Lecture 06: CNNs II – Network Architectures

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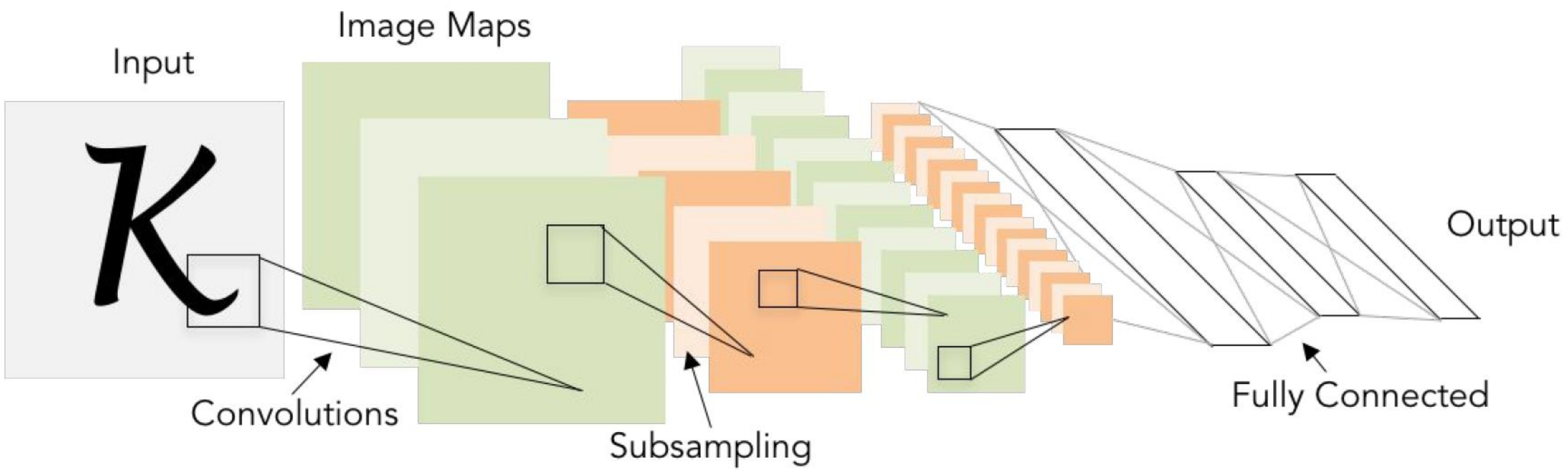
Summary of CNNs

- CNN properties [Bronstein et al., 2018]
  - Convolutional (Translation invariance)
  - Scale Separation (Compositionality)
  - Filters localized in space (Deformation Stability)
  - O(1) parameters per filter (independent of input image size n)
  - O(n) complexity per layer (filtering done in the spatial domain)
  - O(log n) layers in classification tasks

LeNet-5

- Handwritten digit recognition

[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]

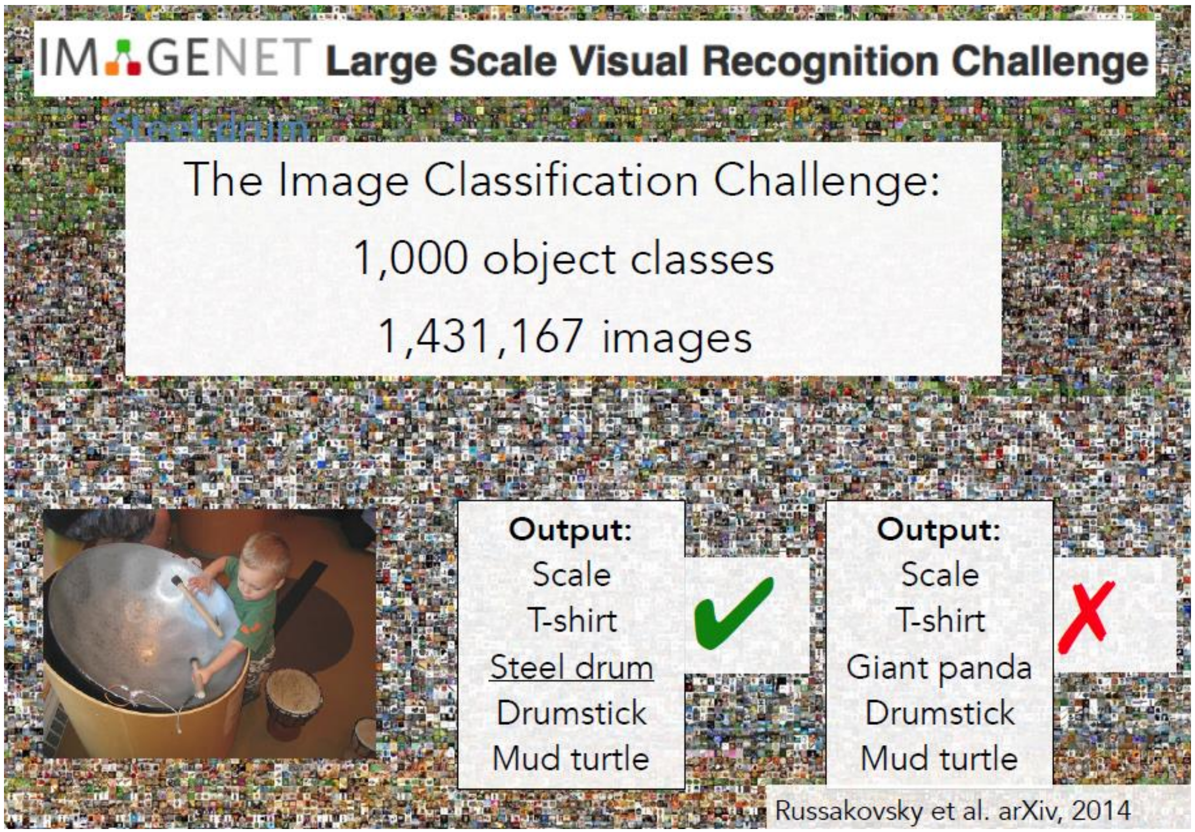
Outline

- CNN architectures
  - Sequential structure: AlexNet/ZFNet/VGGNet
  - Parallel branches: GoogLeNet
  - Residual structure: ResNet/DenseNet

Acknowledgement: Zemel et al's CSC411 and Feifei Li et al's cs231n notes

Background: Image/Object Classification

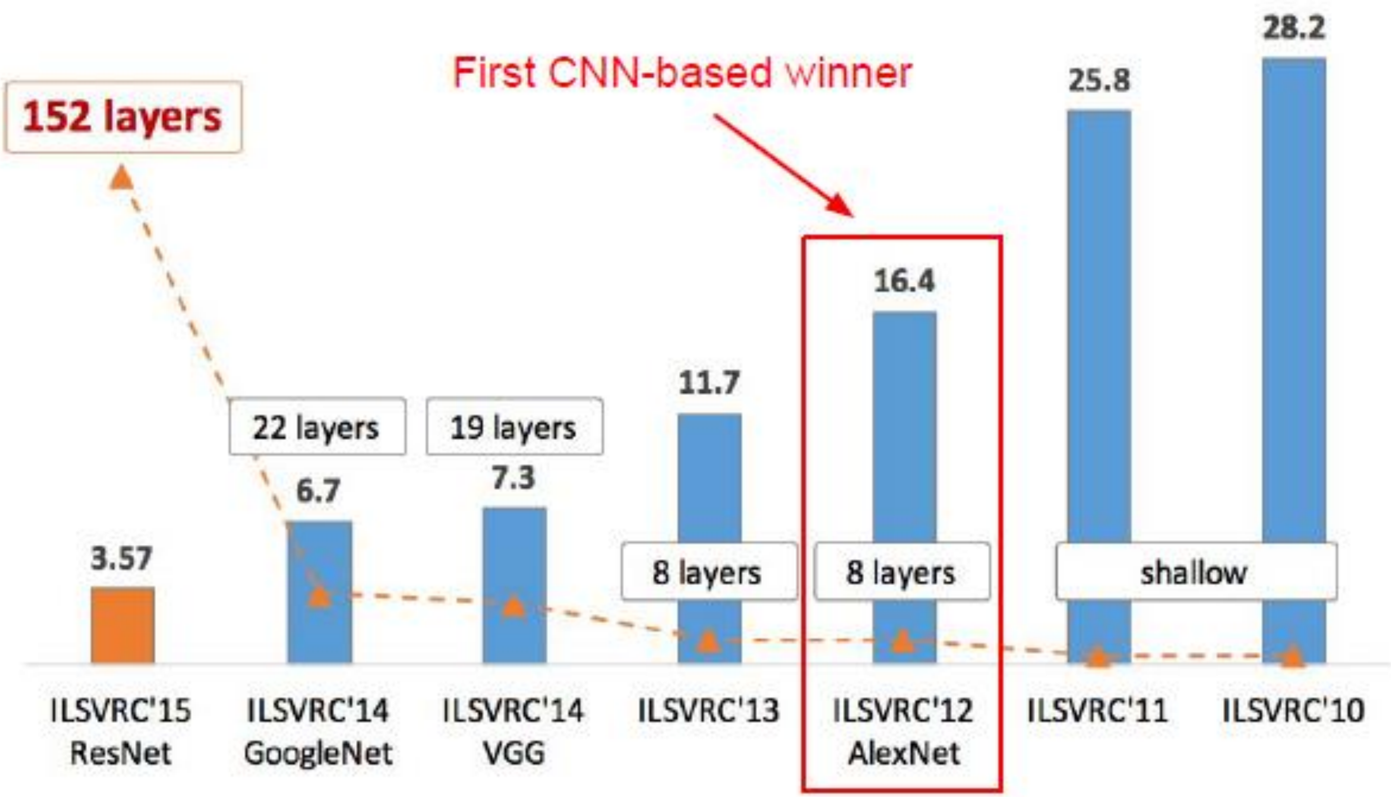
- Problem Setup
  - Input: Image
  - Output: Object class



Sequential structure

- AlexNet/ZFNet
- VGGNet

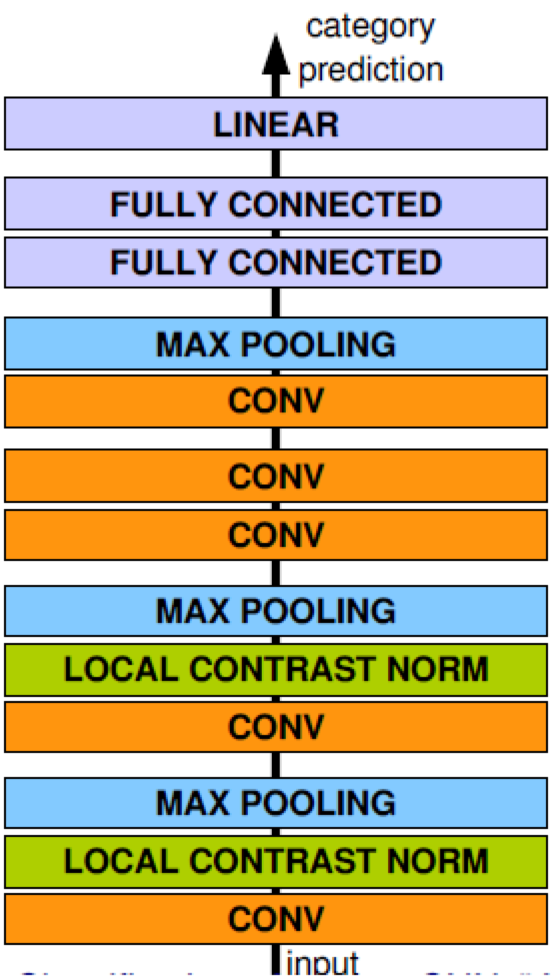
ImageNet (ILSVRC)



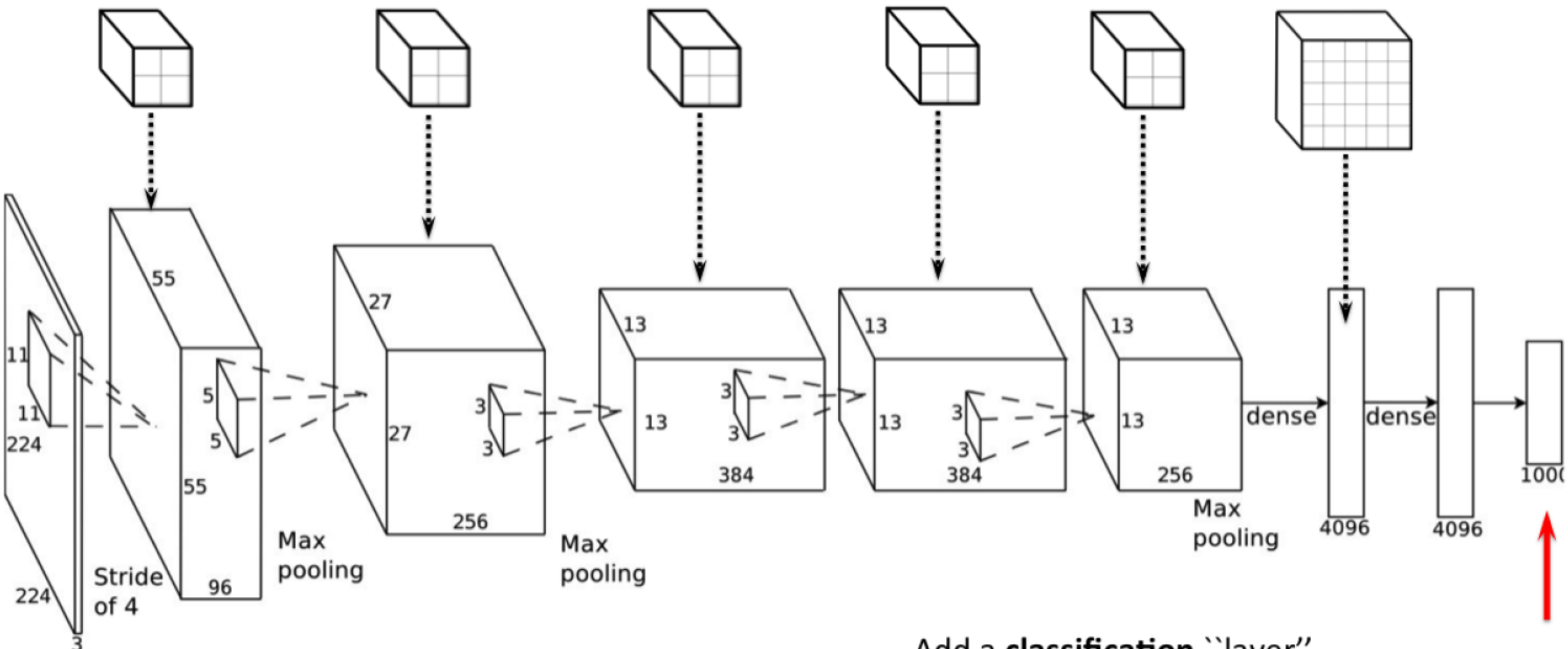
AlexNet

- Deeper network structure
  - More convolution layers
  - Local contrast normalization
  - ReLu instead of Tanh
  - Dropout as regularization

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



AlexNet

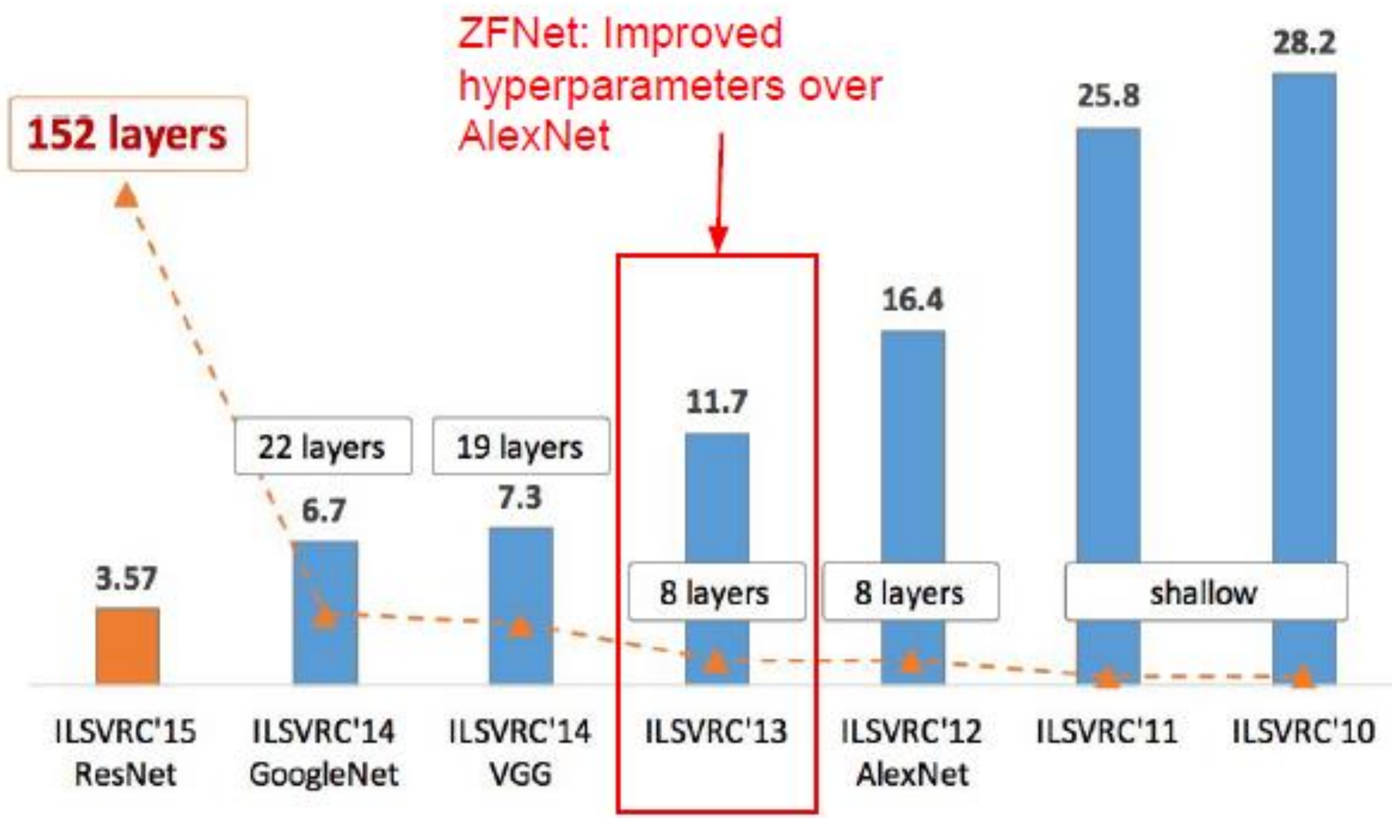


Add a **classification** ``layer''.

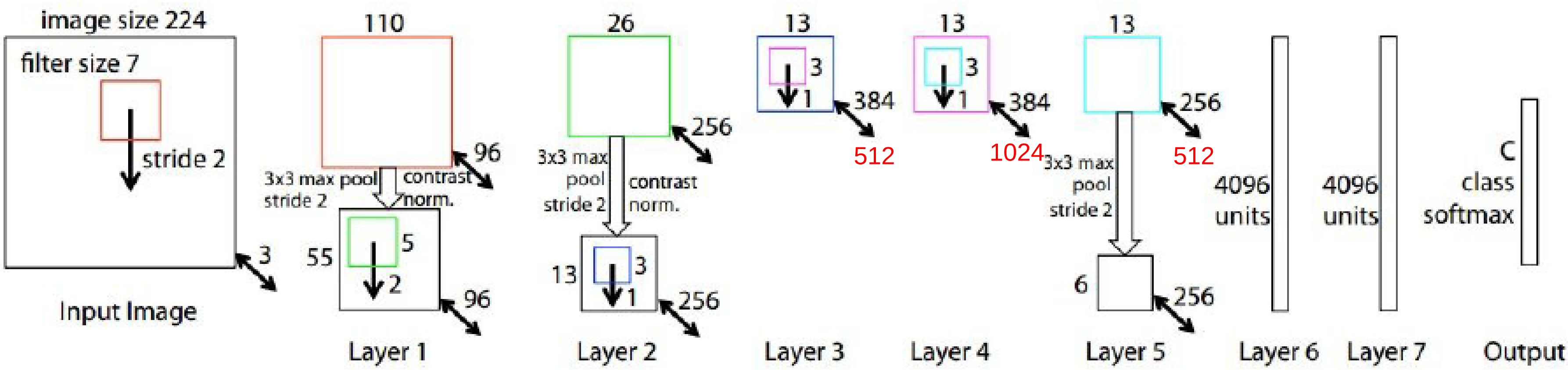
For an input image, the value in a particular dimension of this vector tells you the probability of the corresponding object class.

- 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%

ImageNet (ILSVRC)



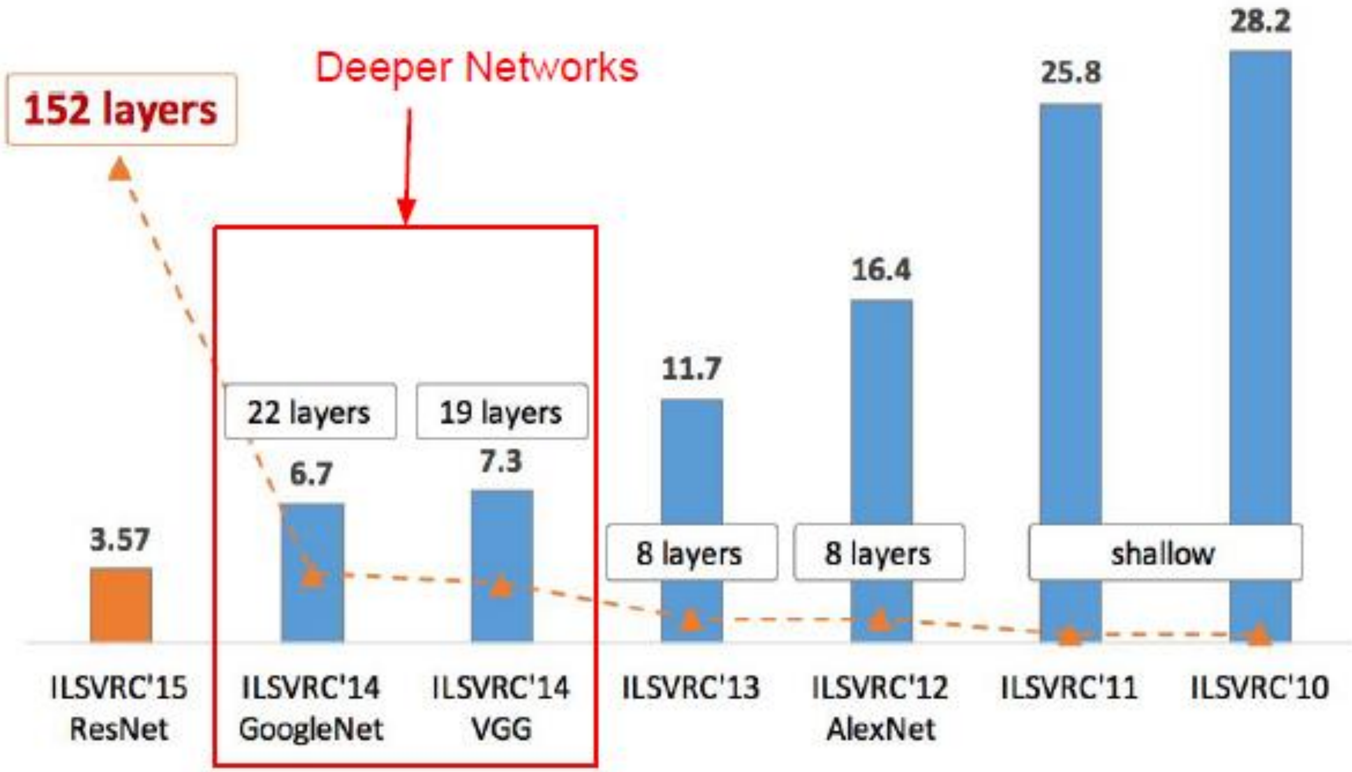
ZFNet



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 (ILSVRC)



VGGNet

Case Study: VGGNet

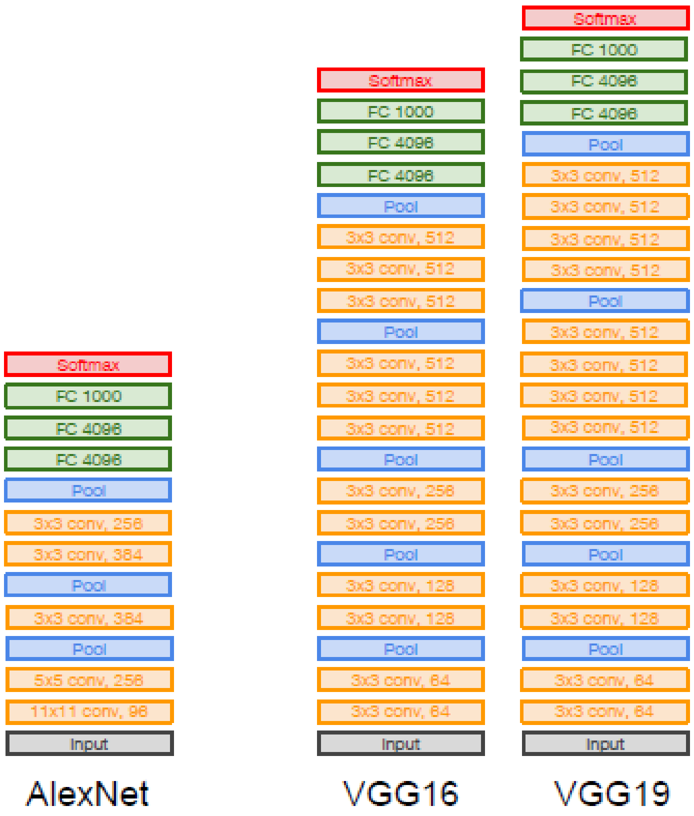
[Simonyan and Zisserman, 2014]

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



VGGNet

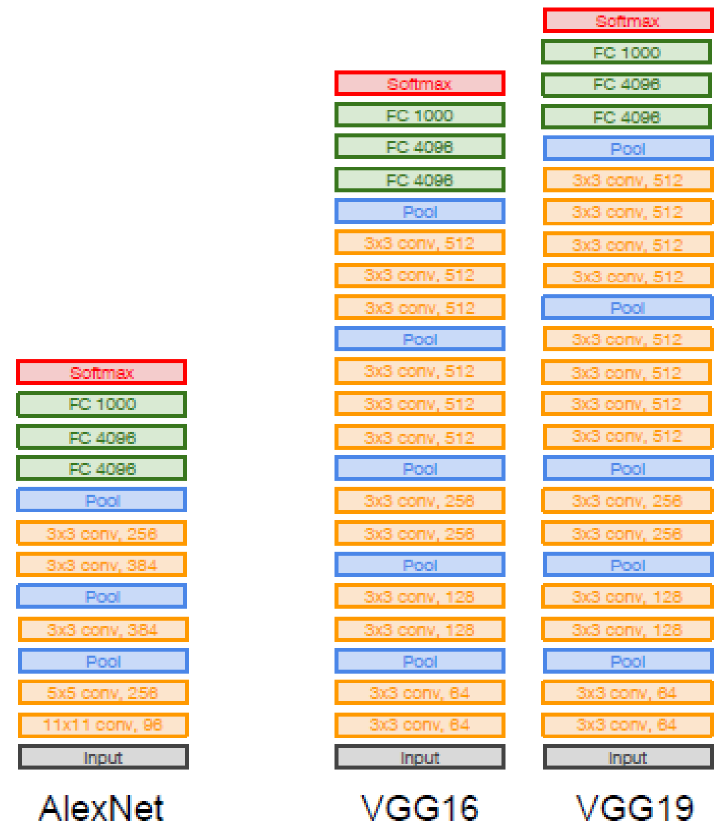
Case Study: VGGNet

[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?



VGGNet

Case Study: VGGNet

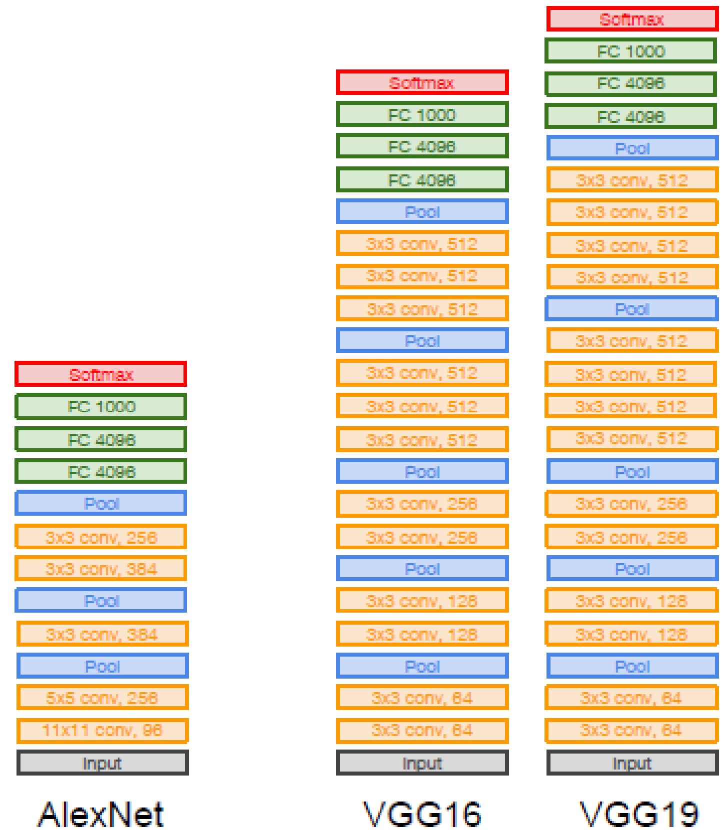
[Simonyan and Zisserman, 2014]

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



VGGNet

- Parameters

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

Note:

Most memory is in early CONV

Most params are in late FC

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

VGGNet

- Summary

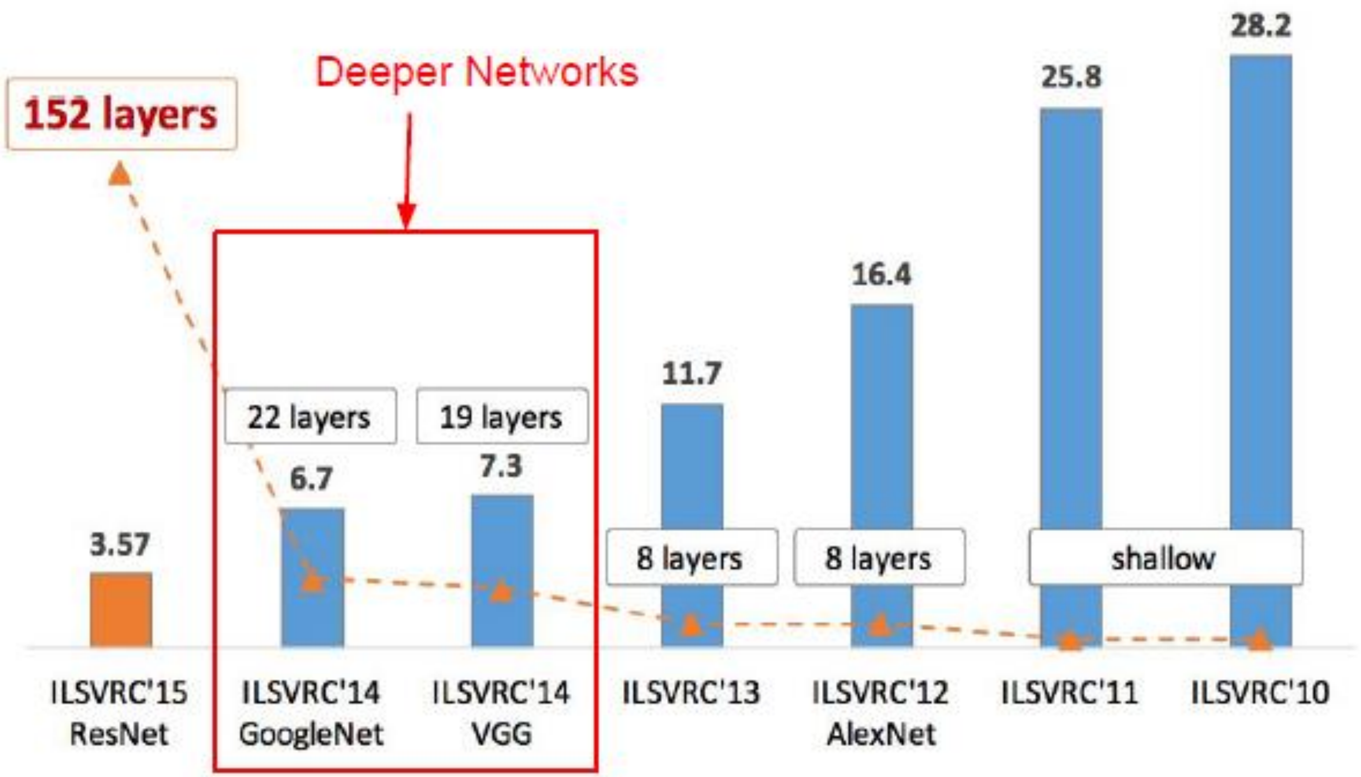
Details:

- 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

Parallel branches

- GooLeNet/Inception modules
- NiN (Network in Network)

ImageNet (ILSVRC)



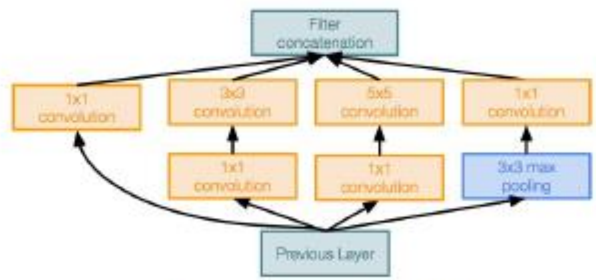
GoogLeNet

Case Study: GoogLeNet

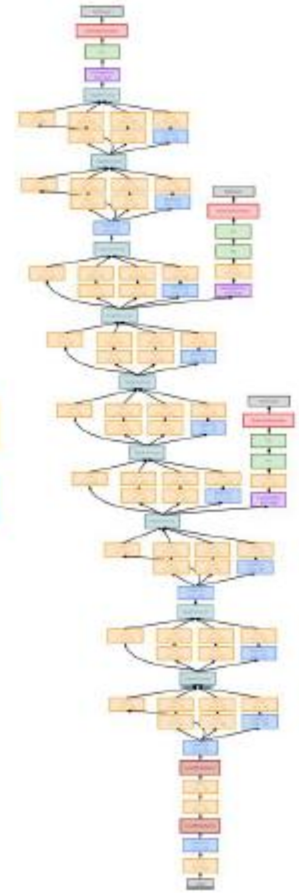
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

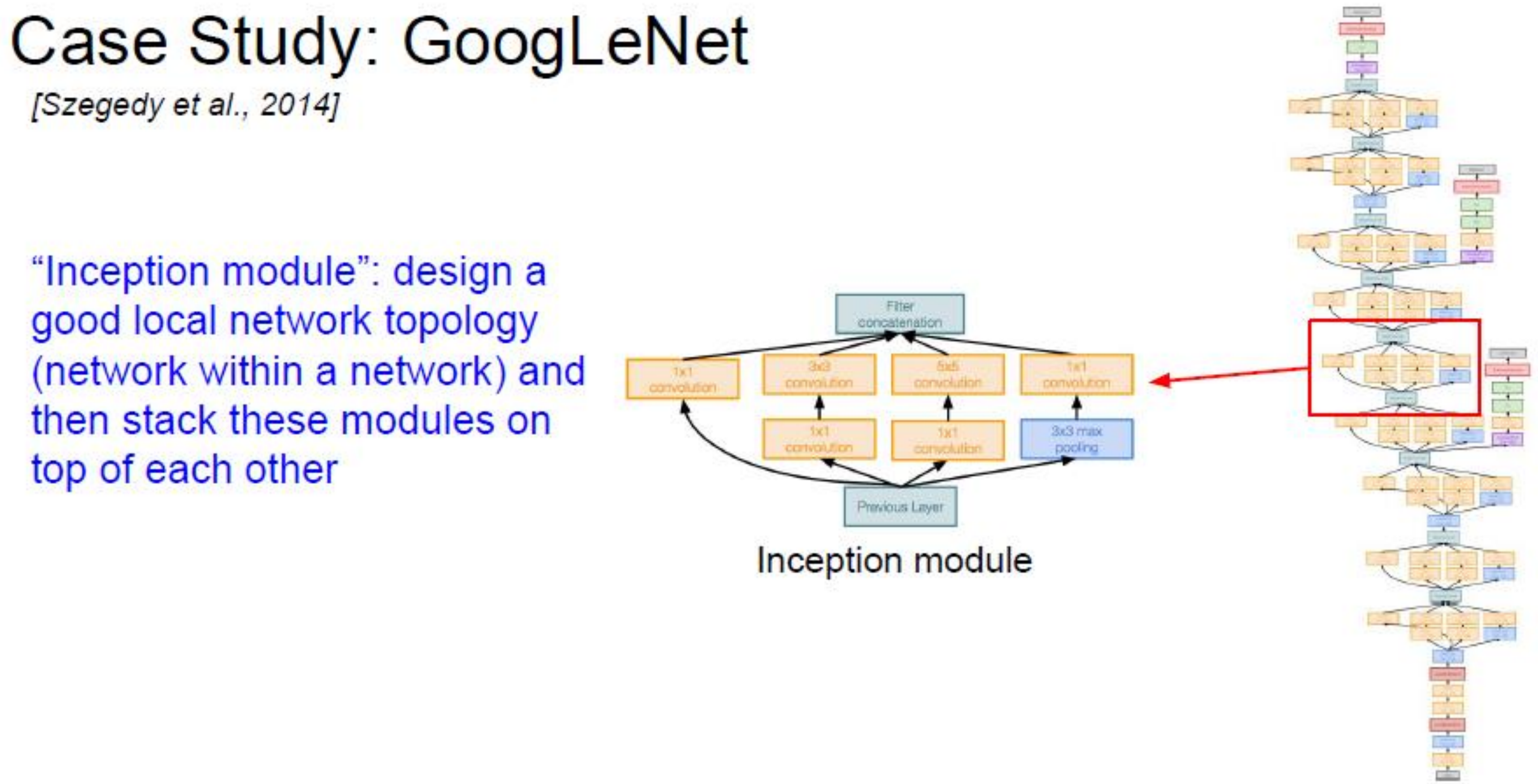
- 22 layers
- Efficient “Inception” module
- No FC layers
- Only 5 million parameters!
  12x less than AlexNet
- ILSVRC’14 classification winner
  (6.7% top 5 error)



Inception module



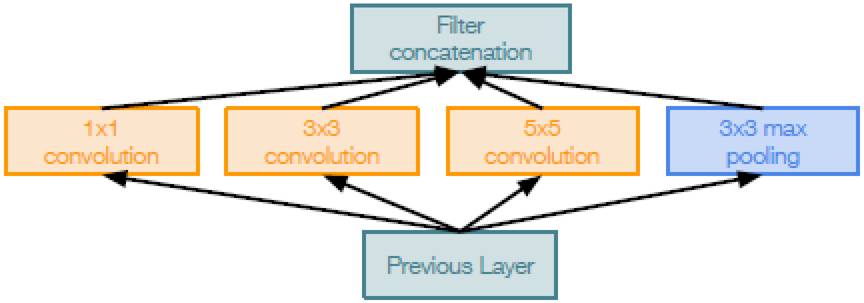
GoogLeNet



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
Filter concatenation
1x1 convolution
3x3 convolution
5x5 convolution
1x1 convolution
1x1 convolution
1x1 convolution
3x3 max pooling
Previous Layer
Inception module

GoogLeNet

- Inception Module



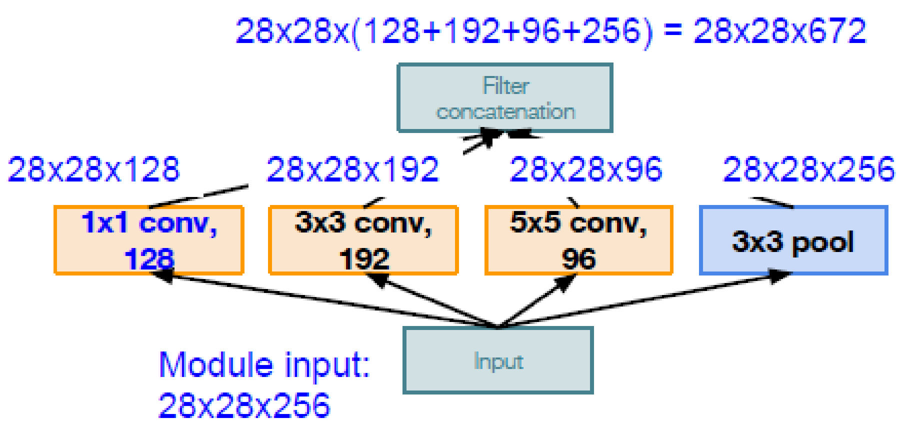
Naive Inception module

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

GoogLeNet

- Inception Module



Naive Inception module

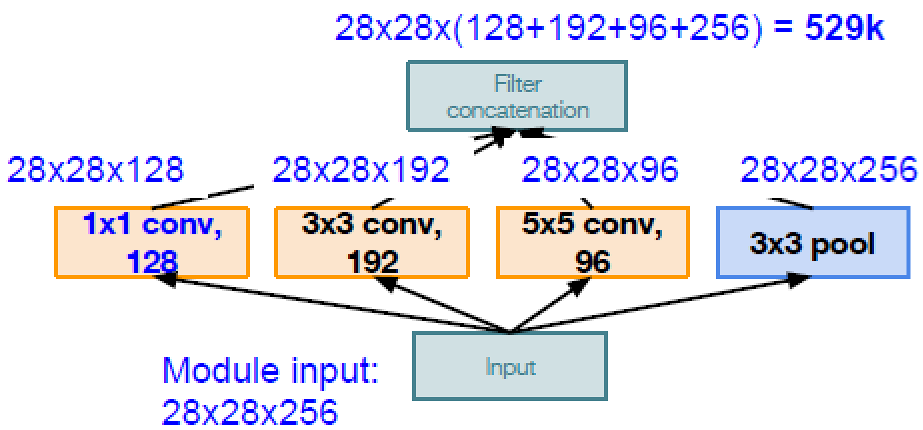
Conv Ops:
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x256
[5x5 conv, 96] 28x28x96x5x5x256
Total: 854M ops

Very expensive compute

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

GoogLeNet

- Inception Module

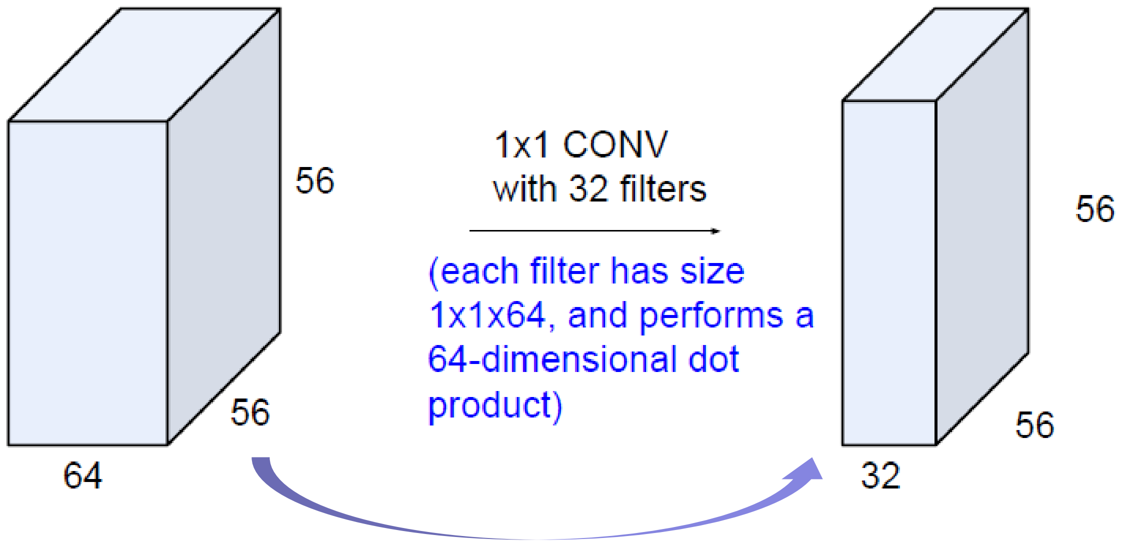


Naive Inception module

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

GoogLeNet

- Bottleneck layer

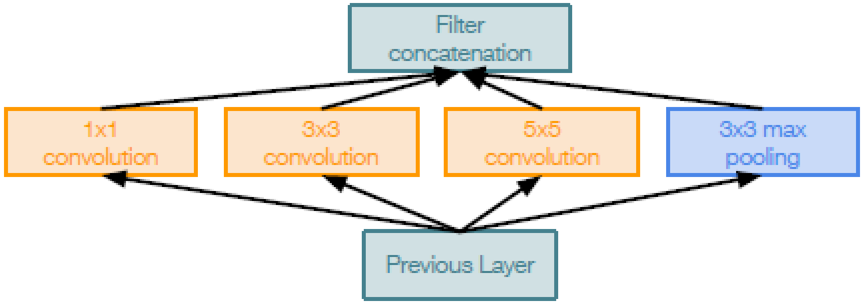


preserves spatial
dimensions, reduces depth!

Projects depth to lower
dimension (combination of
feature maps)

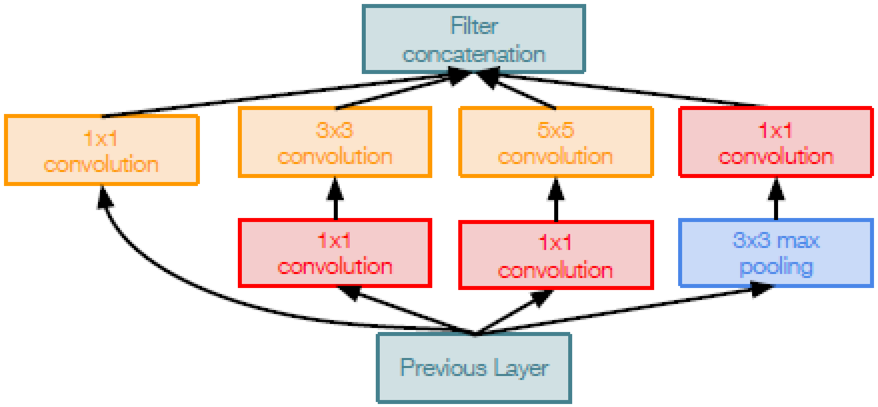
GoogLeNet

- Inception Module



Naive Inception module

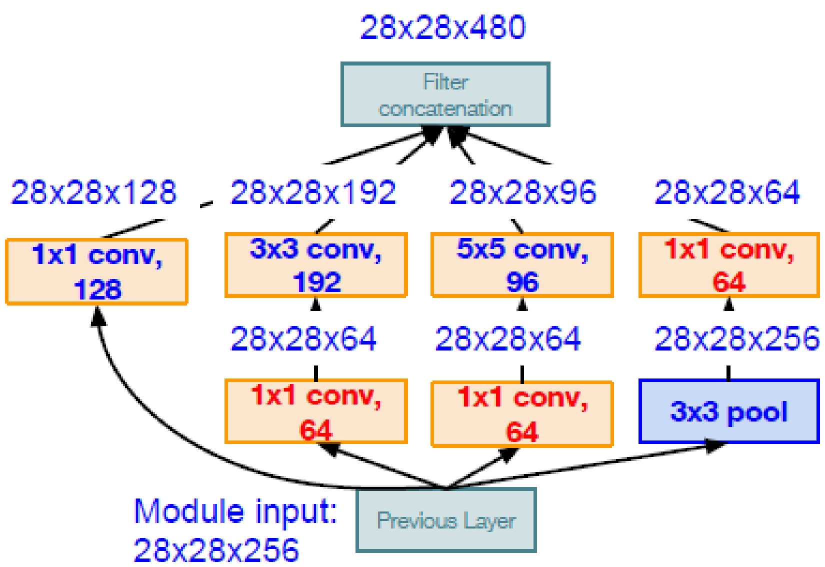
1x1 conv "bottleneck" layers



Inception module with dimension reduction

GoogLeNet

- Inception Module



Inception module with dimension reduction

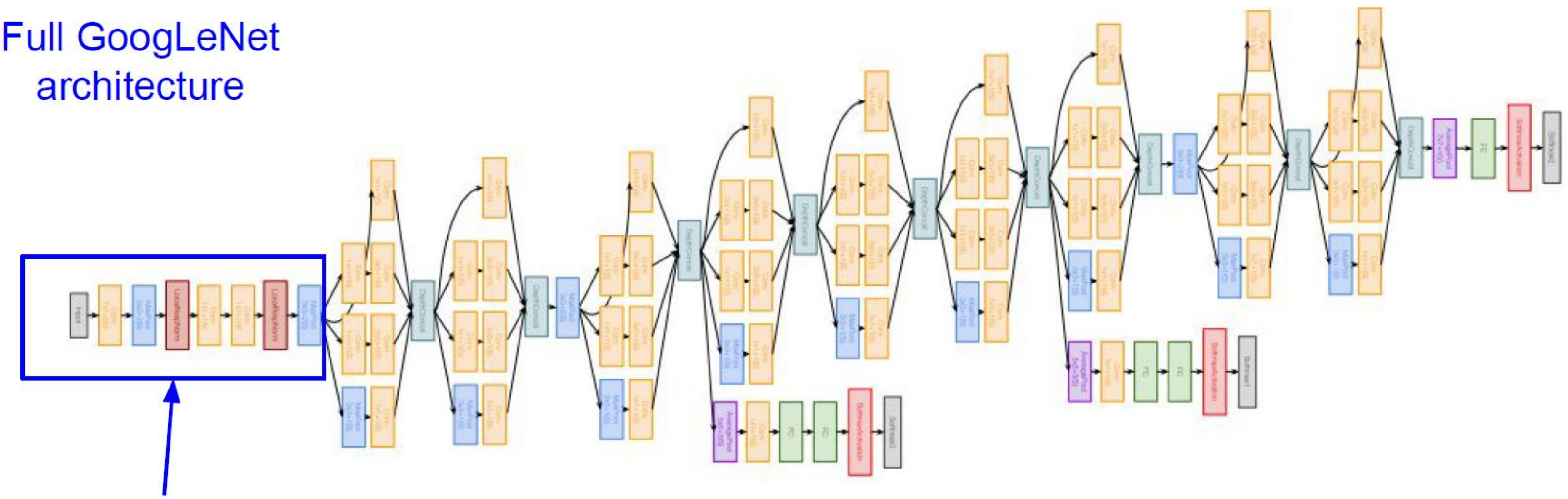
Conv Ops:
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x64
[5x5 conv, 96] 28x28x96x5x5x64
[1x1 conv, 64] 28x28x64x1x1x256
Total: 358M ops

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

GoogLeNet

- Overall network structure

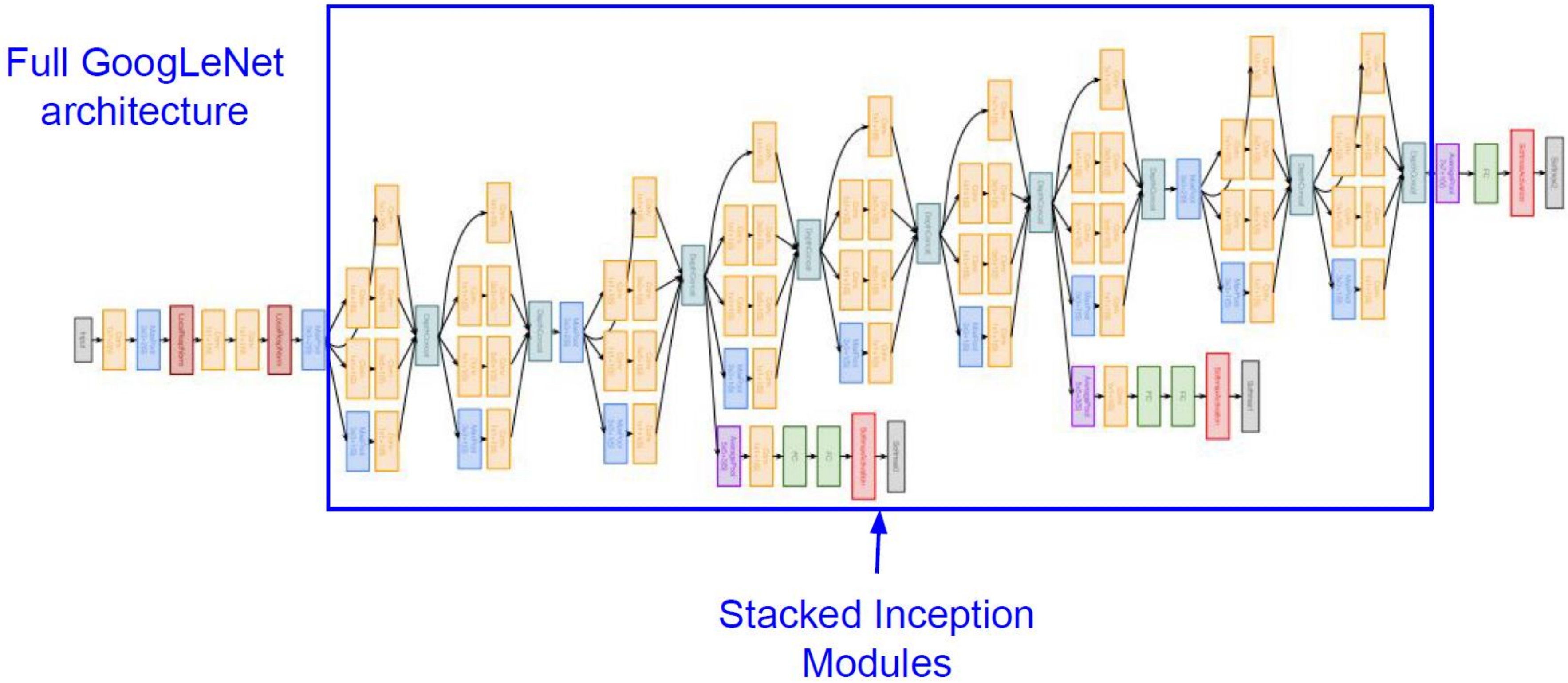
Full GoogLeNet architecture



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

GoogLeNet

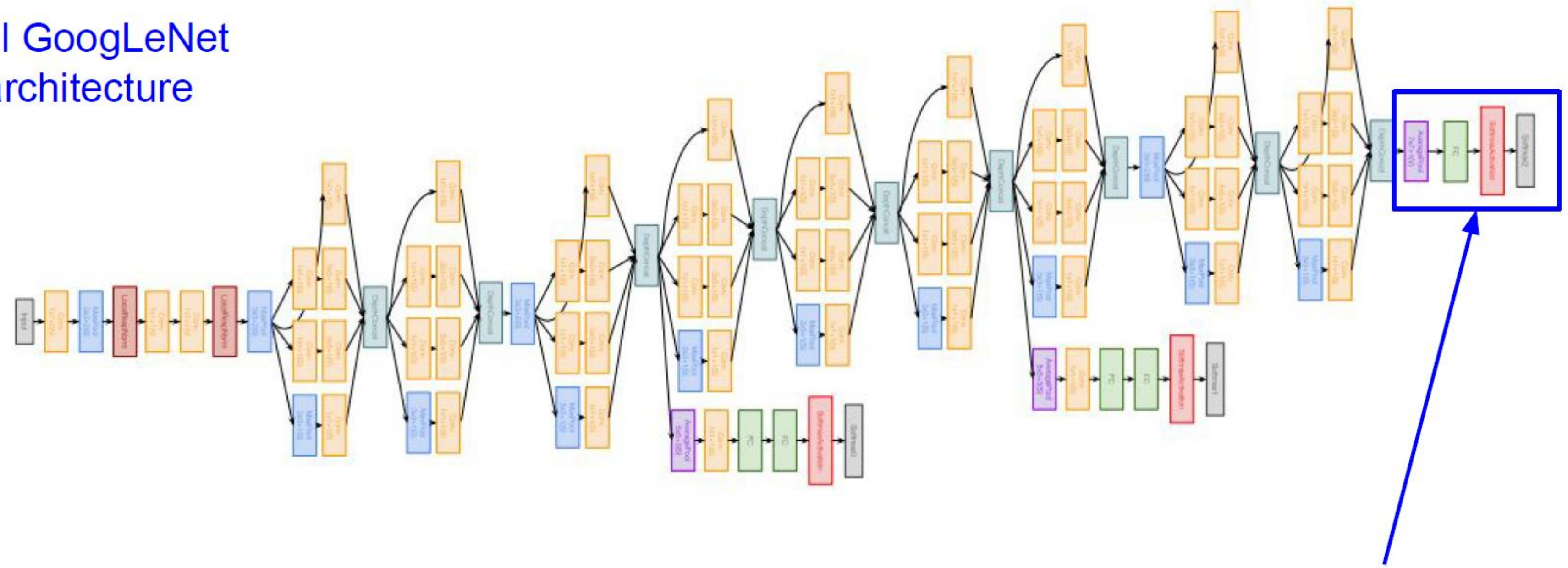
- Overall network structure



GoogLeNet

- Overall network structure

Full GoogLeNet architecture

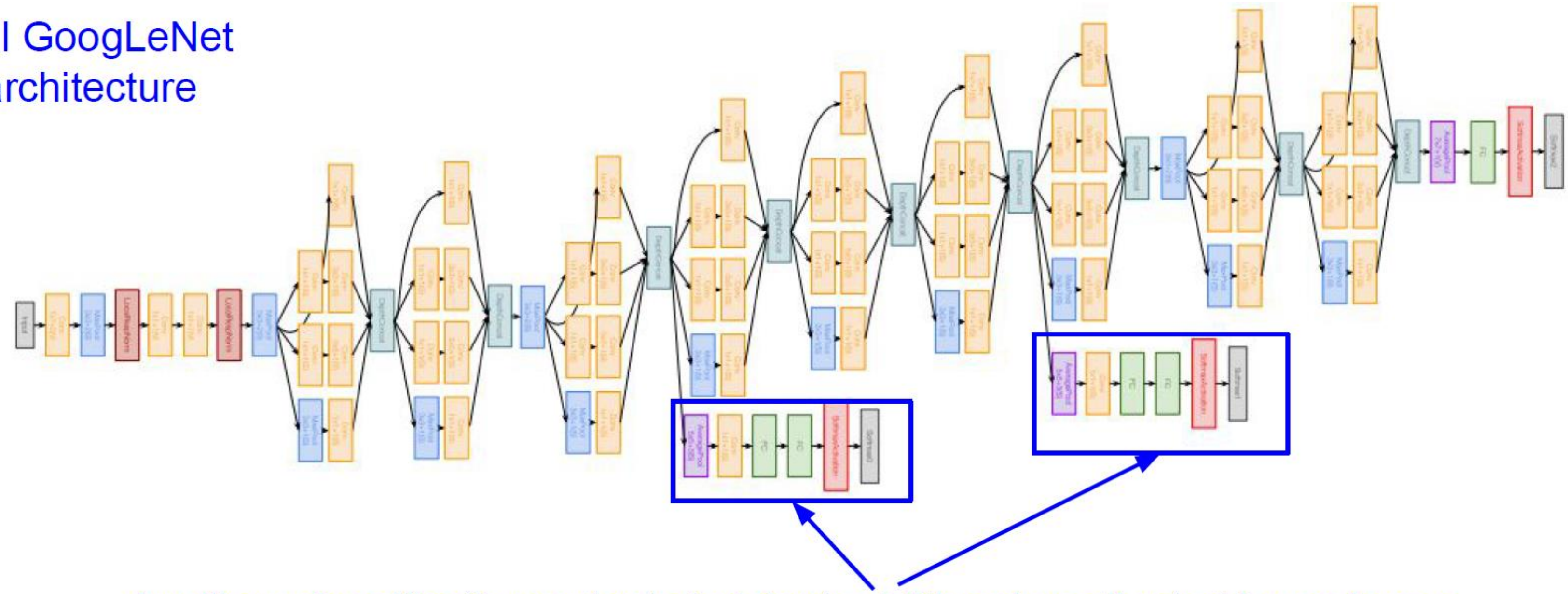


Classifier output
(removed expensive FC layers!)

GoogLeNet

- Overall network structure

Full GoogLeNet architecture

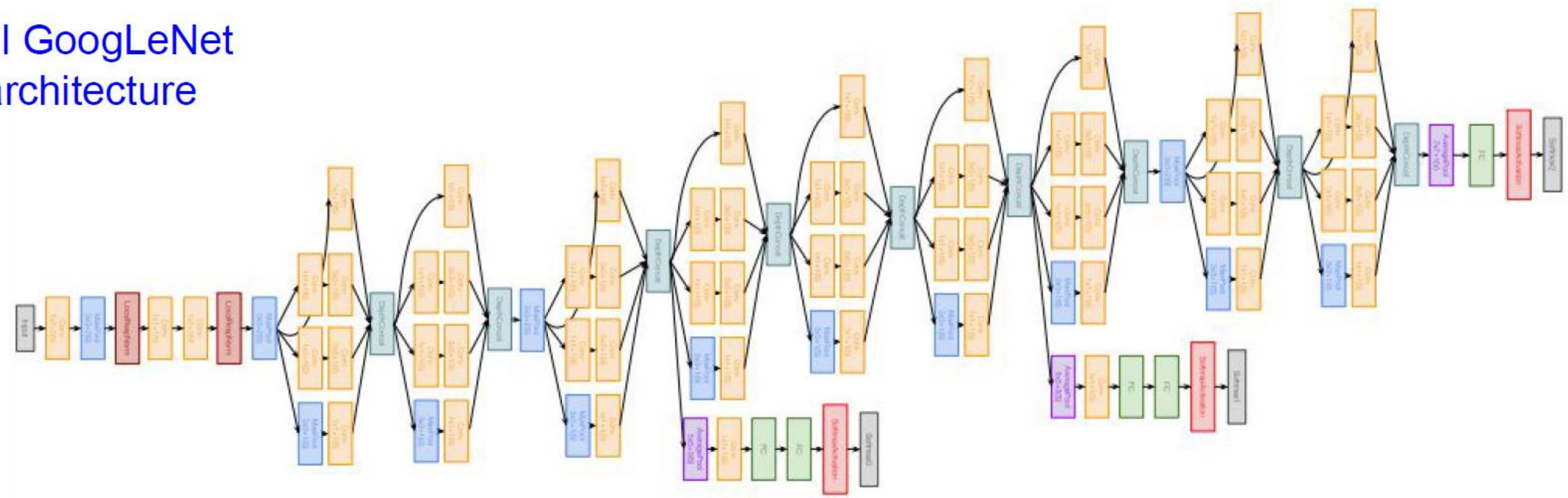


Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

GoogLeNet

- Overall network structure

Full GoogLeNet architecture



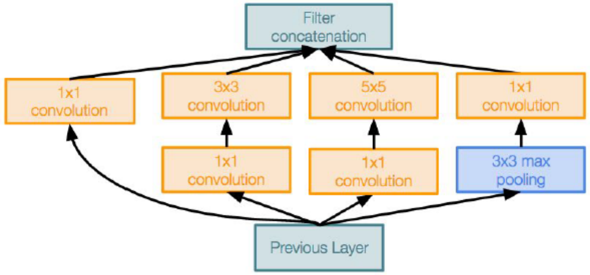
22 total layers with weights (including each parallel layer in an Inception module)

GoogLeNet

- Summary

Deeper networks, with computational efficiency

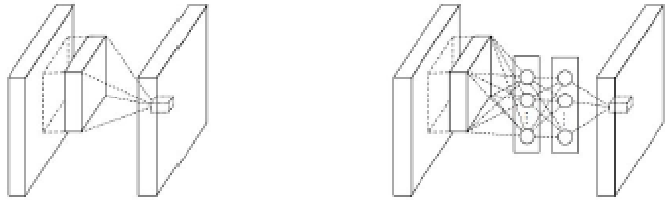
- 22 layers
- Efficient “Inception” module
- No FC layers
- 12x less params than AlexNet
- ILSVRC’14 classification winner (6.7% top 5 error)



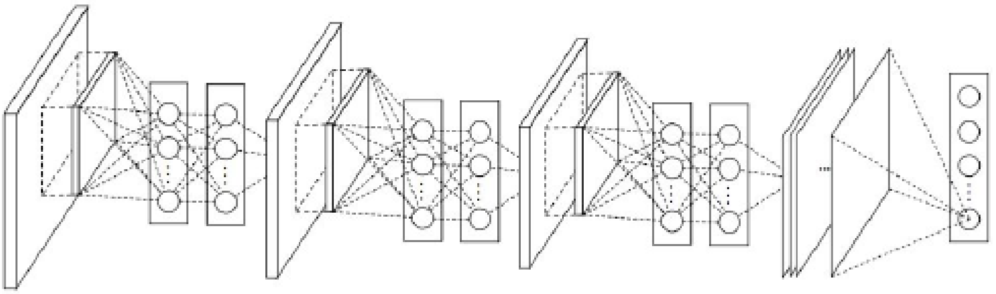
Inception module

Other: Network in Network (NiN)

- 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



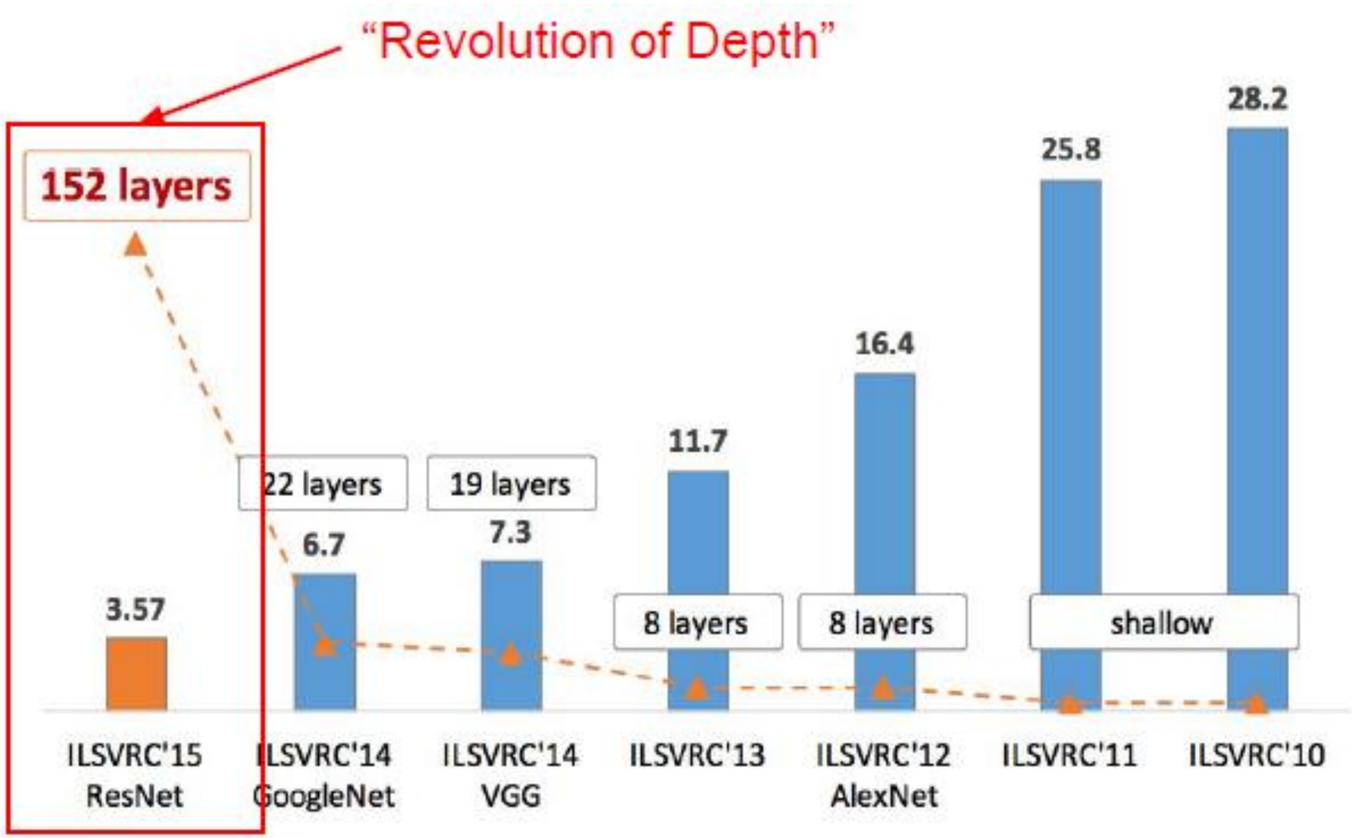
(a) Linear convolution layer (b) Mlpconv layer



Residual structure

- ResNet
- DenseNet

ImageNet (ILSVRC)



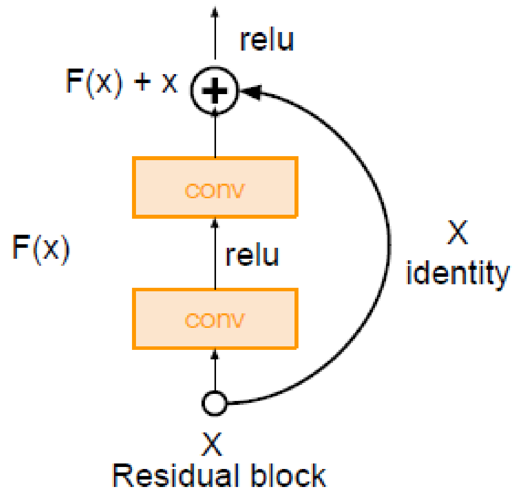
ResNet

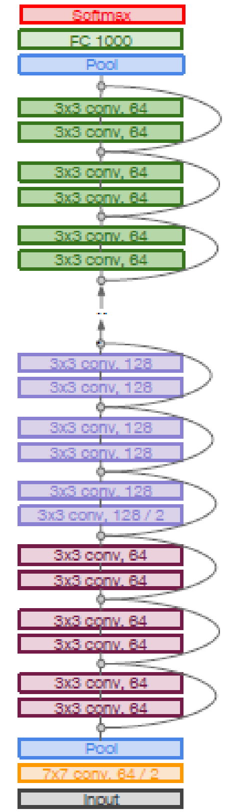
Case Study: ResNet

[He et al., 2015]

Very deep networks using residual connections

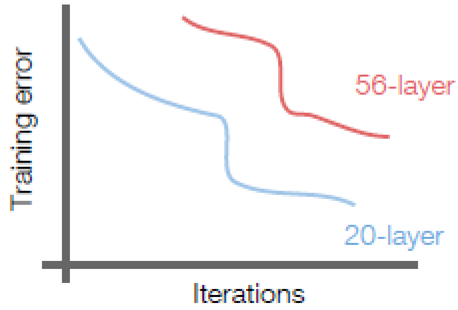
- 152-layer model for ImageNet
- ILSVRC'15 classification winner (3.57% top 5 error)
- Swept all classification and detection competitions in ILSVRC'15 and COCO'15!

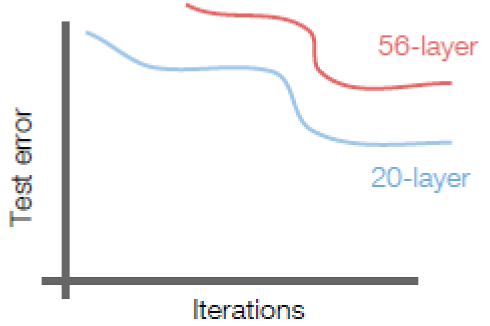




ResNet

- What happens when stacking deeper plain conv layers?





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

ResNet

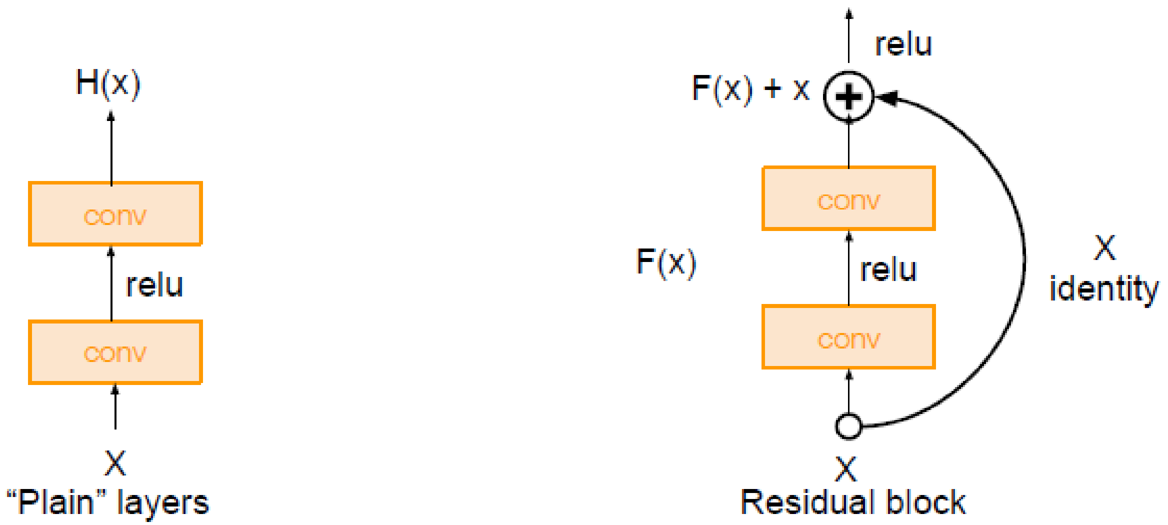
- Hypothesis:
  - The problem is an optimization problem, deeper models are harder to optimize

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.

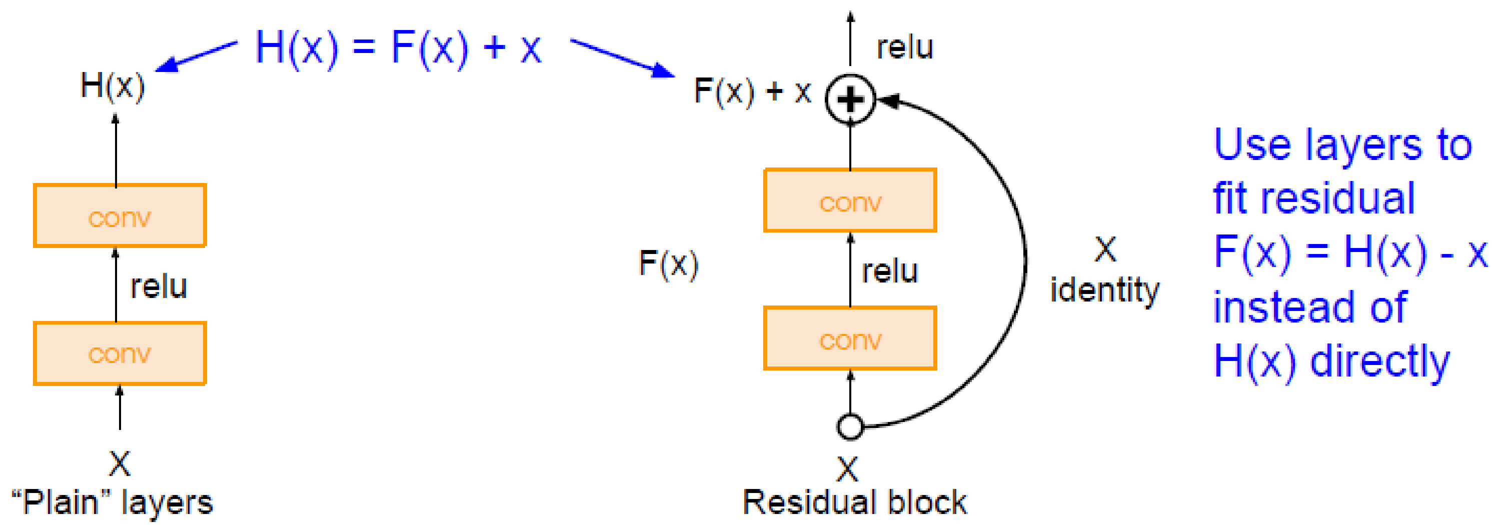
ResNet

- Solution:
  - Use network layers to fit a residual mapping



ResNet

- Solution:
  - Use network layers to fit a residual mapping

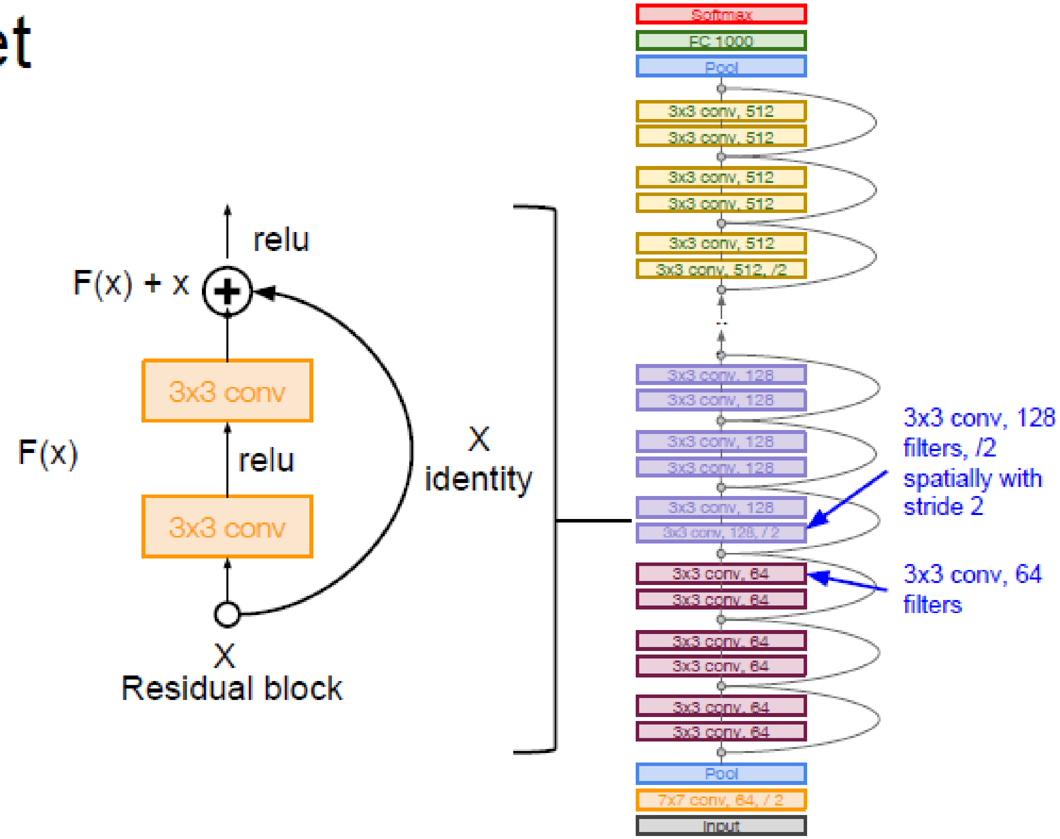


ResNet

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)



ResNet

Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:
- Stack residual blocks
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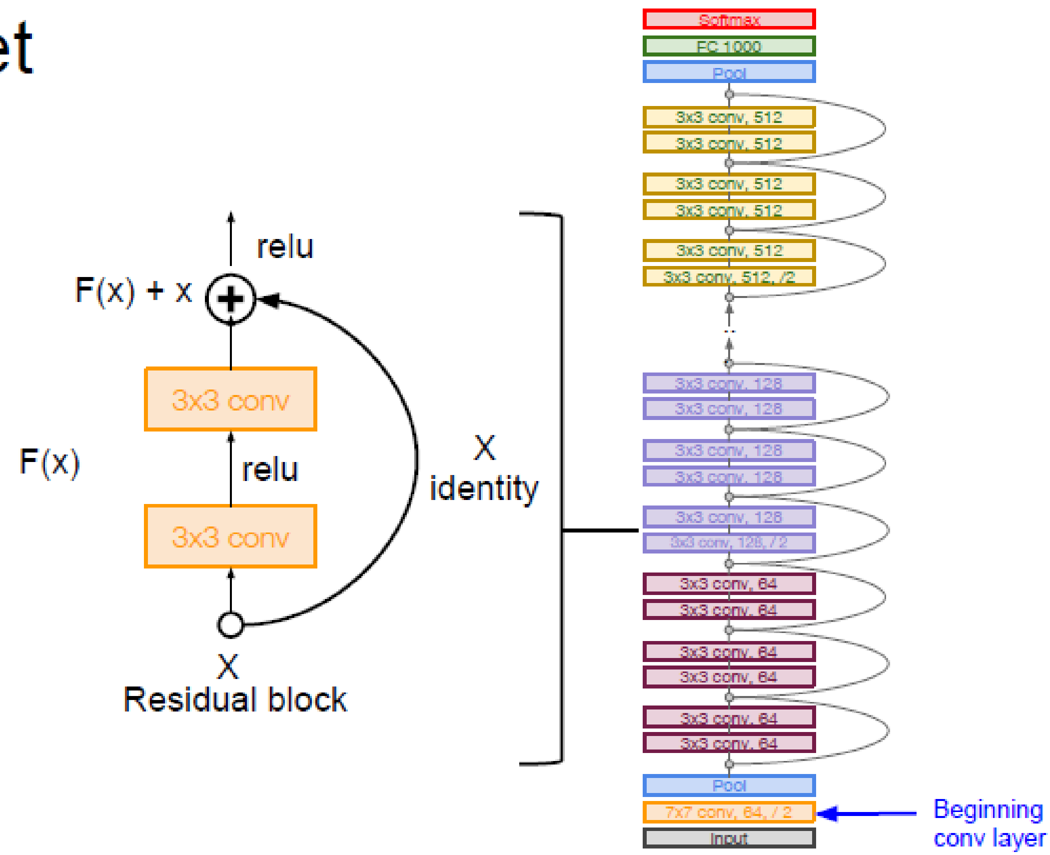
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)
- Additional conv layer at the beginning

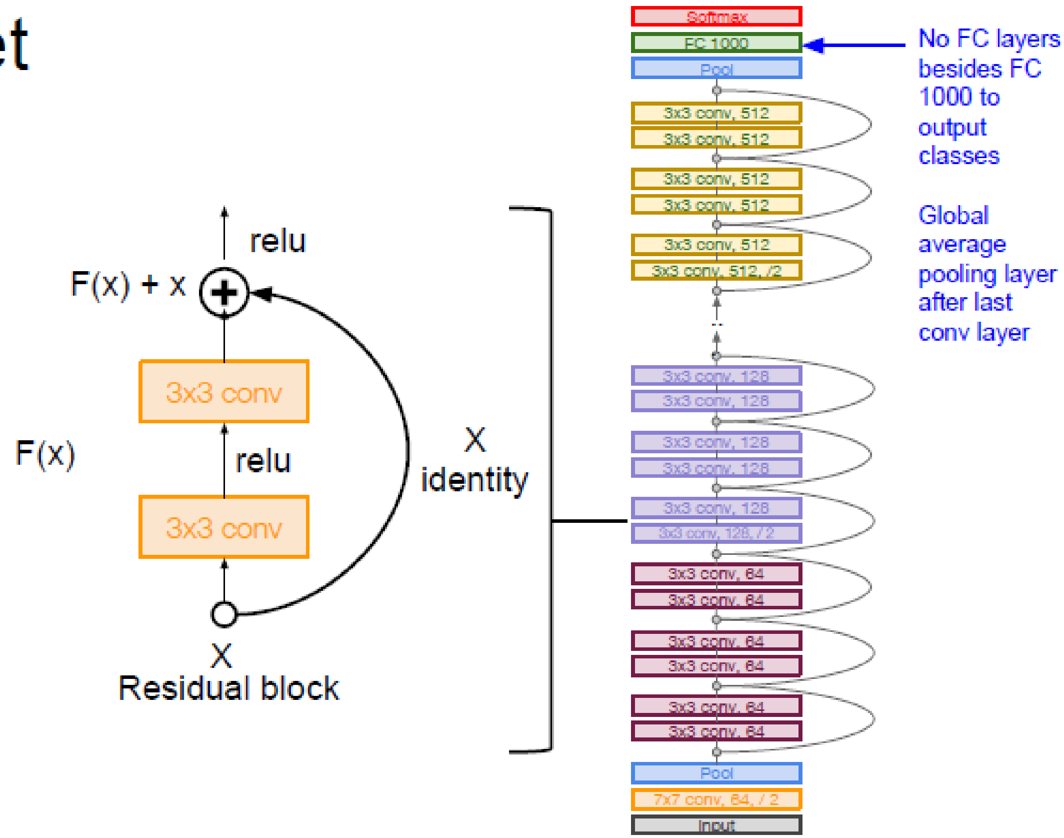


ResNet

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)

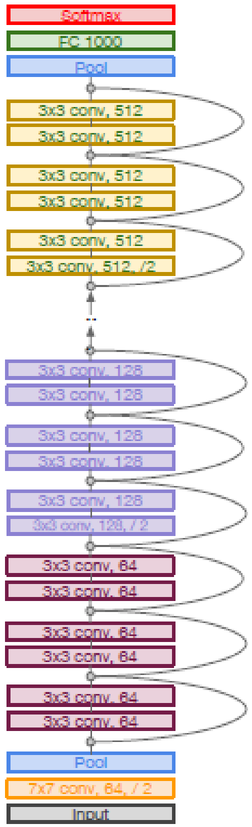


ResNet

Case Study: ResNet

[He et al., 2015]

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

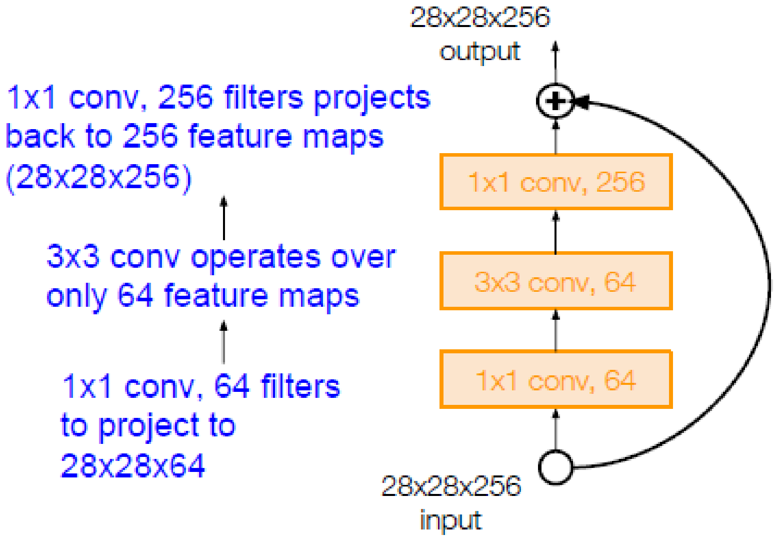


ResNet

Case Study: ResNet

[He et al., 2015]

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



ResNet

- Training details

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

ResNet

- Results

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

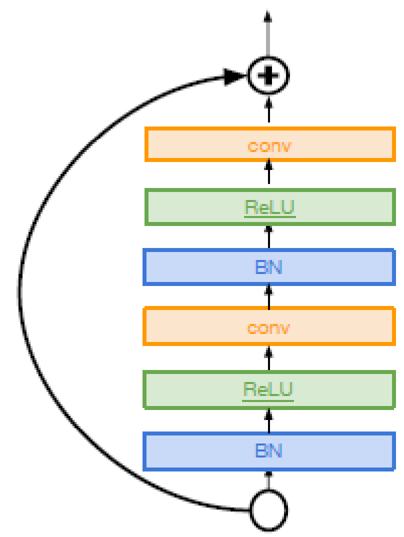
MSRA @ ILSVRC & COCO 2015 Competitions

- **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

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

Other: Identity Mappings in ResNet

- 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

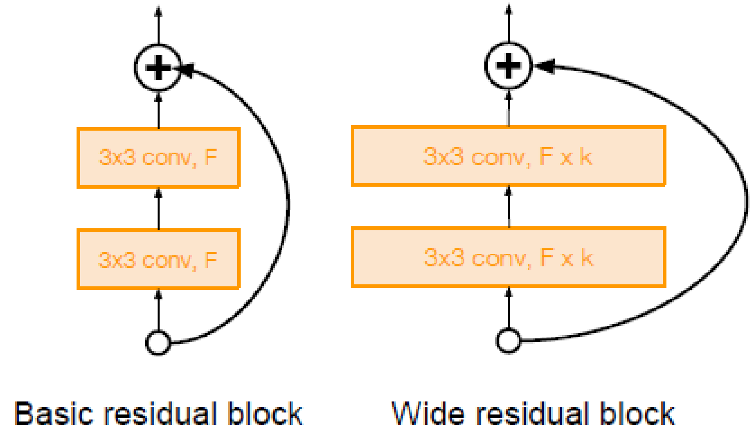


Other: Wide ResNets

Wide Residual Networks

[Zagoruyko et al. 2016]

- Argues that residuals are the important factor, not depth
- User wider residual blocks (F x 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)

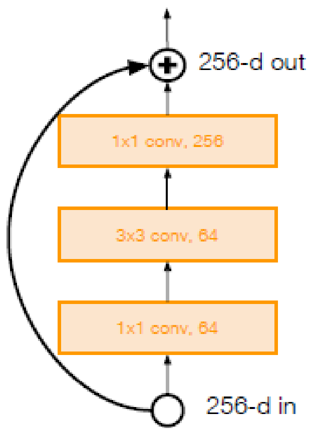


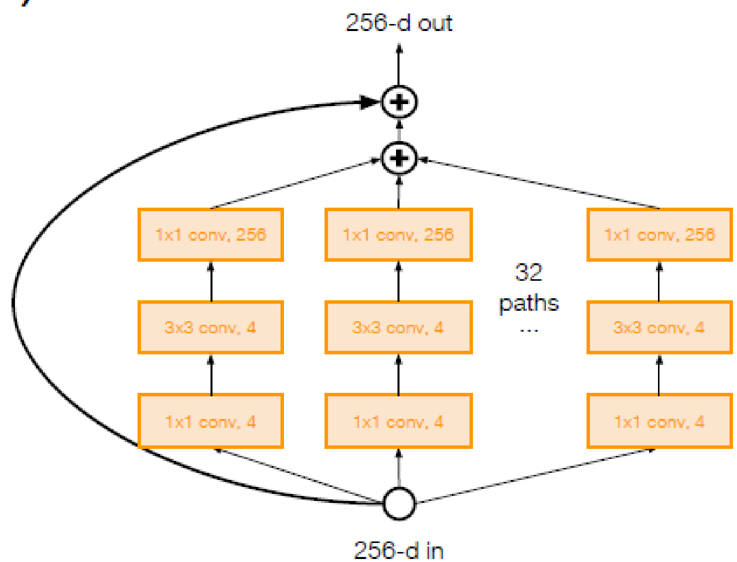
Other: ResNeXt

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



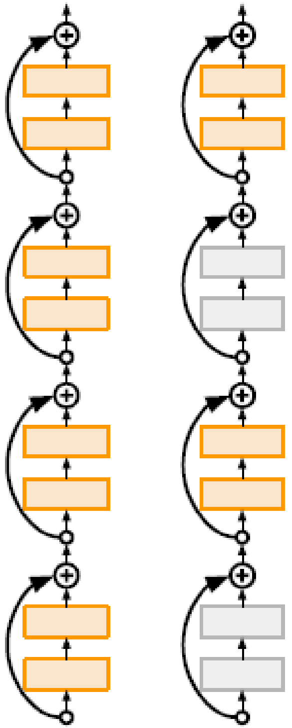


Other:ResNet with Stochastic Depth

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

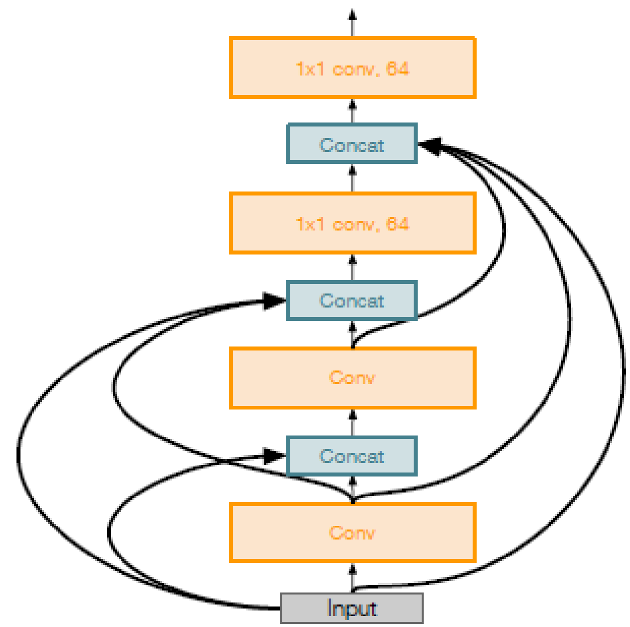


DenseNet

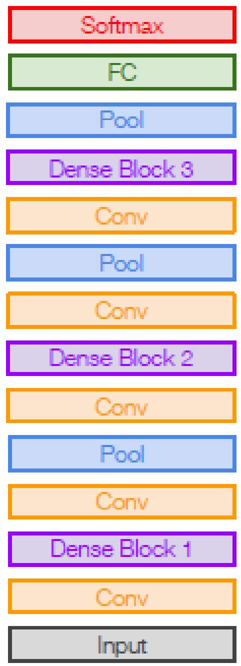
Densely Connected Convolutional Networks

[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

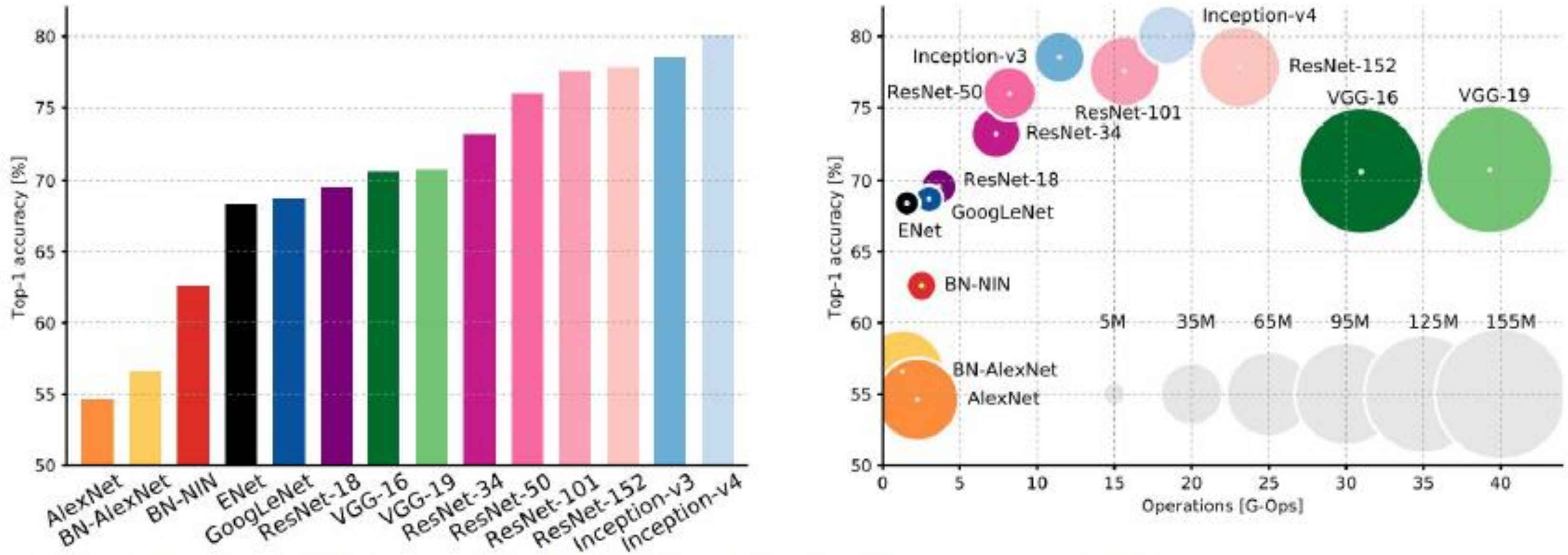


Dense Block



Model complexity

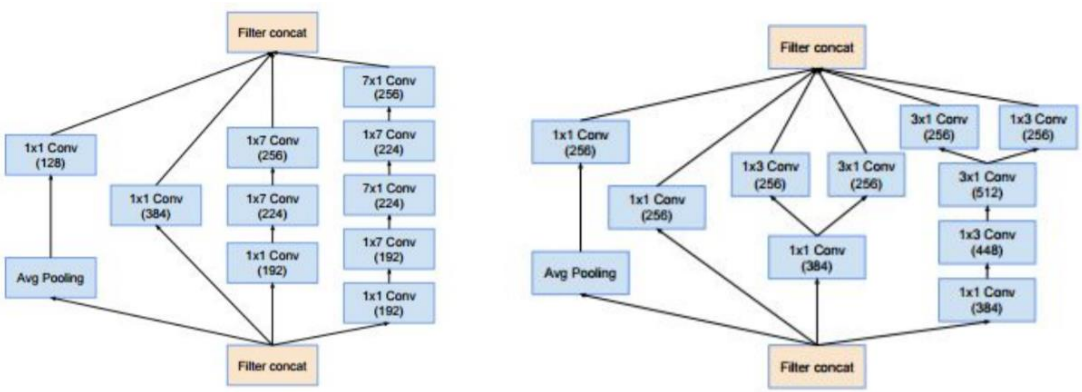
Comparing complexity...



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

Network Architecture

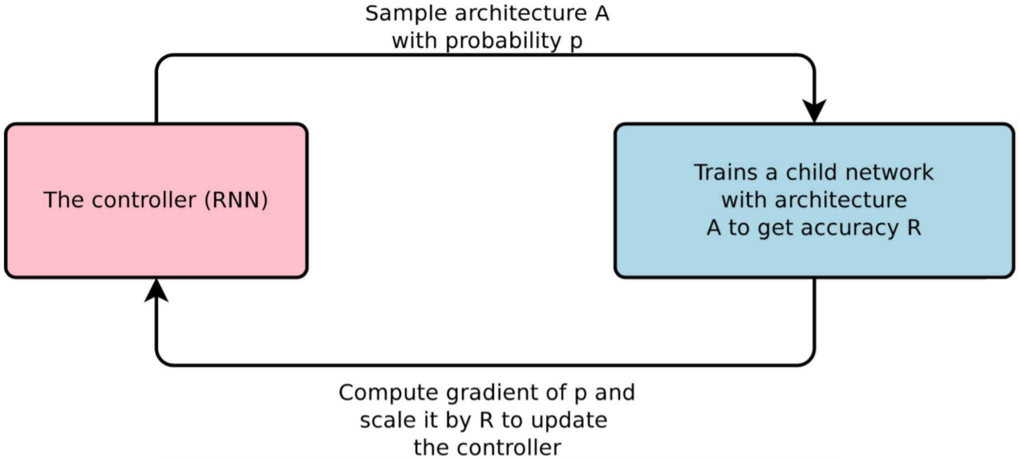
- Problems with network architecture
  - Designing NA is hard
  - Lots of human efforts go into tuning them
  - Not a lot of intuition into how to design them well
  - Can we learn good architectures automatically?



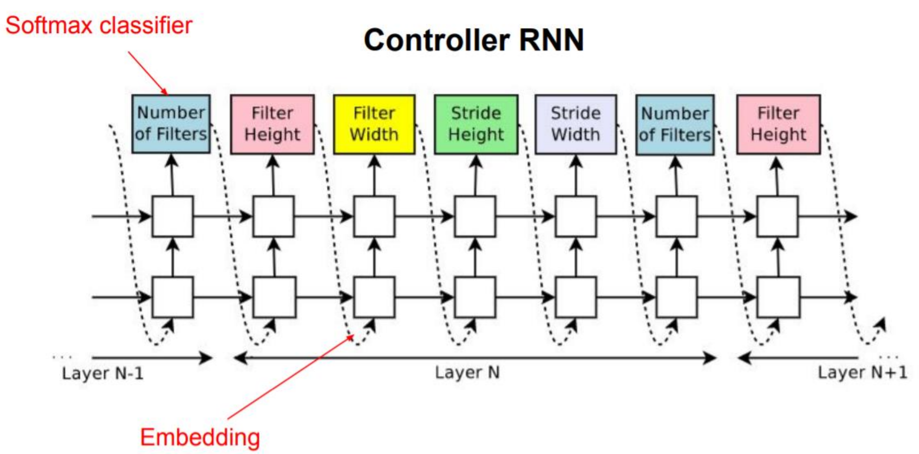
Two layers from the famous Inception V4 computer vision model.
Szegedy et al, 2017

Network Architecture

- Neural architecture search (Zoph and Le, ICLR 2016)



  - CNN example:



Summary

- CNNs for image/object classification

  - 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:
  - Network learning algorithms