Deep Learning for Computer Vision

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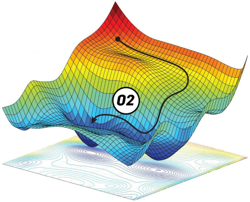
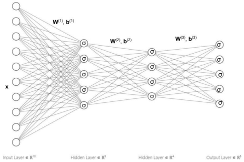
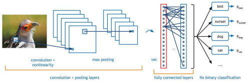
So far in the class..

- Scoring function, loss function, gradient descent
- Artificial Neurons and Multi-Layered Perceptron
- CNN building blocks and a case-study







Overview of different CNN architectures

- We will ground the evolution on ILSVRC

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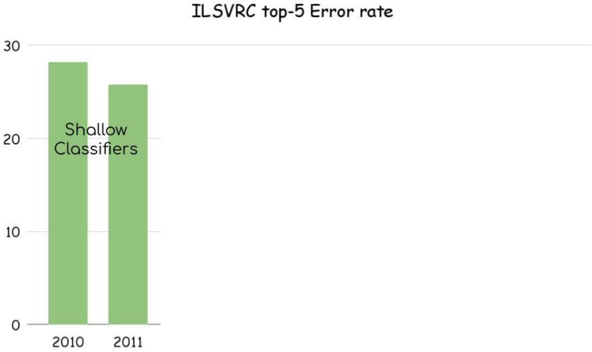

-

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)

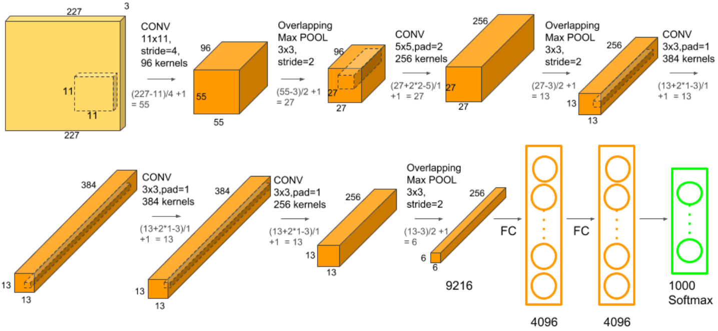

Figure credits: neurohive.io

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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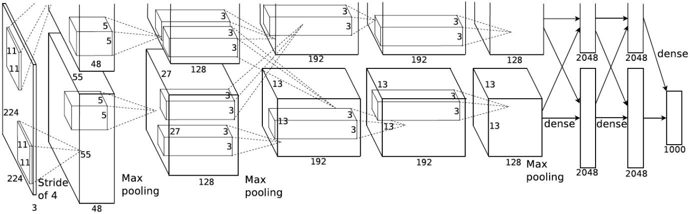
2. 

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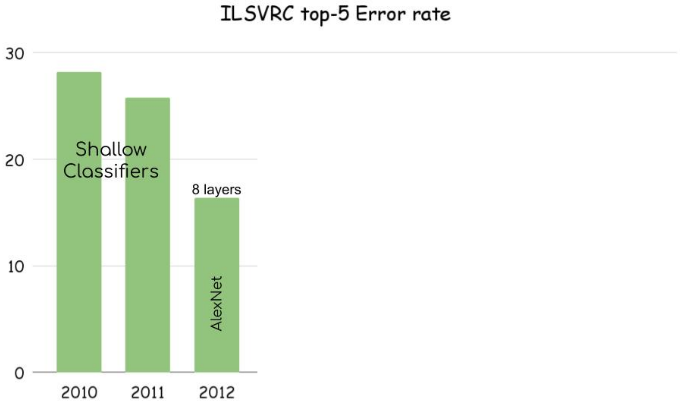


ZFNet (2013)

1. A more worked-out AlexNet

ZFNet (2013)

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

ZFNet (2013)

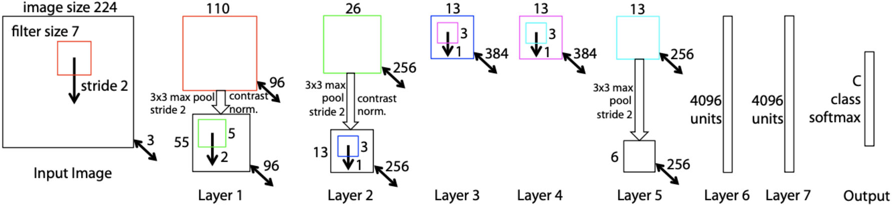
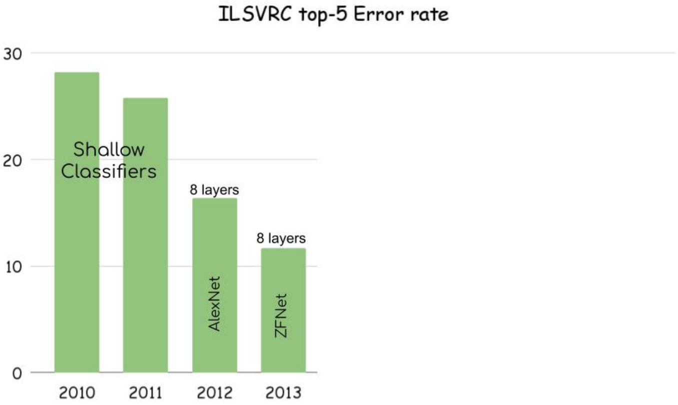


Figure 3. Architecture of our 8 layer convnet model. A 224 by 224 crop of an image (with 3 color planes) is presented as the input. This is convolved with 96 different 1st layer filters (red), each of size 7 by 7, using a stride of 2 in both x and y. The resulting feature maps are then: (i) passed through 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
2013

VGG (2014)

1. First architecture to have a principled design

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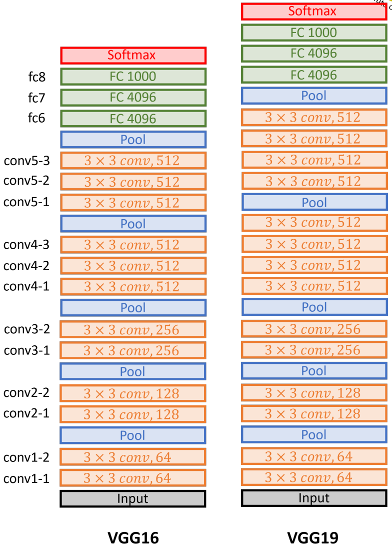
2. - All conv: 3×3, stride:1, pad:1
   - All max pool: 2×2, stride:2
   - After pooling, double the channels

VGG (2014)

1. 5 Conv stages



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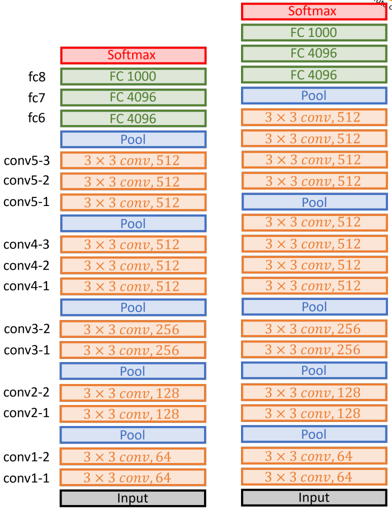
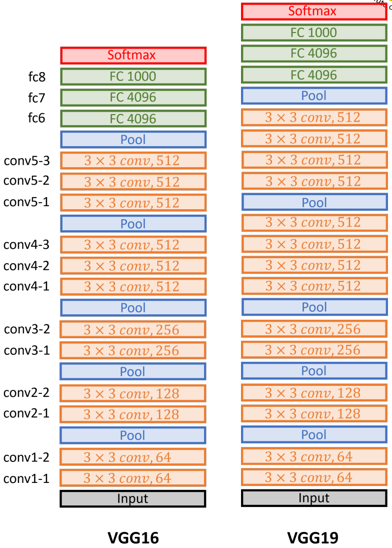
2. (initially) Conv-Conv-Pool



VGG16 **VGG19**

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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2. Case-1: $C \times 2H \times 2W$, Conv $(3 \times 3,\ C \rightarrow C)$
   - Memory: 4CHW, parameters: $9C^2$, Flops: $36HWC^2$
3. Case-2: $2C \times H \times W$, Conv $(3 \times 3,\ 2C \rightarrow 2C)$
   - Memory: 2CHW, parameters: $36C^2$, Flops: $36HWC^2$

VGG (2014)

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

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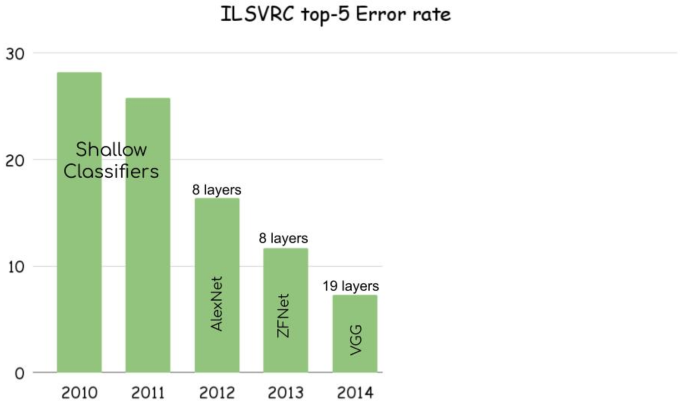
3. Parameters: $61 \rightarrow 138$M (2.3X)
4. Flops: $0.7 \rightarrow 13.6$G Flop (19.4X)

VGG (2014)



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GoogLeNet (2014)

1. Efficiency was the focus of design

Figure credits:Medium.com and Anas Brital

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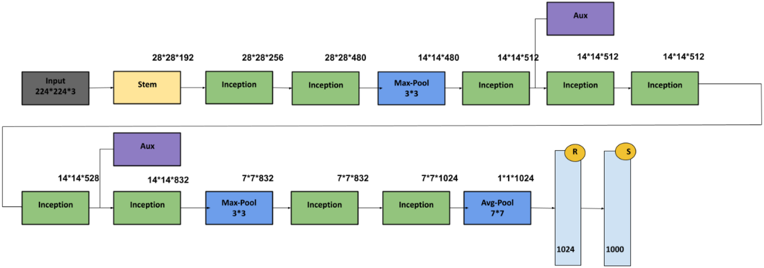

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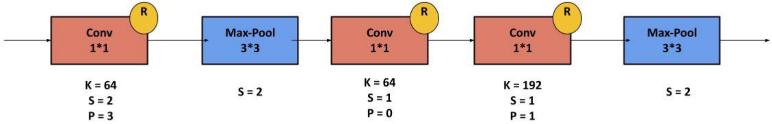

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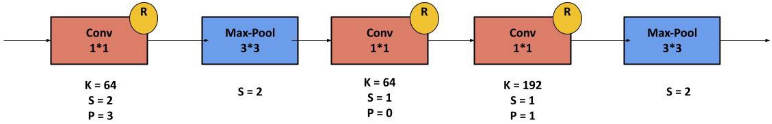

2.
3. From 224×224 to 28×28
   - GoogLeNet: Compute - 7.5MB, parameters - 124K, and MFlops - 418
   - VGG-16: Compute - 42.9MB (5.7X), parameters - 1.1M (8.9X), and MFlops - 7485 (17.8X)

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GoogLenet (2014)

1. Inception module: unit with parallel branches

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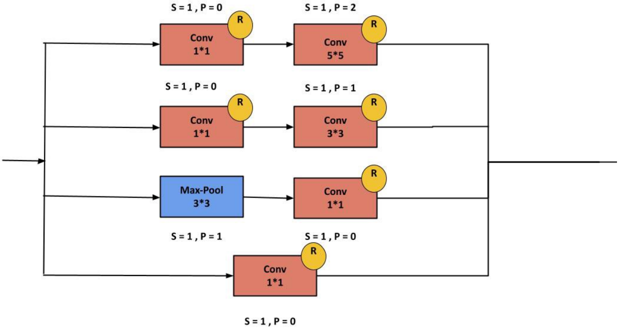
GoogLenet (2014)

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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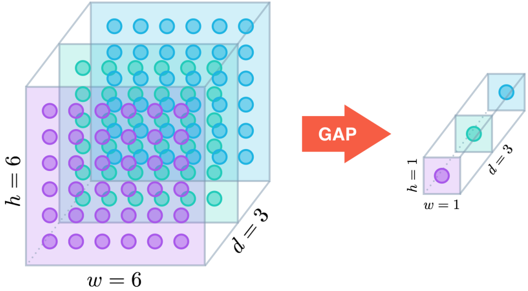
3. Collapses the spatial dimensions by computing the average (kernel size = spatial dimensions of the last conv layer)



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!)

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1. Auxiliary classifiers

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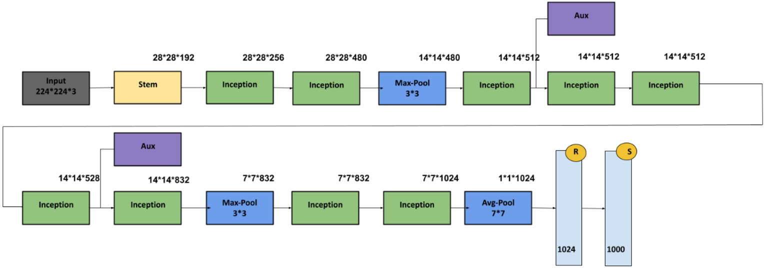
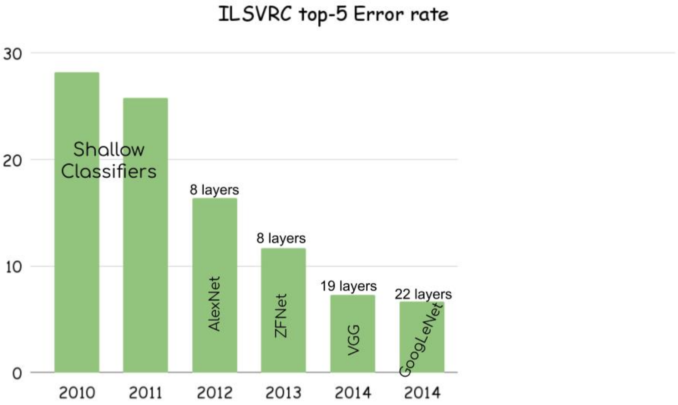
3. Hack: add auxiliary classifiers at intermediate locations to receive loss/gradients



GoogLeNet (2014)



ResNet (2015)

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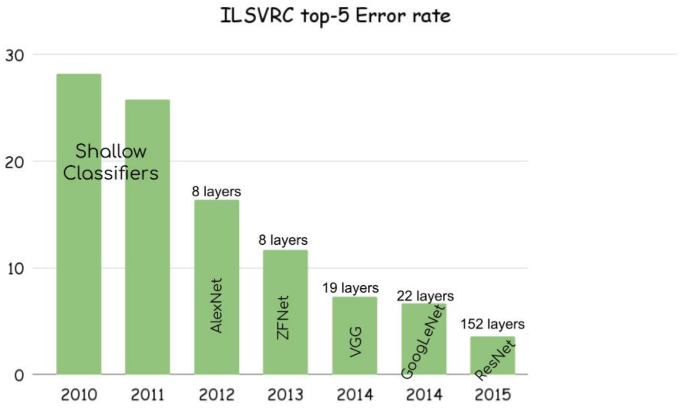
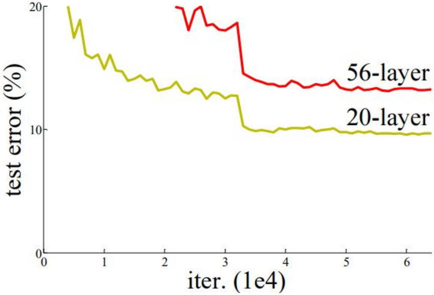


2.

Training Deeper CNNs

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



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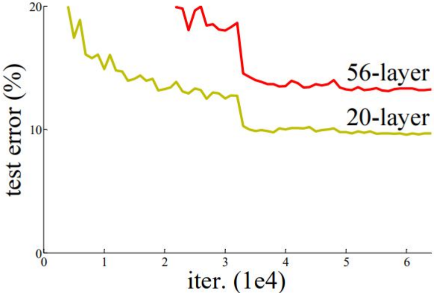

2. Initial suspicion was the 'over-fitting'!

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Training Deeper CNNs

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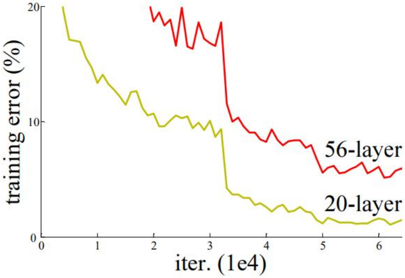
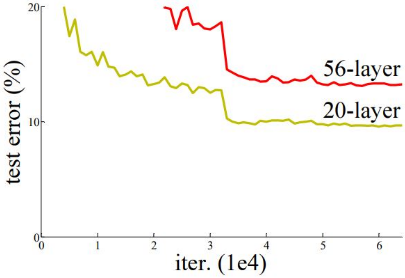
2. However, it was due to the under-fitting





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ResNet (2015)

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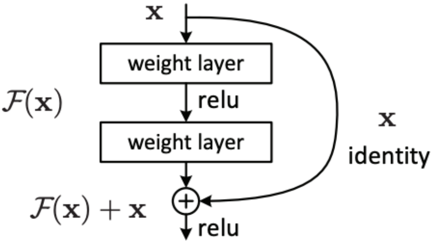
Yuanrui Dong

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

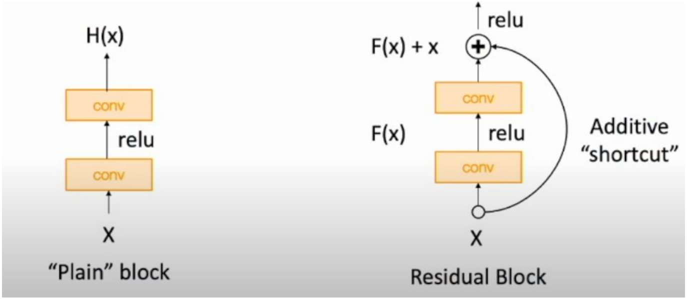


Figure Credits: Dr. Justin Johnson, U Michigan

ResNet (2015)

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2. Inspire from VGG and GoogLeNet

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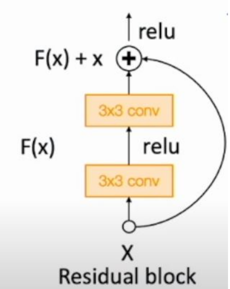
ResNet (2015)

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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2. Aggressive stem in the beginning (downsamples by 4X before the start of the resblocks)
3. Eliminates the FC layers via GAP

ResNet (2015)

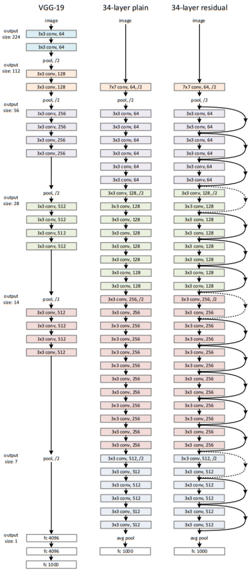

Figure credits: K. he et al., ResNets 92015)

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

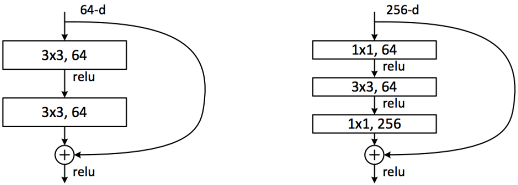

Figure Credits: Nushaine Ferdinand

ResNet (2015)

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

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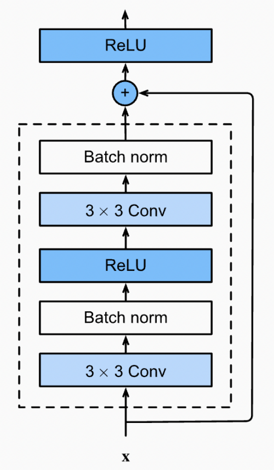
2. More blocks at each stage result in ResNet-101 and Resnet-152 architectures

Resnet (2015)

1. Resblocks have Batch Normalization layers



Yashovardhan Shinde and Analyticsvidhya

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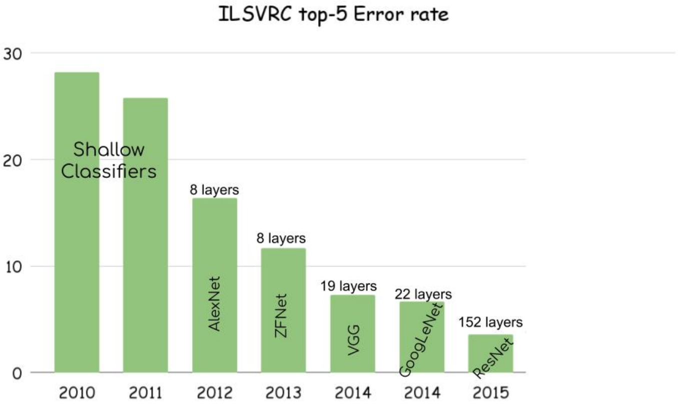

ILSVRC top-5 Error rate
30
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Shallow Classifiers
8 layers
8 layers
19 layers
22 layers
152 layers
AlexNet
ZFNet
VGG
GoogLeNet
ResNet
2010
2011
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Post 2015

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

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5. Deploy-able models: MobileNet, ShuffleNet, etc.
6. Neural Architecture Search (NAS)