Hardware for Machine Learning

Lecture 2: Deep Neural Networks

Sophia Shao

ECE1742S: Programming using CUDA, 2008, U of T

Convolutional Neural Networks for Object Classification

Alex Krizhevsky

Department of Computer Science, University of Toronto

akrizhevsky at gmail.com

Abstract I implemented a convolutional neural network with one layer of convolution. I tested it on the CIFAR-10 dataset, which consists of 6000 32×32 colour images in each of 10 classes. The convolutional net does well on the classification task and takes roughly 140x less time to train than a CPU implementation.

- Presentation: (pdf).
- Report: (pdf).
- Source code: (zip).

Convolutional Neural Networks for Object Classification in CUDA

Alex Krizhevsky (kriz@cs.toronto.edu)

April 16, 2009

1 Introduction

Here I will present my implementation of a simple convolutional neural network in CUDA. The network takes as input a 32 × 32 colour image and produces as its output one of ten possible class labels. The convolution operations, which account for 90% of the time required to train this network, are 125-150x faster on the GPU than on an Intel Core 2 Duo 2.4GHz.

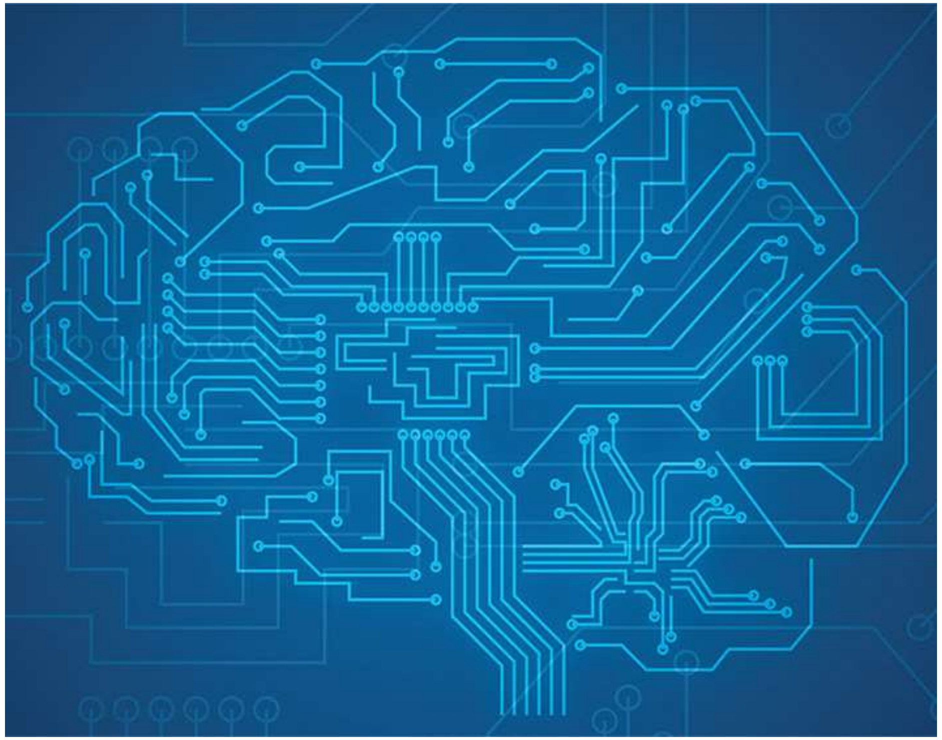
9 Conclusion

It works! The next step is to build convolutional nets with multiple layers of convolution.

http://www.eecg.toronto.edu/~moshovos/CUDA08/arx/convnet_report.pdf

Review

- Course overview:
  - A bridge between hardware and machine learning
  - **Build** efficient hardware for accelerating machine learning applications.
- Class website:
  - http://inst.eecs.berkeley.edu/~ee290-2/sp21/
- Lectures, reading/reviews, labs, and project



DNNs

- **AI, ML, and DL**
- ML Basics
- DL Overview
- AlexNet Example

Artificial Intelligence (AI)

Artificial Intelligence

"The science and engineering of creating intelligent machines"

John McCarthy, 1956

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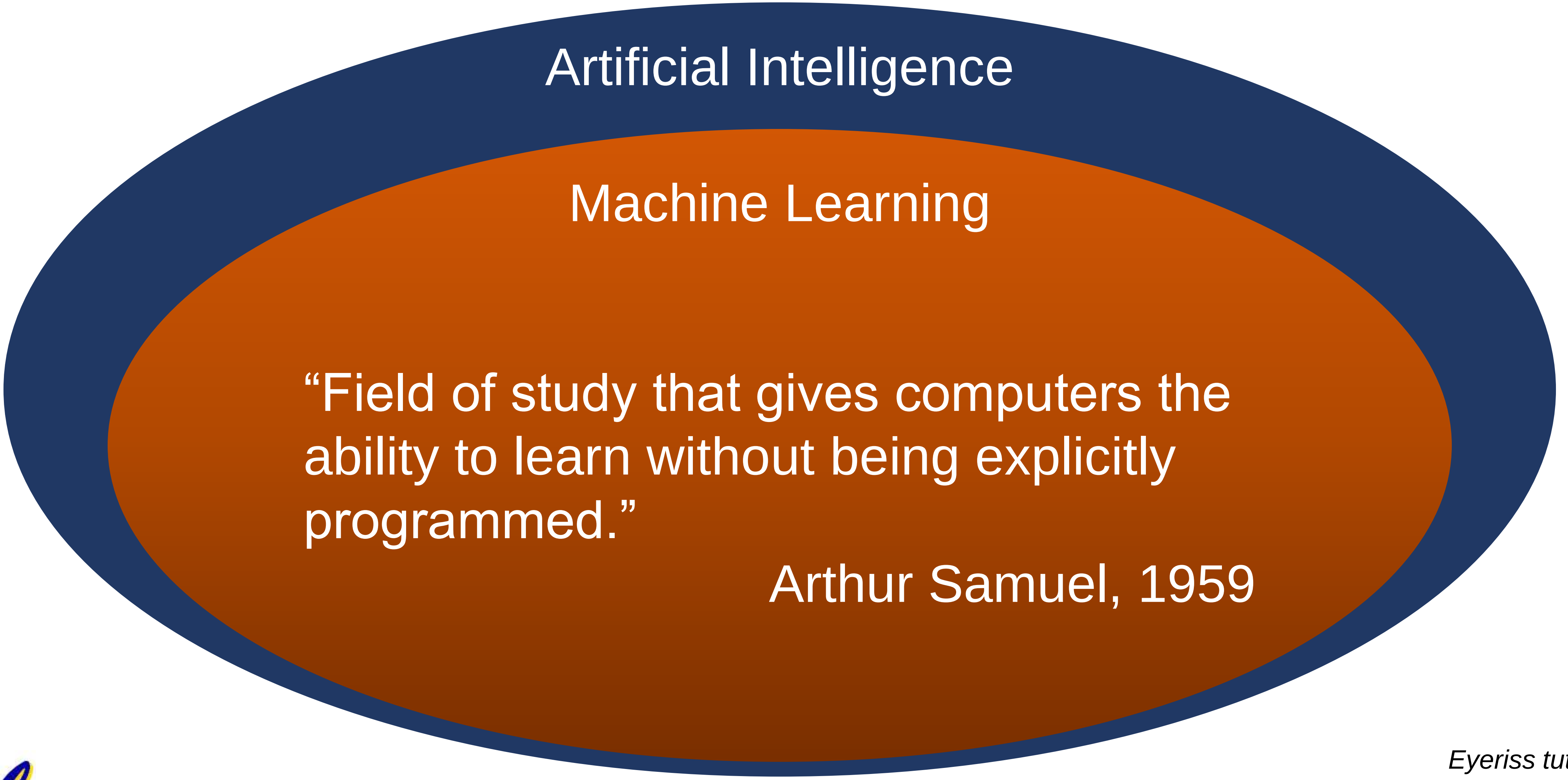
Machine Learning (ML)



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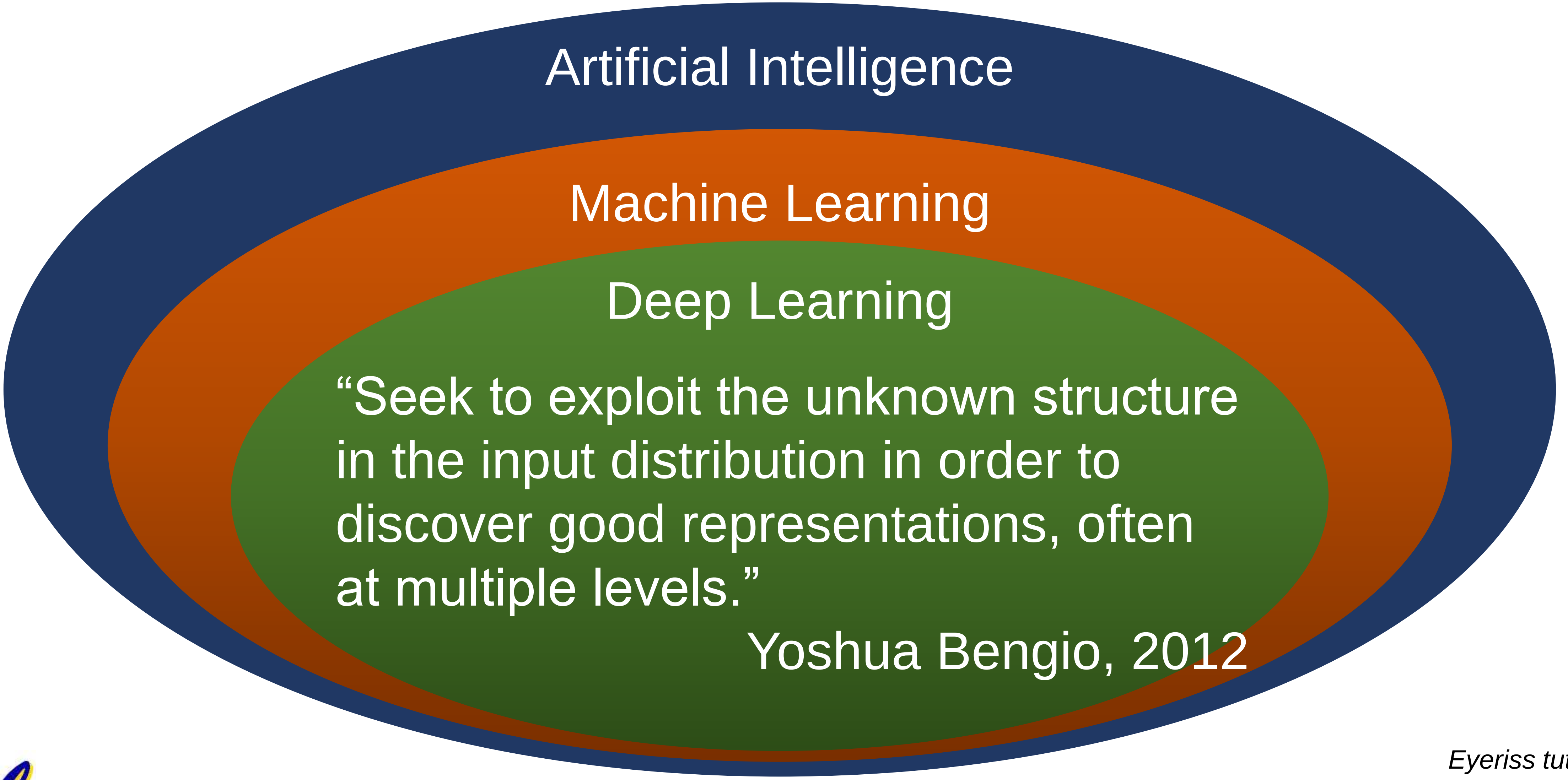
Deep Learning (DL)



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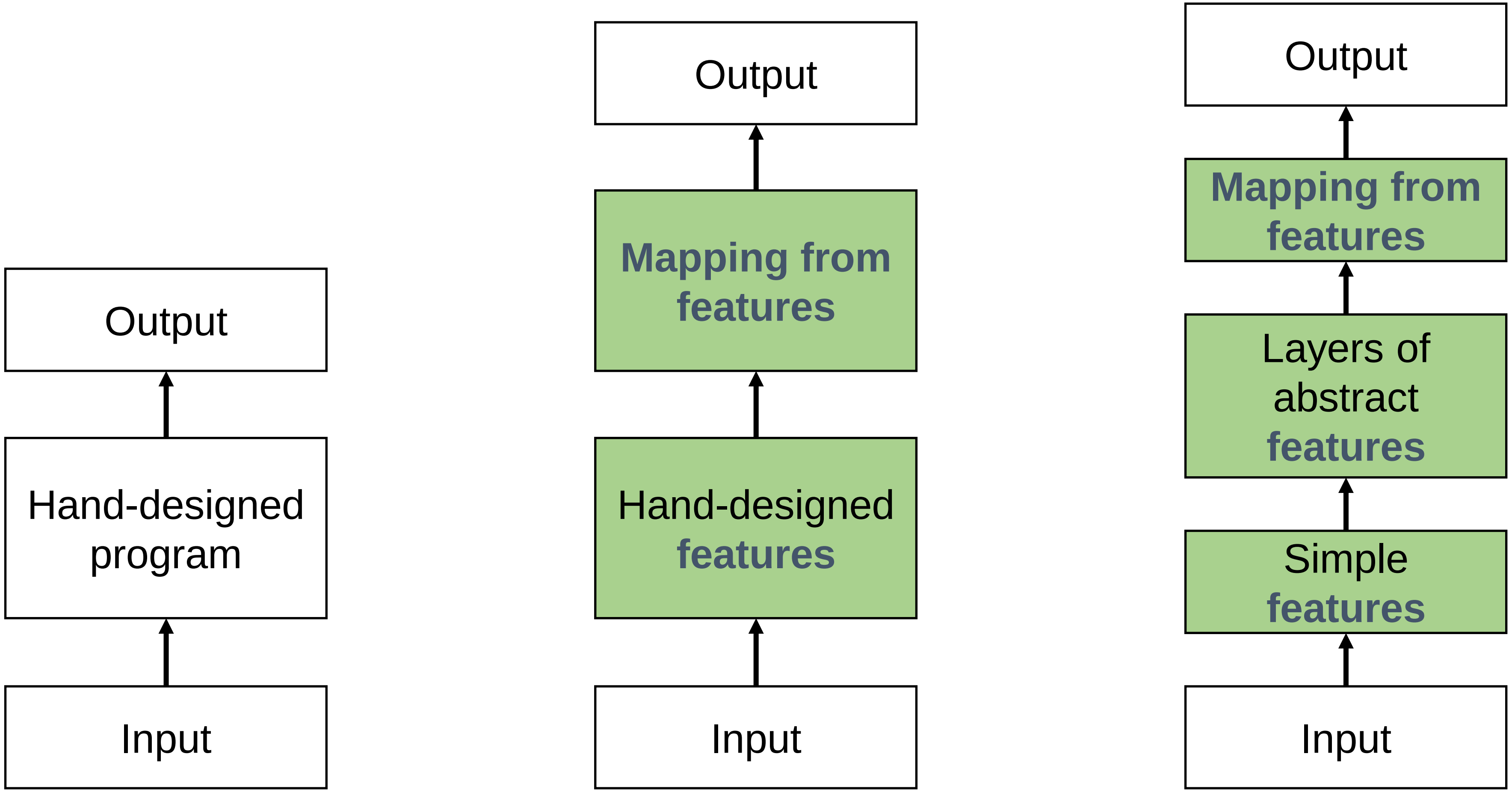
Different AI Systems

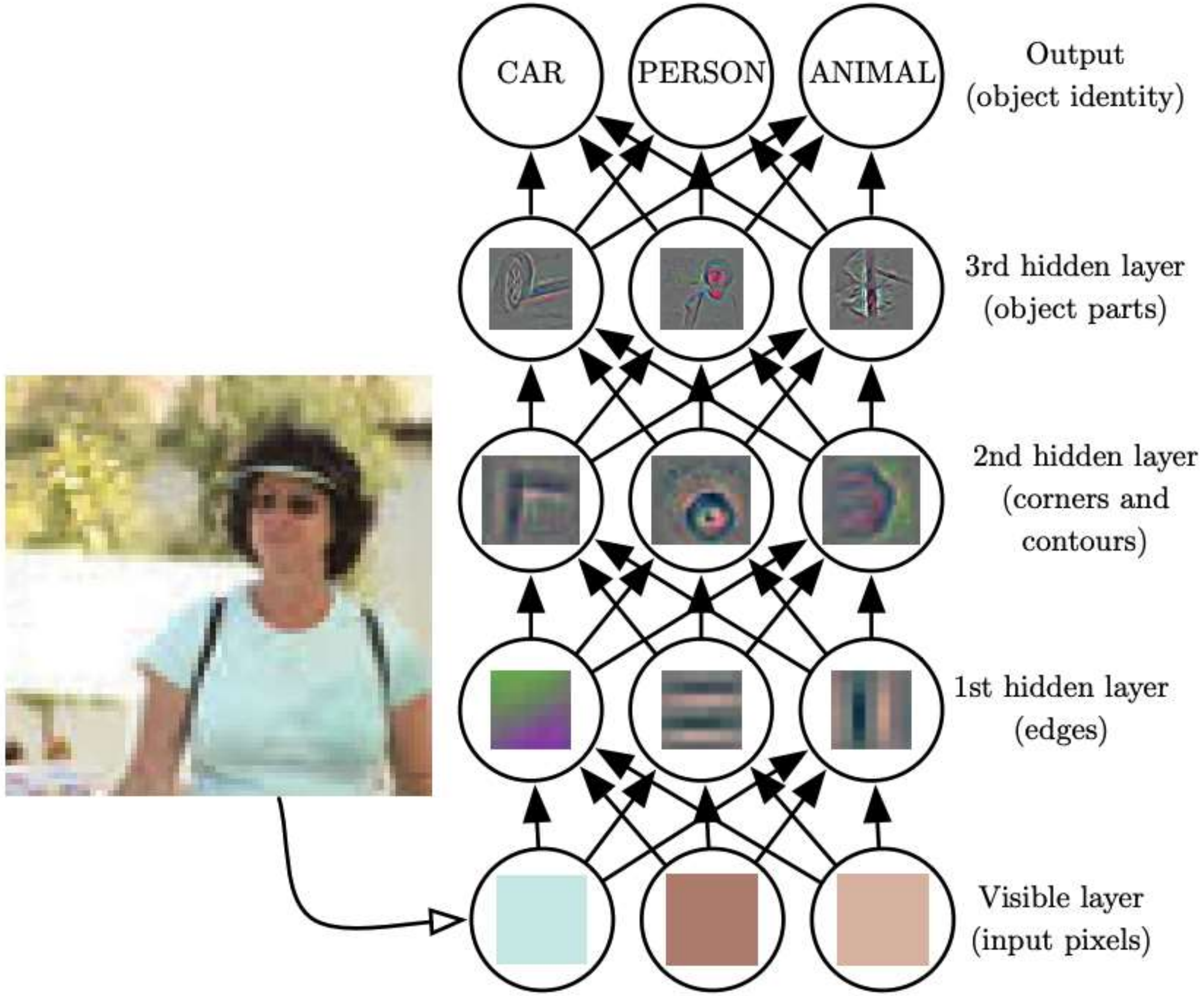


Rule-based system

Classic machine learning

Deep learning

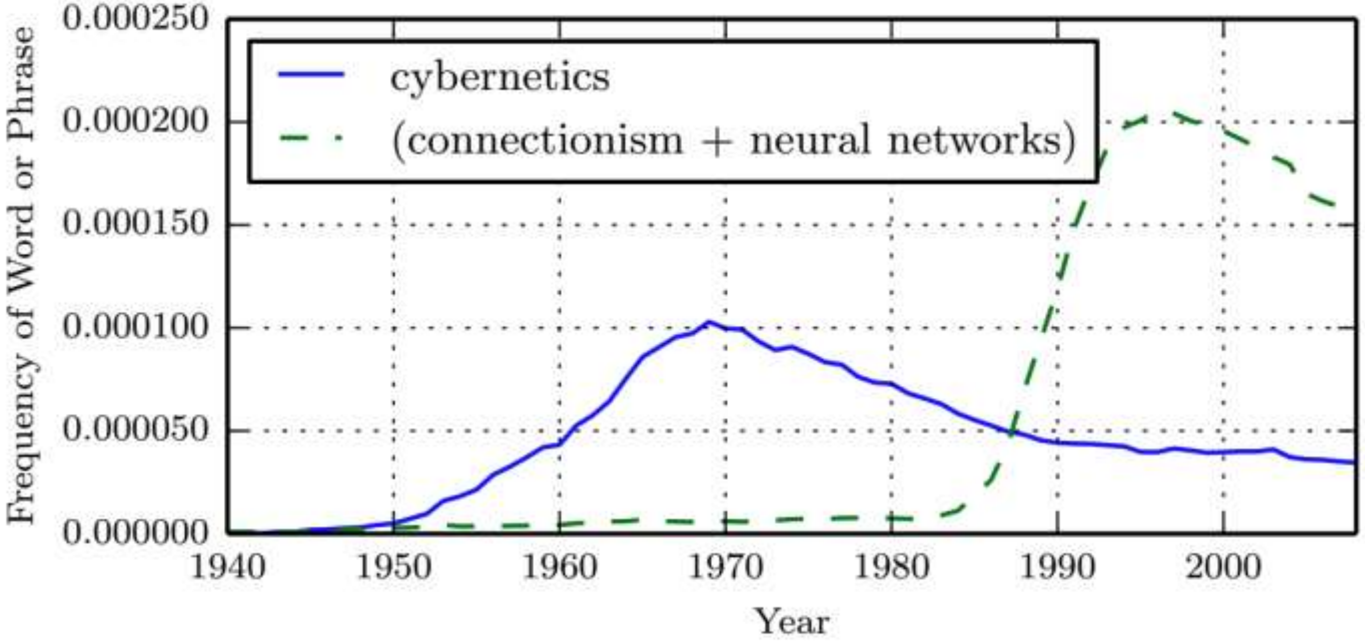
Deep Learning Example



Deep Learning, Goodfellow et. al.

Many Names of Deep Learning

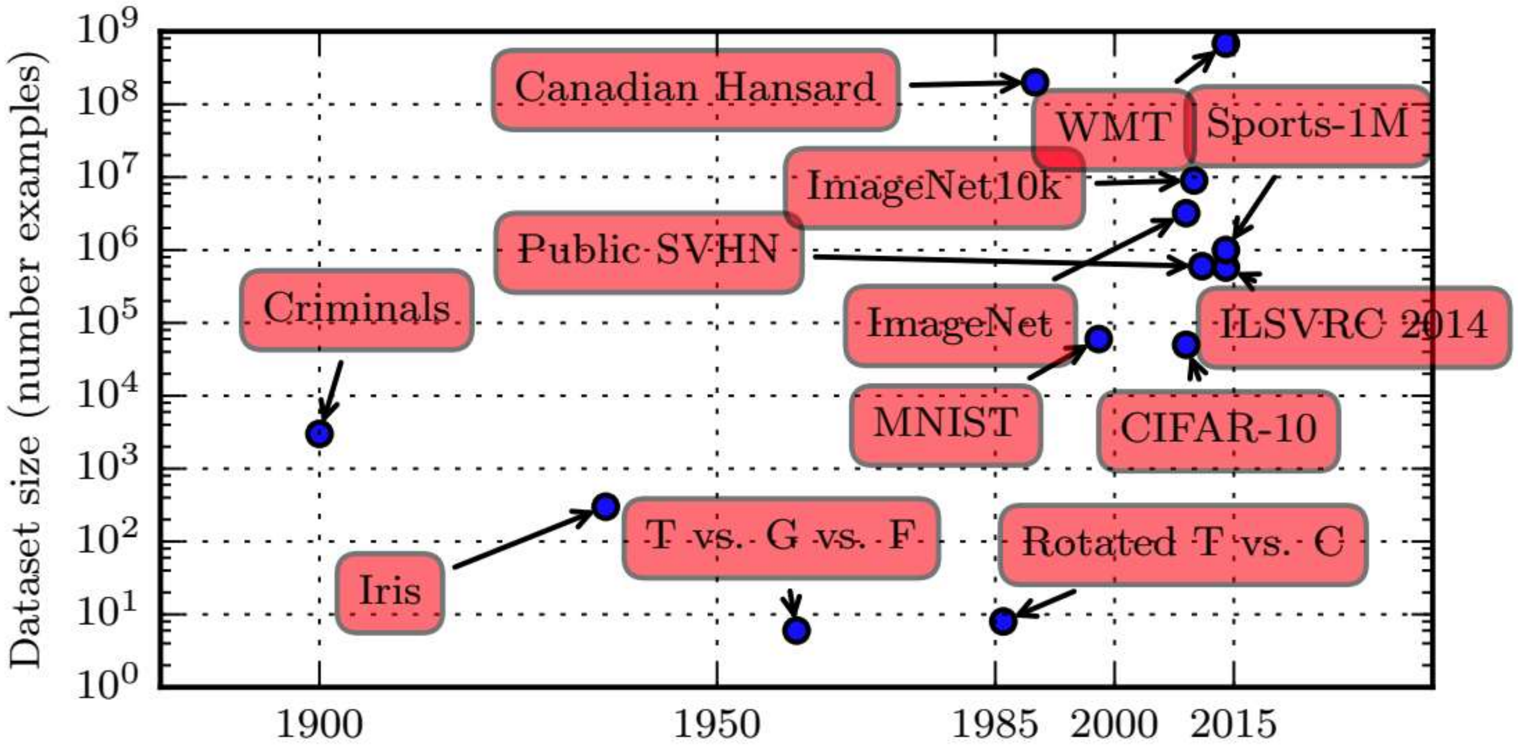
- Three waves of neural networks
  - Cybernetics
    - (1940s – 1960s)
  - Connectionism
    - (1980s – 1990s)
  - Deep learning
    - (2006s – now)
- Diminished role of neuroscience
  - Simply do not have enough information about the brain



Deep Learning, Goodfellow et. al.

Increasing Dataset Sizes

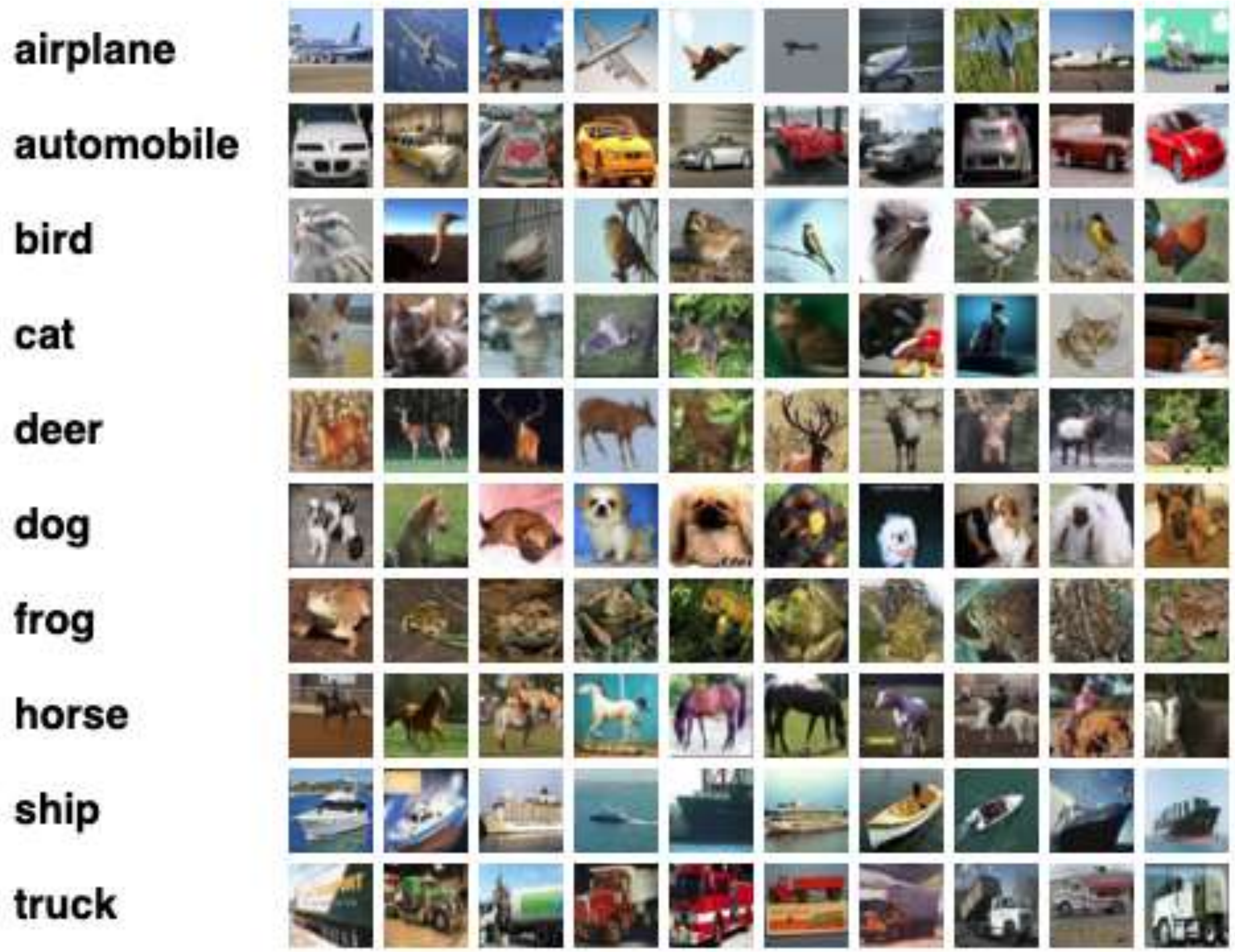
- The size of datasets has expanded remarkably over time.
- The age of “Big Data” has made machine learning easier.



Deep Learning, Goodfellow et. al.

Increasing Dataset Sizes: CIFAR10

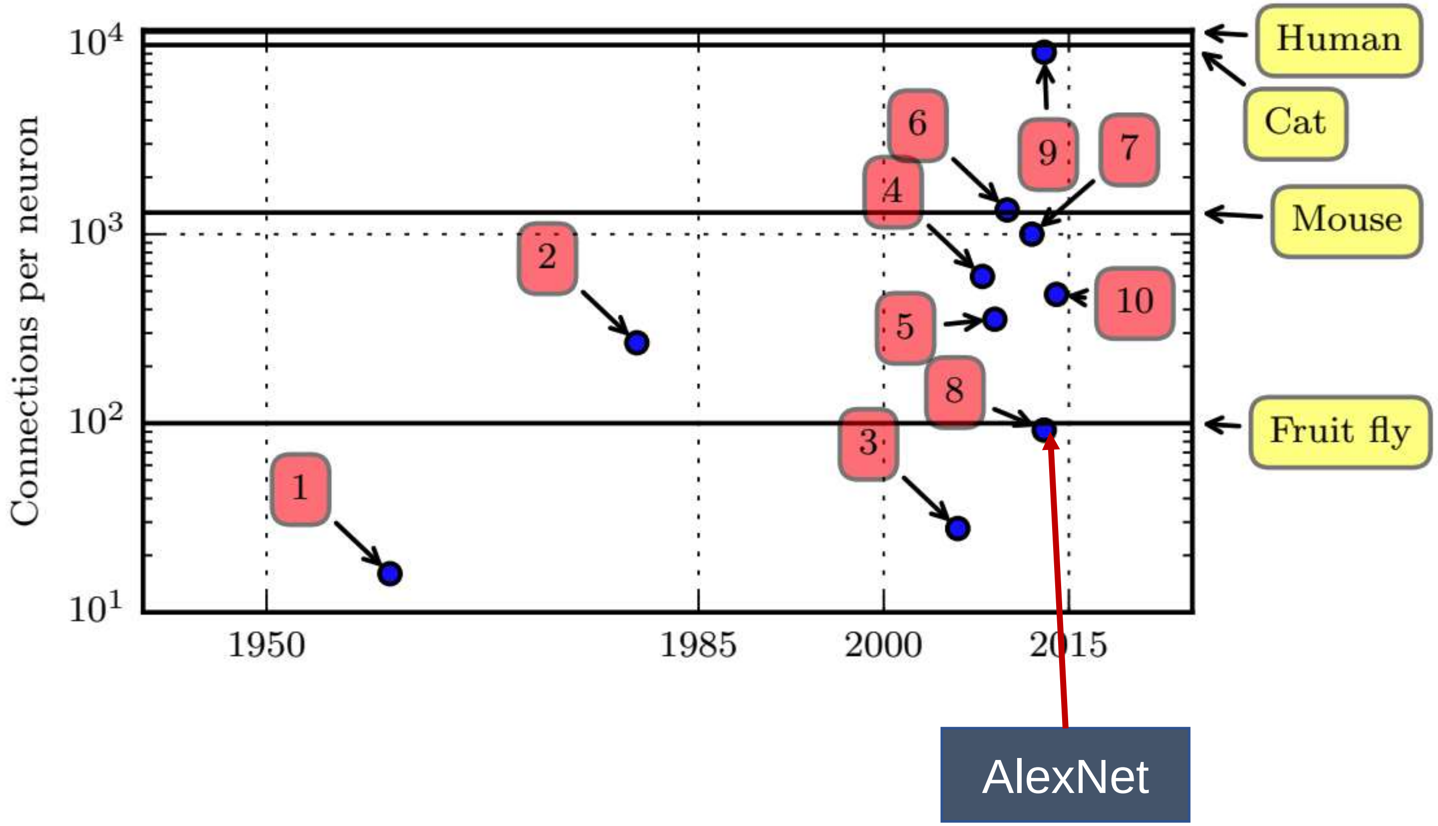
- 60,000 32x32 images
  - 50,000 training
  - 10,000 test
- 10 classes
  - 6,000 images/class



Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton

Increasing Model Sizes

- Model size:
  - # of connections / neuron
  - # of neurons
- Largely due to the availability of faster hardware (CPUs and GPUs)
- Expect to continue



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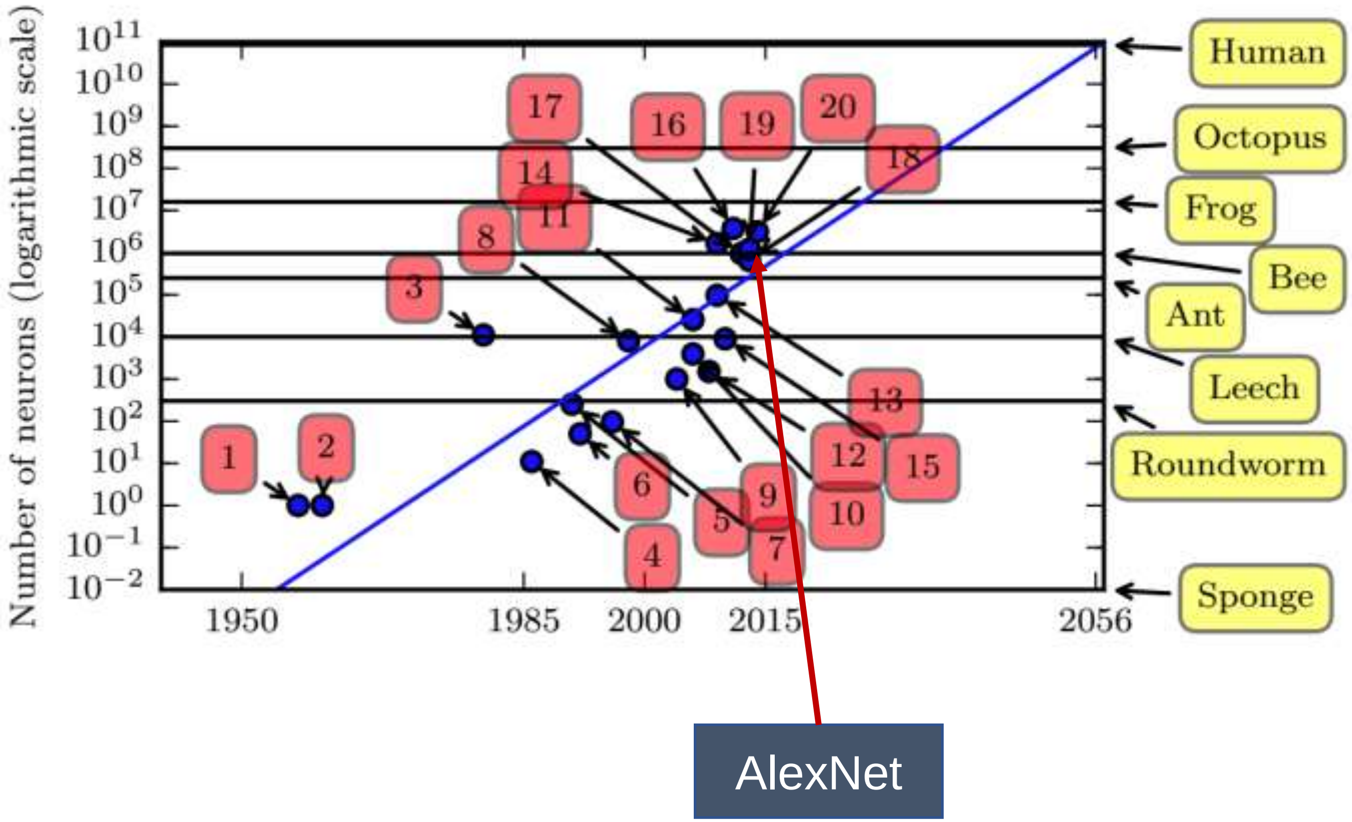
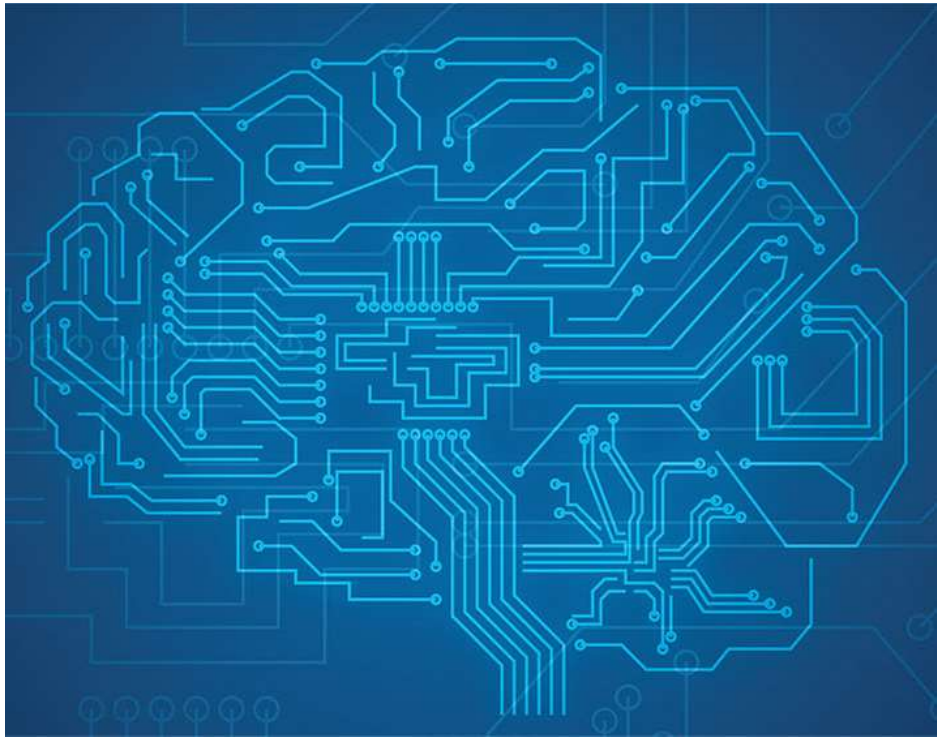




DNNs

- AI, ML, and DL
- **ML Basics**
- DL Overview
- AlexNet Example

Machine Learning Algorithms

- “A computer program is said to ***learn*** from ***experience (E)*** with respect to some ***task (T)*** and some ***performance measure (P),*** if its performance on T, as measured by P, improves with experience E.”, Tom Mitchell, 1998

- Example: spam classification

  - Task (T): Predict emails as spam or not spam.
  - Experience (E): Observe users label emails as spam or not.
  - Performance (P): # of emails that are correctly predicted.

Machine Learning Algorithms

- Suppose a tumor classification program watches which tumor is being marked as “benign” or “malignant” by doctors, and it learns how to better predict benign/malignant tumors.

- What is the task T in this setting?

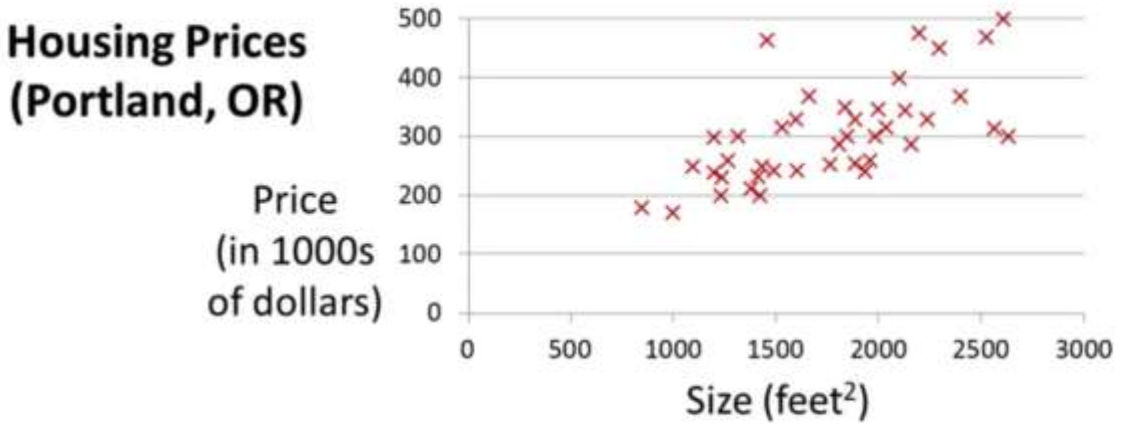
A. The number (or fraction) of tumors correctly classified as benign/malignant
B. Watching doctors label tumors as benign or malignant
C. Classifying tumors as benign or malignant
D. Non of the above. This is not a machine learning problem.

Building a ML Algorithm

- Nearly all ML algorithms can be described as particular instances of a simple recipe:
  - A dataset -> Experience (E)
  - A cost (loss) function -> Performance Measure (P)
  - A model + An optimization method -> Task (T)
- Use this recipe to see the different algorithms:
  - As part of a taxonomy of methods for doing related tasks that work for similar reasons
  - Rather than as a long list of algorithms that each have separate justifications

Example: Linear Regression

- Dataset:
  - (x, y) where x is size and y is price
  - m training examples
- Cost function:
  - Mean Squared error
  - $MSE = \frac{1}{m}\sum_{i=0}^{m}(h(x_i) - y_i)^2$
- Model:
  - $h = w_0 + w_1 * x$
- Optimization method:
  - Solve for where its gradient is 0.
  - Gradient descent



Size in feet² (x)	Price ($) in 1000's (y)
2104	460
1416	232
1534	315
852	178
…	…

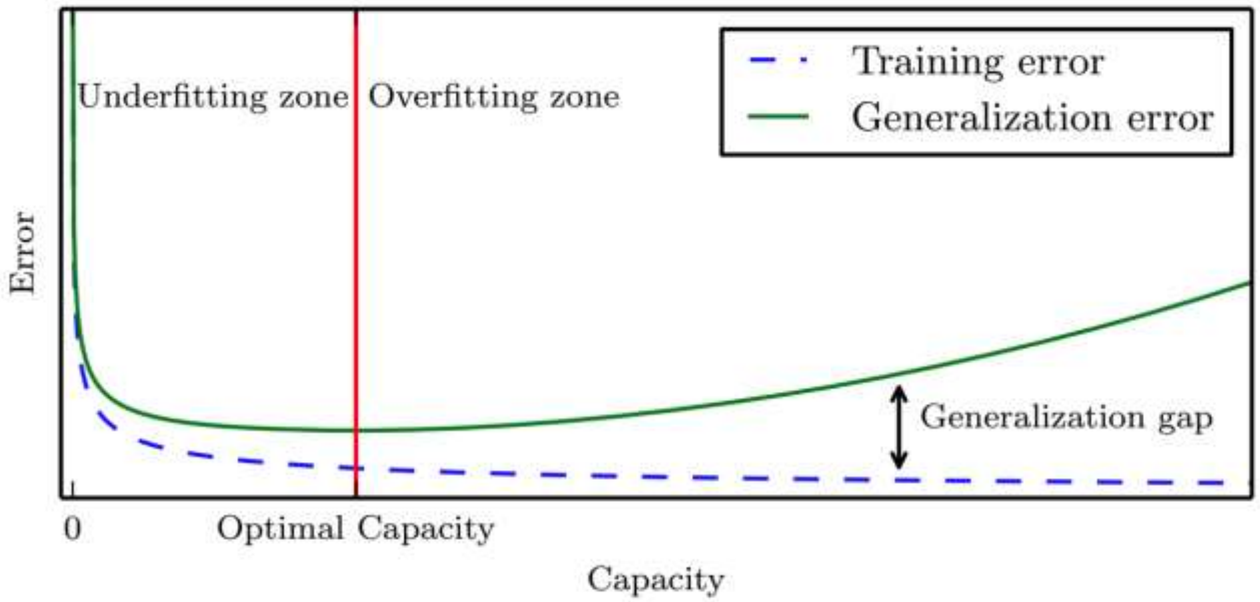
Machine Learning, Andrew Ng

Dataset

- ML tasks are usually described in terms of how the ML system should process an example.
- A dataset is a collection of many examples.
- ML algorithms can be broadly categorized as ***supervised*** and ***unsupervised*** by what kind of dataset they process.
  - Supervised: each example of the dataset is associated with a label or target
    - E.g., Classification, regression
  - Unsupervised: experience dataset without labels
    - E.g., Clustering
  - Reinforcement: Not a fixed dataset, interact with an environment

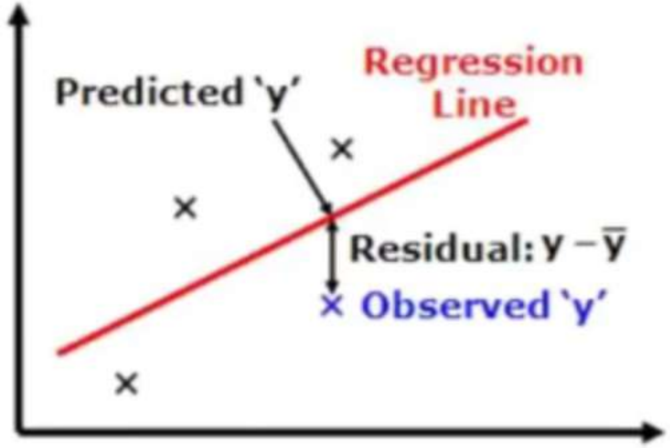
Dataset:

- Generalization:
  - Algorithm performs well on new, previously unseen inputs (not just those on which the model was trained).
- Partition the dataset into:
  - Training set: where the model was trained
  - Test set: where the trained model was tested
- Overfitting:
  - Large gap between training and test errors



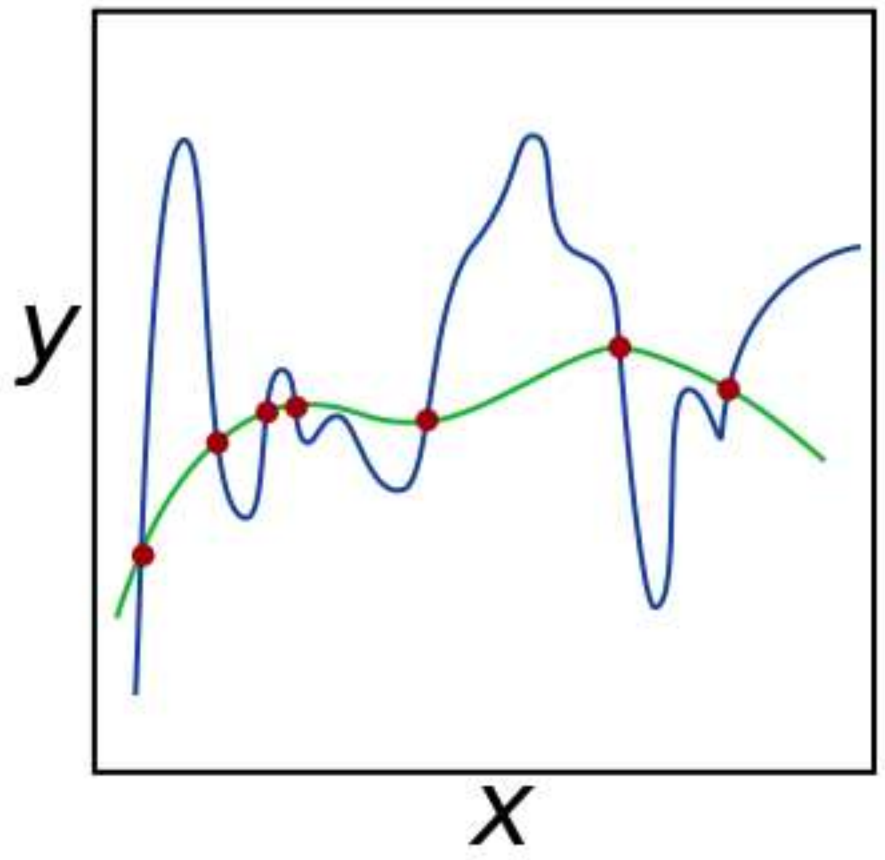
Cost function

- Measures the performance of a ML model for given data
- Quantifies the error between predicted and expected values in the ***training*** set.
  - $CF = MSE_{train} = \frac{1}{m}\sum_{i=0}^{m}(\hat{y}_i - y_i)^2$



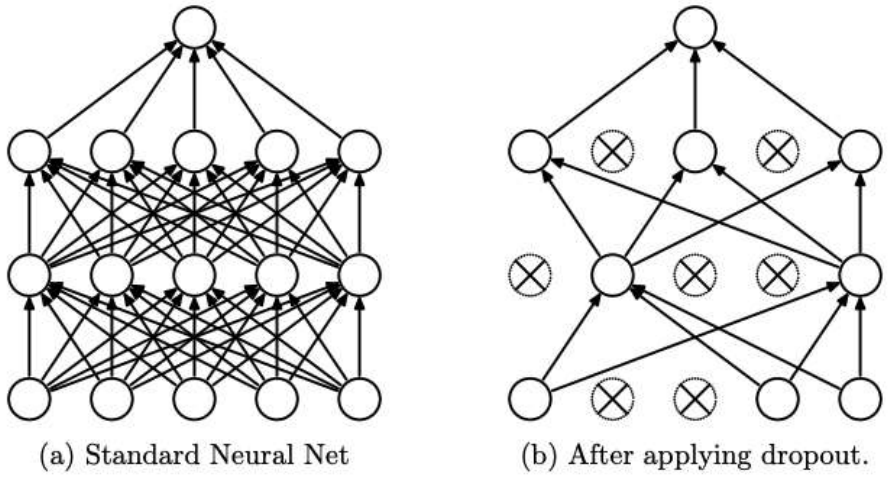
Cost function

- Regularization: modifications to reduce the generalization error but not the training errors
  - Weight decay (L2/1 regularization)
    - Expressing preferences of smaller weights
    - $CF = MSE_{train} + \lambda \sum_i w_i^2 \ (L2)$
    - $CF = MSE_{train} + \lambda \sum_i |w_i| \ (L1)$



Cost function

- Regularization: modifications to reduce the generalization error but not the training errors
  - Dropout
    - Temporally remove nodes from network
    - Train a large ensemble of models that share parameters



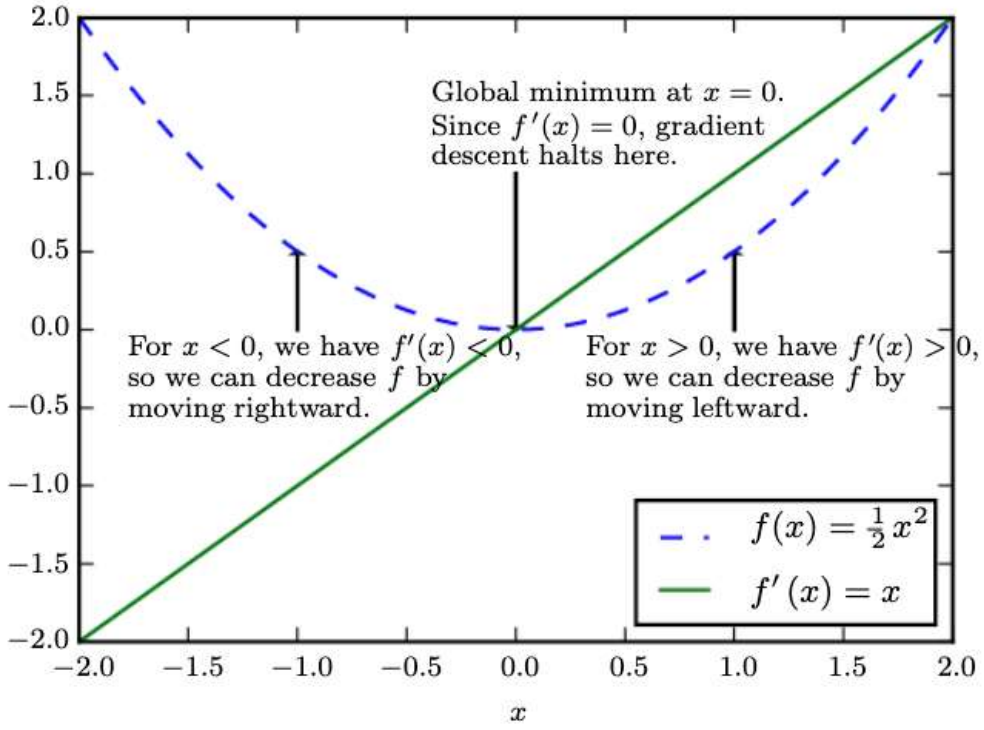
Dropout: A Simple Way to Prevent Neural Networks from Overfitting

Optimization

- Follow the slope

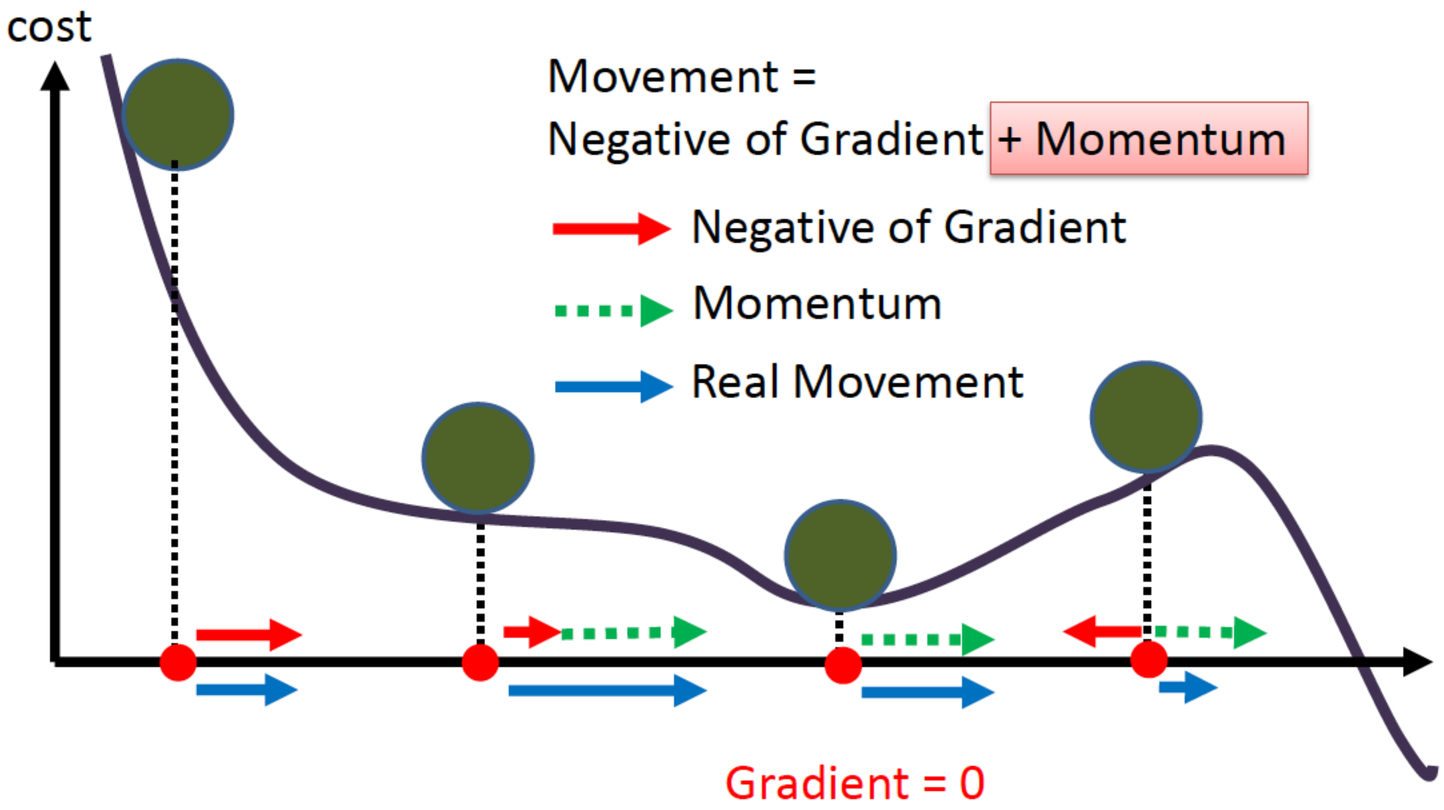
Optimization

- Method to minimize the ***cost function*** by updating weights
- Gradient descent:
  - Iteratively moving in the direction of steepest descent as defined by the negative of the gradient
- Stochastic gradient descent (SGD)
  - To handle large training sets
  - Only run a subset of the training sets (i.e., batch/minibatch) for each update
  - Easier to converge



Optimization

- Momentum:
  - Prefers to go in a similar direction as before



SGD

$$x_{t+1} = x_t - \alpha \nabla f(x_t)$$

```
while True:
  dx = compute_gradient(x)
  x -= learning_rate * dx
```

SGD+Momentum

$$v_{t+1} = \rho v_t + \nabla f(x_t)$$
$$x_{t+1} = x_t - \alpha v_{t+1}$$

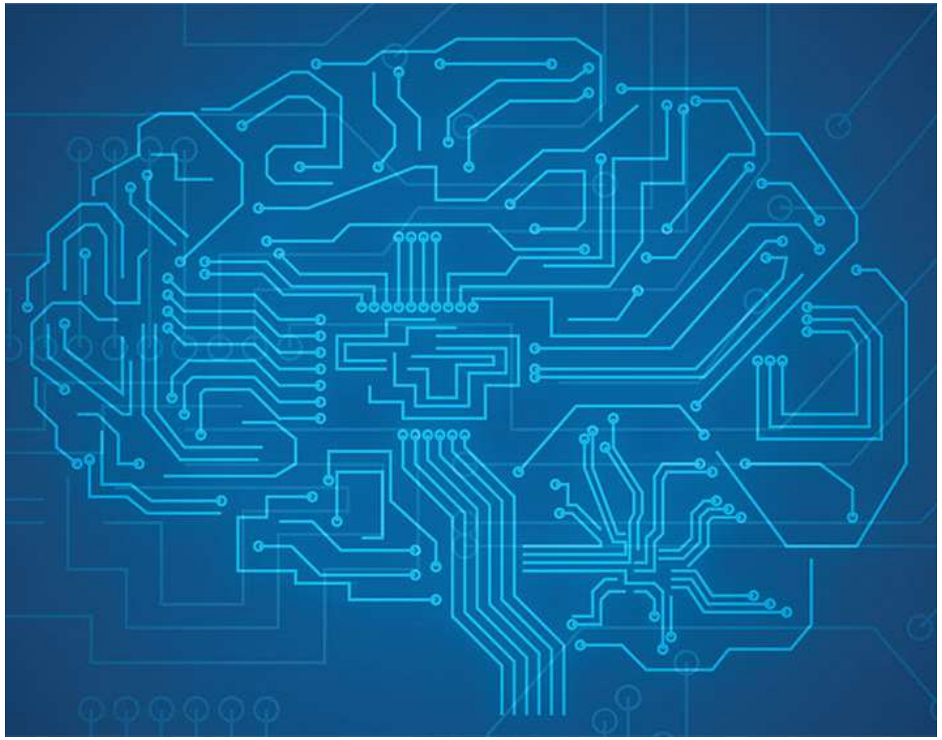
```
vx = 0
while True:
  dx = compute_gradient(x)
  vx = rho * vx + dx
  x -= learning_rate * vx
```

Challenges motivating DL

- The curse of dimensionality
  - Generalizing to new examples become exponentially more difficult when working with high-dimensional data
  - Challenging to learn complicated functions in high-dimensional spaces

Administrivia

- Lab 1 posted!
  - Due in two weeks (2/5)
- Reading for this week is posted.
  - Submit your review by Wednesday
- Joint project is OK.



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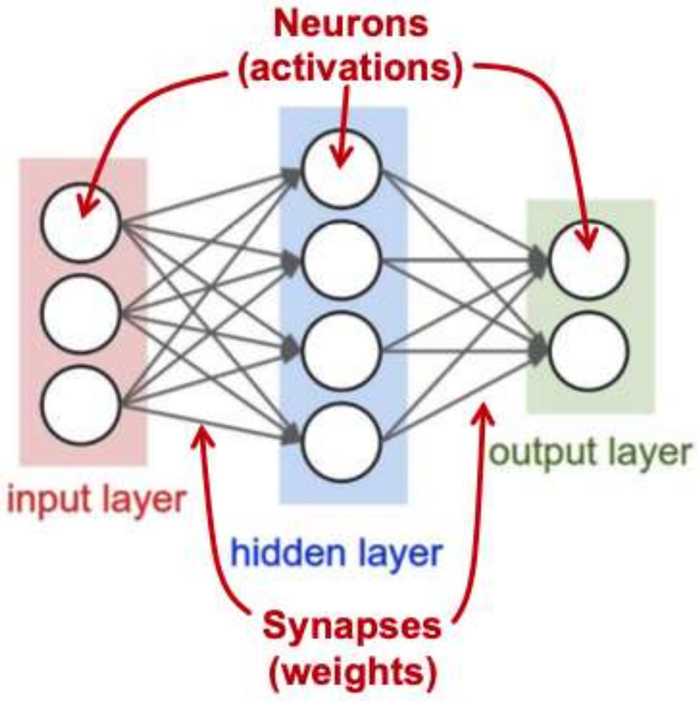
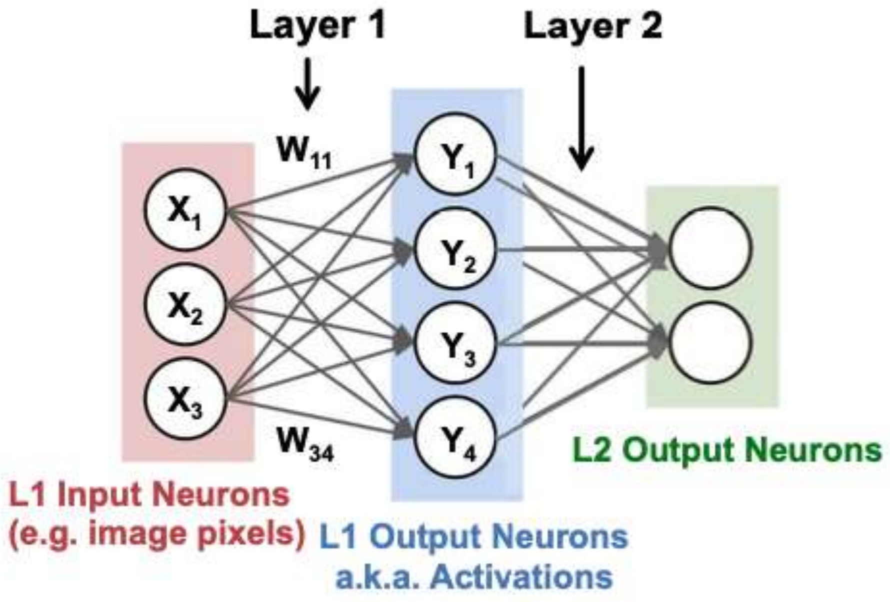
Deep Neural Networks

- A subset of machine learning models
  - Deep -> multiple layers
  - Linear model + nonlinear transformation





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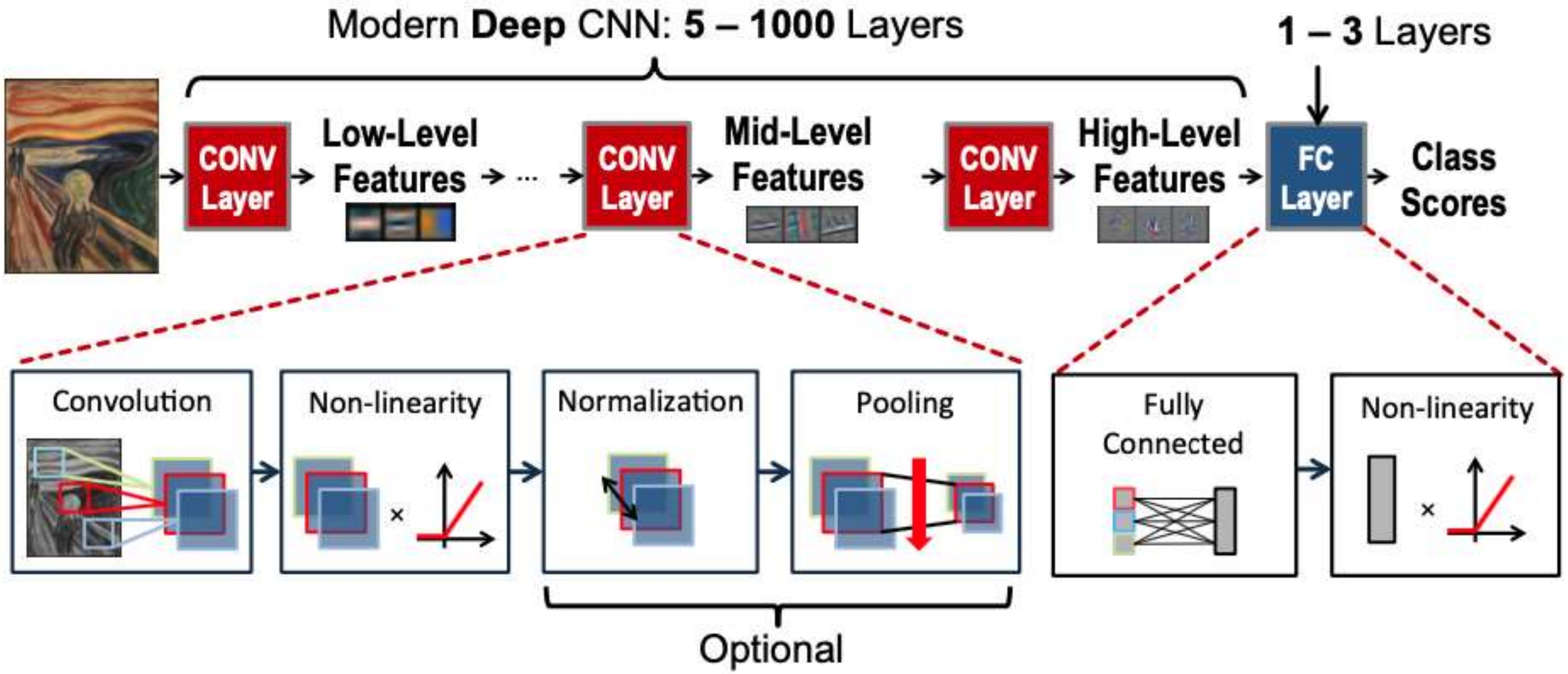
Deep Neural Networks



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Deep Neural Networks: LeNet

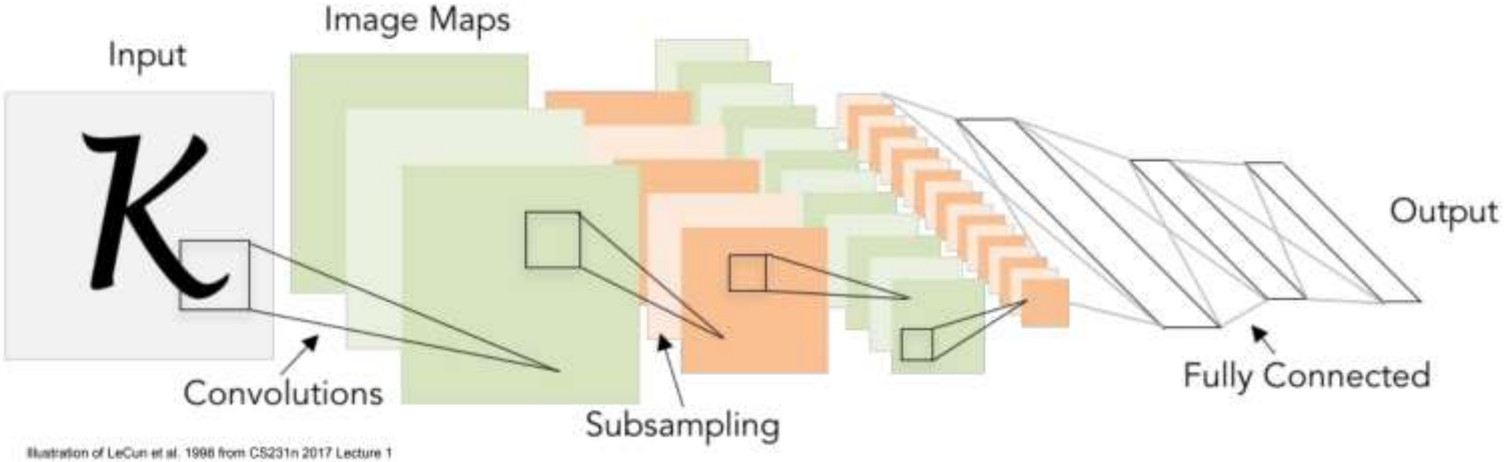
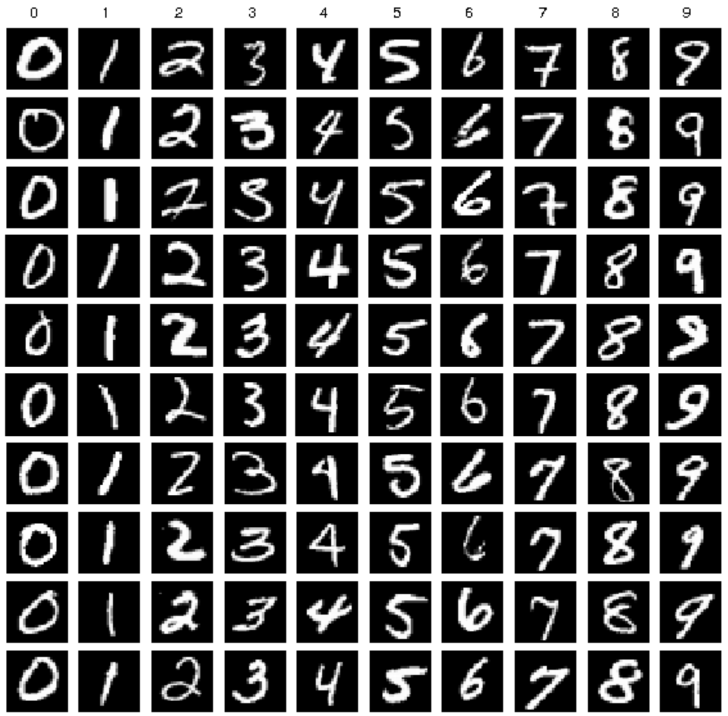


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

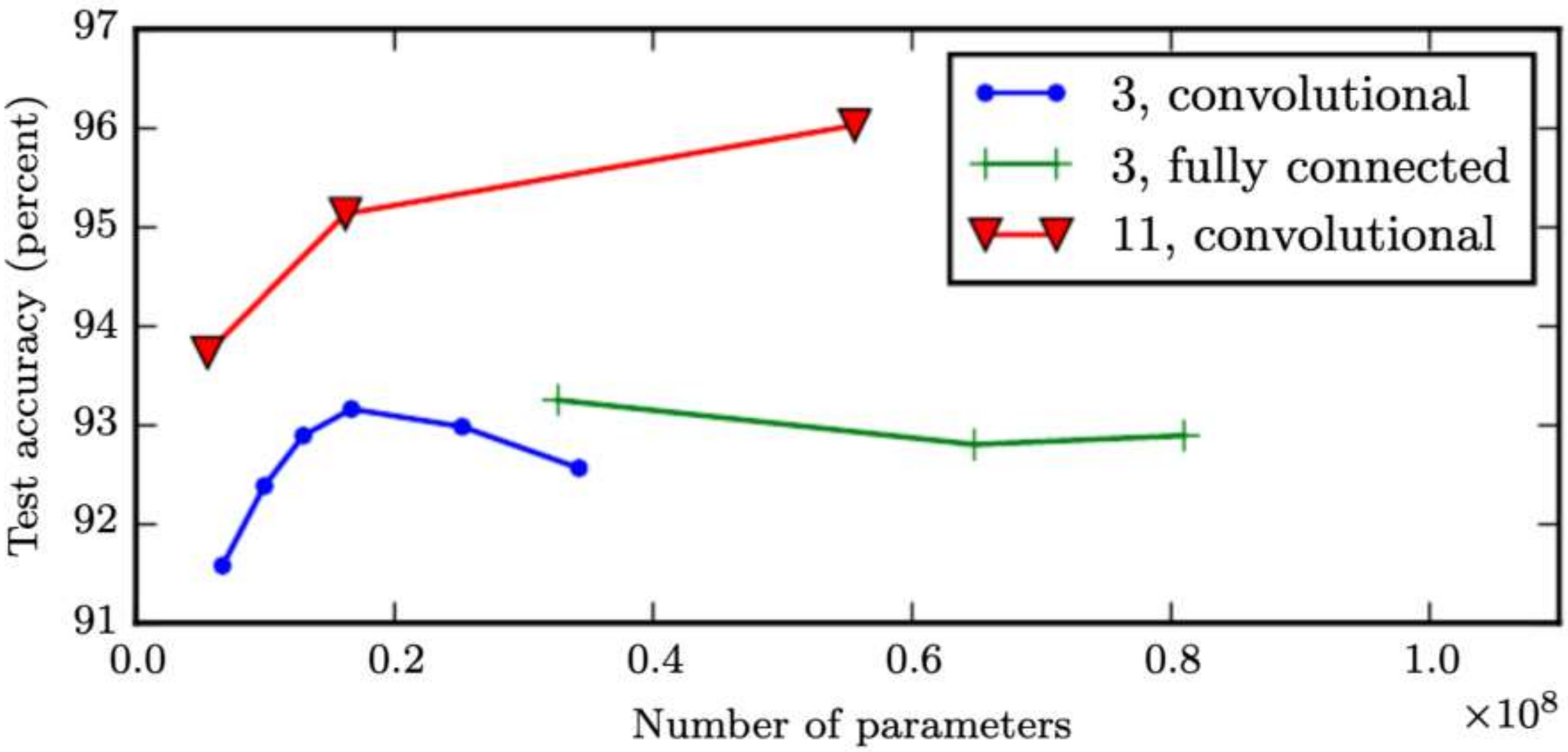


Deep Neural Networks

- Dataset
  - Problem dependent
  - https://github.com/pytorch/vision
  - Training set, validation set, test set
- Cost function
  - Similar to other parametric ML models
  - Backpropagation (using chain rule)
- Optimization
  - Stochastic Gradient Descent

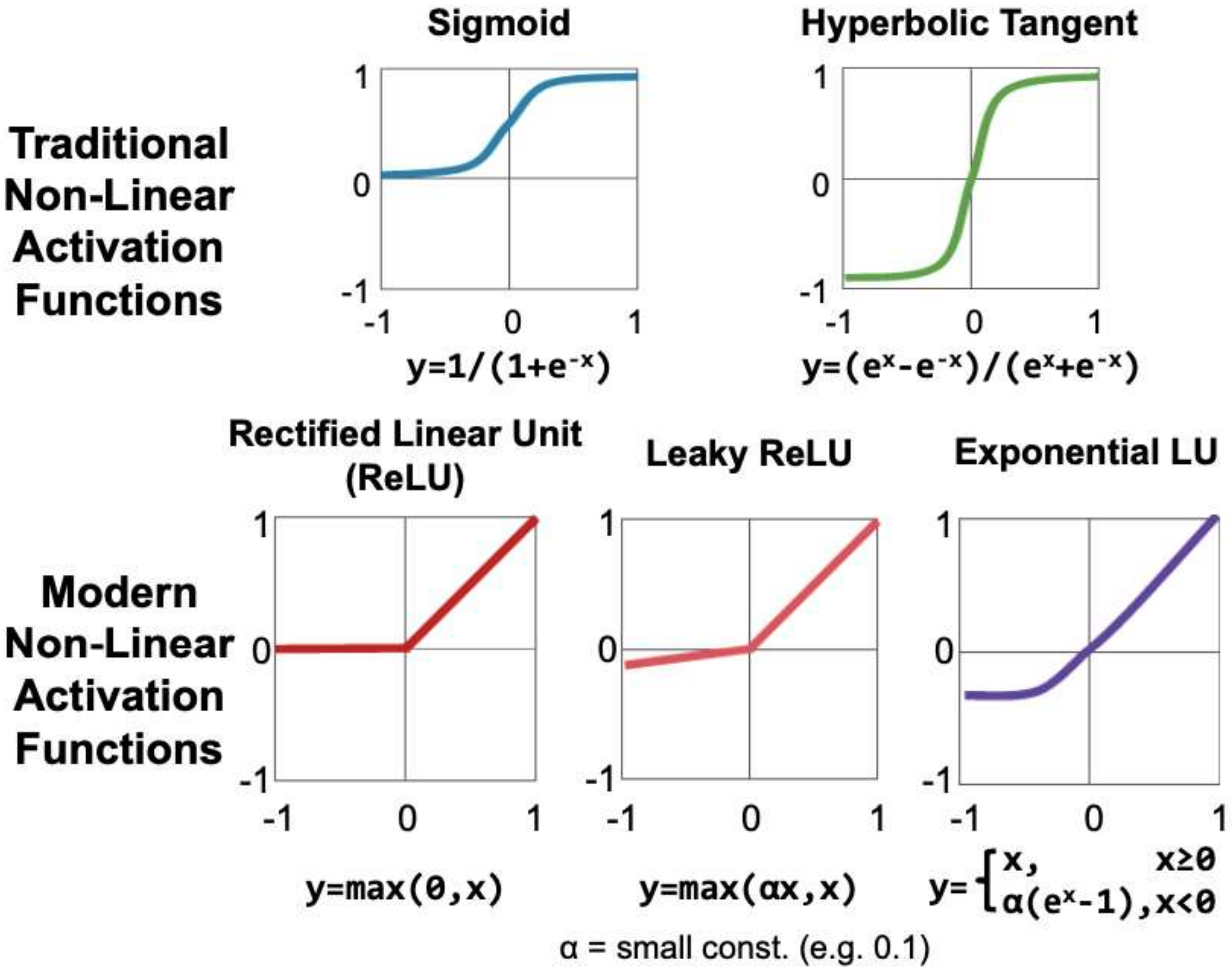
DNN Parameters

- Depth and width of DNNs



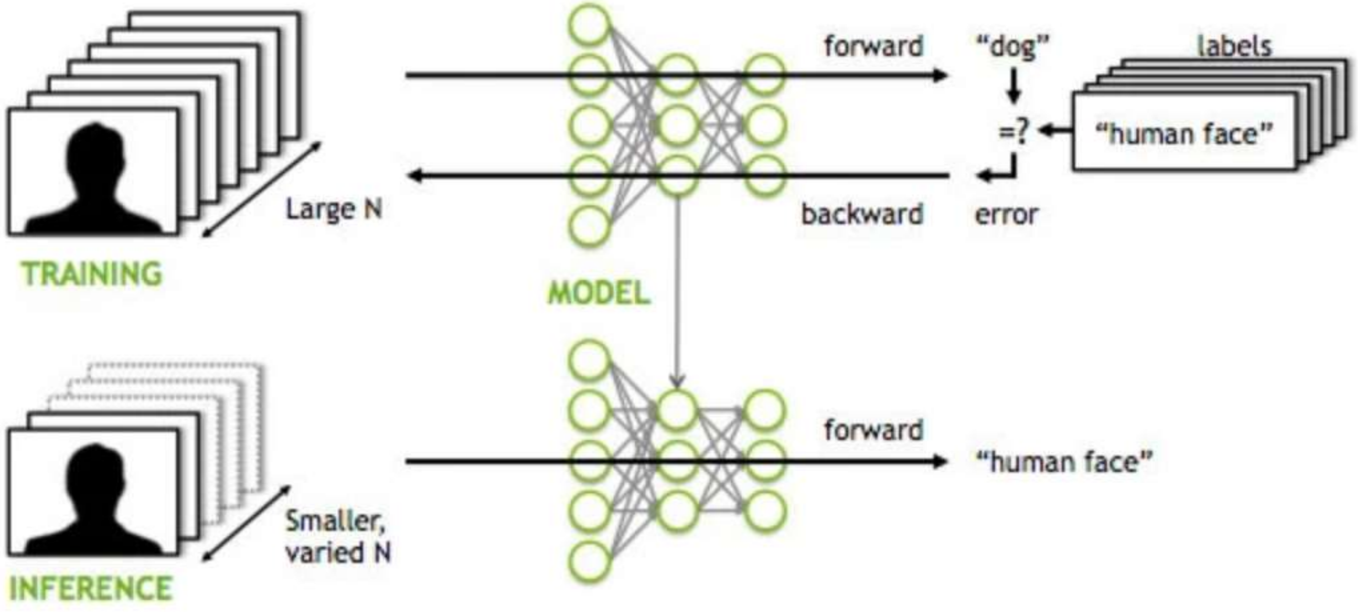
DNN Non-Linearity

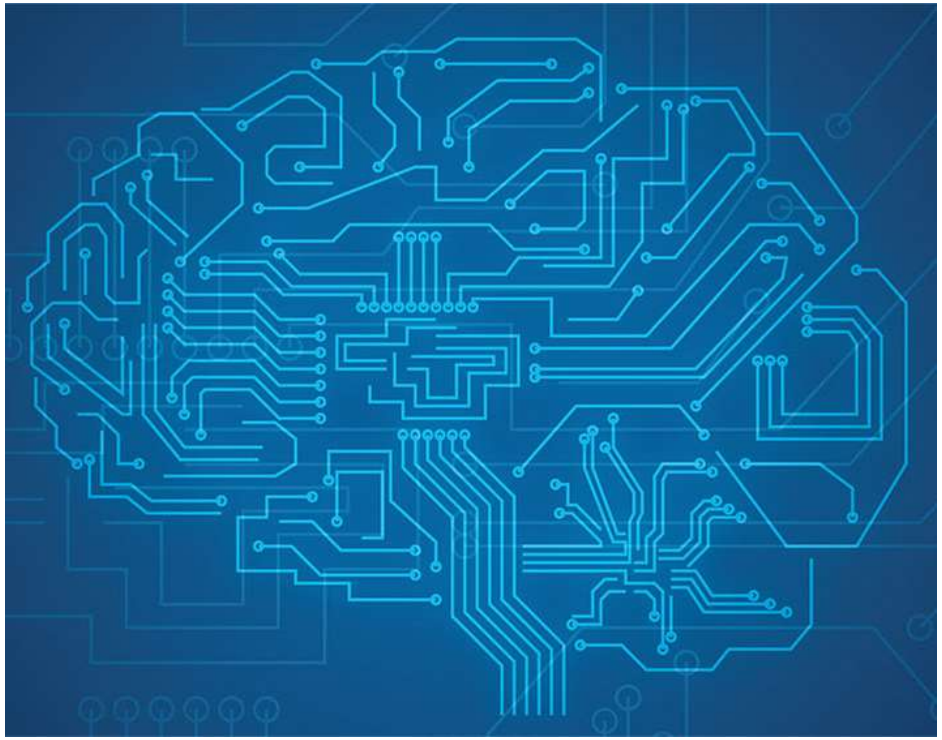
- Rectified Linear Units (ReLU)
  - $y(x) = \max\{0, x\}$
- Benefits:
  - Reduce the likelihood of the gradient vanishing problem.
  - Adding more sparsity/regularization
  - Easy to compute



Training vs Inference

- Training
  - Dataset
  - Cost function
  - Optimization function
  - Model
- Inference
  - Dataset
  - Model





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- **AlexNet Example**

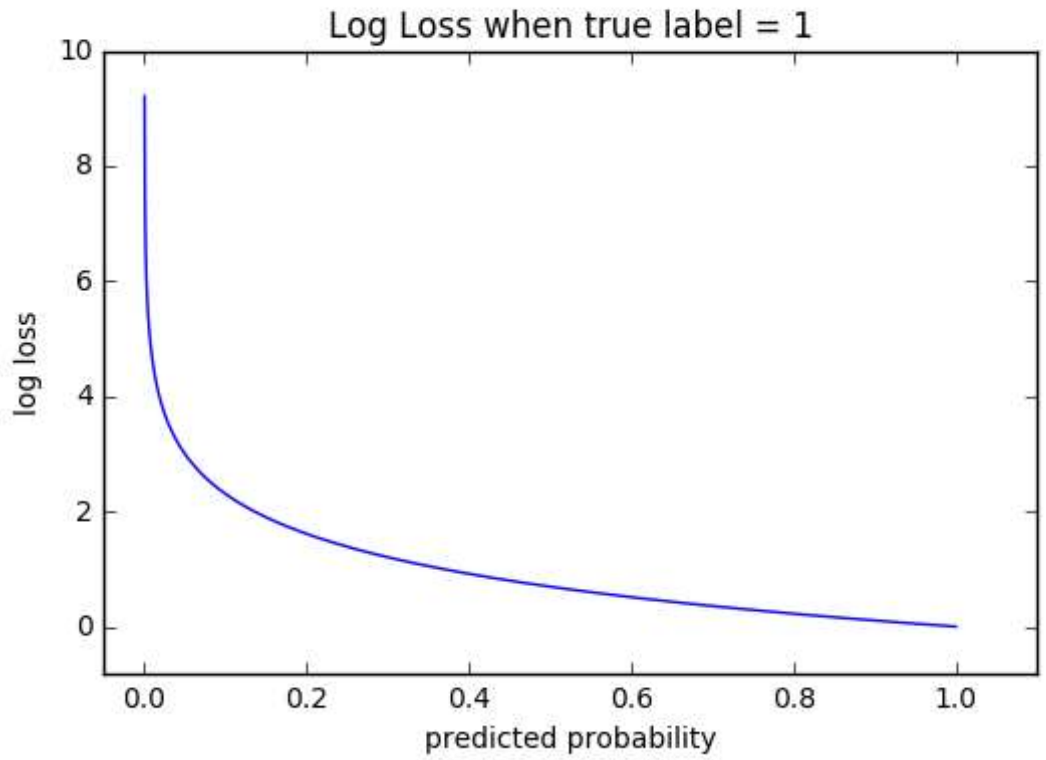
AlexNet Dataset

- ImageNet LSVRC-2010 with 1.2 million images
- Top-1 and top-5 error rate:
  - The fraction of images for which the correct label is not among the 1/5 labels considered most probable by the model.

[A. Krizhevsky, I. Sutskever, G.E. Hinton, *ImageNet Classification with Deep Convolutional Neural Networks*, 2012]

AlexNet Cost (loss) function

- Minimize the cross-entropy loss function
- Measures the performance of a classification model whose output is a probability value between 0 and 1
- $CF = -\frac{1}{N}(\sum_{i-1}^{N} y_i \cdot \log(\hat{y}_i))$



AlexNet Optimization Method

- Stochastic Gradient Descent
  - Batch size = 128
  - Update rule:

Momentum

Weight Decay

$$
\begin{aligned}
v_{i+1} &:= 0.9 \cdot v_i - 0.0005 \cdot \epsilon \cdot w_i - \epsilon \cdot \left\langle \frac{\partial L}{\partial w}\Big|_{w_i} \right\rangle_{D_i} \\
w_{i+1} &:= w_i + v_{i+1}
\end{aligned}
$$

Learning rate

Gradient of cost function

AlexNet Model

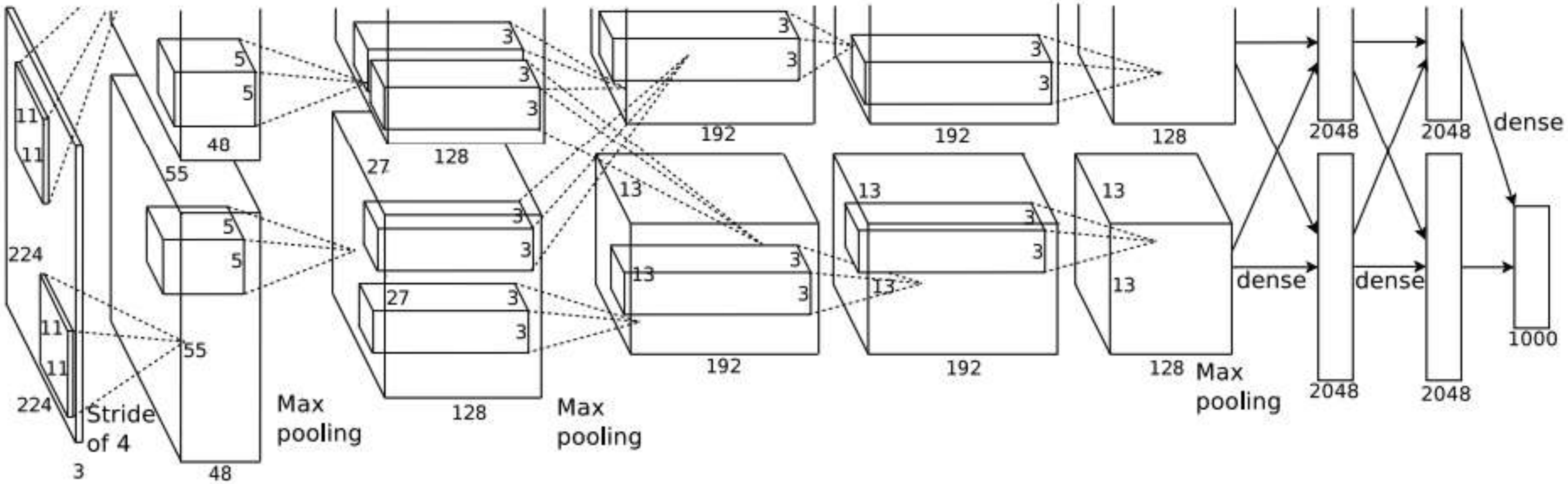


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input 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.

State-of-the-art Training Time

	Batch Size	Processor	DL Library	Time	Accuracy
He et al.	256	Tesla P100 x8	Caffe	29 hours	75.30%
Goyal et al.	8K	Tesla P100 x256	Caffe2	1 hour	76.30%
Smith et al.	8K→16K	full TPU Pod	TensorFlow	30 mins	76.10%
Akiba et al.	32K	Tesla P100 x1024	Chainer	15 mins	74.90%
Jia et al.	64K	Tesla P40 x2048	TensorFlow	6.6 mins	75.80%
This work	**34K→68K**	**Tesla V100 x2176**	**NNL**	**224 secs**	**75.03%**

https://news.developer.nvidia.com/sony-breaks-resnet-50-training-record-with-nvidia-v100-tensor-core-gpus/

Review

- Artificial intelligence, machine learning, and deep learning
- Building a machine learning algorithm:
  - Dataset
  - Cost function
  - Optimization function
  - Model
- Deep learning to automatically extract hierarchical data
  - Better at handle high-dimensional data
  - Key differences are in the Model
    - Multiple layers, i.e., deep
    - Linear + non-linear layers