CNN Architectures

CNN Architectures

- **AlexNet**
- **VGG**
- **GoogleNet**
- **ResNet**

AlexNet

- *ImageNet Classification with Deep Convolutional Neural Networks - Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton; 2012*
- Facilitated by GPUs, highly optimized convolution implementation and large datasets (ImageNet)
- One of the largest CNNs to date
- Has 60 Million parameter compared to 60k parameter of LeNet-5

[**Krizhevsky et al.**, **2012**]

AlexNet

Architecture
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8

- Input: 227x227x3 images (224x224 before padding)
- First layer: 96 11x11 filters applied at stride 4

- **Output volume size?**

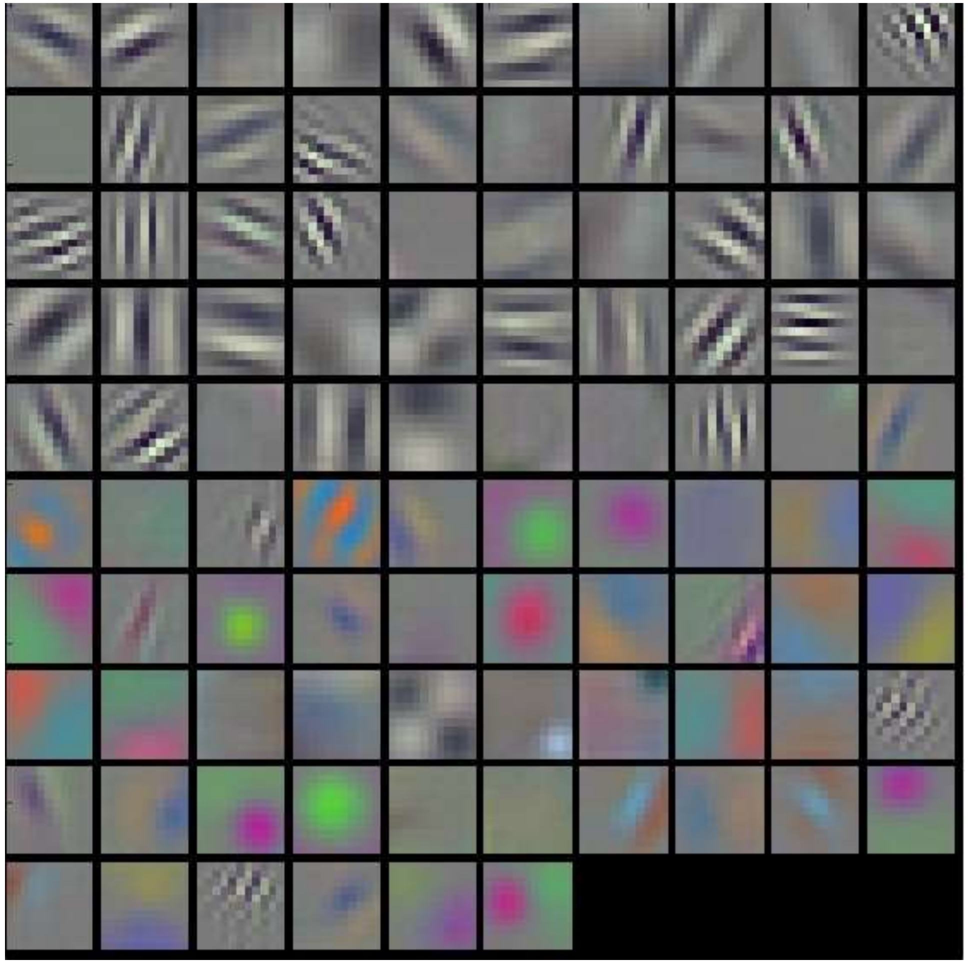
  (N-F)/s+1 = (227-11)/4+1 = 55 -> [55x55x96]

- **Number of parameters in this layer?**

  (11*11*3)*96 = 35K

[Krizhevsky et al., 2012]

AlexNet



[**Krizhevsky et al.**, **2012**]

AlexNet

Details/Retrospectives:

- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- 7 CNN ensemble

[**Krizhevsky et al.**, **2012**]

AlexNet

- Trained on GTX 580 GPU with only 3 GB of memory.

- Network spread across 2 GPUs, half the neurons (feature maps) on each GPU.

- CONV1, CONV2, CONV4, CONV5:
  Connections only with feature maps on same GPU.
- CONV3, FC6, FC7, FC8:
  Connections with all feature maps in preceding layer, communication across GPUs.

[**Krizhevsky et al.**, **2012**]

VGGNet

- *Very Deep Convolutional Networks For Large Scale Image Recognition - Karen Simonyan and Andrew Zisserman; 2015*
- The runner-up at the ILSVRC 2014 competition
- Significantly deeper than AlexNet
- 140 million parameters

[Simonyan and Zisserman, 2014]

Input
3x3 conv, 64
3x3 conv, 64
Pool 1/2
3x3 conv, 128
3x3 conv, 128
Pool 1/2
3x3 conv, 256
3x3 conv, 256
Pool 1/2
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool 1/2
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool 1/2
FC 4096
FC 4096
FC 1000
Softmax

VGGNet

- **Smaller filters**
  Only 3x3 CONV filters, stride 1, pad 1
  and 2x2 MAX POOL , stride 2

- **Deeper network**
  AlexNet: 8 layers
  VGGNet: 16 - 19 layers

- ZFNet: 11.7% top 5 error in ILSVRC'13
- VGGNet: 7.3% top 5 error in ILSVRC'14

[Simonyan and Zisserman, 2014]

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

VGGNet

- **Why use smaller filters? (3x3 conv)**

Stack of three 3x3 conv (stride 1) layers has the same effective receptive field as one 7x7 conv layer.

- **What is the effective receptive field of three 3x3 conv (stride 1) layers?**

7x7

But deeper, more non-linearities

And fewer parameters: $3 * (3^2C^2)$ vs. 7^2C^2 for C channels per layer

[Simonyan and Zisserman, 2014]

VGGNet

Details/Retrospectives :

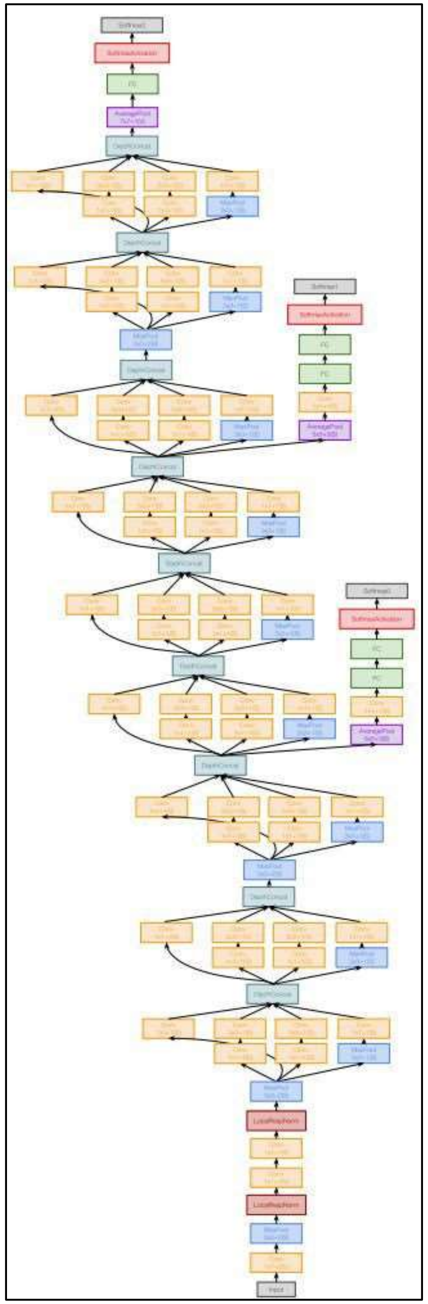
- ILSVRC’14 2nd in classification, 1st in localization
- Similar training procedure as AlexNet
- No Local Response Normalisation (LRN)
- Use VGG16 or VGG19 (VGG19 only slightly better, more memory)
- Use ensembles for best results
- FC7 features generalize well to other tasks
- Trained on 4 Nvidia Titan Black GPUs for **two to three weeks**.

[Simonyan and Zisserman, 2014]

GoogleNet

- *Going Deeper with Convolutions - Christian Szegedy et al.; 2015*
- ILSVRC 2014 competition winner
- Also significantly deeper than AlexNet
- x12 less parameters than AlexNet
- Focused on computational efficiency

[Szegedy et al., 2014]



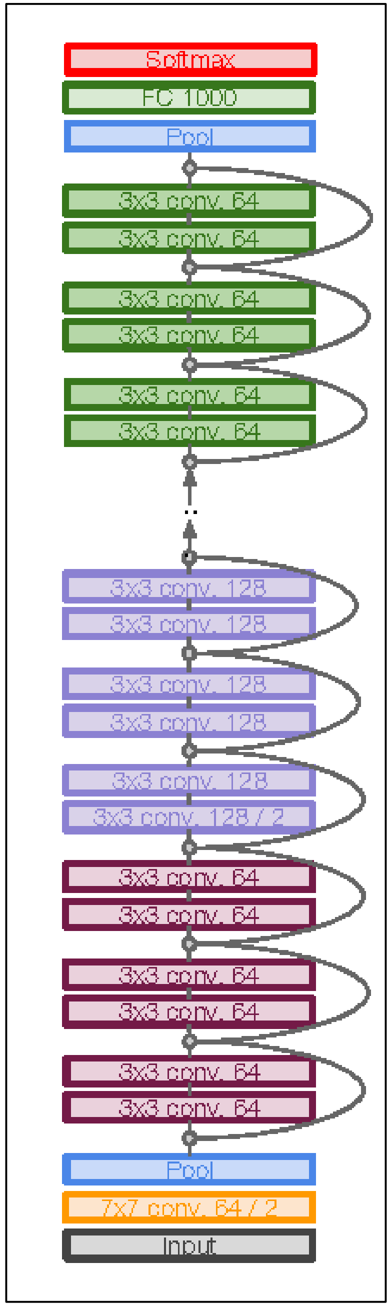
GoogleNet

- 22 layers
- Efficient **“Inception” module** - strayed from the general approach of simply stacking conv and pooling layers on top of each other in a sequential structure
- No FC layers
- Only 5 million parameters!
- ILSVRC’14 classification winner (6.7% top 5 error)

[Szegedy et al., 2014]

ResNet

- *Deep Residual Learning for Image Recognition - Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun; 2015*
- Extremely deep network – 152 layers
- Deeper neural networks are more difficult to train.
- Deep networks suffer from vanishing and exploding gradients.
- Present a residual learning framework to ease the training of networks that are substantially deeper than those used previously.

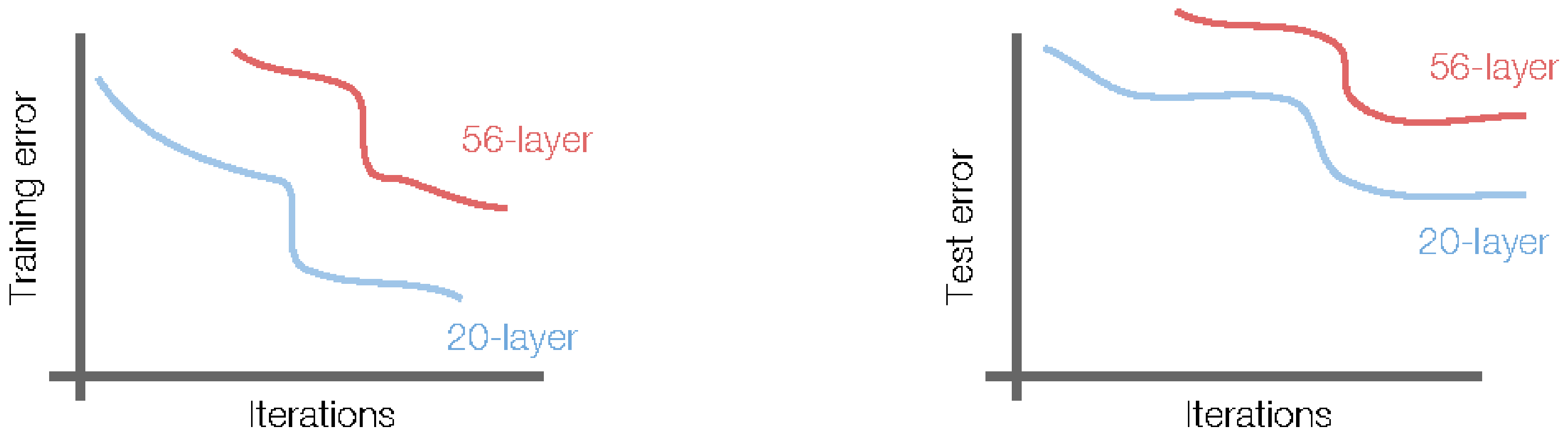


ResNet

- ILSVRC'15 classification winner (3.57% top 5 error, humans generally hover around a 5-10% error rate)
  Swept all classification and detection competitions in ILSVRC'15 and COCO'15!

[He et al., 2015]

ResNet



- What happens when we continue stacking deeper layers on a convolutional neural network?

- 6-layer model performs worse on both training and test error

-> The deeper model performs worse (not caused by overfitting)!

ResNet

- **Hypothesis**: The problem is an optimization problem. Very deep networks are harder to optimize.
- **Solution**: Use network layers to fit residual mapping instead of directly trying to fit a desired underlying mapping.

- We will use **skip connections** allowing us to take the activation from one layer and feed it into another layer, much deeper into the network.
- Use layers to fit residual $F(x) = H(x) - x$
instead of $H(x)$ directly

[He et al., 2015]

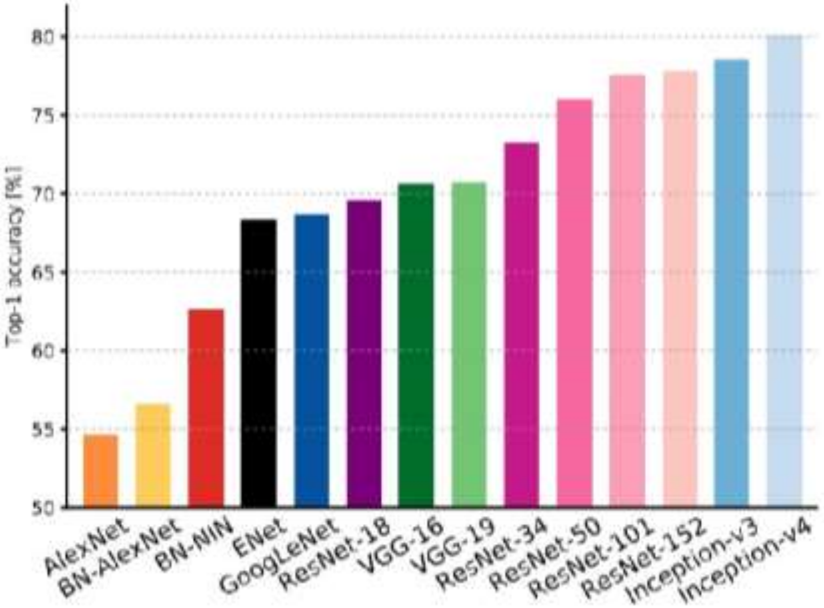
ResNet

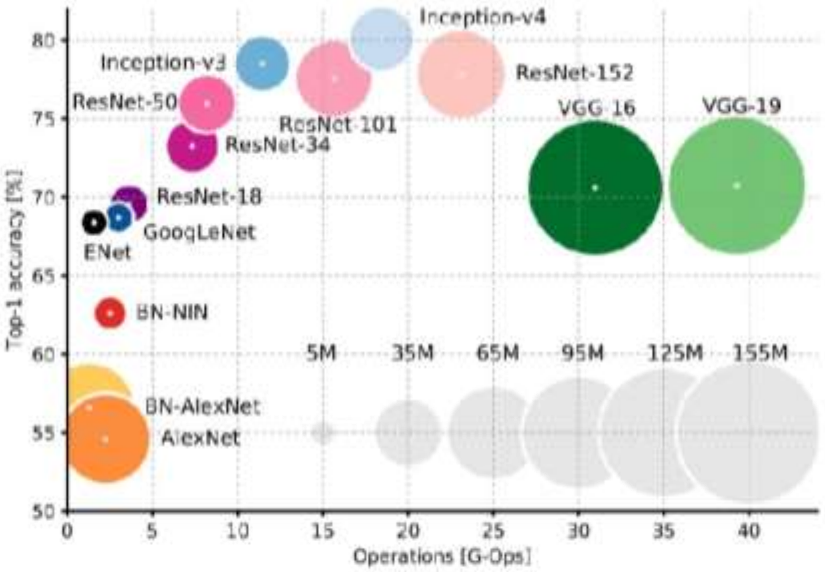
Experimental Results:

- Able to train very deep networks without degrading
- Deeper networks now achieve lower training errors as expected

[He et al., 2015]

Accuracy comparison





References

- *Gradient-based learning applied to document recognition; ann LeCun, Léon Bottou, Yoshua Bengio, Patrick Haffner; 1998*
- *ImageNet Classification with Deep Convolutional Neural Networks - Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton; 2012*
- *Very Deep Convolutional Networks For Large Scale Image Recognition - Karen Simonyan and Andrew Zisserman; 2015*
- *Going Deeper with Convolutions - Christian Szegedy et al.; 2015*
- *Deep Residual Learning for Image Recognition - Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun; 2015*
- *Stanford CS231- Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9*
- *Coursera, Machine Learning course by Andrew Ng.*

References

- *The 9 Deep Learning Papers You Need To Know About (Understanding CNNs Part 3) by Adit Deshpande* https://adeshpande3.github.io/adeshpande3.github.io/The-9-Deep-Learning-Papers-You-Need-To-Know-About.html
- *CNNs Architectures: LeNet, AlexNet, VGG, GoogLeNet, ResNet and more … By Siddharth Das* https://medium.com/@siddharthdas_32104/cnns-architectures-lenet-alexnet-vgg-googlenet-resnet-and-more-666091488df5
- *Slide taken from Forward And Backpropagation in Convolutional Neural Network. – Medium , By Sujit Rai* https://medium.com/@2017csm1006/forward-and-backpropagation-in-convolutional-neural-network-4dfa96d7b37e