Deep Learning

9 Evolution of CNN Architectures

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Overview of different CNN architectures

- We will ground the evolution on ImageNet Large-Scale Visual Recognition Object Challenge (ILSVRC)

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Overview of different CNN architectures

भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

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- Training set of 1.2M (7321300 training samples per class) labelled images from 1000 categories
- 50K validation set and 100K test set
- Evaluation metric: Top-5 error rate

Overview of different CNN architectures

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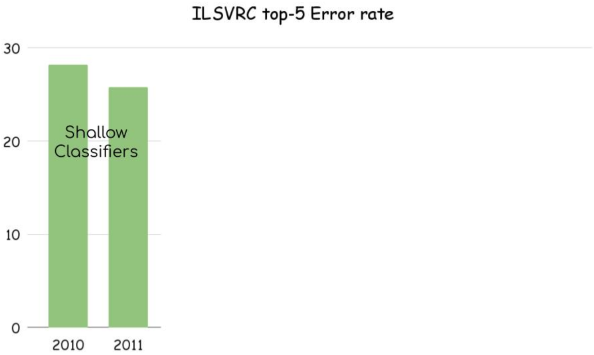

-

AlexNet (2012)

1. 8-layer CNN: 5 Conv layers, 3 FC layers
2. 227×227 input
3. Max pooling, ReLU nonlinearity, LRN (not used anymore now)

AlexNet (2012)

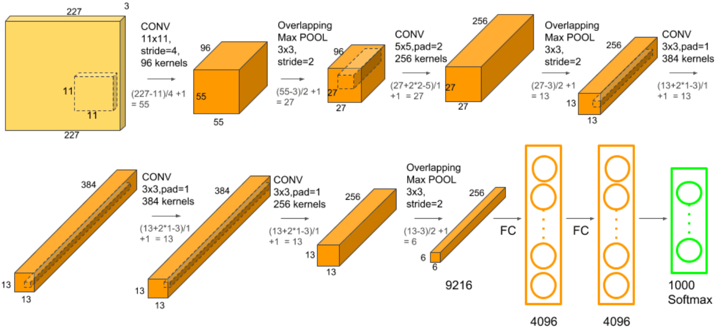

Figure credits:neurohive.io

AlexNet (2012)

1. Implemented on GTX 580 GPUs (2 of them; 3GB of Memory each)

Figure from AlexNet paper by Kryzhevsky et al.

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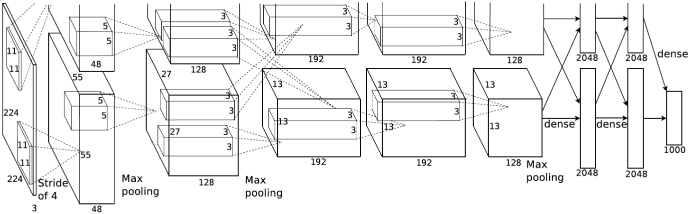

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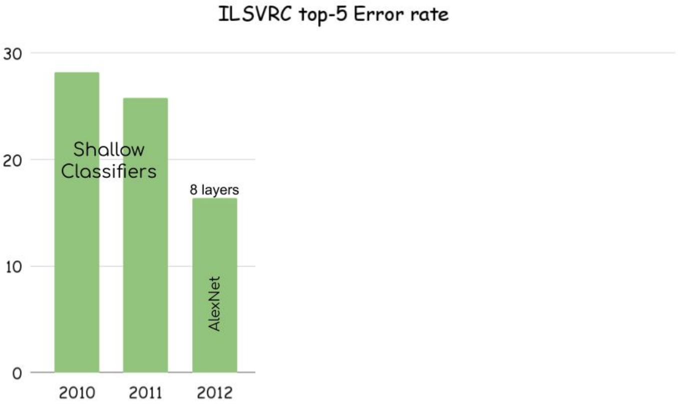

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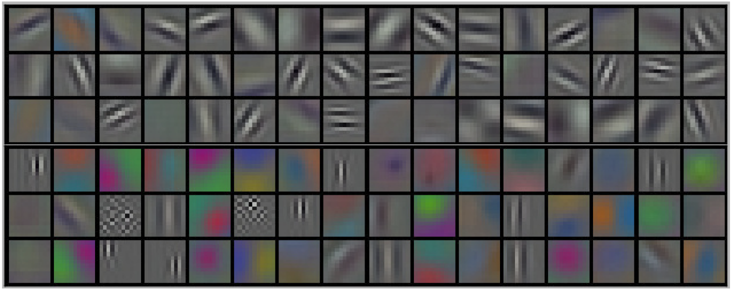


Visualizing the 11x11 filters learned by AlexNet

ZFNet (2013)

1. A more worked-out AlexNet

ZFNet (2013)

1. A more worked-out AlexNet
2. More trials on the AlexNet architecture that resulted in less error
   - $(11 \times 11$ stride 4$) \rightarrow (7 \times 7$ stride 2$)$
   - Conv 3, 4, and 5 (384, 384, 256) $\rightarrow$ (512, 1024, and 512)

ZFNet (2013)

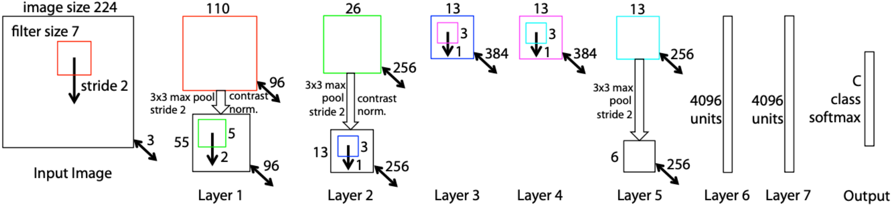
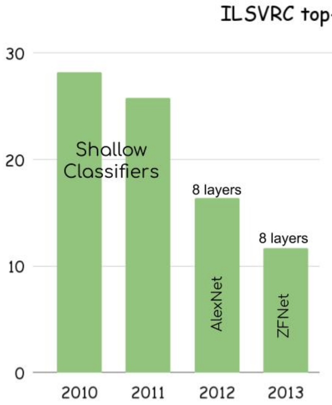


Figure 3. Architecture of our 8 layer convnet model. A 224 by 224 crop of an image (with 3 color planes) is presented as the input. This is convolved with 96 different 1st layer filters (red), each of size 7 by 7, using a stride of 2 in both x and y. The resulting feature maps are then: (i) passed through a rectified linear function (not shown), (ii) pooled (max within 3x3 regions, using stride 2) and (iii) contrast normalized across feature maps to give 96 different 55 by 55 element feature maps. Similar operations are repeated in layers 2,3,4,5. The last two layers are fully connected, taking features from the top convolutional layer as input in vector form ($6 \cdot 6 \cdot 256 = 9216$ dimensions). The final layer is a C-way softmax function, C being the number of classes. All filters and feature maps are square in shape.

Figure from Zeiler and Fergus, ECCV 2014

ZFNet (2013)


ILSVRC top-5 Error rate
30
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Shallow Classifiers
8 layers
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AlexNet
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2010
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VGG (2014)

1. First architecture to have a principled design

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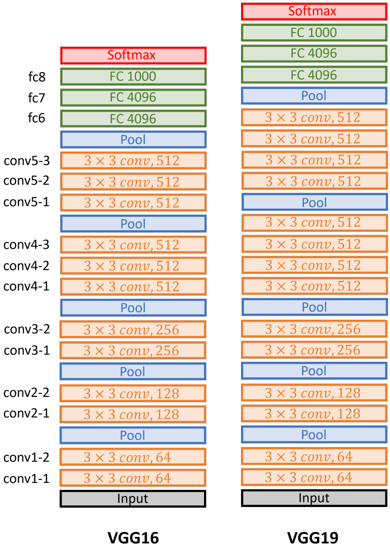
2.
   - All conv: 3×3, stride:1, pad:1
   - All max pool: 2×2, stride:2
   - After pooling, double the channels

VGG (2014)

1. 5 Conv stages



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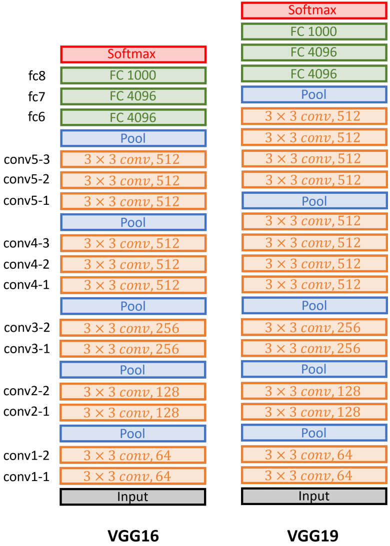
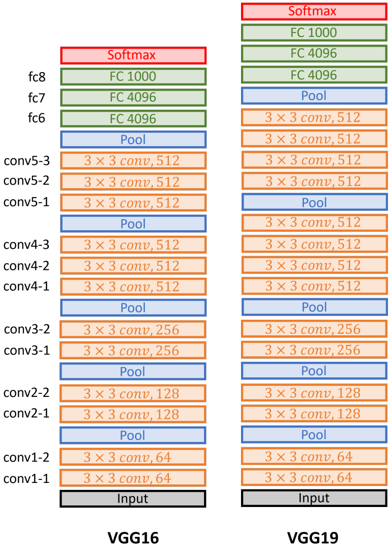


VGG (2014)

1. 5 Conv stages
2. (initially) Conv-Conv-Pool
3. (later) Conv-Conv-Conv-Pool (VGG19 has one more Conv)



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   - Parameters:
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VGG (2014)

1. Huge network (VGG-16) compared to AlexNet

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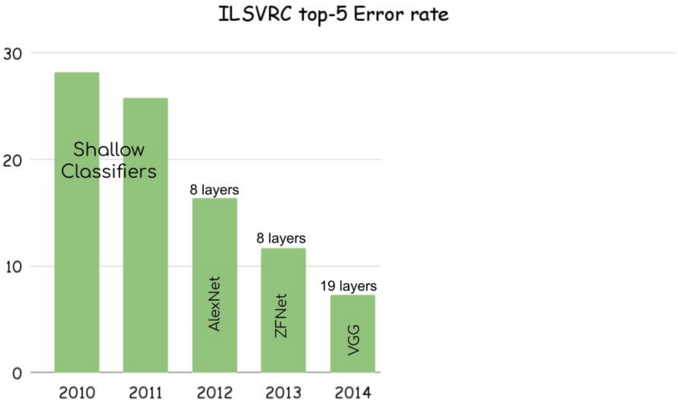
4. Flops: $0.7 \rightarrow 13.6$G Flop (19.4X)

VGG (2014)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1. Efficiency was the focus of design

Figure credits: Medium.com and Anas Brital

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2. Reduce the parameters, memory and the compute requirements (towards deployment)

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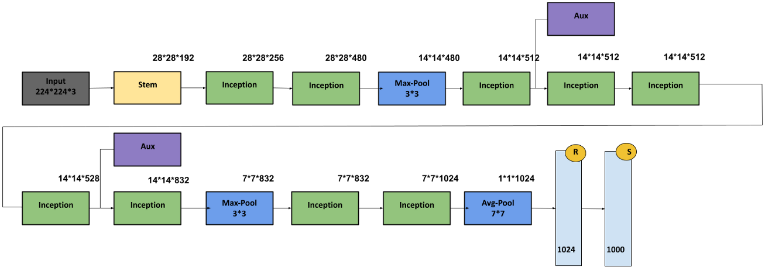

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GoogLeNet (2014)

1. Stem architecture at the early stage $\rightarrow$ aggressive down-sampling

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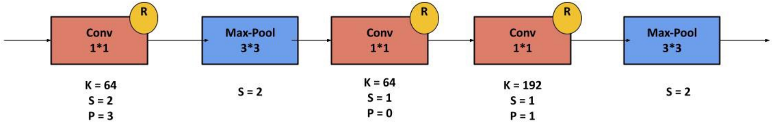

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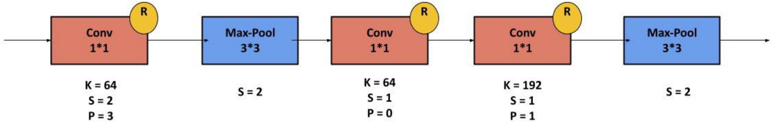


2.
3. From 224×224 to 28×28
   - GoogLeNet: Compute - 7.5MB, parameters - 124K, and MFlops - 418
   - VGG-16: Compute - 42.9MB (5.7X), parameters - 1.1M (8.9X), and MFlops - 7485 (17.8X)

Figure credits: Medium.com and Anas Brital

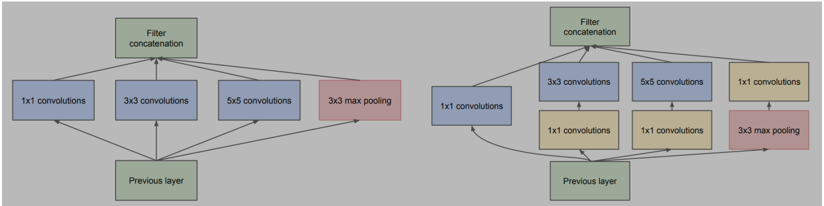
GoogLeNet (2014)

1. Inception module: unit with parallel branches

Figure credits: Original Paper

GoogLeNet (2014)

1. Inception module: unit with parallel branches
2. Repeated through the architecture



(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure credits: Original Paper

GoogLeNet (2014)

1. Global Average Pooling (GAP) layer

Alexis Cook

GoogLeNet (2014)

భారతీయ సాంకేతిక విజ్ఞాన సంస్థ హైదరాబాద్
भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

1. Global Average Pooling (GAP) layer
2. Flattening results in huge weight matrices $\rightarrow$ GoogLeNet introduces GAP layer

Alexis Cook

GoogLeNet (2014)

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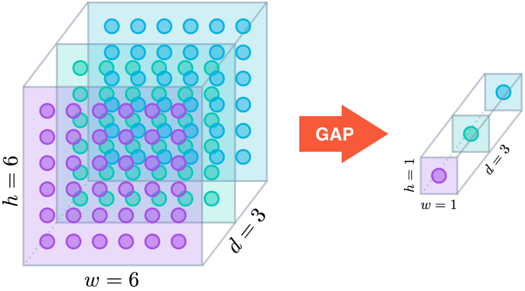
2. Flattening results in huge weight matrices $\rightarrow$ GoogLeNet introduces GAP layer
3. Collapses the spatial dimensions by computing the average (kernel size = spatial dimensions of the last conv layer)



Alexis Cook

GoogLeNet (2014)

1. No more fully connected layers

GoogLeNet (2014)

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2. One linear layer to predict the classification scores (feather light!)

GoogLeNet (2014)

1. Auxiliary classifiers

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2. Training using the gradients at the end of the network didn't work well (too deep, gradient propagation was not robust)

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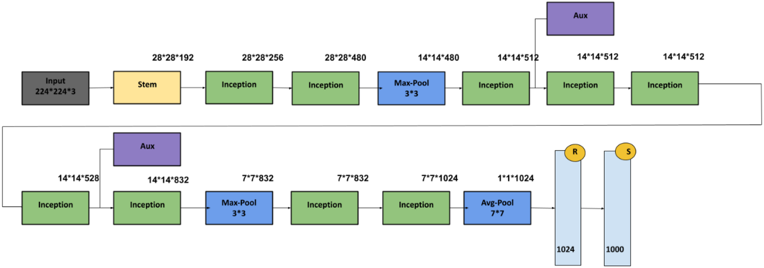
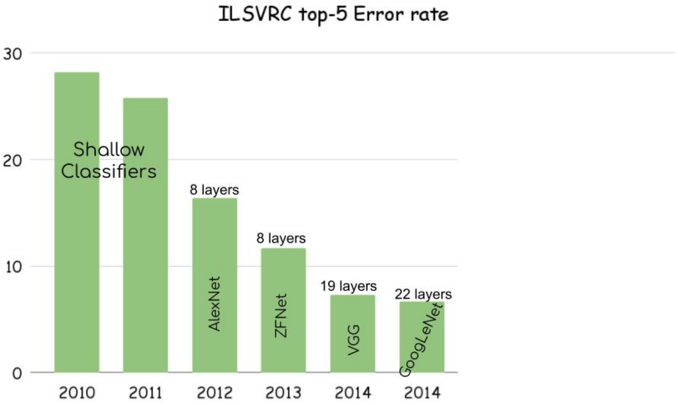
3. Hack: add auxiliary classifiers at intermediate locations to receive loss/gradients



GoogLeNet (2014)



ResNet (2015)

1. Very important time for the DNNs
   - Batch Normalization happened
   - Depth increased by an order $(10 \rightarrow 150+)$
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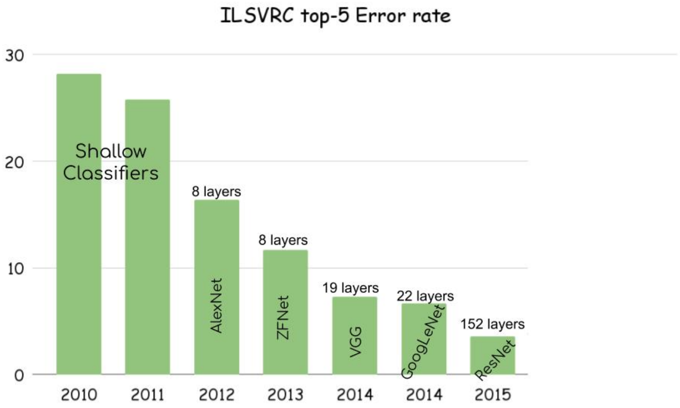
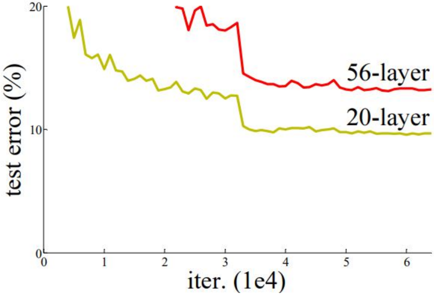


2.

Training Deeper CNNs

1. When training the "deeper" CNNs, people observed that they were worse than shallow ones



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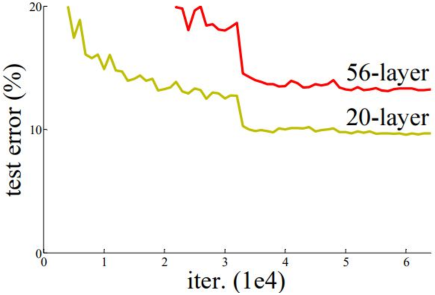
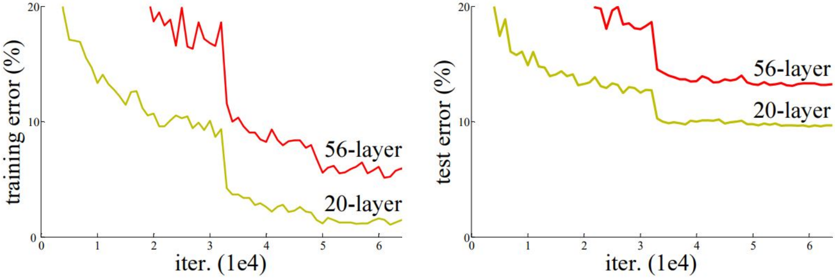


2. Initial suspicion was the 'over-fitting'!

Figure Credits: He et al. 2015

Training Deeper CNNs

1. Initial suspicion was the 'over-fitting'!
2. However, it was due to the under-fitting



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3. Work on the architecture so that learning identity function gets easier with additional layers

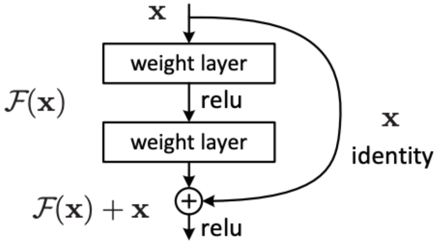
ResNet (2015)

1. Work on the architecture so that learning identity function gets easier with additional layers

Yuanrui Dong

ResNet (2015)

1. Work on the architecture so that learning identity function gets easier with additional layers
2. ResBlock (residual block)



Yuanrui Dong

ResNet (2015)

1. ResBlocks help the gradient backpropagation

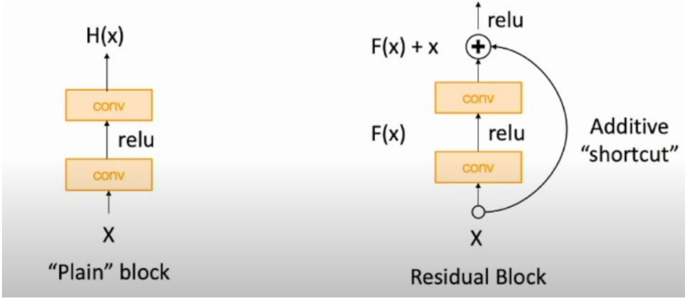


Figure Credits: Dr. Justin Johnson, U Michigan

ResNet (2015)

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ResNet (2015)

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2. Inspire from VGG and GoogLeNet

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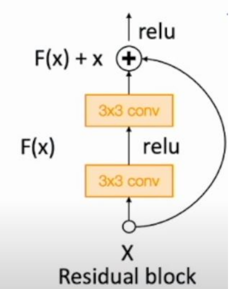
ResNet (2015)

1. ResNet is a stack of Resblocks
2. Inspire from VGG and GoogLeNet
3. Simple and regular design like VGG: each resblock has two 3×3 Conv



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1. Network has stages: first block of each stage halves the resolution and doubles the channels

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1. Network has stages: first block of each stage halves the resolution and doubles the channels
2. Aggressive stem in the beginning (downsamples by 4X before the start of the resblocks)
3. Eliminates the FC layers via GAP

ResNet (2015)

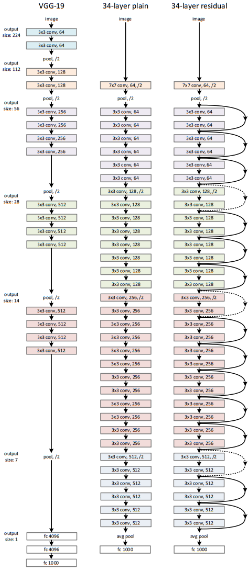

Figure credits: K. he et al., ResNets 2015)

ResNet (2015)

1. ResNet-18
   - Stem: 1 Conv
   - Stage-1 (C=64): 2 resblocks (4 Conv)
   - Stage-2 (C=128): 2 resblocks (4 Conv)
   - Stage-3 (C=256): 2 resblocks (4 Conv)
   - Stage-4 (C=512): 2 resblocks (4 Conv)
   - Linear
   - Top-5 error: 10.92 and GFlop: 1.8

ResNet (2015)

1. ResNet-34
   - Stem: 1 Conv
   - Stage-1 (C=64): 3 resblocks (6 Conv)
   - Stage-2 (C=128): 4 resblocks (8 Conv)
   - Stage-3 (C=256): 6 resblocks (12 Conv)
   - Stage-4 (C=512): 3 resblocks (6 Conv)
   - Linear
   - Top-5 error: 8.58 and GFlop: 3.6 (VGG: 9.6 and 13.6 respectively)

ResNet (2015)

1. Bottlneck Residual block

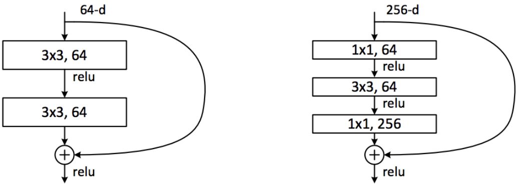

Figure Credits: Nushaine Ferdinand

ResNet (2015)

1. Resnet-34 becomes ResNet-50 if we replace the plain resblocks with bottleneck ones

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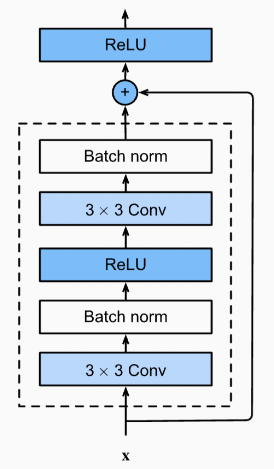
2. More blocks at each stage result in ResNet-101 and Resnet-152 architectures

Resnet (2015)

1. Resblocks have Batch Normalization layers



Yashovardhan Shinde and Analyticsvidhya

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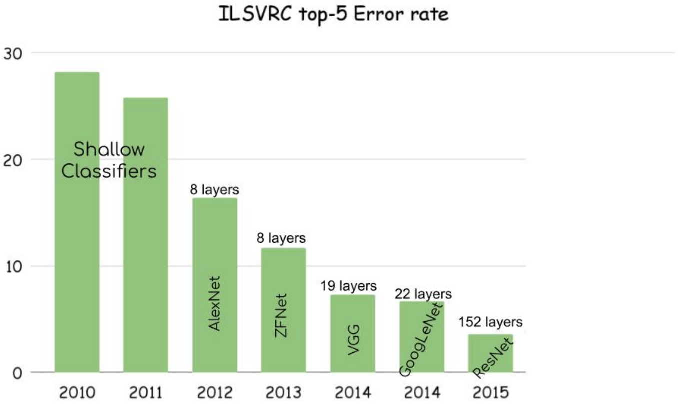

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Shallow Classifiers
8 layers
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AlexNet
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Post 2015

1. 2016 Winners (Trimps Soushen): Multi-scale Ensemble models of Inception, ResNets, WRN, etc.

Post 2015

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2. Improving ResNets: multiple parallel pathways of bottlenecks (ResNeXt), Squeeze and Excitation Nets (SENet)
3. Densenets, Tiny Networks (MobileNets, ShuffleNets), etc.

CNN Architectures: Summary

1. Initial families of architectures (AlexNet, ZFNet, VGG) $\rightarrow$ Bigger the better!

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3. Neural Architecture Search (NAS)

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