

Lecture 9: CNN Architectures

Administrative

A2 due Thu May 4

Midterm: In-class Tue May 9. Covers material through Thu May 4 lecture.

Poster session: Tue June 6, 12-3pm

Last time: Deep learning frameworks

Caffe
(UC Berkeley)



Caffe2
(Facebook)

Torch
(NYU / Facebook)



PyTorch
(Facebook)

Theano
(U Montreal)



TensorFlow
(Google)

Paddle
(Baidu)

CNTK
(Microsoft)

MXNet
(Amazon)
Developed by U Washington, CMU, MIT, Hong Kong U, etc but main framework of choice at AWS

And others...

Last time: Deep learning frameworks

- (1) Easily build big computational graphs
- (2) Easily compute gradients in computational graphs
- (3) Run it all efficiently on GPU (wrap cuDNN, cuBLAS, etc)


Last time: Deep learning frameworks

Modularized layers that
define forward and
backward pass

```
class ReLU(torch.autograd.Function):  
    def forward(self, x):  
        self.save_for_backward(x)  
        return x.clamp(min=0)  
  
    def backward(self, grad_y):  
        x, = self.saved_tensors  
        grad_input = grad_y.clone()  
        grad_input[x < 0] = 0  
        return grad_input
```

Last time: Deep learning frameworks

Define model architecture
as a sequence of layers



```
import torch
from torch.autograd import Variable

N, D_in, H, D_out = 64, 1000, 100, 10
x = Variable(torch.randn(N, D_in))
y = Variable(torch.randn(N, D_out), requires_grad=False)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out))
loss_fn = torch.nn.MSELoss(size_average=False)

learning_rate = 1e-4
for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    model.zero_grad()
    loss.backward()

    for param in model.parameters():
        param.data -= learning_rate * param.grad.data
```

Today: CNN Architectures

Case Studies

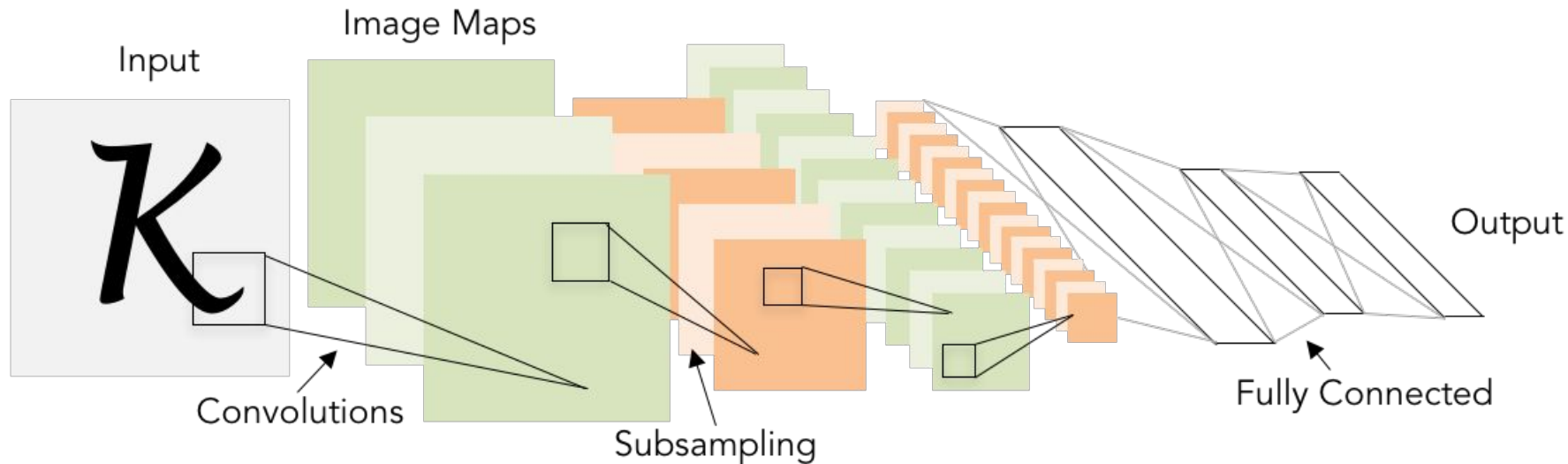
- AlexNet
- VGG
- GoogLeNet
- ResNet

Also....

- NiN (Network in Network)
- Wide ResNet
- ResNeXT
- Stochastic Depth
- DenseNet
- FractalNet
- SqueezeNet

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]

Case Study: AlexNet

[Krizhevsky et al. 2012]

Architecture:

CONV1

MAX POOL1

NORM1

CONV2

MAX POOL2

NORM2

CONV3

CONV4

CONV5

Max POOL3

FC6

FC7

FC8

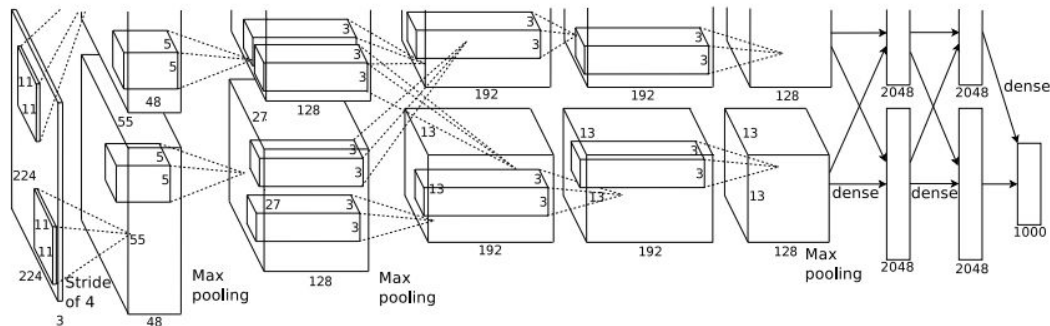
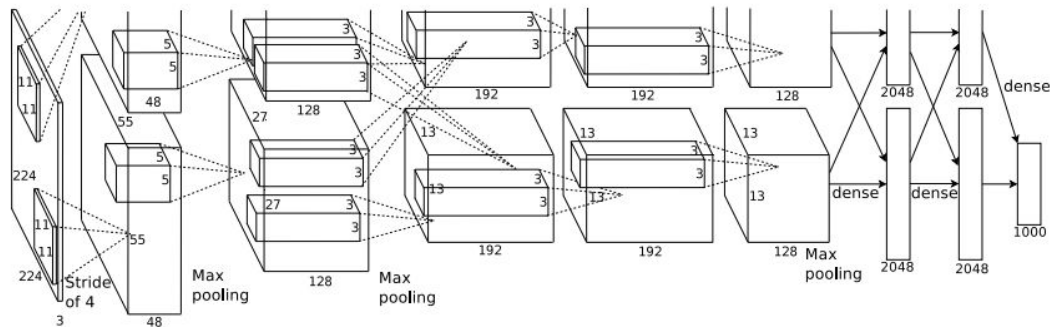


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Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

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

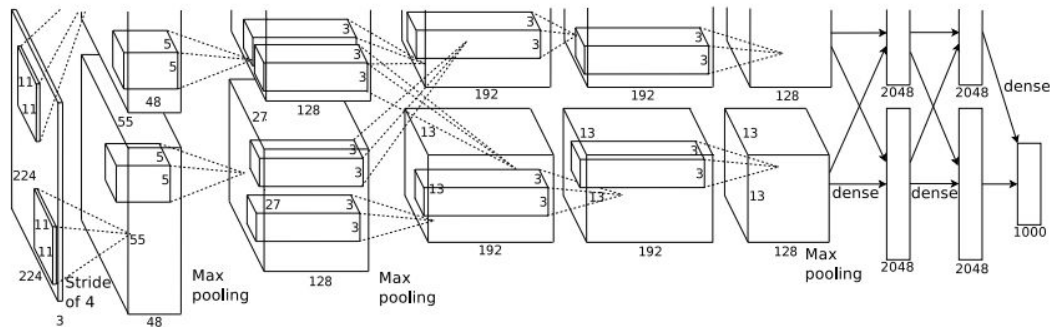
=>

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

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Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

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

=>

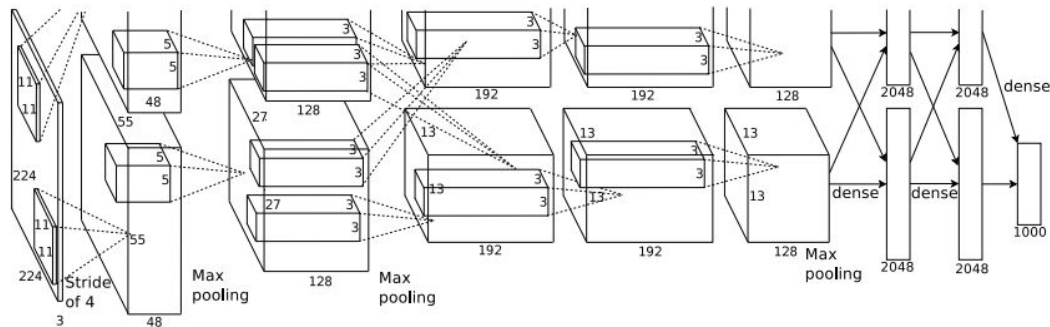
Output volume **[55x55x96]**

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

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Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

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

=>

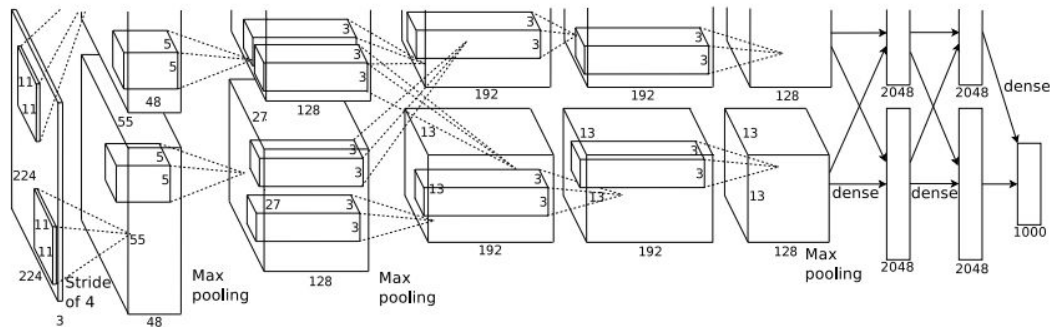
Output volume **[55x55x96]**

Parameters: $(11*11*3)*96 = \mathbf{35K}$

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Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

After CONV1: 55x55x96

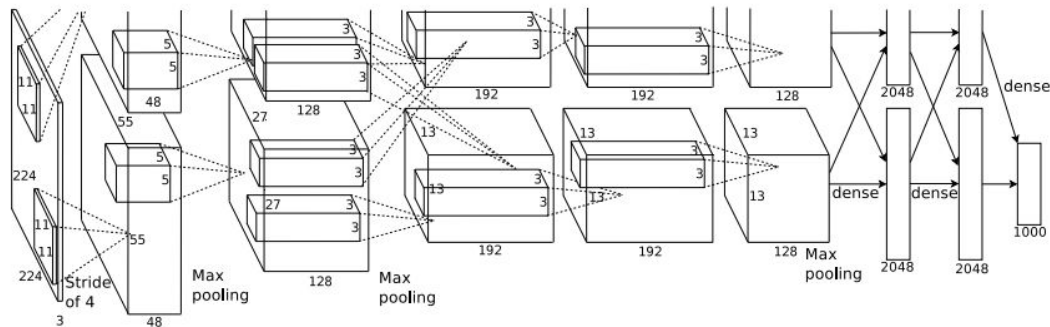
Second layer (POOL1): 3x3 filters applied at stride 2

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

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Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

After CONV1: 55x55x96

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

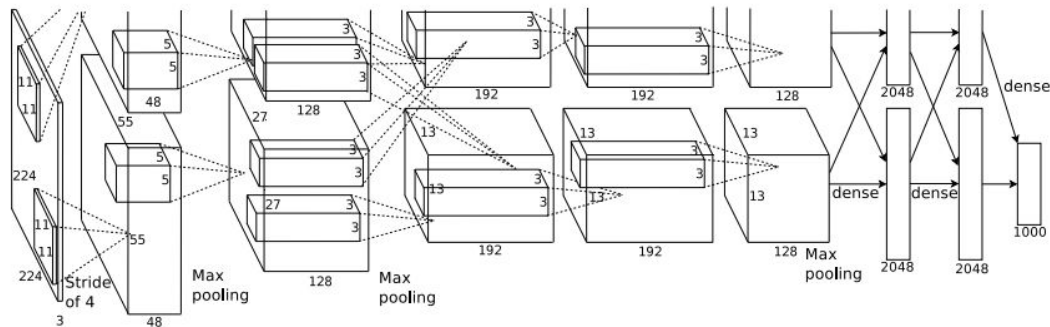
Output volume: 27x27x96

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

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Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

After CONV1: 55x55x96

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

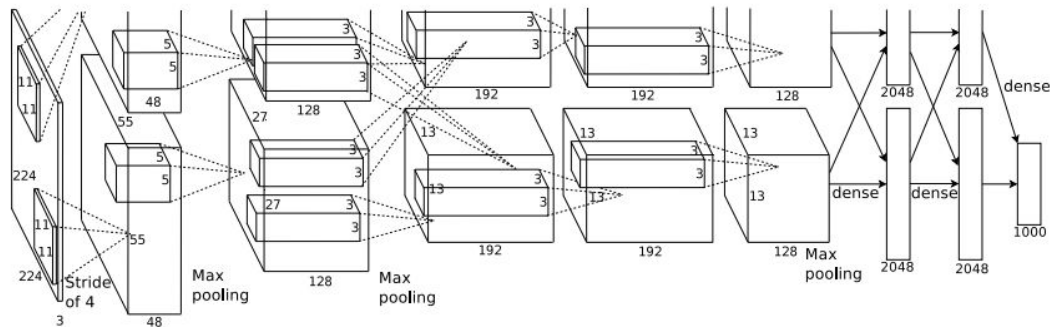
Output volume: 27x27x96

Parameters: 0!

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

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

After CONV1: 55x55x96

After POOL1: 27x27x96

...

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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)

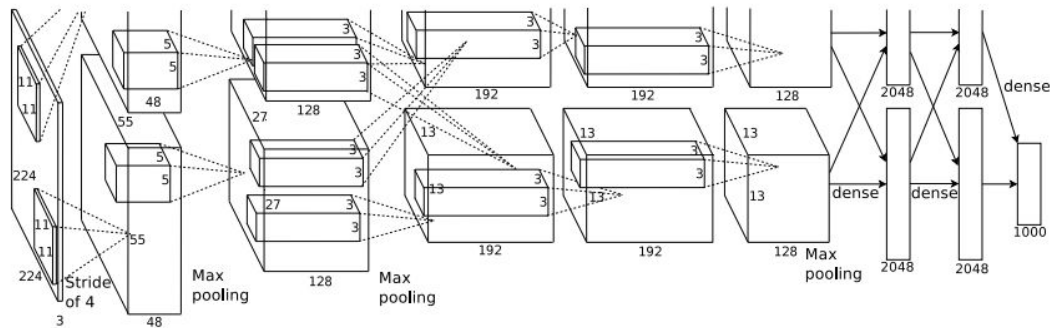


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Case Study: AlexNet

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Full (simplified) AlexNet architecture:

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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

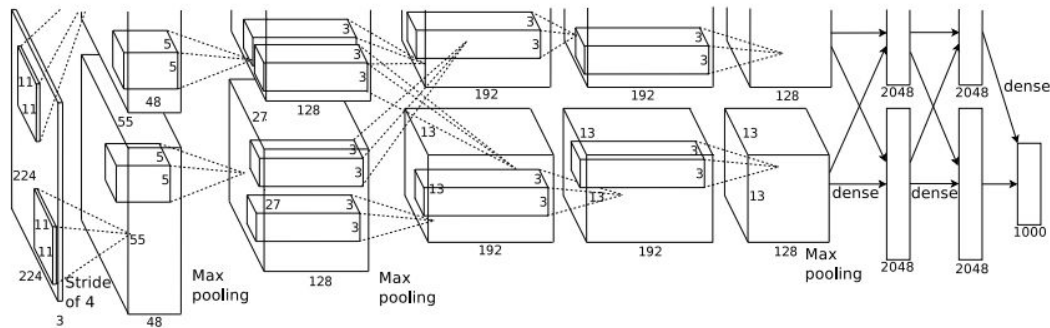
[13x13x256] **CONV5**: 256 3x3 filters at stride 1, pad 1

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

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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

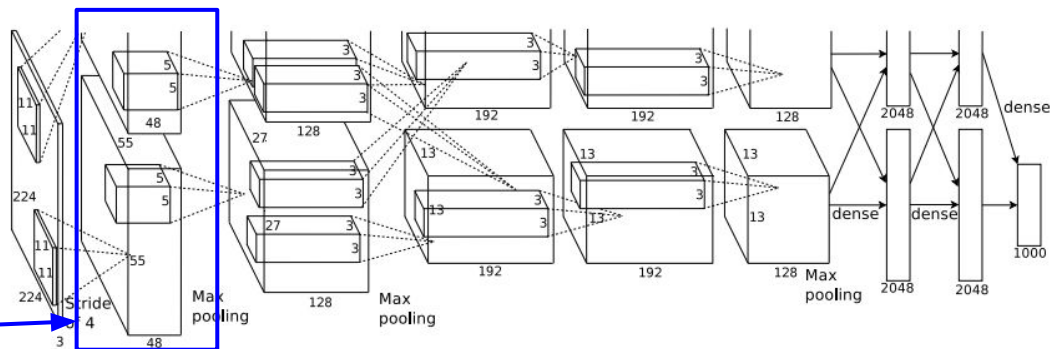
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1

[6x6x256] MAX POOL3: 3x3 filters at stride 2

[4096] FC6: 4096 neurons

[4096] FC7: 4096 neurons

[1000] FC8: 1000 neurons (class scores)



[55x55x48] x 2

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.

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Case Study: AlexNet

[Krizhevsky et al. 2012]

Full (simplified) AlexNet architecture:

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[13x13x256] **NORM2**: Normalization layer

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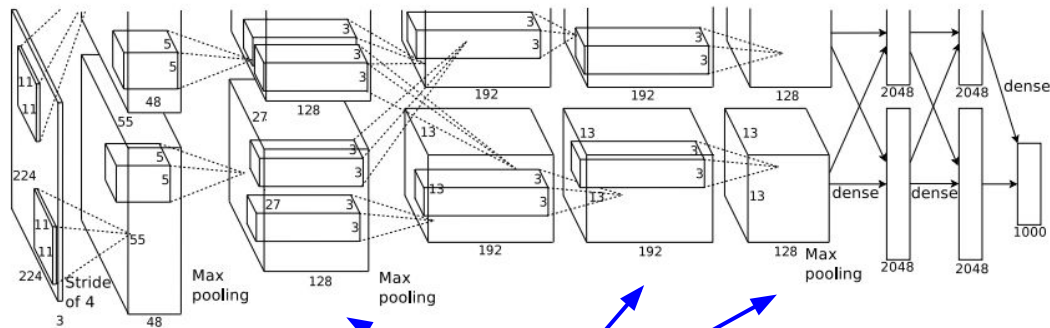
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[4096] **FC6**: 4096 neurons

[4096] **FC7**: 4096 neurons

[1000] **FC8**: 1000 neurons (class scores)



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

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Case Study: AlexNet

[Krizhevsky et al. 2012]

Full (simplified) AlexNet architecture:

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[13x13x256] **NORM2**: Normalization layer

[13x13x384] **CONV3**: 384 3x3 filters at stride 1, pad 1

[13x13x384] **CONV4**: 384 3x3 filters at stride 1, pad 1

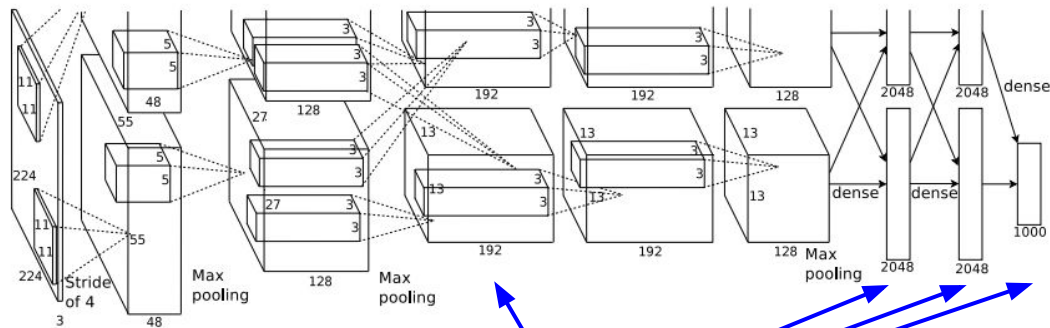
[13x13x256] **CONV5**: 256 3x3 filters at stride 1, pad 1

[6x6x256] **MAX POOL3**: 3x3 filters at stride 2

[4096] **FC6**: 4096 neurons

[4096] **FC7**: 4096 neurons

[1000] **FC8**: 1000 neurons (class scores)



CONV3, FC6, FC7, FC8:

Connections with all feature maps in preceding layer, communication across GPUs

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ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

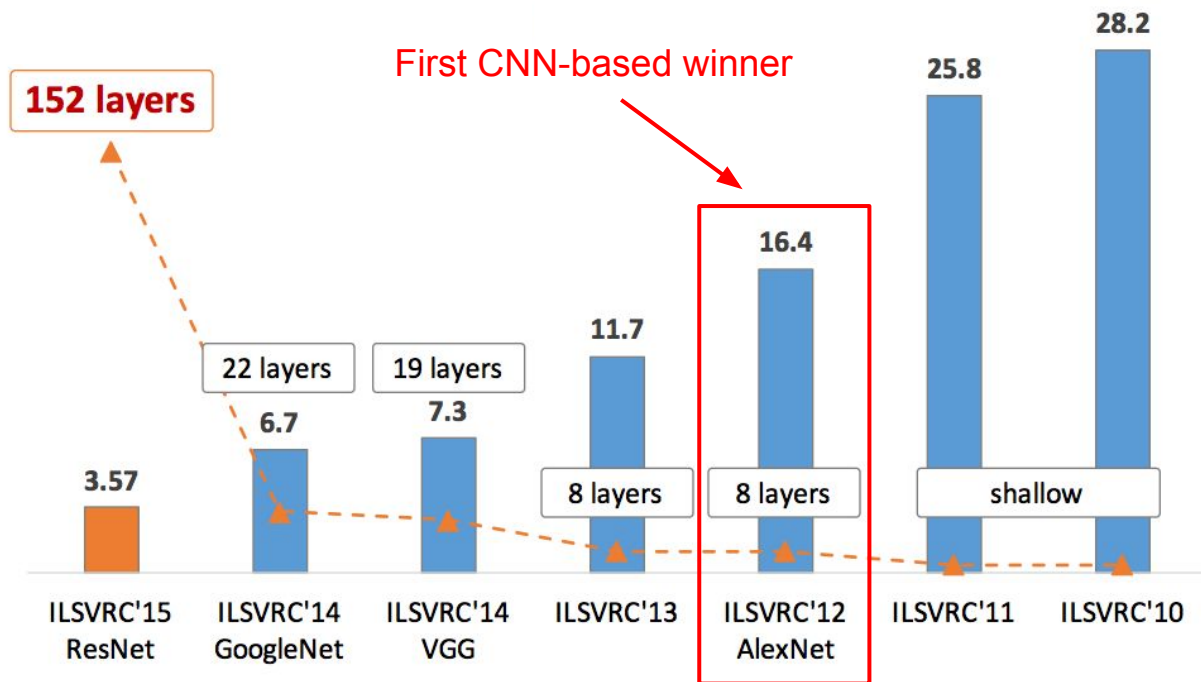


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ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

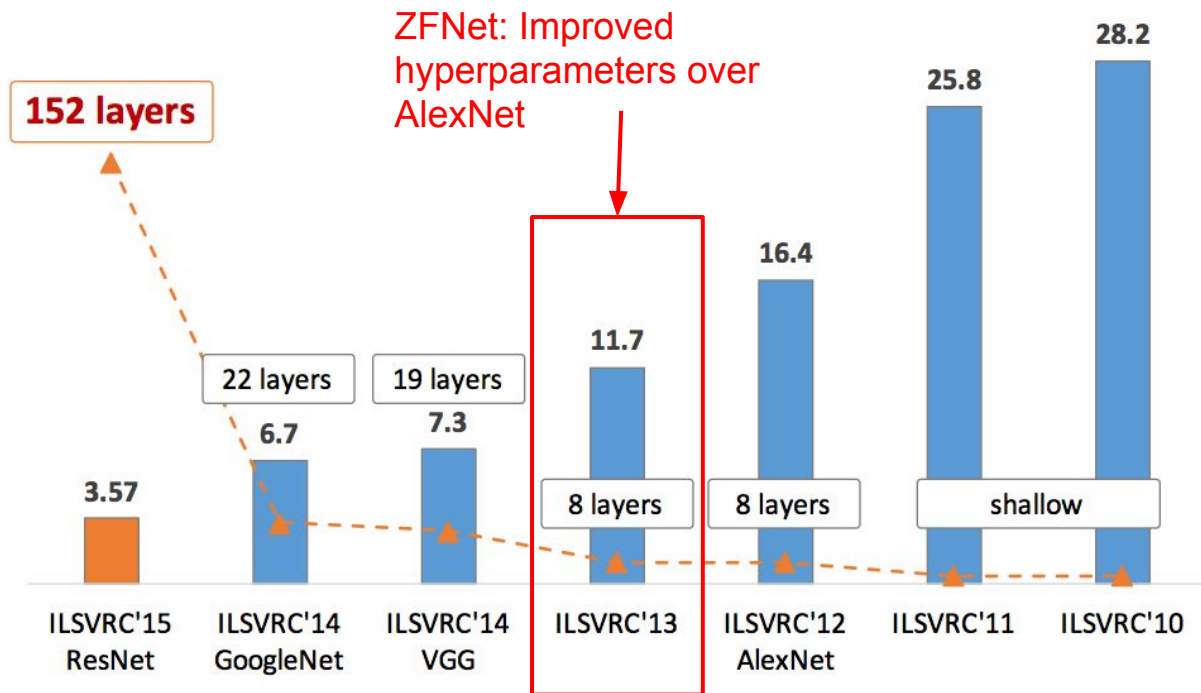
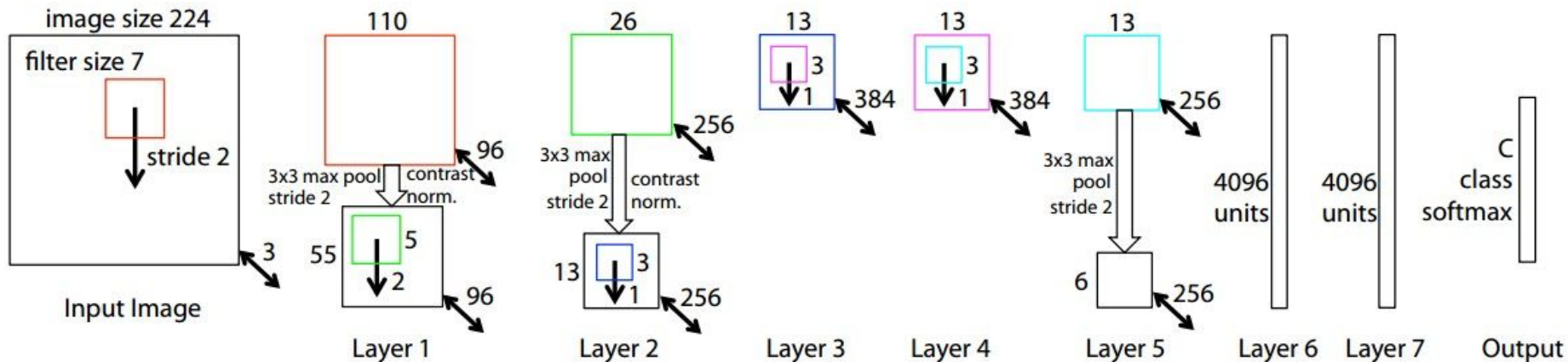


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ZFNet

[Zeiler and Fergus, 2013]



TODO: remake figure

AlexNet but:

CONV1: change from (11x11 stride 4) to (7x7 stride 2)

CONV3,4,5: instead of 384, 384, 256 filters use 512, 1024, 512

ImageNet top 5 error: 16.4% -> 11.7%

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

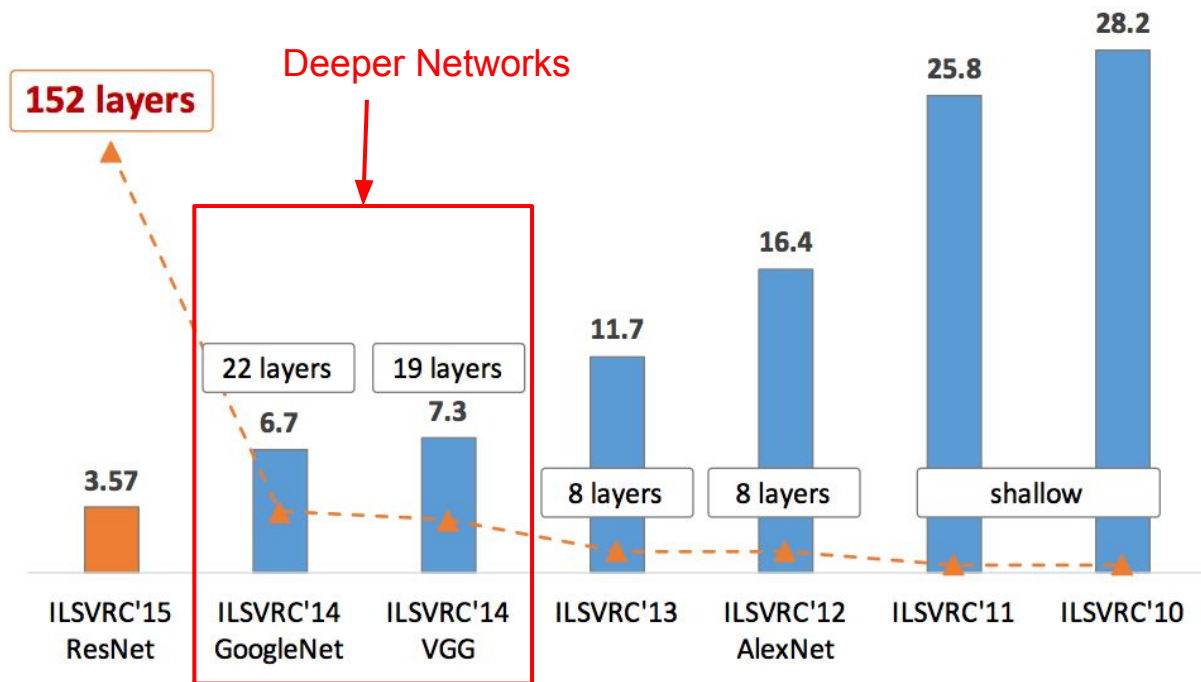


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Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Small filters, Deeper networks

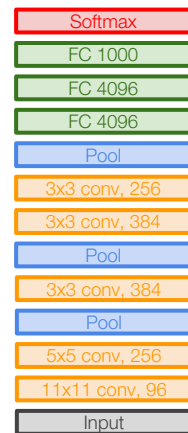
8 layers (AlexNet)

-> 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)

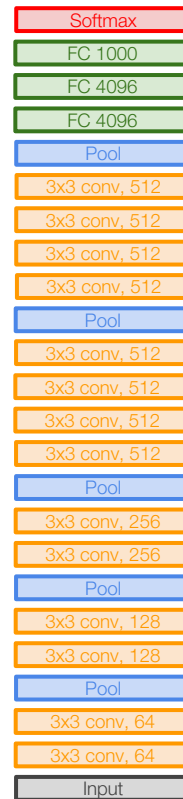
-> 7.3% top 5 error in ILSVRC'14



AlexNet



VGG16

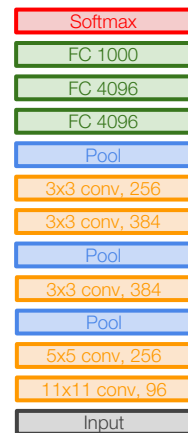


VGG19

Case Study: VGGNet

[Simonyan and Zisserman, 2014]

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



AlexNet



VGG16

VGG19

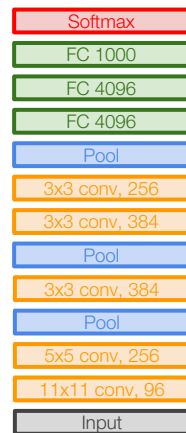
Case Study: VGGNet

[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

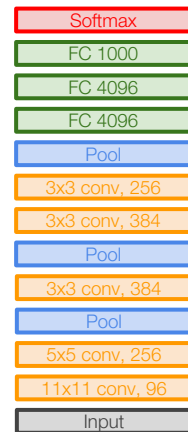
Case Study: VGGNet

[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

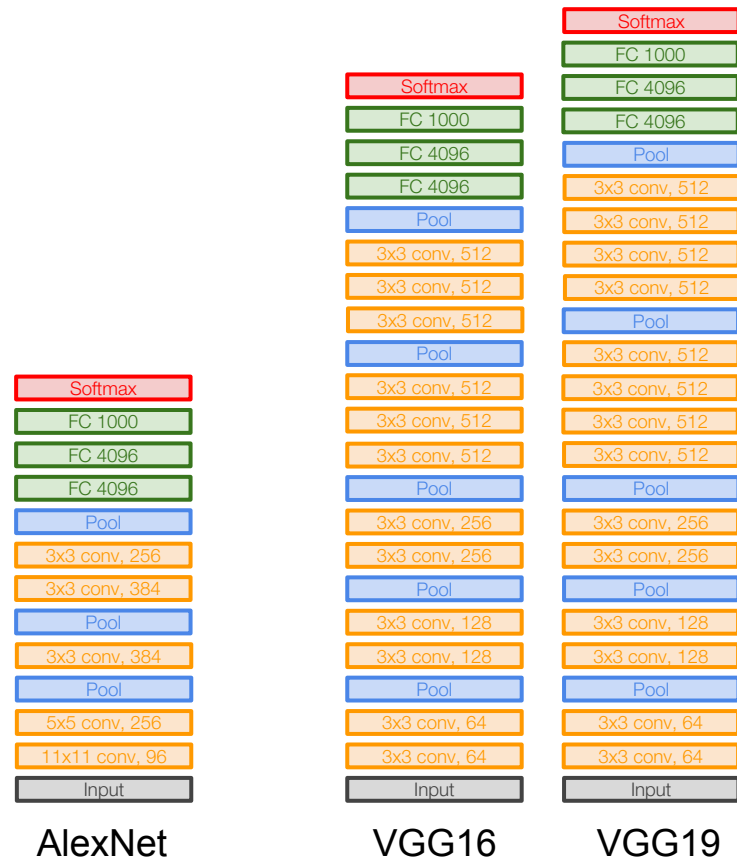
[Simonyan and Zisserman, 2014]

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



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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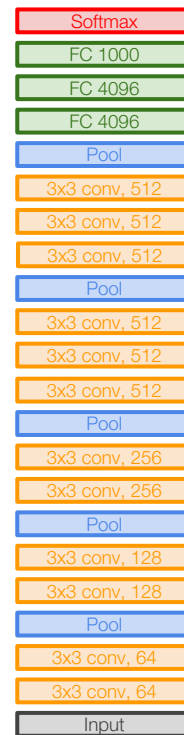
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296

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



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

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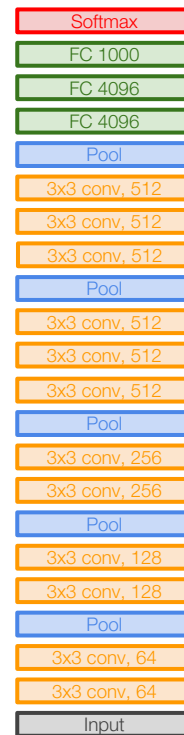
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FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448

FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216

FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000



VGG16

TOTAL memory: 24M * 4 bytes \approx 96MB / image (only forward! \sim *2 for bwd)

TOTAL params: 138M parameters

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

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

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

POOL2: [112x112x64] memory: $112*112*64=800\text{K}$ params: 0

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

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

POOL2: [56x56x128] memory: $56*56*128=400\text{K}$ params: 0

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

CONV3-256: [56x56x256] memory: $56*56*256=800\text{K}$ params: $(3*3*256)*256 = 589,824$

CONV3-256: [56x56x256] memory: $56*56*256=800\text{K}$ params: $(3*3*256)*256 = 589,824$

POOL2: [28x28x256] memory: $28*28*256=200\text{K}$ params: 0

CONV3-512: [28x28x512] memory: $28*28*512=400\text{K}$ params: $(3*3*256)*512 = 1,179,648$

CONV3-512: [28x28x512] memory: $28*28*512=400\text{K}$ params: $(3*3*512)*512 = 2,359,296$

CONV3-512: [28x28x512] memory: $28*28*512=400\text{K}$ params: $(3*3*512)*512 = 2,359,296$

POOL2: [14x14x512] memory: $14*14*512=100\text{K}$ params: 0

CONV3-512: [14x14x512] memory: $14*14*512=100\text{K}$ params: $(3*3*512)*512 = 2,359,296$

CONV3-512: [14x14x512] memory: $14*14*512=100\text{K}$ params: $(3*3*512)*512 = 2,359,296$

CONV3-512: [14x14x512] memory: $14*14*512=100\text{K}$ params: $(3*3*512)*512 = 2,359,296$

POOL2: [7x7x512] memory: $7*7*512=25\text{K}$ 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: $24\text{M} * 4 \text{ bytes} \approx 96\text{MB} / \text{image}$ (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

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

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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

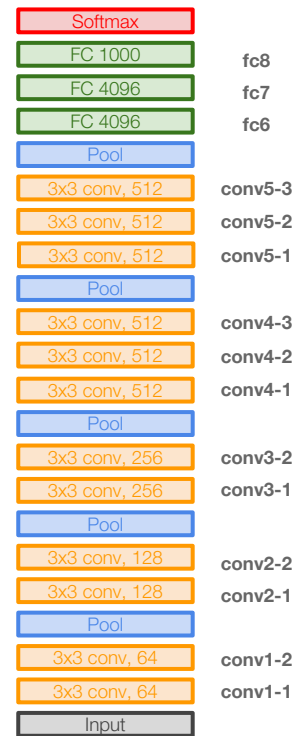
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448

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 \approx 96MB / image (only forward! \sim *2 for bwd)

TOTAL params: 138M parameters



VGG16

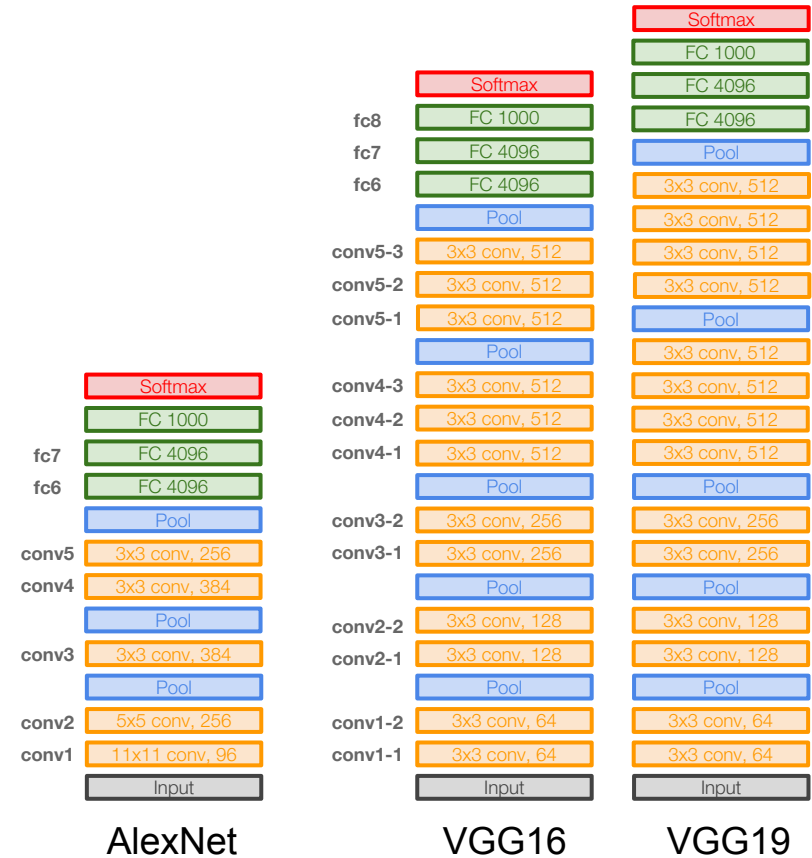
Common names

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

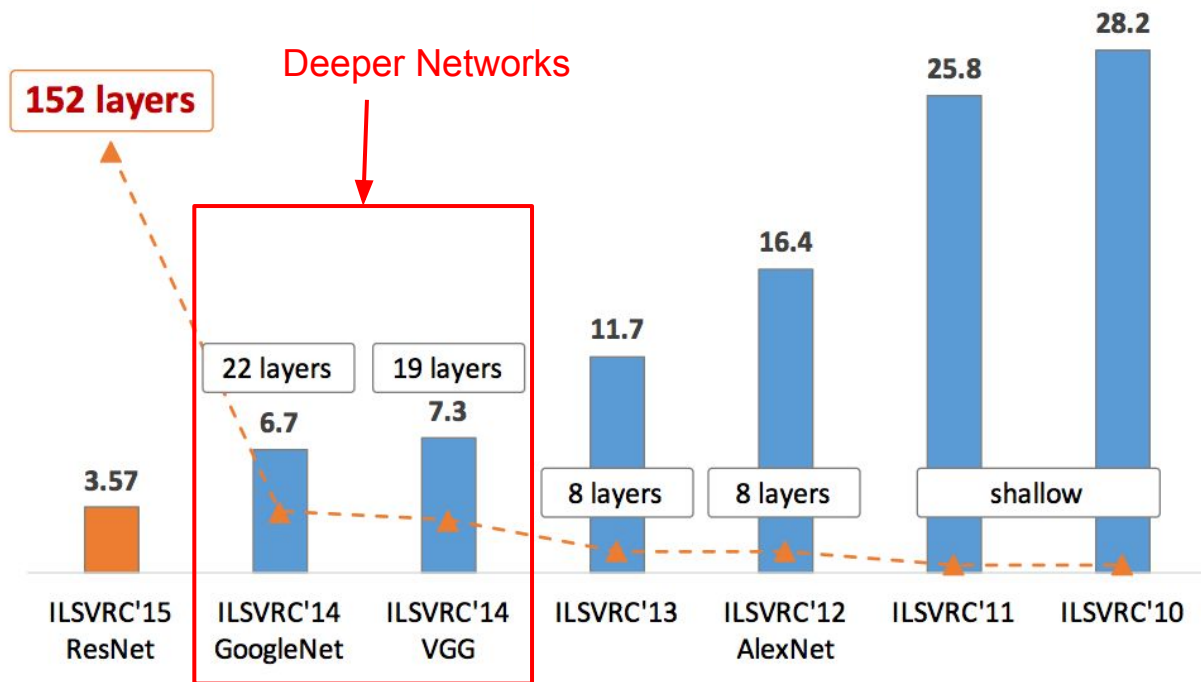


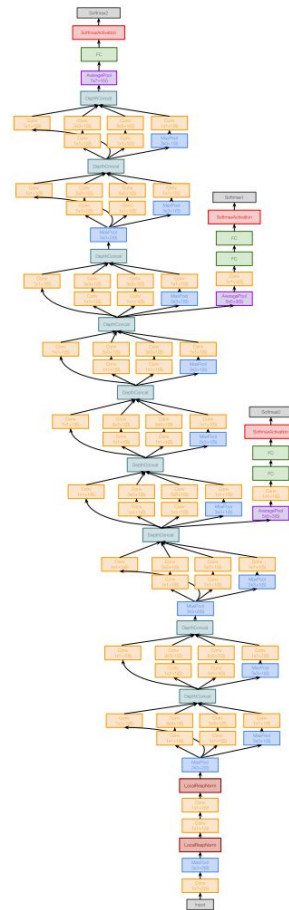
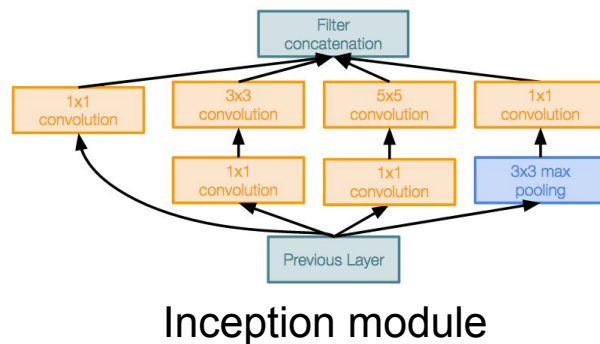
Figure copyright Kaiming He, 2016. Reproduced with permission.

Case Study: GoogLeNet

[Szegedy et al., 2014]

Deeper networks, with computational efficiency

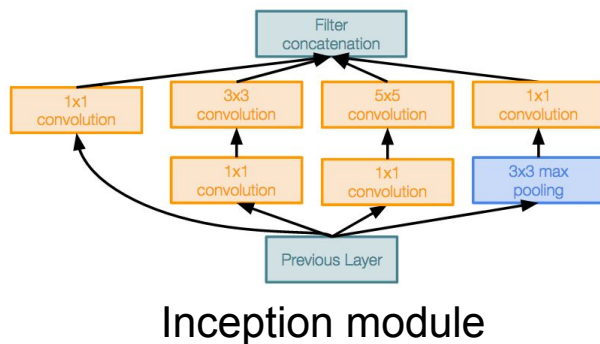
- 22 layers
- Efficient “Inception” module
- No FC layers
- Only 5 million parameters!
12x less than AlexNet
- ILSVRC’14 classification winner
(6.7% top 5 error)



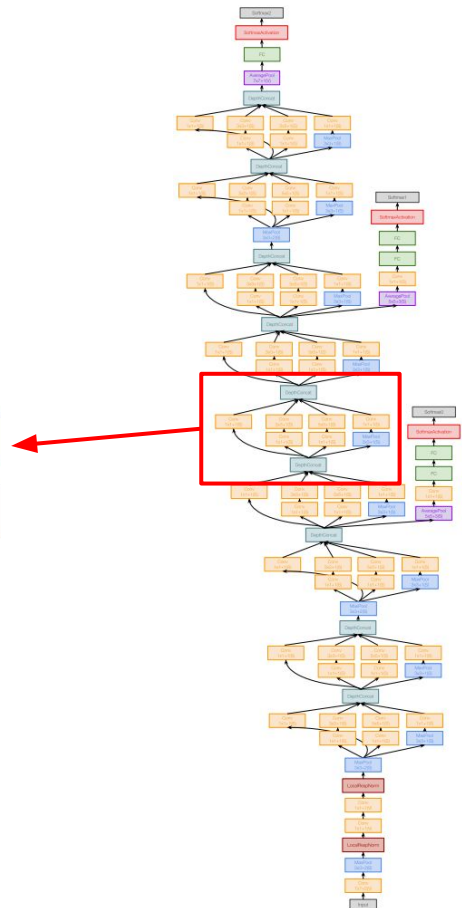
Case Study: GoogLeNet

[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

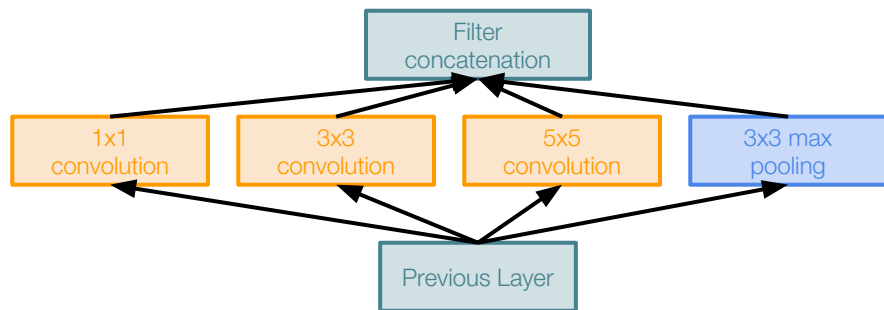


Inception module



Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

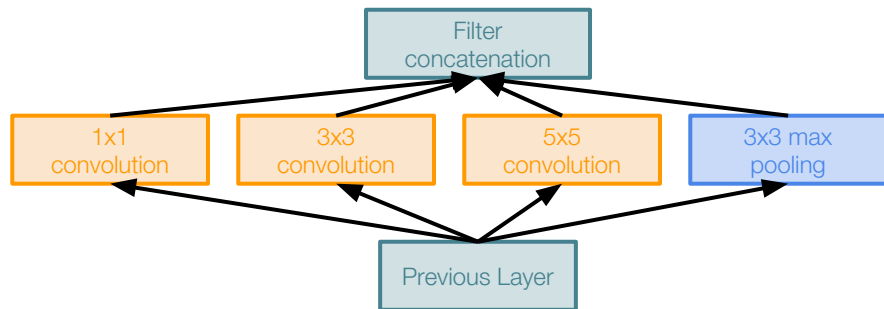
Apply parallel filter operations on the input from previous layer:

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

Concatenate all filter outputs together depth-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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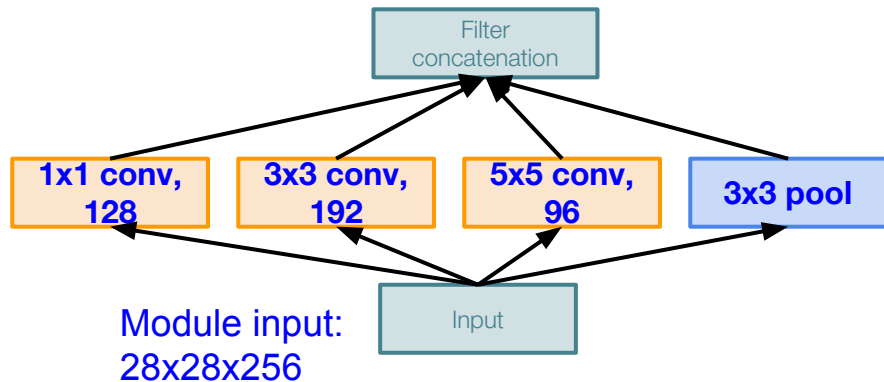
Concatenate all filter outputs together depth-wise

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

Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:



Naive Inception module

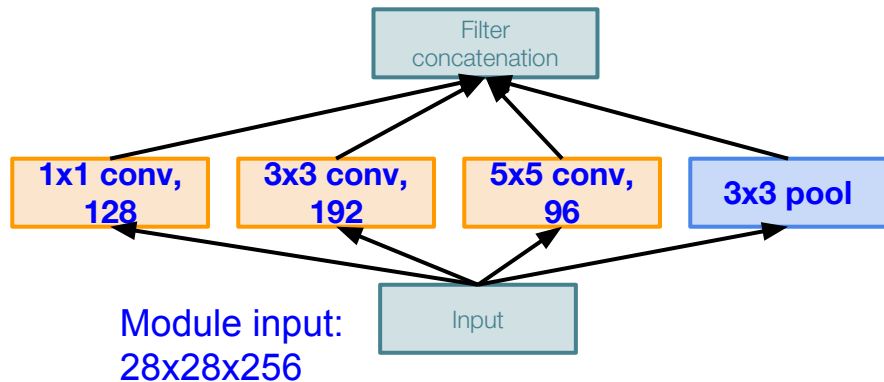
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Case Study: GoogLeNet

[Szegedy et al., 2014]

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

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



Naive Inception module

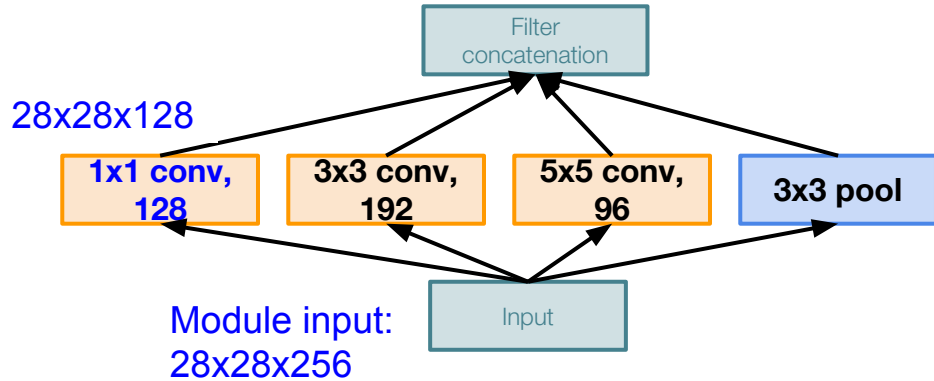
Case Study: GoogLeNet

[Szegedy et al., 2014]

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

Example:

Q1: What is the output size of the
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Naive Inception module

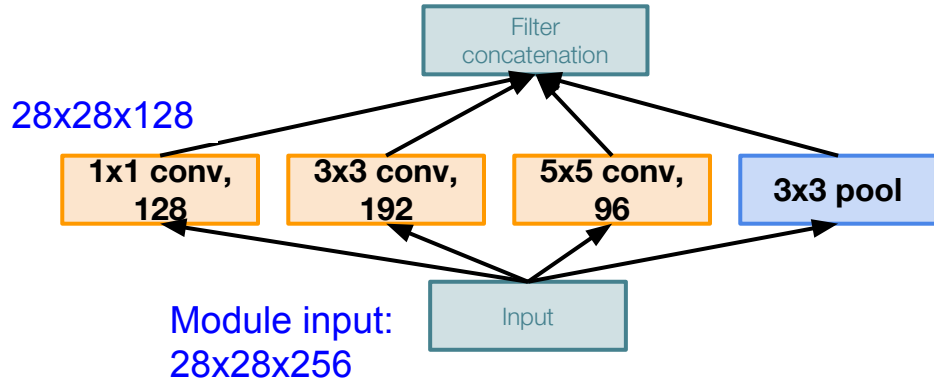
Case Study: GoogLeNet

[Szegedy et al., 2014]

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

Example:

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



Naive Inception module

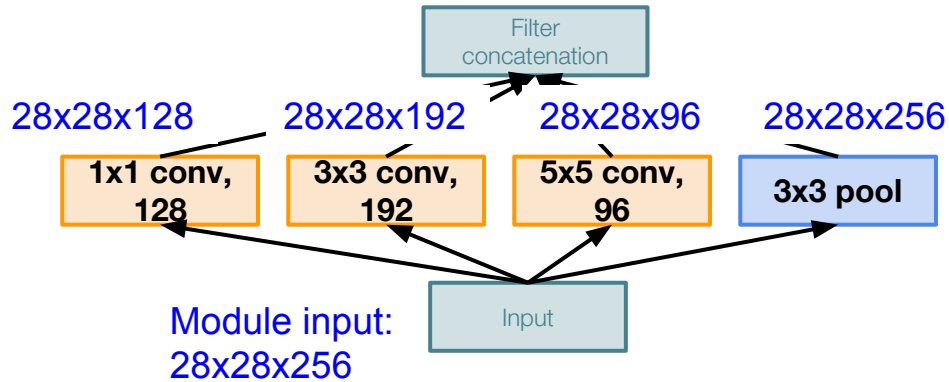
Case Study: GoogLeNet

[Szegedy et al., 2014]

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

Example:

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



Naive Inception module

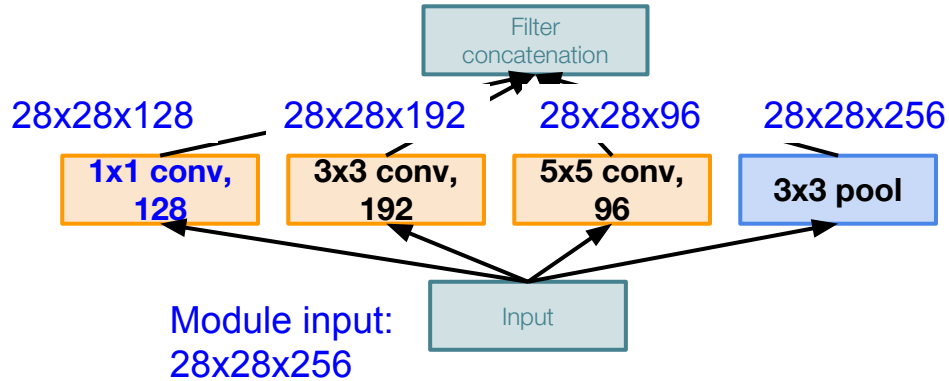
Case Study: GoogLeNet

[Szegedy et al., 2014]

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

Example:

Q3: What is output size after filter concatenation?



Naive Inception module

Case Study: GoogLeNet

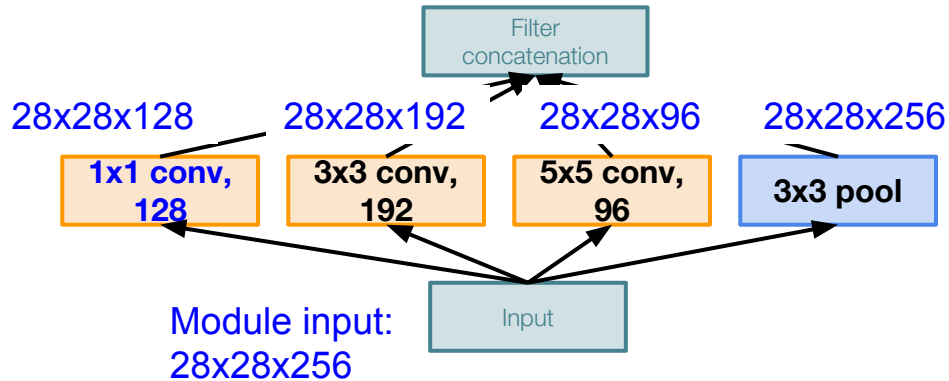
[Szegedy et al., 2014]

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

Example:

Q3: What is output size after filter concatenation?

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



Naive Inception module

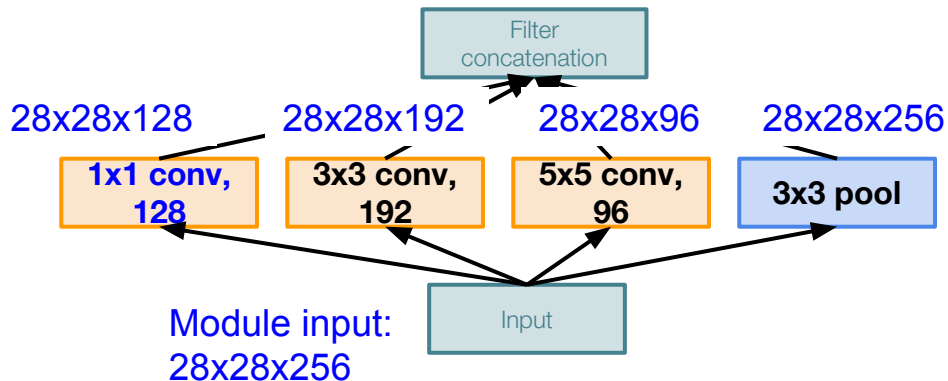
Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3: What is output size after filter concatenation?

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



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

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

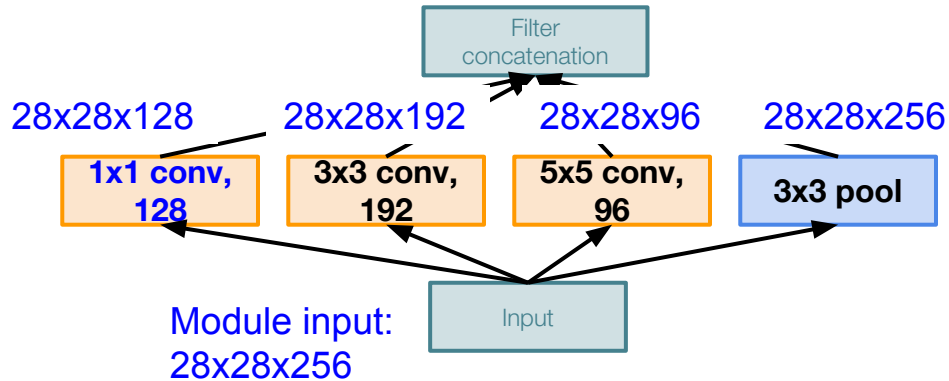
Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

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Naive Inception module

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

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[5x5 conv, 96] $28 \times 28 \times 96 \times 5 \times 5 \times 256$

Total: 854M ops

Very expensive compute

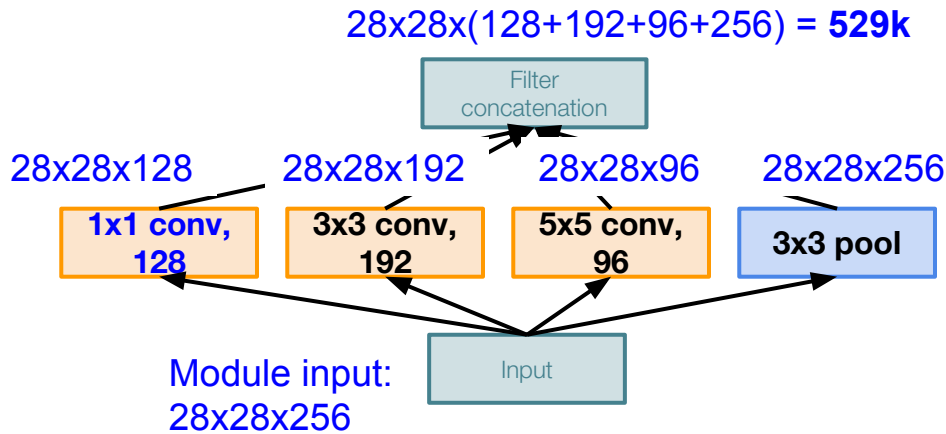
Pooling layer also preserves feature depth, which means total depth after concatenation can only grow at every layer!

Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3: What is output size after filter concatenation?

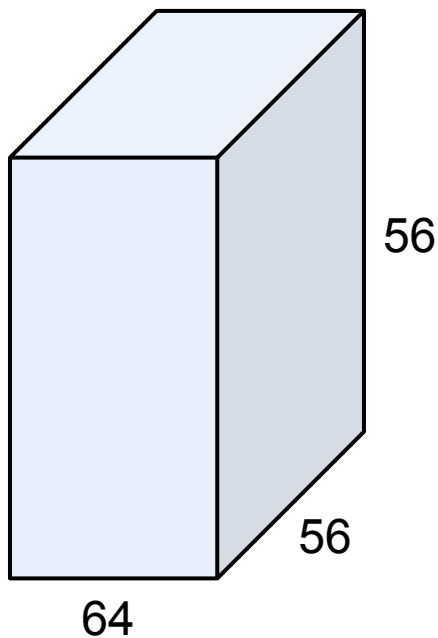


Naive Inception module

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

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

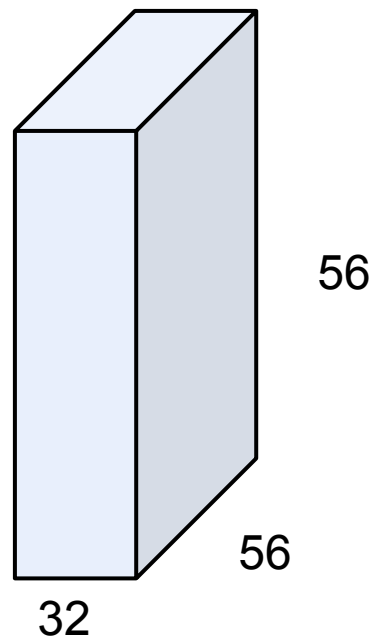
Reminder: 1x1 convolutions



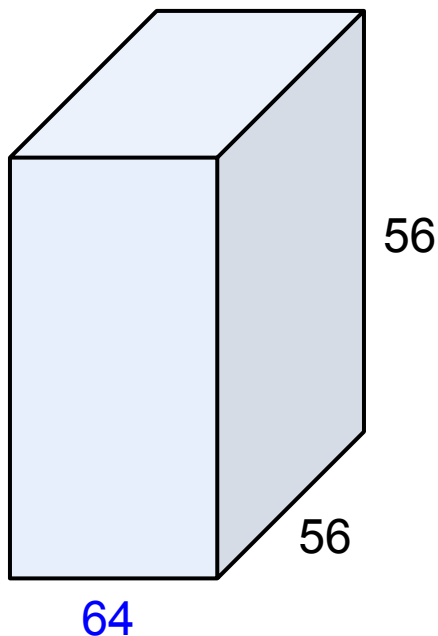
1x1 CONV
with 32 filters

→

(each filter has size
1x1x64, and performs a
64-dimensional dot
product)



Reminder: 1x1 convolutions

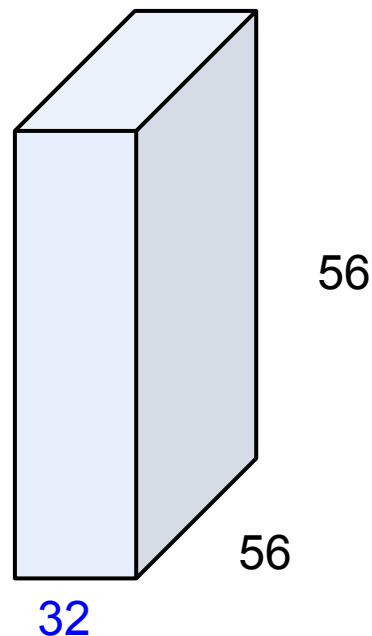


1x1 CONV
with 32 filters



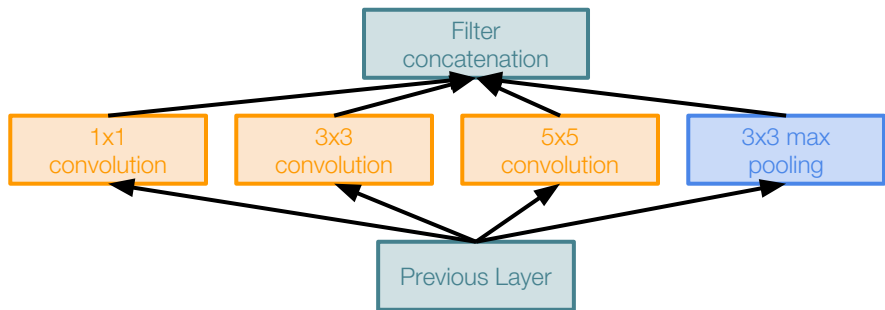
preserves spatial
dimensions, reduces depth!

Projects depth to lower
dimension (combination of
feature maps)

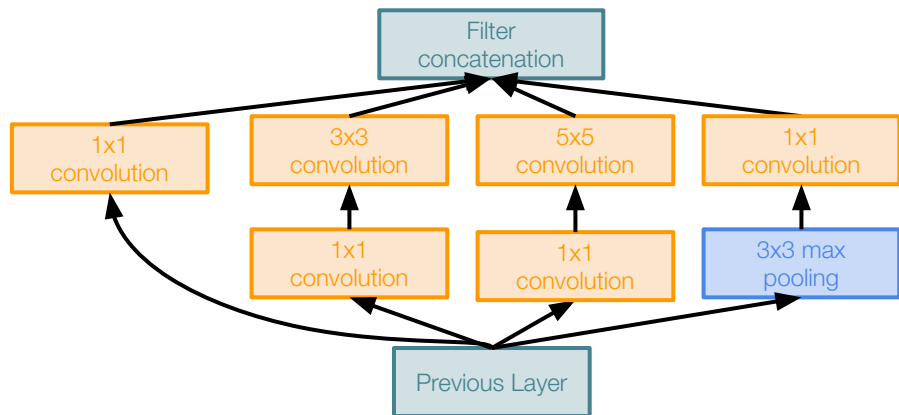


Case Study: GoogLeNet

[Szegedy et al., 2014]



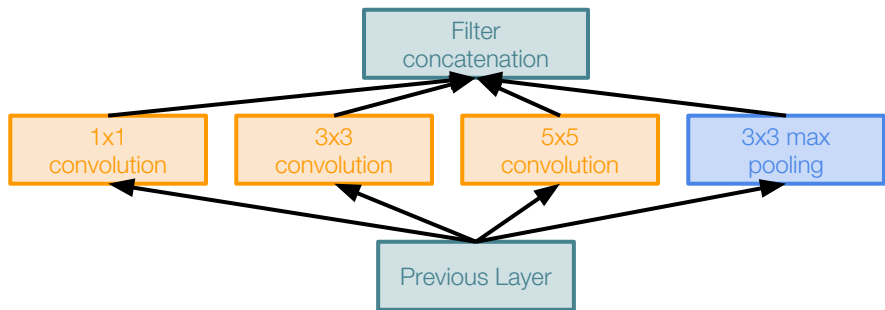
Naive Inception module



Inception module with dimension reduction

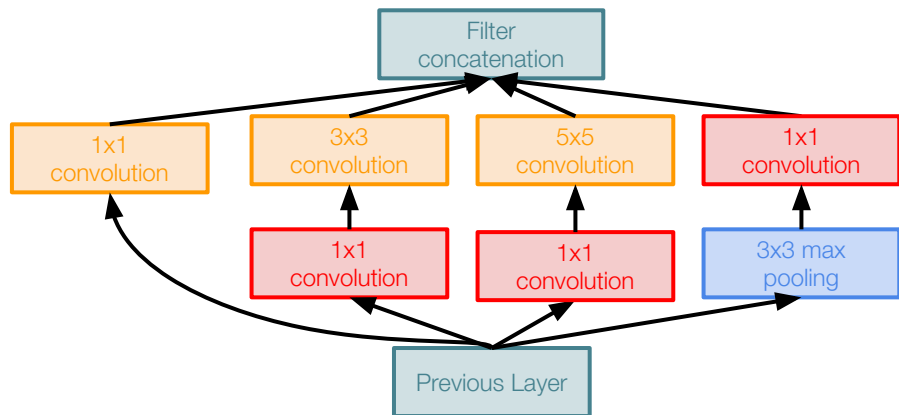
Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

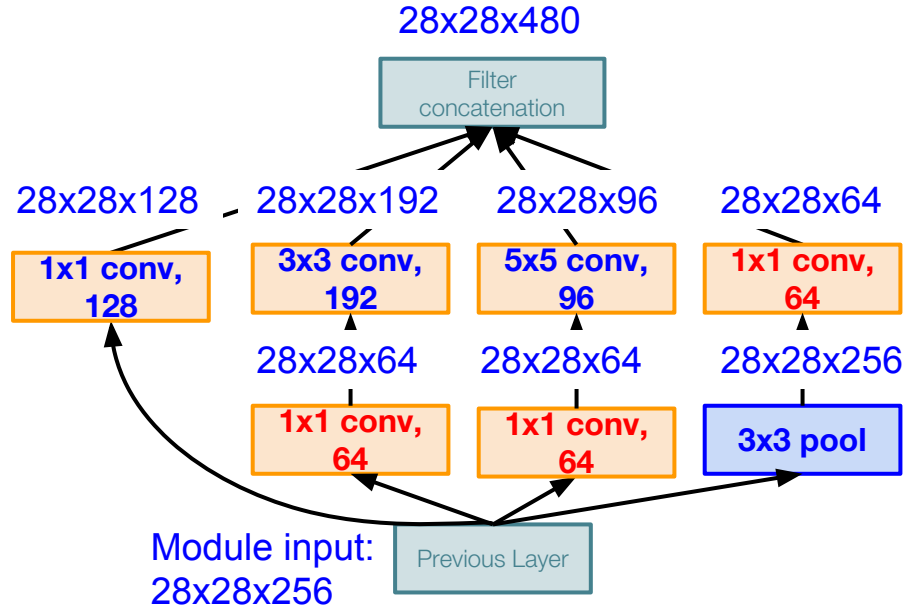
1x1 conv “bottleneck”
layers



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

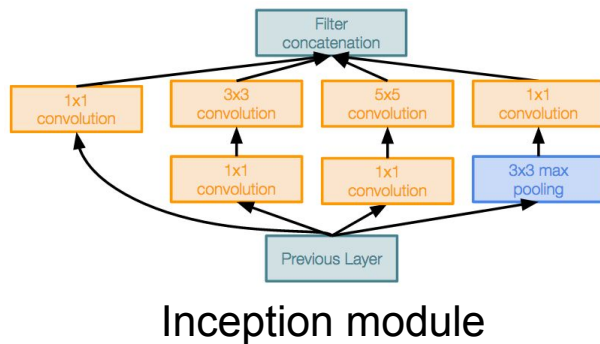
Total: 358M ops

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

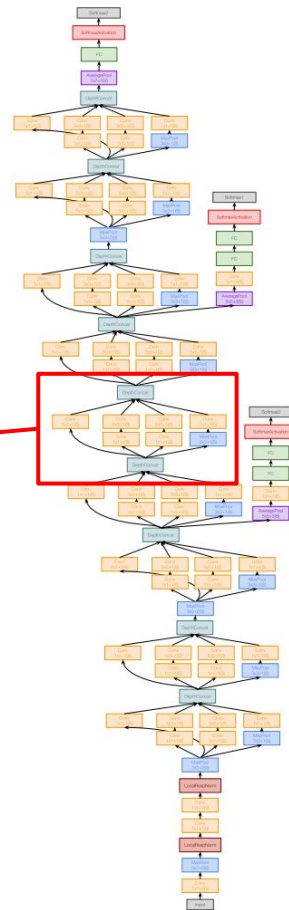
Case Study: GoogLeNet

[Szegedy et al., 2014]

Stack Inception modules with dimension reduction on top of each other



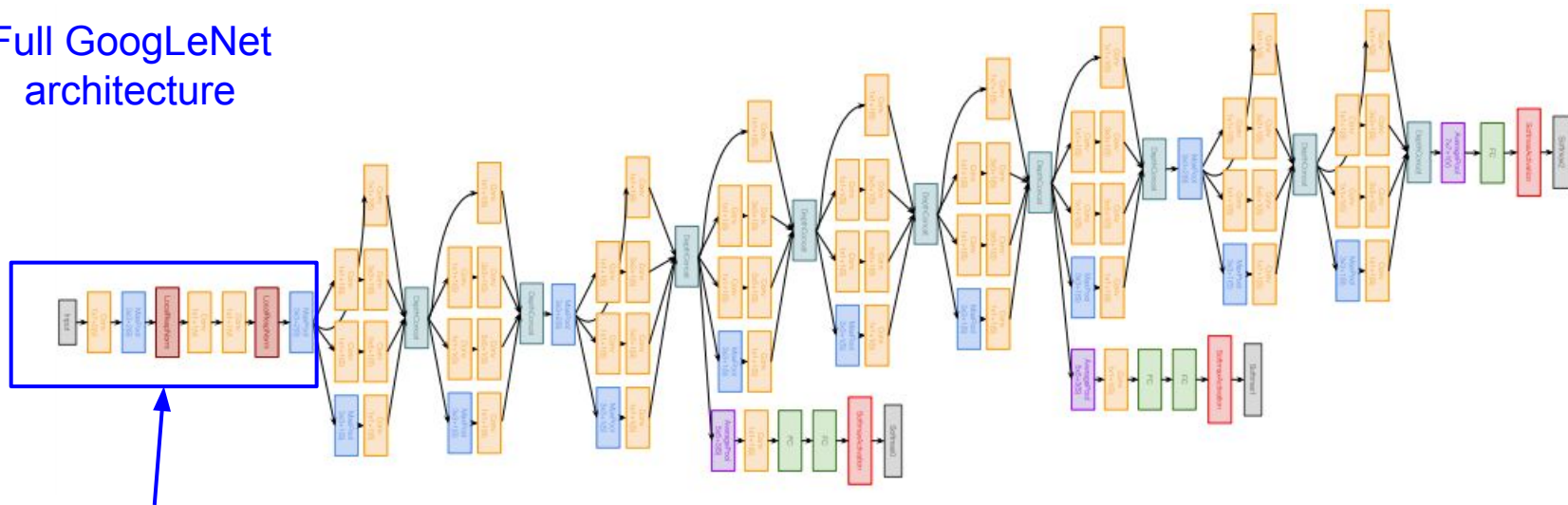
Inception module



Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

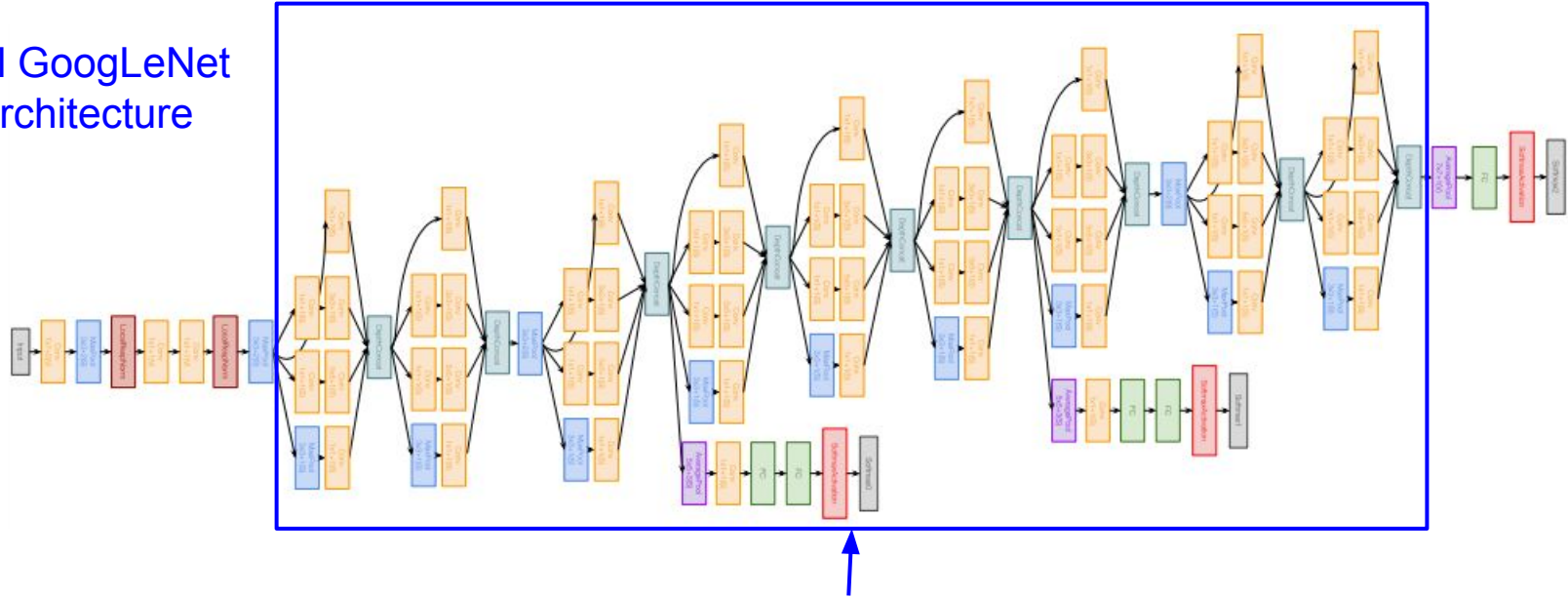


Stem Network:
Conv-Pool-
2x Conv-Pool

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

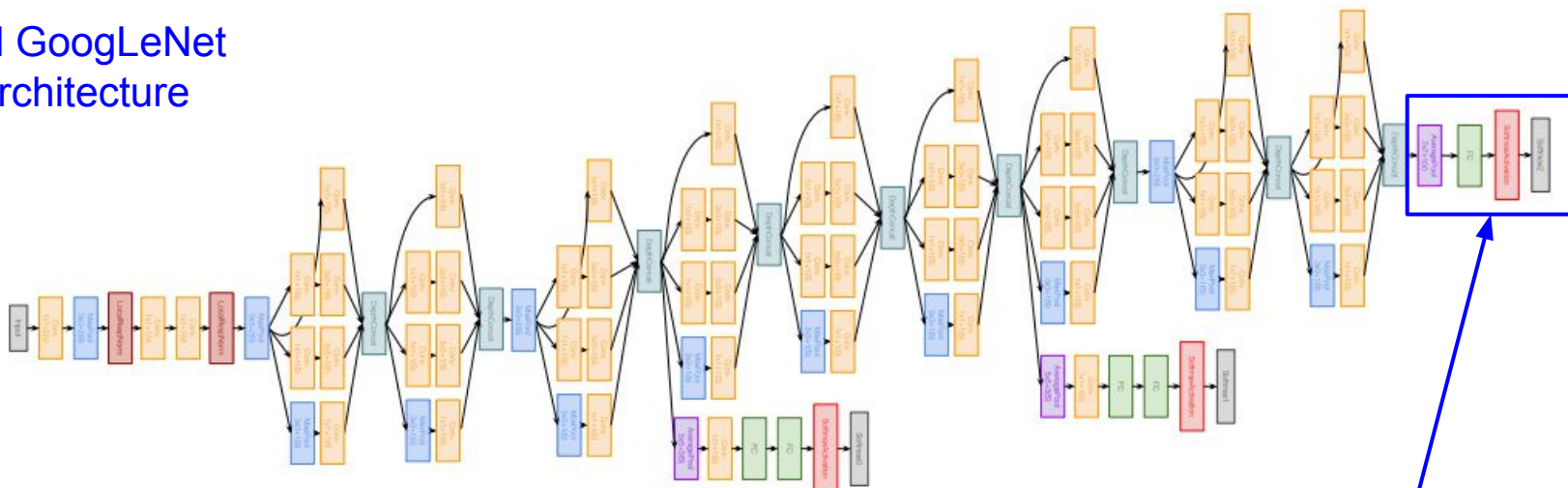


Stacked Inception
Modules

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

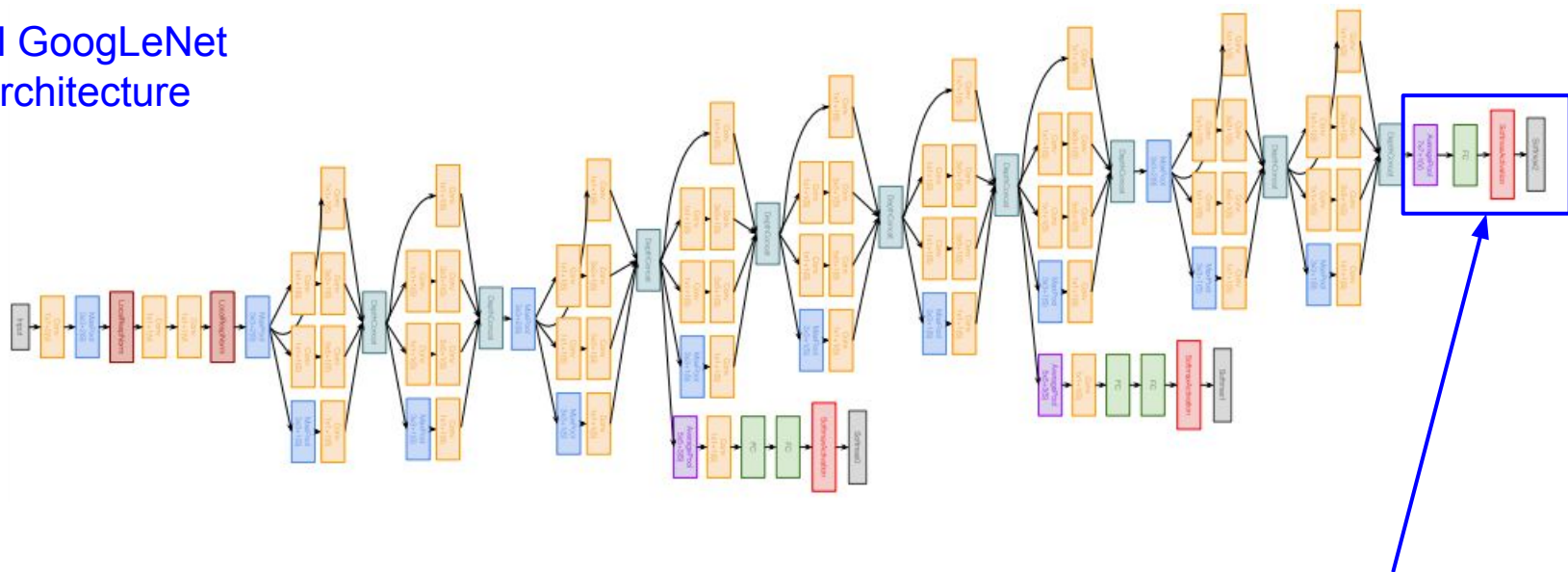


Classifier output

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

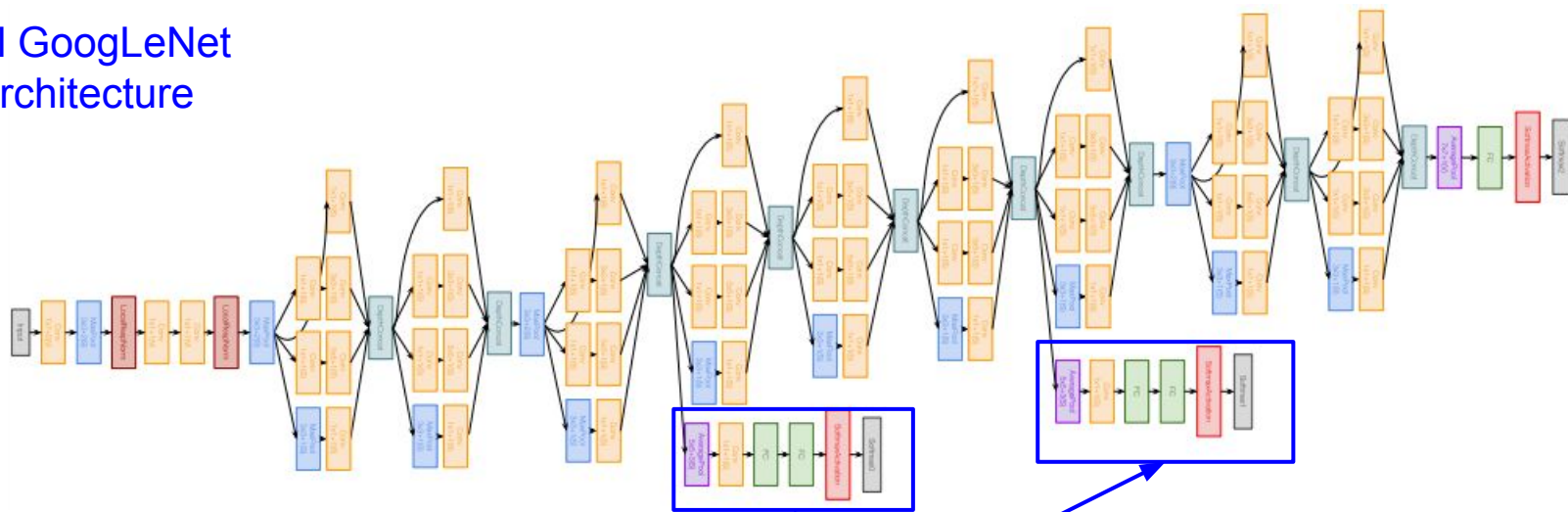


Classifier output
(removed expensive FC layers!)

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

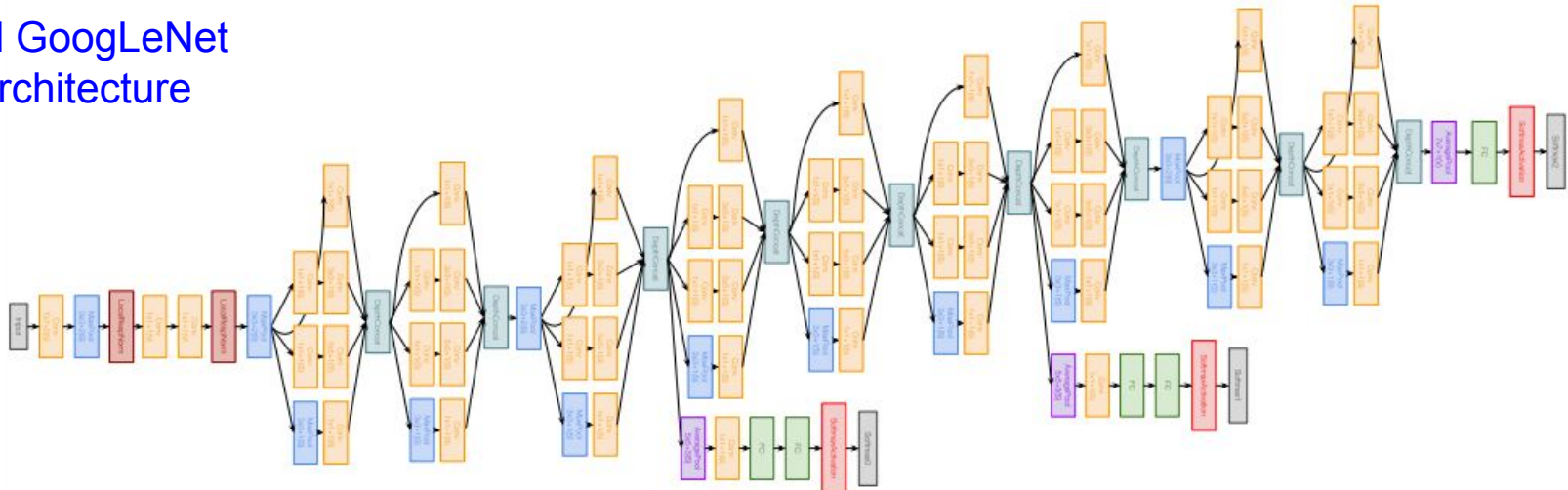


Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture



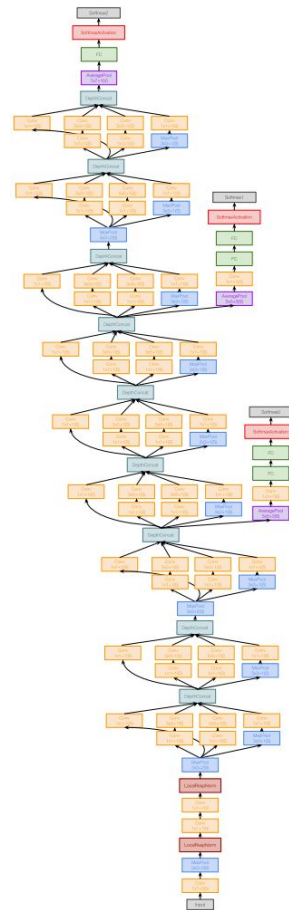
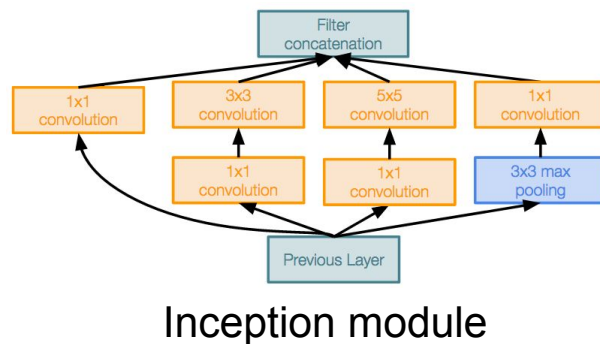
22 total layers with weights (including each parallel layer in an Inception module)

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)



ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

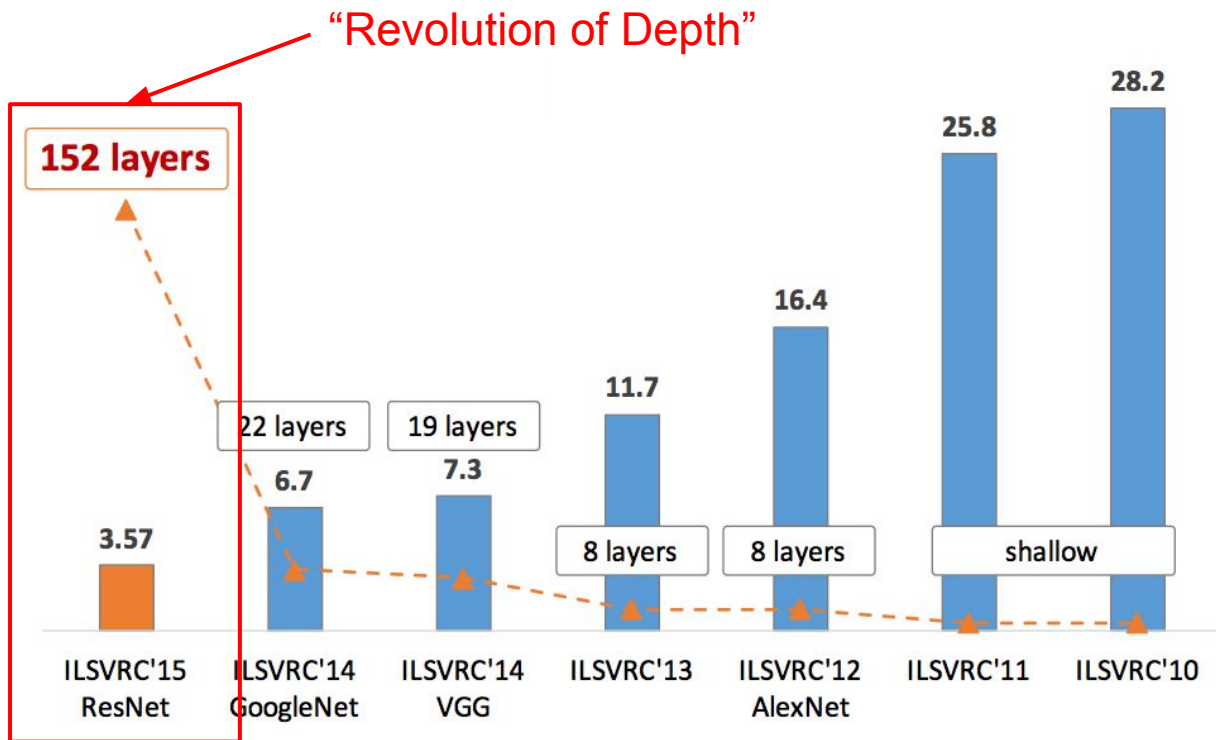


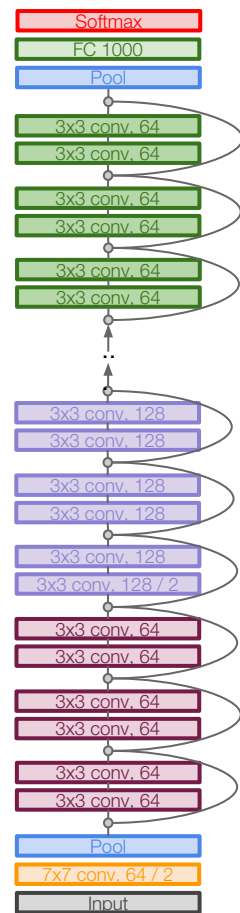
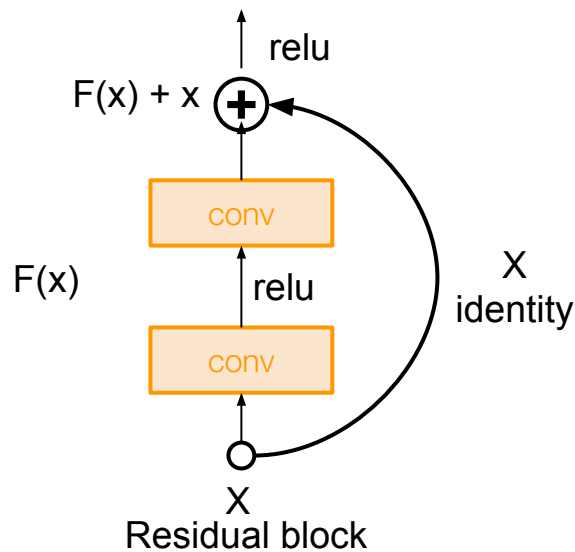
Figure copyright Kaiming He, 2016. Reproduced with permission.

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

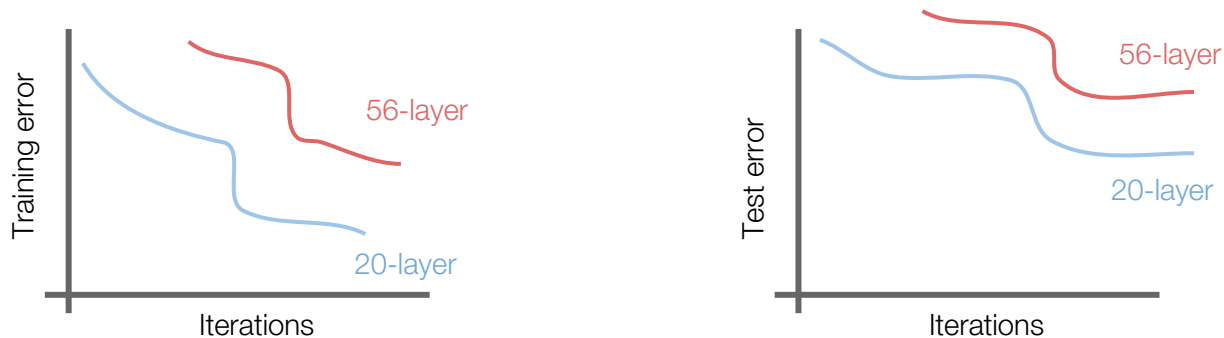
[He et al., 2015]

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

Case Study: ResNet

[He et al., 2015]

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

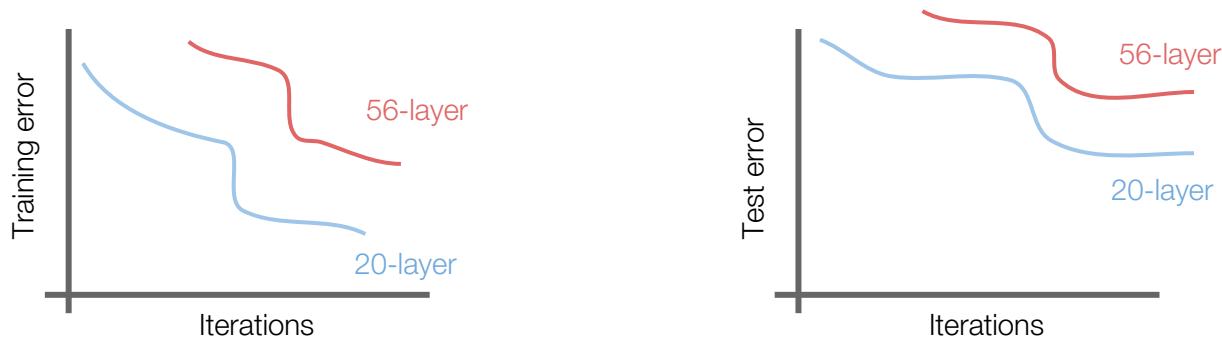


Q: What's strange about these training and test curves?
[Hint: look at the order of the curves]

Case Study: ResNet

[He et al., 2015]

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



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

Case Study: ResNet

[He et al., 2015]

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

Case Study: ResNet

[He et al., 2015]

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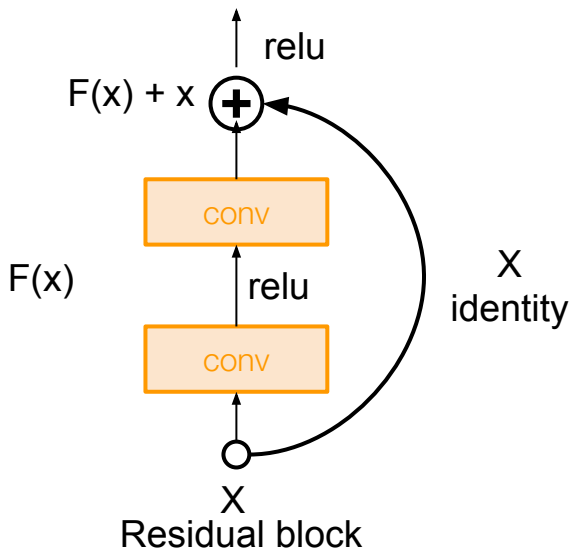
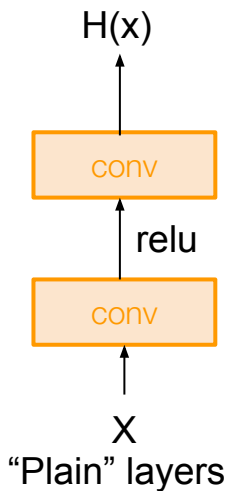
The deeper model should be able to perform at least as well as the shallower model.

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]

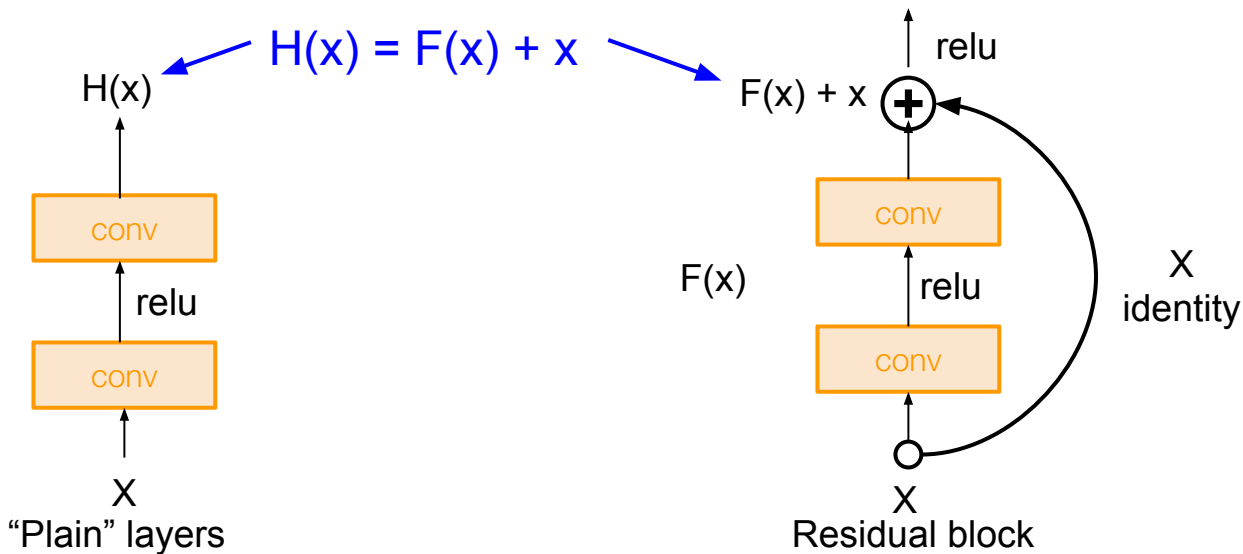
Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping



Case Study: ResNet

[He et al., 2015]

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



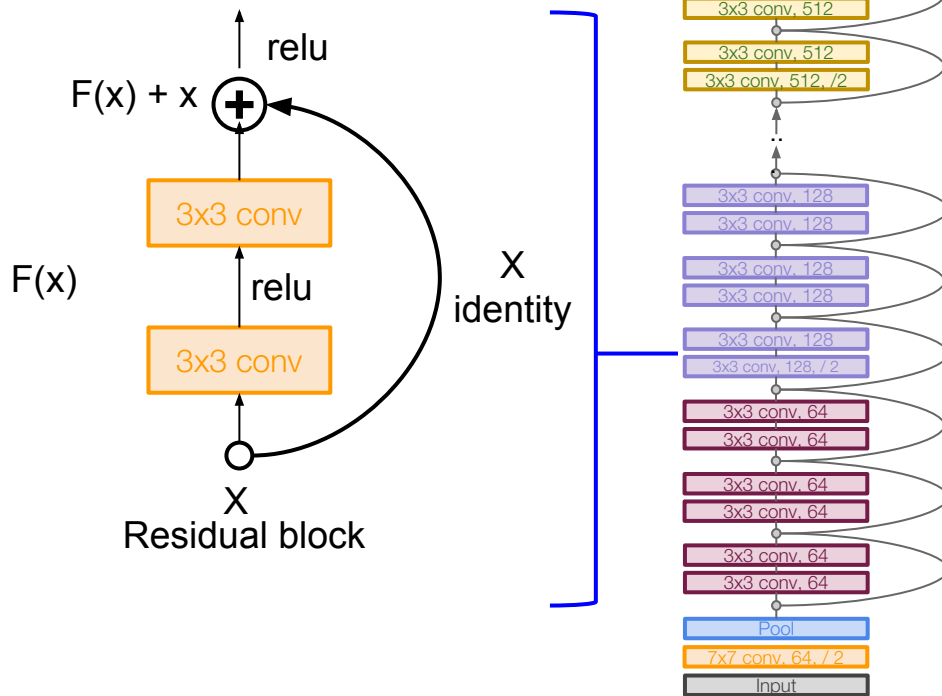
Use layers to fit residual $F(x) = H(x) - x$ instead of $H(x)$ directly

Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:

- Stack residual blocks
- Every residual block has two 3x3 conv layers

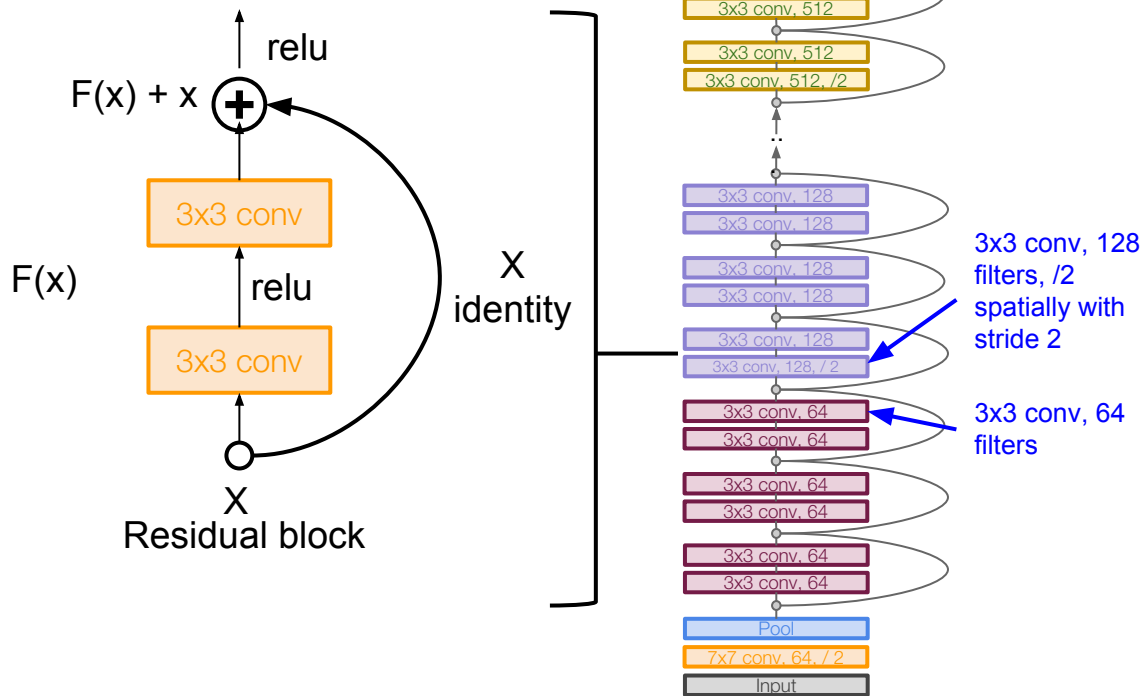


Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:

- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)

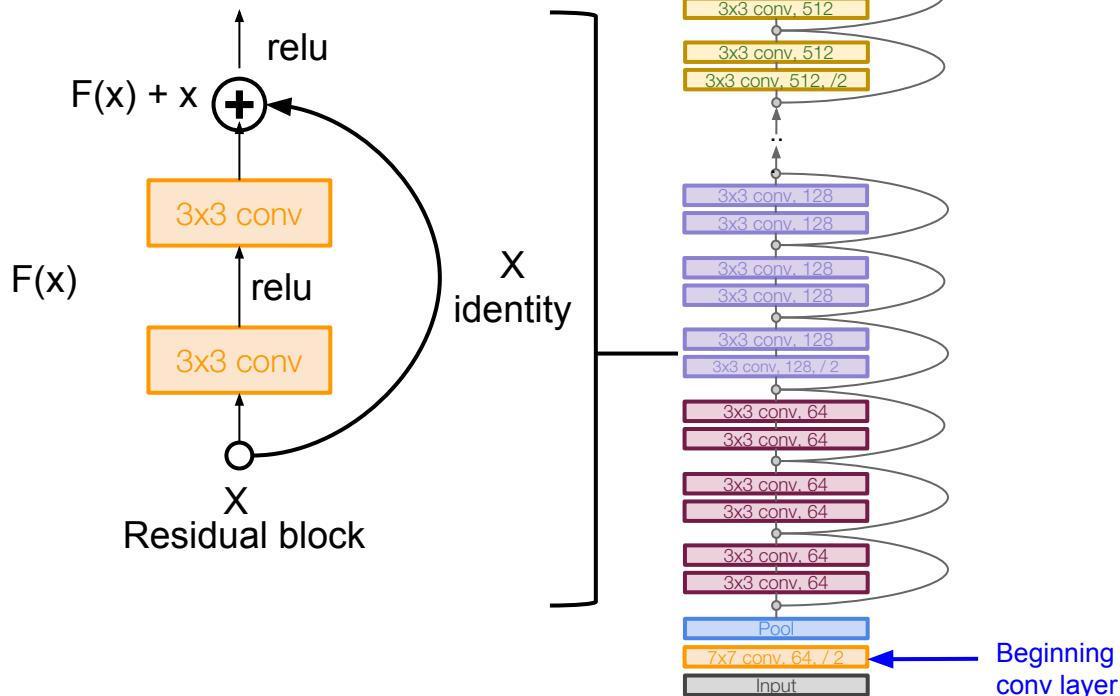


Case Study: ResNet

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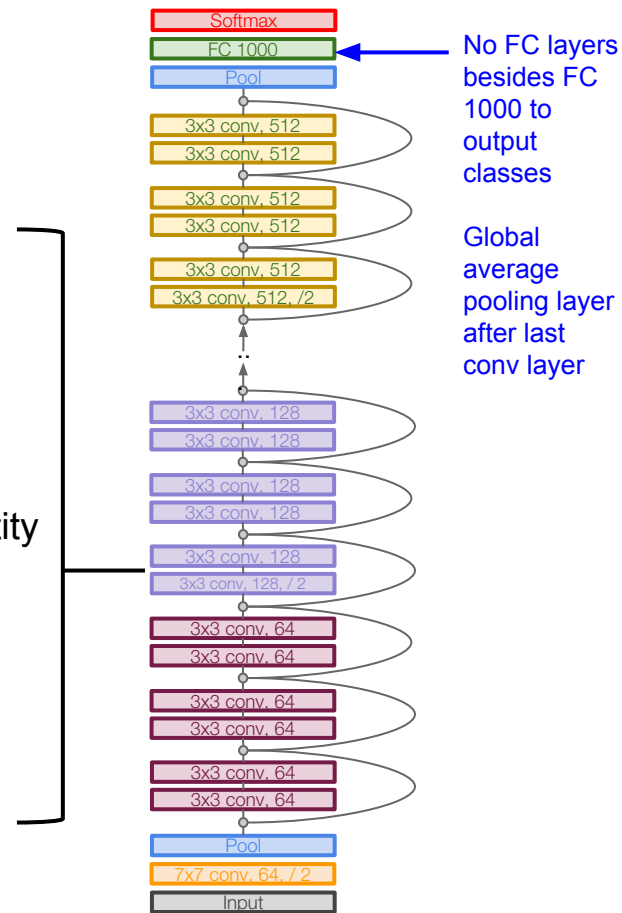
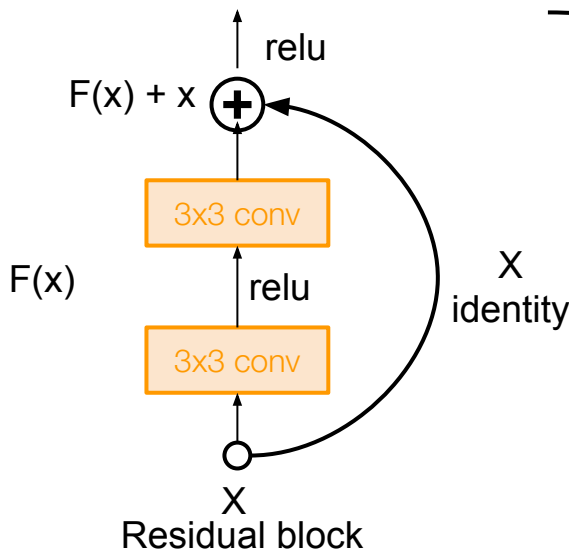


Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:

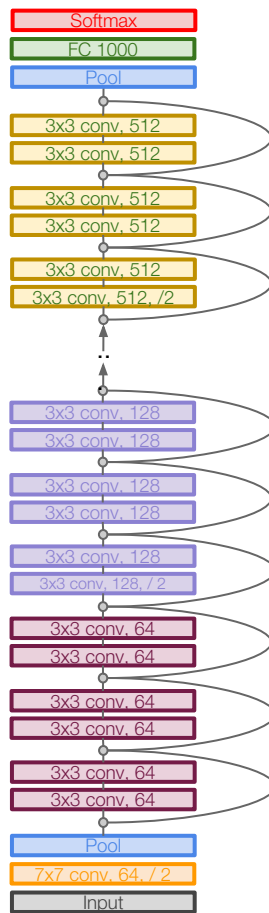
- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)
- Additional conv layer at the beginning
- No FC layers at the end (only FC 1000 to output classes)



Case Study: ResNet

[He et al., 2015]

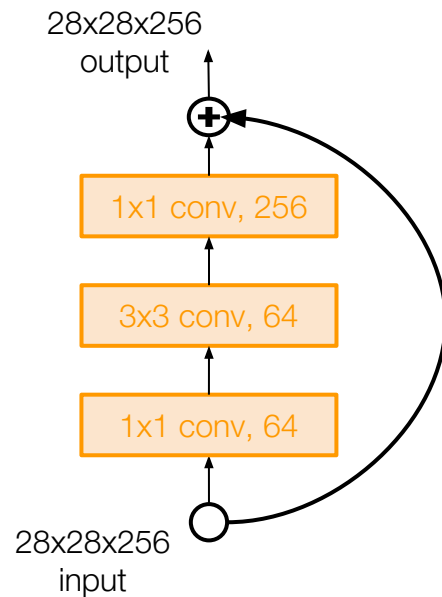
Total depths of 34, 50, 101, or 152 layers for ImageNet



Case Study: ResNet

[He et al., 2015]

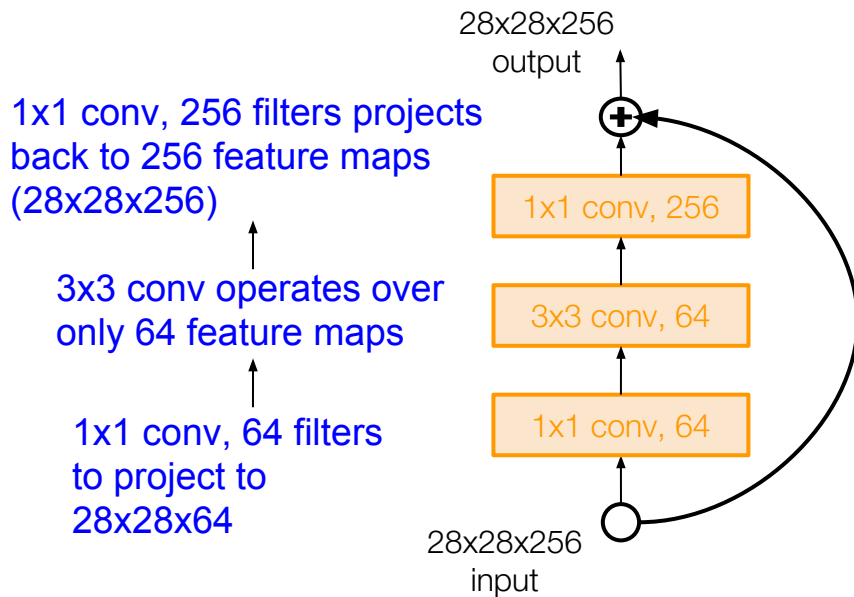
For deeper networks
(ResNet-50+), use “bottleneck”
layer to improve efficiency
(similar to GoogLeNet)



Case Study: ResNet

[He et al., 2015]

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



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

Case Study: ResNet

[He et al., 2015]

Experimental Results

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

MSRA @ ILSVRC & COCO 2015 Competitions

- **1st places in all five main tracks**

- ImageNet Classification: “Ultra-deep” (quote Yann) **152-layer** nets
- ImageNet Detection: **16%** better than 2nd
- ImageNet Localization: **27%** better than 2nd
- COCO Detection: **11%** better than 2nd
- COCO Segmentation: **12%** better than 2nd

Case Study: ResNet

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

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

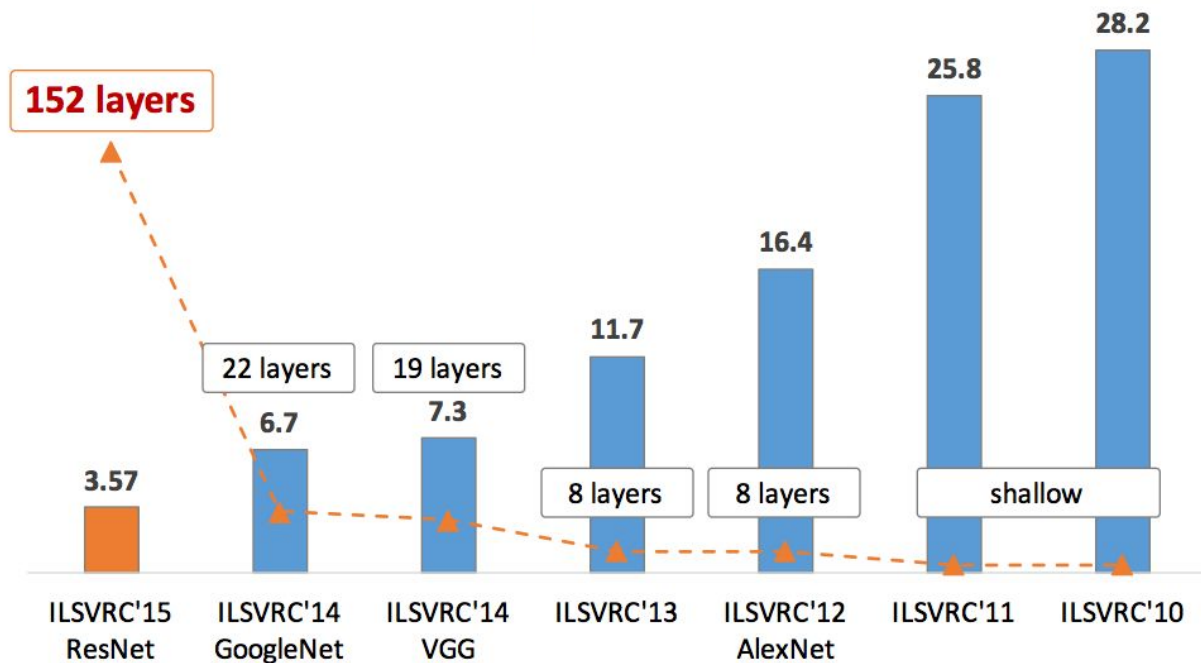
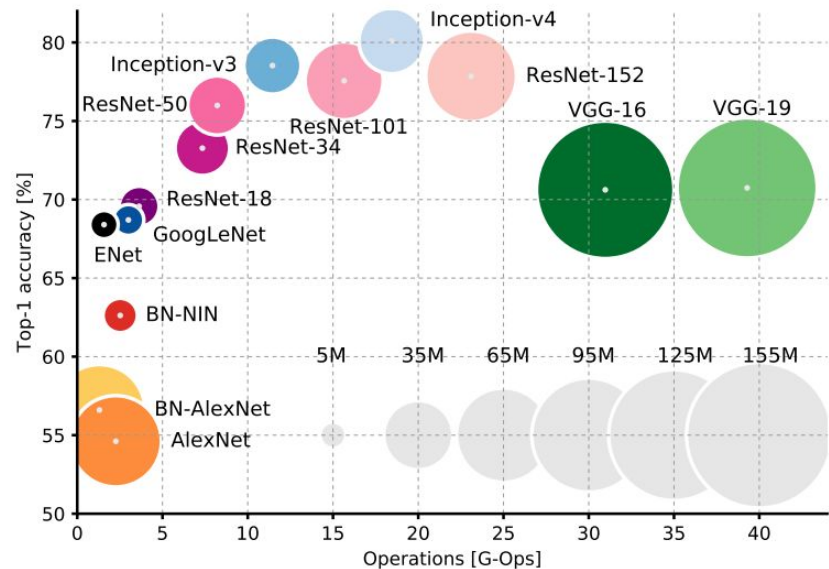
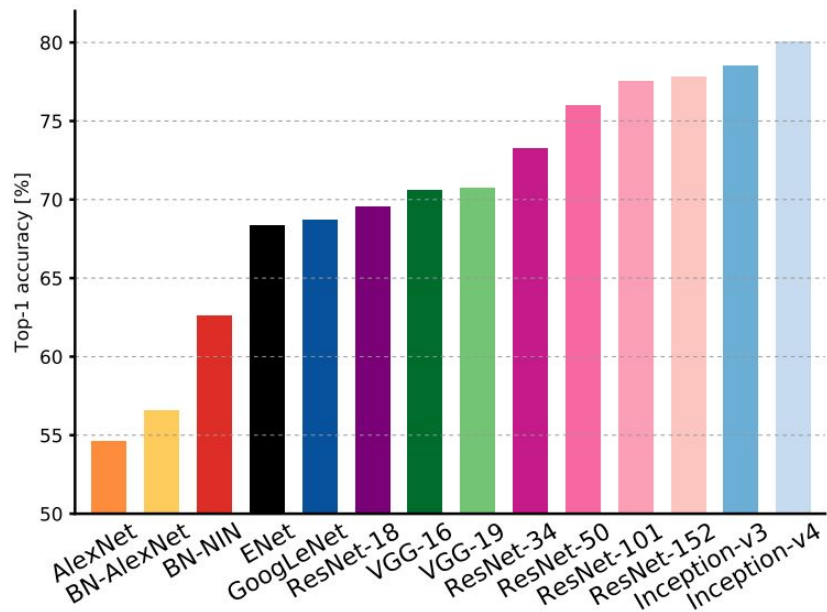


Figure copyright Kaiming He, 2016. Reproduced with permission.

Comparing complexity...

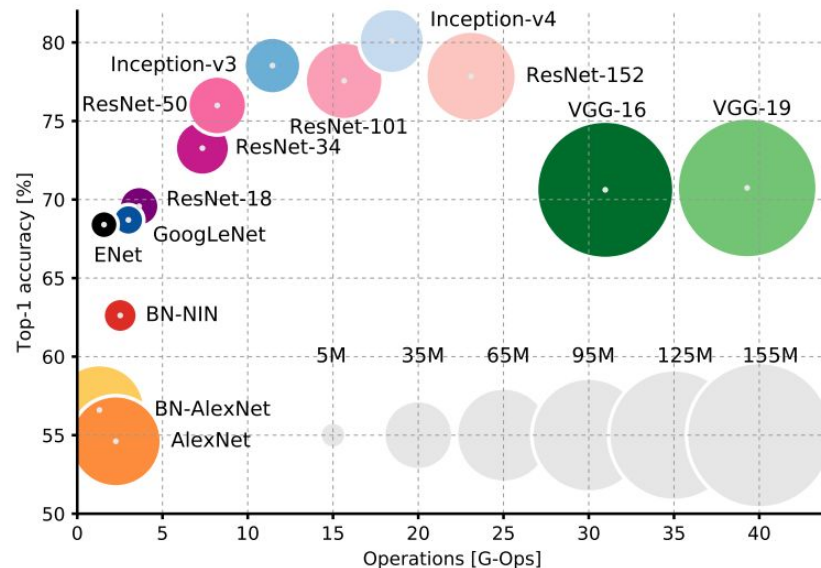
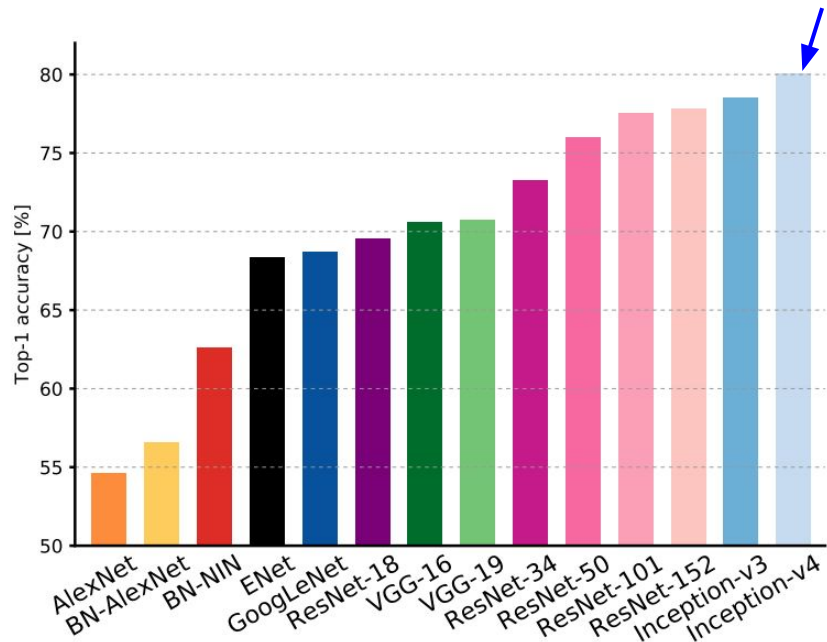


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

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Comparing complexity...

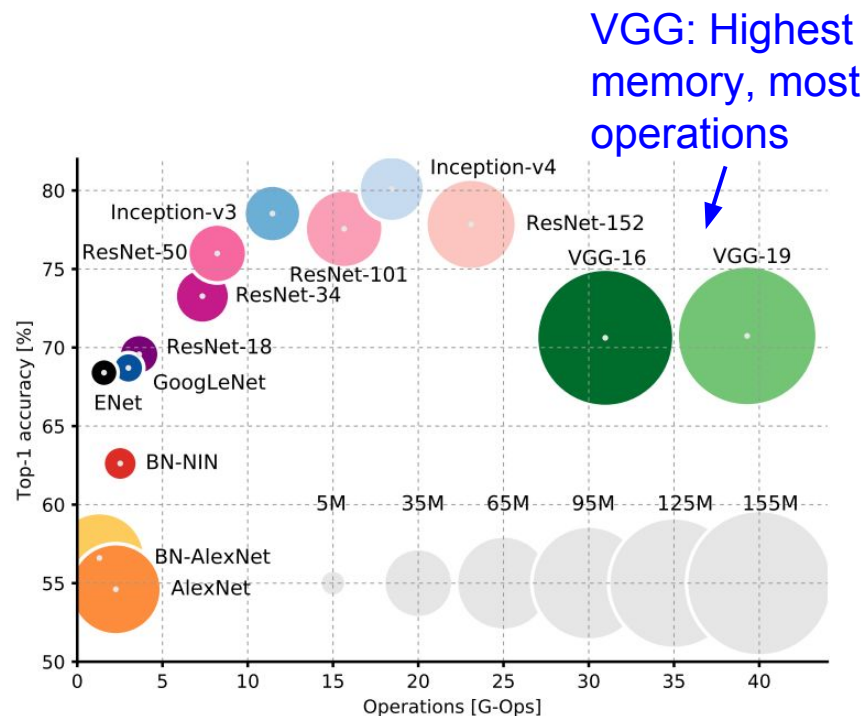
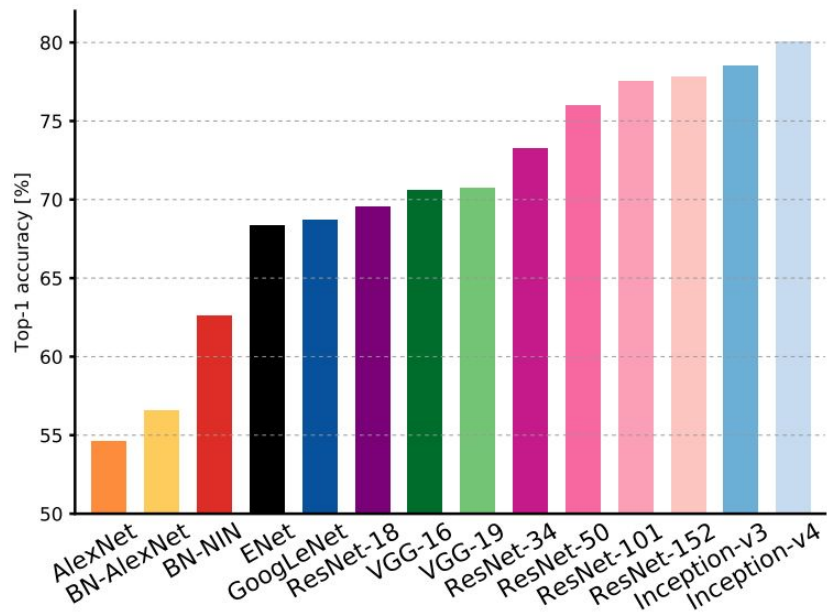
Inception-v4: Resnet + Inception!



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

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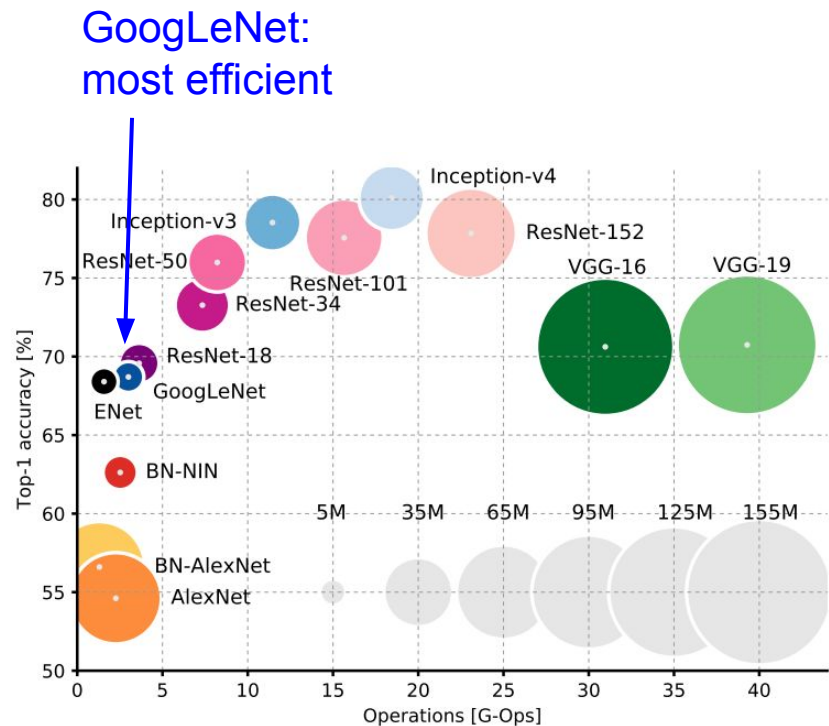
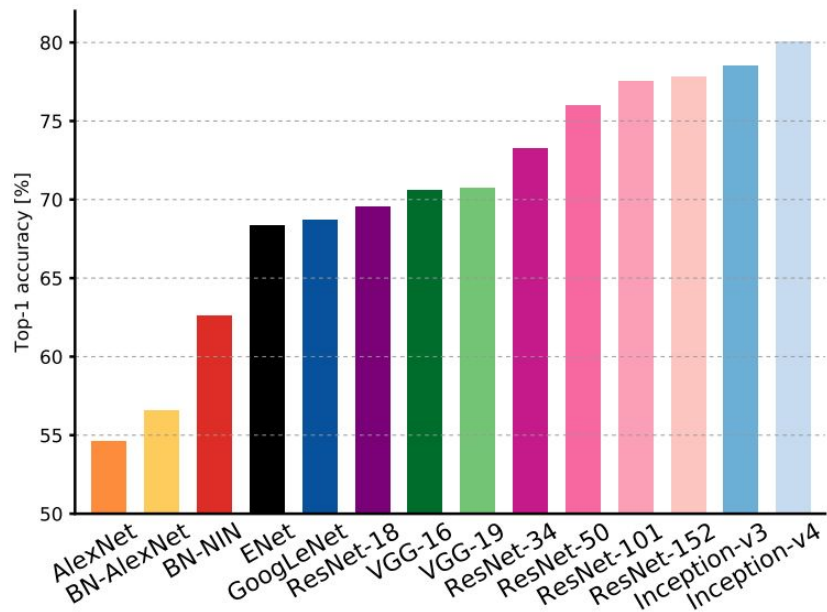
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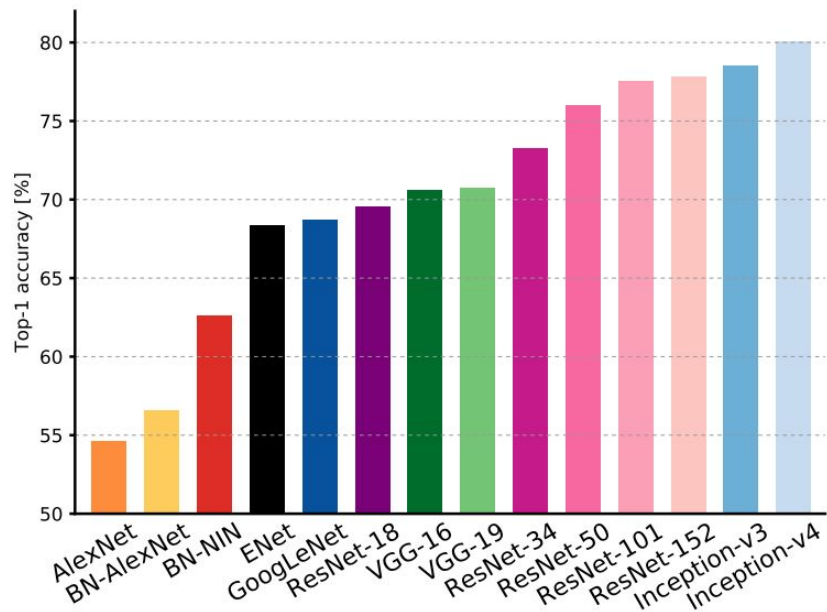
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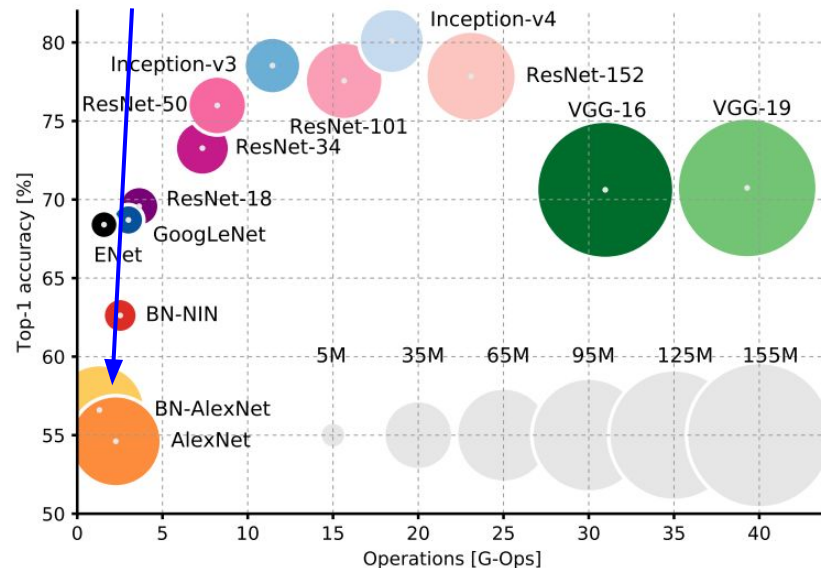
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

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Comparing complexity...



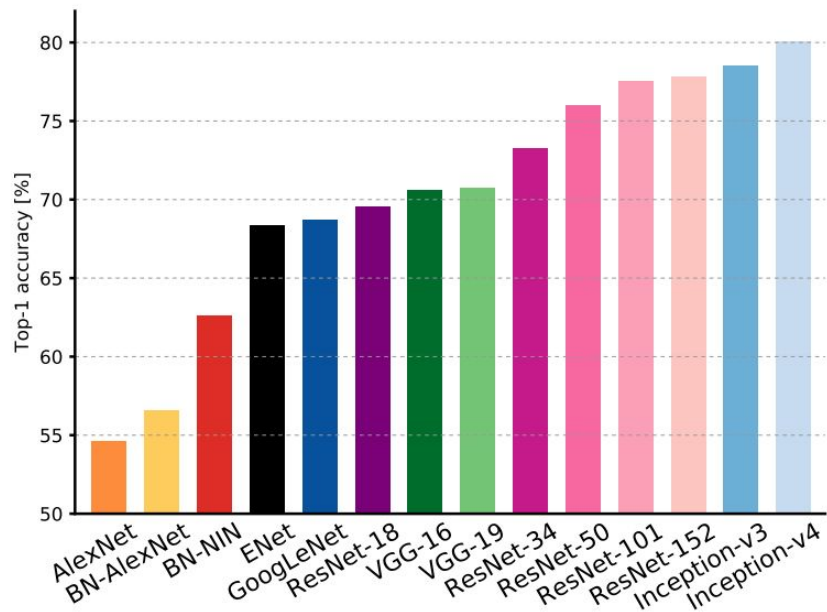
AlexNet:
Smaller compute, still memory heavy, lower accuracy



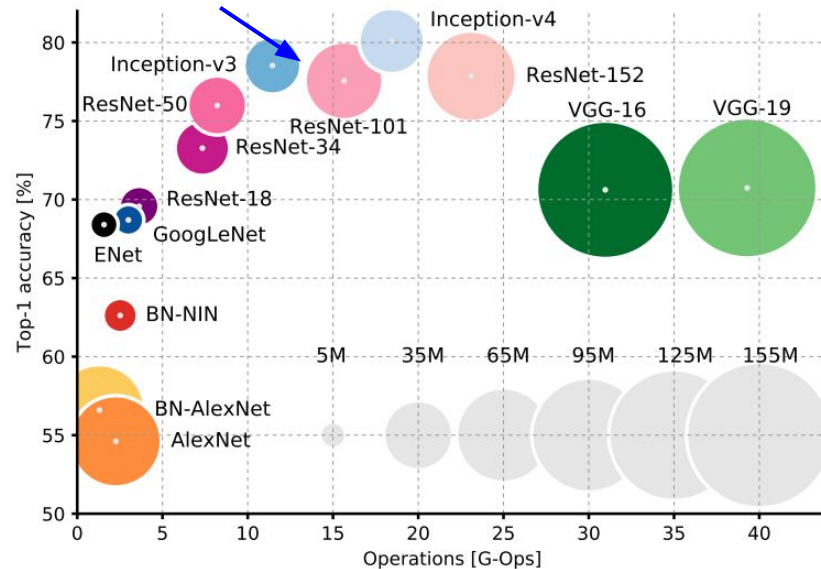
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

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Comparing complexity...



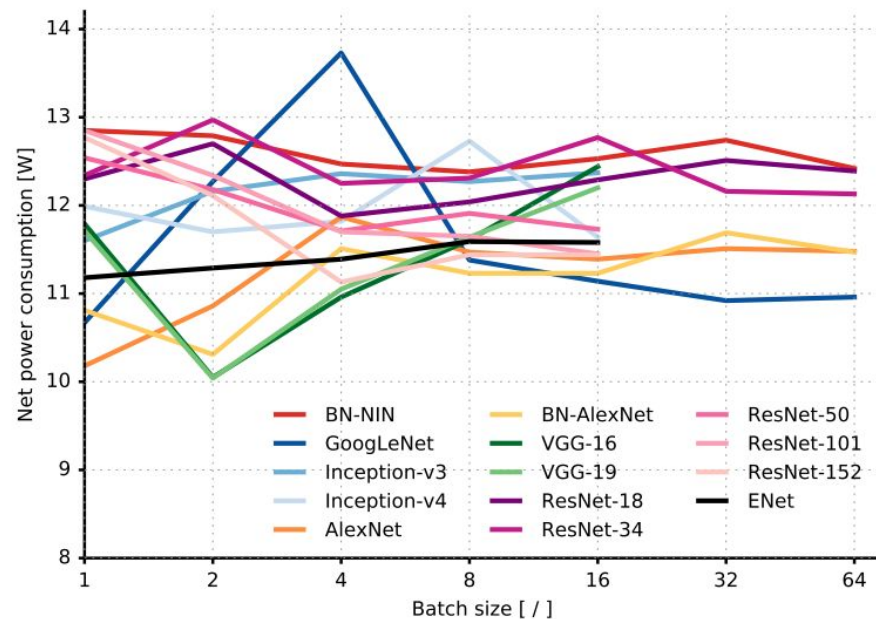
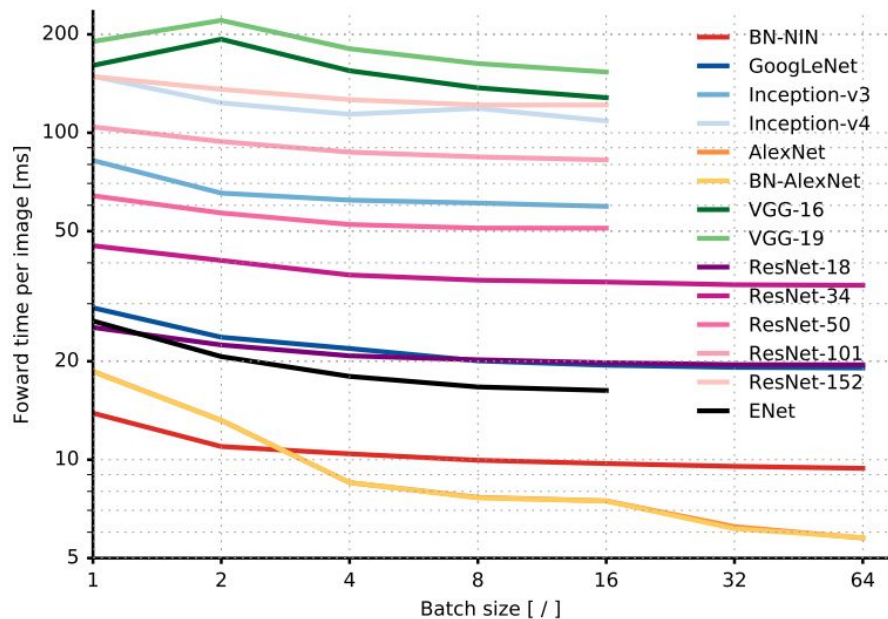
ResNet:
Moderate efficiency depending on
model, highest accuracy



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Forward pass time and power consumption



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

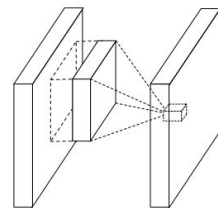
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Other architectures to know...

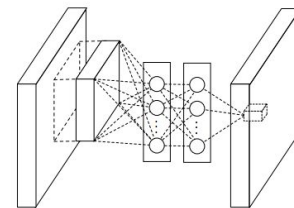
Network in Network (NiN)

[Lin et al. 2014]

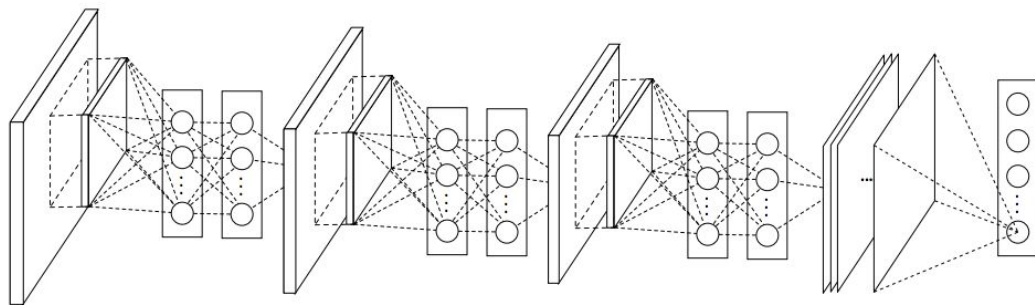
- Mlpconv layer with “micronetwork” within each conv layer to compute more abstract features for local patches
- Micronetwork uses multilayer perceptron (FC, i.e. 1x1 conv layers)
- Precursor to GoogLeNet and ResNet “bottleneck” layers
- Philosophical inspiration for GoogLeNet



(a) Linear convolution layer



(b) Mlpconv layer



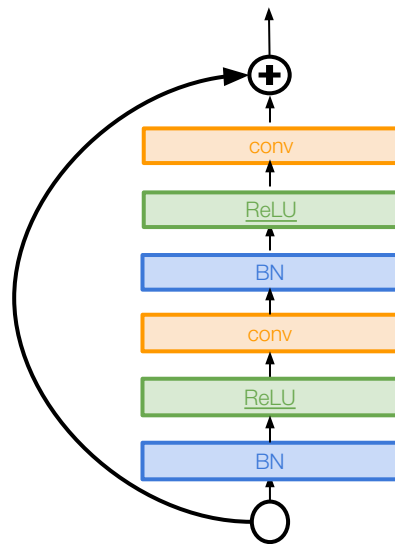
Figures copyright Lin et al., 2014. Reproduced with permission.

Improving ResNets...

Identity Mappings in Deep Residual Networks

[He et al. 2016]

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

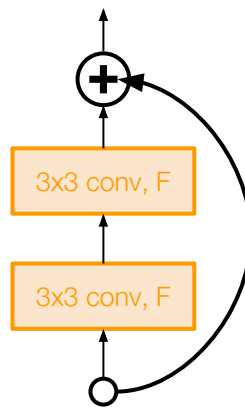


Improving ResNets...

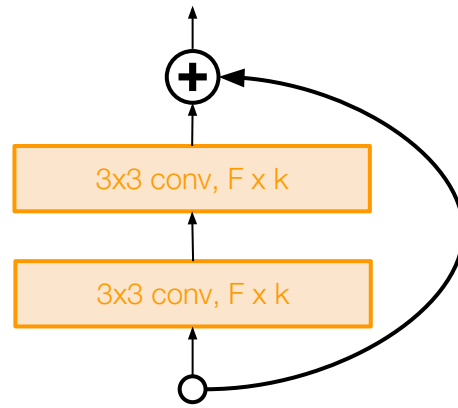
Wide Residual Networks

[Zagoruyko et al. 2016]

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



Basic residual block



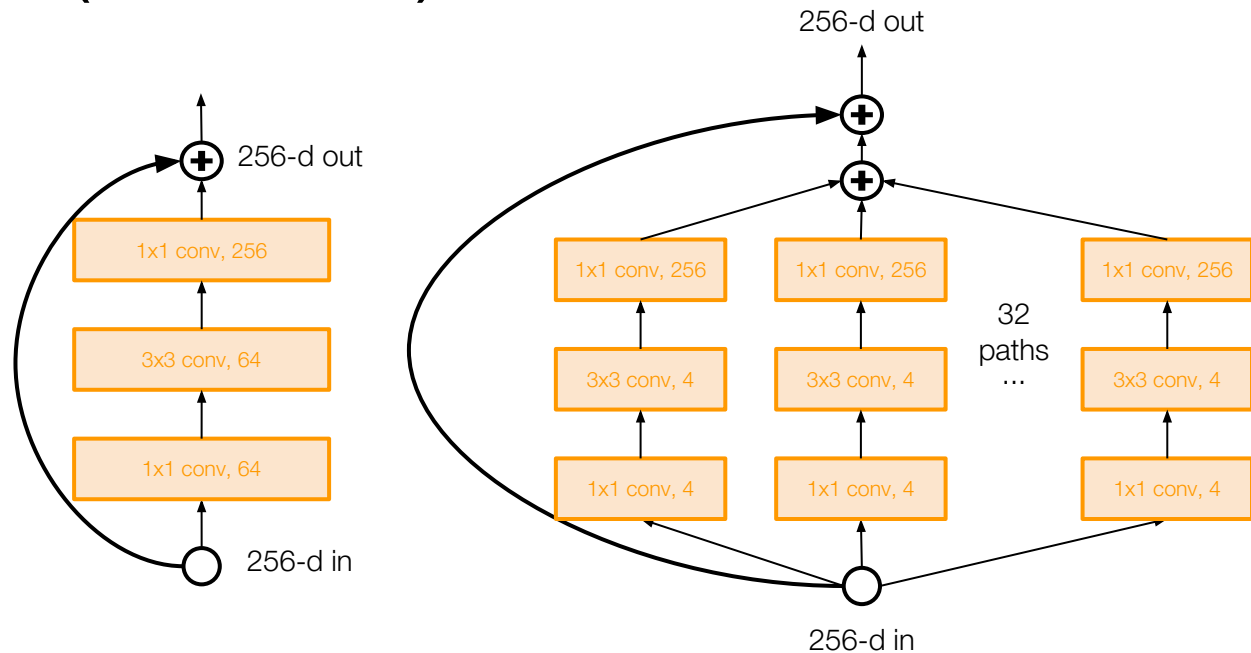
Wide residual block

Improving ResNets...

Aggregated Residual Transformations for Deep Neural Networks (ResNeXt)

[Xie et al. 2016]

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

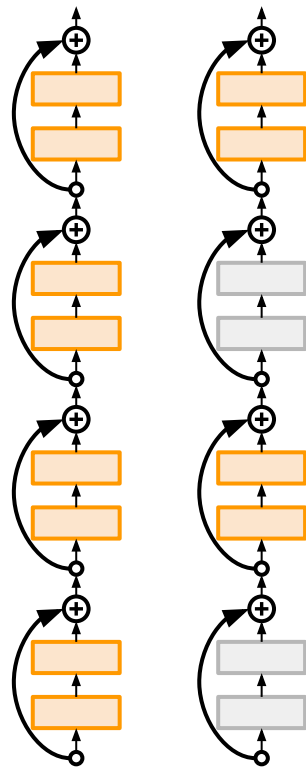


Improving ResNets...

Deep Networks with Stochastic Depth

[Huang et al. 2016]

- Motivation: reduce vanishing gradients and training time through short networks during training
- Randomly drop a subset of layers during each training pass
- Bypass with identity function
- Use full deep network at test time

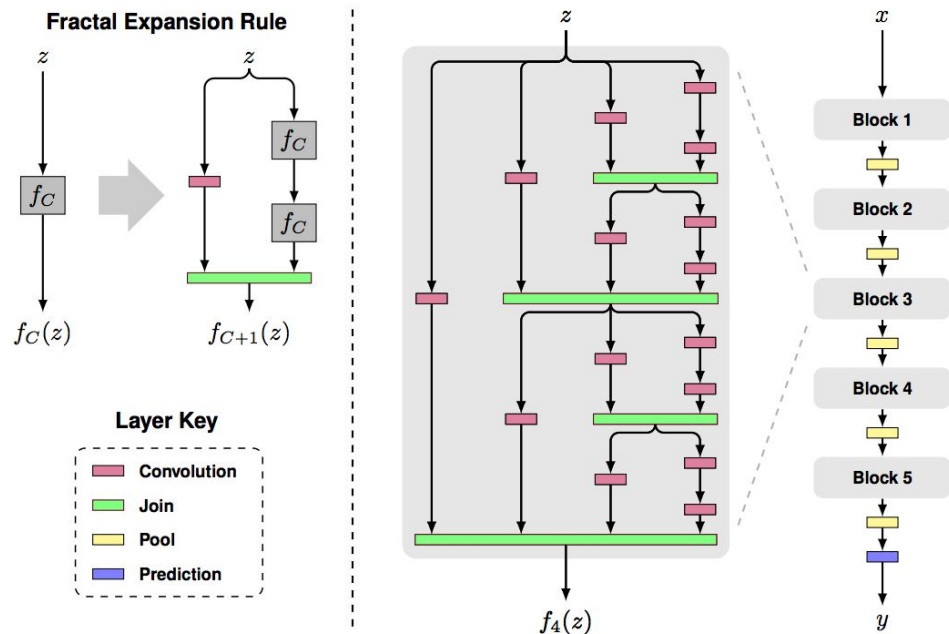


Beyond ResNets...

FractalNet: Ultra-Deep Neural Networks without Residuals

[Larsson et al. 2017]

- Argues that key is transitioning effectively from shallow to deep and residual representations are not necessary
- Fractal architecture with both shallow and deep paths to output
- Trained with dropping out sub-paths
- Full network at test time



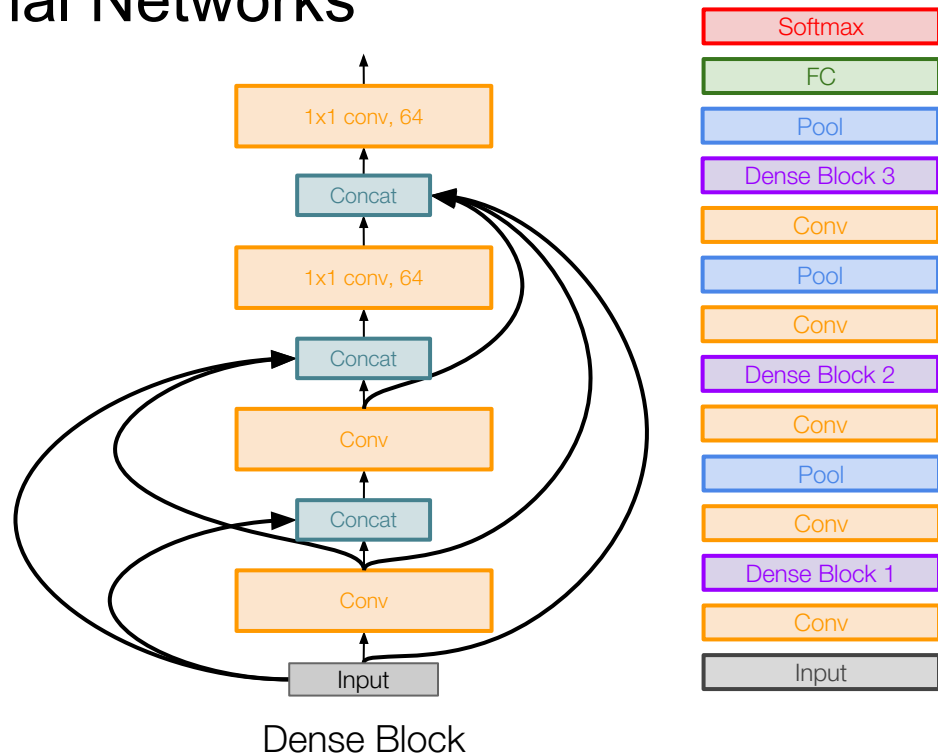
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Beyond ResNets...

Densely Connected Convolutional Networks

[Huang et al. 2017]

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



Efficient networks...

SqueezeNet: AlexNet-level Accuracy With 50x Fewer Parameters and <0.5Mb Model Size

[Iandola et al. 2017]

- Fire modules consisting of a 'squeeze' layer with 1x1 filters feeding an 'expand' layer with 1x1 and 3x3 filters
- AlexNet level accuracy on ImageNet with 50x fewer parameters
- Can compress to 510x smaller than AlexNet (0.5Mb)

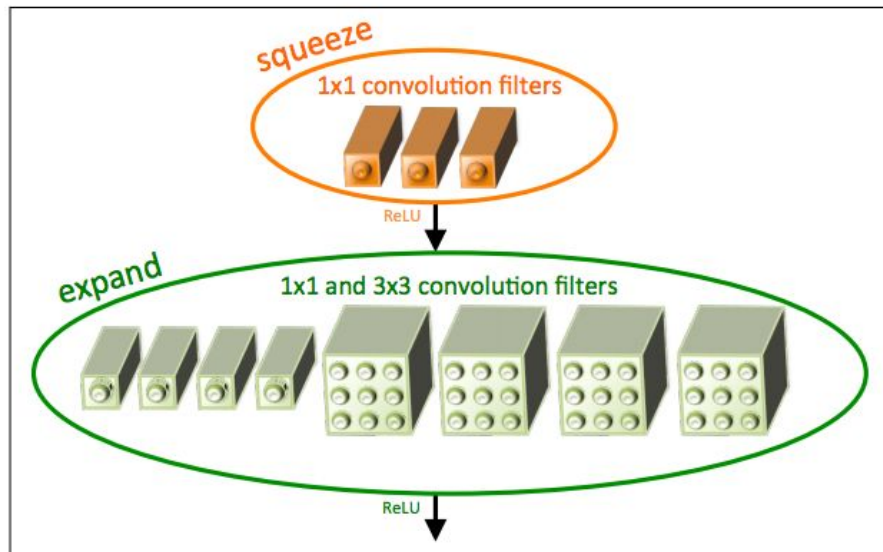


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Summary: CNN Architectures

Case Studies

- AlexNet
- VGG
- GoogLeNet
- ResNet

Also....

- NiN (Network in Network)
- Wide ResNet
- ResNeXT
- Stochastic Depth
- DenseNet
- FractalNet
- SqueezeNet

Summary: CNN Architectures

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

- Next time: Recurrent neural networks