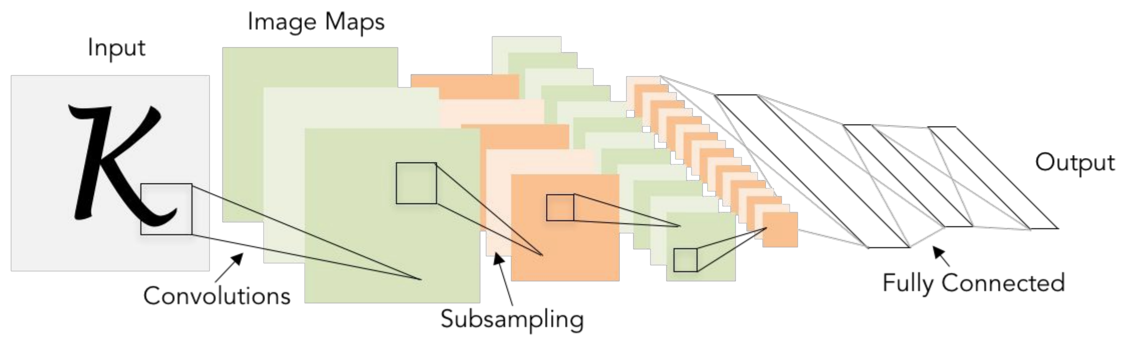
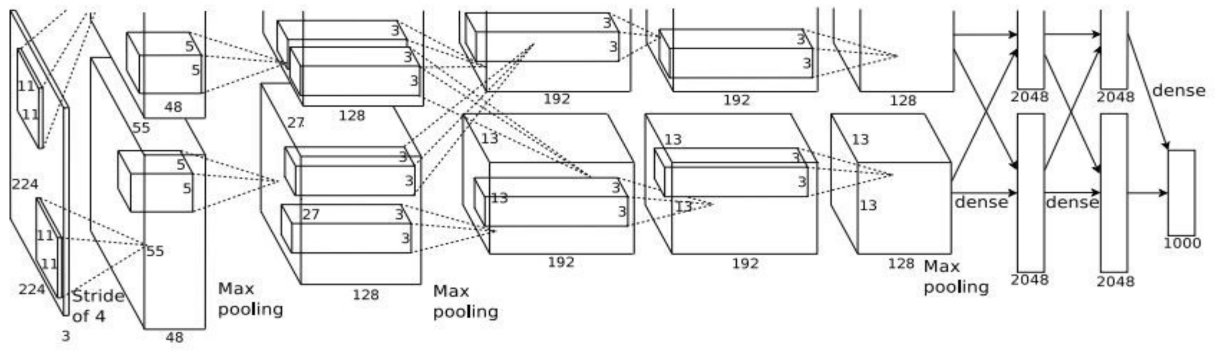
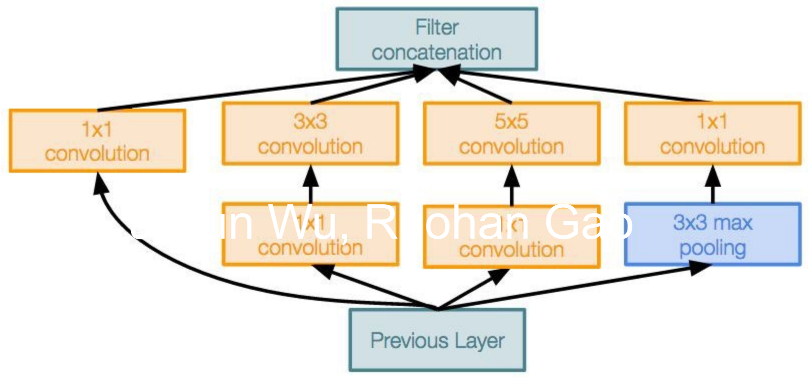
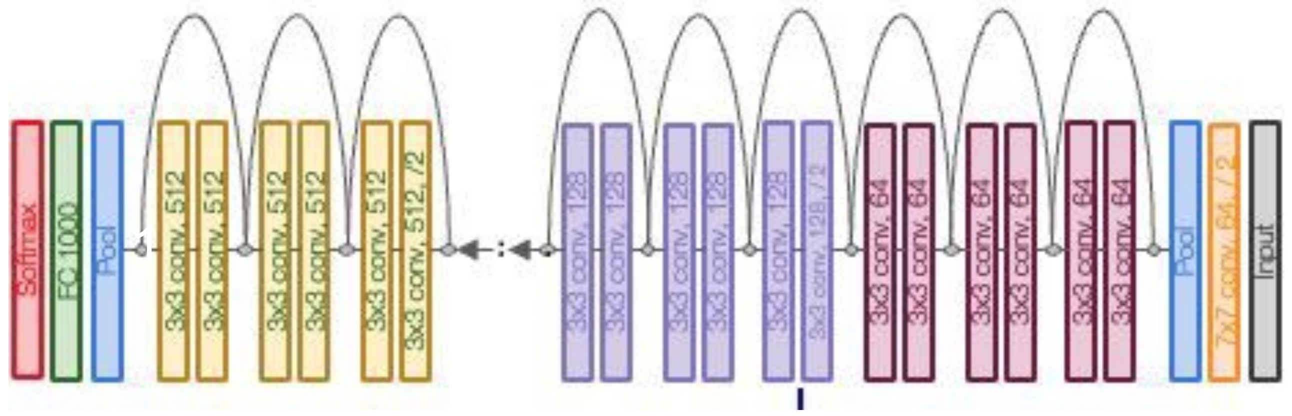
Today: CNN Architectures



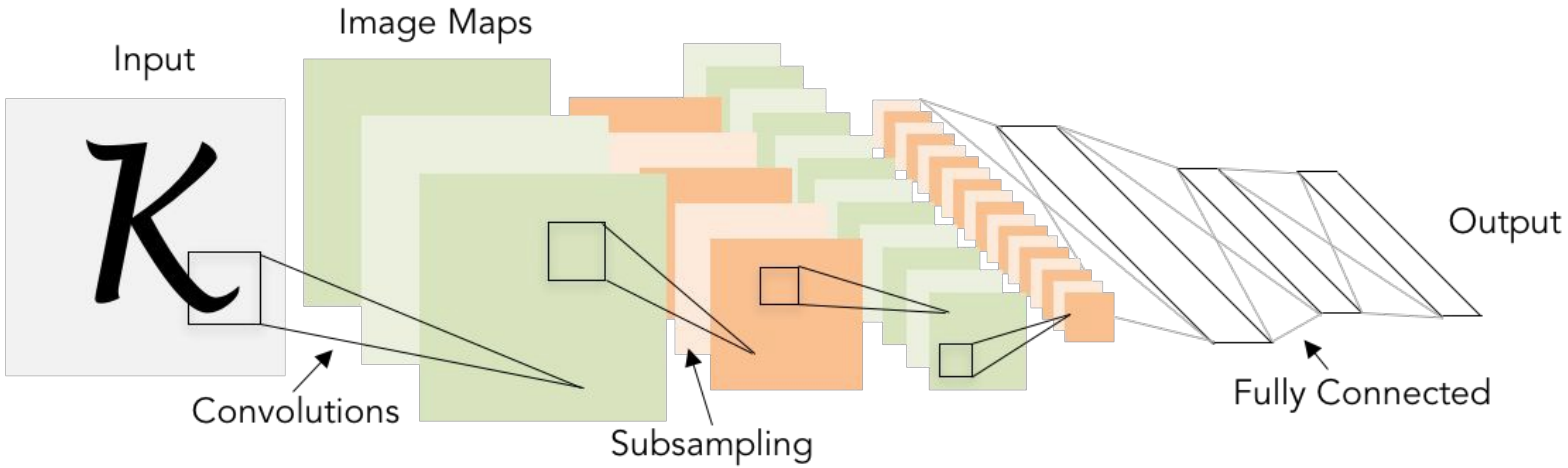






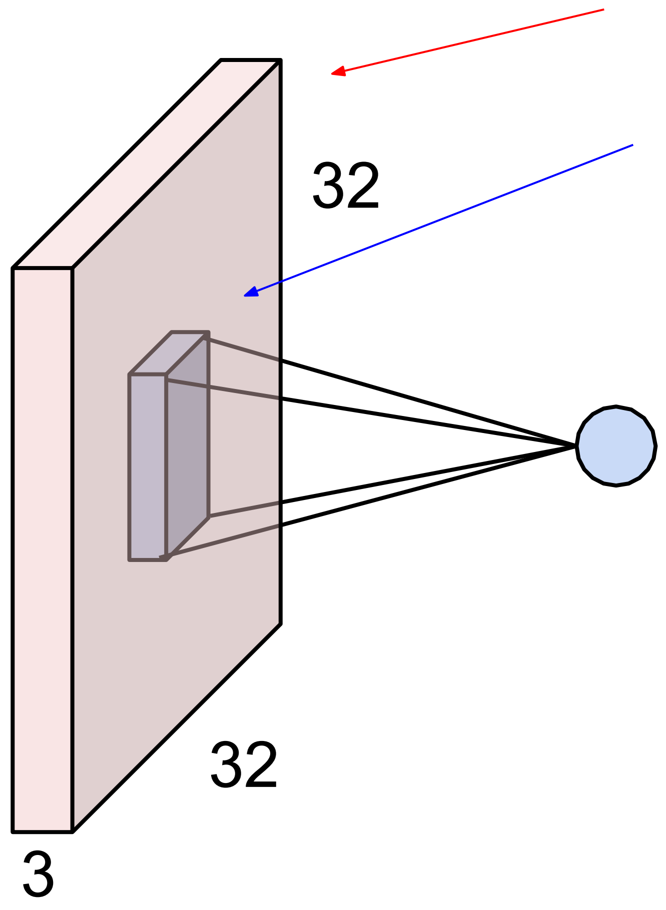
Review: LeNet-5

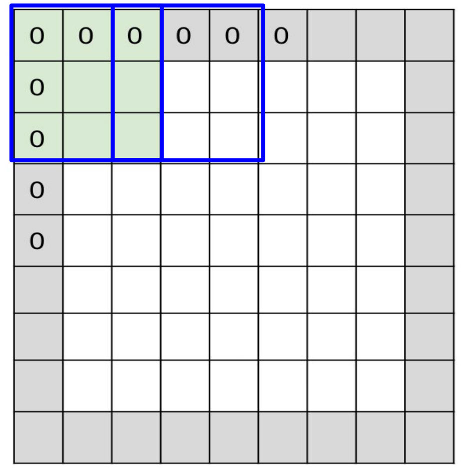
[LeCun et al., 1998]



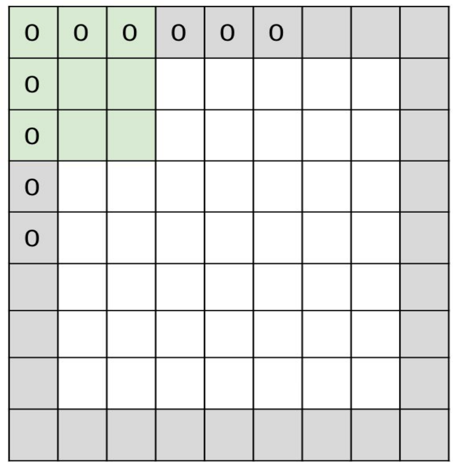
Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-FC-FC]

Review: Convolution



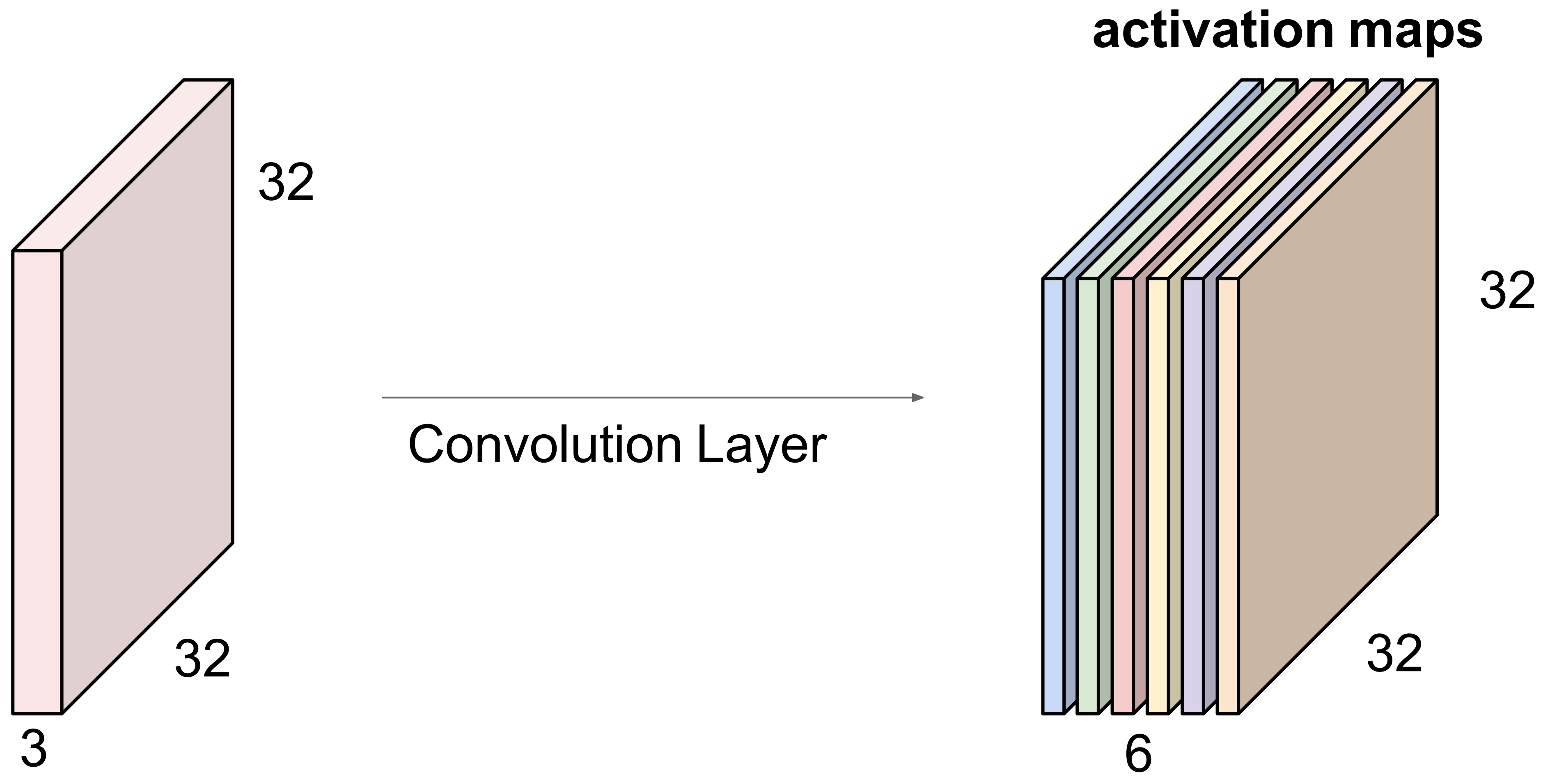


Stride:
Downsample output activations



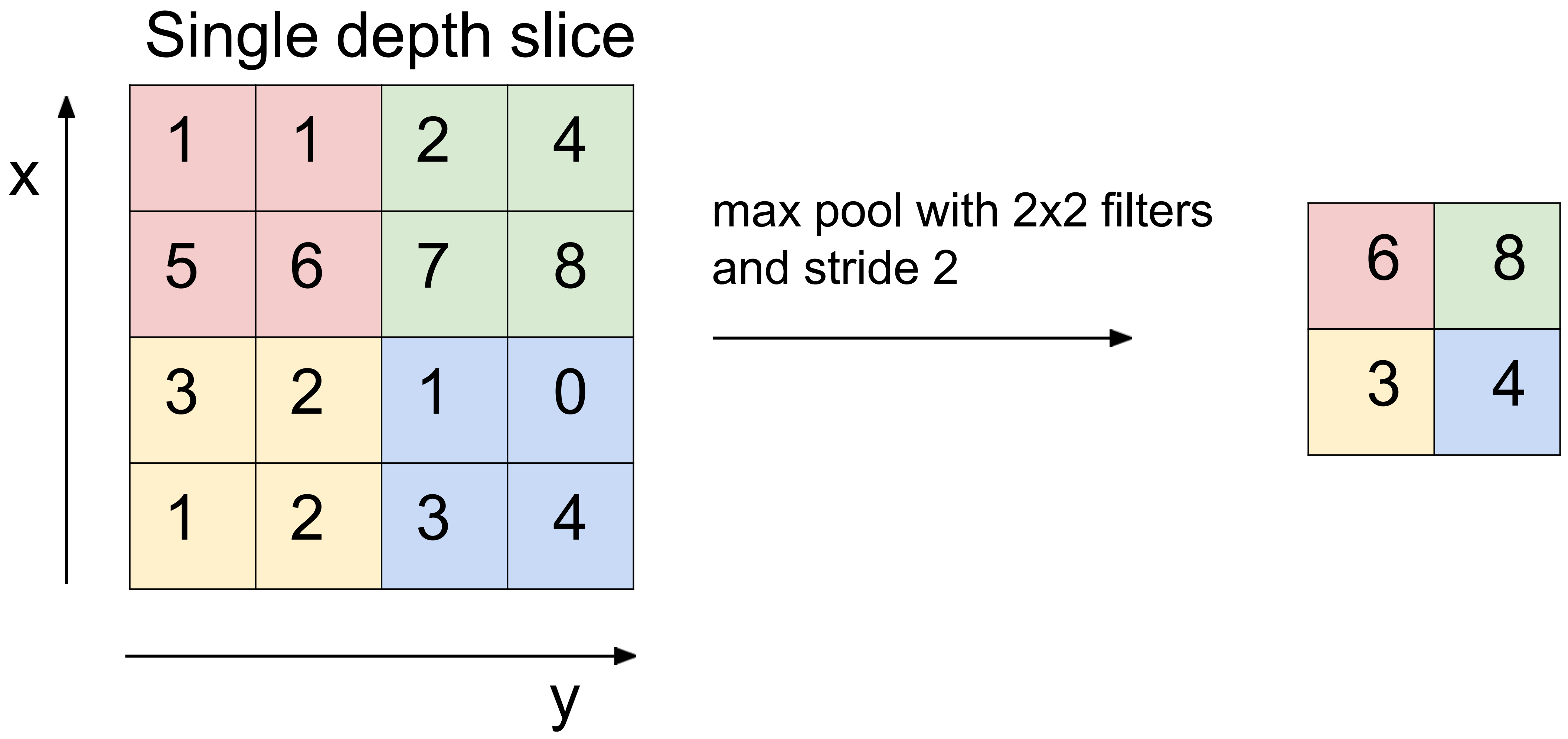
Padding:
Preserve input spatial dimensions in output activations

Review: Convolution



Each conv filter outputs a “slice” in the activation

Review: Pooling



Today: CNN Architectures

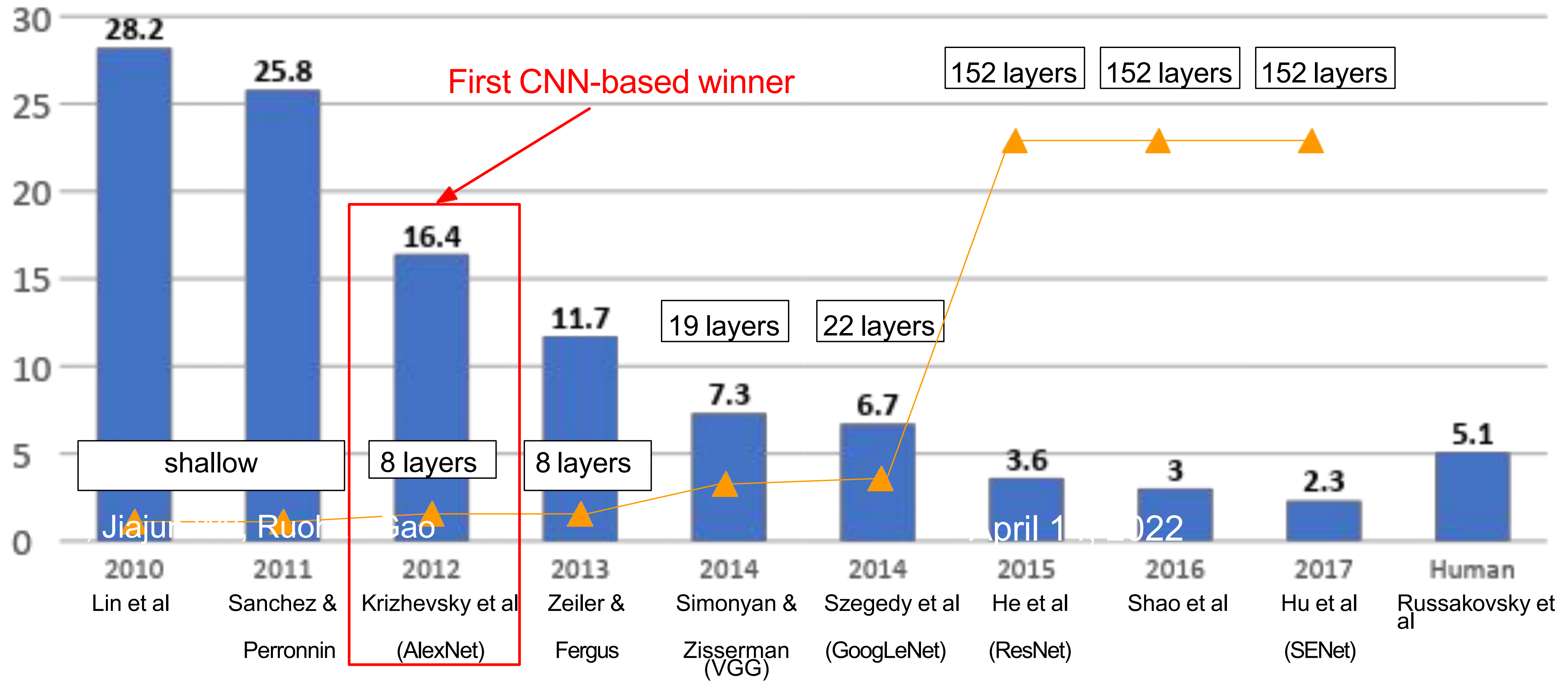
Case Studies

- AlexNet
- VGG
- GoogLeNet
- ResNet

Also....

- SENet
- Wide ResNet
- ResNeXT
- DenseNet
- MobileNets
- NASNet
- EfficientNet

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Case Study: AlexNet

[Krizhevsky et al. 2012]

Architecture:

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

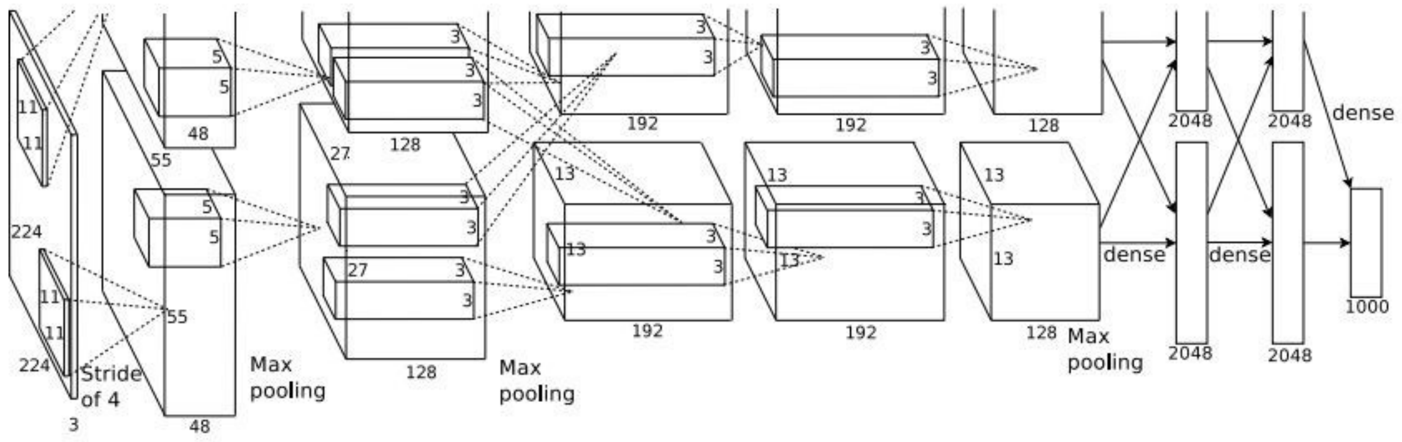
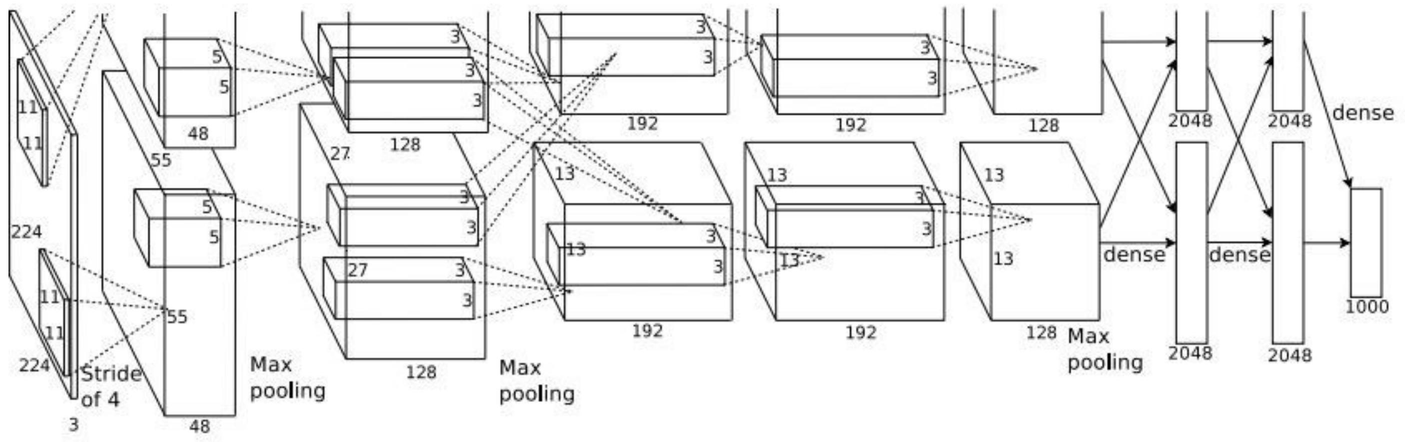


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

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

=>

Q: what is the output volume size?

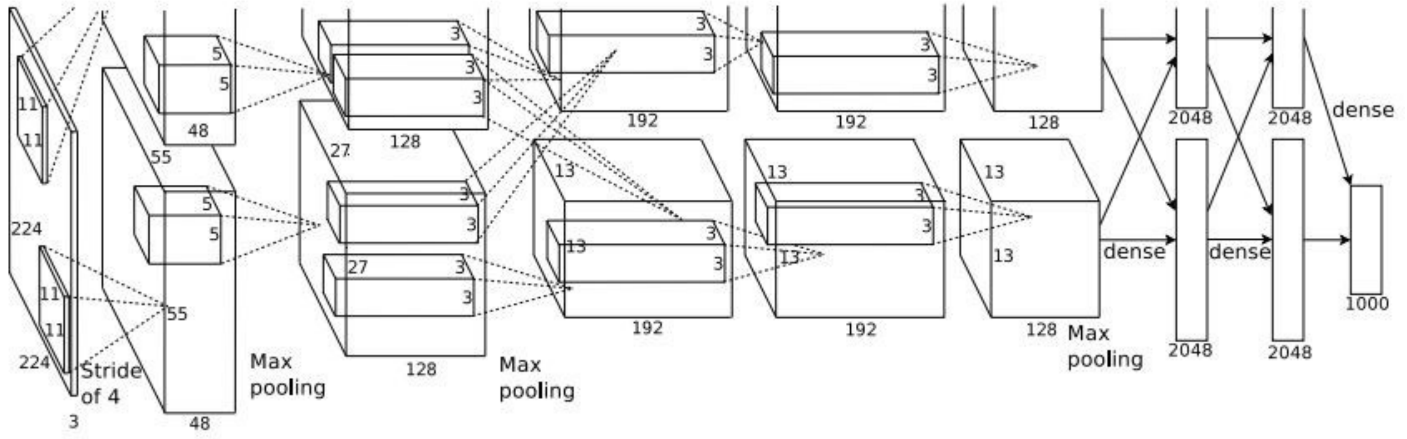
$(W-F+2P)/S+1$

$= (227-11)/4+1 = 55$

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

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

W' = (W - F + 2P) / S + 1

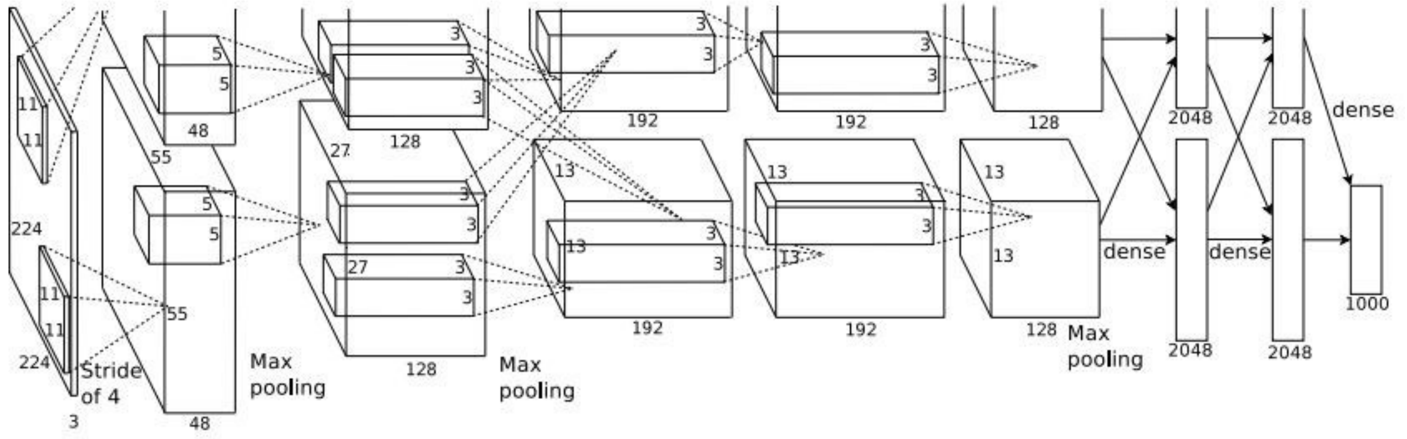
First layer (CONV1): 96 11x11 filters applied at stride 4

=>

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

Case Study: AlexNet

[Krizhevsky et al. 2012]



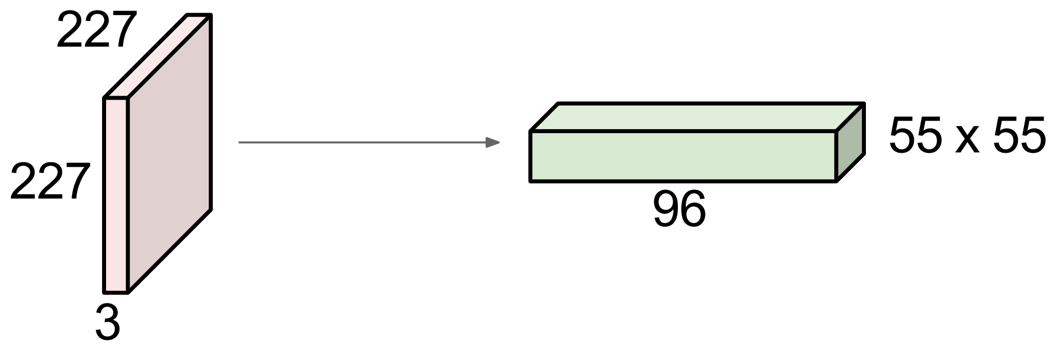
Input: 227x227x3 images

W' = (W - F + 2P) / S + 1

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

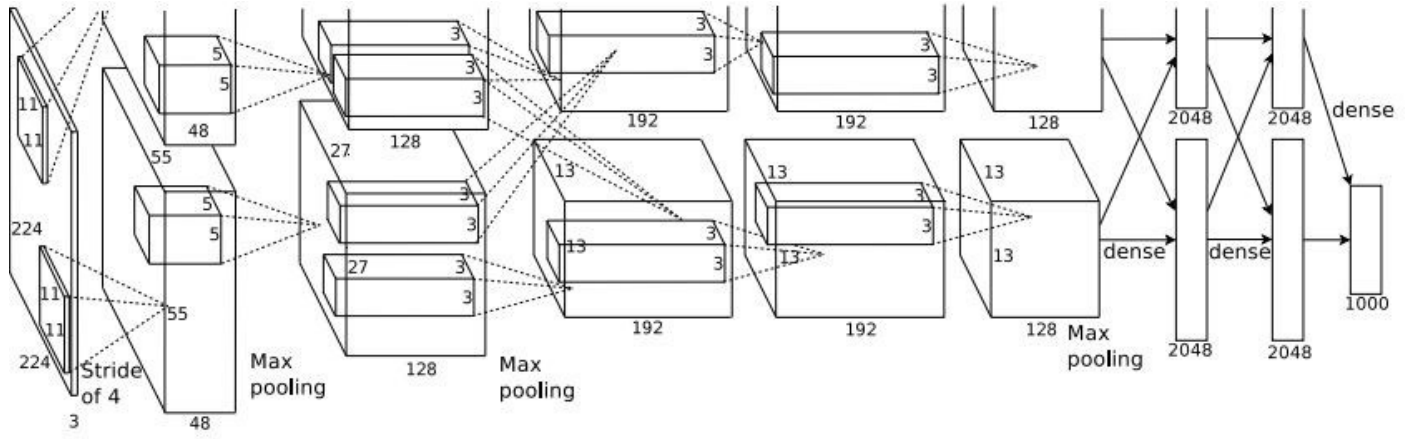
=>

Output volume **[55x55x96]**



Case Study: AlexNet

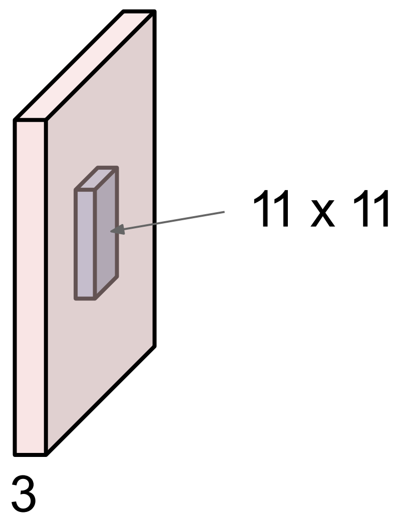
[Krizhevsky et al. 2012]



Input: 227x227x3 images

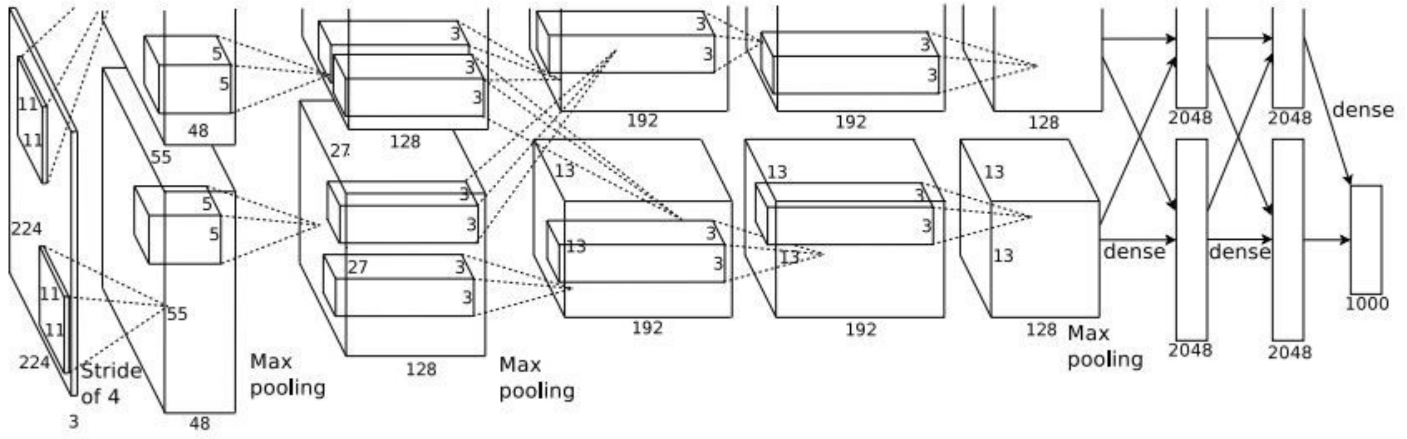
First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**

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



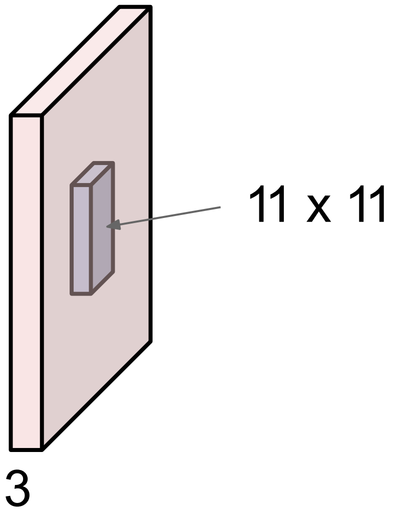
Case Study: AlexNet

[Krizhevsky et al. 2012]



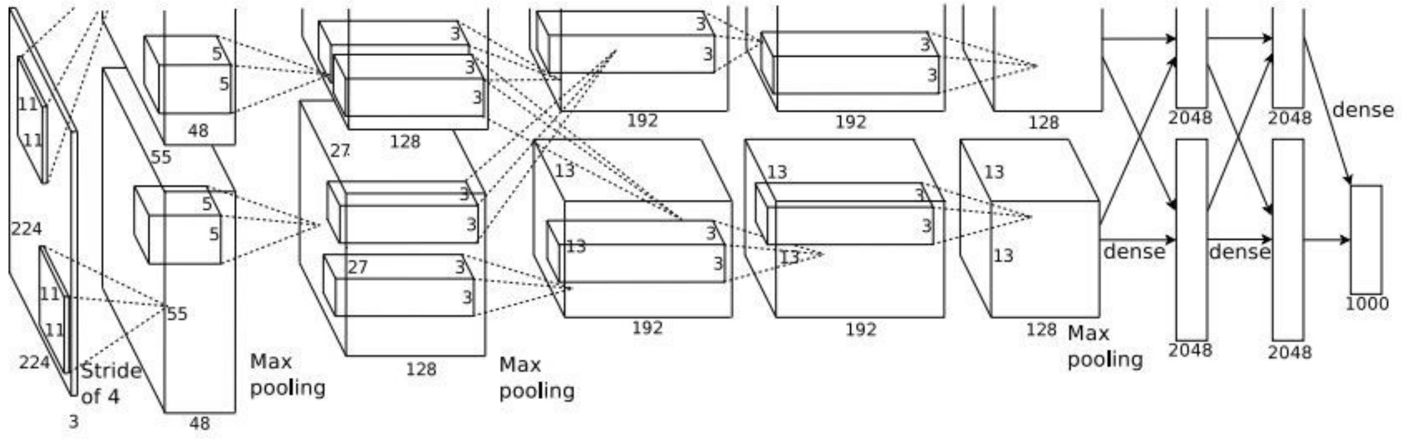
Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**
Parameters: (11*11*3 + 1)*96 = **35K**



Case Study: AlexNet

[Krizhevsky et al. 2012]



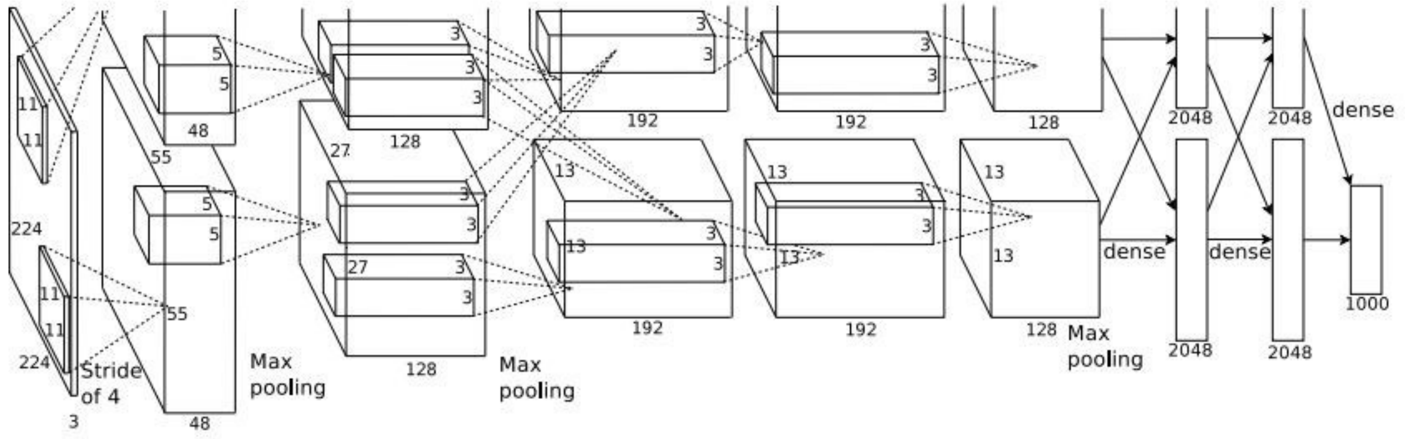
Input: 227x227x3 images
After CONV1: 55x55x96

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

Q: what is the output volume size?

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images
After CONV1: 55x55x96

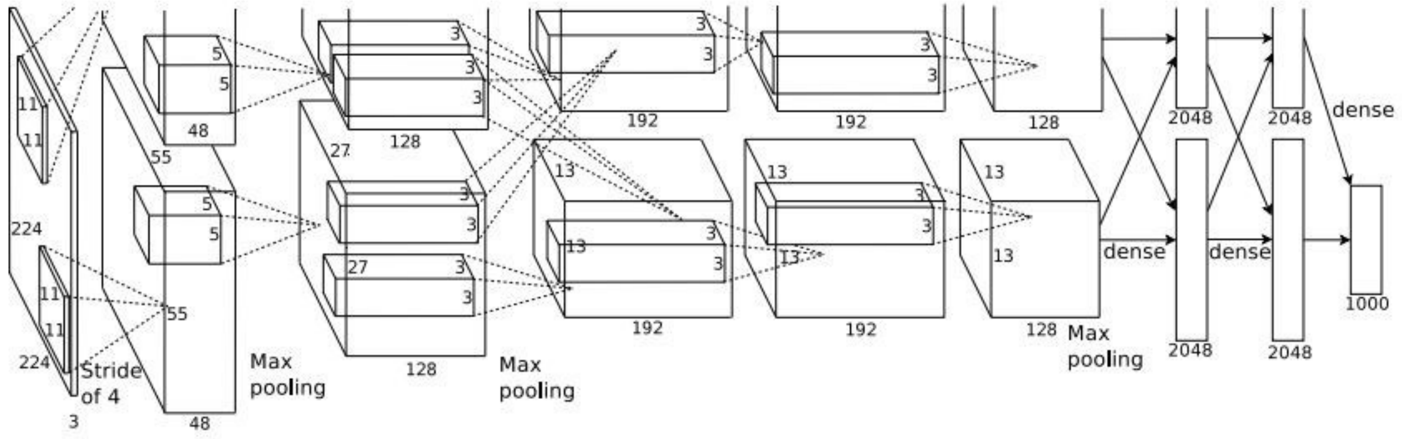
W’ = (W - F + 2P) / S + 1

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

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

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images
After CONV1: 55x55x96

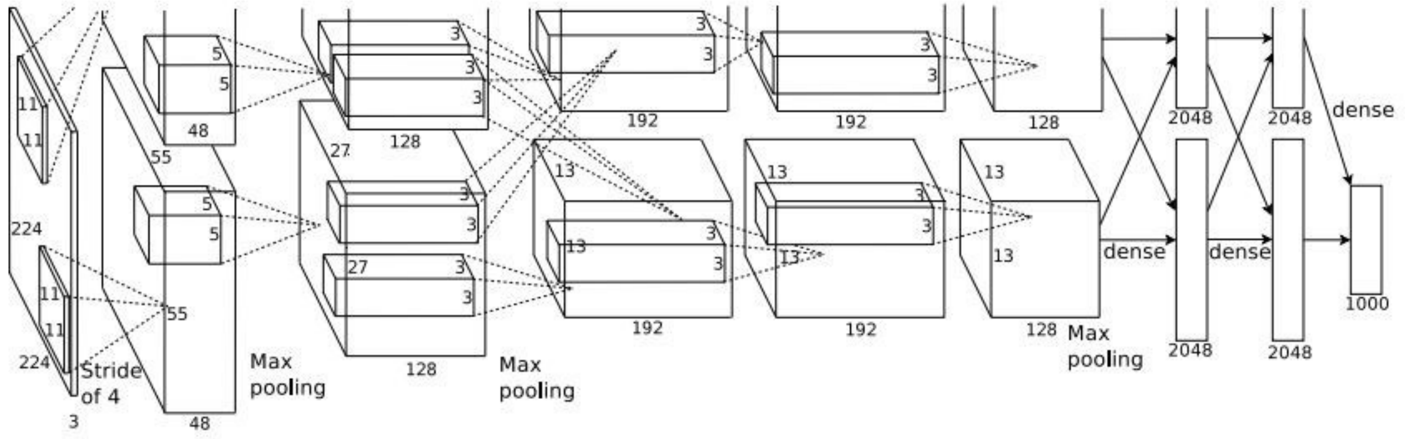
W' = (W - F + 2P) / S + 1

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96

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

Case Study: AlexNet

[Krizhevsky et al. 2012]

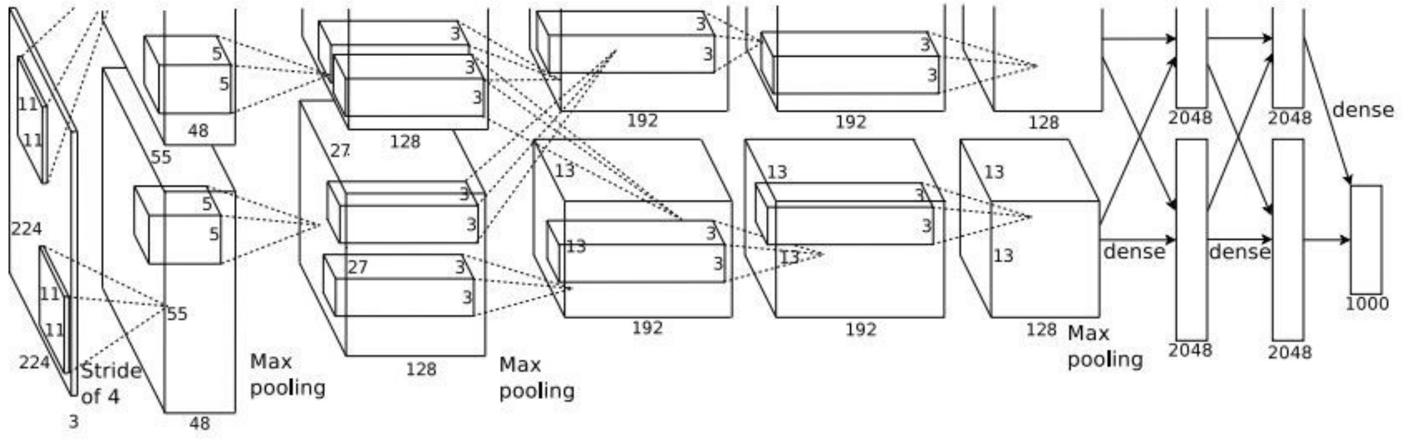


Input: 227x227x3 images
After CONV1: 55x55x96

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

Case Study: AlexNet

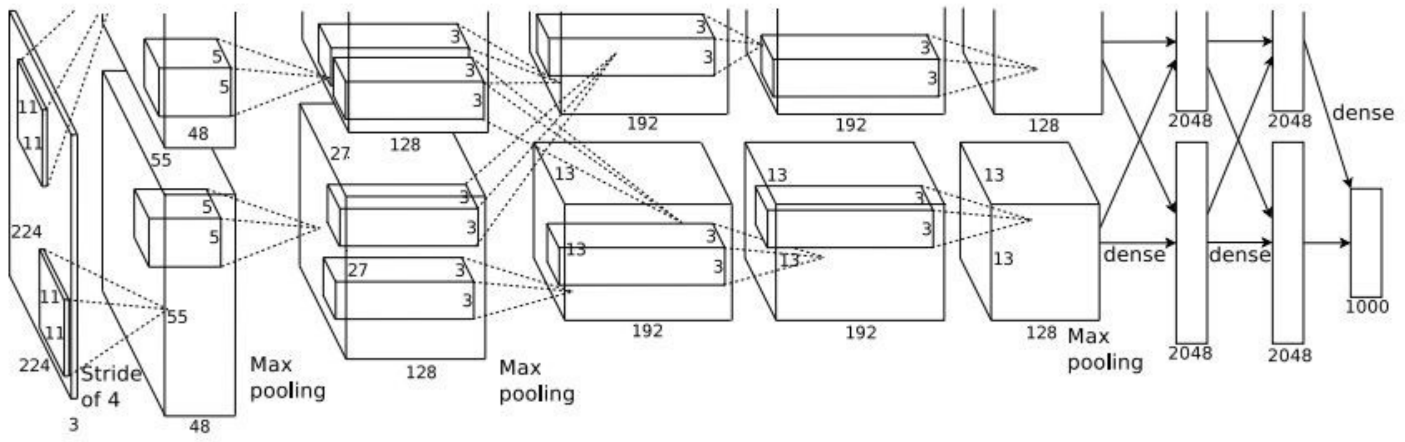
[Krizhevsky et al. 2012]



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

Case Study: AlexNet

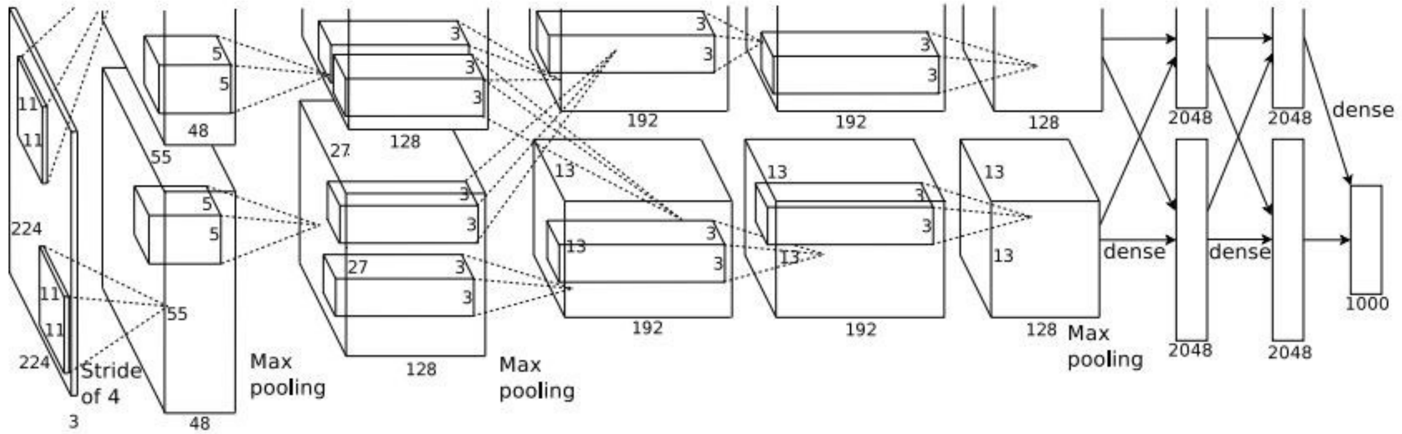
[Krizhevsky et al. 2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Case Study: AlexNet

[Krizhevsky et al. 2012]



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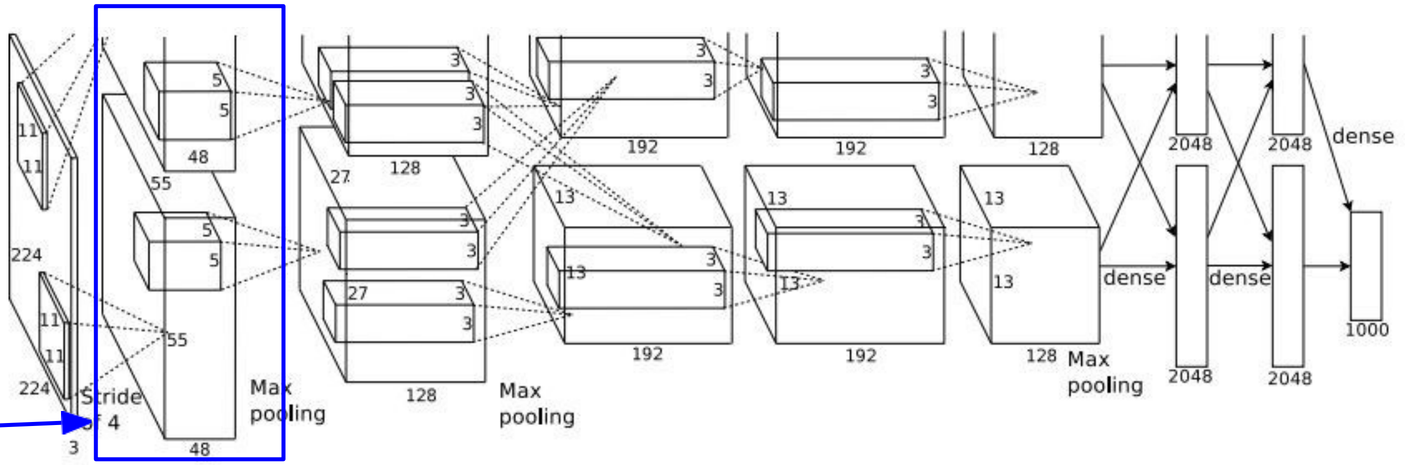
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Details/Retrospectives:
- first use of ReLU
- used LRN layers (not common anymore)
- heavy data augmentation
- dropout 0.5 → random 更新 50% 神经元
- batch size 128 → 128 张图一起进
- 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

[Krizhevsky et al. 2012]



[55x55x48] x 2

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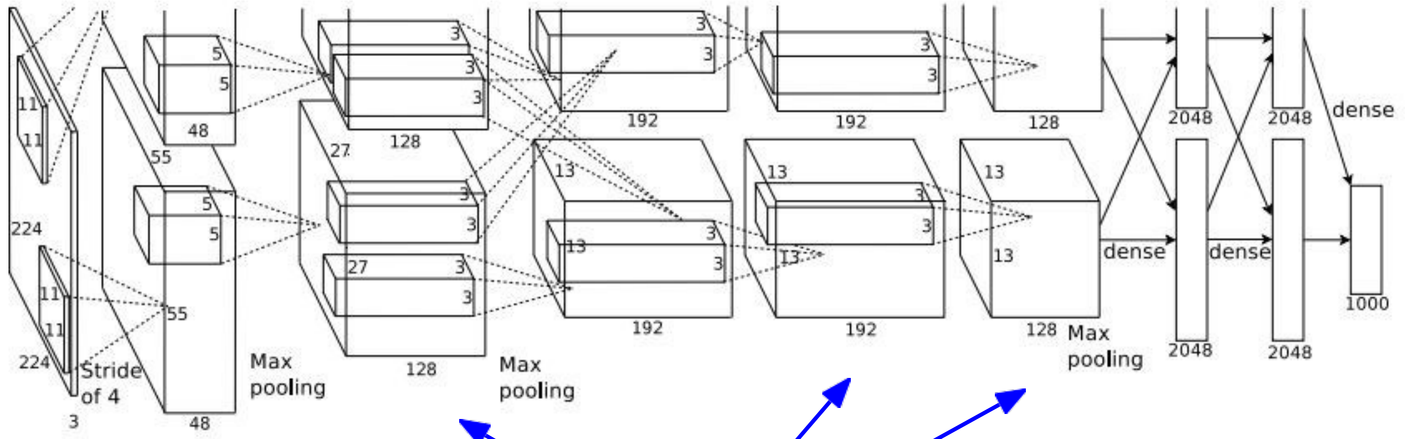
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

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

[Krizhevsky et al. 2012]



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[4096] FC6: 4096 neurons
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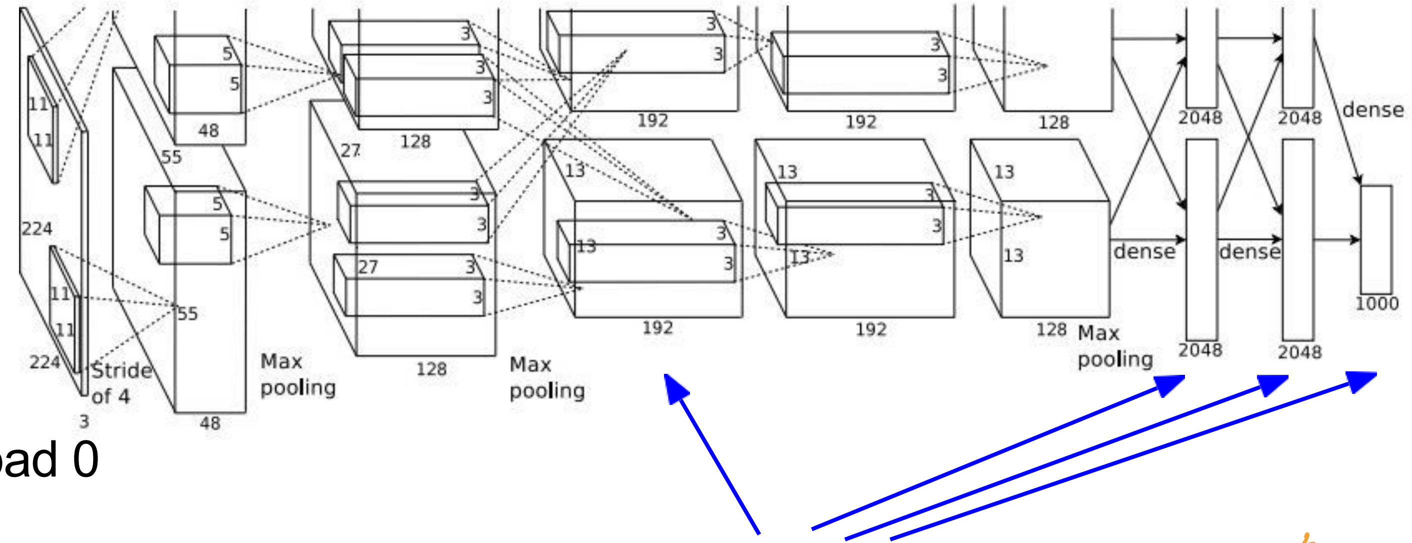
[1000] FC8: 1000 neurons (class scores)

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

Case Study: AlexNet

[Krizhevsky et al. 2012]



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[4096] FC6: 4096 neurons
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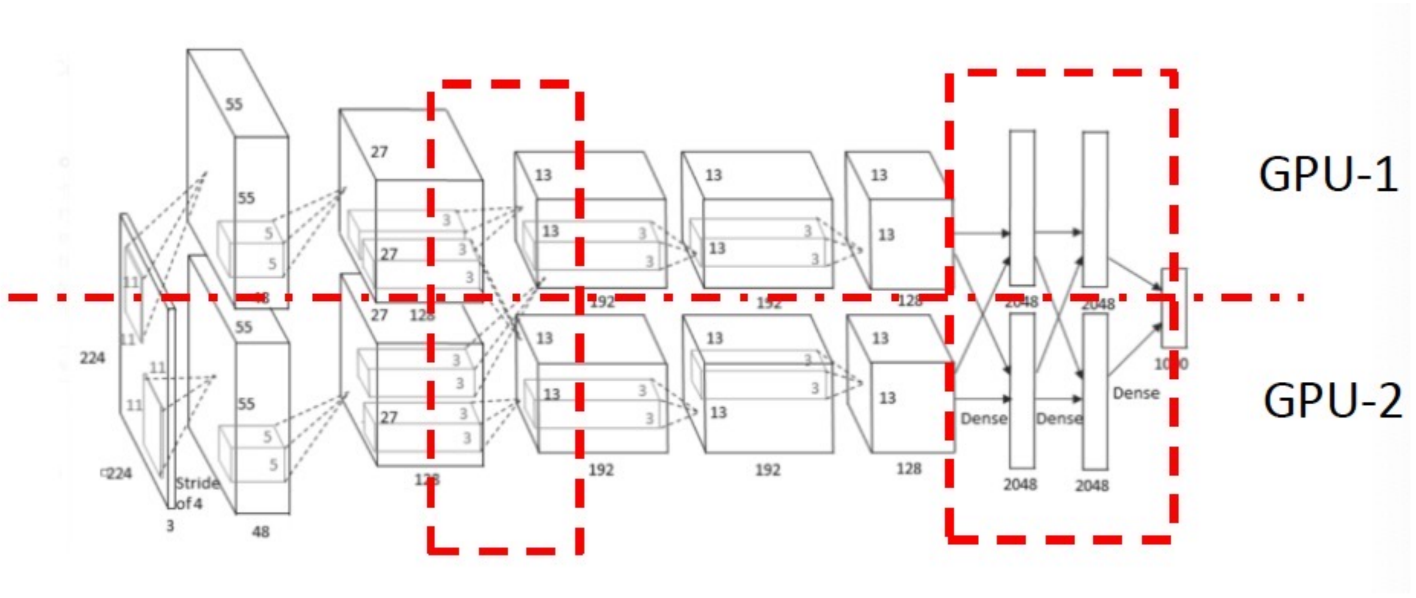
[1000] FC8: 1000 neurons (class scores)

CONV3, FC6, FC7, FC8: 把另-GPU的也拿来
Connections with all feature maps in preceding layer, communication across GPUs

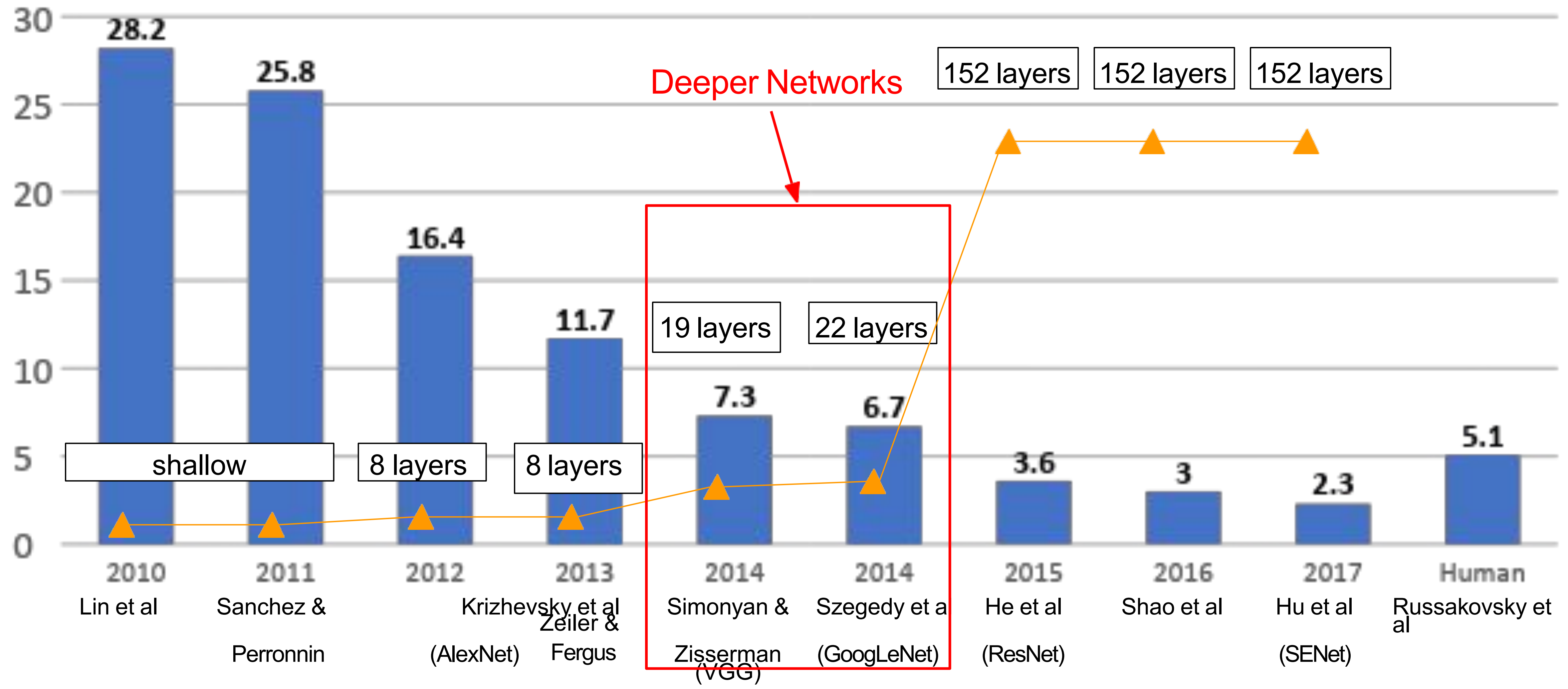
Case Study: AlexNet

[Krizhevsky et al. 2012]

多个GPU



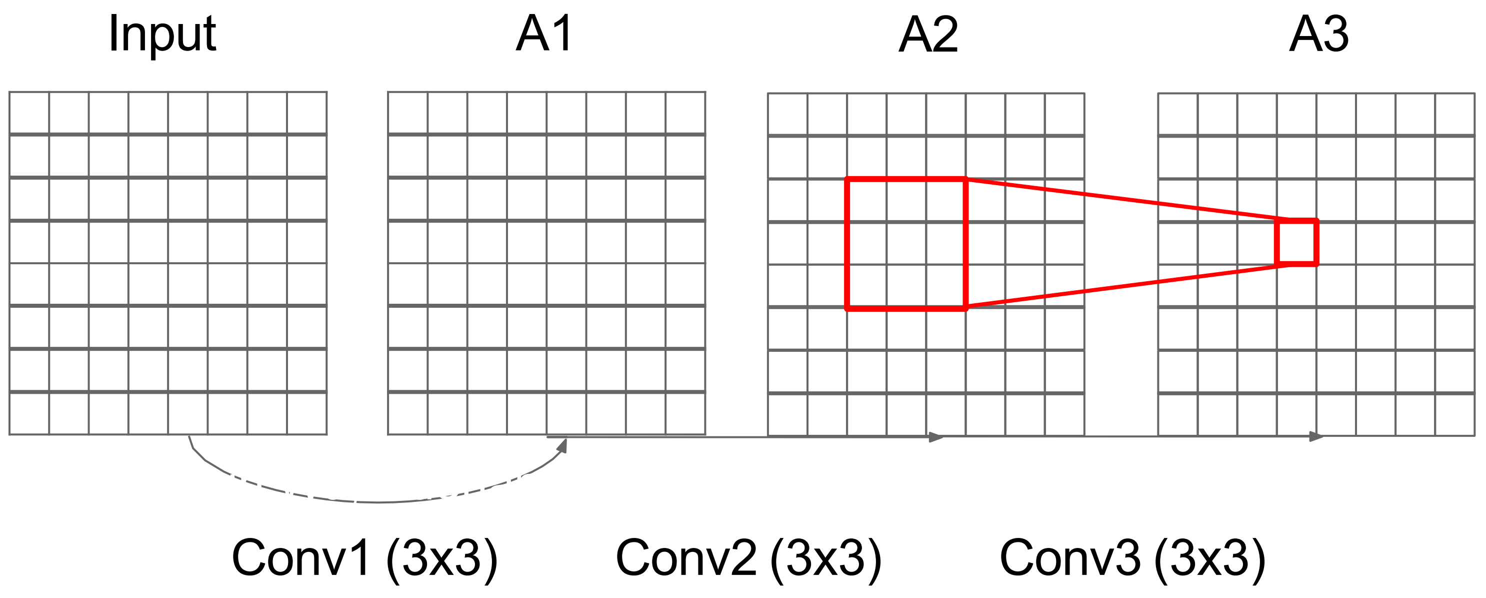
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

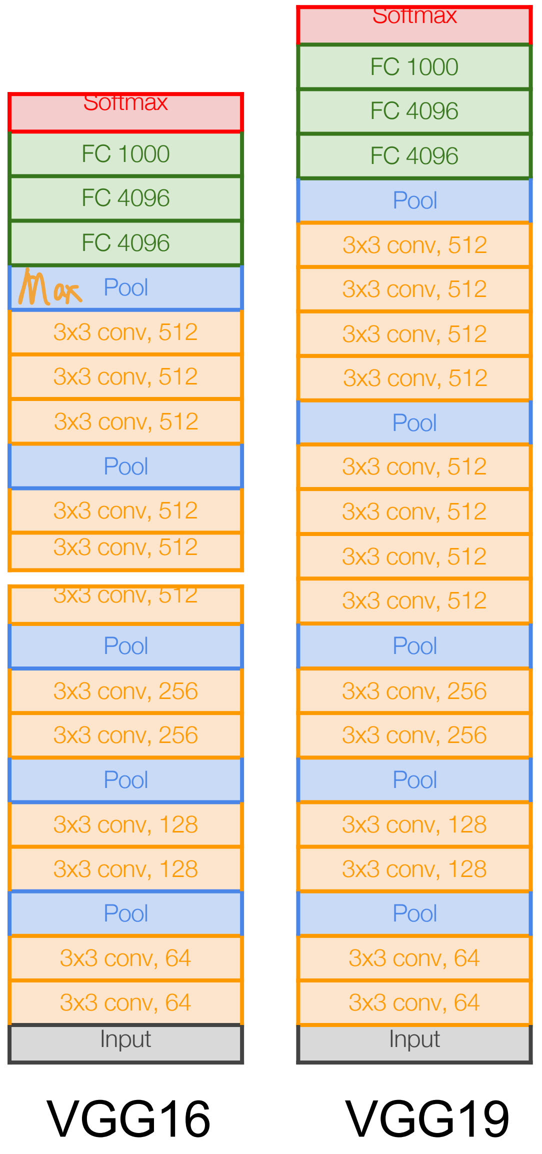


Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: What is the effective receptive field of three 3x3 conv (stride 1) layers?





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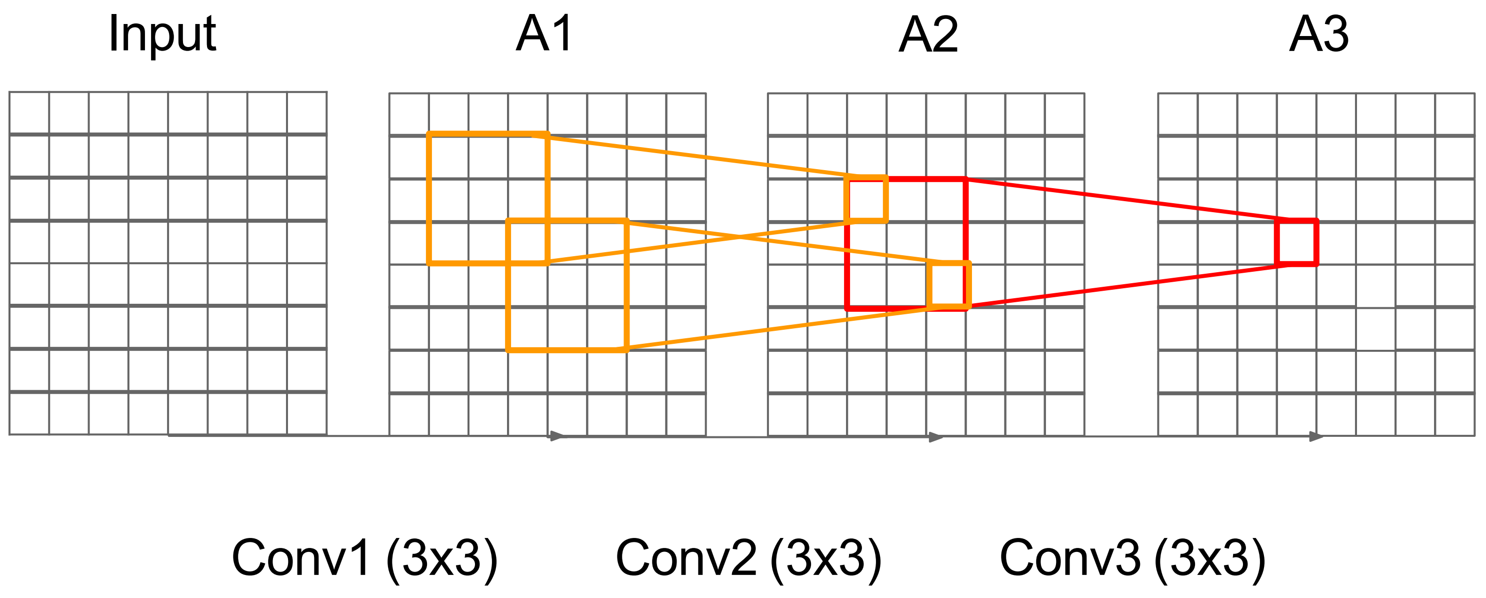
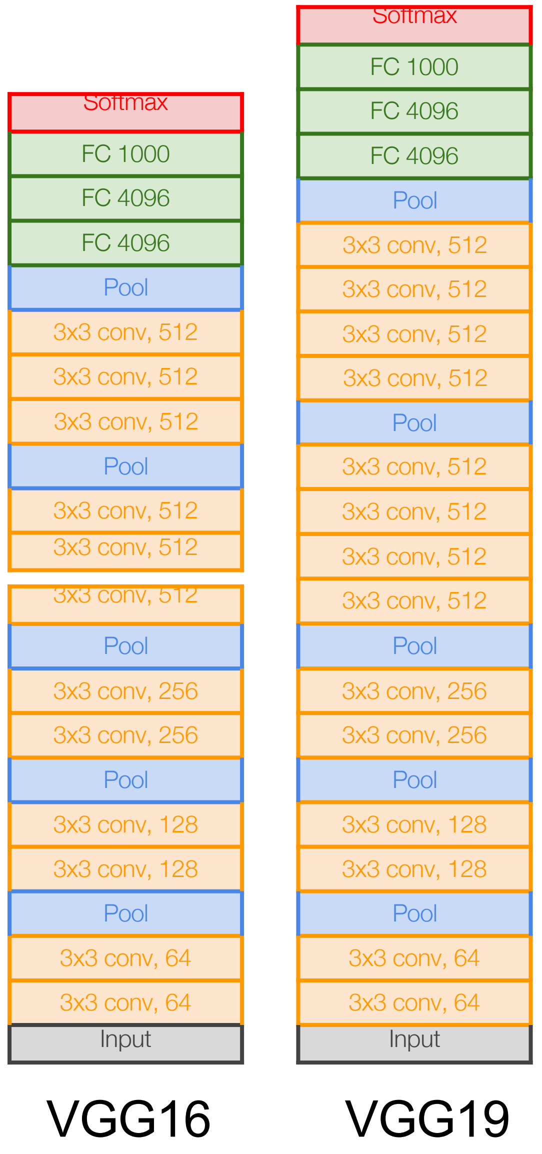


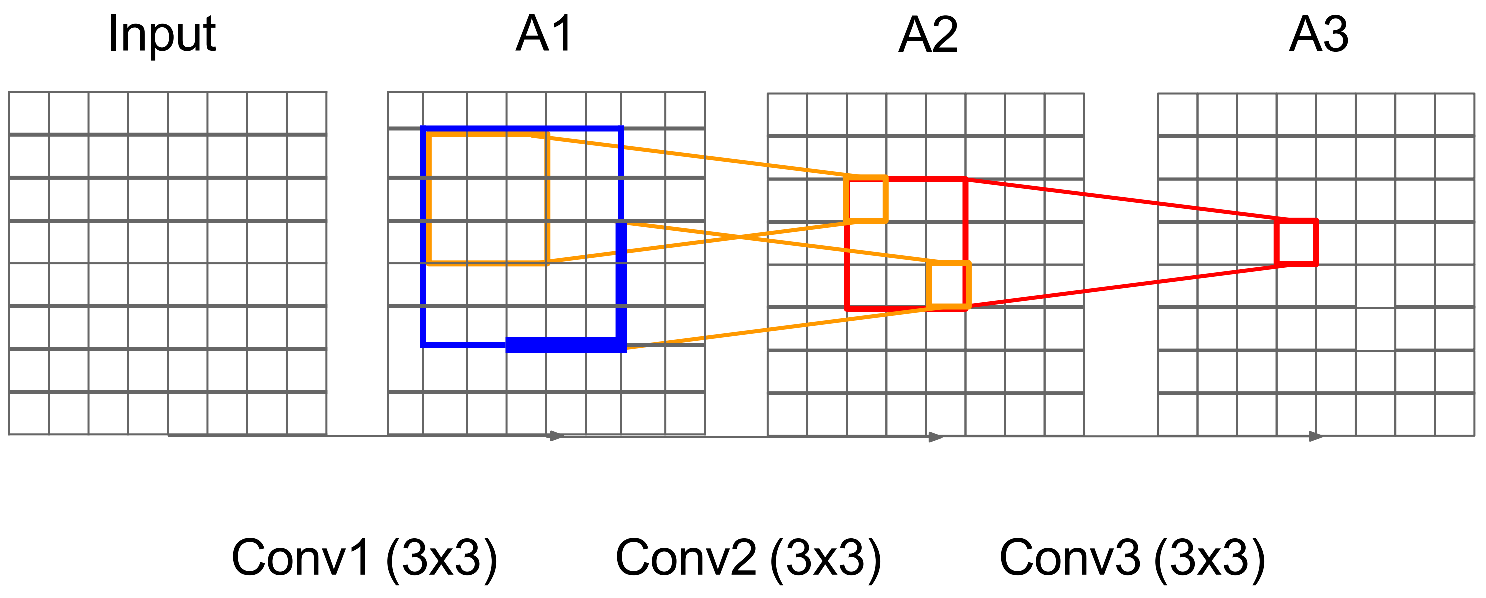


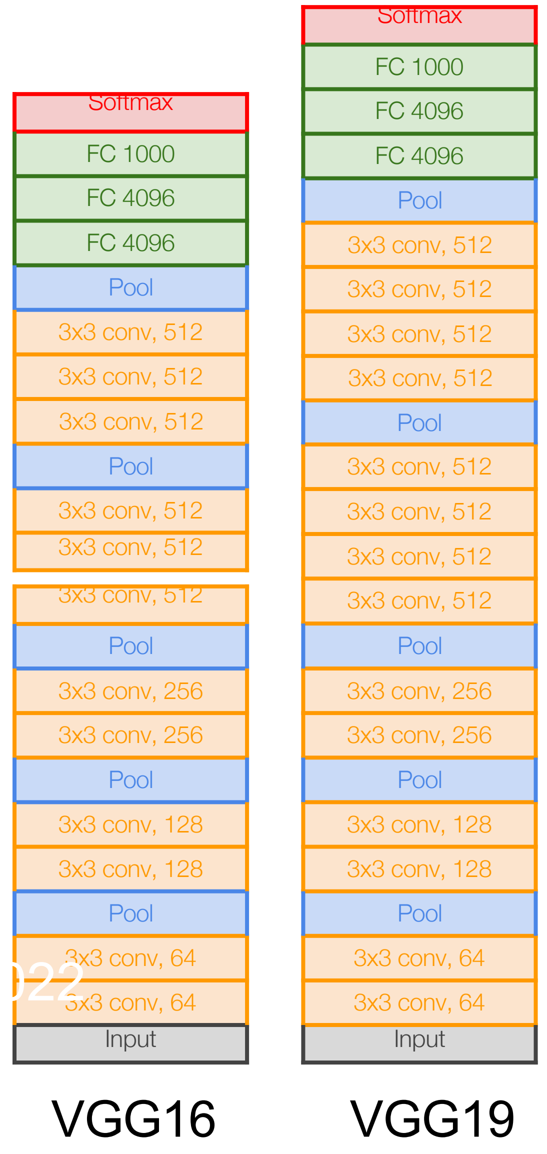
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: What is the effective receptive field of three 3x3 conv (stride 1) layers?

感受野变大





Case Study: VGGNet

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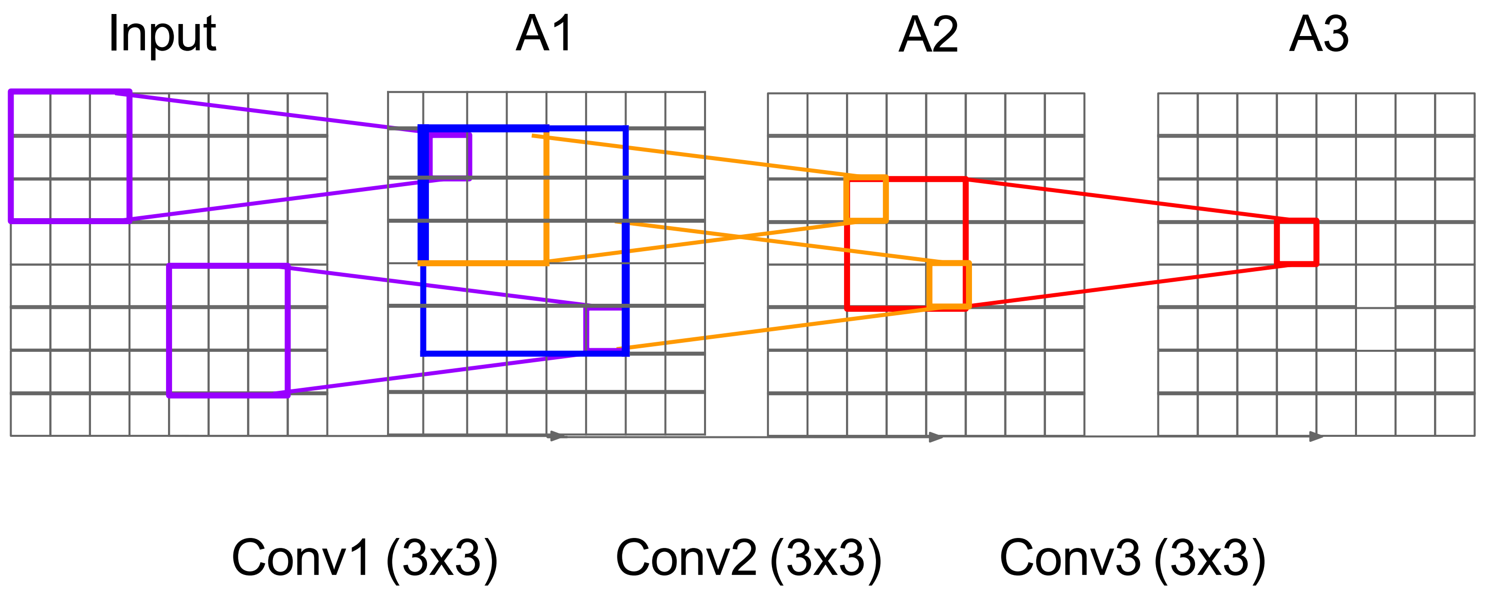

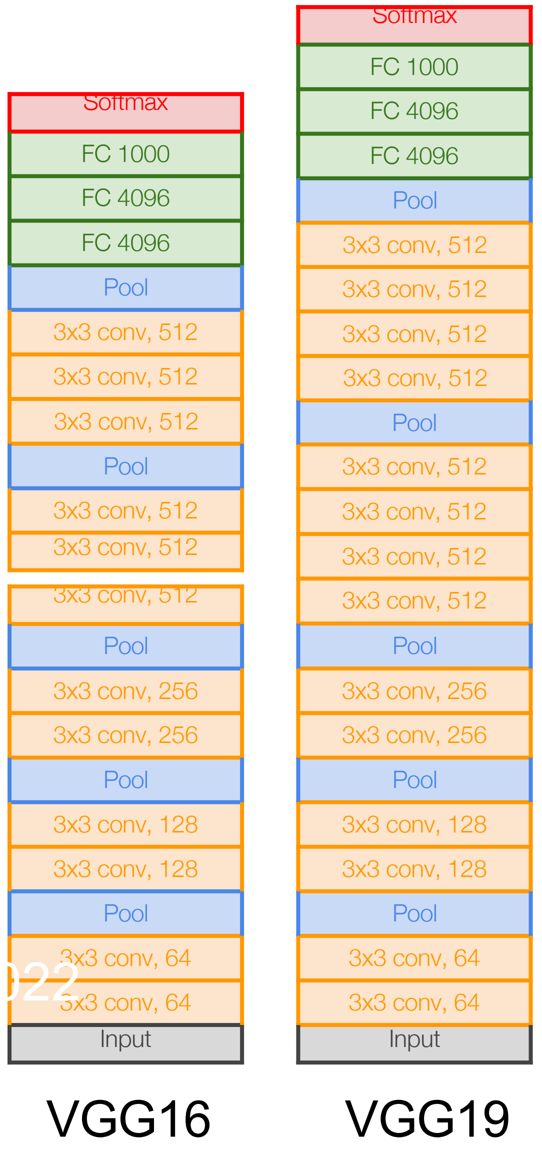

Case Study: VGGNet

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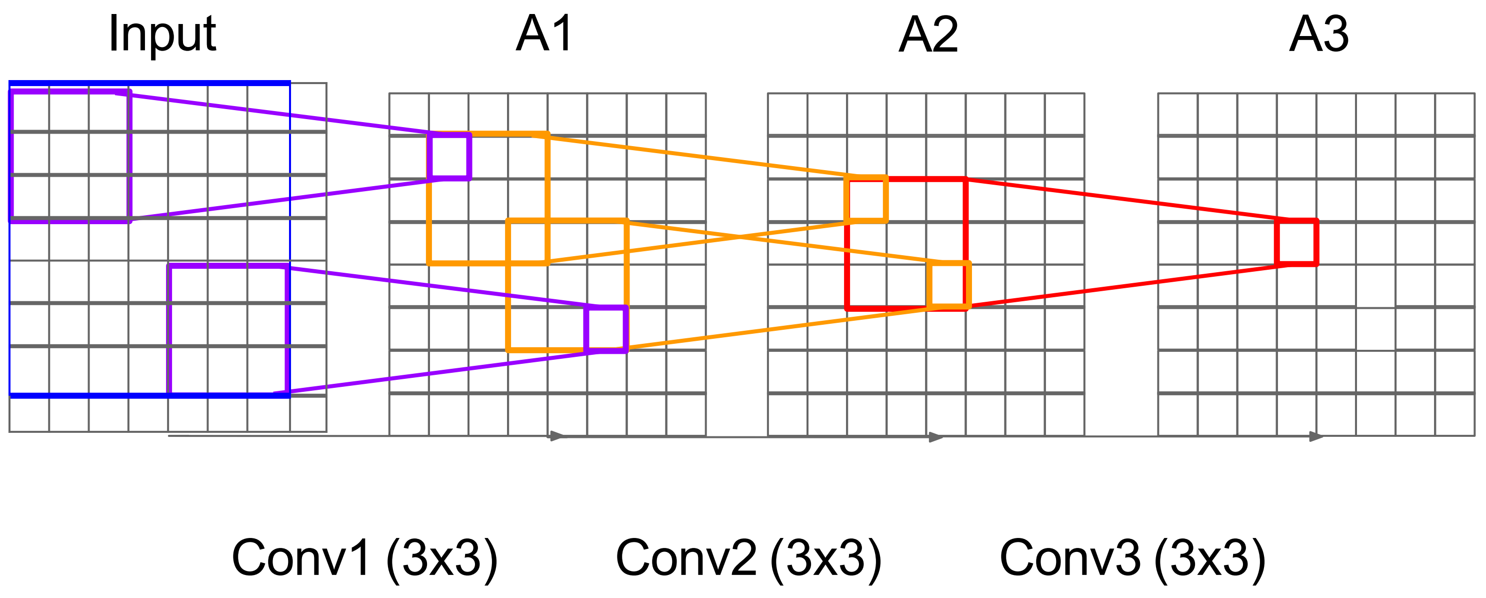
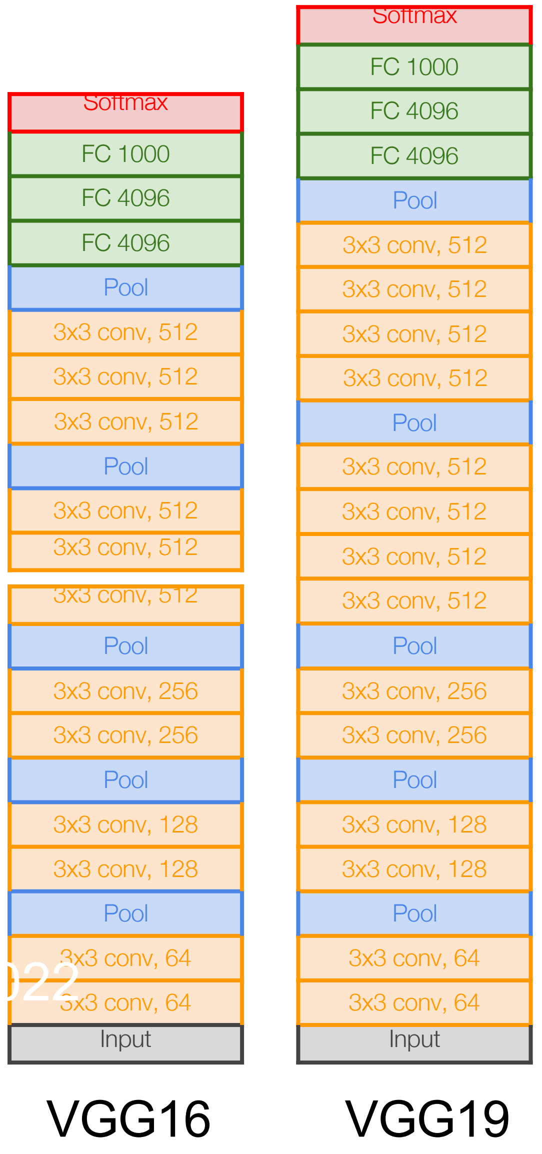




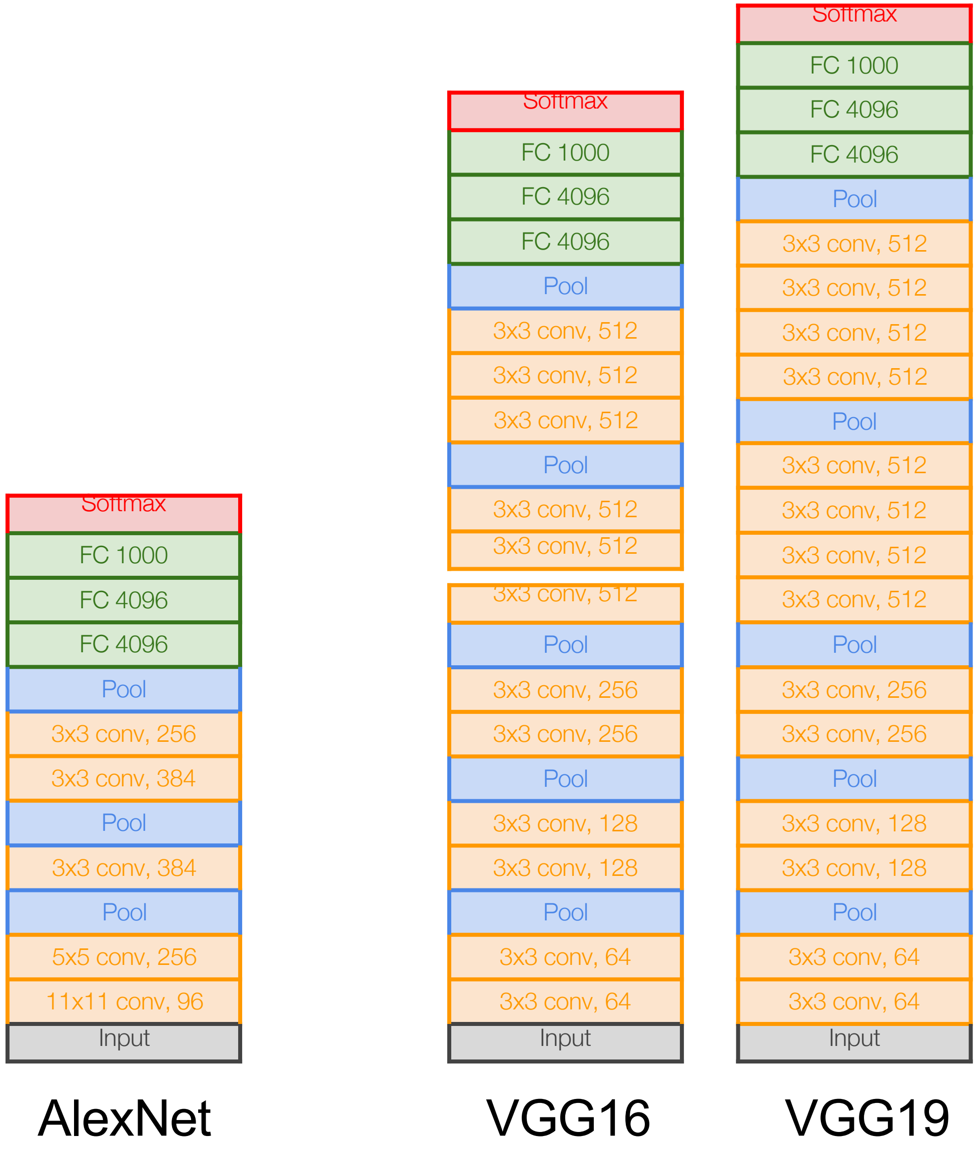
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

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

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

[7x7]



Case Study: VGGNet

[Simonyan and Zisserman, 2014]

开始就256参数量太大

pooling → activation map ↓

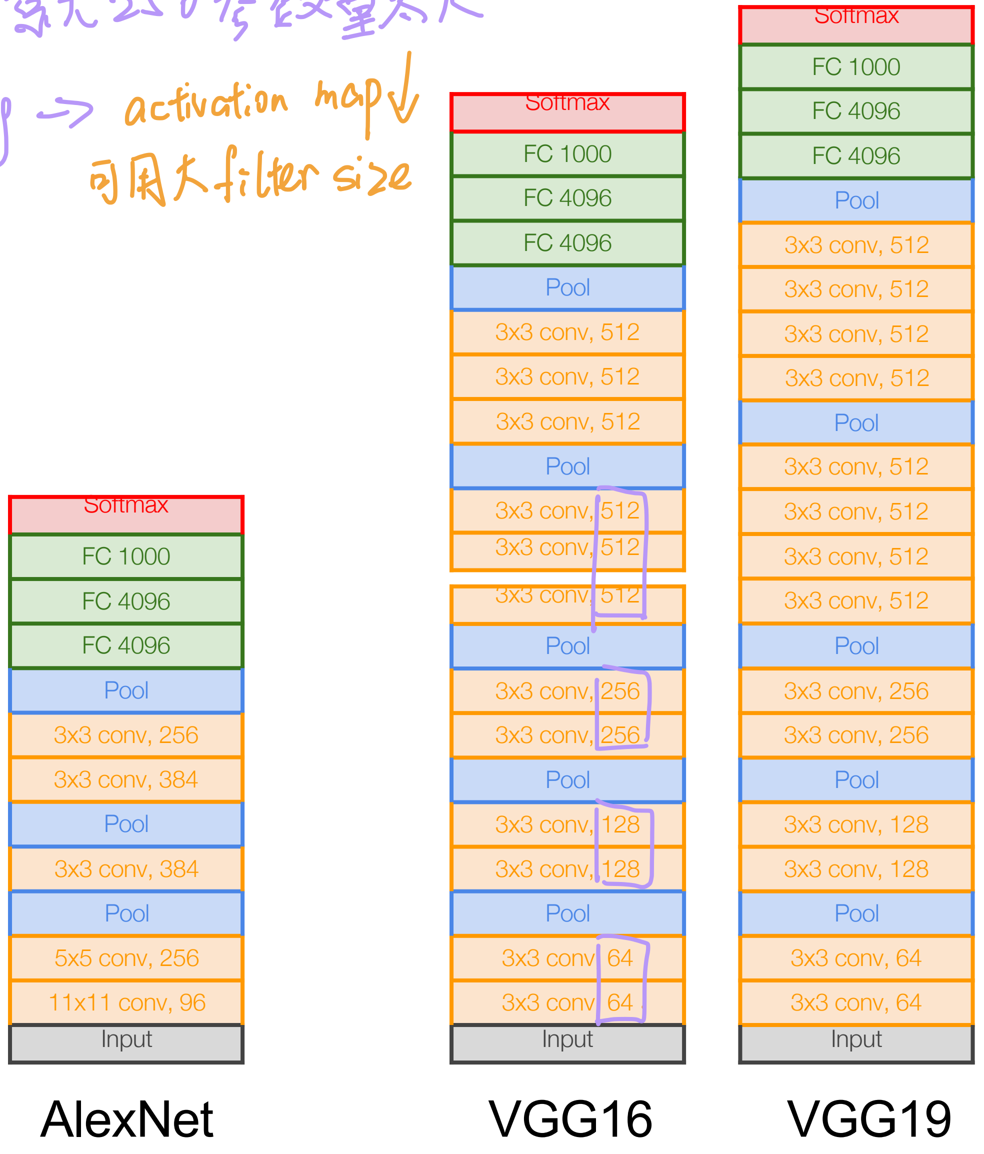
可用大filter size

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

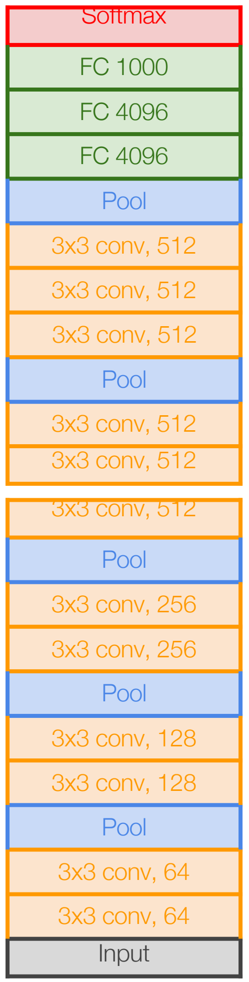
But deeper, more non-linearities

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



(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
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 74%参数量
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000



VGG16

INPUT: [224x224x3] memory: 224*224*3=150K params: 0 (not counting biases)
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
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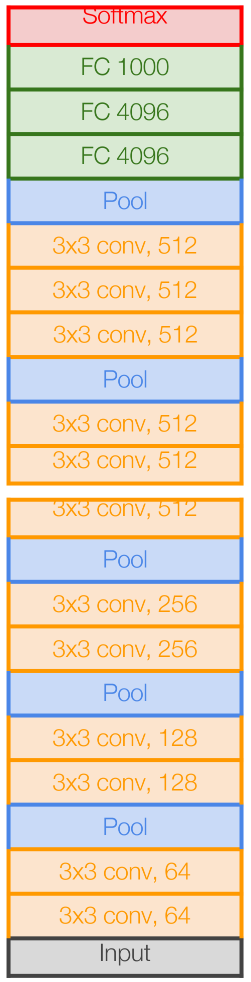
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 96MB / image (for a forward pass)
TOTAL params: 138M parameters



VGG16

(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
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

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 (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
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CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
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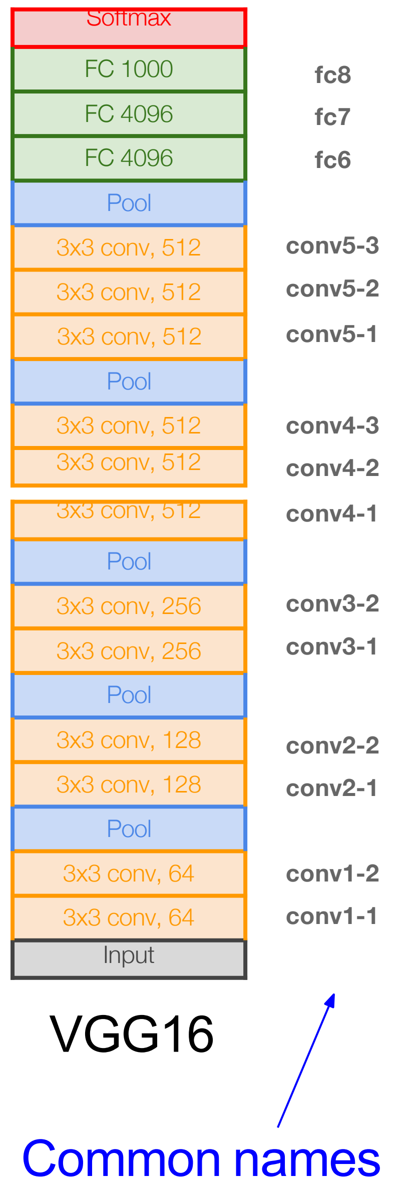
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

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

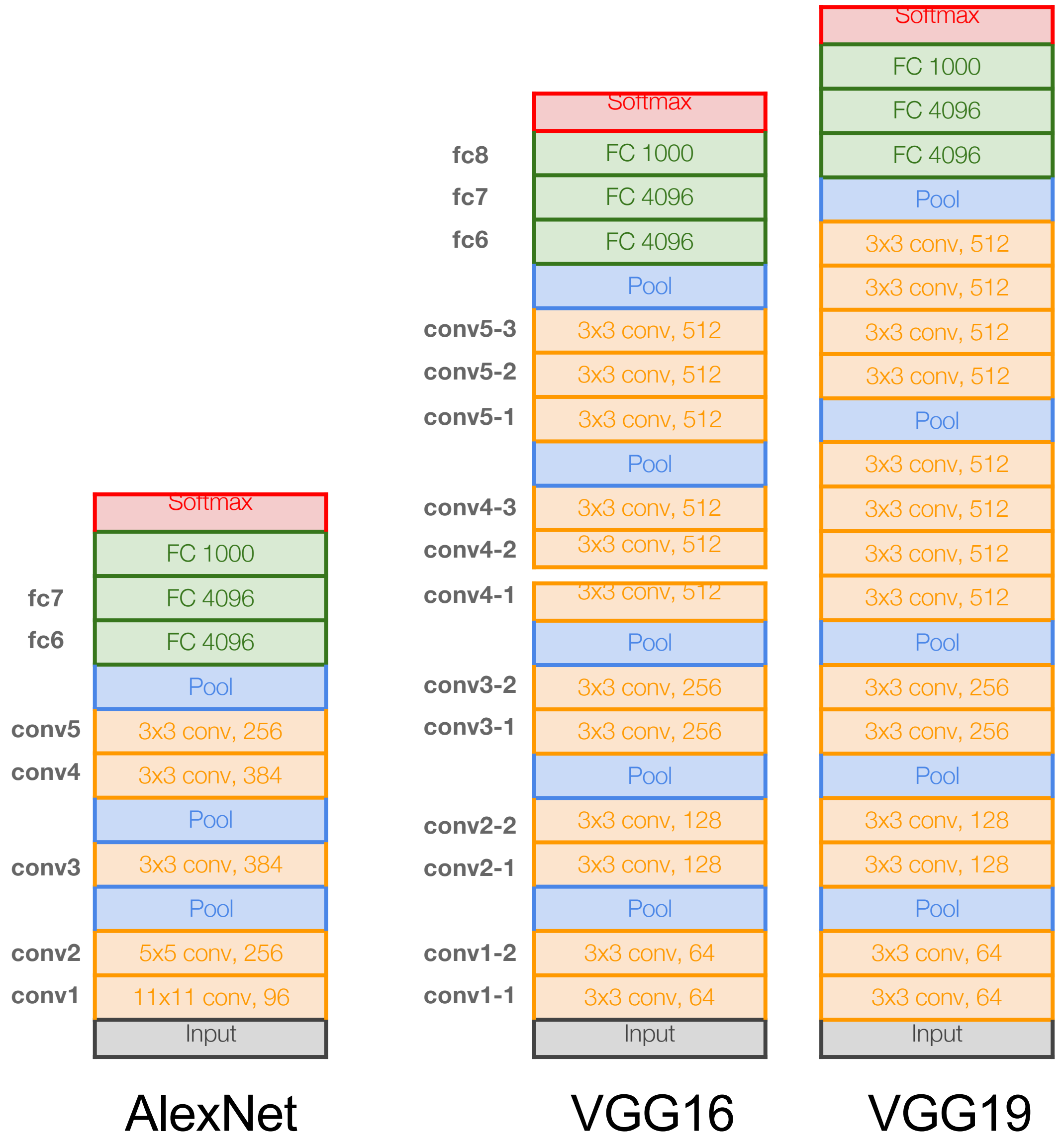


Case Study: VGGNet

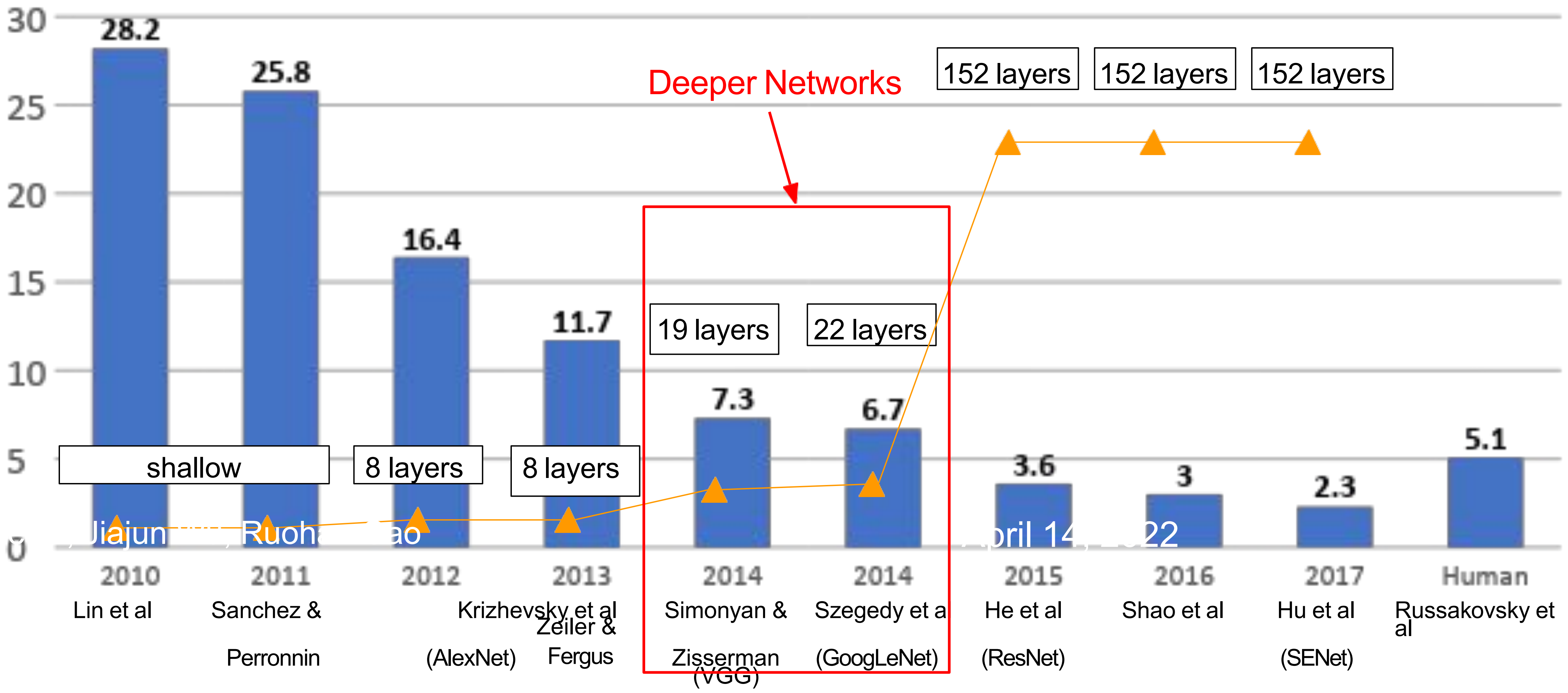
[Simonyan and Zisserman, 2014]

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

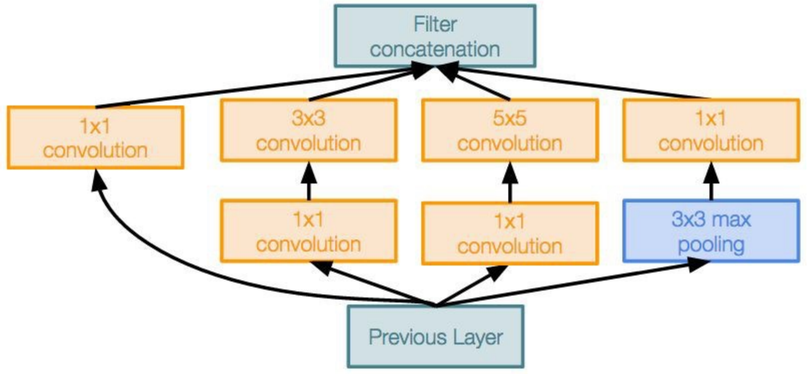
[Szegedy et al., 2014]

串联，前去后无法get

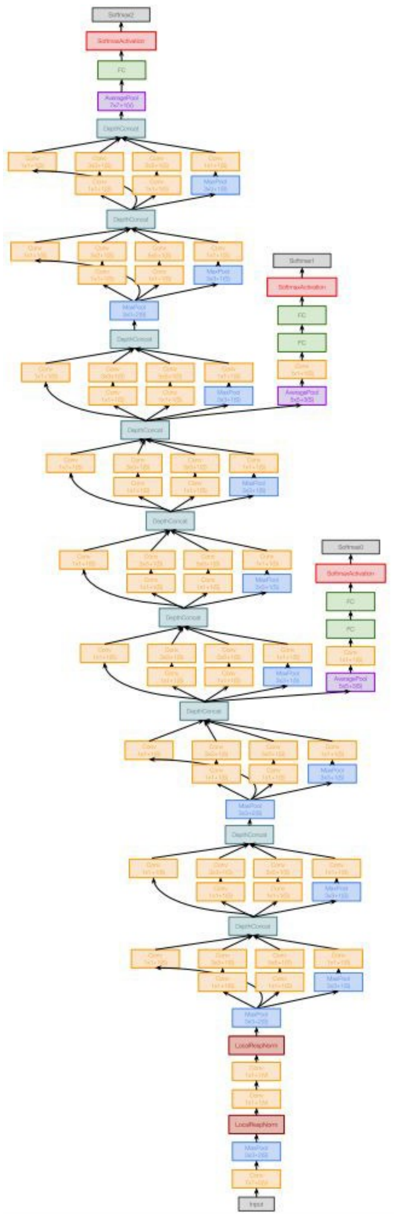
并联

Deeper networks, with computational efficiency

- ILSVRC'14 classification winner (6.7% top 5 error)
- 22 layers
- Only 5 million parameters!
  12x less than AlexNet
  27x less than VGG-16
- Efficient "Inception" module
- No FC layers



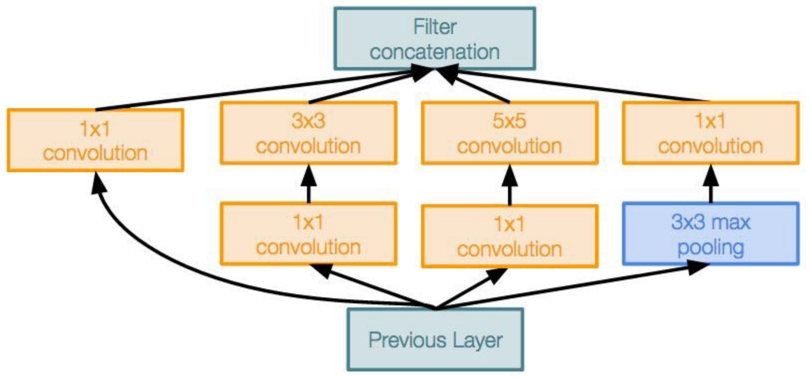
Inception module



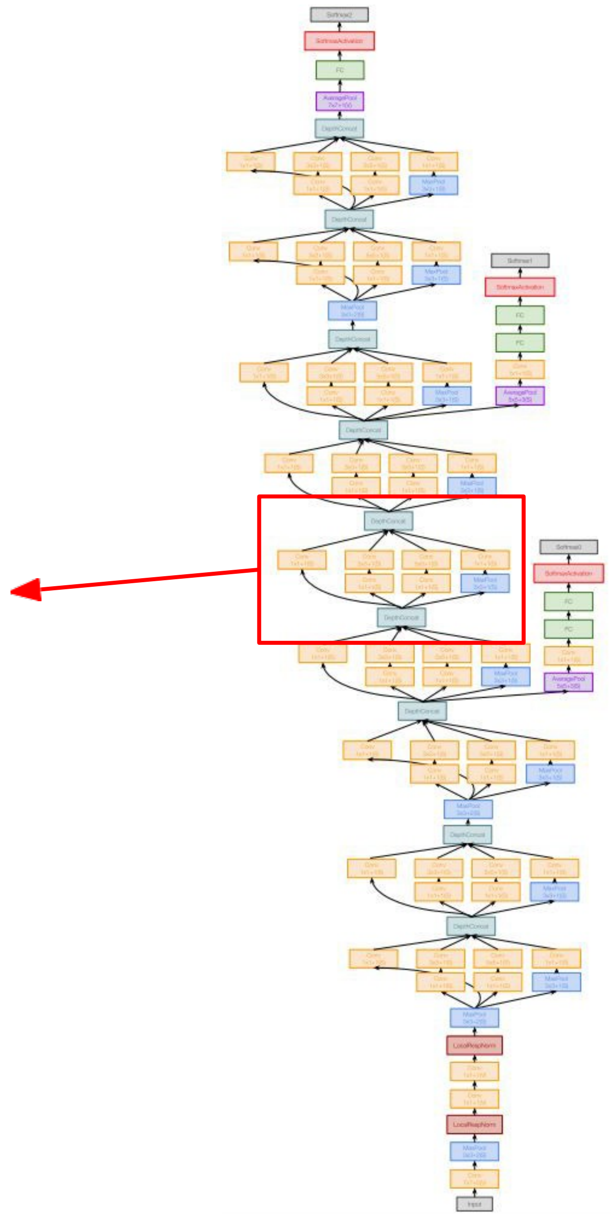
Case Study: GoogLeNet

[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

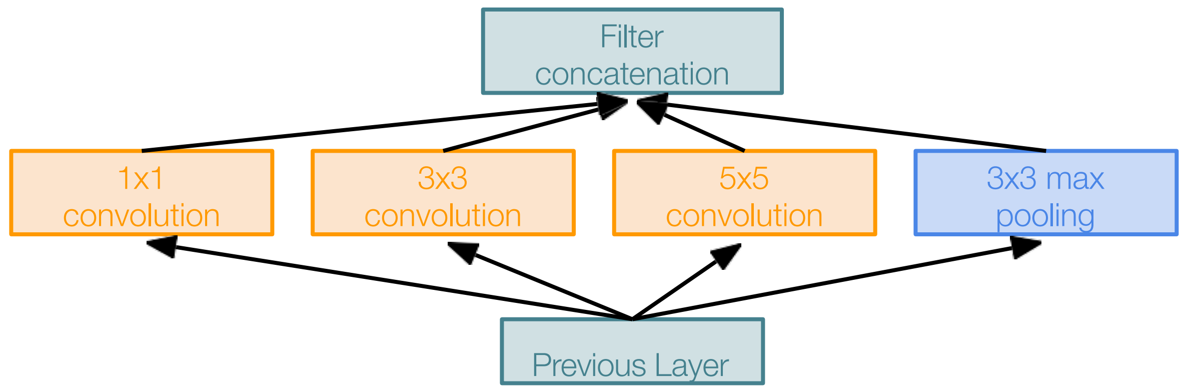


Inception module



Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

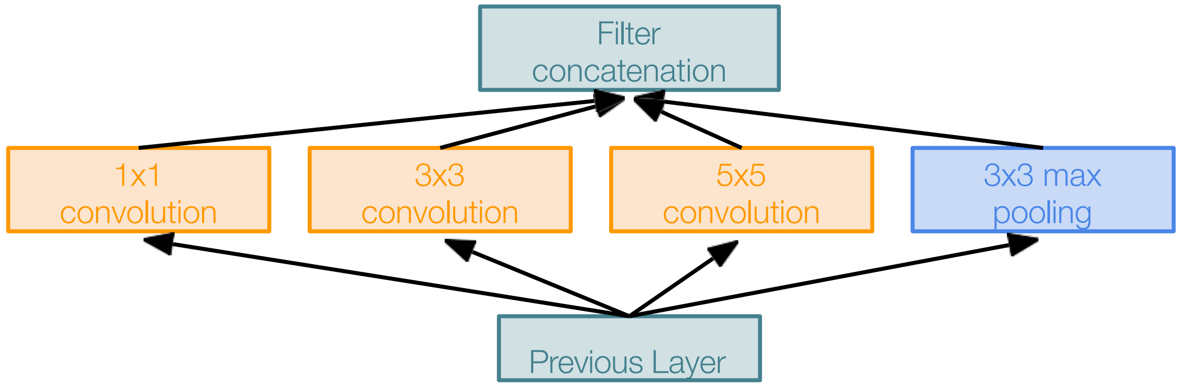
Apply parallel filter operations on the input from previous layer:

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

Concatenate all filter outputs together channel-wise

Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

Apply parallel filter operations on the input from previous layer:

- Multiple receptive field sizes for convolution (1x1, 3x3, 5x5)
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Concatenate all filter outputs together channel-wise

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

Case Study: GoogLeNet

[Szegedy et al., 2014]

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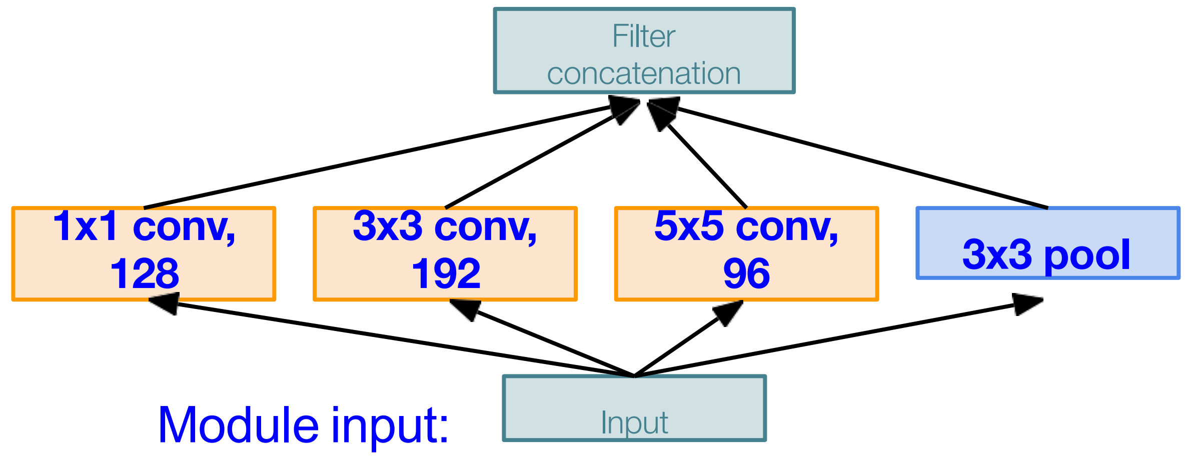
[Hint: Computational complexity]

Example:



Module input: 28x28x256

Naive Inception module

Case Study: GoogLeNet

[Szegedy et al., 2014]

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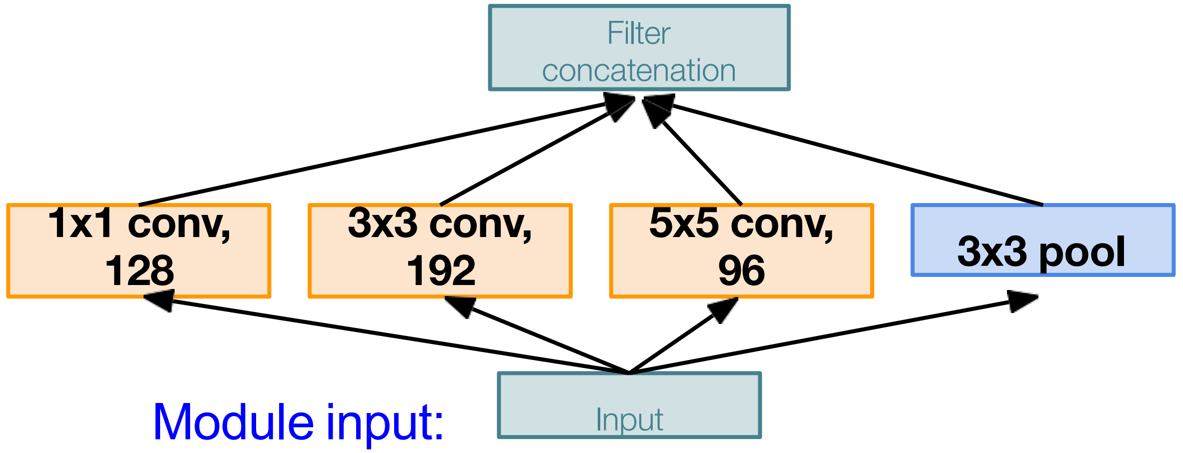
[Hint: Computational complexity]

Example:

Q1: What are the output sizes of all different filter operations?



Module input: 28x28x256

Naive Inception module

Case Study: GoogLeNet

[Szegedy et al., 2014]

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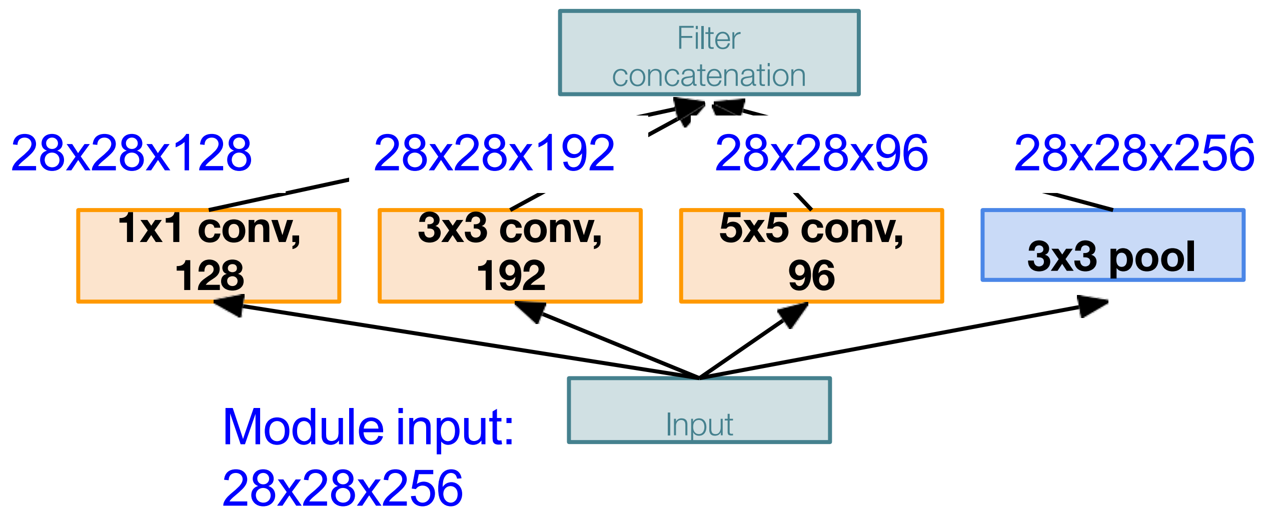
[Hint: Computational complexity]

Example:

Q1: What are the output sizes of all different filter operations?



Naive Inception module

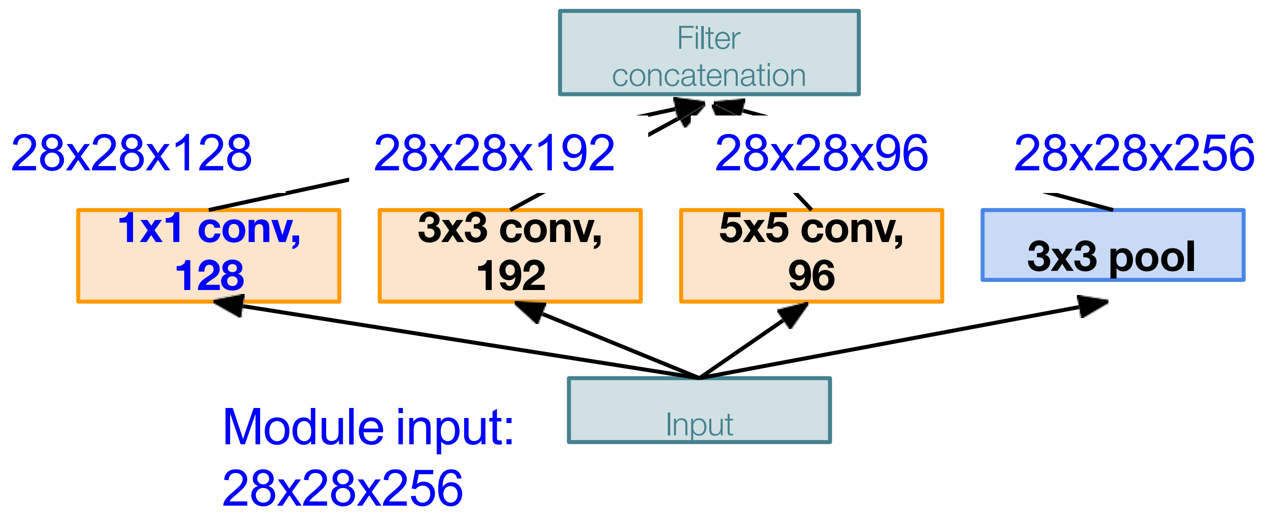
Case Study: GoogLeNet

[Szegedy et al., 2014]

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

Example:

Q2:What is output size after filter concatenation?



Naive Inception module

Case Study: GoogLeNet

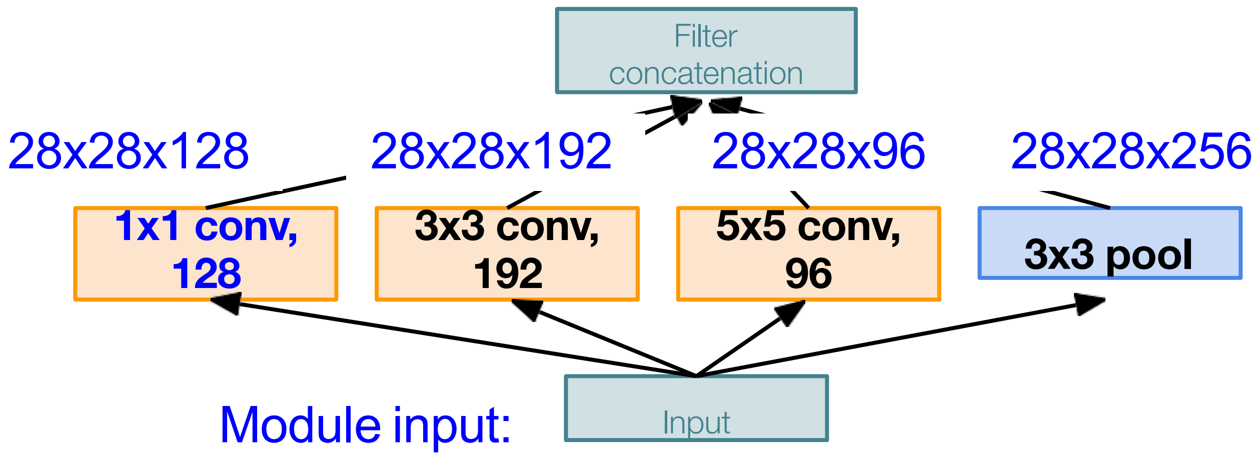
[Szegedy et al., 2014]

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

Example:

Q2:What is output size after filter concatenation?

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



Module input: 28x28x256

Naive Inception module

Case Study: GoogLeNet

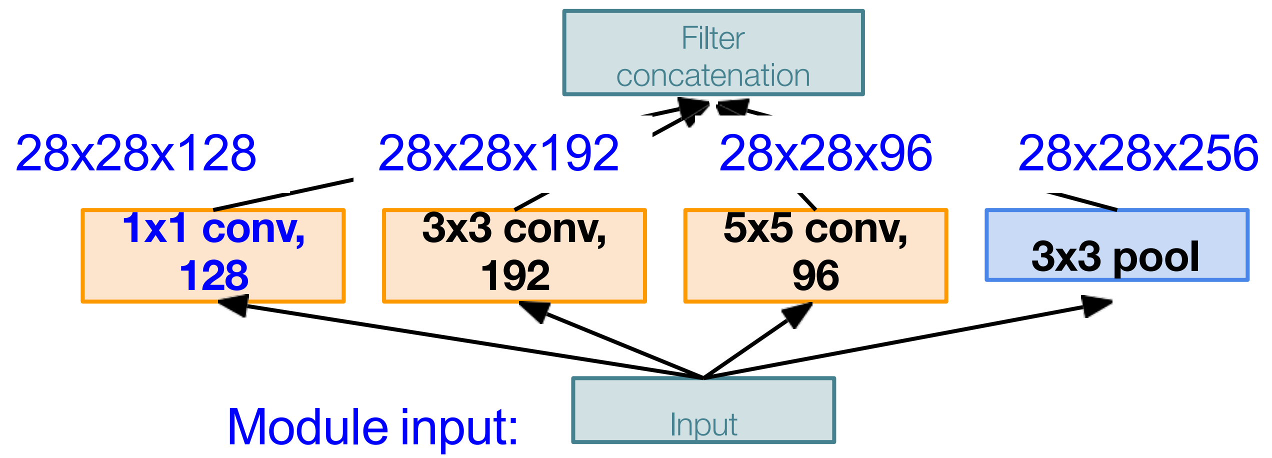
[Szegedy et al., 2014]

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

Example:

Q2: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] 28x28x**192x3x3x256**

[5x5 conv, 96] 28x28x**96x5x5x256**

Total: 854M ops

Case Study: GoogLeNet

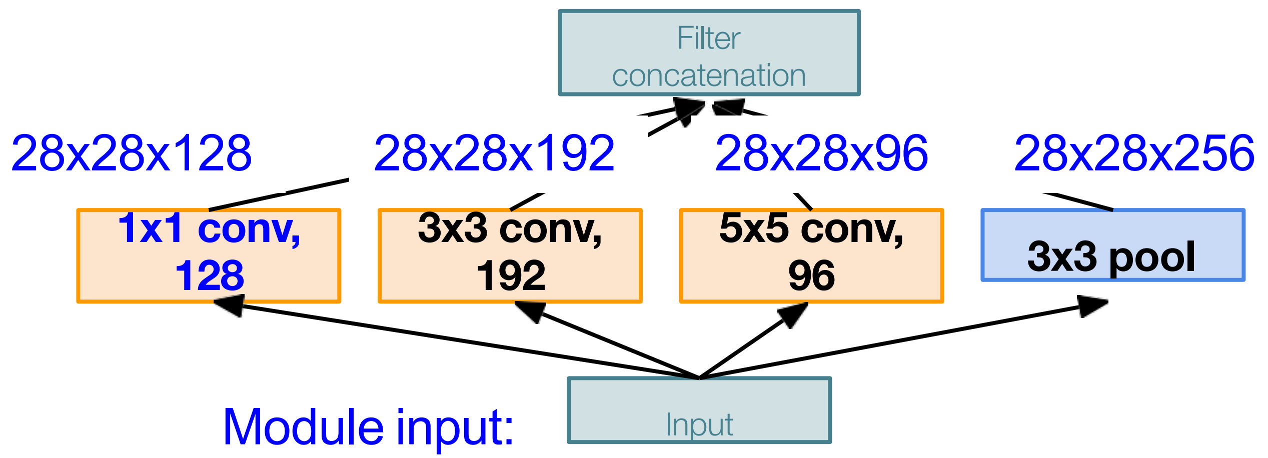
[Szegedy et al., 2014]

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

Example:

Q2: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] 28x28x**192x3x3x256**
[5x5 conv, 96] 28x28x**96x5x5x256**
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

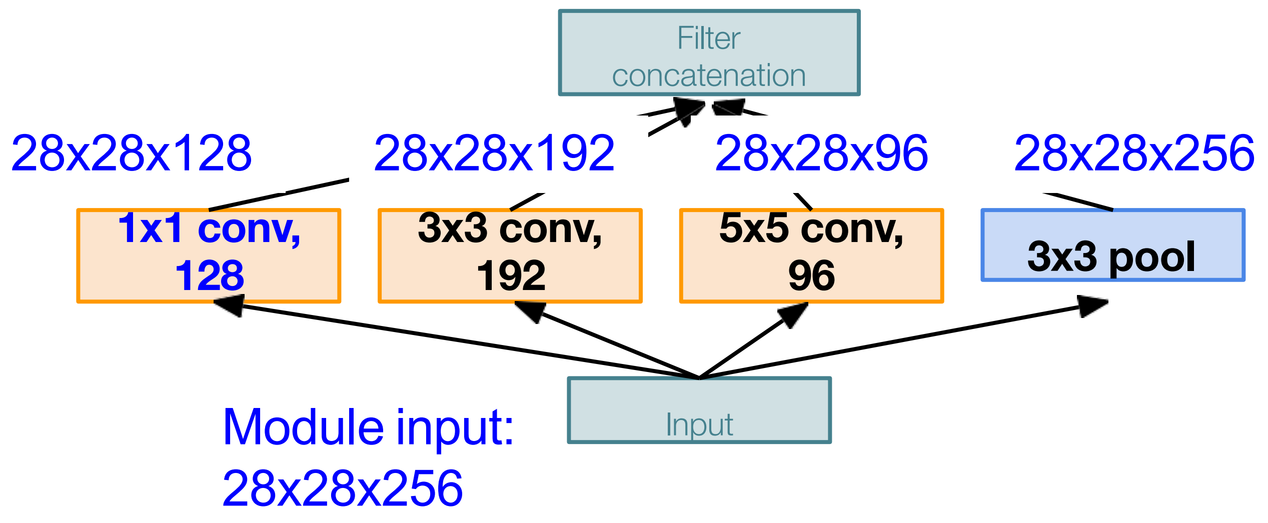
[Szegedy et al., 2014]

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

Example:

Q2:What is output size after filter concatenation?

28x28x(128+192+96+256) = **529k**



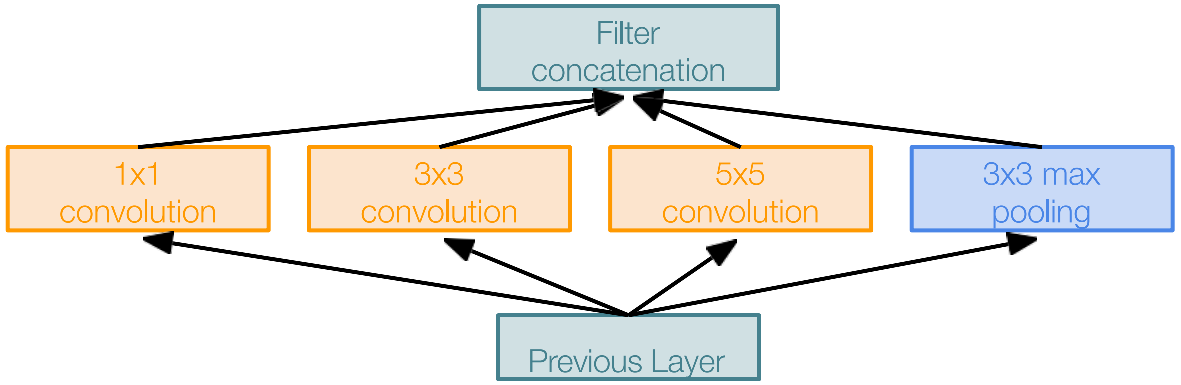
Naive Inception module

Solution: "bottleneck" layers that use 1x1 convolutions to reduce feature channel size

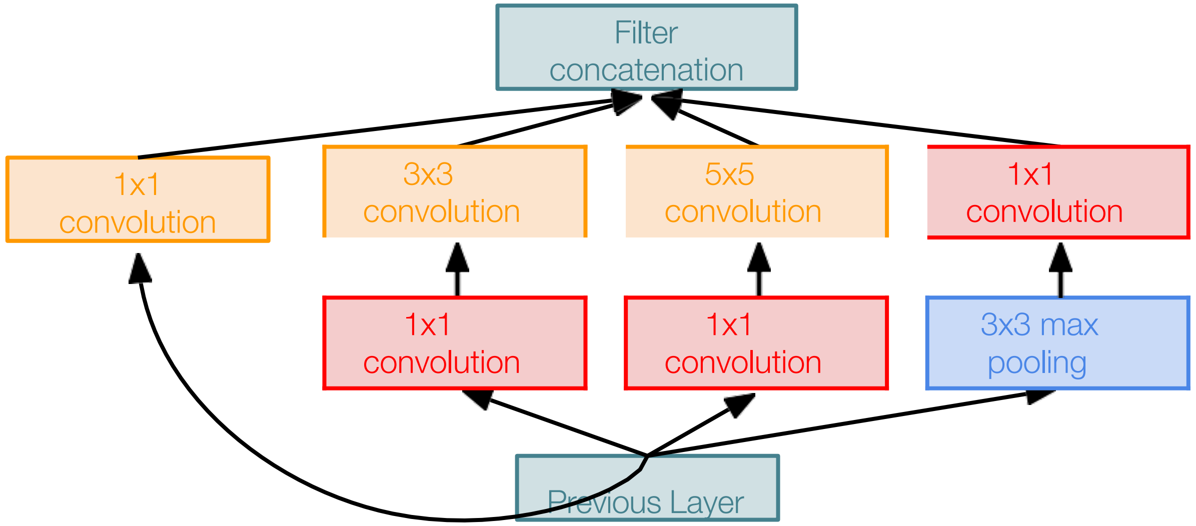
Case Study: GoogLeNet

[Szegedy et al., 2014]

1x1 conv “bottleneck” layers



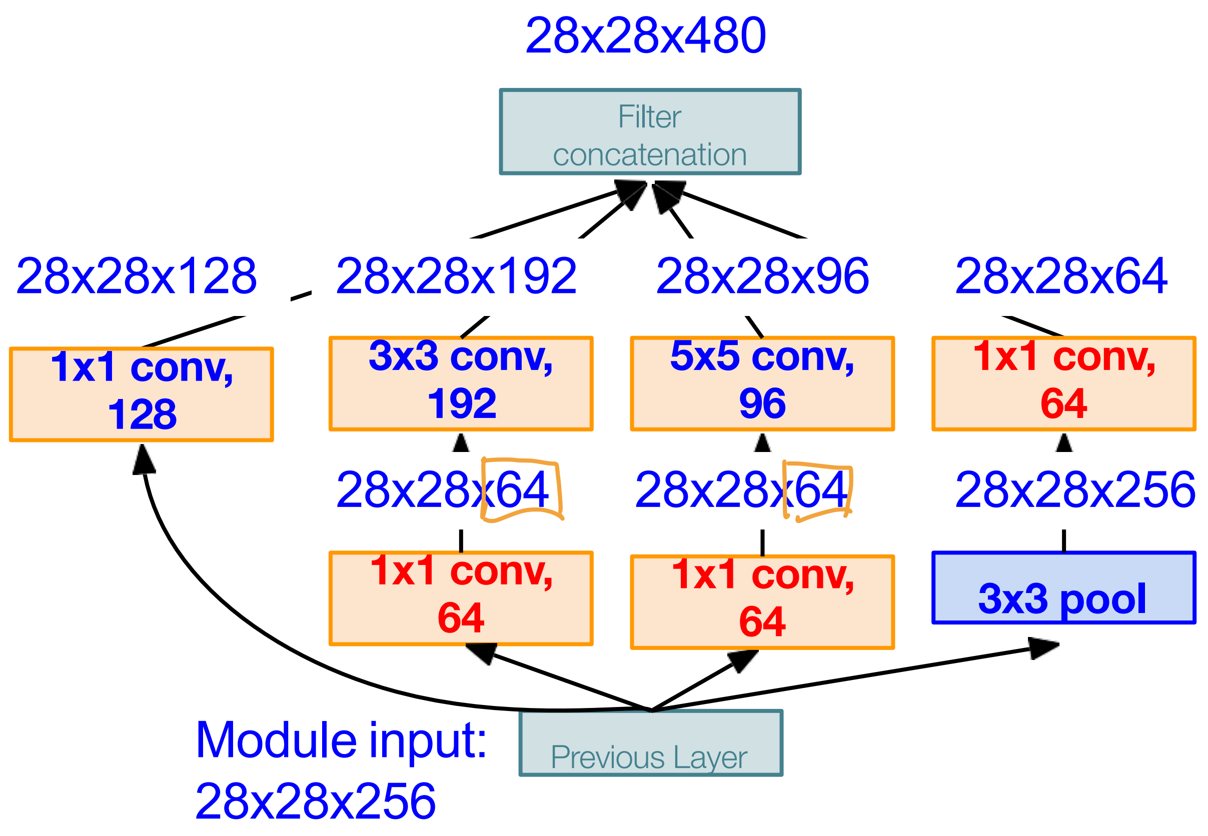
Naive Inception module



Inception module with dimension reduction

Case Study: GoogLeNet

[Szegedy et al., 2014]



Inception module with dimension reduction

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

加了1x1 降低参数量

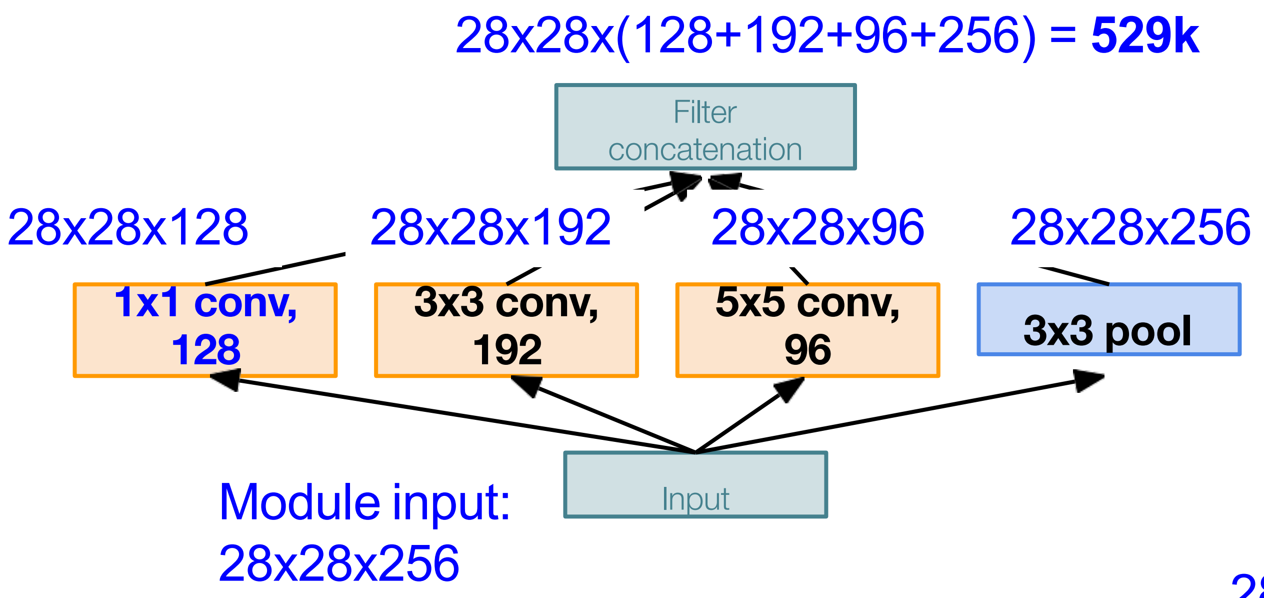
Conv Ops:

[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]



Naive Inception module

Conv Ops:

[1x1 conv, 128] 28x28x128x1x1x256

[3x3 conv, 192] 28x28x**192x3x3x256**

[5x5 conv, 96] 28x28x**96x5x5x256**

Total: 854M ops

Conv Ops:

[1x1 conv, 64] 28x28x64x1x1x256

[1x1 conv, 64] 28x28x64x1x1x256

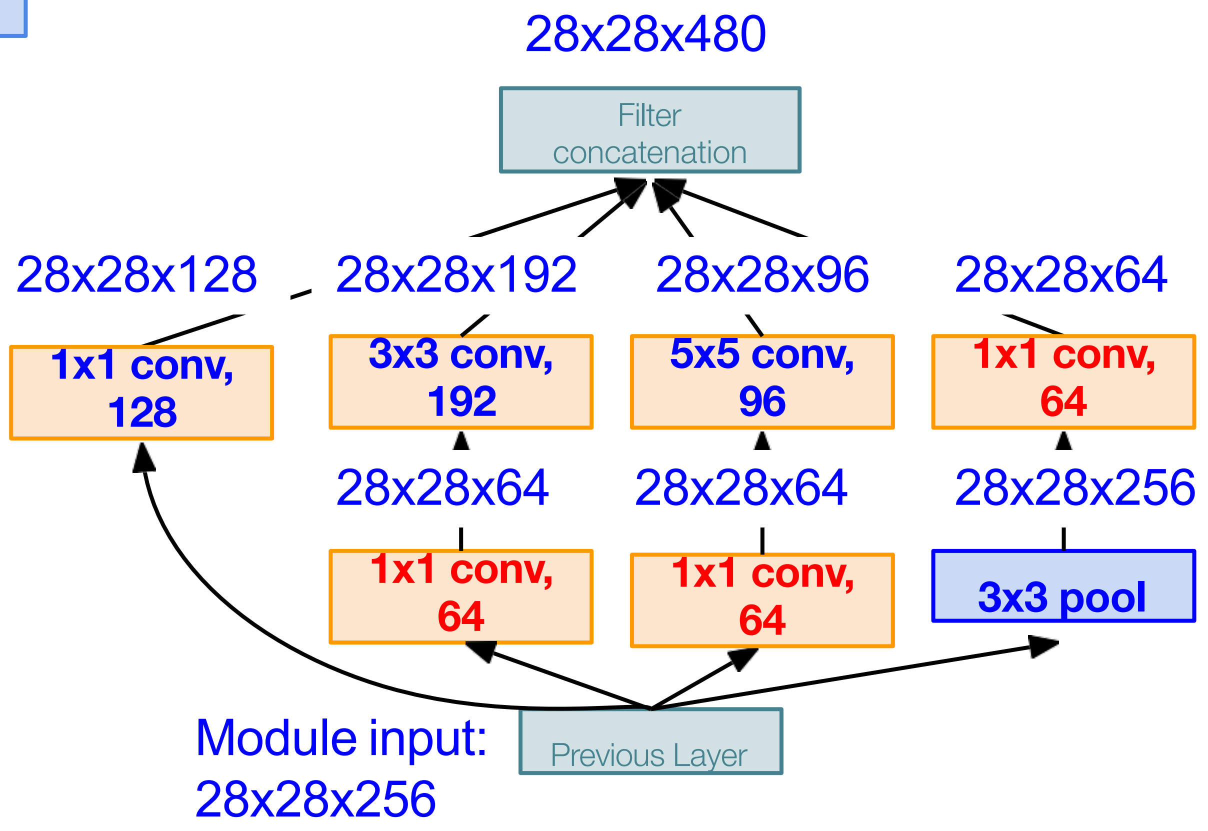
[1x1 conv, 128] 28x28x128x1x1x256

[3x3 conv, 192] 28x28x192x3x3x64

[5x5 conv, 96] 28x28x96x5x5x64

[1x1 conv, 64] 28x28x64x1x1x256

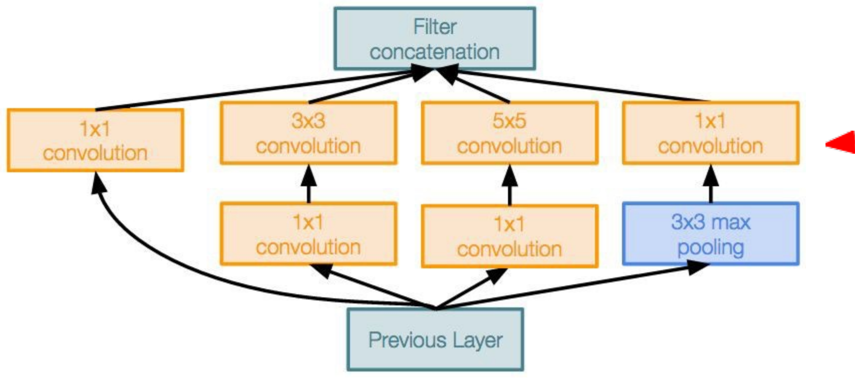
Total: 358M ops



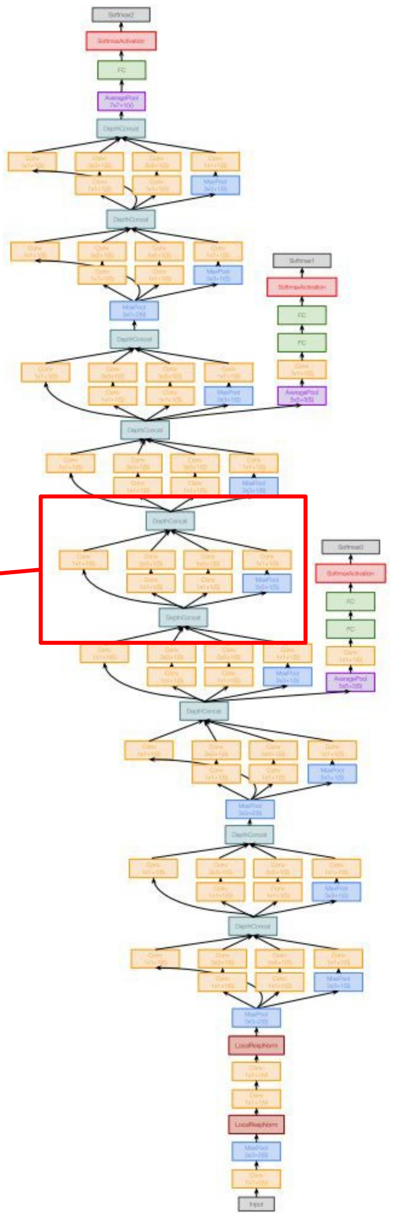
Case Study: GoogLeNet

[Szegedy et al., 2014]

Stack Inception modules
with dimension reduction
on top of each other



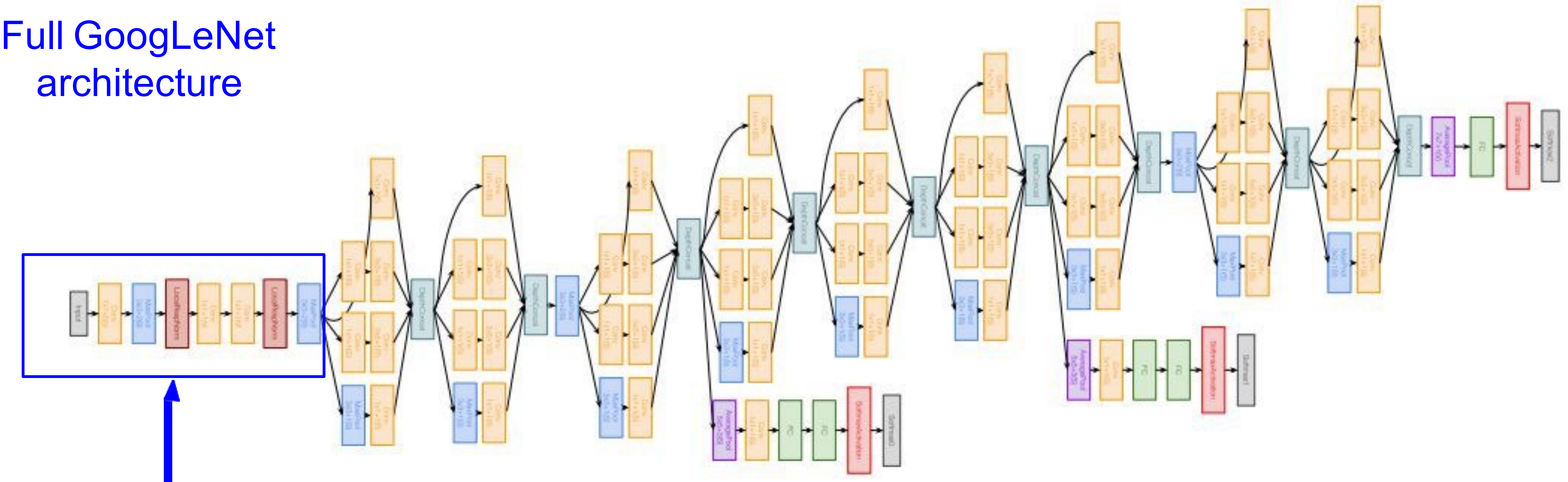
Inception module



Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

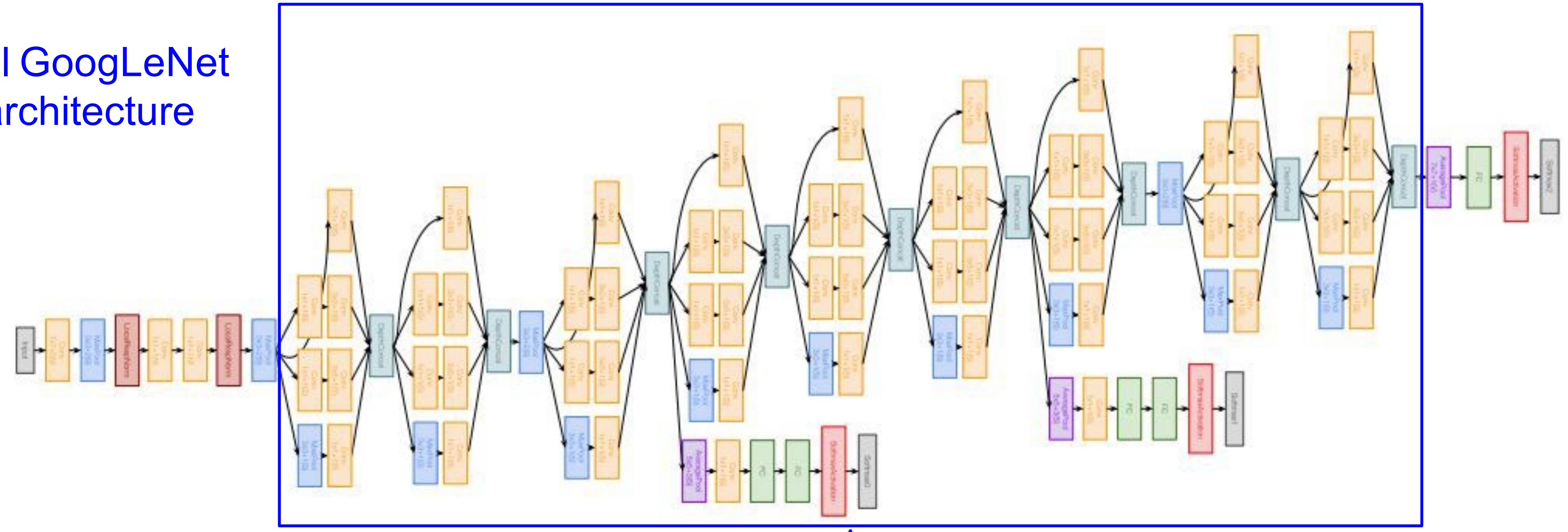


Stem Network:
Conv-Pool-
2x Conv-Pool

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

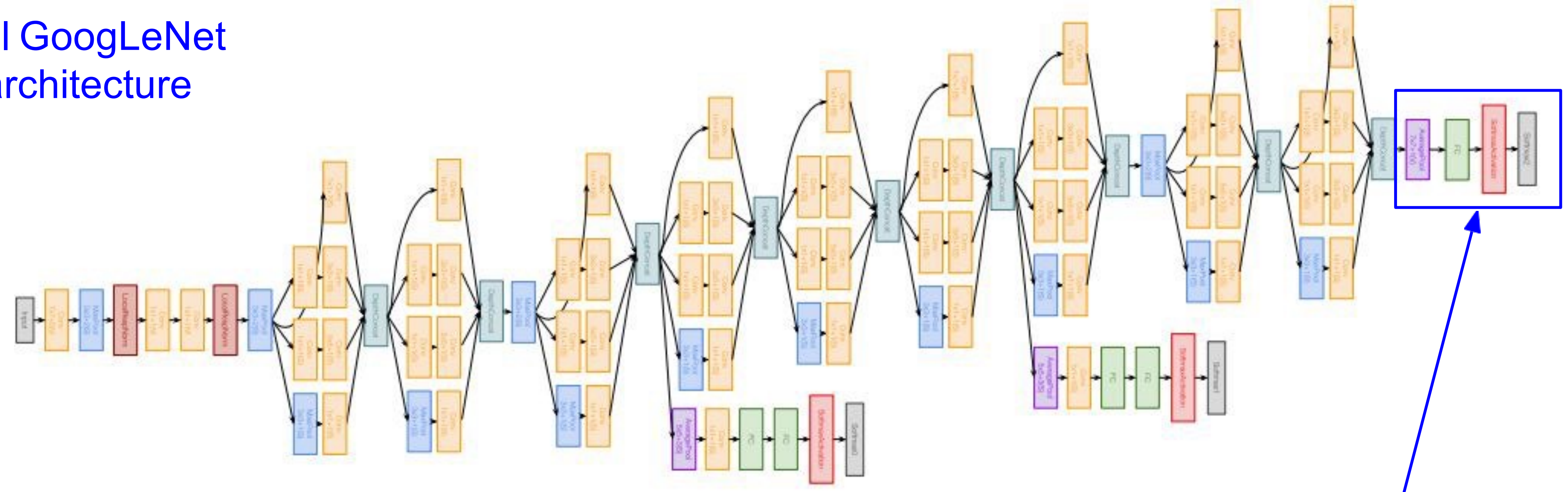


Stacked Inception Modules

Case Study: GoogLeNet

[Szegedy et al., 2014]

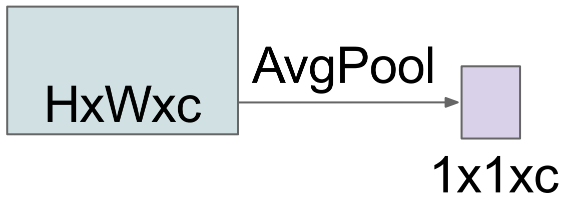
Full GoogLeNet architecture



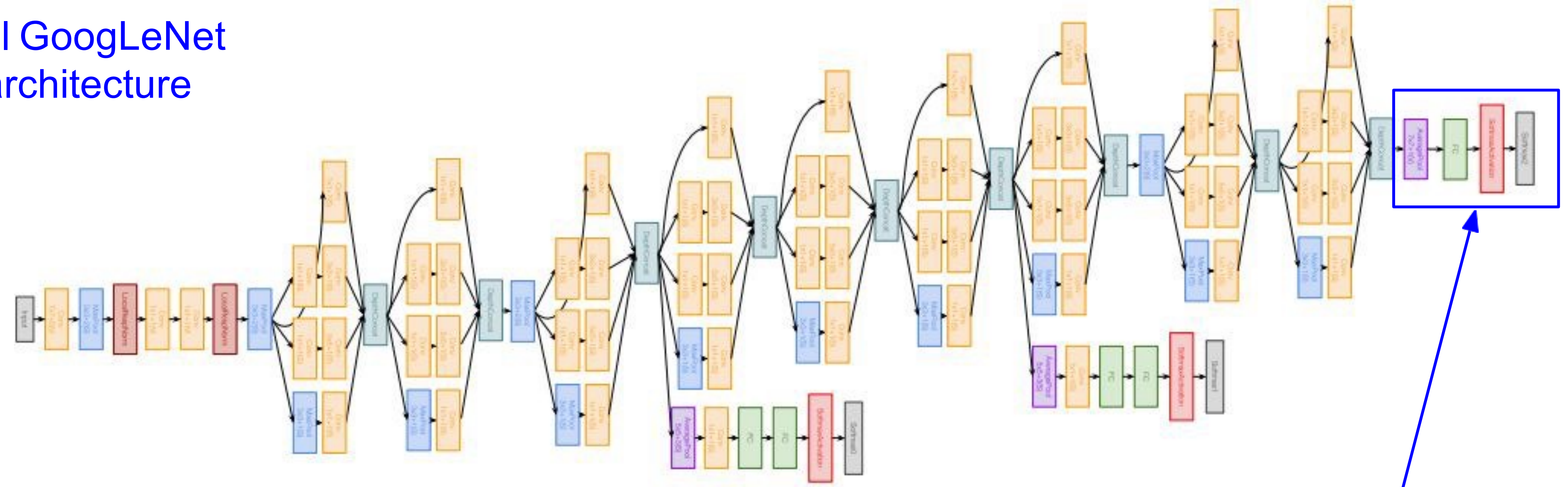
Classifier output

Case Study: GoogLeNet

[Szegedy et al., 2014]



Full GoogLeNet architecture

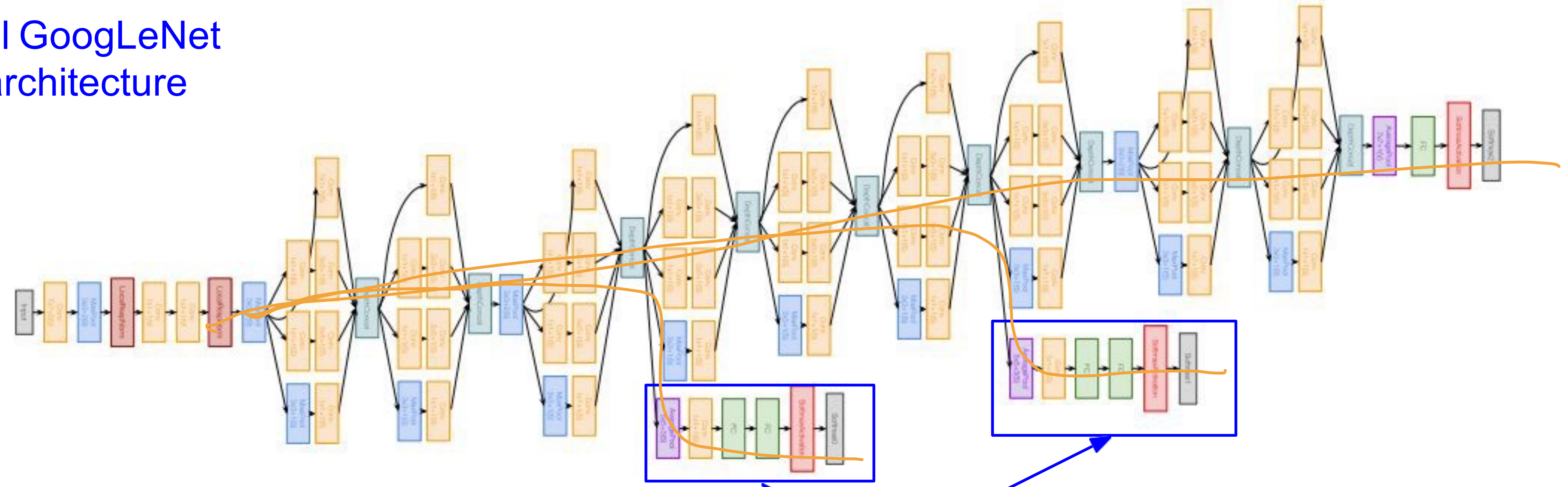


Note: after the last convolutional layer, a global average pooling layer is used that spatially averages across each feature map, before final FC layer. No longer multiple expensive FC layers!

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture



辅助的

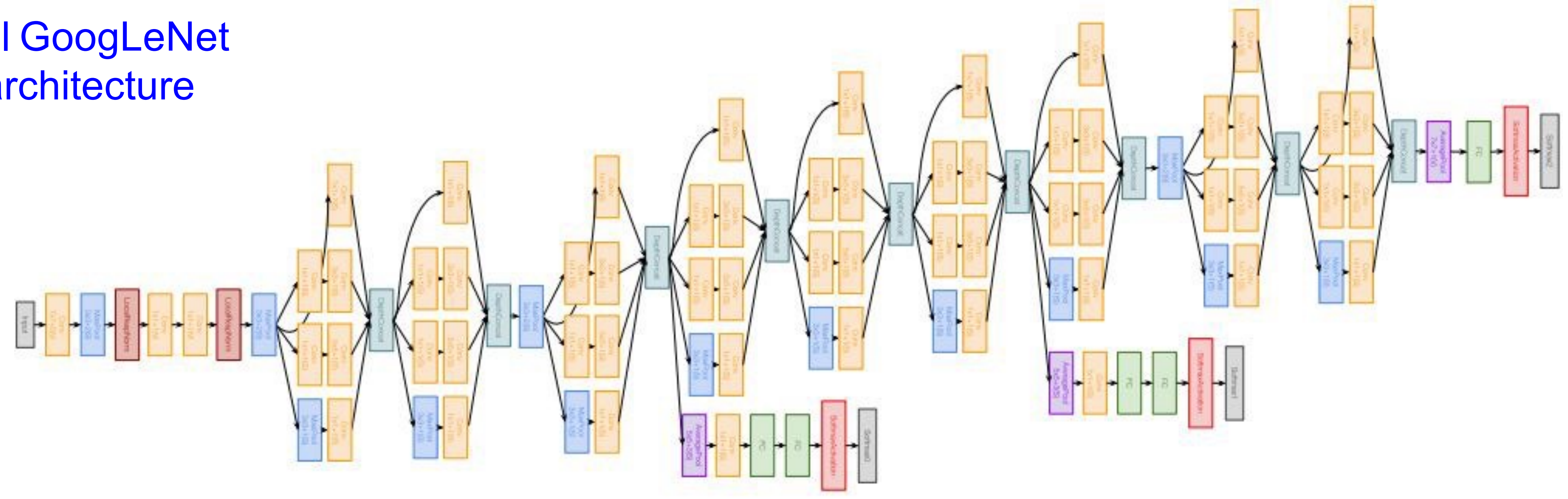
Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

⇒ solve 梯度消失

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



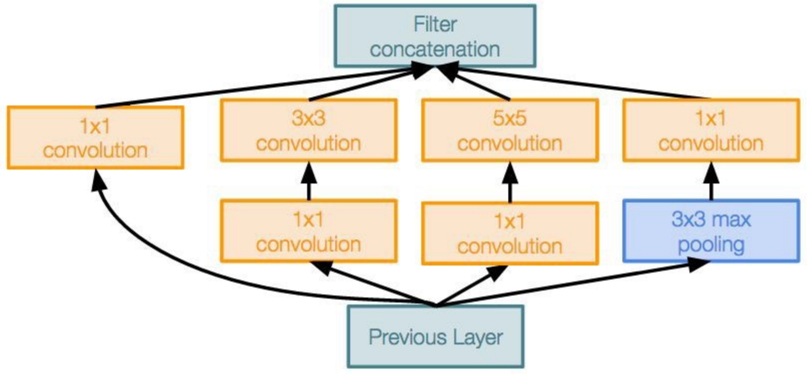
22 total layers with weights
(parallel layers count as 1 layer => 2 layers per Inception module. Don’t count auxiliary output layers)

Case Study: GoogLeNet

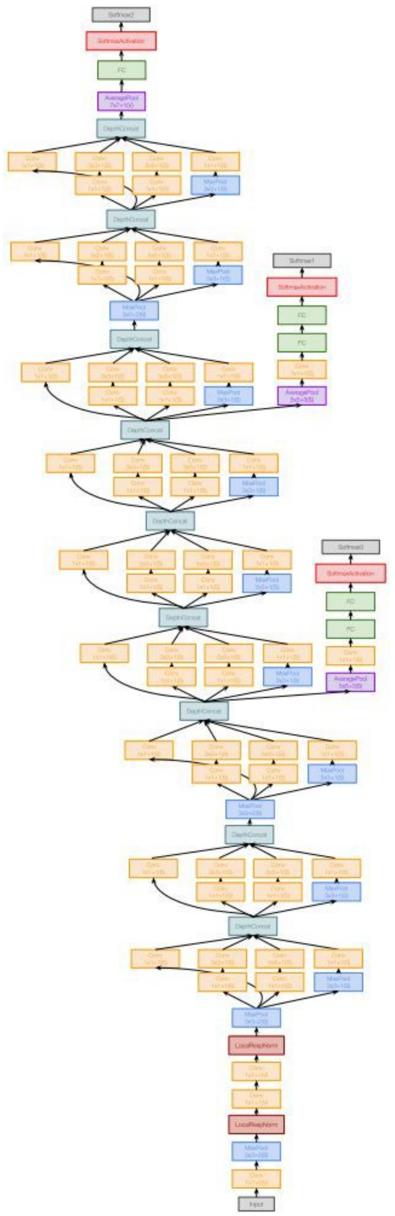
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

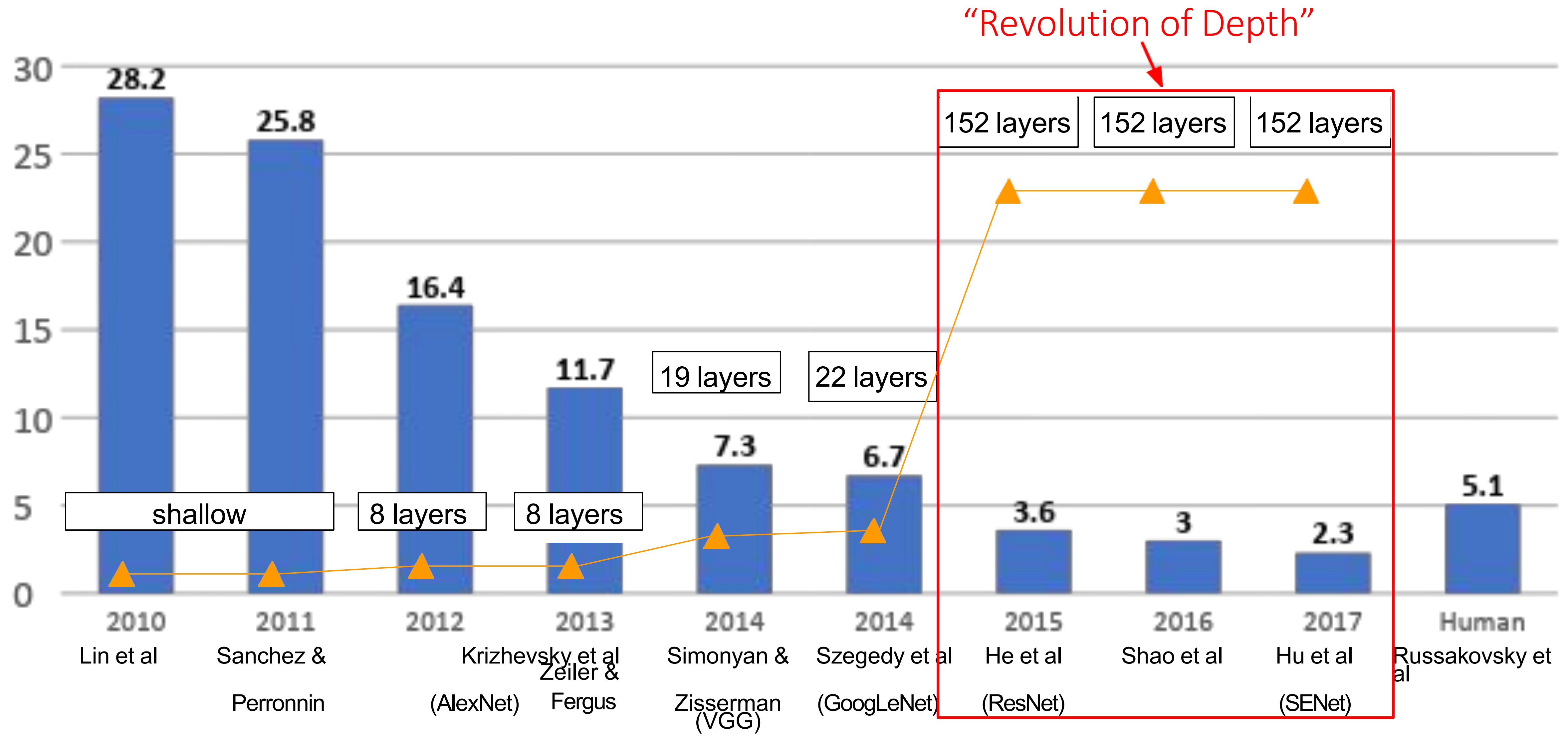
- 22 layers
- Efficient “Inception” module 保留更多信息
- Avoids expensive FC layers
- 12x less params than AlexNet
- 27x less params than VGG-16
- ILSVRC’14 classification winner (6.7% top 5 error)



Inception module



ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

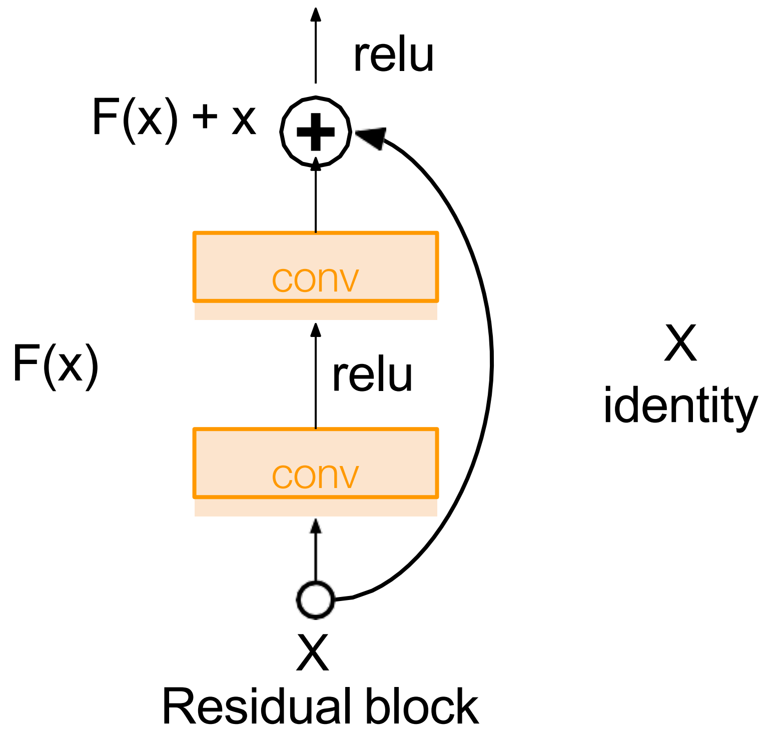


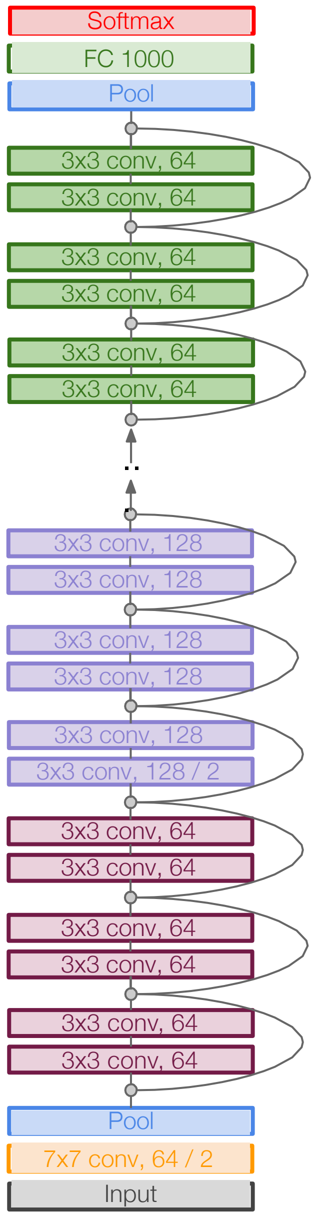
Case Study: ResNet

[He et al., 2015]

Very deep networks using residual connections

- 152-layer model for ImageNet
- ILSVRC'15 classification winner (3.57% top 5 error)
- Swept all classification and detection competitions in ILSVRC'15 and COCO'15!





Case Study: ResNet

[He et al., 2015]

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

Case Study: ResNet

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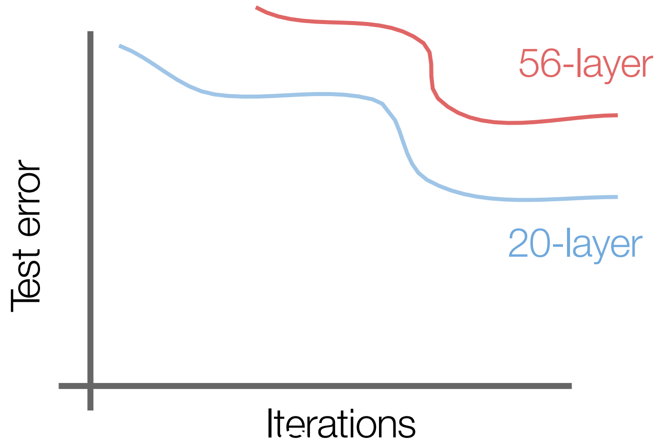
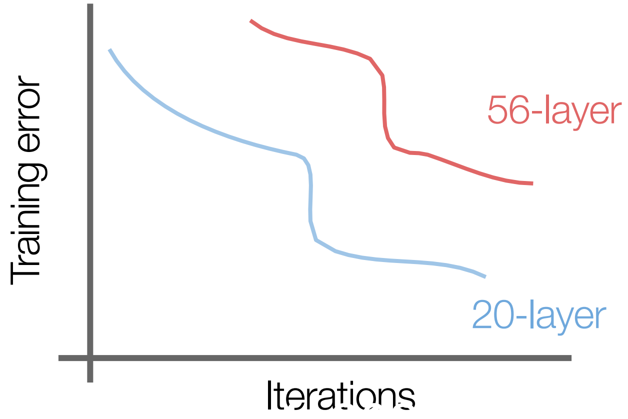
What happens when we continue stacking deeper layers on a “plain” convolutional neural network?





Case Study: ResNet

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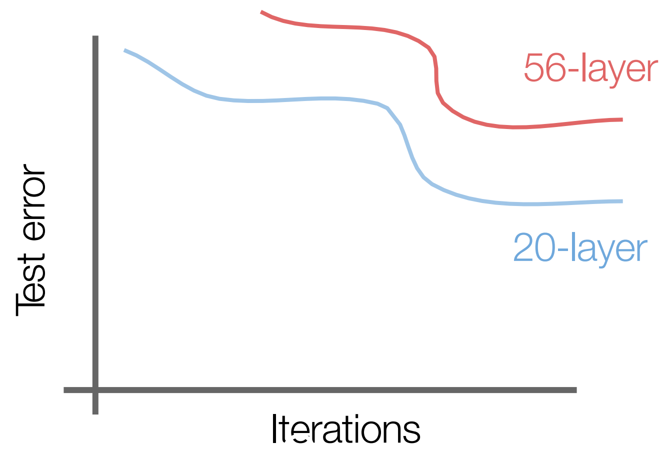
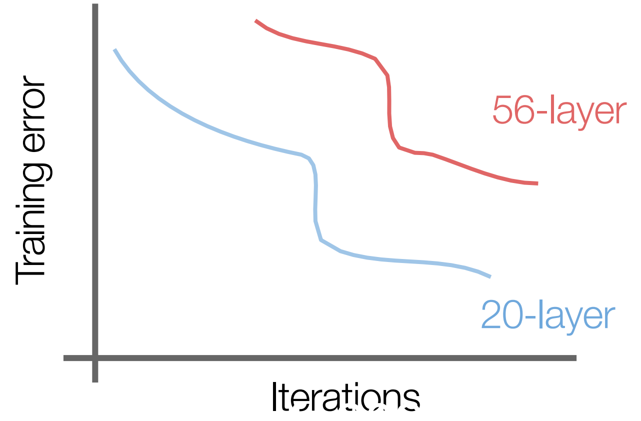




56-layer model performs worse on both test and training error
-> The deeper model performs worse, but it’s not caused by overfitting!

Case Study: ResNet

[He et al., 2015]

Fact: Deep models have more representation power (more parameters) than shallower models.

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

Case Study: ResNet

[He et al., 2015]

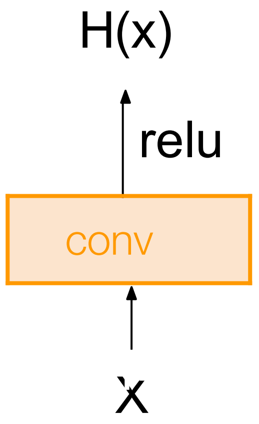
Fact: Deep models have more representation power (more parameters) than shallower models.

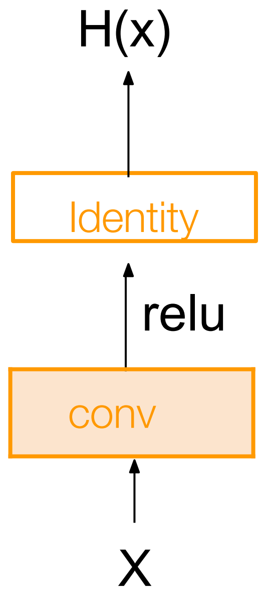
Hypothesis: the problem is an *optimization* problem, deeper models are harder to optimize

What should the deeper model learn to be at least as good as the shallower model?

浅的

A solution by construction is copying the learned layers from the shallower model and setting additional layers to identity mapping.

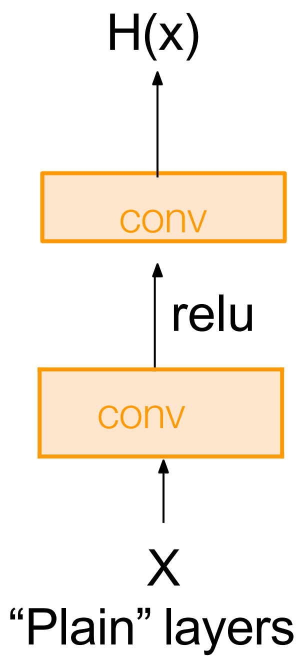




Case Study: ResNet

[He et al., 2015]

Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping



Case Study: ResNet

[He et al., 2015]

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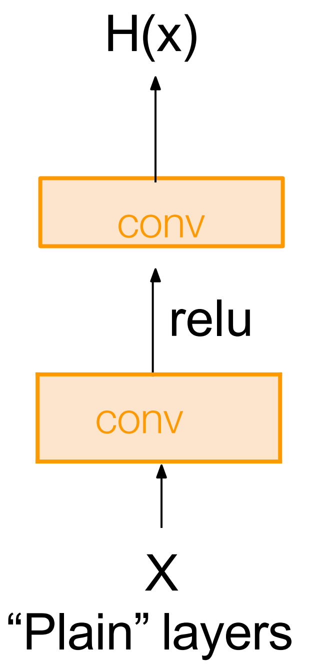
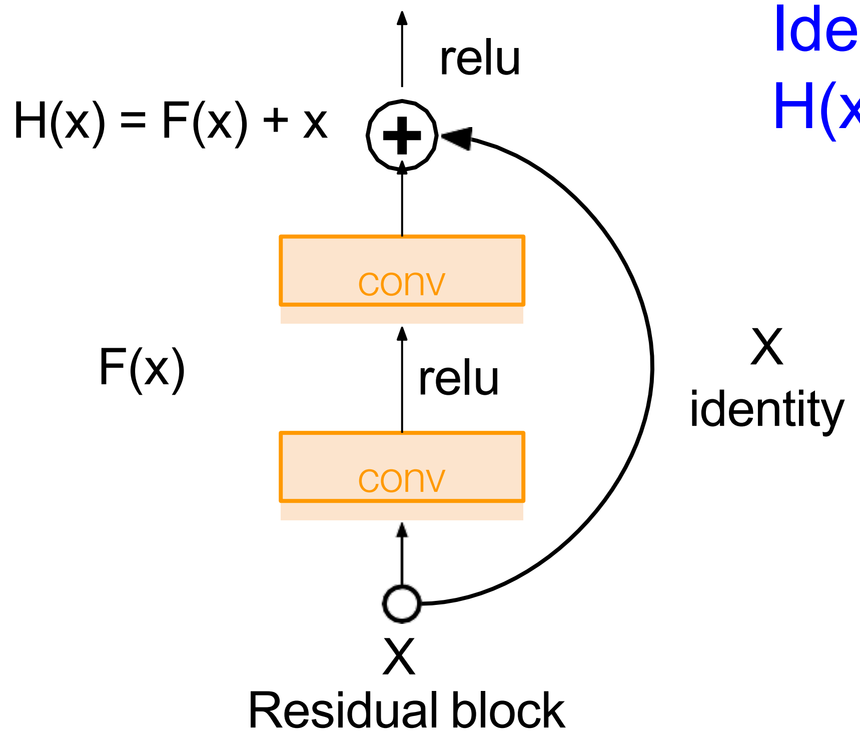


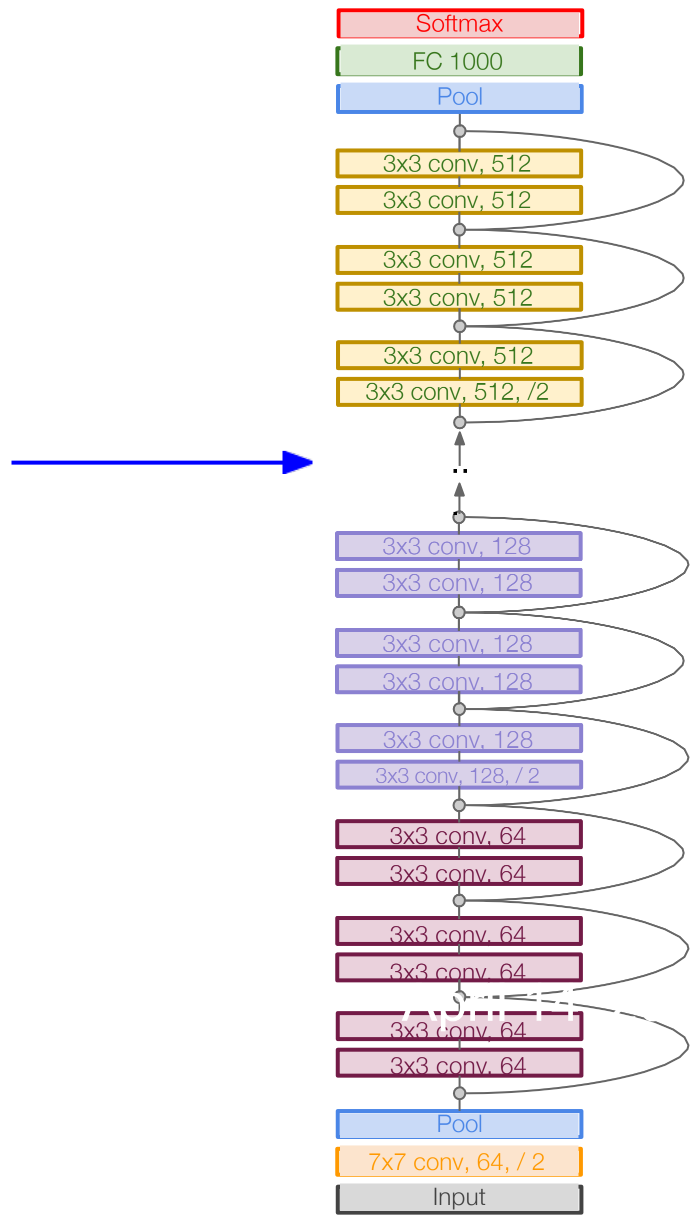


Identity mapping:
H(x) = x if F(x) = 0

Case Study: ResNet

[He et al., 2015]

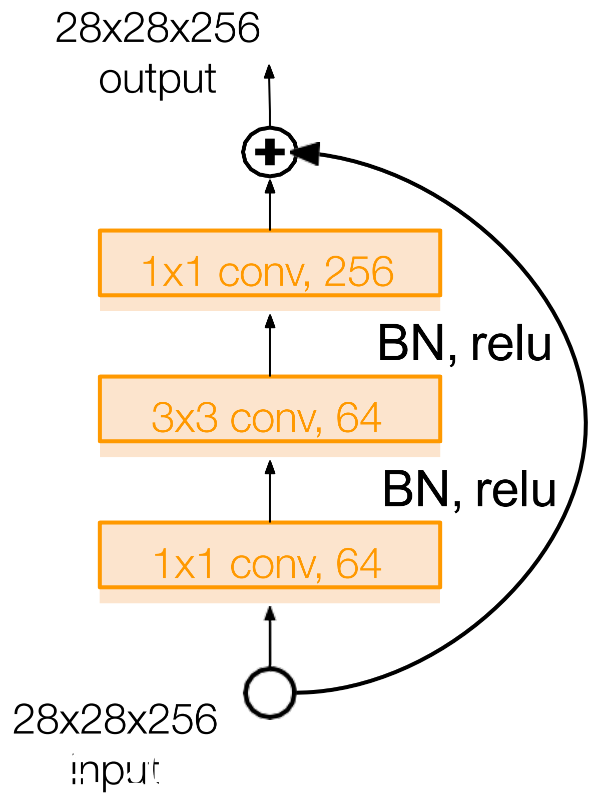
Total depths of 18, 34, 50, 101, or 152 layers for ImageNet



Case Study: ResNet

[He et al., 2015]

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



Case Study: ResNet

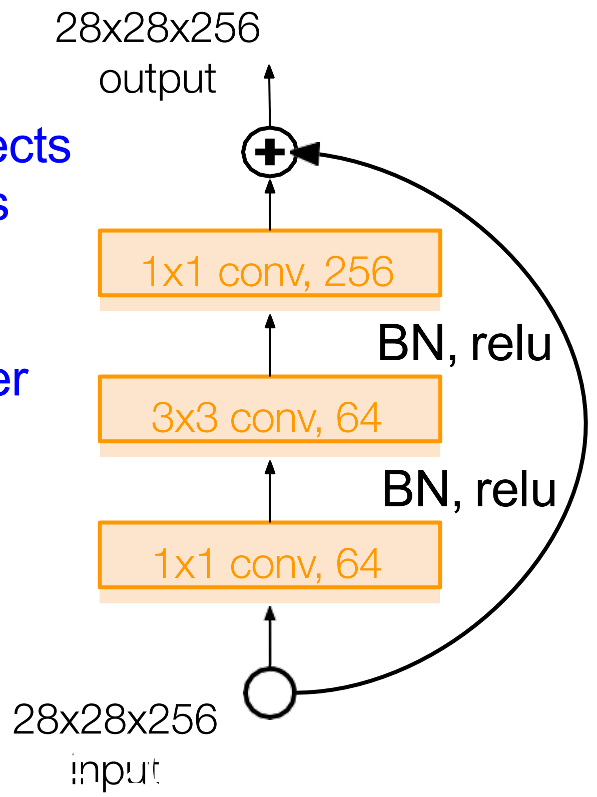
[He et al., 2015]

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

1x1 conv, 256 filters projects back to 256 feature maps (28x28x256)

3x3 conv operates over only 64 feature maps

1x1 conv, 64 filters to project to 28x28x64



Case Study: ResNet

[He et al., 2015]

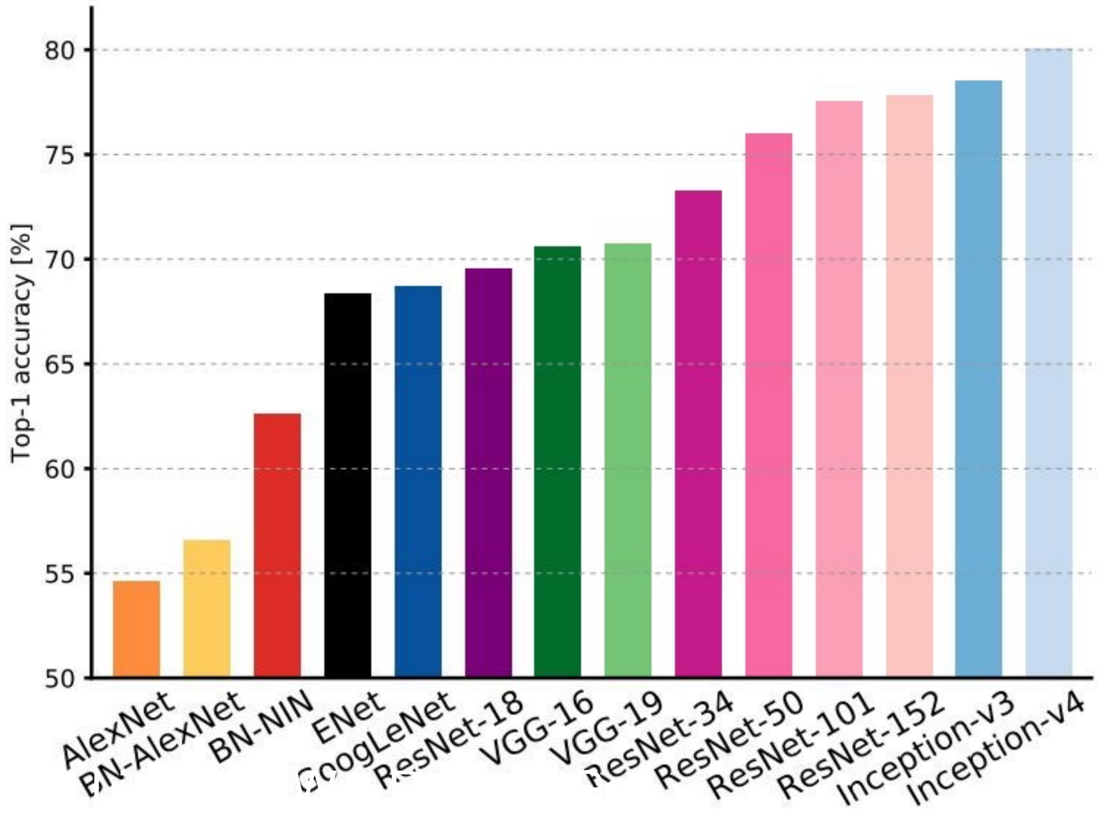
Training ResNet in practice:

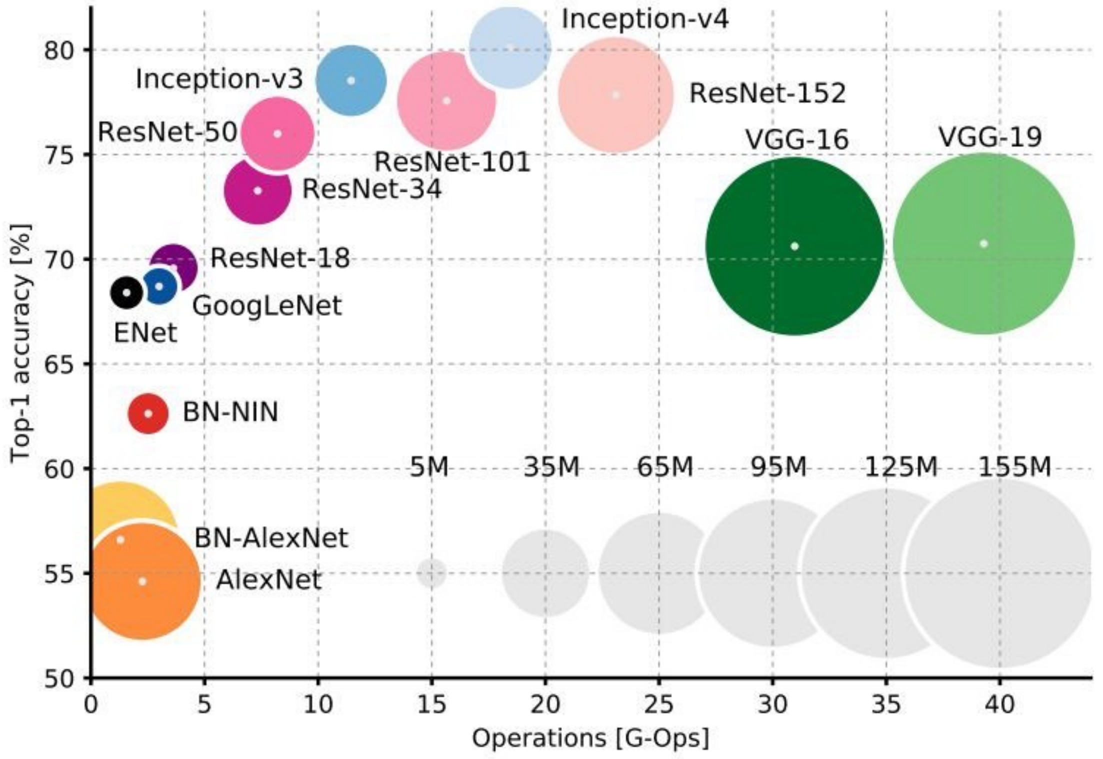
对个batch-size 样本内每个特征归一化

Layernorm 对每个样本所有特征归一化

- Batch Normalization after every CONV layer
- Xavier 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

Comparing complexity...

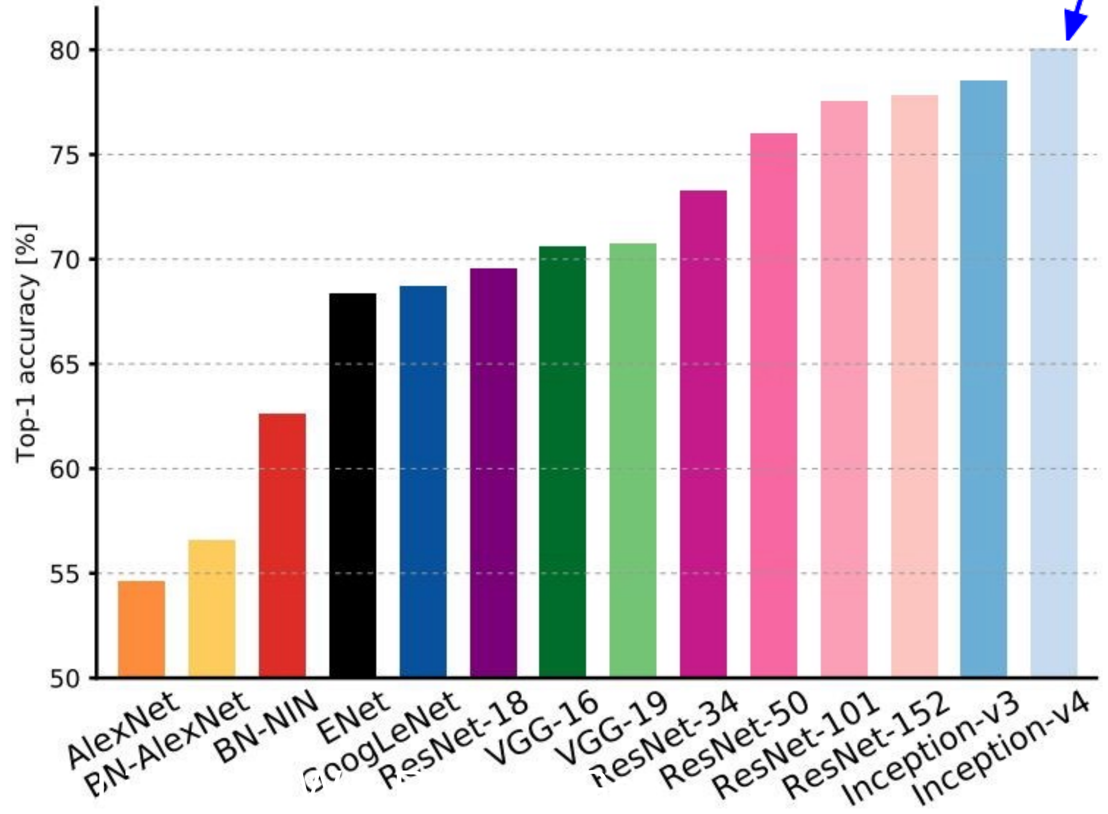


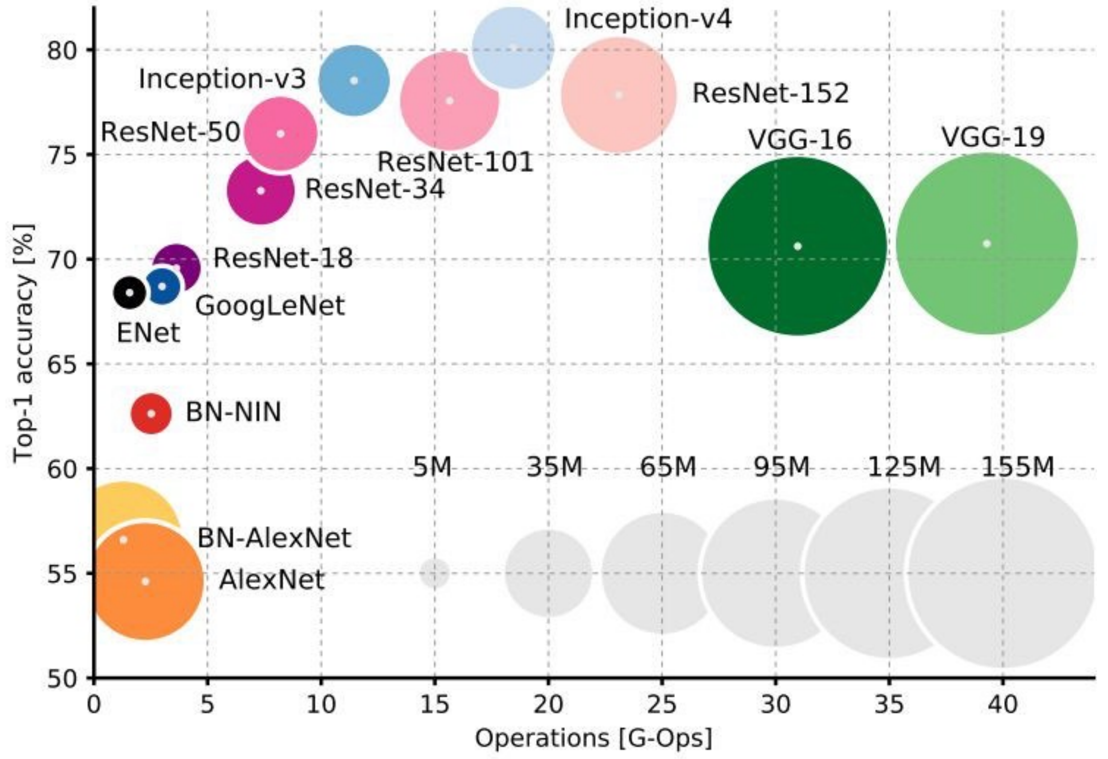


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Comparing complexity...

Inception-v4: Resnet + Inception!

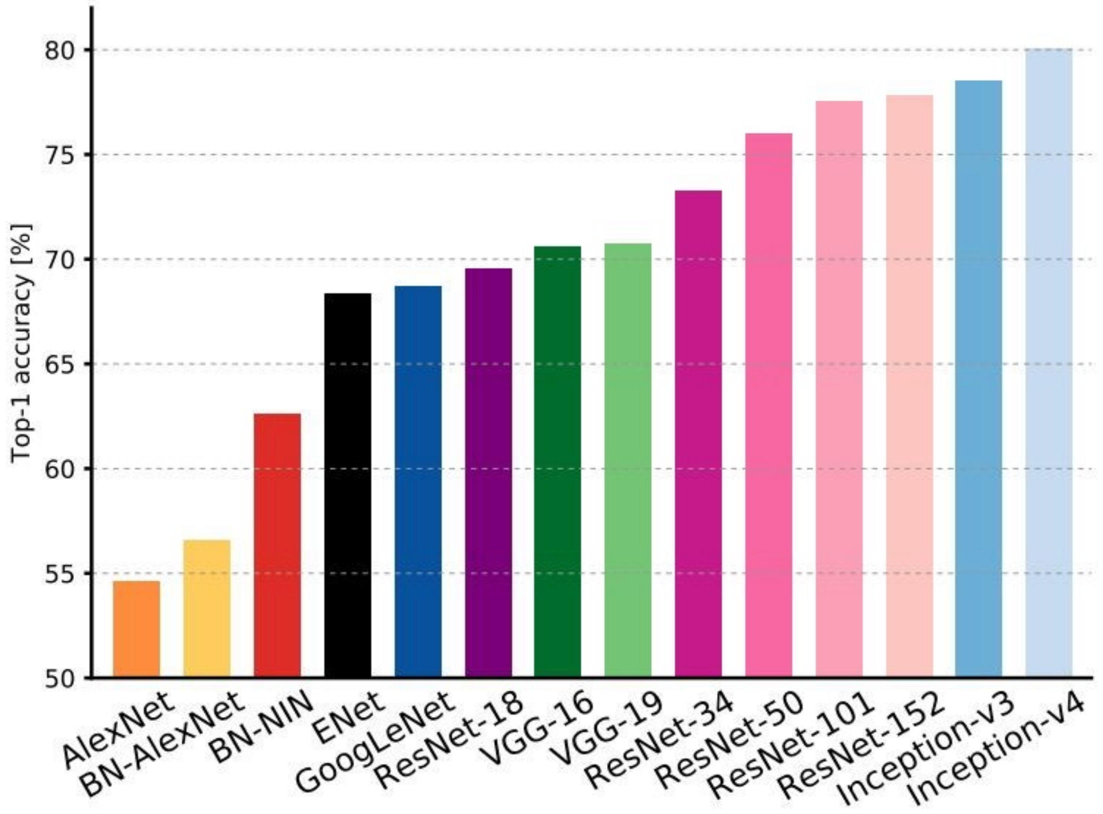


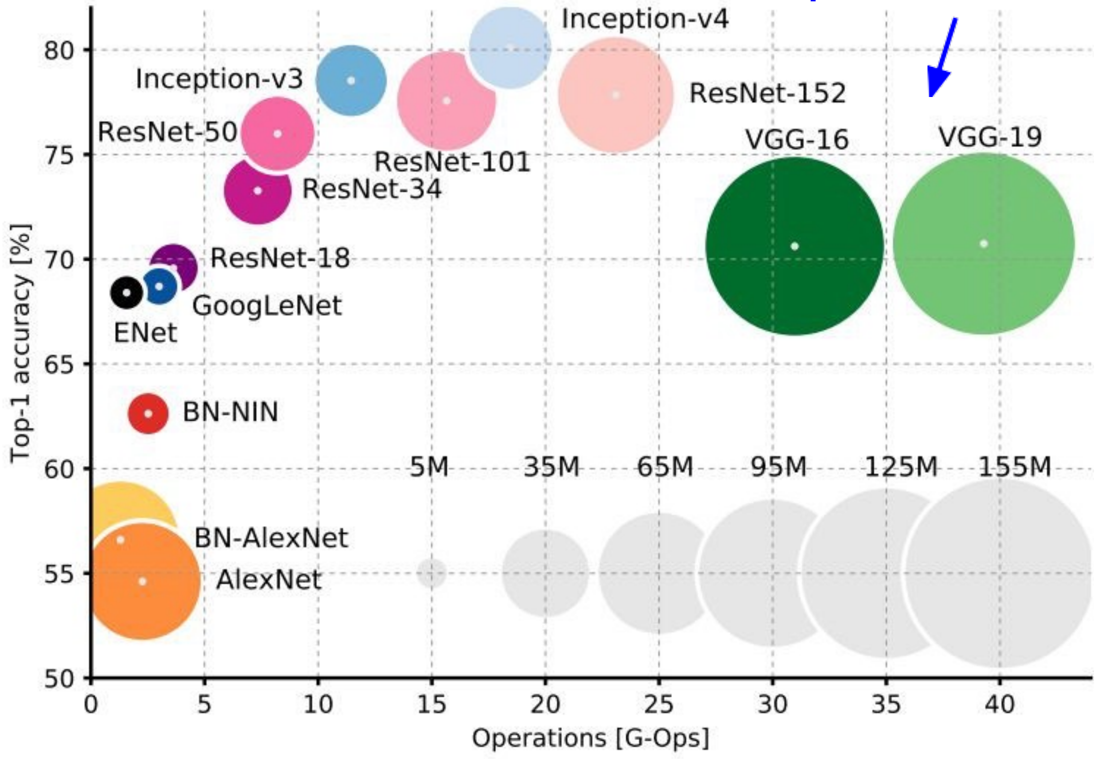


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Comparing complexity...

VGG: most parameters, most operations





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

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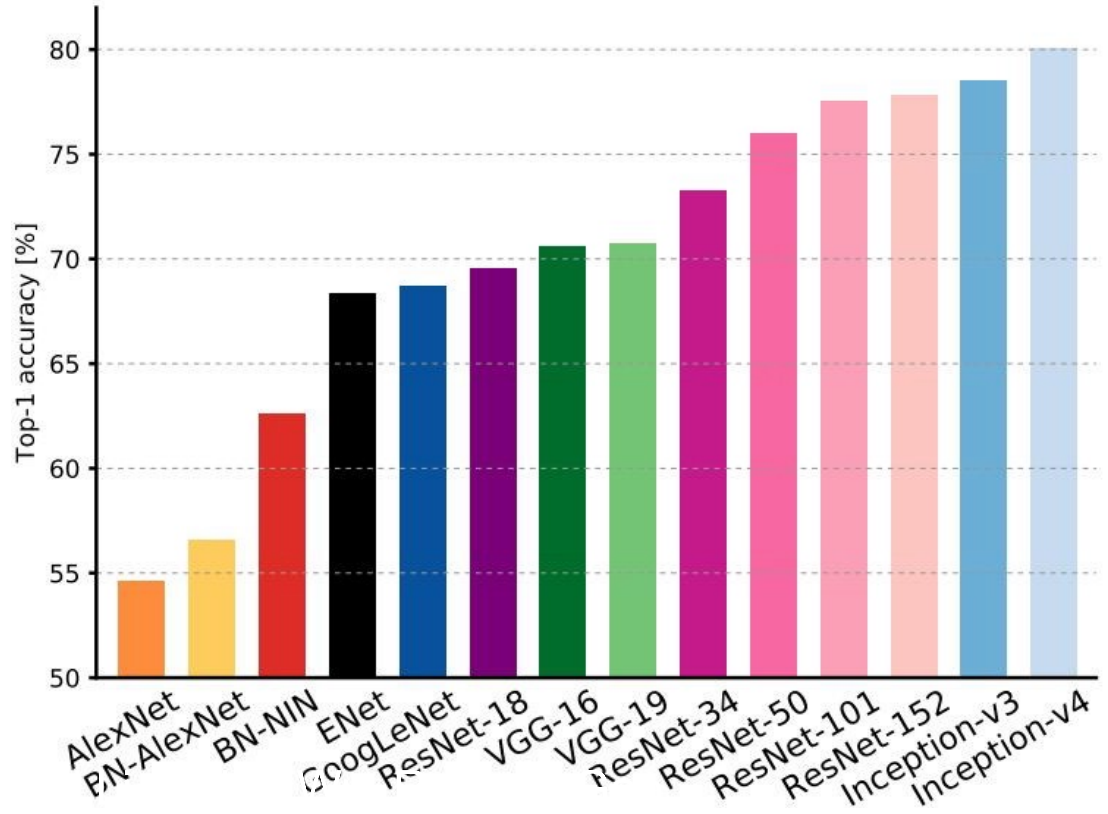
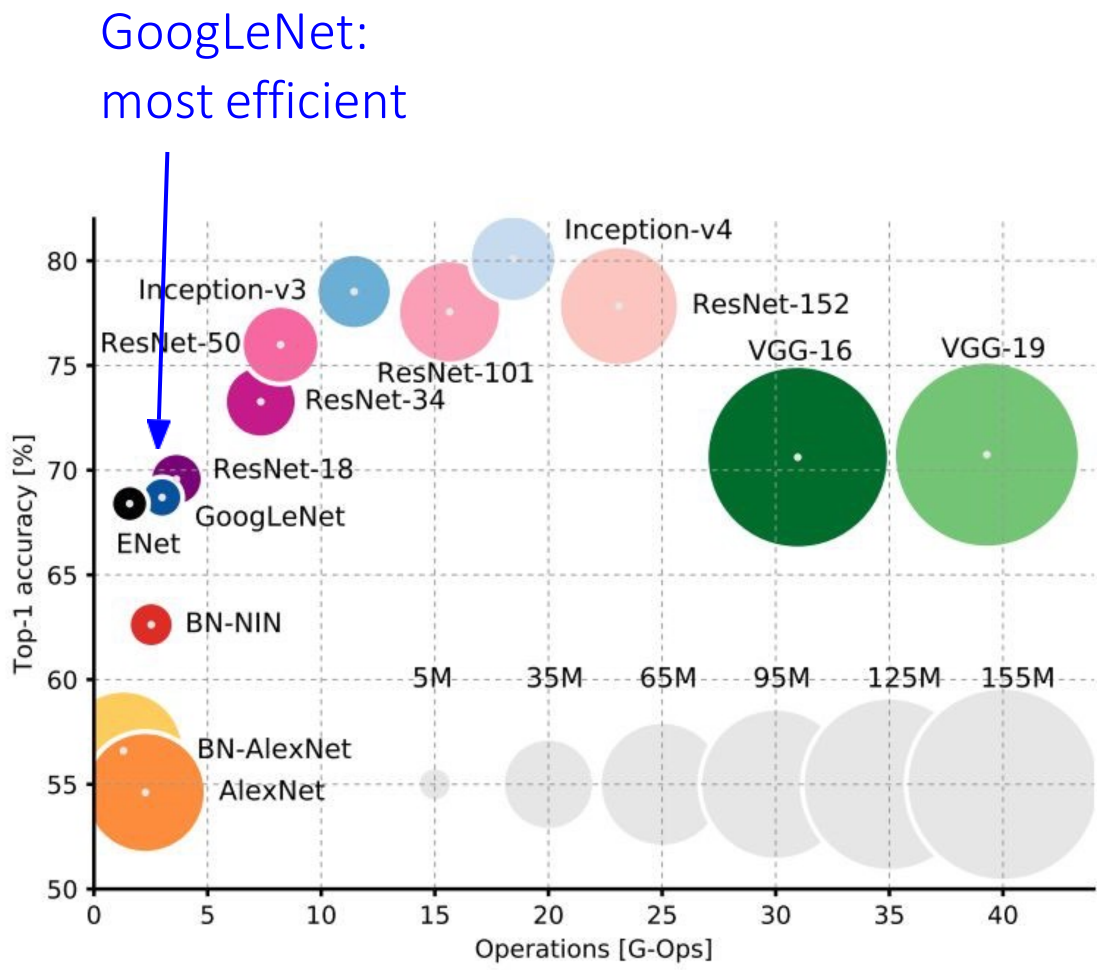
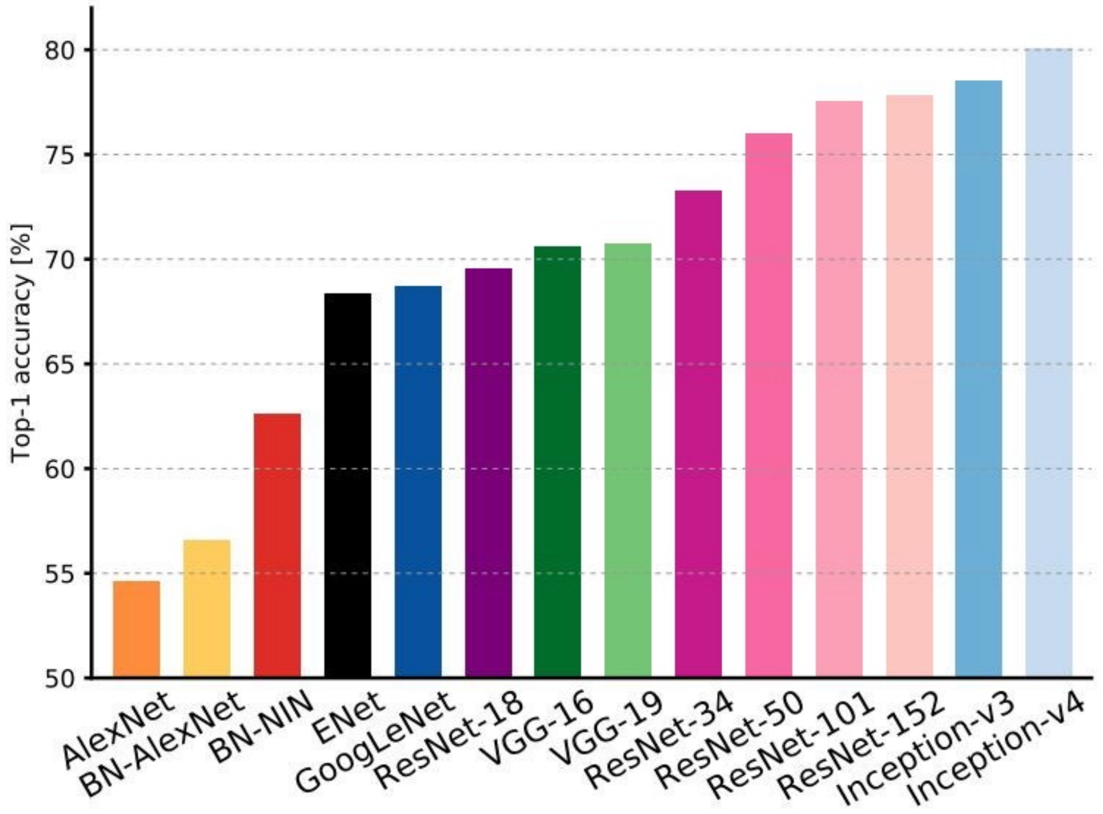


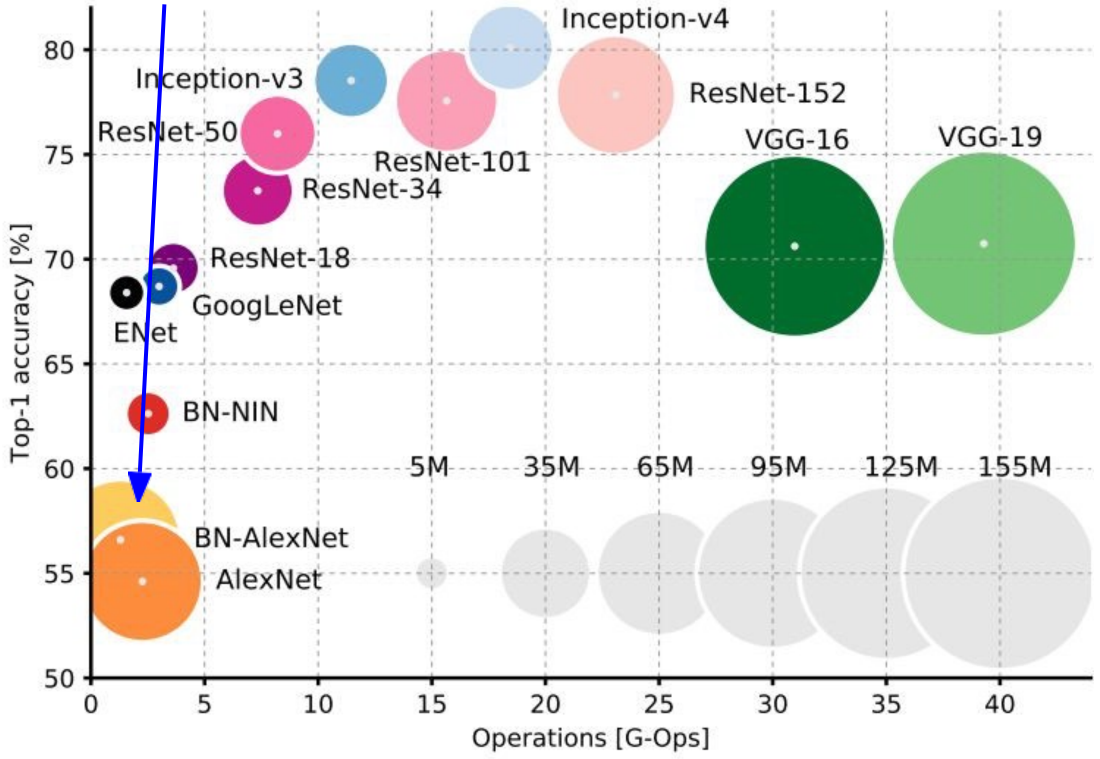


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Comparing complexity...



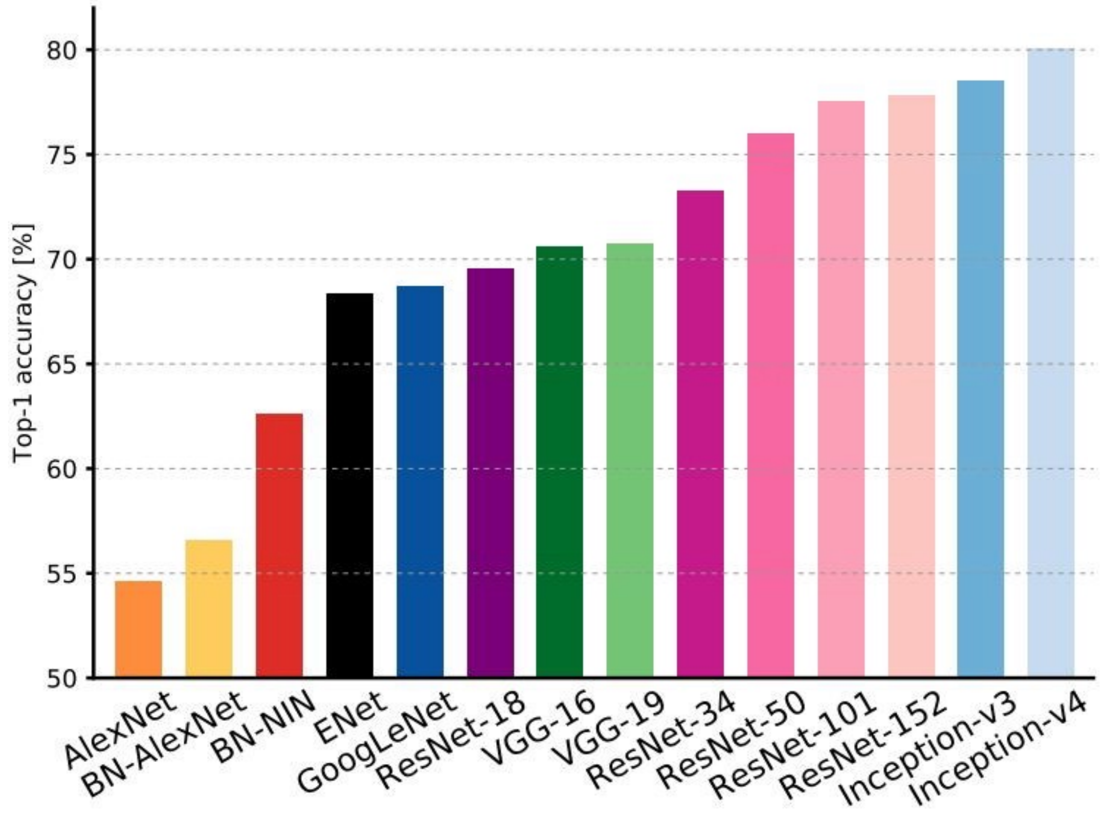
AlexNet:
Smaller compute, still memory heavy, lower accuracy

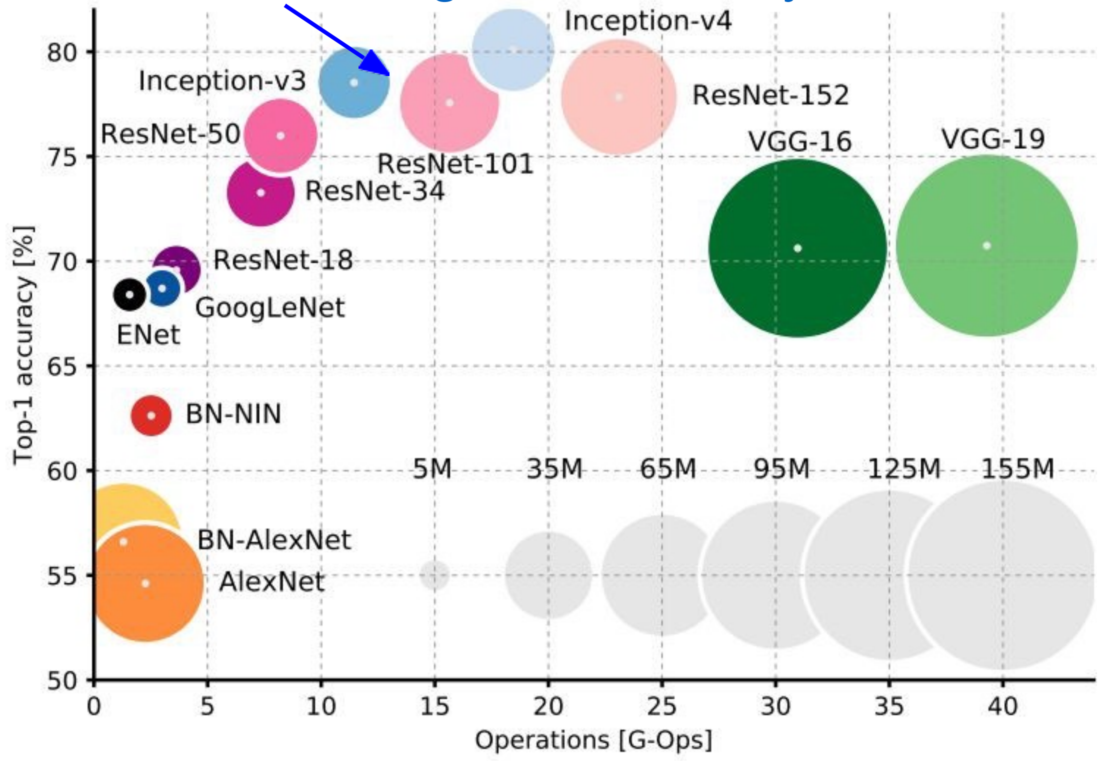


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Comparing complexity...

ResNet:
Moderate efficiency depending on model, highest accuracy





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

Main takeaways

AlexNet showed that you can use CNNs to train Computer Vision models.
ZFNet, **VGG** shows that bigger networks work better
GoogLeNet is one of the first to focus on efficiency using 1x1 bottleneck convolutions and global avg pool instead of FC layers
ResNet showed us how to train extremely deep networks

- Limited only by GPU & memory!
- Showed diminishing returns as networks got bigger

After ResNet: CNNs were better than the human metric and focus shifted to Efficient networks:
- Lots of tiny networks aimed at mobile devices: **MobileNet**, **ShuffleNet**

Neural Architecture Search can now automate architecture design

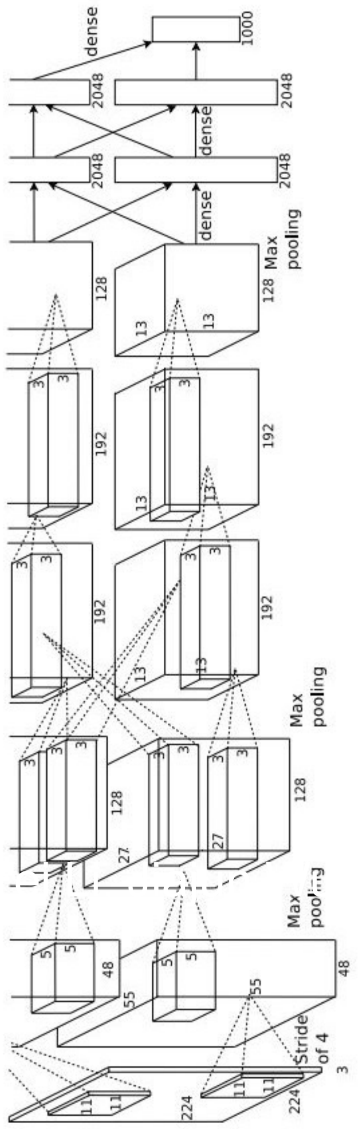
Summary: CNN Architectures

- Many popular architectures are available in model zoos.
- ResNets are currently good defaults to use.
- Networks have gotten increasingly deep over time.
- Many other aspects of network architectures are also continuously being investigated and improved.

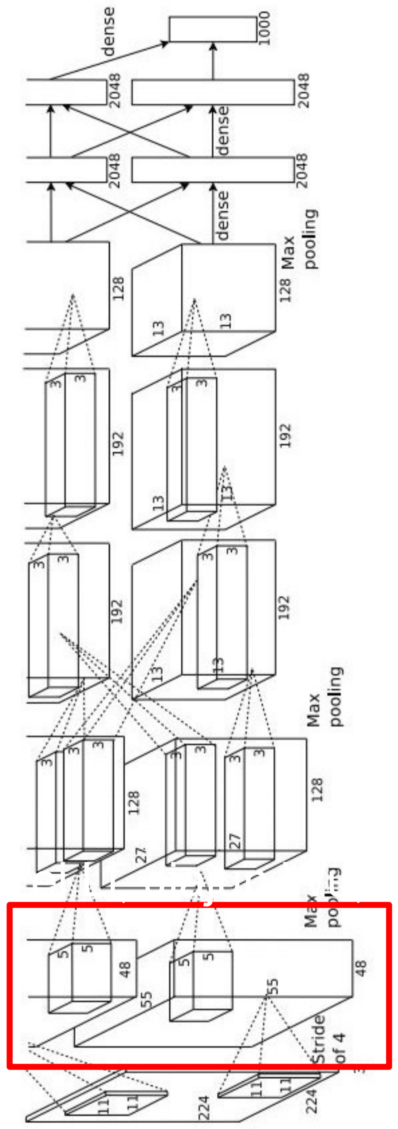
Transfer learning

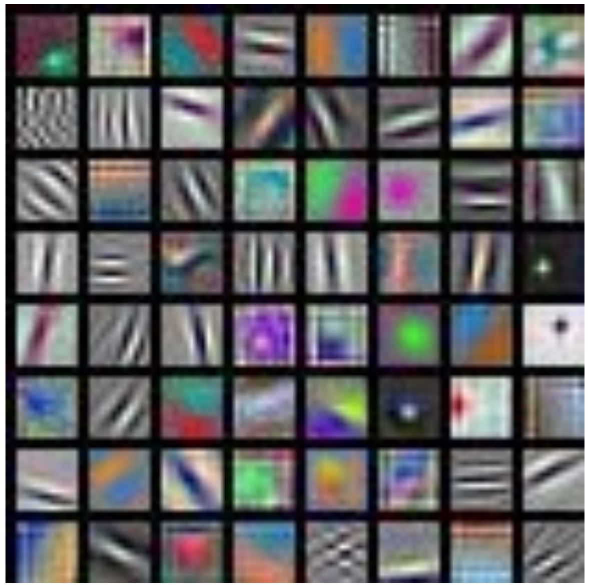
You need a lot of a data if you want to train/use CNNs?

Transfer Learning with CNNs



Transfer Learning with CNNs

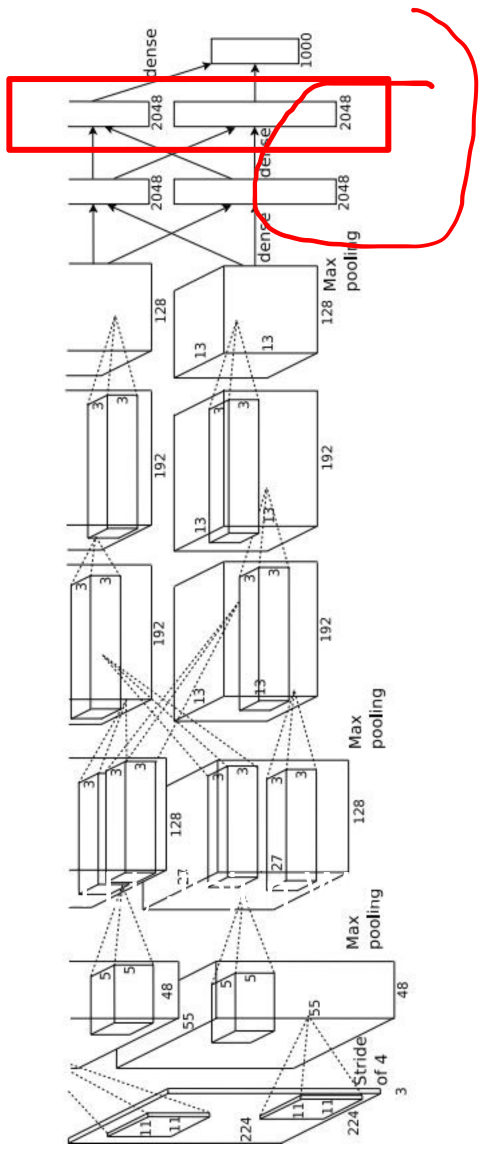




AlexNet:
64 x 3 x 11 x 11

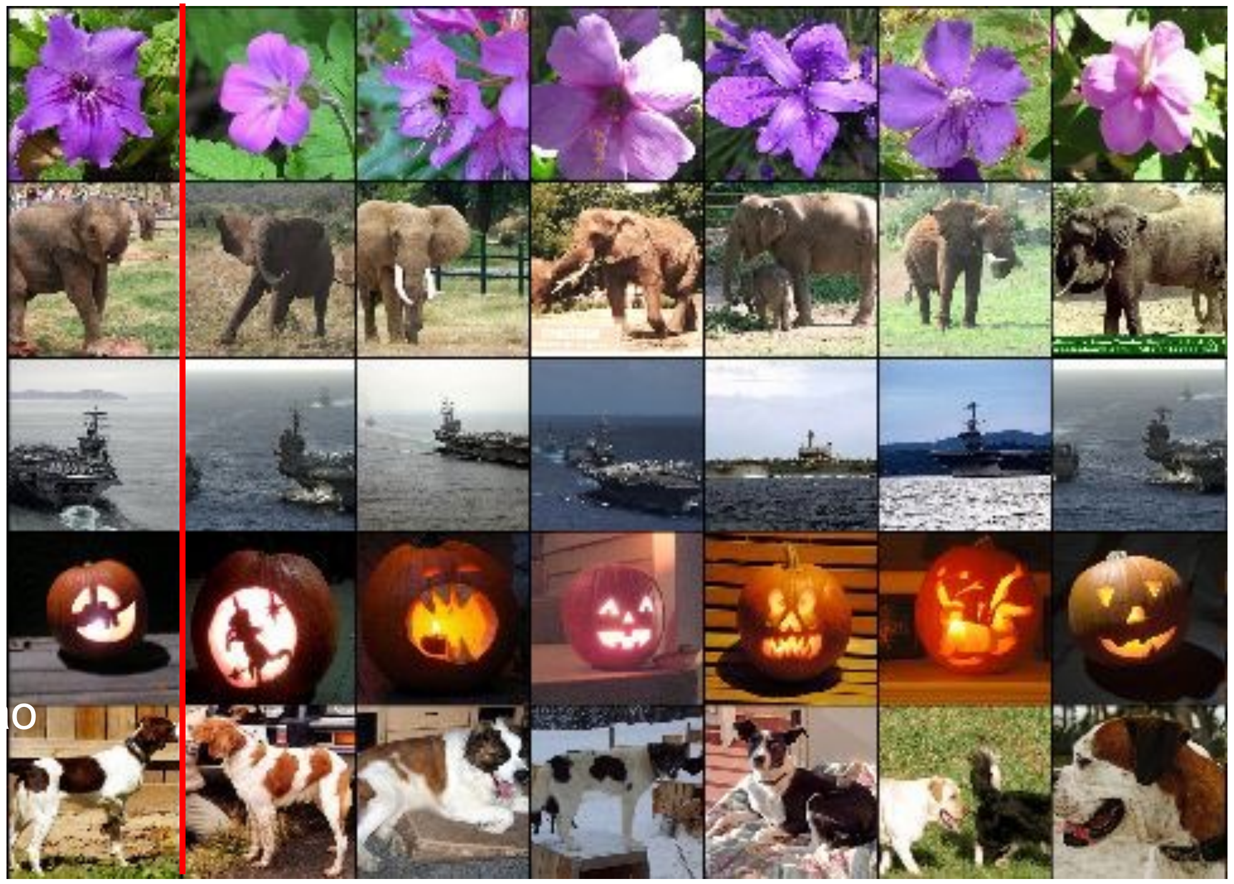
(More on this in Lecture 13)

Transfer Learning with CNNs



Test image

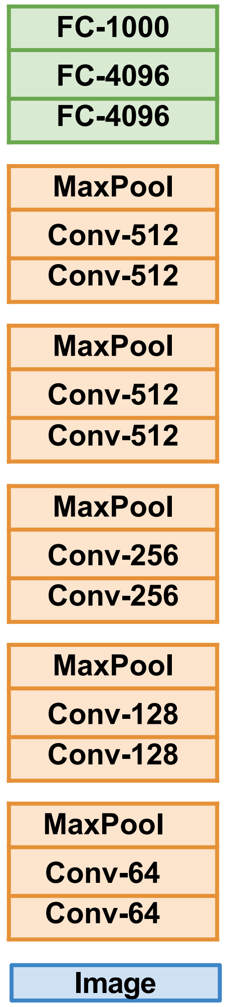
L2 Nearest neighbors in feature space



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

1. Train on Imagenet



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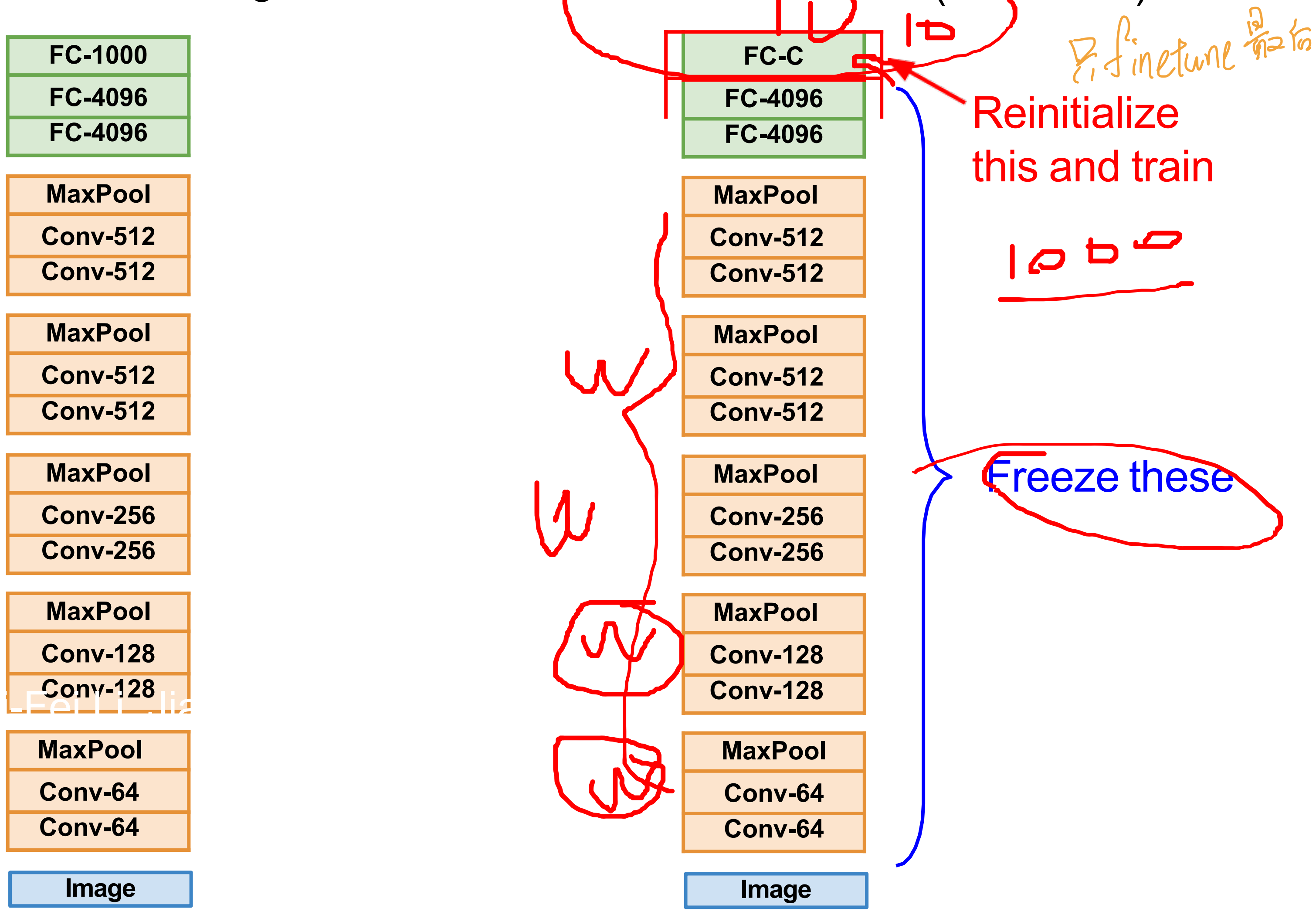
Transfer Learning with CNNs

1. Train on Imagenet

2. Small Dataset (C classes)

只finetune最后一层分类



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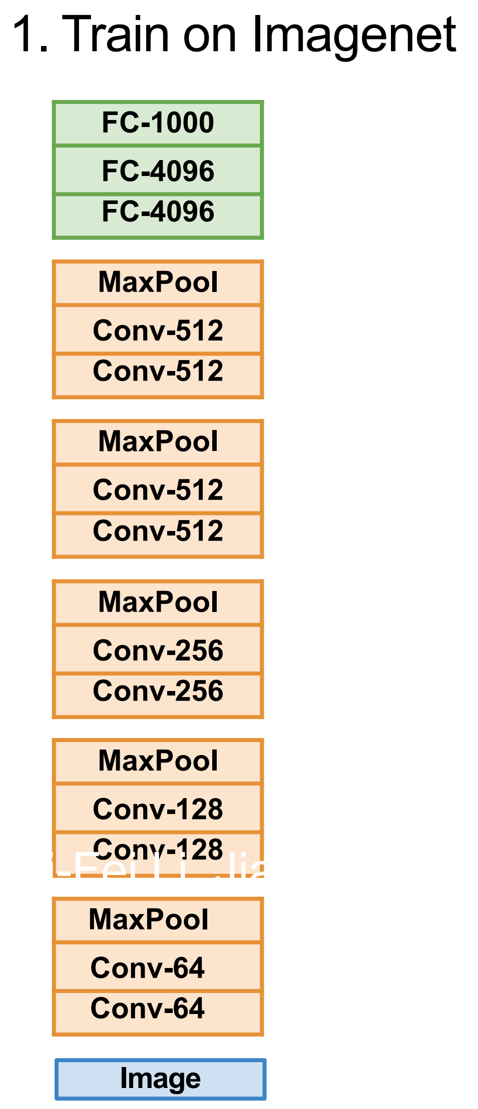

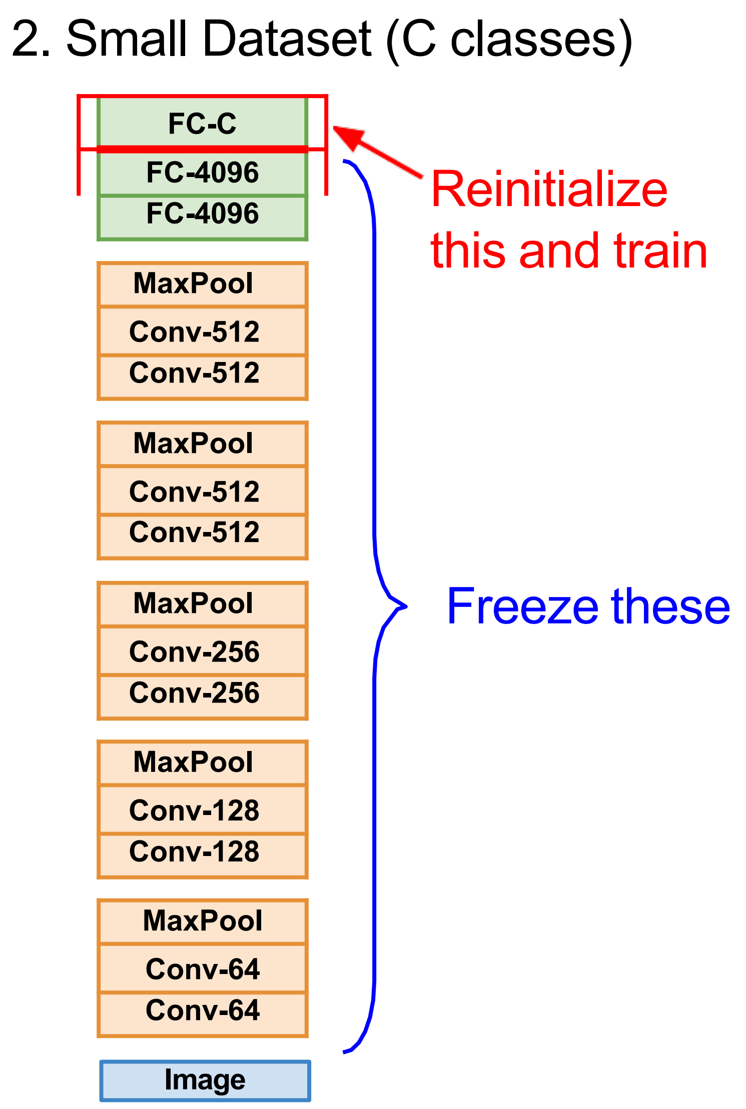

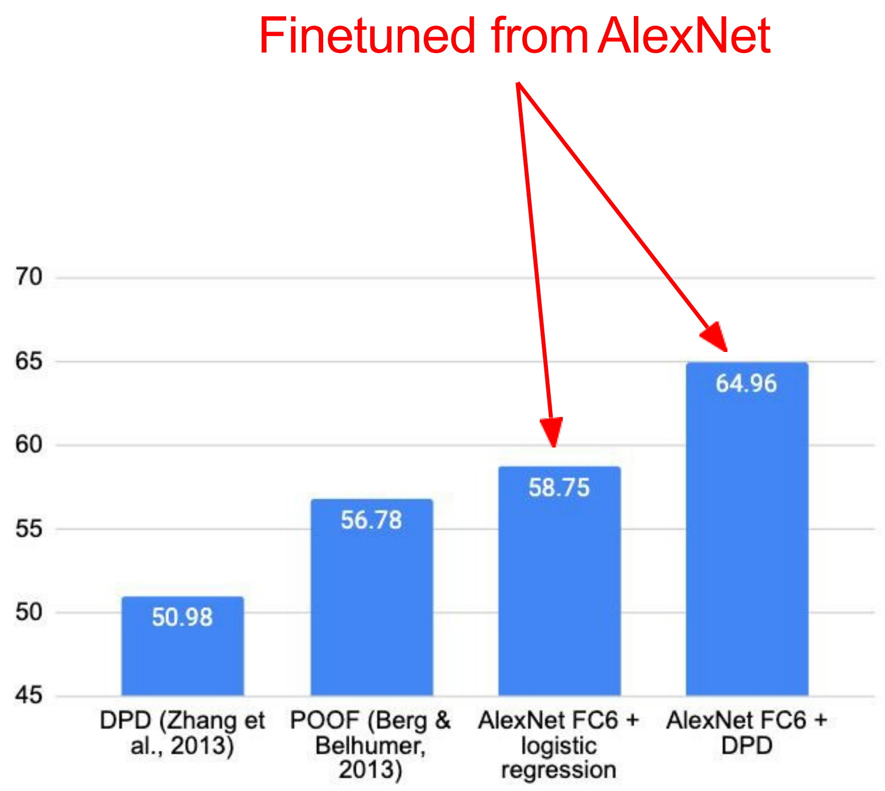

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Transfer Learning with CNNs

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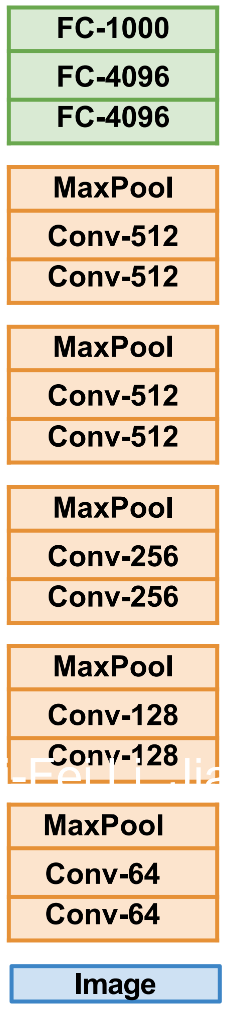
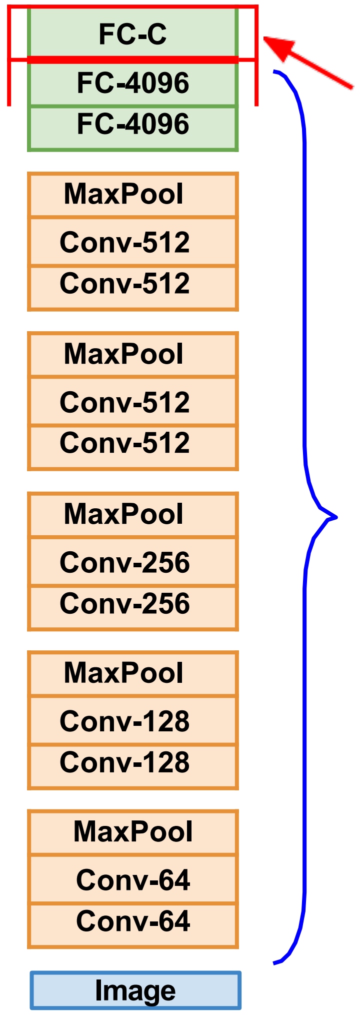


2. Small Dataset (C classes)

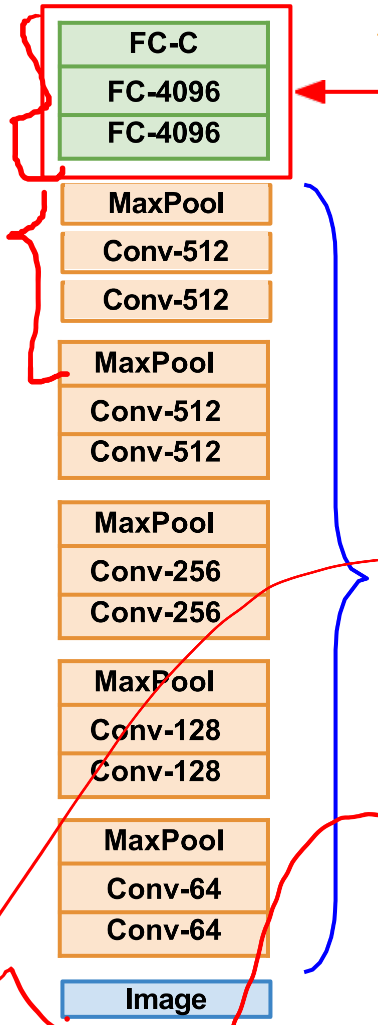


Reinitialize this and train

Freeze these

3. Bigger dataset

dataset越大 finetune层数更多

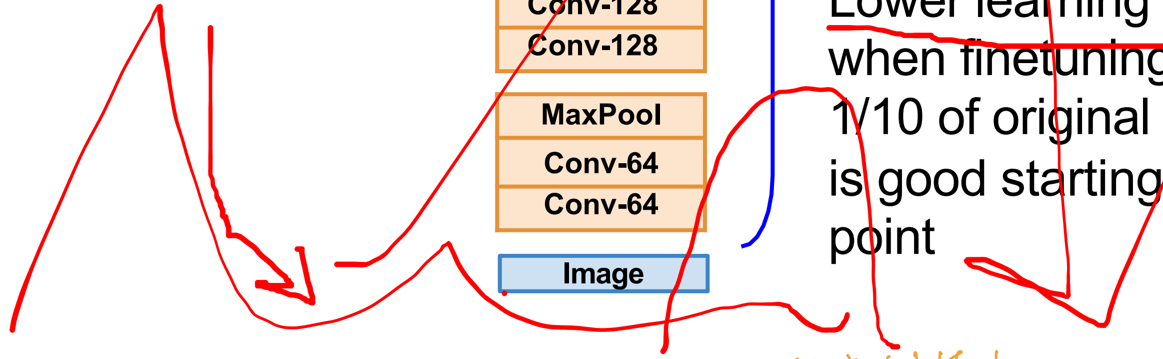


Train these

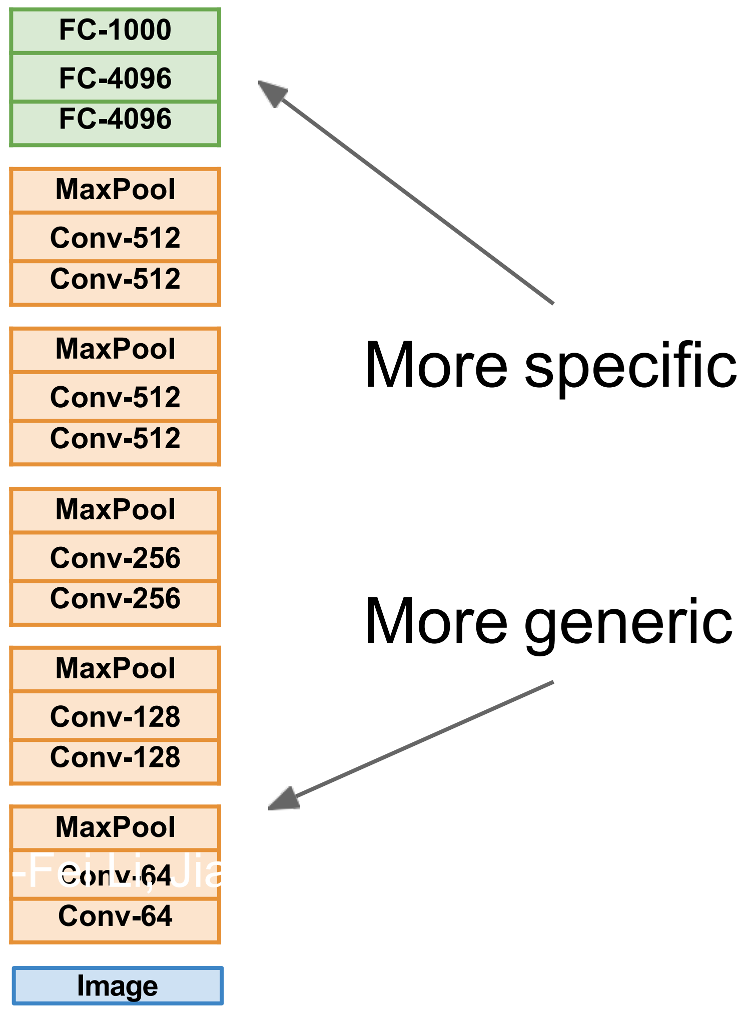
With bigger dataset, train more layers

Freeze these

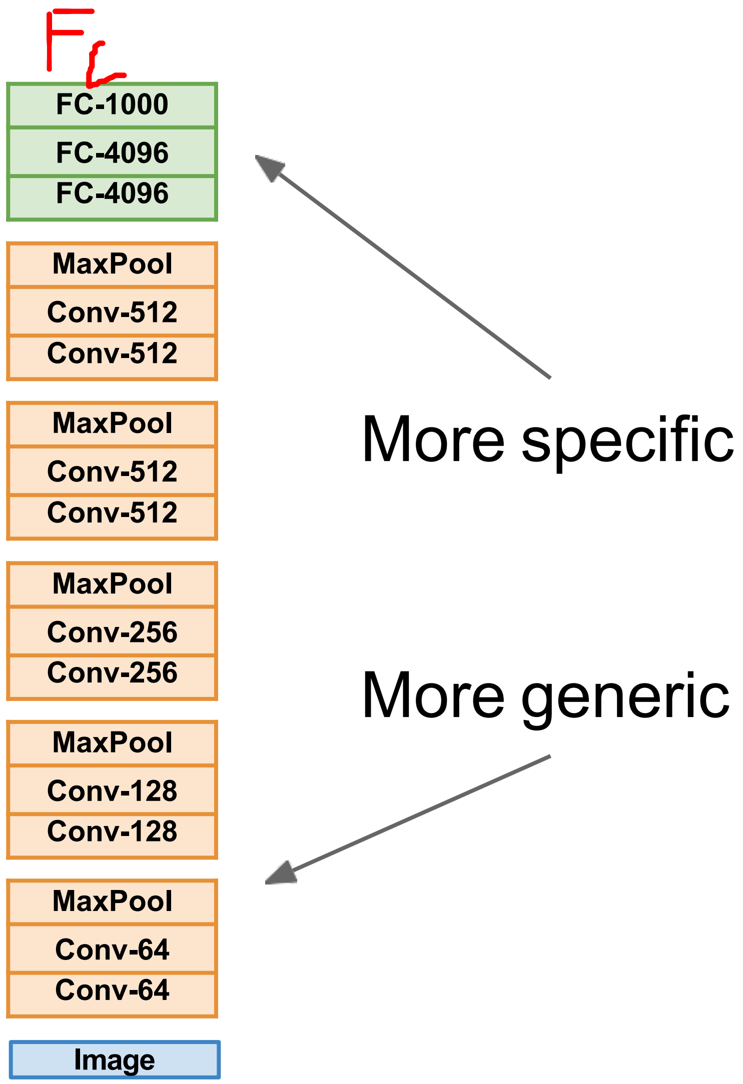
Lower learning rate when finetuning; 1/10 of original LR is good starting point



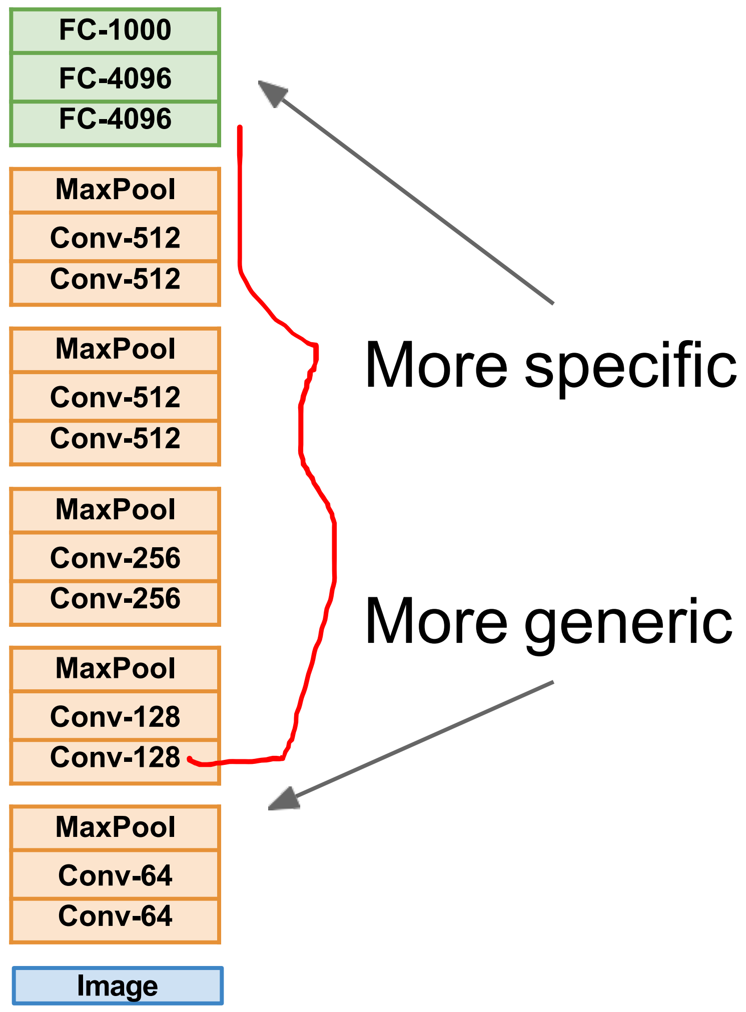
从头训练 lr大
finetune lr小



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



	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	?
quite a lot of data	Finetune a few layers	?

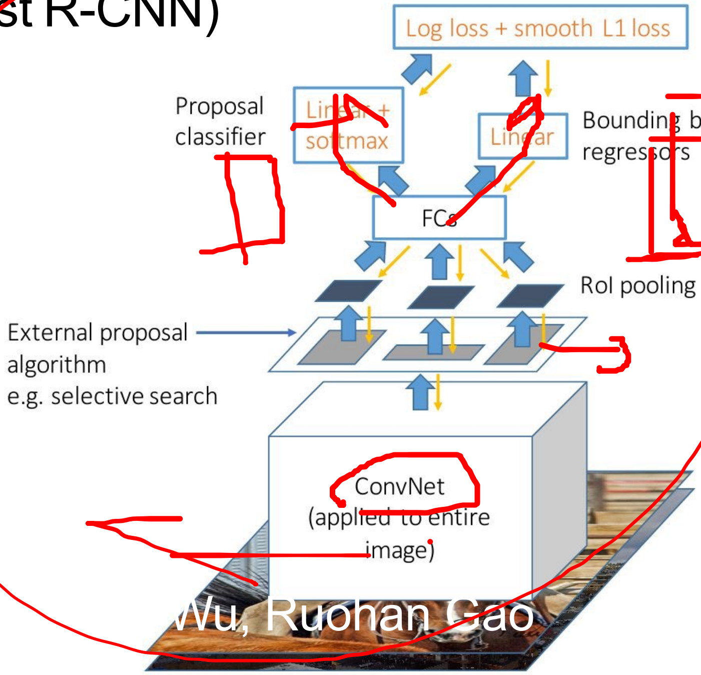


	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Object Detection

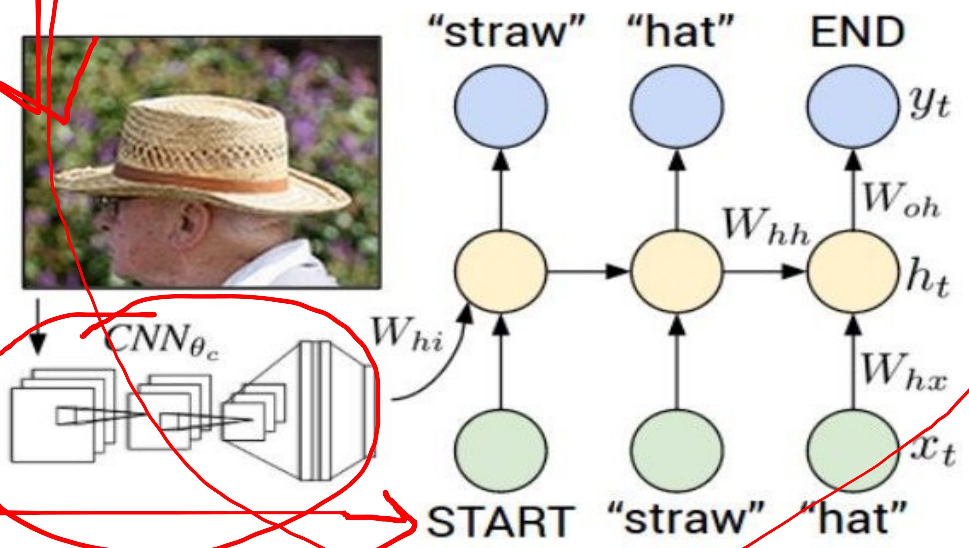
Transfer learning with CNNs is pervasive…

(Fast R-CNN)



Log loss + smooth L1 loss
Proposal classifier
Linear + softmax
Linear
Bounding box regressors
FCs
RoI pooling
External proposal algorithm e.g. selective search
ConvNet (applied to entire image)
Wu, Ruohan Gao

Image Captioning: CNN + RNN



Girshick, "Fast R-CNN", ICCV 2015
Figure copyright Ross Girshick, 2015. Reproduced with permission.

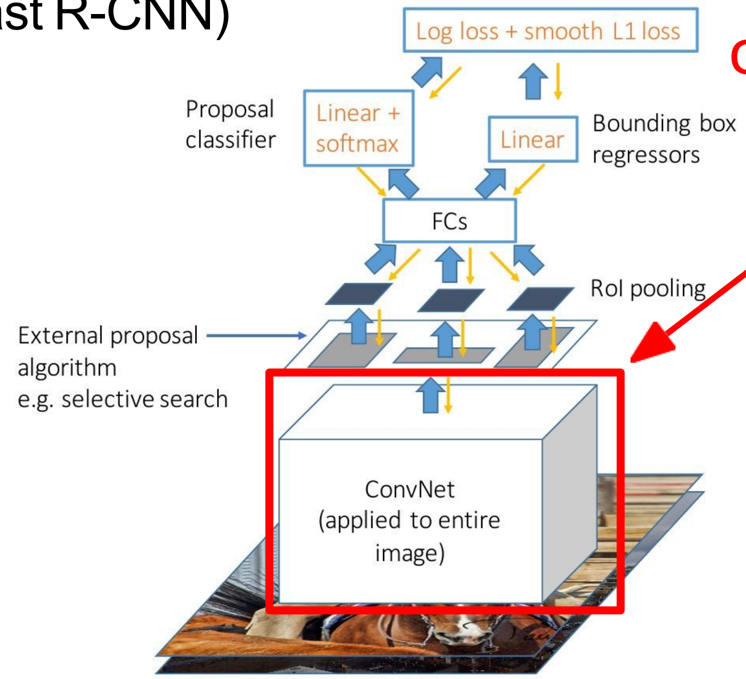
Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
Figure copyright IEEE, 2015. Reproduced for educational purposes.

Transfer learning with CNNs is pervasive…

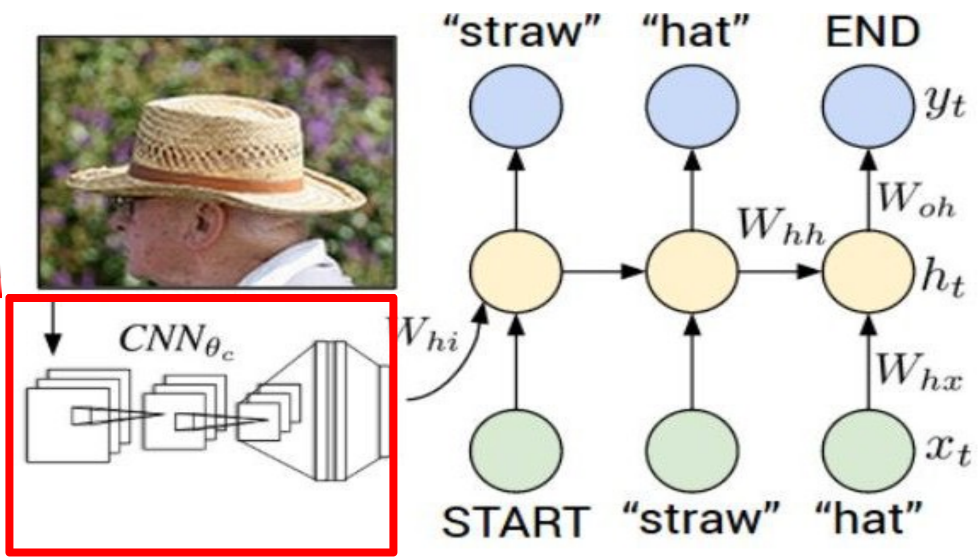
Object Detection
(Fast R-CNN)

CNN pretrained on ImageNet

Image Captioning: CNN + RNN



Log loss + smooth L1 loss
Proposal classifier
Linear + softmax
Linear
Bounding box regressors
FCs
RoI pooling
External proposal algorithm e.g. selective search
ConvNet (applied to entire image)



Girshick, "Fast R-CNN", ICCV 2015
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Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
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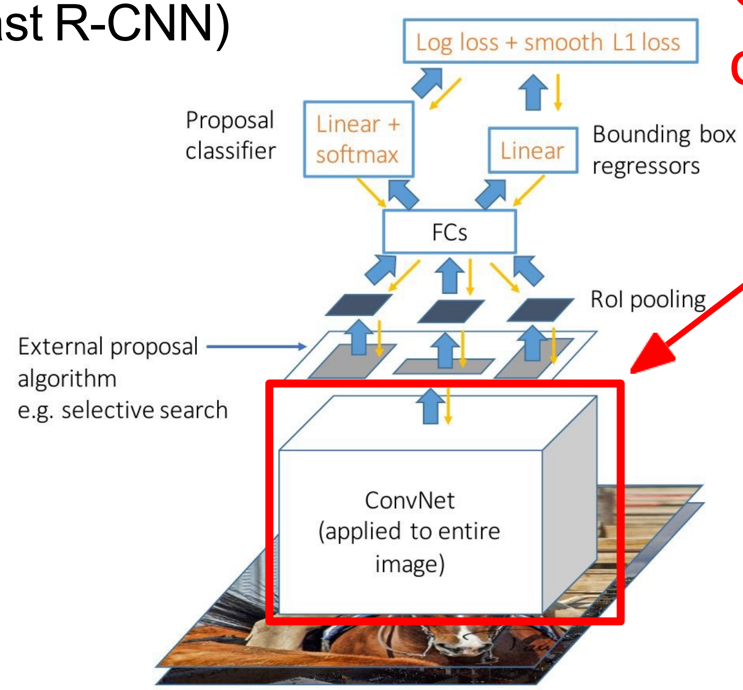
Transfer learning with CNNs is pervasive…

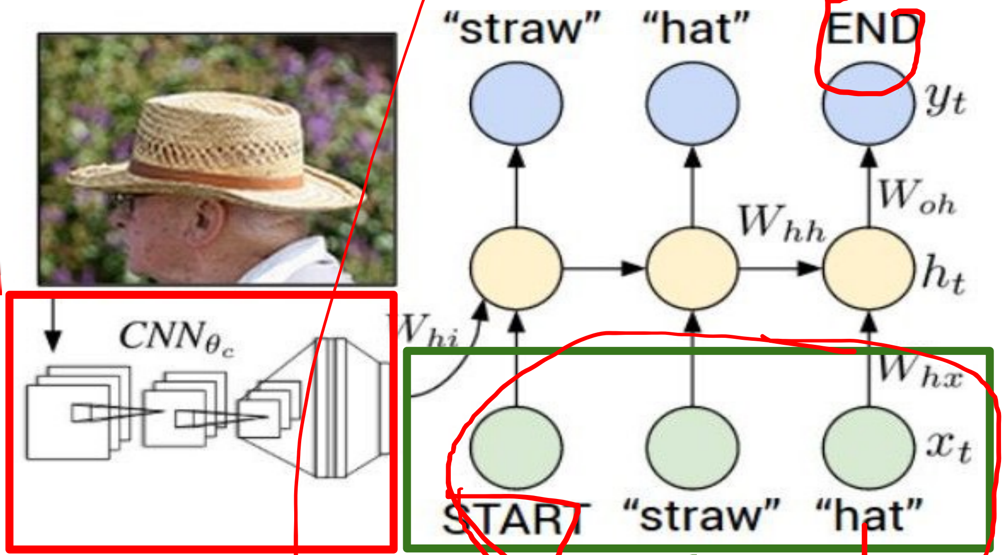
Object Detection
(Fast R-CNN)



Log loss + smooth L1 loss
Proposal classifier
Linear + softmax
Linear
Bounding box regressors
FCs
RoI pooling
External proposal algorithm e.g. selective search
ConvNet (applied to entire image)

CNN pretrained on ImageNet

Image Captioning: CNN + RNN



Word vectors pretrained with word2vec

Girshick, "Fast R-CNN", ICCV 2015
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Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
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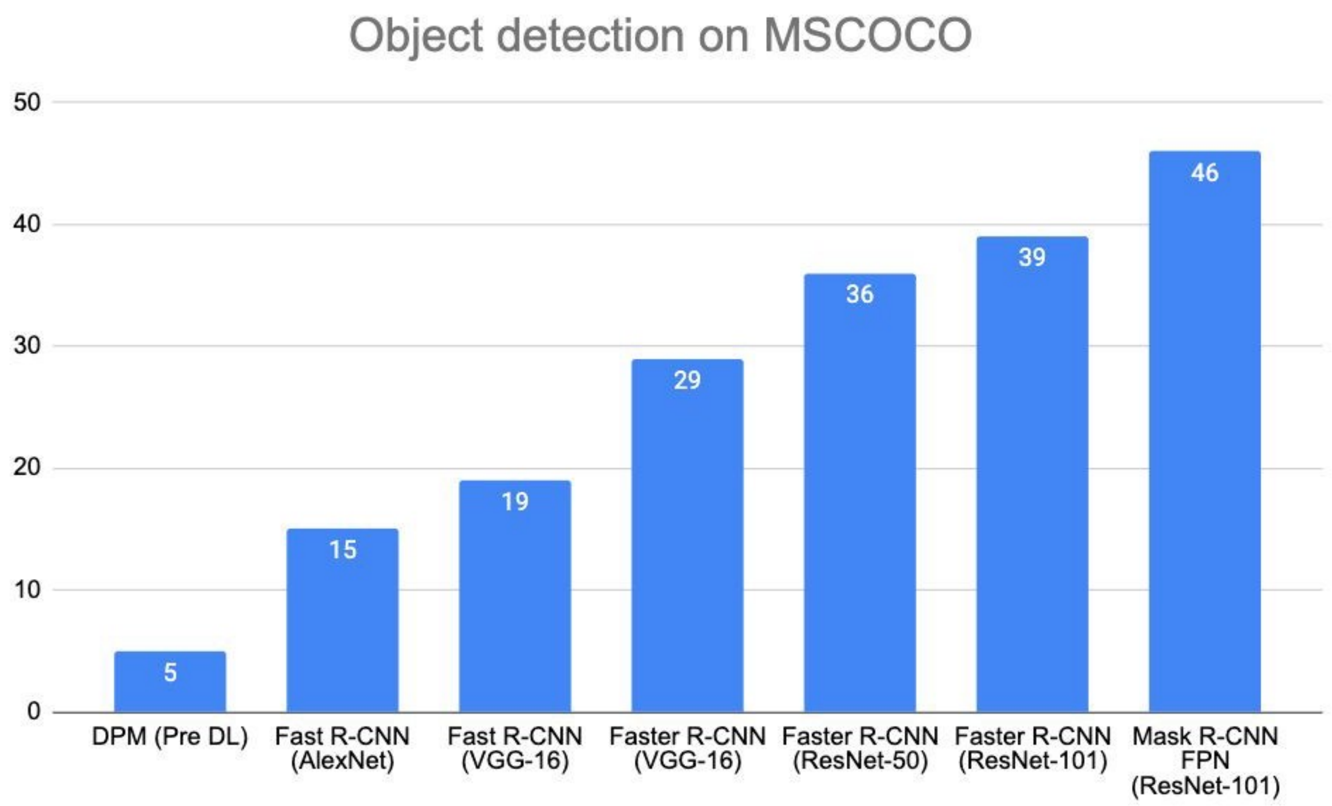
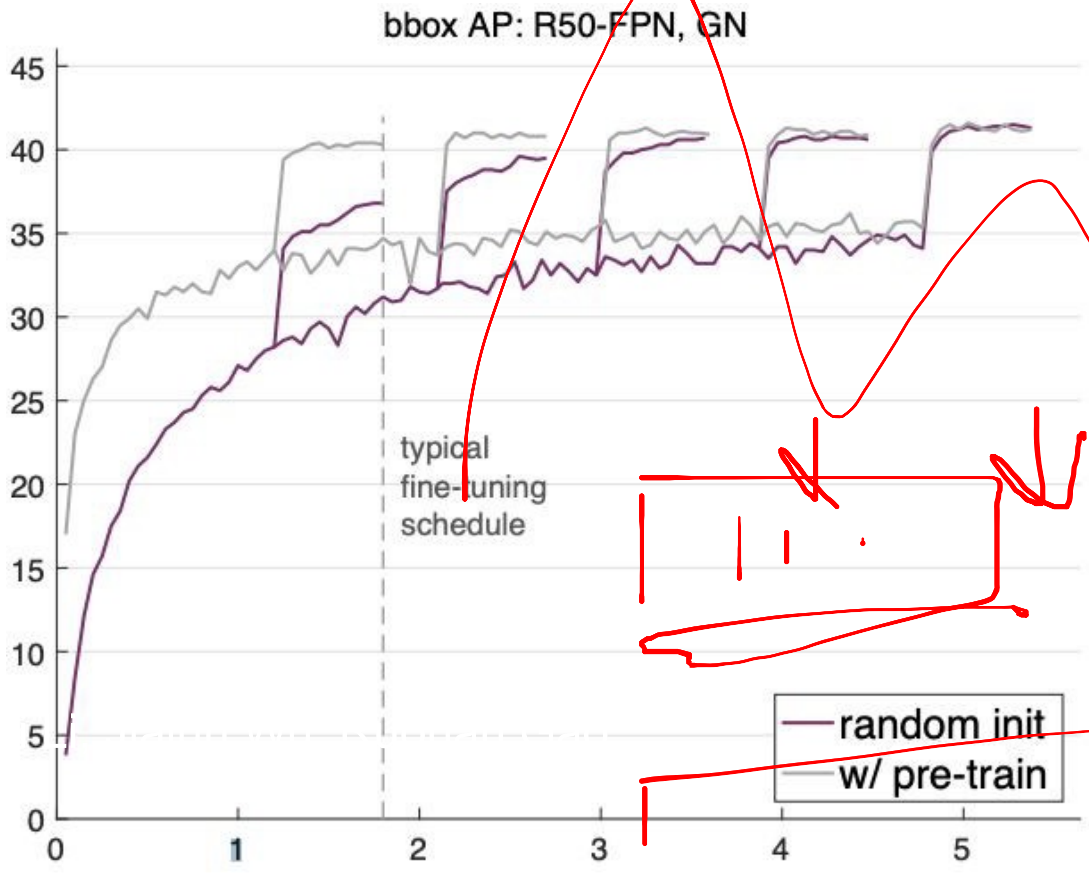
Transfer learning with CNNs - Architecture matters



Girshick, “The Generalized R-CNN Framework for Object Detection”, ICCV 2017 Tutorial on Instance-Level Visual Recognition

Transfer learning with CNNs is pervasive…

But recent results show it might not always be necessary!



He et al, "Rethinking ImageNet Pre-training", ICCV 2019
Figure copyright Kaiming He, 2019. Reproduced with permission.

Training from scratch can work just as well as training from a pretrained ImageNet model for object detection

But it takes 2-3x as long to train.

They also find that collecting more data is better than finetuning on a related task