DATA ANALYTICS USING DEEP LEARNING

GT 8803 // FALL 2019 // JOY ARULRAJ

LECTURE #14:CNN ARCHITECTURES

CREATING THE NEXT®

ADMINISTRIVIA

- Reminders
  - Signup for a weekly project discussion slot
  - One member from each team for ~15 minutes
  - Goal is to ensure to accomplish something significant in the project
  - Project progress updates due in two weeks

LAST TWO LECTURES: TRAINING NEURAL NETWORKS

- **One time setup**
  - Activation Functions, Preprocessing, Weight Initialization, Regularization, Gradient Checking
- **Training dynamics**
  - Babysitting the Learning Process, Parameter updates, Hyperparameter Optimization
- **Evaluation**
  - Model ensembles, Test-time augmentation

ONE MORE THING: TRANSFER LEARNING

"You need a lot of a data if you want to train/use CNNs"

ONE MORE THING: TRANSFER LEARNING

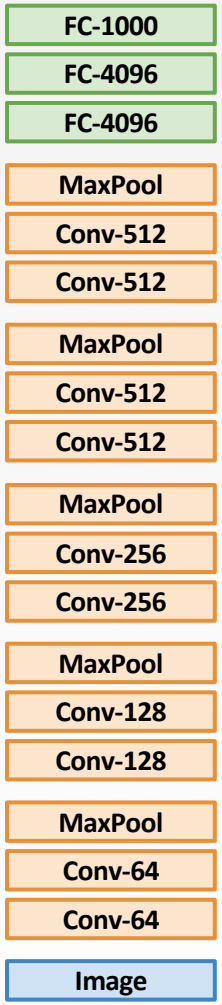
"You need a lot of data if you want to train/use CNNs"

TRANSFER LEARNING

TRANSFER LEARNING WITH CNNS

Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014
Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

1. Train on Imagenet



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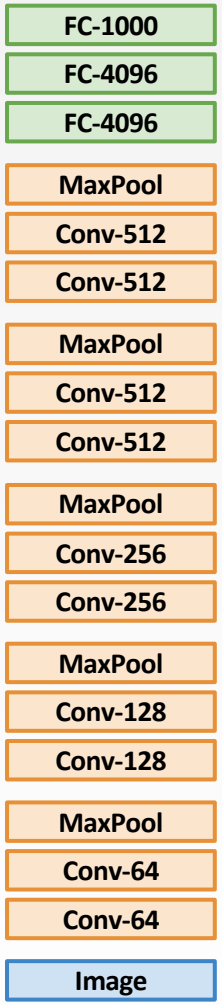
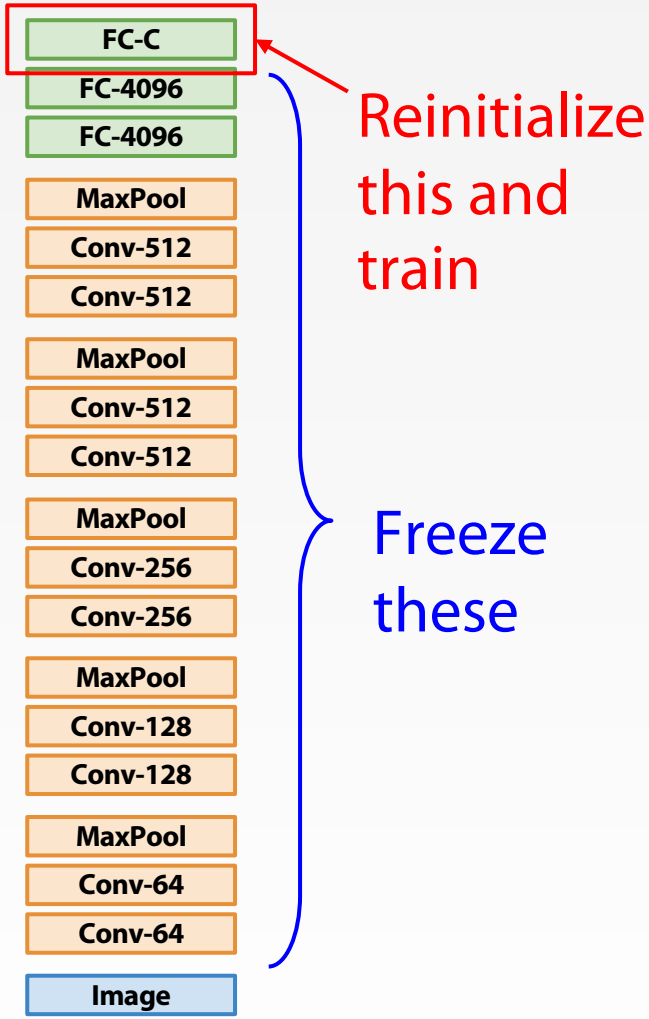


2. Small Dataset (C classes)



Reinitialize this and train

Freeze these

TRANSFER LEARNING WITH CNNS

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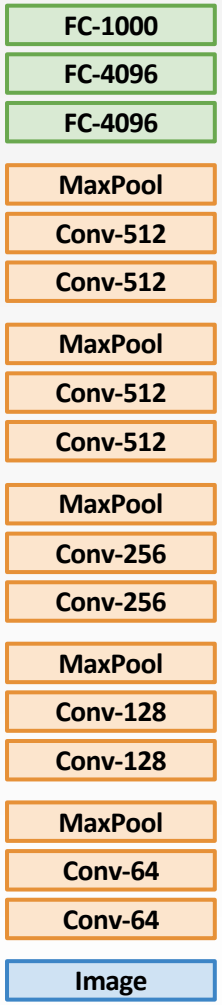

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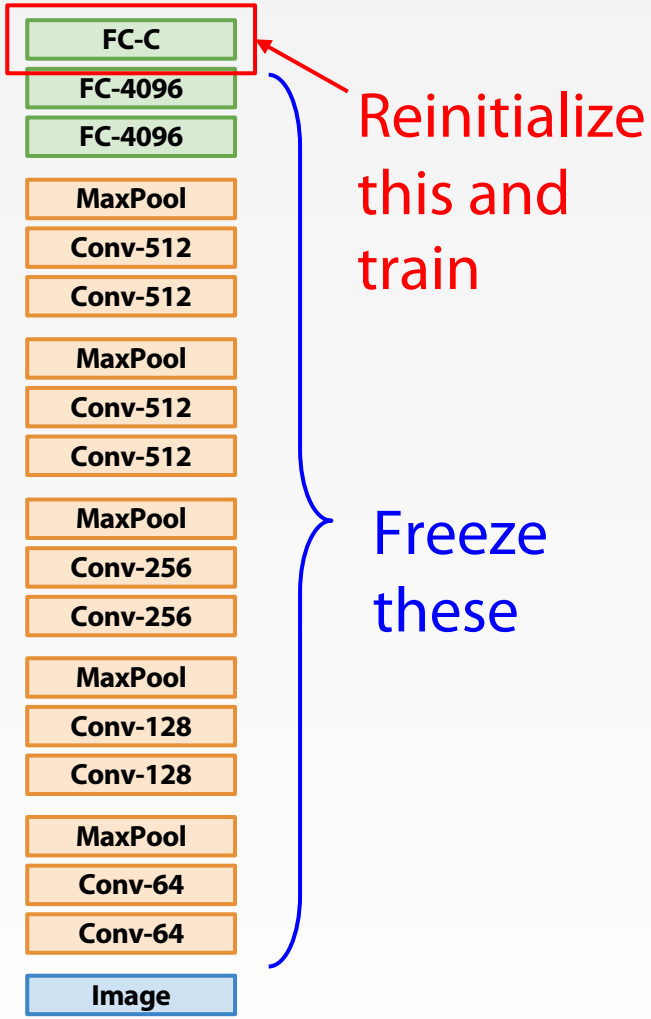
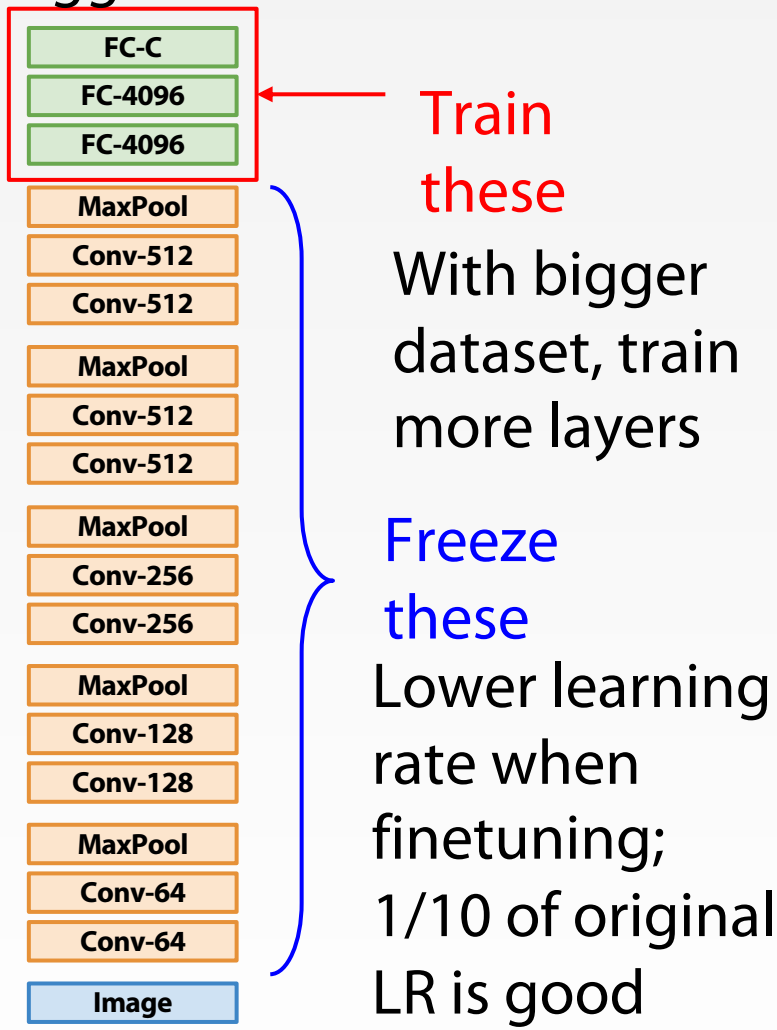
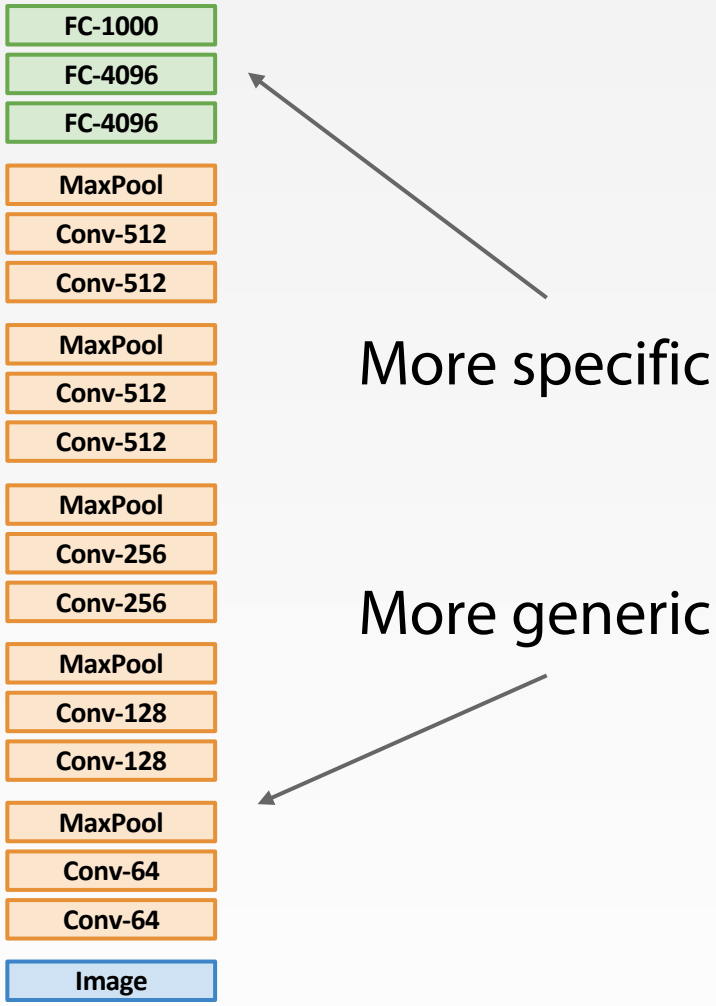
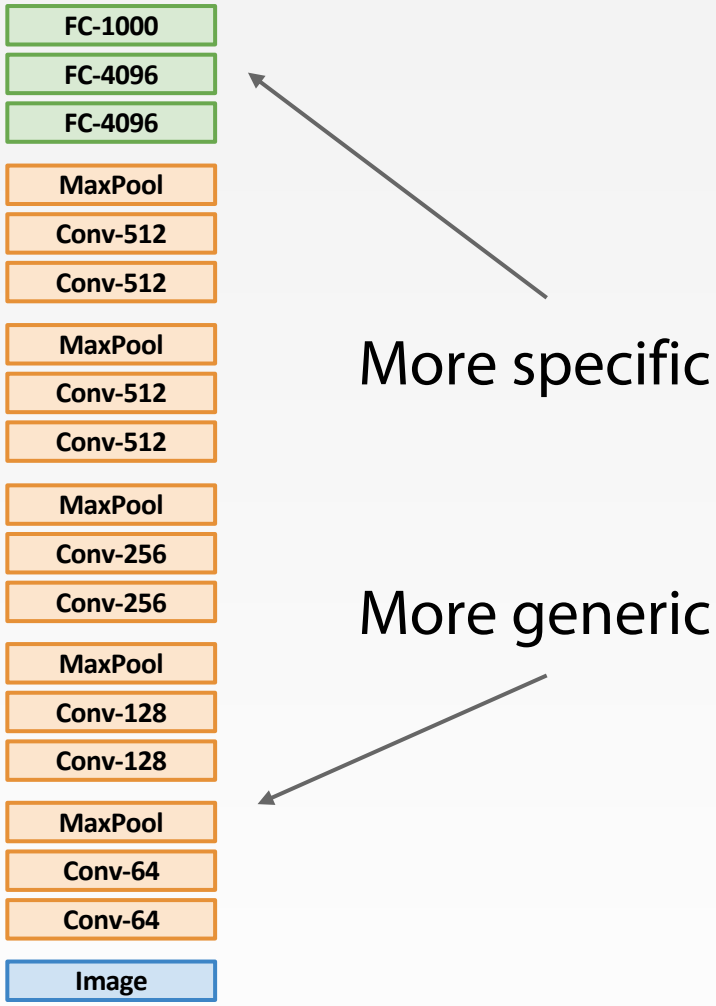


3. Bigger dataset

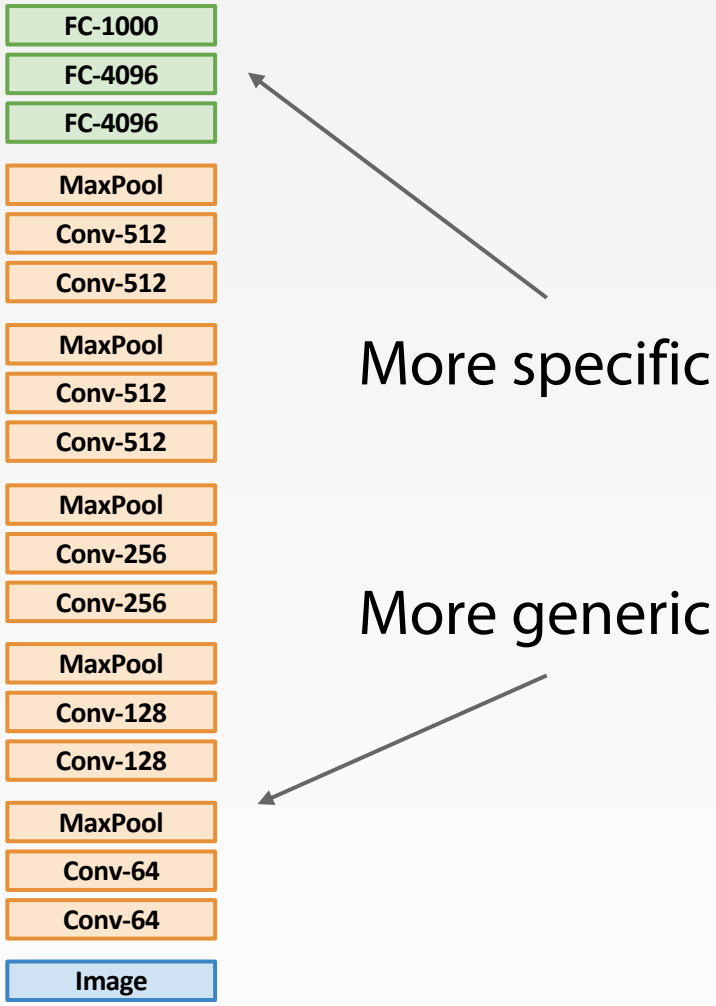




	very similar dataset	very different dataset
very little data	?	?
quite a lot of data	?	?



	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	?
quite a lot of data	Finetune a few layers	?

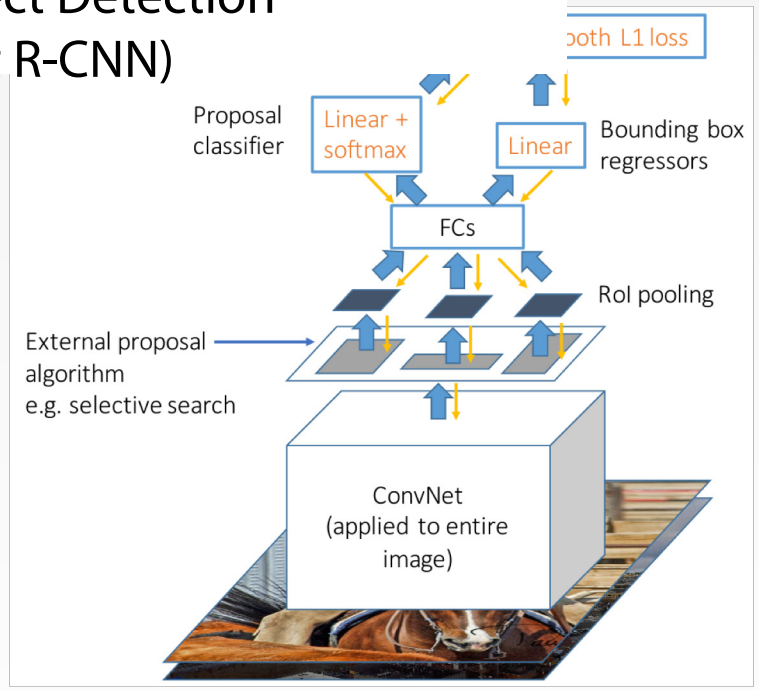


	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

TRANSFER LEARNING WITH CNNS IS PERVASIVE…

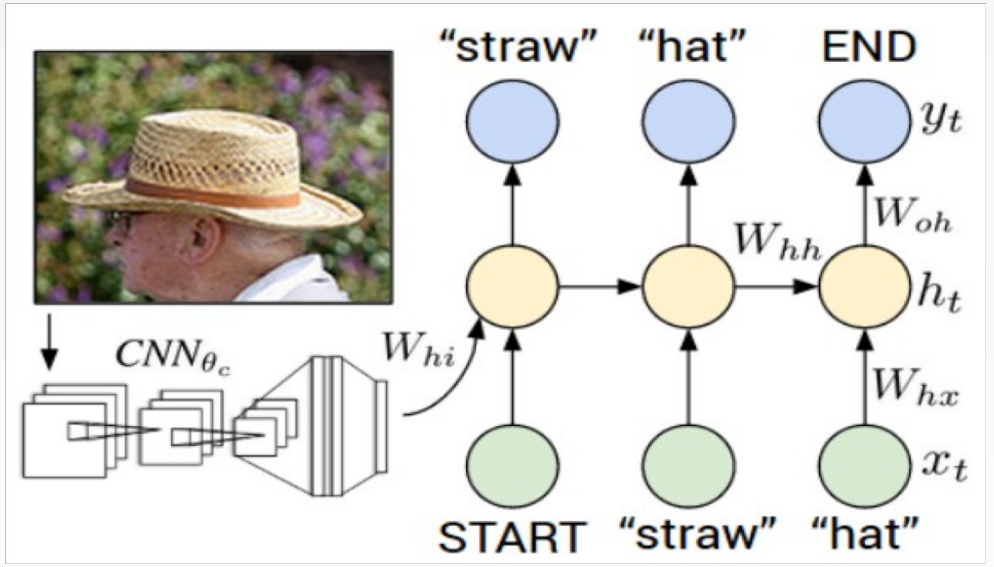
(IT'S THE NORM, NOT AN EXCEPTION)

Object Detection
(Fast R-CNN)



Girshick, "Fast R-CNN", ICCV 2015
Figure copyright Ross Girshick, 2015. Reproduced with permission.

Image Captioning: CNN + RNN



Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
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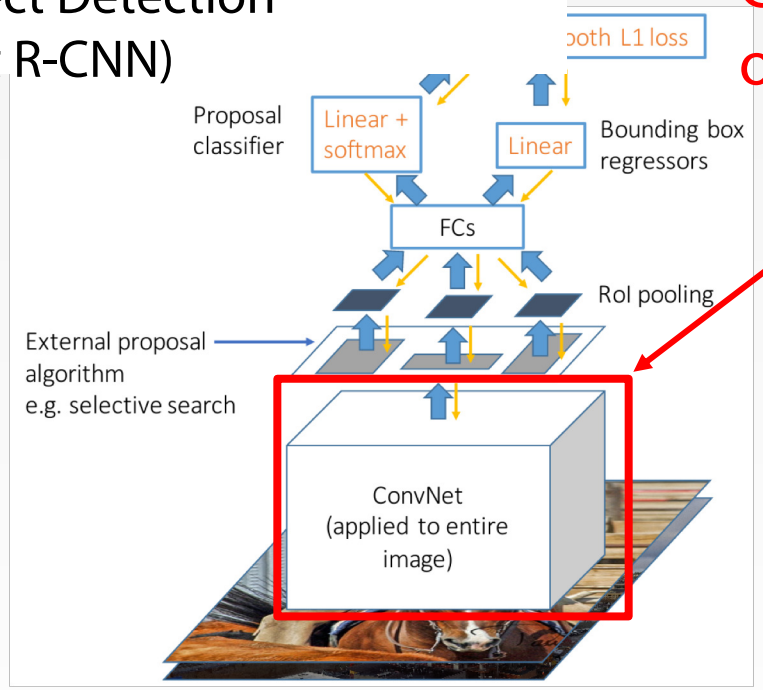
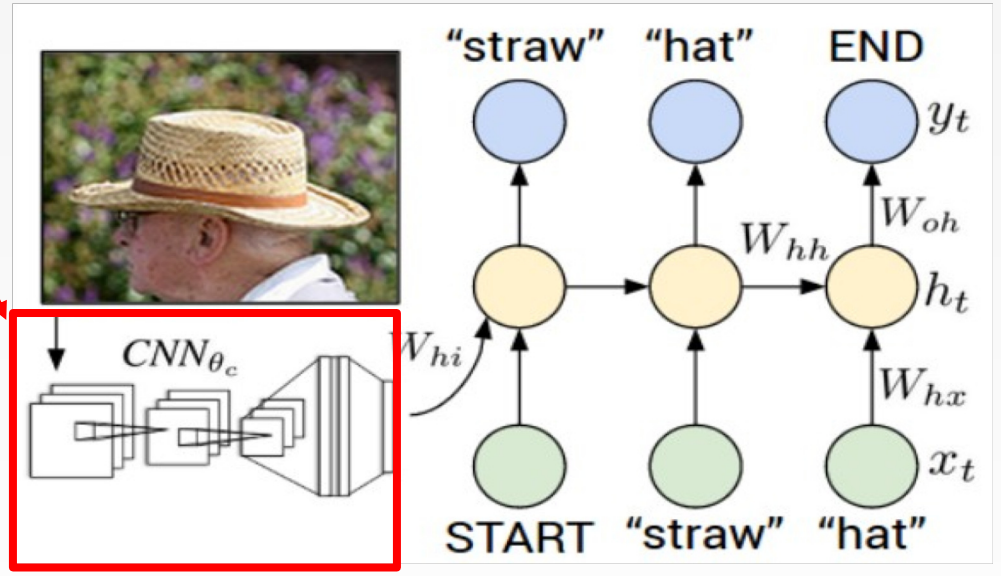


CNN pretrained on ImageNet

Image Captioning: CNN + RNN



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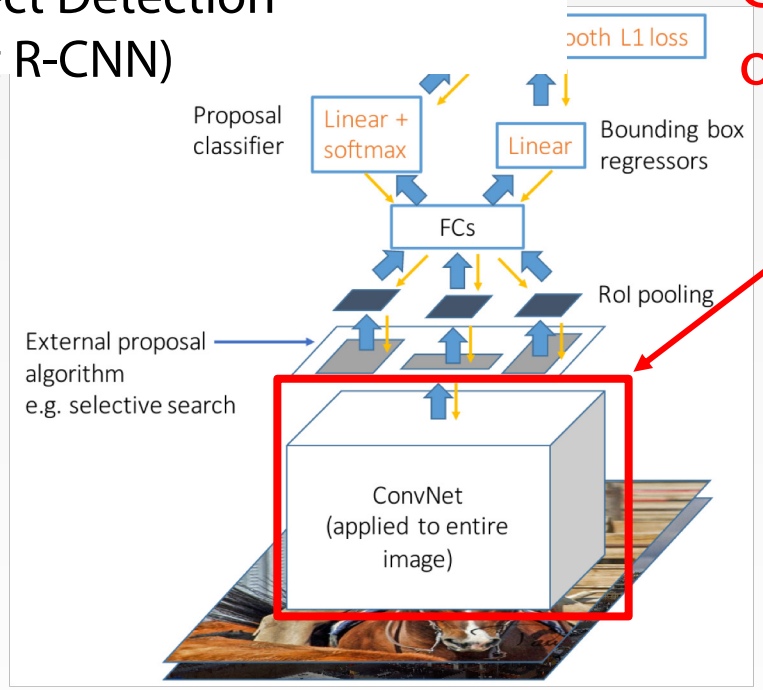

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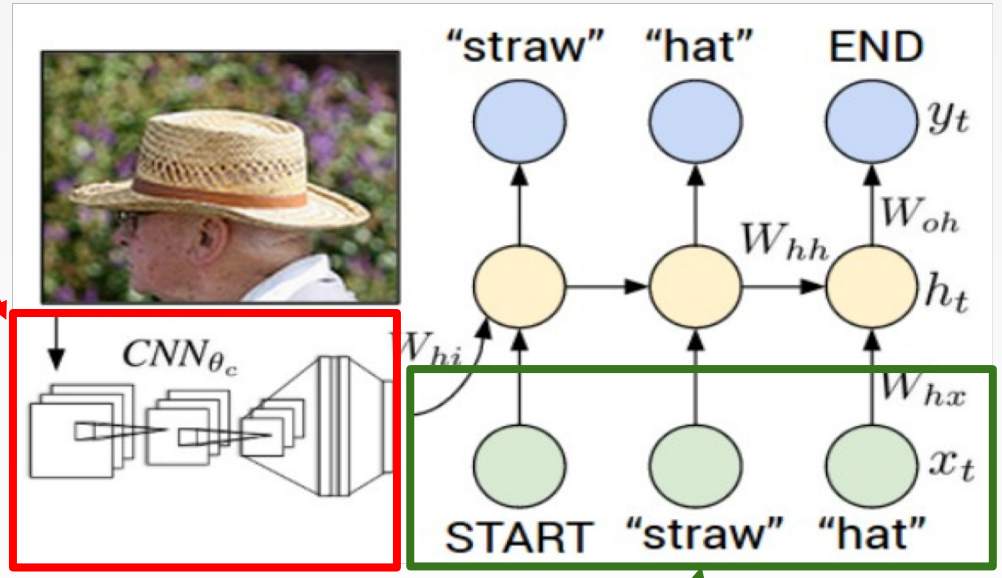

Word vectors pretrained with word2vec

Girshick, "Fast R-CNN", ICCV 2015
Figure copyright Ross Girshick, 2015. Reproduced with permission.

Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
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TAKEAWAY FOR YOUR PROJECTS AND BEYOND

Have some dataset of interest but it has < ~1M images?

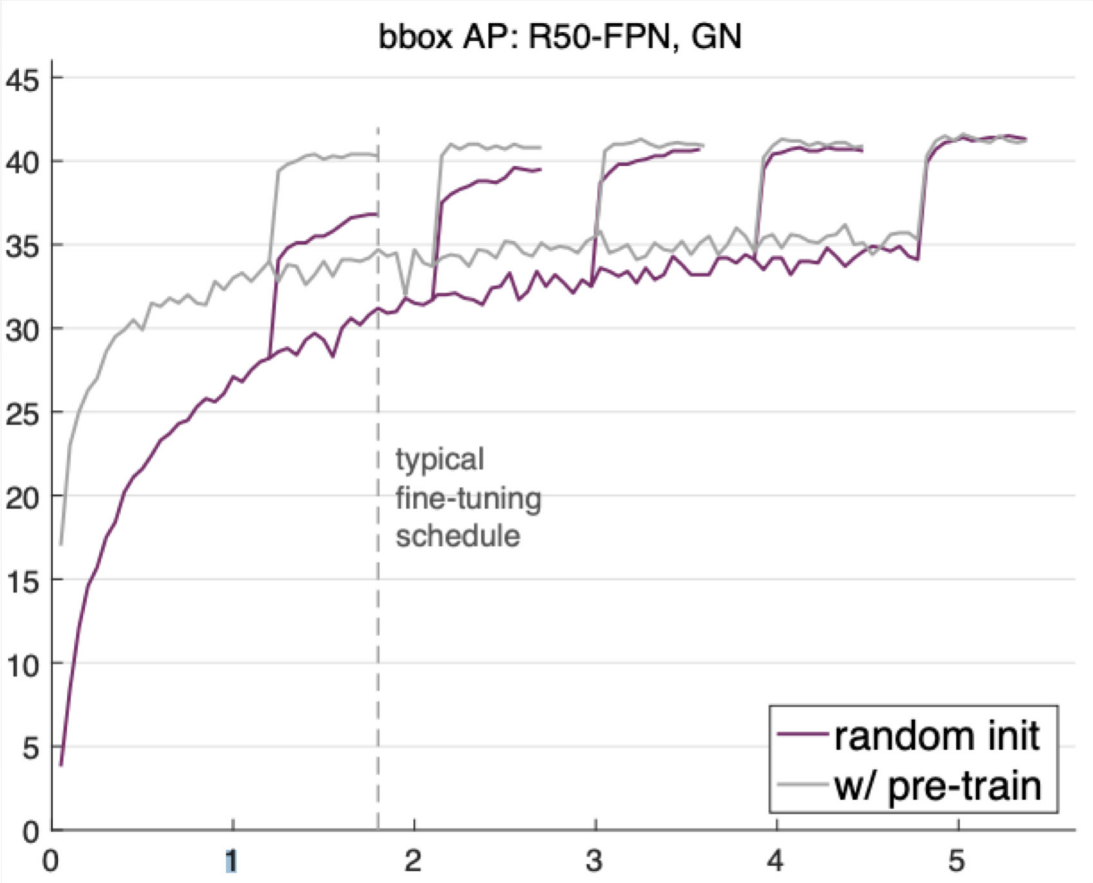
1. Find a very large dataset that has similar data, train a big ConvNet there
2. Transfer learn to your dataset

Deep learning frameworks provide a "Model Zoo" of pretrained models so you don't need to train your own

TensorFlow: https://github.com/tensorflow/models
PyTorch: https://github.com/pytorch/vision

TRANSFER LEARNING WITH CNNS IS PERVASIVE…

BUT RECENT RESULTS SHOW IT MIGHT NOT ALWAYS BE NECESSARY!



He et al, “Rethinking ImageNet Pre-training”, arXiv 2018

TODAY'S AGENDA: CNN ARCHITECTURES

Case Studies

- AlexNet
- VGG
- GoogLeNet
- ResNet

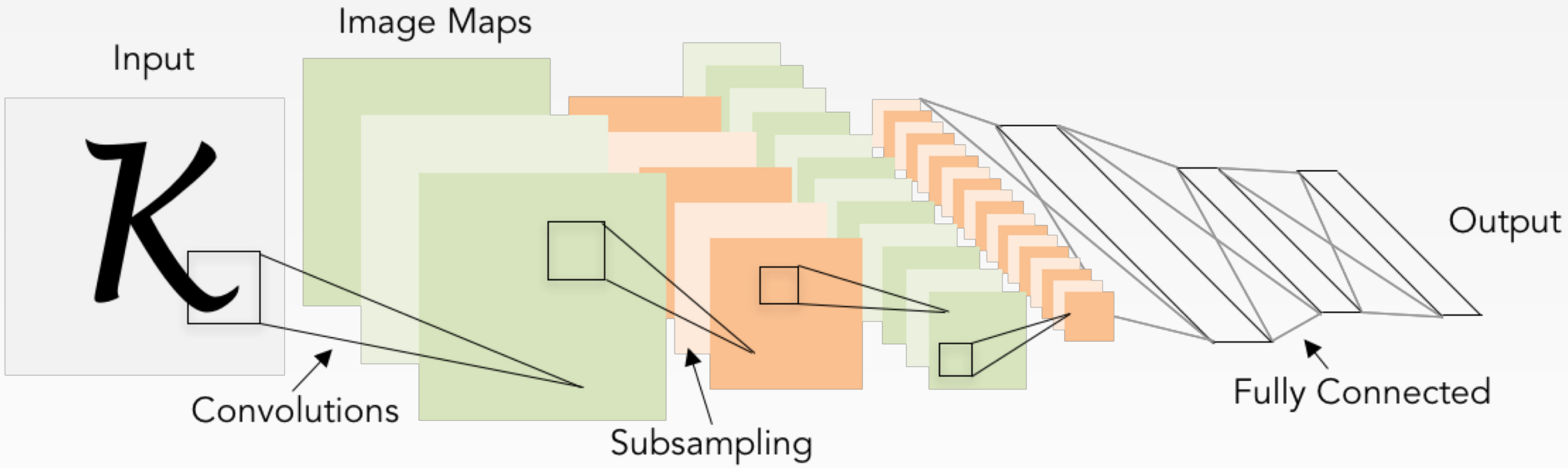
Also....

- SENet
- NiN (Network in Network)
- Wide ResNet
- ResNeXT
- DenseNet
- FractalNet
- MobileNets
- NASNet

ALEXNET

REVIEW: LENET-5

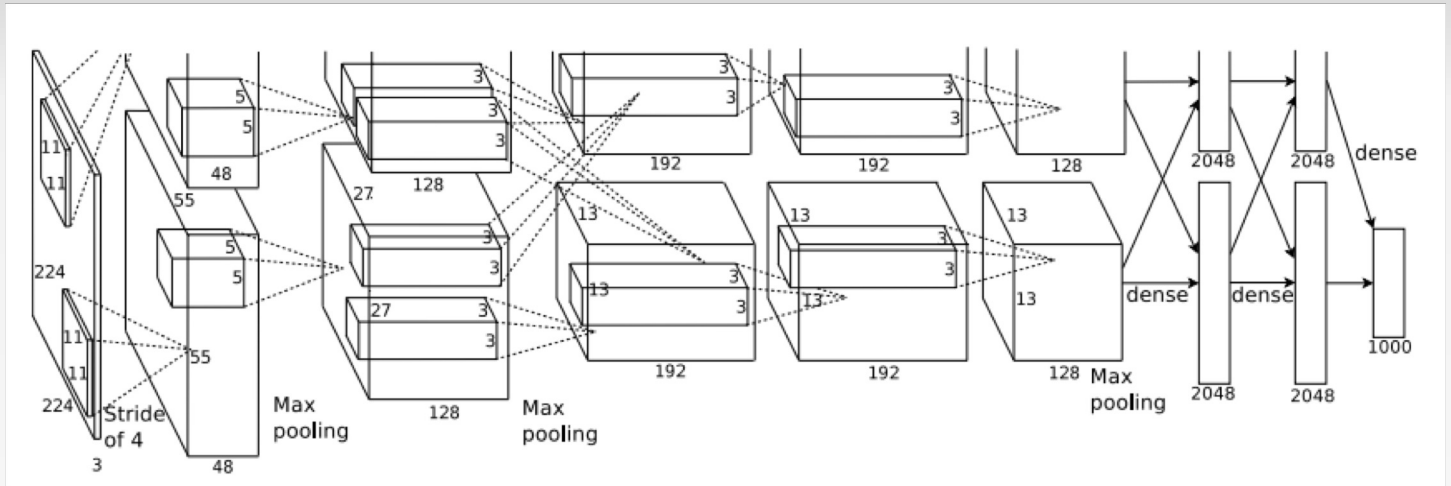
[LeCun et al., 1998]



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

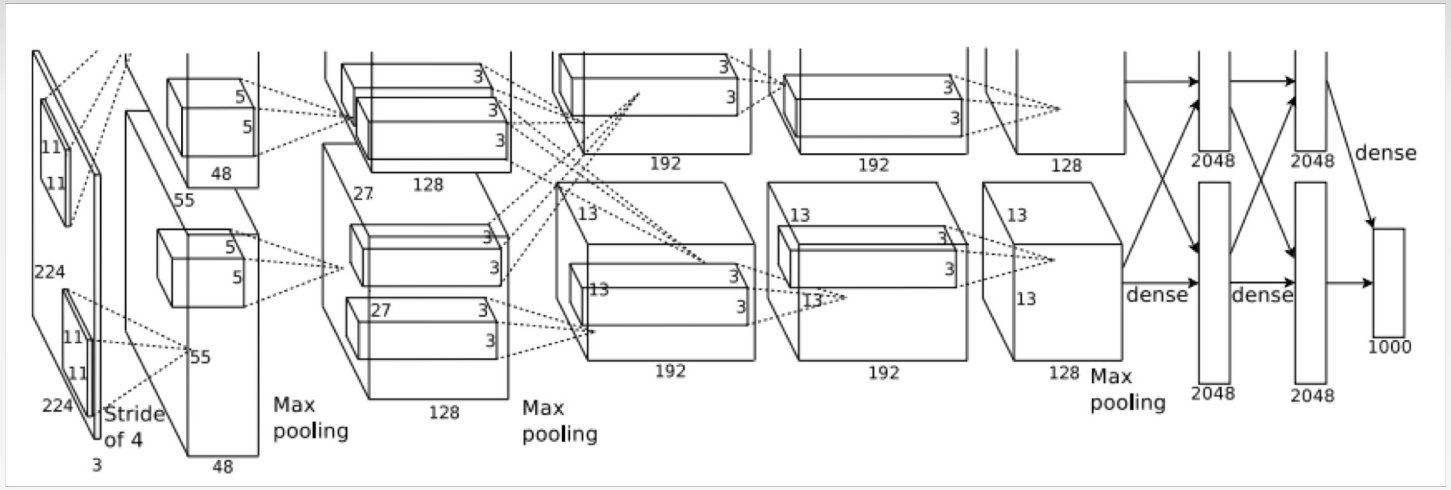
FC6

FC7

FC8

CASE STUDY: ALEXNET

[Krizhevsky et al. 2012]



Input: 227x227x3 images

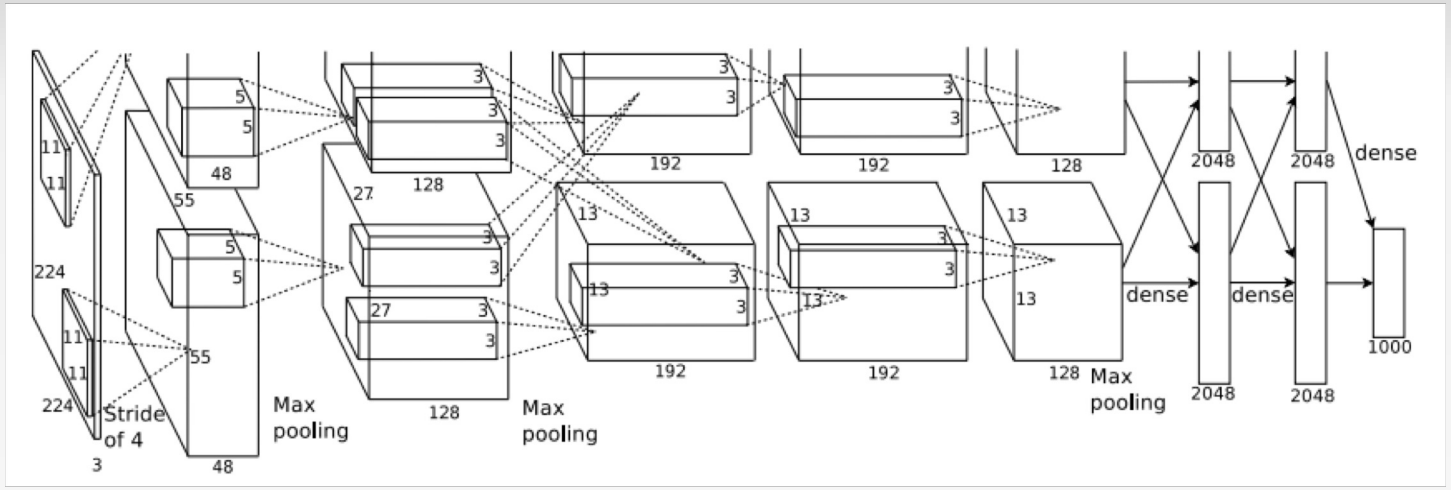
First layer (CONV1): **96** 11x11 filters applied at stride 4

=>

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

CASE STUDY: ALEXNET

[Krizhevsky et al. 2012]



Input: 227x227x3 images

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

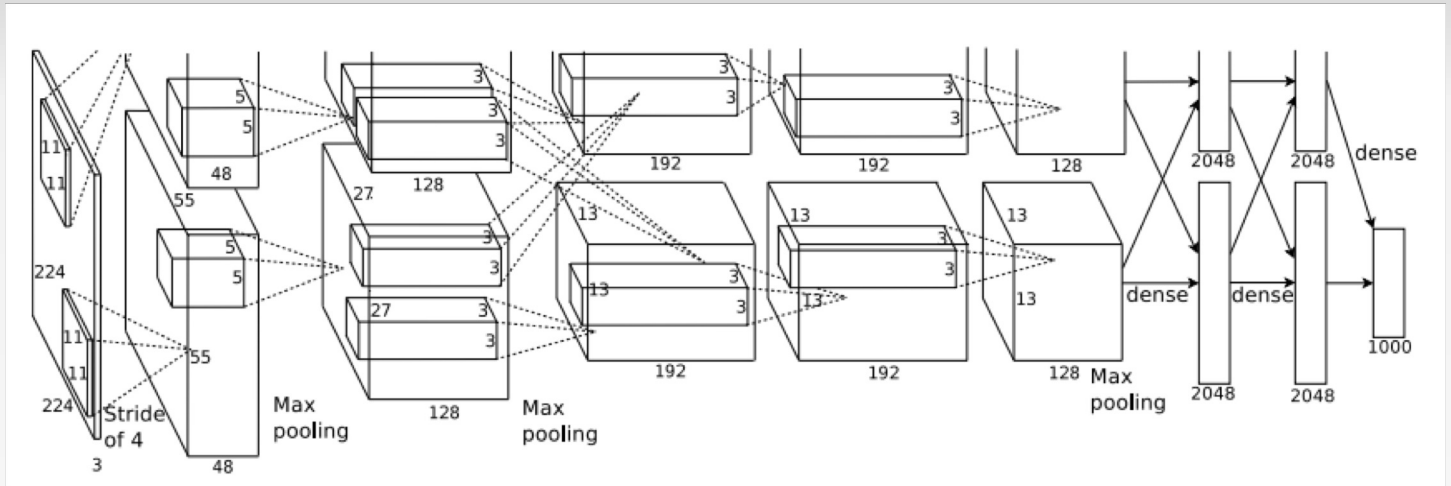
=>

Output volume **[55x55x96]**

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

CASE STUDY: ALEXNET

[Krizhevsky et al. 2012]



Input: 227x227x3 images

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

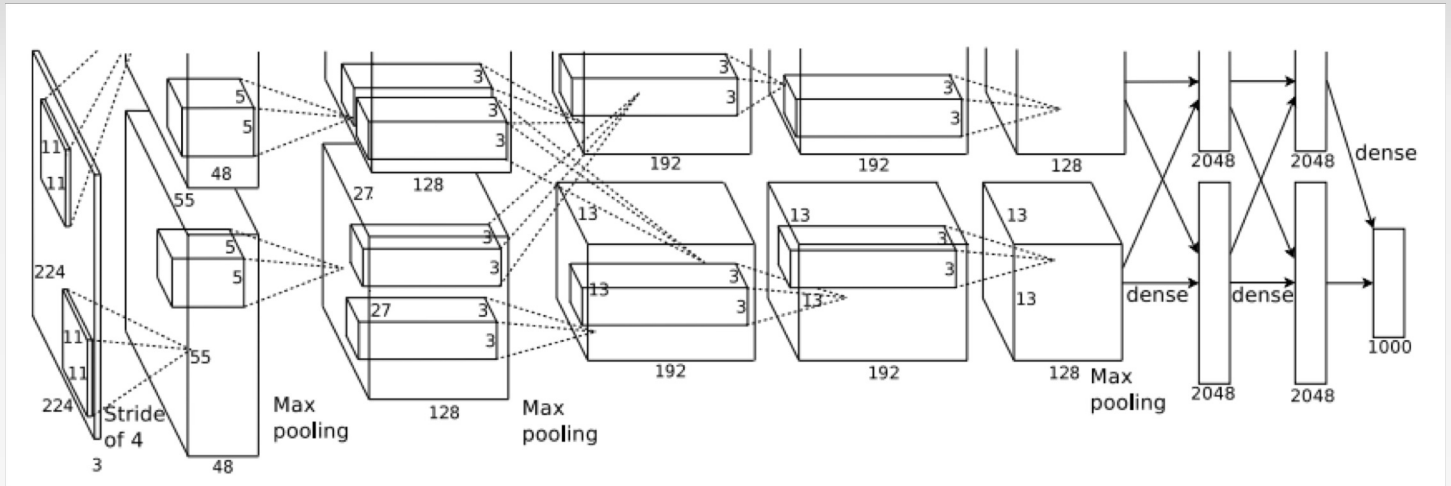
=>

Output volume **[55x55x96]**

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

CASE STUDY: ALEXNET

[Krizhevsky et al. 2012]



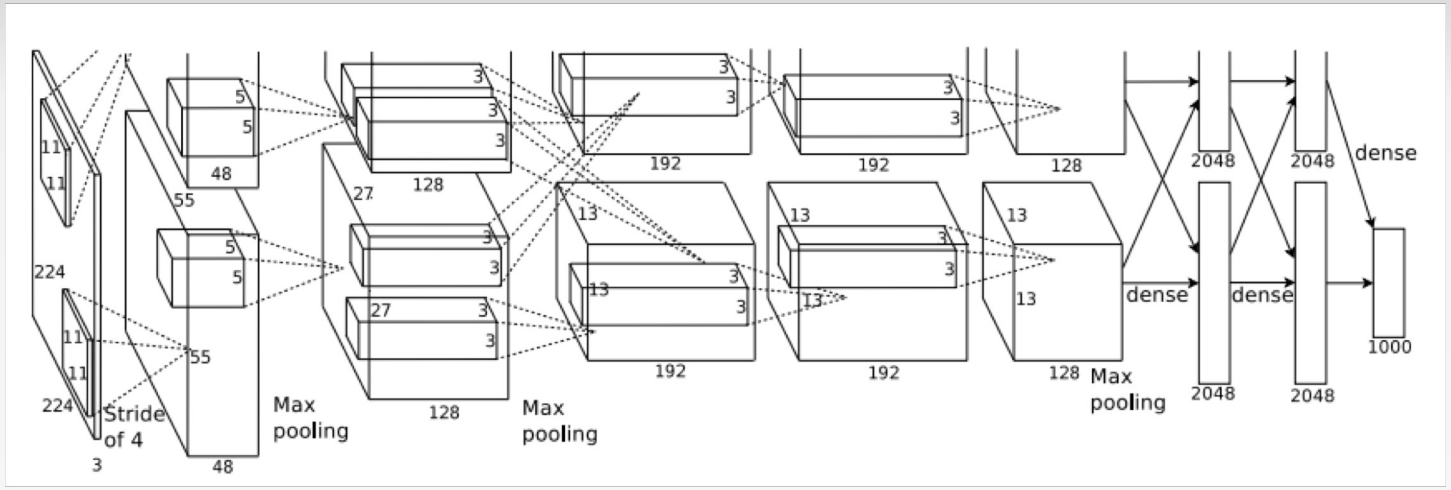
Input: 227x227x3 images
After CONV1: 55x55x96

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

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

CASE STUDY: ALEXNET

[Krizhevsky et al. 2012]



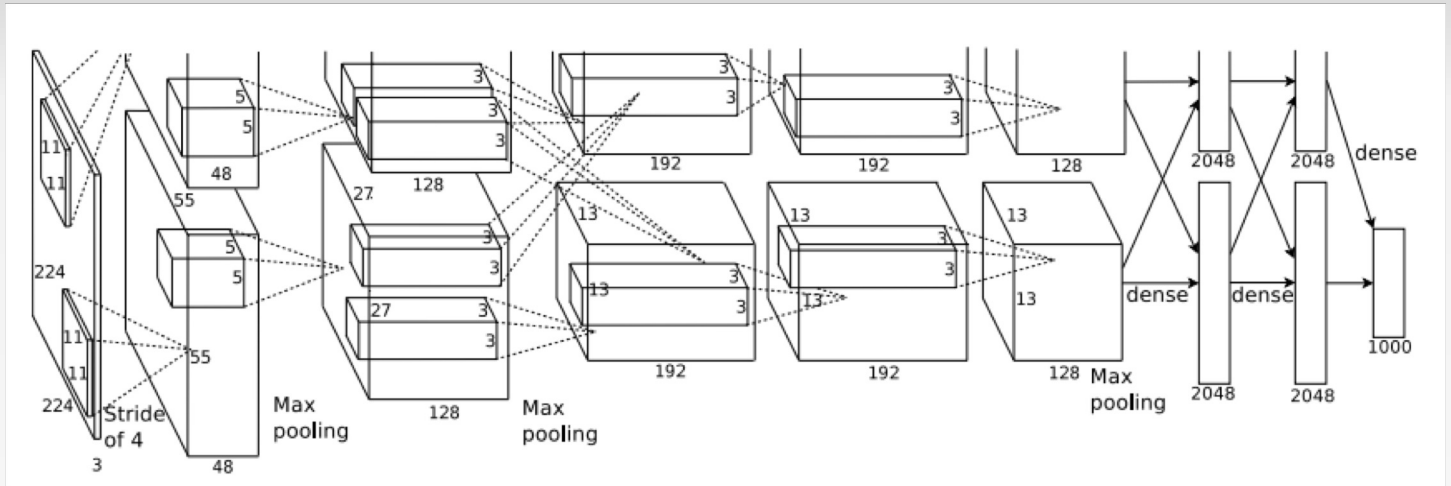
Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96

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

CASE STUDY: ALEXNET

[Krizhevsky et al. 2012]

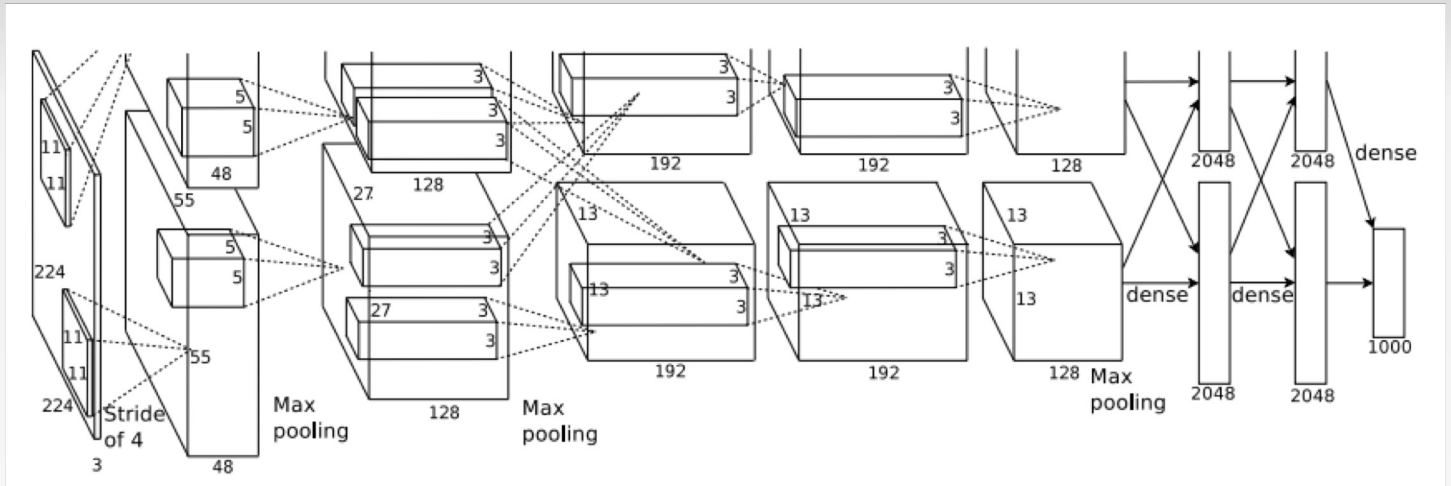


Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96
Parameters: 0!

CASE STUDY: ALEXNET

[Krizhevsky et al. 2012]



Input: 227x227x3 images
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After POOL1: 27x27x96
...

CASE STUDY: ALEXNET

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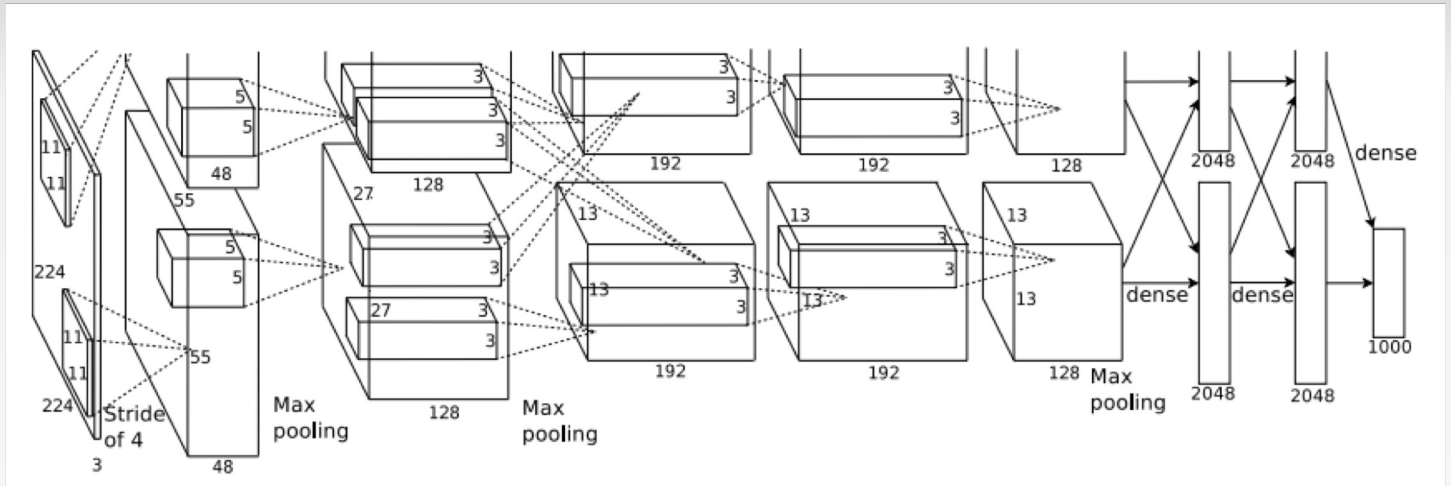
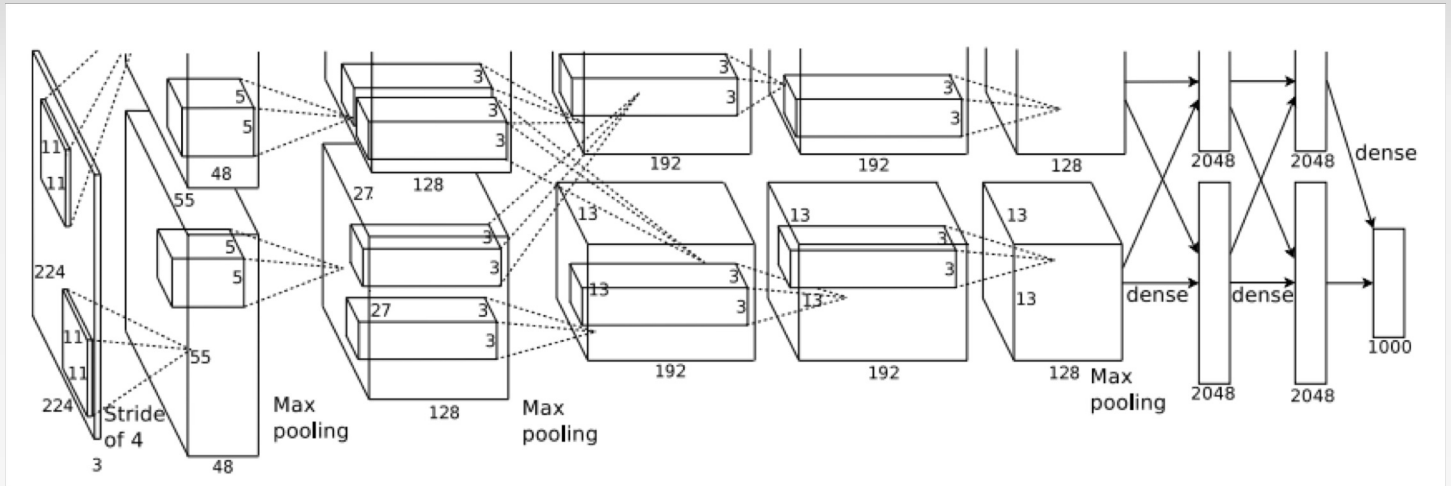


Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256]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

CASE STUDY: ALEXNET

[Krizhevsky et al. 2012]



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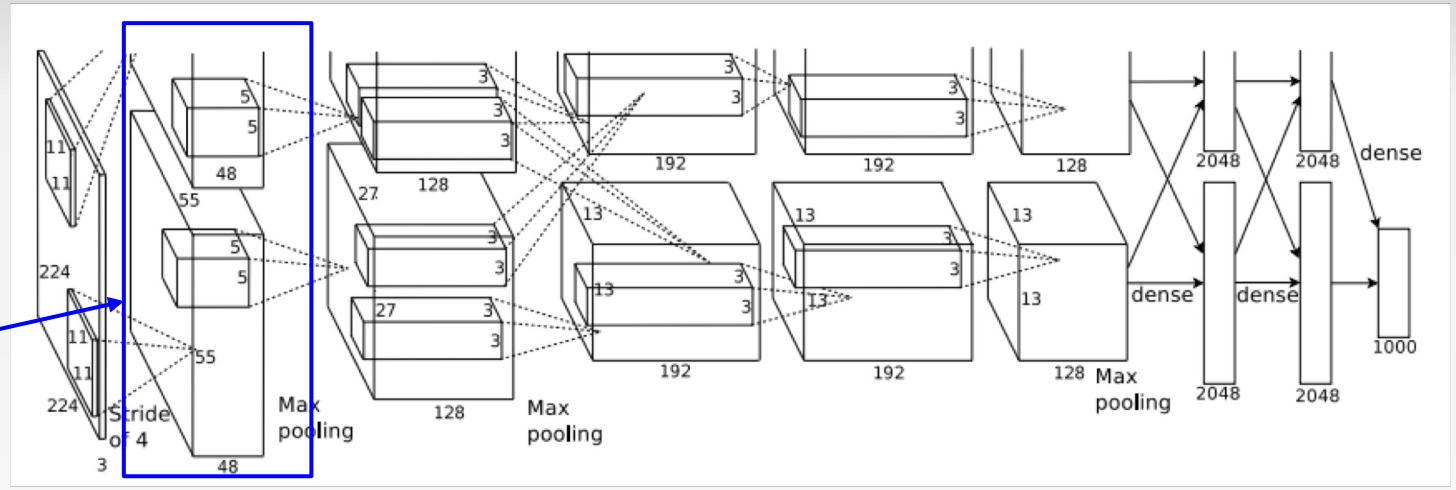
[1000] FC8: 1000 neurons (class scores)

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%

CASE STUDY: ALEXNET

[Krizhevsky et al. 2012]



[55x55x48] x 2

Full (simplified) AlexNet architecture:
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[4096] FC6: 4096 neurons
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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.

CASE STUDY: ALEXNET

[Krizhevsky et al. 2012]

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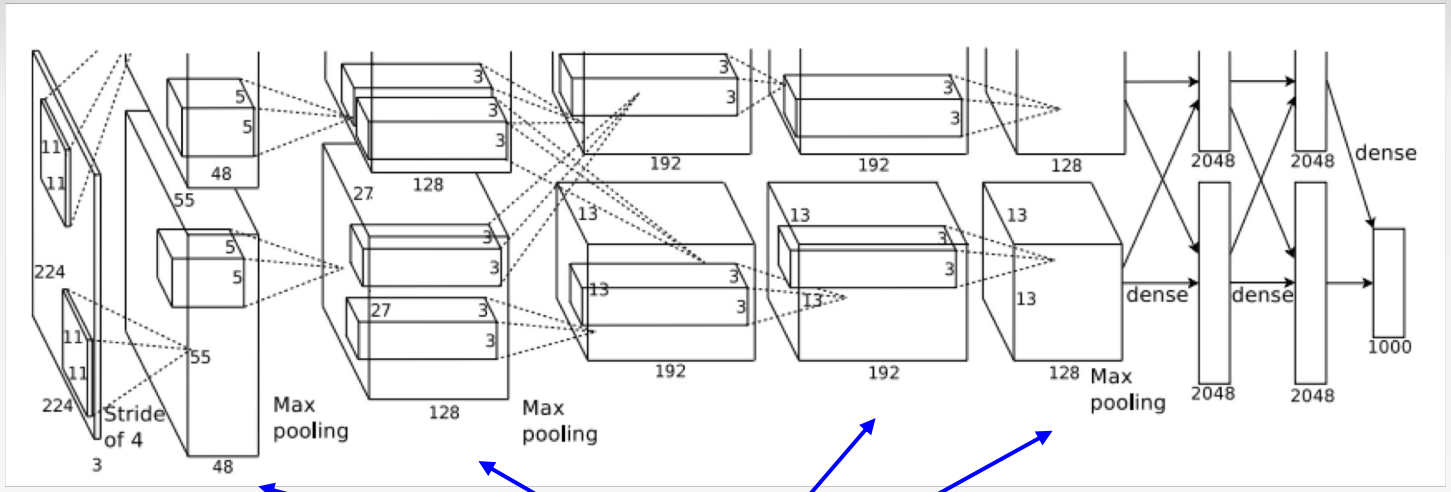

CONV1, CONV2, CONV4, CONV5:
Connections only with feature maps on same GPU

CASE STUDY: ALEXNET

[Krizhevsky et al. 2012]

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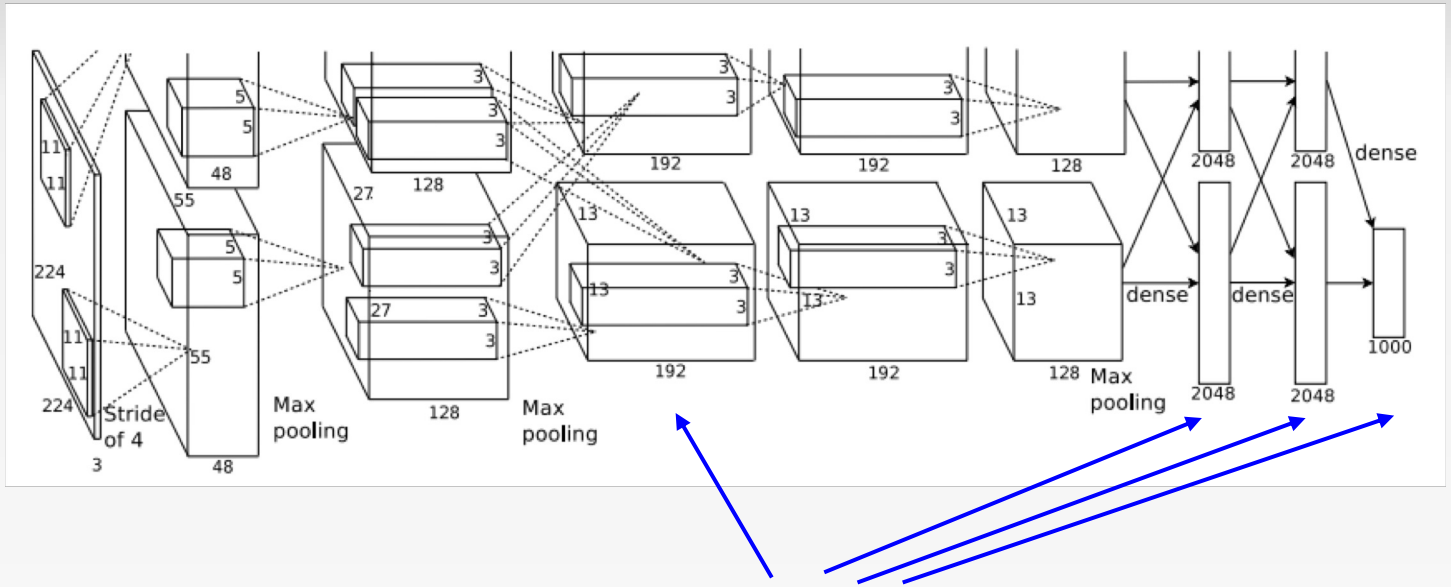
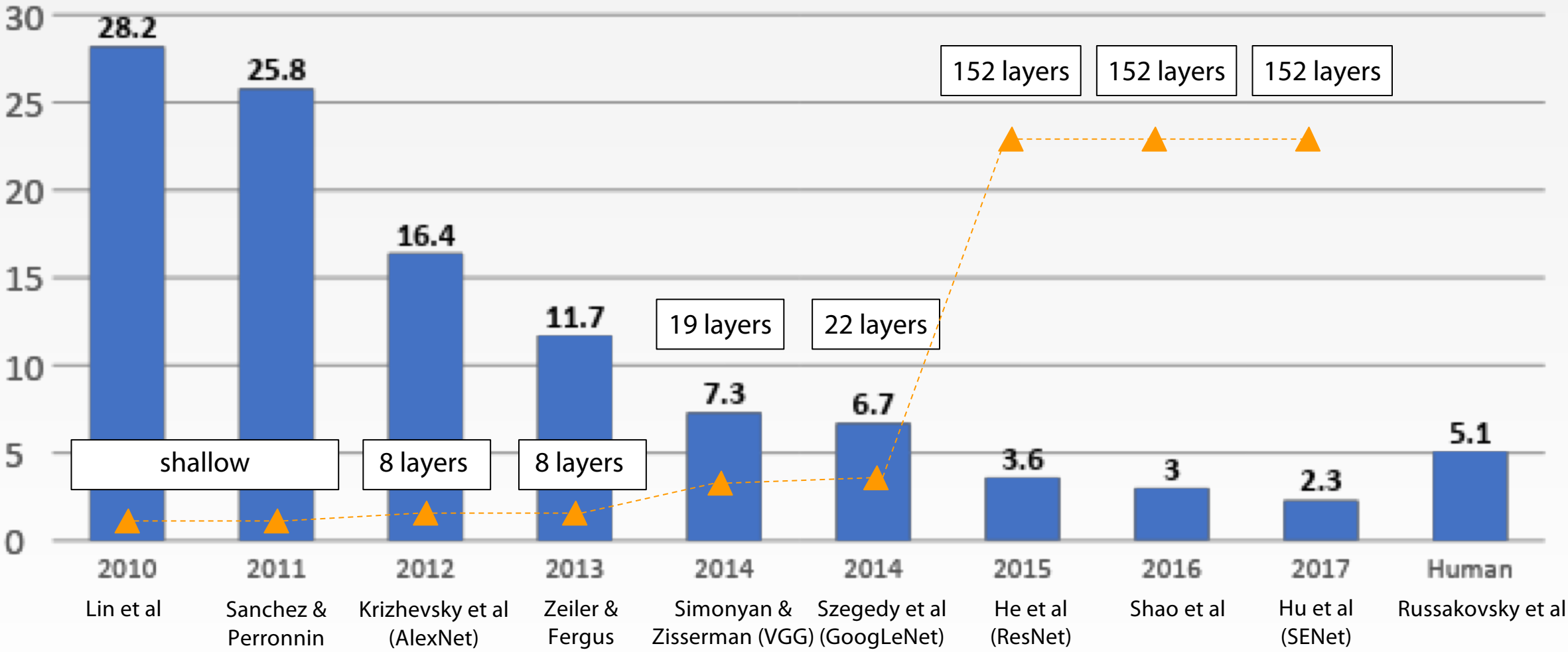


CONV3, FC6, FC7, FC8: Connections with all feature maps in preceding layer, communication across GPUs

IMAGENET LARGE SCALE VISUAL RECOGNITION CHALLENGE (ILSVRC) WINNERS



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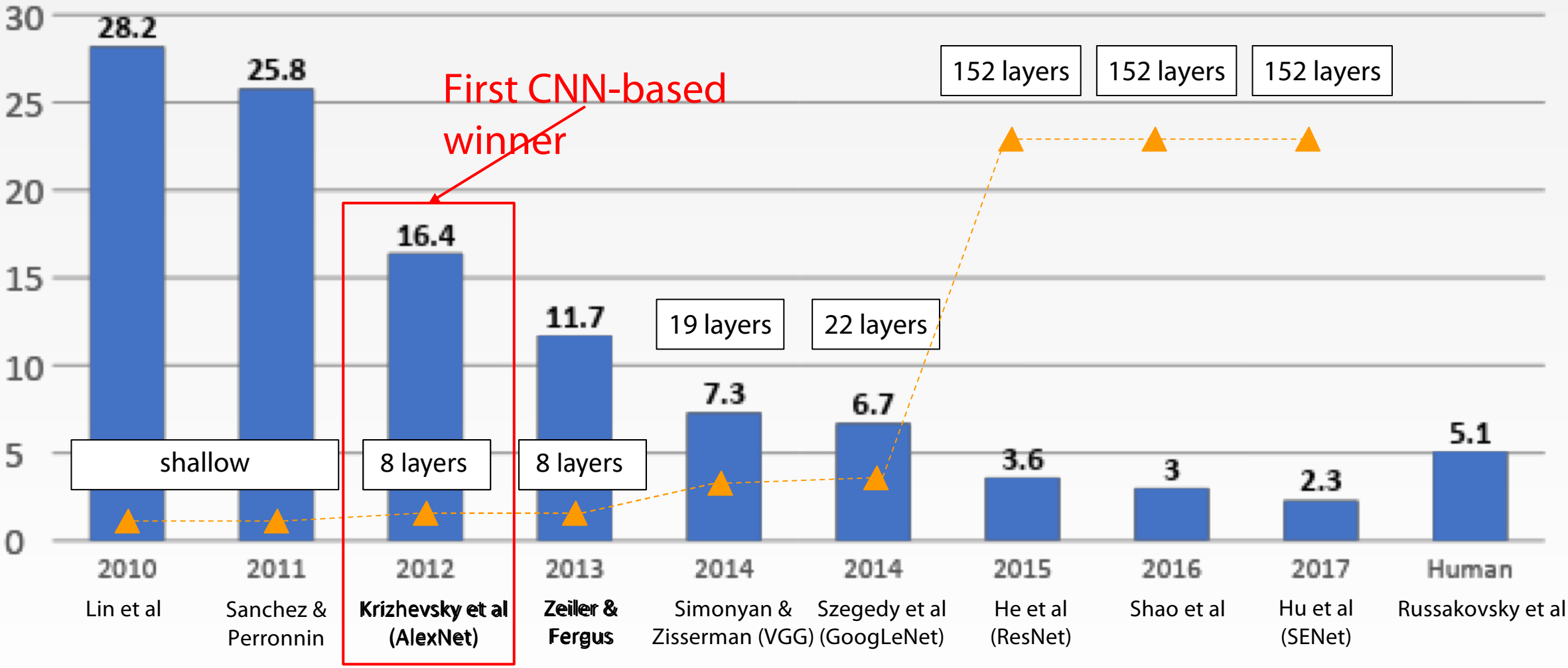

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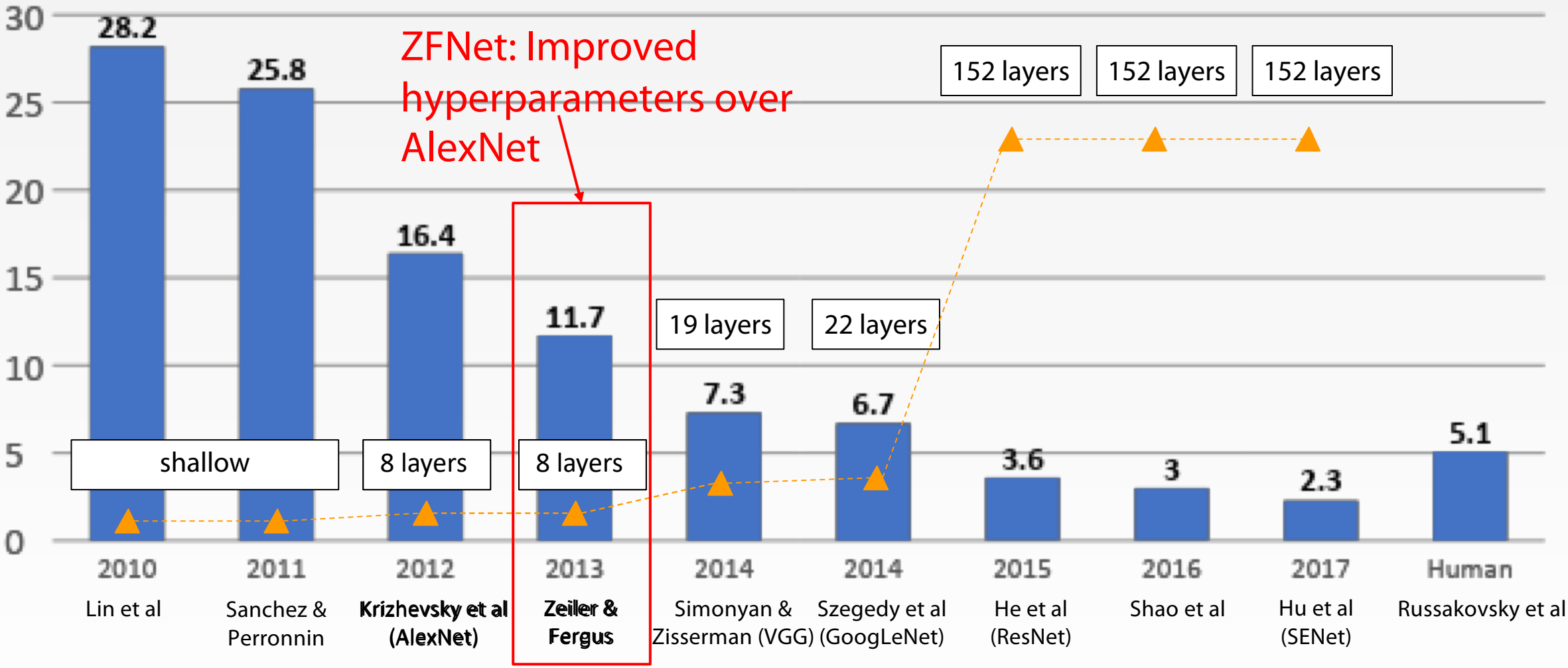
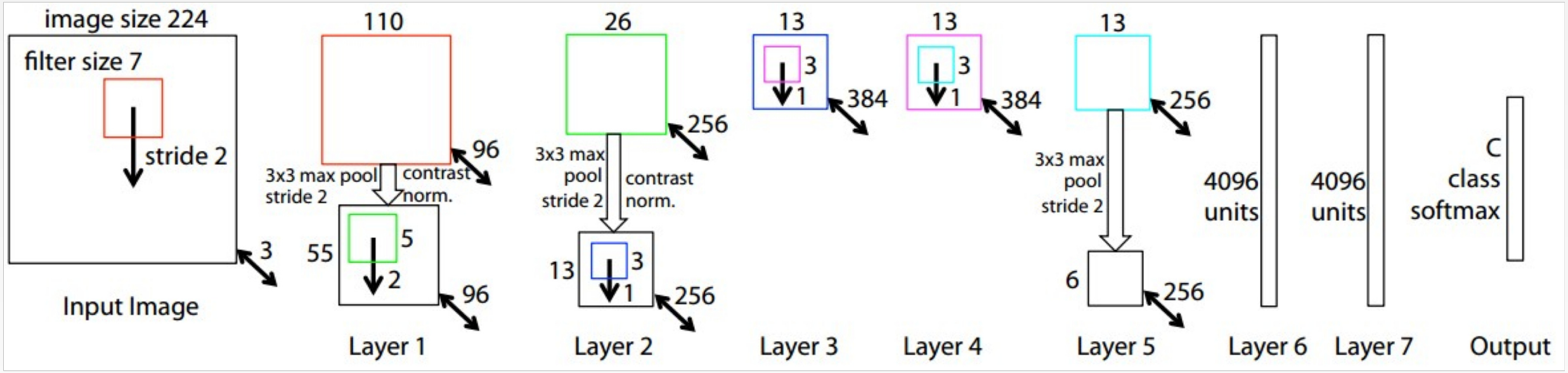


ZFNET

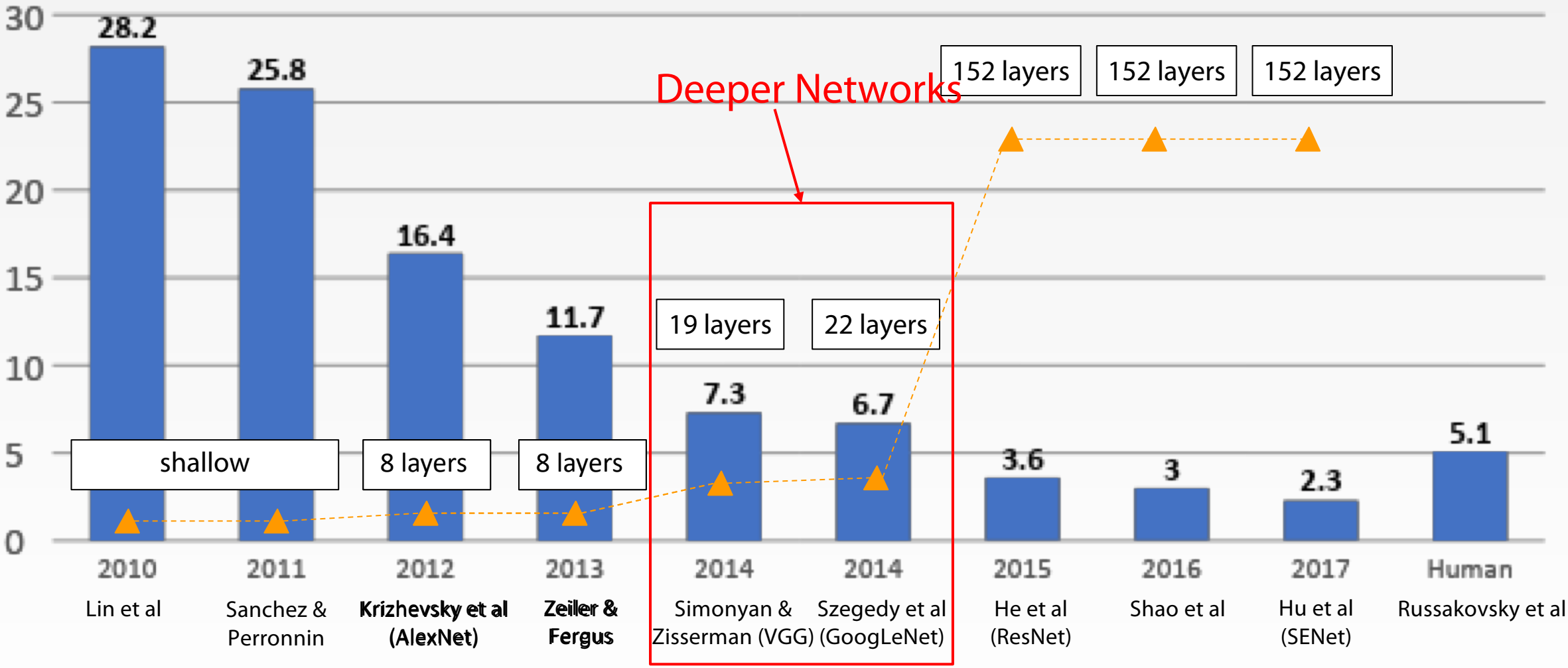
[Zeiler and Fergus, 2013]



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%

IMAGENET LARGE SCALE VISUAL RECOGNITION CHALLENGE (ILSVRC) WINNERS



VGGNET

CASE STUDY: VGGNET

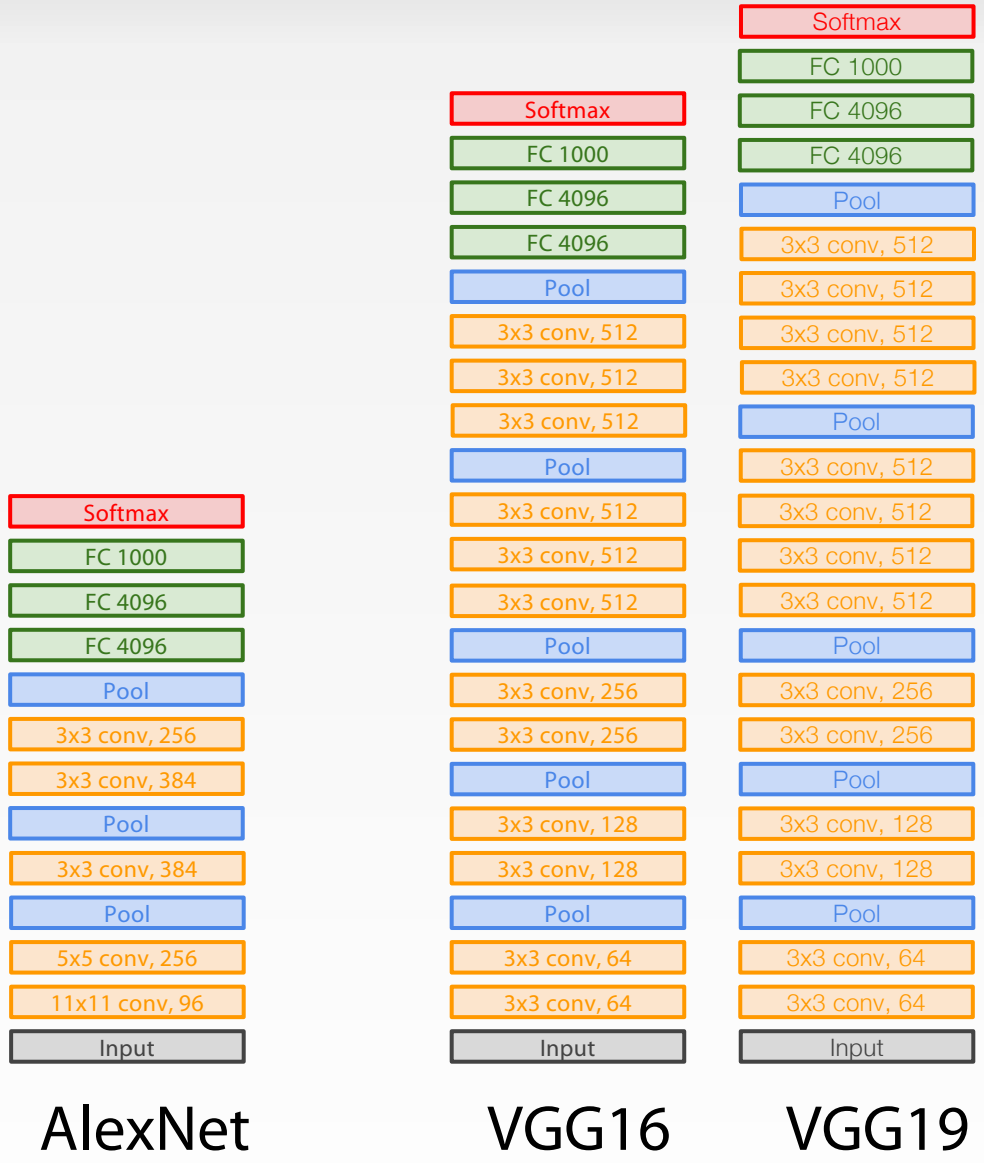
[Simonyan and Zisserman, 2014]

Small filters, Deeper networks

8 layers (AlexNet)
-> 16 - 19 layers (VGG16Net)

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

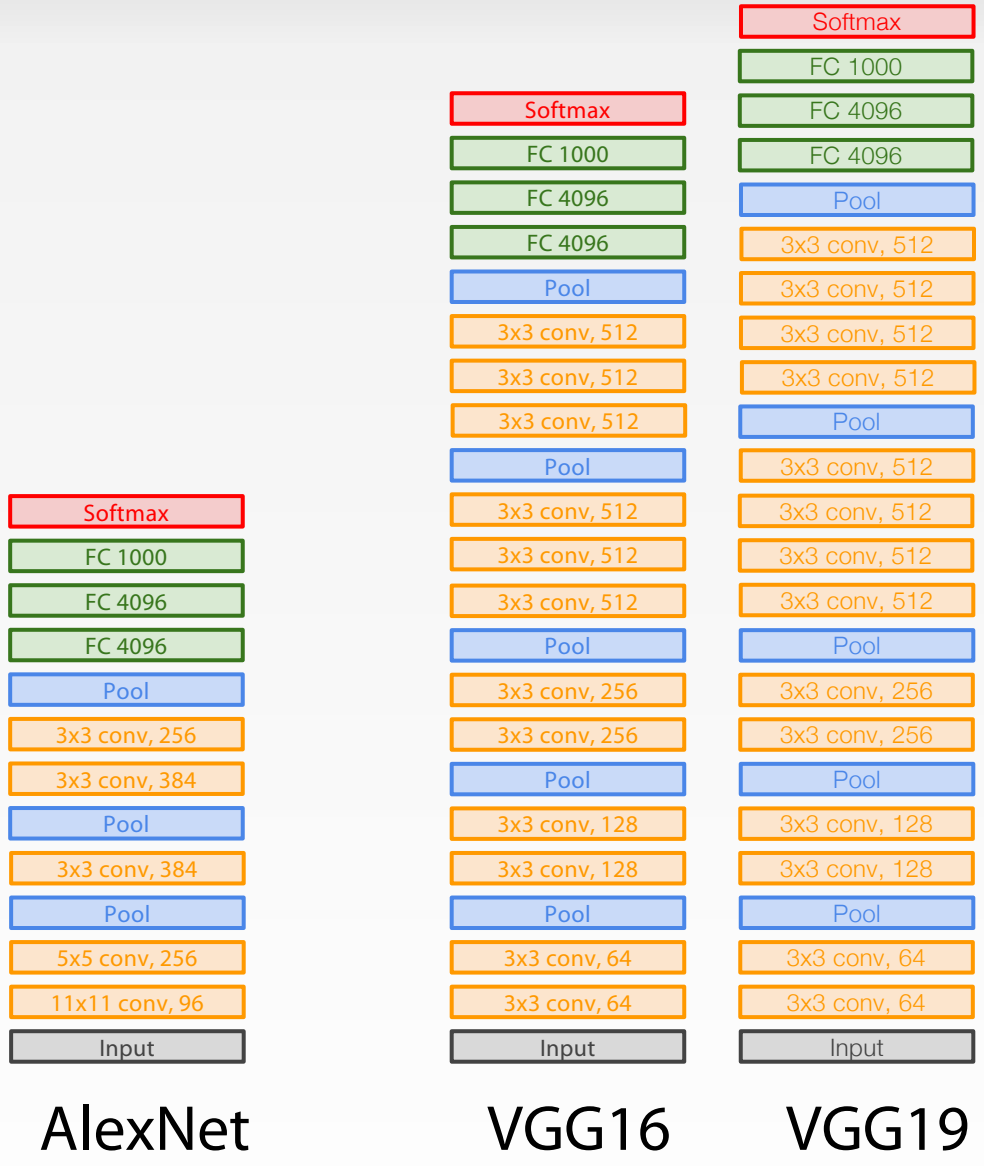
11.7% top 5 error in ILSVRC'13 (ZFNet)
-> 7.3% top 5 error in ILSVRC'14



CASE STUDY: VGGNET

[Simonyan and Zisserman, 2014]

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



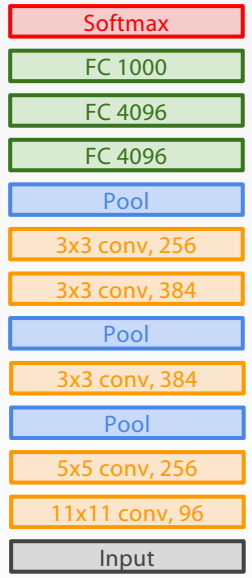
CASE STUDY: VGGNET

[Simonyan and Zisserman, 2014]

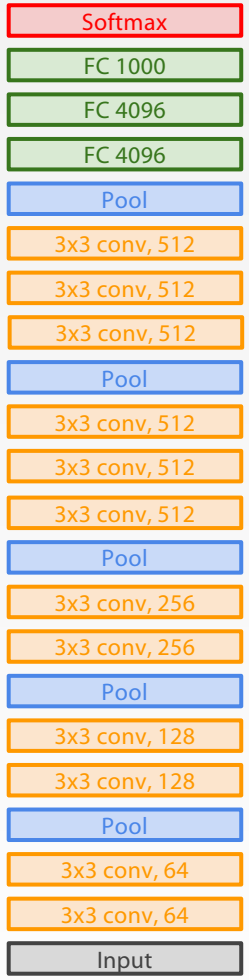
Q: Why use smaller filters? (3x3 conv)

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

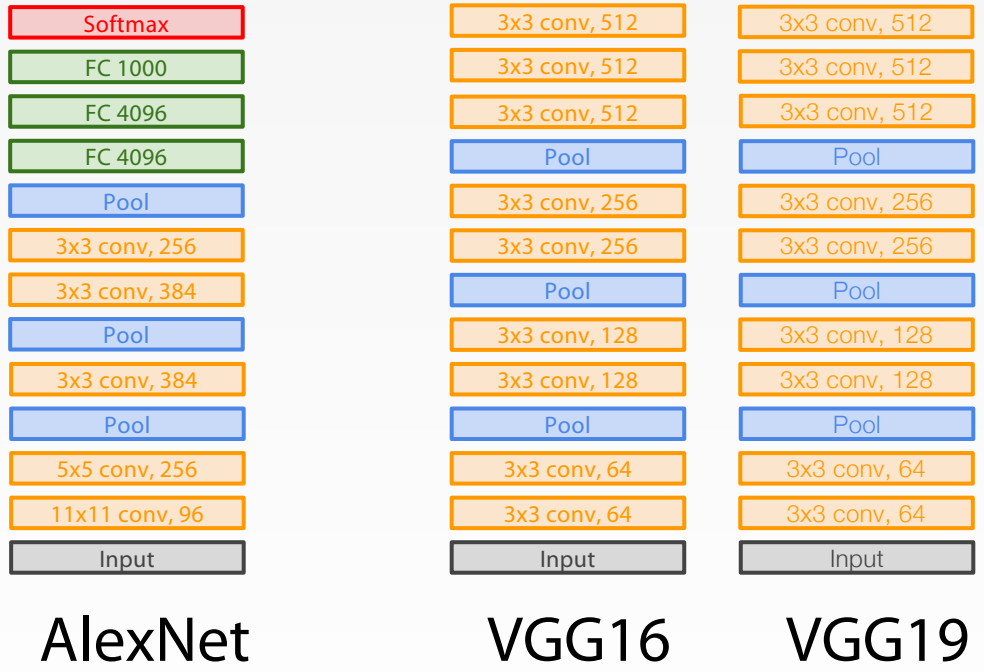
CASE STUDY: VGGNET

[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]



CASE STUDY: VGGNET

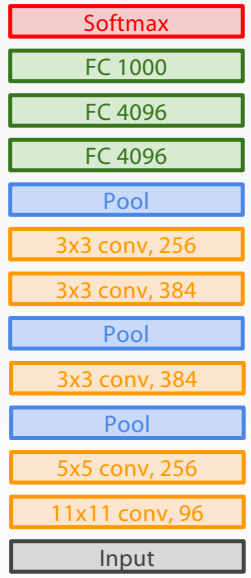
[Simonyan and Zisserman, 2014]

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

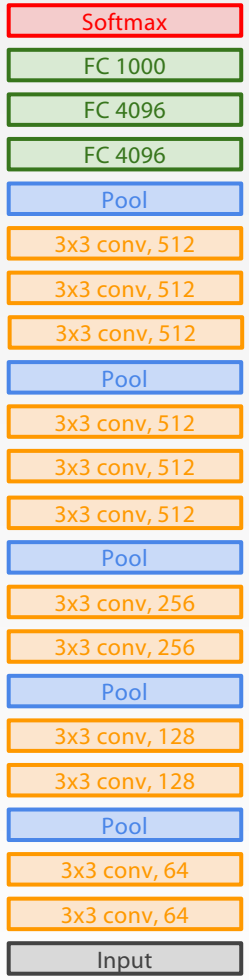
Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

But deeper, more non-linearities

And fewer parameters: $3 * (3^2C^2)$ vs. 7^2C^2 for C channels per layer
Input depth = C
Number of output feature maps = C



AlexNet



VGG16

VGG19

(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
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
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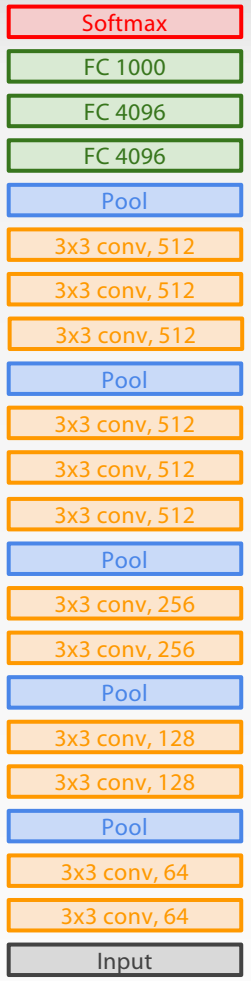
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000



VGG16

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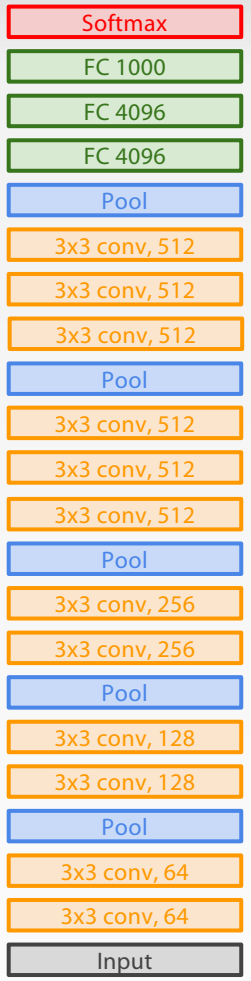

VGG16

TOTAL memory: 24M * 4 bytes ~= 96MB / image (for a forward pass)

TOTAL params: 138M parameters

(not counting biases)

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Note:

Most memory is in early CONV

Most params are in late FC

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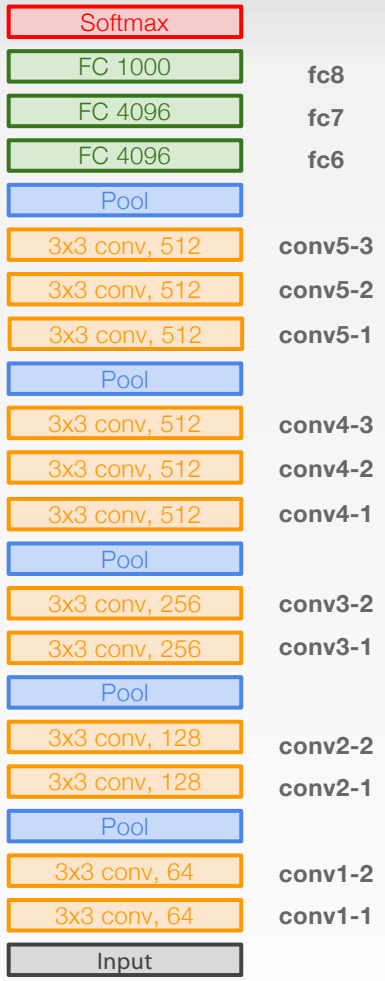

VGG16

Common names

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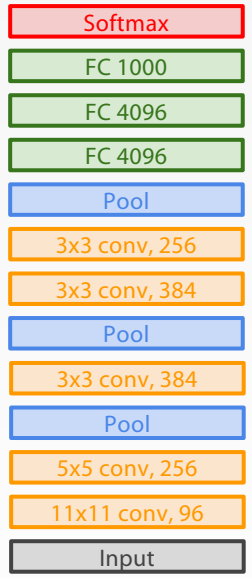
TOTAL params: 138M parameters

CASE STUDY: VGGNET

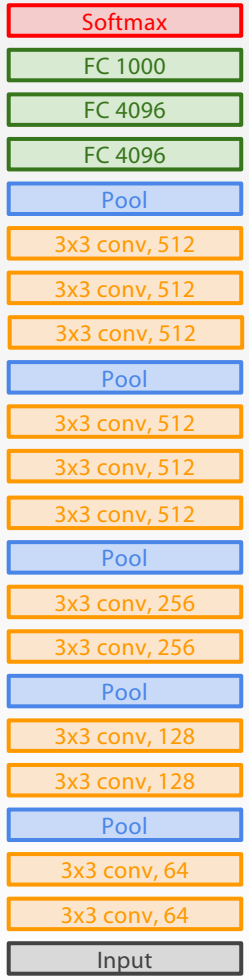
[Simonyan and Zisserman, 2014]

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



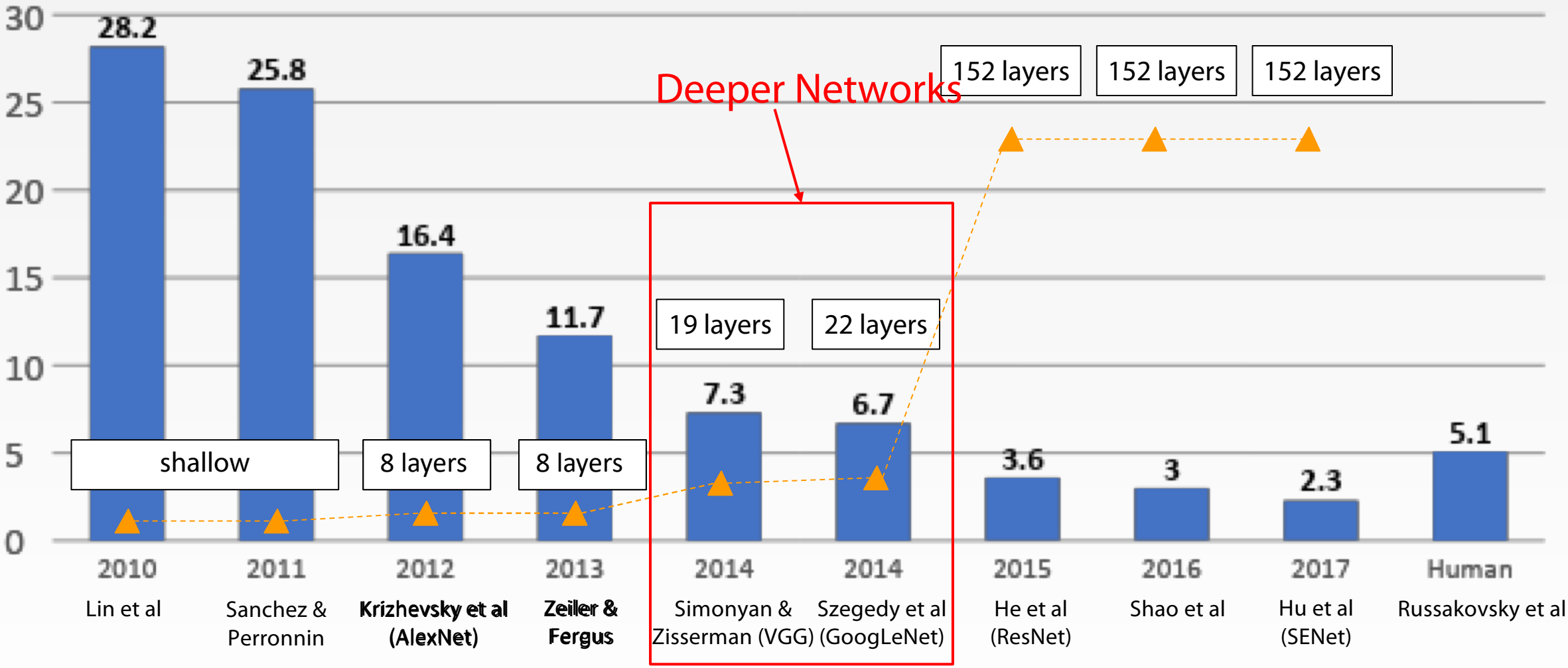
AlexNet



VGG16

VGG19

IMAGENET LARGE SCALE VISUAL RECOGNITION CHALLENGE (ILSVRC) WINNERS



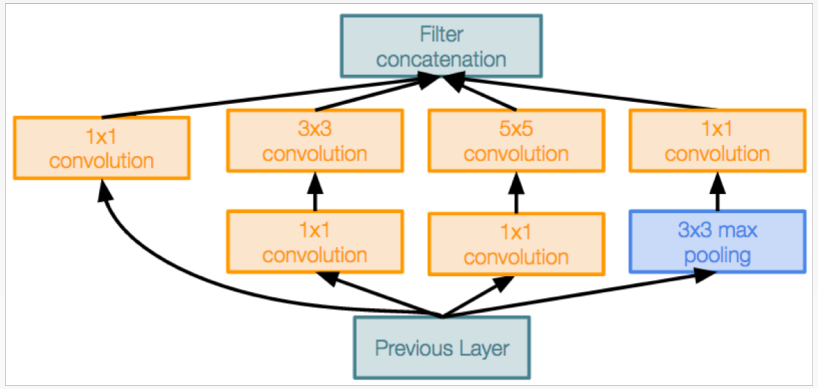
GOOGLENET

CASE STUDY: GOOGLENET

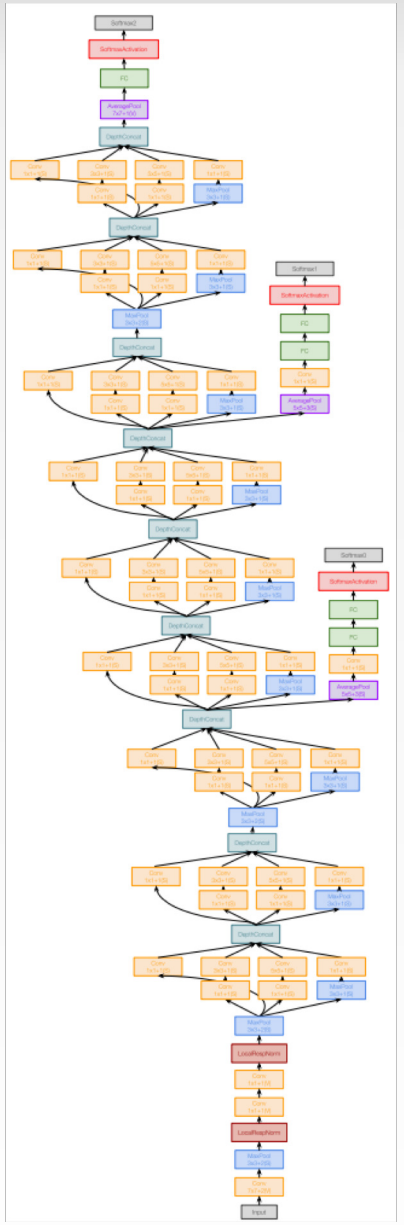
[Szegedy et al., 2014]

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)



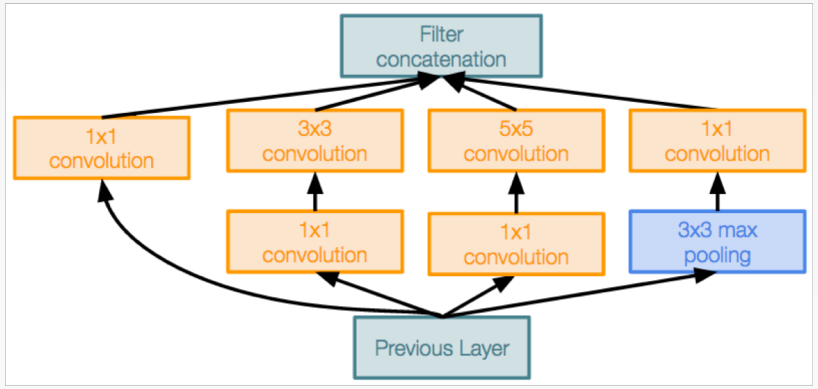
Inception module



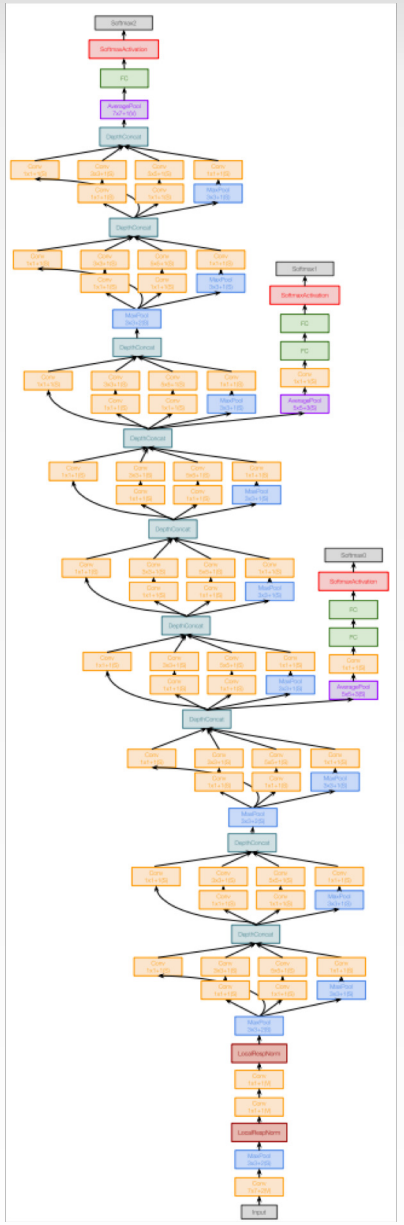
CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

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

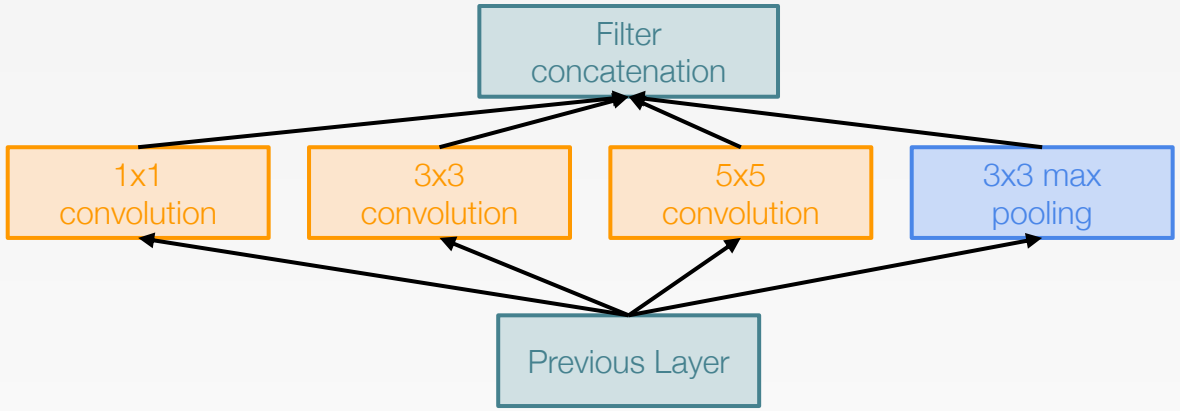


Inception module



CASE STUDY: GOOGLENET

[Szegedy et al., 2014]



Naive Inception module

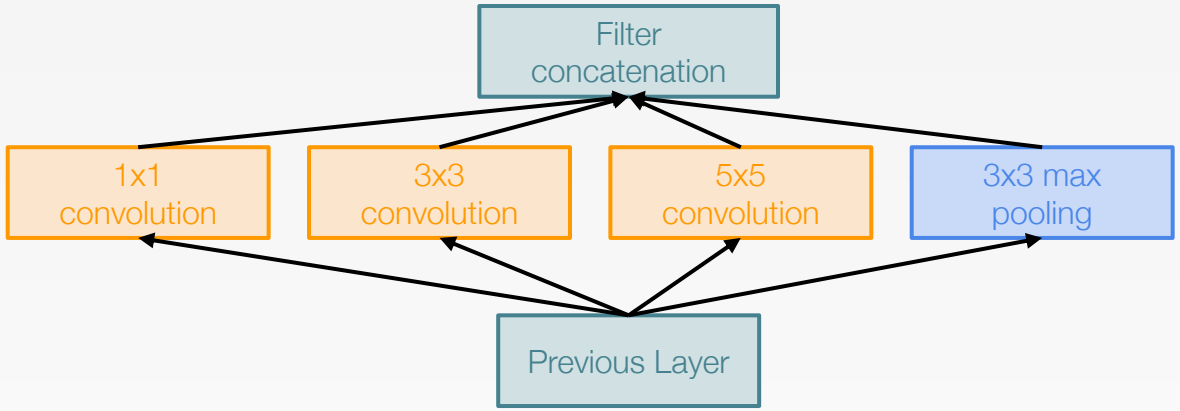
Apply parallel filter operations on the input from previous layer:

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

Concatenate all filter outputs together depth-wise

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]



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

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

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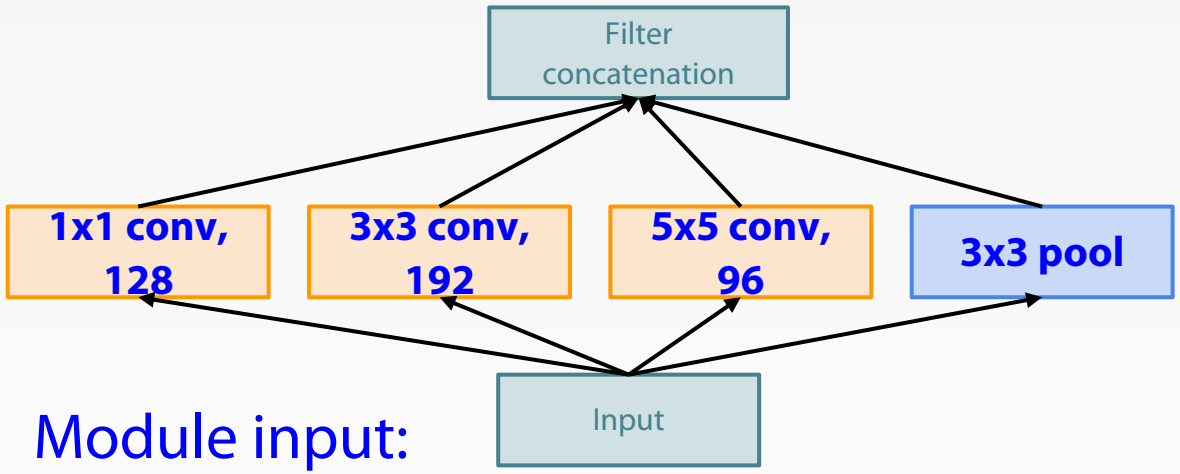
Example:



Module input:
28x28x256

Naive Inception module

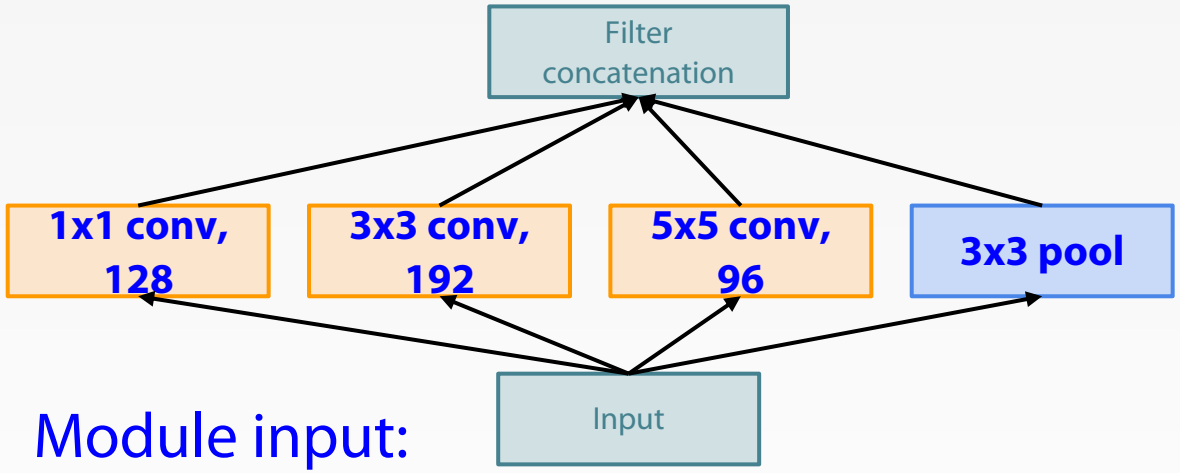
CASE STUDY: GOOGLENET

[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?



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Naive Inception module

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

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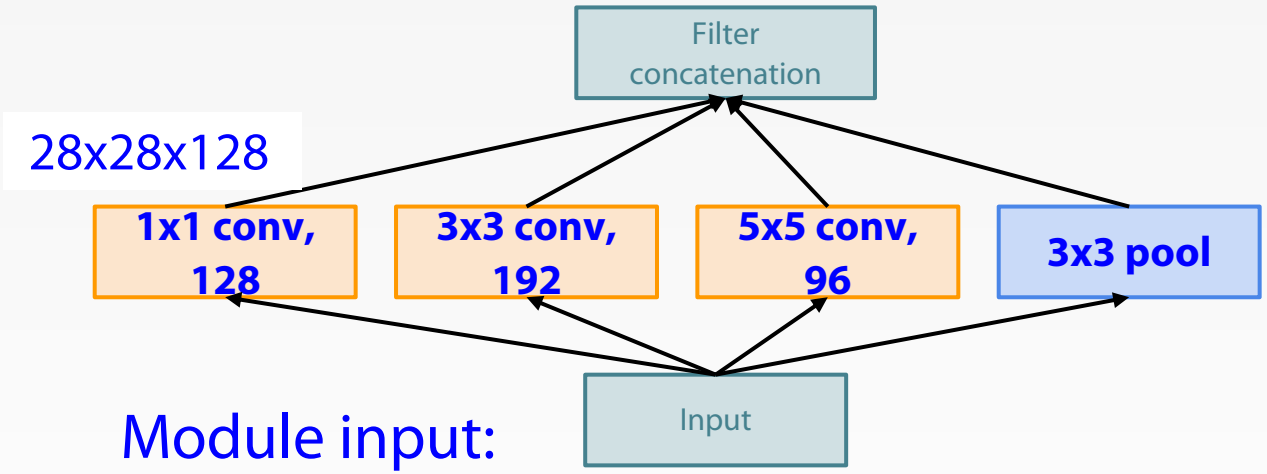

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28x28x256

Naive Inception module

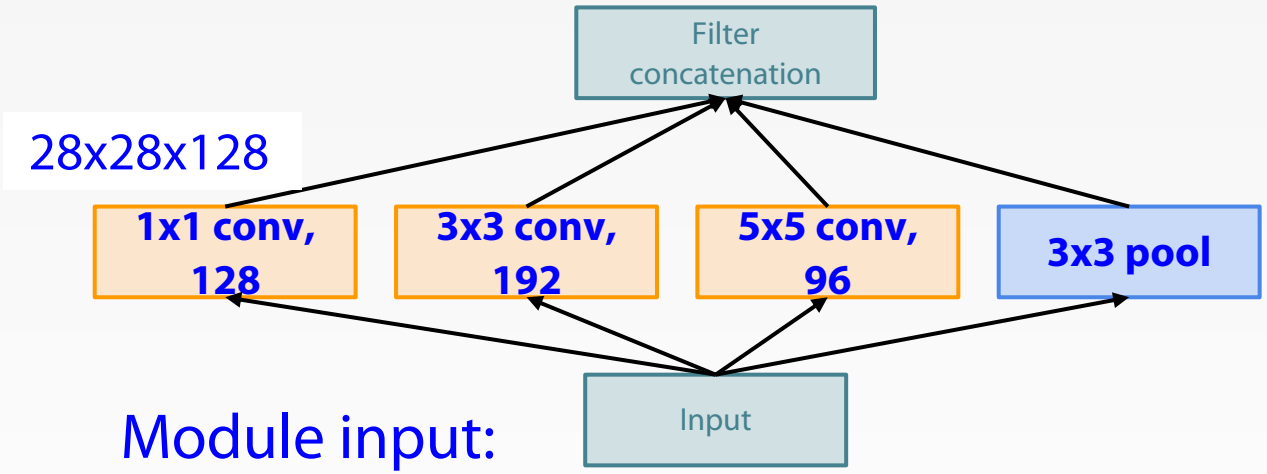
CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

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

Example:

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



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Naive Inception module

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

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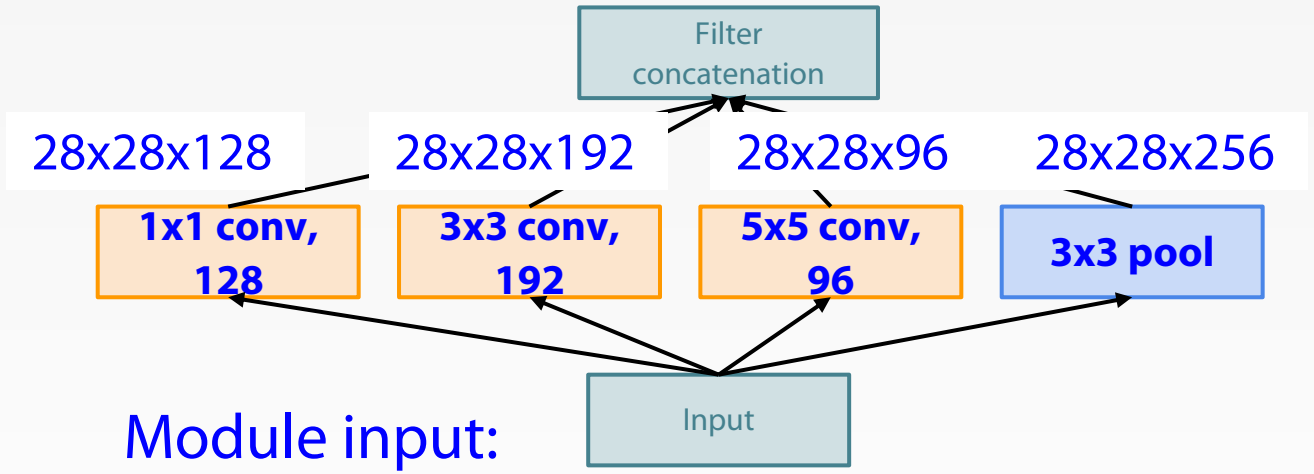


Module input:
28x28x256

Naive Inception module

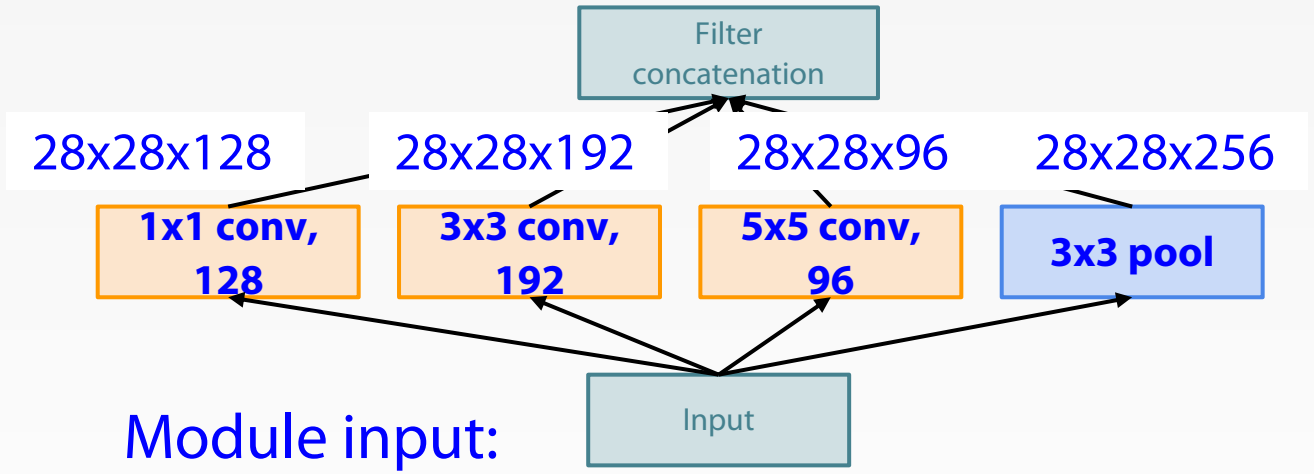
CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

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

Example:

Q3:What is output size after filter concatenation?



Module input:
28x28x256

Naive Inception module

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

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

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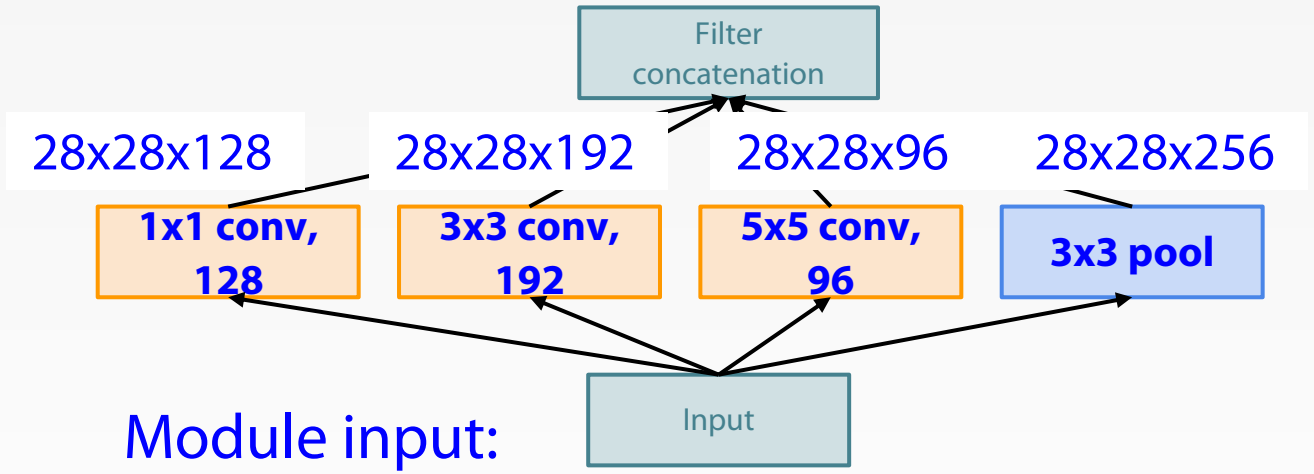
28x28x(128+192+96+256) = 28x28x672



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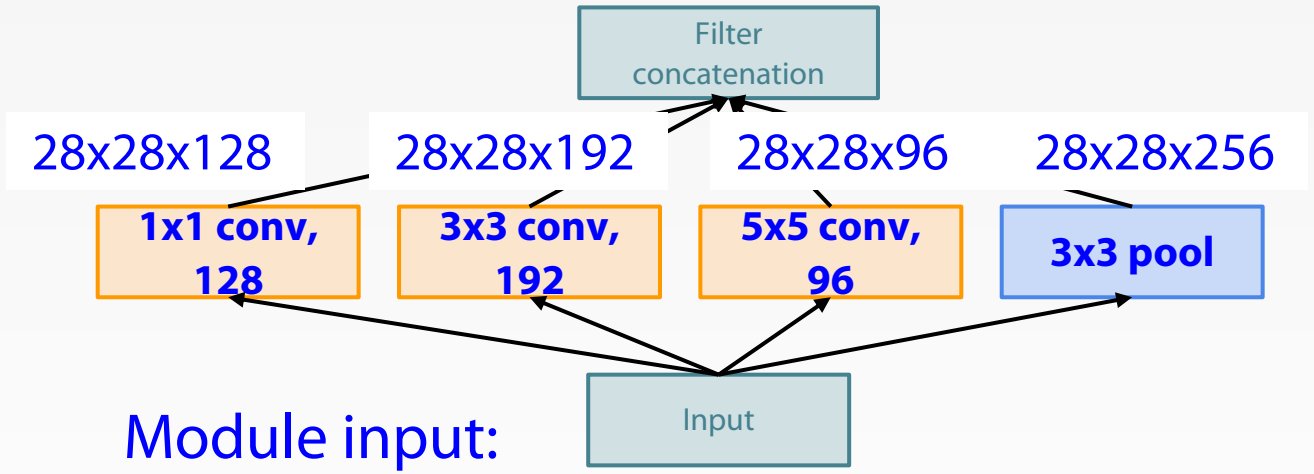

Module input:
28x28x256

Naive Inception module

Conv Ops:

[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x256
[5x5 conv, 96] 28x28x96x5x5x256

Total: 854M ops

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

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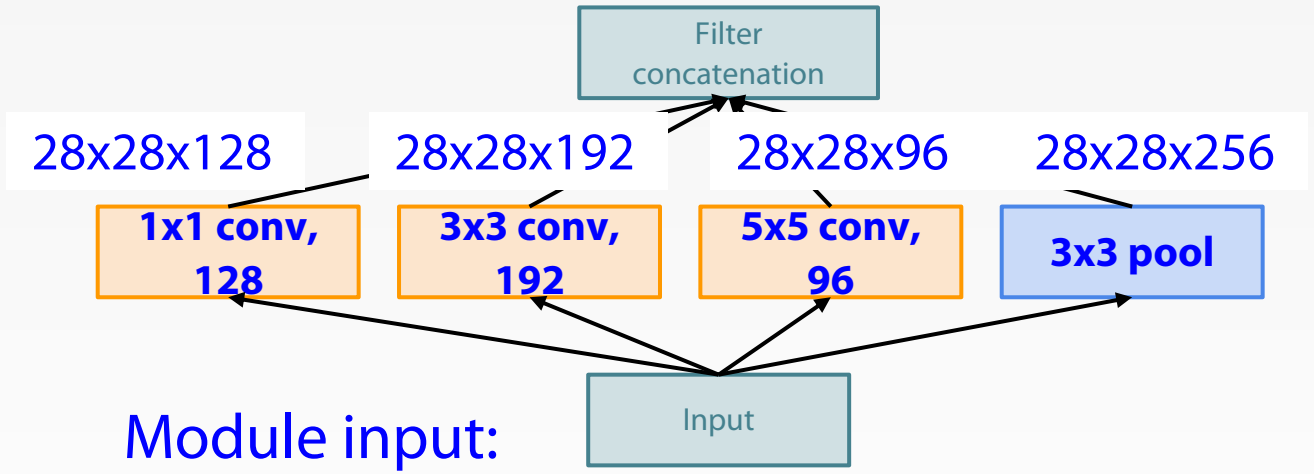

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[5x5 conv, 96] 28x28x96x5x5x256
Total: 854M ops

Very expensive compute

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

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

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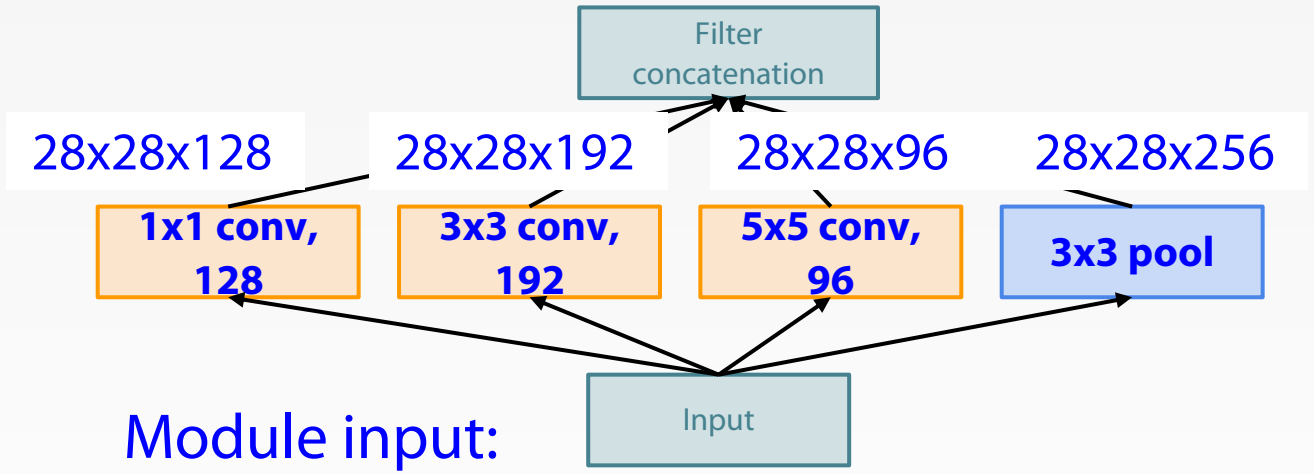
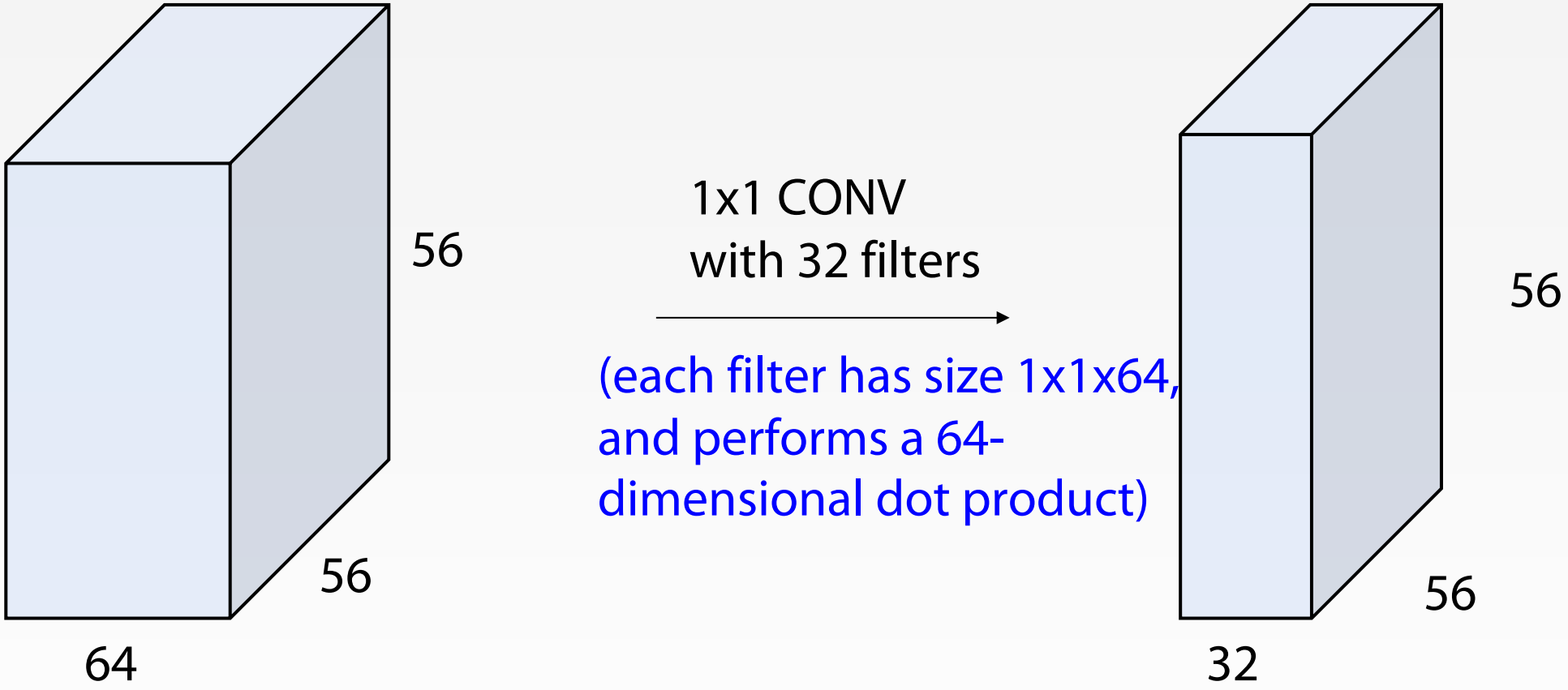


Module input:
28x28x256

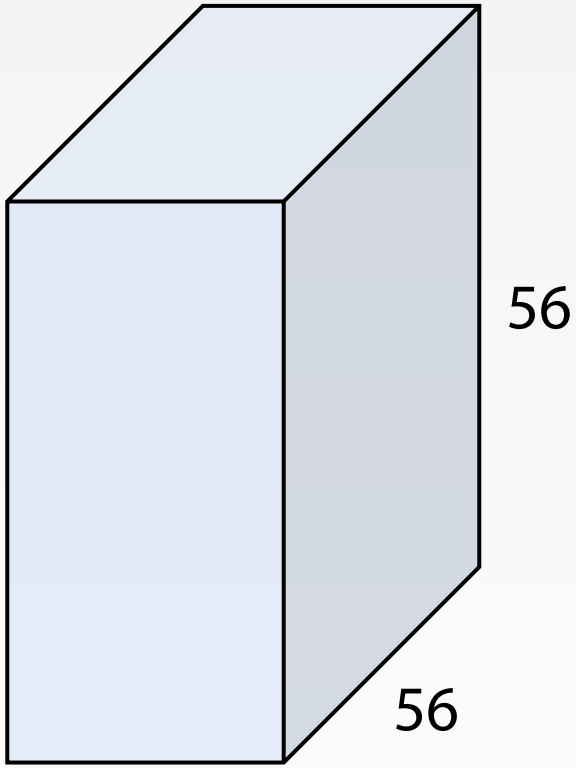
Naive Inception module

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

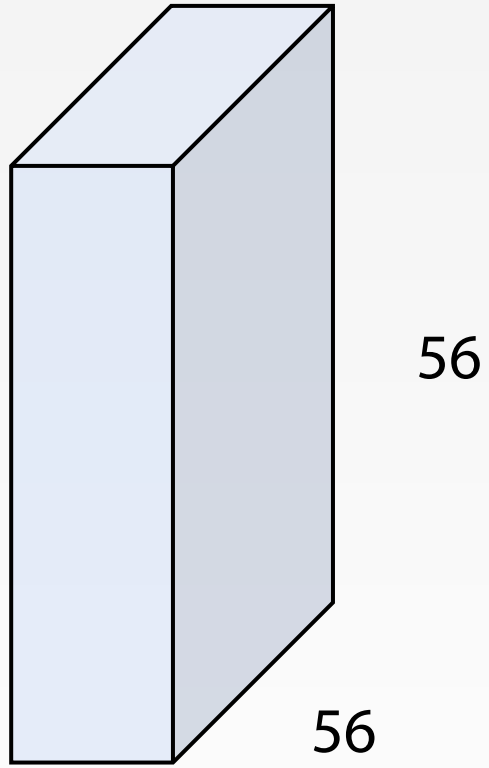
REMINDER: 1X1 CONVOLUTIONS



REMINDER: 1X1 CONVOLUTIONS



1x1 CONV
with 32 filters

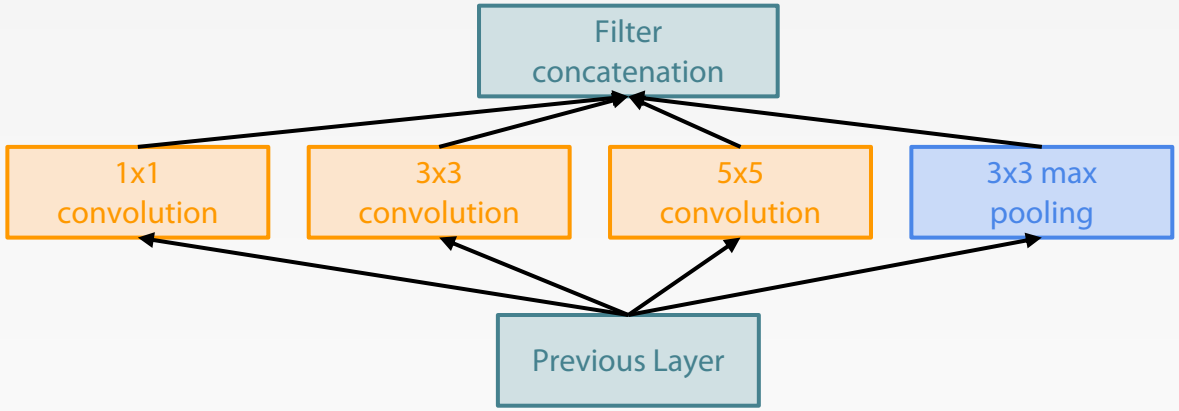


preserves spatial dimensions, reduces depth!

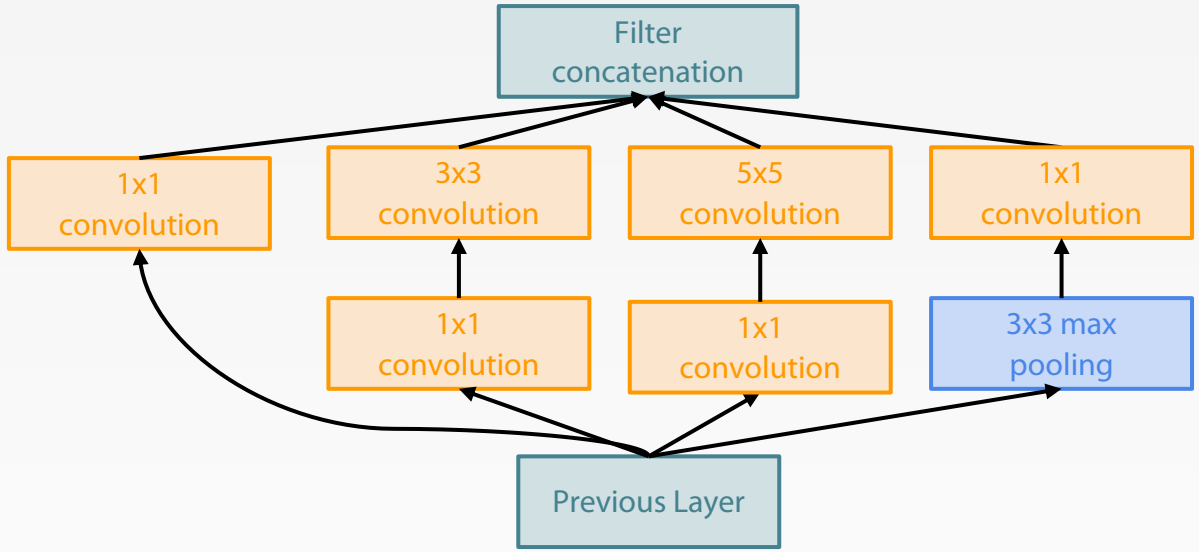
Projects depth to lower dimension (combination of feature maps)

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]



Naive Inception module

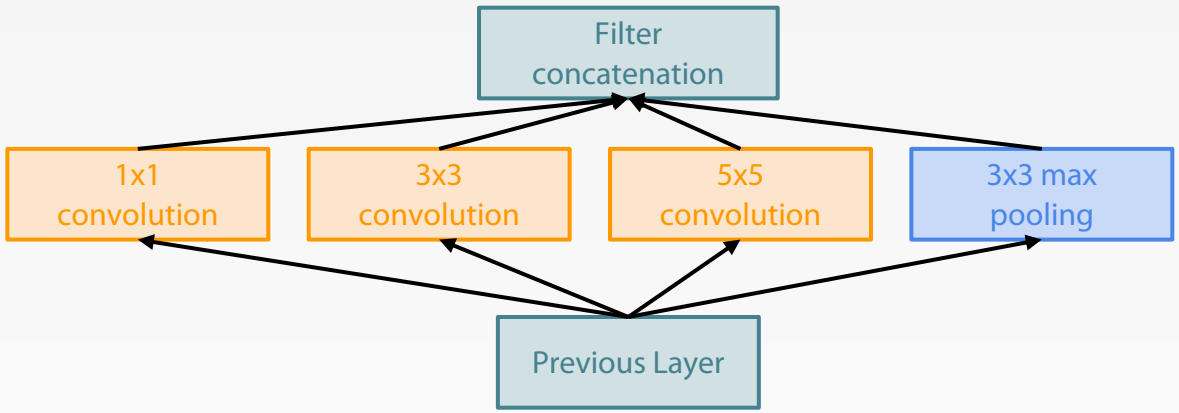


Inception module with dimension reduction

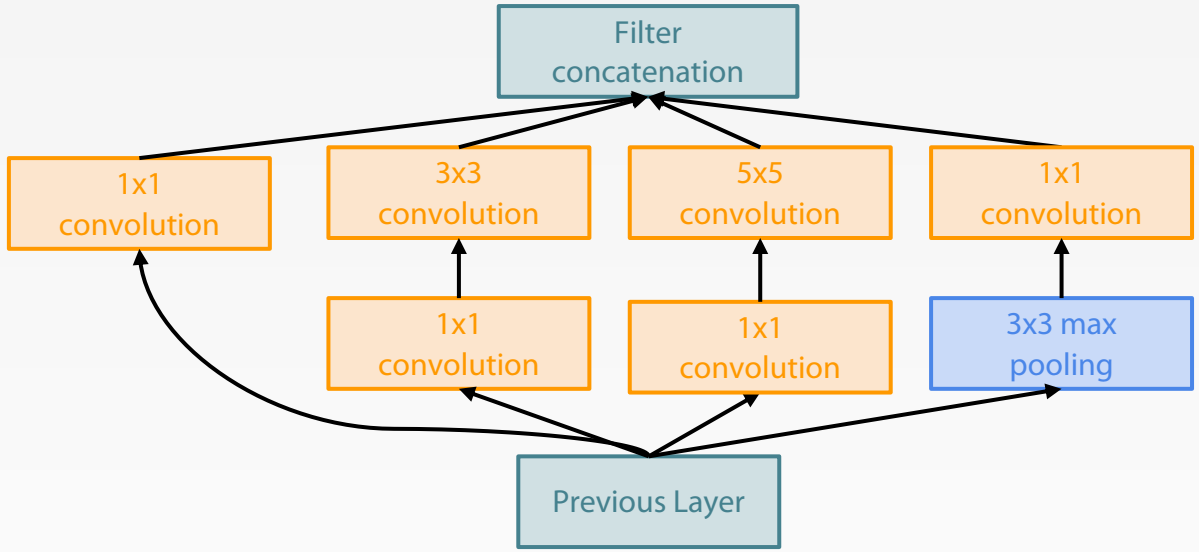
CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

1x1 conv "bottleneck" layers



Naive Inception module



Inception module with dimension reduction

CASE STUDY: GOOGLENET

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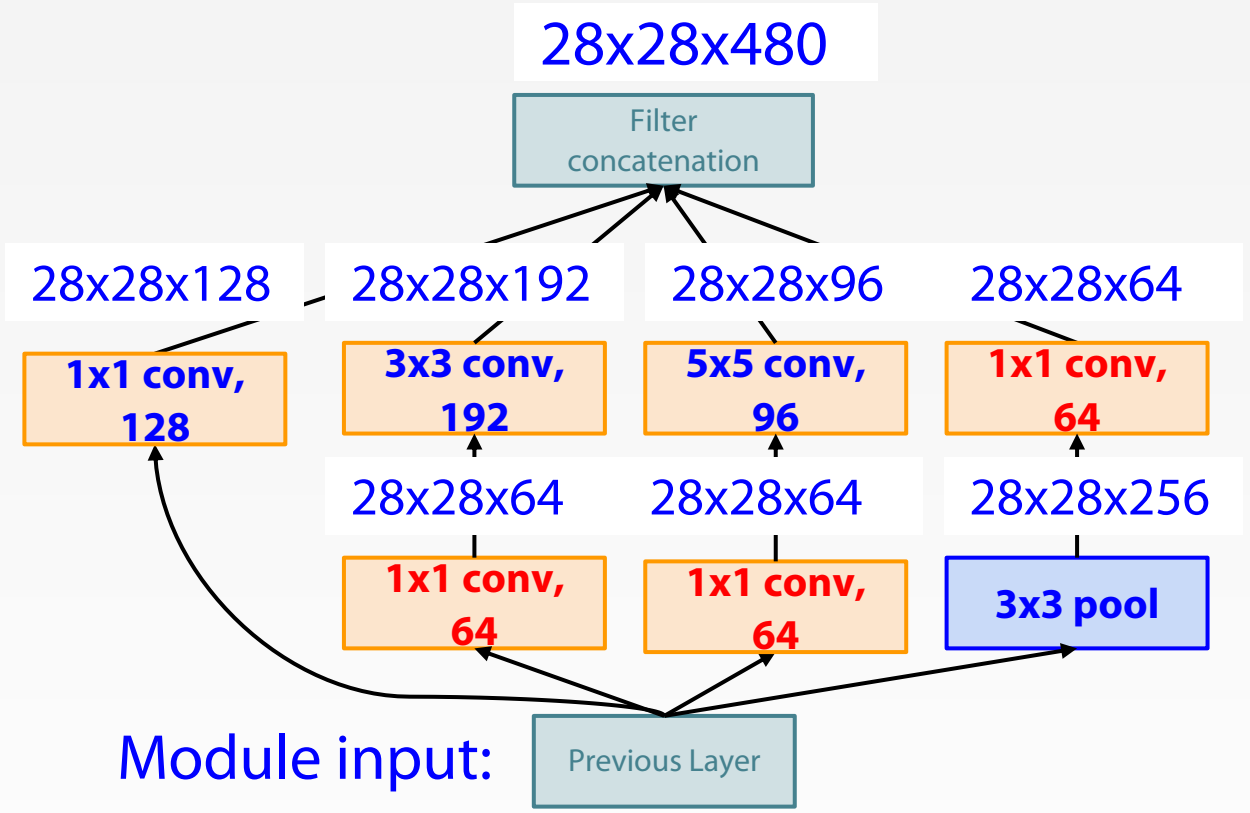


Module input: 28x28x256

Inception module with dimension reduction

Using same parallel layers as naive example, and adding "1x1 conv, 64 filter" bottlenecks:

Conv Ops:

[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x64
[5x5 conv, 96] 28x28x96x5x5x64
[1x1 conv, 64] 28x28x64x1x1x256

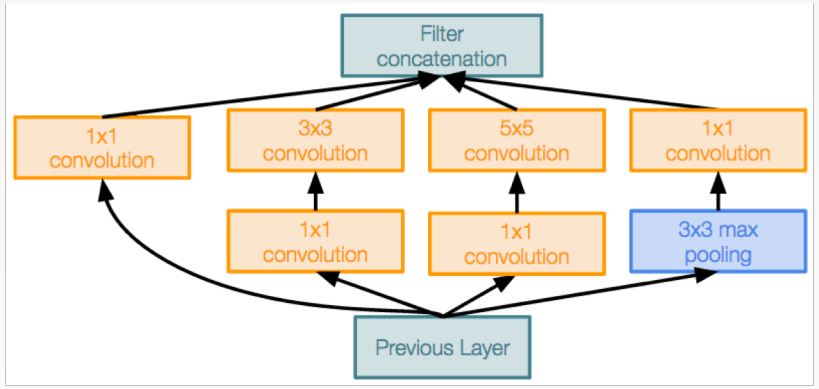
Total: 358M ops

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

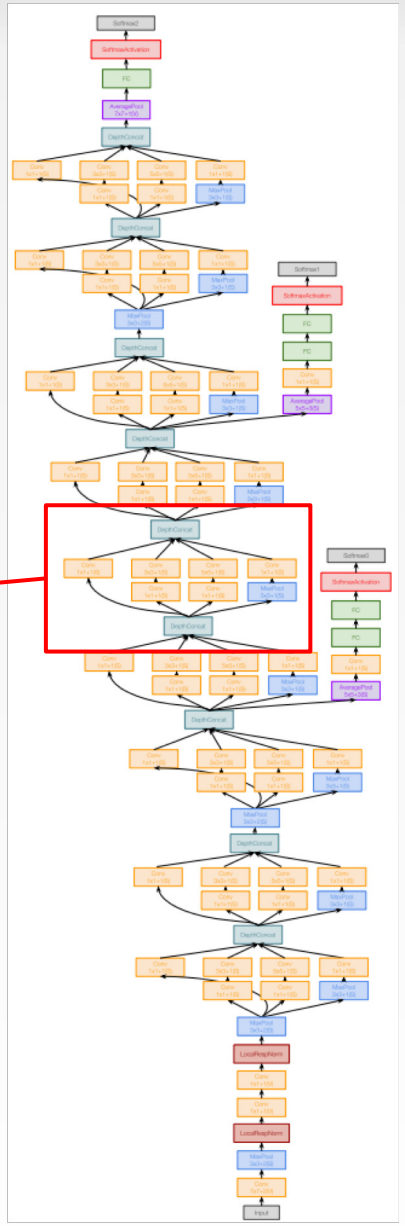
CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

Stack Inception modules with dimension reduction on top of each other



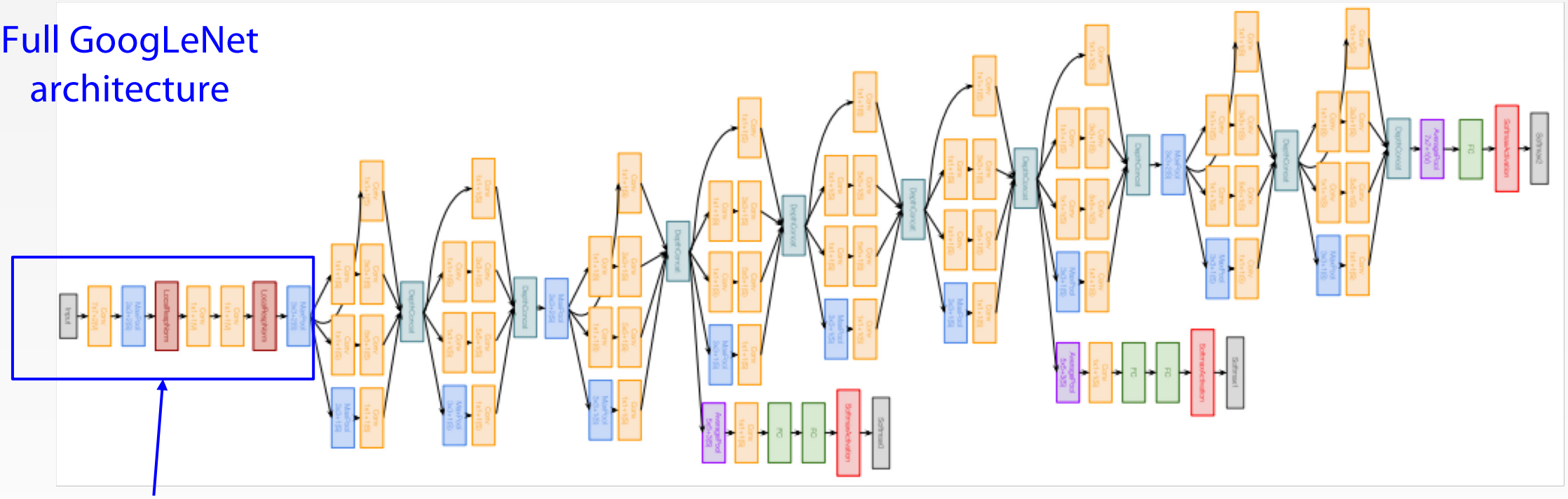
Inception module



CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

Full GoogLeNet architecture

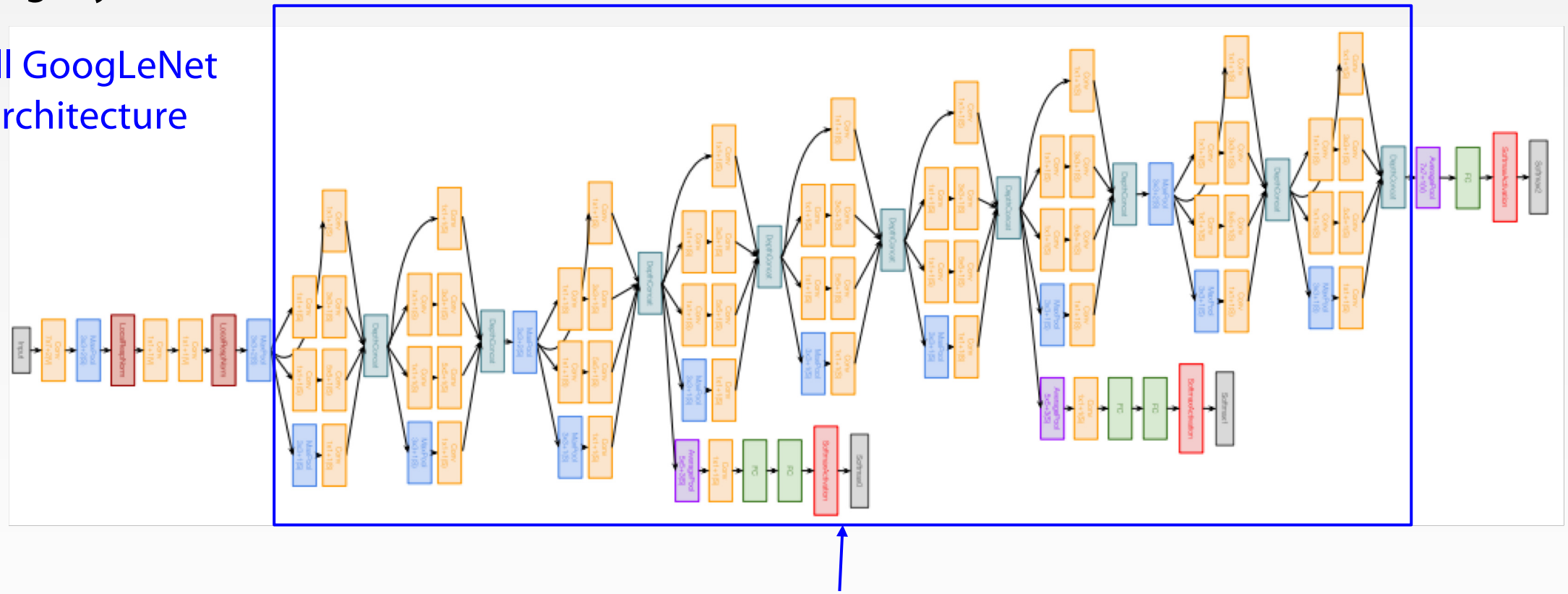


Stem Network: Conv-Pool- 2x Conv-Pool

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

Full GoogLeNet architecture

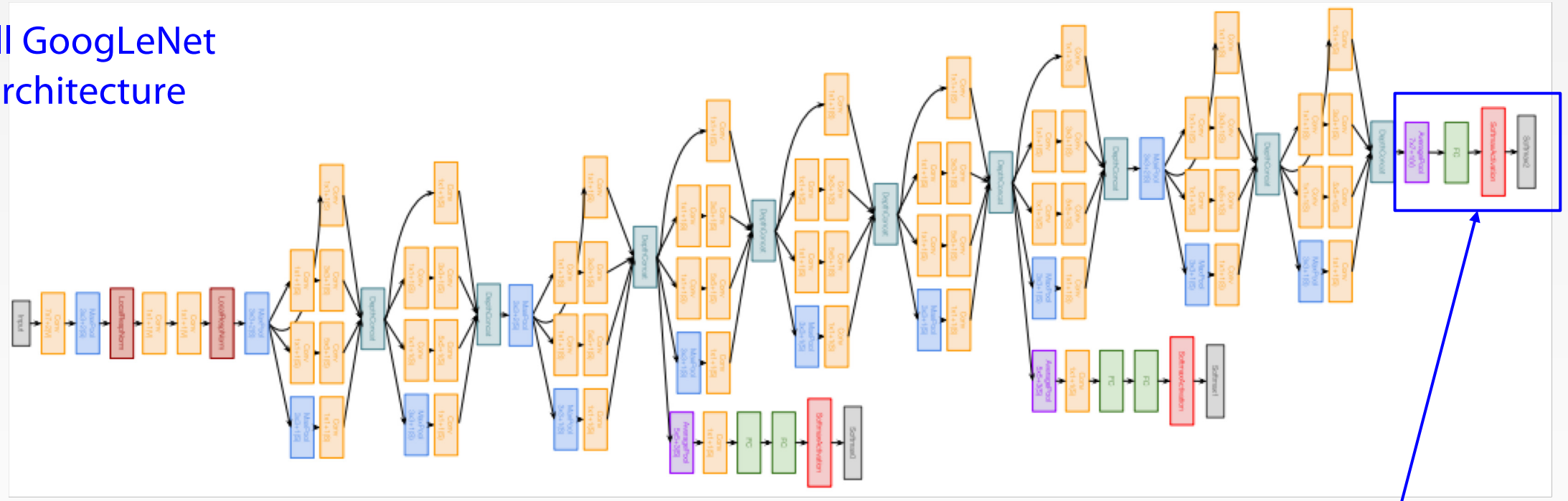


Stacked Inception Modules

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

Full GoogLeNet architecture

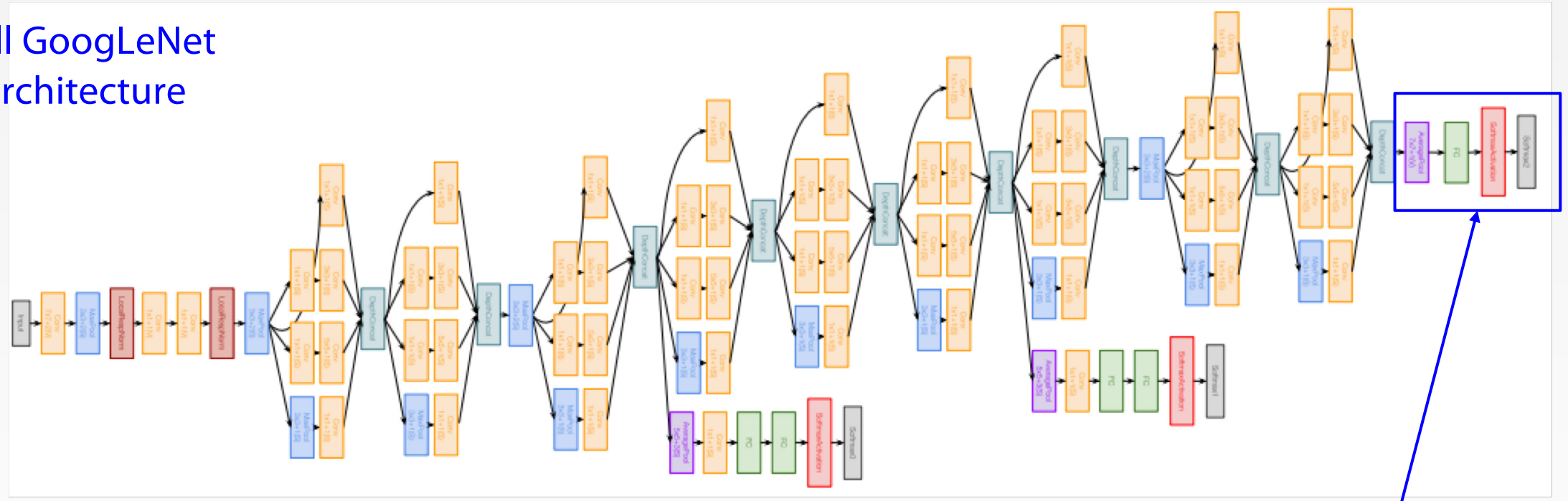


Classifier output

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

Full GoogLeNet architecture



Note: after the last convolutional layer, a global average pooling layer is used that spatially averages across each feature map, before final FC layer.

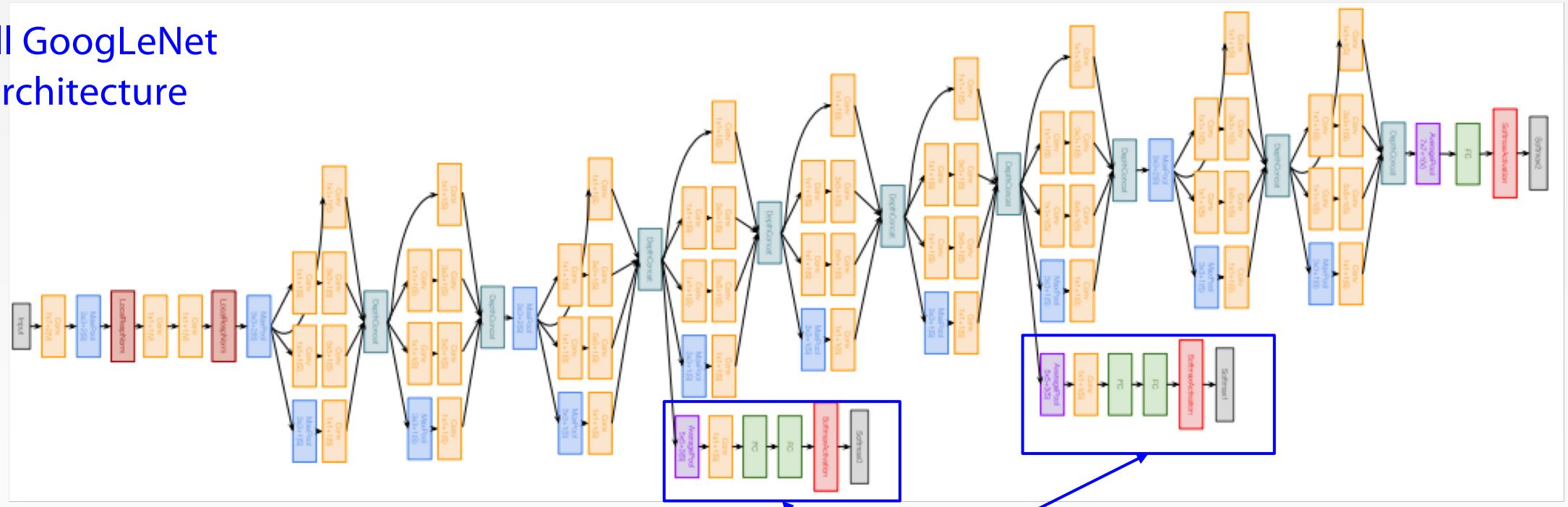
No longer multiple expensive FC layers!

Classifier output

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

Full GoogLeNet architecture

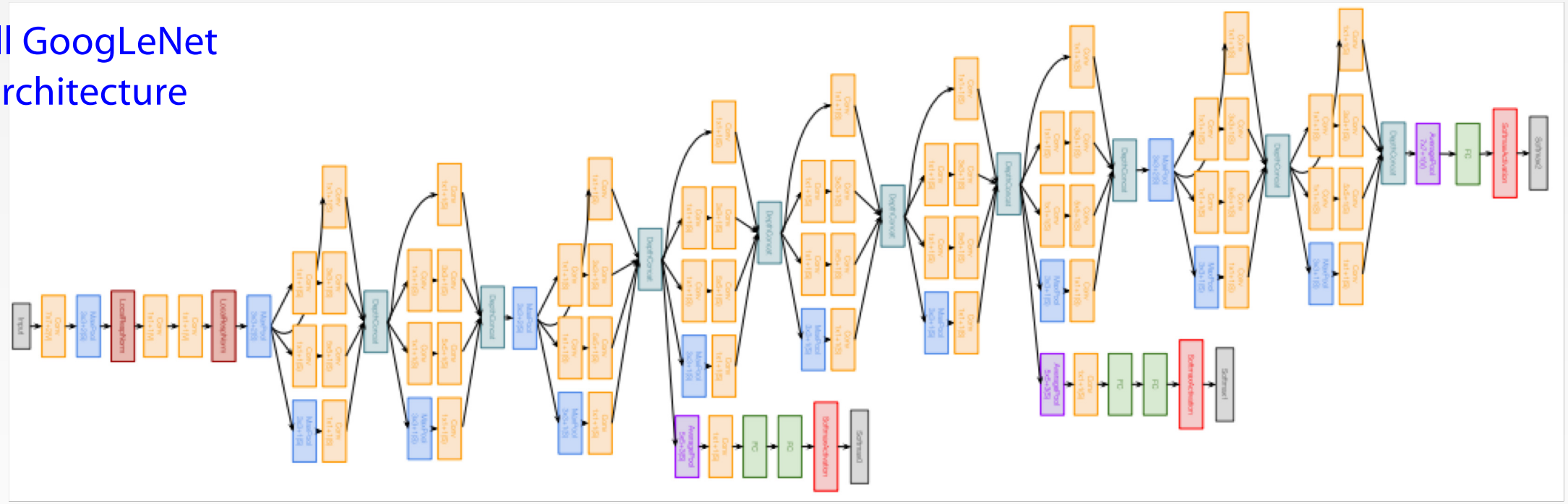


Auxiliary classification outputs to inject additional gradient at lower layers (AvgPool-1x1Conv-FC-FC-Softmax)

CASE STUDY: GOOGLENET

[Szegedy et al., 2014]

Full GoogLeNet architecture



22 total layers with weights

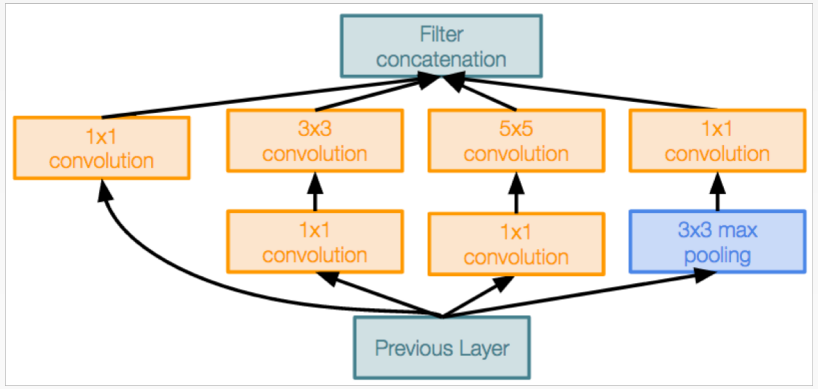
(parallel layers count as 1 layer => 2 layers per Inception module. Don't count auxiliary output layers)

CASE STUDY: GOOGLENET

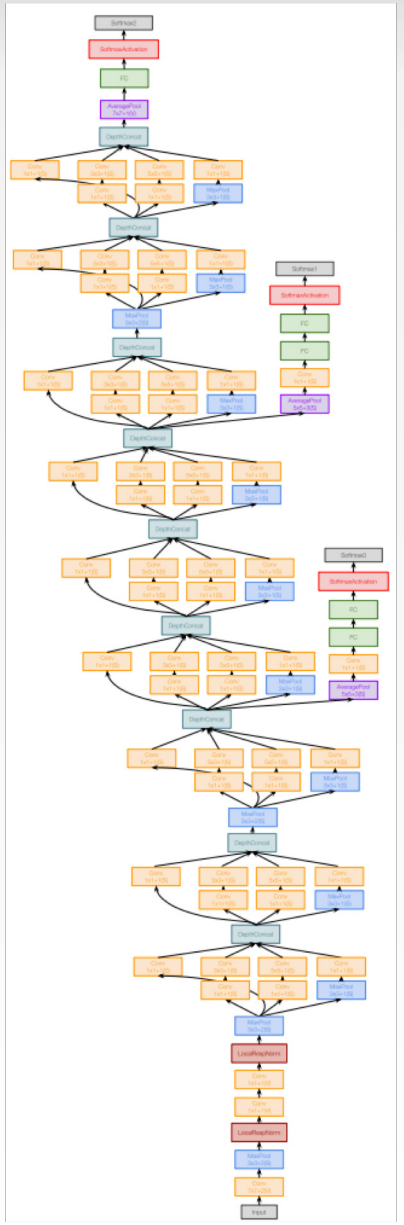
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

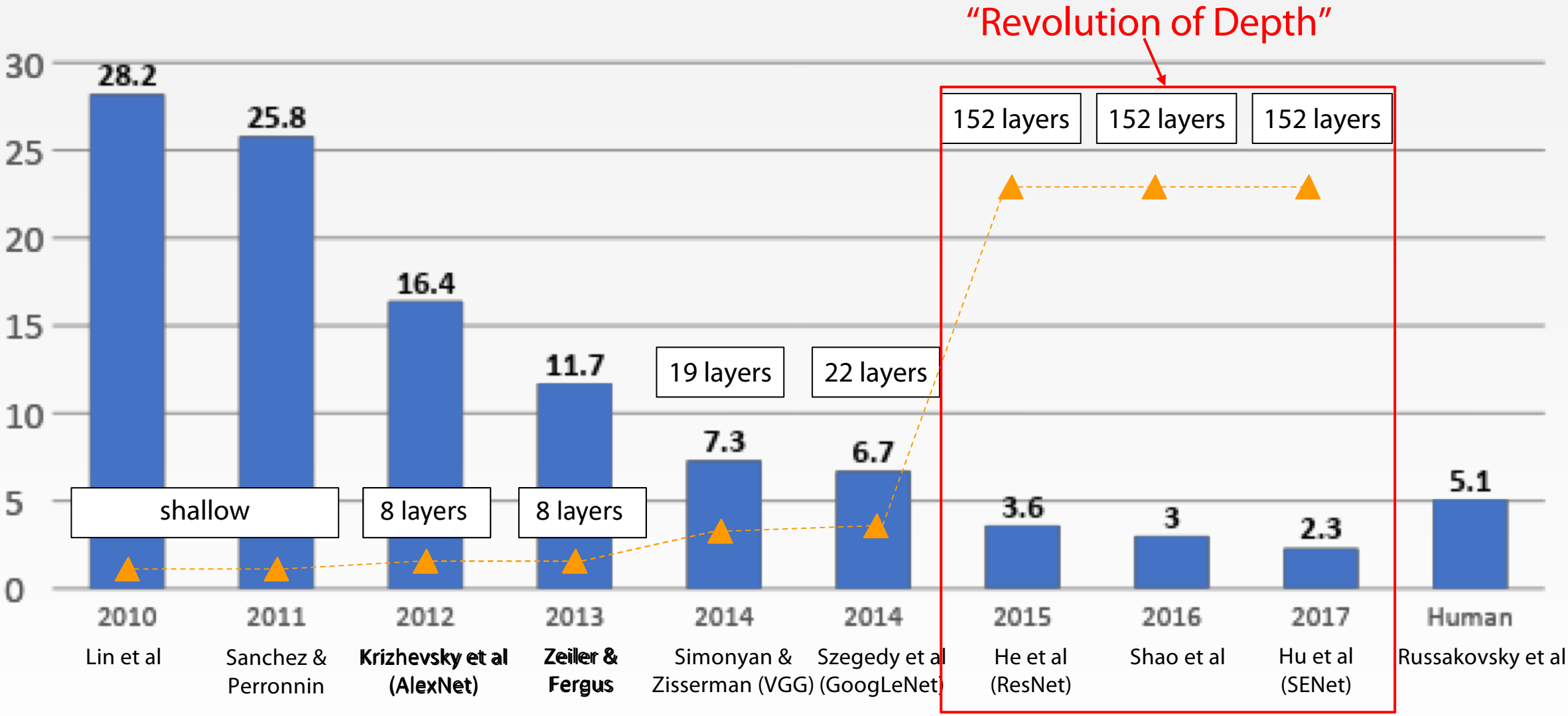
- 22 layers
- Efficient "Inception" module
- Avoids expensive FC layers
- 12x less params than AlexNet
- ILSVRC'14 classification winner (6.7% top 5 error)



Inception module



IMAGENET LARGE SCALE VISUAL RECOGNITION CHALLENGE (ILSVRC) WINNERS



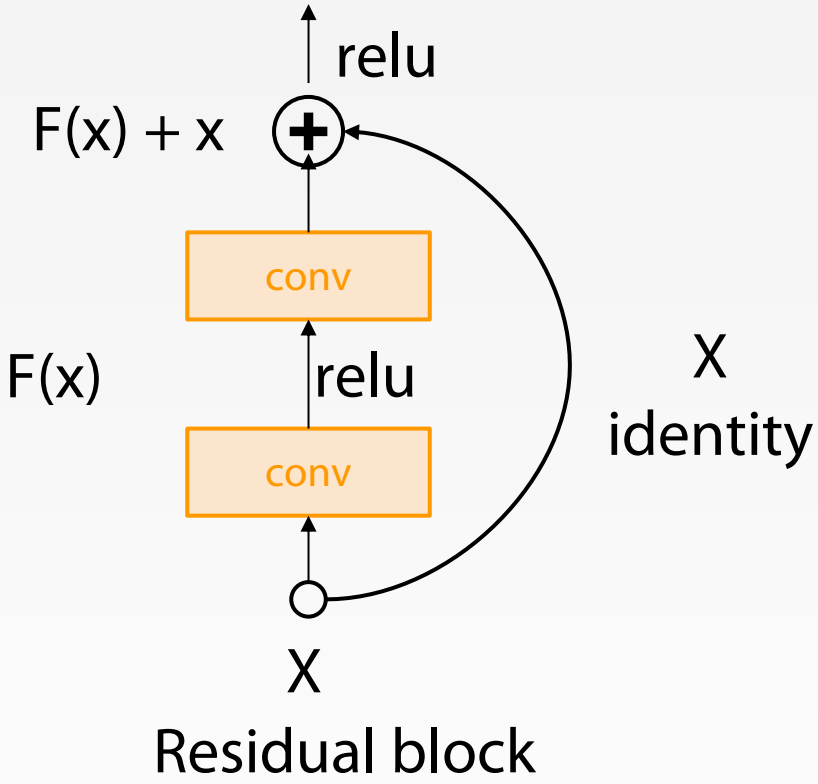
RESNET

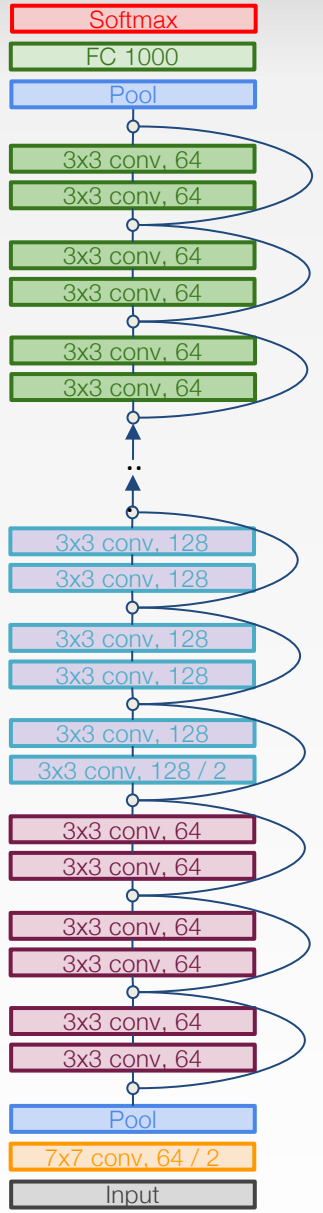
CASE STUDY: RESNET

[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!





CASE STUDY: RESNET

[He et al., 2015]

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

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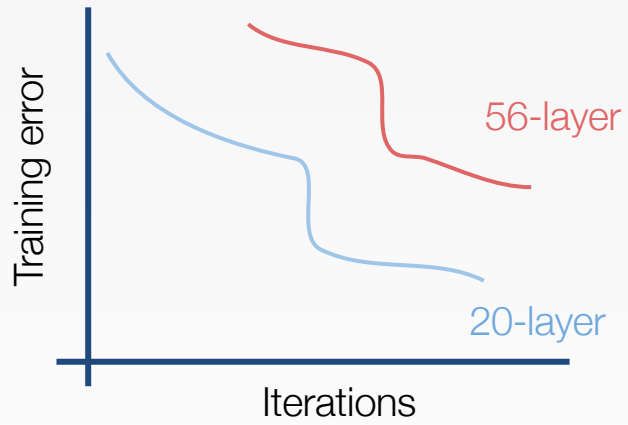
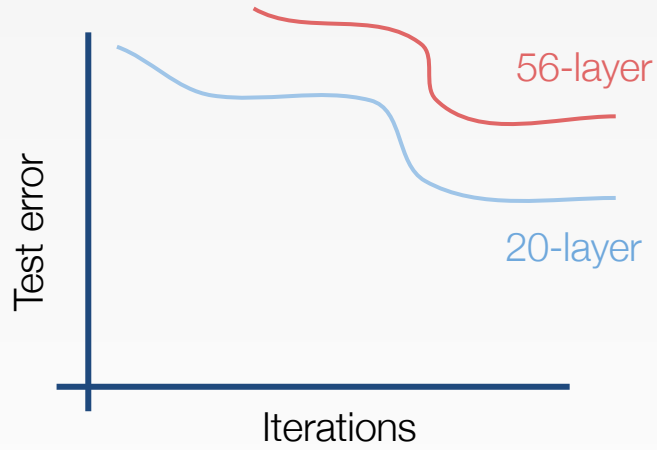


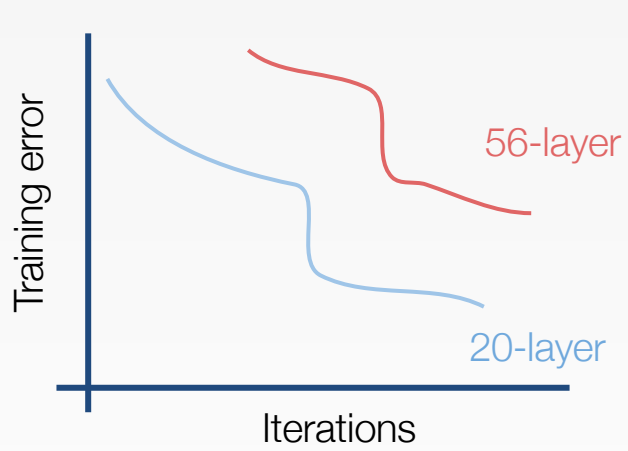


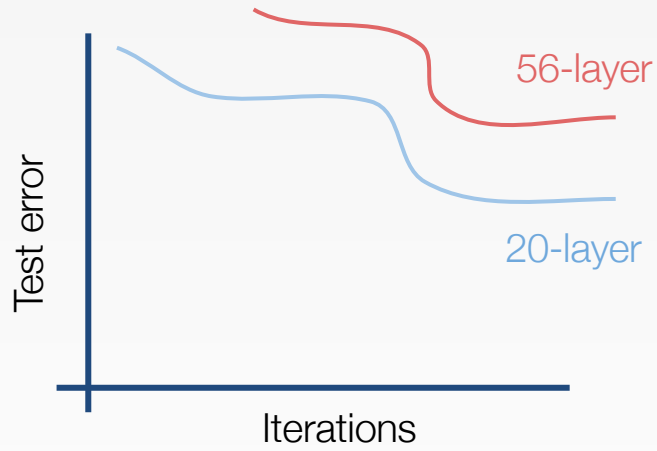
Q: What's strange about these training and test curves?
[Hint: look at the order of the curves]

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

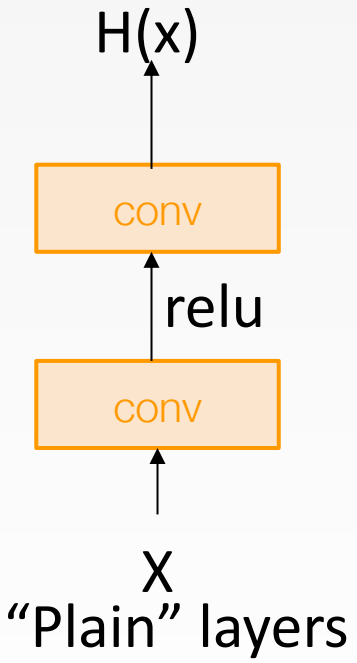
The deeper model should be able to perform at least as well as the shallower model.

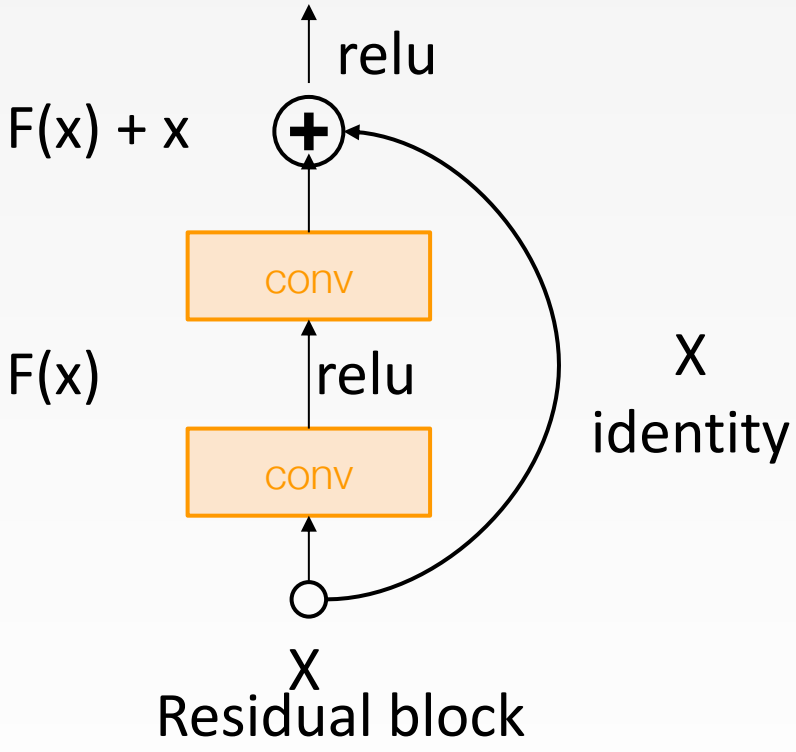
A **solution by construction** is copying the learned layers from the shallower model and setting additional layers to identity mapping.

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

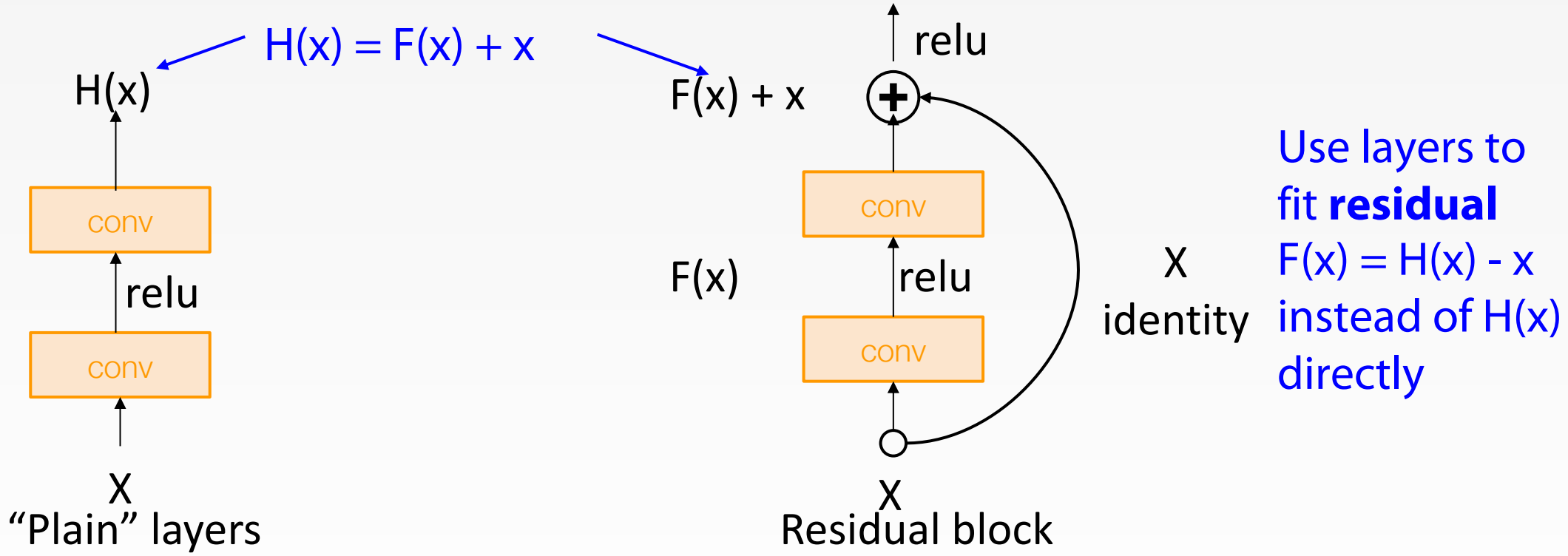




CASE STUDY: RESNET

[He et al., 2015]

Solution: Use network layers to fit a **residual mapping** (**F(x)**) instead of directly trying to fit a desired **underlying mapping** (**H(x)**)

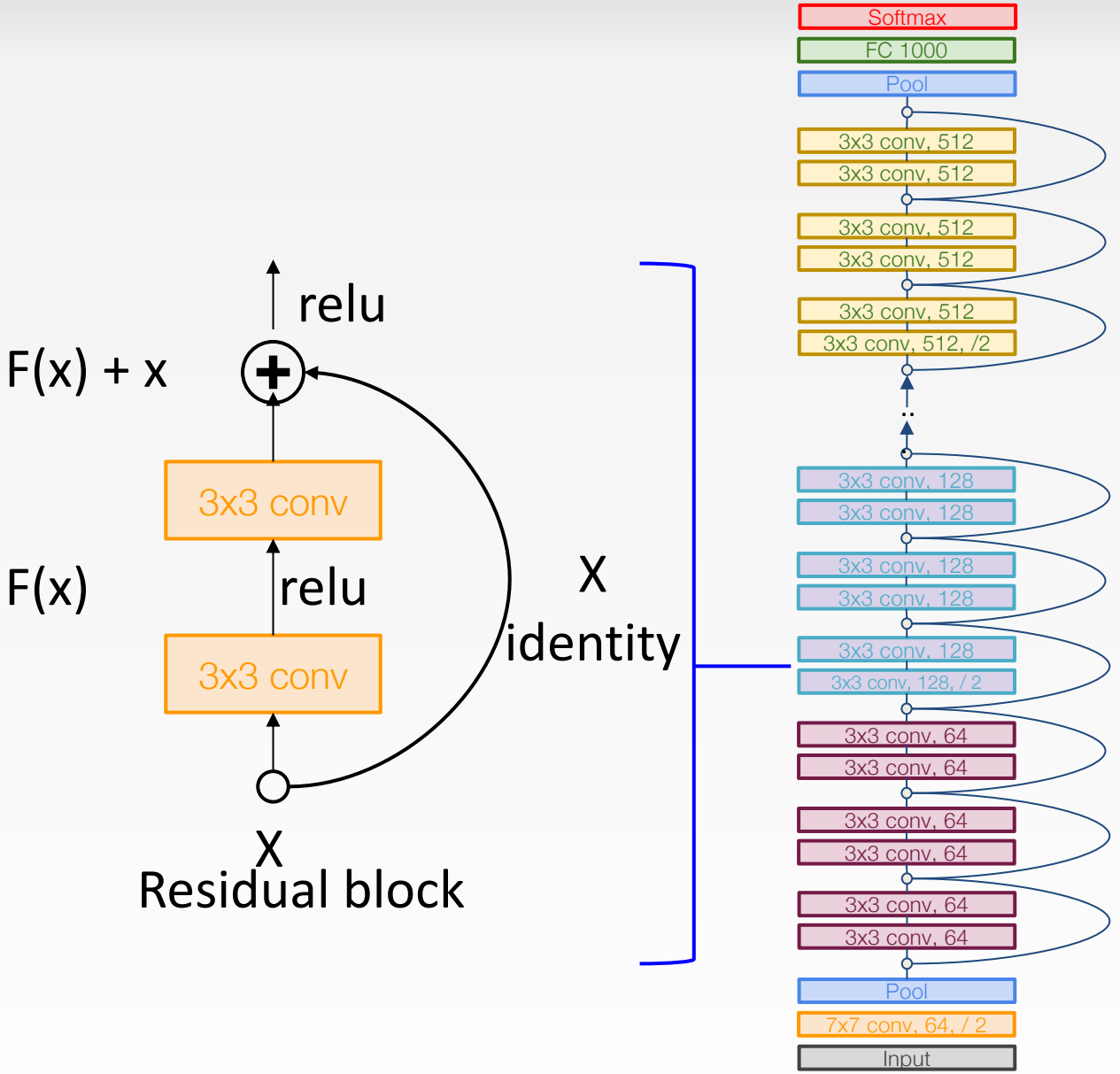


CASE STUDY: RESNET

[He et al., 2015]

Full ResNet architecture:

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

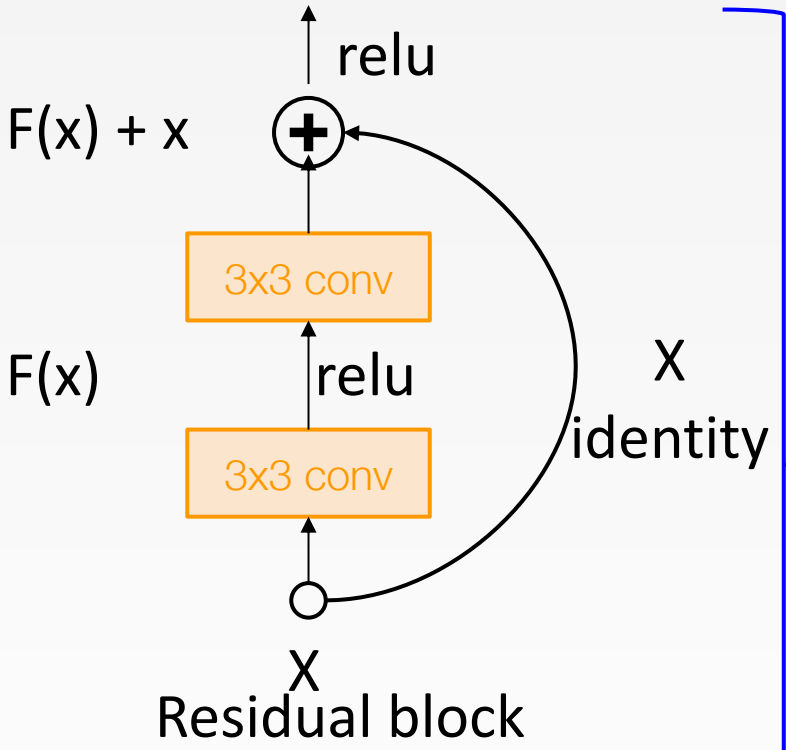


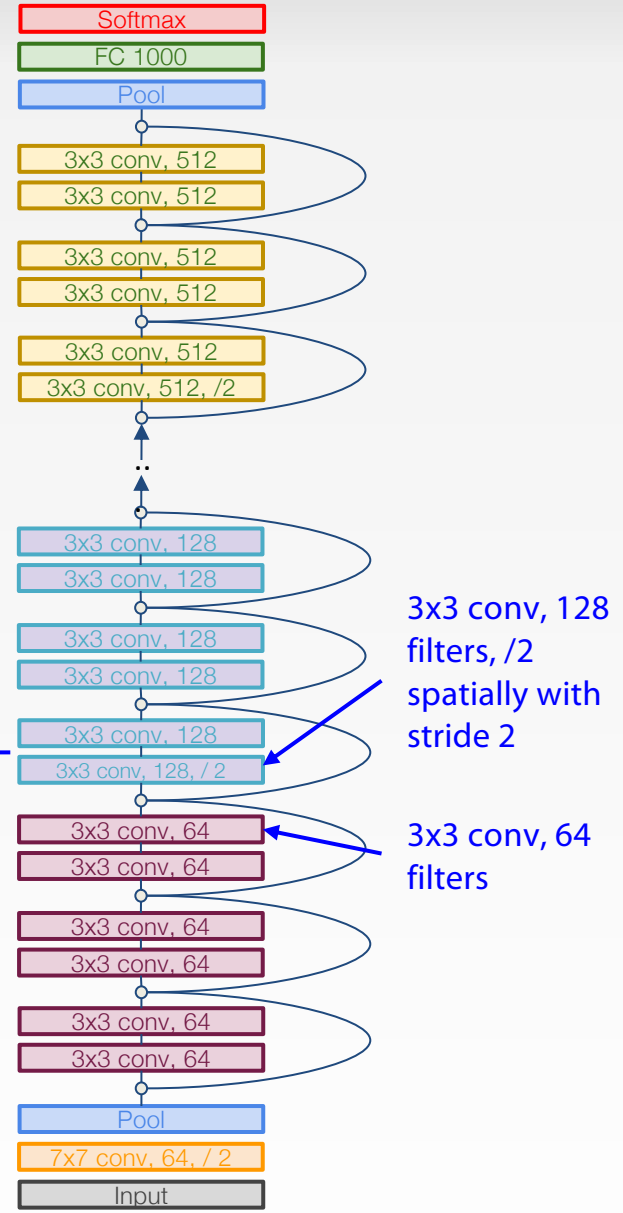
CASE STUDY: RESNET

[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)





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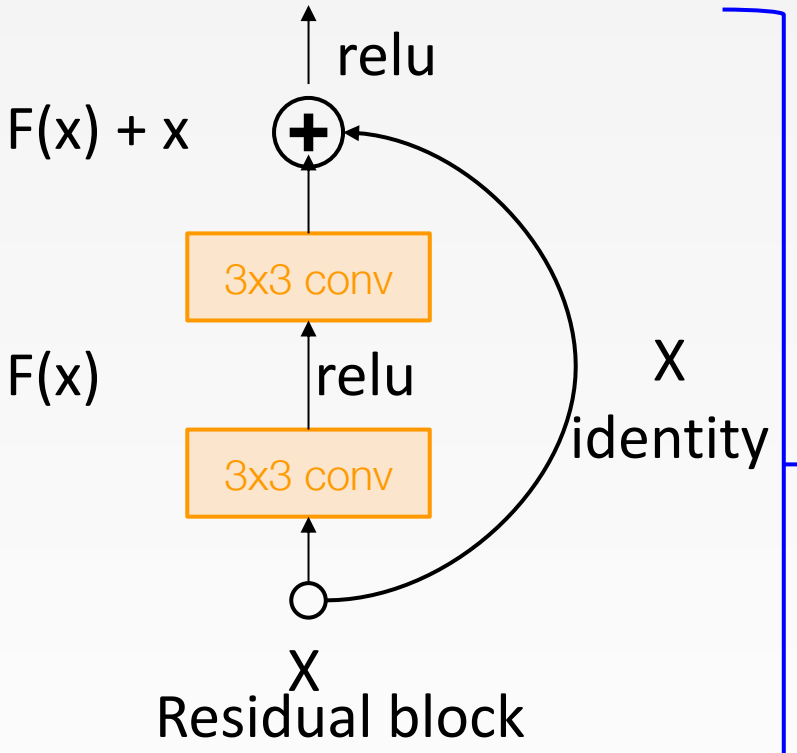
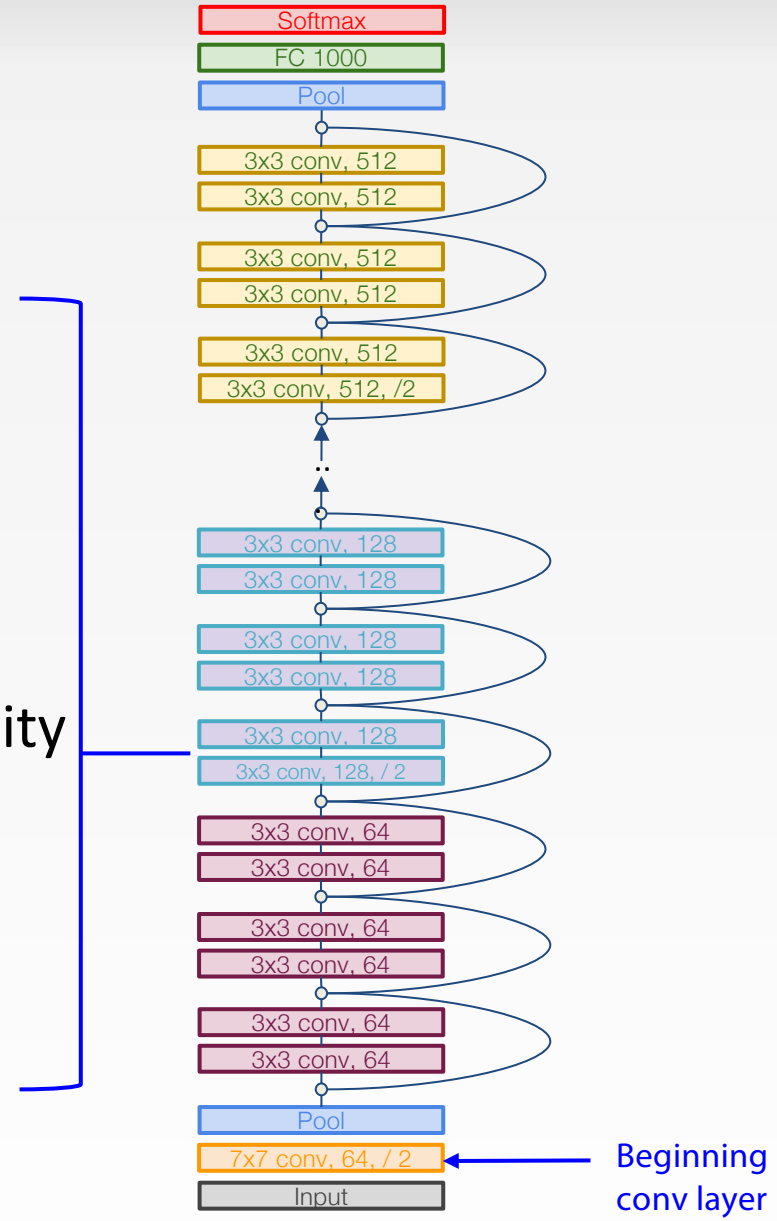
- Additional conv layer at the beginning



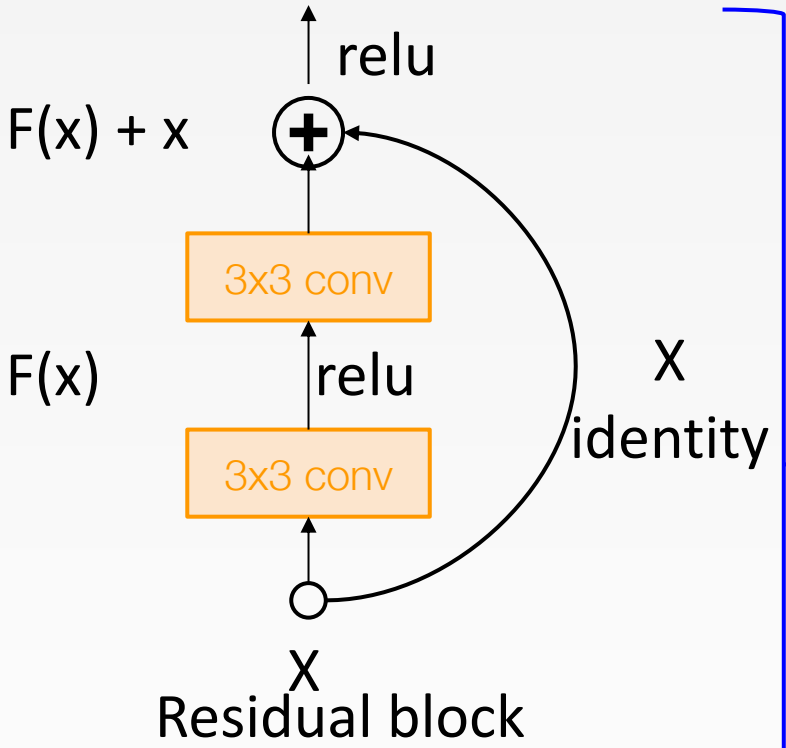


CASE STUDY: RESNET

[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)



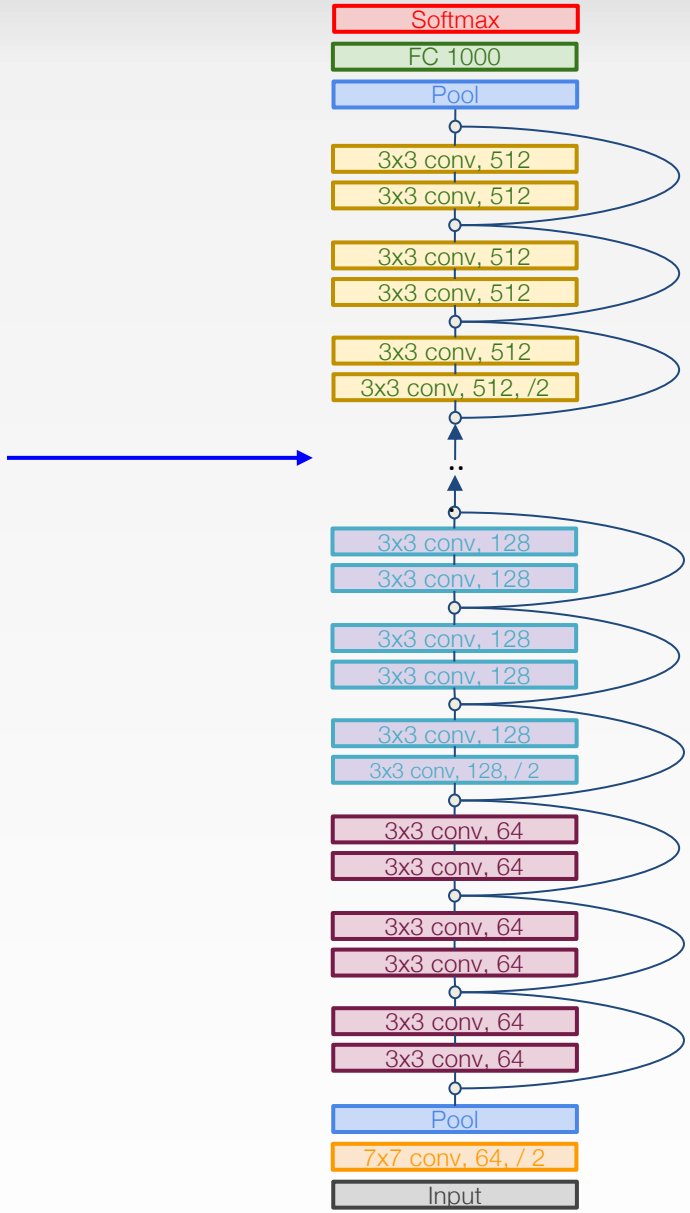
No FC layers besides FC 1000 to output classes

Global average pooling layer after last conv layer

CASE STUDY: RESNET

[He et al., 2015]

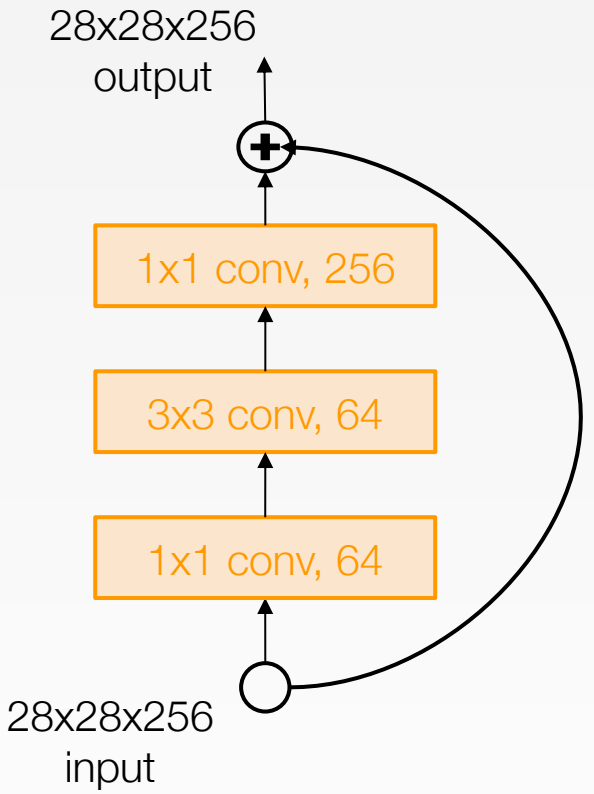
Total depths of 34, 50, 101, or 152 layers for ImageNet



CASE STUDY: RESNET

[He et al., 2015]

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



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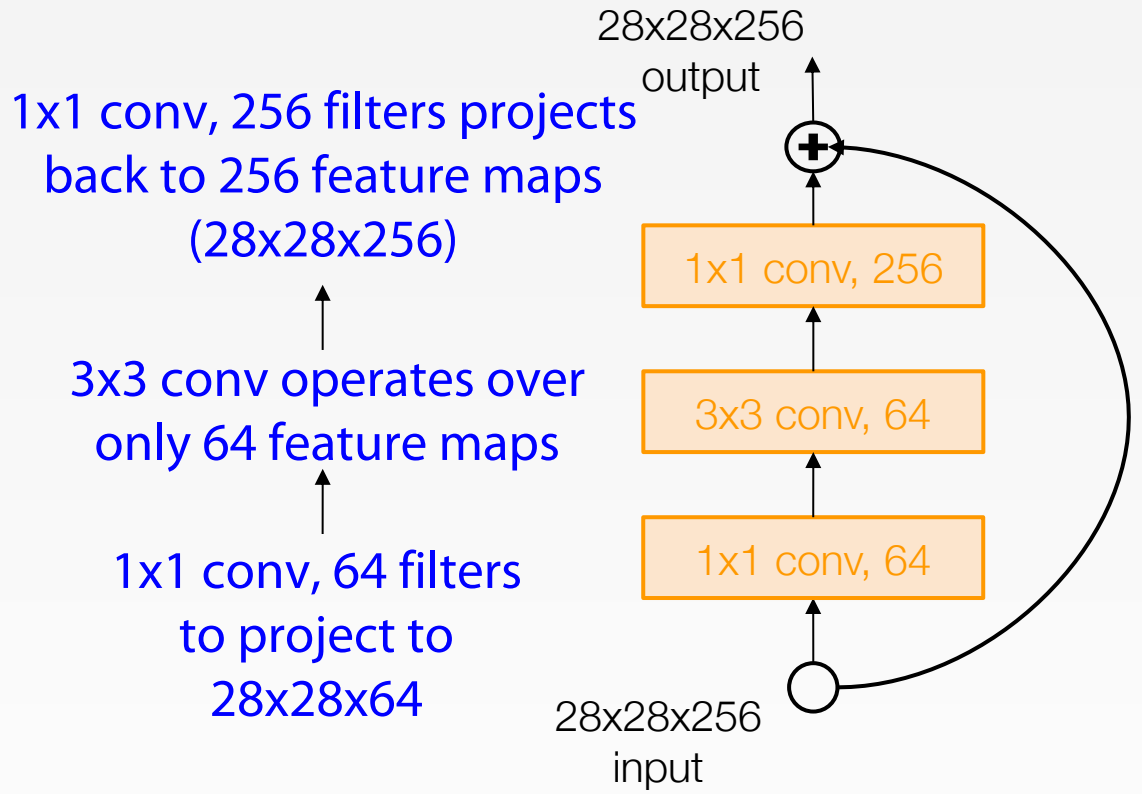


CASE STUDY: RESNET

[He et al., 2015]

Training ResNet in practice:

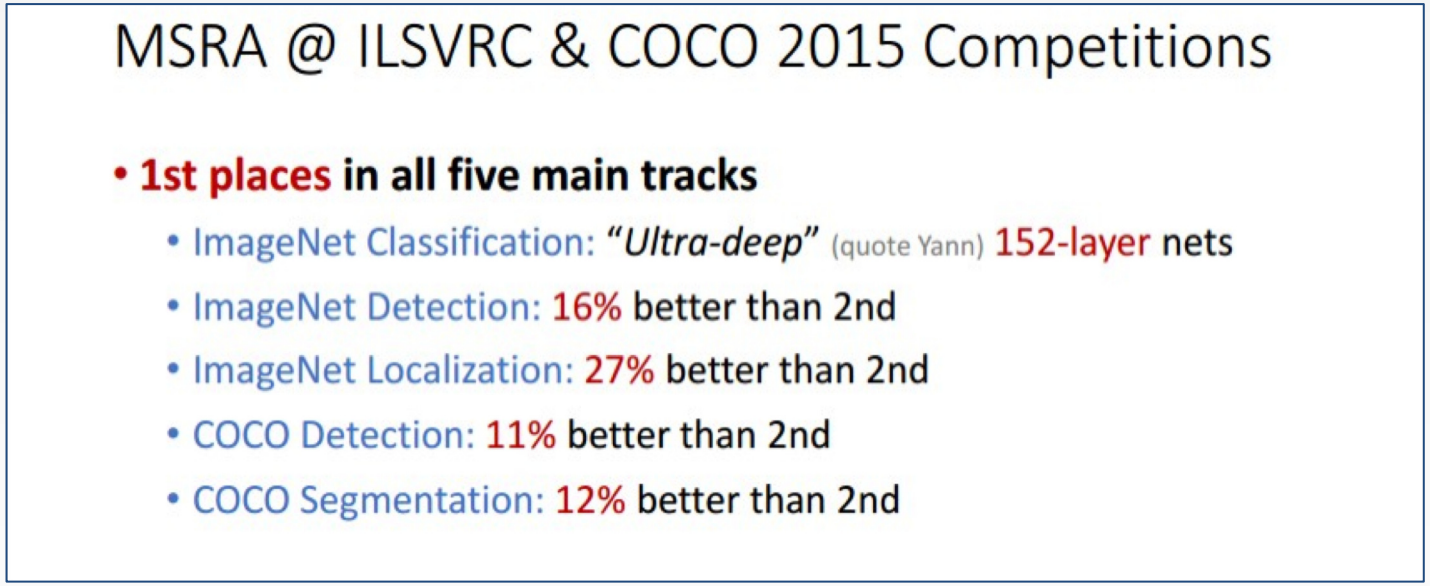
- Batch Normalization after every CONV layer
- Xavier 2/ initialization from He et al.
- SGD + Momentum (0.9)
- Learning rate: 0.1, divided by 10 when validation error plateaus
- Mini-batch size 256
- Weight decay of 1e-5
- No dropout used

CASE STUDY: RESNET

[He et al., 2015]

Experimental Results

- Able to train very deep networks without degrading gradient flow (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

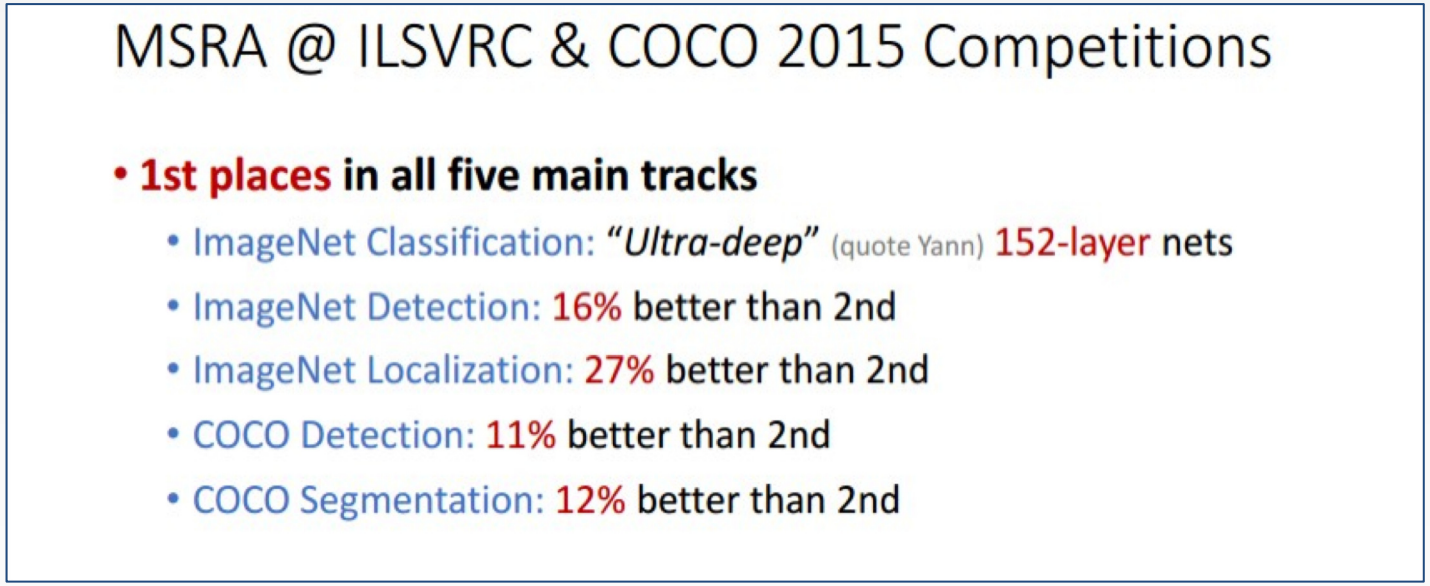


CASE STUDY: RESNET

[He et al., 2015]

Experimental Results

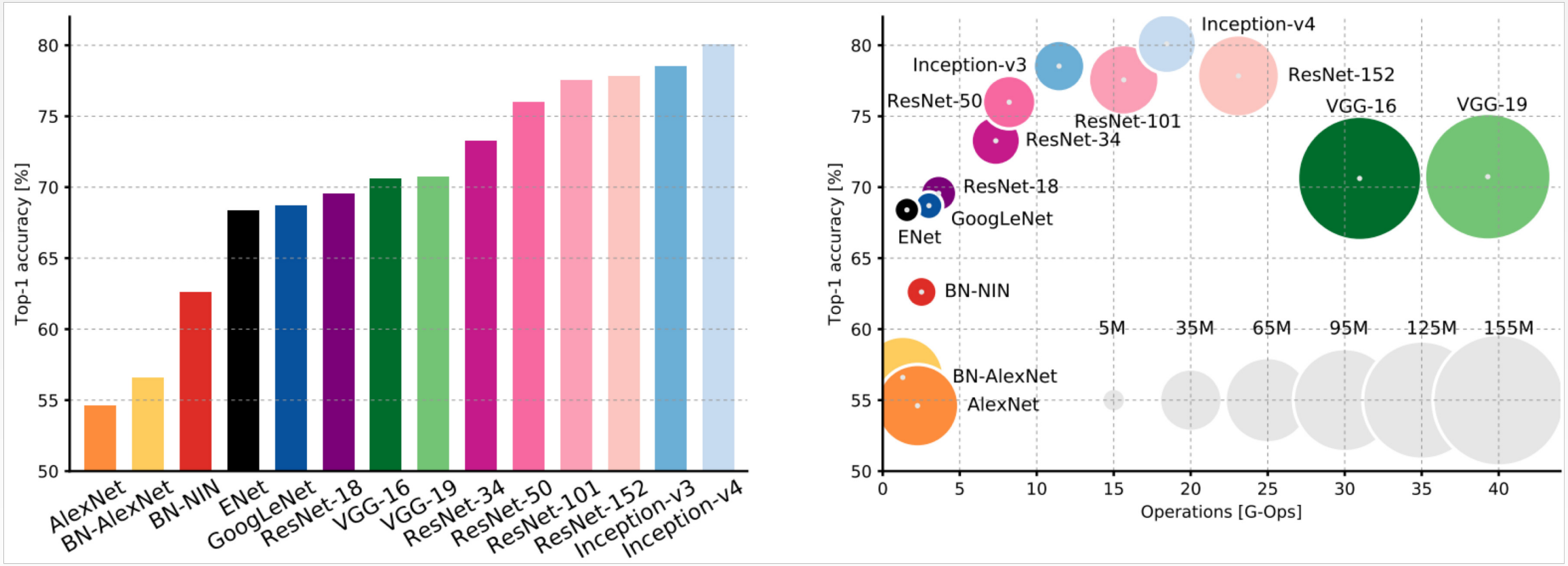
- Able to train very deep networks without degrading (152 layers on ImageNet, 1202 on Cifar)
- Deeper networks now achieve lowing training error as expected
- Swept 1st place in all ILSVRC and COCO 2015 competitions



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

COMPARATIVE ANALYSIS

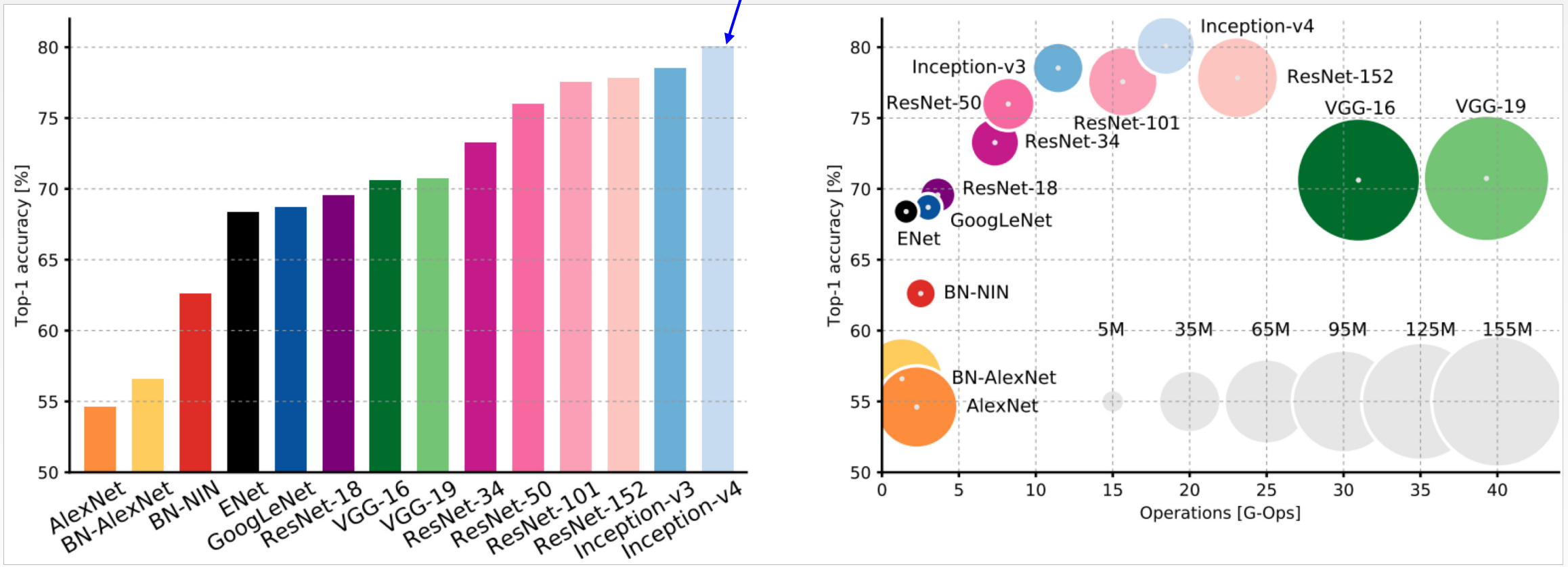
COMPARING COMPLEXITY



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

COMPARING COMPLEXITY

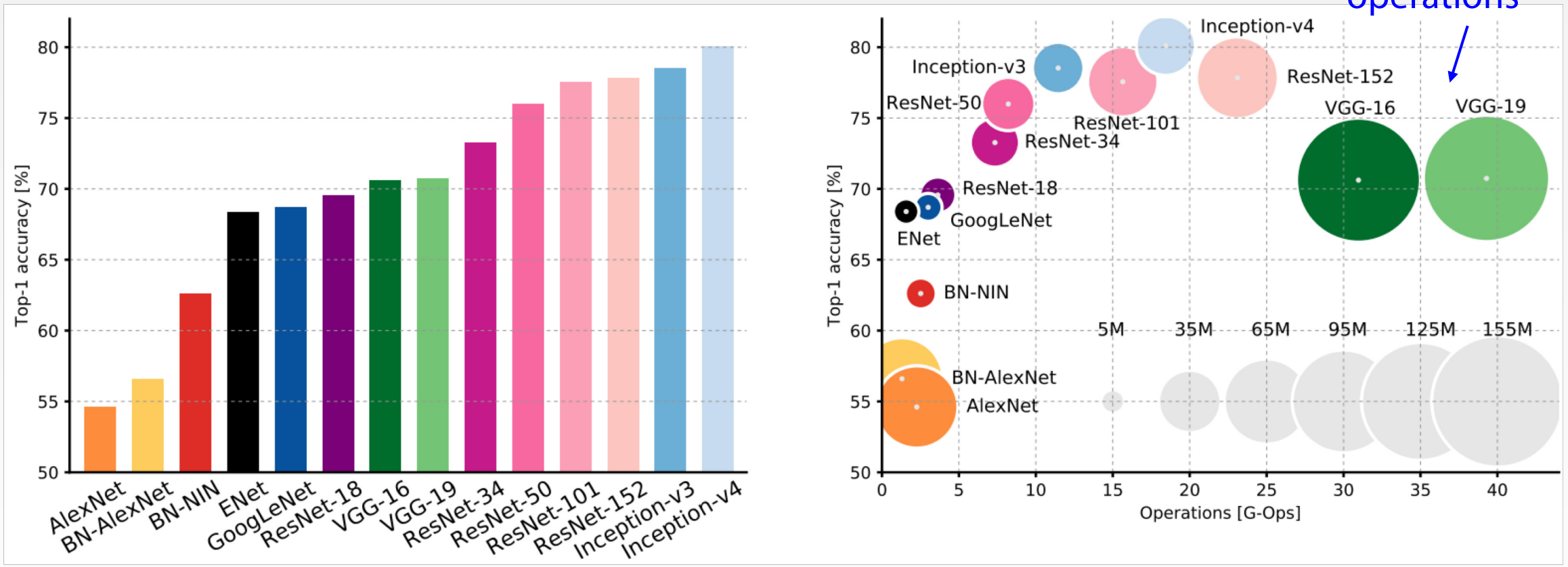
Inception-v4: Resnet + Inception!



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

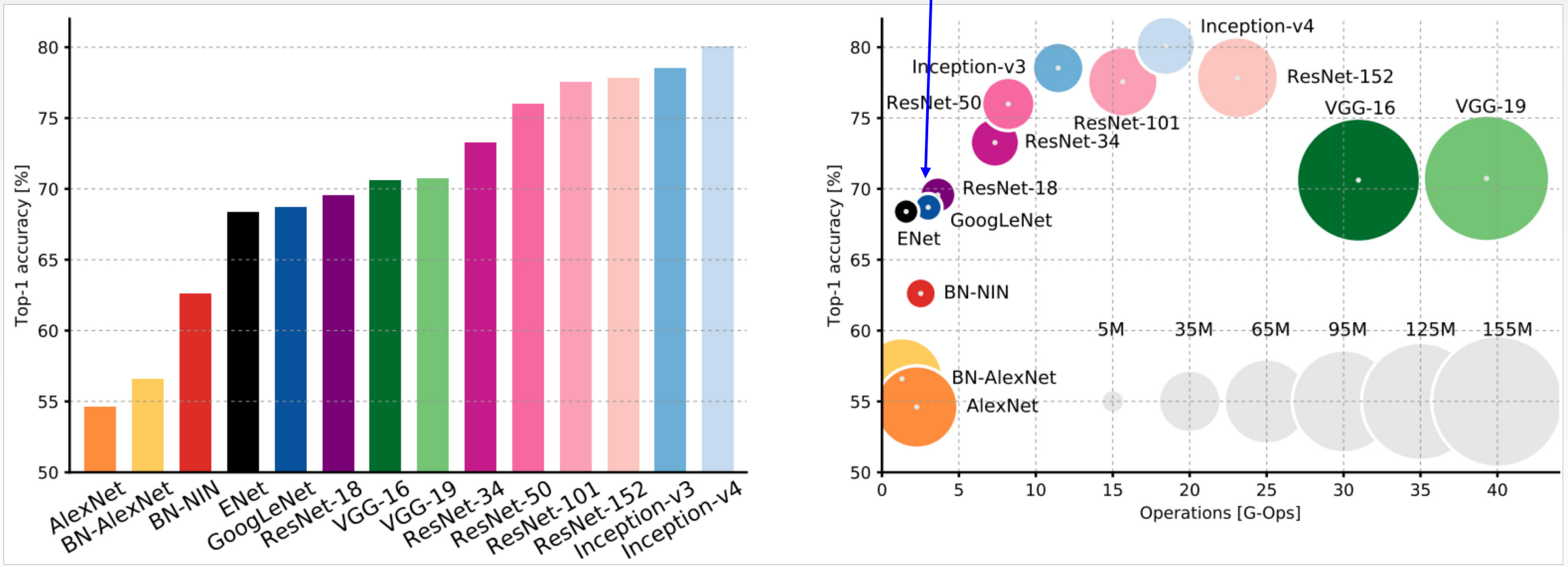
COMPARING COMPLEXITY

VGG: Highest memory, most operations



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

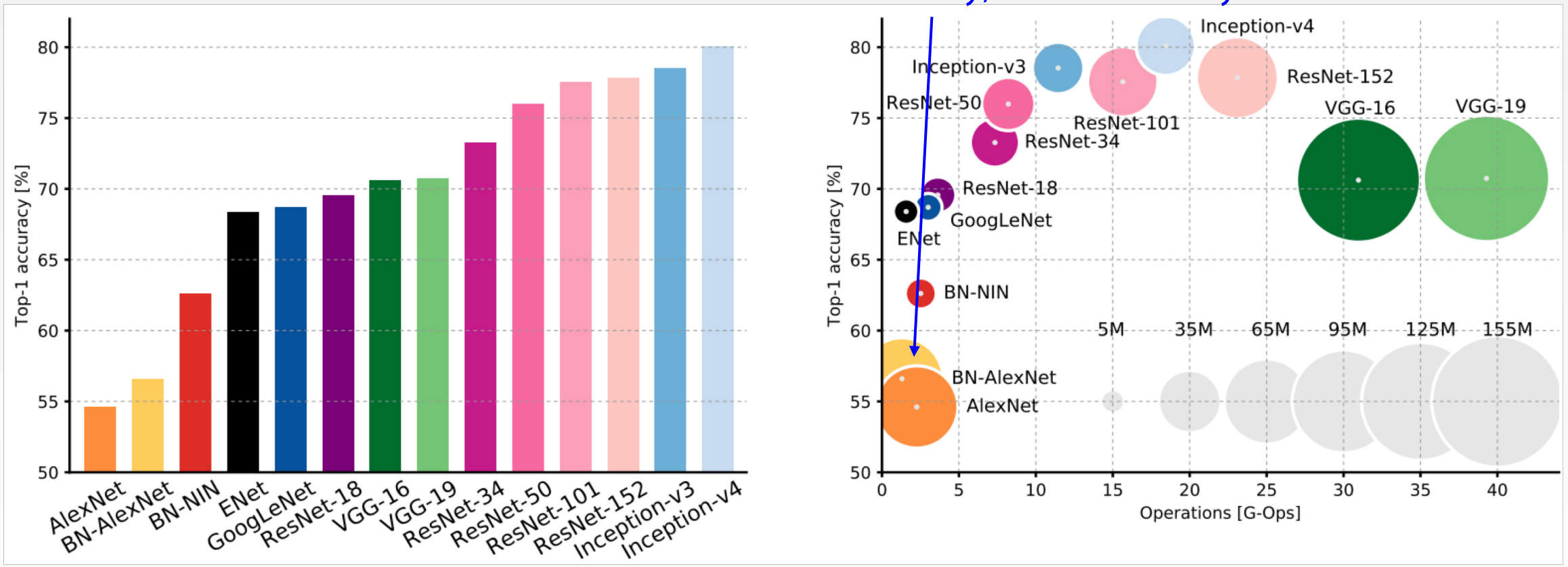
COMPARING COMPLEXITY



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

COMPARING COMPLEXITY

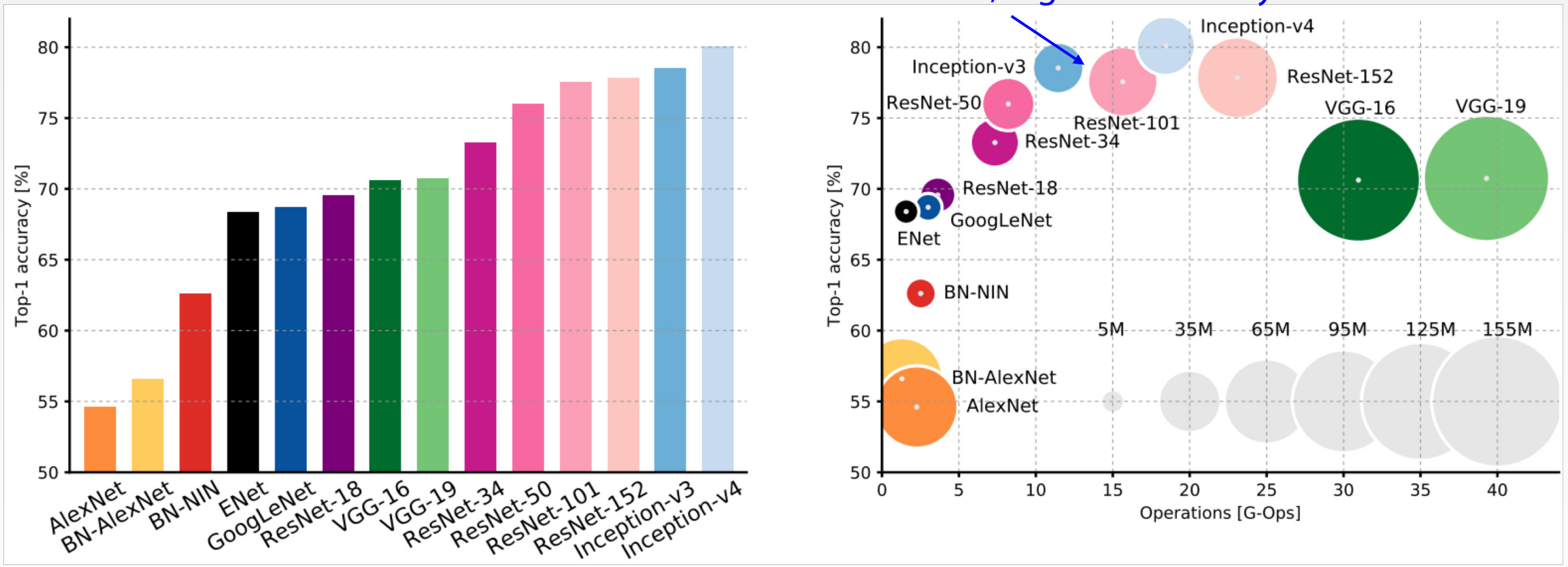
AlexNet:
Smaller compute, still memory heavy, lower accuracy



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

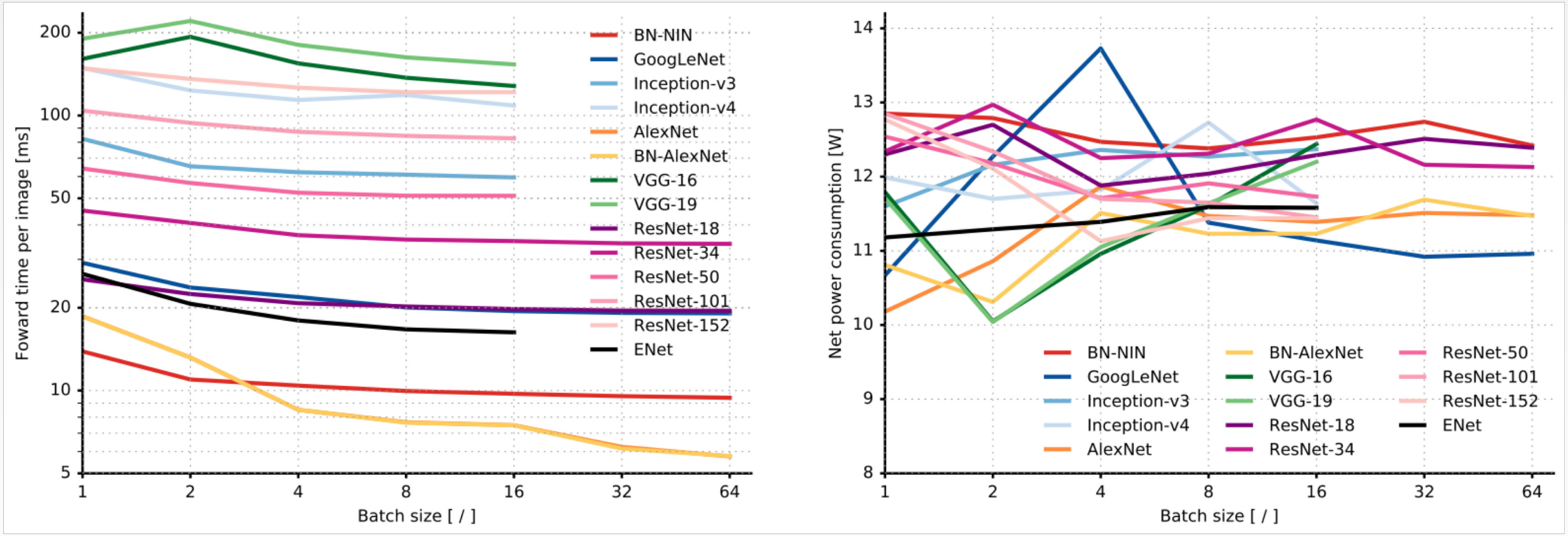
COMPARING COMPLEXITY

ResNet:
Moderate efficiency depending on model, highest accuracy



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

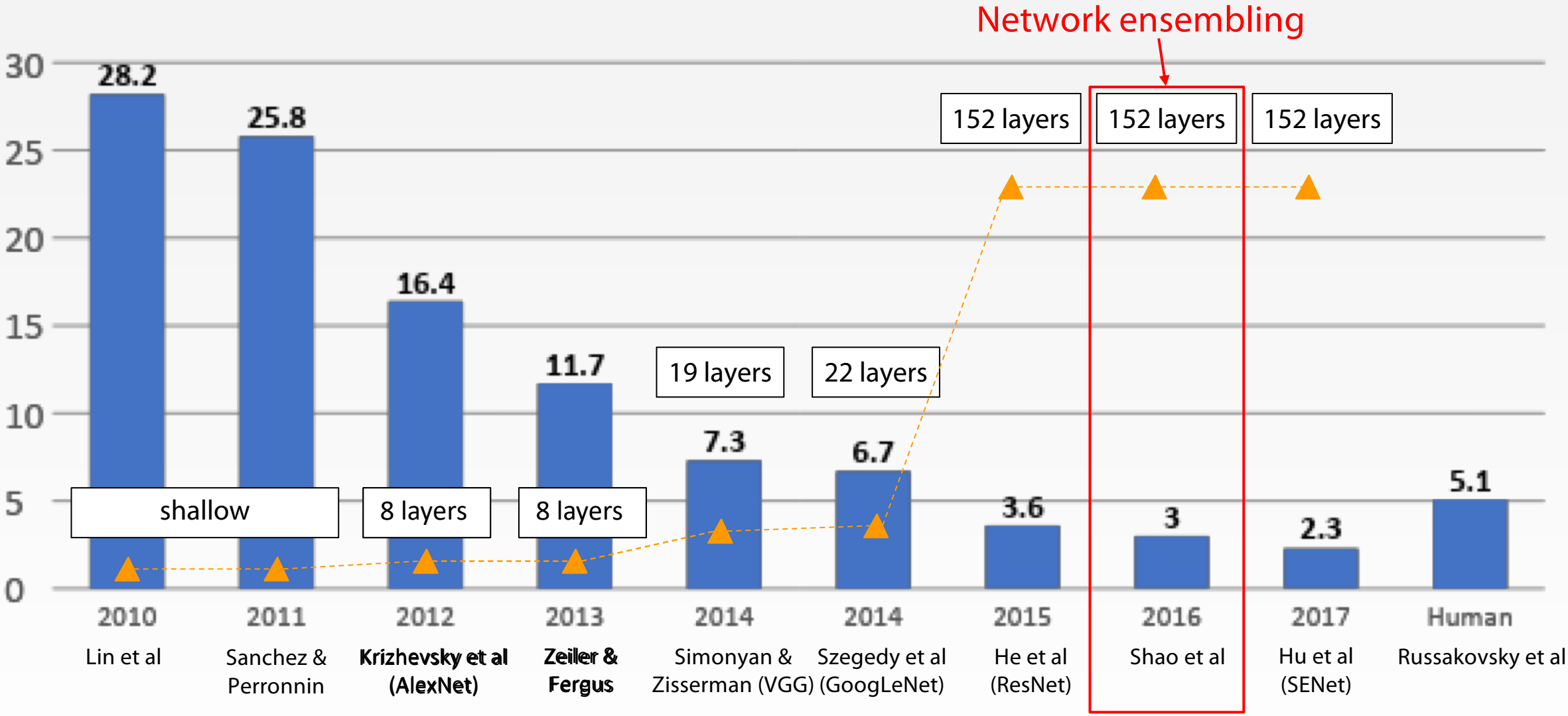
FORWARD PASS TIME AND POWER CONSUMPTION



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

IMPROVING RESNETS

IMAGENET LARGE SCALE VISUAL RECOGNITION CHALLENGE (ILSVRC) WINNERS



IMPROVING RESNETS...

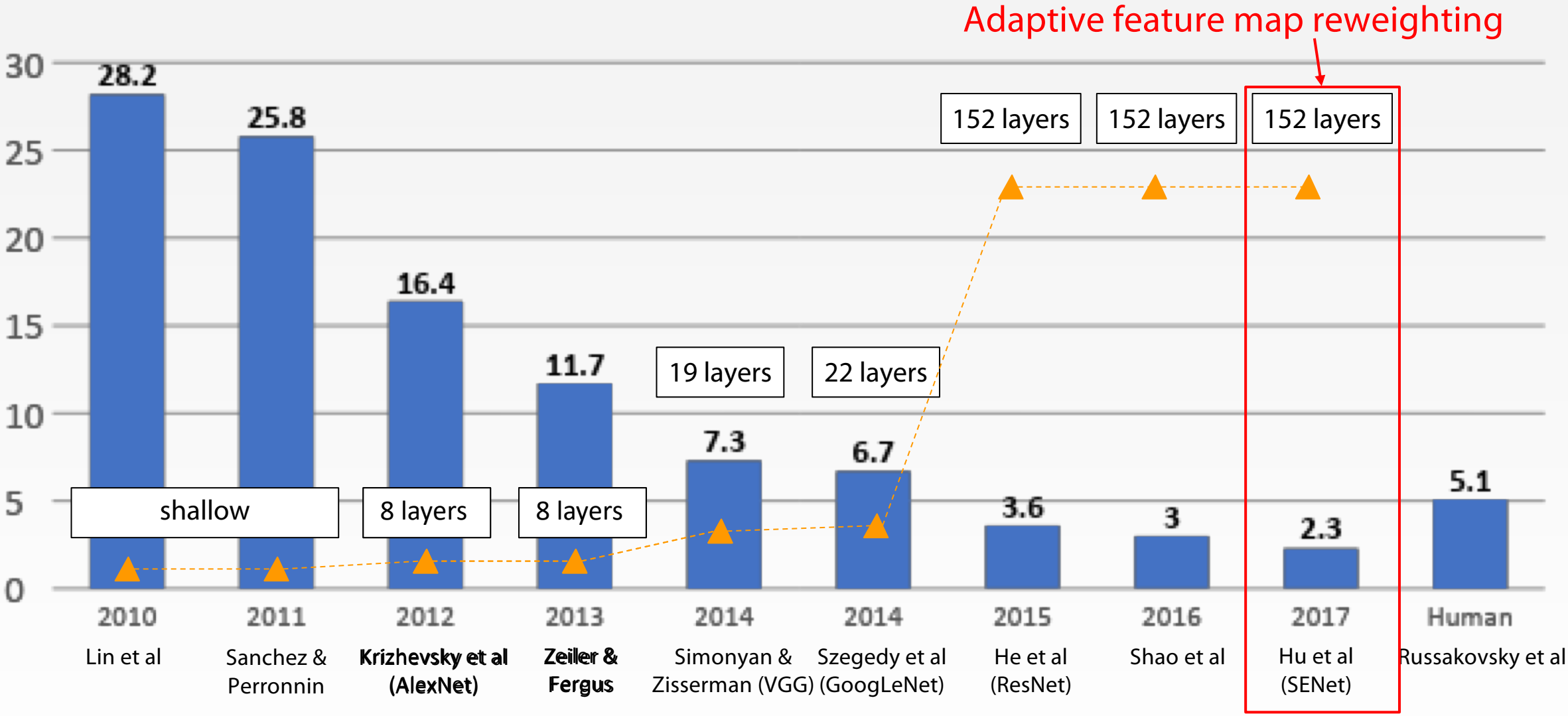
"GOOD PRACTICES FOR DEEP FEATURE FUSION"

[Shao et al. 2016]

- Multi-scale ensembling of Inception, Inception-Resnet, Resnet, Wide Resnet models
- ILSVRC'16 classification winner

	Inception-v3	Inception-v4	Inception-Resnet-v2	Resnet-200	Wrn-68-3	Fusion（Val.）	Fusion（Test）
Err. (%)	4.20	4.01	3.52	4.26	4.65	2.92 (-0.6)	2.99

IMAGENET LARGE SCALE VISUAL RECOGNITION CHALLENGE (ILSVRC) WINNERS

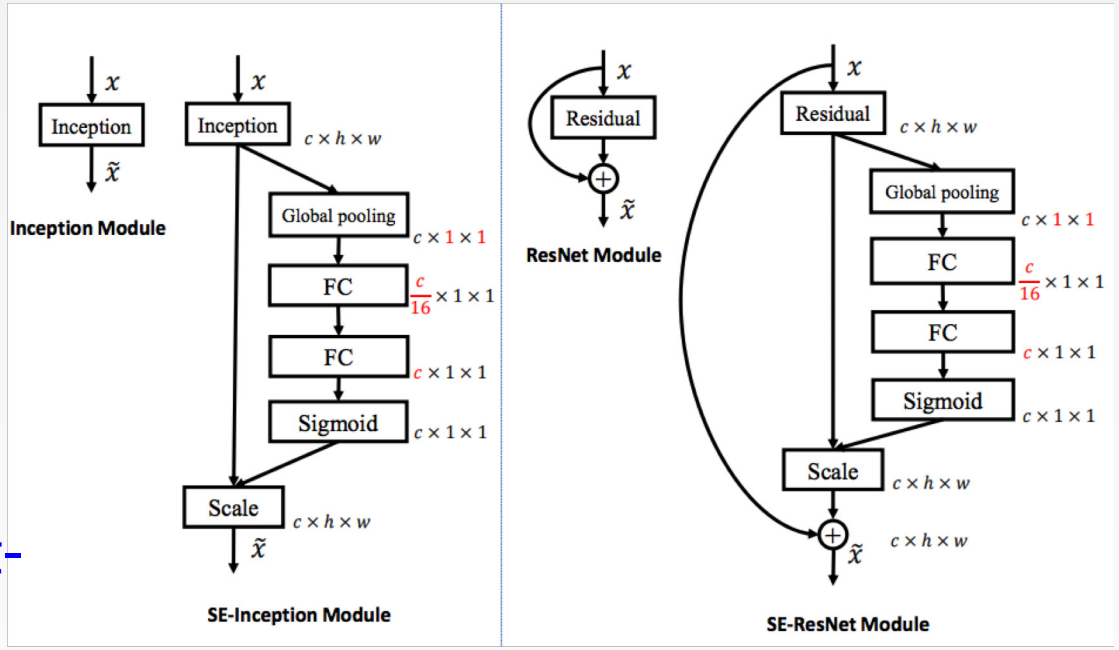


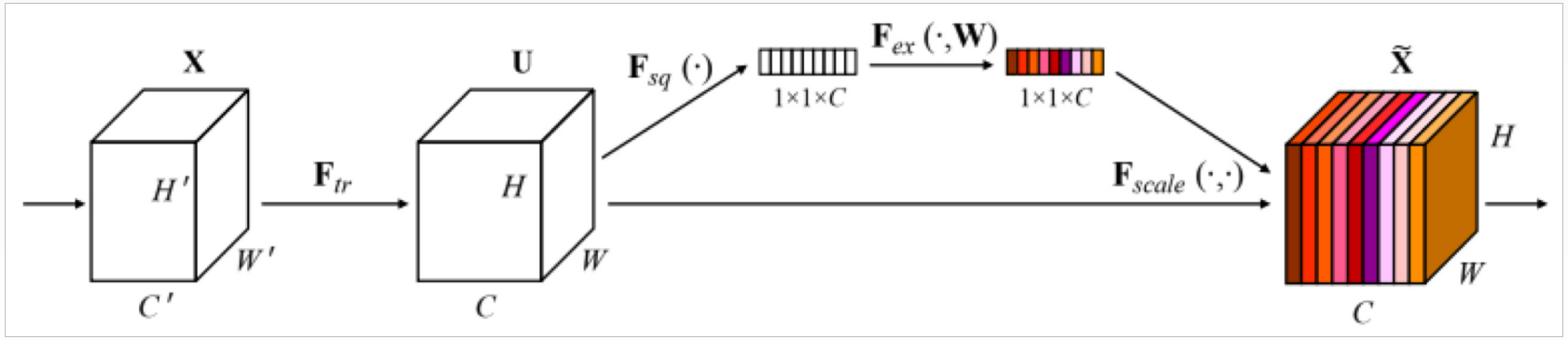
IMPROVING RESNETS...

SQUEEZE-AND-EXCITATION NETWORKS (SENET)

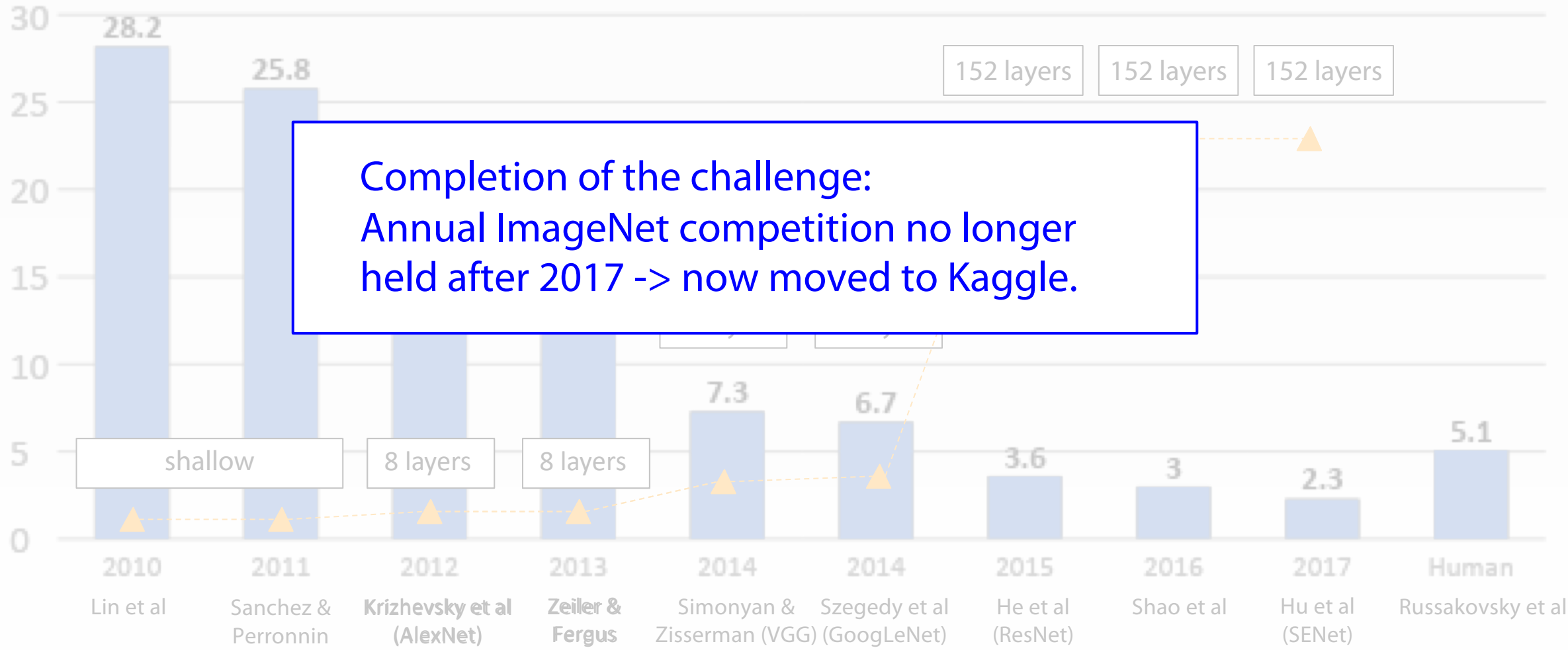
[Hu et al. 2017]

- Add a "feature recalibration" module that learns to **adaptively reweight feature maps**
- Global information (global avg. pooling layer) + 2 FC layers used to determine feature map weights
- ILSVRC'17 classification winner (using ResNeXt-152 as a base architecture)





IMAGENET LARGE SCALE VISUAL RECOGNITION CHALLENGE (ILSVRC) WINNERS



Completion of the challenge:
Annual ImageNet competition no longer held after 2017 -> now moved to Kaggle.

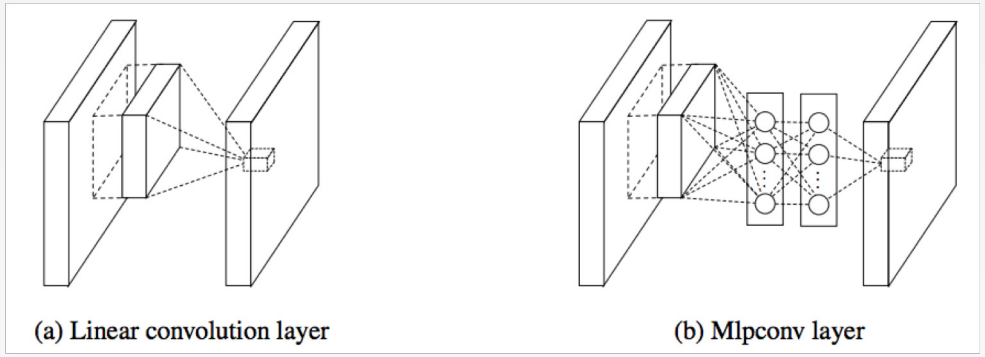
BUT RESEARCH INTO CNN ARCHITECTURES IS STILL FLOURISHING

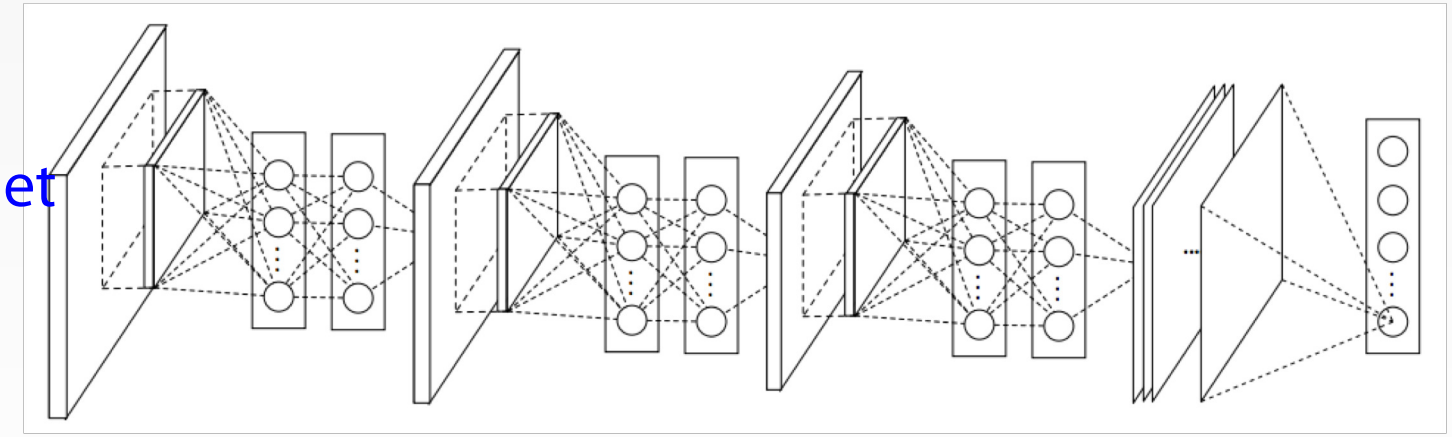
OF HISTORICAL NOTE...

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
- Precursor to GoogLeNet and ResNet "bottleneck" layers
- Philosophical inspiration for GoogLeNet





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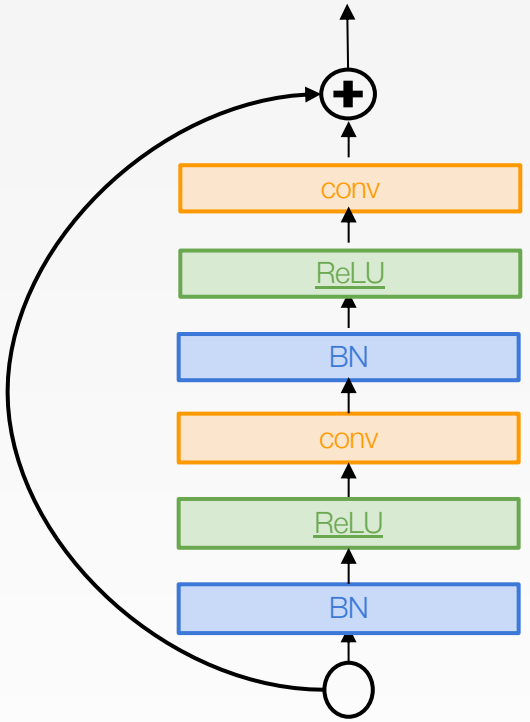
IDENTITY MAPPINGS IN DEEP RESIDUAL NETWORKS

[He et al. 2016]

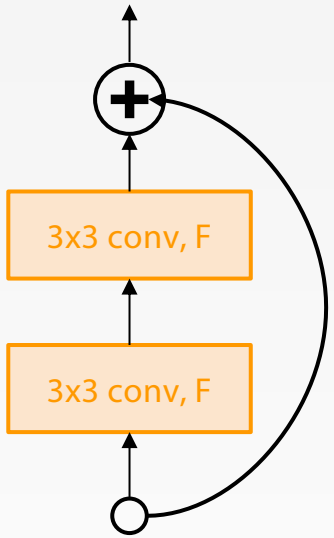
- Improved ResNet block design from creators of ResNet
- Creates a more direct path for propagating information throughout network (moves activation to residual mapping pathway)
- Gives better performance



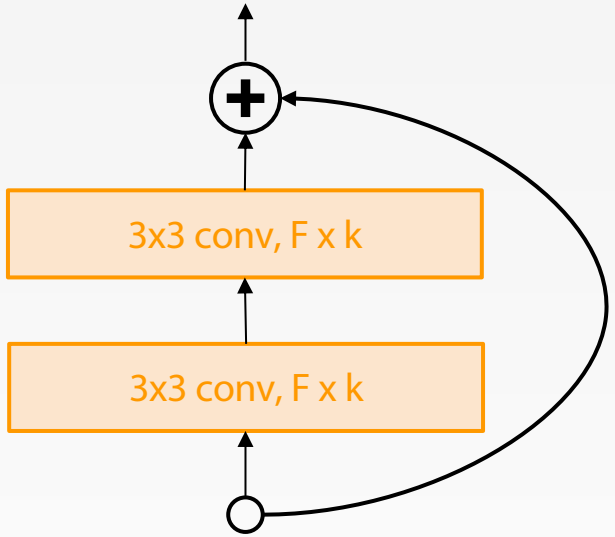
WIDE RESIDUAL NETWORKS

[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)



Basic residual block



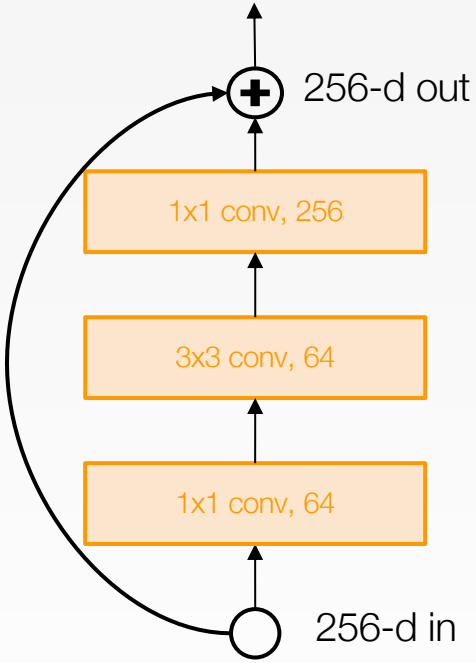
Wide residual block

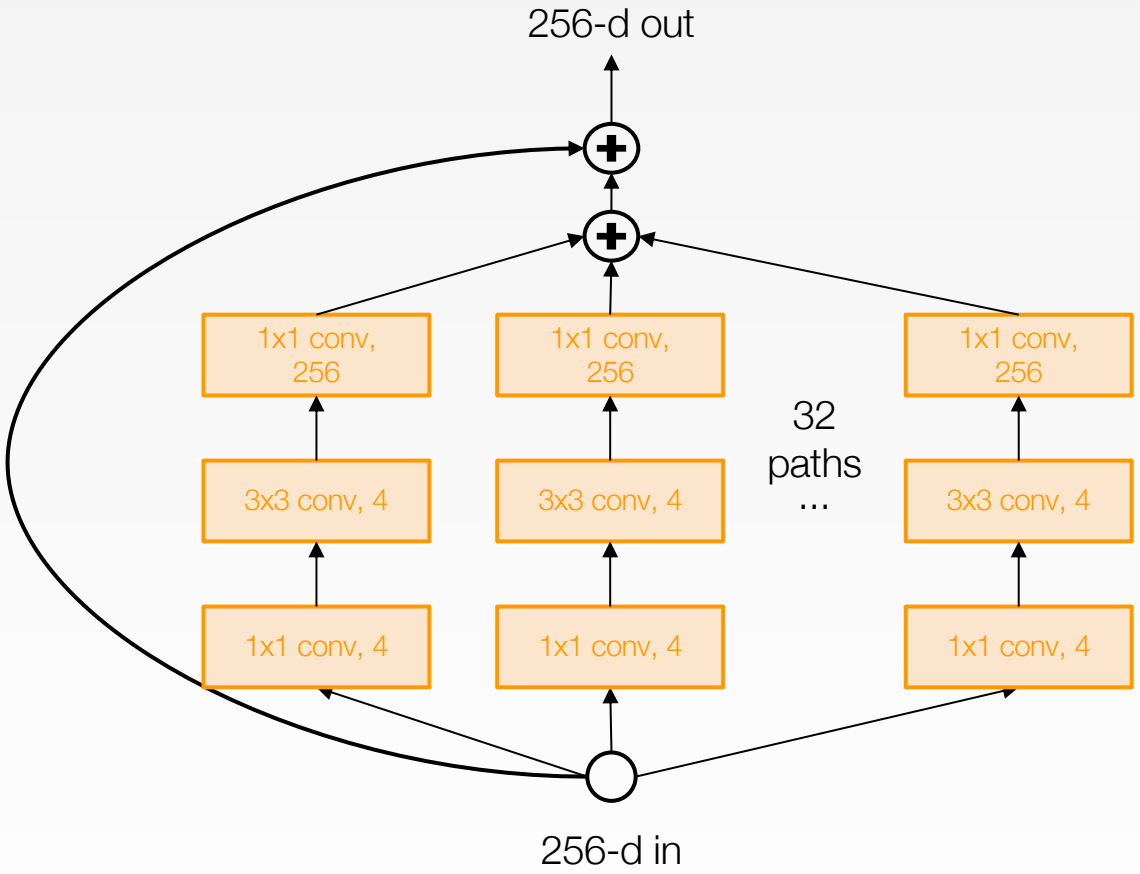
IMPROVING RESNETS...

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



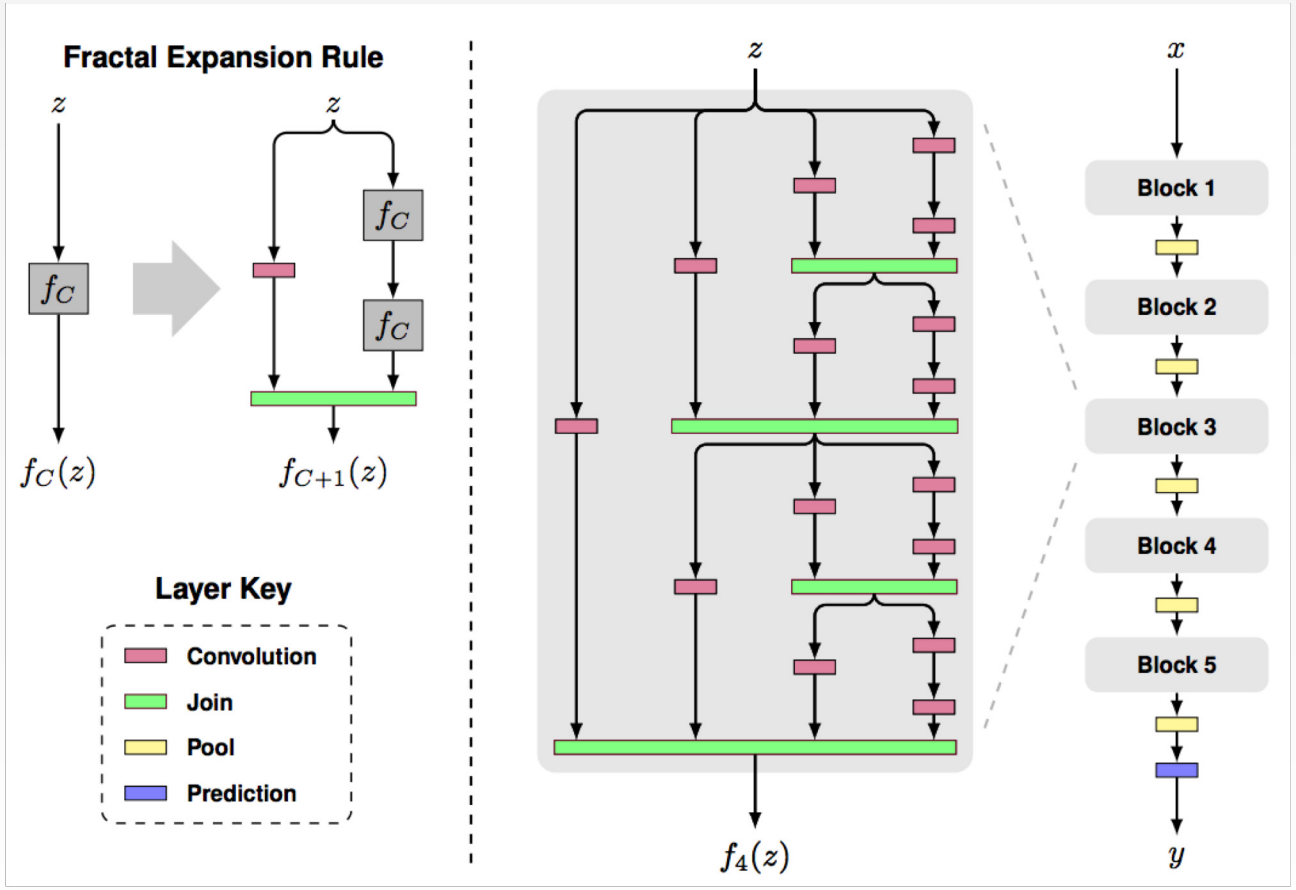


OTHER IDEAS...

FRACTALNET: ULTRA-DEEP NEURAL NETWORKS WITHOUT RESIDUALS

[Larsson et al. 2017]

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



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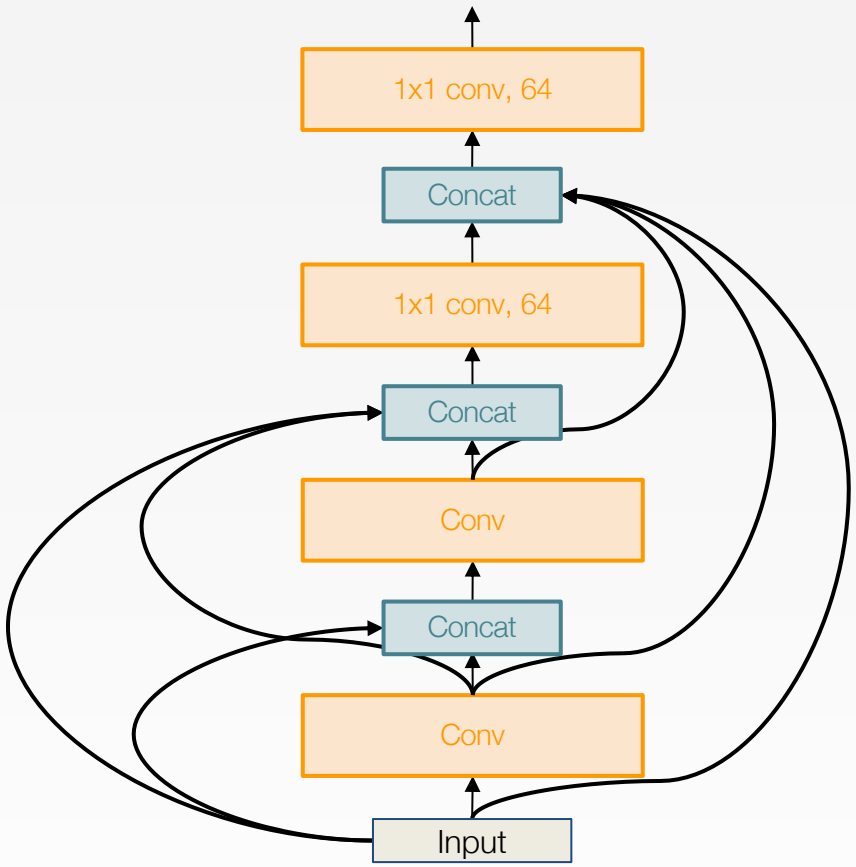
OTHER IDEAS...

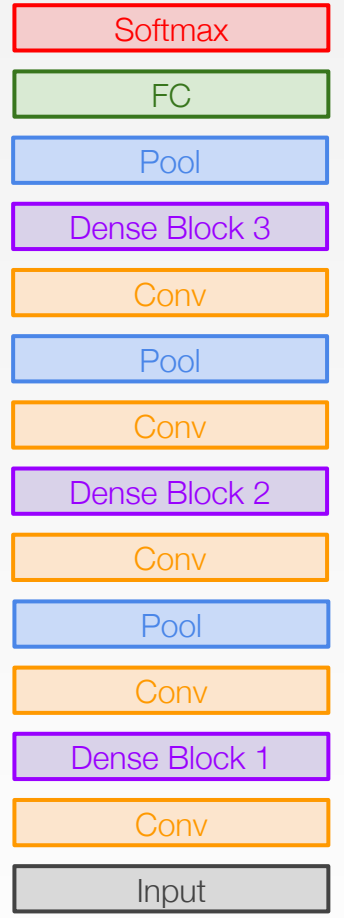
DENSELY CONNECTED CONVOLUTIONAL NETWORKS

[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

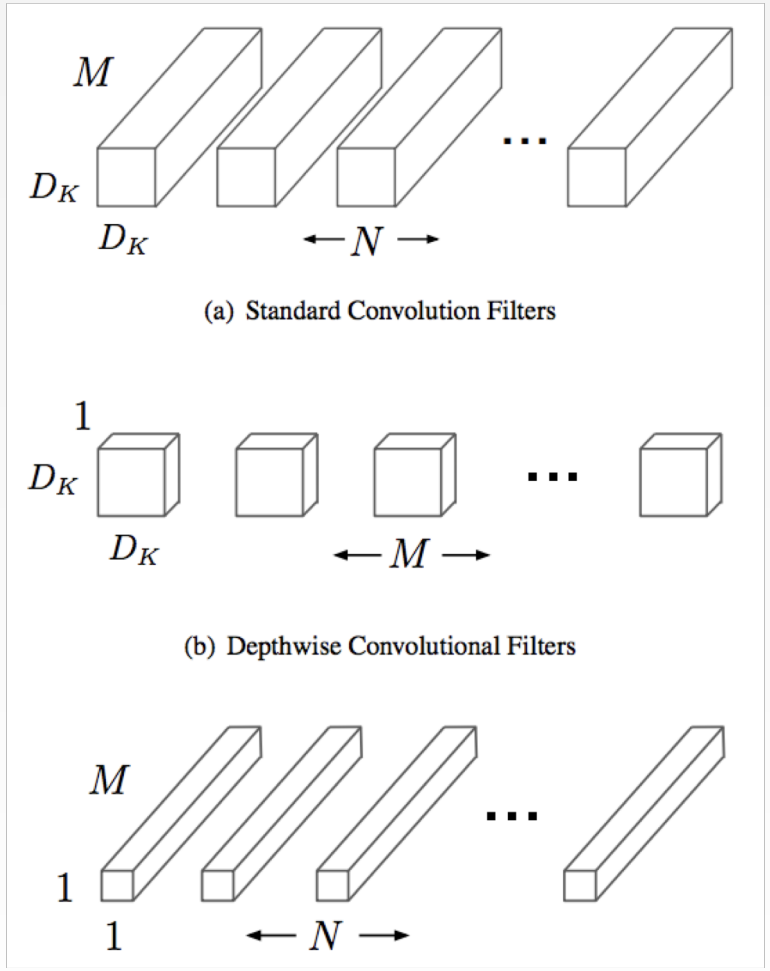


EFFICIENT NETWORKS...

MOBILENETS: EFFICIENT CONVOLUTIONAL NEURAL NETWORKS FOR MOBILE APPLICATIONS

[Howard et al. 2017]

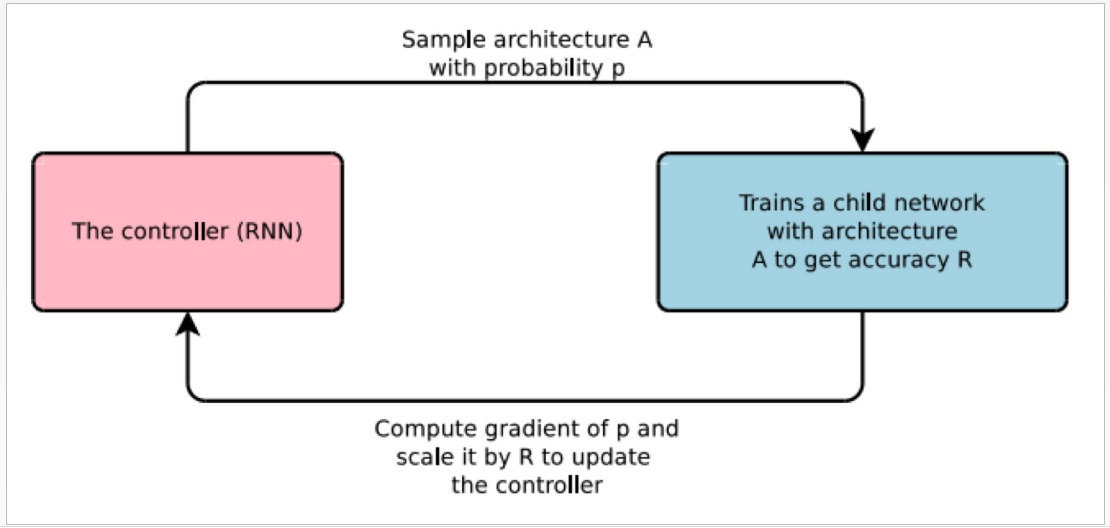
- Depthwise separable convolutions replace standard convolutions by factorizing them into a depthwise convolution and a 1x1 convolution that is much more efficient
- Much more efficient, with little loss in accuracy
- Follow-up MobileNetV2 work in 2018 (Sandler et al.)
- Other works in this space e.g. ShuffleNet (Zhang et al. 2017)

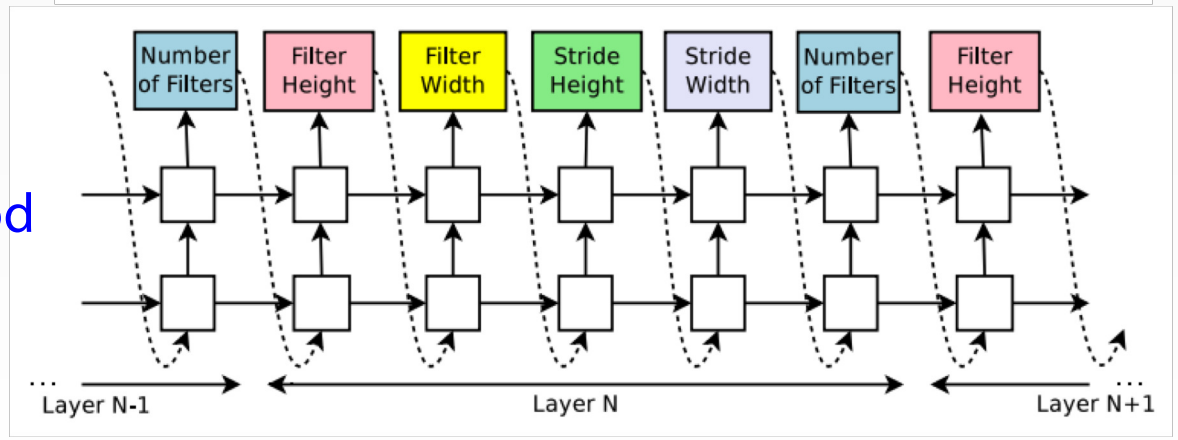


META-LEARNING: LEARNING TO LEARN NETWORK ARCHITECTURES... NEURAL ARCHITECTURE SEARCH WITH REINFORCEMENT LEARNING (NAS)

[Zoph et al. 2016]

- "Controller" network that learns to design a good network architecture (output a string corresponding to network design)
- Iterate:
  - Sample an architecture from search space
  - Train the architecture to get a "reward" R corresponding to accuracy
  - Compute gradient of sample probability, and scale by R to **perform controller parameter update** (i.e. increase likelihood of good architecture being sampled, decrease likelihood of bad architecture)



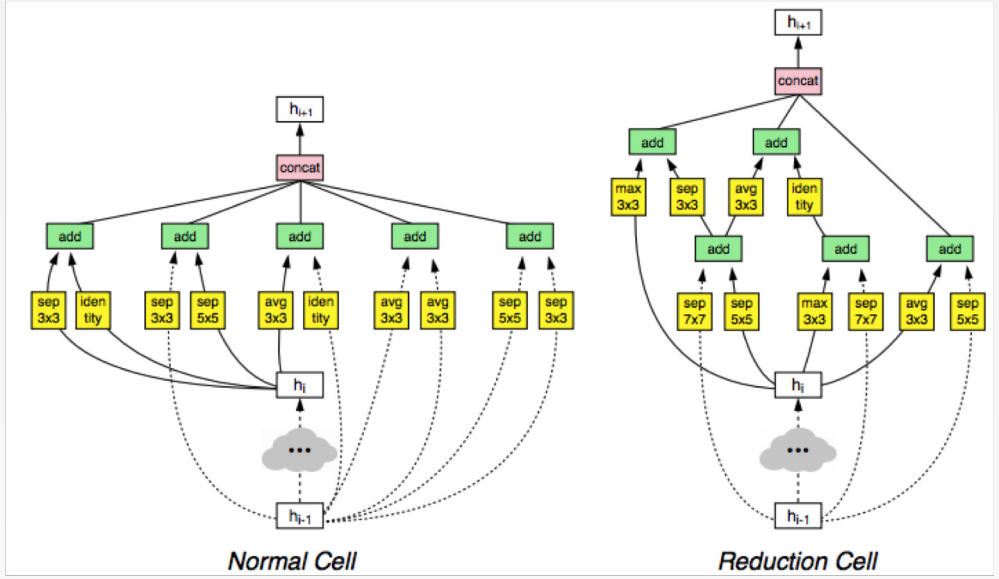


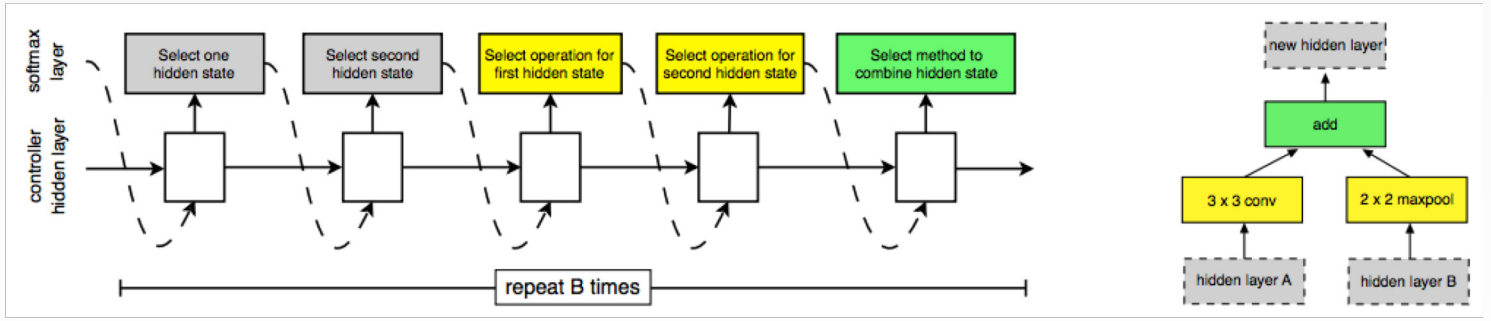
META-LEARNING: LEARNING TO LEARN NETWORK ARCHITECTURES...

LEARNING TRANSFERABLE ARCHITECTURES FOR SCALABLE IMAGE RECOGNITION

[Zoph et al. 2017]

- Applying neural architecture search (NAS) to a large dataset like ImageNet is expensive
- Design a **search space of building blocks** ("cells") that can be flexibly stacked
- NASNet: Use NAS to **find best cell structure on smaller CIFAR-10 dataset, then transfer architecture to ImageNet**
- Many follow-up works in this space e.g. AmoebaNet (Real et al. 2019) and ENAS (Pham, Guan et al. 2018)





SUMMARY: CNN ARCHITECTURES

Case Studies

- AlexNet
- VGG
- GoogLeNet
- ResNet

Also....

- SENet
- NiN (Network in Network)
- Wide ResNet
- ResNeXT
- DenseNet
- FractalNet
- MobileNets
- NASNet

SUMMARY: CNN ARCHITECTURES

- Many popular architectures available in model zoos
- ResNet and SENet currently good defaults to use
- Networks have gotten increasingly deep over time
- Many other aspects of network architectures are also continuously being investigated and improved
- Even more recent trend towards meta-learning
- Next time: Recurrent neural networks