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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- Evaluation metric: Top-5 error rate

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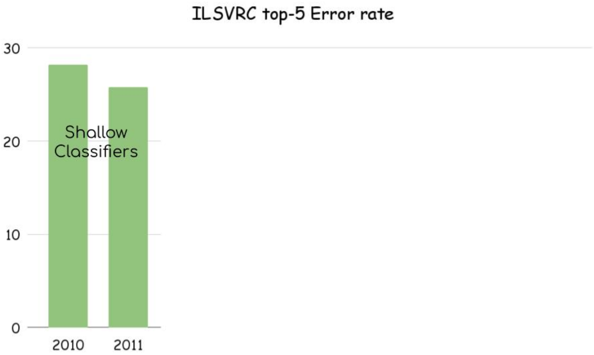

-

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)

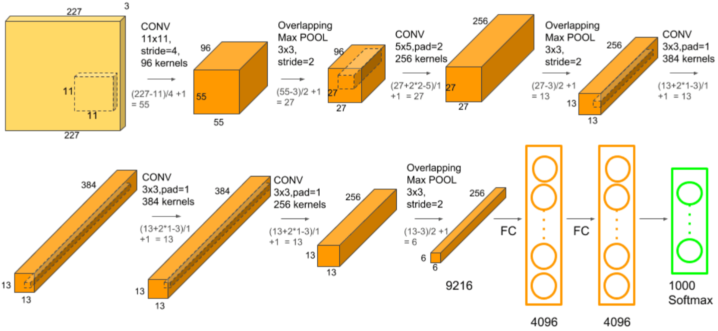

Figure credits:neurohive.io

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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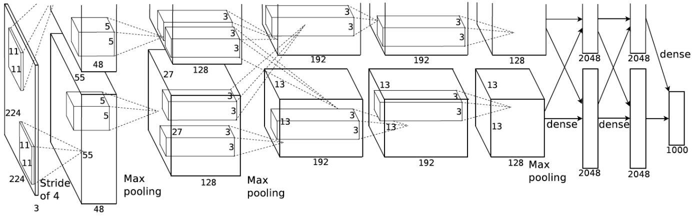

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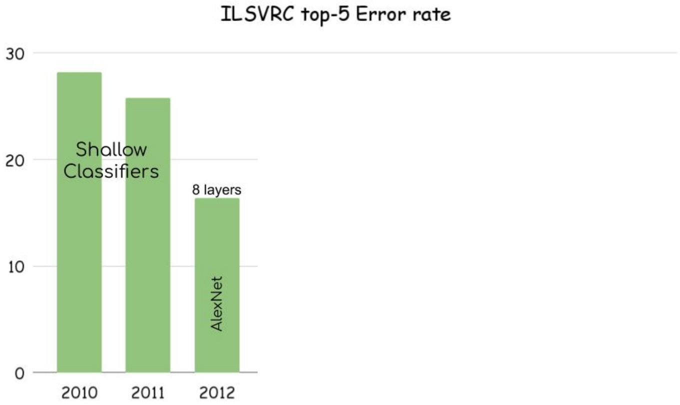

ZFNet (2013)

1. A more worked-out AlexNet

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1. A more worked-out AlexNet
2. More trails 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)

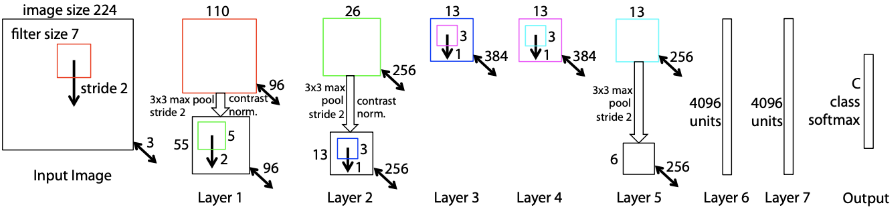
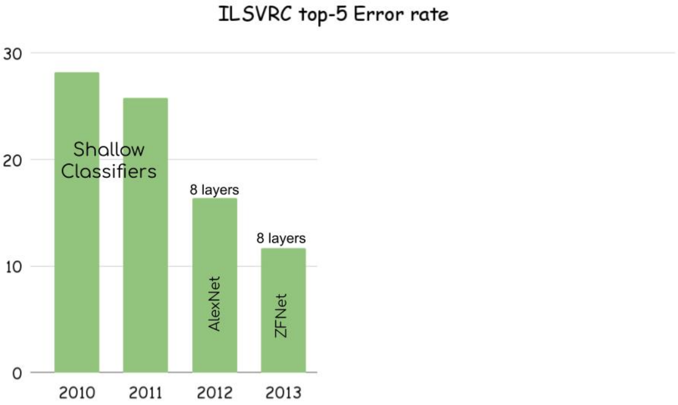


Figure 3. Architecture of our 8 layer convnet model. A 224 by 224 crop of an image (with 3 color planes) is presented as the input. This is convolved with 96 different 1st layer filters (red), each of size 7 by 7, using a stride of 2 in both x and y. The resulting feature maps are then: (i) passed through 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
20
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Shallow Classifiers
8 layers
8 layers
AlexNet
ZFNet
2010
2011
2012
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VGG (2014)

1. First architecture to have a principled design

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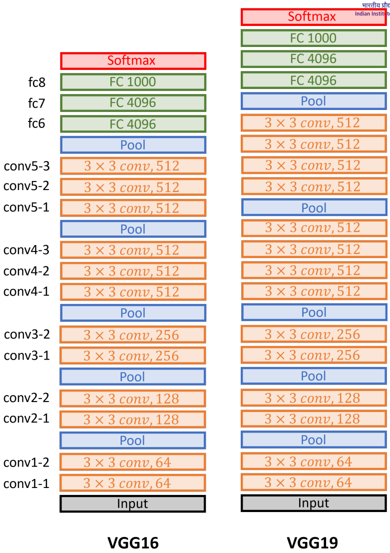
2. - All conv: 3×3, stride:1, pad:1
   - All max pool: 2×2, stride:2
   - After pooling, double the channels

VGG (2014)

1. 5 Conv stages



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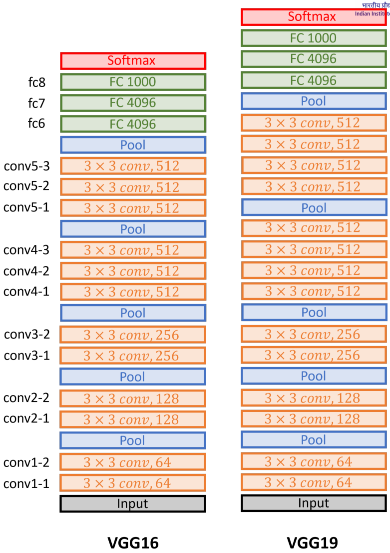
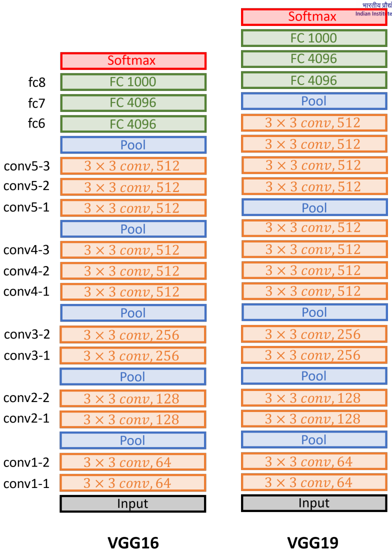
2. (initially) Conv-Conv-Pool



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: $2 \times C \times C \times 3 \times 3 = 18C^2$

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   - Memory: 2CHW, parameters: $36C^2$, Flops: $36HWC^2$

VGG (2014)

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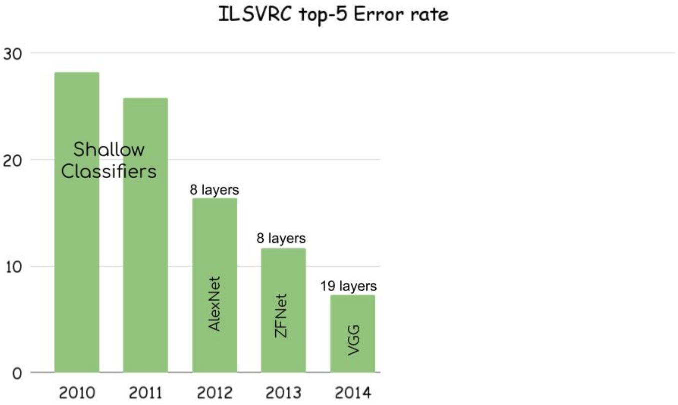
1. Huge network (VGG-16) compared to AlexNet
2. Memory: $1.9 \rightarrow 48.6$MB (25X)
3. Parameters: $61 \rightarrow 138$M (2.3X)
4. Flops: $0.7 \rightarrow 13.6$G Flop (19.4X)

VGG (2014)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8 layers
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AlexNet
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GoogLeNet (2014)

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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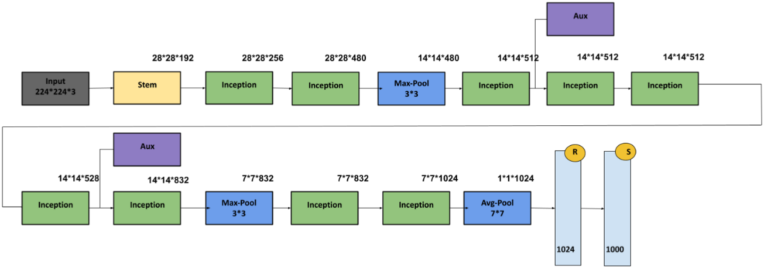

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GoogLeNet (2014)

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

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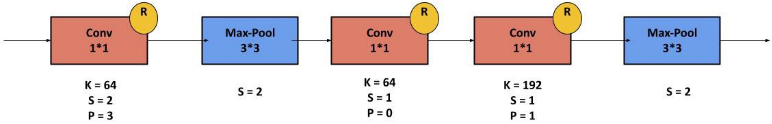

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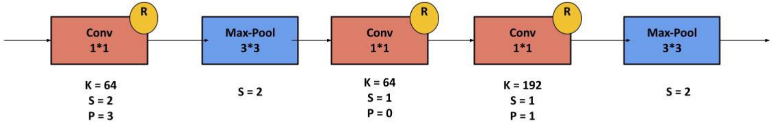

2.
3. From 224×224 to 28×28
   - GoogLeNet: Compute - 7.5MB, parameters - 124K, and MFlops - 418
   - VGG-16: Compute - 42.9MB (5.7X), parameters - 1.1M (8.9X), and MFlops - 7485 (17.8X)

Figure credits: Medium.com and Anas Brital

GoogLeNet (2014)

1. Inception module: unit with parallel branches

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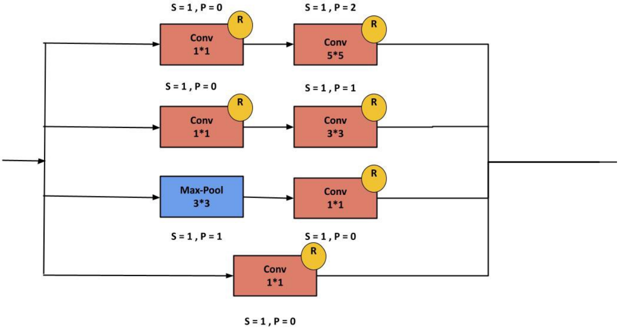
GoogLeNet (2014)

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



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GoogLeNet (2014)

1. Global Average Pooling (GAP) layer

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2. Flattening results in huge weight matrices $\rightarrow$ GoogLeNet introduces GAP layer

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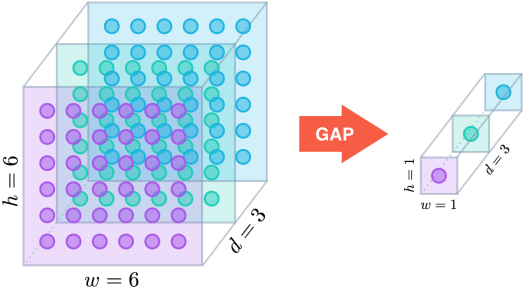
1. Global Average Pooling (GAP) layer
2. Flattening results in huge weight matrices → GoogLeNet introduces GAP layer
3. Collapses the spatial dimensions by computing the average (kernel size = spatial dimensions of the last conv layer)



Alexis Cook

GoogLeNet (2014)

1. No more fully connected layers

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

GoogLeNet (2014)

1. Auxiliary classifiers

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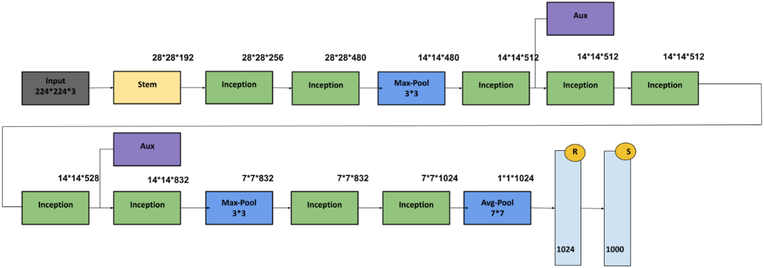
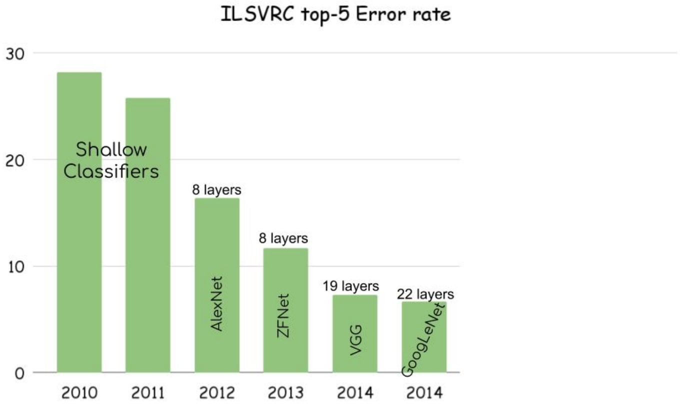
3. Hack: add auxiliary classifiers at intermediate locations to receive loss/gradients



GoogLeNet (2014)



ResNet (2015)

1. Very important time for the DNNs
   - Batch Normalization happened
   - Depth increased by an order $(10 \rightarrow 150+)$
   - ILSVRC error almost halved from that of 2014

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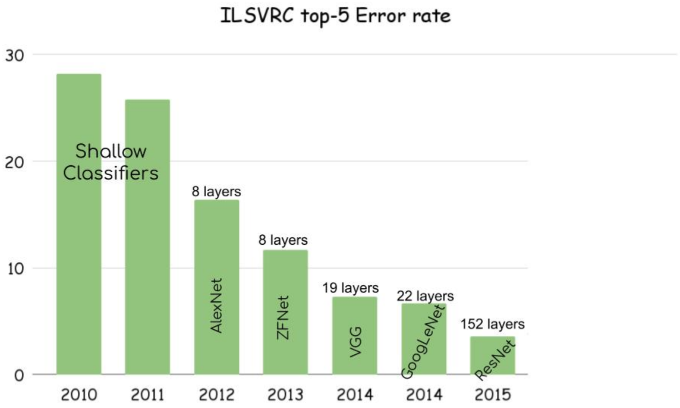
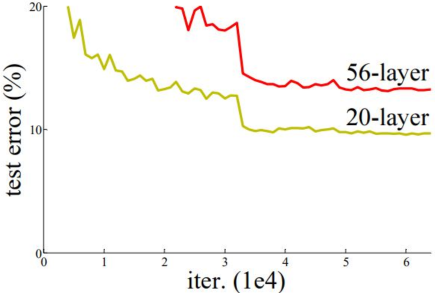


2.

Training Deeper CNNs

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



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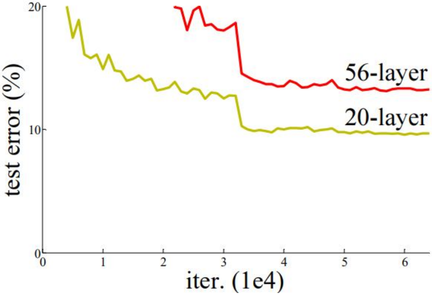

2. Initial suspicion was the 'over-fitting'!

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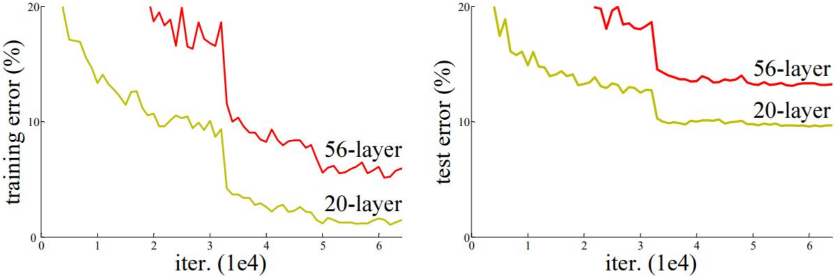
Training Deeper CNNs

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



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2. This is not the case $\rightarrow$ some issue in the optimization!
3. Work on the architecture so that learning identity function gets easier with additional layers

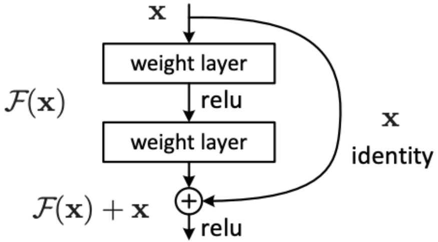
ResNet (2015)

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

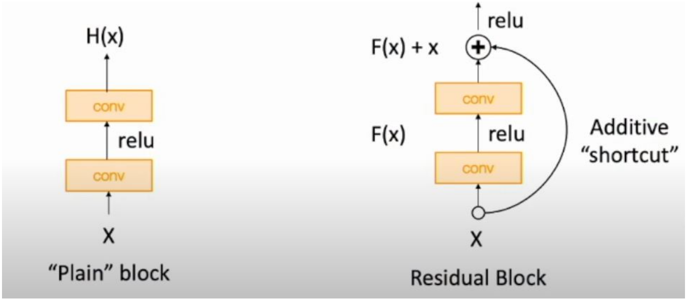


Figure Credits: Dr. Justin Johnson, U Michigan

ResNet (2015)

1. ResNet is a stack of Resblocks

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2. Inspire from VGG and GoogLeNet

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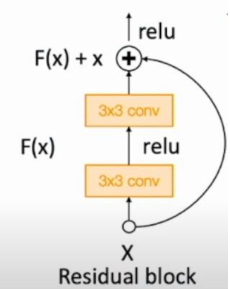
ResNet (2015)

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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ResNet (2015)

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)

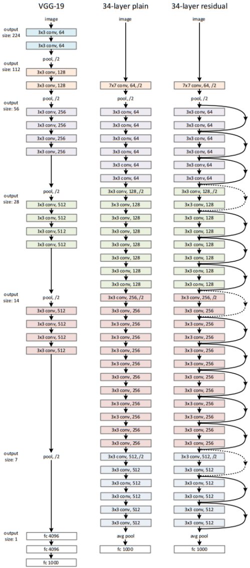

Figure credits: K. he et al., ResNets 92015)

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

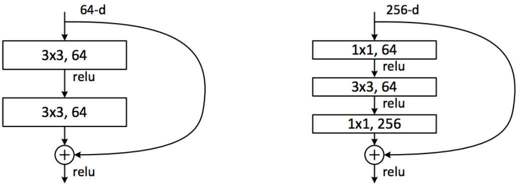

Figure Credits:Nushaine Ferdinand

ResNet (2015)

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

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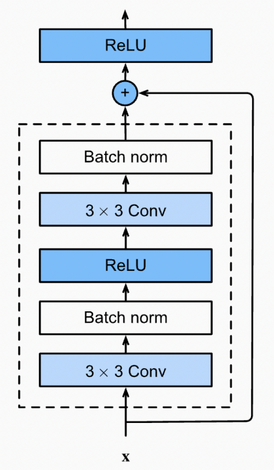
2. More blocks at each stage result in ResNet-101 and Resnet-152 architectures

Resnet (2015)

1. Resblocks have Batch Normalization layers



Yashovardhan Shinde and Analyticsvidhya

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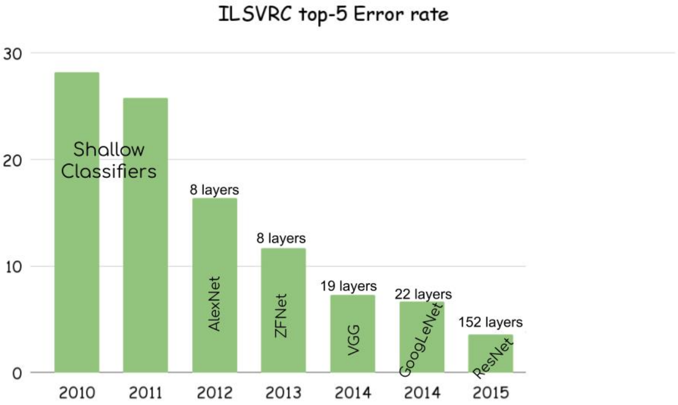
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Post 2015

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

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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. ResNet enabled extreme depth

CNN Architectures: Summary

भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

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3. Neural Architecture Search (NAS)

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