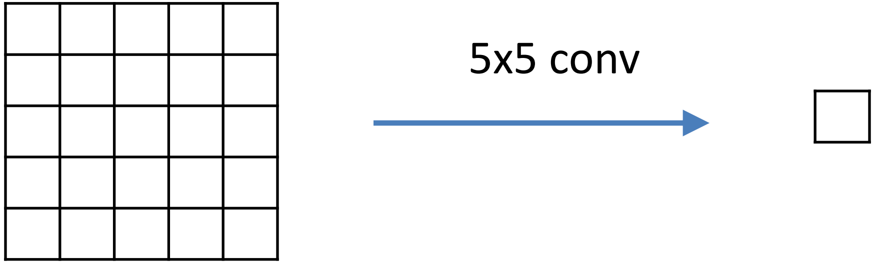
Only 3x3 CONV stride 1, pad 1
and 2x2 MAX POOL stride 2



AlexNet VGG16 VGG19

VGGNet

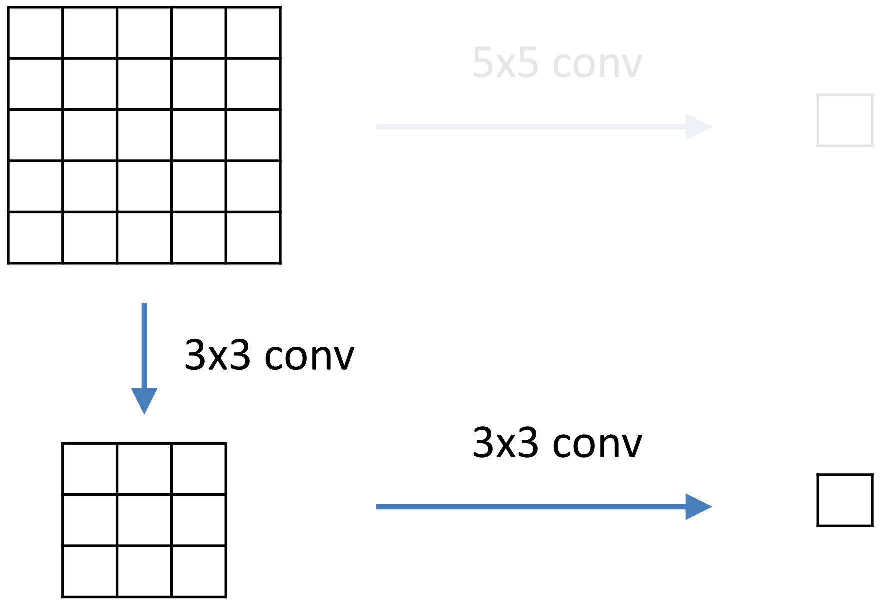
Large Filters vs Small Filters



25 params

VGGNet

Large Filters vs Small Filters



25 params

9+9 prams
More non-linearity

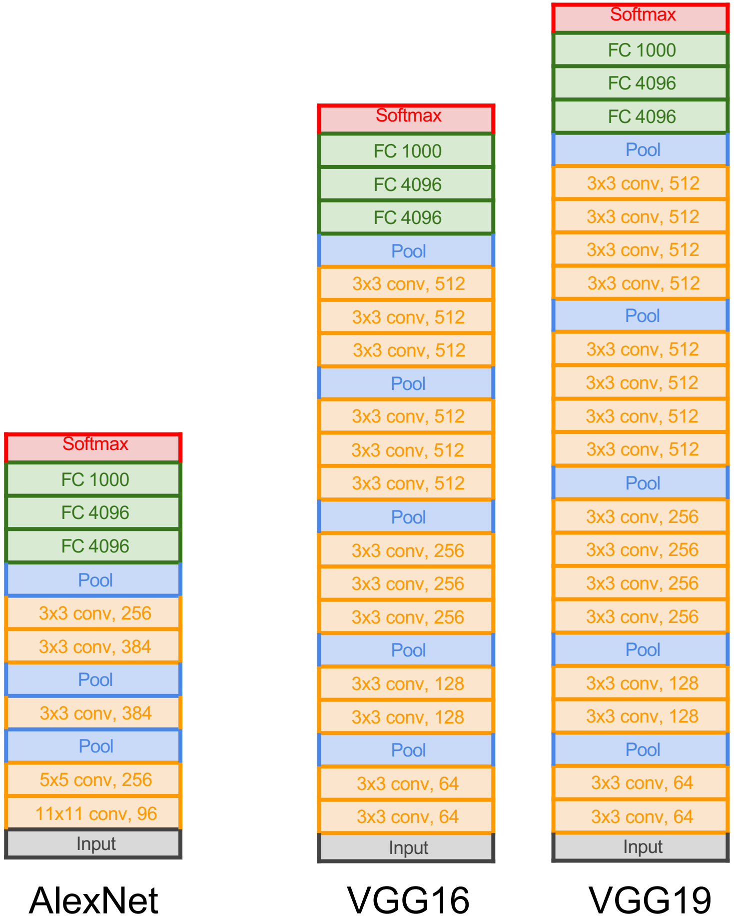
VGGNet

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

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

But deeper, more non-linearities



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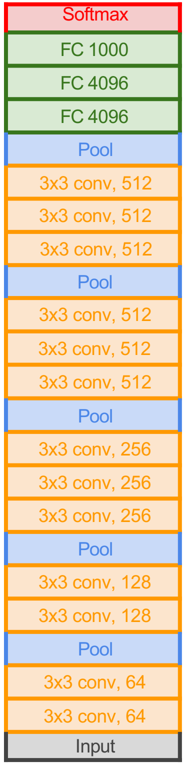
INPUT: [224x224x3] memory: 224*224*3=150K params: 0 (not counting biases)
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] 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

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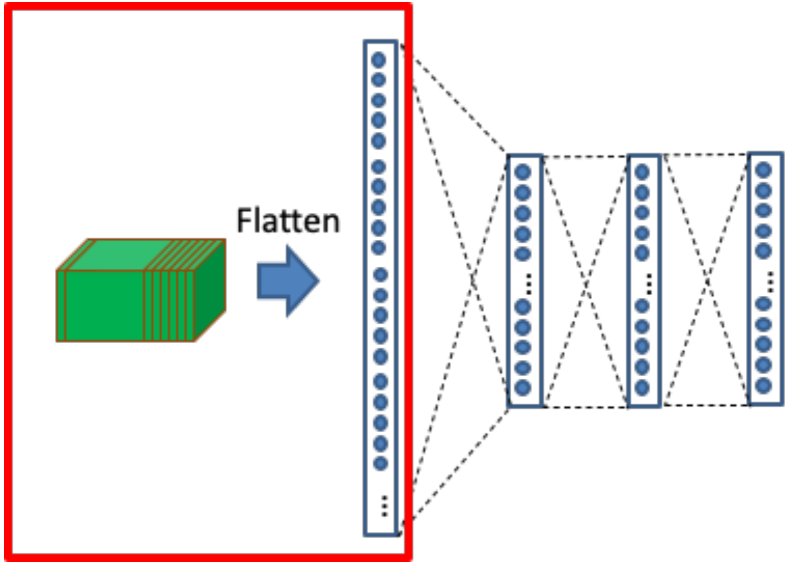
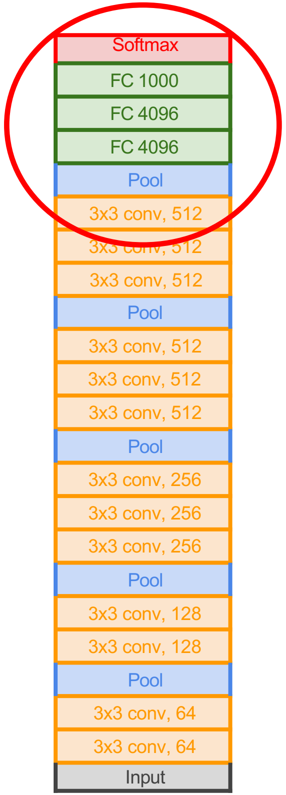
VGGNet

Too many parameters. Especially in FC layers

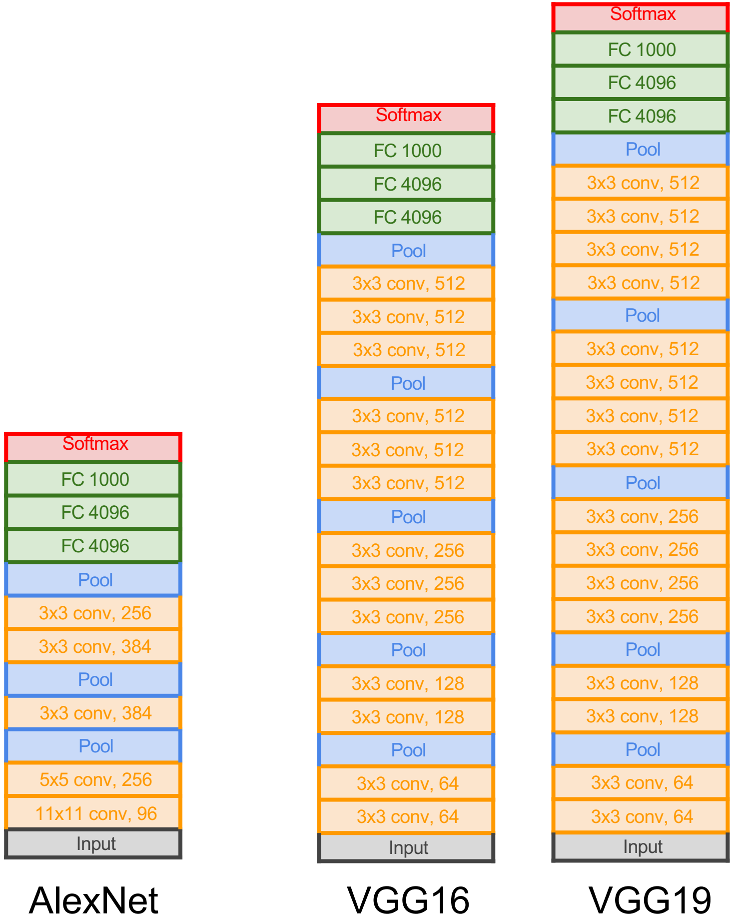




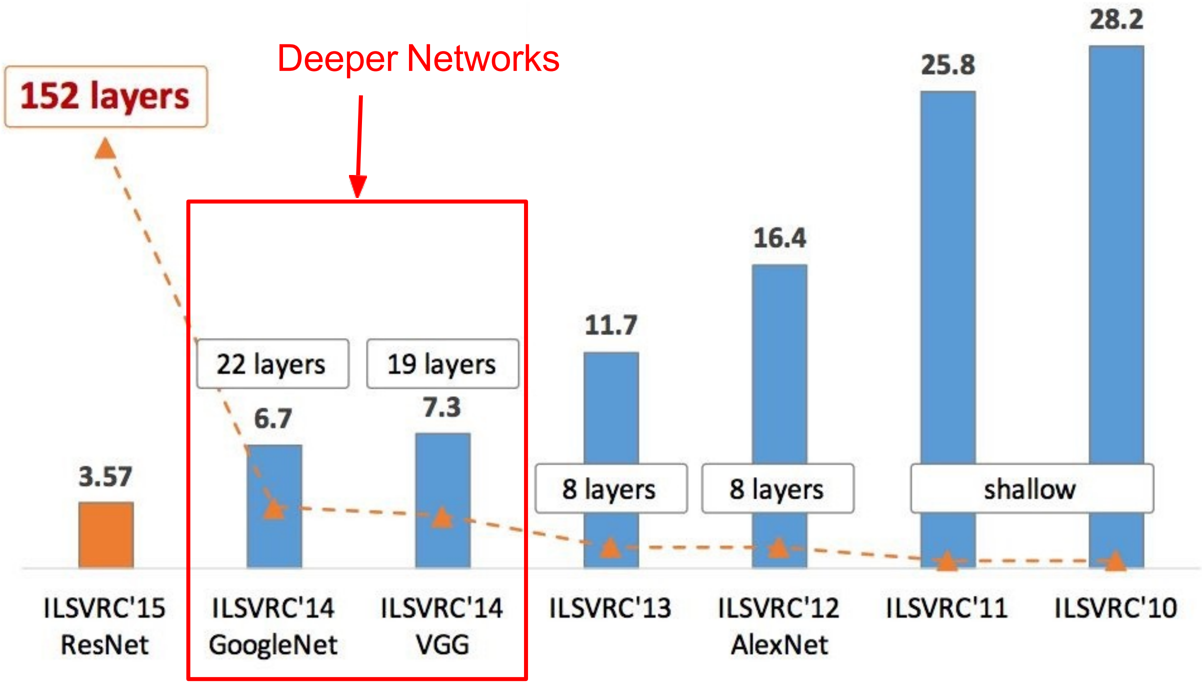
VGG16

VGGNet

Summary:
- Only 3x3 filters
- Deeper Structure
- Huge # of parameters

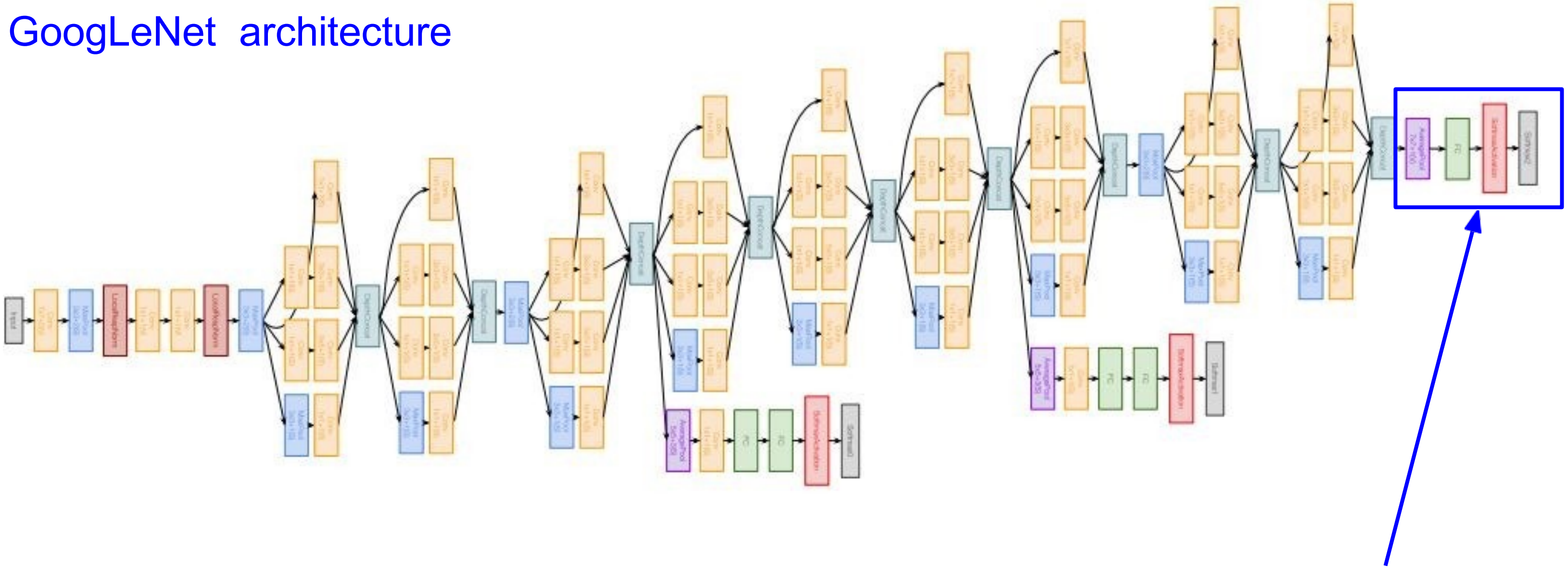


ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



GoogLeNet

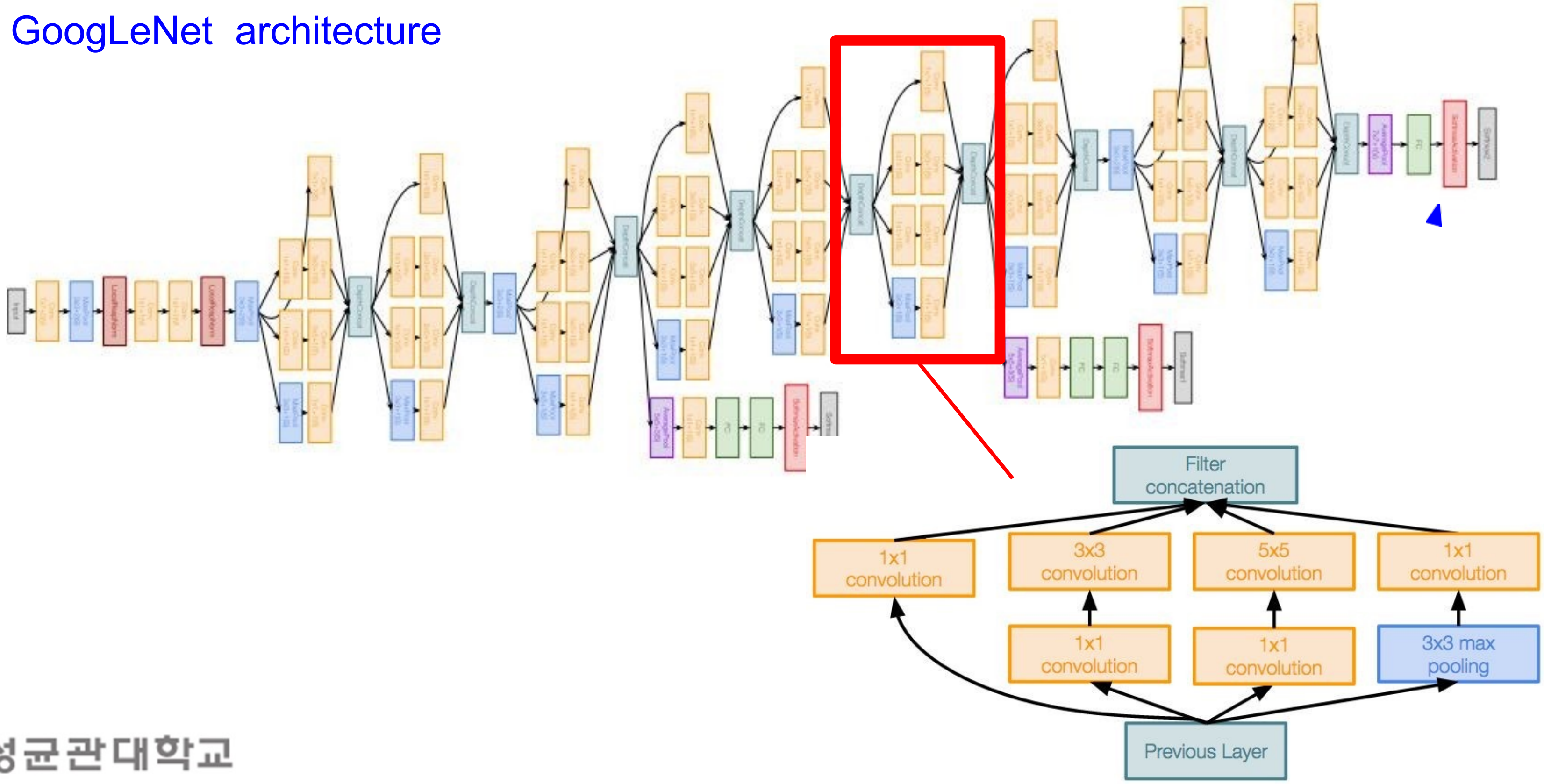
Full GoogLeNet architecture



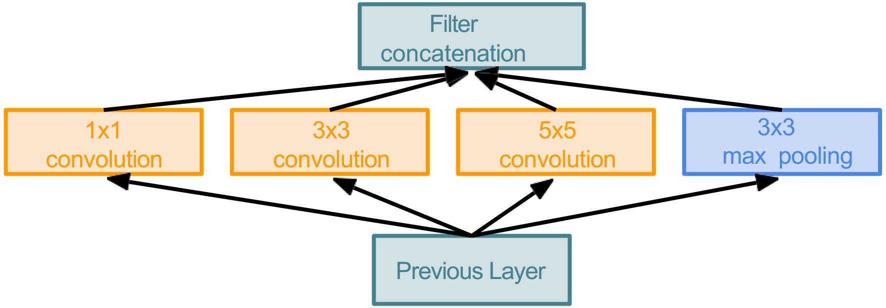
Classifier output

GoogLeNet

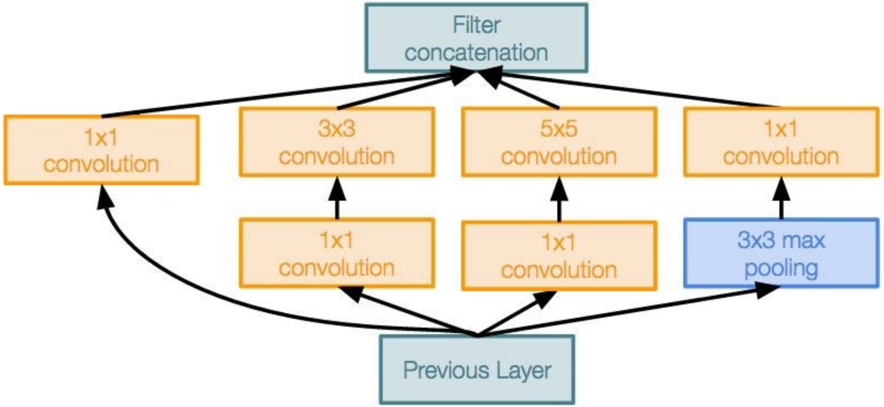
Full GoogLeNet architecture



GoogLeNet: Inception Module

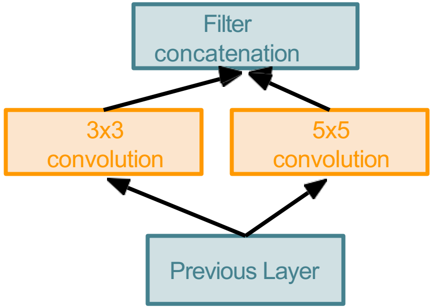


Naive Inception module

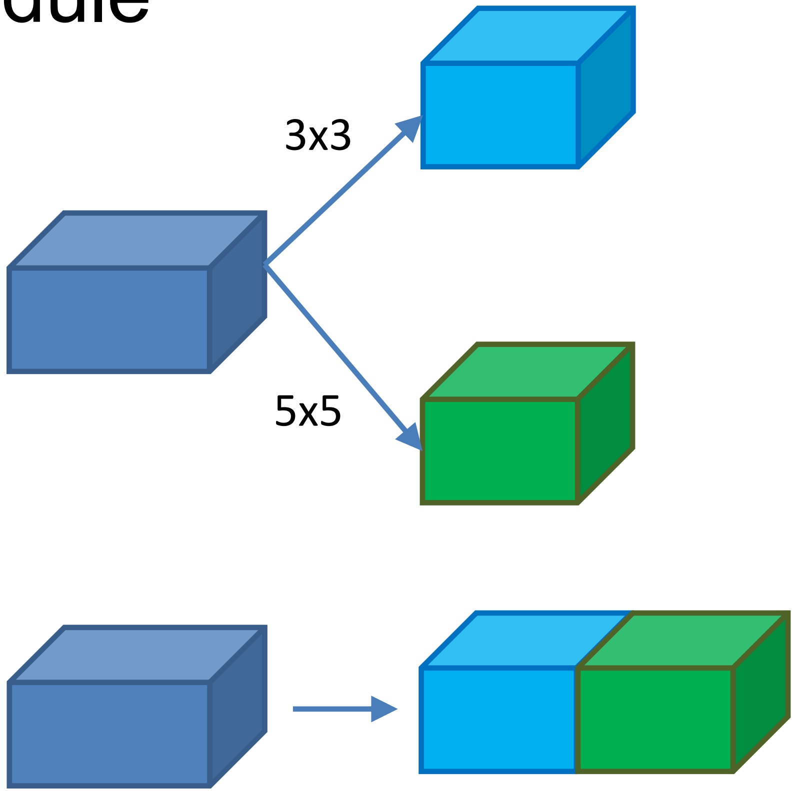


Inception module with dimension reduction

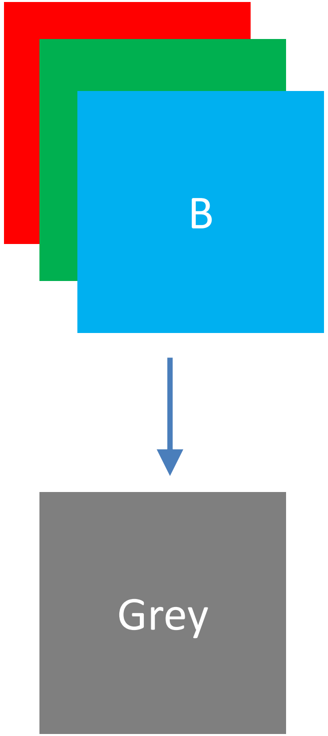
GoogLeNet: Inception Module

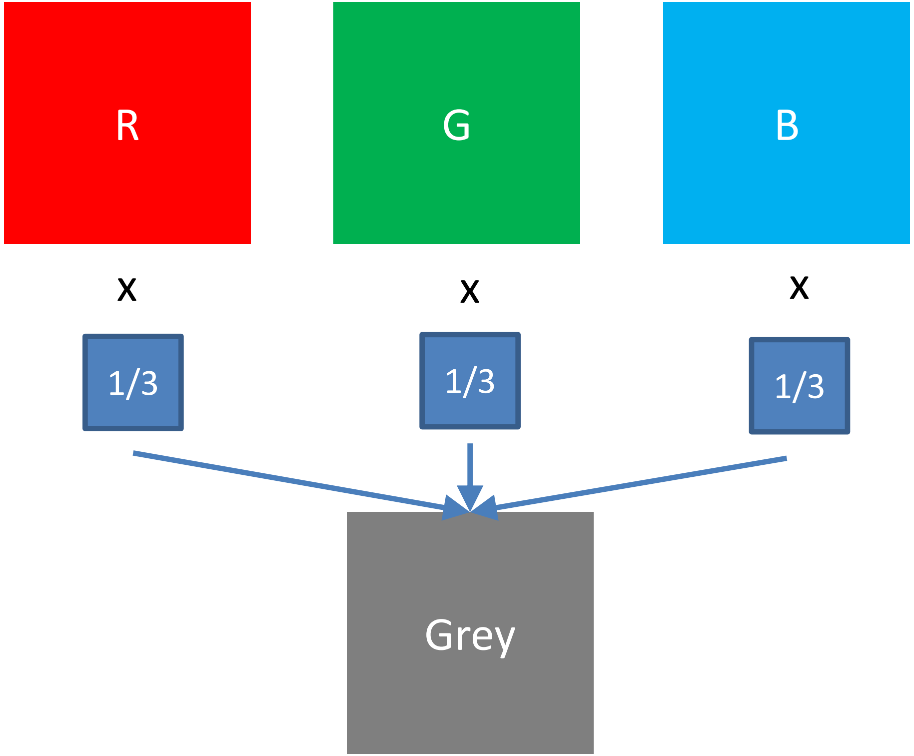


Naive Inception module

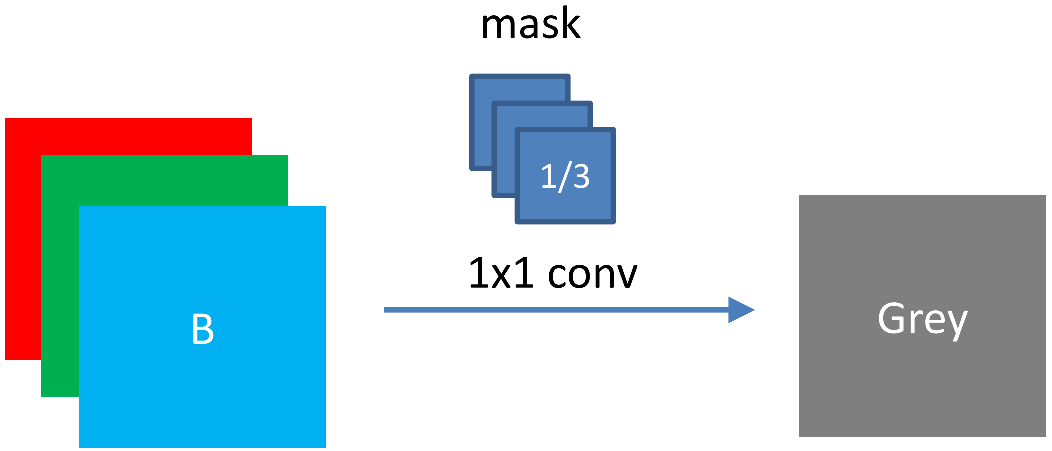


GoogLeNet : 1x1 convolutions

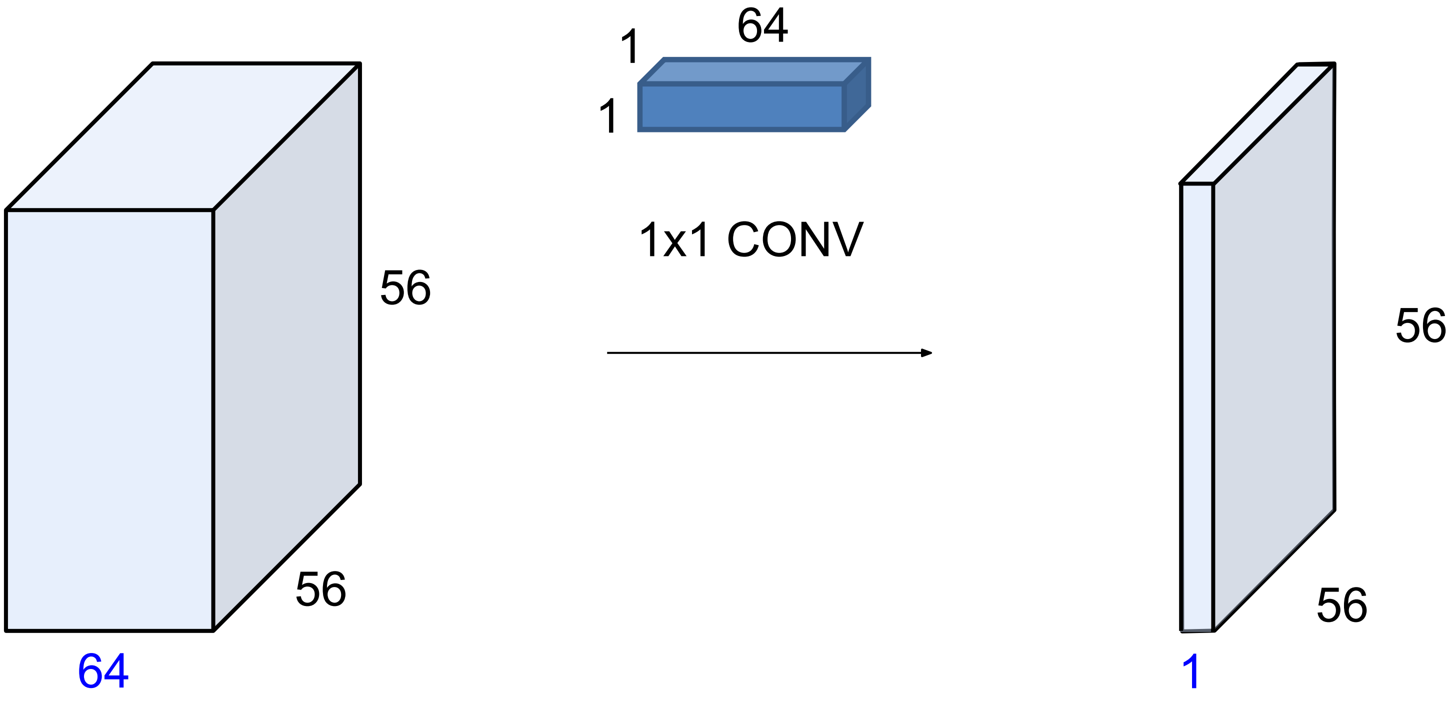




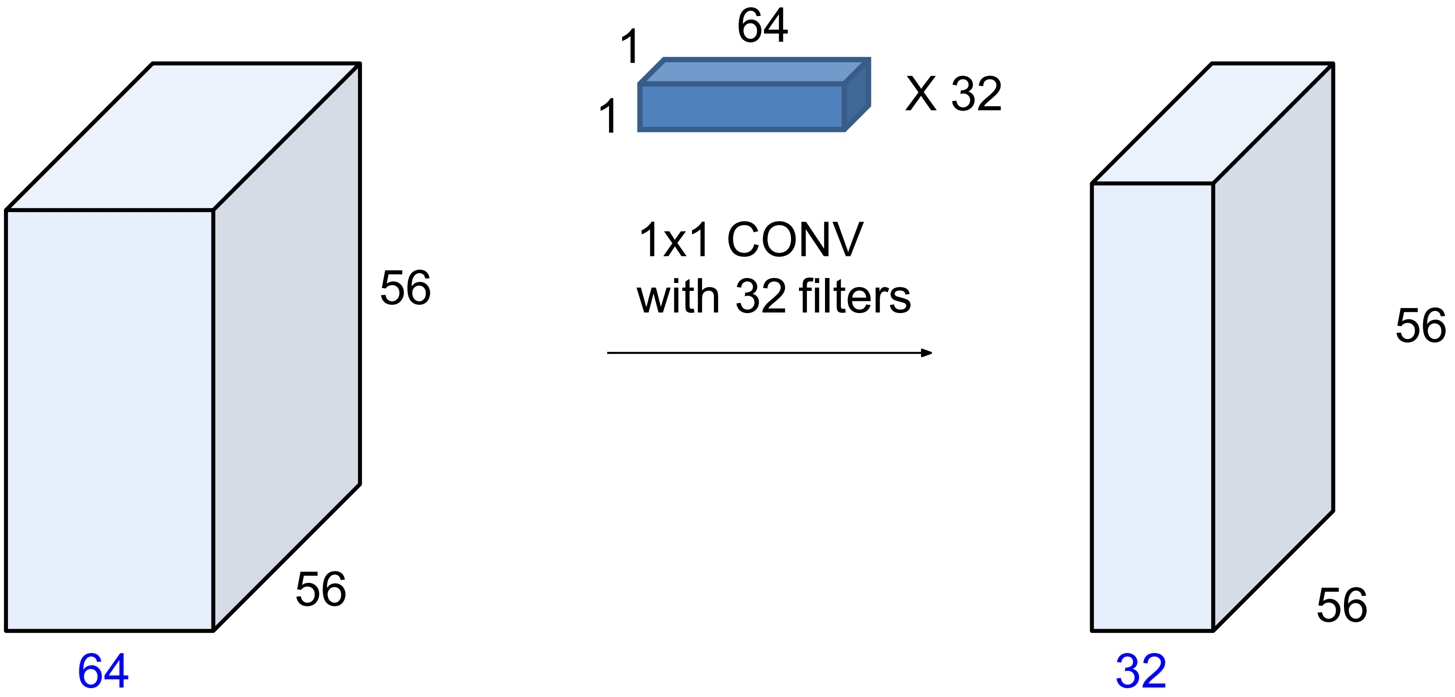
GoogLeNet : 1x1 convolutions



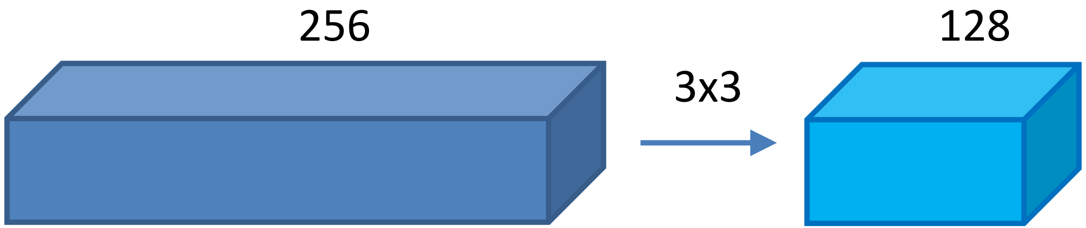
GoogLeNet : 1x1 convolutions



GoogLeNet : 1x1 convolutions

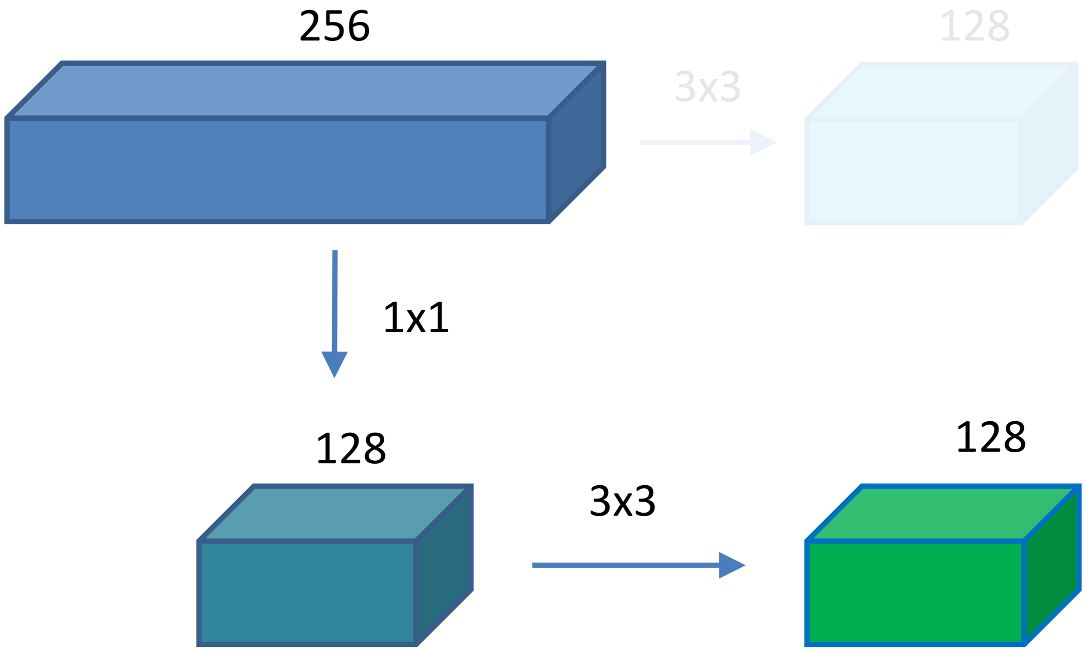


GoogLeNet: Convolution with 1x1 Convolution



256 X 3X3 X 128
= 294,912

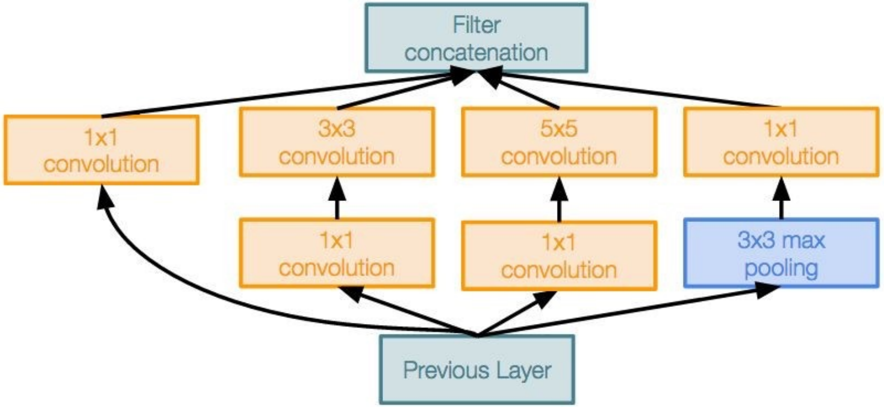
GoogLeNet: Convolution with 1x1 Convolution



256 X 3X3 X 128
= 294,912

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

GoogLeNet: Inception Module



Inception module with dimension reduction

3x3 max pooling, stride=1

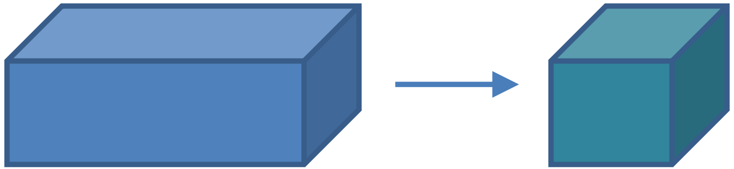
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	3	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

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

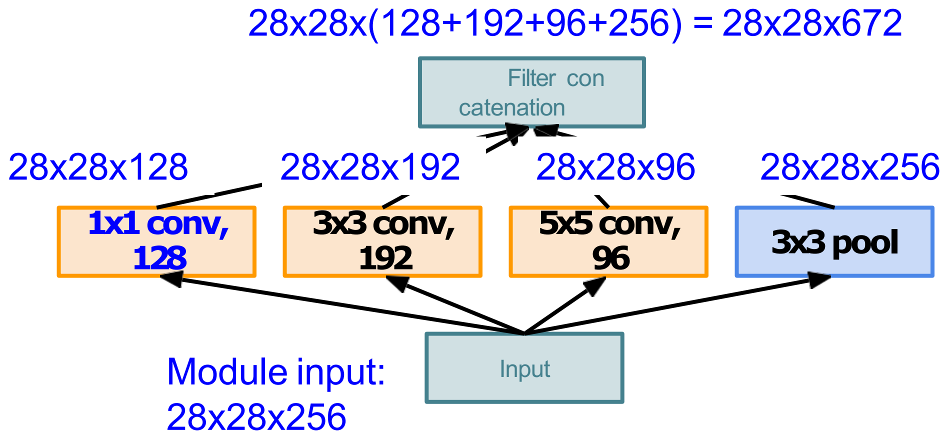
Enhanced feature map

1x1 Convolution



GoogLeNet: Inception Module

Example:



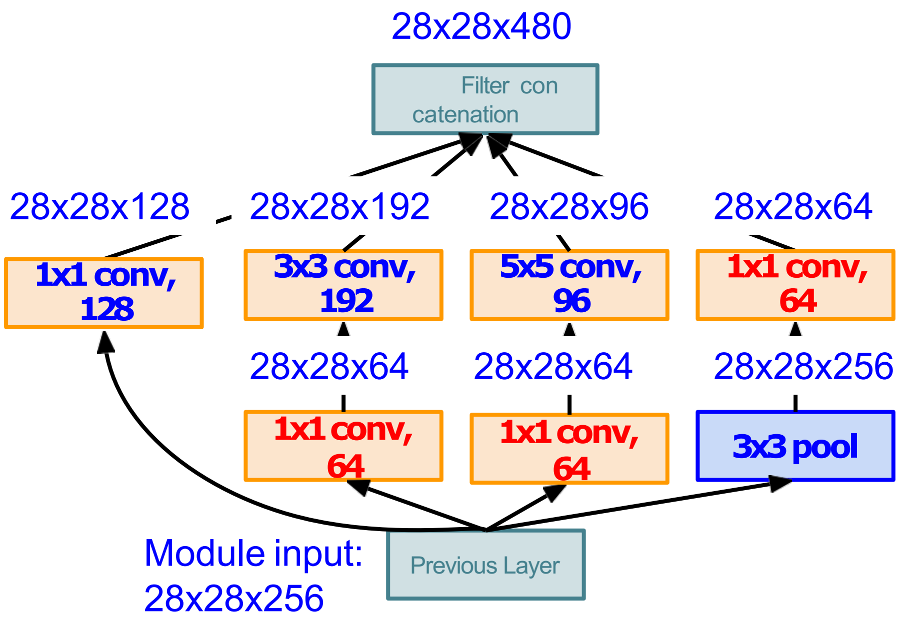
Naive Inception module

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

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

Very expensive compute

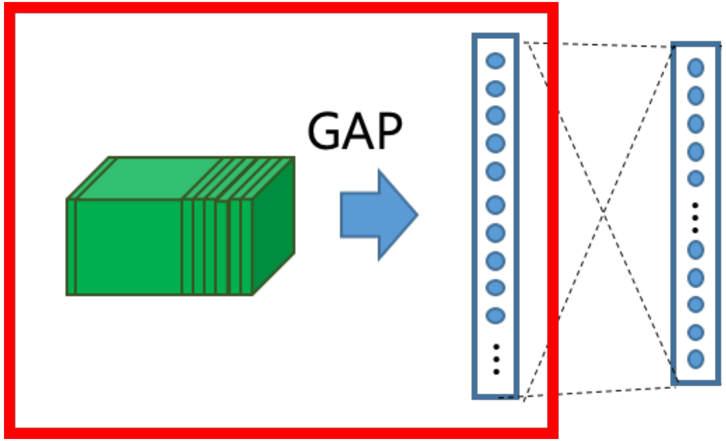
GoogLeNet: Inception Module

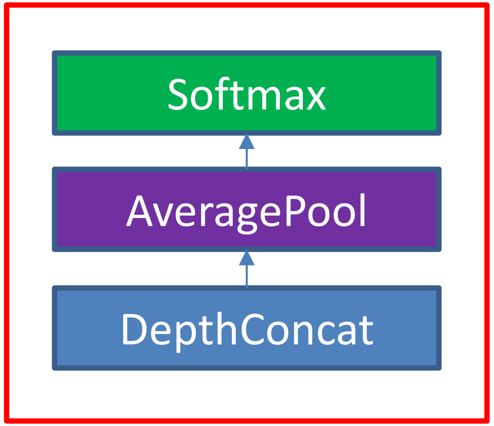


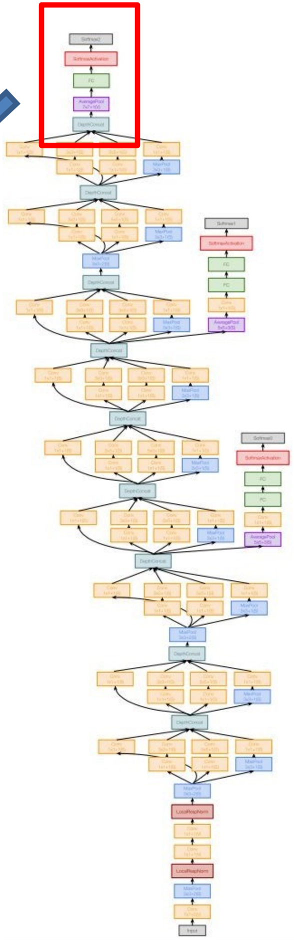
Inception module with dimension reduction

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

GoogLeNet: FC Layers







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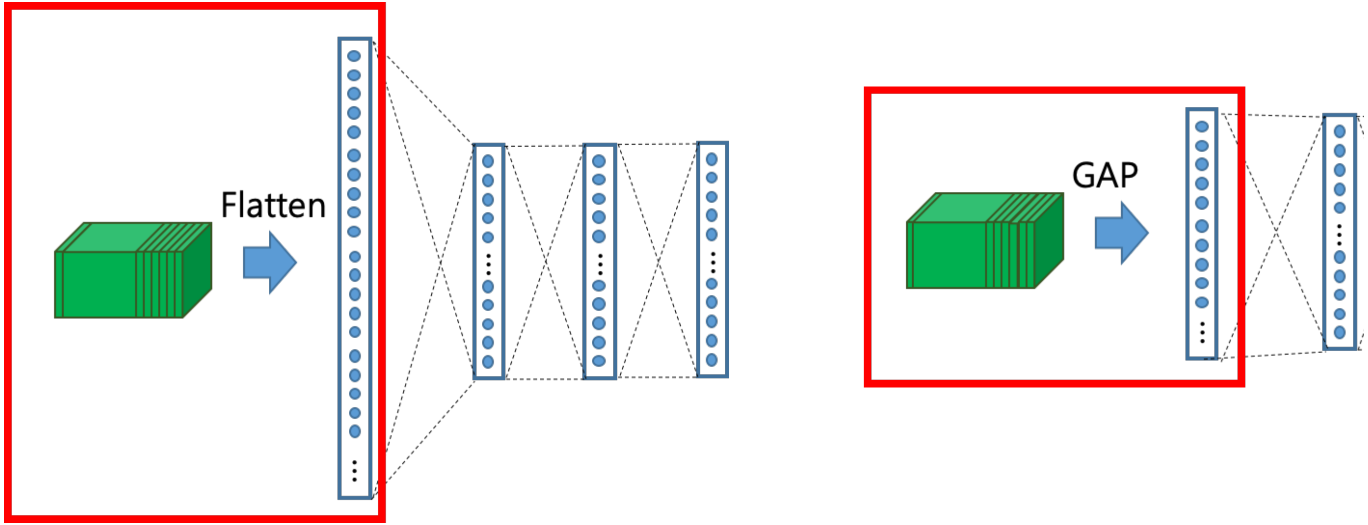
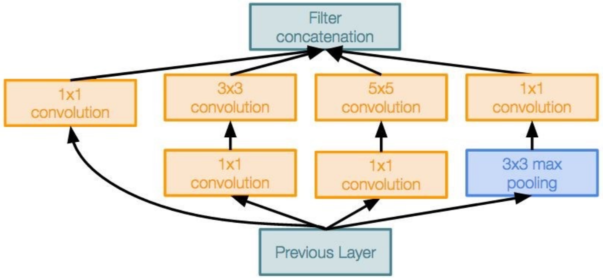
GoogLeNet: FC Layers



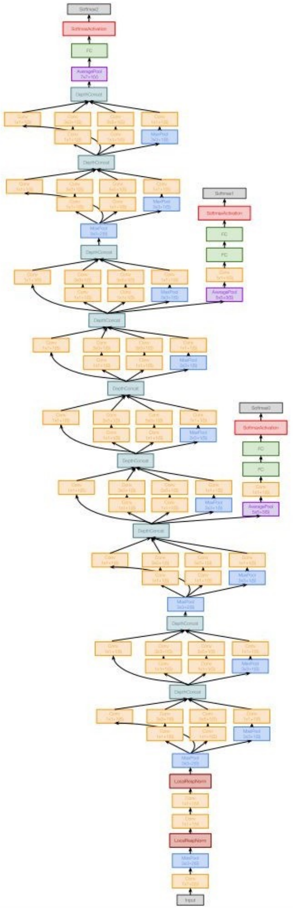
GoogLeNet

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



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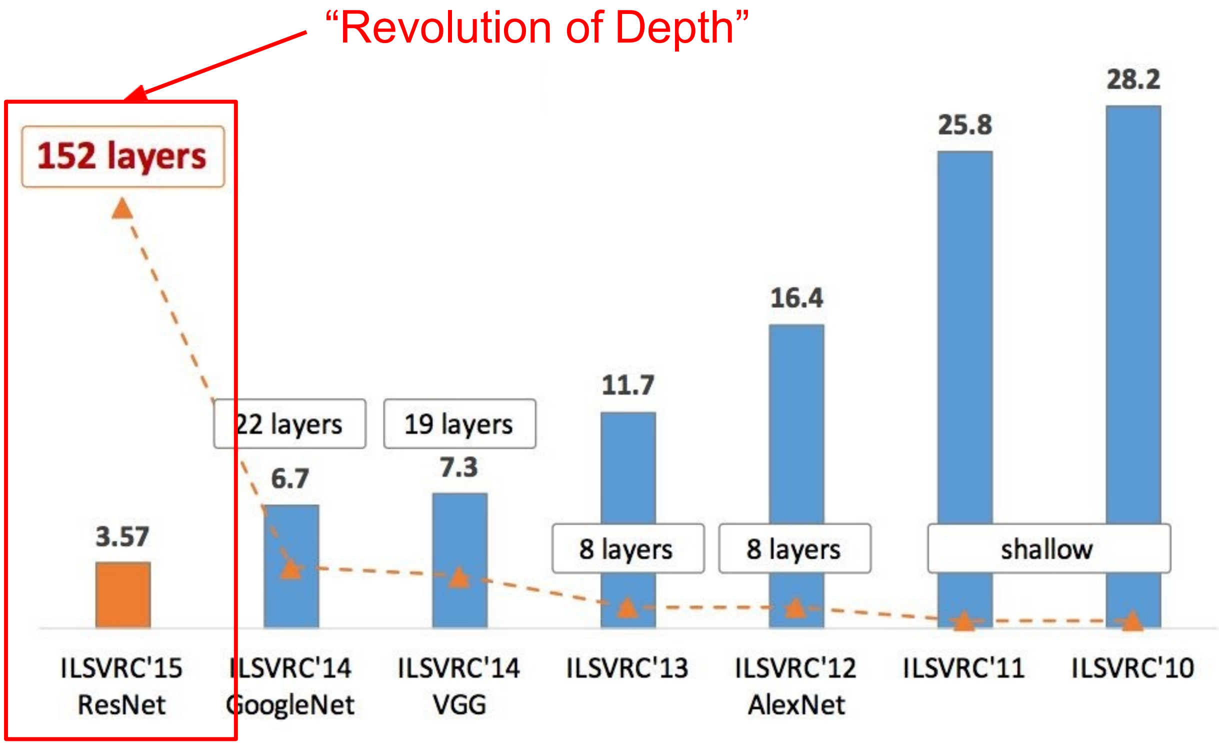
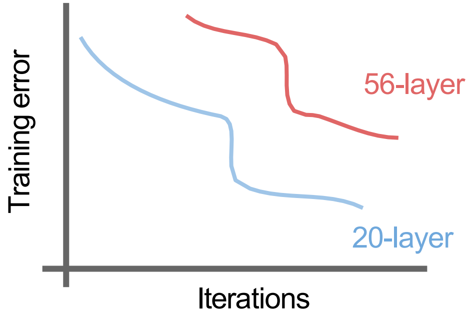
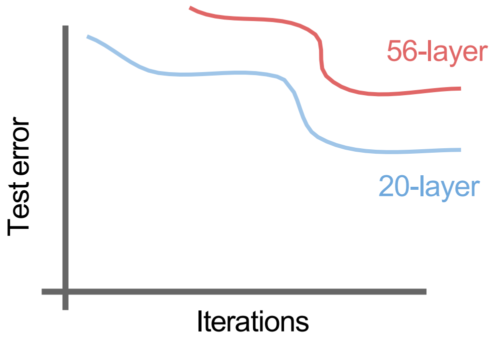
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



ResNet

What happens with deeper networks?

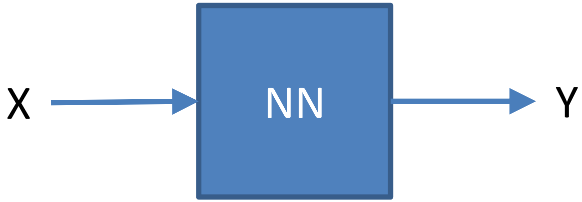




56-layer model performs worse on both training and test error
-> The deeper model performs worse, but it’s not caused by overfitting!

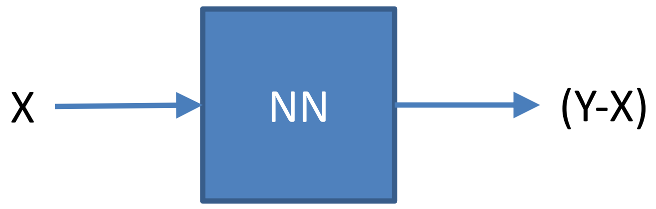
ResNet: Another Form of NN

X	Y
1	0.9
2	2.1
3	3.0
4	4.2



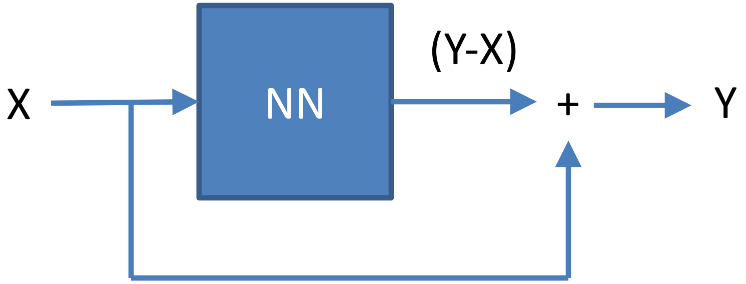
ResNet: Another Form of NN

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



ResNet: Another Form of NN

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



ResNet: Another Form of NN

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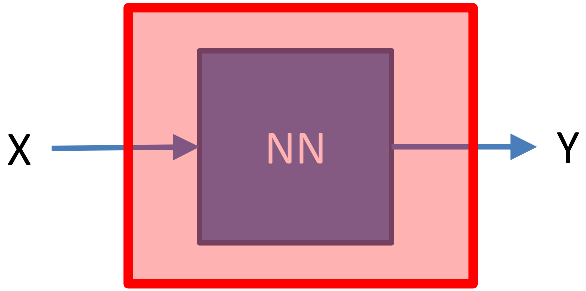
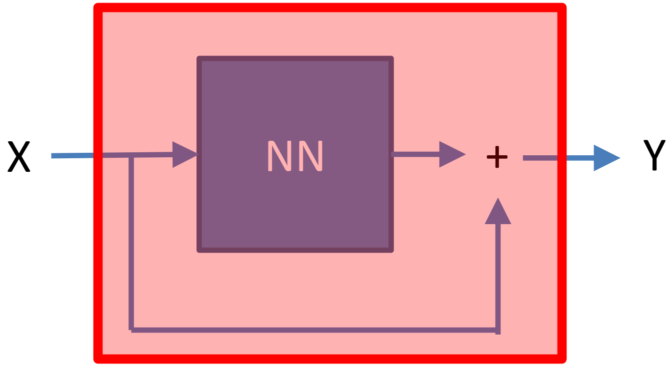
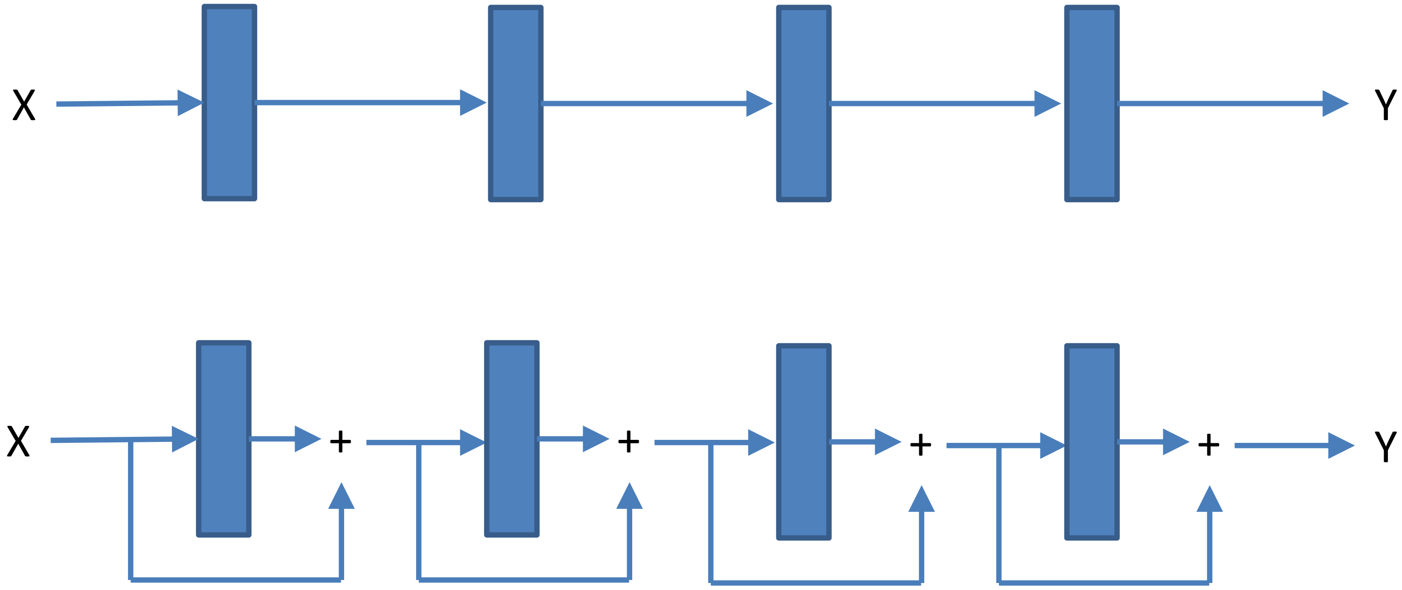
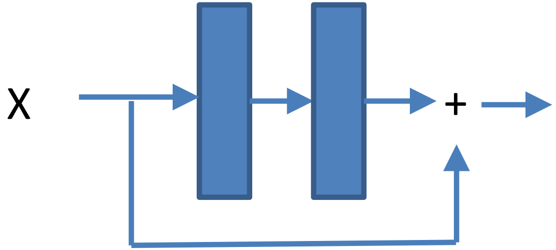


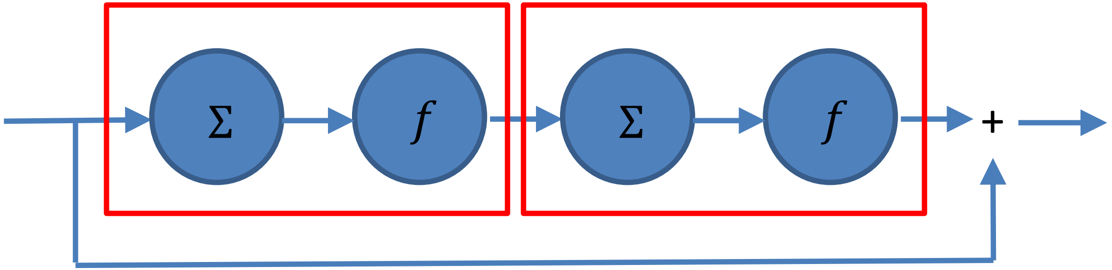


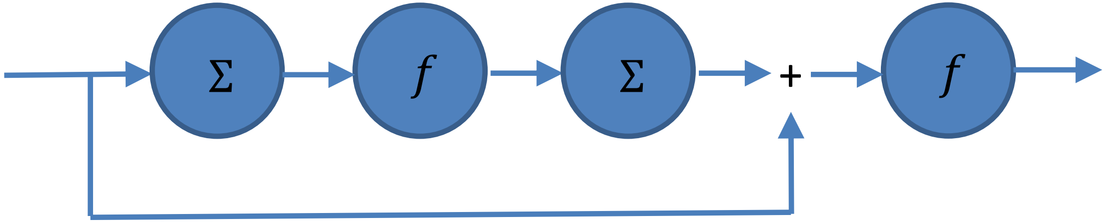
ResNet: Another Form of NN



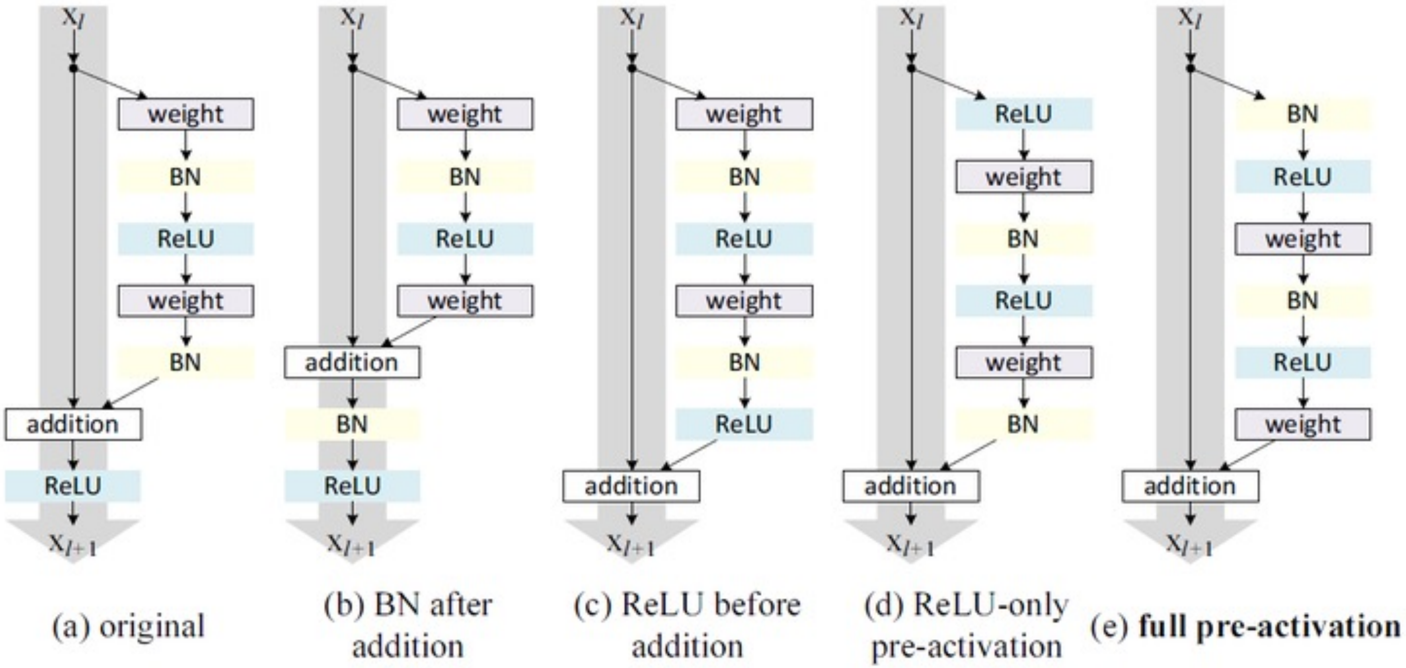
ResNet







ResNet

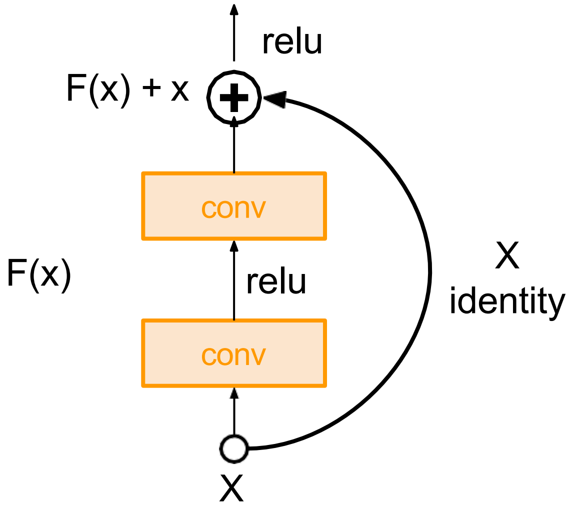


x_l
weight
BN
ReLU
weight
BN
addition
ReLU
x_{l+1}
(a) original
x_l
weight
BN
ReLU
weight
addition
BN
ReLU
x_{l+1}
(b) BN after addition
x_l
weight
BN
ReLU
weight
BN
ReLU
addition
x_{l+1}
(c) ReLU before addition
x_l
ReLU
weight
BN
ReLU
weight
BN
addition
x_{l+1}
(d) ReLU-only pre-activation
x_l
BN
ReLU
weight
BN
ReLU
weight
addition
x_{l+1}
(e) **full pre-activation**

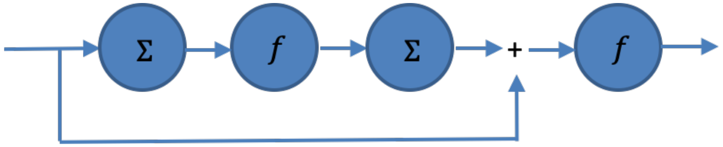
ResNet

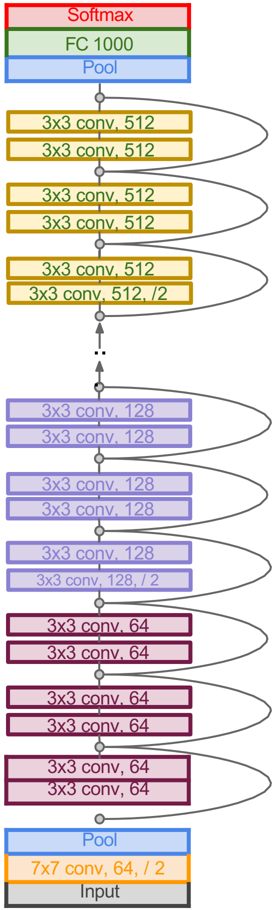
Very deep networks using residual connections

- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2
- Additional conv layer at the beginning
- Global average pooling layer after last conv. layer



Residual block





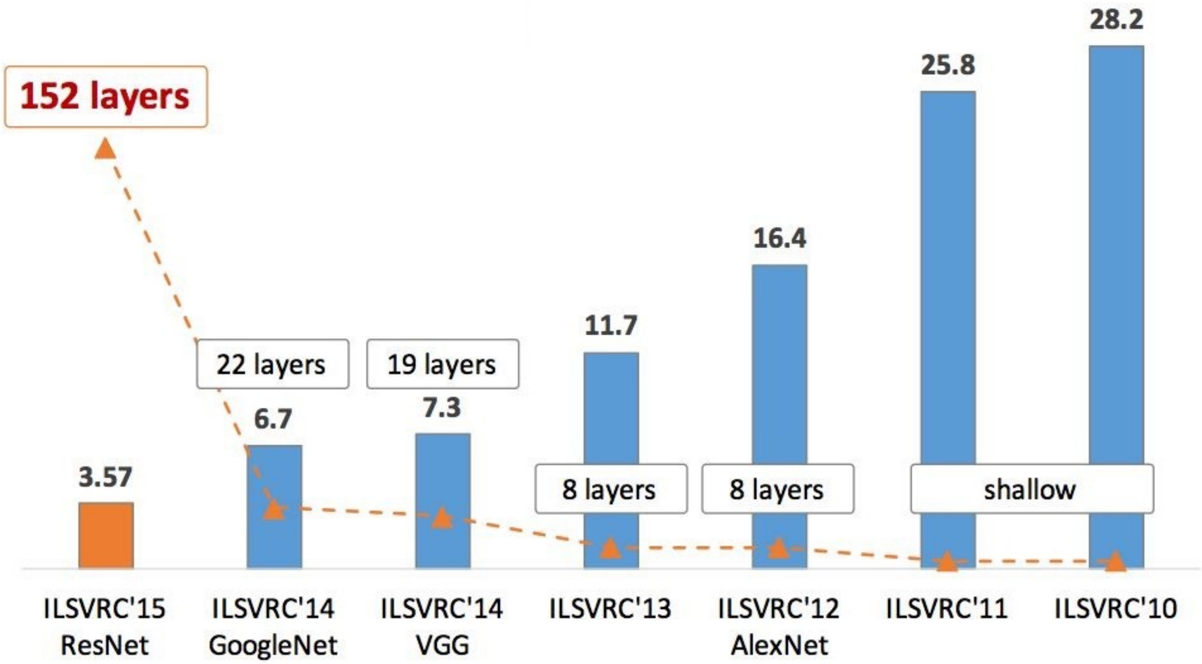
Case Study: ResNet

[He et al., 2015]

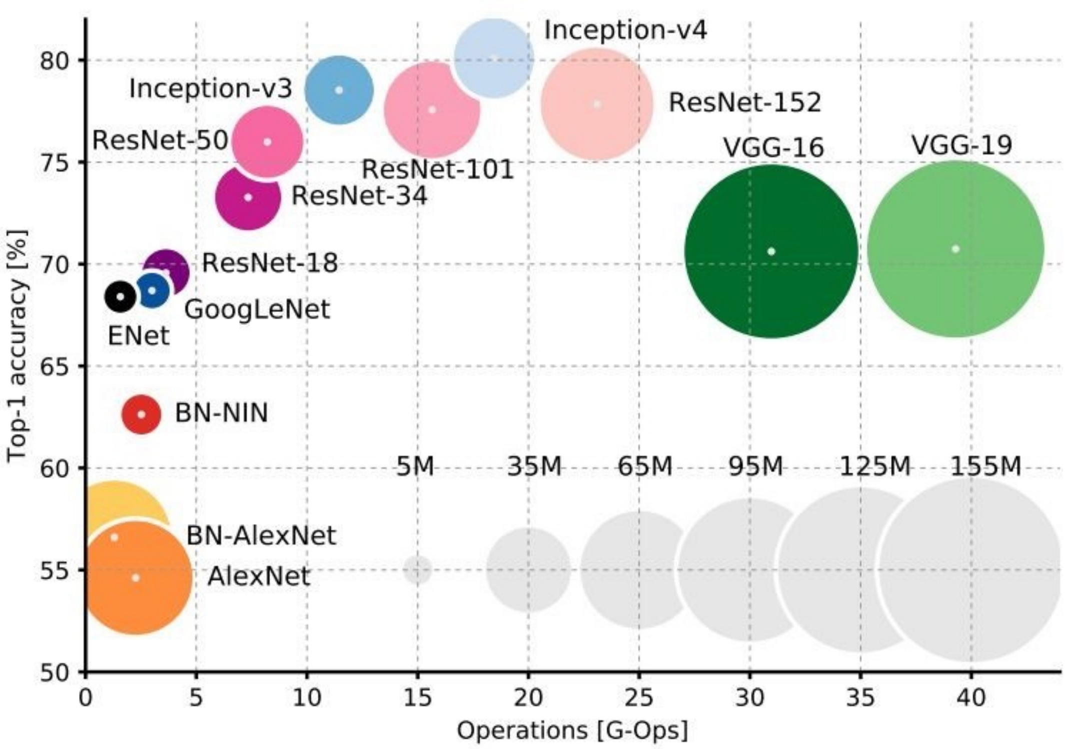
Training ResNet in practice:

- 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



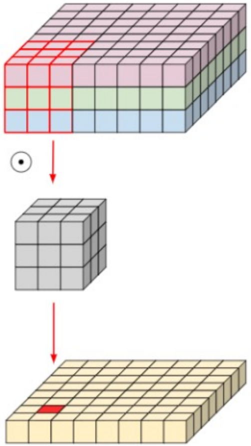
Comparing complexity...



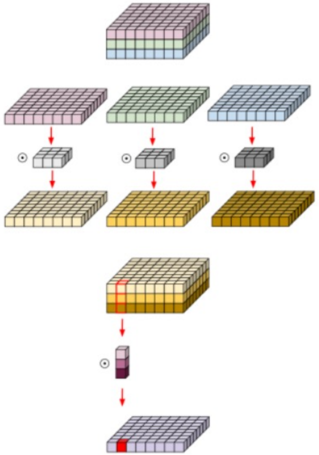
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Depthwise Separable Convolution: Much Lighter Conv.

Regular Conv

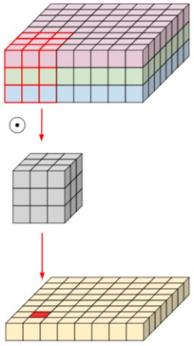


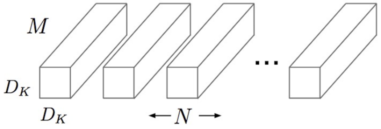
Depthwise Separable Conv



Depthwise Separable Convolution: Much Lighter Conv.

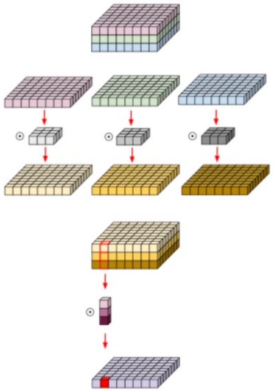
Regular Conv

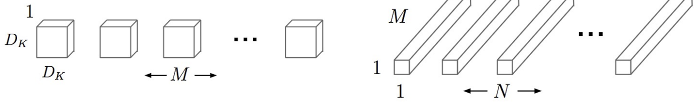




$$D_K \times D_K \times M \times N \times D_F \times D_F$$

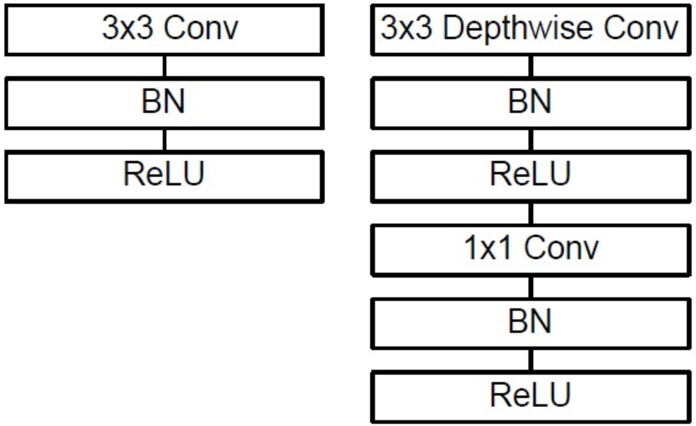
Depthwise Separable Conv





$$D_K \times D_K \times M \times D_F \times D_F + M \times N \times D_F \times D_F$$

Depthwise Separable Convolution: Much Lighter Conv.



or ReLU6

or ReLU6

Figure 3. Left: Standard convolutional layer with batchnorm and ReLU. Right: Depthwise Separable convolutions with Depthwise and Pointwise layers followed by batchnorm and ReLU.

Depthwise Separable Convolution: Much Lighter Conv.

Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
$5\times$ Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Table 2. Resource Per Layer Type

Type	Mult-Adds	Parameters
Conv 1×1	94.86%	74.59%
Conv DW 3×3	3.06%	1.06%
Conv 3×3	1.19%	0.02%
Fully Connected	0.18%	24.33%