Supervised Learning

Dr. Jianlin Cheng

Electrical Engineering and Computer Science Department
University of Missouri, Columbia

Fall, 2019

Slides Adapted from Book and CMU, Stanford Machine Learning Courses, and my research

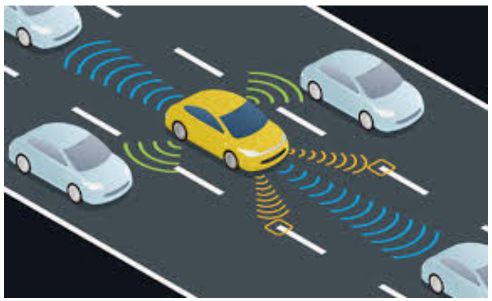
Syllabus

- **Course web site**: http://calla.rnet.missouri.edu/cheng_courses/supervised_learning/index.htm
- **Location**: Lafferre Hall E3403 ; **Time**: MWF 11:00 pm – 11:50 am
- **Assignments**: 4 homework assignments, one group project (up to 4 students)
- **Grading**: participation (25%), assignment (30%), project report (20%), project representation (25%); grade scale (A+, A, A-, B+, B, B-, C+, C, C-, and F)
- **Questions / Assignment submission**: mumachinelearning@gmail.com

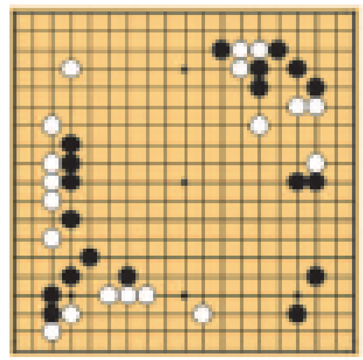
Topics

- Introduction to machine learning and Bayes optimal learning rule
- Learning distributions, parametric distribution, Maximum Likelihood Estimation (MLE) and Maximum a Posterior Estimation (MAP)
- MLE, MAP, Bayes Optimal Classifier, Naïve Bayes Classifier, Generative Classifier
- Discriminative classifier and logistic regression
- Linear and non-linear regression
- Nonparametric methods for density estimation, classification and regression
- Model selection
- Boosting
- **Deep learning (a focus)**

Artificial Intelligence (AI) Revolution



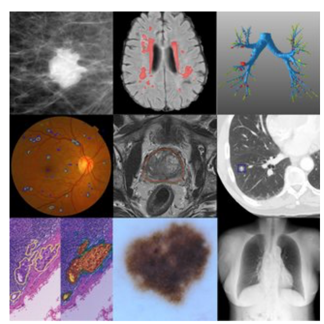
Self Driving Car



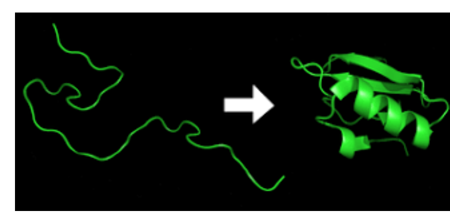
GO Game

Face Recognition

Voice Recognition



Medical Imaging



Protein Folding

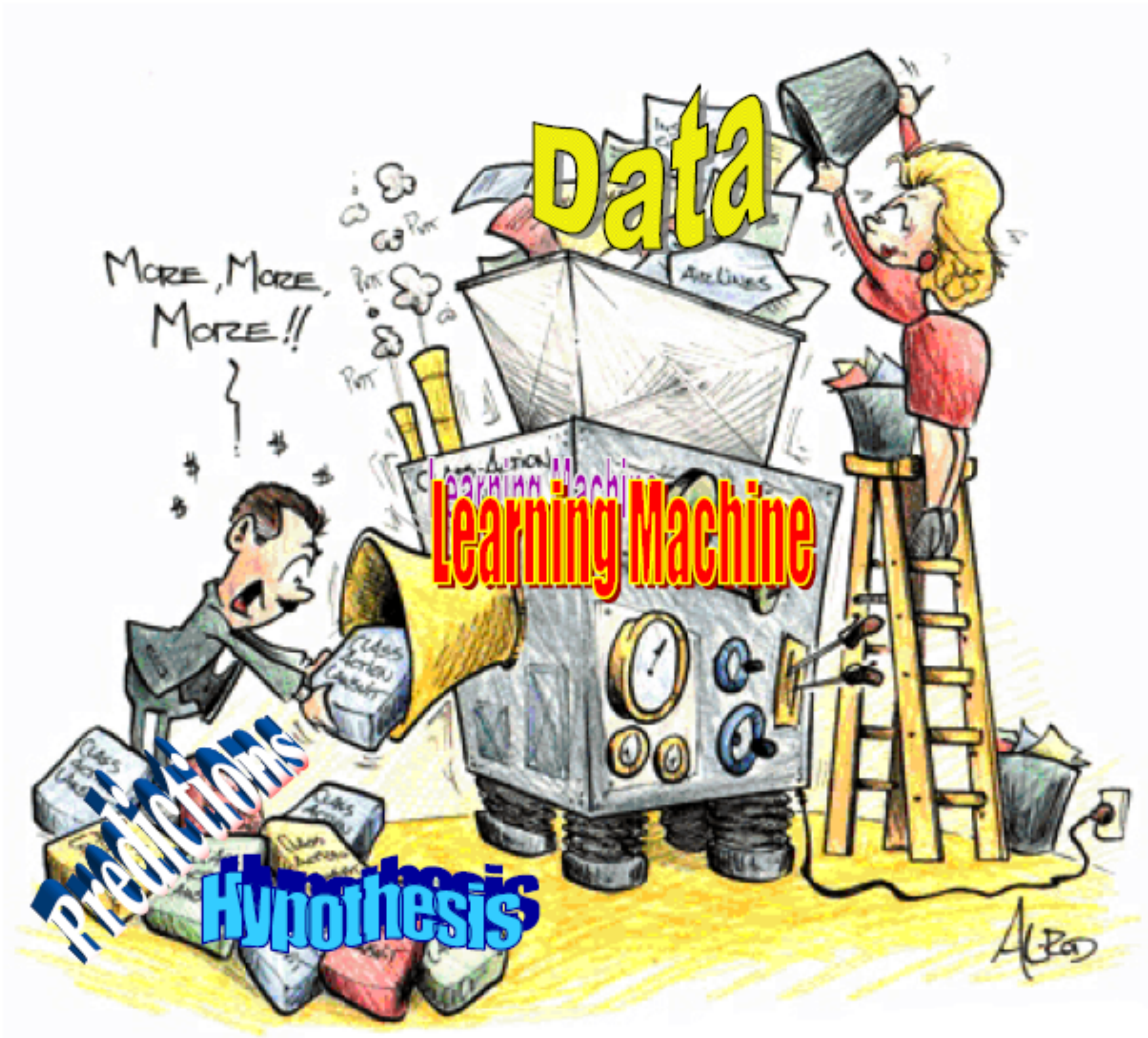
What is Artificial Intelligence (AI) and Deep Learning?

- **AI**: a technology to enable computational devices to gain human intelligence (speak, walk, drive, think, …, **learning**)

- **Machine Learning**: an area of AI that enables computer to learn from data to acquire any specific intelligence

- **Deep Learning**: the most powerful machine learning technology mimicking human learning

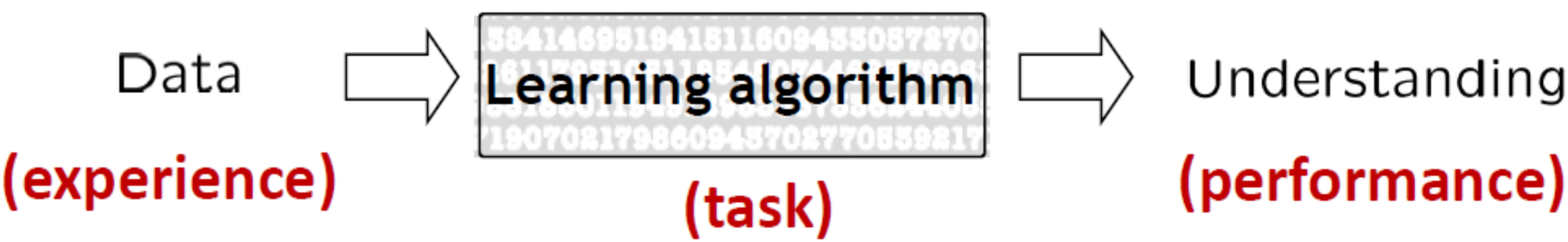
What is Machine Learning?



What is Machine Learning?

Study of algorithms that

- improve their performance
- at some task
- with experience

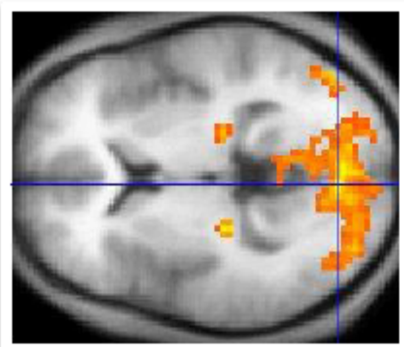


Question

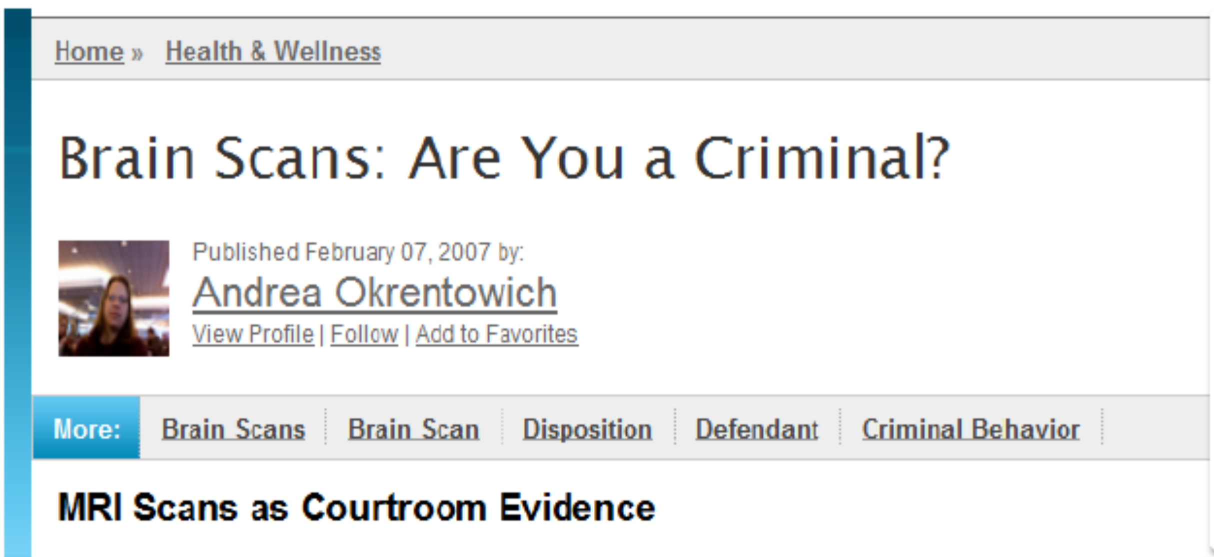
- **What is the difference between a machine learning and a traditional instruction-based program such as a calculator, windows, Linux?**

Machine Learning in Action

- Decoding thoughts from brain scans



Rob a bank …



Home » Health & Wellness

Brain Scans: Are You a Criminal?

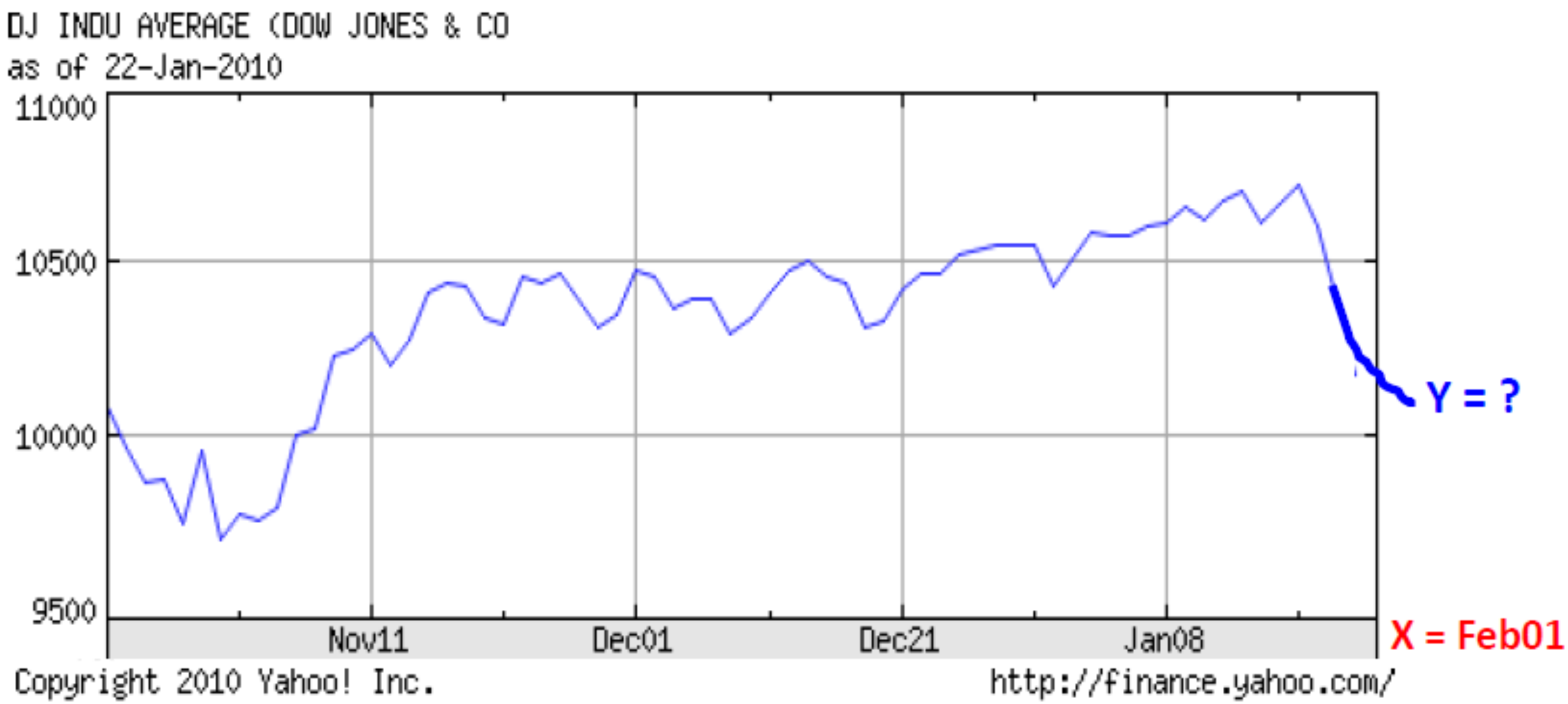
Published February 07, 2007 by:
Andrea Okrentowich
View Profile | Follow | Add to Favorites

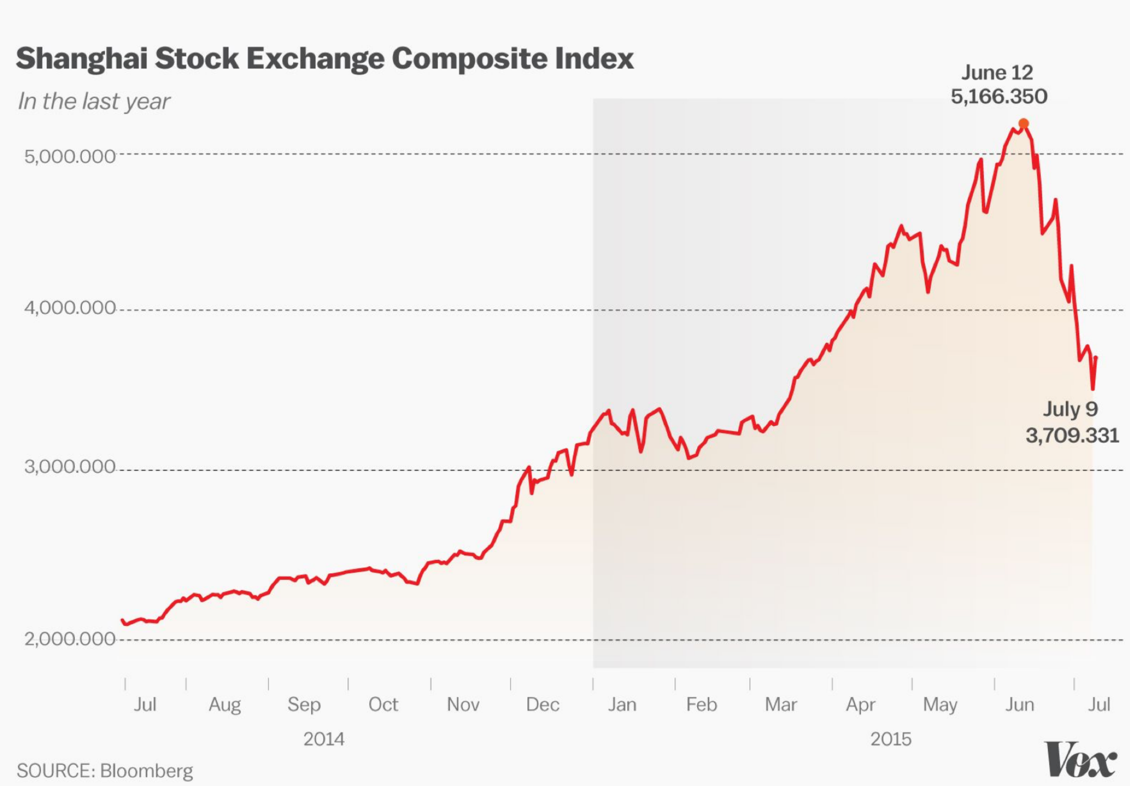
More: Brain Scans | Brain Scan | Disposition | Defendant | Criminal Behavior

MRI Scans as Courtroom Evidence

Machine Learning in Action

- Stock Market Prediction




Shanghai Stock Exchange Composite Index
In the last year
June 12
5,166.350
5,000.000
4,000.000
3,000.000
2,000.000
July 9
3,709.331
Jul
Aug
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul
2014
2015
SOURCE: Bloomberg
Vox

2017

Dow Jones August 12-16, 2019

Market Summary > Dow Jones Industrial Average

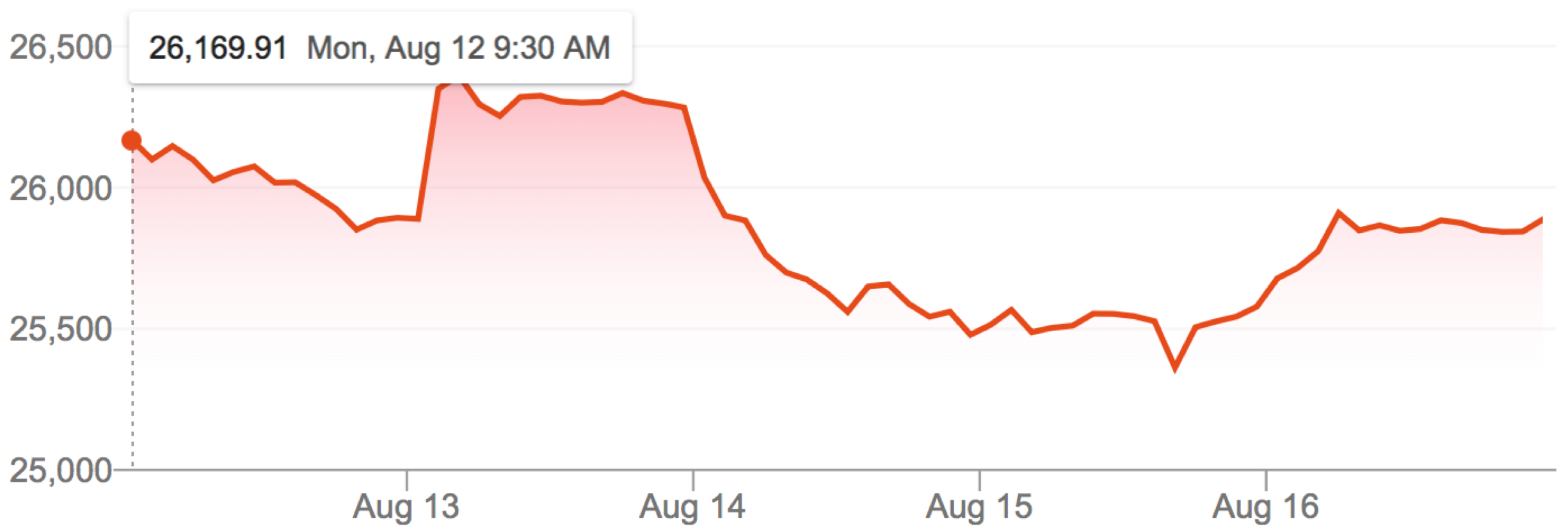
INDEXDJX: .DJI

+ Follow

25,886.01 +306.62 (1.20%) ↑

Aug 16, 4:51 PM EDT · Disclaimer

1 day | 5 days | 1 month | 6 months | YTD | 1 year | 5 years | Max



Open	25,678.17	Low	25,678.17
High	25,929.65		

Machine Learning in Action

- Document classification

Sports
Science
News

Machine Learning in Action

- Spam filtering

Welcome to New Media Installation: Art that Learns

Hi everyone,

Welcome to New Media Installation:Art that Learns

The class will start tomorrow.
Make sure you attend the first class, even if you are on the Wait List.
The classes are held in Doherty Hall C316, and will be Tue, Thu 01:30-4:20 PM.

By now, you should be subscribed to our course mailing list: 10615-announce@cs.cmu.edu.

→ Spam/
Not spam

Natural _LoseWeight SuperFood Endorsed by Oprah Winfrey, Free Trial 1 bottle, pay only $5.95 for shipping mfw rlk Spam | X

=== Natural WeightL0SS Solution ===

Vital Acai is a natural WeightL0SS product that Enables people to lose wieght and cleansing their bodies faster than most other products on the market.

Here are some of the benefits of Vital Acai that You might not be aware of. These benefits have helped people who have been using Vital Acai daily to Achieve goals and reach new heights in there dieting that they never thought they could.

* Rapid WeightL0SS
* Increased metabolism - BurnFat & calories easily!
* Better Mood and Attitude

Machine Learning in Action

- Cars navigating on their own

Boss, the self-driving SUV
1st place in the DARPA Urban Challenge.
Photo courtesy of Tartan Racing.

Google Self-Driving Car

Laser
This sensor gives the vehicle a 360-degree understanding of its environment so the car can sense objects in front of, beside, and behind itself at the same time, all the time. The laser also helps the vehicle to determine its location in the world.

Safety drivers
Drivers also test the vehicles daily, reporting feedback on how to make the ride more safe and comfortable.

Processor
Information from the sensors is cross-checked and processed by the software so that different objects around the vehicle can be sensed and differentiated accurately, and safe driving decisions can then be made based on all the information received.

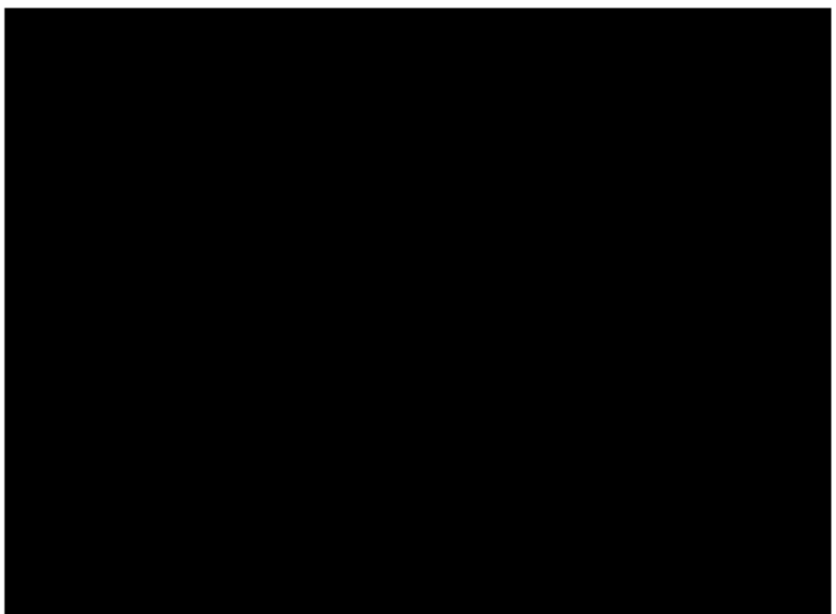
Position sensor
This sensor, located in the wheel hub, detects the rotations made by the wheels of the car to help the vehicle understand its position in the world.

Orientation sensor
Similar to the way a person's inner ear gives them a sense of motion and balance, this sensor, located in the interior of the car, works to give the car a clear sense of orientation.

Radar
This sensor detects vehicles far ahead and measures their speed so that the car can safely slow down or speed up with other vehicles on the road.

Machine Learning in Action

- The **best** helicopter pilot is now a computer!
  - it runs a program that learns how to fly and make acrobatic maneuvers by itself!
  - no taped instructions, joysticks, or things like that …



[http://heli.stanford.edu/]

Drones

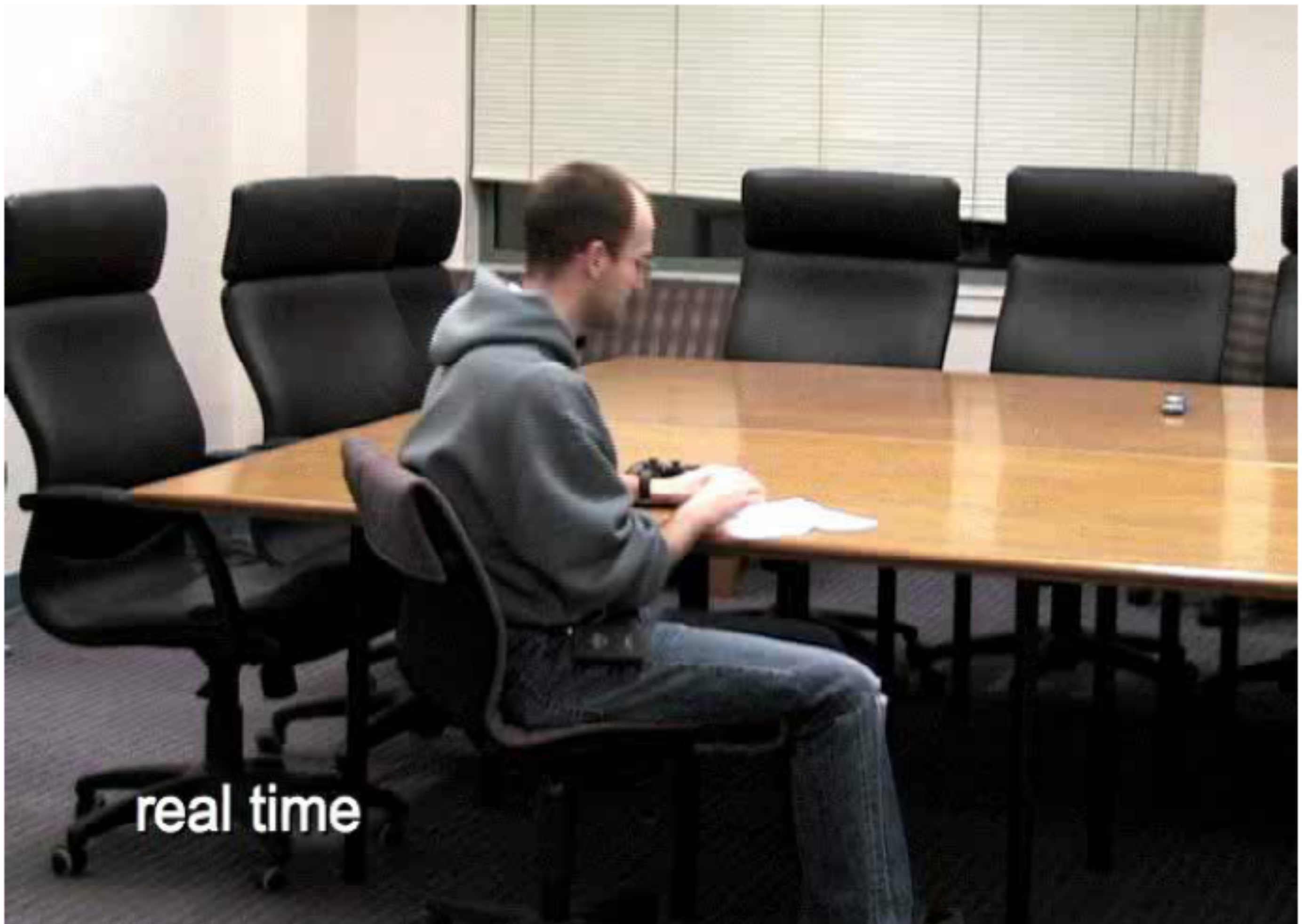
Amazon

US Air Force

Machine Learning in Action

- Robot assistant?

[http://stair.stanford.edu/]



Industrial Robots

Natural language processing and speech recognition

- Now most pocket **Speech Recognizers** or **Translators** are running on some sort of learning device --- the more you play/use them, the smarter they become!

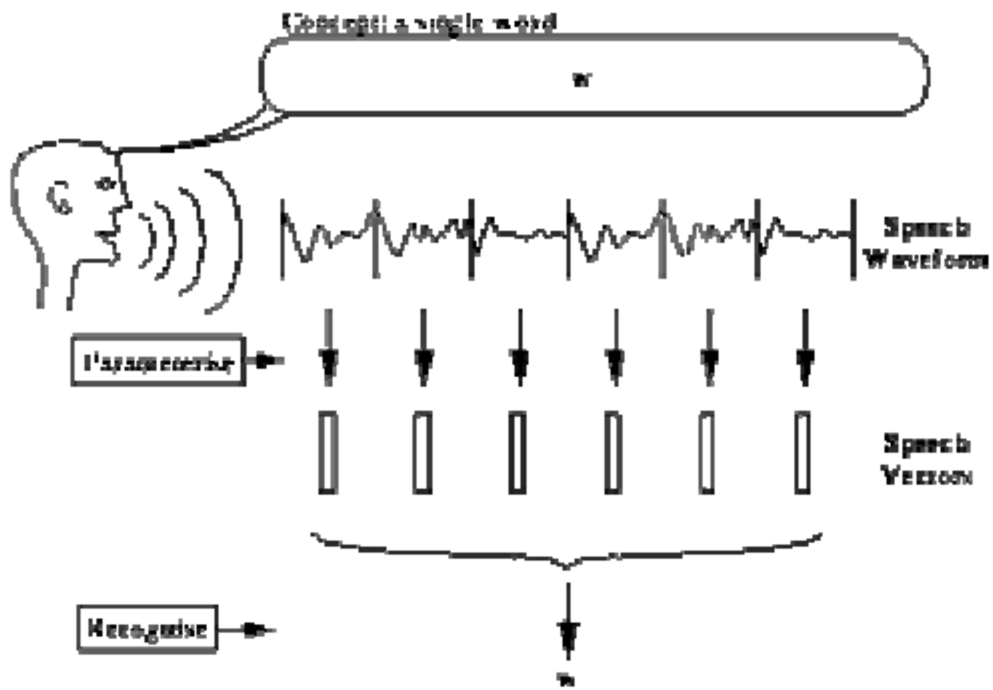


Fig. 1.2 Isolated Word Problem


Siri

Object Recognition

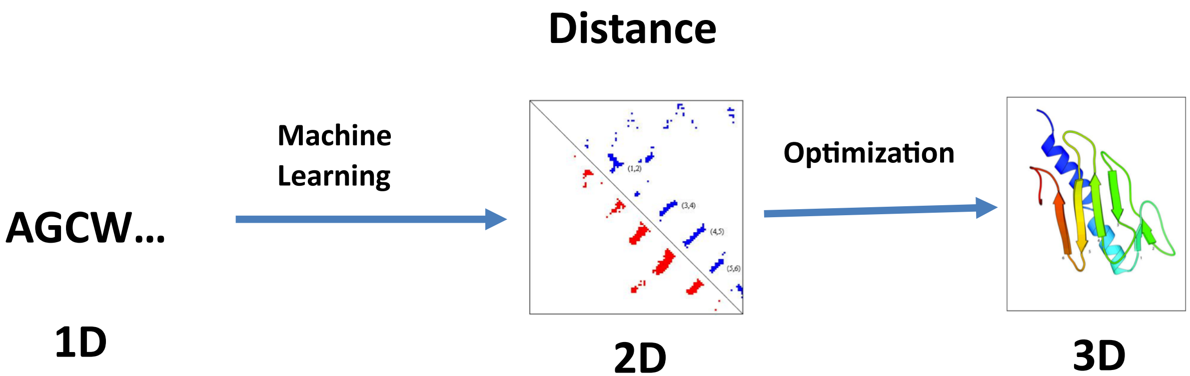
- Behind a security camera, most likely there is a computer that is learning and/or checking!

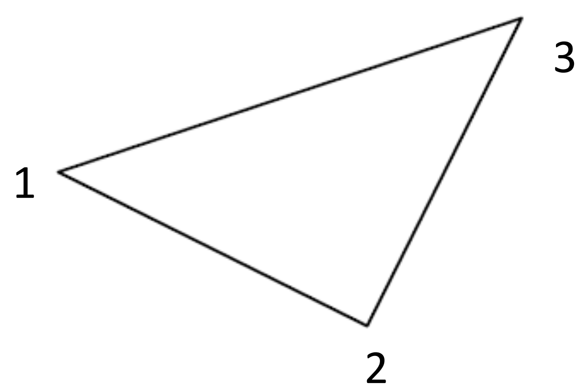
Face Recognition

Face Recognition

Scientific Discovery

Protein Folding

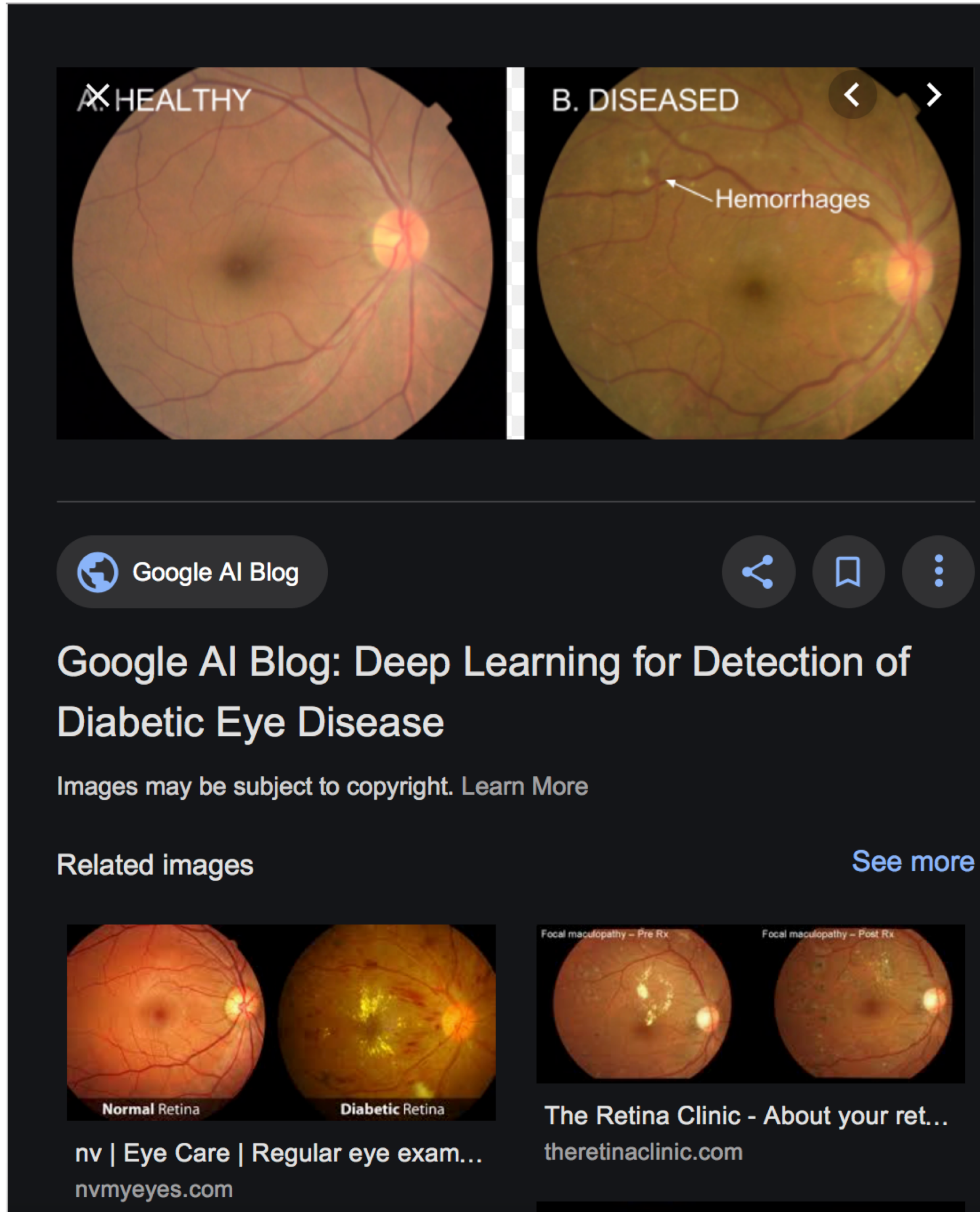




Google's AlphaFold (1st) and MU's MULTICOM (3rd)

Disease Diagnosis

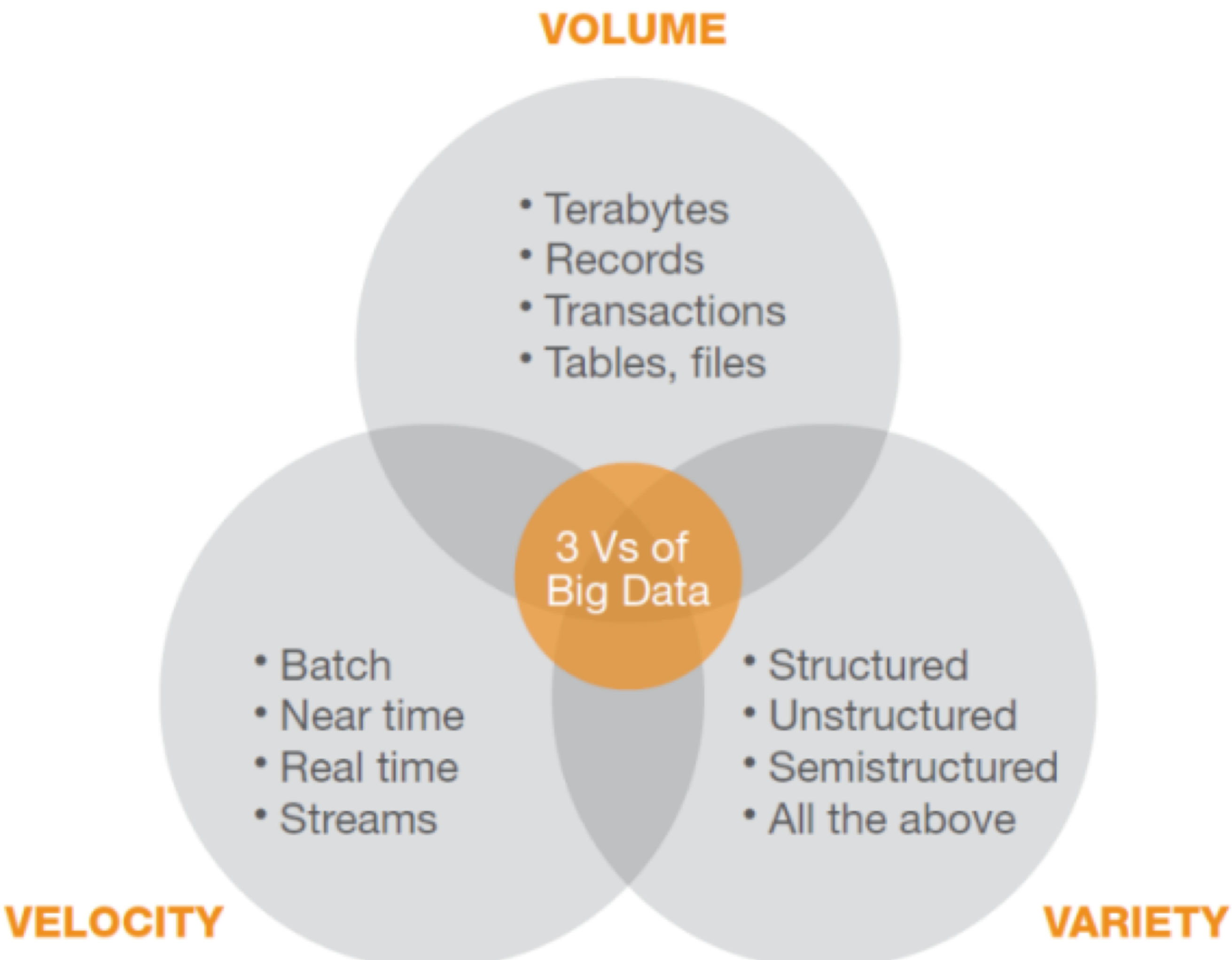
https://ai.googleblog.com/2016/11/deep-learning-for-detection-of-diabetic.html



Question

- In your opinion, what other problems can be addressed by machine learning?
- Why?

Big Data Challenges & Machine Learning



What this course is about

- Covers a wide range of Machine Learning techniques – from basic to state-of-the-art
- You will learn about the methods you heard about:
  - Naïve Bayes, logistic regression, nearest-neighbor, decision trees, boosting, neural nets, overfitting, regularization, dimensionality reduction, PCA, error bounds, VC dimension, SVMs, kernels, margin bounds, K-means, EM, mixture models, semi-supervised learning, HMMs, graphical models, active learning, reinforcement learning…

Deep Learning

- Covers algorithms, theory and applications
- **It's going to be fun and hard work ☺**

Machine Learning Tasks

Broad categories -

- **Supervised learning**

  Classification, Regression

- **Unsupervised learning**

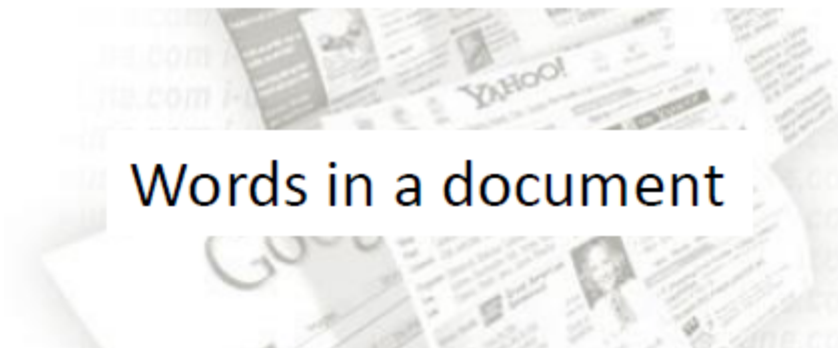
  Density estimation, Clustering, Dimensionality reduction

- Semi-supervised learning
- Active learning
- Reinforcement learning
- Many more …

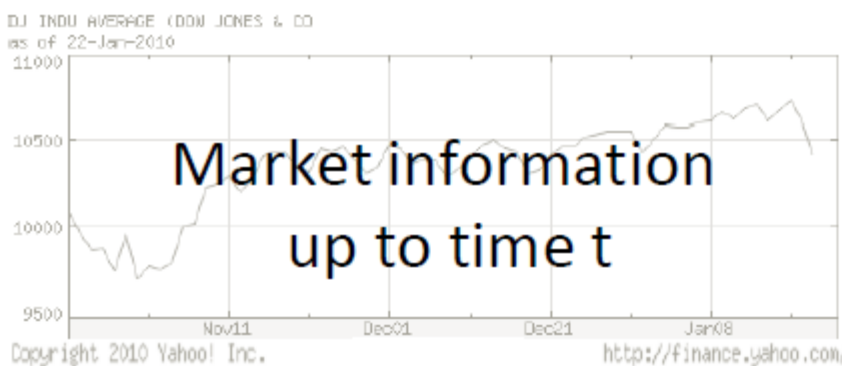
Supervised Learning

Feature Space $\mathcal{X}$

Label Space $\mathcal{Y}$



“Sports”
“News”
“Science”
…



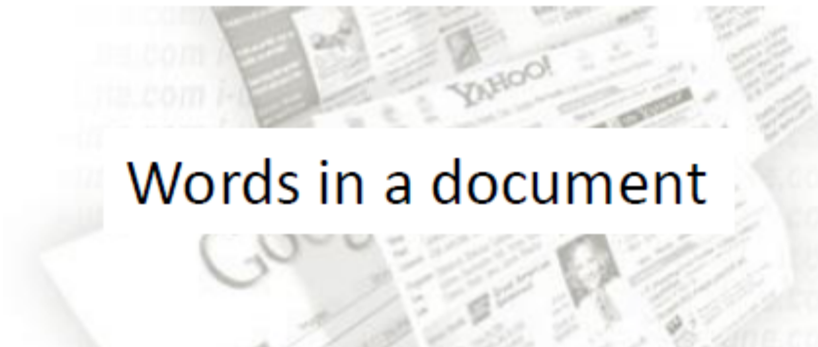
Share Price
“$ 24.50”

Task: Given $X \in \mathcal{X}$, predict $Y \in \mathcal{Y}$.

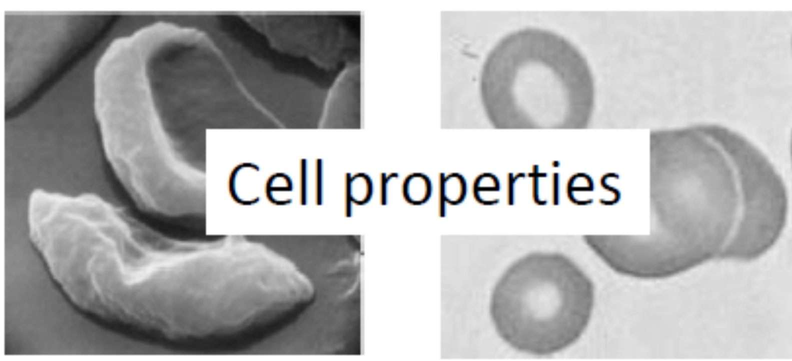
Supervised Learning - Classification

Feature Space $\mathcal{X}$

Label Space $\mathcal{Y}$



“Sports”
“News”
“Science”
…

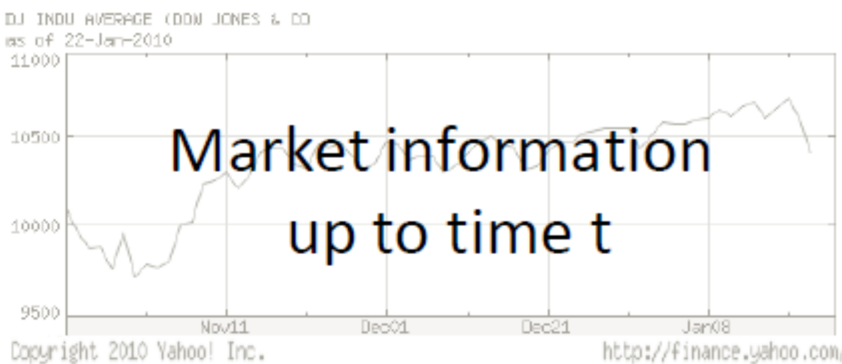


“Anemic cell”
“Healthy cell”

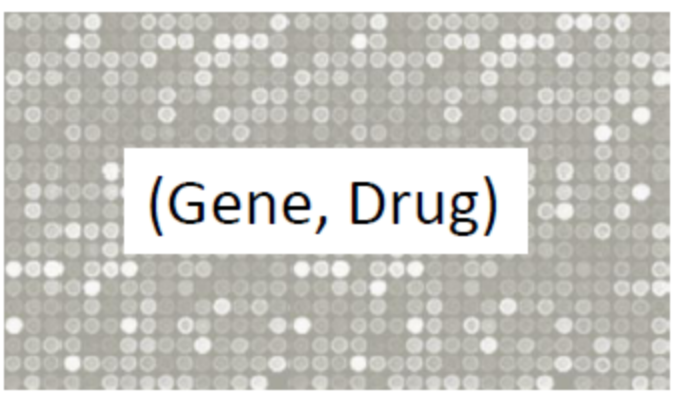
Discrete Labels

Supervised Learning - Regression

Feature Space $\mathcal{X}$ | **Label** Space $\mathcal{Y}$



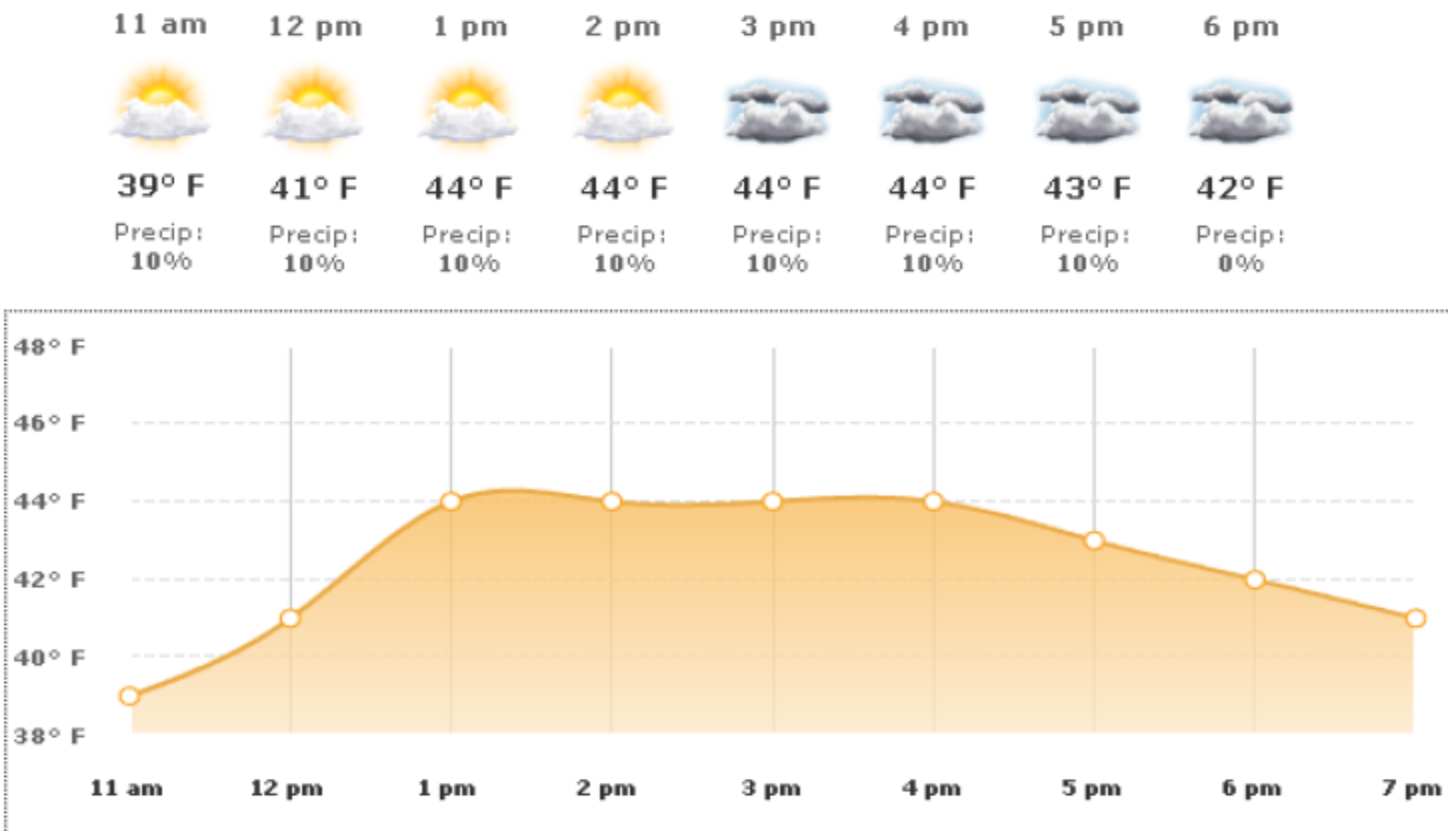
Share Price
"$ 24.50"



Expression level
"0.01"

Supervised Learning problems

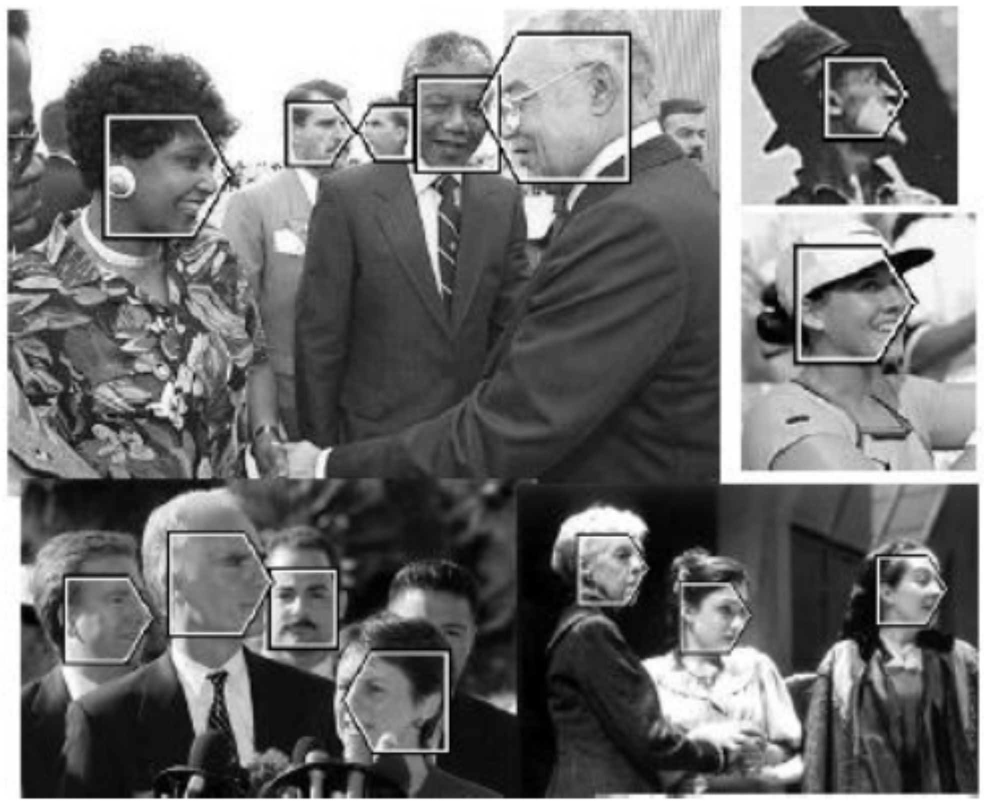
Features? **Labels?** **Classification/Regression?**



Temperature/Weather prediction

Supervised Learning problems

Features? **Labels?** **Classification/Regression?**



Face Detection

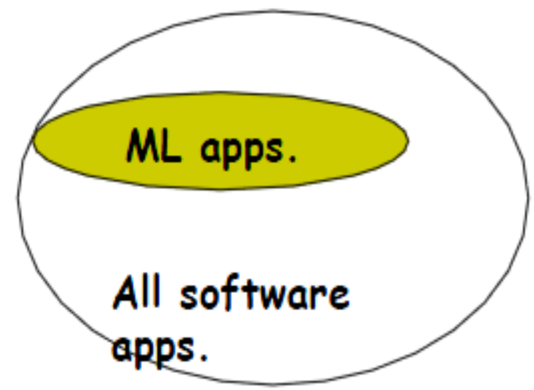
Supervised Learning problems

Features? **Labels?** **Classification/Regression?**

Environmental Mapping

Growth of Machine Learning

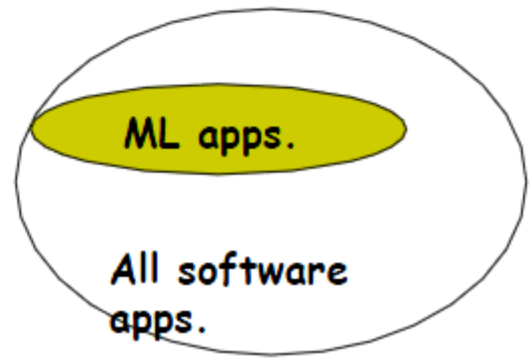
- Machine learning already the preferred approach to
  - Speech recognition, Natural language processing
  - Computer vision
  - Medical outcomes analysis
  - Robot control
  - …



- This ML niche is growing (why?)

Growth of Machine Learning

- Machine learning already the preferred approach to
  - Speech recognition, Natural language processing
  - Computer vision
  - Medical outcomes analysis
  - Robot control
  - …



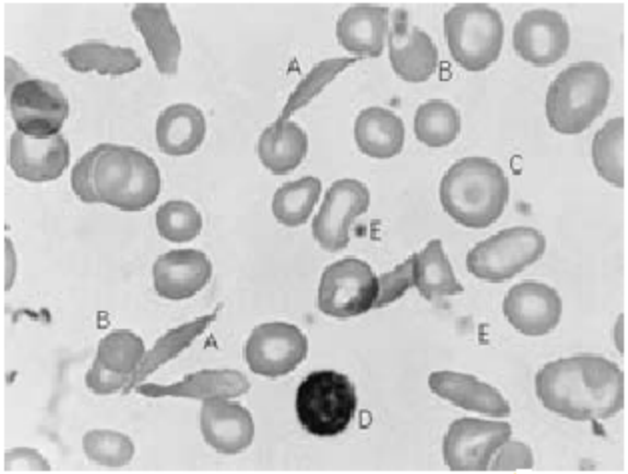
- This ML niche is growing
  - Improved machine learning algorithms
  - Increased data capture, networking
  - Software too complex to write by hand
  - New sensors / IO devices
  - Demand for self-customization to user, environment

Function Approximation

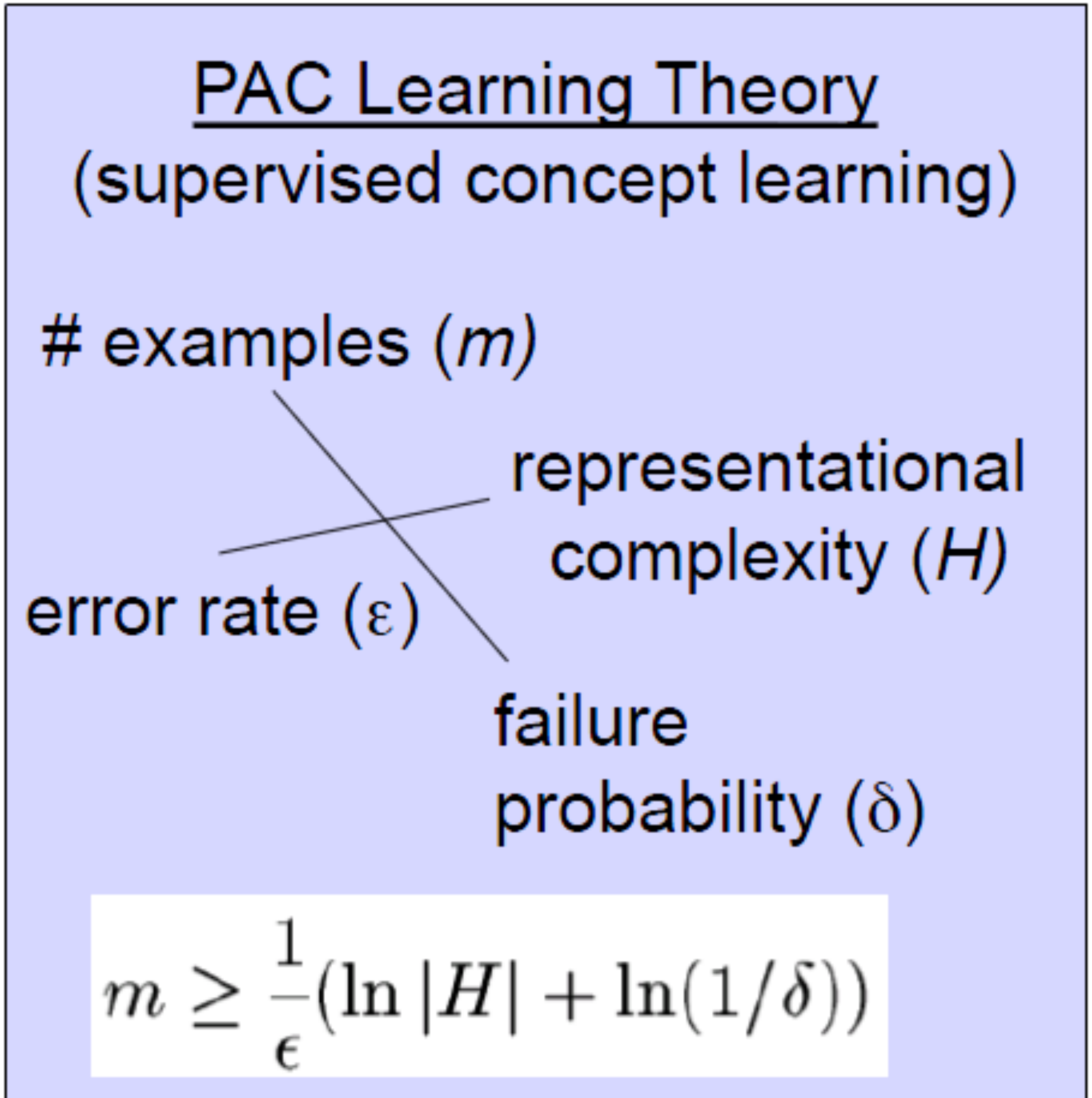
- **Setting**:
  - Set of possible instances *X*
  - Unknown target function $f: X \rightarrow Y$
  - Set of function hypotheses $H = \{ h \mid h: X \rightarrow Y \}$

- **Given**:
  - Training examples $\{<x_i, y_i>\}$ of unknown target function *f*

- **Determine**:
  - Hypothesis $h \in H$ that best approximates *f*



Probably Approximately Correct Learning



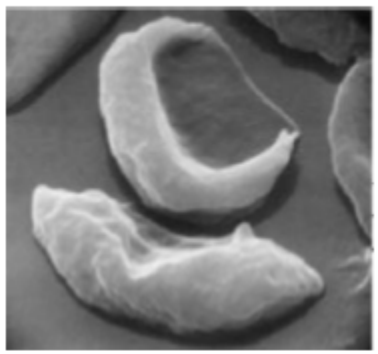
Occam's Razor – When everything is equal, a simple solution is better.

Supervised Learning Task

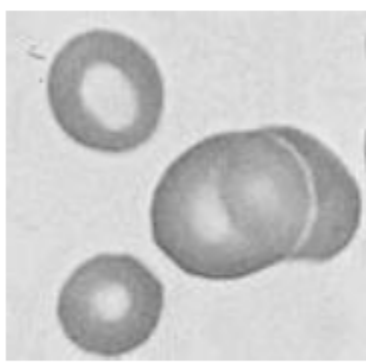
Task: Given $X \in \mathcal{X}$, predict $Y \in \mathcal{Y}$.

X - test data

$\equiv$ Construct **prediction rule** $f : \mathcal{X} \to \mathcal{Y}$



"Anemic cell (0)"

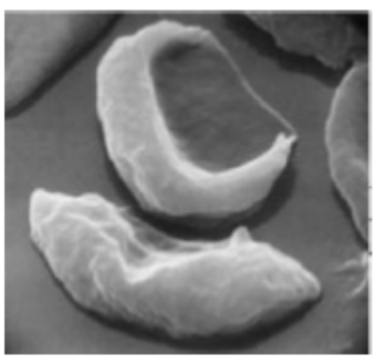


"Healthy cell (1)"

Performance Measures

Performance:

$\text{loss}(Y, f(X))$ - Measure of closeness between true label *Y* and prediction *f*(*X*)

X	*Y*	*f*(*X*)	$\text{loss}(Y, f(X))$
	"Anemic cell"	"Anemic cell"	0
		"Healthy cell"	1

$\text{loss}(Y, f(X)) = 1_{\{f(X) \neq Y\}}$ **0/1 loss**

Performance Measures

Performance:

$\text{loss}(Y, f(X))$ - Measure of closeness between true label *Y* and prediction *f*(*X*)

X	Share price, *Y*	*f*(*X*)	$\text{loss}(Y, f(X))$
Past performance, trade volume etc. as of Sept 8, 2010	"$24.50"	"$24.50"	0
		"$26.00"	1?
		"$26.10"	2?

$$\text{loss}(Y, f(X)) = (f(X) - Y)^2$$ **square loss**

Performance Measures

Performance:

$\text{loss}(Y, f(X))$ - Measure of closeness between true label *Y* and prediction *f*(*X*)

Don't just want label of one test data (cell image), but any cell image $X \in \mathcal{X}$

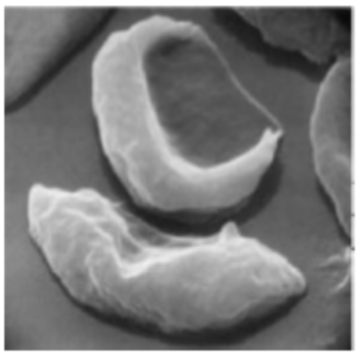
$$(X, Y) \sim P_{XY}$$

Given a cell image drawn randomly from the collection of all cell images, how well does the predictor perform on average?

$$\text{Risk } R(f) \equiv \mathbb{E}_{XY}\left[\text{loss}(Y, f(X))\right]$$

Performance Measures

Performance: Risk $R(f) \equiv \mathbb{E}_{XY}[\text{loss}(Y, f(X))]$



$\Rightarrow$ "Anemic cell"

$\Rightarrow$ Share Price "$ 24.50"

$\text{loss}(Y, f(X))$	Risk $R(f)$
$1_{\{f(X) \neq Y\}}$ **0/1 loss**	$P(f(X) \neq Y)$ **Probability of Error**
$(f(X) - Y)^2$ **square loss**	$\mathbb{E}[(f(X) - Y)^2]$ **Mean Square Error**

Bayes Optimal Rule

Ideal goal: Construct **prediction rule** $f^* : \mathcal{X} \to \mathcal{Y}$

$$f^* = \arg\min_f \mathbb{E}_{XY}\left[\text{loss}(Y, f(X))\right]$$

Bayes optimal rule

Best possible performance:

Bayes Risk $\quad R(f^*) \leq R(f) \text{ for all } f$

BUT… Optimal rule is not computable - depends on unknown P_{XY} !

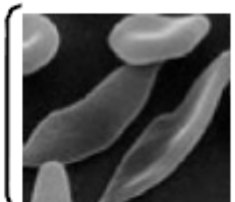
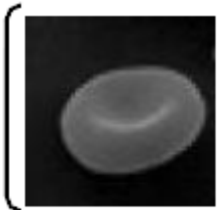
Experience - Training Data

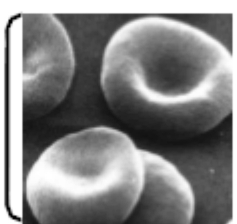
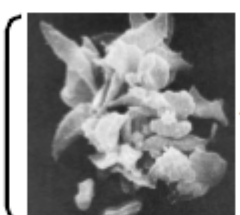
Can't minimize risk since P_{XY} unknown!

Training data (experience) provides a glimpse of P_{XY}

(observed) $\{(X_i, Y_i)\}_{i=1}^{n} \overset{i.i.d.}{\sim} P_{XY}$ **(unknown)**

↳ independent, identically distributed

( , Anemic cell) ( , Healthy cell)

( , Healthy cell) ( , Anemic cell)

Provided by expert, measuring device, some experiment, ...

Supervised Learning

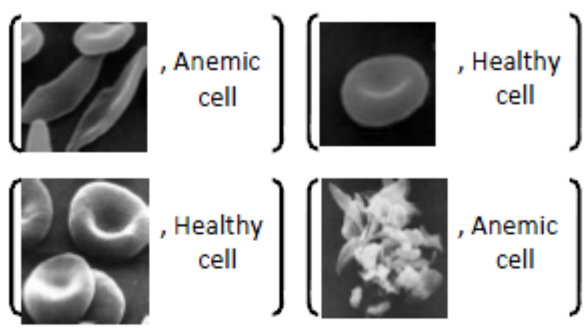
Task: Given $X \in \mathcal{X}$, predict $Y \in \mathcal{Y}$.

$\equiv$ Construct **prediction rule** $f : \mathcal{X} \rightarrow \mathcal{Y}$

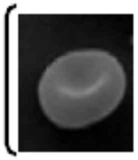
Performance: Risk $R(f) \equiv \mathbb{E}_{XY}\left[\text{loss}(Y, f(X))\right]$

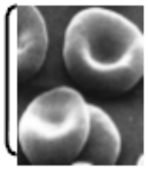
$$(X, Y) \sim P_{XY}$$

Experience: Training data $\{(X_i, Y_i)\}_{i=1}^{n} \overset{i.i.d.}{\sim} P_{XY}$ **(unknown)**



Machine Learning Algorithm

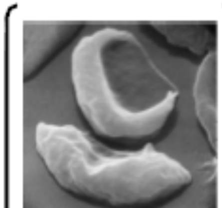
( , Anemic cell) ( , Healthy cell)

( , Healthy cell) ( , Anemic cell)

→ **Learning algorithm** → $\widehat{f}_n$

Training data $\{(X_i, Y_i)\}_{i=1}^n$

$\widehat{f}_n$ is a mapping from $\mathcal{X} \to \mathcal{Y}$

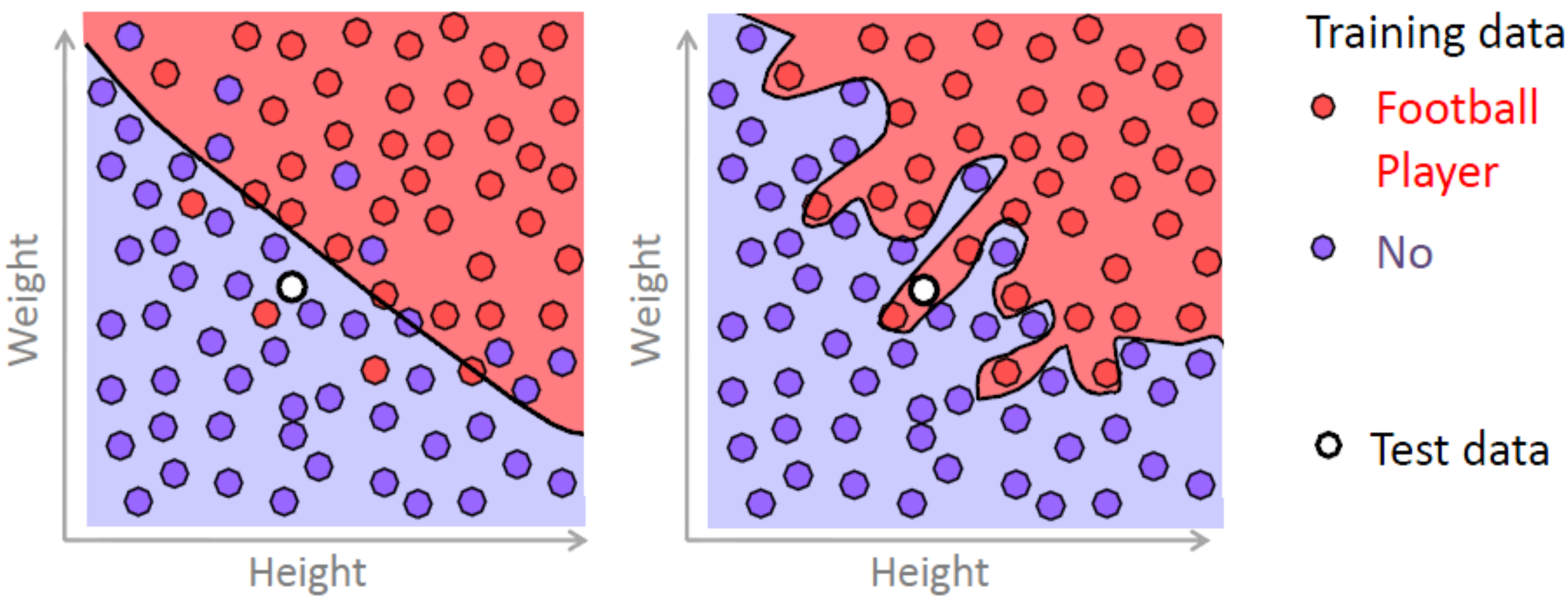
$\widehat{f}_n$ () = "Anemic cell"

Test data X

Note: test data ≠ training data

Issues in ML

- A good machine learning algorithm
  - Does not **overfit** training data



  - **Generalizes** well to test data

More later …

How to sense Generalization Error?

- Can't compute generalization error. How can we get a sense of how well algorithm is performing in practice?

- One approach -
  - Split available data into two sets $\{(X_i, Y_i)\}_{i=1}^n$ $\{(X'_i, Y'_i)\}_{i=1}^n$
  - Training Data – used for training the algorithm

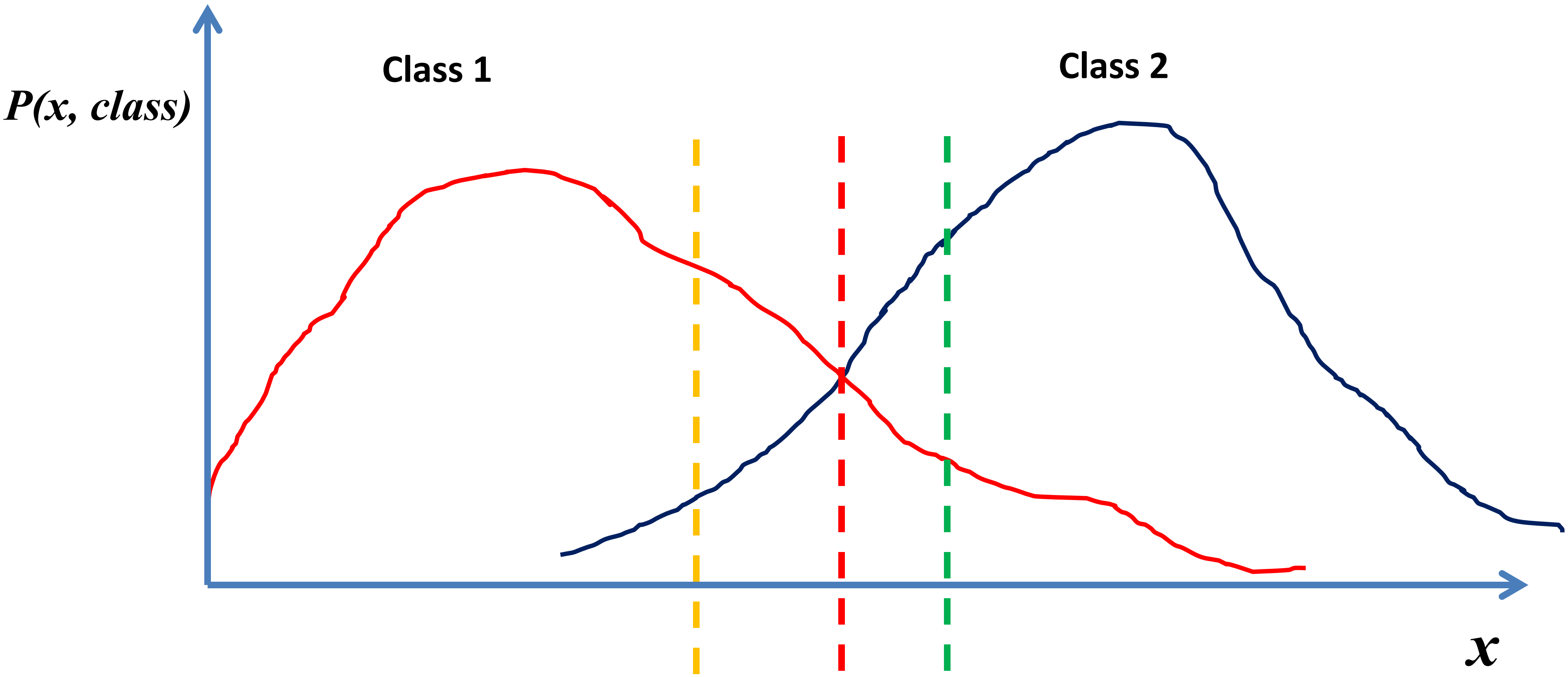
$\{(X_i, Y_i)\}_{i=1}^n \Rightarrow$  $\Rightarrow \widehat{f}_n$

  - Test Data (a.k.a. Validation Data, Hold-out Data) – provides estimate of generalization error

Test Error = $\frac{1}{n}\sum_{i=1}^{n}\left[\text{loss}(Y'_i, \widehat{f}_n(X'_i))\right]$

Why not use Training Error?

How to minimize errors?

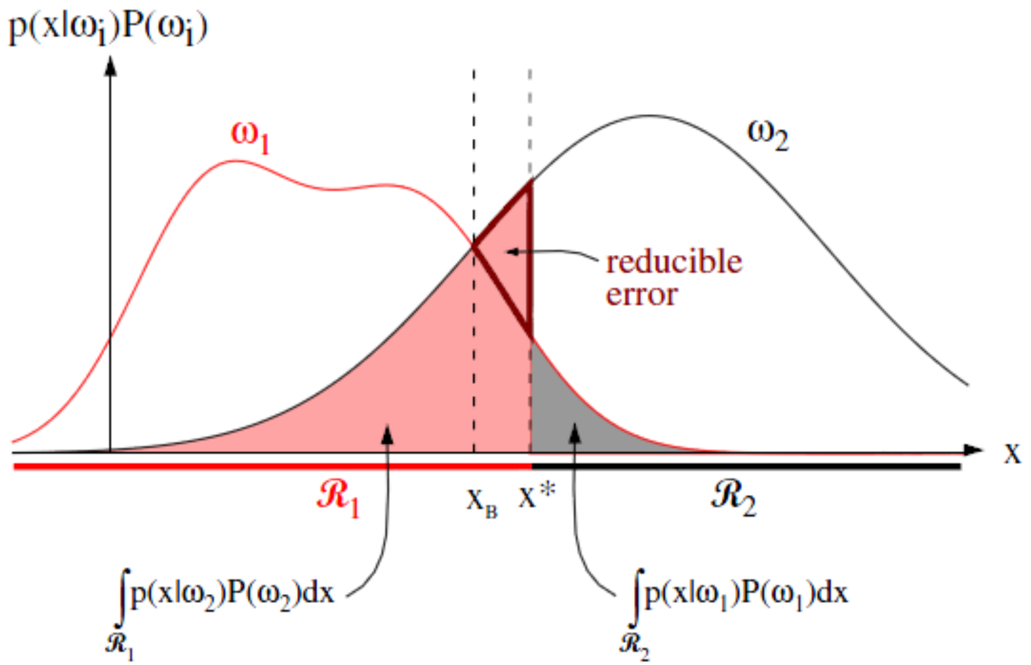


Where to set a threshold on x to make classification in order to minimize classification errors?

Can you get 100% classification accuracy?

Bayes Errors

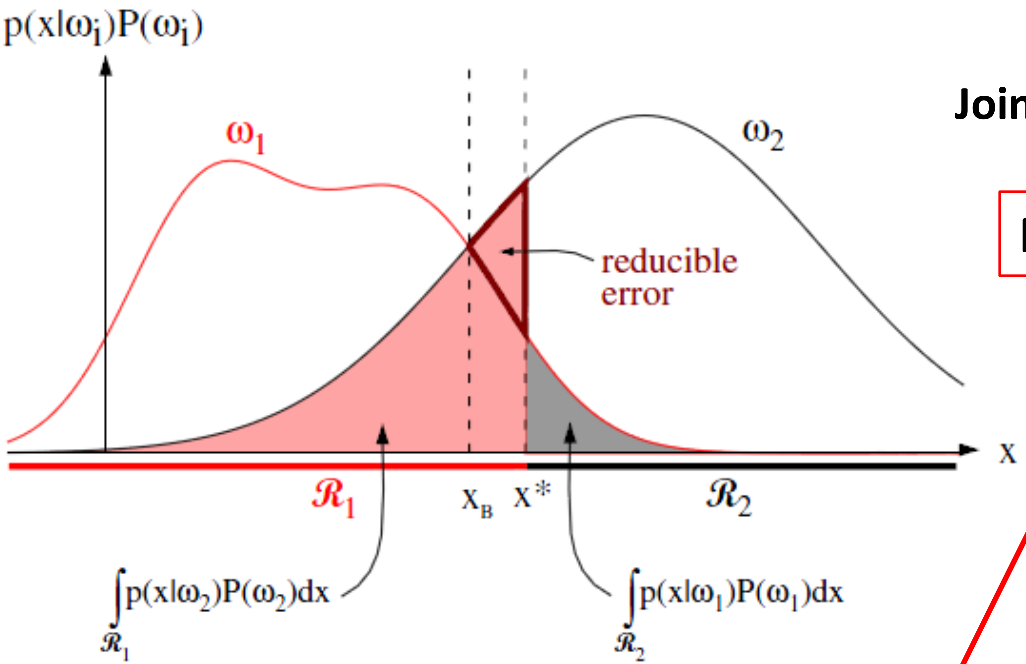
Calculate the probability of an error – Bayes error



$$
\begin{aligned}
P(error) &= P(\mathbf{x} \in \mathcal{R}_2, \omega_1) + P(\mathbf{x} \in \mathcal{R}_1, \omega_2) \\
&= P(\mathbf{x} \in \mathcal{R}_2 | \omega_1) P(\omega_1) + P(\mathbf{x} \in \mathcal{R}_1 | \omega_2) P(\omega_2) \\
&= \int_{\mathcal{R}_2} p(\mathbf{x}|\omega_1) P(\omega_1)\, d\mathbf{x} + \int_{\mathcal{R}_1} p(\mathbf{x}|\omega_2) P(\omega_2)\, d\mathbf{x}.
\end{aligned}
$$

Bayes Errors

Calculate the probability of an error – Bayes error



Joint Prob = Con. Prob * Marginal Prob.

P(x,y) = P(x|y)P(y)

$$
\begin{aligned}
P(error) &= P(\mathbf{x} \in \mathcal{R}_2, \omega_1) + P(\mathbf{x} \in \mathcal{R}_1, \omega_2) \\
&= P(\mathbf{x} \in \mathcal{R}_2 | \omega_1) P(\omega_1) + P(\mathbf{x} \in \mathcal{R}_1 | \omega_2) P(\omega_2) \\
&= \int_{\mathcal{R}_2} p(\mathbf{x}|\omega_1) P(\omega_1) \, d\mathbf{x} + \int_{\mathcal{R}_1} p(\mathbf{x}|\omega_2) P(\omega_2) \, d\mathbf{x}.
\end{aligned}
$$

Bayes optimal classifiers

- Classifier that minimizes the Bayes error is called the Bayes optimal classifier:

- classify x as $\begin{cases} C_0 \text{ if } P(C_0 \mid x) > P(C_1 \mid x) \\ C_1 \text{ otherwise} \end{cases}$