Data Analytics
EEE 4774 & 6777

Module 4 - Classification

Deep Learning, Convolutional Neural Network

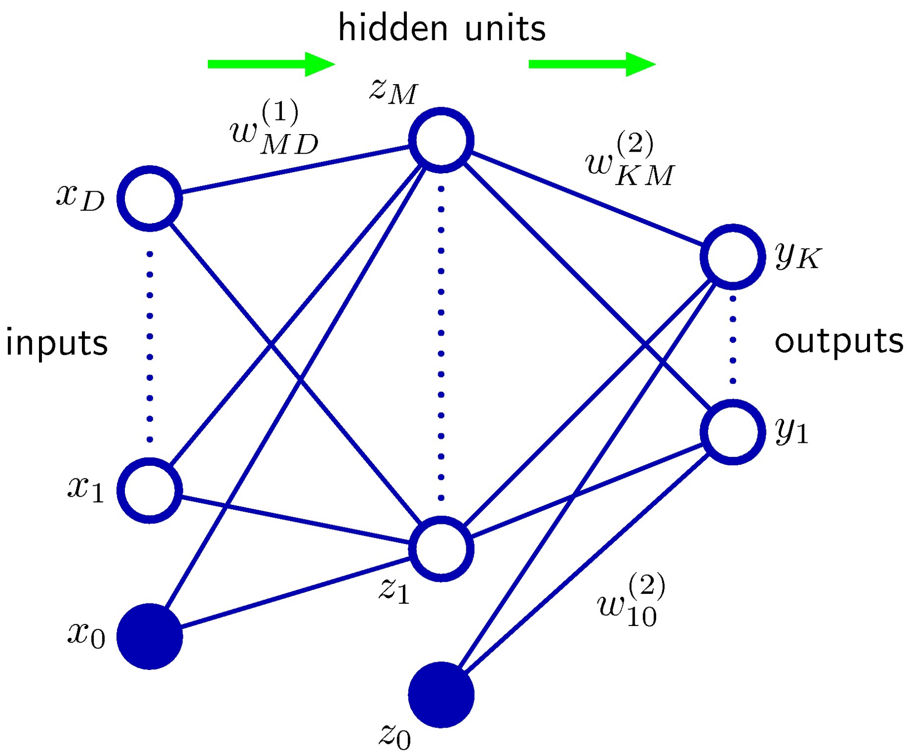
Spring 2022

Artificial Neural Network

- Origins in attempts to find mathematical representations of information processing in biological systems
- Also known as ***Multilayer Perceptron*** / Can be also regarded as ***Multilayer Logistic Regression***
- Finds basis functions $\boldsymbol{\phi}(\boldsymbol{x})$ adaptive to the training data

$$y(\boldsymbol{x}) = f\left(c\boldsymbol{\phi}(\boldsymbol{x})\right) = \sigma\left(\boldsymbol{w}_2^T\boldsymbol{\phi}(\boldsymbol{x})\right)$$

$$\boldsymbol{\phi}(\boldsymbol{x}) = h(\boldsymbol{w}_1^T\boldsymbol{x})$$

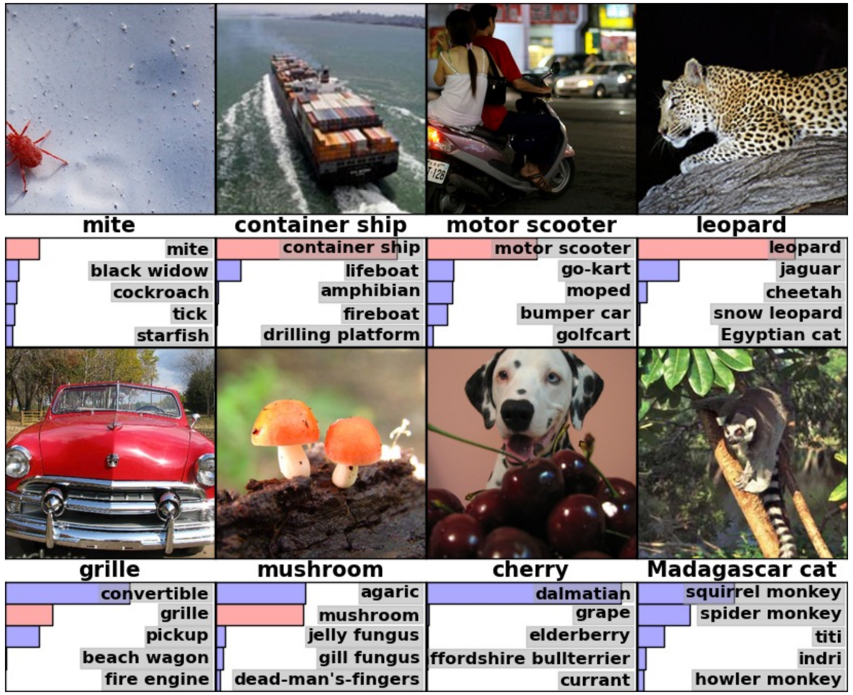


Extensions

Deep Neural Networks (Deep Learning), e.g.,

- Convolutional Neural Network (CNN)
- Recurrent Neural Network (RNN)
- Transformer (self-attention)
- Deep Generative Models
- Deep Reinforcement Learning

Applications



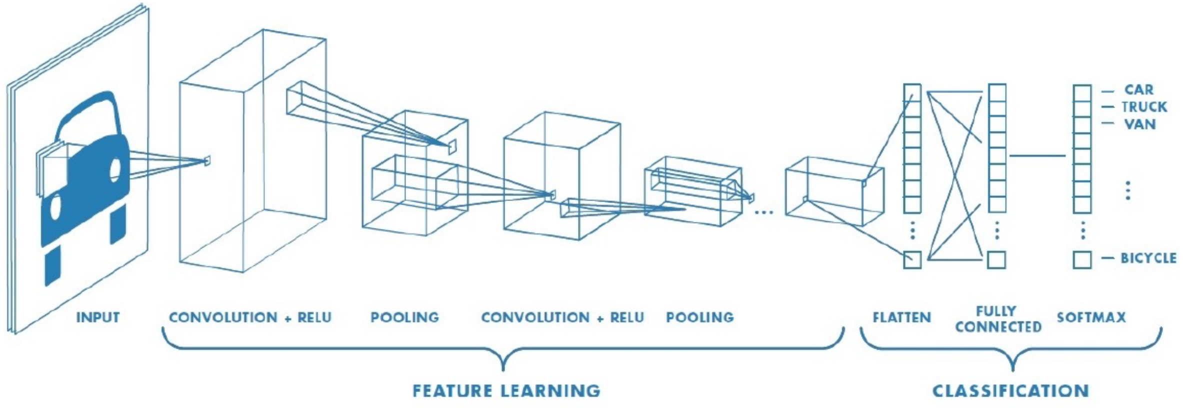
- Object Recognition
- Action Recognition
- Face Recognition
- Speech Recognition
- Natural Language Processing
- Video Understanding
- Time-series Prediction
- Anomaly Detection
- Robotics
- Autonomous Driving
- …

Convolutional Neural Networks

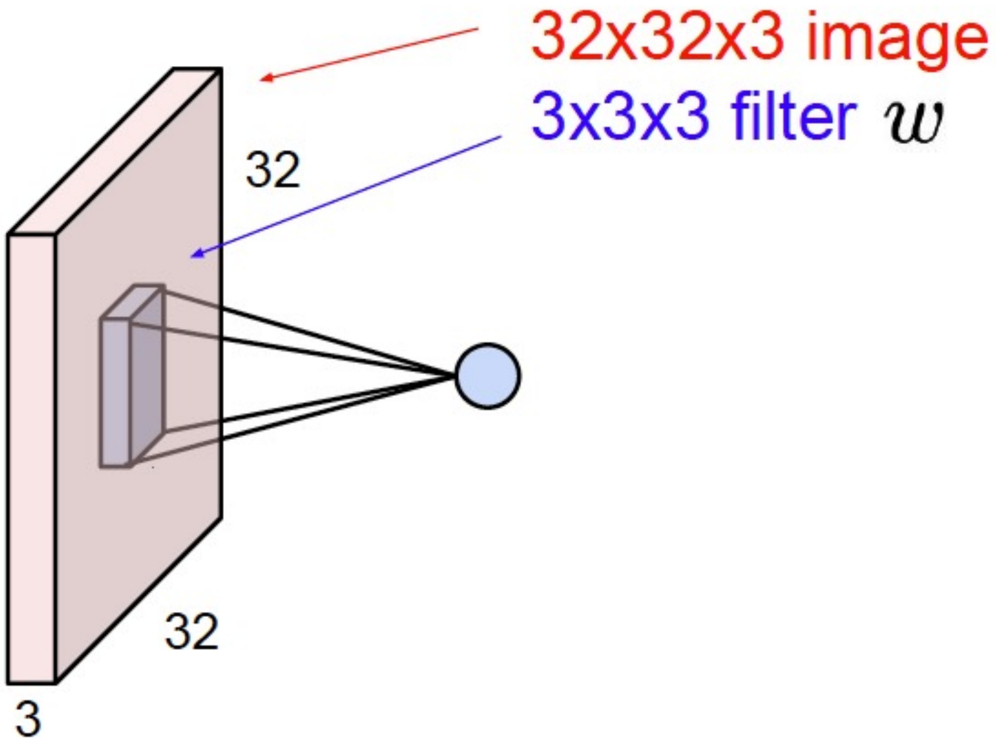
- Uses **convolution** in place of general matrix multiplication in at least one of the layers
- Convolution is a specialized kind of linear operation:

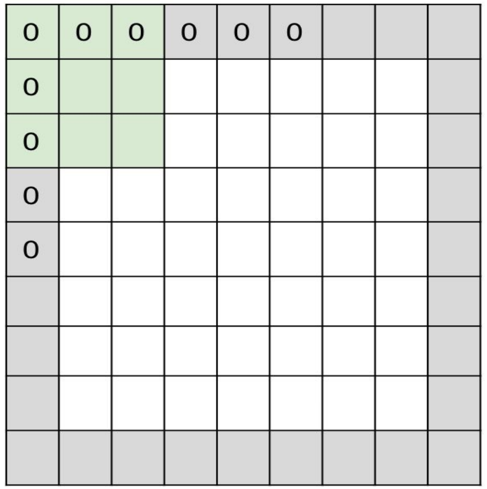
$$s(t) = x(t) * w(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a)$$

- Used for processing data that has a grid-like topology, e.g., time-series data (1-D grid), image data (2-D grid)
- Very successful in practice

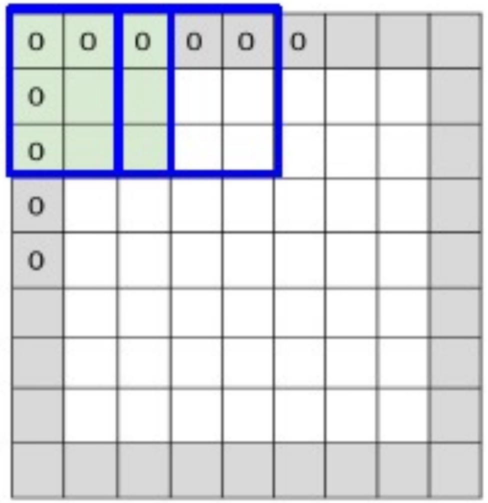


Convolution





Padding

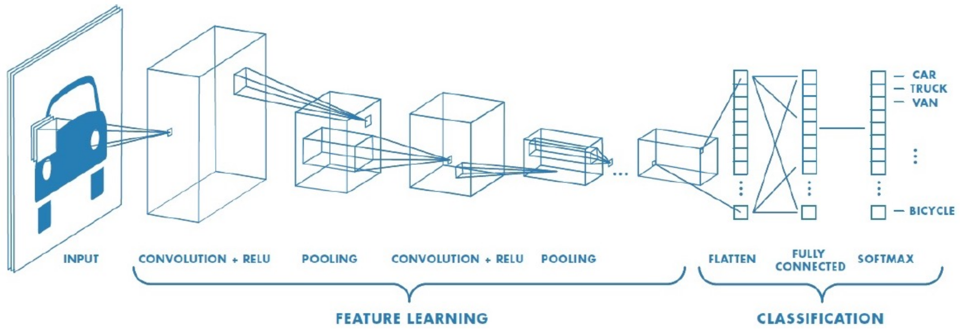


Stride

Image courtesy of Fei-Fei Li, Ranjay Krishna, Danfei Xu

Convolutional Neural Networks

- 3 stages:
  - convolutional stage: linear activations
  - detector stage: nonlinear activation function such as Rectified Linear Unit (ReLU)
  - pooling stage: modify the output with a summary statistic of nearby outputs, e.g.,
- **Max Pooling:** reports the maximum output within a rectangular neighborhood
- **Average Pooling:** average of a rectangular neighborhood
- Pooling helps to make the representation approximately invariant (i.e., robust) to small translations of the input



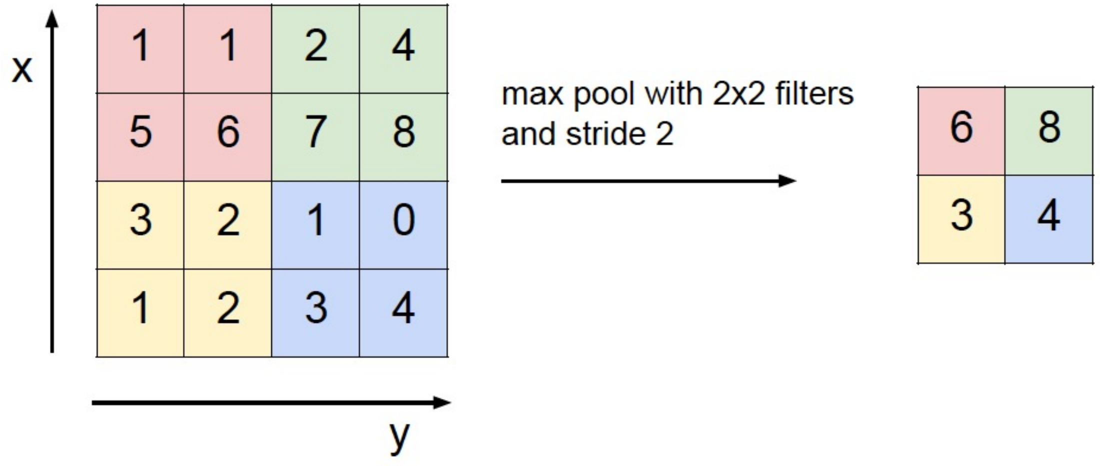
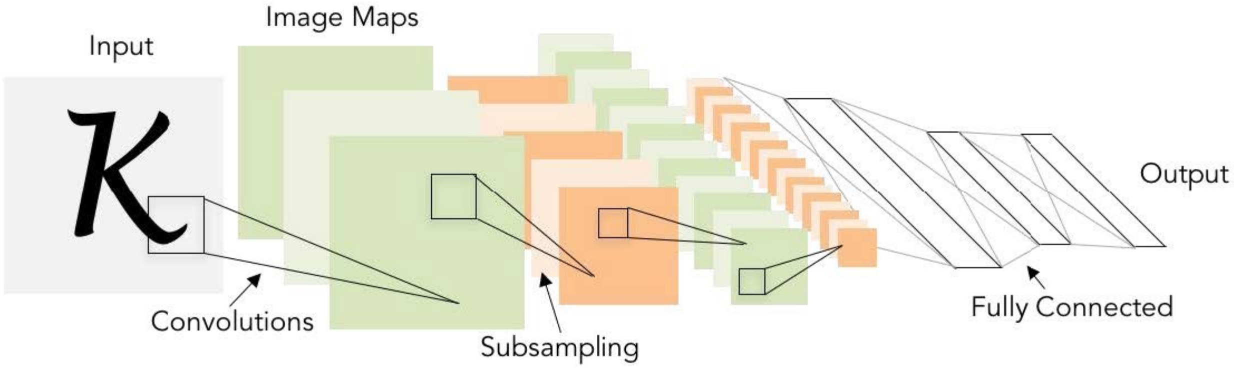


Image courtesy of Fei-Fei Li, Ranjay Krishna, Danfei Xu

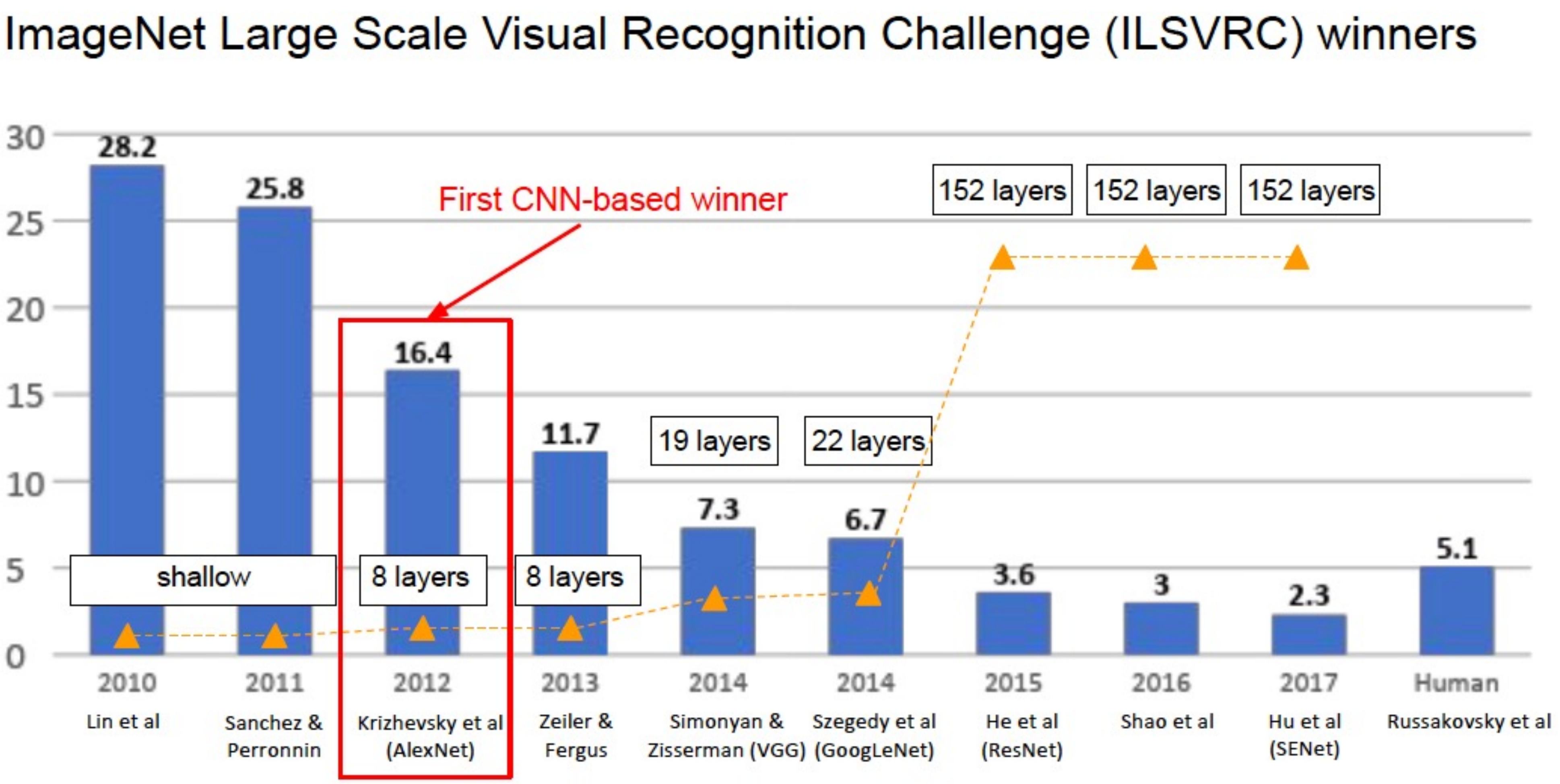
CNN Architectures

- LeNet-5 [LeCunn et al. 1998]
- AlexNet [Krizhevsky et al. 2012]
- VGG [Simonyan et al. 2014]
- GoogLeNet [Szegedy et al. 2015]
- ResNet [He et al. 2016]
- …
- …



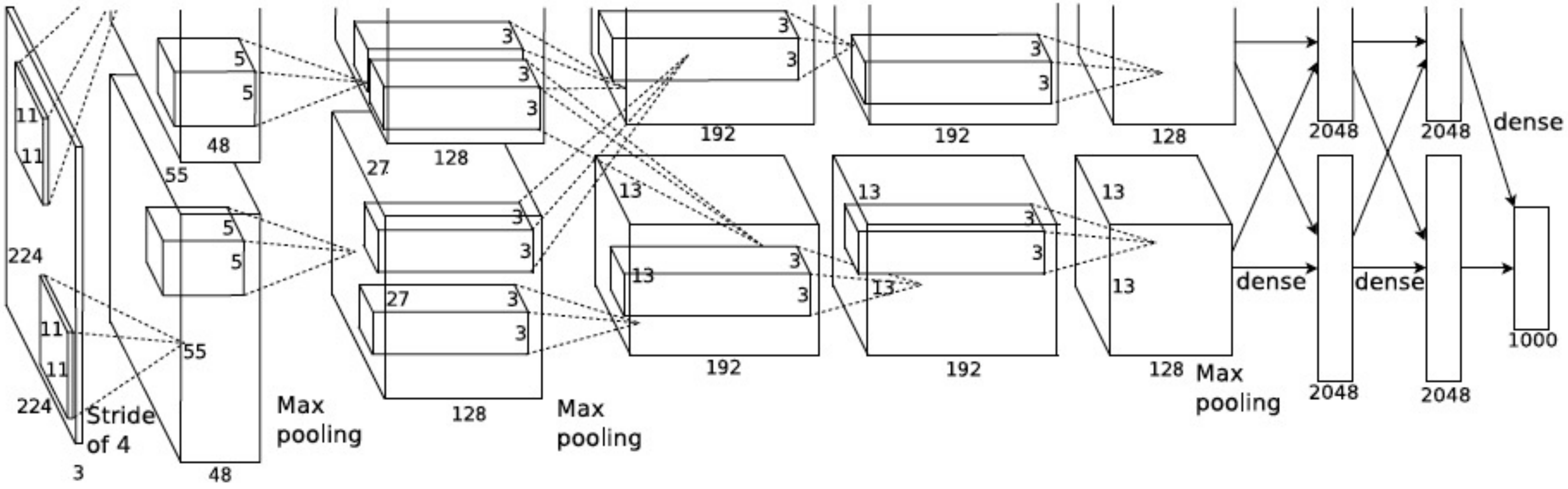
LeNet-5: Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-FC-FC]

Rise of Deep Learning

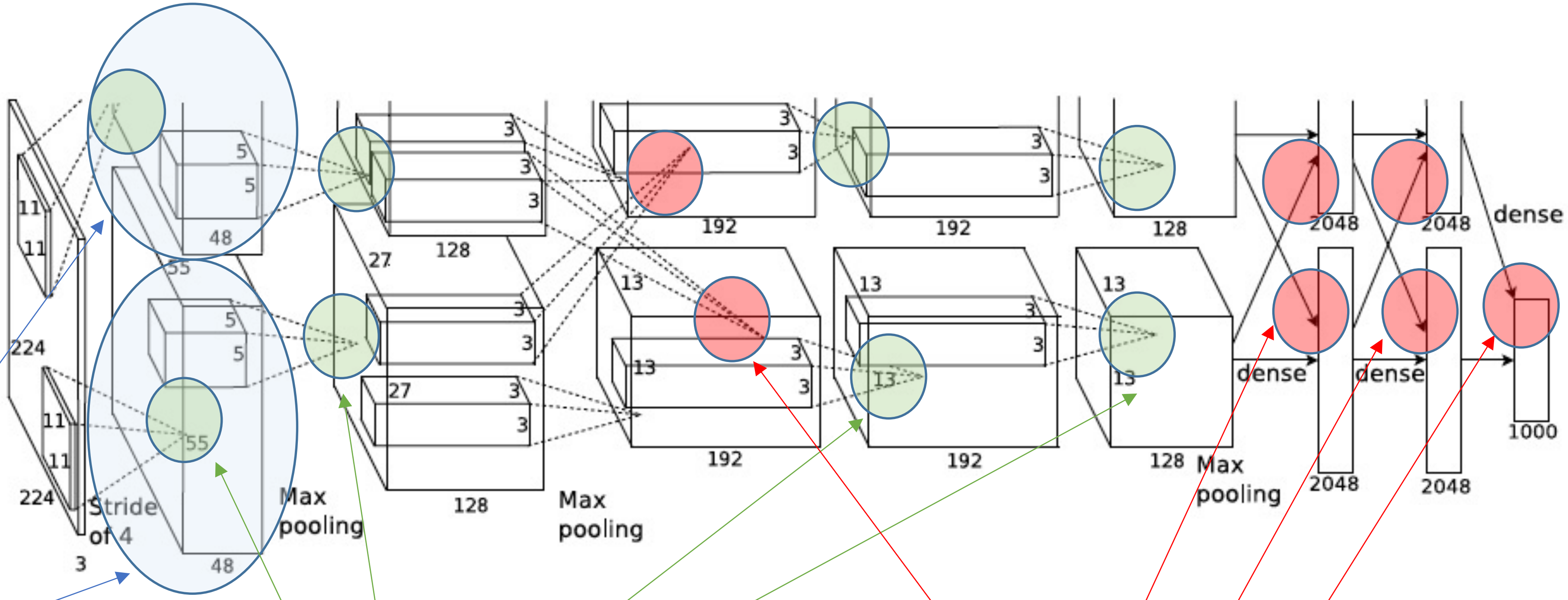


AlexNet

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



AlexNet



Trained on 2 GPUs.
Half the neurons on
each GPU.

Connections only
within the same
GPU

Connections
across GPUs

AlexNet

- First use of ReLU
- Used Norm layers
- **Data augmentation (overfitting)**
- **Dropout (overfitting)**
    - Randomly drop neurons for each training instance in feedforward and backpropagation with probability 0.5
    - “Every time an input is presented, the neural network samples a different architecture, but all these architectures share weights”
    - “At test time, use all the neurons but multiply their outputs by 0.5”
- SGD for weight update in training
    - Gradient batch size 128
    - Momentum 0.9
    - Learning rate 1e-2, reduced by 10 manually when validation accuracy plateaus
- 7 CNN ensemble: 18.2% -> 15.4%

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
University of Toronto
kriz@cs.utoronto.ca

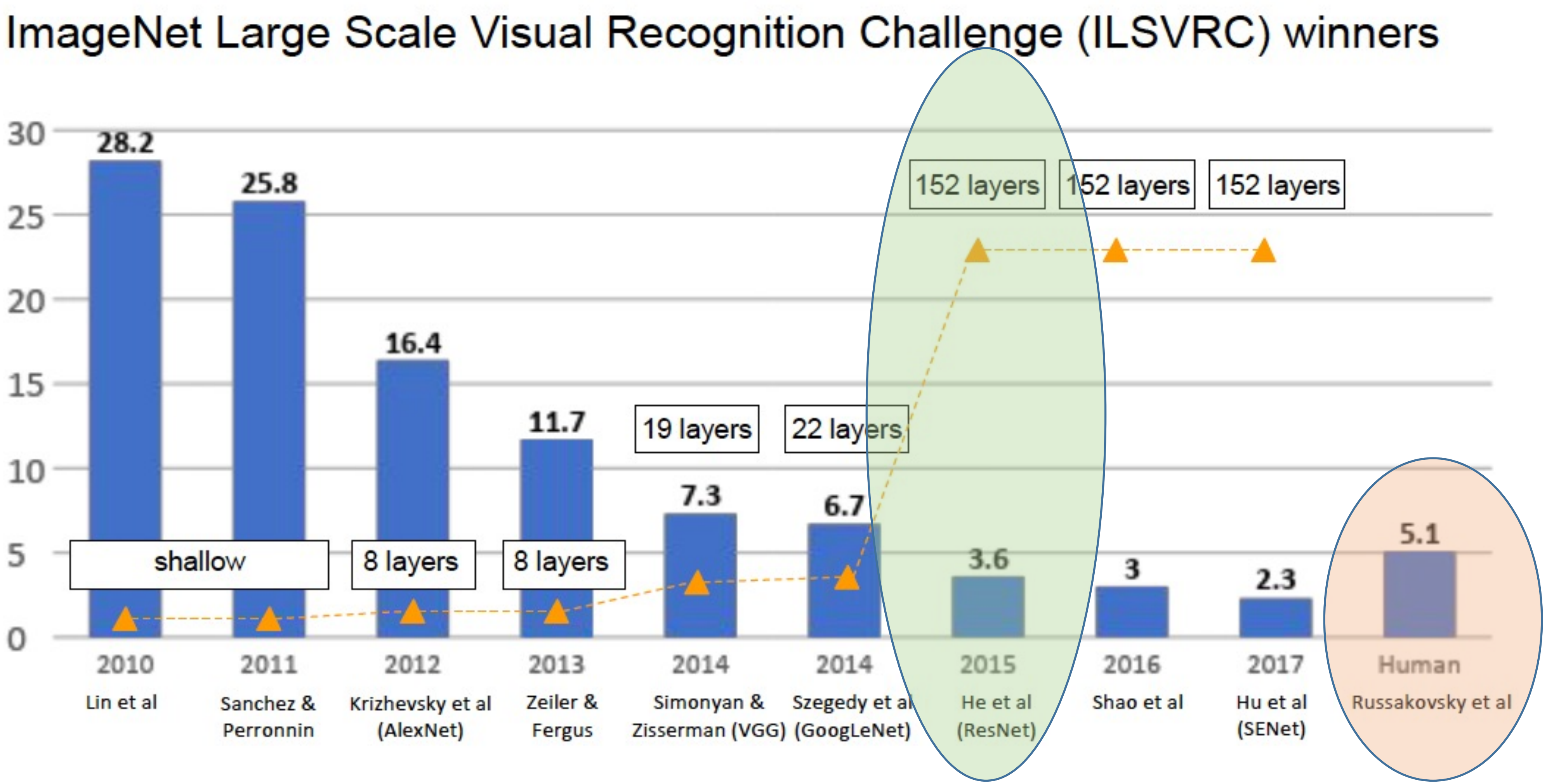
Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called “dropout” that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

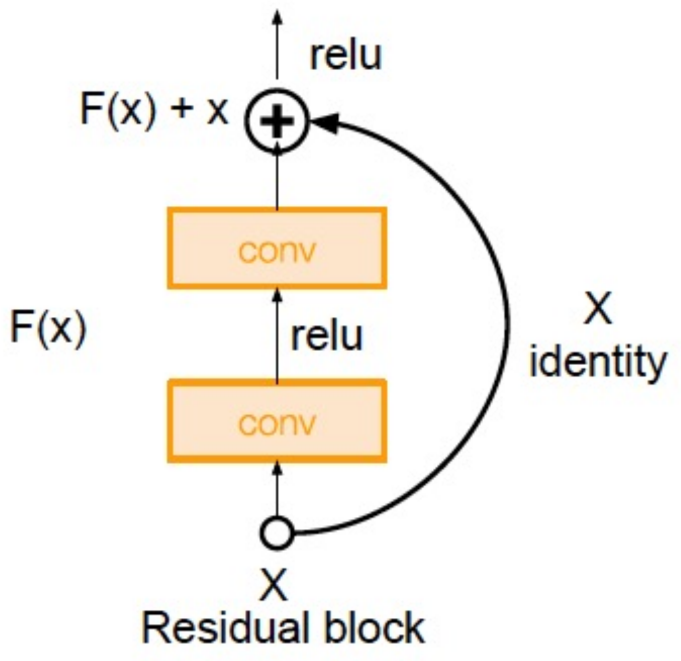
ResNet

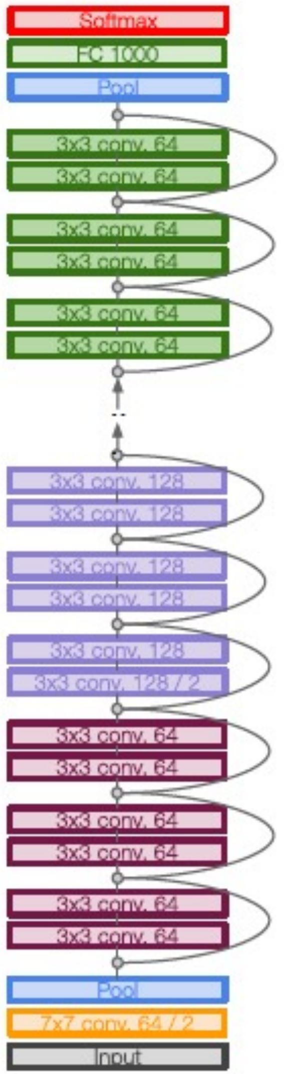


ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners
30
25
20
15
10
5
0
28.2
25.8
16.4
11.7
7.3
6.7
3.6
3
2.3
5.1
shallow
8 layers
8 layers
19 layers
22 layers
152 layers
152 layers
152 layers
2010
Lin et al
2011
Sanchez & Perronnin
2012
Krizhevsky et al (AlexNet)
2013
Zeiler & Fergus
2014
Simonyan & Zisserman (VGG)
2014
Szegedy et al (GoogLeNet)
2015
He et al (ResNet)
2016
Shao et al
2017
Hu et al (SENet)
Human
Russakovsky et al

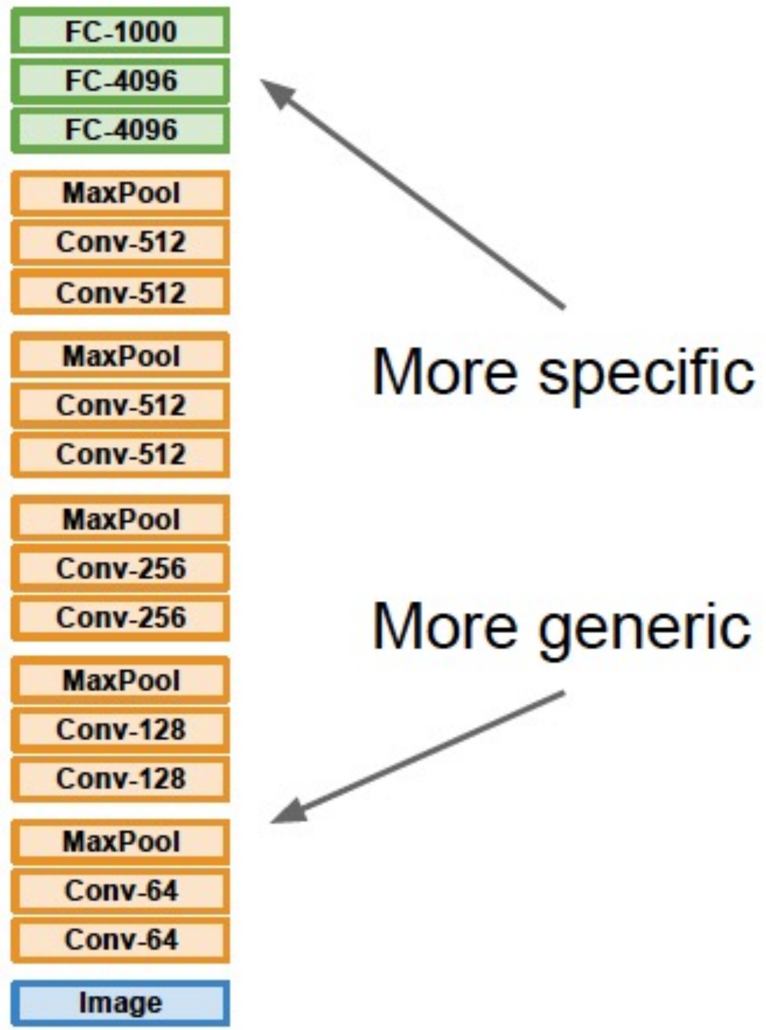
ResNet

- Very deep networks using residual connections
- 152-layer model for ImageNet
    - Outperformed the human-level performance
- Now focus shifted to Efficient Networks:
    - Lots of tiny networks aimed at mobile devices: MobileNet, ShuffleNet, etc.





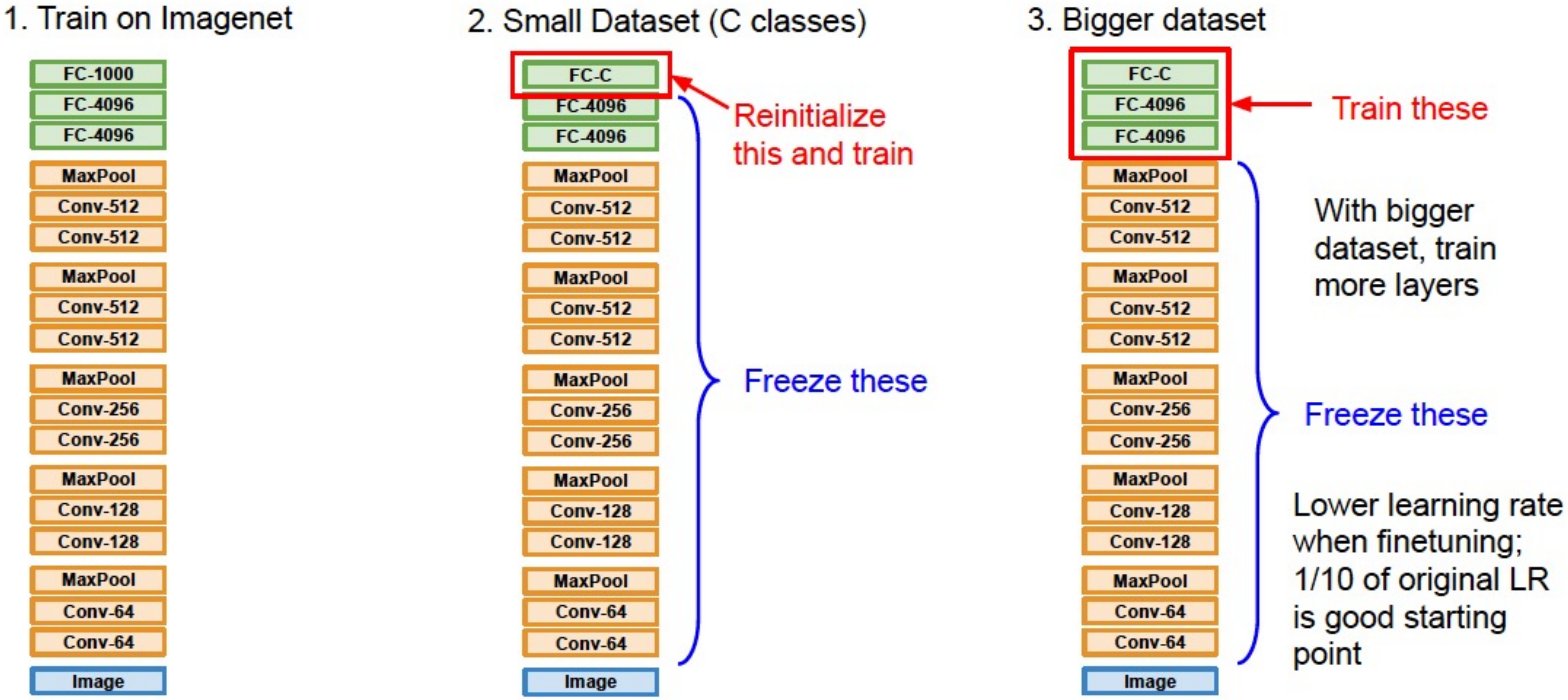
Transfer Learning



	very similar dataset	**very different dataset**
very little data	Finetune linear classifier on top layer	You're in trouble… Try data augmentation / collect more data
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Transfer Learning with CNNs

Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014
Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014



Transfer Learning

In practice:

- Take a pretrained model
  - Trained on a very large dataset such as ImageNet
  - "Model Garden" of pretrained models:
    https://github.com/tensorflow/models
    https://github.com/pytorch/vision

- Train only a few last layers on your dataset