

Tema 10 : VGG y GoogleNet

Case Study: VGGNet

[Simonyan and Zisserman, 2014]

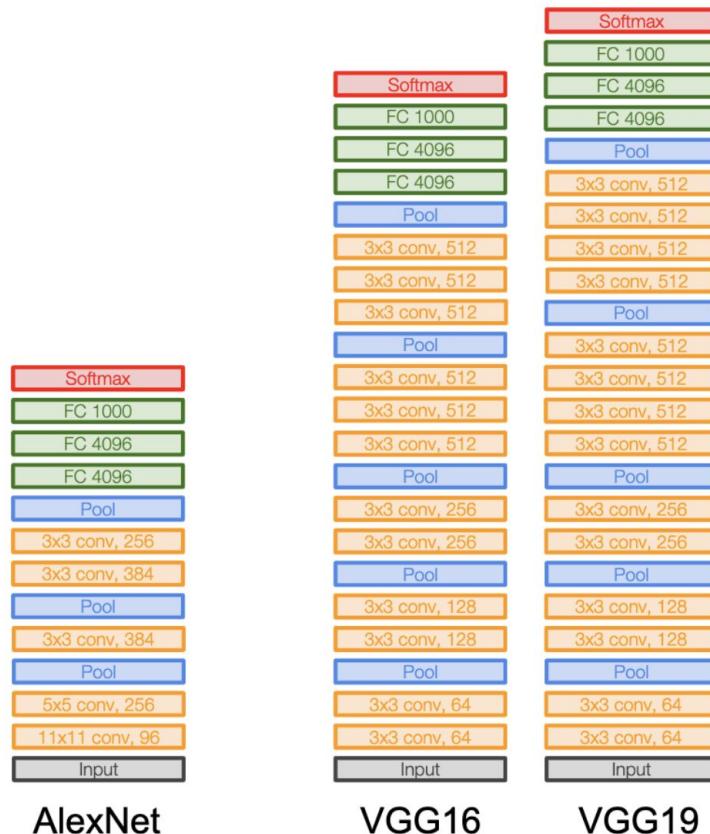
Small filters, Deeper networks

8 layers (AlexNet)

-> 16 - 19 layers (VGG16Net)

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

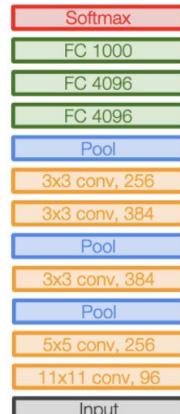
11.7% top 5 error in ILSVRC'13
(ZFNet)
-> 7.3% top 5 error in ILSVRC'14



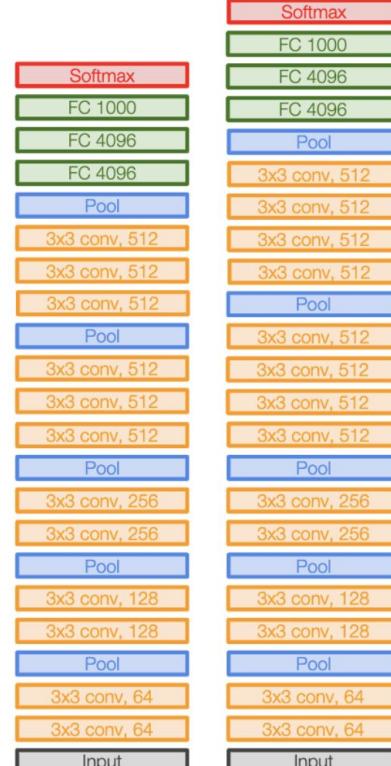
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

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



AlexNet



VGG16

VGG19

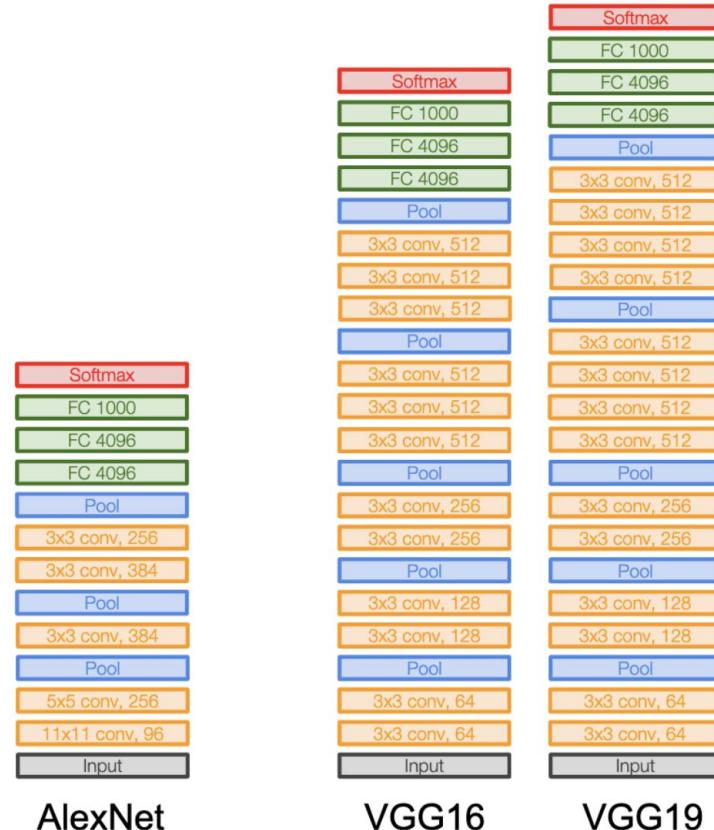
Case Study: VGGNet

[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

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



AlexNet

VGG16

VGG19

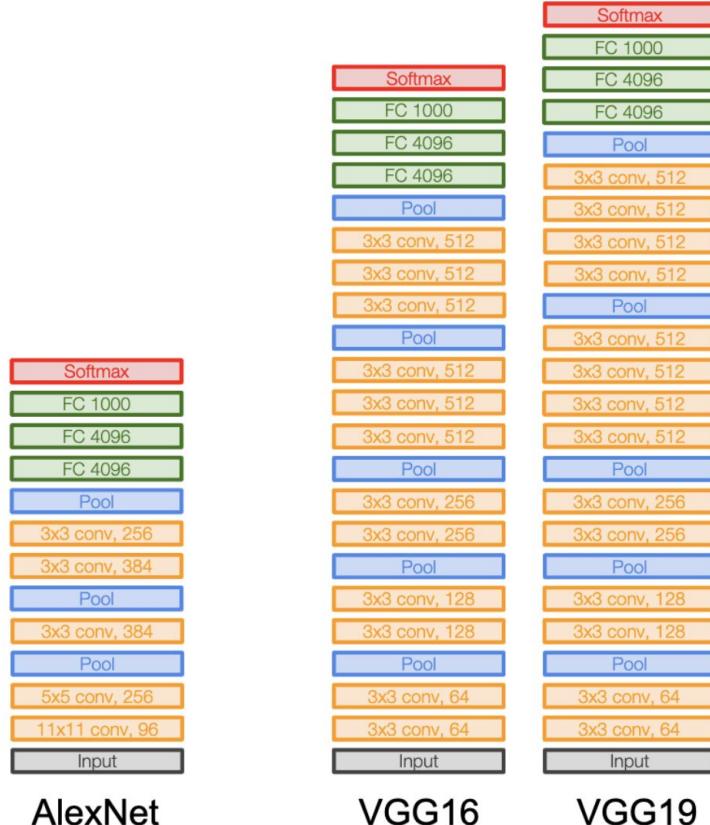
Case Study: VGGNet

[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]



AlexNet

VGG16

VGG19

Case Study: VGGNet

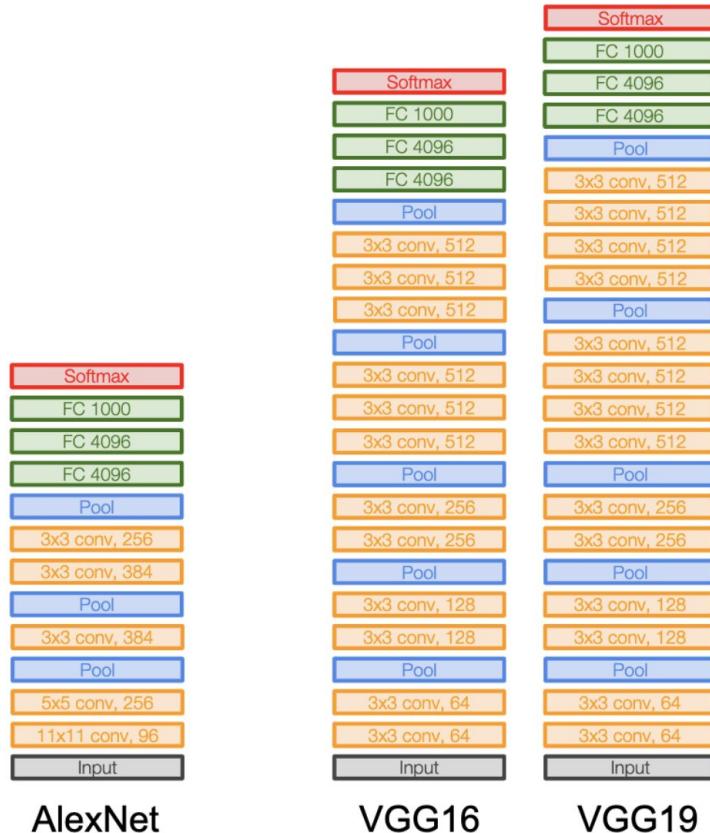
[Simonyan and Zisserman, 2014]

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



AlexNet

VGG16

VGG19

INPUT: [224x224x3] memory: $224 \times 224 \times 3 = 150K$ params: 0 (not counting biases)

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 3) \times 64 = 1,728$

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 64) \times 64 = 36,864$

POOL2: [112x112x64] memory: $112 \times 112 \times 64 = 800K$ params: 0

CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 64) \times 128 = 73,728$

CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 128) \times 128 = 147,456$

POOL2: [56x56x128] memory: $56 \times 56 \times 128 = 400K$ params: 0

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 128) \times 256 = 294,912$

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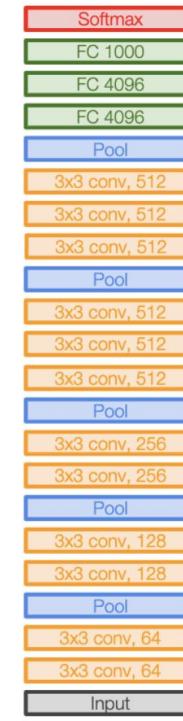
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POOL2: [7x7x512] memory: $7 \times 7 \times 512 = 25K$ params: 0

FC: [1x1x4096] memory: 4096 params: $7 \times 7 \times 512 \times 4096 = 102,760,448$

FC: [1x1x4096] memory: 4096 params: $4096 \times 4096 = 16,777,216$

FC: [1x1x1000] memory: 1000 params: $4096 \times 1000 = 4,096,000$



VGG16

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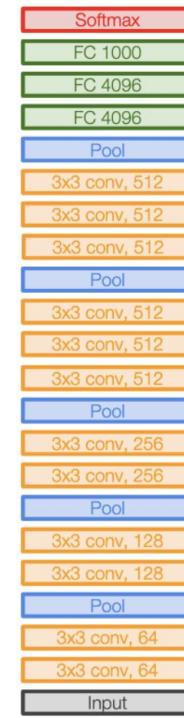
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VGG16

TOTAL memory: $24M * 4 \text{ bytes} \approx 96\text{MB} / \text{image}$ (only forward! ~ 2 for bwd)

TOTAL params: 138M parameters

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Note:

Most memory is in early CONV

Most params are in late FC

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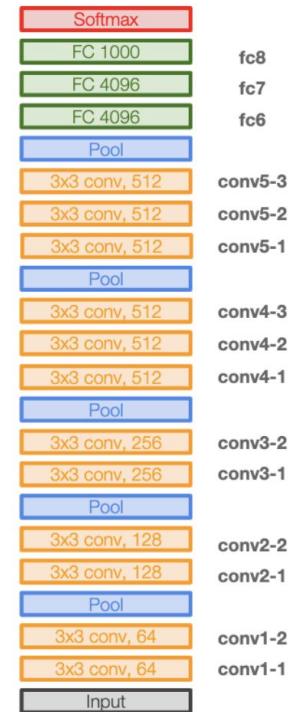
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VGG16

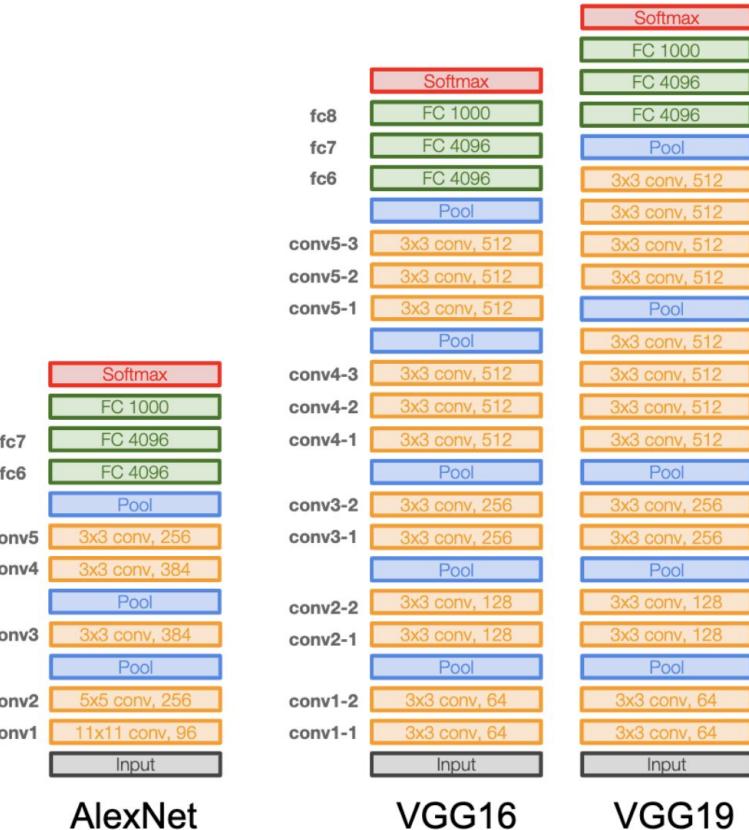
Common names

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

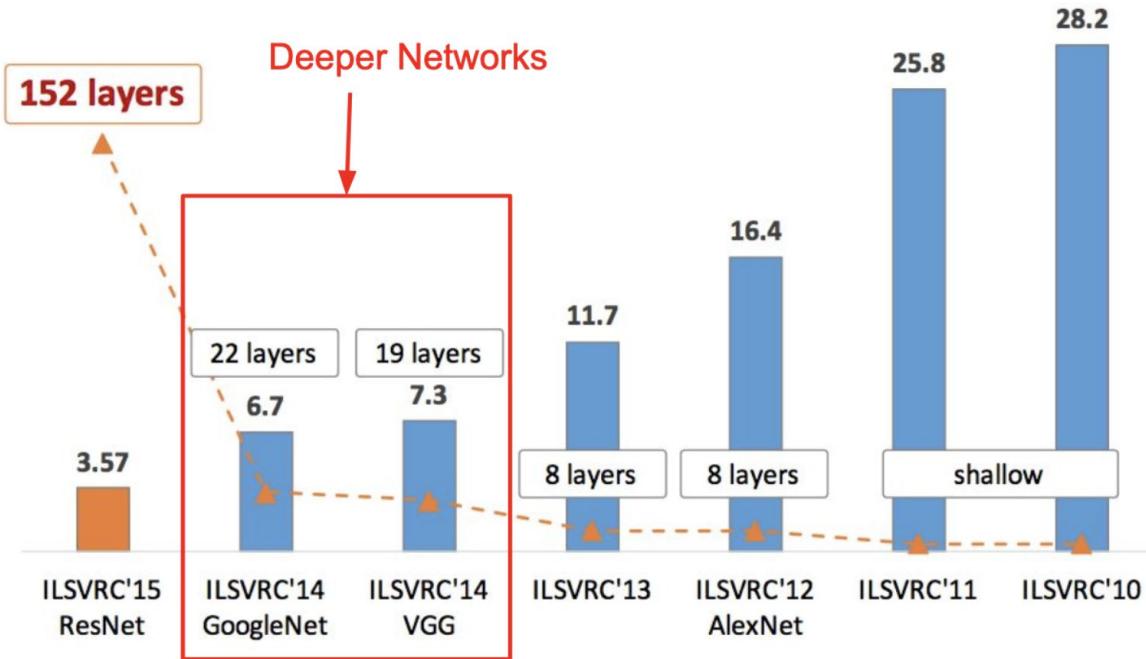


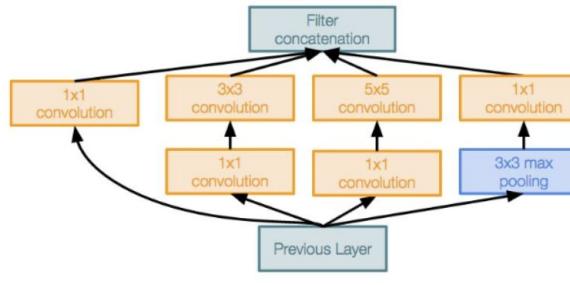
Figure copyright Kaiming He, 2016. Reproduced with permission.

Case Study: GoogLeNet

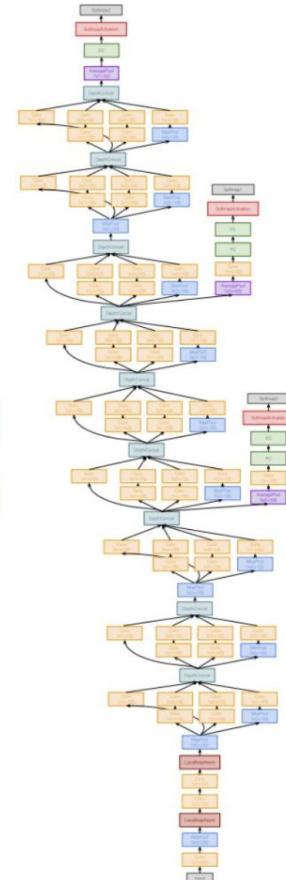
[Szegedy et al., 2014]

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)



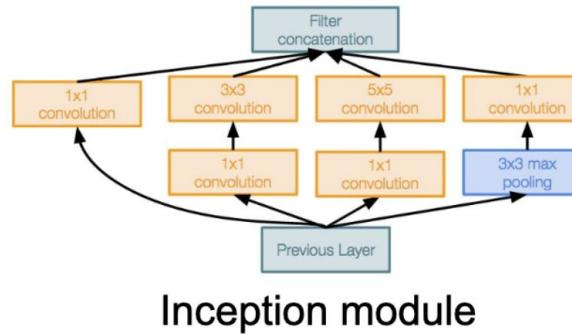
Inception module



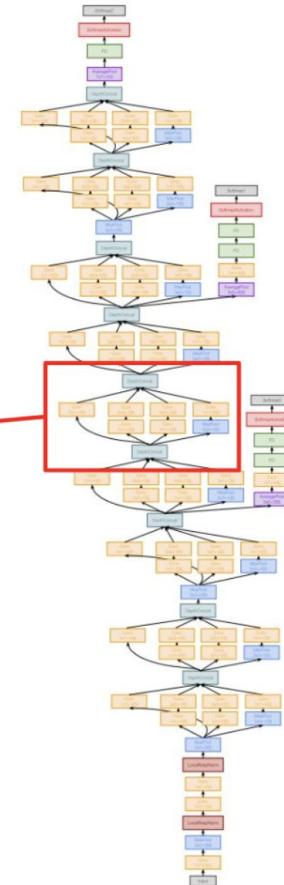
Case Study: GoogLeNet

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

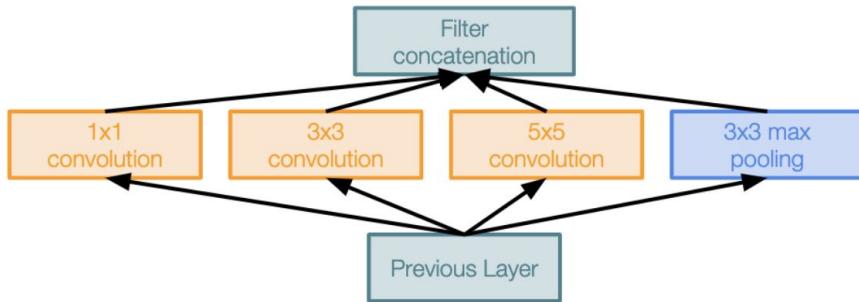


Inception module



Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

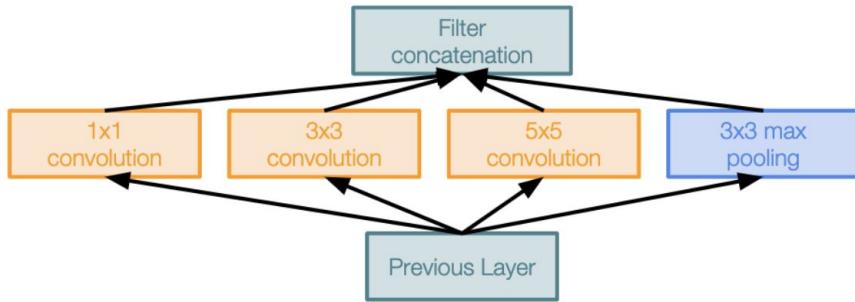
Apply parallel filter operations on the input from previous layer:

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

Concatenate all filter outputs together depth-wise

Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

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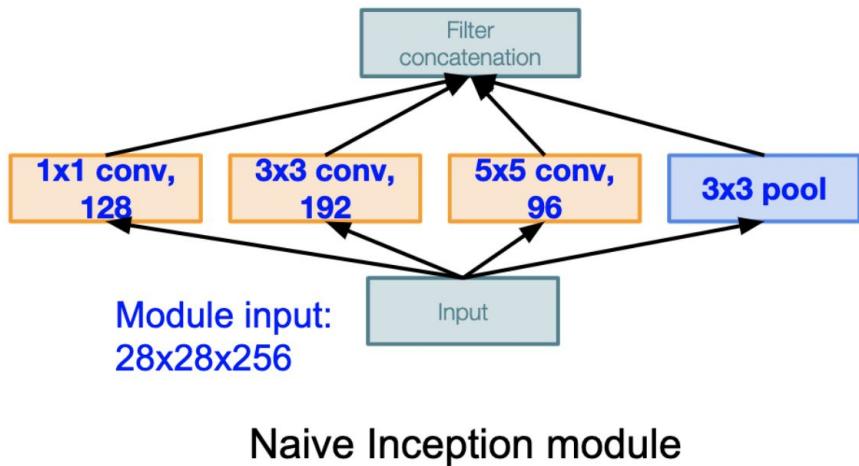
Q: What is the problem with this?
[Hint: Computational complexity]

Case Study: GoogLeNet

[Szegedy et al., 2014]

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Example:

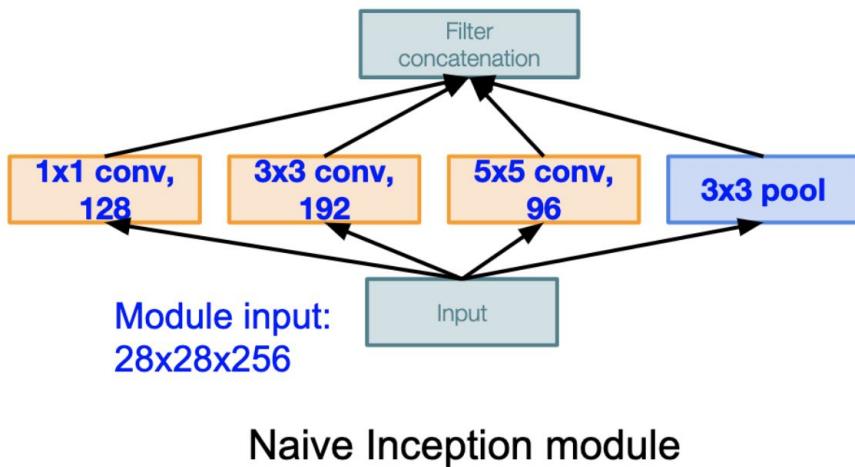


Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

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



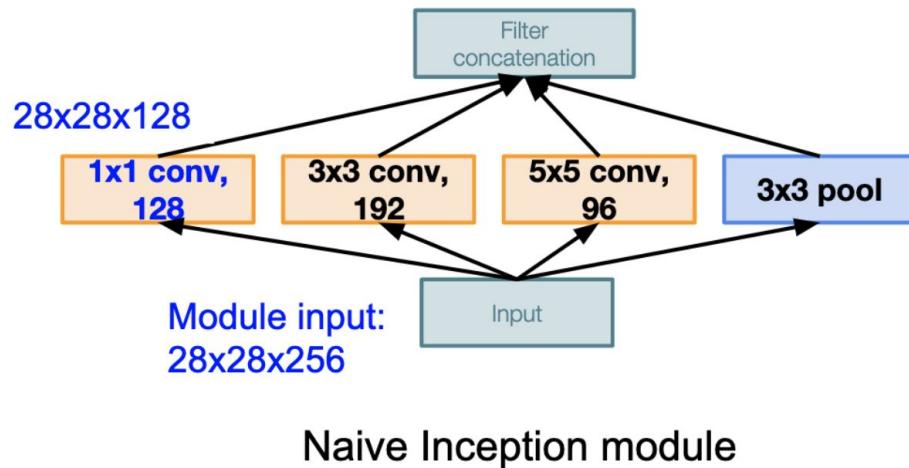
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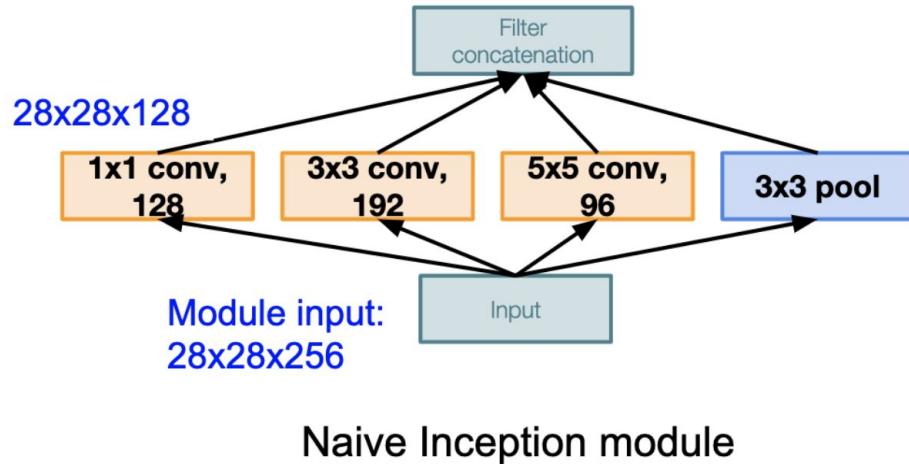
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Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q2: What are the output sizes of all different filter operations?



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

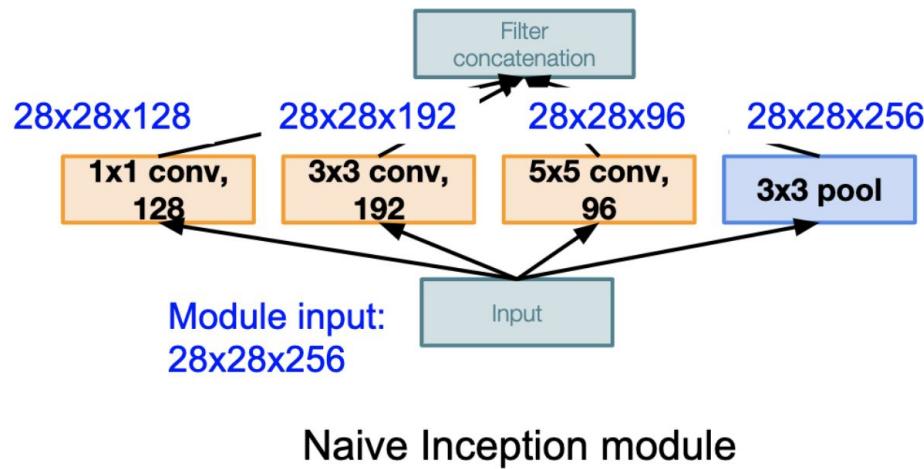
Case Study: GoogLeNet

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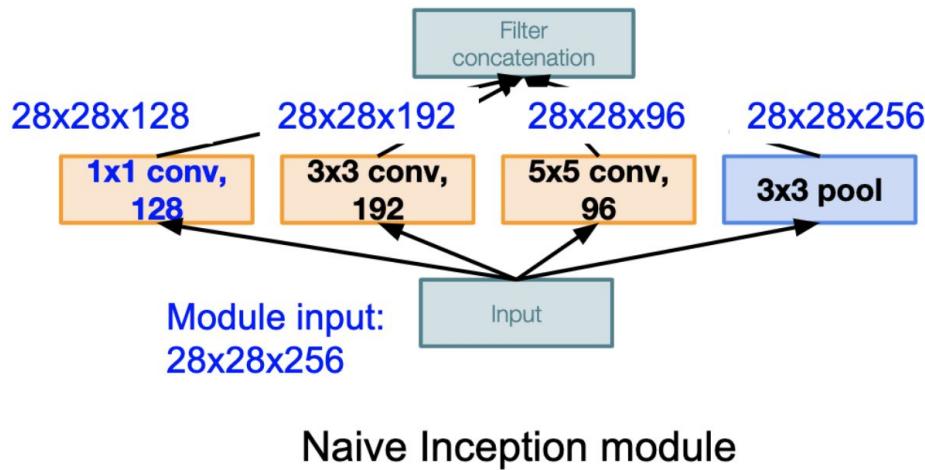
Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3: What is output size after
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Q: What is the problem with this?
[Hint: Computational complexity]



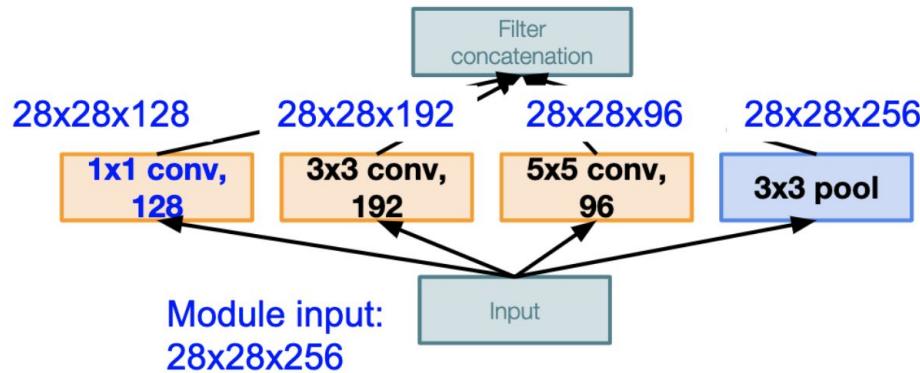
Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3: What is output size after filter concatenation?

$$28 \times 28 \times (128 + 192 + 96 + 256) = 28 \times 28 \times 672$$



Naive Inception module

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

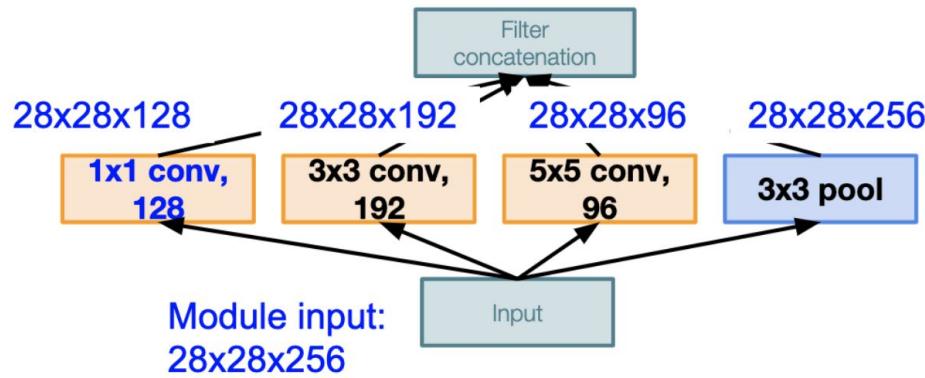
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Naive Inception module

Q: What is the problem with this?
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Conv Ops:

[1x1 conv, 128] $28 \times 28 \times 128 \times 1 \times 1 \times 256$
[3x3 conv, 192] $28 \times 28 \times 192 \times 3 \times 3 \times 256$
[5x5 conv, 96] $28 \times 28 \times 96 \times 5 \times 5 \times 256$

Total: 854M ops

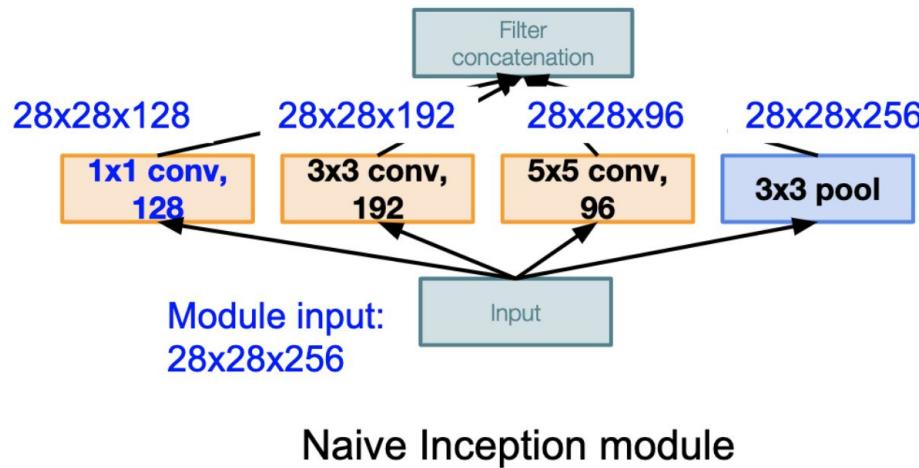
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Very expensive compute

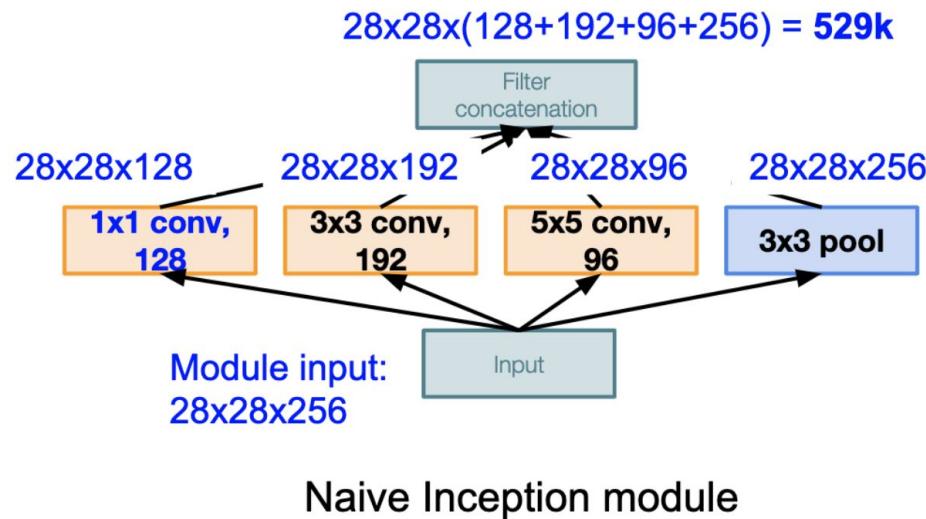
Pooling layer also preserves feature depth, which means total depth after concatenation can only grow at every layer!

Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

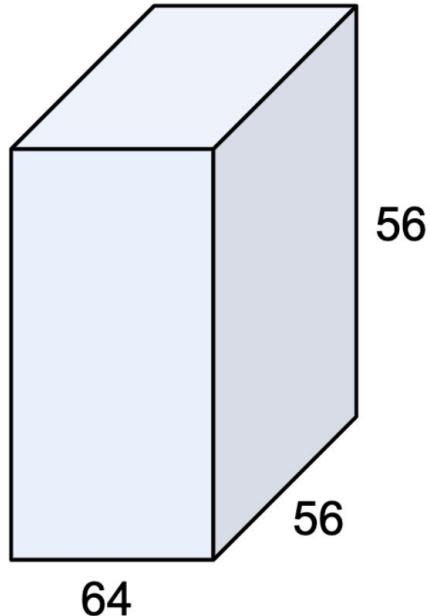
Q3: What is output size after filter concatenation?



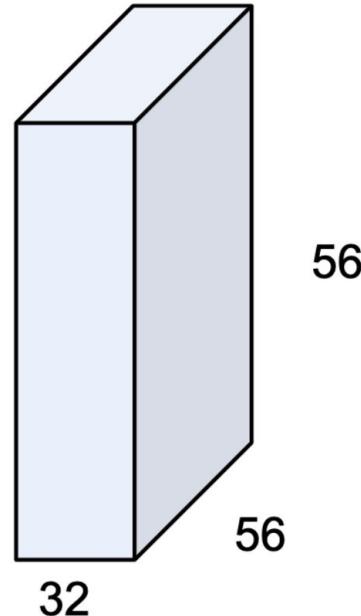
Q: What is the problem with this?
[Hint: Computational complexity]

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

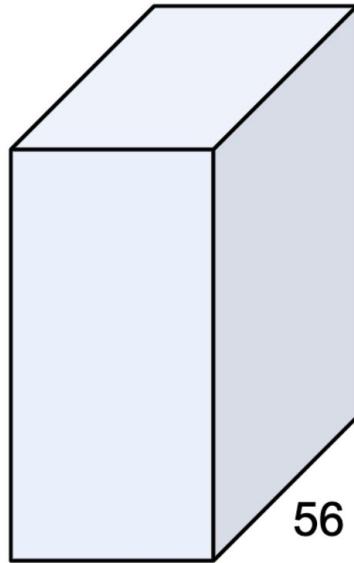
Reminder: 1x1 convolutions



1x1 CONV
with 32 filters
→
(each filter has size
1x1x64, and performs a
64-dimensional dot
product)



Reminder: 1x1 convolutions

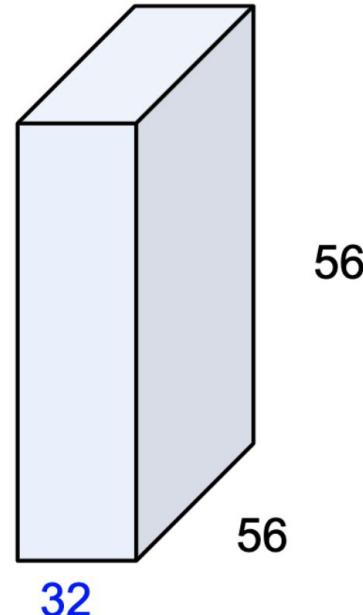


1x1 CONV
with 32 filters



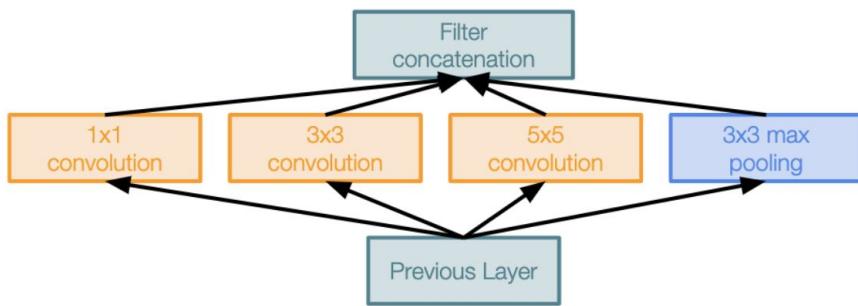
preserves spatial
dimensions, reduces depth!

Projects depth to lower
dimension (combination of
feature maps)

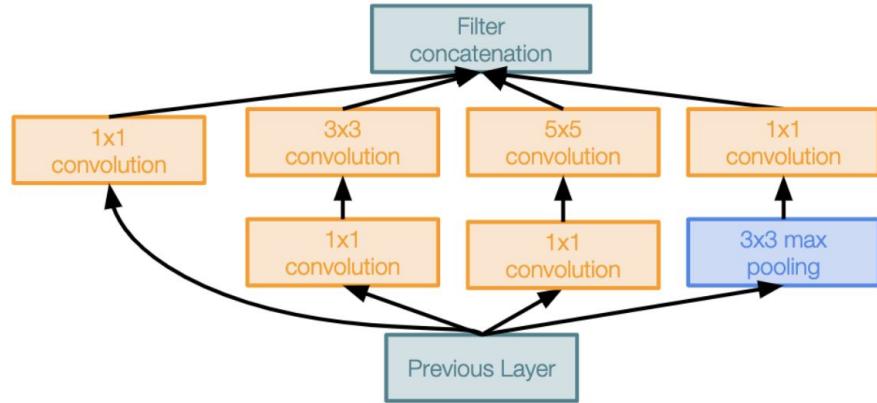


Case Study: GoogLeNet

[Szegedy et al., 2014]



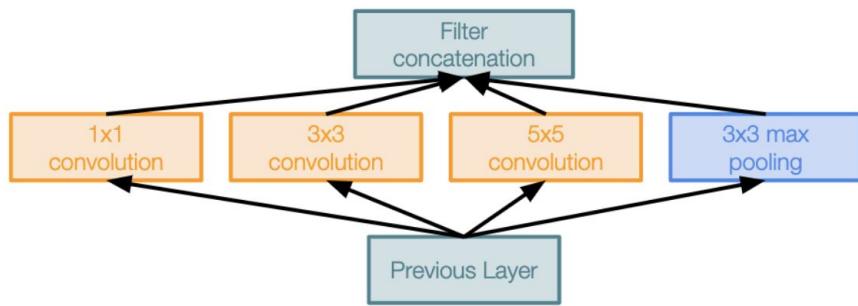
Naive Inception module



Inception module with dimension reduction

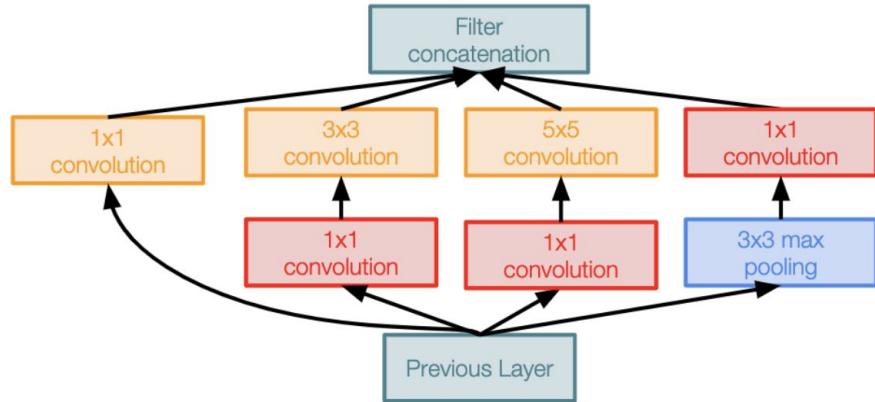
Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

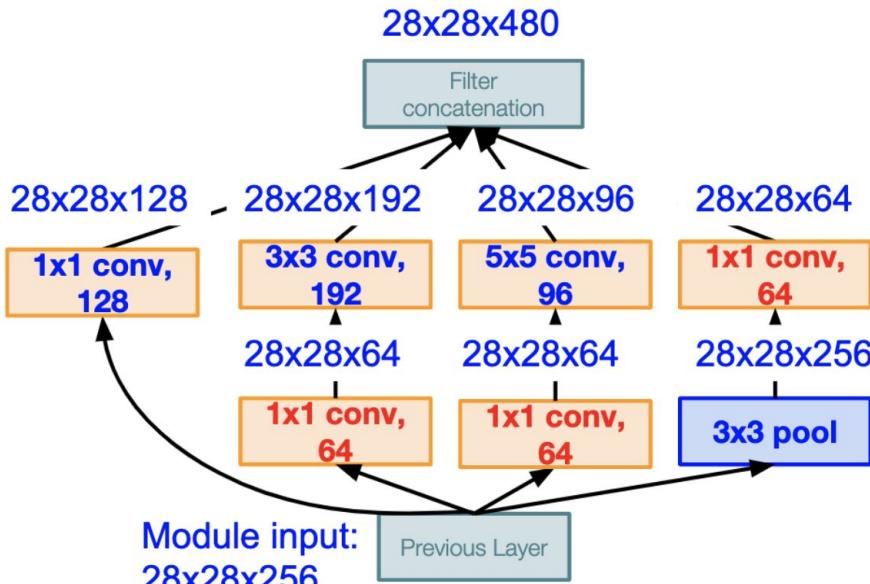
1x1 conv “bottleneck”
layers



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:

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

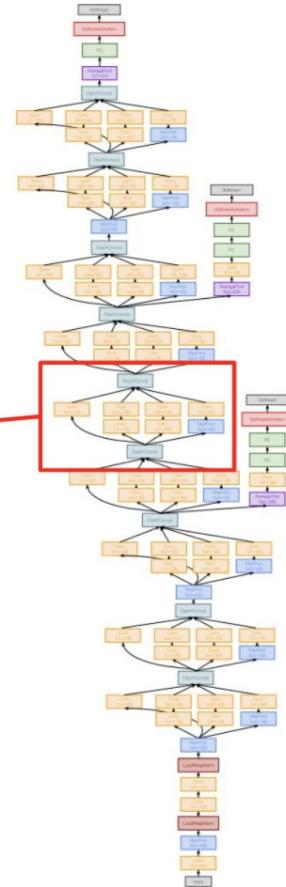
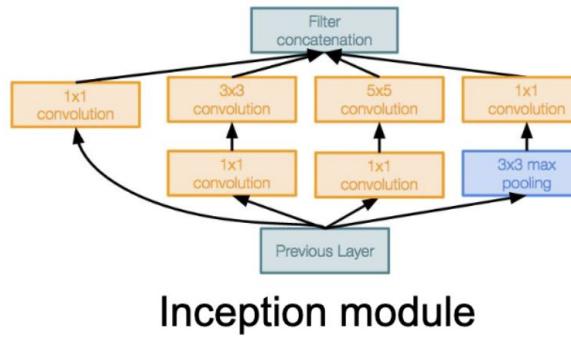
Total: 358M ops

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

Case Study: GoogLeNet

[Szegedy et al., 2014]

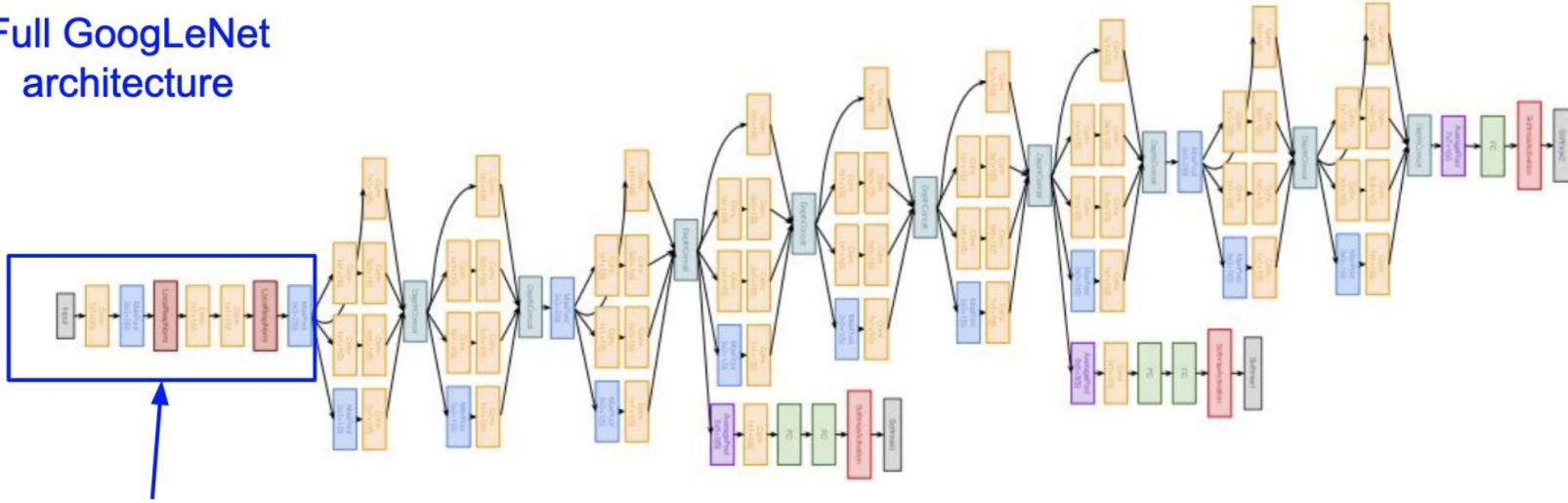
Stack Inception modules
with dimension reduction
on top of each other



Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

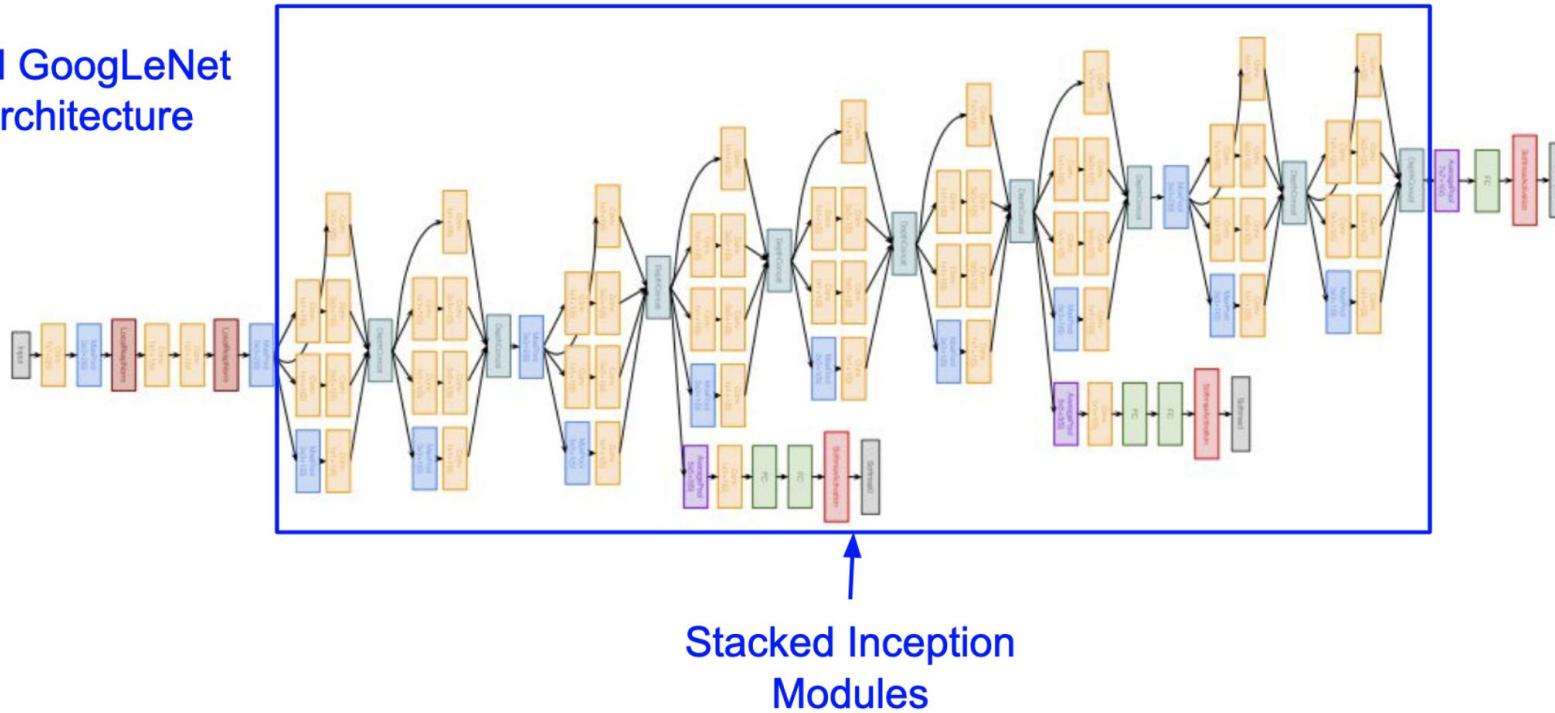


Stem Network:
Conv-Pool-
2x Conv-Pool

Case Study: GoogLeNet

[Szegedy et al., 2014]

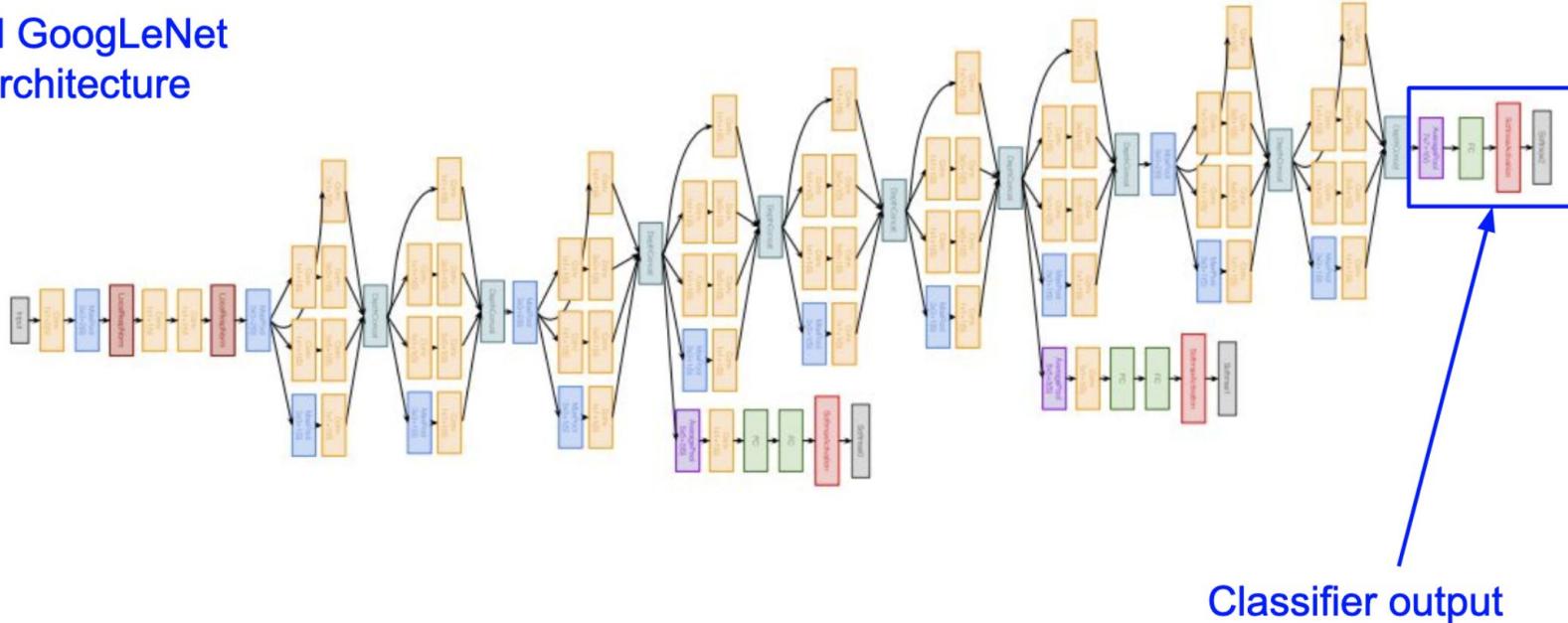
Full GoogLeNet
architecture



Case Study: GoogLeNet

[Szegedy et al., 2014]

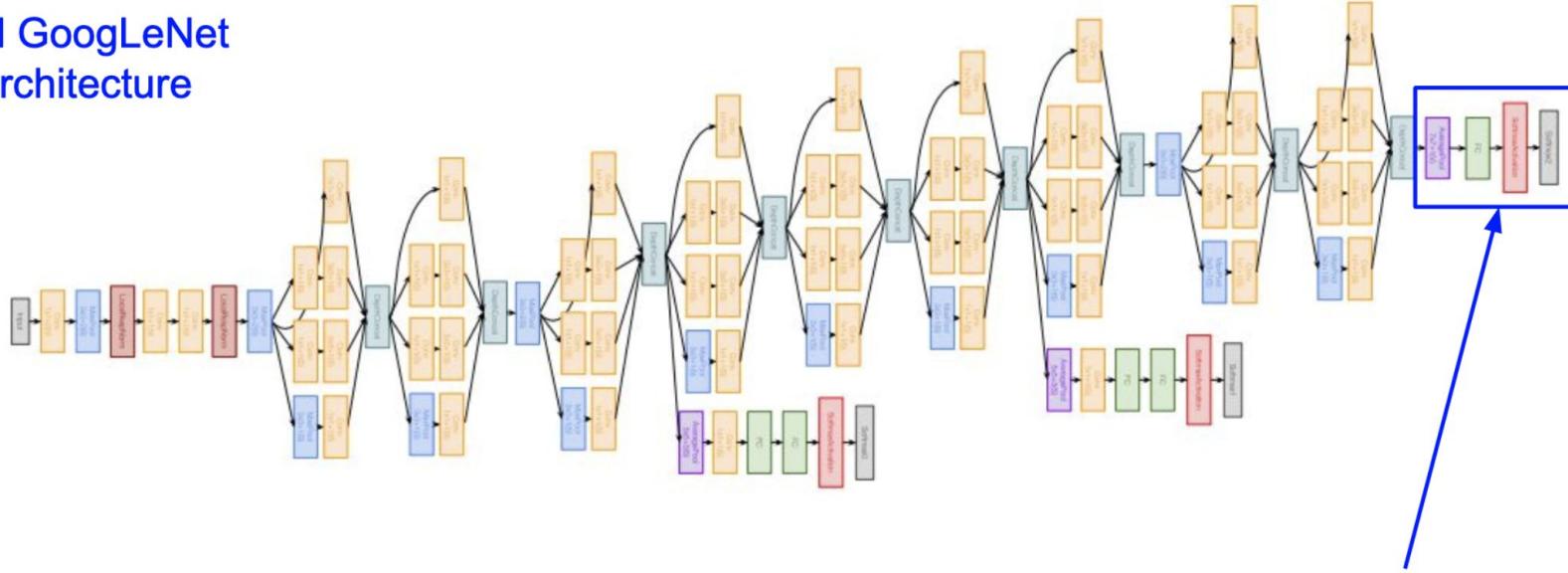
Full GoogLeNet
architecture



Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

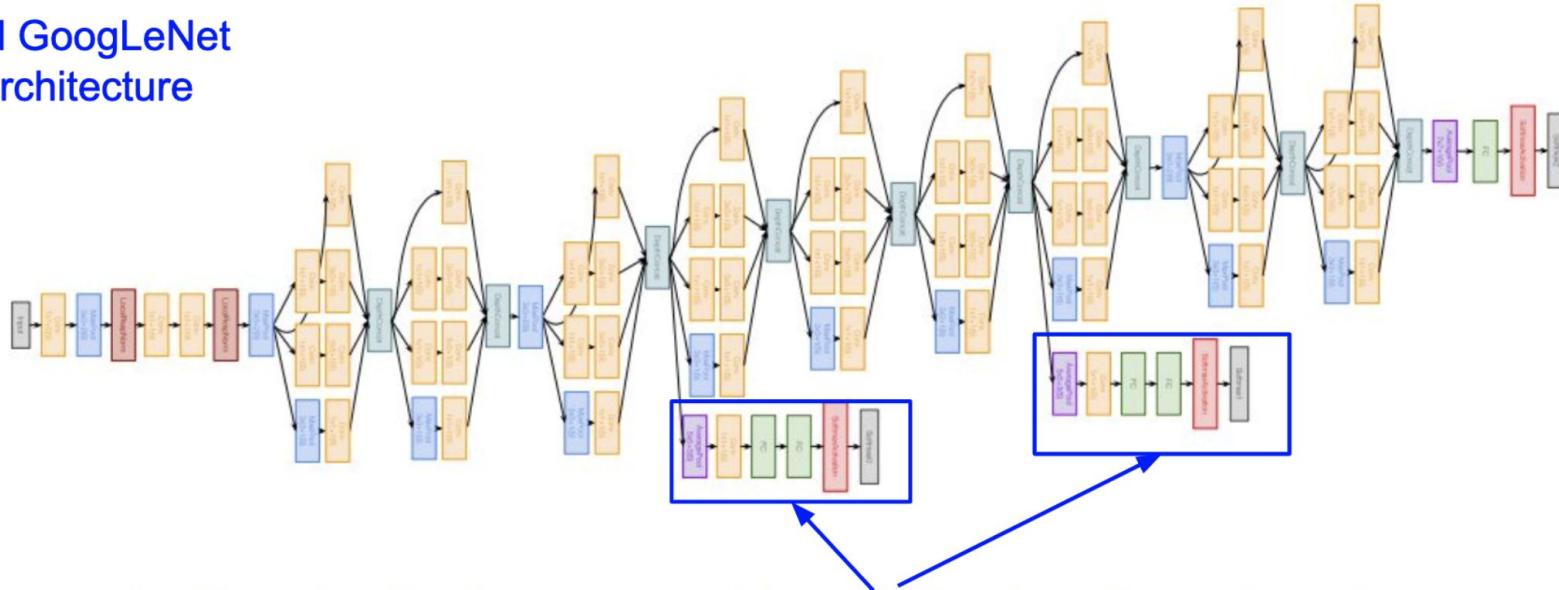


Classifier output
(removed expensive FC layers!)

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

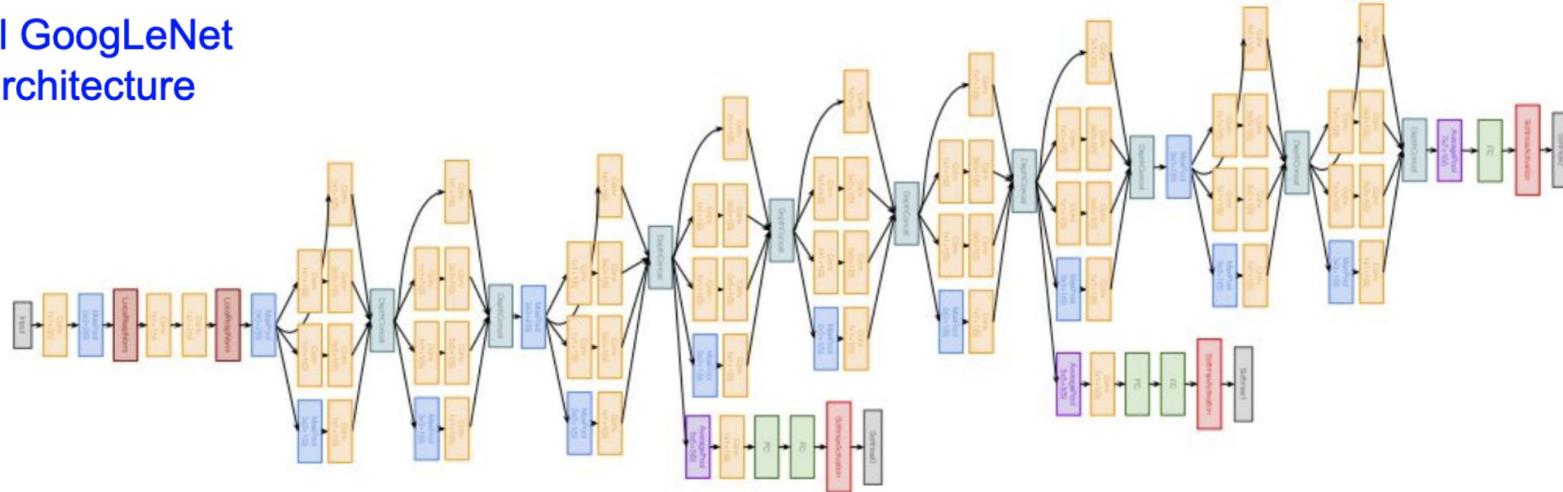


Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture



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

Case Study: GoogLeNet

[Szegedy et al., 2014]

Deeper networks, with computational efficiency

- 22 layers
- Efficient “Inception” module
- No FC layers
- 12x less params than AlexNet
- ILSVRC’14 classification winner (6.7% top 5 error)

