

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

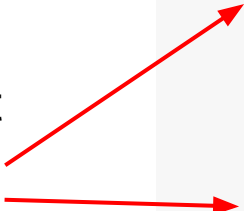
And others...

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

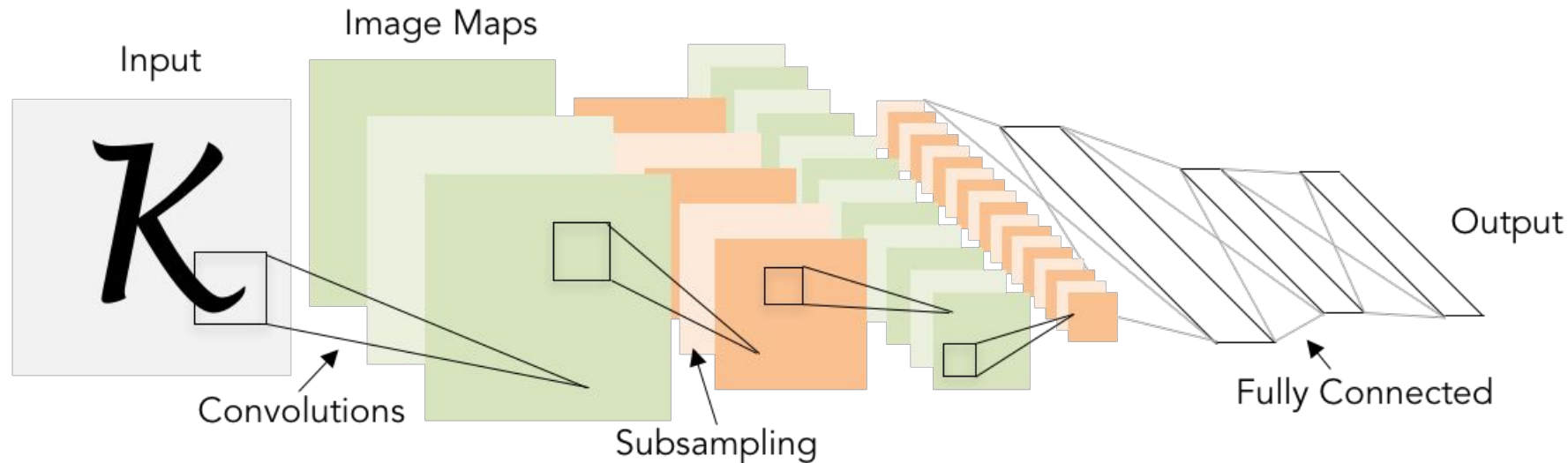
- AlexNet
- VGG
- GoogLeNet
- ResNet

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

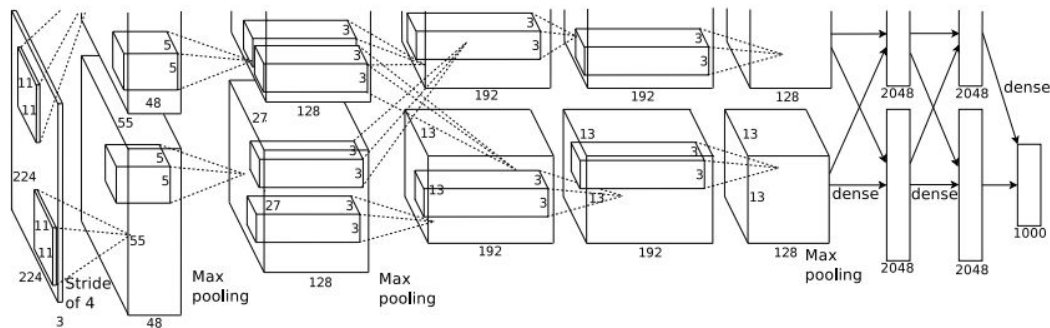
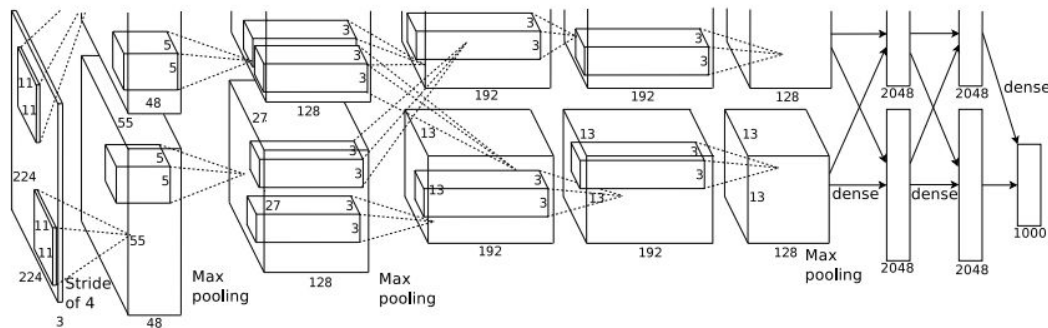


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

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

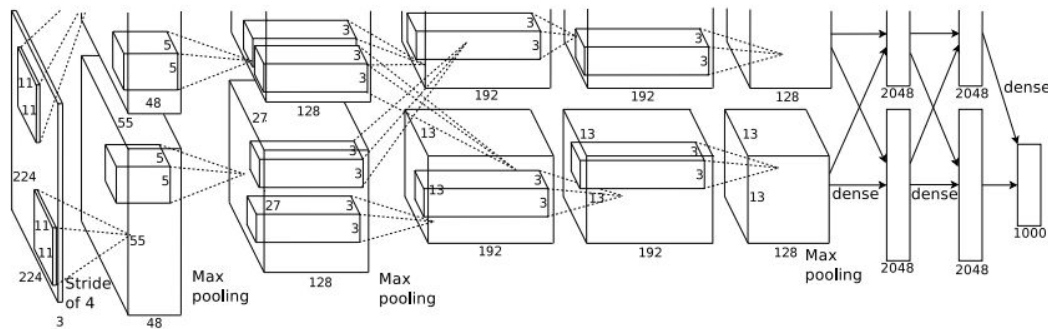
=>

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

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

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

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

=>

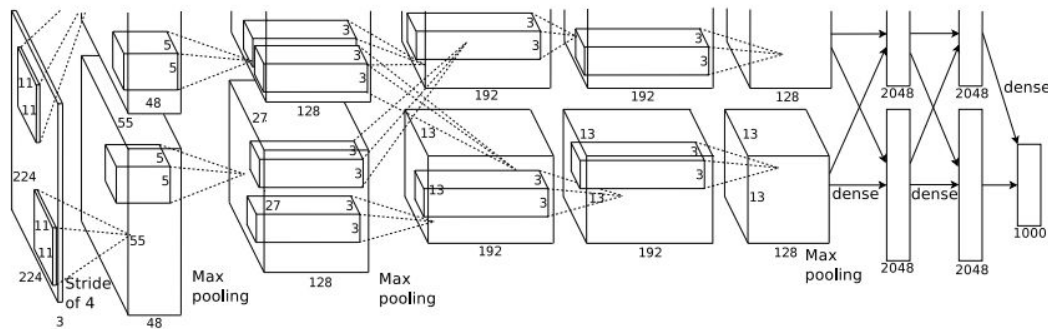
Output volume **[55x55x96]**

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

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

=>

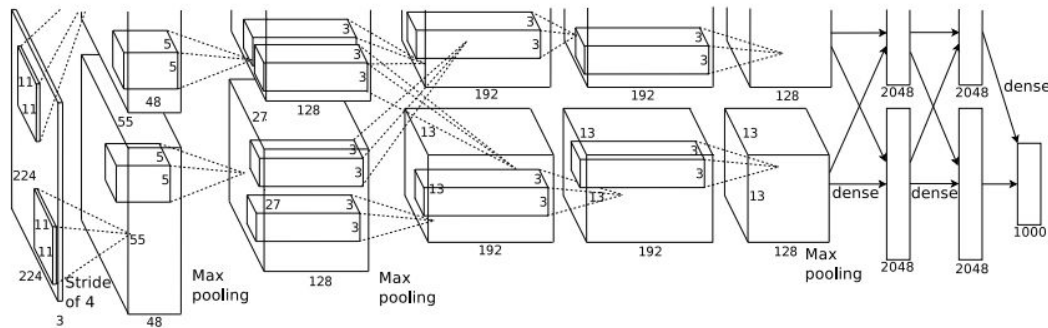
Output volume **[55x55x96]**

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

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

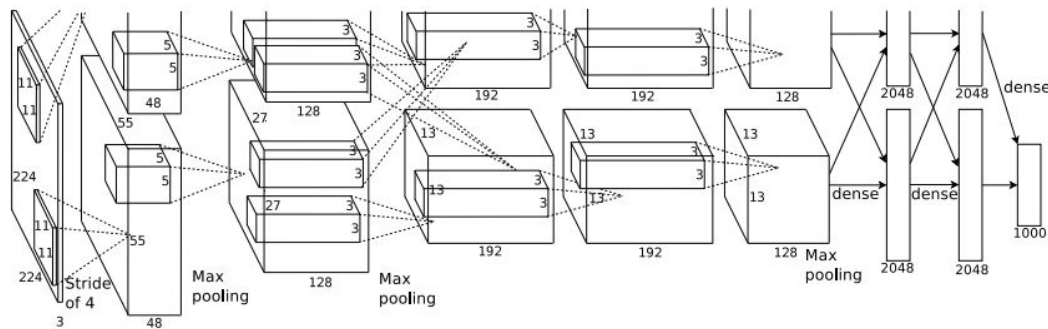
Second layer (POOL1): 3x3 filters applied at stride 2

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

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

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

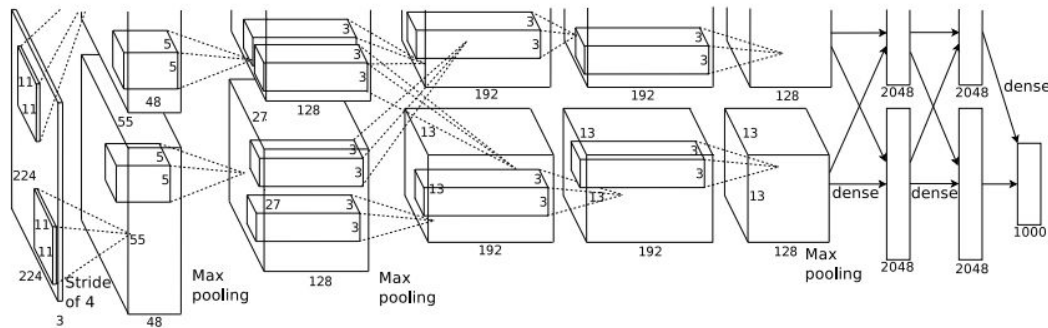
Output volume: 27x27x96

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

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

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

...

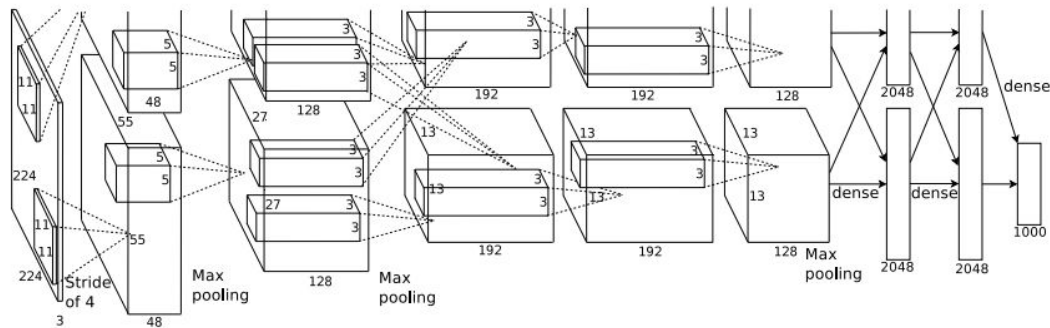


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

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)

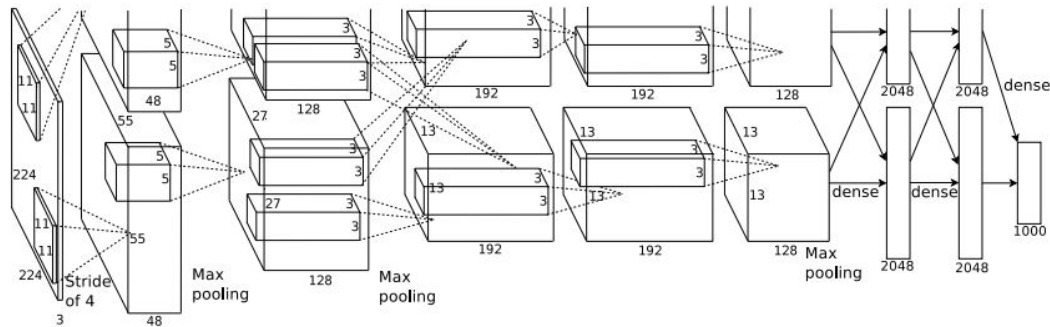


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

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

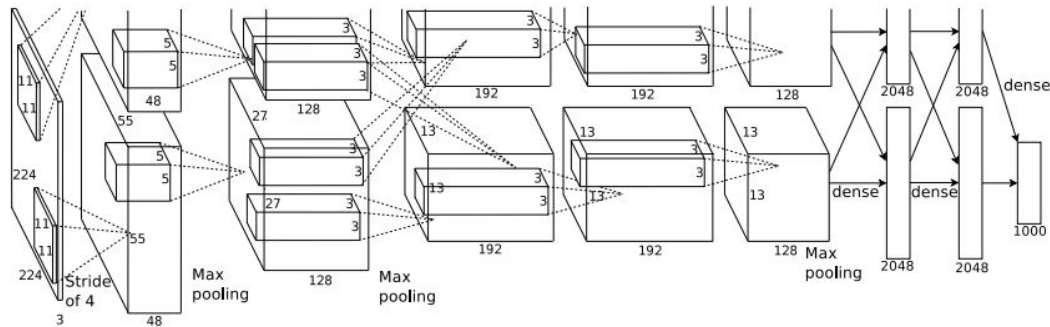
[13x13x256] **CONV5**: 256 3x3 filters at stride 1, pad 1

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

[4096] **FC6**: 4096 neurons

[4096] **FC7**: 4096 neurons

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



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%

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

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

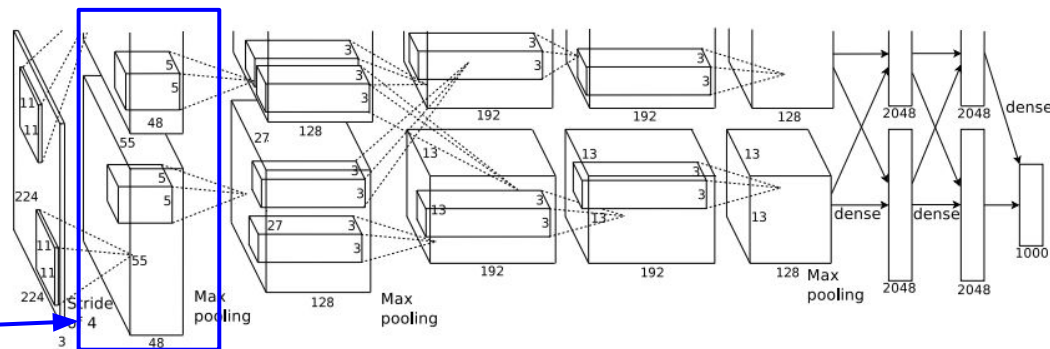
[13x13x256] **CONV5**: 256 3x3 filters at stride 1, pad 1

[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.

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

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

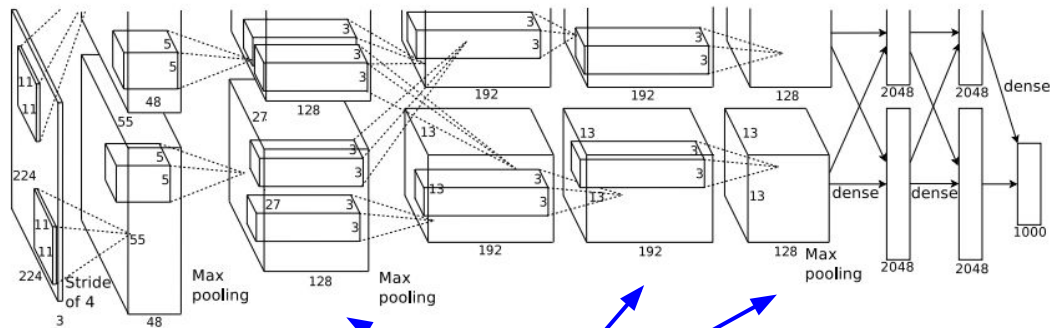
[13x13x256] **CONV5**: 256 3x3 filters at stride 1, pad 1

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

[4096] **FC6**: 4096 neurons

[4096] **FC7**: 4096 neurons

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



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

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

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

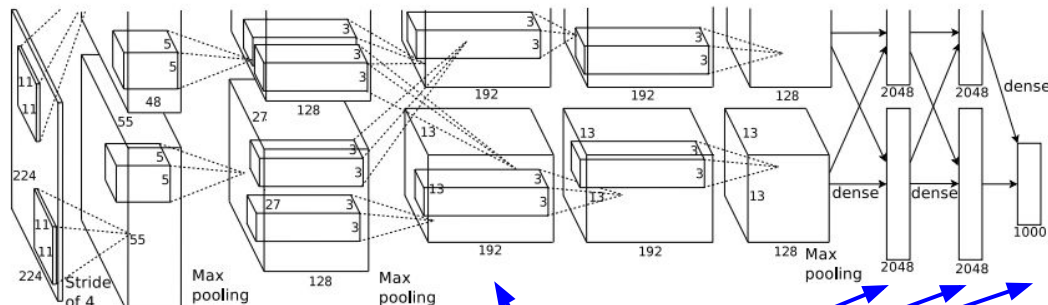
[13x13x256] **CONV5**: 256 3x3 filters at stride 1, pad 1

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

[4096] **FC6**: 4096 neurons

[4096] **FC7**: 4096 neurons

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



CONV3, FC6, FC7, FC8:

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

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

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

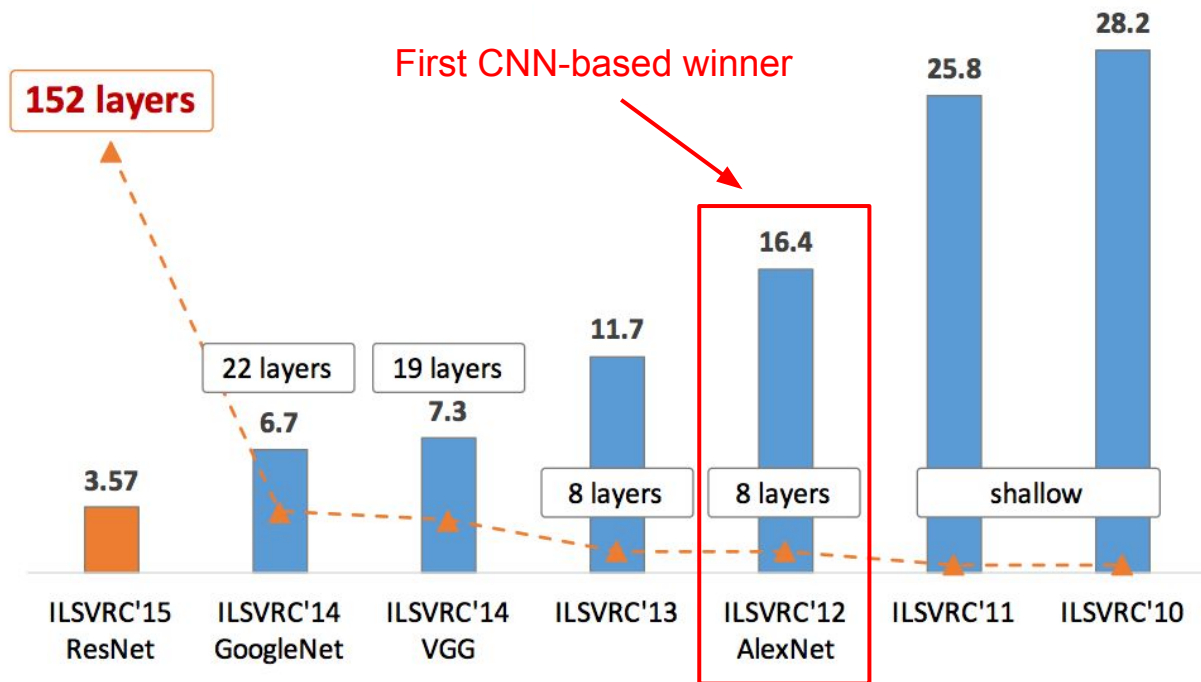


Figure copyright Kaiming He, 2016. Reproduced with permission.

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

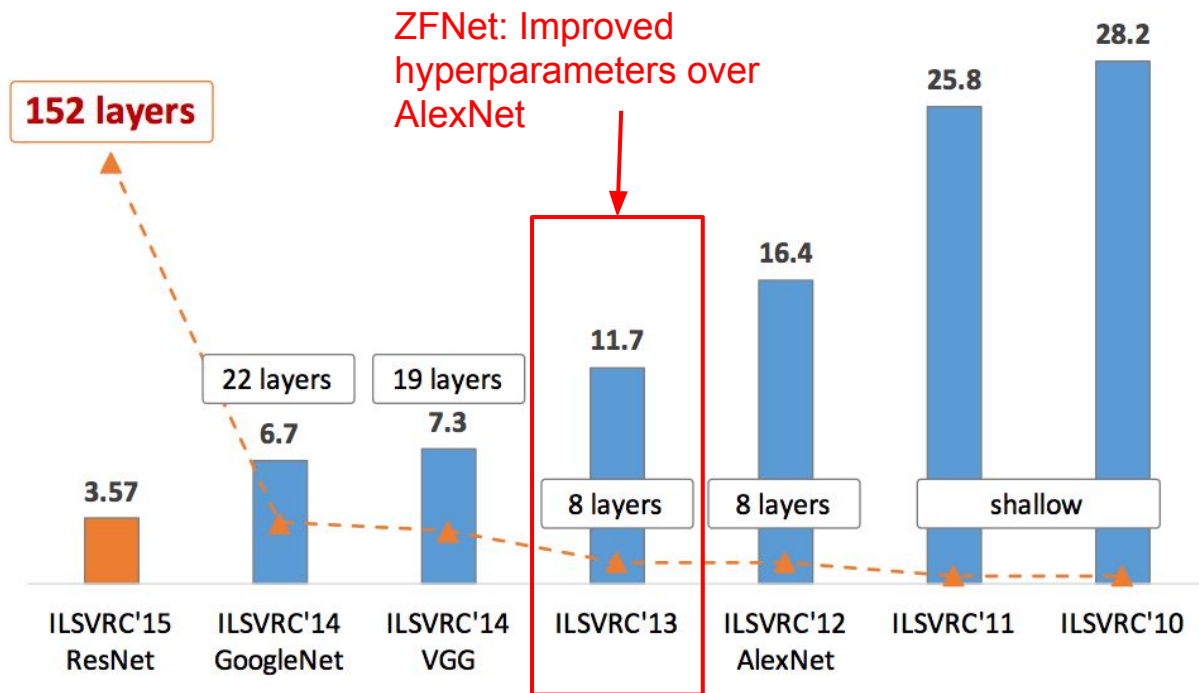
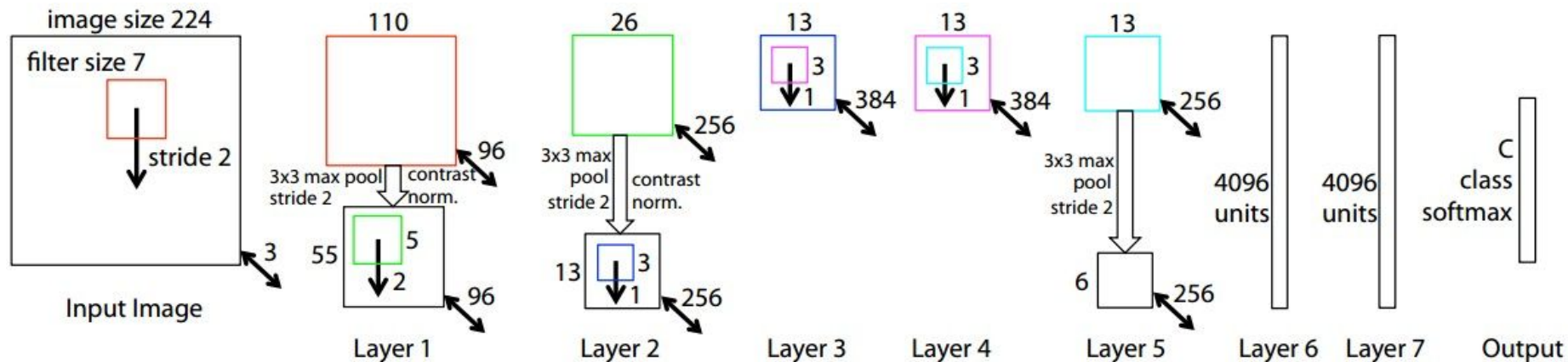


Figure copyright Kaiming He, 2016. Reproduced with permission.

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

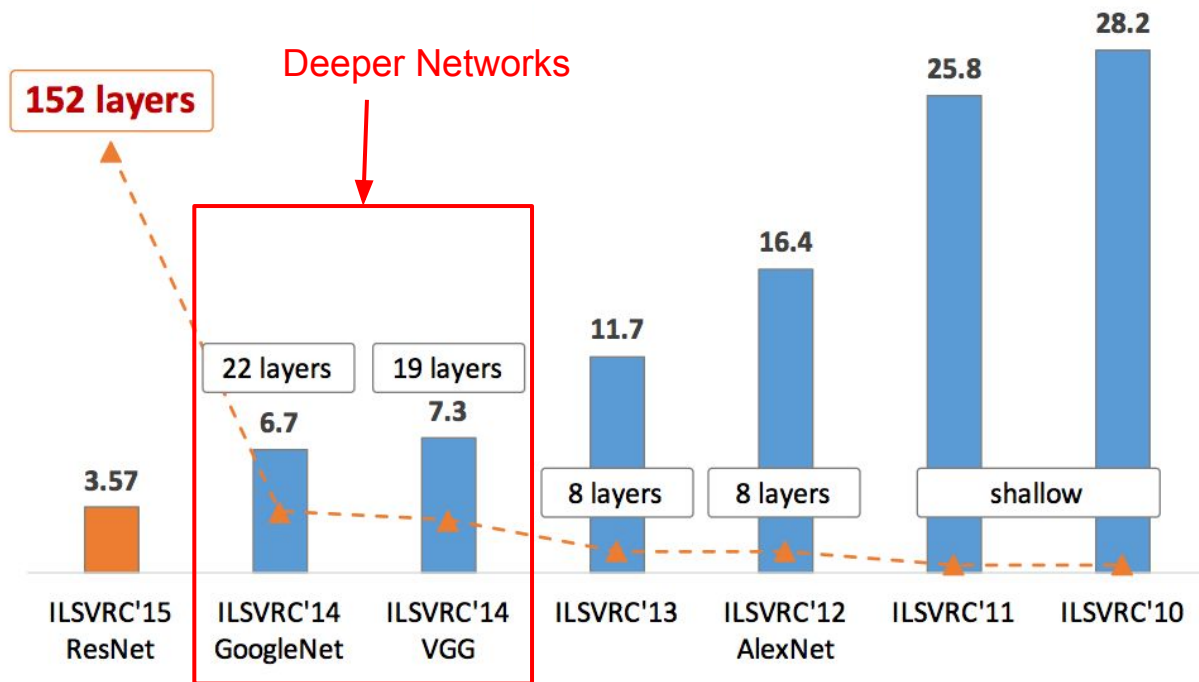


Figure copyright Kaiming He, 2016. Reproduced with permission.

Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Small filters, Deeper networks

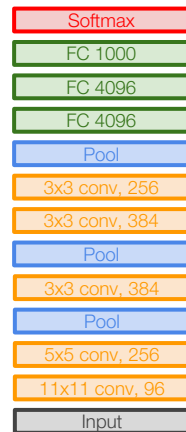
8 layers (AlexNet)

-> 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)

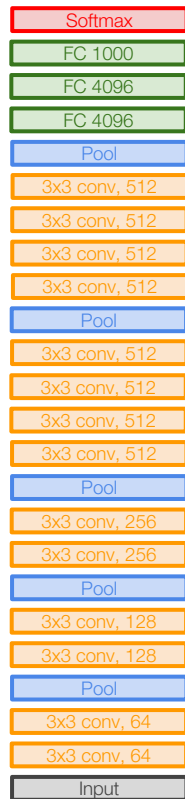
-> 7.3% top 5 error in ILSVRC'14



AlexNet



VGG16

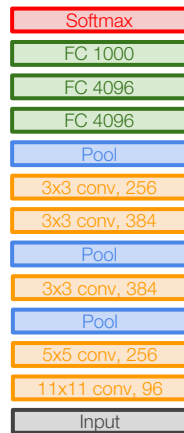


VGG19

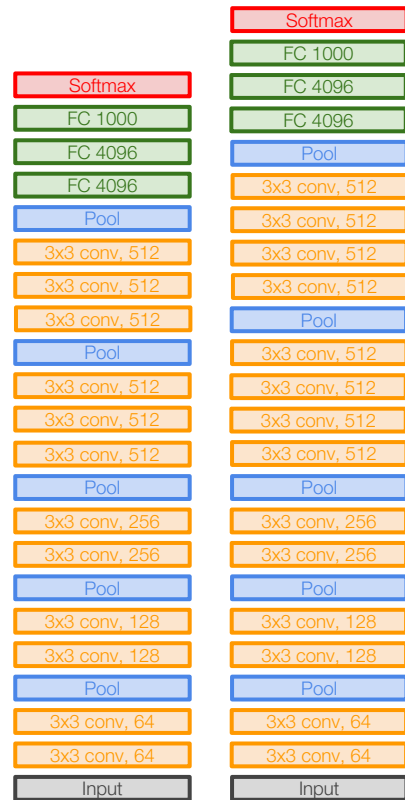
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

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



AlexNet



VGG16

VGG19

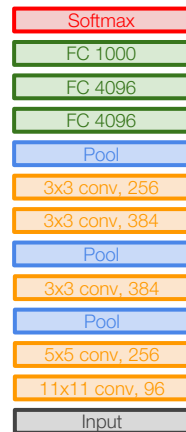
Case Study: VGGNet

[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

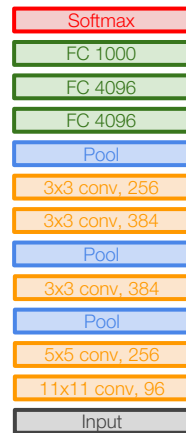
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

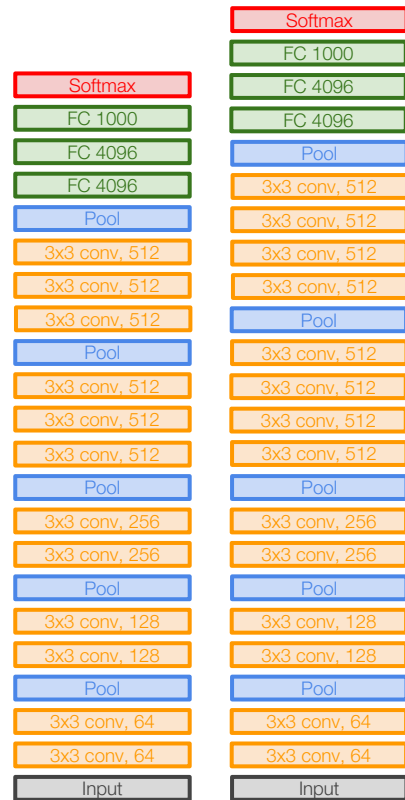
Q: Why use smaller filters? (3x3 conv)

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

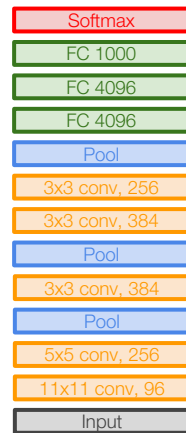
[Simonyan and Zisserman, 2014]

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



AlexNet



VGG16

VGG19

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: $(3*3*512)*512 = 2,359,296$

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: $4096*1000 = 4,096,000$



VGG16

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

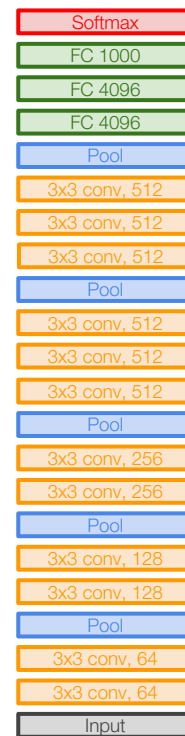
FC: [1x1x4096] memory: 4096 params: $7*7*512*4096 = 102,760,448$

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

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

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

TOTAL params: 138M parameters



VGG16

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: $24\text{M} * 4 \text{ bytes} \sim 96\text{MB}$ / 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: $(3*3*128)*256 = 294,912$

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



VGG16

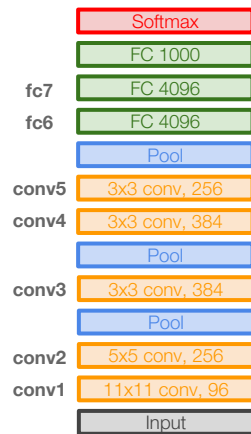
Common names

Case Study: VGGNet

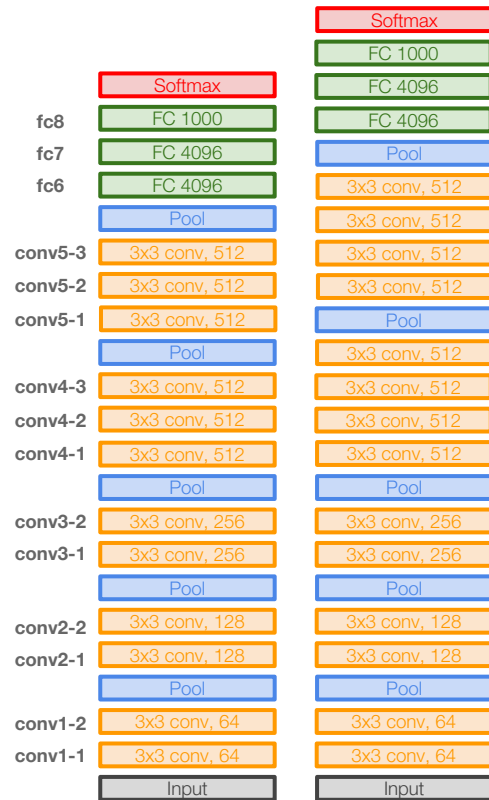
[Simonyan and Zisserman, 2014]

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



AlexNet



VGG16

VGG19

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

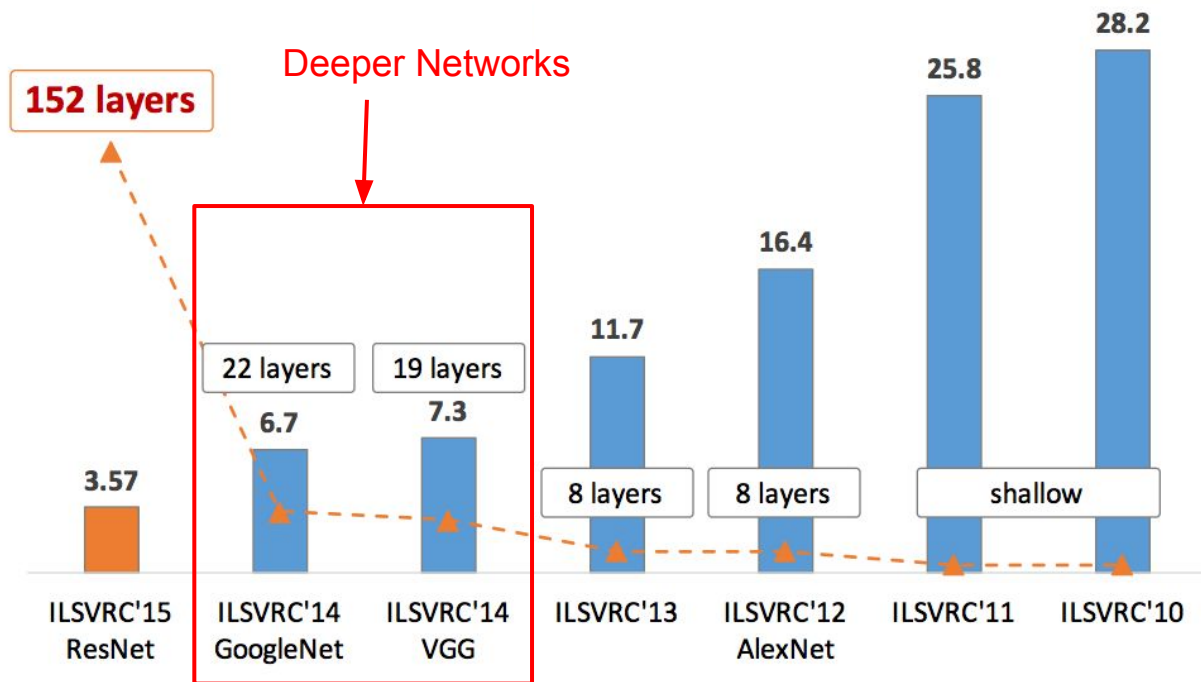


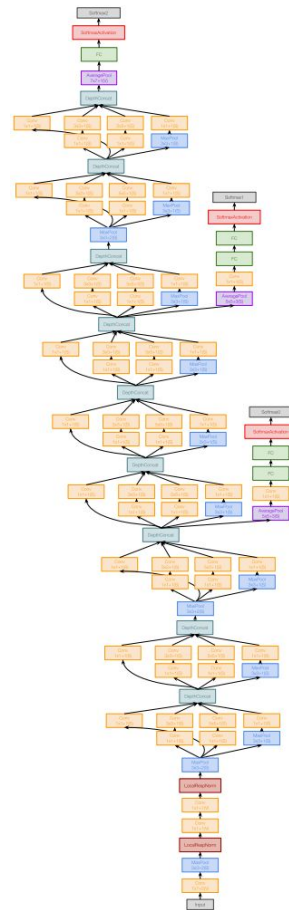
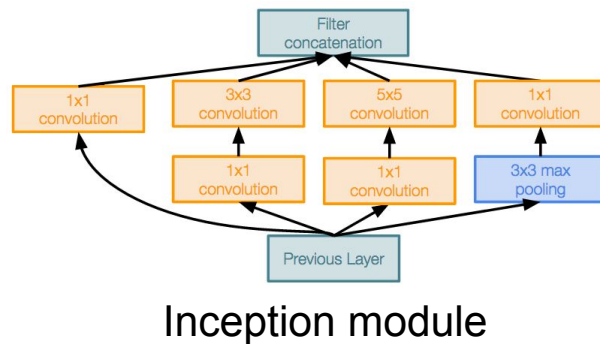
Figure copyright Kaiming He, 2016. Reproduced with permission.

Case Study: GoogLeNet

[Szegedy et al., 2014]

Deeper networks, with computational efficiency

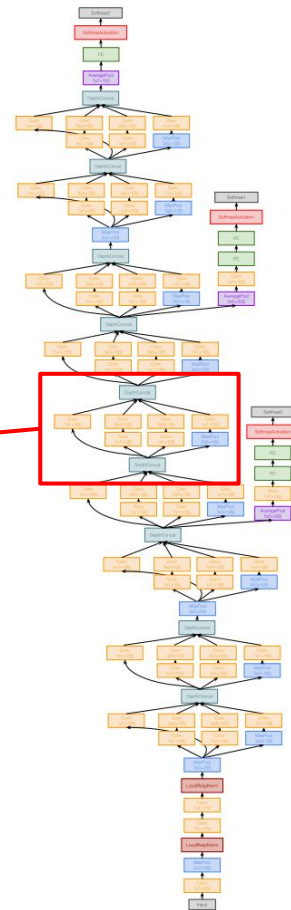
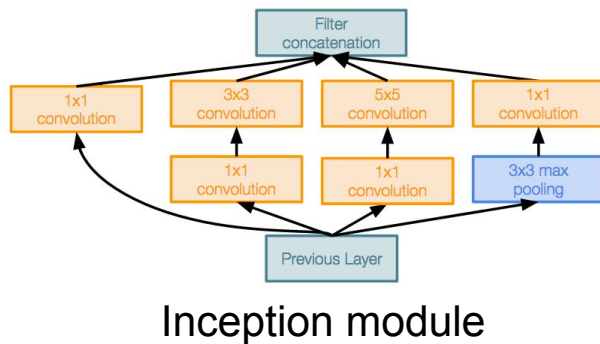
- 22 layers
- Efficient “Inception” module
- No FC layers
- Only 5 million parameters!
12x less than AlexNet
- ILSVRC’14 classification winner
(6.7% top 5 error)



Case Study: GoogLeNet

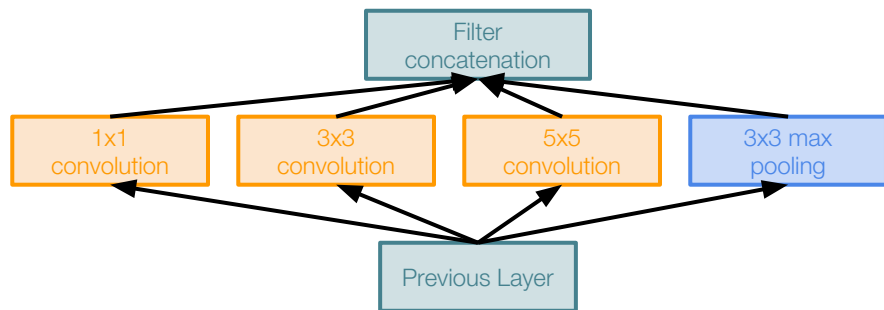
[Szegedy et al., 2014]

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



Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

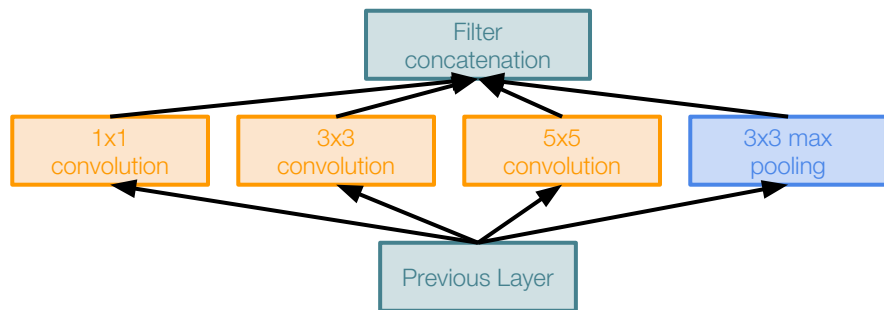
Apply parallel filter operations on the input from previous layer:

- 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)
- Pooling operation (3x3)

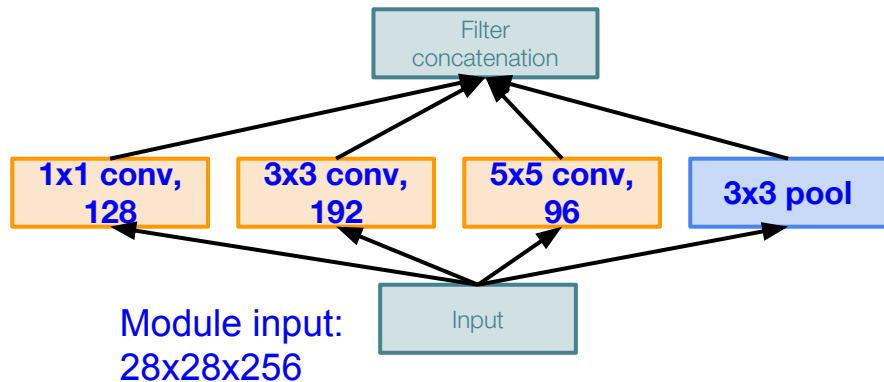
Concatenate all filter outputs together depth-wise

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

Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:



Naive Inception module

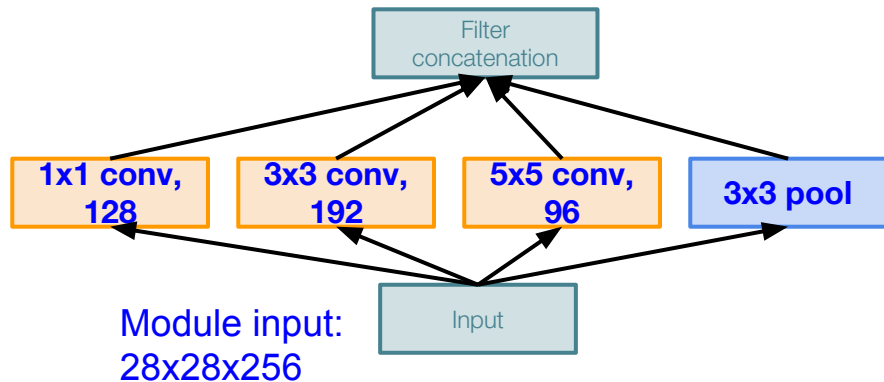
Q: What is the problem with this?
[Hint: Computational complexity]

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

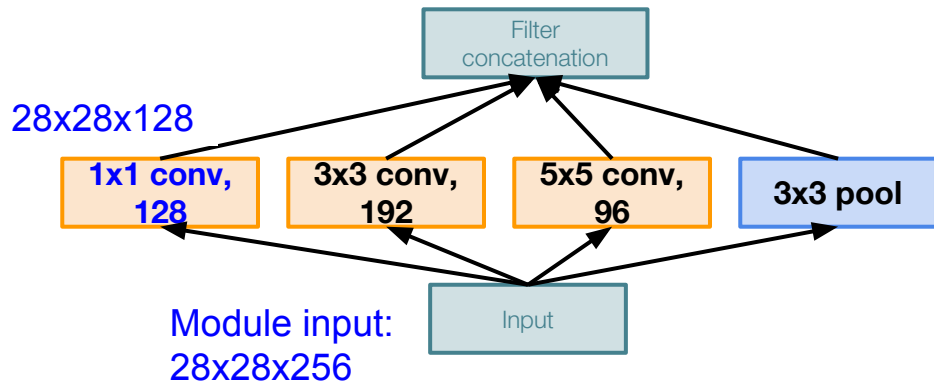
Case Study: GoogLeNet

[Szegedy et al., 2014]

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

Example:

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



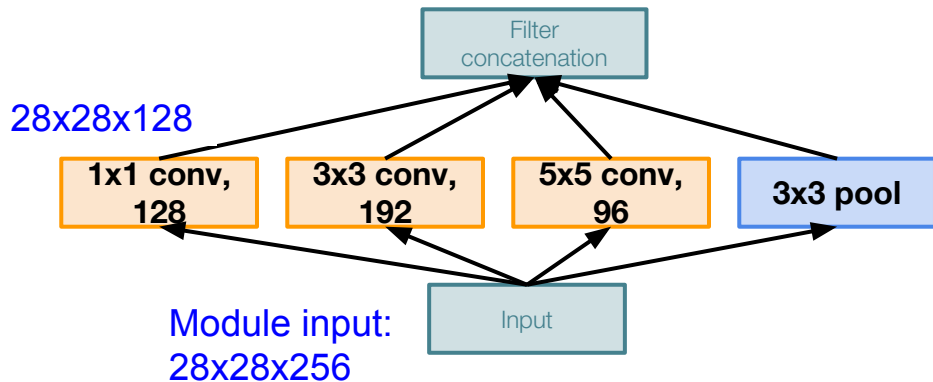
Naive Inception module

Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

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



Naive Inception module

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

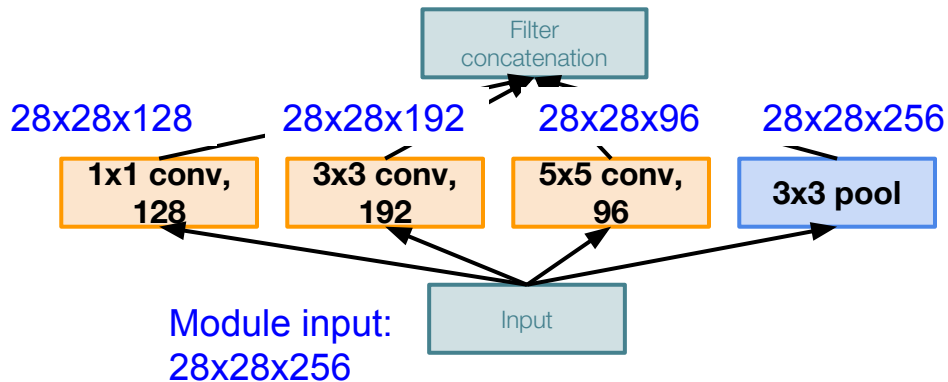
Case Study: GoogLeNet

[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?



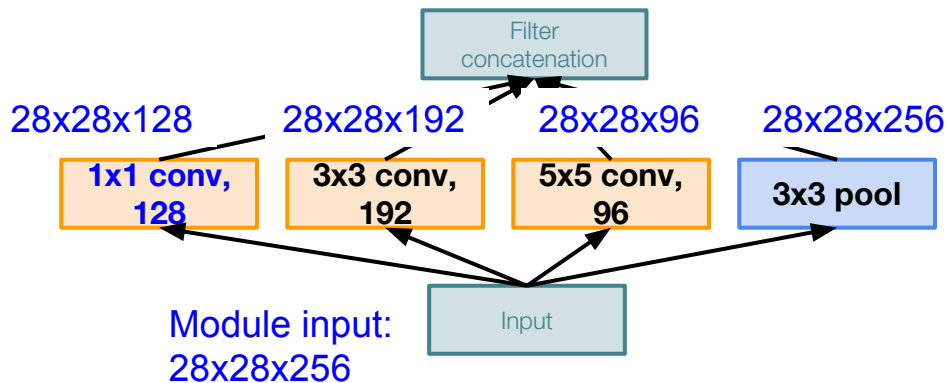
Naive Inception module

Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3: What is output size after filter concatenation?



Naive Inception module

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

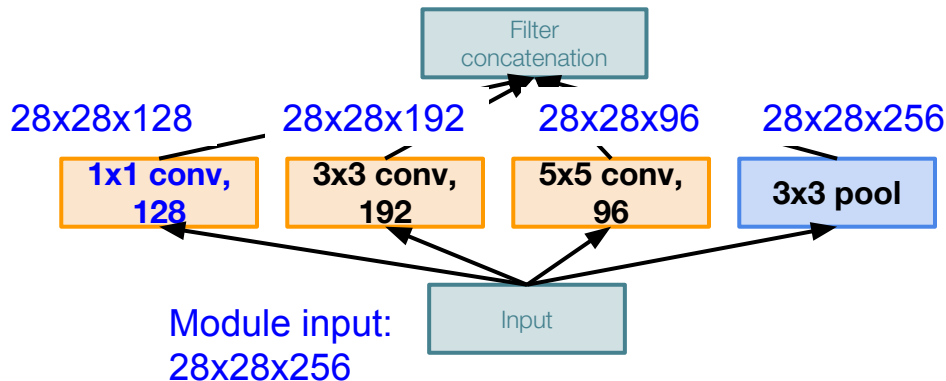
Case Study: GoogLeNet

[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

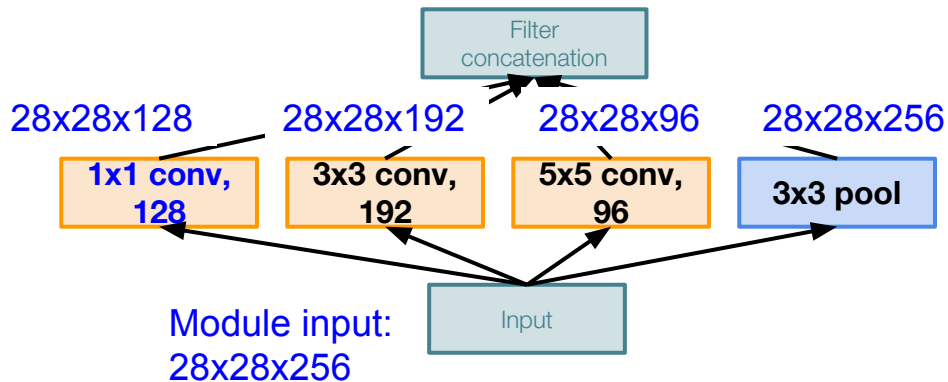
Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3: What is output size after filter concatenation?

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



Naive Inception module

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

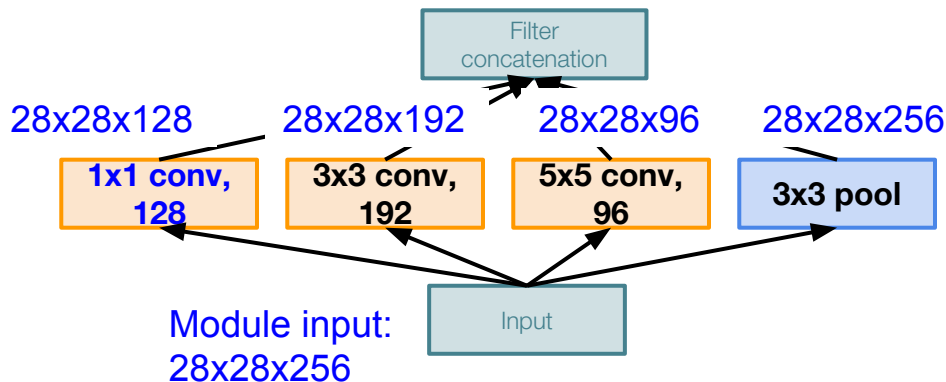
Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

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]

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

Very expensive compute

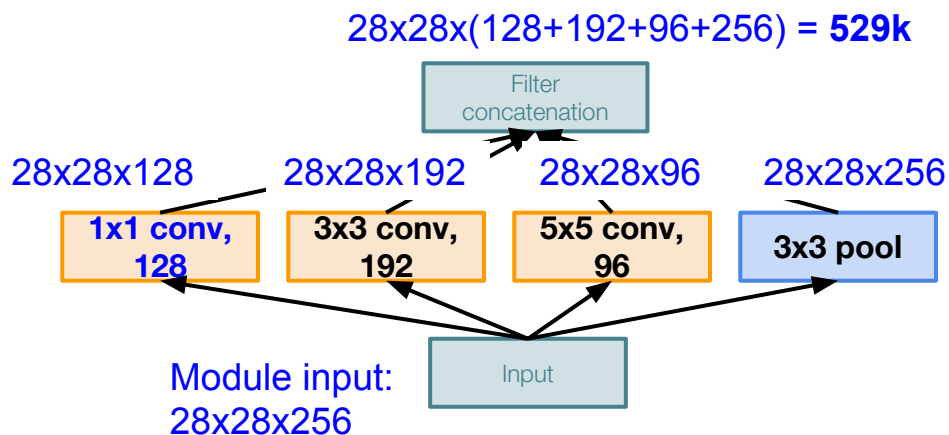
Pooling layer also preserves feature depth, which means total depth after concatenation can only grow at every layer!

Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3: What is output size after filter concatenation?

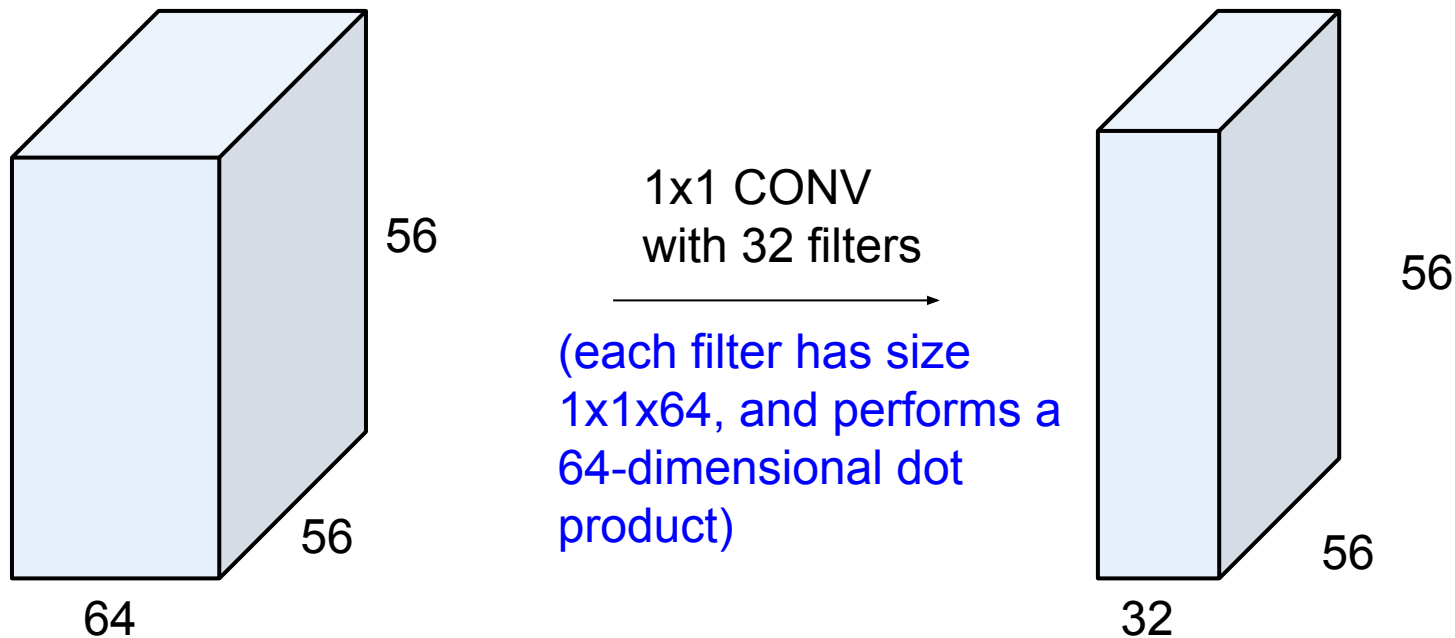


Naive Inception module

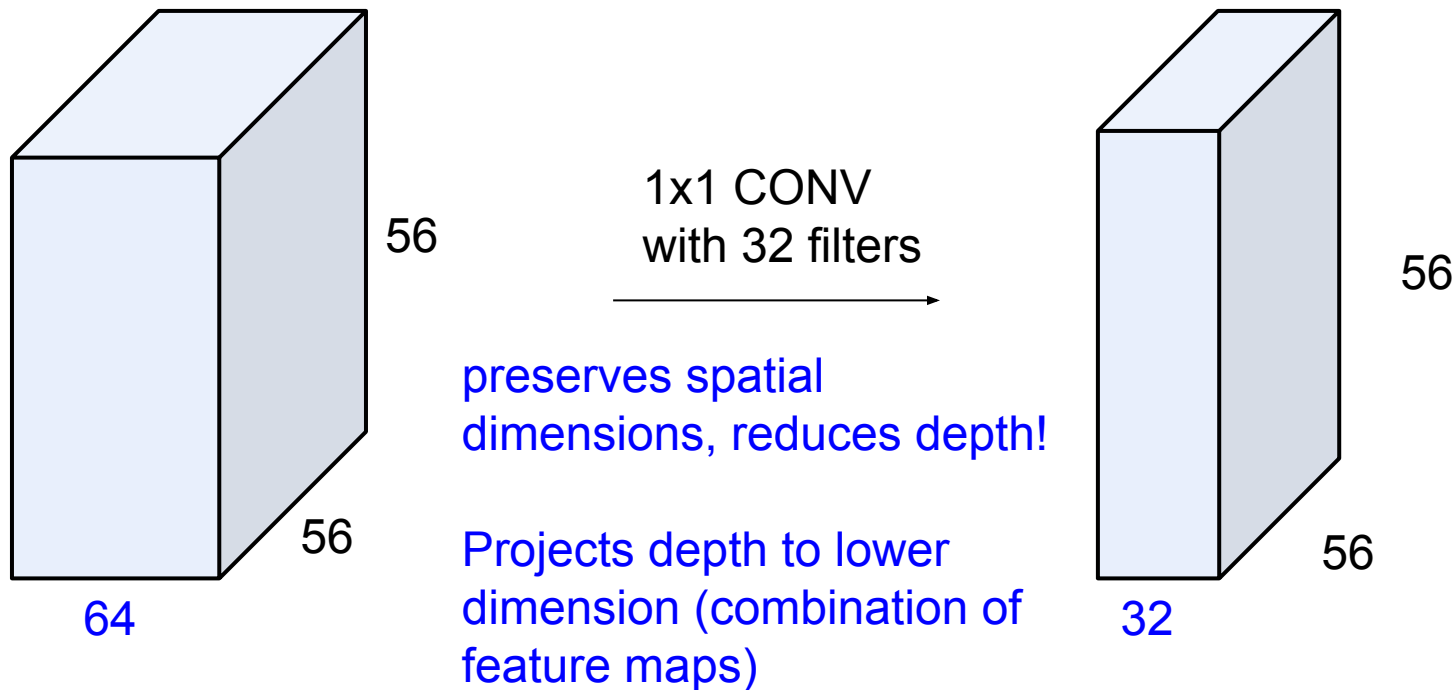
Q: What is the problem with this?
[Hint: Computational complexity]

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

Reminder: 1x1 convolutions

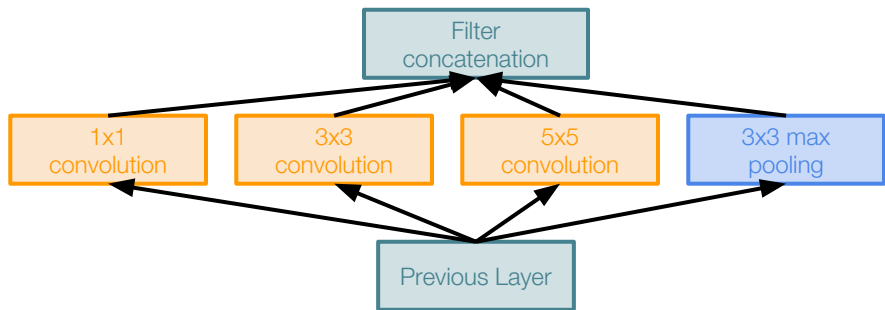


Reminder: 1x1 convolutions

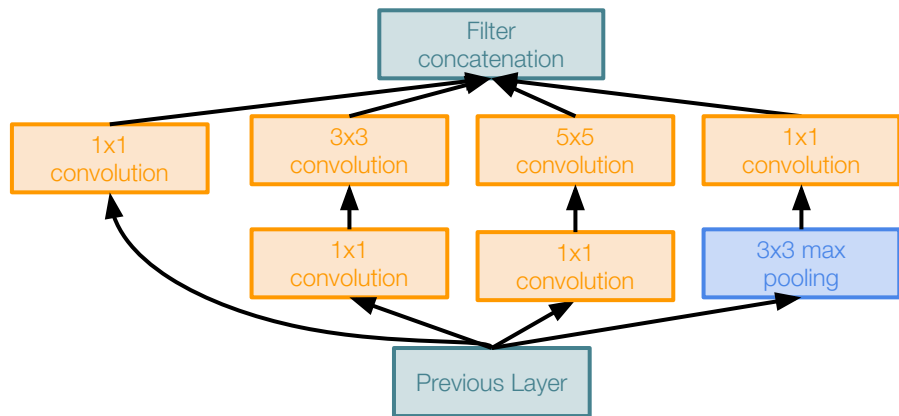


Case Study: GoogLeNet

[Szegedy et al., 2014]



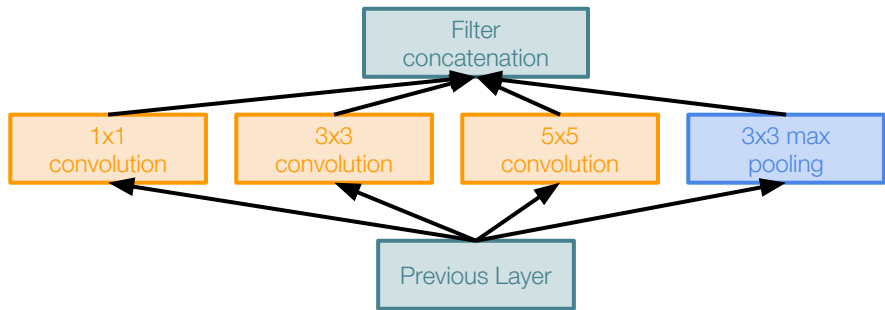
Naive Inception module



Inception module with dimension reduction

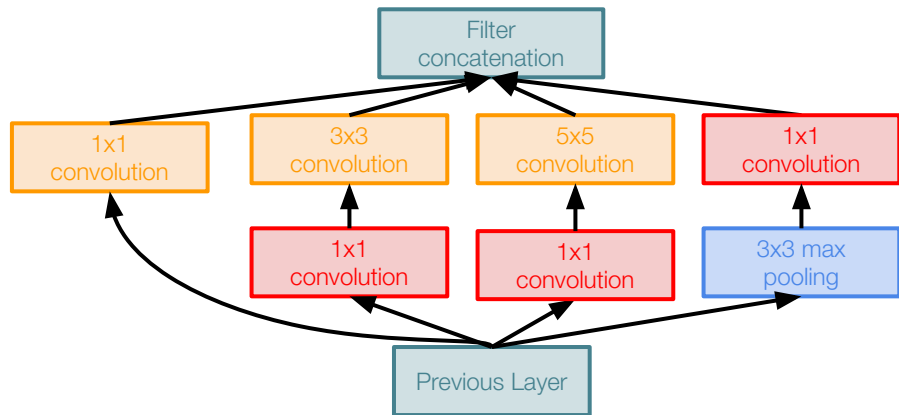
Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

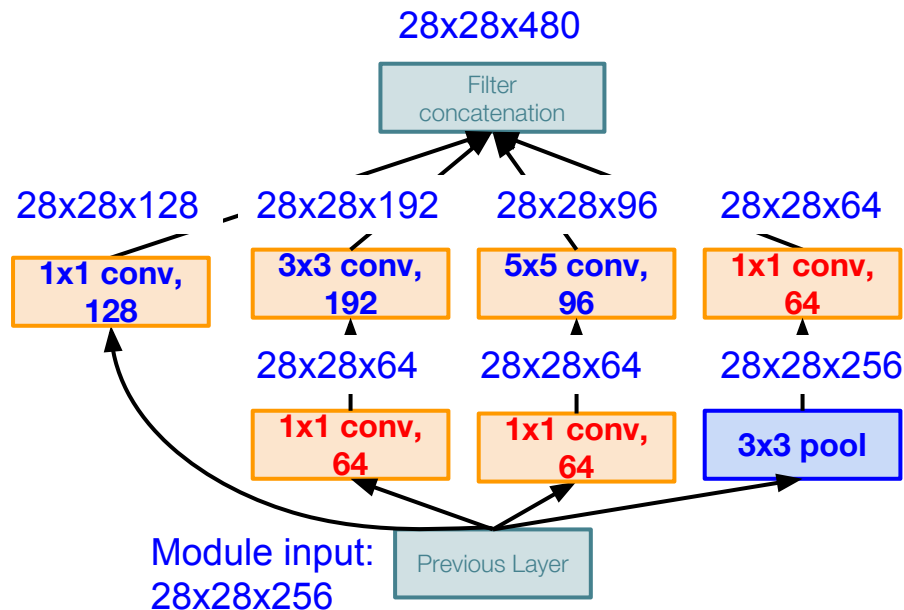
1x1 conv “bottleneck”
layers



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

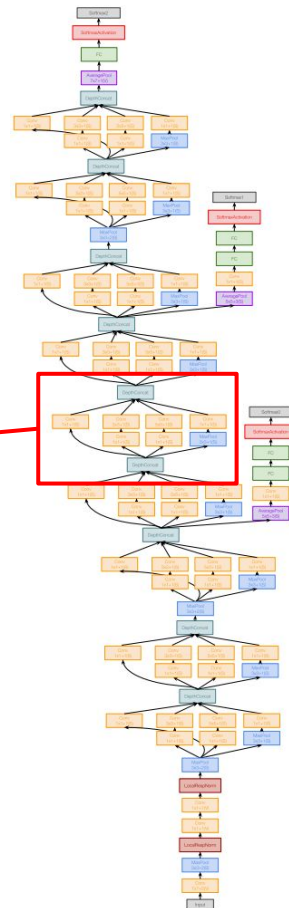
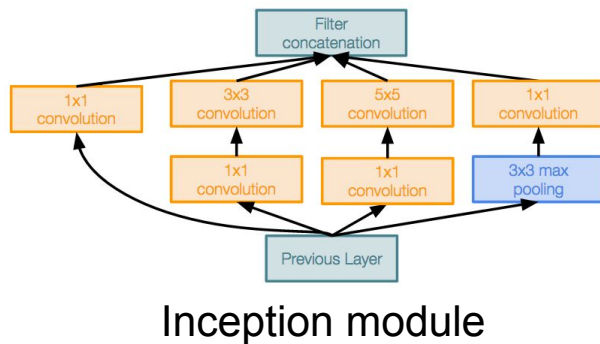
Total: 358M ops

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

Case Study: GoogLeNet

[Szegedy et al., 2014]

Stack Inception modules
with dimension reduction
on top of each other



[Szegedy et al., 2014]

Full GoogLeNet architecture

The diagram illustrates the Full GoogLeNet architecture, which is a deep convolutional neural network designed for image classification and localization. The architecture is composed of several key components:

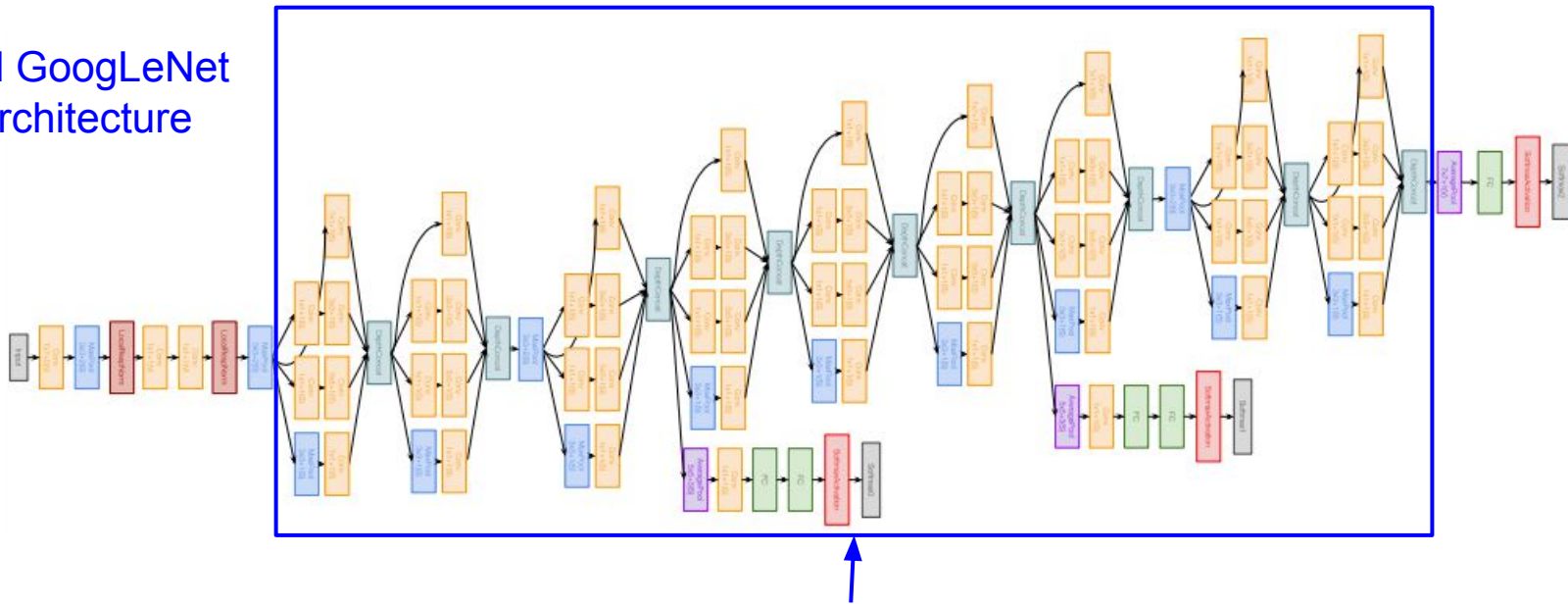
- Input Layer:** The process begins with an input image, which is processed by a **TensorFlow** layer.
- Preprocessing:** The input is passed through a **Preprocessing** layer, which includes operations like **Resize**, **Normalize**, and **Pad**.
- Feature Extraction:** The core of the network consists of multiple **Inception** modules. Each module is designed to extract features at multiple scales simultaneously. The diagram shows several **Inception** modules, each containing multiple parallel branches (e.g., **Inception v1**, **Inception v2**, **Inception v3**, **Inception v4**, **Inception v5**, **Inception v6**, **Inception v7**, **Inception v8**, **Inception v9**, **Inception v10**, **Inception v11**, **Inception v12**, **Inception v13**, **Inception v14**, **Inception v15**, **Inception v16**, **Inception v17**, **Inception v18**, **Inception v19**, **Inception v20**, **Inception v21**, **Inception v22**, **Inception v23**, **Inception v24**, **Inception v25**, **Inception v26**, **Inception v27**, **Inception v28**, **Inception v29**, **Inception v30**, **Inception v31**, **Inception v32**, **Inception v33**, **Inception v34**, **Inception v35**, **Inception v36**, **Inception v37**, **Inception v38**, **Inception v39**, **Inception v40**, **Inception v41**, **Inception v42**, **Inception v43**, **Inception v44**, **Inception v45**, **Inception v46**, **Inception v47**, **Inception v48**, **Inception v49**, **Inception v50**, **Inception v51**, **Inception v52**, **Inception v53**, **Inception v54**, **Inception v55**, **Inception v56**, **Inception v57**, **Inception v58**, **Inception v59**, **Inception v60**, **Inception v61**, **Inception v62**, **Inception v63**, **Inception v64**, **Inception v65**, **Inception v66**, **Inception v67**, **Inception v68**, **Inception v69**, **Inception v70**, **Inception v71**, **Inception v72**, **Inception v73**, **Inception v74**, **Inception v75**, **Inception v76**, **Inception v77**, **Inception v78**, **Inception v79**, **Inception v80**, **Inception v81**, **Inception v82**, **Inception v83**, **Inception v84**, **Inception v85**, **Inception v86**, **Inception v87**, **Inception v88**, **Inception v89**, **Inception v90**, **Inception v91**, **Inception v92**, **Inception v93**, **Inception v94**, **Inception v95**, **Inception v96**, **Inception v97**, **Inception v98**, **Inception v99**, **Inception v100**, **Inception v101**, **Inception v102**, **Inception v103**, **Inception v104**, **Inception v105**, **Inception v106**, **Inception v107**, **Inception v108**, **Inception v109**, **Inception v110**, **Inception v111**, **Inception v112**, **Inception v113**, **Inception v114**, **Inception v115**, **Inception v116**, **Inception v117**, **Inception v118**, **Inception v119**, **Inception v120**, **Inception v121**, **Inception v122**, **Inception v123**, **Inception v124**, **Inception v125**, **Inception v126**, **Inception v127**, **Inception v128**, **Inception v129**, **Inception v130**, **Inception v131**, **Inception v132**, **Inception v133**, **Inception v134**, **Inception v135**, **Inception v136**, **Inception v137**, **Inception v138**, **Inception v139**, **Inception v140**, **Inception v141**, **Inception v142**, **Inception v143**, **Inception v144**, **Inception v145**, **Inception v146**, **Inception v147**, **Inception v148**, **Inception v149**, **Inception v150**, **Inception v151**, **Inception v152**, **Inception v153**, **Inception v154**, **Inception v155**, **Inception v156**, **Inception v157**, **Inception v158**, **Inception v159**, **Inception v160**, **Inception v161**, **Inception v162**, **Inception v163**, **Inception v164**, **Inception v165**, **Inception v166**, **Inception v167**, **Inception v168**, **Inception v169**, **Inception v170**, **Inception v171**, **Inception v172**, **Inception v173**, **Inception v174**, **Inception v175**, **Inception v176**, **Inception v177**, **Inception v178**, **Inception v179**, **Inception v180**, **Inception v181**, **Inception v182**, **Inception v183**, **Inception v184**, **Inception v185**, **Inception v186**, **Inception v187**, **Inception v188**, **Inception v189**, **Inception v190**, **Inception v191**, **Inception v192**, **Inception v193**, **Inception v194**, **Inception v195**, **Inception v196**, **Inception v197**, **Inception v198**, **Inception v199**, **Inception v200**, **Inception v201**, **Inception v202**, **Inception v203**, **Inception v204**, **Inception v205**, **Inception v206**, **Inception v207**, **Inception v208**, **Inception v209**, **Inception v210**, **Inception v211**, **Inception v212**, **Inception v213**, **Inception v214**, **Inception v215**, **Inception v216**, **Inception v217**, **Inception v218**, **Inception v219**, **Inception v220**, **Inception v221**, **Inception v222**, **Inception v223**, **Inception v224**, **Inception v225**, **Inception v226**, **Inception v227**, **Inception v228**, **Inception v229**, **Inception v230**, **Inception v231**, **Inception v232**, **Inception v233**, **Inception v234**, **Inception v235**, **Inception v236**, **Inception v237**, **Inception v238**, **Inception v239**, **Inception v240**, **Inception v241**, **Inception v242**, **Inception v243**, **Inception v244**, **Inception v245**, **Inception v246**, **Inception v247**, **Inception v248**, **Inception v249**, **Inception v250**, **Inception v251**, **Inception v252**, **Inception v253**, **Inception v254**, **Inception v255**, **Inception v256**, **Inception v257**, **Inception v258**, **Inception v259**, **Inception v260**, **Inception v261**, **Inception v262**, **Inception v263**, **Inception v264**, **Inception v265**, **Inception v266**, **Inception v267**, **Inception v268**, **Inception v269**, **Inception v270**, **Inception v271**, **Inception v272**, **Inception v273**, **Inception v274**, **Inception v275**, **Inception v276**, **Inception v277**, **Inception v278**, **Inception v279**, **Inception v280**, **Inception v281**, **Inception v282**, **Inception v283**, **Inception v284**, **Inception v285**, **Inception v286**, **Inception v287**, **Inception v288**, **Inception v289**, **Inception v290**, **Inception v291**, **Inception v292**, **Inception v293**, **Inception v294**, **Inception v295**, **Inception v296**, **Inception v297**, **Inception v298**, **Inception v299**, **Inception v300**, **Inception v301**, **Inception v302**, **Inception v303**, **Inception v304**, **Inception v305**, **Inception v306**, **Inception v307**, **Inception v308**, **Inception v309**, **Inception v310**, **Inception v311**, **Inception v312**, **Inception v313**, **Inception v314**, **Inception v315**, **Inception v316**, **Inception v317**, **Inception v318**, **Inception v319**, **Inception v320**, **Inception v321**, **Inception v322**, **Inception v323**, **Inception v324**, **Inception v325**, **Inception v326**, **Inception v327**, **Inception v328**, **Inception v329**, **Inception v330**, **Inception v331**, **Inception v332**, **Inception v333**, **Inception v334**, **Inception v335**, **Inception v336**, **Inception v337**, **Inception v338**, **Inception v339**, **Inception v340**, **Inception v341**, **Inception v342**, **Inception v343**, **Inception v344**, **Inception v345**, **Inception v346**, **Inception v347**, **Inception v348**, **Inception v349**, **Inception v350**, **Inception v351**, **Inception v352**, **Inception v353**, **Inception v354**, **Inception v355**, **Inception v356**, **Inception v357**, **Inception v358**,

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

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

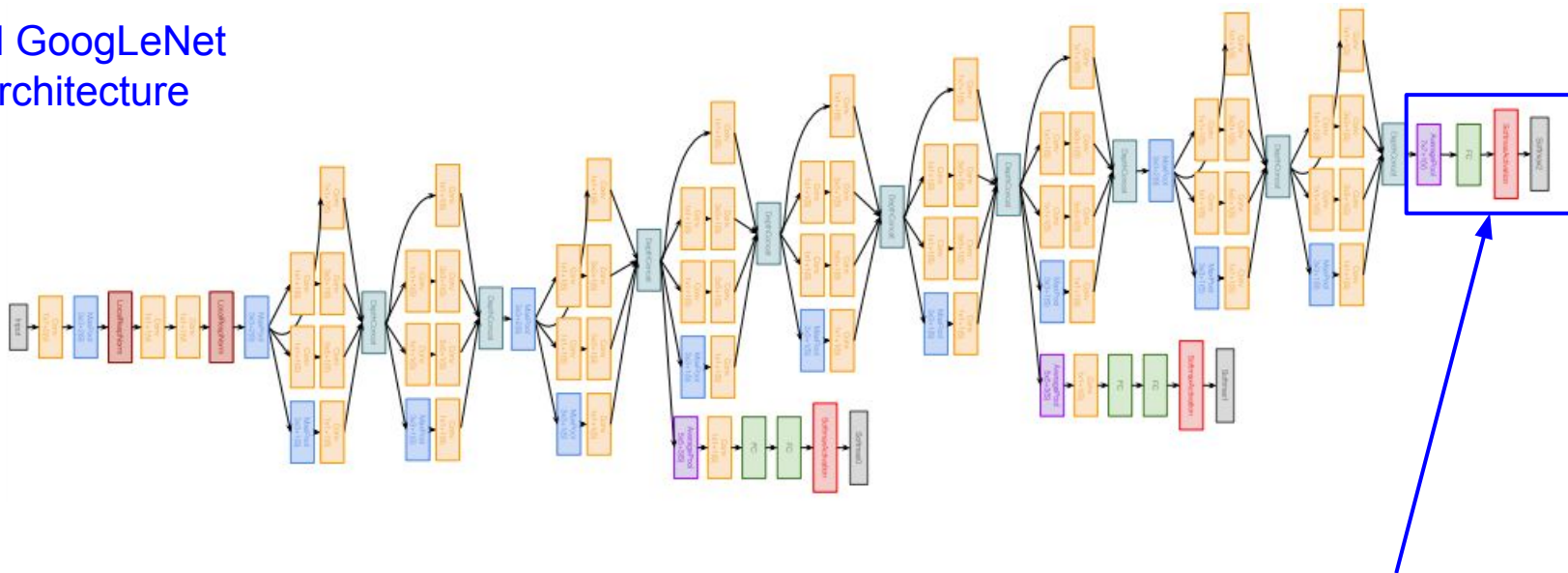


Stacked Inception
Modules

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

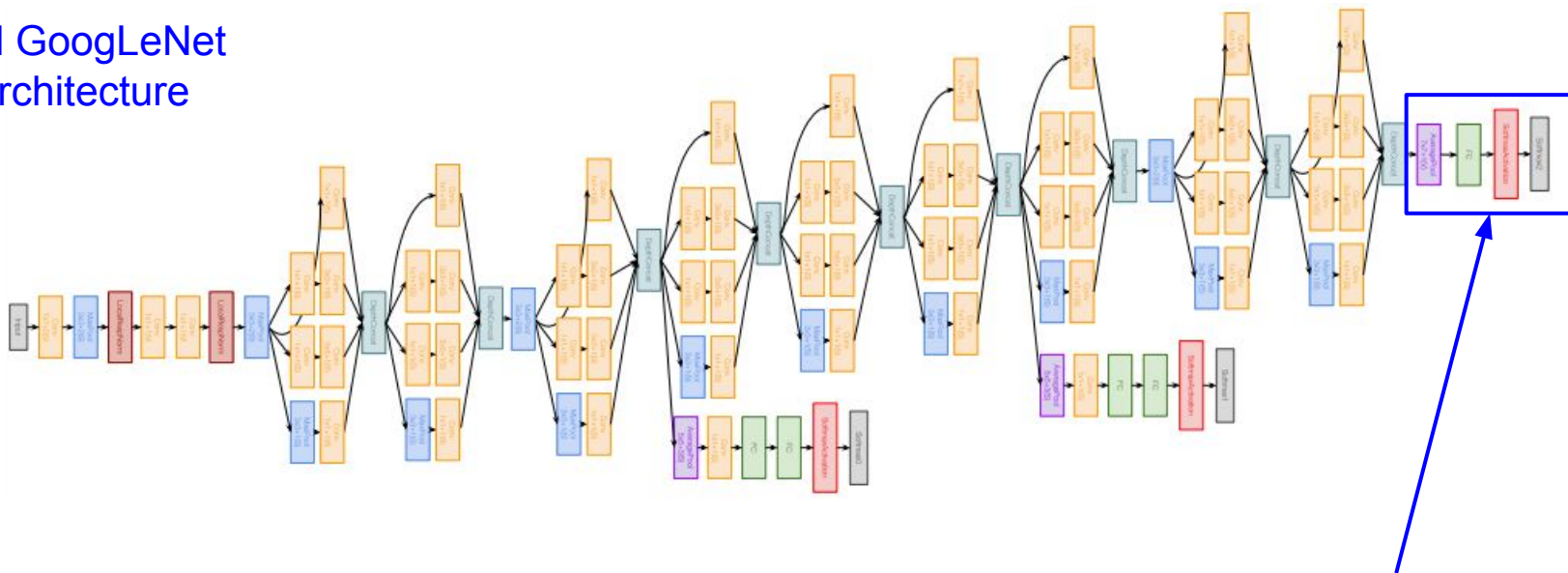


Classifier output

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

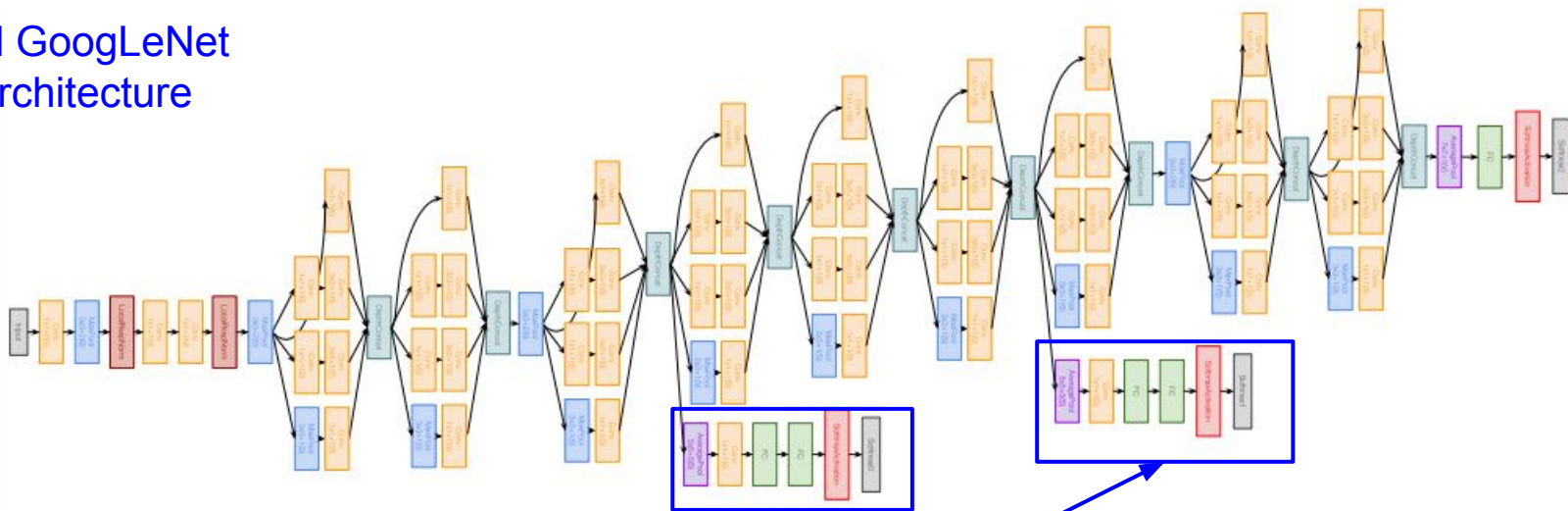


Classifier output
(removed expensive FC layers!)

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet
architecture

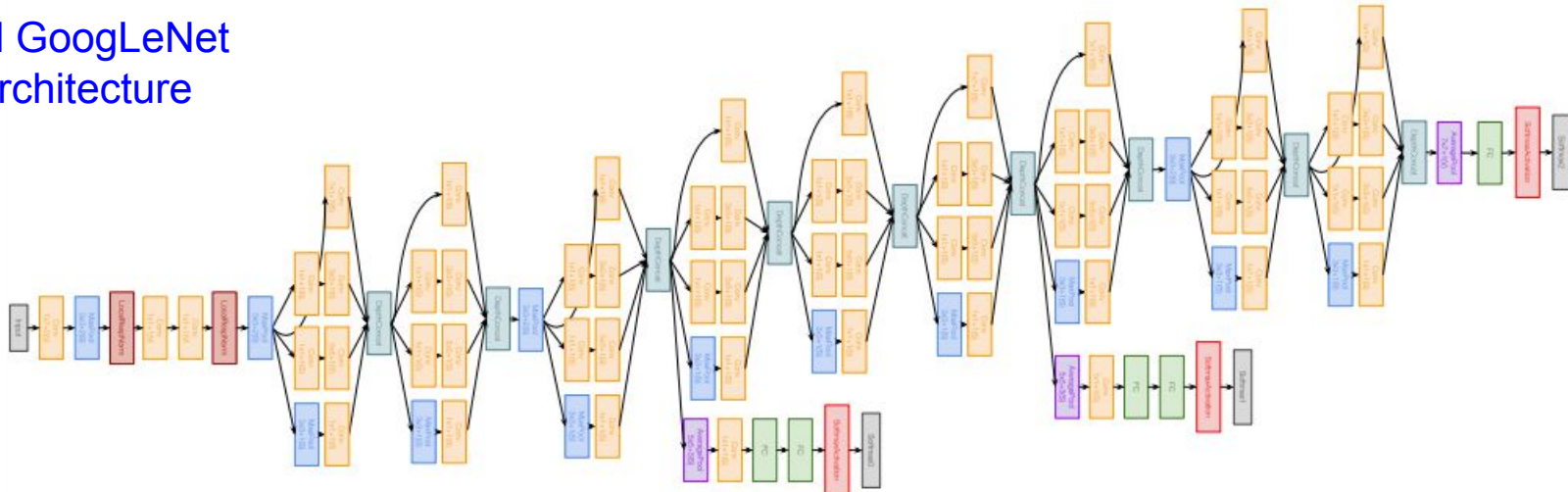


Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



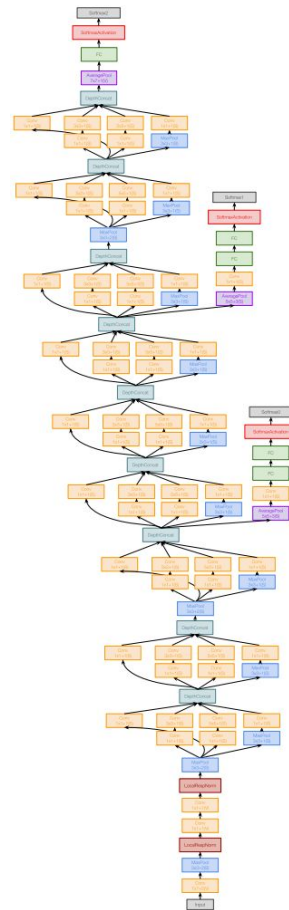
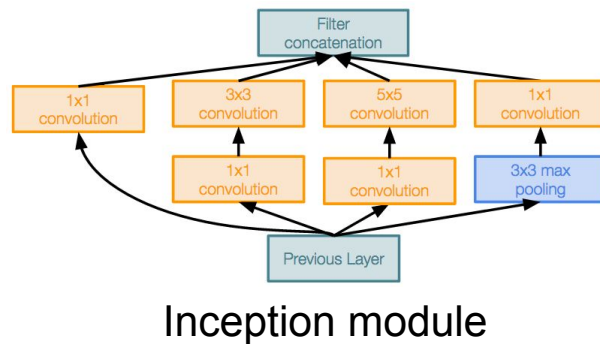
22 total layers with weights (including each parallel layer in an Inception module)

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

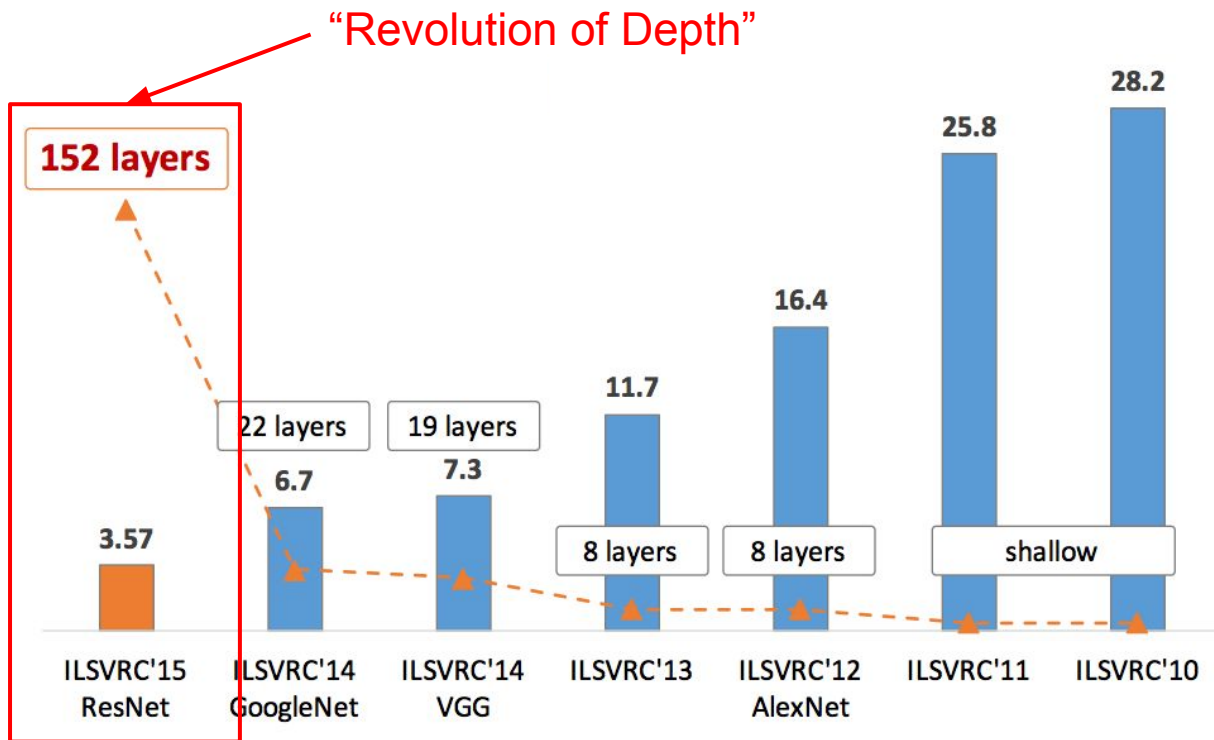


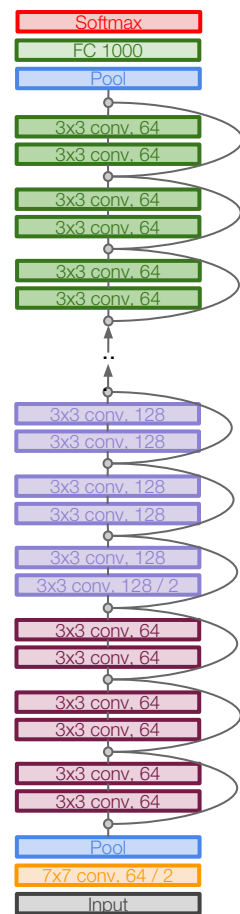
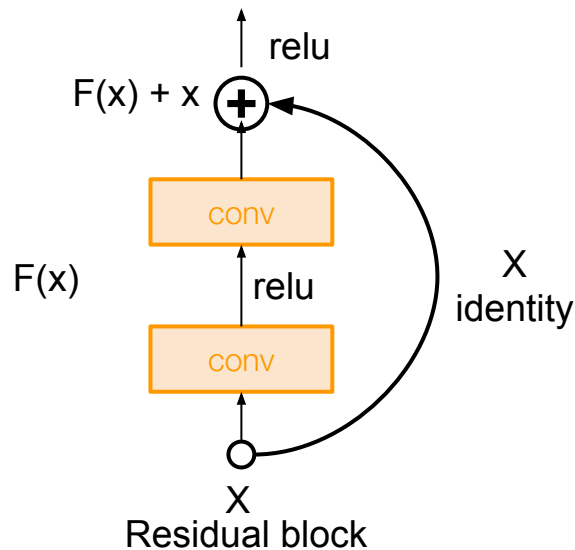
Figure copyright Kaiming He, 2016. Reproduced with permission.

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

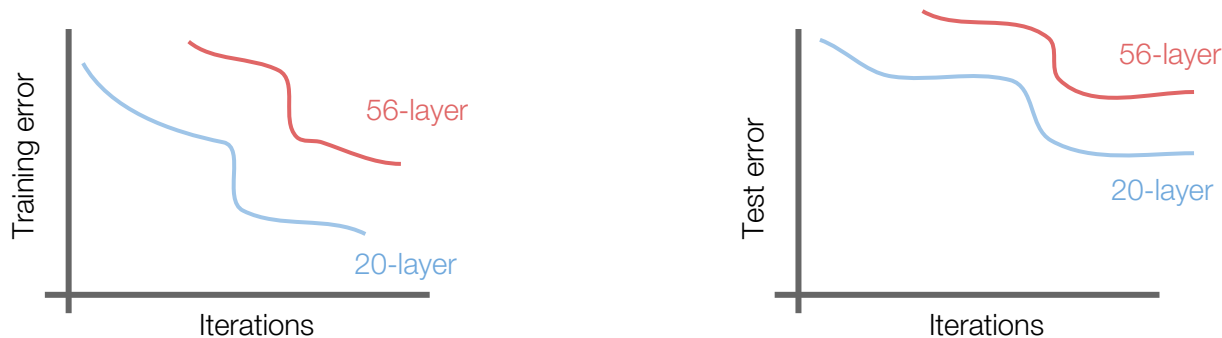
[He et al., 2015]

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?

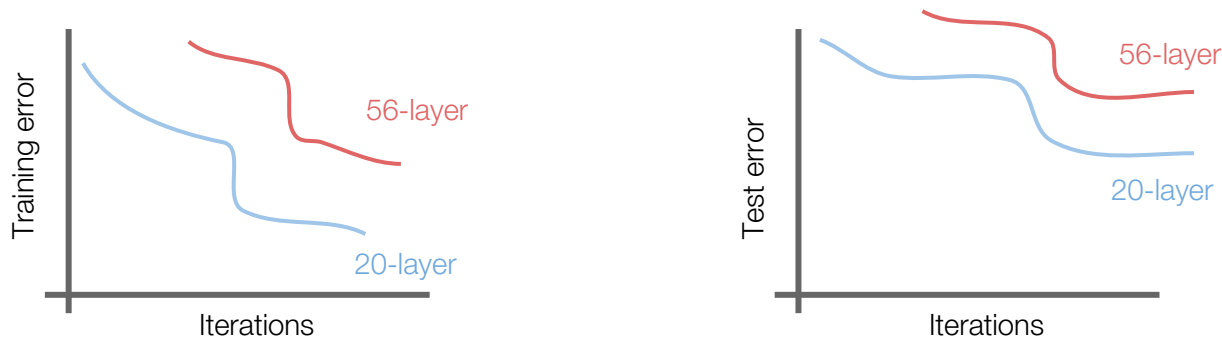


Q: What's strange about these training and test curves?
[Hint: look at the order of the curves]

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]

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

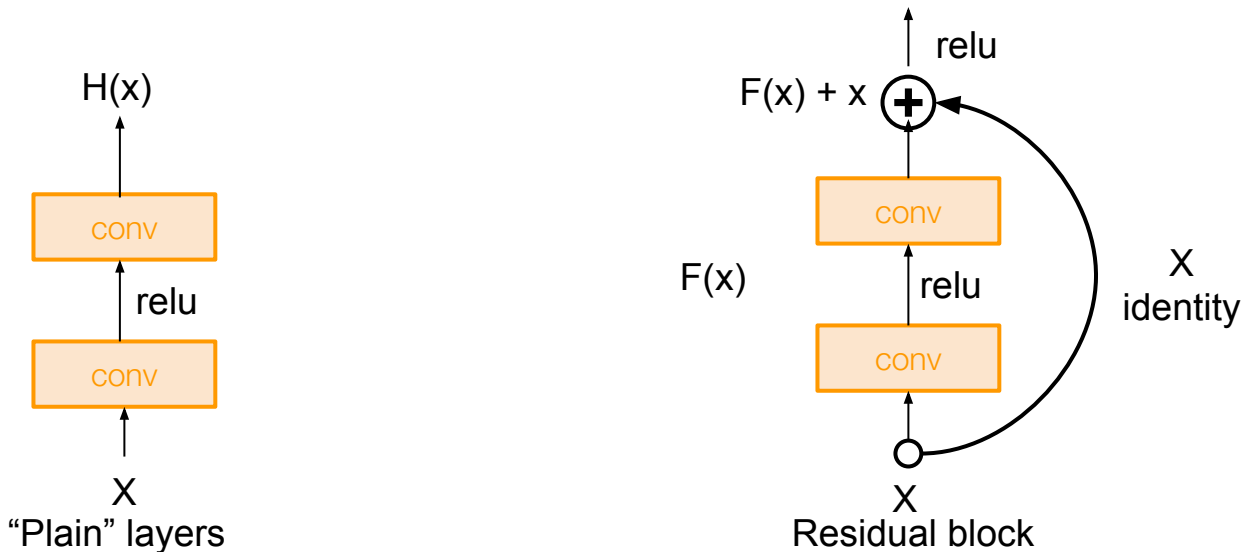
The deeper model should be able to perform at least as well as the shallower model.

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]

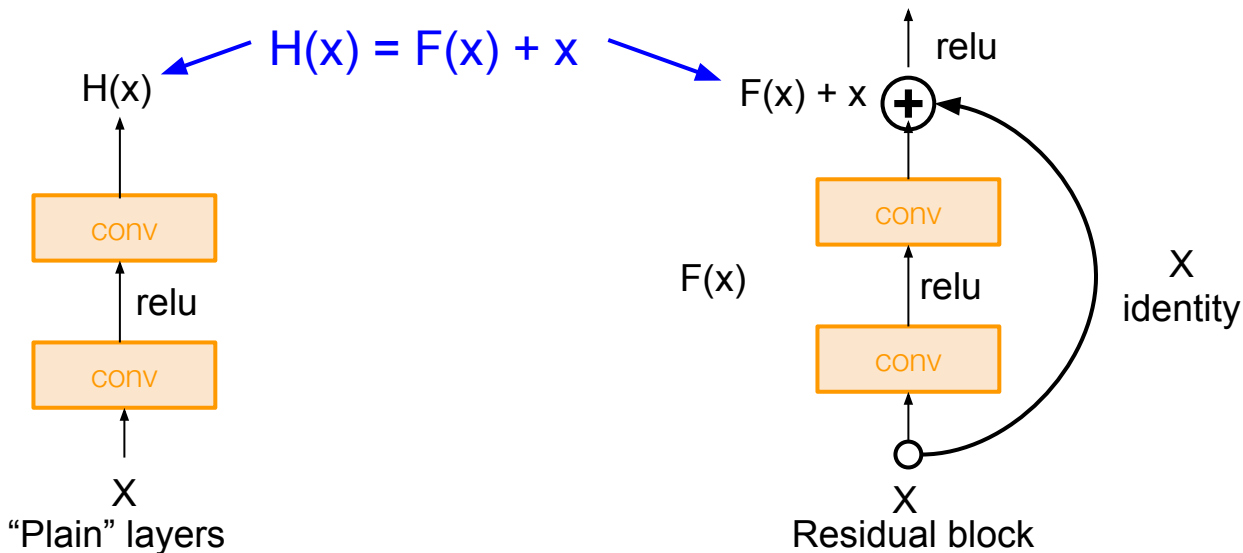
Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping



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



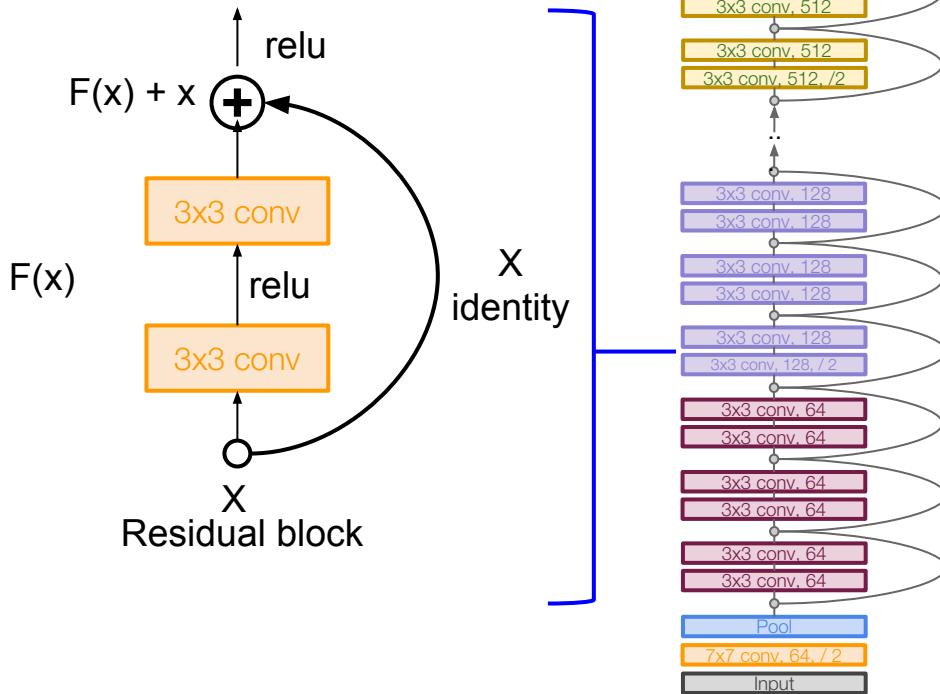
Use layers to
fit residual
 $F(x) = H(x) - x$
instead of
 $H(x)$ directly

Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:

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

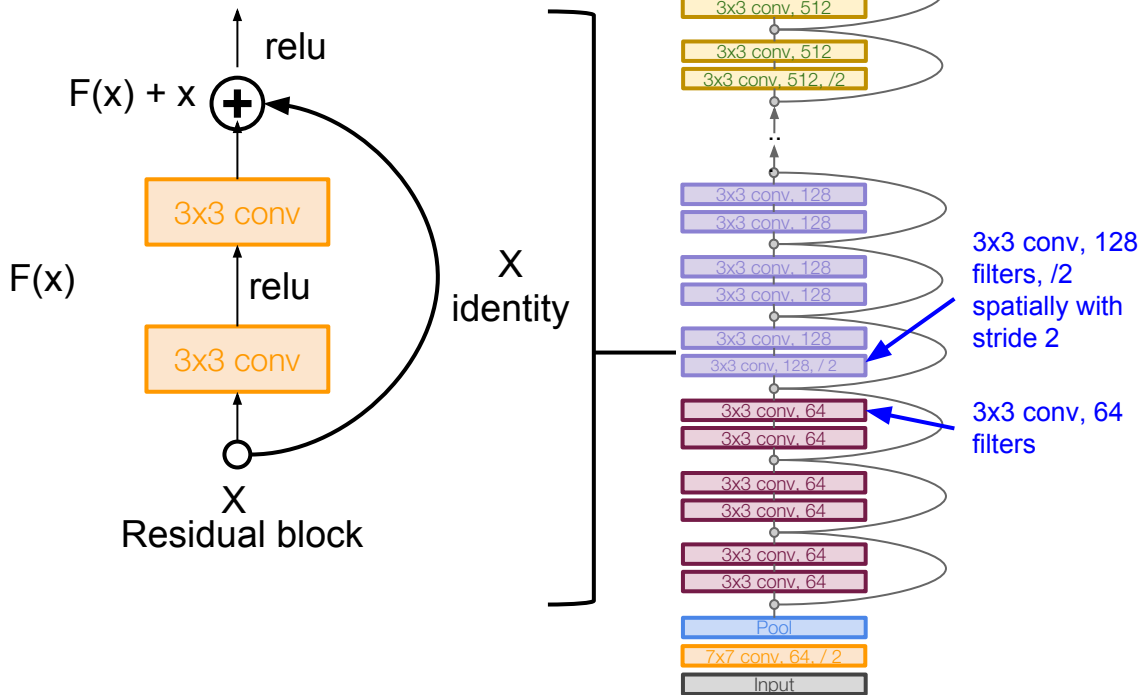


Case Study: ResNet

[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)

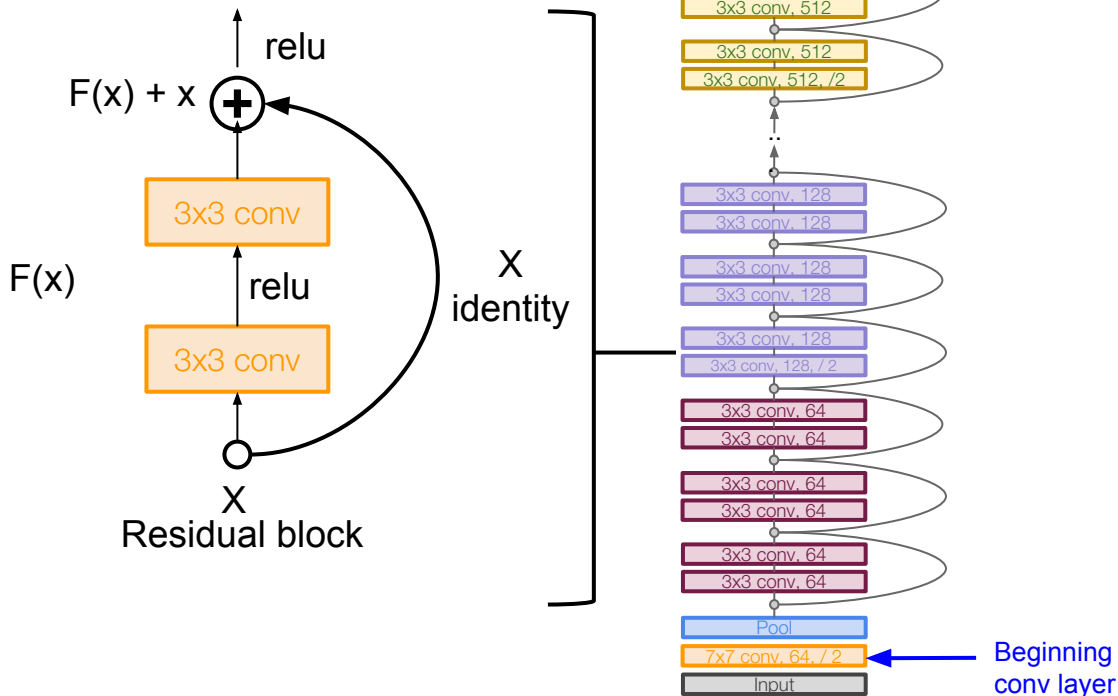


Case Study: ResNet

[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

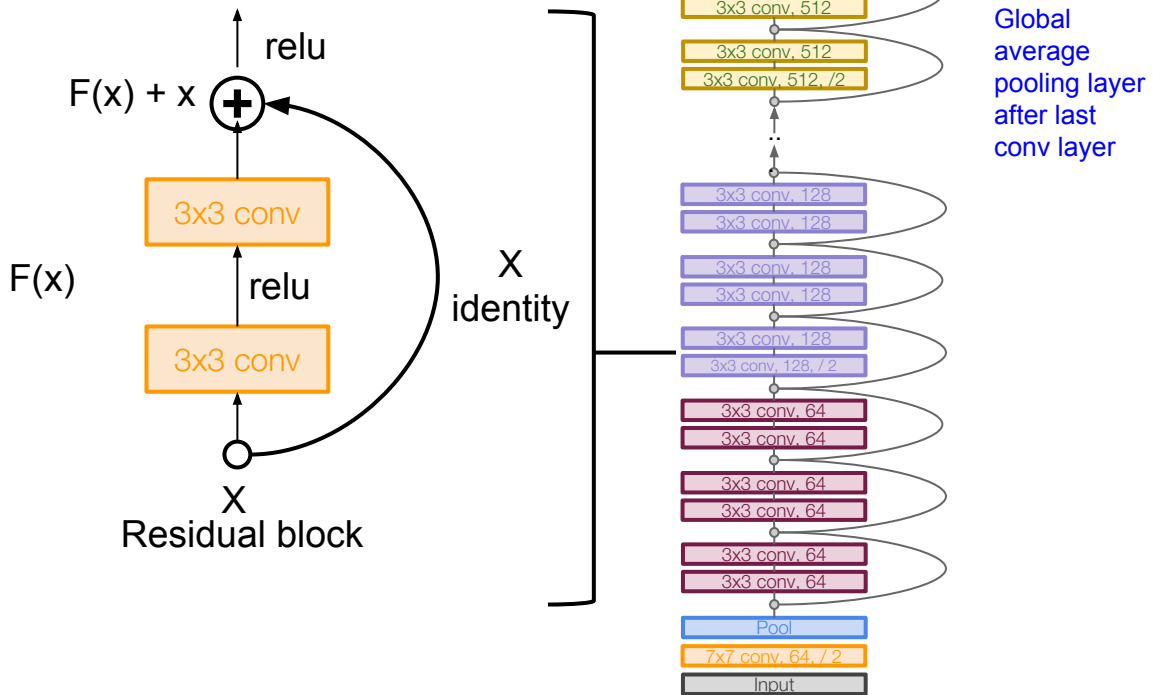


Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:

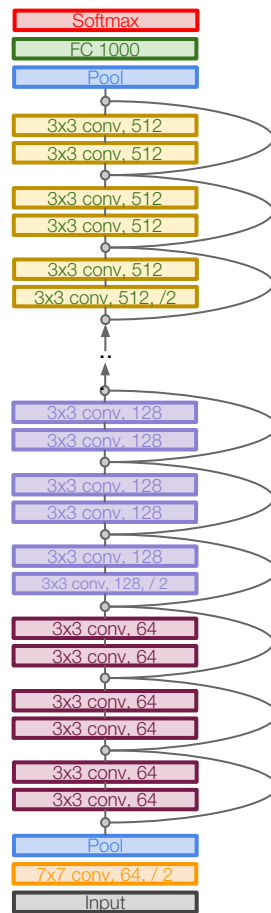
- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)
- Additional conv layer at the beginning
- No FC layers at the end (only FC 1000 to output classes)



Case Study: ResNet

[He et al., 2015]

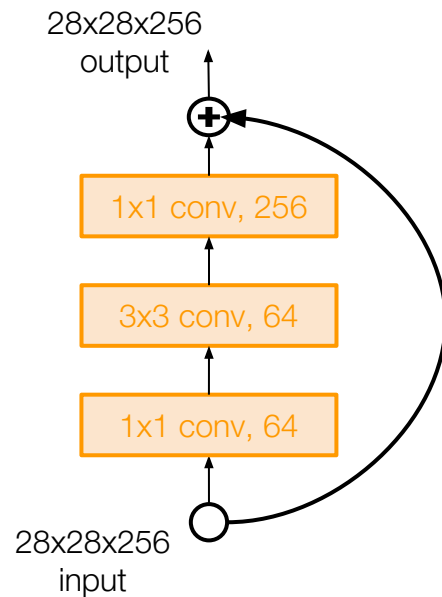
Total depths of 34, 50, 101, or
152 layers for ImageNet



Case Study: ResNet

[He et al., 2015]

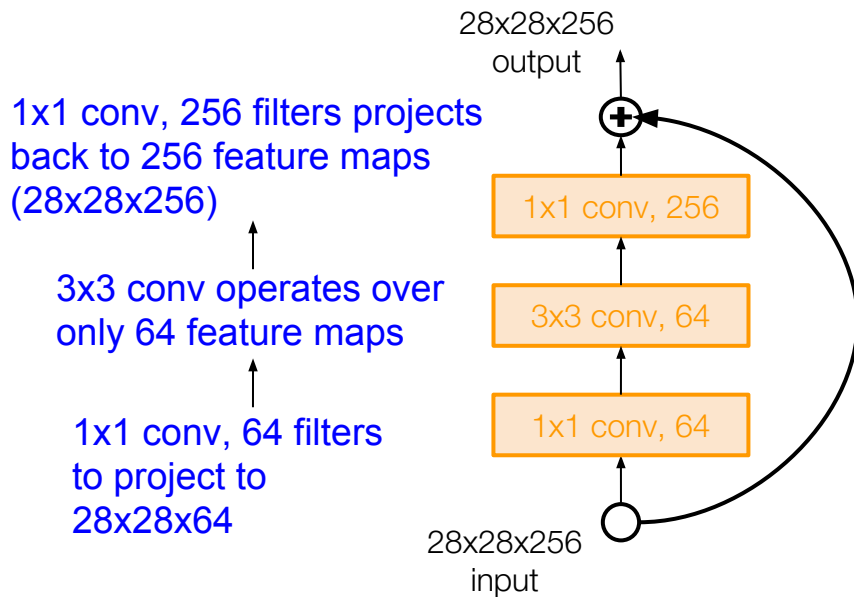
For deeper networks
(ResNet-50+), use “bottleneck”
layer to improve efficiency
(similar to GoogLeNet)



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

[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

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

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

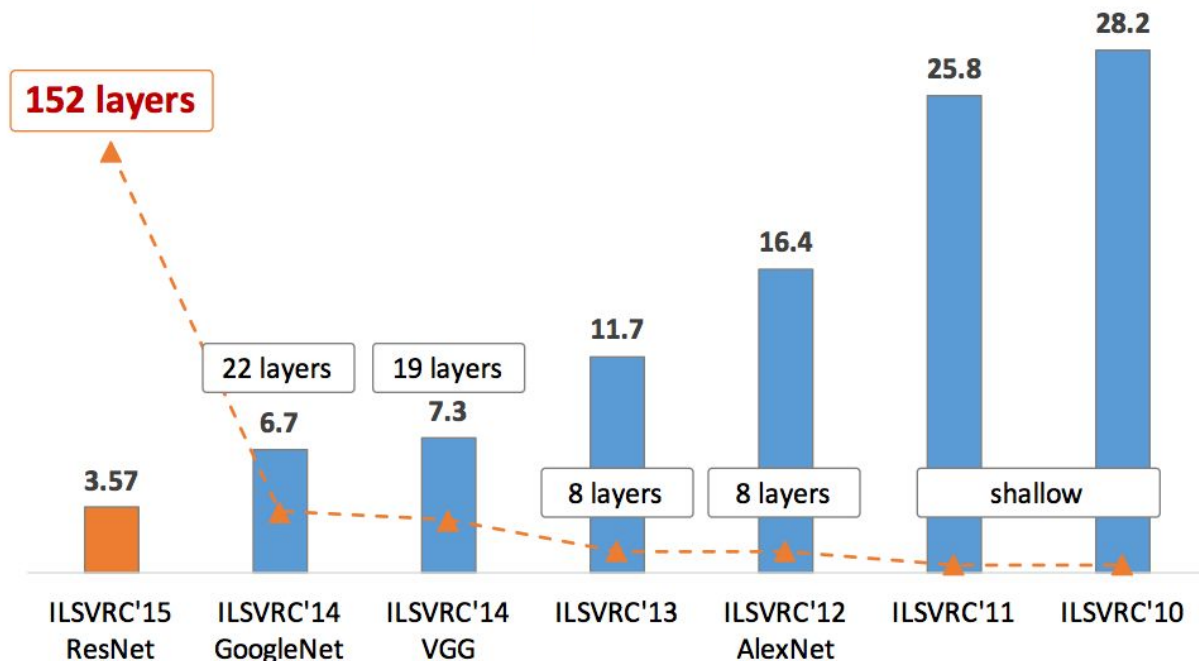
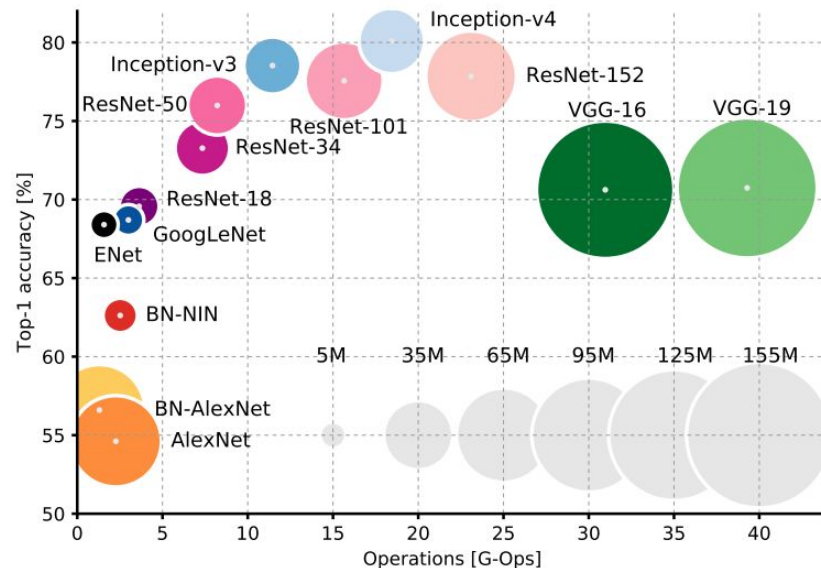
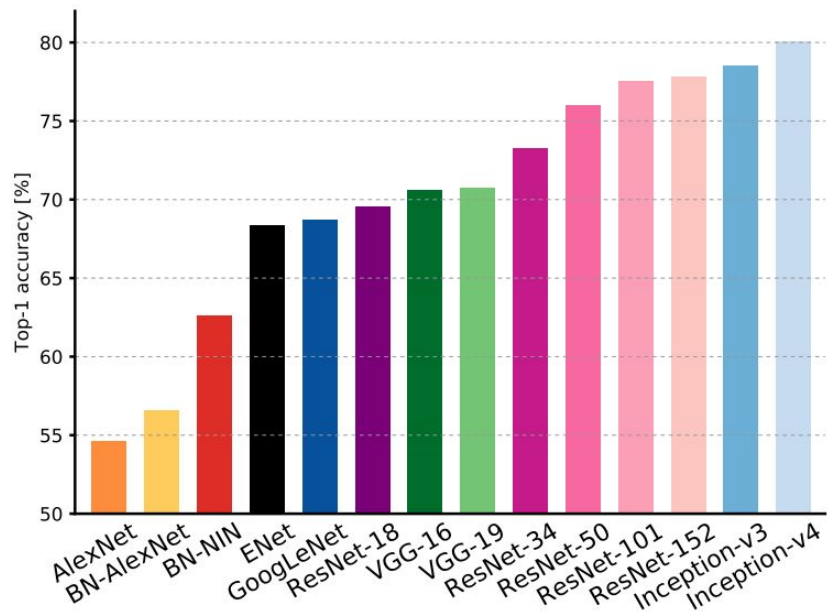


Figure copyright Kaiming He, 2016. Reproduced with permission.

Comparing complexity...

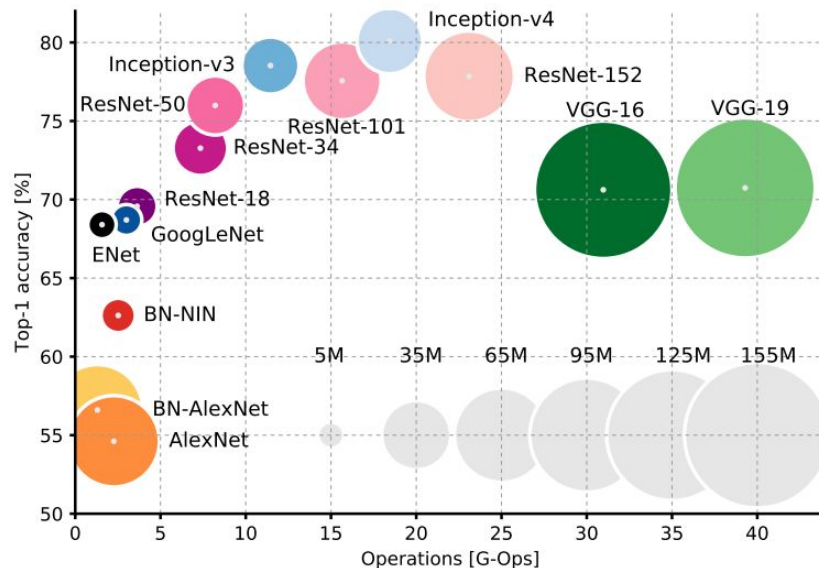
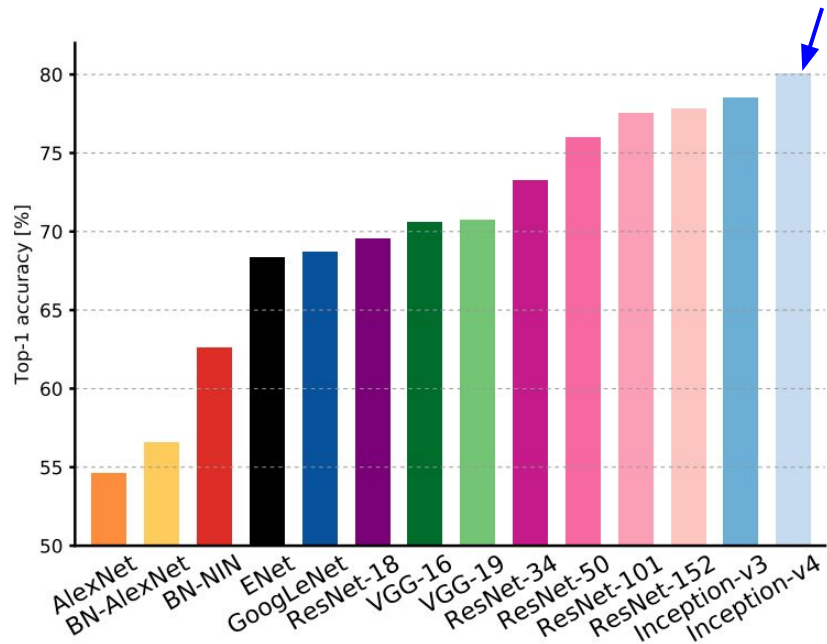


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Figures copyright Alfredo Canziani, Adam Paszke, Eugenio Culurciello, 2017. Reproduced with permission.

Comparing complexity...

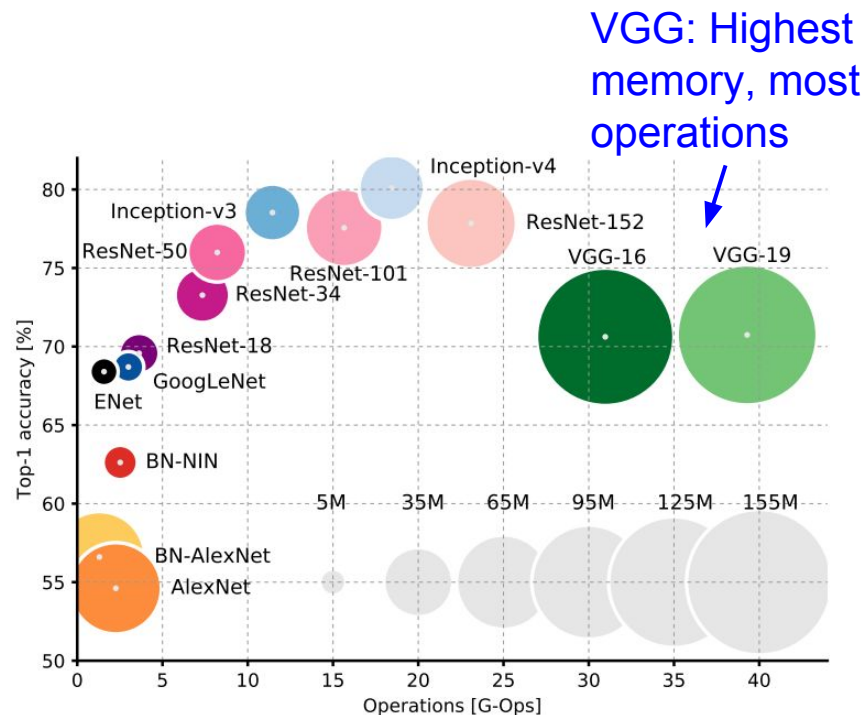
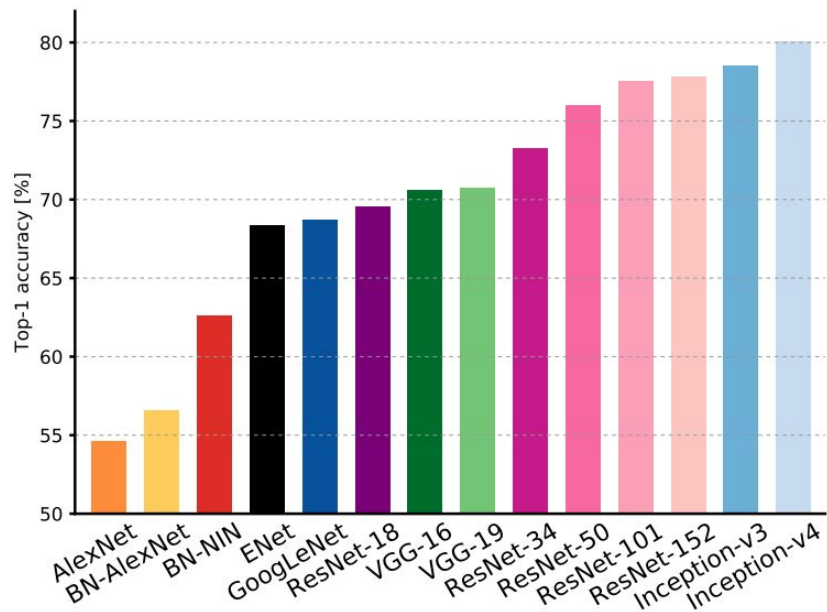
Inception-v4: Resnet + Inception!



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

Figures copyright Alfredo Canziani, Adam Paszke, Eugenio Culurciello, 2017. Reproduced with permission.

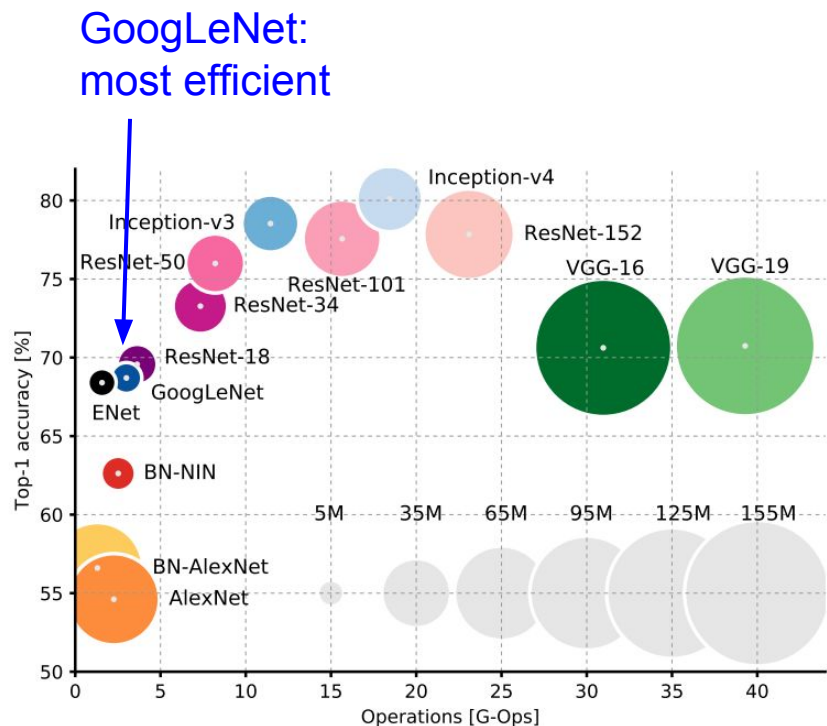
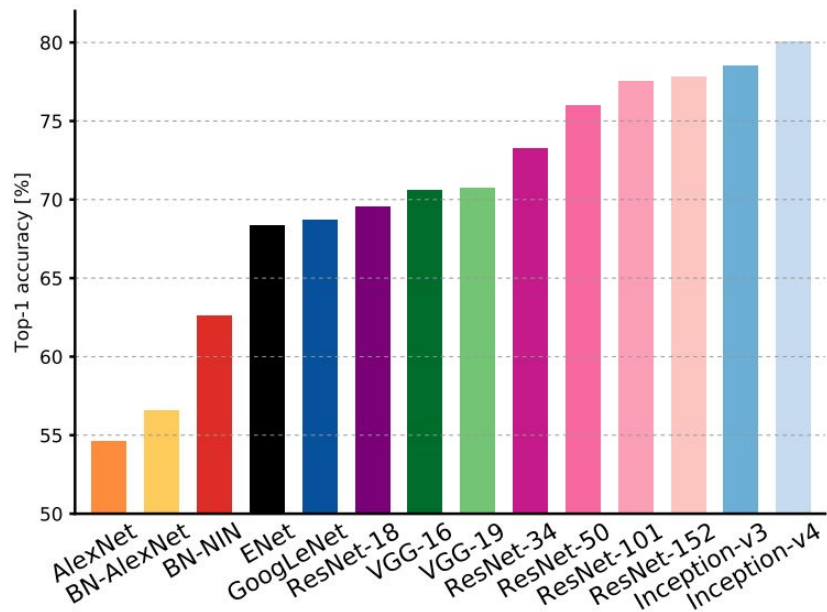
Comparing complexity...



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

Figures copyright Alfredo Canziani, Adam Paszke, Eugenio Culurciello, 2017. Reproduced with permission.

Comparing complexity...



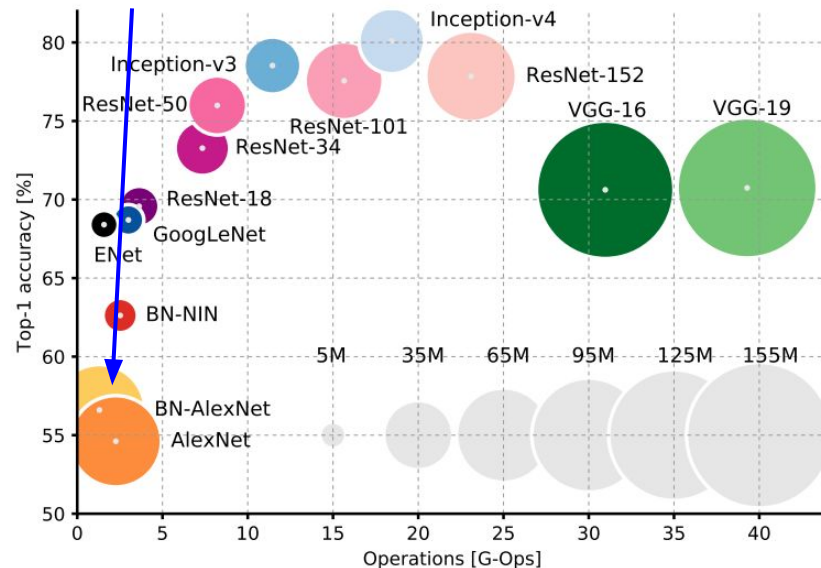
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Figures copyright Alfredo Canziani, Adam Paszke, Eugenio Culurciello, 2017. Reproduced with permission.

Comparing complexity...



AlexNet:
Smaller compute, still memory heavy, lower accuracy



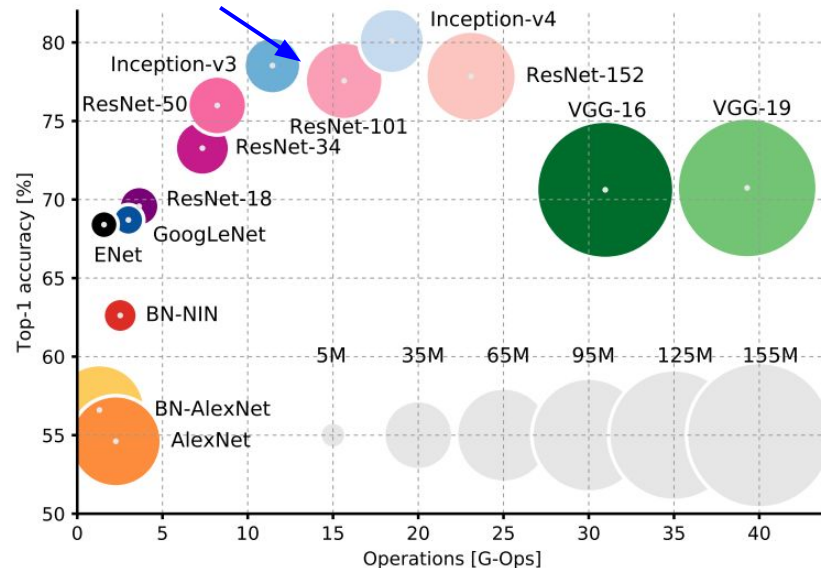
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Figures copyright Alfredo Canziani, Adam Paszke, Eugenio Culurciello, 2017. Reproduced with permission.

Comparing complexity...



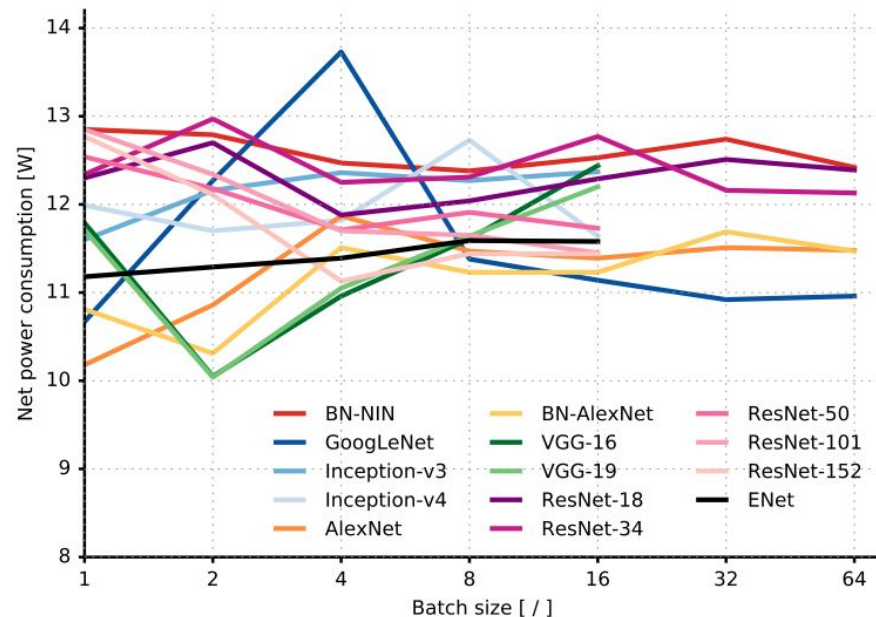
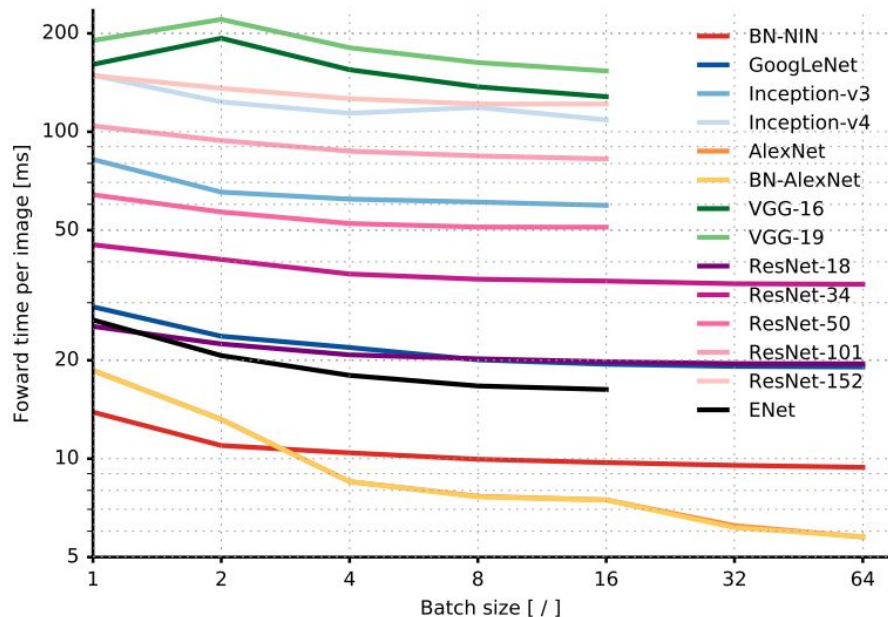
ResNet:
Moderate efficiency depending on
model, highest accuracy



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

Figures copyright Alfredo Canziani, Adam Paszke, Eugenio Culurciello, 2017. Reproduced with permission.

Forward pass time and power consumption



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

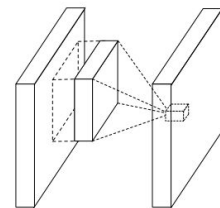
Figures copyright Alfredo Canziani, Adam Paszke, Eugenio Culurciello, 2017. Reproduced with permission.

Other architectures to know...

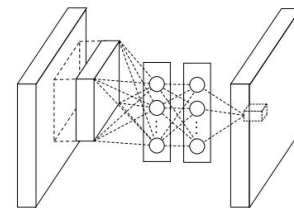
Network in Network (NiN)

[Lin et al. 2014]

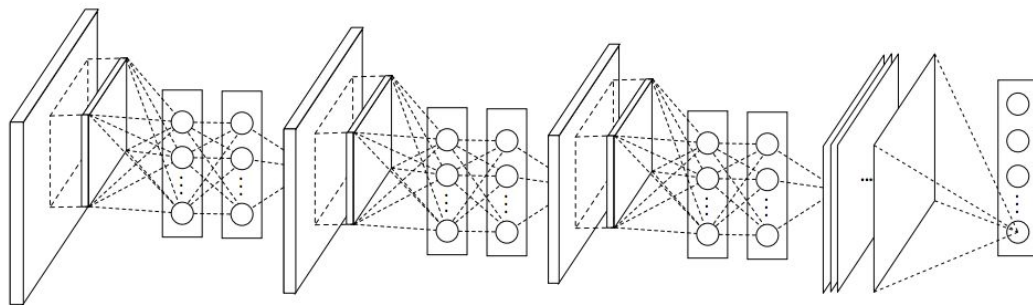
- Mlpconv layer with “micronetwork” within each conv layer to compute more abstract features for local patches
- Micronetwork uses multilayer perceptron (FC, i.e. 1x1 conv layers)
- Precursor to GoogLeNet and ResNet “bottleneck” layers
- Philosophical inspiration for GoogLeNet



(a) Linear convolution layer



(b) Mlpconv layer



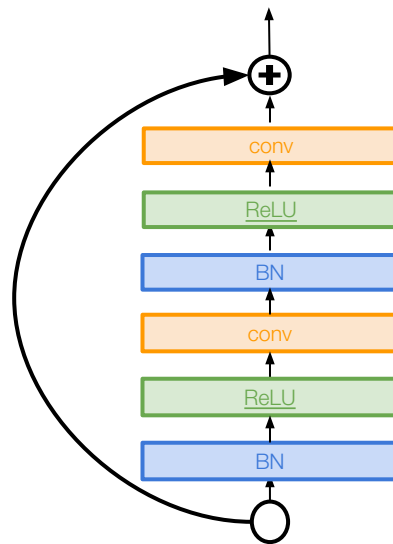
Figures copyright Lin et al., 2014. Reproduced with permission.

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

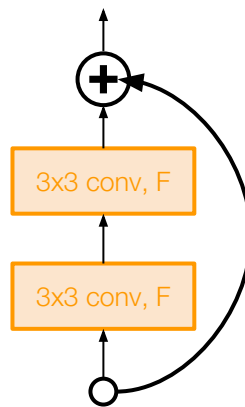


Improving ResNets...

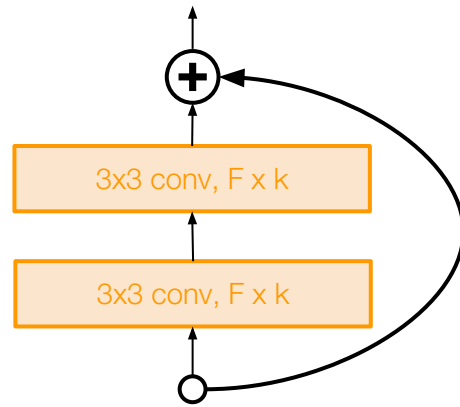
Wide Residual Networks

[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



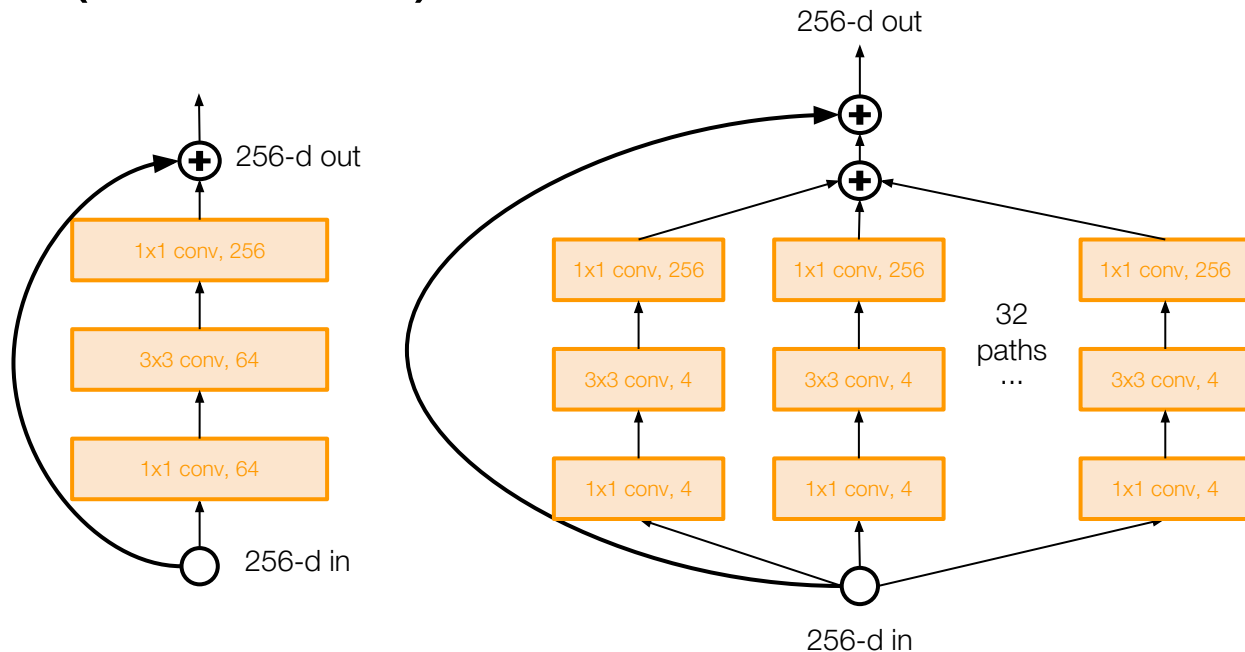
Wide residual block

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

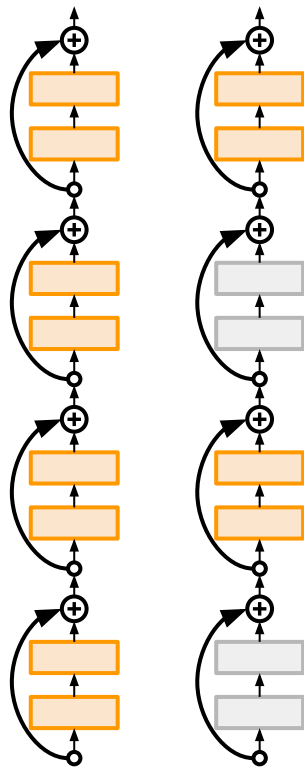


Improving ResNets...

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

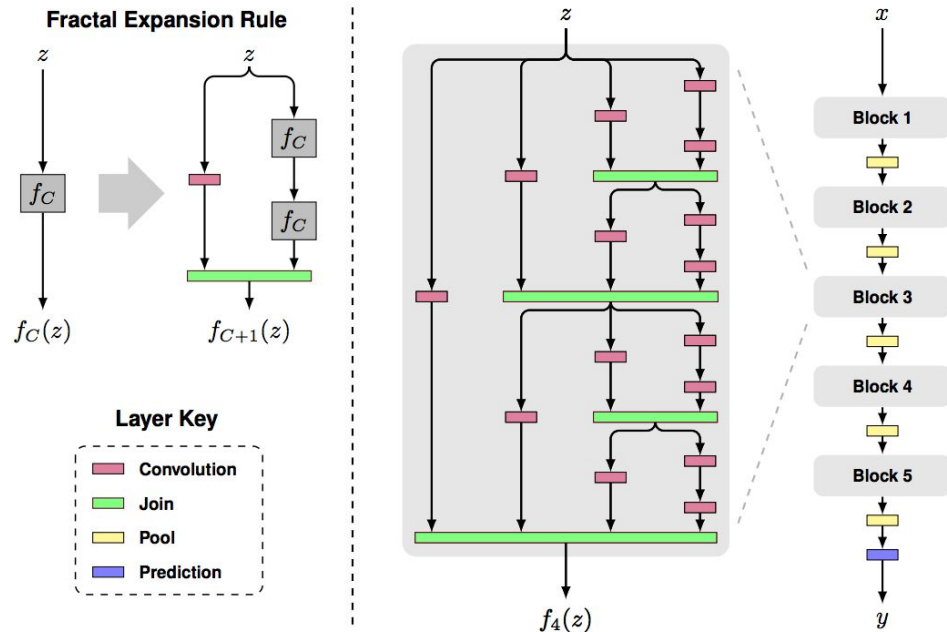


Beyond ResNets...

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



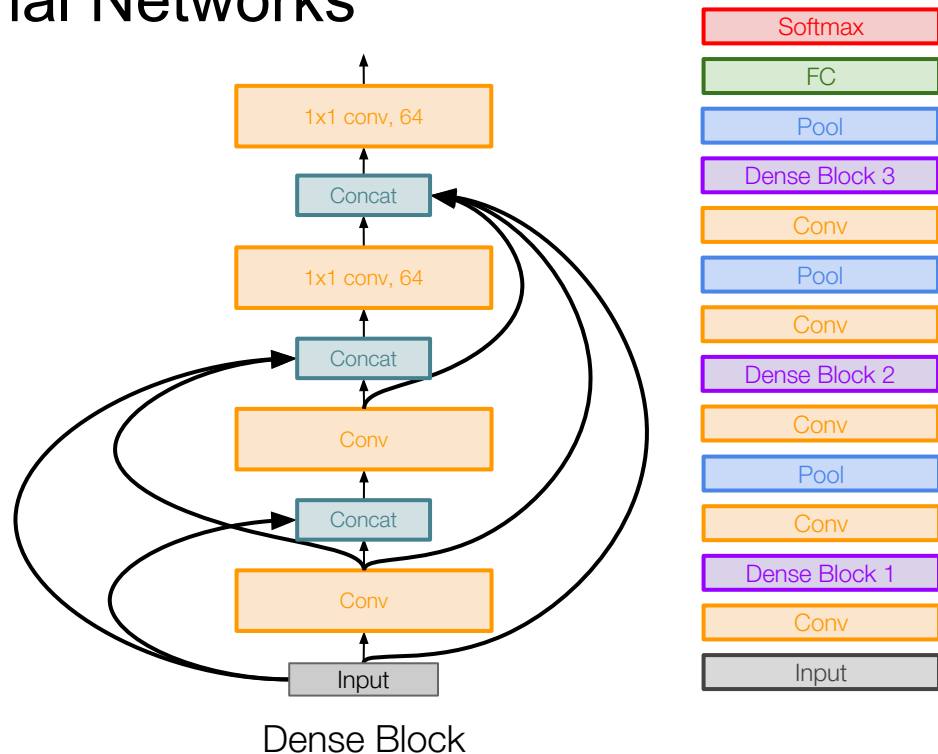
Figures copyright Larsson et al., 2017. Reproduced with permission.

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)

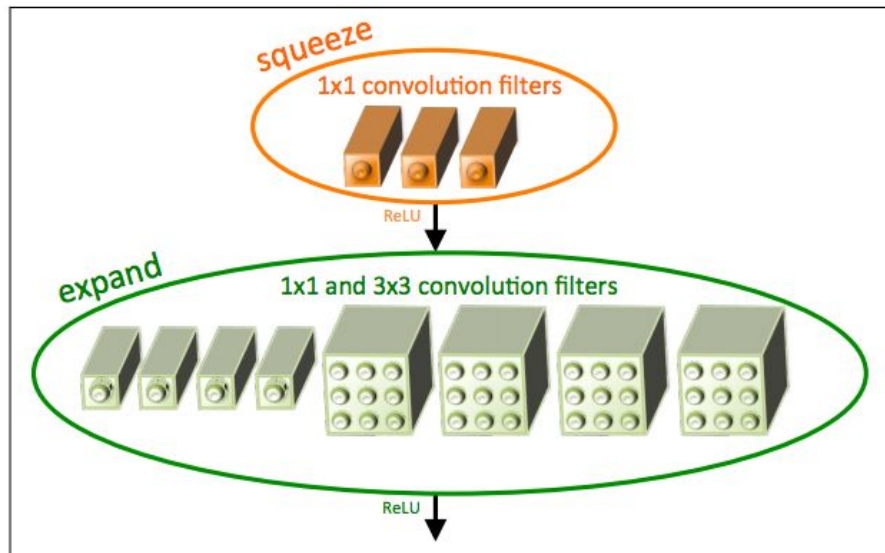


Figure copyright Iandola, Han, Moskewicz, Ashraf, Dally, Keutzer, 2017. Reproduced with permission.

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