

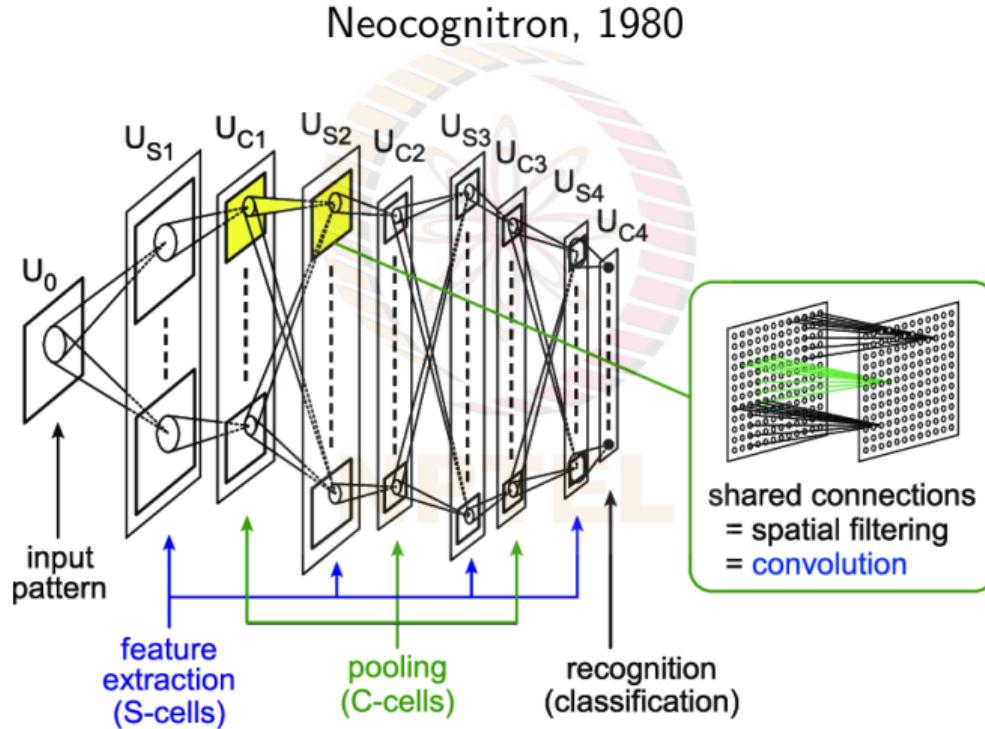
Evolution of CNN Architectures for Image Classification

Vineeth N Balasubramanian

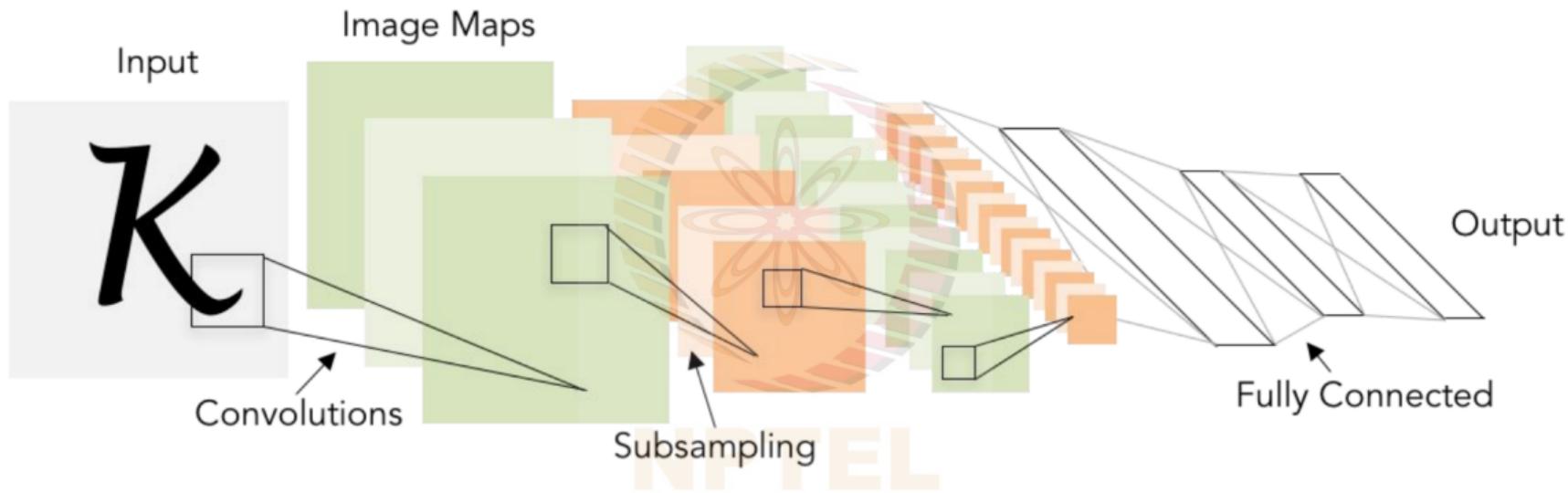
Department of Computer Science and Engineering
Indian Institute of Technology, Hyderabad



History of CNNs



LeNet-5 (1989-1998)



- Conv filters were 5×5 , applied at stride 1
- Subsampling (Pooling) layers were 2×2 applied at stride 2
- **Overall Architecture:** [CONV-POOL-CONV-POOL-FC-FC]

Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford, Spring 2019

ImageNet Classification Challenge

- Image database organized according to WordNet hierarchy (currently only nouns)
- Currently, over five hundred images per node
- Started the ImageNet LSVRC in 2010, for benchmarking of methods for image classification
- Performance measure in Top-1 error and Top-5 error
- <http://www.image-net.org/>



Loss Functions: Beyond Mean Square Error

- **Cross-Entropy Loss Function:** Most popular for classification
- Given by:

$$\begin{aligned} L &= -\frac{1}{C} \sum_{i=1}^C y_i \log \hat{y}_i \\ &= -y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i) \text{(binary case)} \end{aligned}$$



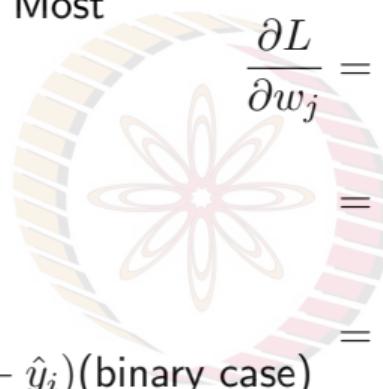
NPTEL

- When activation function is sigmoid $(\sigma(x) = \frac{1}{1+e^{-x}})$, derivative of cross-entropy loss function, $\frac{\partial L}{\partial w_j}$, w.r.t. a weight in last layer, w_j , is:

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- When activation function is sigmoid $(\sigma(x) = \frac{1}{1+e^{-x}})$, derivative of cross-entropy loss function, $\frac{\partial L}{\partial w_j}$, w.r.t. a weight in last layer, w_j , is:

$$\begin{aligned}\frac{\partial L}{\partial w_j} &= -\frac{1}{n} \sum_x \left(\frac{y}{\sigma(z)} - \frac{1-y}{1-\sigma(z)} \right) \frac{\partial \sigma}{\partial w_j} \\ &= -\frac{1}{n} \sum_x \left(\frac{y}{\sigma(z)} - \frac{1-y}{1-\sigma(z)} \right) \sigma'(z) x_j \\ &= \frac{1}{n} \sum_x \frac{\sigma'(z) x_j}{\sigma(z)(1-\sigma(z))} (\sigma(z) - y) \\ &= \frac{1}{n} \sum_x x_j (\sigma(z) - y)\end{aligned}$$

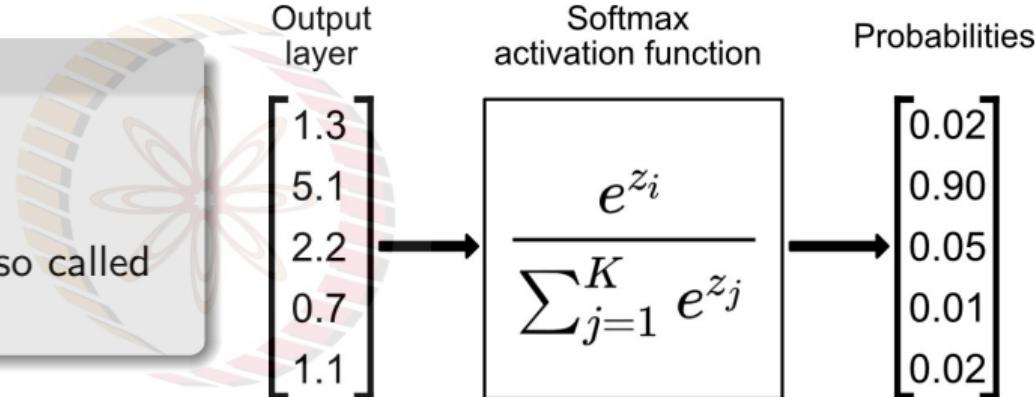
Note the last term in the final expression, very similar to gradient of MSE loss function

Activation Function in Output Layer

Softmax activation function

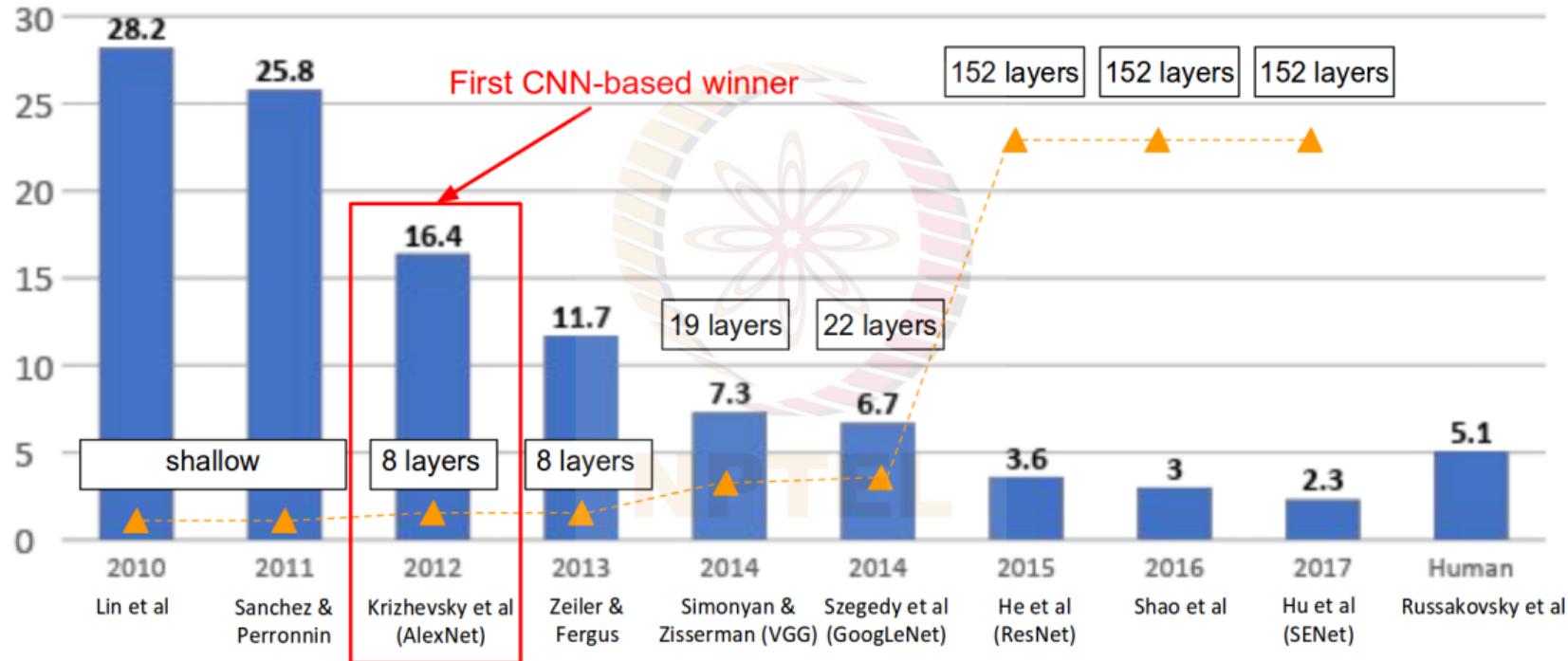
$$a_j = \frac{e^{z_j}}{\sum_k e^{z_k}}$$

Helps convert output layer values (also called **logits**) to probability scores



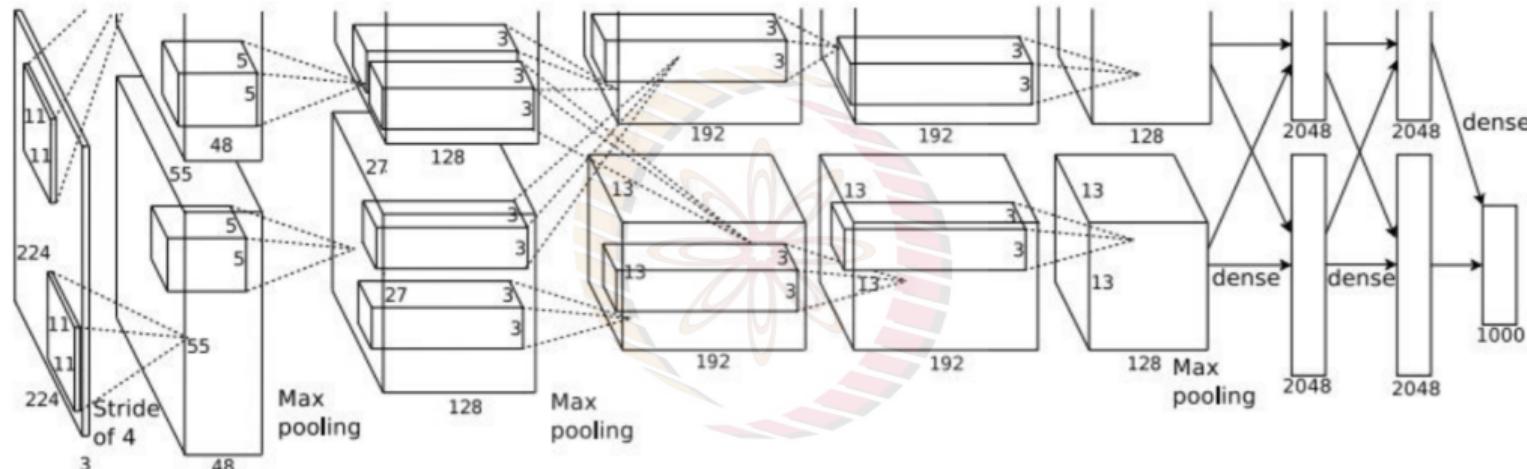
Credit: Dario Redicic, TowardsDataScience blog

Winners of ImageNet Classification Challenge



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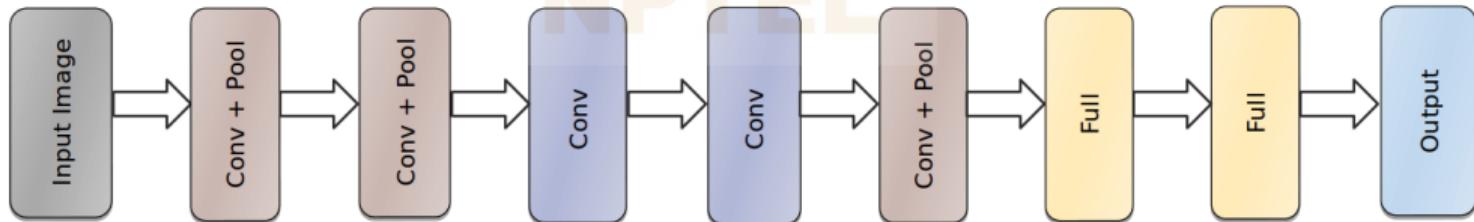
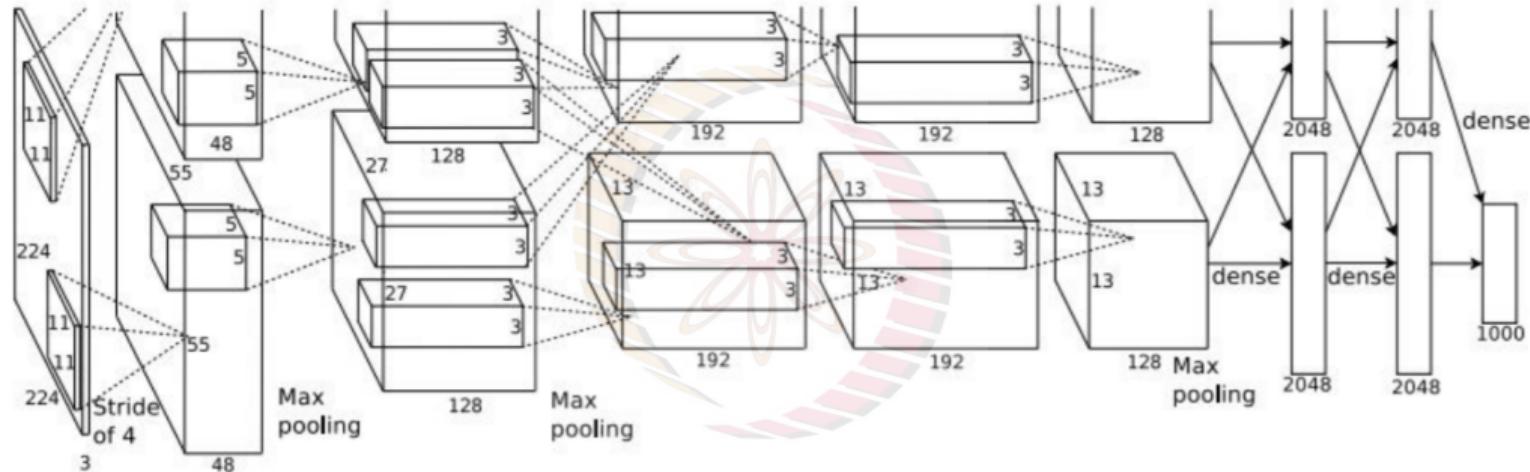
AlexNet¹



- Winner of ImageNet LSVRC-2012
- Overall architecture design similar to LeNet; but deeper with conv layers stacked on top of each other
- Trained over 1.2M images using SGD with regularization

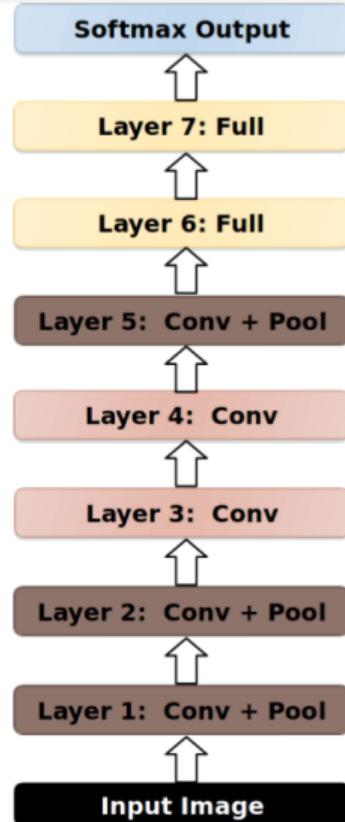
¹Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." NIPS 2012.

AlexNet



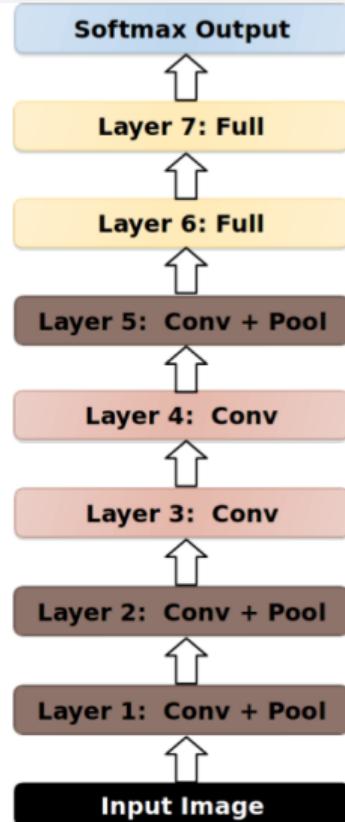
AlexNet

- 8 layers in total (5 convolutional layers, 3 fully connected layers)
- Trained on ImageNet Dataset



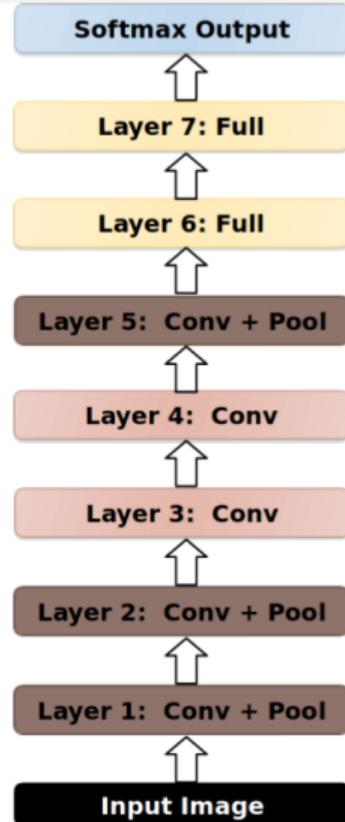
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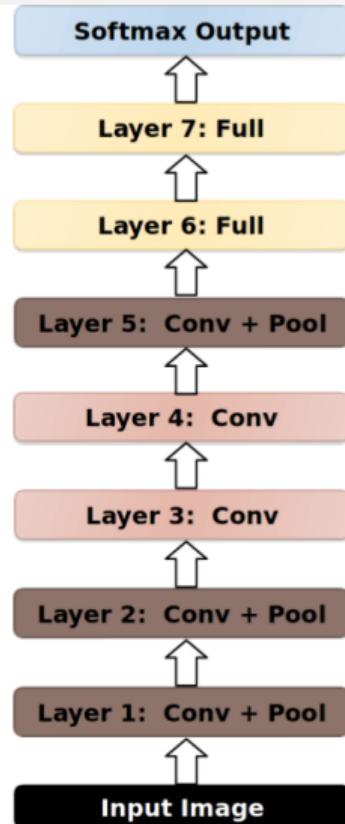


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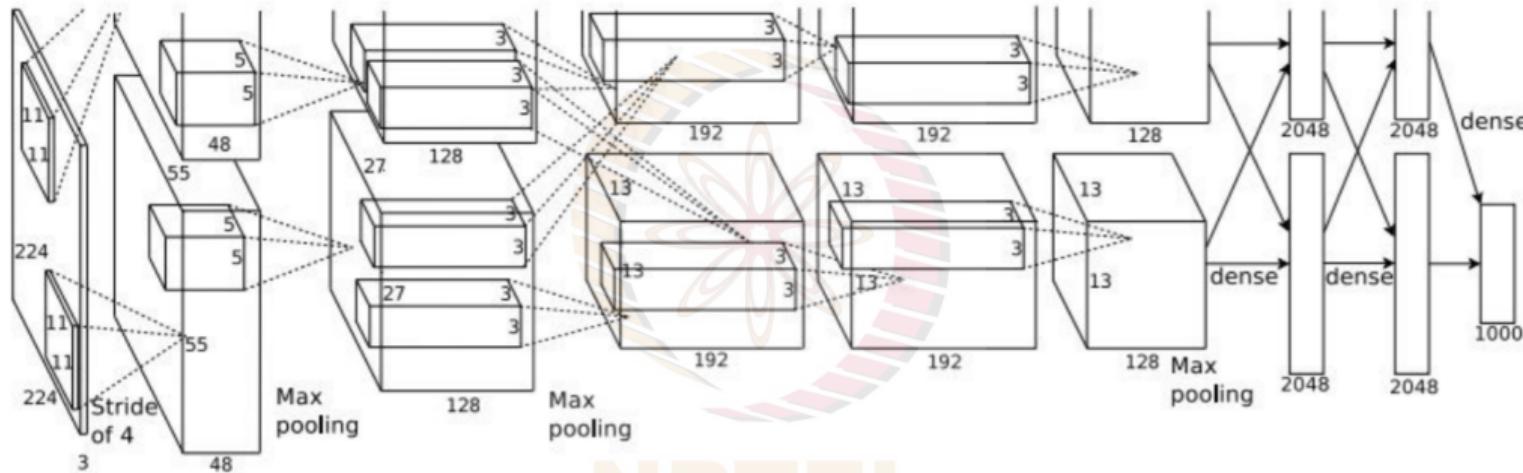
- 8 layers in total (5 convolutional layers, 3 fully connected layers)
- Trained on ImageNet Dataset
- **Response normalization layers** follow the first and second convolutional layers.
- Max-pooling follow first, second and the fifth convolutional layers
- The ReLU non-linearity is applied to the output of every layer



NPTEL



AlexNet



About 57 M parameters are in the fully connected layers

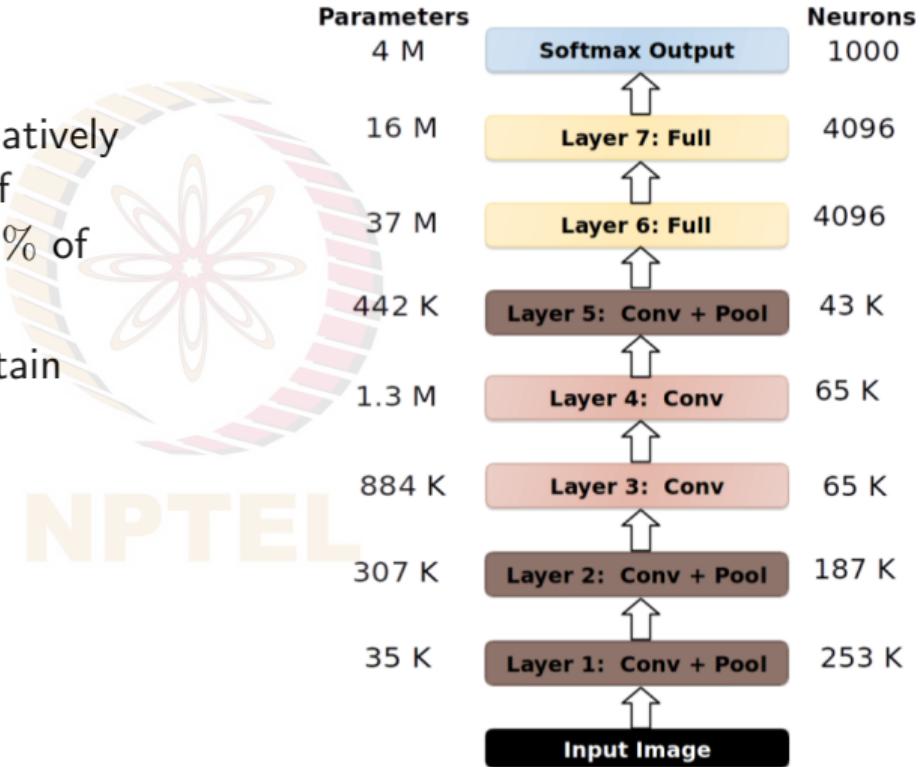


Total

Parameters :	$[(11 \times 11 \times 3) + 1] \times 96 = 35 \text{ K}$	$[5 \times 5 \times 48] \times 256 = 307 \text{ K}$	$[3 \times 3 \times 256] \times 384 = 884 \text{ K}$	663 K	442 K	37 M	16 M	4 M	60 M
Neurons :	253,440	$27 \times 27 \times 256 = 186,624$	$13 \times 13 \times 384 = 64,896$	$13 \times 13 \times 384 = 64,896$	$13 \times 13 \times 256 = 43,264$	4096	4096	1000	0.63 M

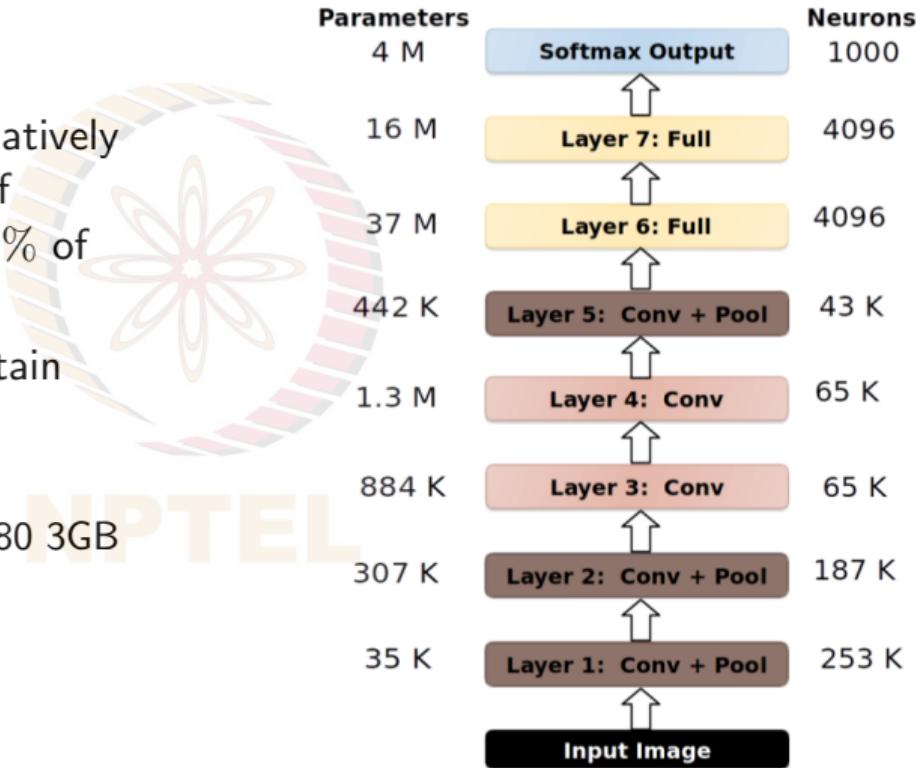
AlexNet

- Convolutional layers cumulatively contain about 90 – 95% of computation, only about 5% of the parameters
- Fully-connected layers contain about 95% of parameters.

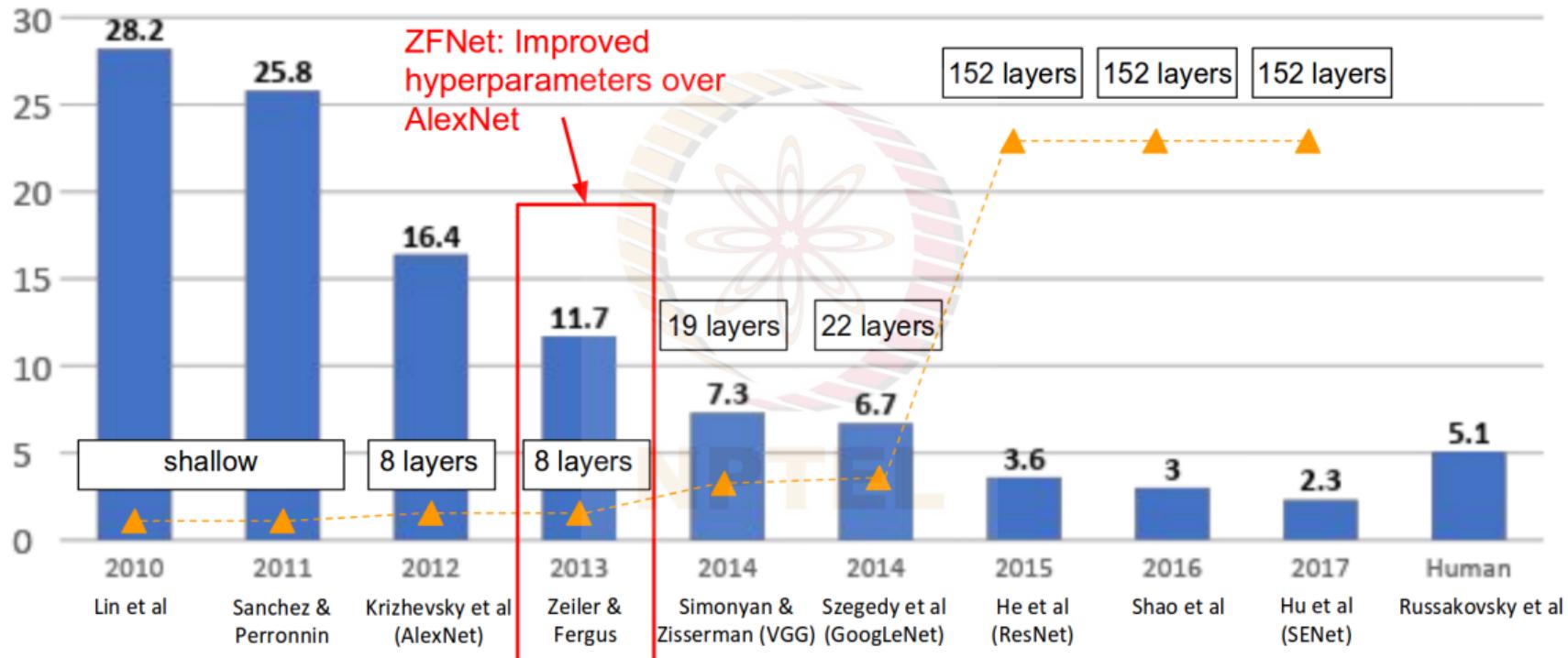


AlexNet

- Convolutional layers cumulatively contain about 90 – 95% of computation, only about 5% of the parameters
- Fully-connected layers contain about 95% of parameters.
- Trained with SGD
 - on **two** NVIDIA GTX 580 3GB GPUs
 - for about a week

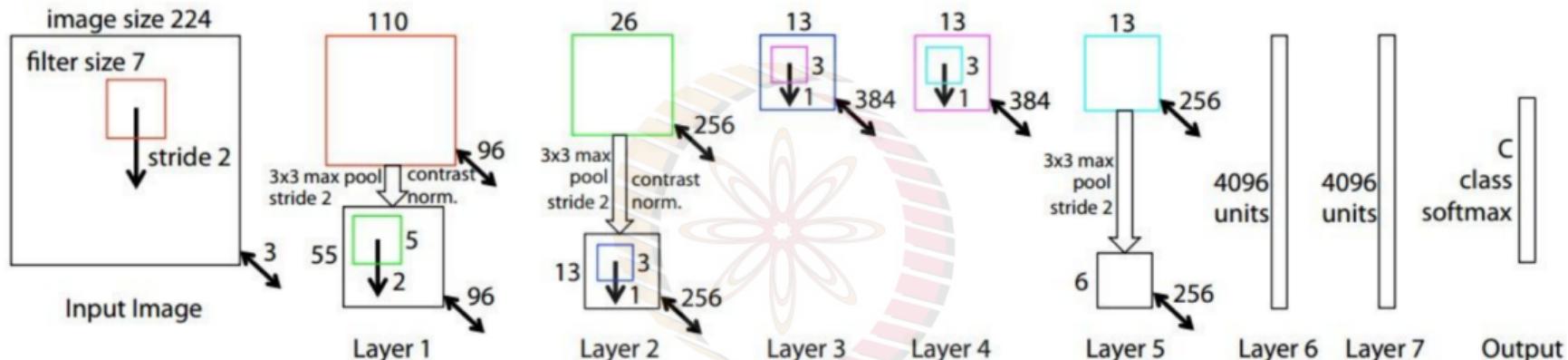


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ZFNet (2013)²

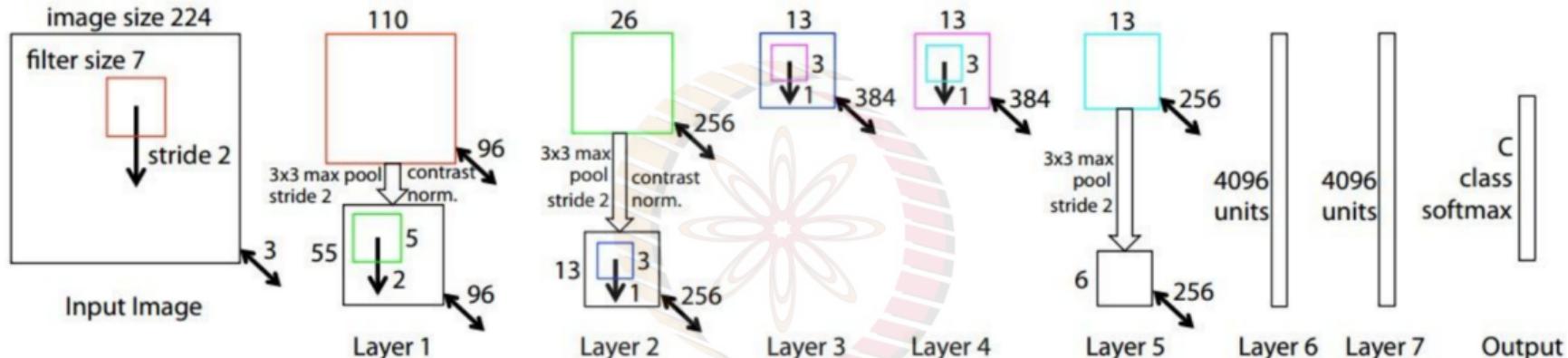


- Similar to AlexNet but:

NPTEL

²Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks", ECCV 2014

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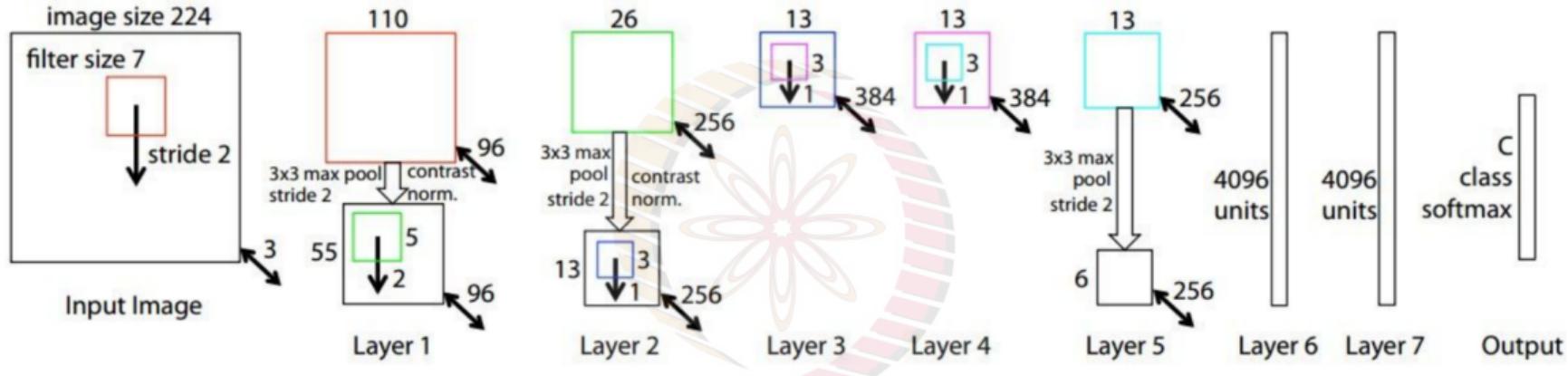


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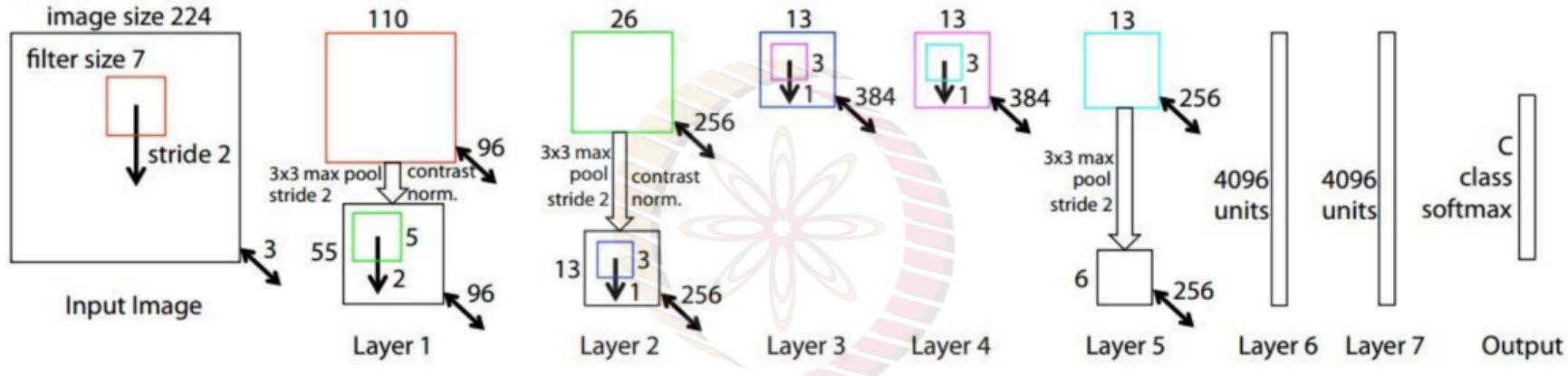
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 - CONV1: change from $(11 \times 11 \text{ stride } 4)$ to $(7 \times 7 \text{ stride } 2)$

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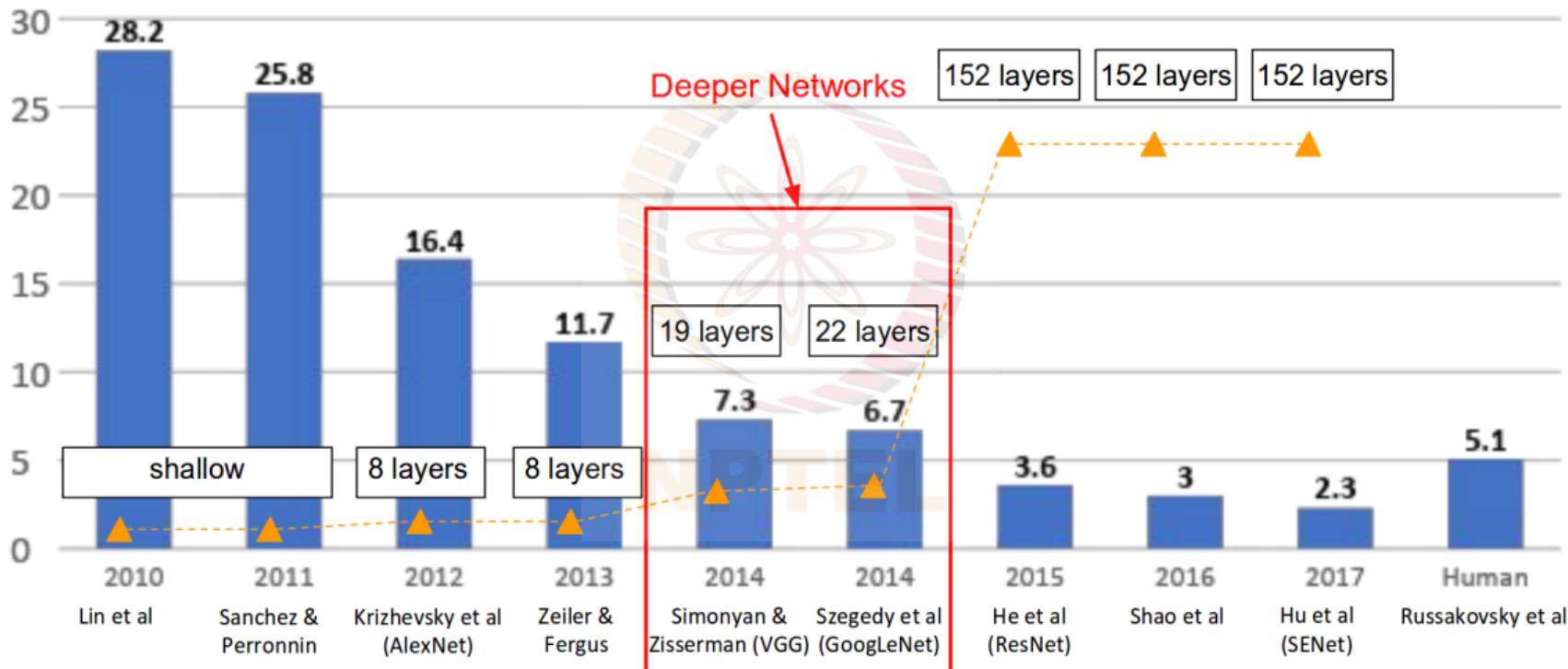


- Similar to AlexNet but:
 - CONV1: change from $(11 \times 11 \text{ stride } 4)$ to $(7 \times 7 \text{ stride } 2)$
 - CONV3,4,5: instead of 384, 384, 256 filters, use 512, 1024, 512
- ImageNet top-5 error: $16.4\% \rightarrow 11.7\%$

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VGGNet

image

conv-64

maxpool

conv-128

maxpool

conv-256

conv-256

maxpool

conv-512

conv-512

maxpool

conv-512

conv-512

maxpool

FC-4096

FC-4096

FC-1000

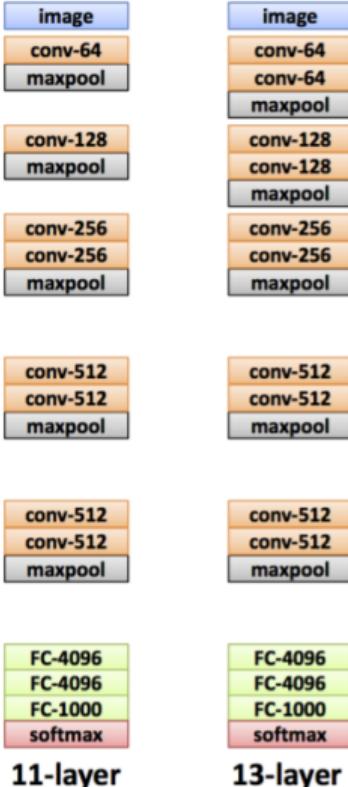
softmax

11-layer



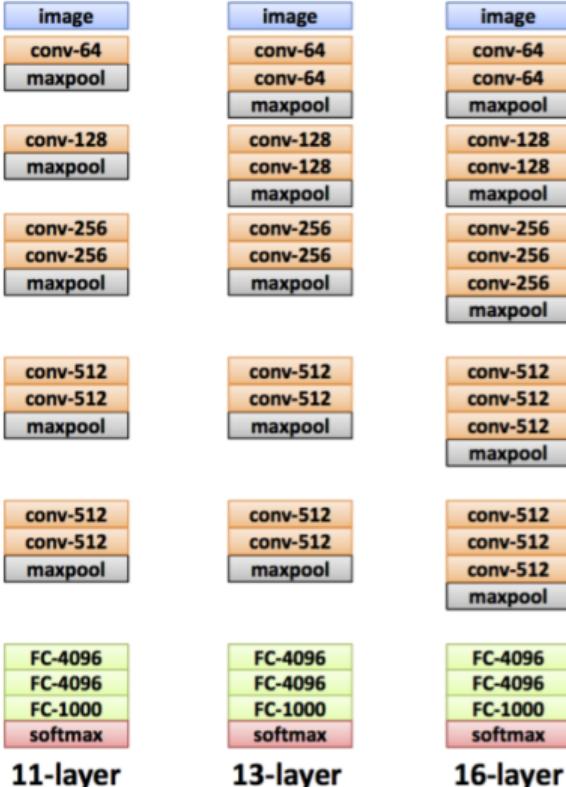
NPTEL

VGGNet



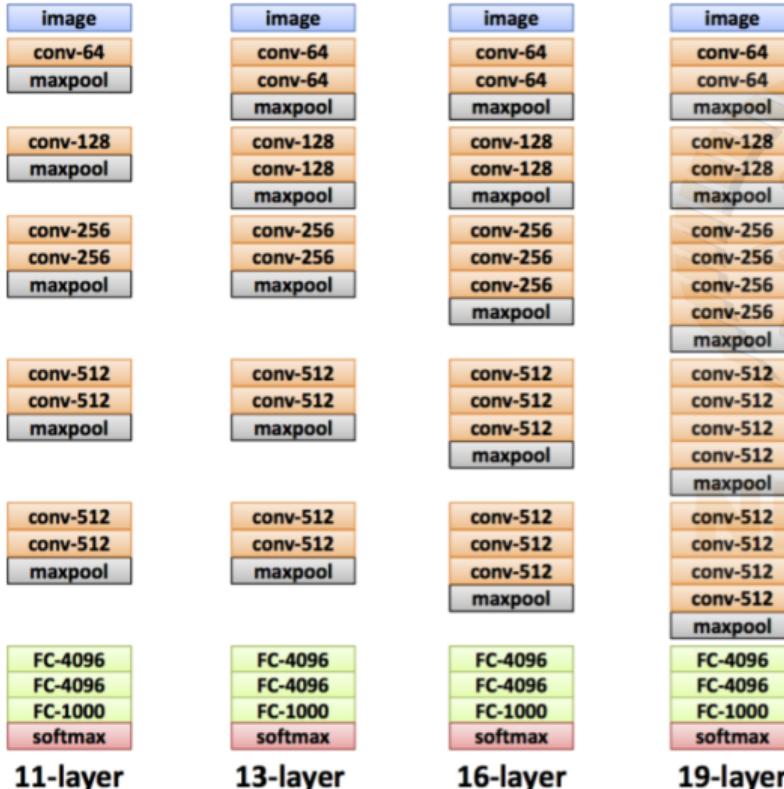
NPTEL

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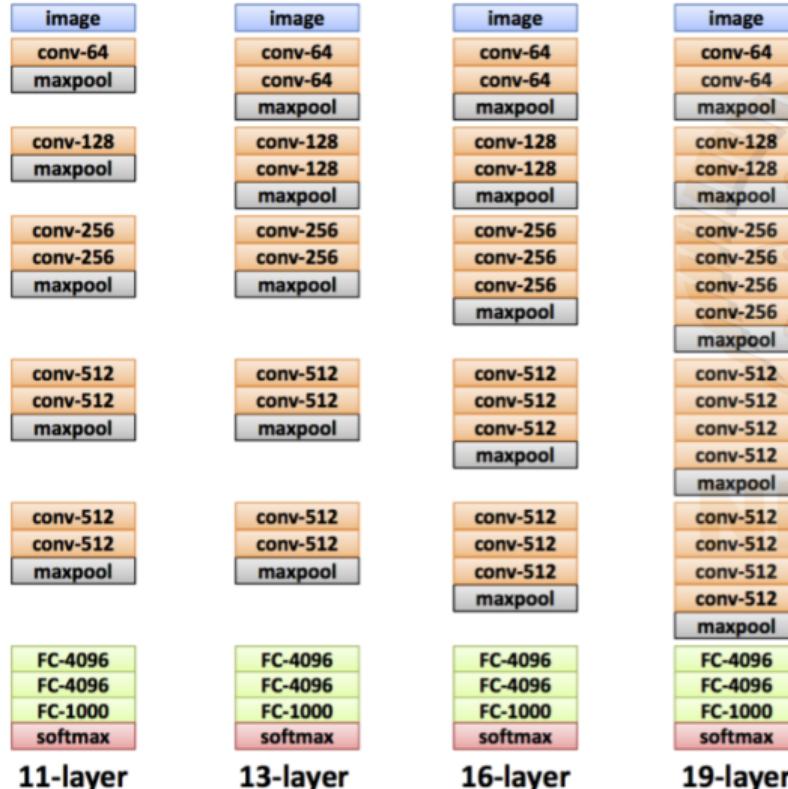


NPTEL

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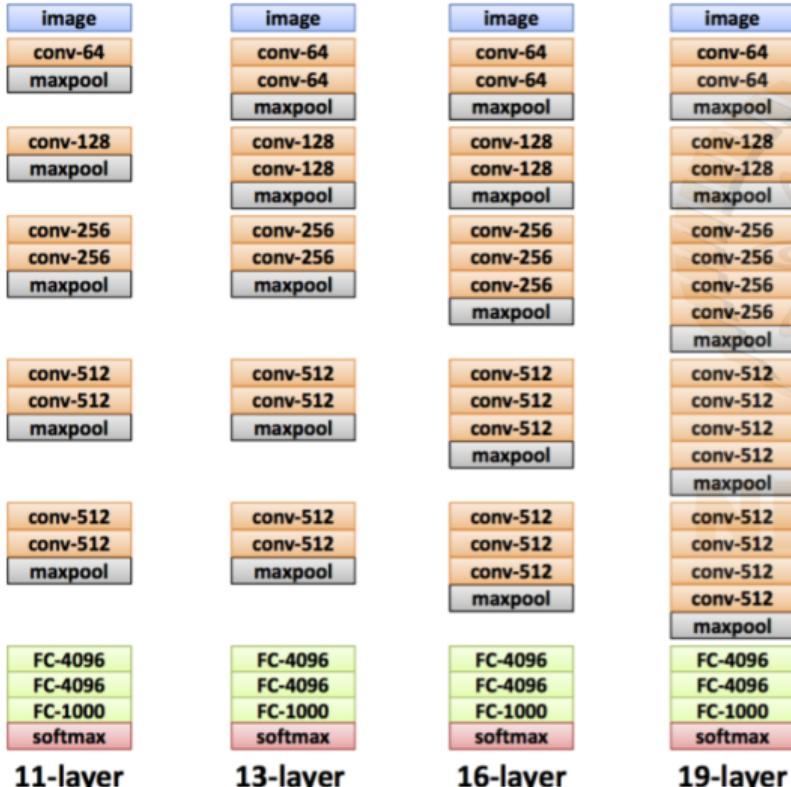


VGGNet



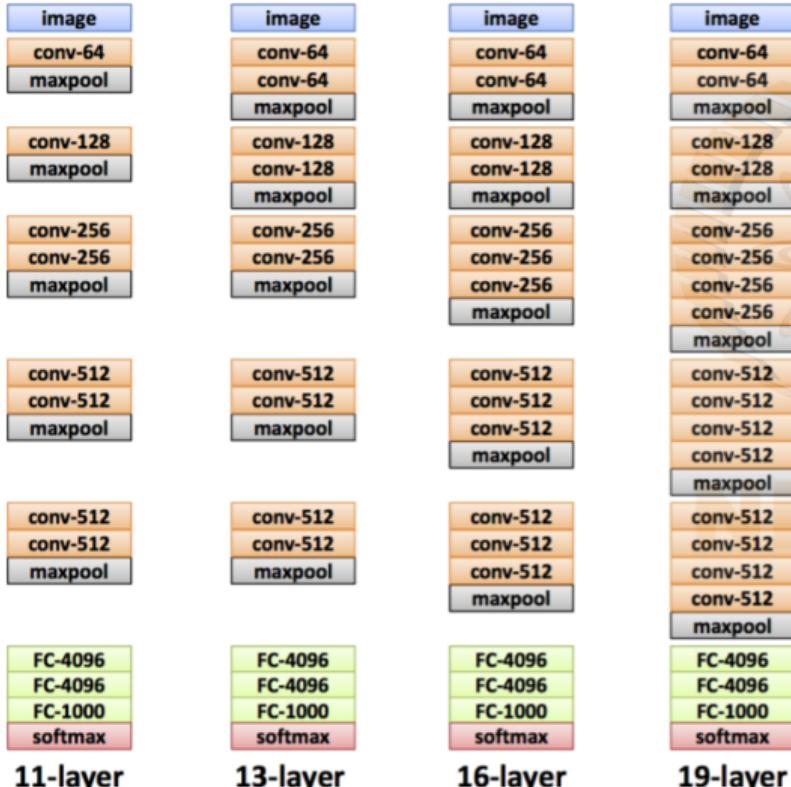
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VGGNet



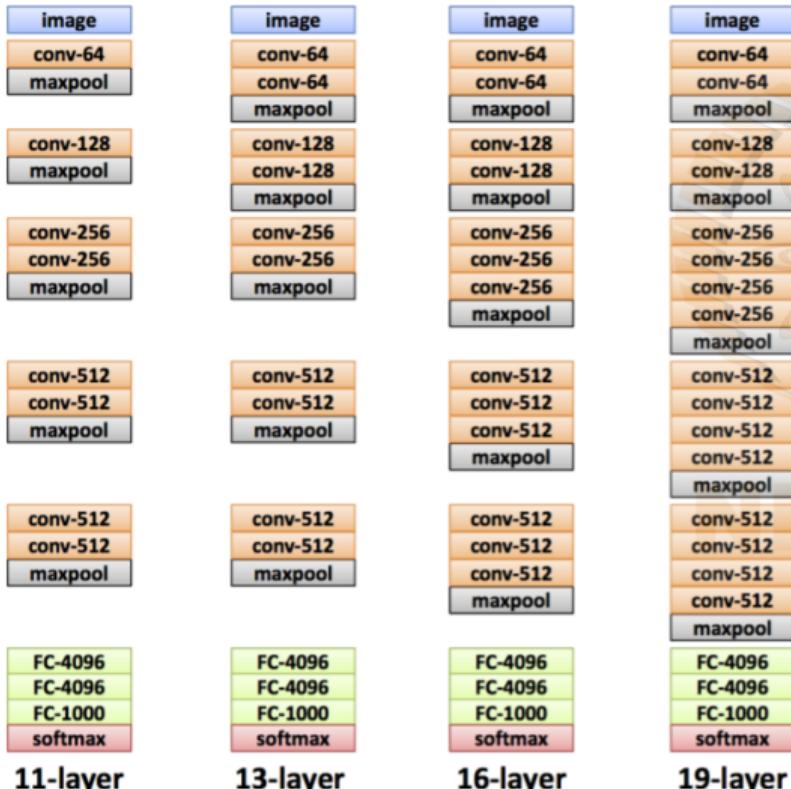
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- More layers lead to more nonlinearities

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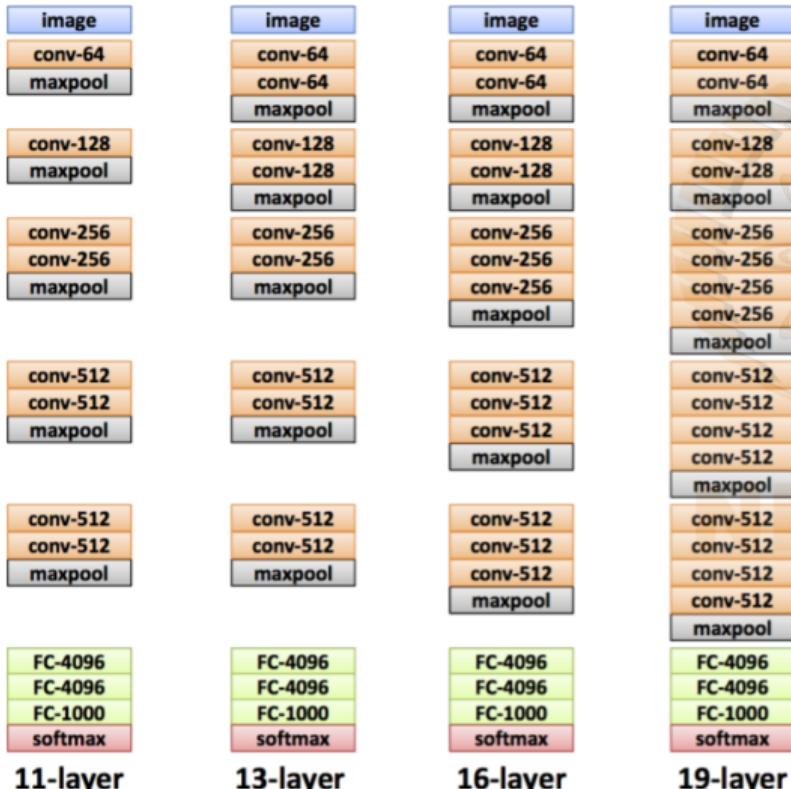
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- **Key contribution:** Depth of the network is a critical component for good performance

VGGNet



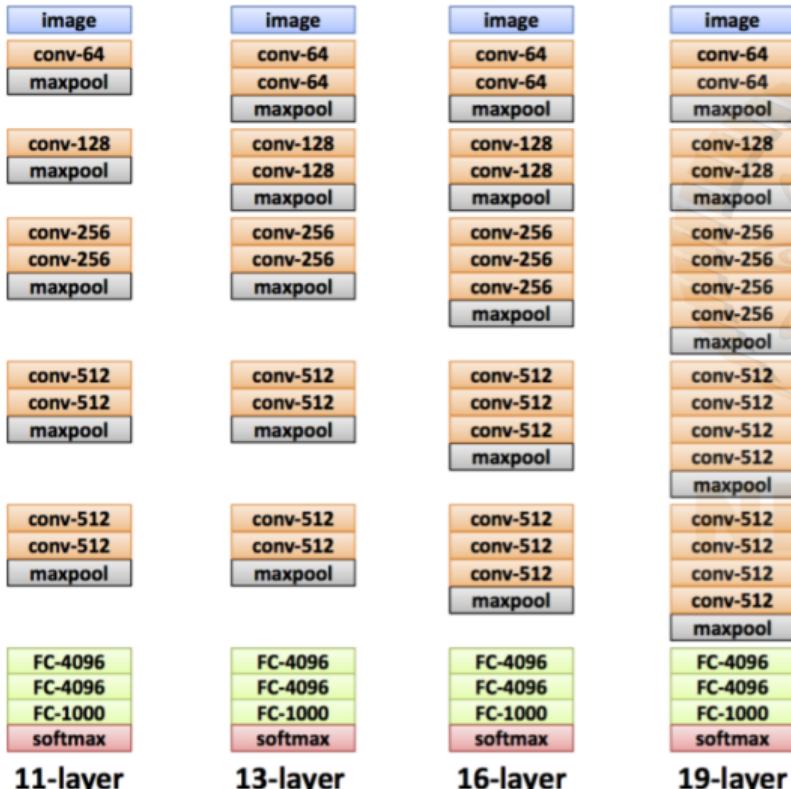
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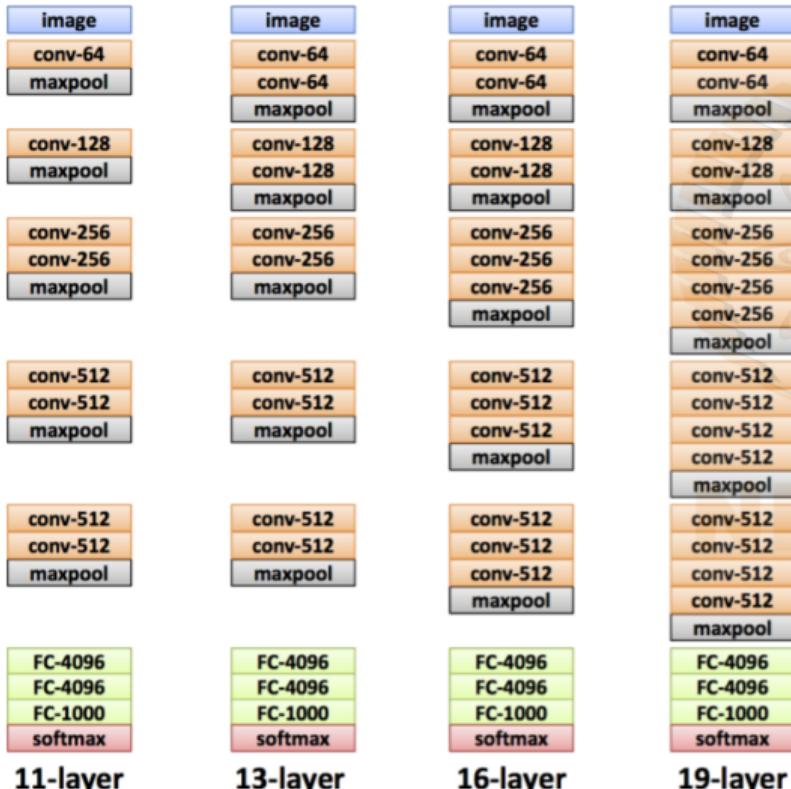
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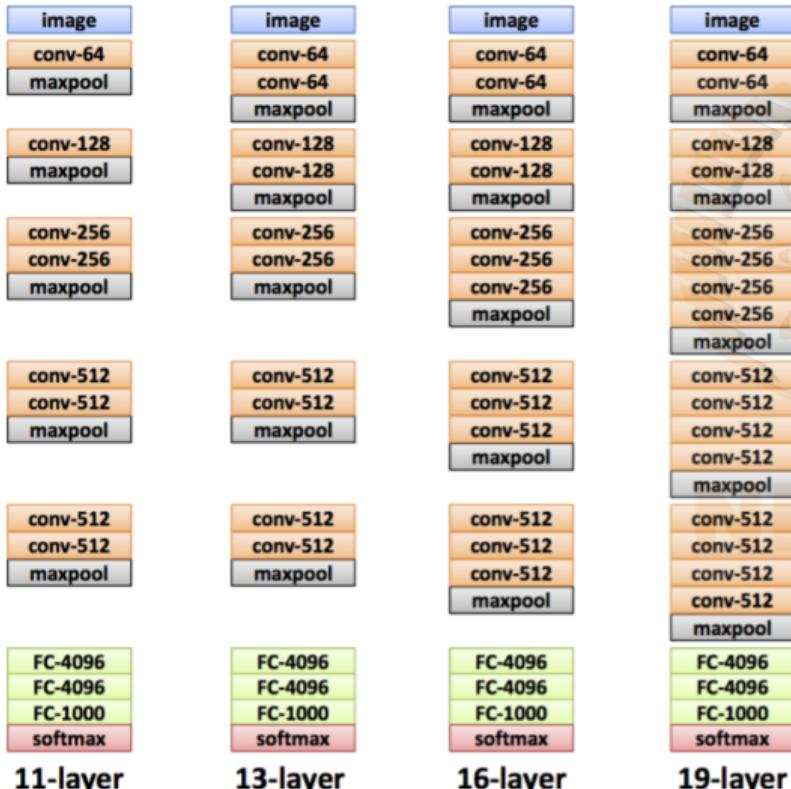
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VGGNet



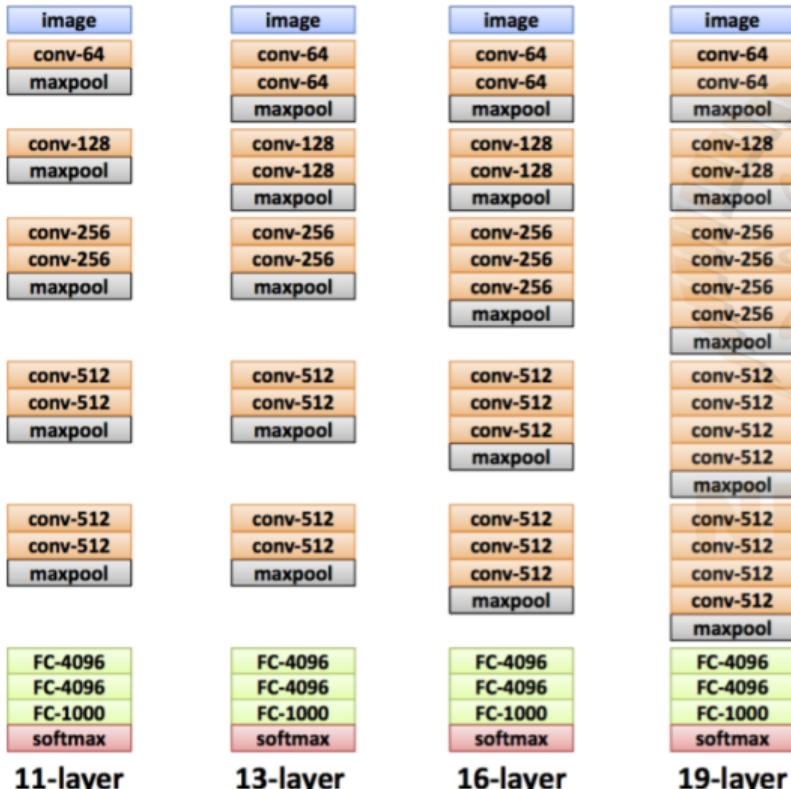
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- Smaller receptive fields:

VGGNet



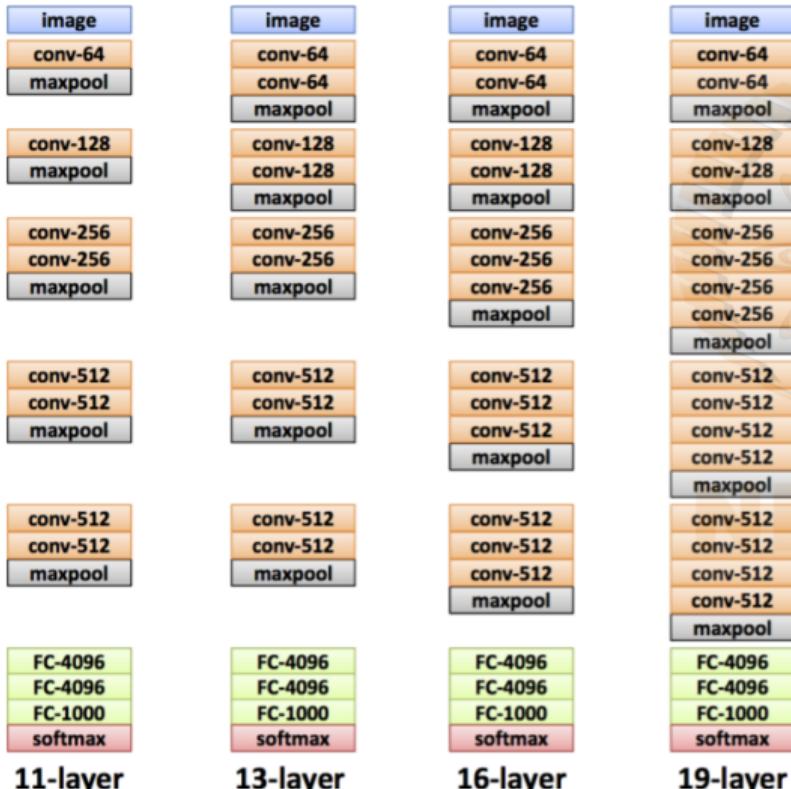
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 - less parameters; faster

VGGNet



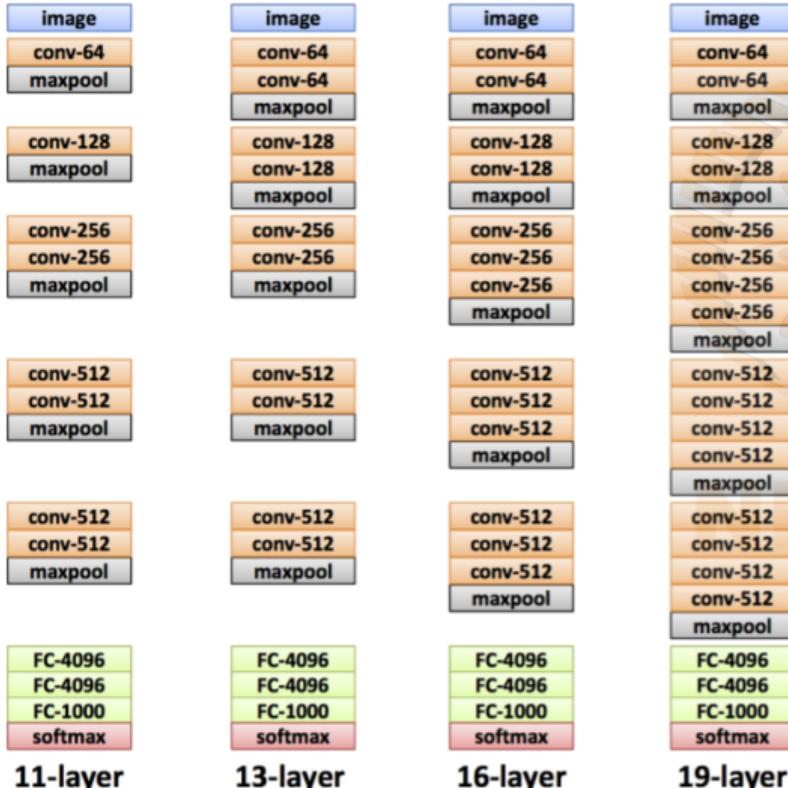
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VGGNet



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- Fewer parameters: $3 \times 3^2 C^2$ (vs) $7^2 C^2$

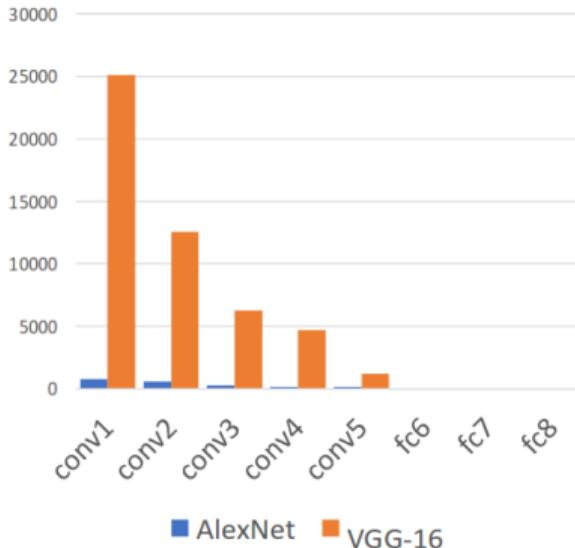
VGGNet



- VGG19 only slightly better than VGG16
- Used ensembles of networks for best results

VGGNet

AlexNet vs VGG-16
(Memory, KB)

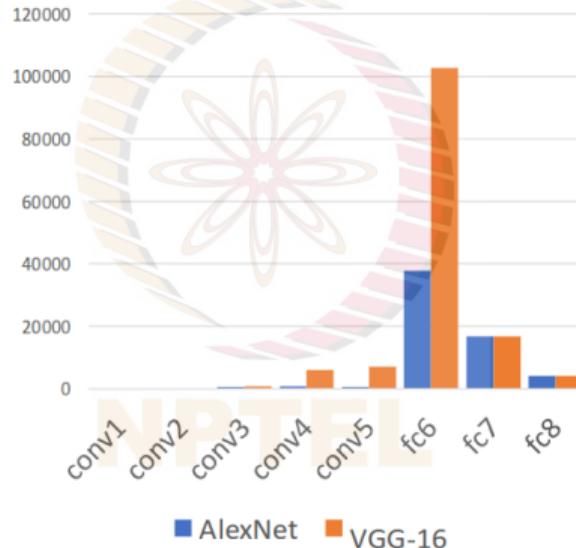


AlexNet total: 1.9 MB

VGG-16 total: 48.6 MB (25x)

Credit: Justin Johnson, Univ of Michigan

AlexNet vs VGG-16
(Params, M)

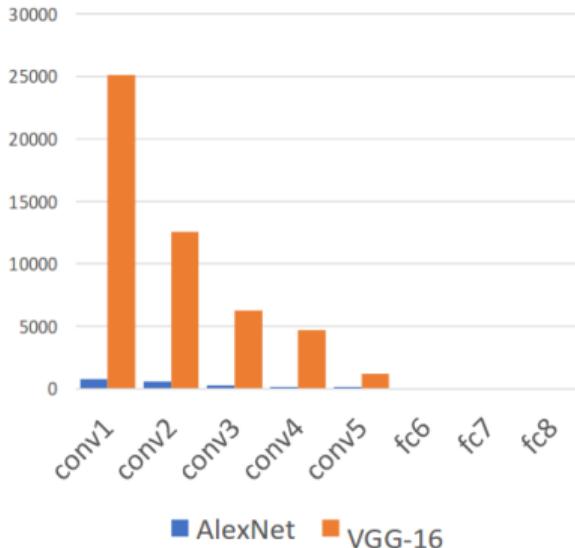


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VGG-16 total: 138M (2.3x)

VGGNet

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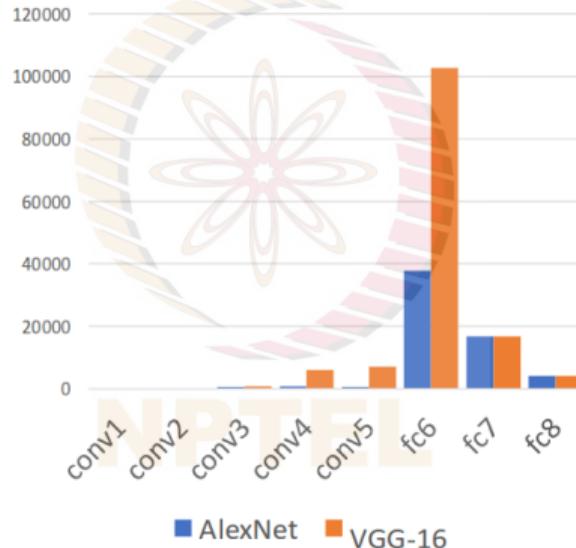


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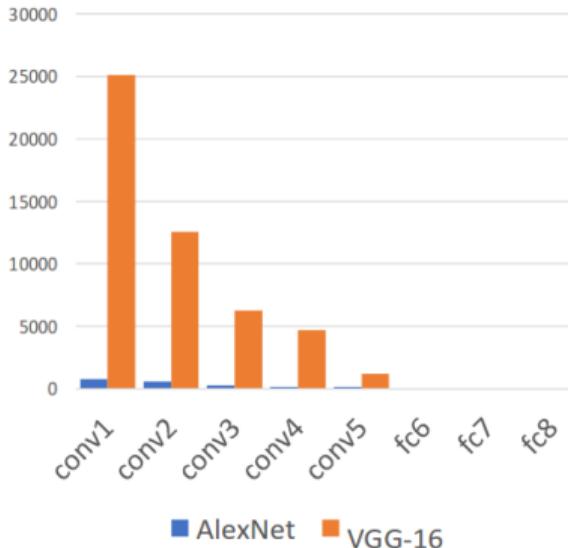
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VGGNet

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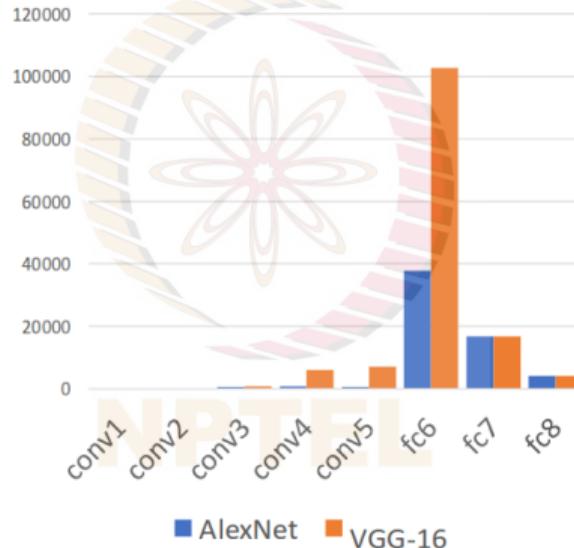


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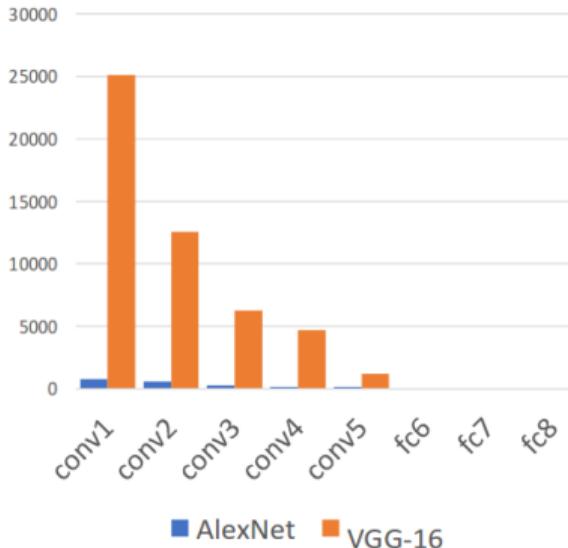
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- Most of these parameters are in the first fully connected layer

VGGNet

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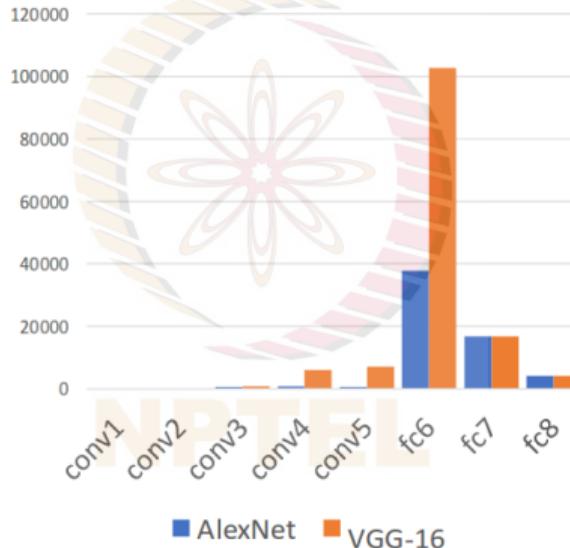


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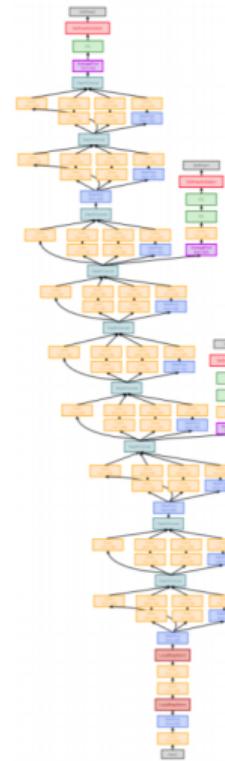
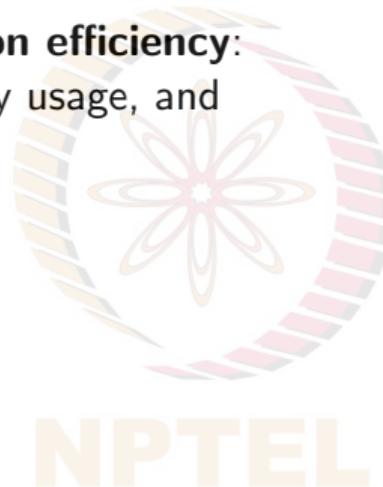
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- Most of these parameters are in the first fully connected layer
- Most of the memory is used in early CONV layer

GoogleNet

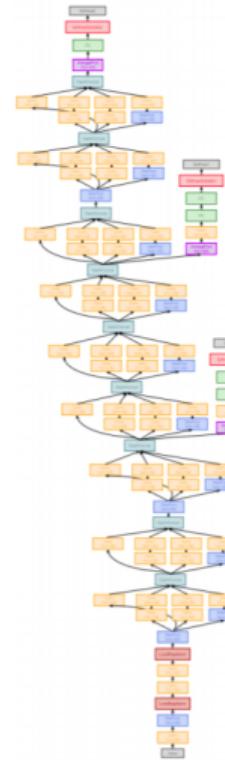
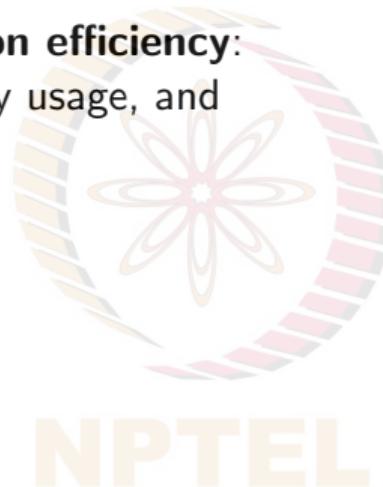
- **Deeper networks with focus on efficiency:**
reduce parameter count, memory usage, and computation



Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford; Justin Johnson, Univ of Michigan

GoogleNet

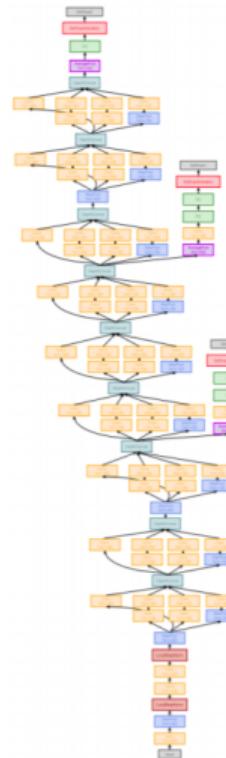
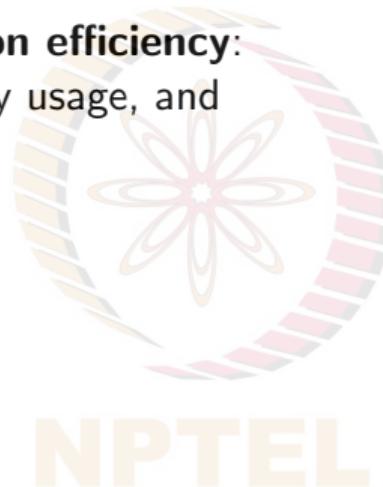
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GoogleNet

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- No FC layers



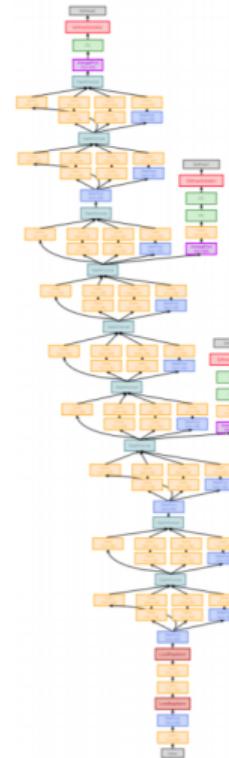
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GoogleNet

- **Deeper networks with focus on efficiency:**
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- 22 layers
- No FC layers
- Efficient “**Inception**” module



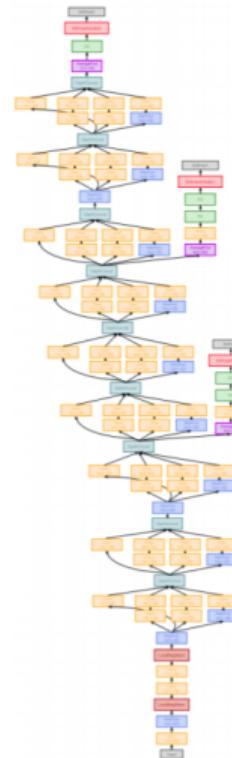
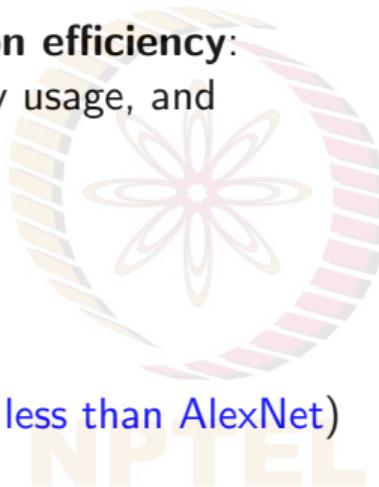
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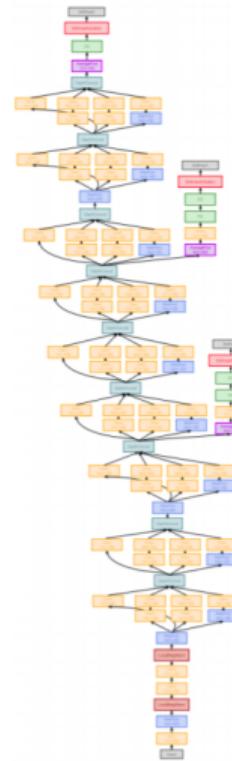
- Deeper networks with focus on efficiency:
reduce parameter count, memory usage, and
computation
- 22 layers
- No FC layers
- Efficient “**Inception**” module
- Only 5 million parameters! ([12x less than AlexNet](#))



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GoogleNet

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



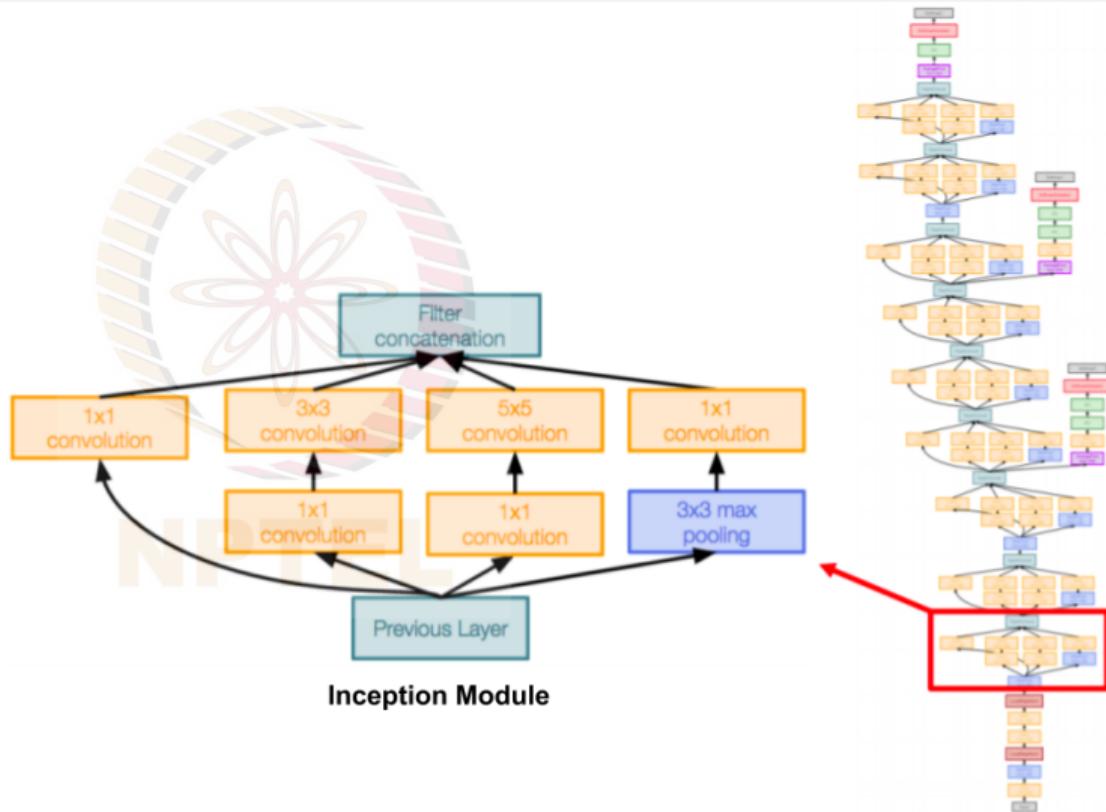
Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford; Justin Johnson, Univ of Michigan

GoogleNet

- **Inception module:**

Local unit with parallel branches

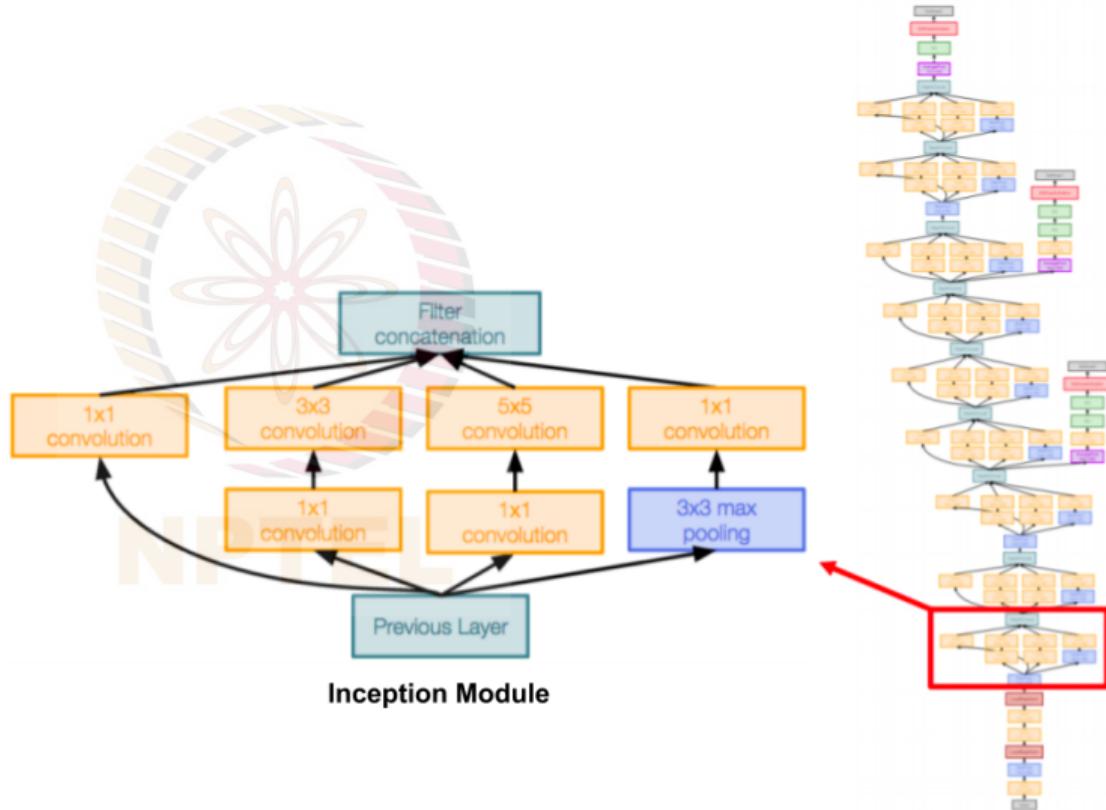
- Local structure
repeated many times
throughout the network



Credit: Justin Johnson, Univ of Michigan

GoogleNet

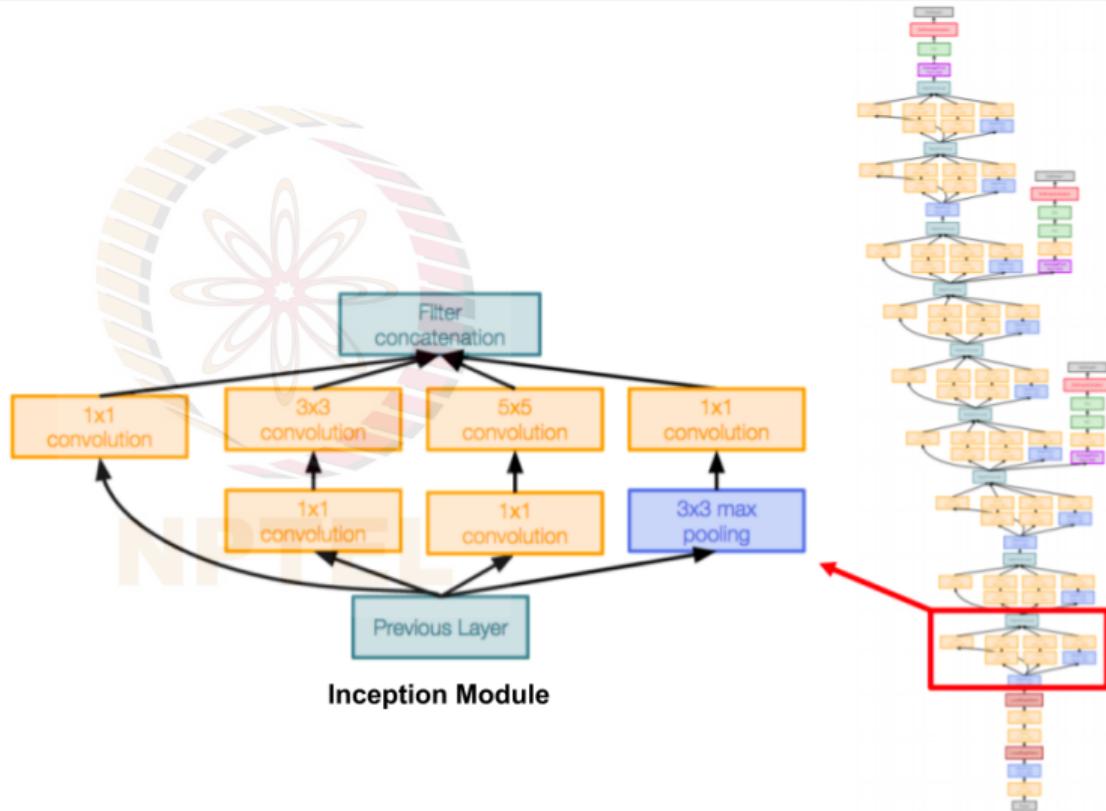
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Credit: Justin Johnson, Univ of Michigan

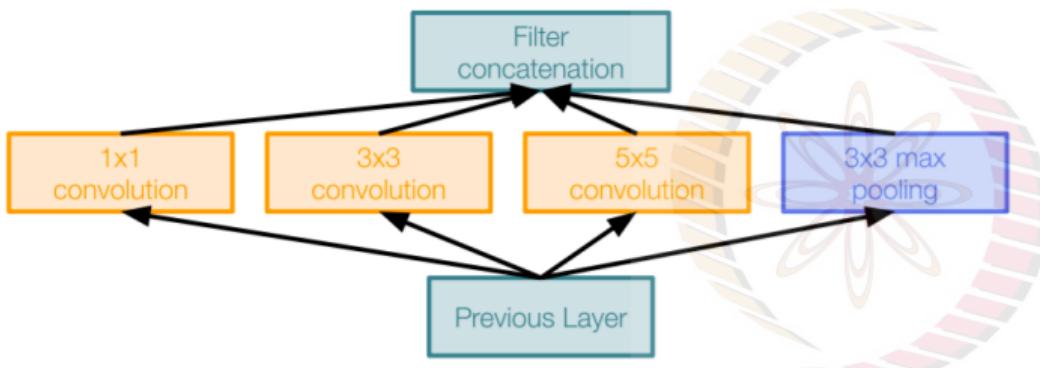
GoogleNet

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Credit: Justin Johnson, Univ of Michigan

GoogleNet

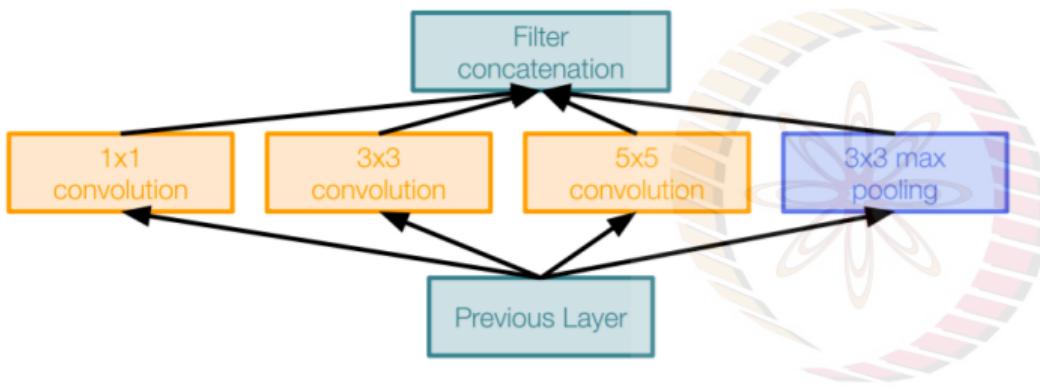


Naive Inception module

- Apply parallel filter operations on the input from previous layer:
 - Multiple receptive field sizes for convolution (1×1 , 3×3 , 5×5)
 - Pooling operation (3×3 max pooling)
- Concatenate all filter outputs together depth-wise

NPTEL

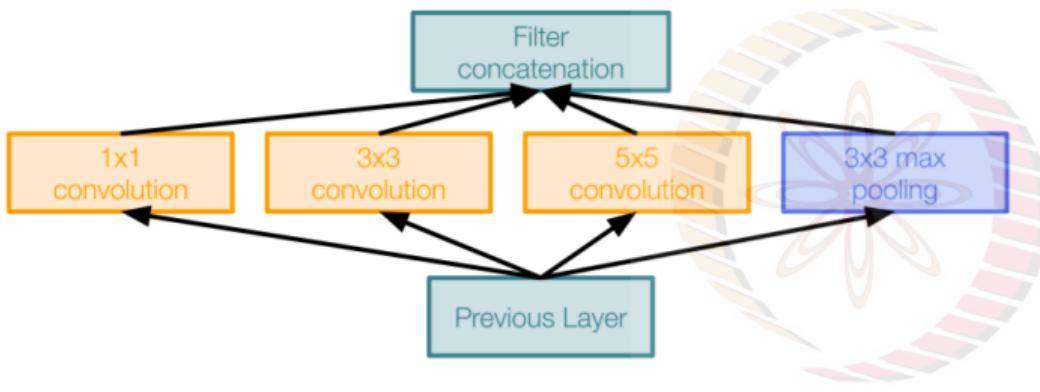
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GoogleNet



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- **What's the problem with this?**
Computationally very expensive

Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford, Spring 2019

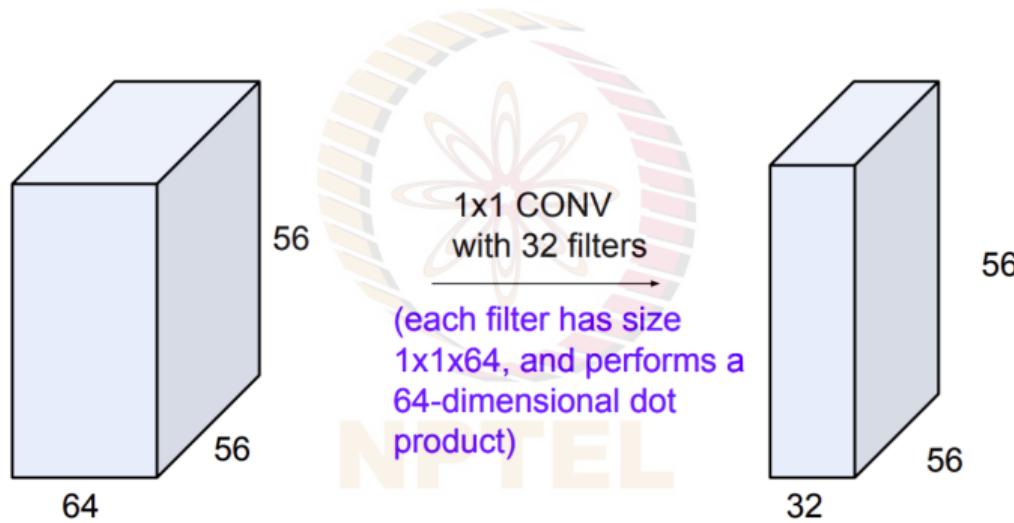
GoogleNet

Solution: Use 1×1 “Bottleneck” layers to reduce channel dimension before expensive conv layers



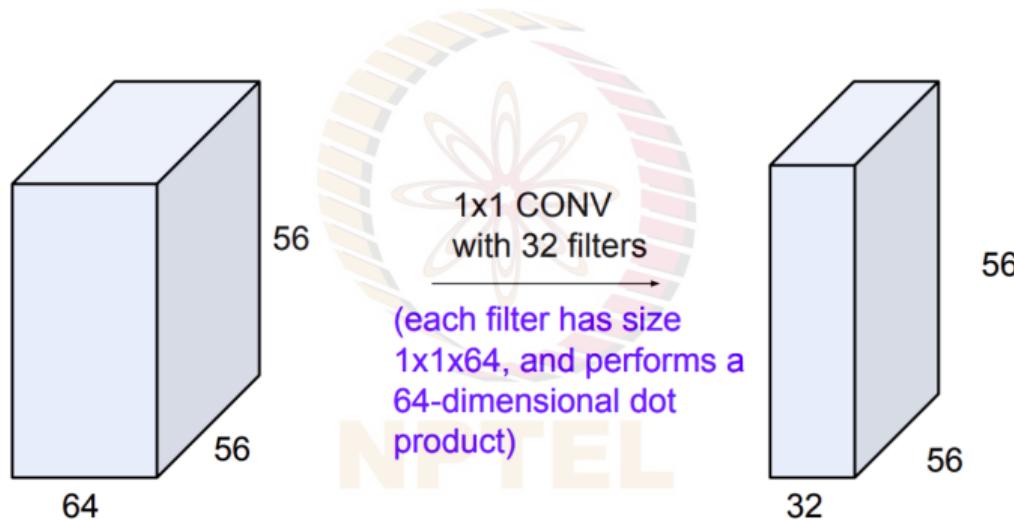
GoogleNet

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GoogleNet

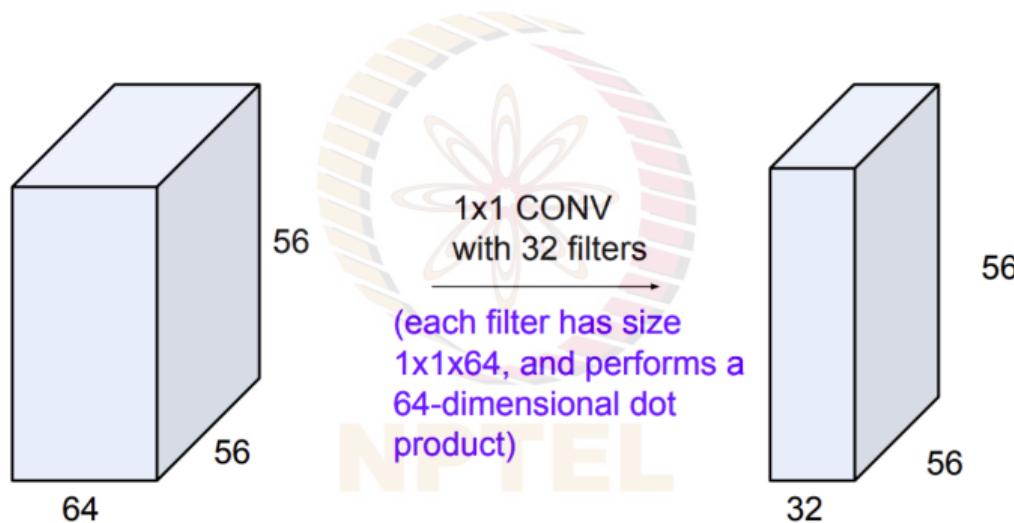
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- Preserves spatial dimensions, reduces depth!

GoogleNet

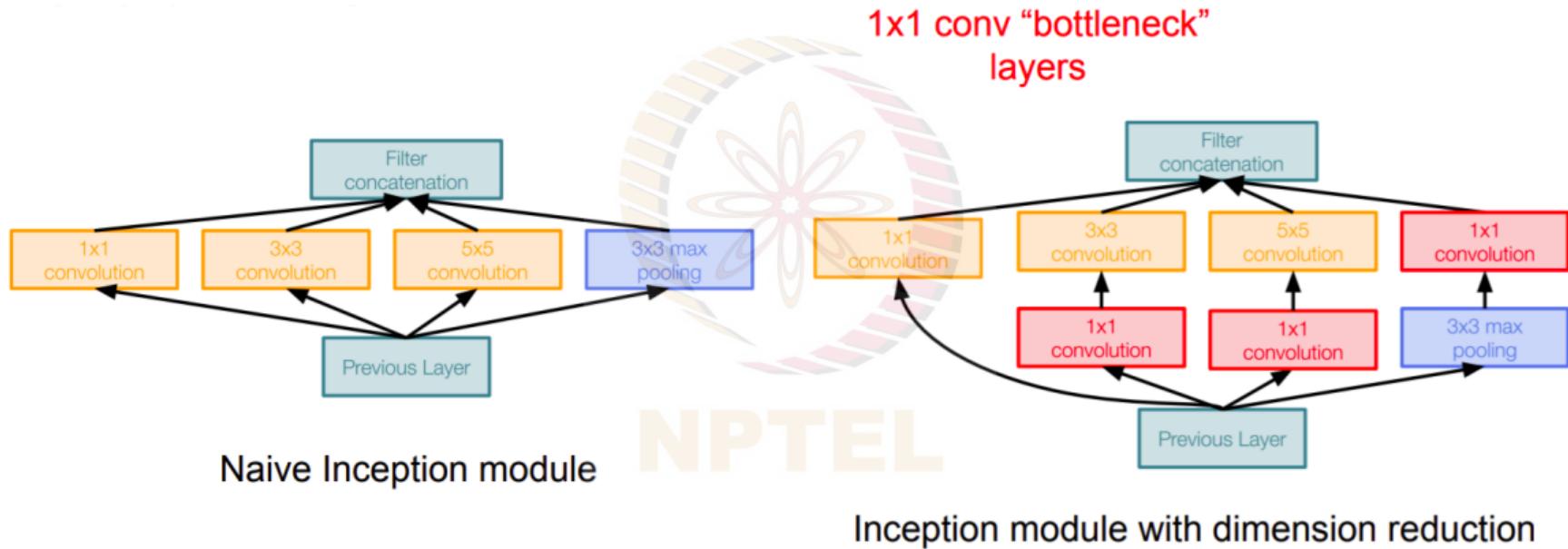
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- Preserves spatial dimensions, reduces depth!
- Projects depth to lower dimension (combination of feature maps)

Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford, Spring 2019

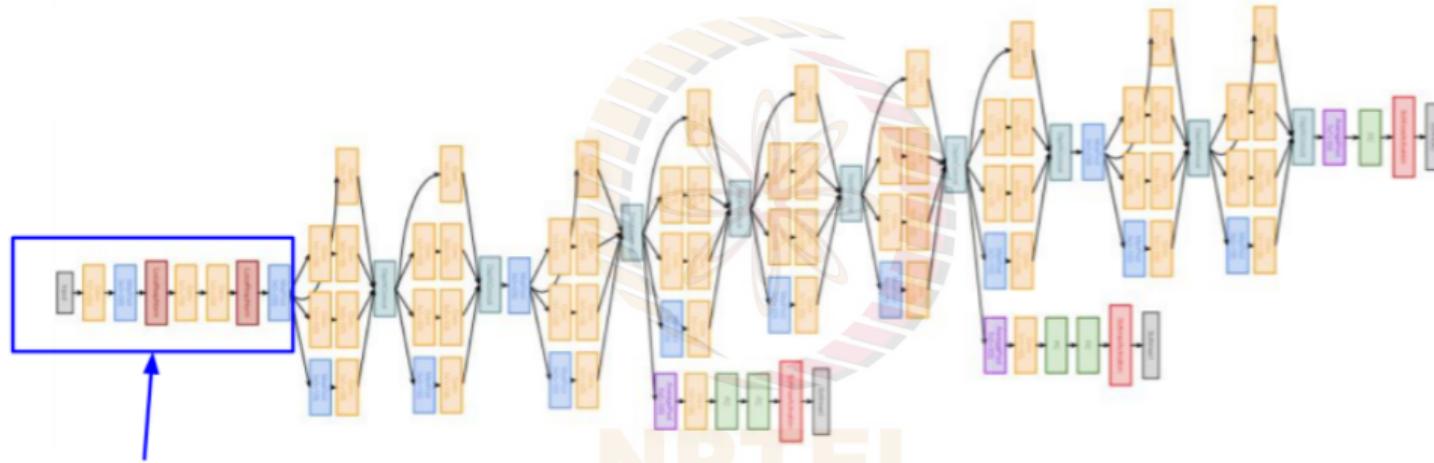
GoogleNet



Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford, Spring 2019

GoogleNet

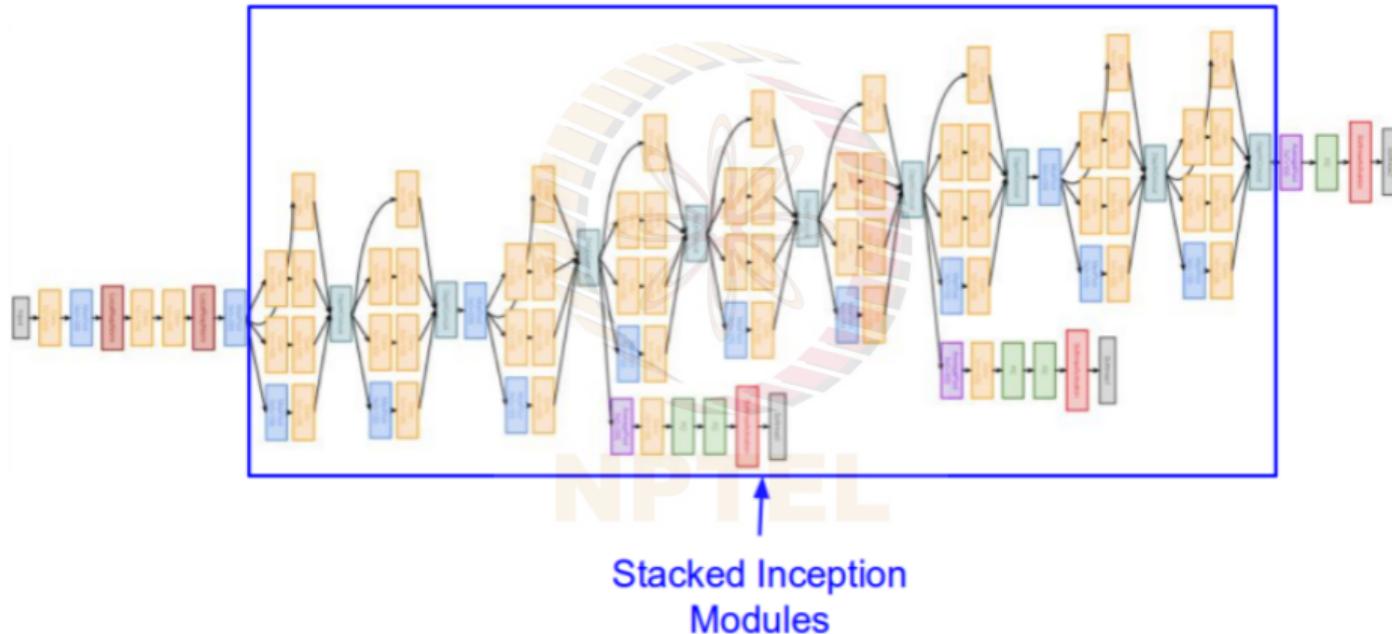
Full Architecture:



Stem Network:
Conv-Pool
2x Conv-Pool

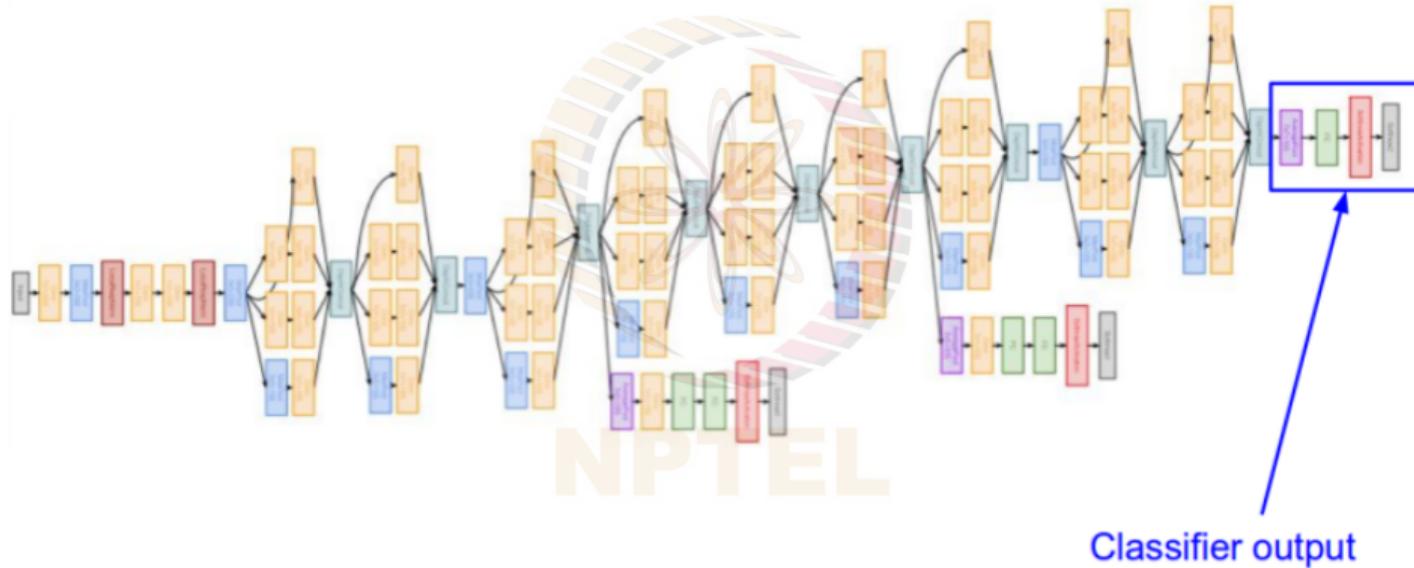
GoogleNet

Full Architecture:



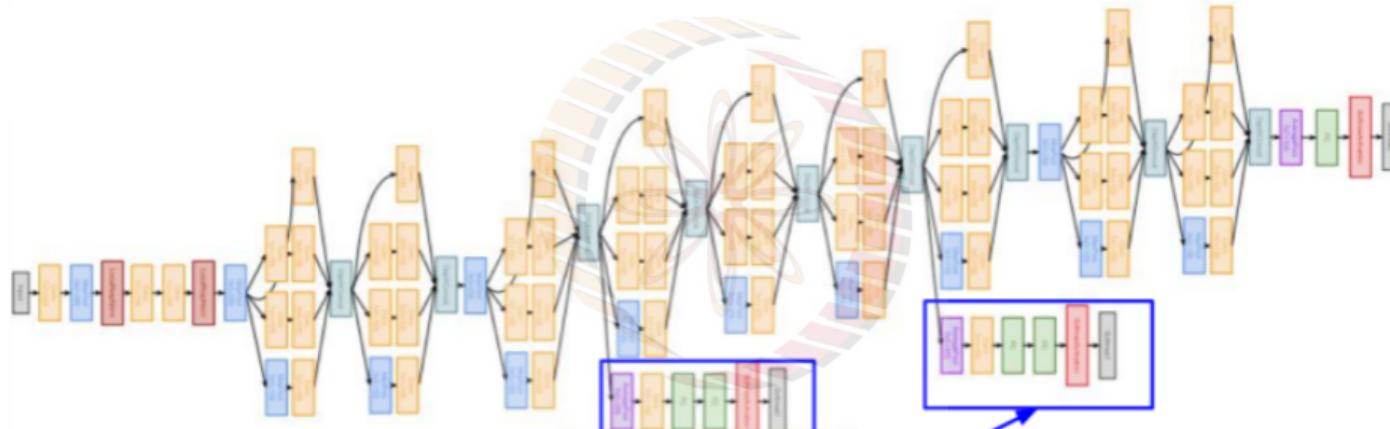
GoogleNet

Full Architecture:



GoogleNet

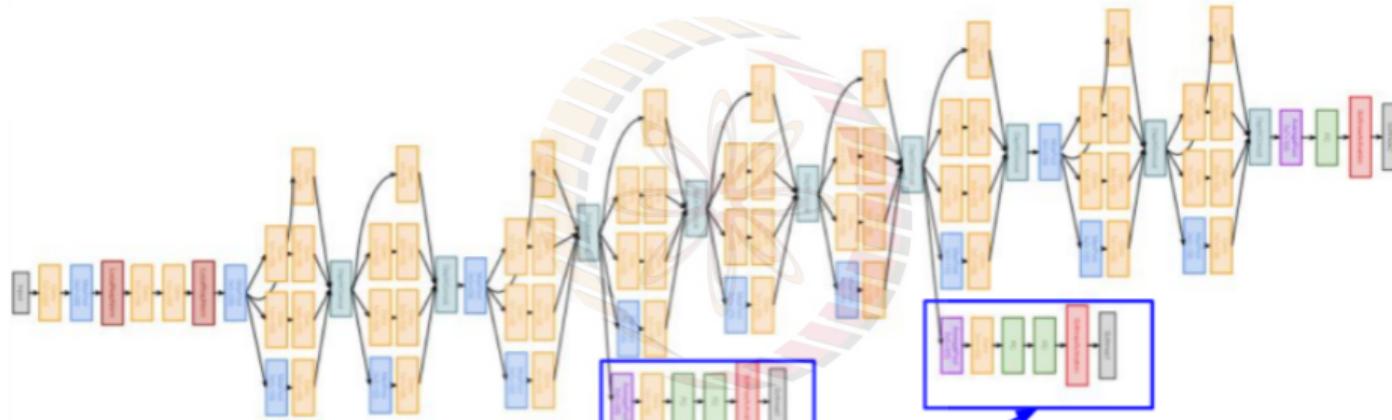
Full Architecture:



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

GoogleNet

Full Architecture:

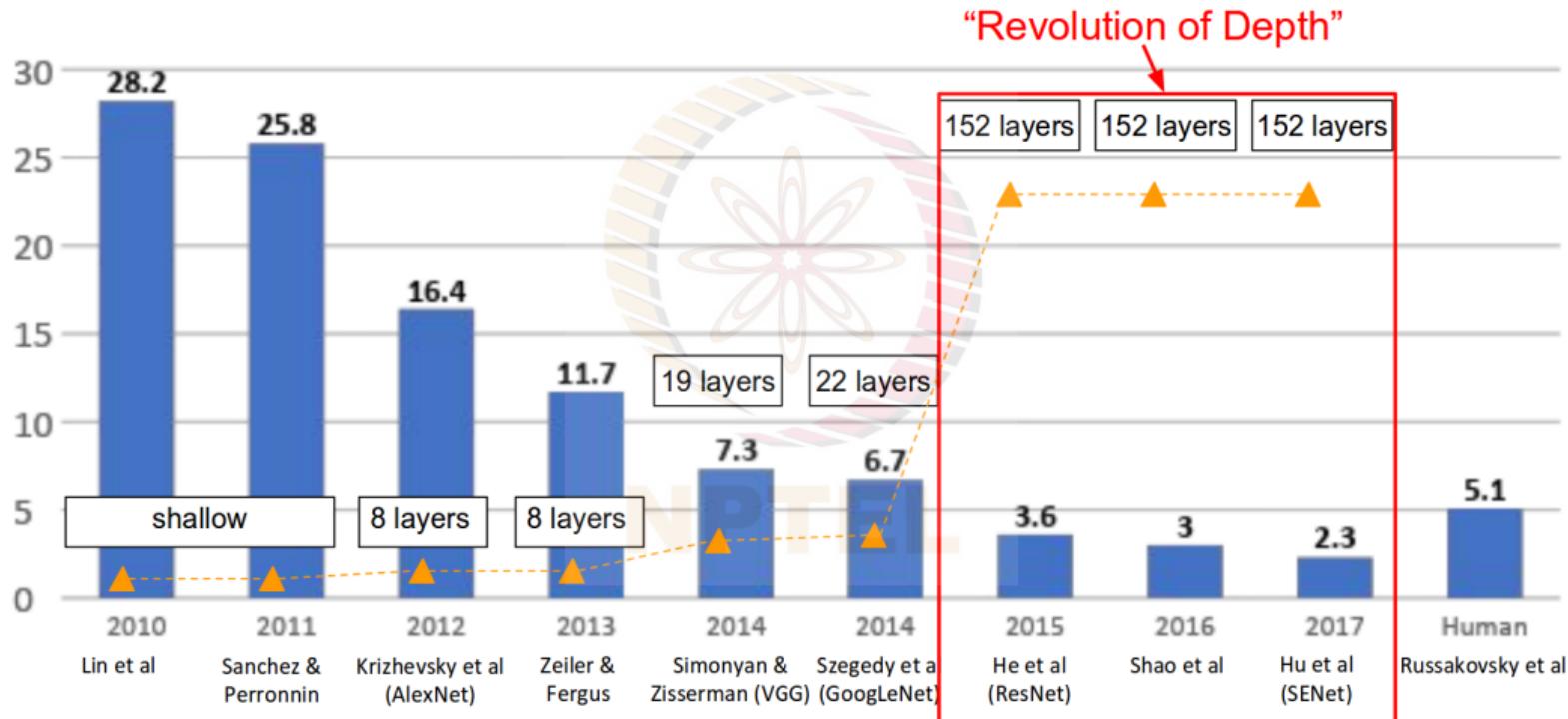


Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-Softmax)

22 total layers (parallel layers count as 1 layer. Auxiliary output layers not counted)

Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford, Spring 2019

Deeper the Merrier



Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford, Spring 2019

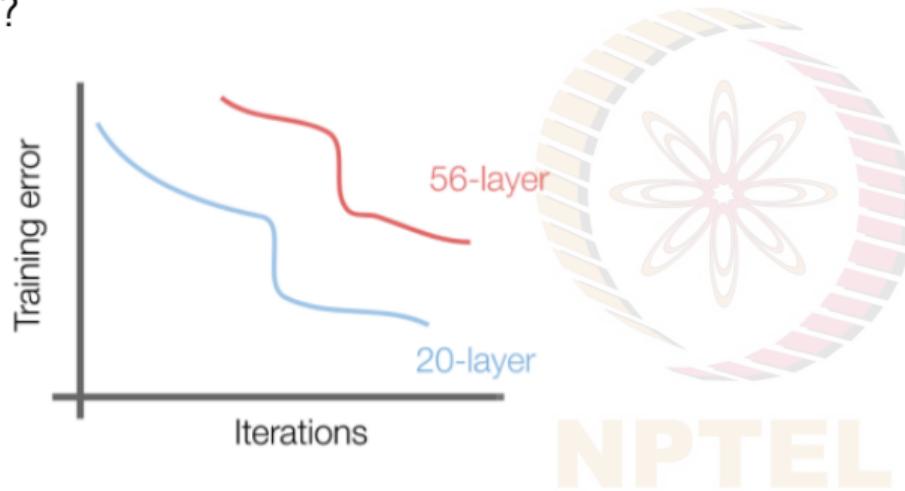
How deep can we go?

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



How deep can we go?

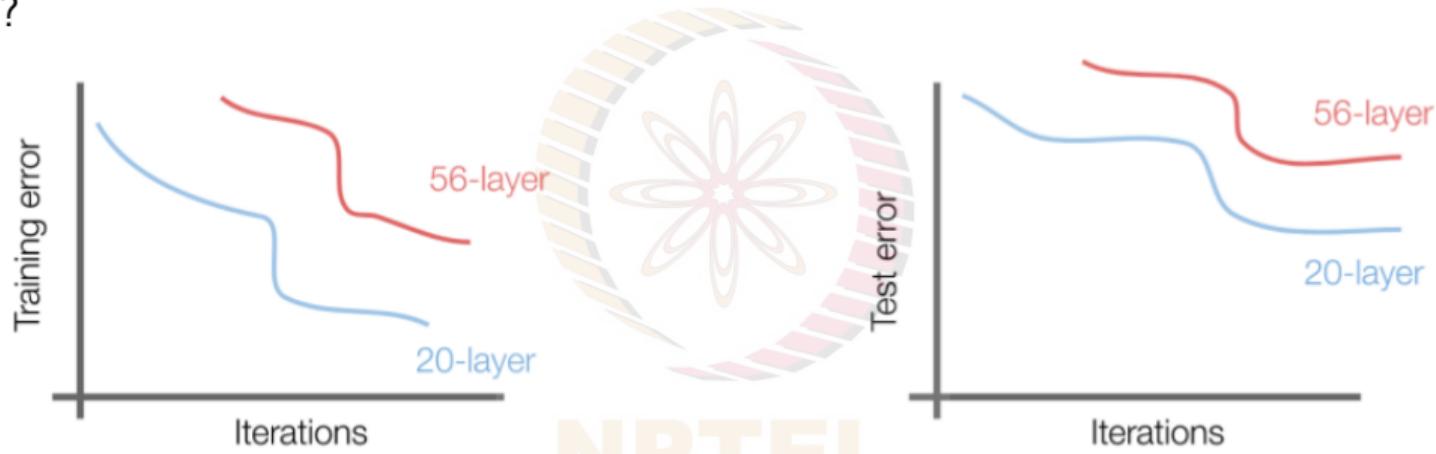
What happens when we continue stacking deeper layers on a “plain” convolutional neural network?



NPTEL

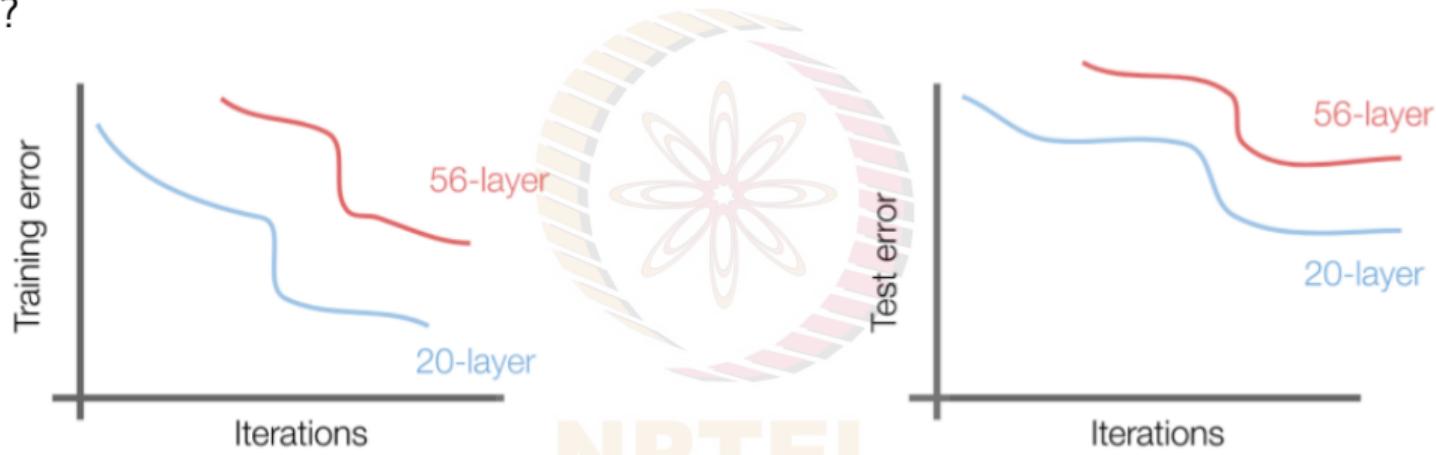
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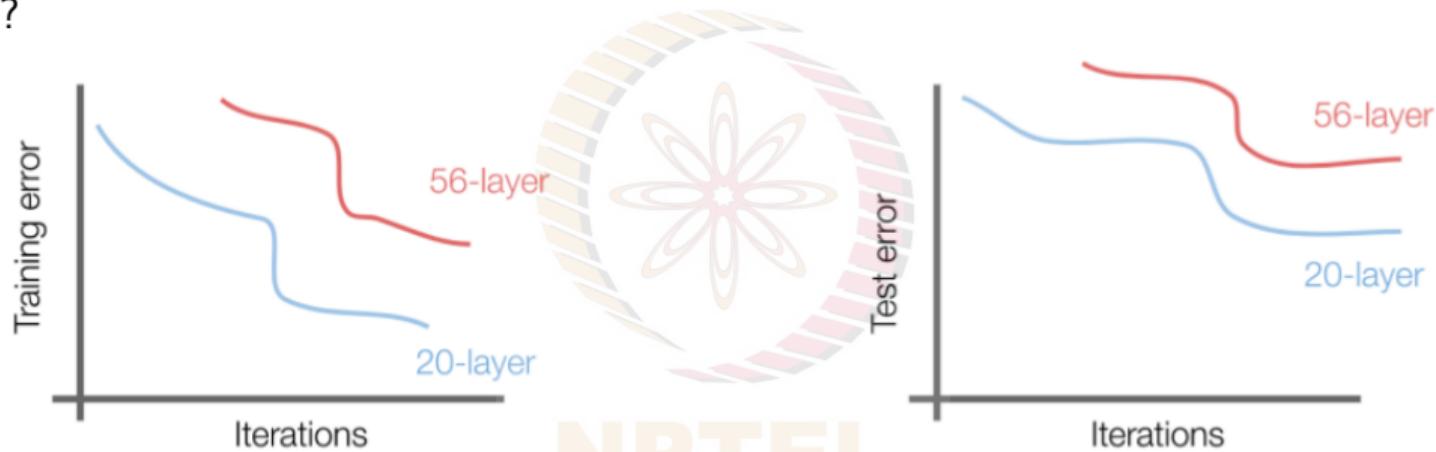


Deeper model does worse than shallow model!

NPTEL

How deep can we go?

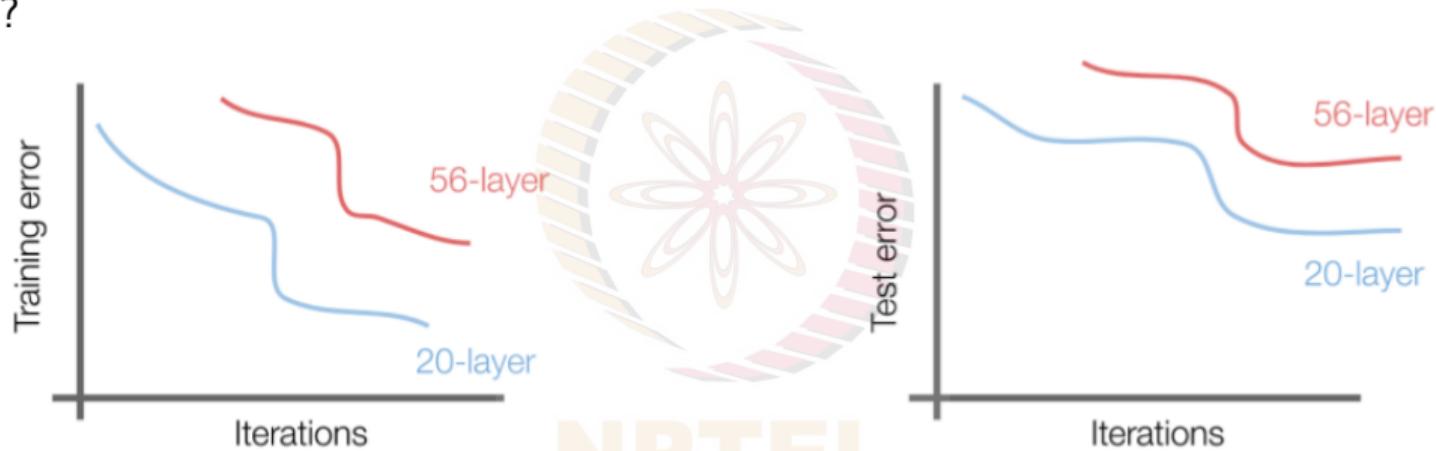
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Deeper model does worse than shallow model! **Why?**

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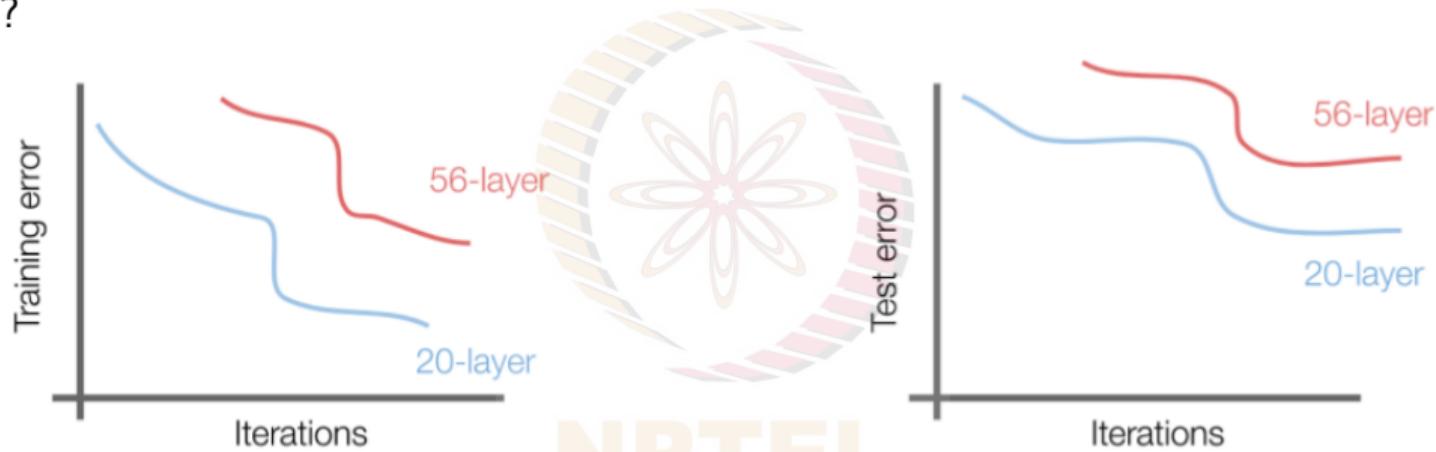


Deeper model does worse than shallow model! **Why?**

The initial guess is that the deep model is **overfitting** since it is much bigger than the shallow model

How deep can we go?

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



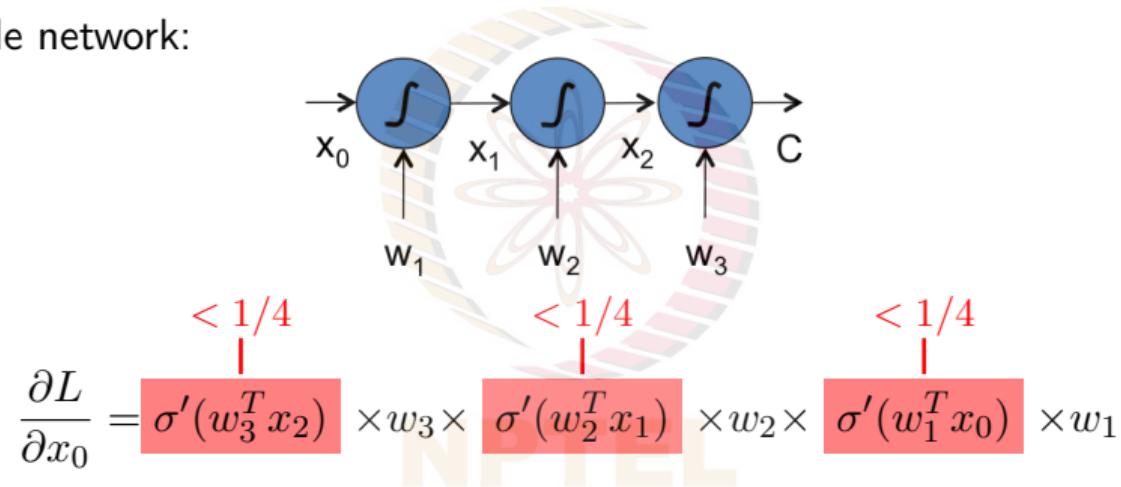
Deeper model does worse than shallow model! **Why?**

The deep model is actually **underfitting** since it also performs worse than the shallow model on the training set

Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford; Justin Johnson, Univ of Michigan

How deep can we go? Vanishing/Exploding Gradient

Consider a simple network:



Why?

How deep can we go? Vanishing/Exploding Gradient

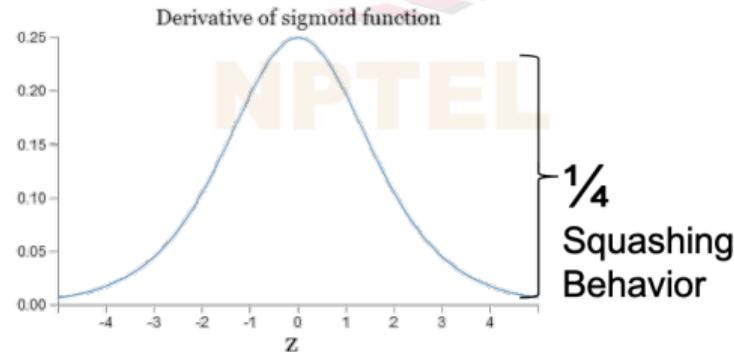
Consider a simple network:

$$\frac{\partial L}{\partial x_0} = \sigma'(w_3^T x_2) \times w_3 \times \sigma'(w_2^T x_1) \times w_2 \times \sigma'(w_1^T x_0) \times w_1$$

$< 1/4$

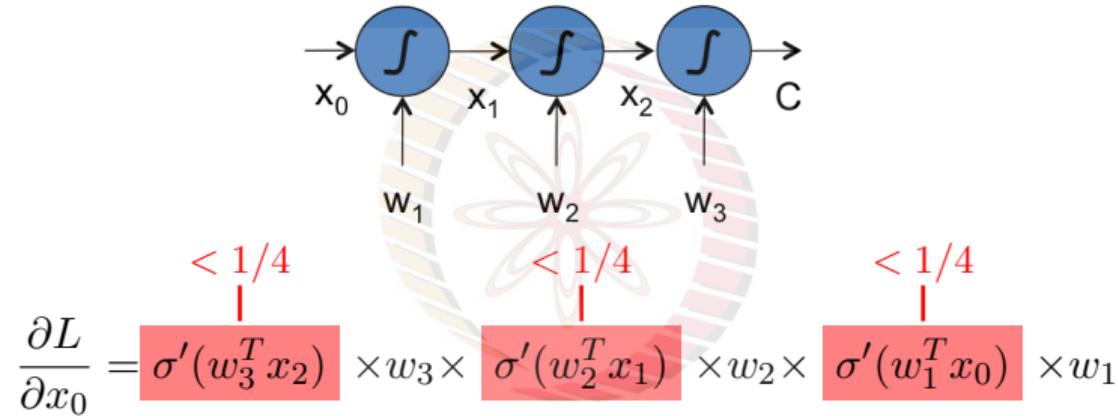
$< 1/4$

$< 1/4$



How deep can we go? Vanishing/Exploding Gradient

Consider a simple network:



- **Vanishing gradients:** Deeper the network, gradients vanish quickly, thereby slowing the rate of change in initial layers
- **Exploding gradients:** Happen when the individual layer gradients are much higher than 1, for instance - can be overcome by **gradient clipping**

ResNet

The deeper model should be able to perform at least as well as the shallower model;[how?](#)



ResNet

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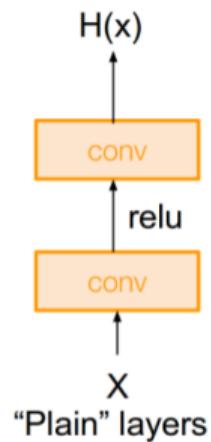
Solution: Change the network with identity connections between layers:



ResNet

The deeper model should be able to perform at least as well as the shallower model;[how?](#)

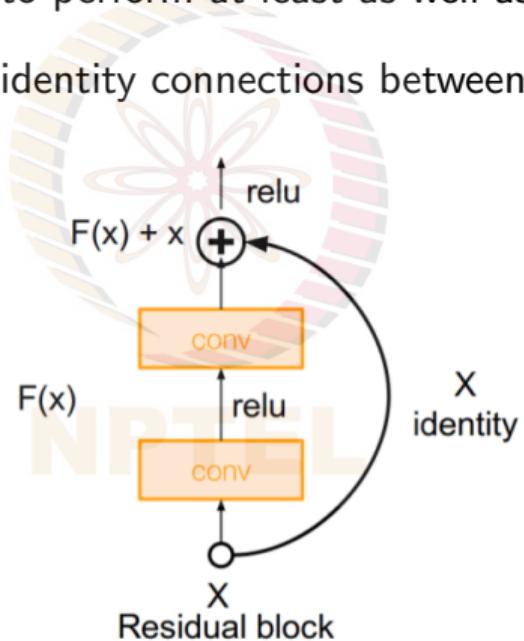
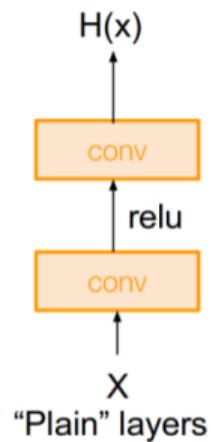
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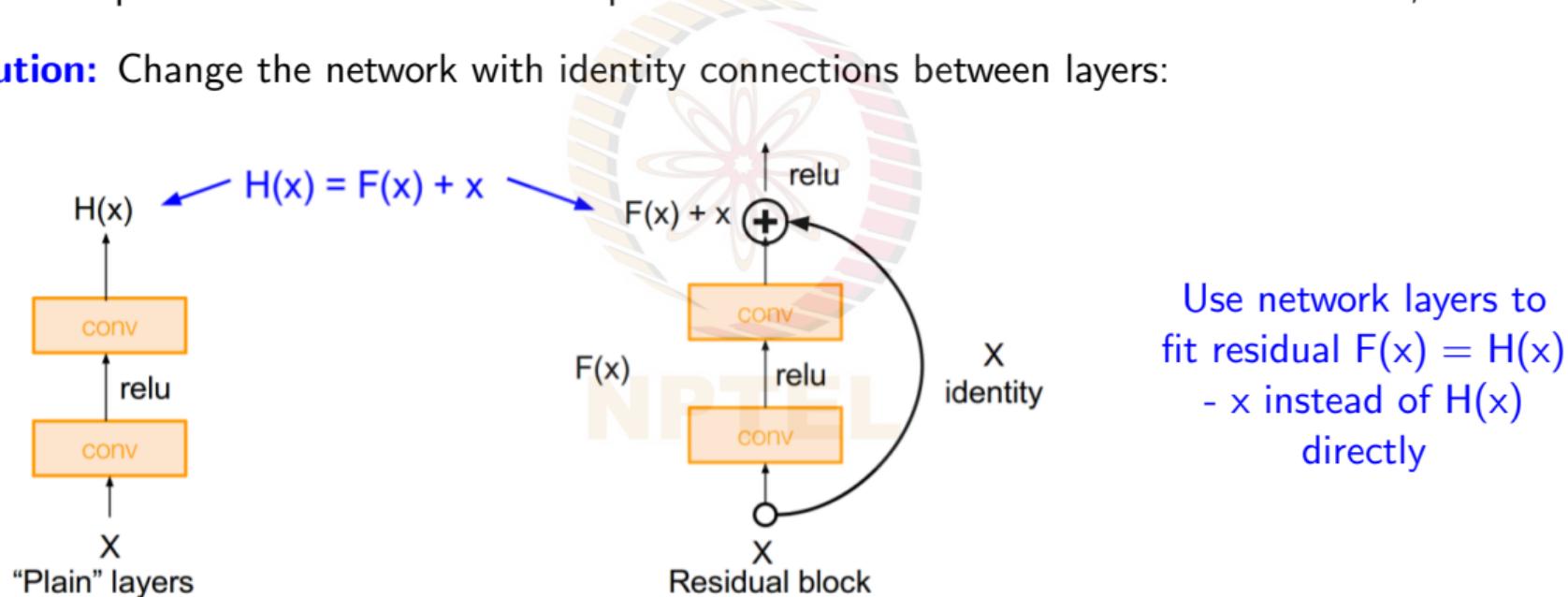
Use network layers to fit residual $F(x) = H(x) - x$ instead of $H(x)$ directly

Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford, Spring 2019

ResNet

The deeper model should be able to perform at least as well as the shallower model; [how?](#)

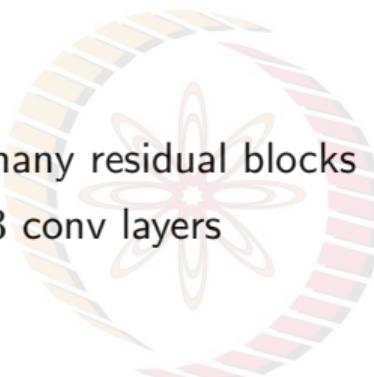
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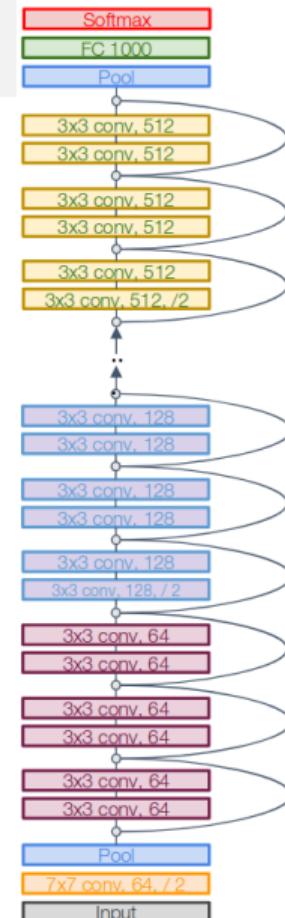
Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford, Spring 2019

ResNet

- A residual network is a stack of many residual blocks
- Each residual block has two 3×3 conv layers



NPTEL

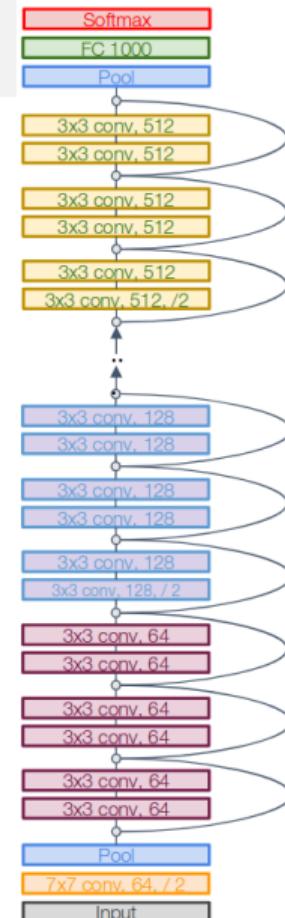


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- Periodically, double number of filters and downsample spatially using stride 2 (/2 in each dimension)

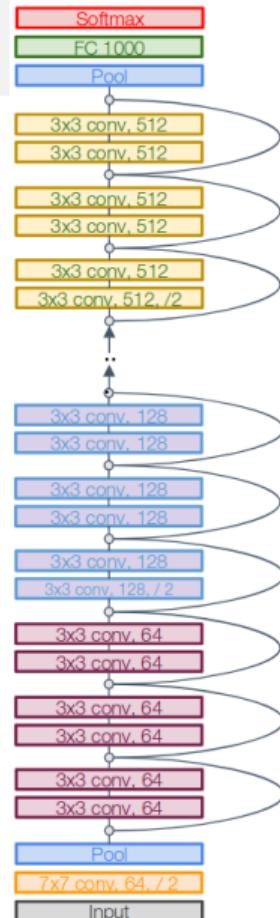
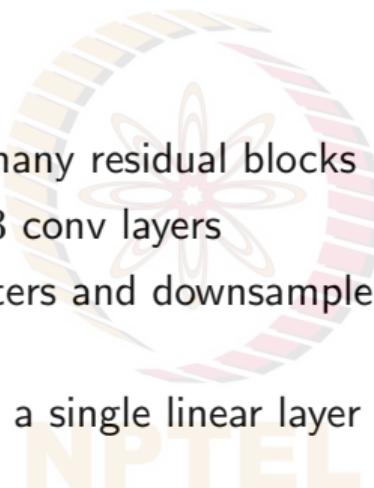


NPTEL



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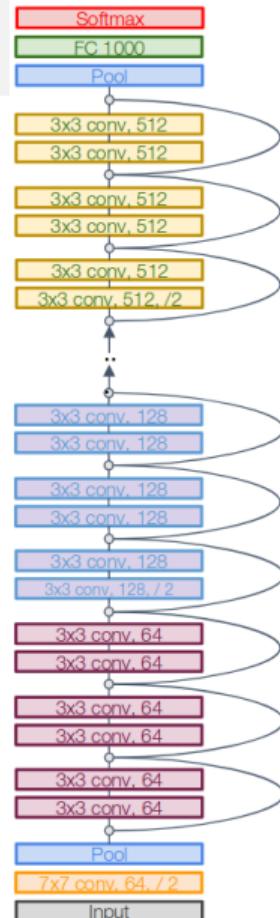


ResNet

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- Periodically, double number of filters and downsample spatially using stride 2 ($/2$ in each dimension)
- Use **global average pooling** and a single linear layer at the end (FC 1000 to output classes)
- Total depths of 34, 50, 101, or 152 layers for ImageNet dataset

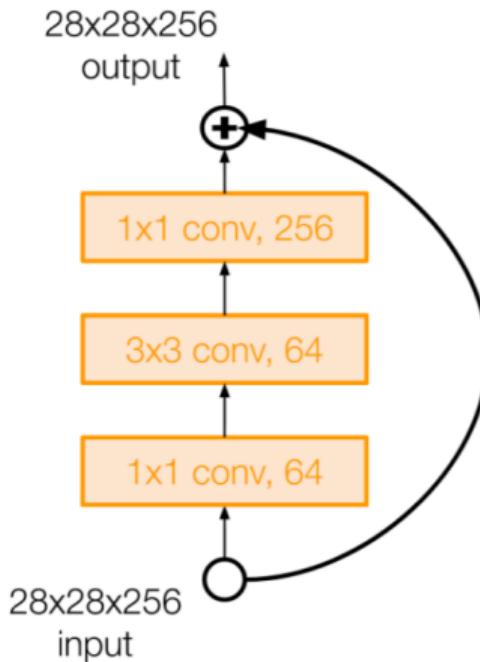


NPTEL



ResNet

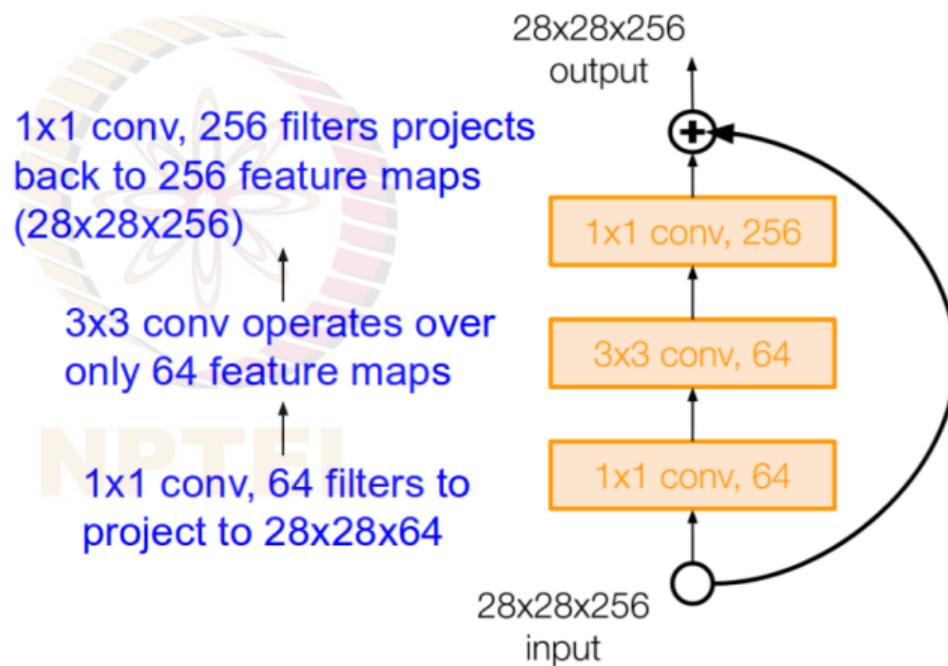
For deeper networks (ResNet-50+), use “bottleneck” layer to improve efficiency (similar to GoogLeNet)



Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford, Spring 2019

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ResNet

- Able to train very deep networks
- Deeper networks performs better than shallow networks now (as expected); residual blocks help avoid vanishing gradient
- 1st place in all ILSVRC and COCO 2015 competitions
- We will discuss detection, localization, segmentation and the COCO dataset a bit later



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ResNet @ ILSVRC & COCO 2015 Competitions

1st place in all five major challenges

- ImageNet Classification: "Ultra-deep" 152-layer nets
- ImageNet Detection: 16% better than the 2nd best
- ImageNet Localization: 27% better than the 2nd best
- COCO Detection: 11% better than the 2nd best
- COCO Segmentation: 12% better than the 2nd best

Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford, Spring 2019

Homework

Readings

- Tutorial: [Illustrated: 10 CNN Architectures](#)
- (Optional) For more details, skim through the following papers:
 - [ImageNet Classification with Deep Convolutional Neural Networks](#)
 - [Very Deep Convolutional Networks for Large-Scale Image Recognition](#)
 - [Going Deeper with Convolutions](#)
 - [Deep Residual Learning for Image Recognition](#)

Exercise

- Show that minimizing negative log likelihood in a neural network with a softmax activation function in the last layer is equivalent to minimizing cross-entropy error function (*Hint:* Read [Chapter 3 of Nielsen's online book on basics of NNs](#))

References

-  Yann LeCun et al. "Gradient-based learning applied to document recognition". In: 1998.
-  Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet Classification with Deep Convolutional Neural Networks". In: *NIPS*. 2012.
-  Karen Simonyan and Andrew Zisserman. "Very Deep Convolutional Networks for Large-Scale Image Recognition". In: *CoRR* abs/1409.1556 (2015).
-  Christian Szegedy et al. "Going deeper with convolutions". In: *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2015), pp. 1–9.
-  Kaiming He et al. "Deep Residual Learning for Image Recognition". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2016), pp. 770–778.
-  Johnson, Justin, EECS 498-007 / 598-005 - Deep Learning for Computer Vision (Fall 2019). URL: <https://web.eecs.umich.edu/~justincj/teaching/eecs498/> (visited on 06/29/2020).
-  Li, Fei-Fei; Johnson, Justin; Serena, Yeung; CS 231n - Convolutional Neural Networks for Visual Recognition (Spring 2019). URL: <http://cs231n.stanford.edu/2019/> (visited on 06/29/2020).