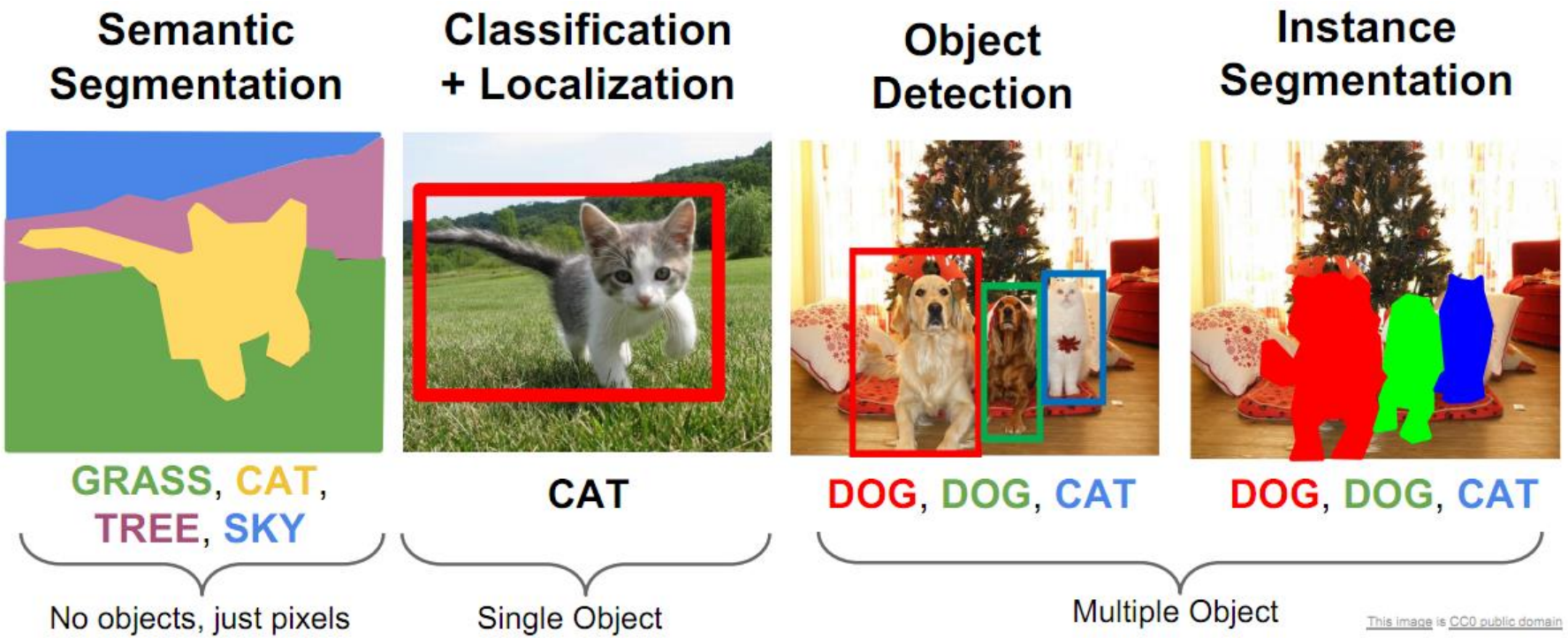
Lecture 12. Typical CNNs

Outline

- Introduction to DL and CNNs
- LeNet-5
- AlexNet
- VGG
- GoogleNet
- ResNet

Computer Vision Tasks



Objectives

- We will examine classic CNN architectures with the goal of:
  - Gaining intuition for building CNNs
  - Reusing CNN architectures

LeNet-5

- *Gradient Based Learning Applied To Document Recognition - Y. Lecun, L. Bottou, Y. Bengio, P. Haffner; 1998*
- Helped establish how we use CNNs today
- Replaced manual feature extraction

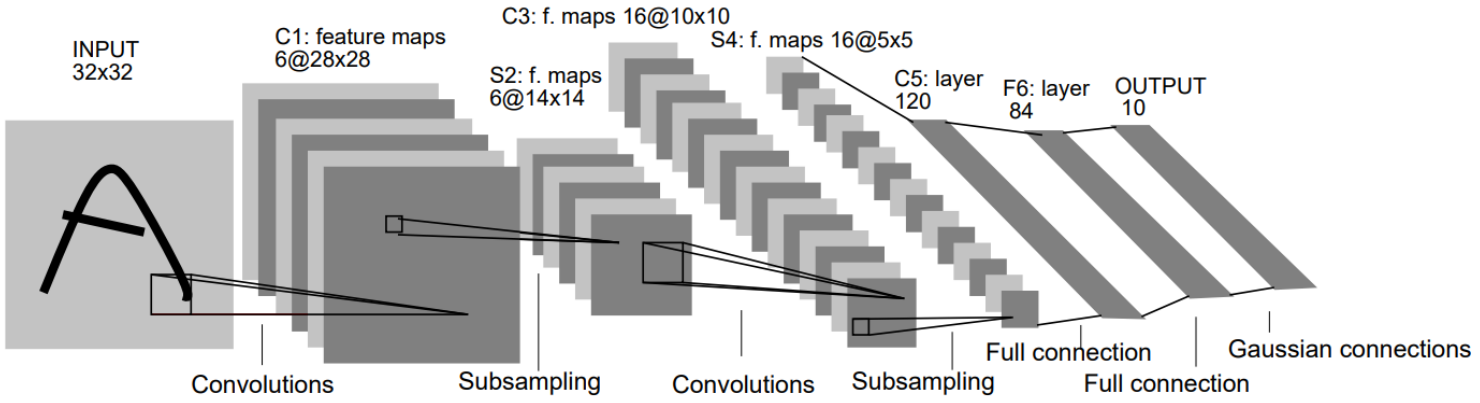
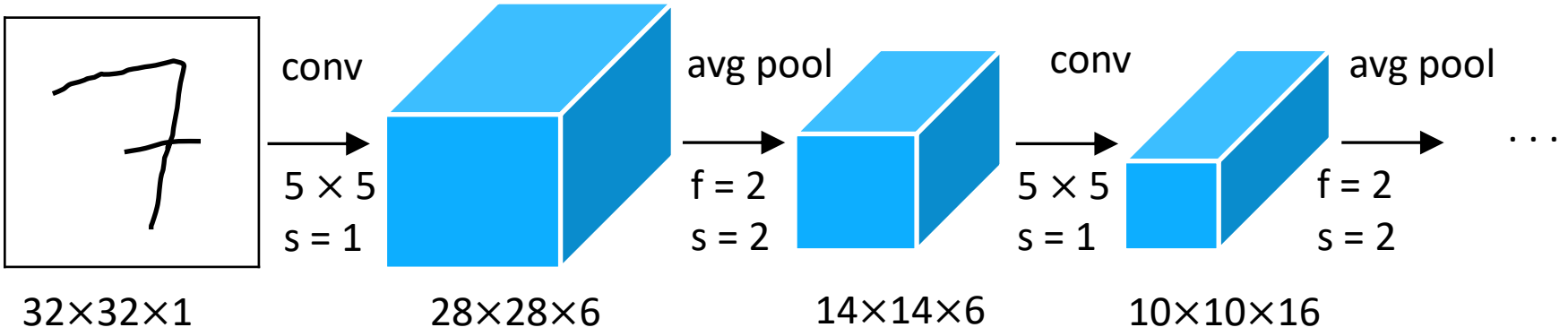
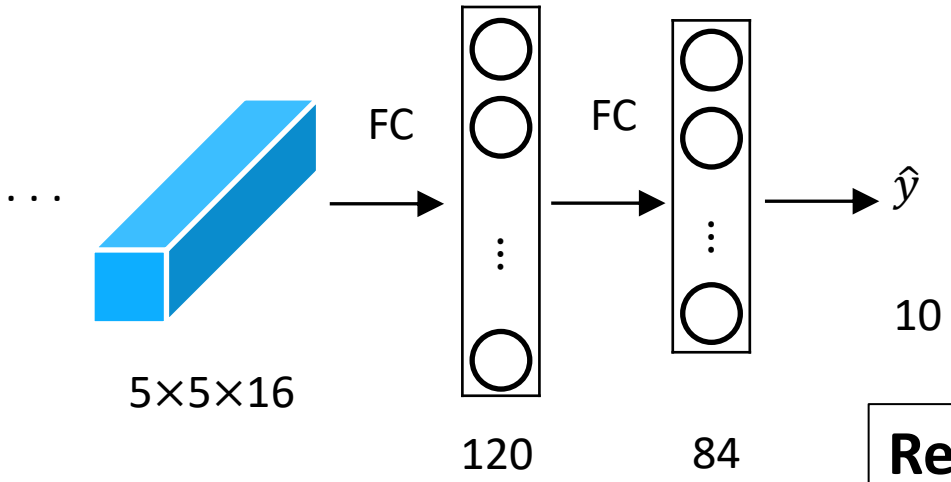


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

[LeCun et al., 1998]

LeNet-5

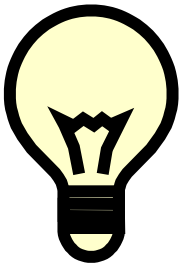




Reminder:
Output size = (N+2P-F)/stride + 1

This slide is taken from Andrew Ng

[LeCun et al., 1998]



LeNet-5

- Only 60K parameters
- As we go deeper in the network: $N_H \downarrow,\ N_W \downarrow,\ N_C \uparrow$
- General structure:
  conv->pool->conv->pool->FC->FC->output

- Different filters look at different channels
- Sigmoid and Tanh nonlinearity

[**LeCun et al., 1998**]

AlexNet

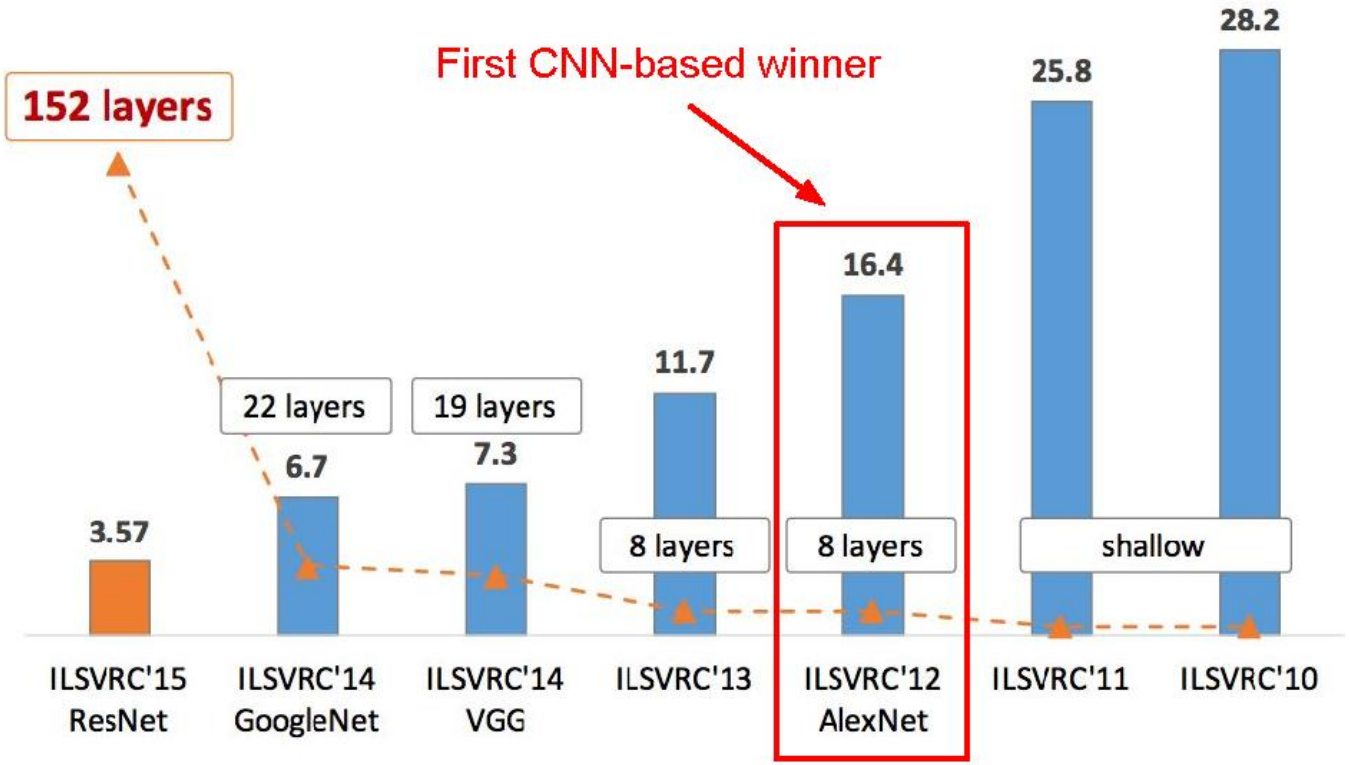
- *ImageNet Classification with Deep Convolutional Neural Networks - Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton; 2012*
- Facilitated by GPUs, highly optimized convolution implementation and large datasets (ImageNet)
- One of the largest CNNs to date
- Has 60 Million parameter compared to 60k parameter of LeNet-5

[**Krizhevsky et al.**, **2012**]

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

- The annual “Olympics” of computer vision.
- Teams from across the world compete to see who has the best computer vision model for tasks such as classification, localization, detection, and more.
- **2012** marked **the first year where a CNN was used** to achieve a top 5 test error rate of 15.3%.
- The next best entry achieved an error of 26.2%.

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

AlexNet

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

- Input: 227x227x3 images (224x224 before padding)
- First layer: 96 11x11 filters applied at stride 4

- **Output volume size?**

  (N-F)/s+1 = (227-11)/4+1 = 55 -> [55x55x96]

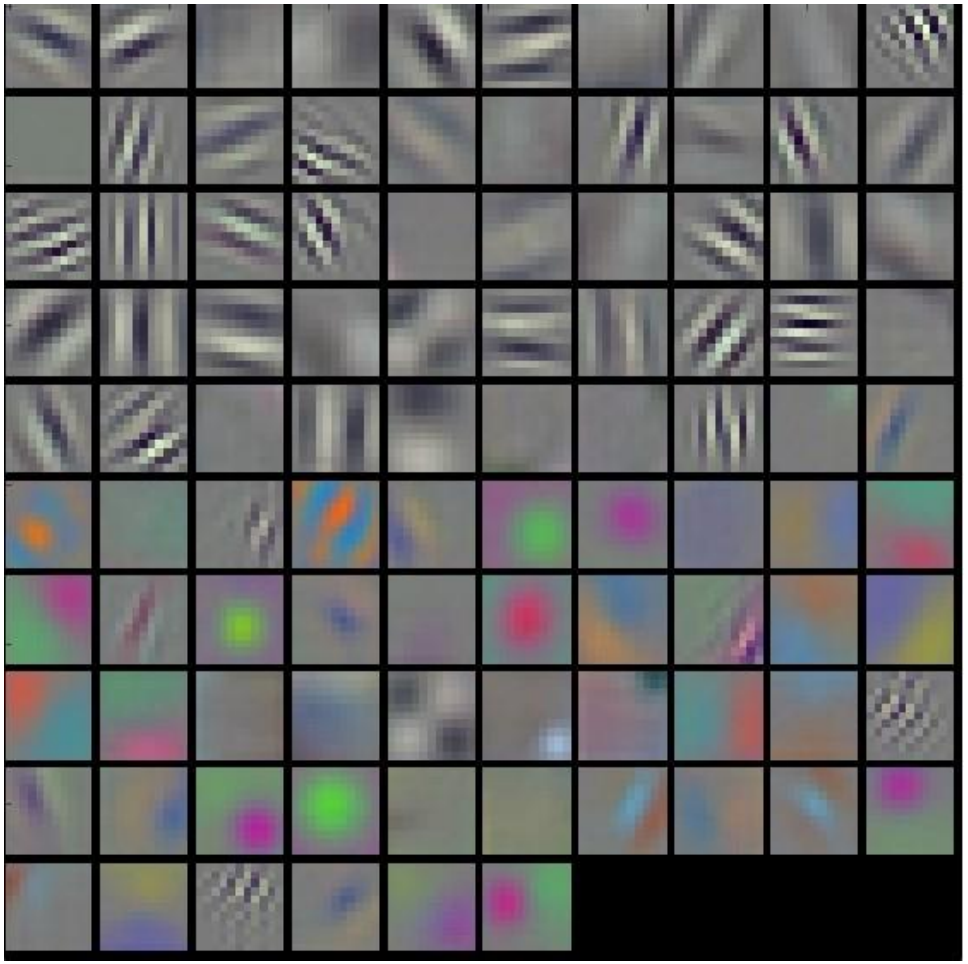
- **Number of parameters in this layer?**

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

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Krizhevsky et al., 2012]

AlexNet



[**Krizhevsky et al.**, **2012**]

AlexNet

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

- Input: 227x227x3 images (224x224 before padding)
- After CONV1: 55x55x96
- Second layer: 3x3 filters applied at stride 2

- **Output volume size?**

  (N-F)/s+1 = (55-3)/2+1 = 27 -> [27x27x96]

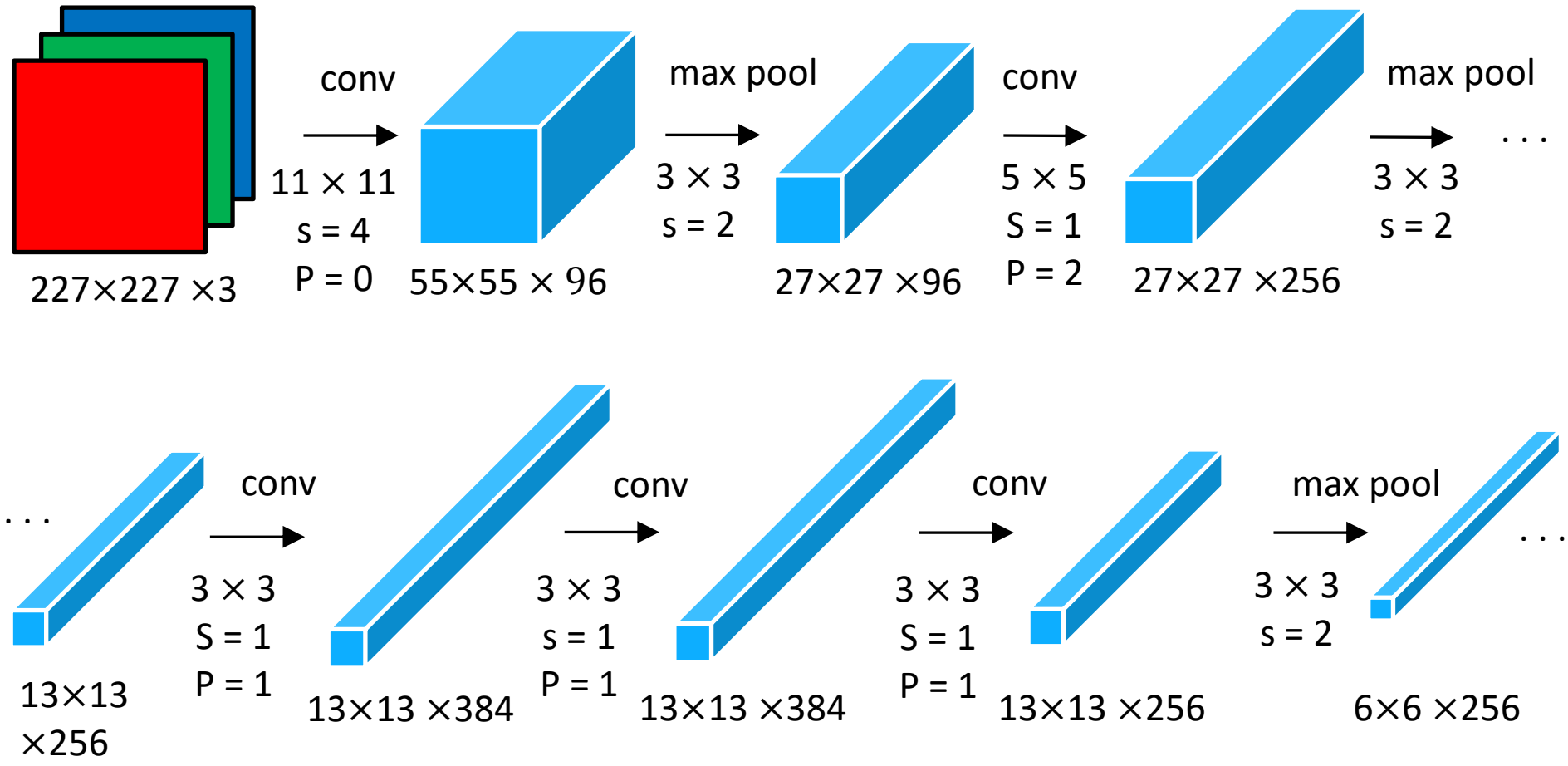
- **Number of parameters in this layer?**

  0!

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Krizhevsky et al., 2012]

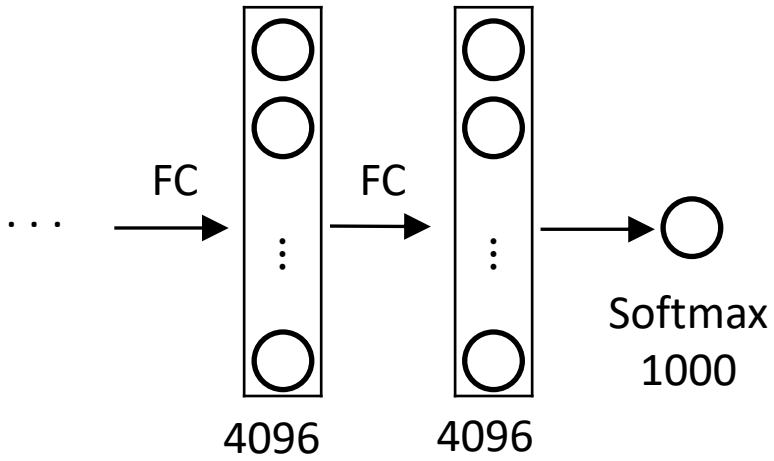
AlexNet



This slide is taken from Andrew Ng

[Krizhevsky et al., 2012]

AlexNet



This slide is taken from Andrew Ng

[**Krizhevsky et al.**, **2012**]

AlexNet

Details/Retrospectives:

- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- 7 CNN ensemble

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

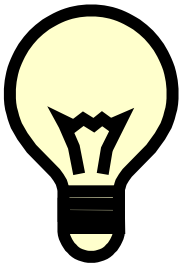
[**Krizhevsky et al.**, **2012**]

AlexNet

- Trained on GTX 580 GPU with only 3 GB of memory.
- Network spread across 2 GPUs, half the neurons (feature maps) on each GPU.
- CONV1, CONV2, CONV4, CONV5:
  Connections only with feature maps on same GPU.
- CONV3, FC6, FC7, FC8:
  Connections with all feature maps in preceding layer, communication across GPUs.

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[**Krizhevsky et al.**, **2012**]

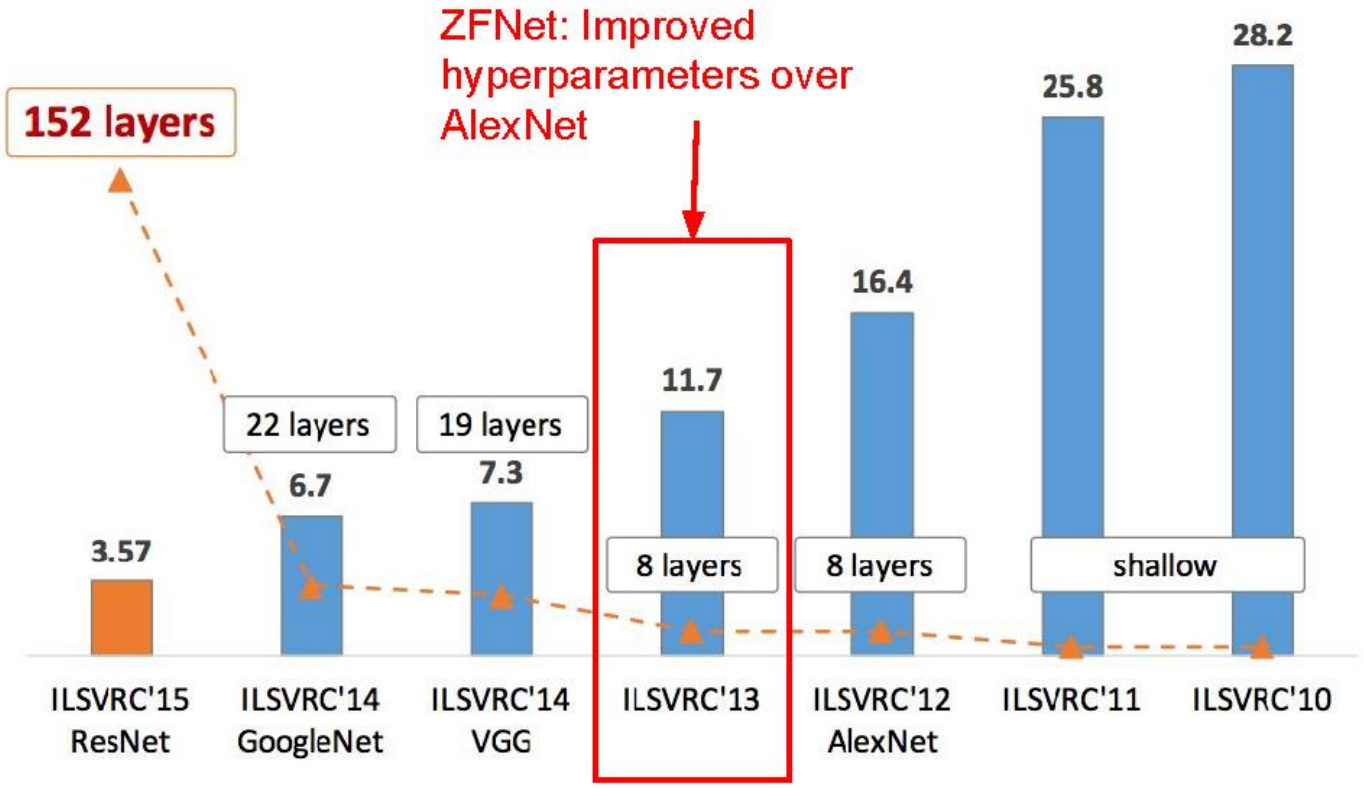


AlexNet

AlexNet was the coming out party for CNNs in the computer vision community. This was **the first time a model performed so well on a historically difficult ImageNet dataset**. This paper illustrated the benefits of CNNs and backed them up with record breaking performance in the competition.

[**Krizhevsky et al.**, **2012**]

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



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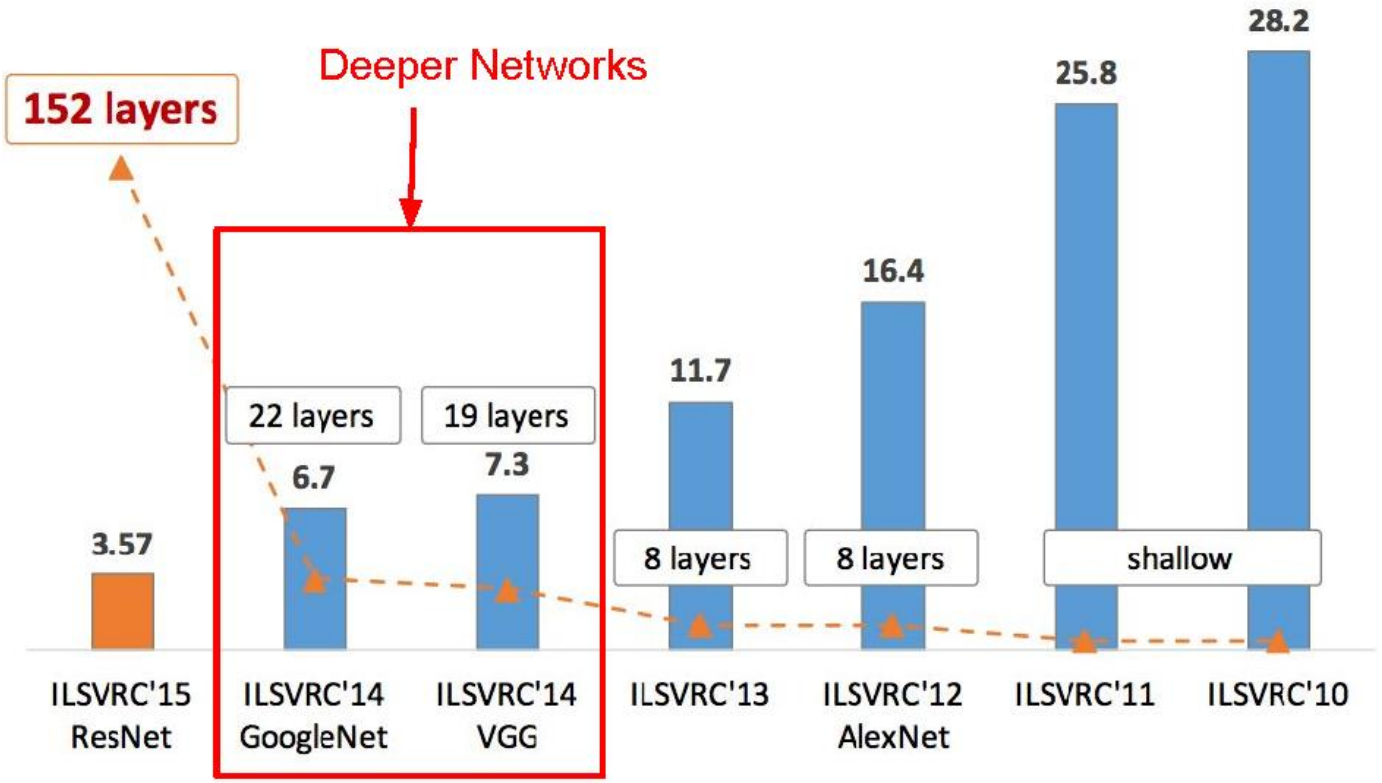
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

VGGNet

- *Very Deep Convolutional Networks For Large Scale Image Recognition - Karen Simonyan and Andrew Zisserman; 2015*
- The runner-up at the ILSVRC 2014 competition
- Significantly deeper than AlexNet
- 140 million parameters

[Simonyan and Zisserman, 2014]

Input
3x3 conv, 64
3x3 conv, 64
Pool 1/2
3x3 conv, 128
3x3 conv, 128
Pool 1/2
3x3 conv, 256
3x3 conv, 256
Pool 1/2
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool 1/2
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool 1/2
FC 4096
FC 4096
FC 1000
Softmax

VGGNet

- **Smaller filters**
  Only 3x3 CONV filters, stride 1, pad 1
  and 2x2 MAX POOL , stride 2

- **Deeper network**
  AlexNet: 8 layers
  VGGNet: 16 - 19 layers

- ZFNet: 11.7% top 5 error in ILSVRC'13
- VGGNet: 7.3% top 5 error in ILSVRC'14

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Simonyan and Zisserman, 2014]

VGGNet

- **Why use smaller filters? (3x3 conv)**

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

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

7x7

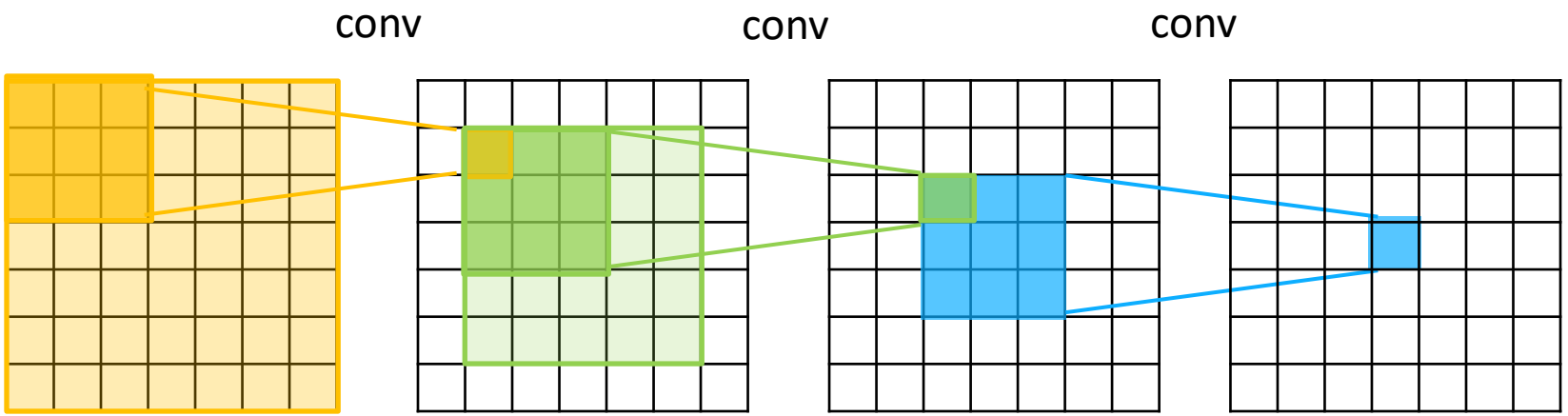
But deeper, more non-linearities

And fewer parameters: 3 * (3^2C^2) vs. 7^2C^2 for C channels per layer

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Simonyan and Zisserman, 2014]

Reminder: Receptive Field



Input	memory: 224*224*3=150K	params: 0
3x3 conv, 64	memory: 224*224*64=3.2M	params: (3*3*3)*64 = 1,728
3x3 conv, 64	memory: 224*224*64=3.2M	params: (3*3*64)*64 = 36,864
Pool	memory: 112*112*64=800K	params: 0
3x3 conv, 128	memory: 112*112*128=1.6M	params: (3*3*64)*128 = 73,728
3x3 conv, 128	memory: 112*112*128=1.6M	params: (3*3*128)*128 = 147,456
Pool	memory: 56*56*128=400K	params: 0
3x3 conv, 256	memory: 56*56*256=800K	params: (3*3*128)*256 = 294,912
3x3 conv, 256	memory: 56*56*256=800K	params: (3*3*256)*256 = 589,824
3x3 conv, 256	memory: 56*56*256=800K	params: (3*3*256)*256 = 589,824
Pool	memory: 28*28*256=200K	params: 0
3x3 conv, 512	memory: 28*28*512=400K	params: (3*3*256)*512 = 1,179,648
3x3 conv, 512	memory: 28*28*512=400K	params: (3*3*512)*512 = 2,359,296
3x3 conv, 512	memory: 28*28*512=400K	params: (3*3*512)*512 = 2,359,296
Pool	memory: 14*14*512=100K	params: 0
3x3 conv, 512	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
3x3 conv, 512	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
3x3 conv, 512	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
Pool	memory: 7*7*512=25K	params: 0
FC 4096	memory: 4096	params: 7*7*512*4096 = 102,760,448
FC 4096	memory: 4096	params: 4096*4096 = 16,777,216
FC 1000	memory: 1000	params: 4096*1000 = 4,096,000

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Simonyan and Zisserman, 2014]

Input
3x3 conv, 64
3x3 conv, 64
Pool
3x3 conv, 128
3x3 conv, 128
Pool
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
Pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool
FC 4096
FC 4096
FC 1000
Softmax

VGGNet

VGG16:

TOTAL memory: 24M * 4 bytes ~= 96MB / image

TOTAL params: 138M parameters

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Simonyan and Zisserman, 2014]

Input	memory: 224*224*3=150K	params: 0
3x3 conv, 64	memory: 224*224*64=3.2M	params: (3*3*3)*64 = 1,728
3x3 conv, 64	memory: 224*224*64=3.2M	params: (3*3*64)*64 = 36,864
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3x3 conv, 512	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
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3x3 conv, 512	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
Pool	memory: 7*7*512=25K	params: 0
FC 4096	memory: 4096	params: 7*7*512*4096 = 102,760,448
FC 4096	memory: 4096	params: 4096*4096 = 16,777,216
FC 1000	memory: 1000	params: 4096*1000 = 4,096,000

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Simonyan and Zisserman, 2014]

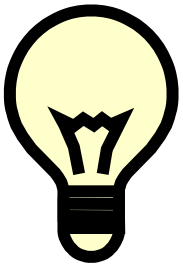
VGGNet

Details/Retrospectives :

- ILSVRC'14 2nd in classification, 1st in localization
- Similar training procedure as AlexNet
- 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
- Trained on 4 Nvidia Titan Black GPUs for **two to three weeks**.

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Simonyan and Zisserman, 2014]



VGGNet

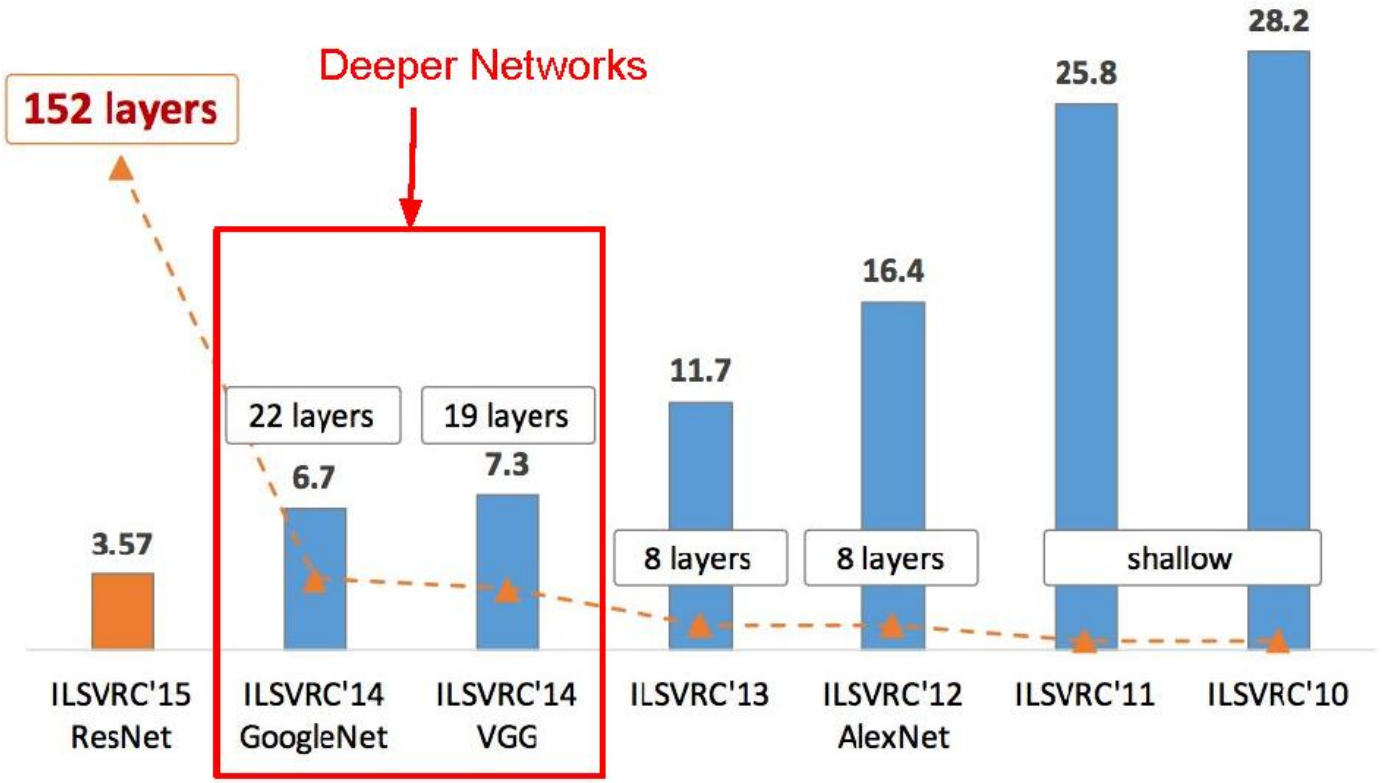
VGG Net reinforced the notion that **convolutional neural networks have to have a deep network of layers in order for this hierarchical representation of visual data to work**.

Keep it deep.

Keep it simple.

[Simonyan and Zisserman, 2014]

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

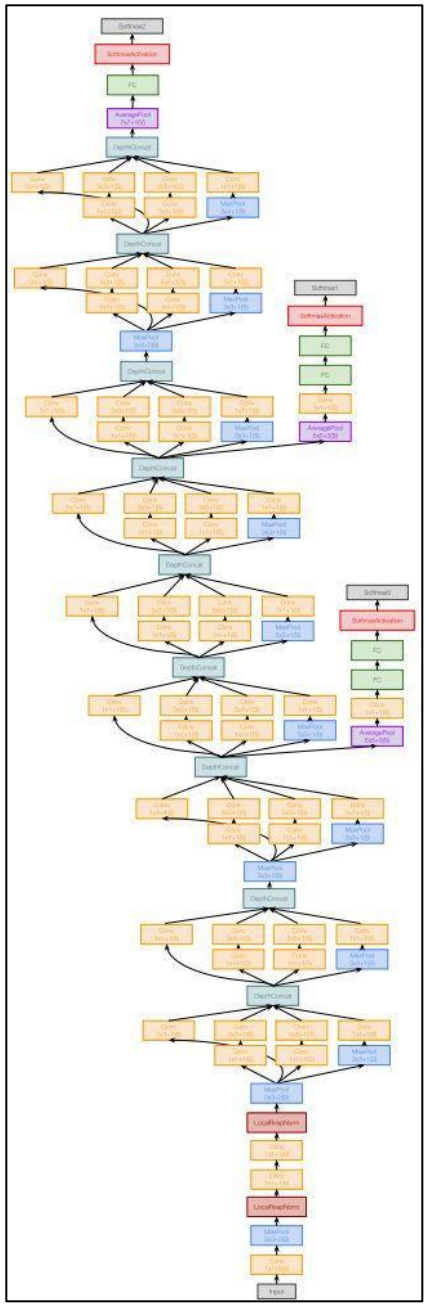


Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

GoogleNet

- *Going Deeper with Convolutions - Christian Szegedy et al.; 2015*
- ILSVRC 2014 competition winner
- Also significantly deeper than AlexNet
- x12 less parameters than AlexNet
- Focused on computational efficiency

[Szegedy et al., 2014]



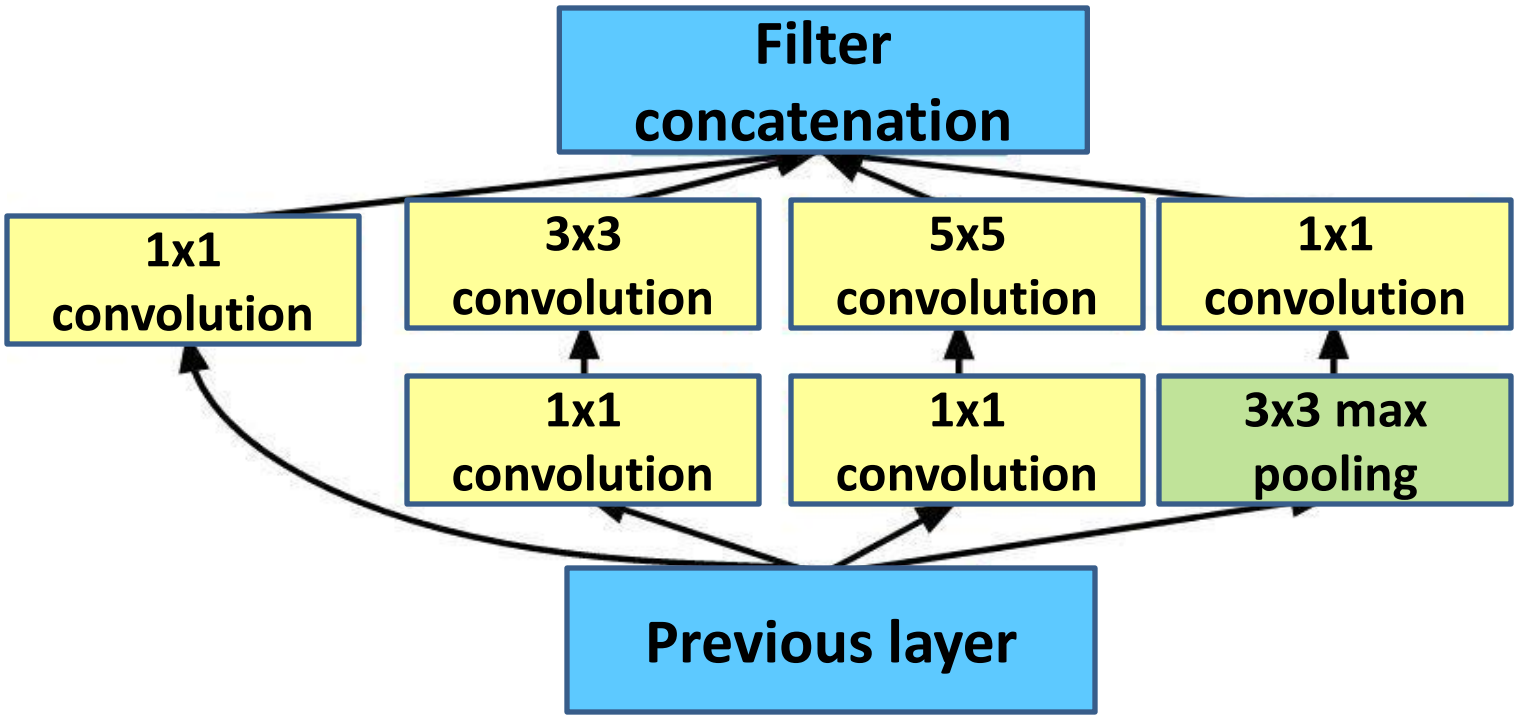
GoogleNet

- 22 layers
- Efficient **“Inception” module** - strayed from the general approach of simply stacking conv and pooling layers on top of each other in a sequential structure
- No FC layers
- Only 5 million parameters!
- ILSVRC’14 classification winner (6.7% top 5 error)

[Szegedy et al., 2014]

GoogleNet

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



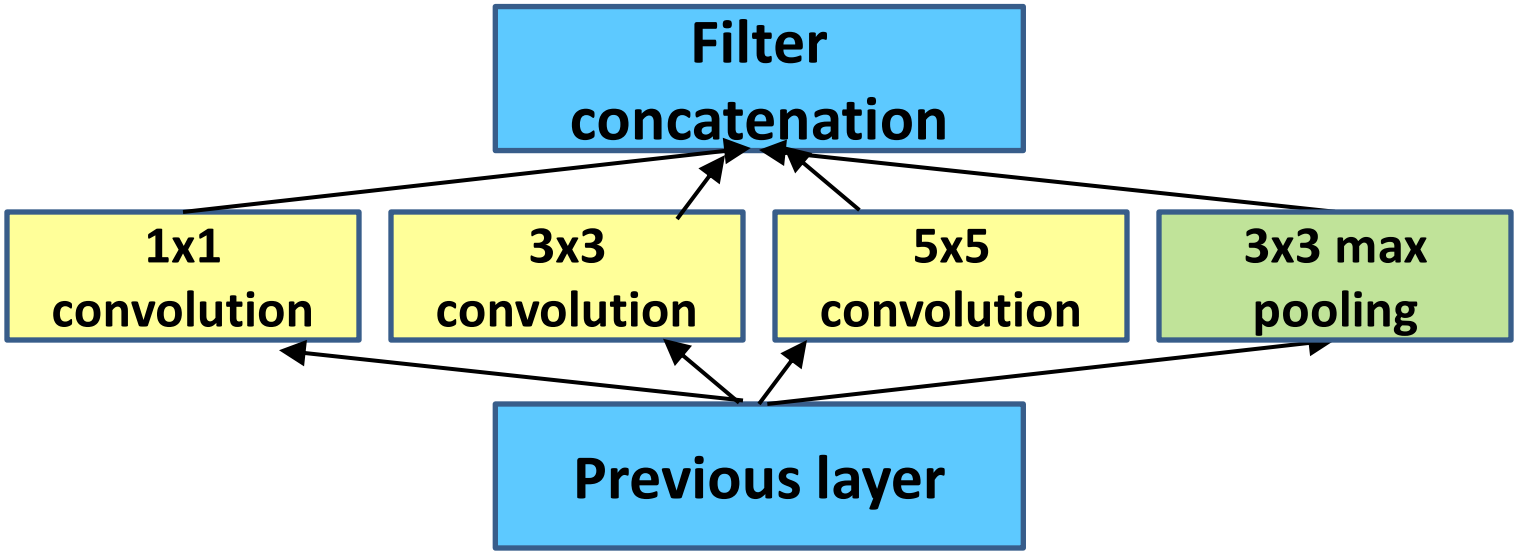
Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Szegedy et al., 2014]

GoogleNet

Naïve Inception Model

- Apply parallel filter operations on the input :
  - Multiple receptive field sizes for convolution (1x1, 3x3, 5x5)
  - Pooling operation (3x3)
- Concatenate all filter outputs together depth-wise

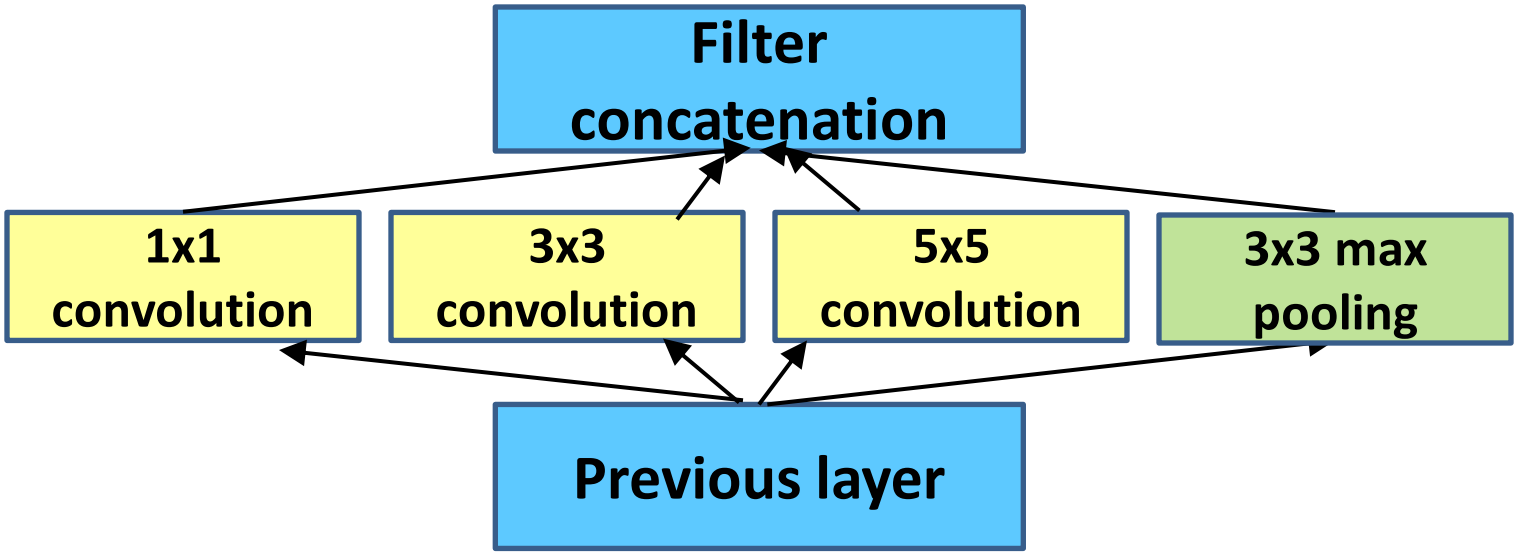


Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Szegedy et al., 2014]

GoogleNet

- **What's the problem with this?**
  High computational complexity



Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Szegedy et al., 2014]

GoogleNet

- **Output volume sizes:**

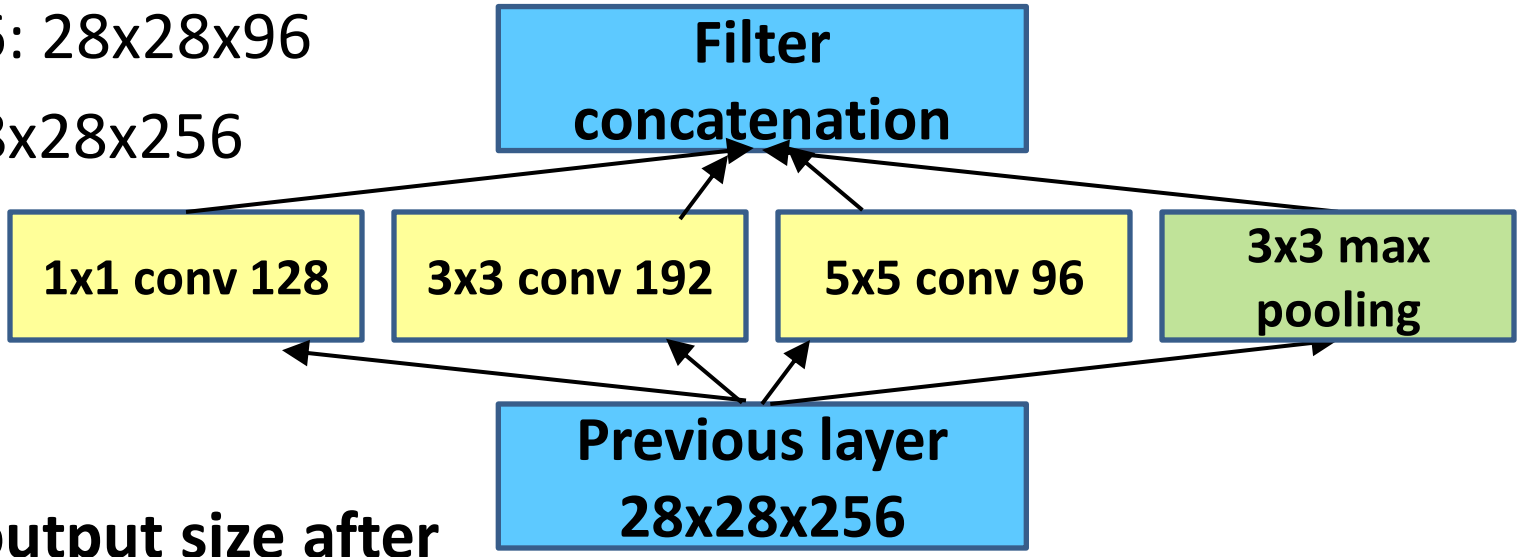
1x1 conv, 128: 28x28x128

3x3 conv, 192: 28x28x192

5x5 conv, 96: 28x28x96

3x3 pool: 28x28x256

Example:



- **What is output size after filter concatenation?**

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

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Szegedy et al., 2014]

GoogleNet

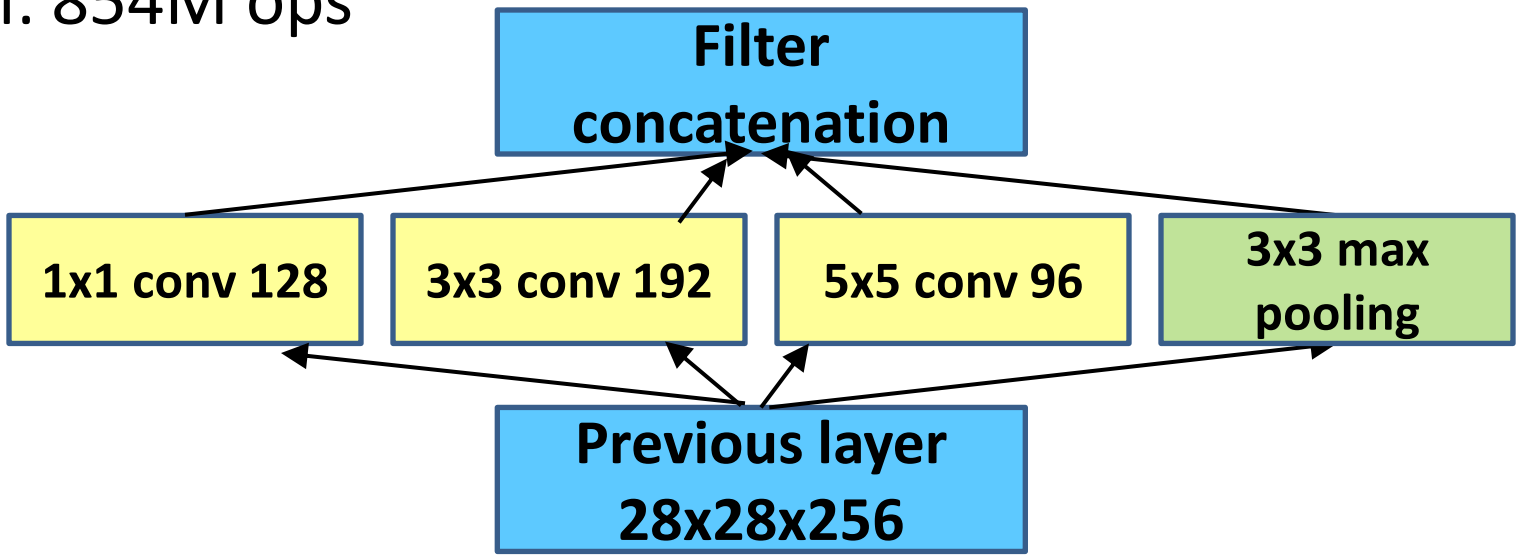
- **Number of convolution operations:**

1x1 conv, 128: 28x28x128x1x1x256

3x3 conv, 192: 28x28x192x3x3x256

5x5 conv, 96: 28x28x96x5x5x256

Total: 854M ops

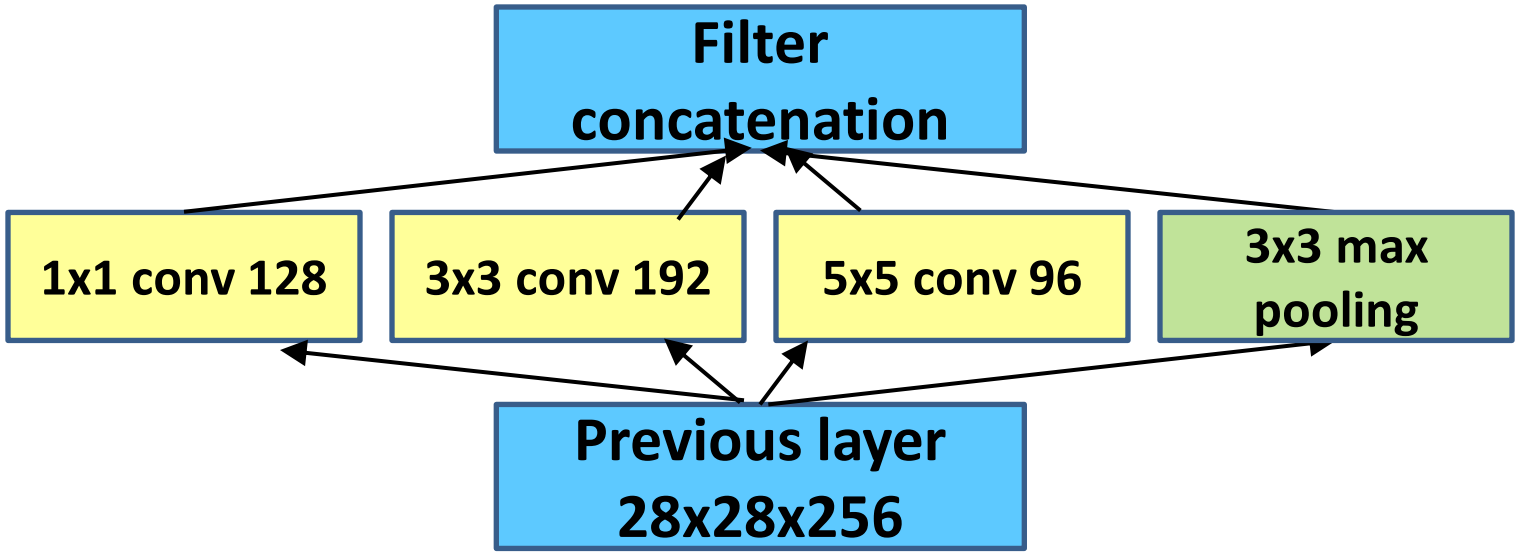


Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Szegedy et al., 2014]

GoogleNet

- **Very expensive compute!**
- Pooling layer also preserves feature depth, which means total depth after concatenation can only grow at every layer.

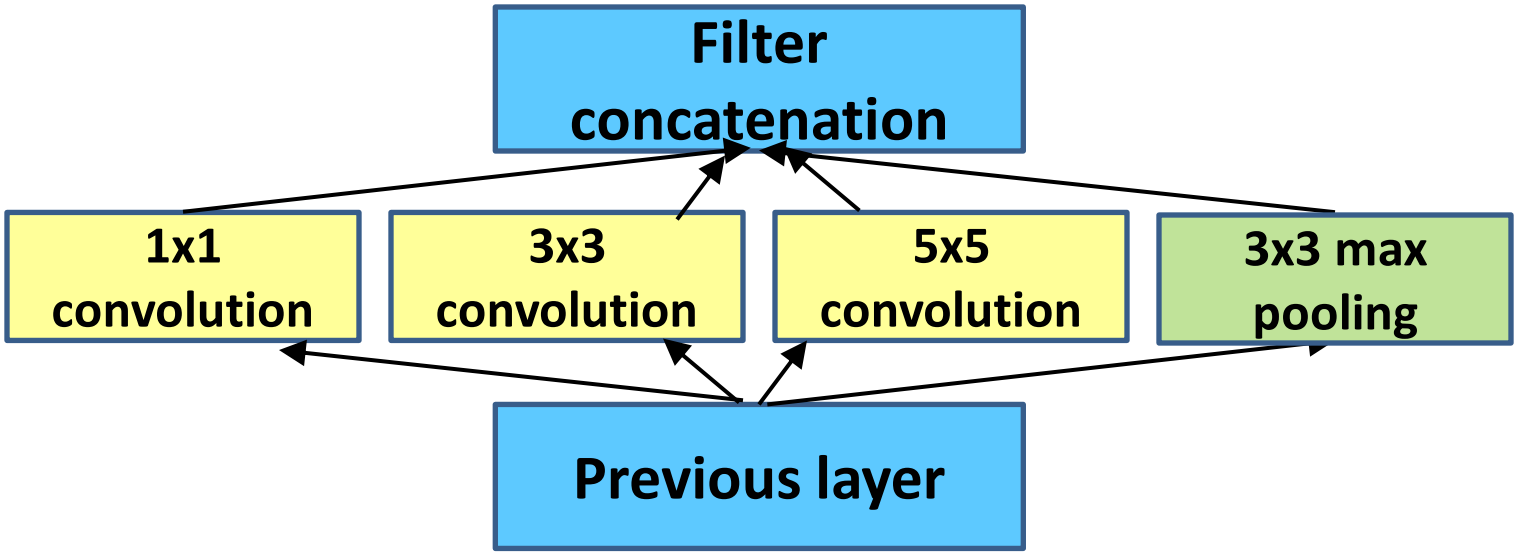


Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Szegedy et al., 2014]

GoogleNet

- **Solution:** “bottleneck” layers that use 1x1 convolutions to reduce feature depth (from previous hour).



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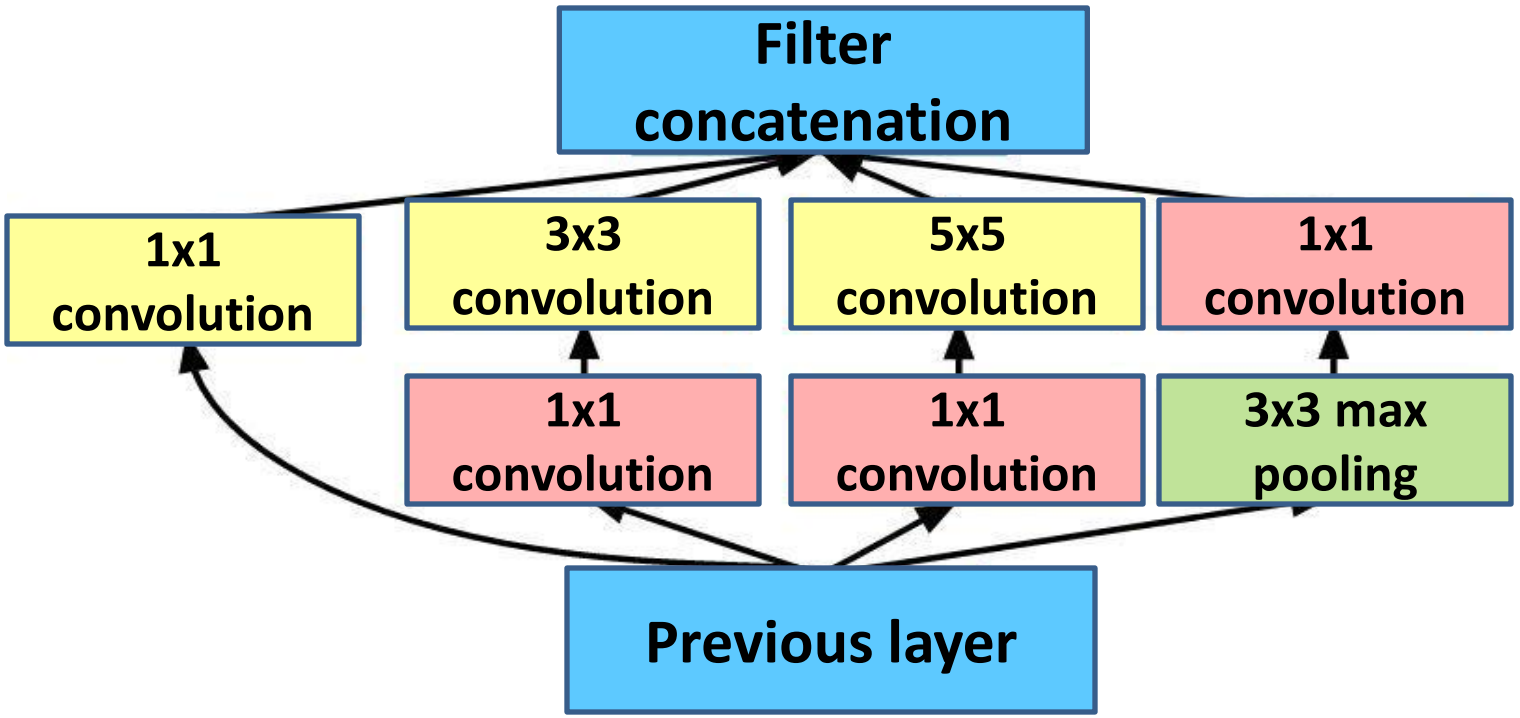
[Szegedy et al., 2014]

GoogleNet

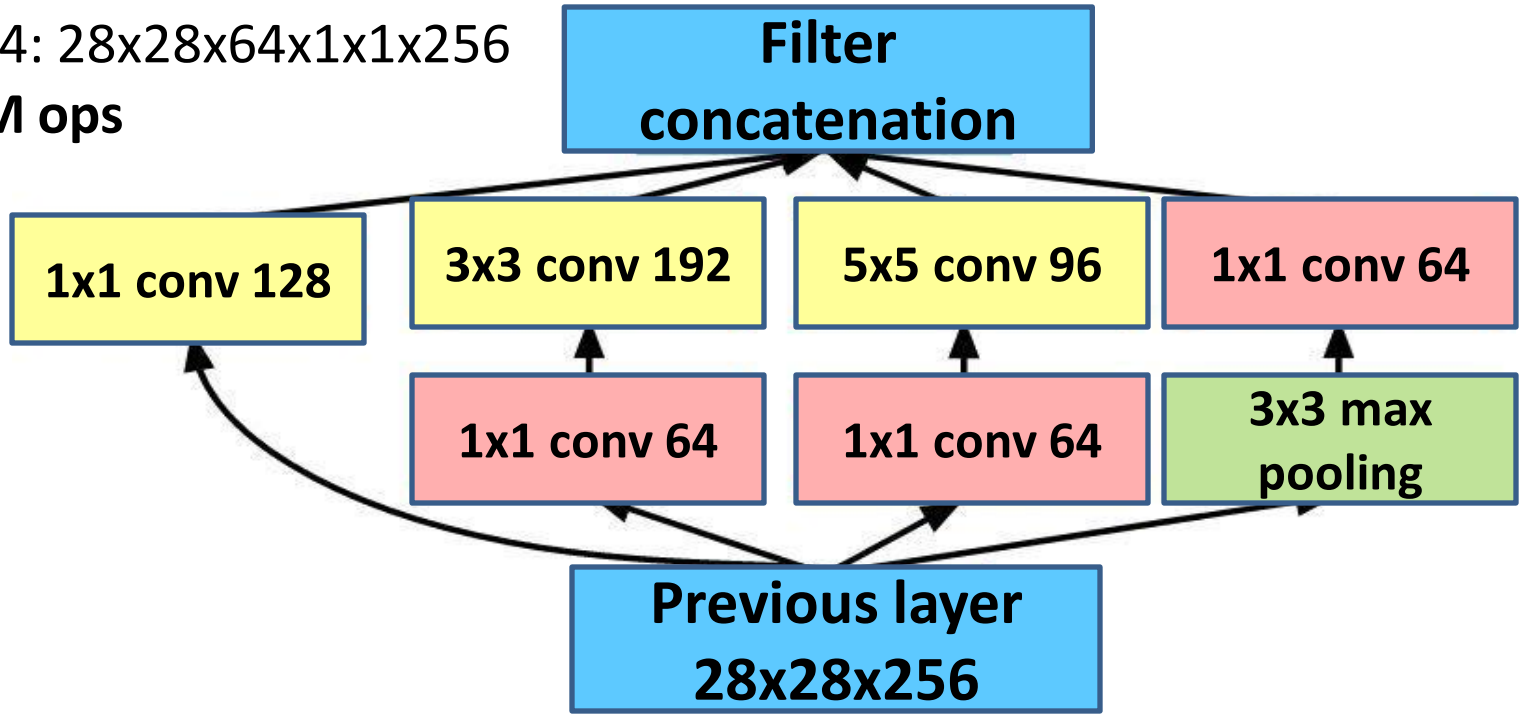
- **Solution:** “bottleneck” layers that use 1x1 convolutions to reduce feature depth (from previous hour).



Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Szegedy et al., 2014]

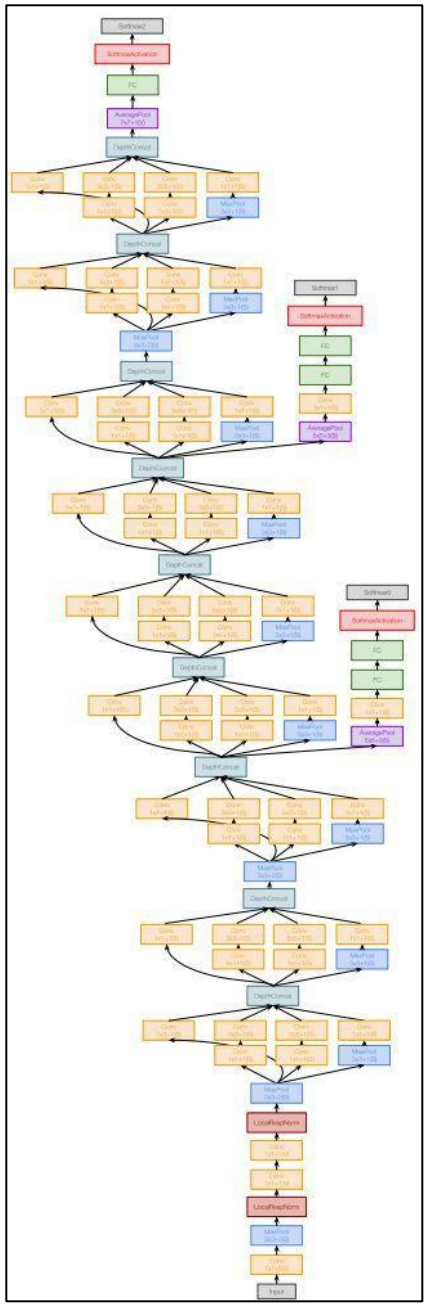
- **Number of convolution operations:**
  1x1 conv, 64: 28x28x64x1x1x256
  1x1 conv, 64: 28x28x64x1x1x256
  1x1 conv, 128: 28x28x128x1x1x256
  3x3 conv, 192: 28x28x192x3x3x64
  5x5 conv, 96: 28x28x96x5x5x264
  1x1 conv, 64: 28x28x64x1x1x256
  Total: 353M ops



- Compared to 854M ops for naive version

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Szegedy et al., 2014]



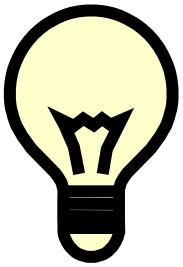
GoogleNet

Details/Retrospectives :

- 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)

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Szegedy et al., 2014]

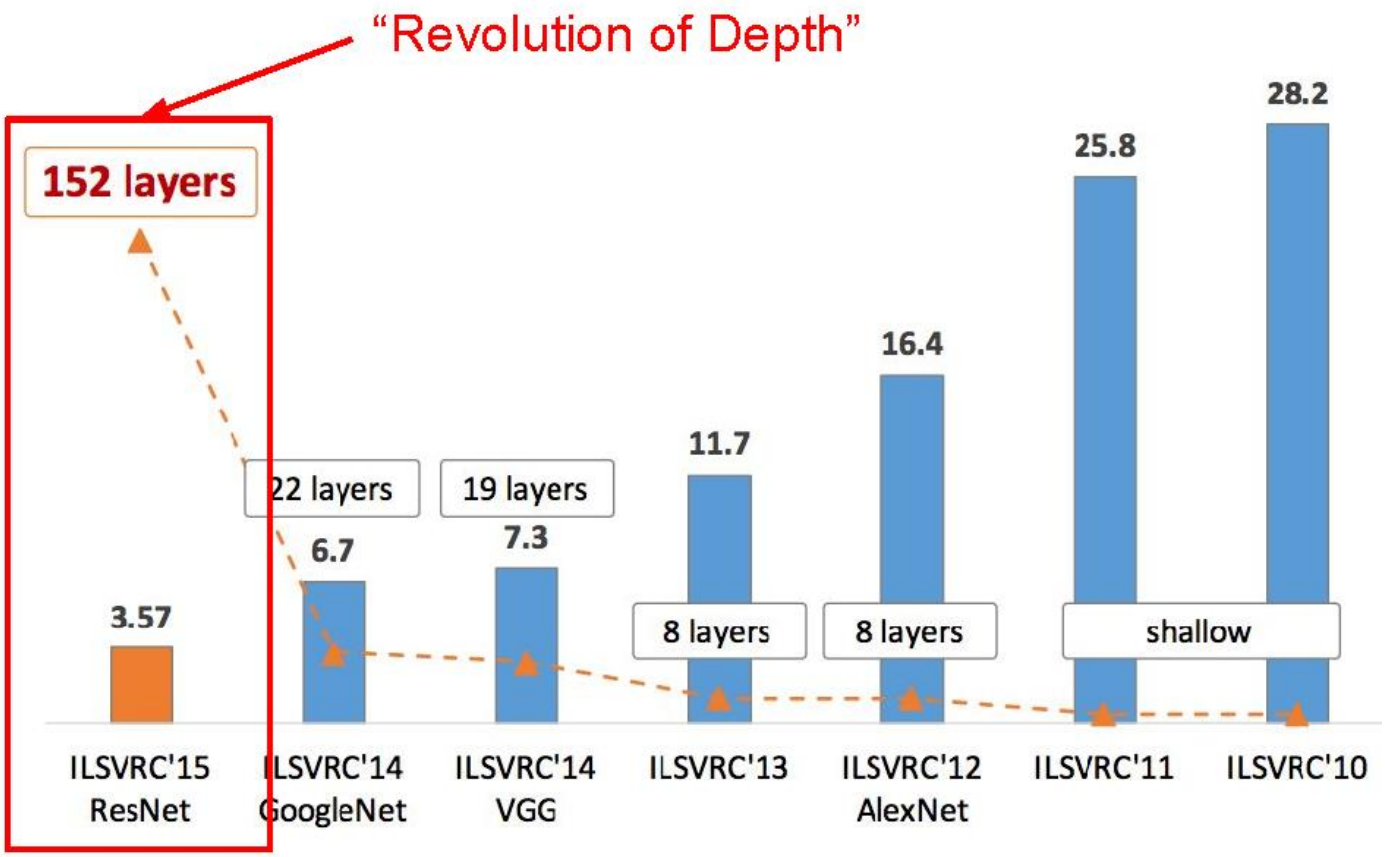


GoogleNet

Introduced the idea that CNN layers **didn't always have to be stacked up sequentially**. Coming up with the Inception module, the authors showed that a creative structuring of layers can lead to improved performance and **computationally efficiency**.

[Szegedy et al., 2014]

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

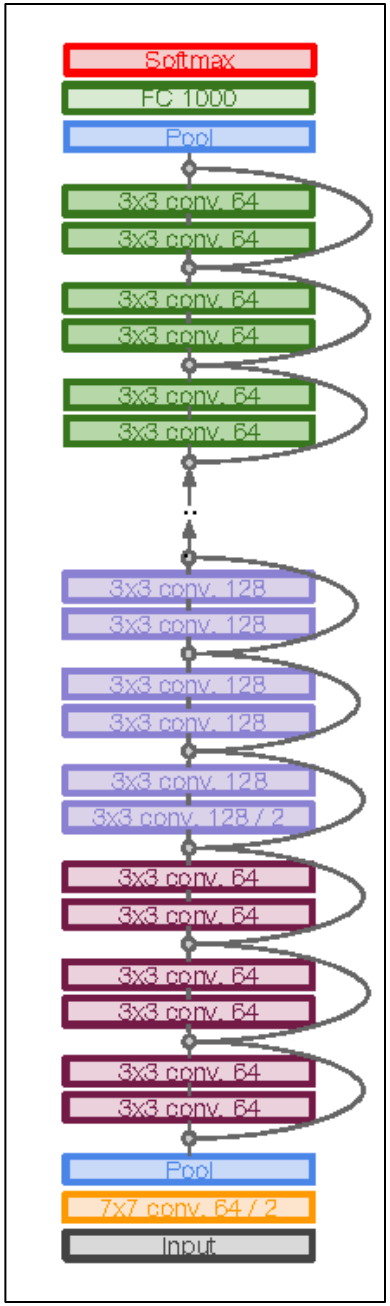


Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

ResNet

- *Deep Residual Learning for Image Recognition - Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun; 2015*
- Extremely deep network – 152 layers
- Deeper neural networks are more difficult to train.
- Deep networks suffer from vanishing and exploding gradients.
- Present a residual learning framework to ease the training of networks that are substantially deeper than those used previously.

[He et al., 2015]



ResNet

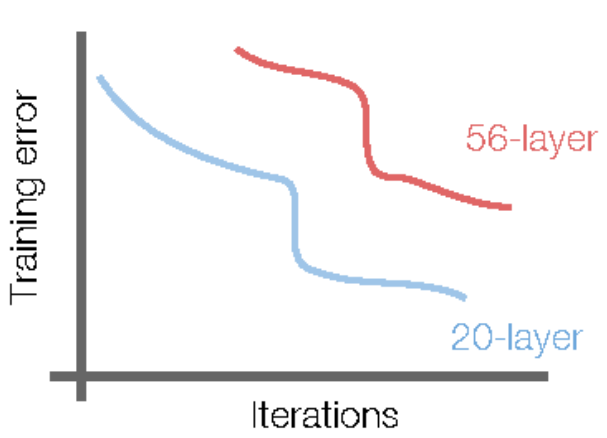
- ILSVRC'15 classification winner (3.57% top 5 error, humans generally hover around a 5-10% error rate)
  Swept all classification and detection competitions in ILSVRC'15 and COCO'15!

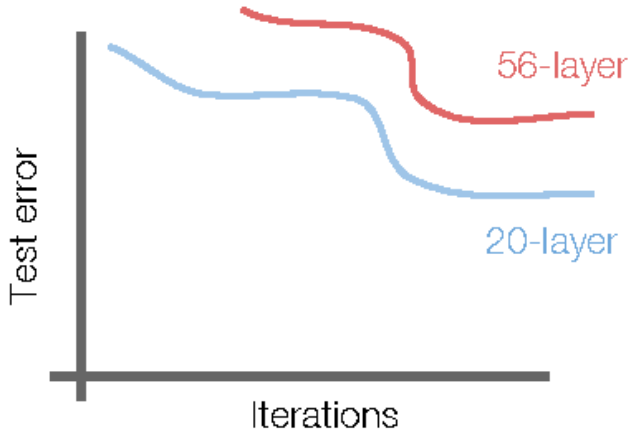
Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[He et al., 2015]

ResNet

- What happens when we continue stacking deeper layers on a convolutional neural network?





- 56-layer model performs worse on both training and test error

-> The deeper model performs worse (not caused by overfitting)!

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[He et al., 2015]

ResNet

- **Hypothesis**: The problem is an optimization problem. Very deep networks are harder to optimize.
- **Solution**: Use network layers to fit residual mapping instead of directly trying to fit a desired underlying mapping.

- We will use **skip connections** allowing us to take the activation from one layer and feed it into another layer, much deeper into the network.
- Use layers to fit residual $F(x) = H(x) - x$
  instead of $H(x)$ directly

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

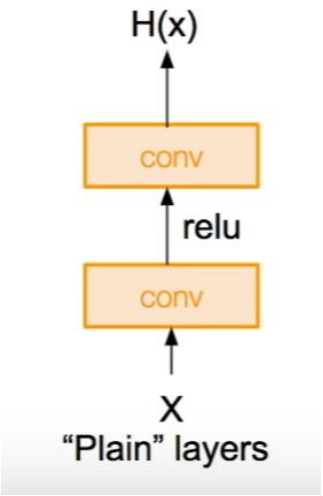
[He et al., 2015]

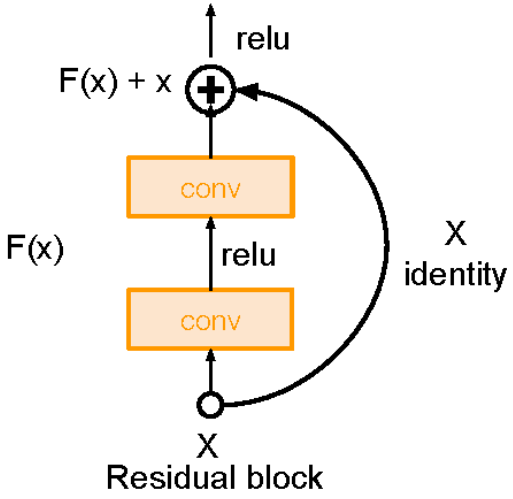
ResNet

Residual Block

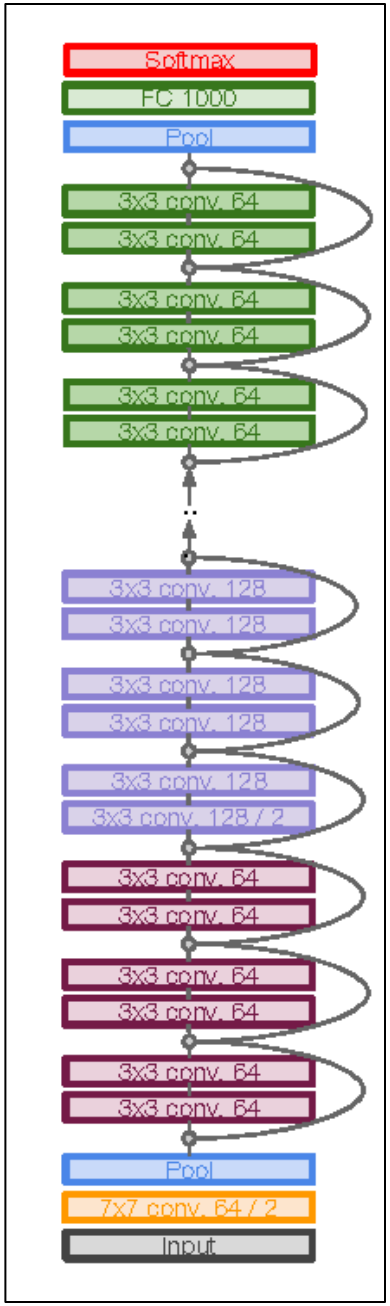
Input x goes through conv-relu-conv series and gives us F(x). That result is then added to the original input x. Let's call that H(x) = F(x) + x.

In traditional CNNs, H(x) would just be equal to F(x). So, instead of just computing that transformation (straight from x to F(x)), we're computing the term that we have to *add*, F(x), to the input, x.





[He et al., 2015]



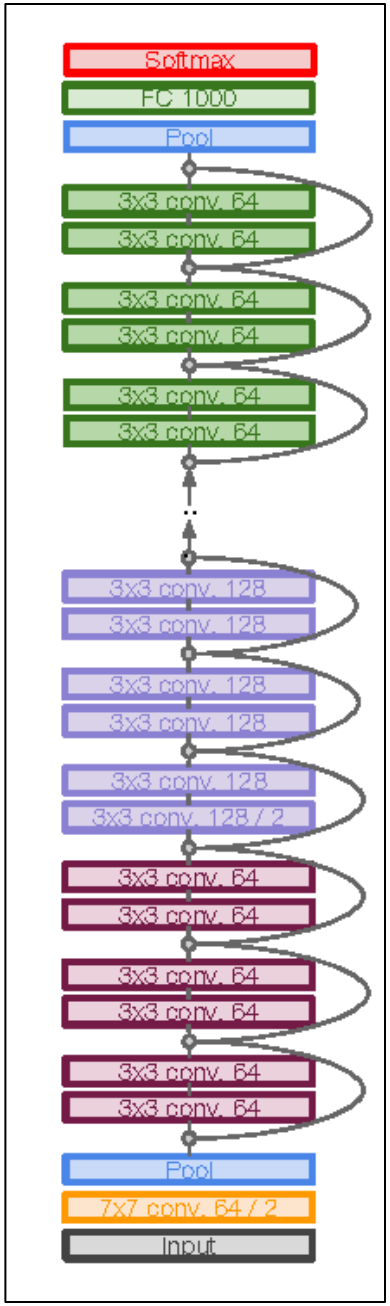
ResNet

Full ResNet architecture:

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

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[He et al., 2015]



ResNet

- Total depths of 34, 50, 101, or 152 layers for ImageNet
- For deeper networks (ResNet-50+), use "bottleneck" layer to improve efficiency (similar to GoogLeNet)

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[He et al., 2015]

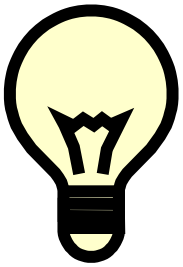
ResNet

Experimental Results:

- Able to train very deep networks without degrading
- Deeper networks now achieve lower training errors as expected

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[He et al., 2015]



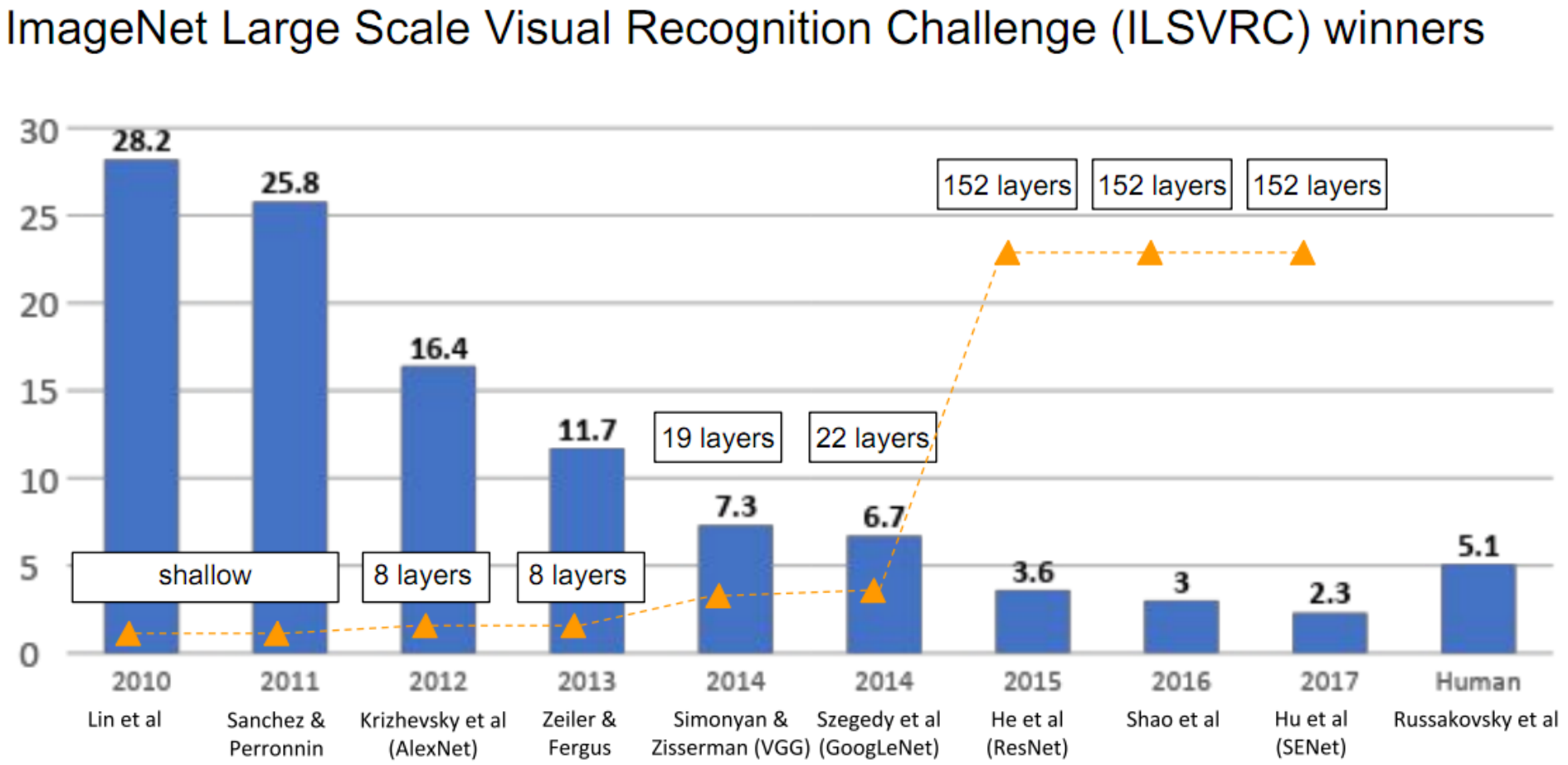
ResNet

The **best** CNN architecture that we currently have and is a great innovation for the idea of residual learning.

Even better than human performance!

[He et al., 2015]

Recent SOTA



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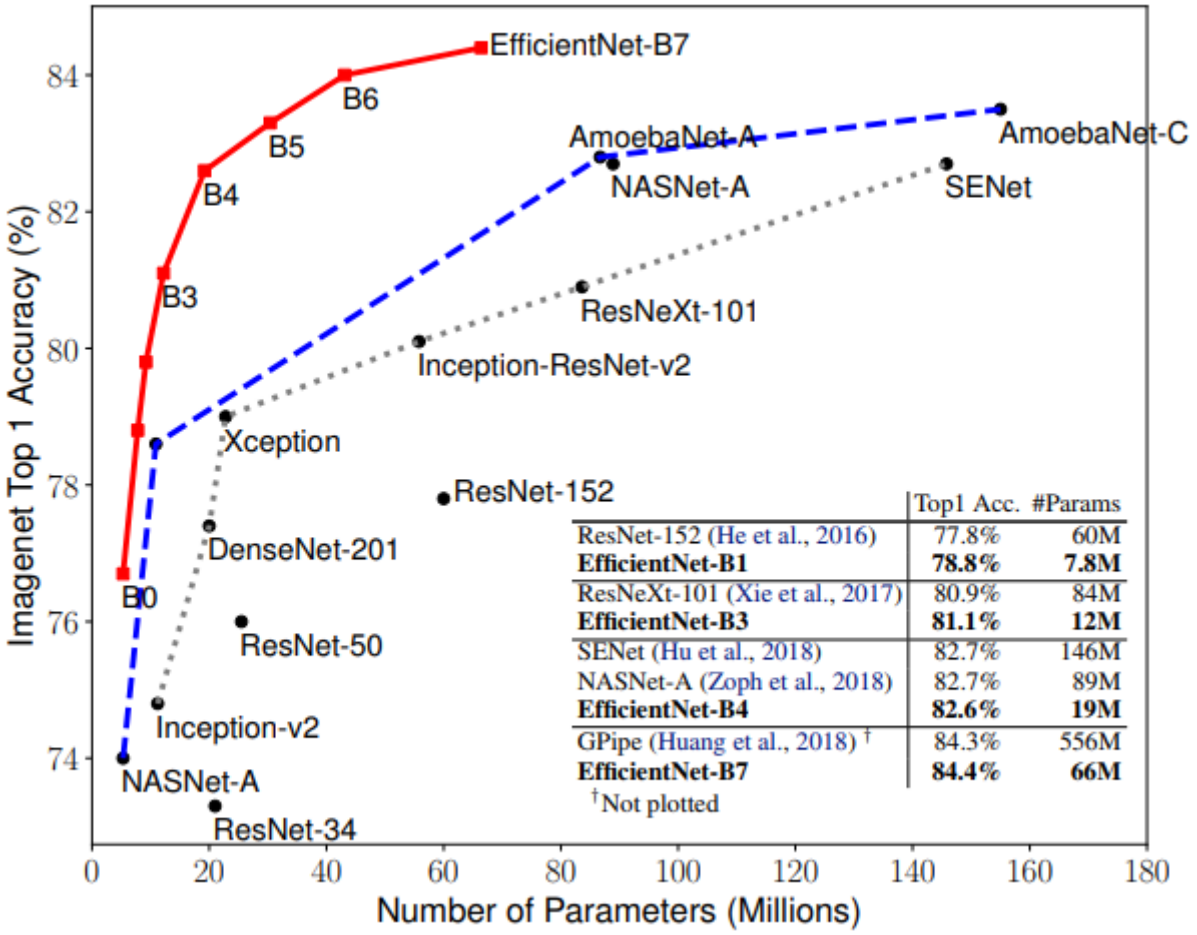
Recent SOTA



	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**78.8%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.1%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**82.6%**	**19M**
GPipe (Huang et al., 2018) †	84.3%	556M
EfficientNet-B7	**84.4%**	**66M**

†Not plotted

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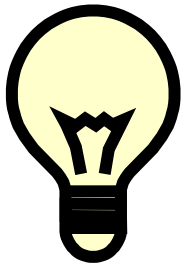
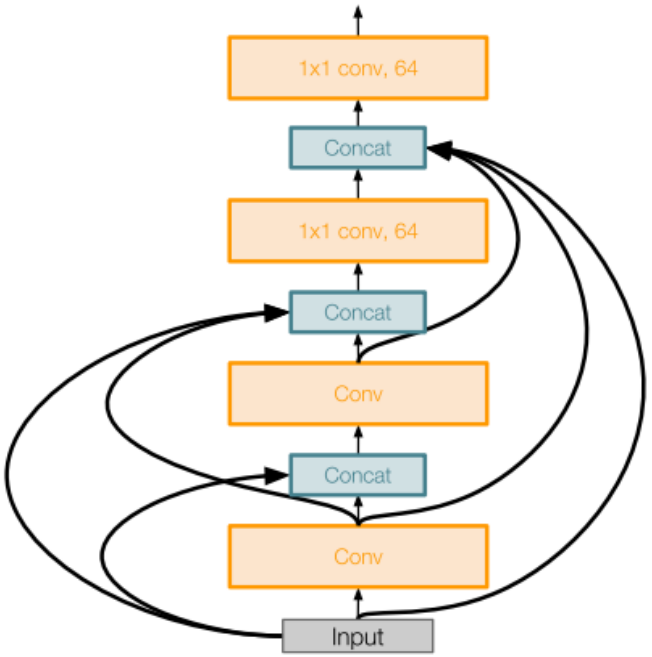


Beyond ResNet…

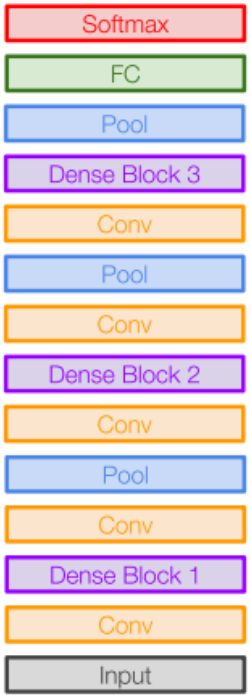
Densely Connected Convolutional Networks

[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



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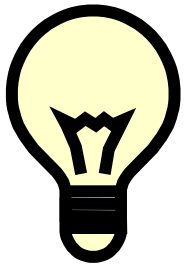
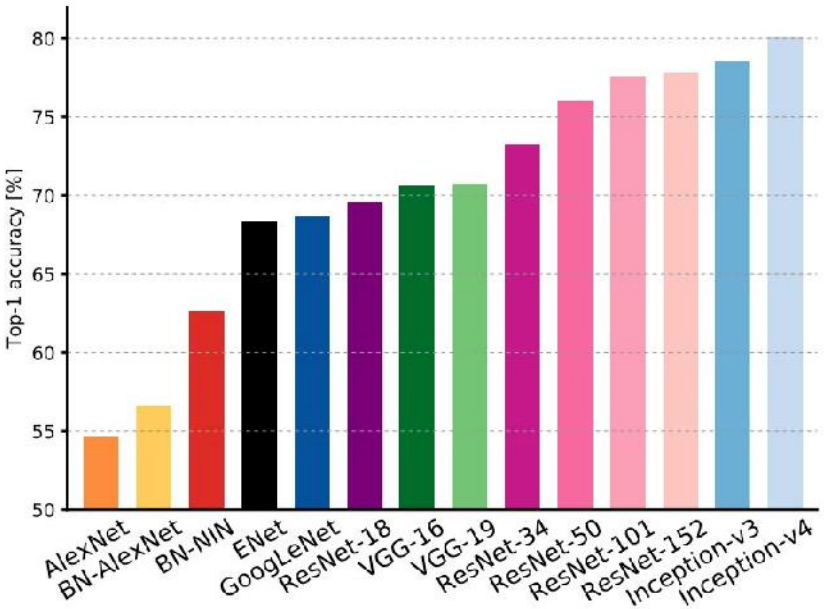
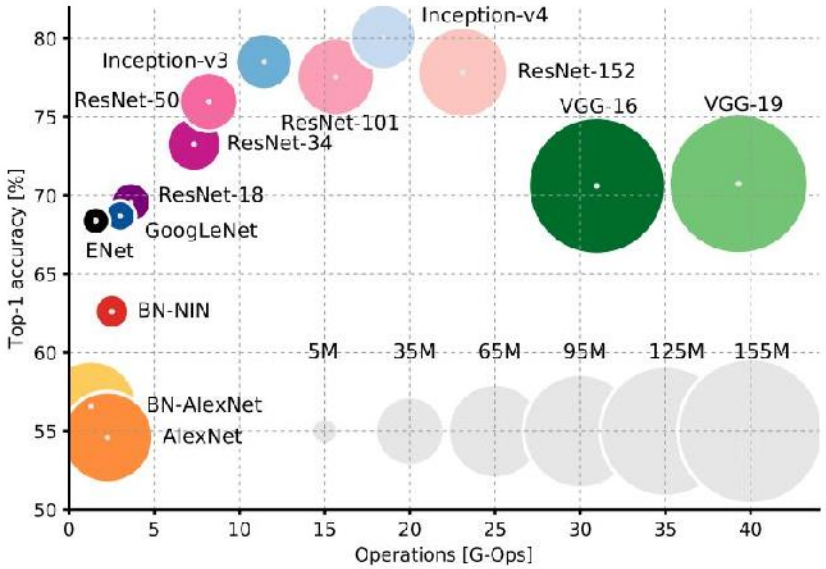


Accuracy comparison





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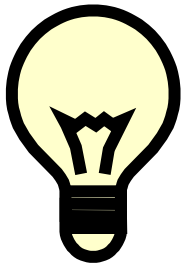
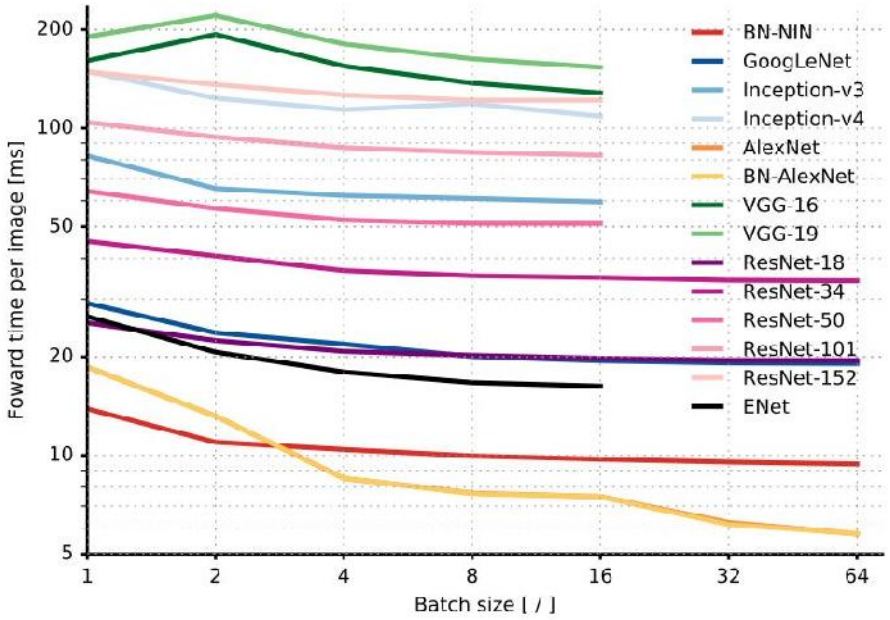
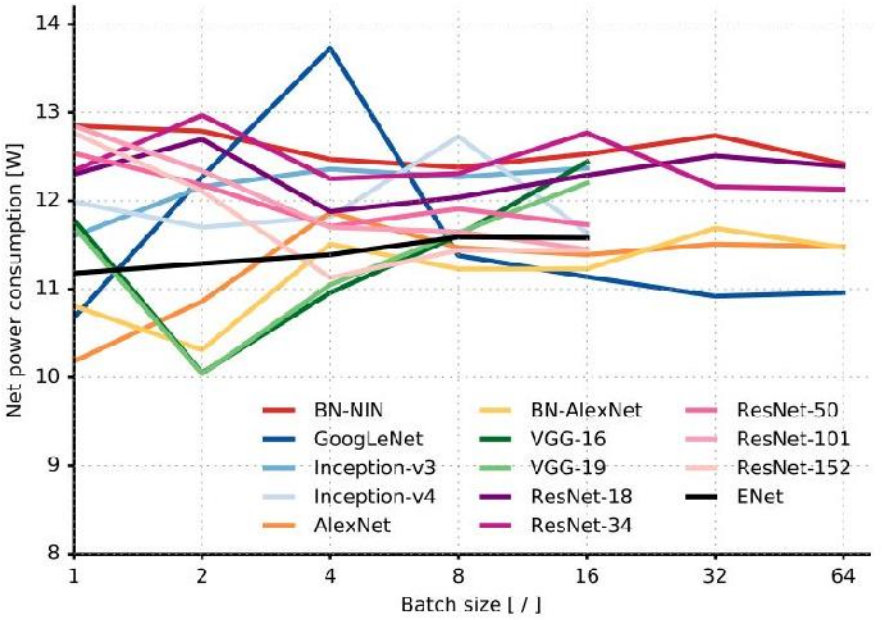


Forward pass time and power consumption





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