Image Classification Networks: classical architectures and common design patterns

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Motivation: Image Classification

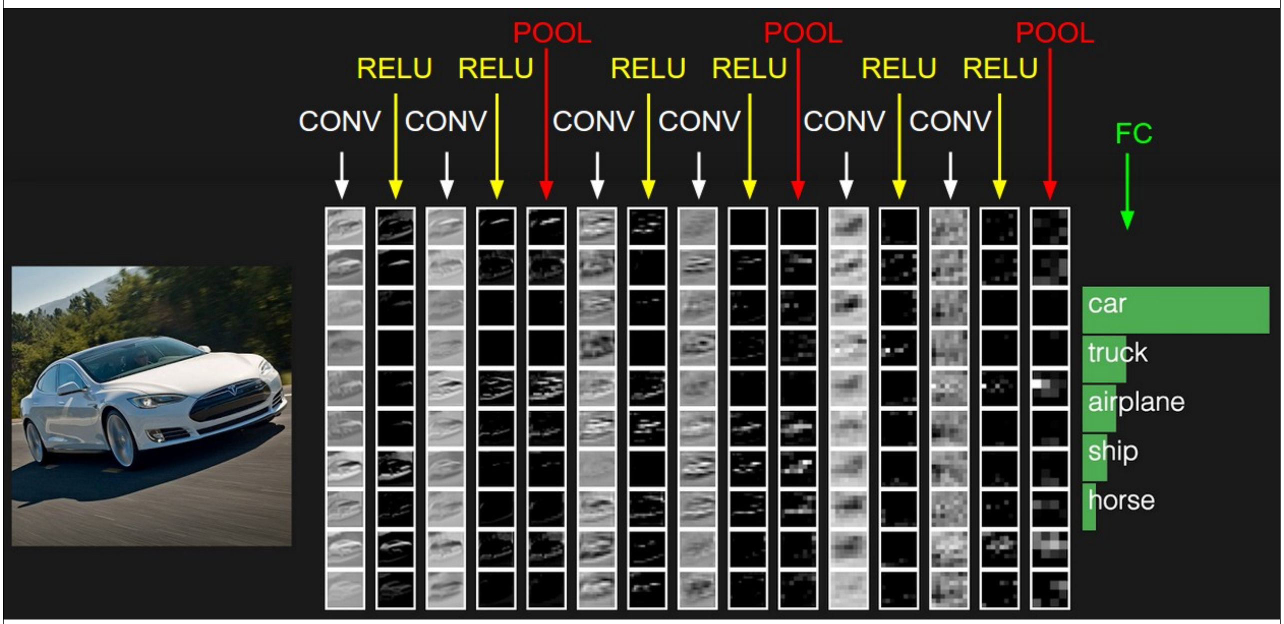
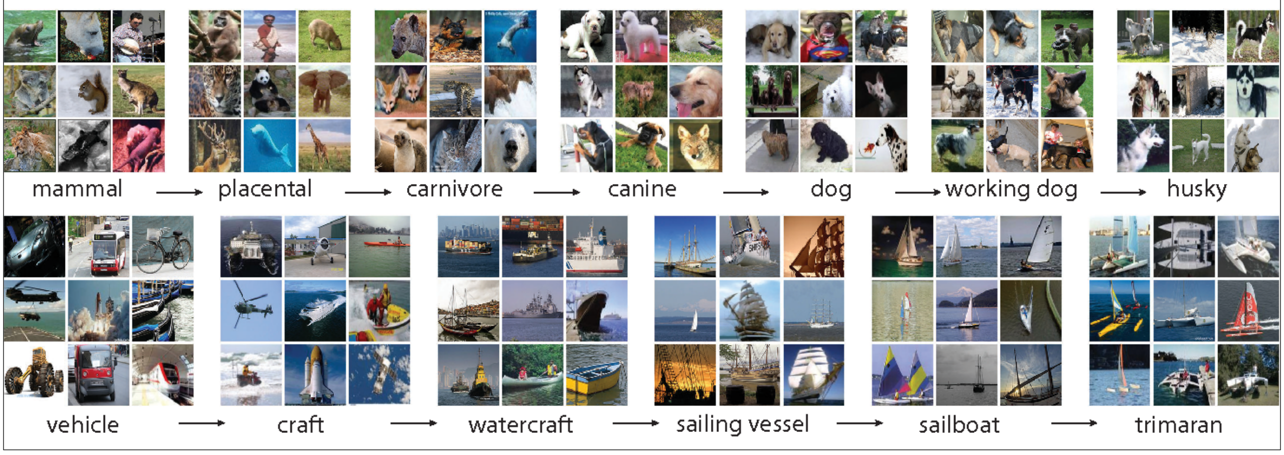


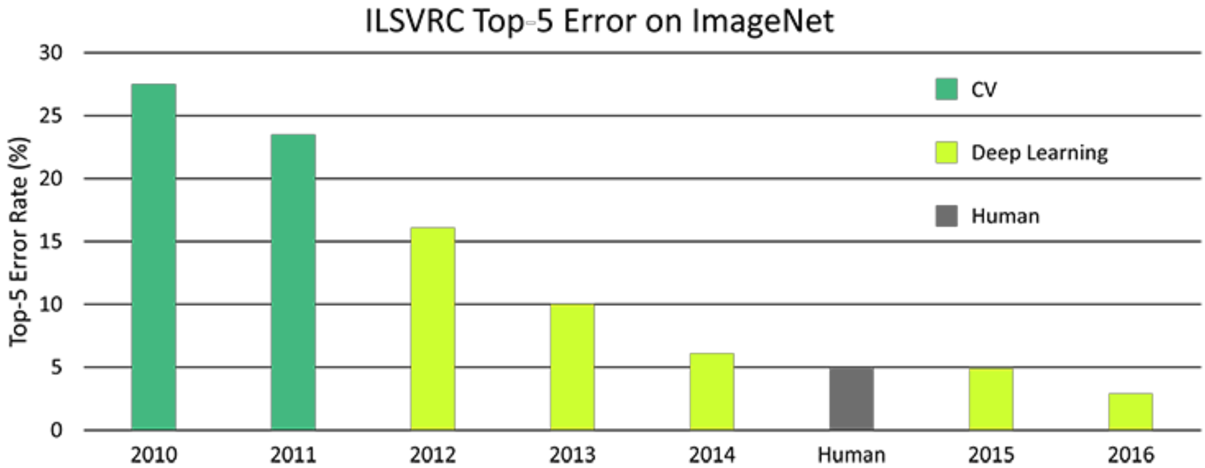
Image Classification Competitions

- Corel Dataset, early 2000's
  - Annotation/multi-label classification
  - ~4500/500 small images
- PASCAL VOC Challenges ~2007
  - Object detection and classification

The ImageNet Challenge

- Circa 2009/2010
- ILSVRC Challenge Dataset: 1.3 Million Images in 1000 classes from a larger superset





Classic Architectures

AlexNet

ImageNet Classification with Deep Convolutional Neural Networks. https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf

CaffeNet

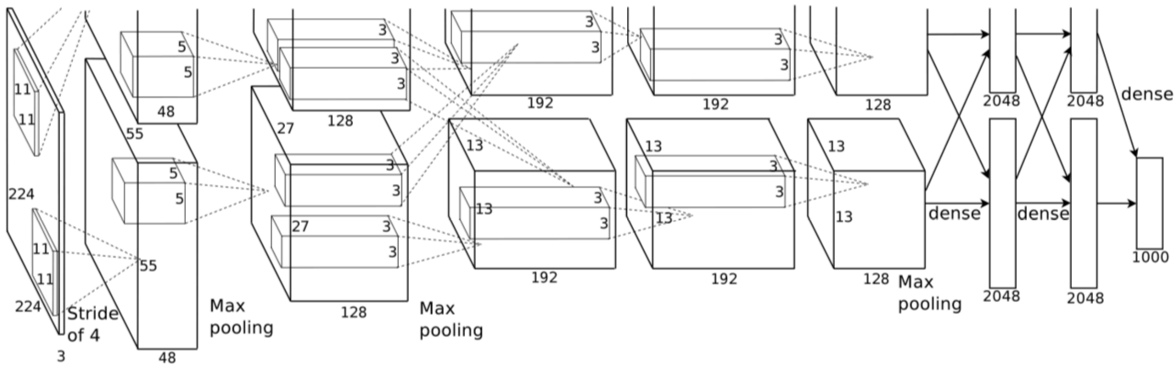


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

LRN Layers

- The original AlexNet contained (and the VGG & GoogleLetNet) networks "Local Response Normalisation" layers
    - The motivation was to provide locally higher contrast in feature maps

The All CNN

Striving for Simplicity: The All Convolutional Net. https://arxiv.org/pdf/1412.6806.pdf

Model

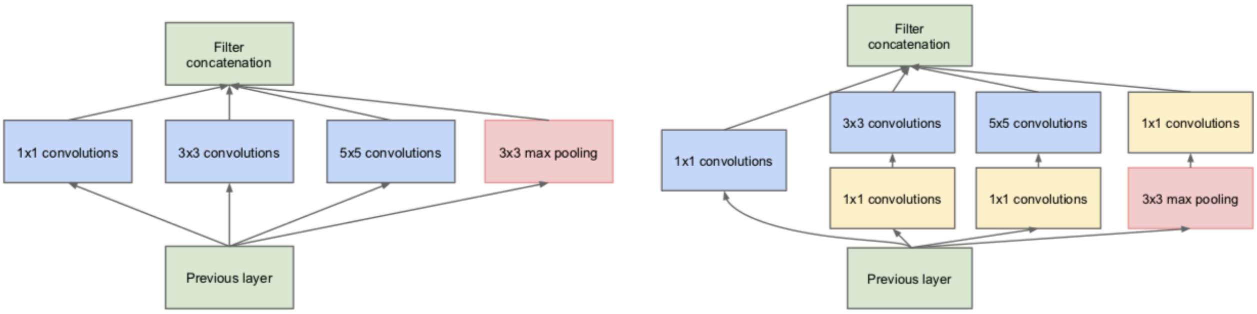
A	B	C
	Input 32×32 RGB image	
5×5 conv. 96 ReLU	5×5 conv. 96 ReLU 1×1 conv. 96 ReLU	3×3 conv. 96 ReLU 3×3 conv. 96 ReLU
	3×3 max-pooling stride 2	
5×5 conv. 192 ReLU	5×5 conv. 192 ReLU 1×1 conv. 192 ReLU	3×3 conv. 192 ReLU 3×3 conv. 192 ReLU
	3×3 max-pooling stride 2	
	3×3 conv. 192 ReLU	
	1×1 conv. 192 ReLU	
	1×1 conv. 10 ReLU	
	global averaging over 6×6 spatial dimensions	
	10 or 100-way softmax	

The VGG Networks

Very Deep Convolutional Networks for Large-Scale Image Recognition. https://arxiv.org/pdf/1409.1556.pdf

GoogLeNet and the Inception Module

Going Deeper with Convolutions. https://arxiv.org/pdf/1409.4842

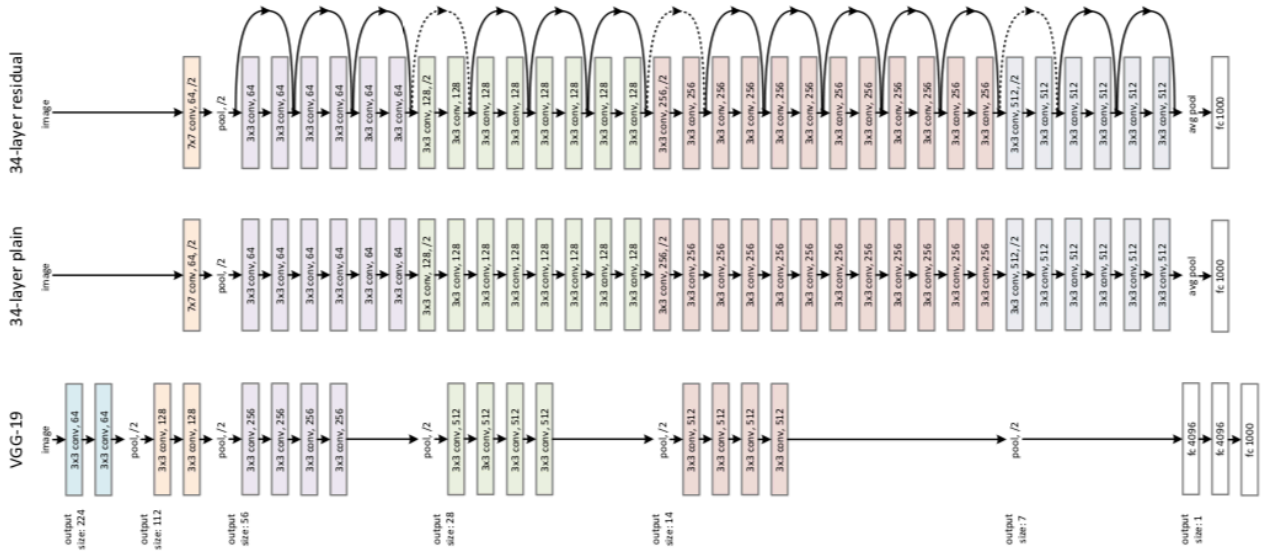


(a) Inception module, naïve version (b) Inception module with dimension reductions

58.9M params

Deep Residual Networks / ResNet

Deep Residual Learning for Image Recognition. https://arxiv.org/pdf/1512.03385.pdf



Do deeper ResNets get you better performance?

method			error (%)
Maxout [10]			9.38
NIN [25]			8.81
DSN [24]			8.22
	# layers	# params	
FitNet [35]	19	2.5M	8.39
Highway [42, 43]	19	2.3M	7.54 (7.72±0.16)
Highway [42, 43]	32	1.25M	8.80
ResNet	20	0.27M	8.75
ResNet	32	0.46M	7.51
ResNet	44	0.66M	7.17
ResNet	56	0.85M	6.97
ResNet	110	1.7M	**6.43** (6.61±0.16)
ResNet	1202	19.4M	7.93

Table 6. Classification error on the **CIFAR-10** test set. All methods are with data augmentation. For ResNet-110, we run it 5 times and show "best (mean±std)" as in [43].

Are ResNets really deep?

Training Classification Networks

Overfitting is a serious concern

- Early nets used dropout extensively
  - BatchNorm has replaced this in more recent architectures
- Significant amounts of data augmentation (the original AlexNet had 2048 augmentations for each training image!)

Competing in ImageNet

- Almost all the winners use a form of test-time augmentation
    - Take multiple views of the input image (e.g. AlexNet took 10 augmentations) and average over the classifications.