CNN Architectures

CS60010: Deep Learning

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IIT Kharagpur

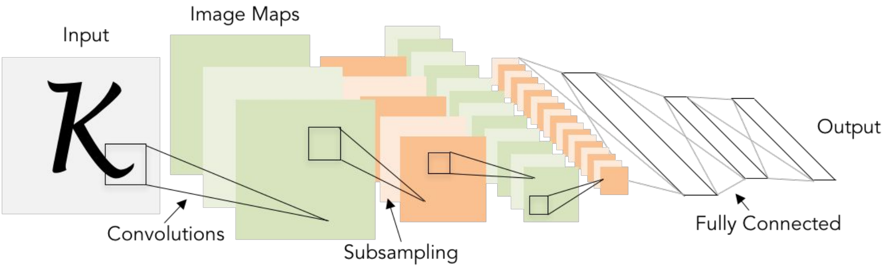
Feb 03, 04, 09 and 10, 2022

Agenda

To discuss in detail about some of the highly successful deep CNN architectures

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]

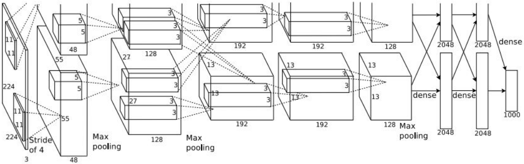
§ Citation of the paper as on Feb 03, 2022 is 42,871

Source: CS231n course, Stanford University

AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]



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

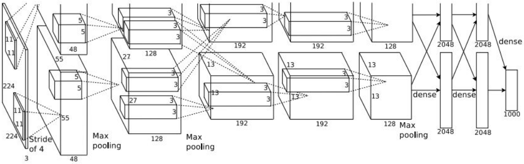
§ Citation of the paper as on Feb 03, 2022 is 1,02,838

Source: CS231n course, Stanford University

AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]



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

Input: 227x227x3 images

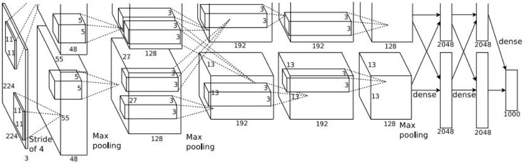
First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Q: what is the output volume size? Hint: (227-11)/4+1 = 55

Source: CS231n course, Stanford University

AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]



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

Input: 227x227x3 images

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

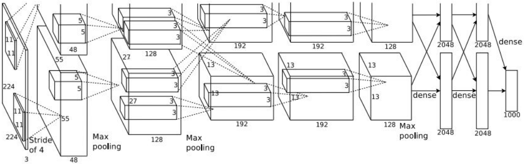
Q: What is the total number of parameters in this layer?

Source: CS231n course, Stanford University

AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]



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

Input: 227x227x3 images

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

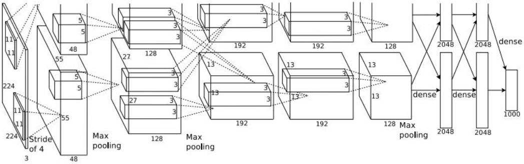
Parameters: (11*11*3)*96 = 35K

Source: CS231n course, Stanford University

AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]



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

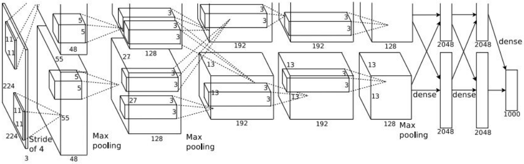
Input: 227x227x3 images
After CONV1: 55x55x96
Second layer (POOL1): 3x3 filters applied at stride 2
Q: what is the output volume size? Hint: (55-3)/2+1 = 27

Source: CS231n course, Stanford University

AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]



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

Input: 227x227x3 images
After CONV1: 55x55x96
Second layer (POOL1): 3x3 filters applied at stride 2.
Output volume: 27x27x96

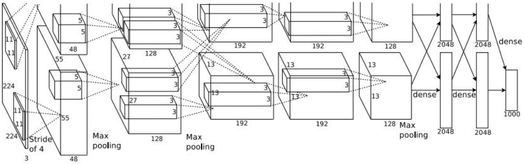
Q: what is the number of parameters in this layer?

Source: CS231n course, Stanford University

AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]



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

Input: 227x227x3 images
After CONV1: 55x55x96
Second layer (POOL1): 3x3 filters applied at stride 2.
Output volume: 27x27x96

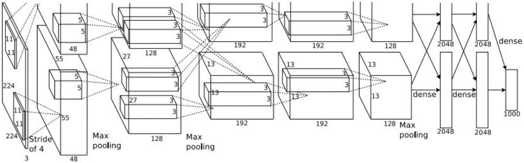
Parameters: 0!

Source: CS231n course, Stanford University

AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]



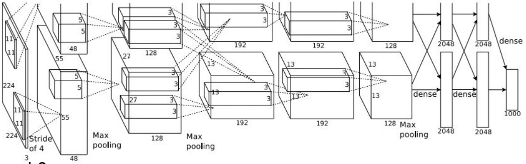
Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] 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)

Source: CS231n course, Stanford University

AlexNet

Case Study: AlexNet

[Krizhevsky et al. 2012]

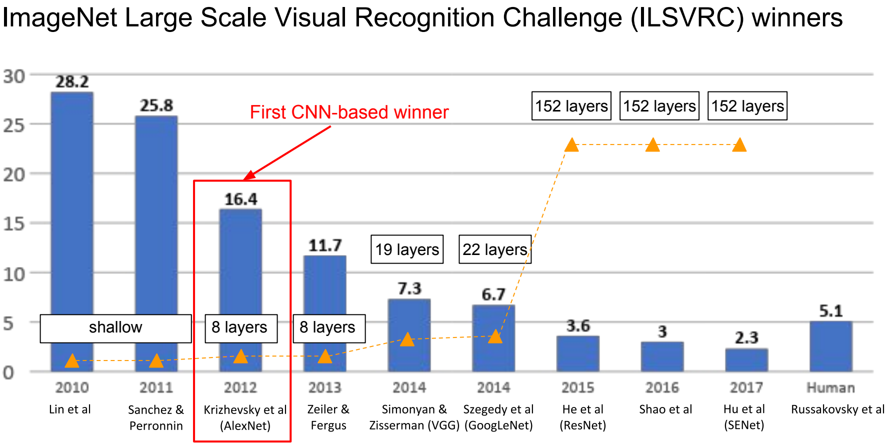


Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] 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
- Pooling is overlapping
- 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%

Source: CS231n course, Stanford University

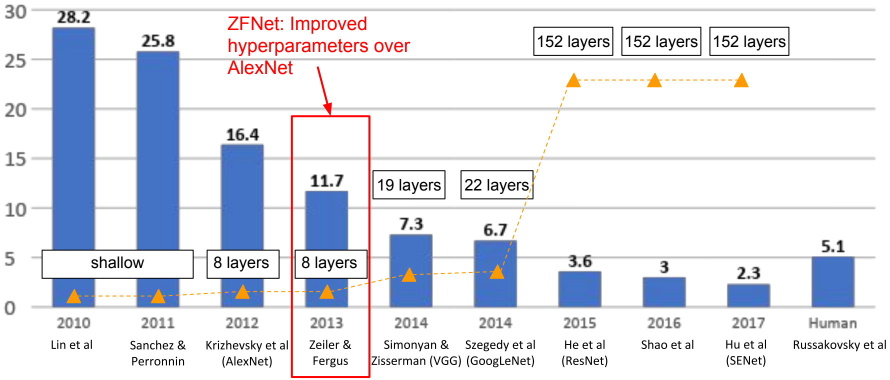
Imagenet Leaderboard



Source: CS231n course, Stanford University

Imagenet Leaderboard

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

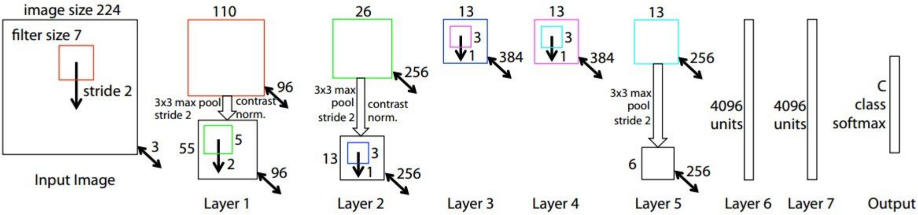


Source: CS231n course, Stanford University

ZFNet

ZFNet

[Zeiler and Fergus, 2013]



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

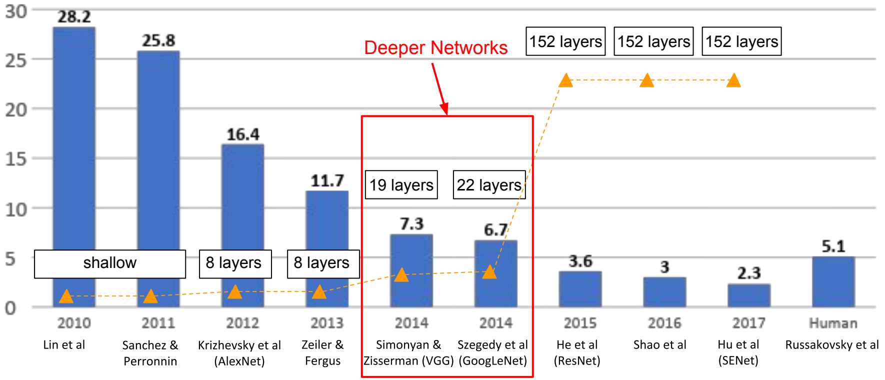
ImageNet top 5 error: 16.4% -> 11.7%

§ Citation of the paper as on Feb 03, 2021 is 14,464

Source: CS231n course, Stanford University

ZFNet

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Source: CS231n course, Stanford University

VGG

Case Study: VGGNet

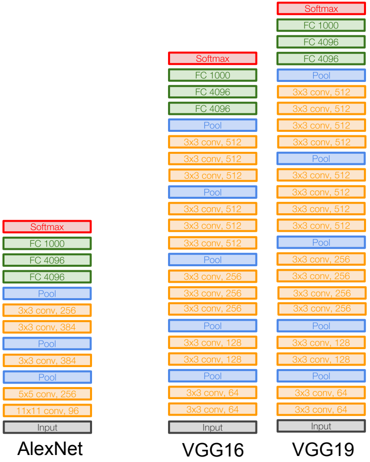
[Simonyan and Zisserman, 2014]

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



§ Citation of the paper as on Feb 03, 2022 is 72,788

Source: CS231n course, Stanford University

VGG

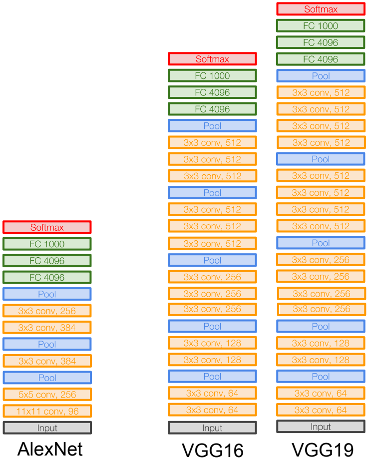
Case Study: VGGNet

[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

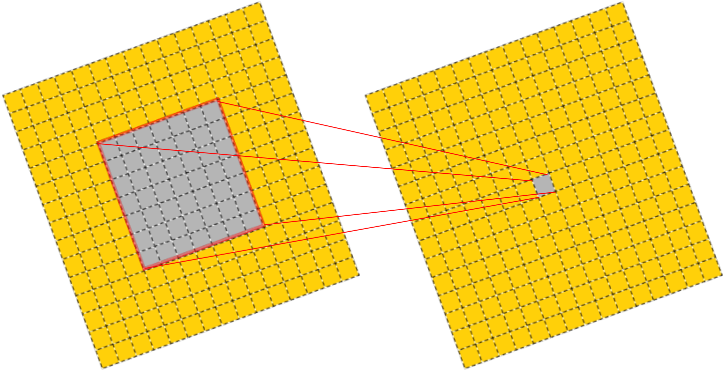
Q: What is the effective receptive field of three 3x3 conv (stride 1) layers?



Source: CS231n course, Stanford University

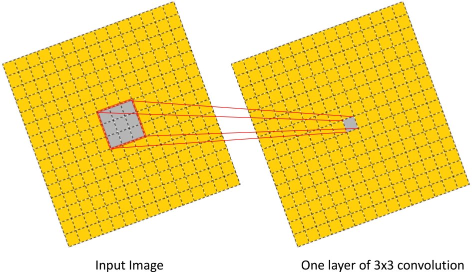
VGG

- Receptive field is the region in the input space that a particular CNN's feature (activation value) is looking at (or getting computed due to)



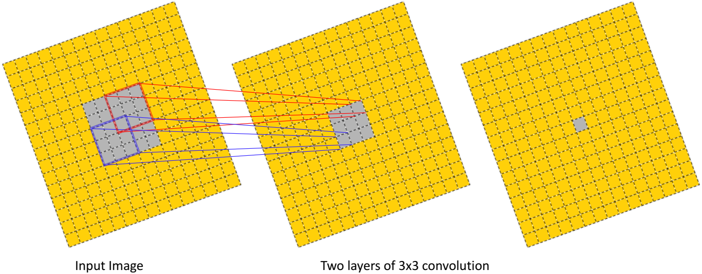
Input Image One layer of 7x7 convolution

VGG



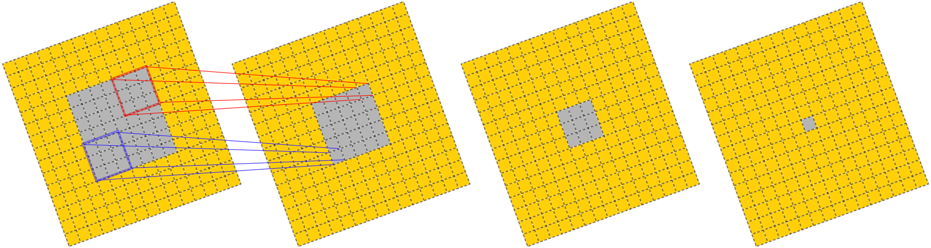
- Receptive field is 3×3

VGG



§ Receptive field is 5×5

VGG



Input Image

Three layers of 3x3 convolution

- Receptive field is 7×7

VGG

Case Study: VGGNet

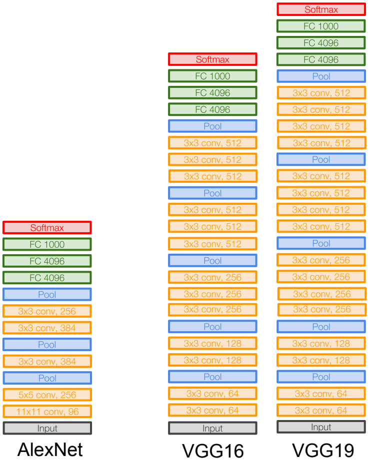
[Simonyan and Zisserman, 2014]

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



Source: CS231n course, Stanford University

VGG

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

TOTAL memory: 15.2M * 4 bytes ~= 58MB / image (for a forward pass)
TOTAL params: 138M parameters

Source: CS231n course, Stanford University

VGG

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: **224*224*64=3.2M** params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: **224*224*64=3.2M** params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
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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

Note:

Most memory is in early CONV

Most params are in late FC

TOTAL memory: 15.2M * 4 bytes ~= 58MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters

Source: CS231n course, Stanford University

VGG

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
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CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
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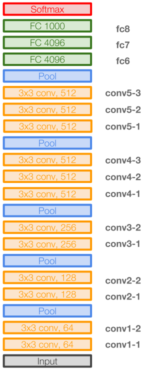
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

TOTAL memory: 15.2M * 4 bytes ~= 58MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters



VGG16

Common names

Source: CS231n course, Stanford University

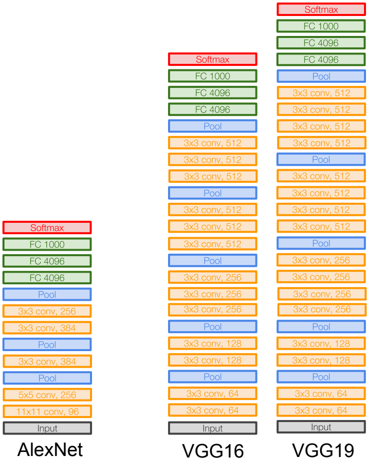
VGG

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



Source: CS231n course, Stanford University

Video Classification

Examples from UCF-101 dataset.

ApplyEyeMakeup

CuttingInKitchen

BalanceBeam

TableTennisShot

C3D

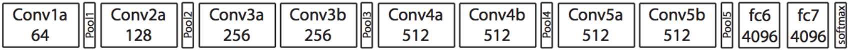


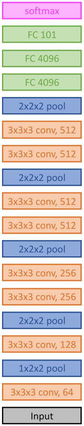
Figure 3. **C3D architecture**. C3D net has 8 convolution, 5 max-pooling, and 2 fully connected layers, followed by a softmax output layer. All 3D convolution kernels are $3 \times 3 \times 3$ with stride 1 in both spatial and temporal dimensions. Number of filters are denoted in each box. The 3D pooling layers are denoted from `pool1` to `pool5`. All pooling kernels are $2 \times 2 \times 2$, except for `pool1` is $1 \times 2 \times 2$. Each fully connected layer has 4096 output units.

- Citation of the paper as on Feb 03, 2022 is 5,925

C3D

INPUT: [16x112x112x3] memory: 16*112*112*3=602K params: 0 (not counting biases)
CONV1a: [16x112x112x64] memory: 16*112*112*64=12.8M params: 3*(3*3*3)*64 = 5,184
POOL1: [16x56x56x64] memory: 16*56*56*64=3.2M params: 0
CONV2a: [16x56x56x128] memory: 16*56*56*128=6.4M params: 64*(3*3*3)*128 = 221,184
POOL2: [8x28x28x128] memory: 8*28*28*128=802K params: 0
CONV3a: [8x28x28x256] memory: 8*28*28*256=1.6M params: 128*(3*3*3)*256 = 884,736
CONV3b: [8x28x28x256] memory: 8*28*28*256=1.6M params: 256*(3*3*3)*256 = 1,769,472
POOL3: [4x14x14x256] memory: 4*14*14*256=200K params: 0
CONV4a: [4x14x14x512] memory: 4*14*14*512=401K params: 256*(3*3*3)*512 = 3,538,944
CONV4b: [4x14x14x512] memory: 4*14*14*512=401K params: 512*(3*3*3)*512 = 7,077,888
POOL4: [2x7x7x512] memory: 2*7*7*512=50K params: 0
CONV5a: [2x7X7x512] memory: 2*7*7*512=50K params: 512*(3*3*3)*512 = 7,077,888
CONV5b: [2x7X7x512] memory: 2*7*7*512=50K params: 512*(3*3*3)*512 = 7,077,888
POOL5: [1x4x4x512] memory: 1*4*4*512=8,192 params: 0
FC6: [4096] memory: 4096 params: 4*4*512*4096 = 33,554,432
FC: [4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [101] memory: 101 params: 4096*101 = 413,696

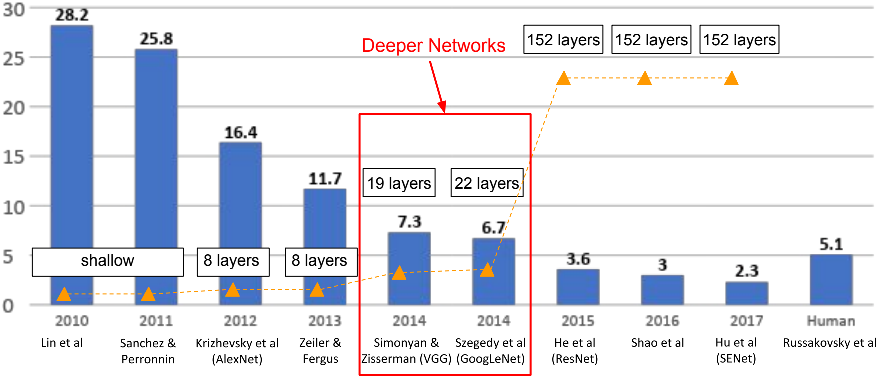
TOTAL memory: 28.3M * 4 bytes ~= 107.82MB / image (for a forward pass)
TOTAL params: 78.4M parameters



C3D

GoogLeNet

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

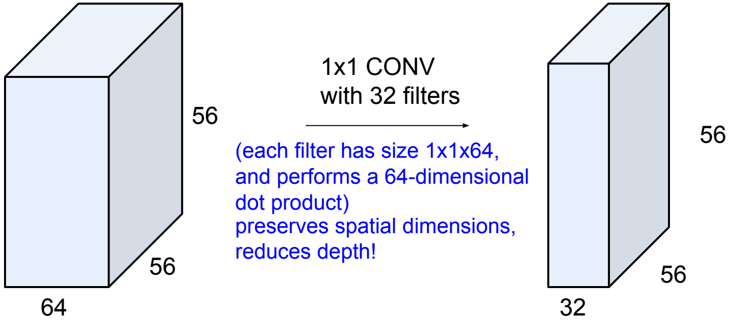


§ Citation of the paper as on Feb 03, 2022 is 37,061

Source: CS231n course, Stanford University

GoogLeNet

1x1 convolutions



Source: CS231n course, Stanford University

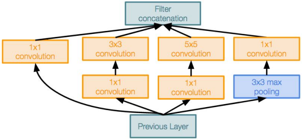
GoogLeNet

Case Study: GoogLeNet

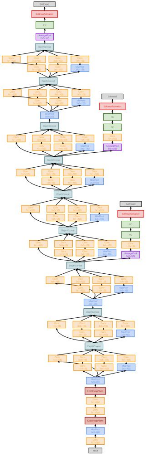
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

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



Inception module



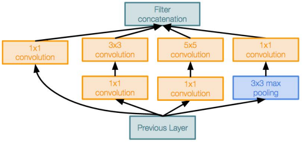
Source: CS231n course, Stanford University

GoogLeNet

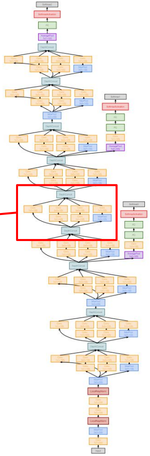
Case Study: GoogLeNet

[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

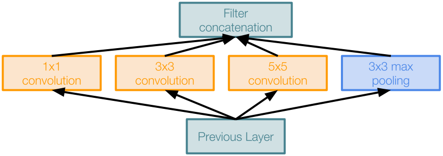


Source: CS231n course, Stanford University

GoogLeNet

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)

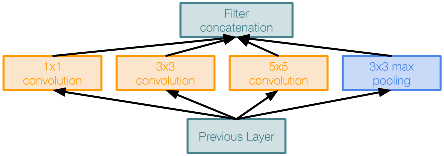
Concatenate all filter outputs together depth-wise

Source: CS231n course, Stanford University

GoogLeNet

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]

Source: CS231n course, Stanford University

GoogLeNet

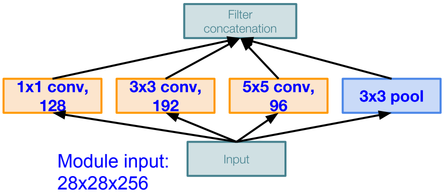
Case Study: GoogLeNet

[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

Source: CS231n course, Stanford University

GoogLeNet

Case Study: GoogLeNet

[Szegedy et al., 2014]

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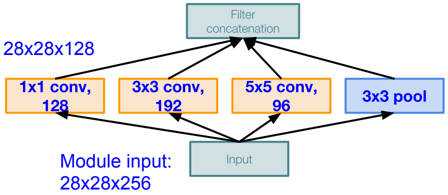


Naive Inception module

Source: CS231n course, Stanford University

GoogLeNet

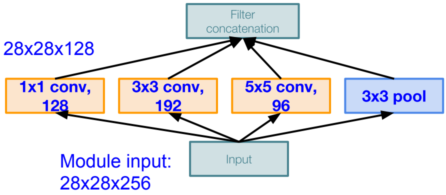
Case Study: GoogLeNet

[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

Source: CS231n course, Stanford University

GoogLeNet

Case Study: GoogLeNet

[Szegedy et al., 2014]

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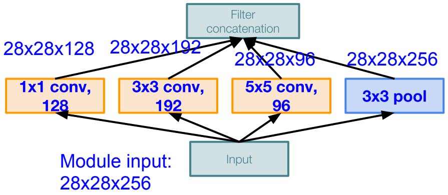


Naive Inception module

Source: CS231n course, Stanford University

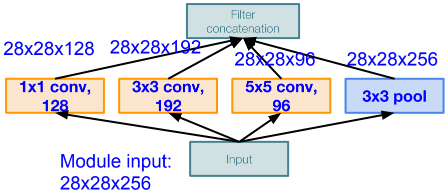
GoogLeNet

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]

Source: CS231n course, Stanford University

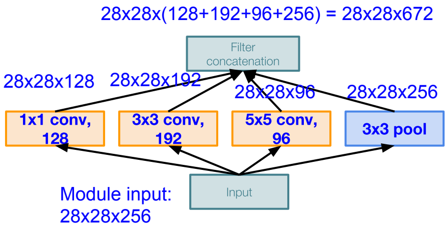
GoogLeNet

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]

Source: CS231n course, Stanford University

GoogLeNet

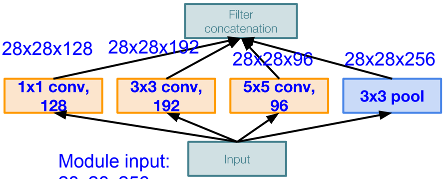
Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3:What is output size after filter concatenation?

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



Module input: 28x28x256

Naive Inception module

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

Conv Ops:

[1x1 conv, 128] 28x28x128x1x1x256

[3x3 conv, 192] 28x28x192x3x3x256

[5x5 conv, 96] 28x28x96x5x5x256

Total: 854M ops

Source: CS231n course, Stanford University

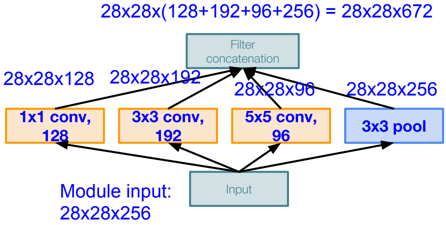
GoogLeNet

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]

Conv Ops:

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

Very expensive compute

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

Source: CS231n course, Stanford University

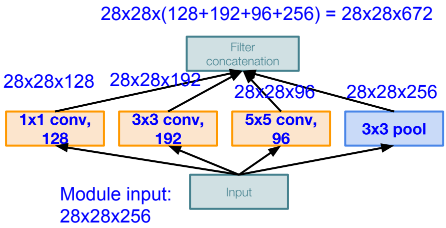
GoogLeNet

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

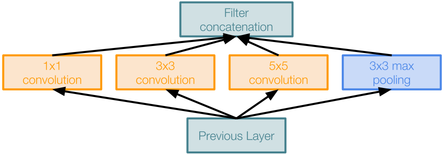
Source: CS231n course, Stanford University

GoogLeNet

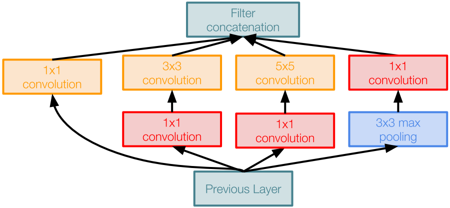
Case Study: GoogLeNet

[Szegedy et al., 2014]

1x1 conv "bottleneck" layers



Naive Inception module



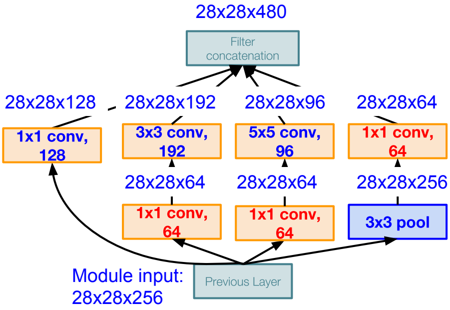
Inception module with dimension reduction

Source: CS231n course, Stanford University

GoogLeNet

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

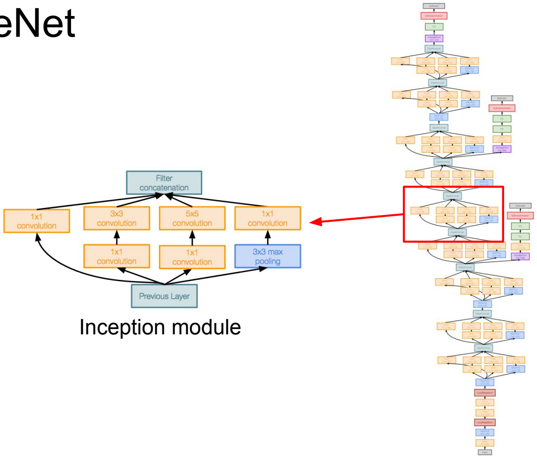
Source: CS231n course, Stanford University

GoogLeNet

Case Study: GoogLeNet

[Szegedy et al., 2014]

Stack Inception modules with dimension reduction on top of each other



Inception module

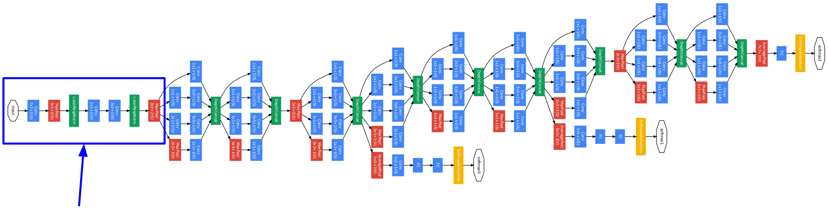
Source: CS231n course, Stanford University

GoogLeNet

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



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

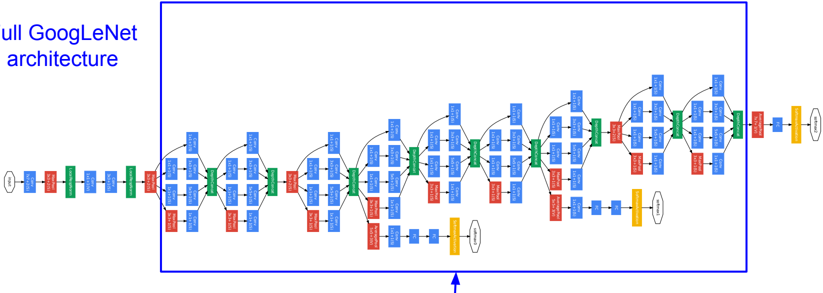
Source: CS231n course, Stanford University

GoogLeNet

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



Stacked Inception Modules

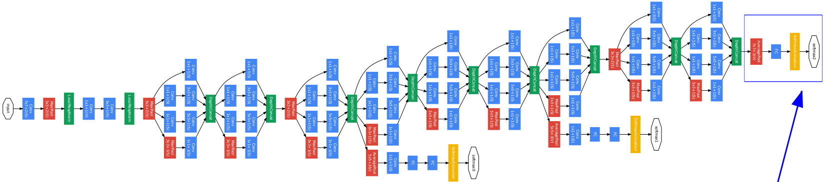
Source: CS231n course, Stanford University

GoogLeNet

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



Classifier output
(removed expensive FC layers!)

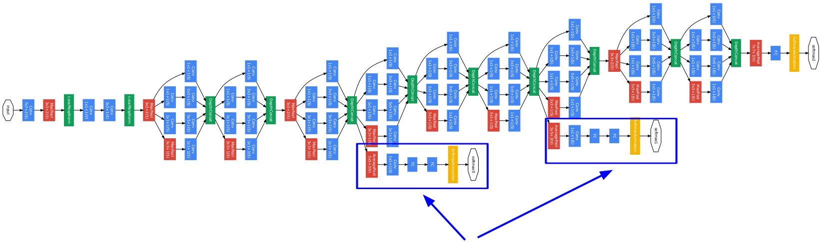
Source: CS231n course, Stanford University

GoogLeNet

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)

Source: CS231n course, Stanford University

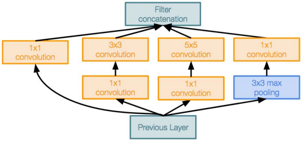
GoogLeNet

Case Study: GoogLeNet

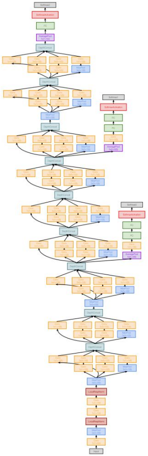
[Szegedy et al., 2014]

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)



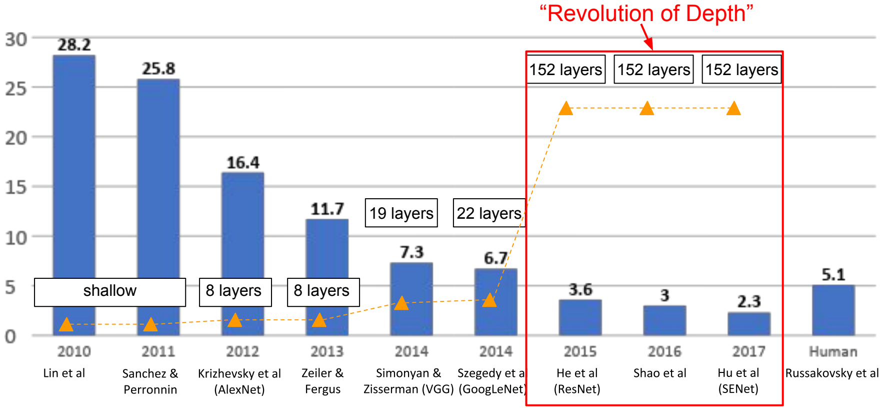
Inception module



Source: CS231n course, Stanford University

ResNet

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



§ Citation of the paper as on Feb 03, 2022 is 1,05,614

Source: CS231n course, Stanford University

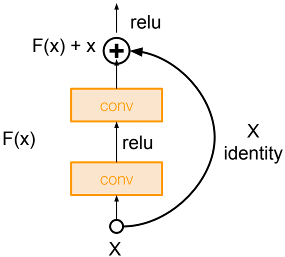
ResNet

Case Study: ResNet

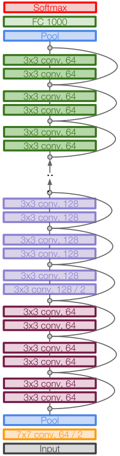
[He et al., 2015]

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!



Residual block



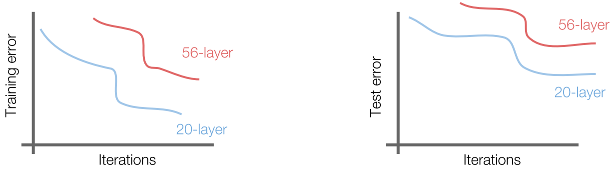
Source: CS231n course, Stanford University

ResNet

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]

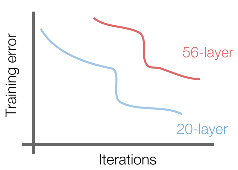
Source: CS231n course, Stanford University

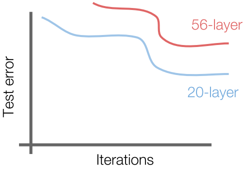
ResNet

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!

Source: CS231n course, Stanford University

ResNet

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.

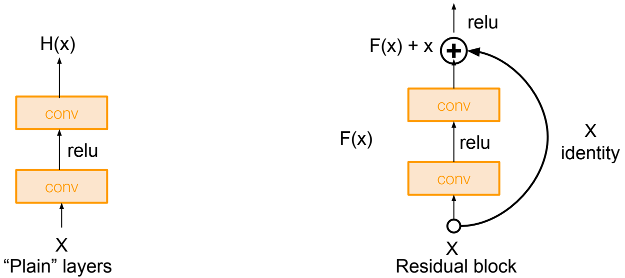
Source: CS231n course, Stanford University

ResNet

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



Source: CS231n course, Stanford University

ResNet

Case Study: ResNet

[He et al., 2015]

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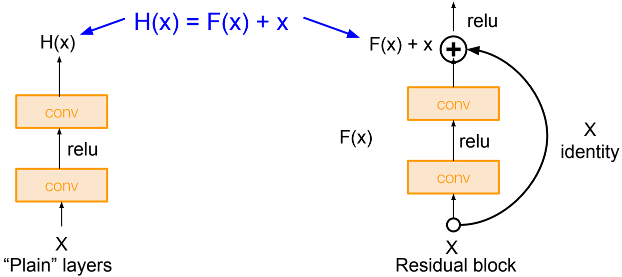


Use layers to fit residual F(x) = H(x) - x instead of H(x) directly

Source: CS231n course, Stanford University

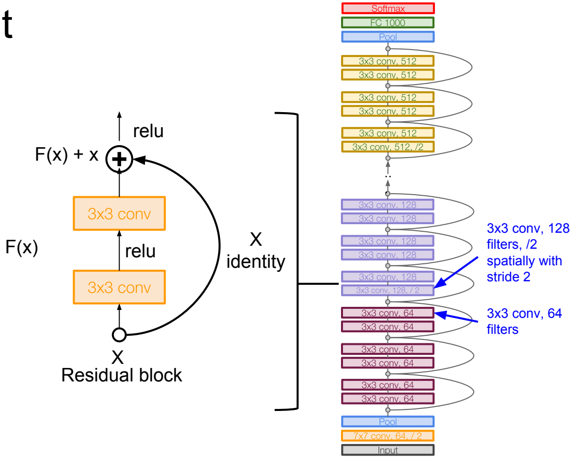
ResNet

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)



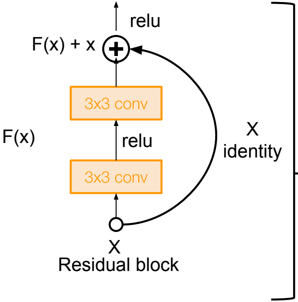
Source: CS231n course, Stanford University

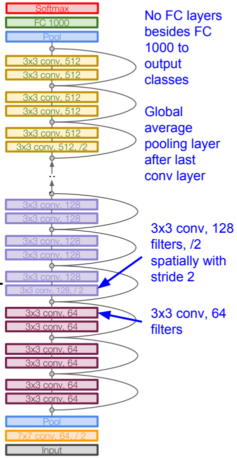
ResNet

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)





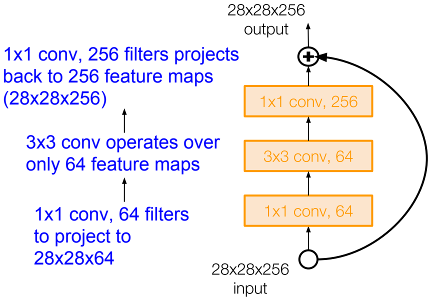
Source: CS231n course, Stanford University

ResNet

Case Study: ResNet

[He et al., 2015]

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



Source: CS231n course, Stanford University

ResNet

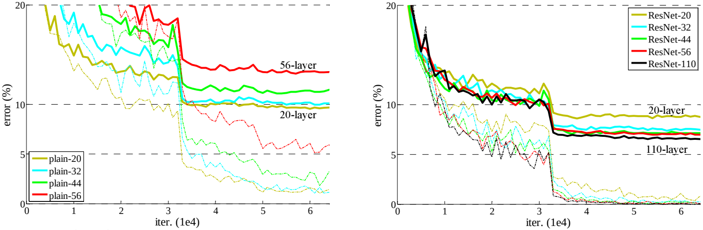


Figure 6. Training on **CIFAR-10**. Dashed lines denote training error, and bold lines denote testing error

Source: He et. al., 2015

ResNet

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 lowing 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

Source: CS231n course, Stanford University

MobileNet-v1

- ConvNets, in general, are compute and memory heavy
- MobileNet-v1 from Google [in 2017] describes an efficient network in terms of compute and memory so that many real world vision applications can be performed in mobile or similar embedded platforms

MobileNet-v1

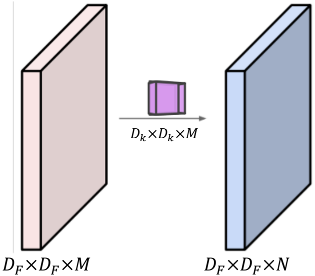
- ConvNets, in general, are compute and memory heavy
- MobileNet-v1 from Google [in 2017] describes an efficient network in terms of compute and memory so that many real world vision applications can be performed in mobile or similar embedded platforms
- Used depthwise separable convolution which is depthwise convolution and then pointwise convolution

MobileNet-v1

- ConvNets, in general, are compute and memory heavy
- MobileNet-v1 from Google [in 2017] describes an efficient network in terms of compute and memory so that many real world vision applications can be performed in mobile or similar embedded platforms
- Used depthwise separable convolution which is depthwise convolution and then pointwise convolution
- Also introduced two simple scaling hyperparameters

Depthwise Separable Convolution

§ Suppose, we have $D_F \times D_F \times M$ input feature map, $D_F \times D_F \times N$ output feature map and $D_k \times D_k$ spatial sized conventional convolution filters.



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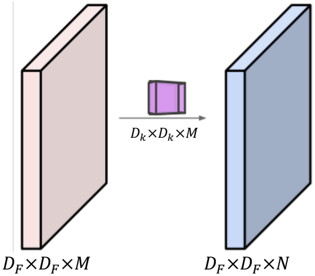

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—$D_k \cdot D_k \cdot M \cdot D_F \cdot D_F \cdot N$

§ What is the number of parameters?

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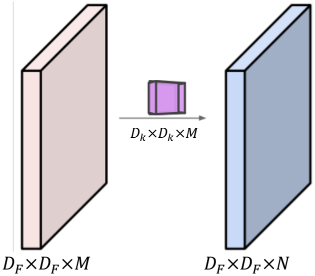
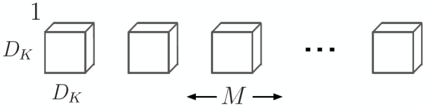


- What is the computational cost for such a convolution operation? —$D_k \cdot D_k \cdot M \cdot D_F \cdot D_F \cdot N$
- What is the number of parameters? —$D_k \cdot D_k \cdot M \cdot N$

Depthwise Separable Convolution

- Now, think of M filters which are $D_K \times D_K$ (not $D_K \times D_K \times M$) and think each M of these filters are operated separately on M channels of input of spatial size $D_F \times D_F$



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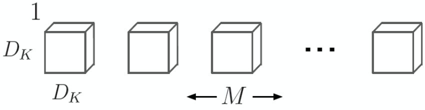

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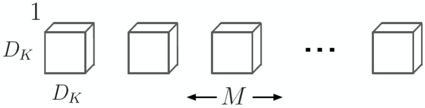

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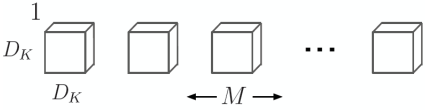

- What is the computational cost for such a convolution operation? —$D_K \cdot D_K \cdot D_F \cdot D_F \cdot M$
- And what is the number of parameters? —$D_K \cdot D_K \cdot M$
- This operation is known as Depthwise Convolution operation

Depthwise Separable Convolution

§ What is the output shape now?

Depthwise Separable Convolution

- What is the output shape now? —$D_F \times D_F \times M$
- Where did the N (output channels) go?

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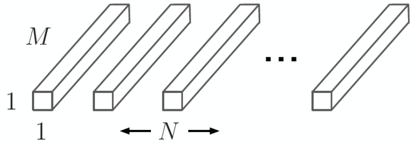

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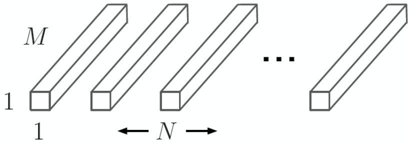

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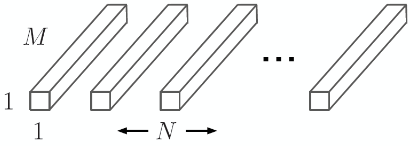

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- What is the number of parameters? —$1 \cdot 1 \cdot M \cdot N$
- This operation is called 1×1 pointwise convolution

Depthwise Separable Convolution

- So, traditional convolution with $D_K \times D_K \times M \times N$ filters, we get feature map of size $D_F \times D_F \times N$
- Also with depthwise separable convolution (*i.e.*, depthwise convolution $+ \; 1 \times 1$ pointwise convolution), we get $D_F \times D_F \times N$ feature map
- The computation is less
  - $D_k \cdot D_k \cdot M \cdot D_F \cdot D_F \cdot N$ vs
  - $D_k \cdot D_k \cdot M \cdot D_F \cdot D_F + D_F \cdot D_F \cdot M \cdot N$
- The reduction in computation $\frac{D_k \cdot D_k \cdot M \cdot D_F \cdot D_F + D_F \cdot D_F \cdot M \cdot N}{D_k \cdot D_k \cdot M \cdot D_F \cdot D_F \cdot N} = \frac{1}{N} + \frac{1}{D_K^2}$
- Also the reduction in number of parameters $\frac{M \cdot D_K \cdot D_K + M \cdot N}{D_K \cdot D_K \cdot M \cdot N} = \frac{1}{N} + \frac{1}{D_K^2}$

MobileNet-v1 Structure

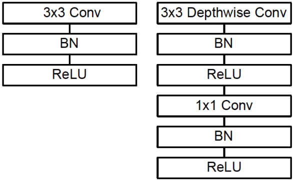

Figure 3. Left: Standard convolutional layer with batchnorm and ReLU. Right: Depthwise Separable convolutions with Depthwise and Pointwise layers followed by batchnorm and ReLU.

Image taken from: *MobileNet Paper*

Table 1. MobileNet Body Architecture

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

Image taken from: *MobileNet Paper*

Width and Resolution Multiplier

- The role of the width multiplier $\alpha \in (0, 1]$ is to thin a network uniformly at each layer
- the number of input channels M becomes αM and the number of output channels N becomes αN
- The computational cost of a depthwise separable convolution with width multiplier α is $D_k \cdot D_k \cdot \alpha M \cdot D_F \cdot D_F + D_F \cdot D_F \cdot \alpha M \cdot \alpha N$
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- Width multiplier has the effect of reducing computational cost and the number of parameters quadratically by roughly α^2
- Resolution multiplier $\rho \in (0, 1]$ reduces the image resolution by this factor and the internal representation of every layer is subsequently reduced by the same multiplier
- With width multiplier α and resolution multiplier ρ, the computational cost is α is $D_k \cdot D_k \cdot \alpha M \cdot \rho D_F \cdot \rho D_F + \rho D_F \cdot \rho D_F \cdot \alpha M \cdot \alpha N$
- Resolution multiplier has the effect of reducing computational cost by ρ^2

Experimental Results

Table 4. Depthwise Separable vs Full Convolution MobileNet

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
Conv MobileNet	71.7%	4866	29.3
MobileNet	70.6%	569	4.2

Image taken from: *MobileNet Paper*

Table 6. MobileNet Width Multiplier

Width Multiplier	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
0.75 MobileNet-224	68.4%	325	2.6
0.5 MobileNet-224	63.7%	149	1.3
0.25 MobileNet-224	50.6%	41	0.5

Table 7. MobileNet Resolution

Resolution	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
1.0 MobileNet-192	69.1%	418	4.2
1.0 MobileNet-160	67.2%	290	4.2
1.0 MobileNet-128	64.4%	186	4.2

Image taken from: *MobileNet Paper*