Deep Learning for Computer Vision

CNN Architectures for Image Classification: AlexNet, VGG

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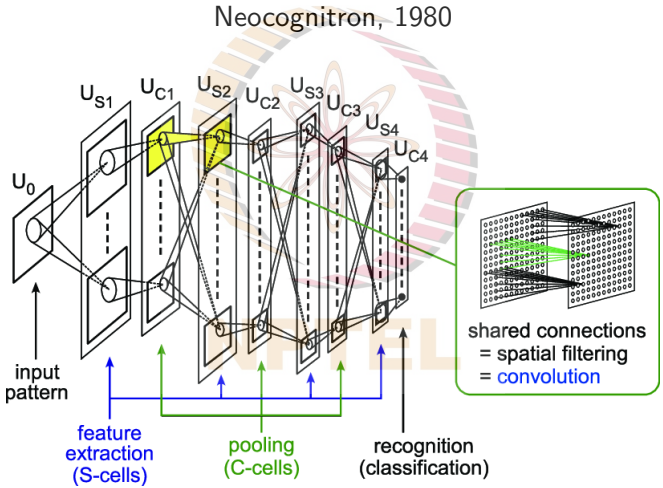
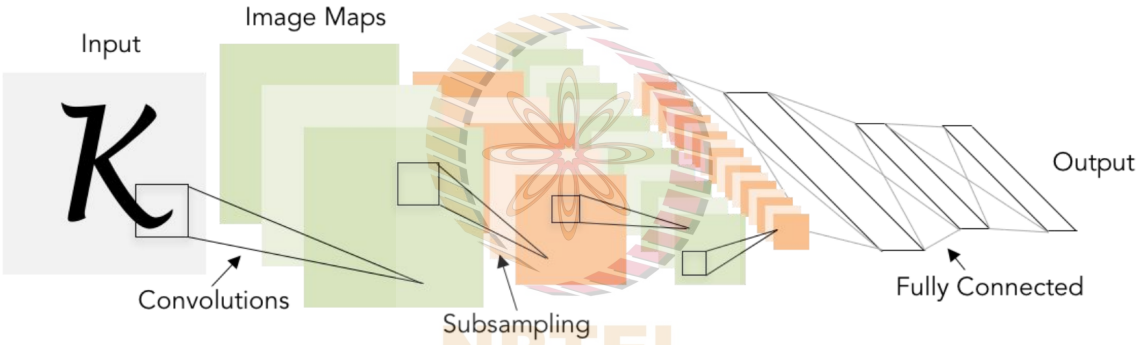
History of CNNs



LeNet-5 (1989-1998)

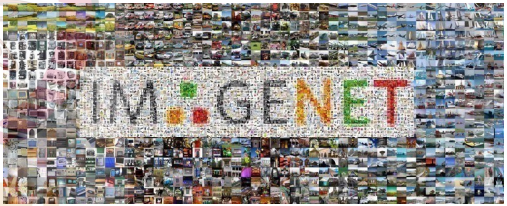


- Conv filters were 5×5, applied at stride 1
- Subsampling (Pooling) layers were 2×2 applied at stride 2
- **Overall Architecture:** [**CONV-POOL-CONV-POOL-FC-FC**]

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:

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

- When activation function is sigmoid $\left(\sigma(x) = \frac{1}{1+e^{-x}}\right)$, 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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$$\frac{\partial L}{\partial w_j} = -\frac{1}{n}\sum_x \left(\frac{y}{\sigma(z)} - \frac{1-y}{1-\sigma(z)}\right)\frac{\partial \sigma}{\partial w_j}$$
$$= -\frac{1}{n}\sum_x \left(\frac{y}{\sigma(z)} - \frac{1-y}{1-\sigma(z)}\right)\sigma'(z)x_j$$
$$= \frac{1}{n}\sum_x \frac{\sigma'(z)x_j}{\sigma(z)(1-\sigma(z))}(\sigma(z)-y)$$
$$= \frac{1}{n}\sum_x x_j\,(\sigma(z)-y)$$

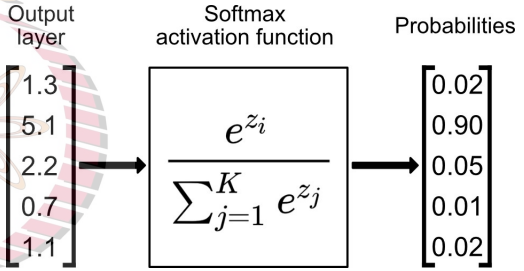
Note the last term in the final expression, very similar to gradient of MSE loss function

Activation Function in Output Layer

Softmax activation function

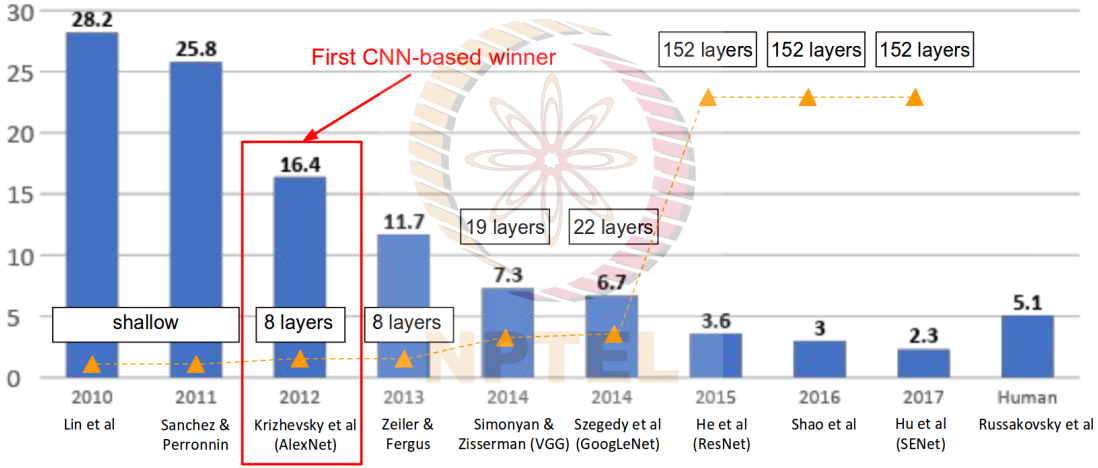
$$a_j = \frac{e^{z_j}}{\sum_k e^{z_k}}$$

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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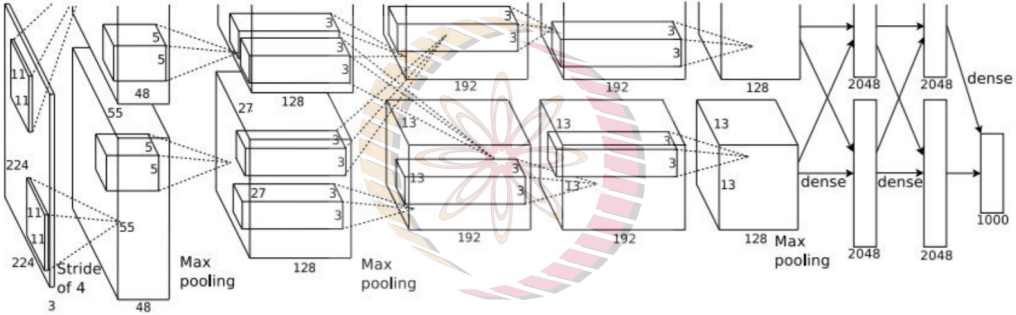
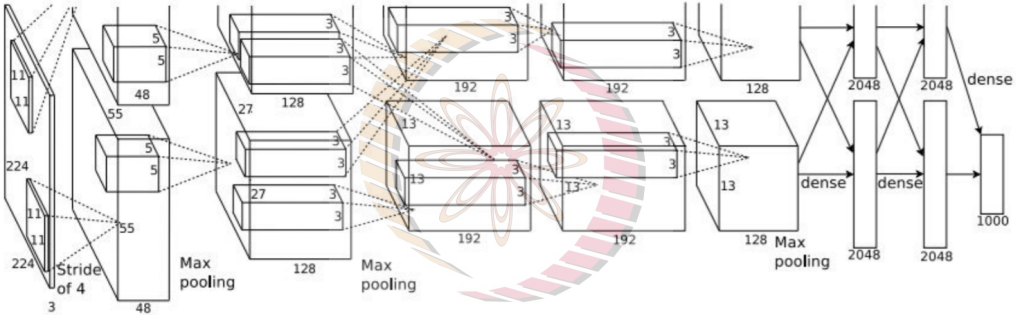
AlexNet[1]



- 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

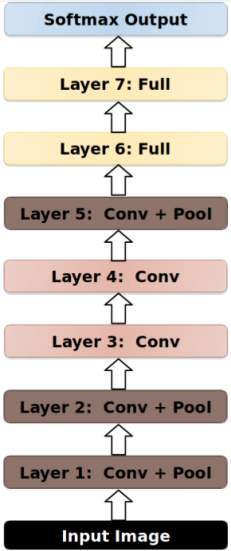
[1]Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." NIPS 2012.

AlexNet


224
224
3
11
11
Stride
of 4
55
48
5
5
Max
pooling
27
128
3
Max
pooling
13
192
128
dense
2048
1000
Input Image
Conv + Pool
Conv + Pool
Conv
Conv
Conv + Pool
Full
Full
Output

AlexNet

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



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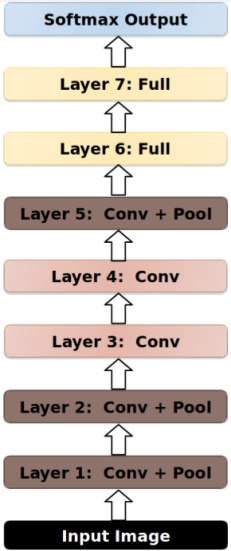
- **Response normalization layers** follow the first and second convolutional layers.



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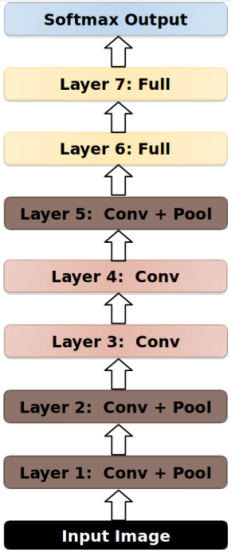
- Max-pooling follow first, second and the fifth convolutional layers



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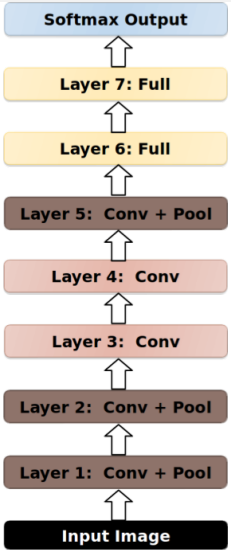
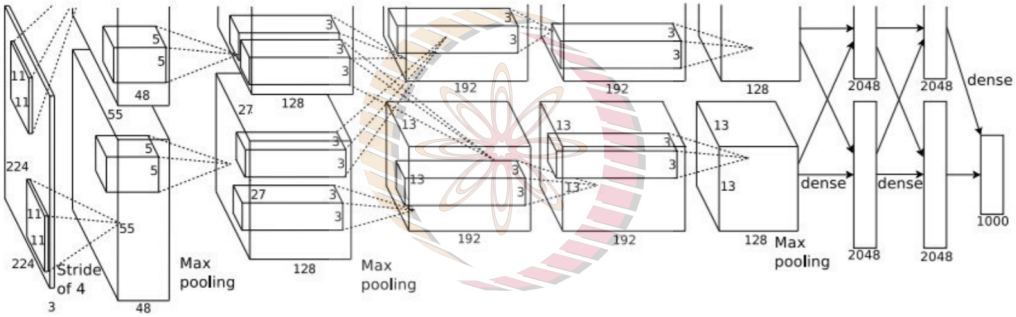
- Trained on ImageNet Dataset
- **Response normalization layers** follow the first and second convolutional layers.
- Max-pooling follow first, second and the fifth convolutional layers
- The ReLU non-linearity is applied to the output of every layer



AlexNet

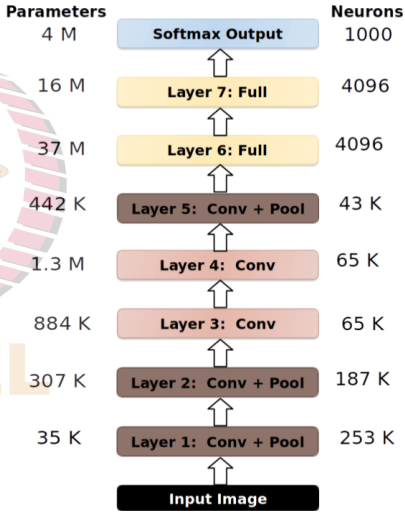


About 57 M parameters are in the fully connected layers

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

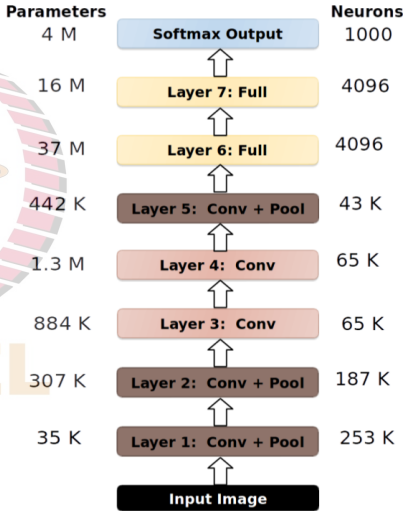
AlexNet

- 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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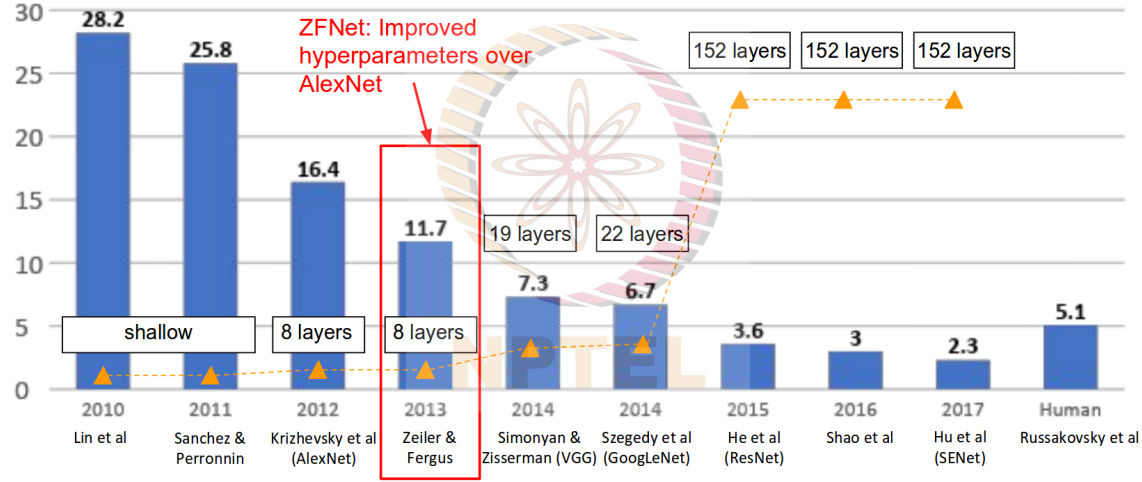

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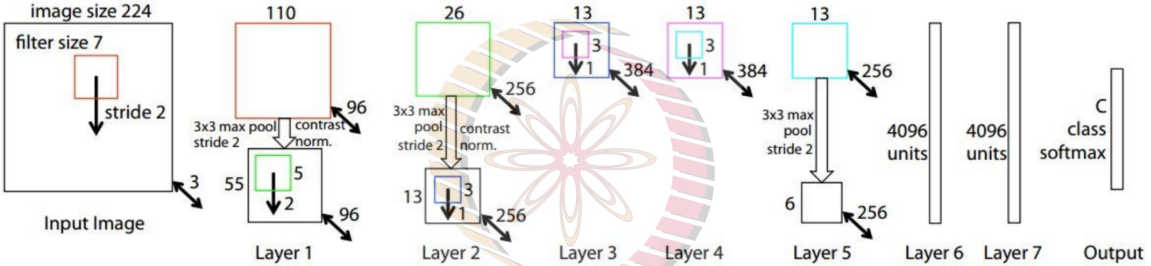
ZFNet (2013)[2]



- Similar to AlexNet but:

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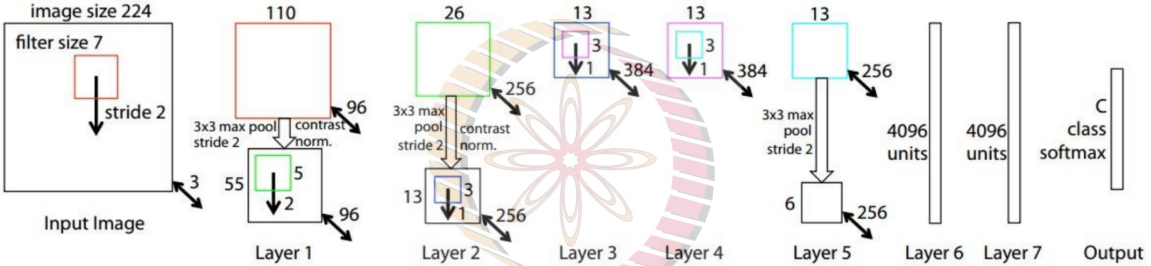

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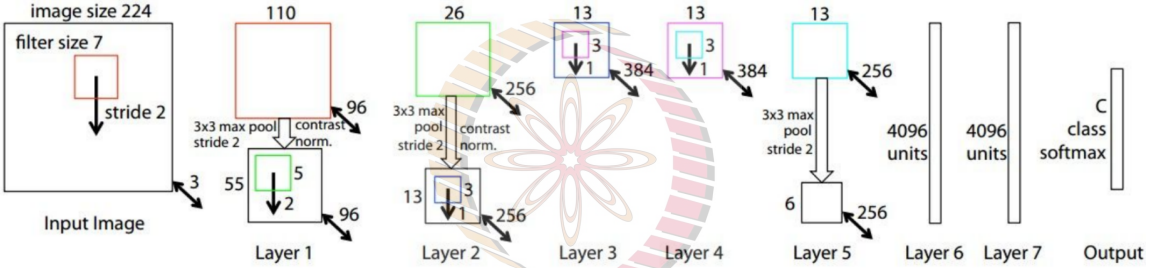

- Similar to AlexNet but:
  - CONV1: change from (11×11 stride 4) to (7×7 stride 2)

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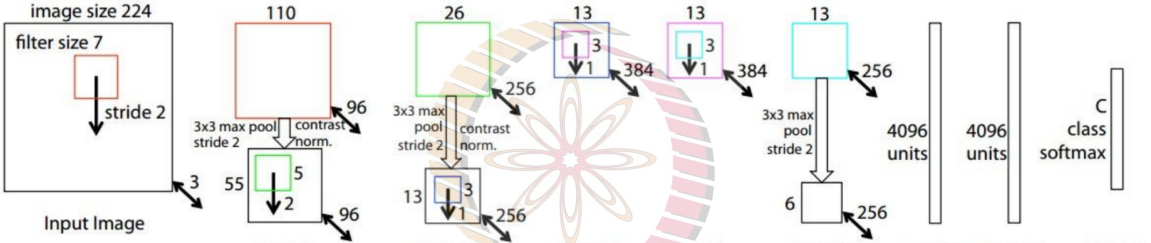

- Similar to AlexNet but:
  - CONV1: change from (11×11 stride 4) to (7×7 stride 2)
  - CONV3,4,5: instead of 384, 384, 256 filters, use 512, 1024, 512
- ImageNet top-5 error: $16.4\% \rightarrow 11.7\%$

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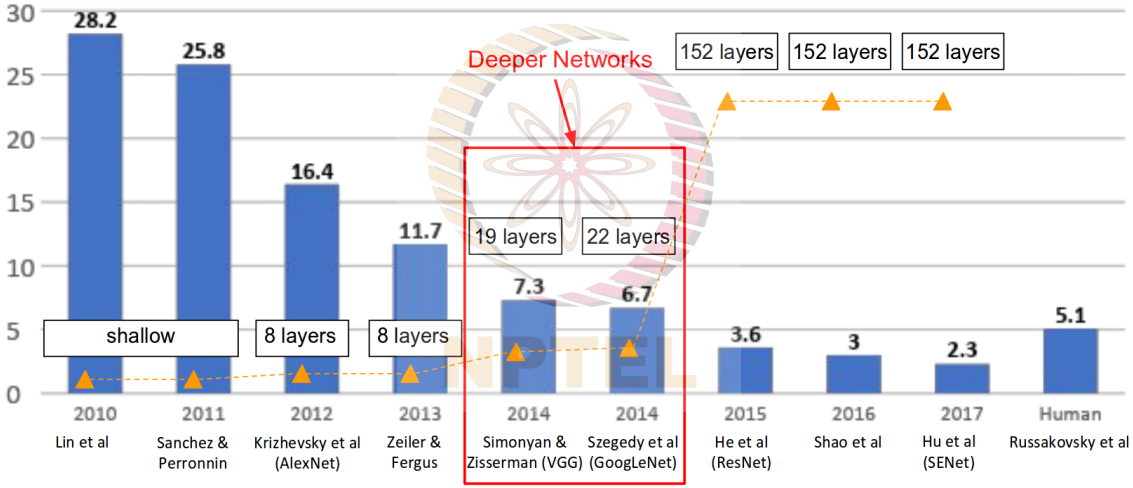

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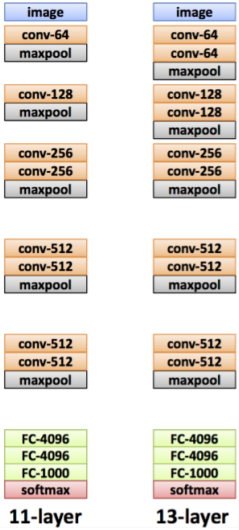
VGGNet

VGGNet



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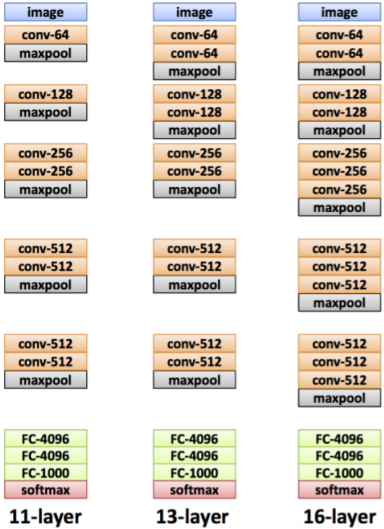

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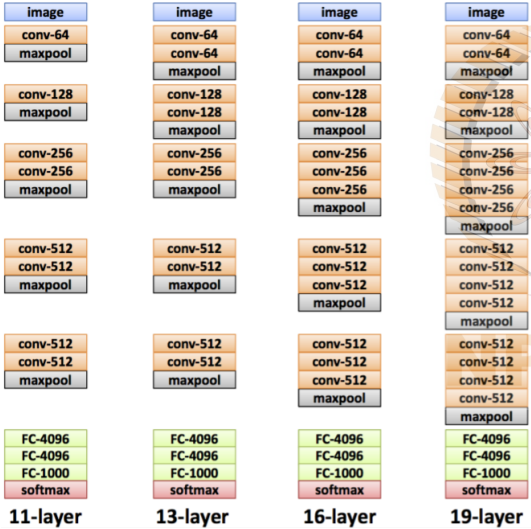
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conv-64
maxpool
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
FC-1000
softmax
11-layer
image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
FC-1000
softmax
13-layer
image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
conv-256
maxpool
conv-512
conv-512
conv-512
maxpool
conv-512
conv-512
conv-512
maxpool
FC-4096
FC-4096
FC-1000
softmax
16-layer
image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
conv-256
conv-256
maxpool
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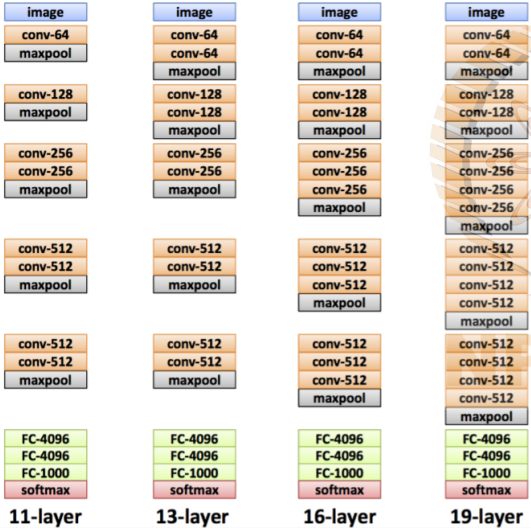
maxpool
FC-4096
FC-4096
FC-1000
softmax
19-layer

VGGNet



- Runner-up in ILSVRC 2014

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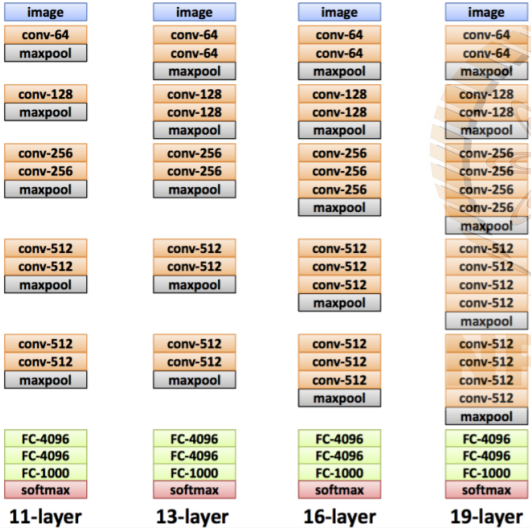
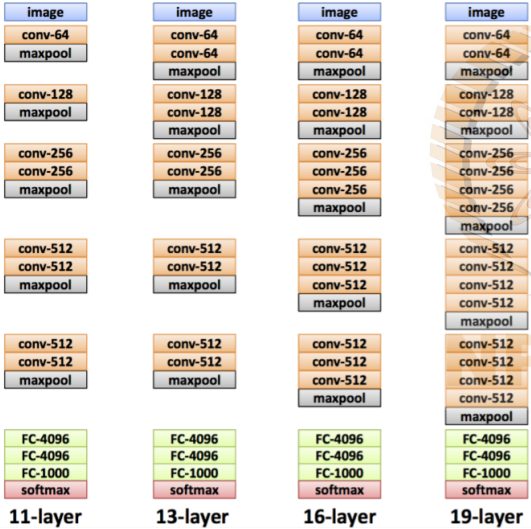


- Runner-up in ILSVRC 2014
- More layers lead to more nonlinearities

VGGNet



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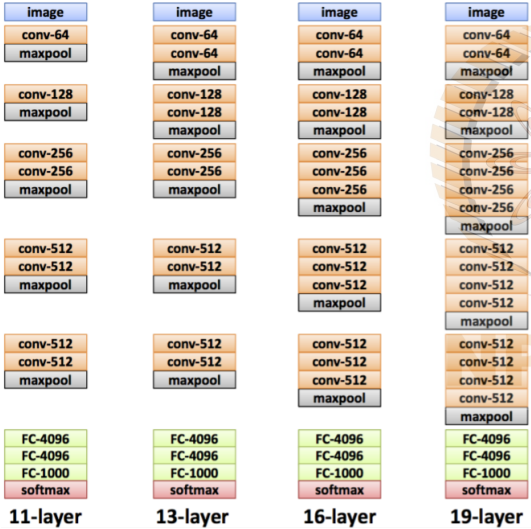
- More layers lead to more nonlinearities
- Key contribution: Depth of the network is a critical component for good performance

VGGNet



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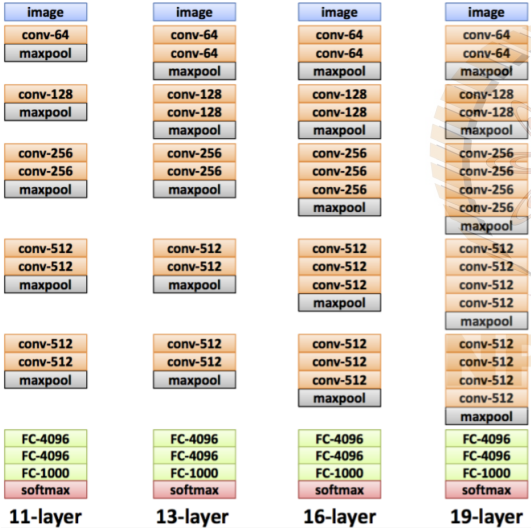
- Homogeneous Architecture: From beginning to end:

VGGNet



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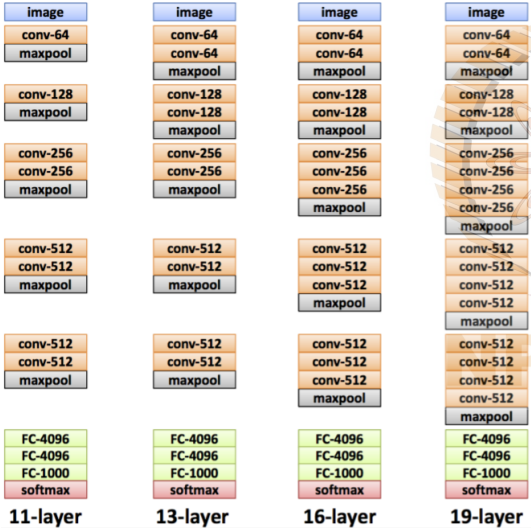
- Homogeneous Architecture: From beginning to end:
  - 3×3 CONV stride 1 pad 1

VGGNet



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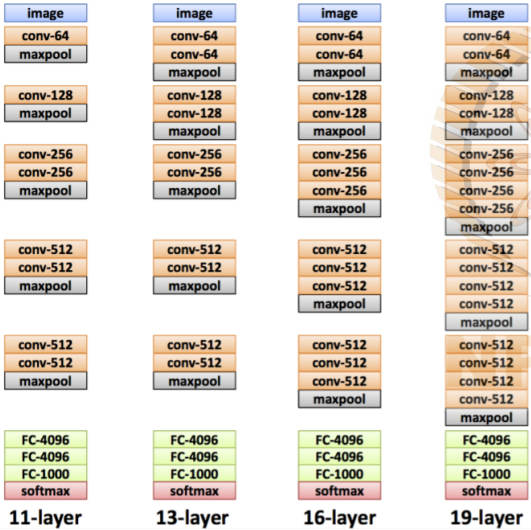
VGGNet



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- Key contribution: Depth of the network is a critical component for good performance
- Homogeneous Architecture: From beginning to end:
  - 3×3 CONV stride 1 pad 1
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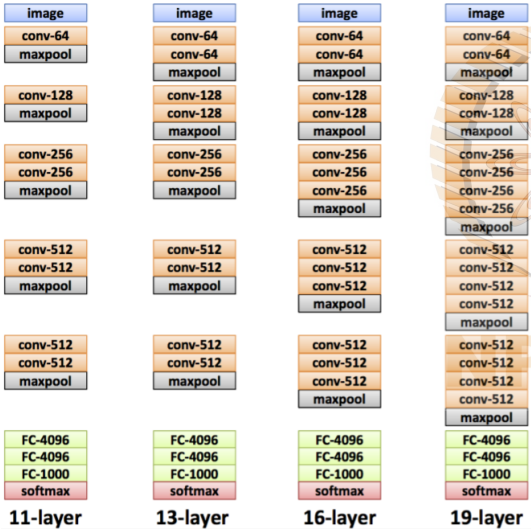
- Smaller receptive fields:

VGGNet



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  - less parameters; faster

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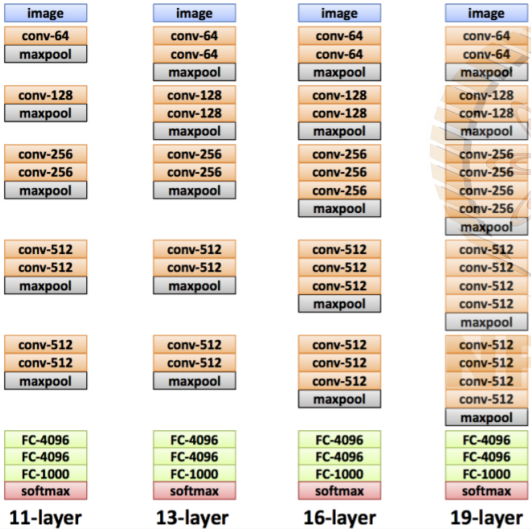

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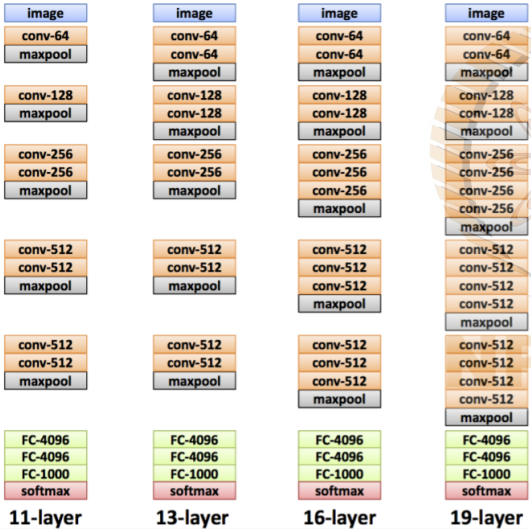
  - two 3×3 conv has same receptive field as a single 5×5 conv; three 3×3 conv has same receptive field as a single 7×7 conv

VGGNet



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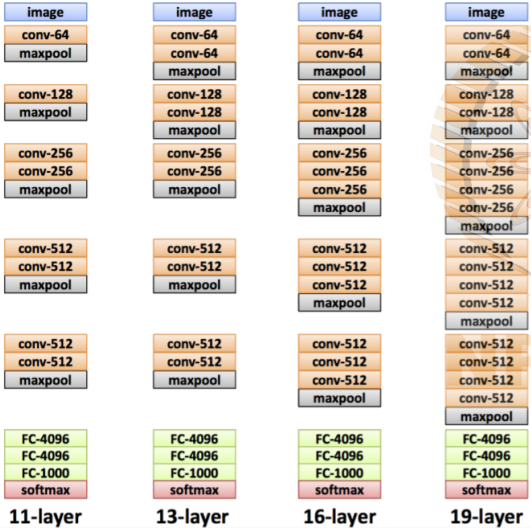
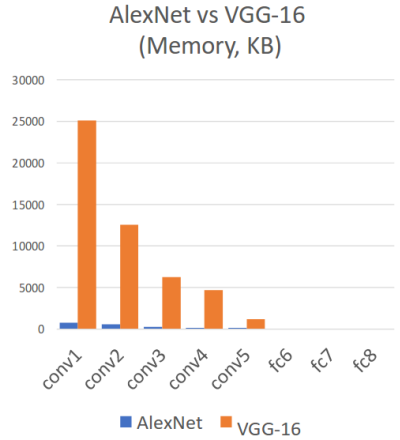
- Smaller receptive fields:
  - less parameters; faster
  - two 3 x 3 conv has same receptive field as a single 5 x 5 conv; three 3 x 3 conv has same receptive field as a single 7 x 7 conv
  - Fewer parameters: $3 \times 3^2C^2$ (vs) 7^2C^2

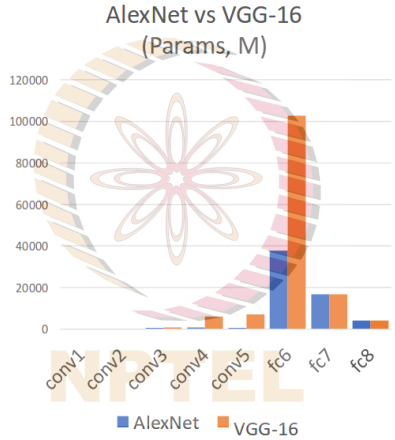
VGGNet



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

VGGNet



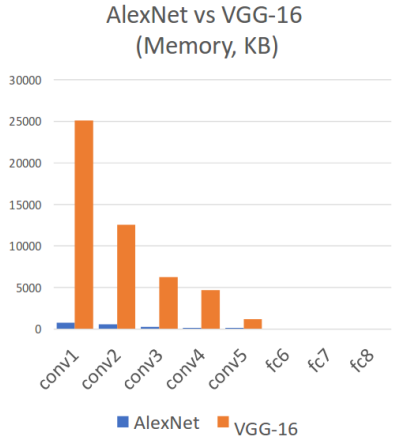


AlexNet total: 1.9 MB
VGG-16 total: 48.6 MB (25x)

AlexNet total: 61M
VGG-16 total: 138M (2.3x)

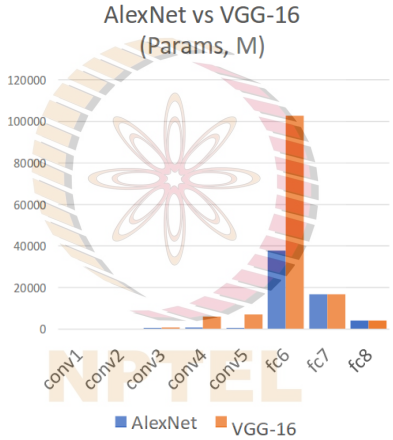
Credit: Justin Johnson, Univ of Michigan

VGGNet



AlexNet total: 1.9 MB

VGG-16 total: 48.6 MB (25x)



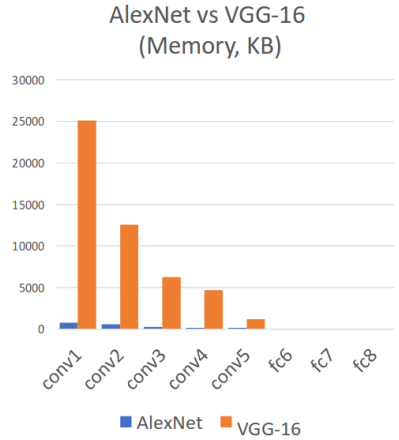
AlexNet total: 61M

VGG-16 total: 138M (2.3x)

- Uses a lot more memory and parameters

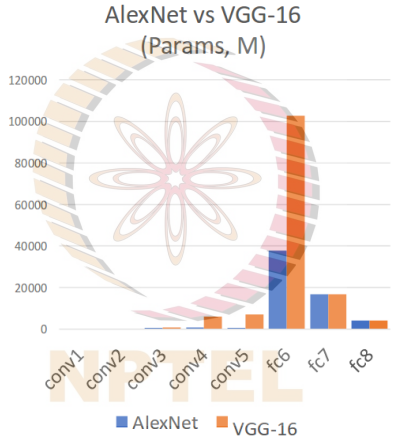
Credit: Justin Johnson, Univ of Michigan

VGGNet



AlexNet total: 1.9 MB

VGG-16 total: 48.6 MB (25x)



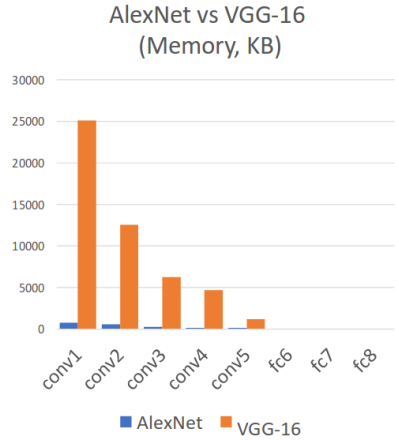
AlexNet total: 61M

VGG-16 total: 138M (2.3x)

Credit: Justin Johnson, Univ of Michigan

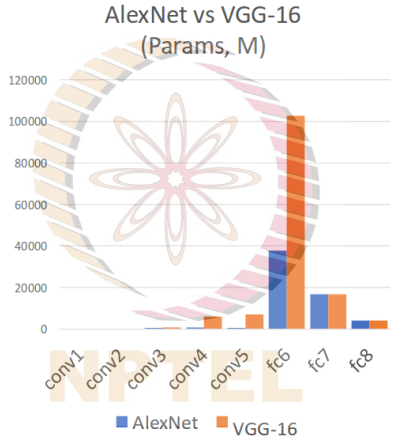
- Uses a lot more memory and parameters
- Most of these parameters are in the first fully connected layer

VGGNet



AlexNet total: 1.9 MB

VGG-16 total: 48.6 MB (25x)



AlexNet total: 61M

VGG-16 total: 138M (2.3x)

Credit: Justin Johnson, Univ of Michigan

- Uses a lot more memory and parameters
- Most of these parameters are in the first fully connected layer
- Most of the memory is used in early CONV layer

Homework

Readings

- Tutorial: Illustrated: 10 CNN Architectures
  - Read the first 3: LeNet, AlexNet, VGG
- (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

References

[1] Yann LeCun et al. "Gradient-based learning applied to document recognition". In: 1998.

[2] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet Classification with Deep Convolutional Neural Networks". In: *NIPS*. 2012.

[3] Karen Simonyan and Andrew Zisserman. "Very Deep Convolutional Networks for Large-Scale Image Recognition". In: *CoRR* abs/1409.1556 (2015).

[4] Christian Szegedy et al. "Going deeper with convolutions". In: *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2015), pp. 1–9.

[5] 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.

[6] *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).

[7] *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).