What is Machine Learning?

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Motivating example

- I am interested in finding out which UTD students get internships (or jobs).
- Think of it as a function:
  f: X -> Y (the best function for entire UTD)

X is an instance (student), Y is boolean.

X has certain attributes

$X = \langle X_1, X_2, \ldots, X_n \rangle$

e.g.

X1= GPA, X2=Taken CS 6375?

X3=Years experience, ...

It's a binary classification problem.

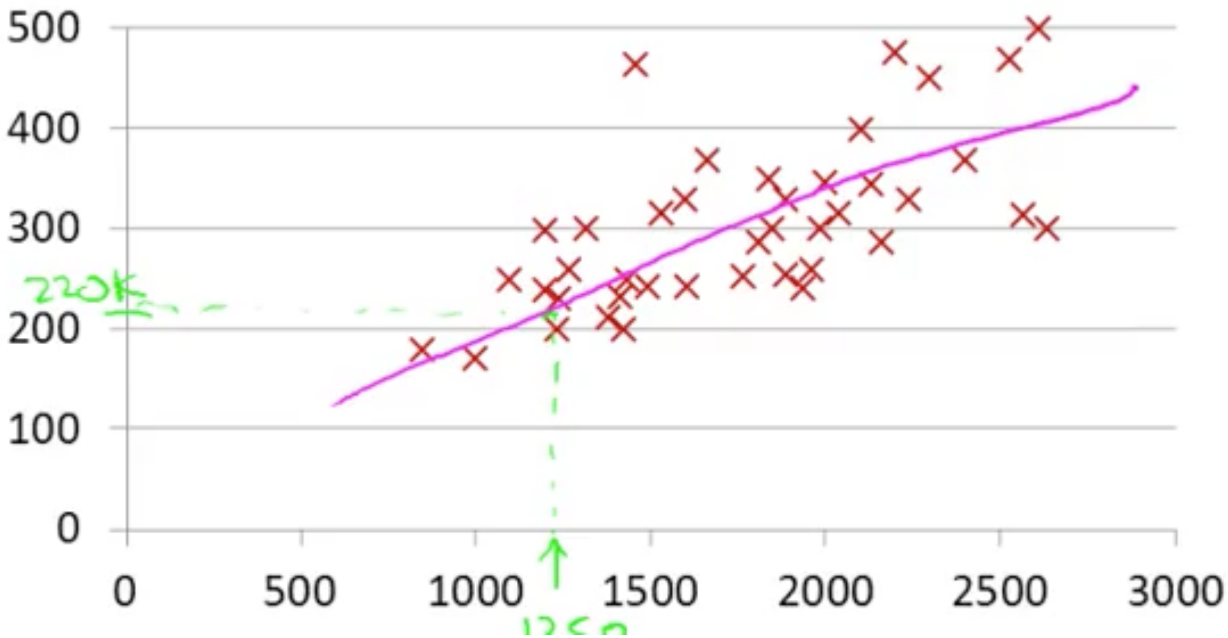
You will see lots of such cases in this course.

Think of the issues

- Do I have access to entire dataset for UTD?
  - Can I even see 50%?
- Are all attributes equally important?
  - Do employers care about X_n
- What if an instance is noise?
- What is the distribution of attributes?
  e.g. What is the probability of finding a 30 year old, with 0 prior experience, having a GPA of 4.0??

Think of the issues

- If the output was real-valued, this problem can be solved by statistics.



Statisticians love regression – linear or non-linear.
It can be used to fit a curve to data points.

Think of the issues

- Computer scientists love all things <u>Boolean</u>
- So, we have Boolean attributes, Boolean output.
- How do we handle this scenario??

0

OR

1

Can ML help??

- Can ML help me in this case?
- Let’s see.

What is ML?

- There is a task – generally involving prediction
  -e.g.
  Will a student at UTD get internship?
  Will a stock go up?
  Will you play tennis?
  Will a person be approved for credit card?
  What is the price of a house?
  Which digit does a handwritten image represent?

What is ML?

- It has an associated performance measure i.e. how close is your prediction to actual value
- Error metric: If your hypothesis doesn’t match the actual value, penalize the model.

$$E_D = \sum_{x \in D} 1(h(x) \neq y)$$

The above is the simplest error function.

h(x) denotes your hypothesis and y is the actual value. D is the dataset.

What is ML?

- The model learns from experience i.e. data.
  - More data => Better performance
  - Is it always true?
  Only if data is meaningful i.e. it's not noise
- If you could see the entire population (entire dataset), you would get the best learning model.
  - Is it possible?
  Can you poll the entire US population?
  Probably Not!!
  In this class, we will work with samples of data

Definition

"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, Carnegie Mellon University

Simpler Definition

- Design of algorithms that learn from data and improve performance on a predictive task.
- Development of computational methods using experience to improve performance.

Common Theme of this class:

- More training data is always good

Provided data is meaningful and is labeled (in case of supervised learning).

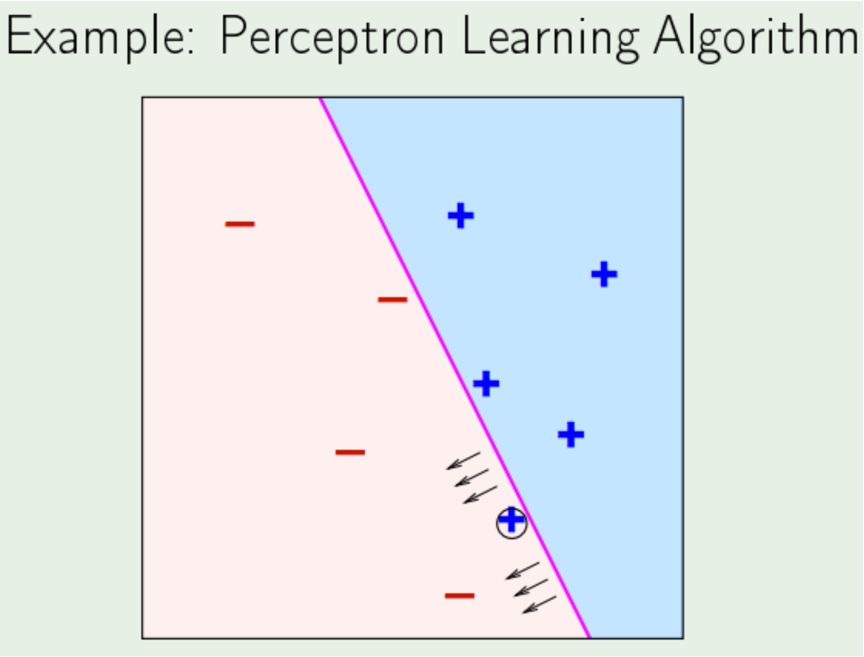
Think:

Why does Google work so well?

When is ML a good choice?

- **Learning used when**
  - A pattern exists
  - There exists a correlation between predicted variable and features.
  - We have data

- **Supervised learning**
  - Unknown target function f
  y = f(x)
  - You get data & labels
  (x1, y1) (x2, y2) ,…
  - Learning algorithm picks a function g ≈ f (approximation)



Simple, but not obvious

- When can we use ML?
- There is some definite relation/correlation between X and Y.
  i.e. there is a deterministic or highly probable function f
- X comes from a well-defined distribution (we don't need to know the details yet)
  <u>=> X is not a set of random variables.</u>

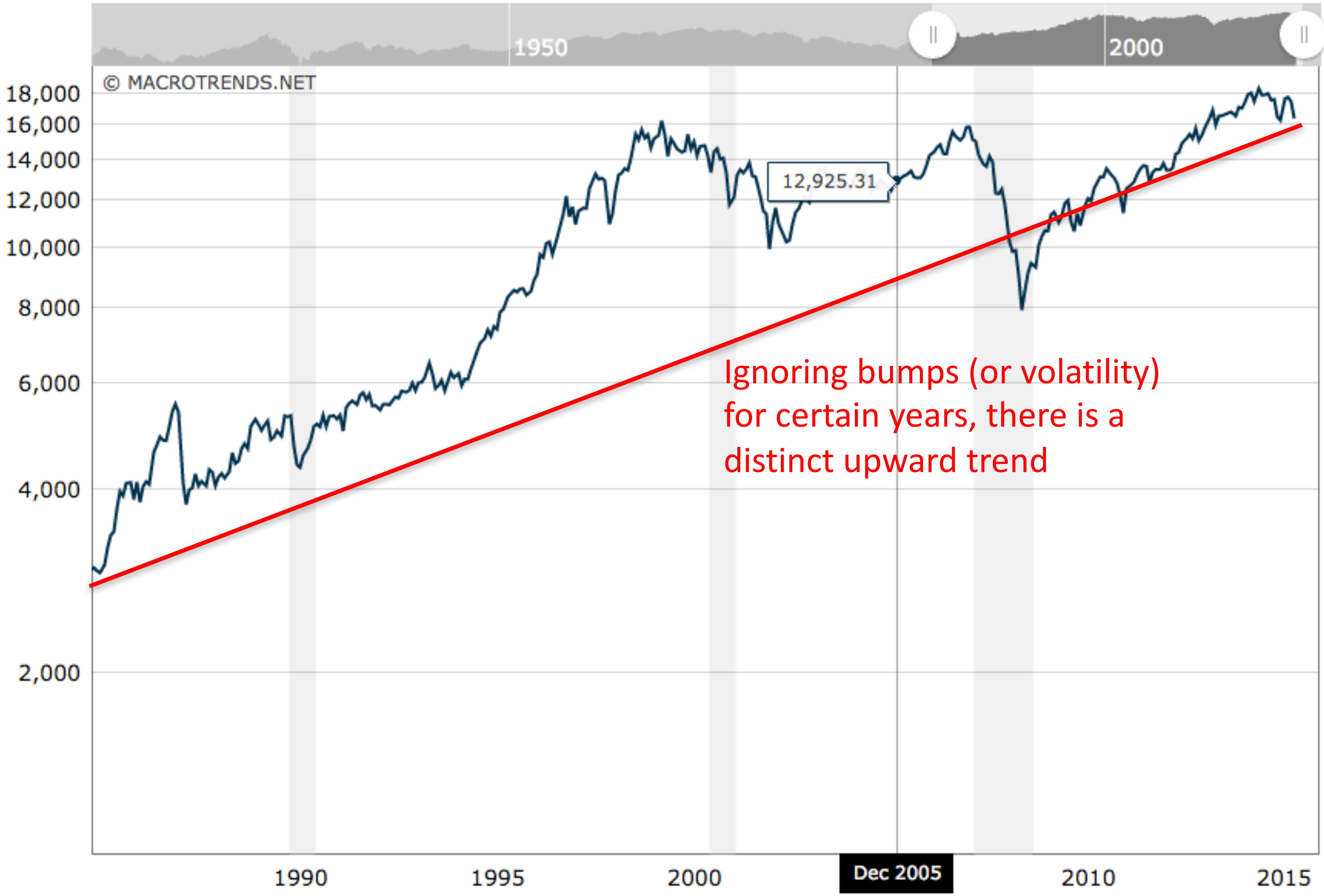
Simple, but not obvious

- When can we <u>NOT</u> use ML?

- There is no correlation between X and Y.
- There is no clear function f
- X is a set of random variables
  => Can ML predict the lottery?
  => Can you use it at the casino?

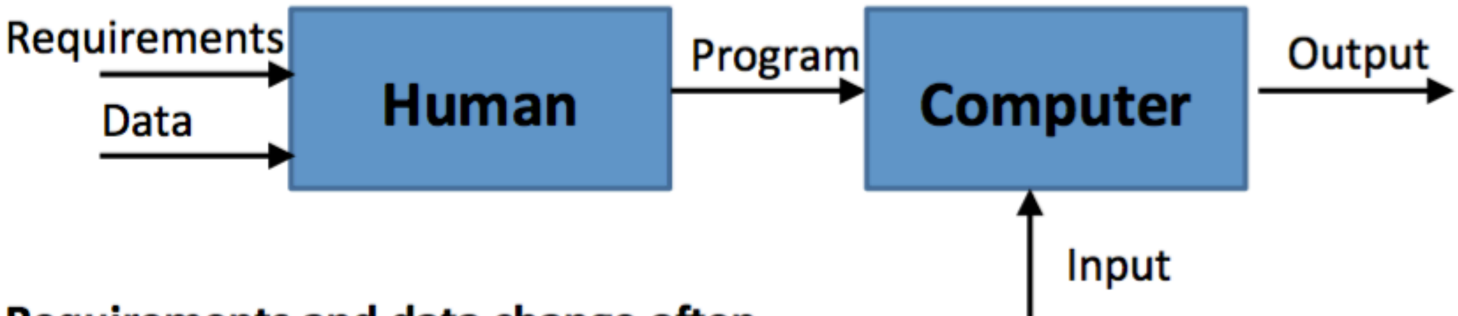
- Can we use it to predict the stock market?

Stock Market



- Getting computers to program themselves
- Writing software is the bottleneck, let data do the work

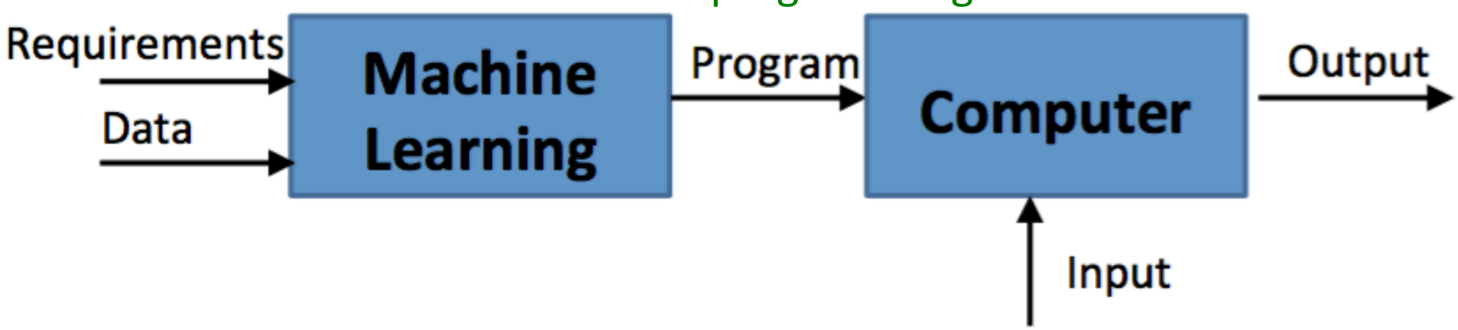
Traditional Programming



Requirements and data change often

In ML, the algorithm learns from data and outputs a program. For example, a self-programming robot.

Machine Learning

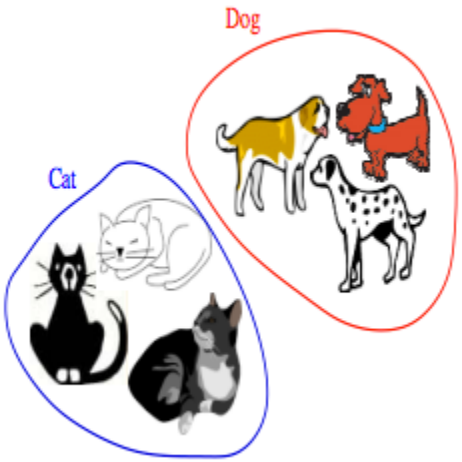


Types of Learning

- **Supervised (inductive) learning**
  - Training data includes desired outputs
- **Unsupervised learning**
  - Training data does not include desired outputs
  - Find hidden/interesting structure in data
- **Semi-supervised learning**
  - Training data includes a few desired outputs
- **Reinforcement learning**
  - the learner interacts with the world via “actions” and tries to find an optimal policy of behavior with respect to “rewards” it receives from the environment

Supervised Learning - Inductive

- Inductive: Tries to discover general concepts from a limited set of training examples.
  => Generalization
  - Based on search of similar characteristics in different classes of examples.
  - e.g.

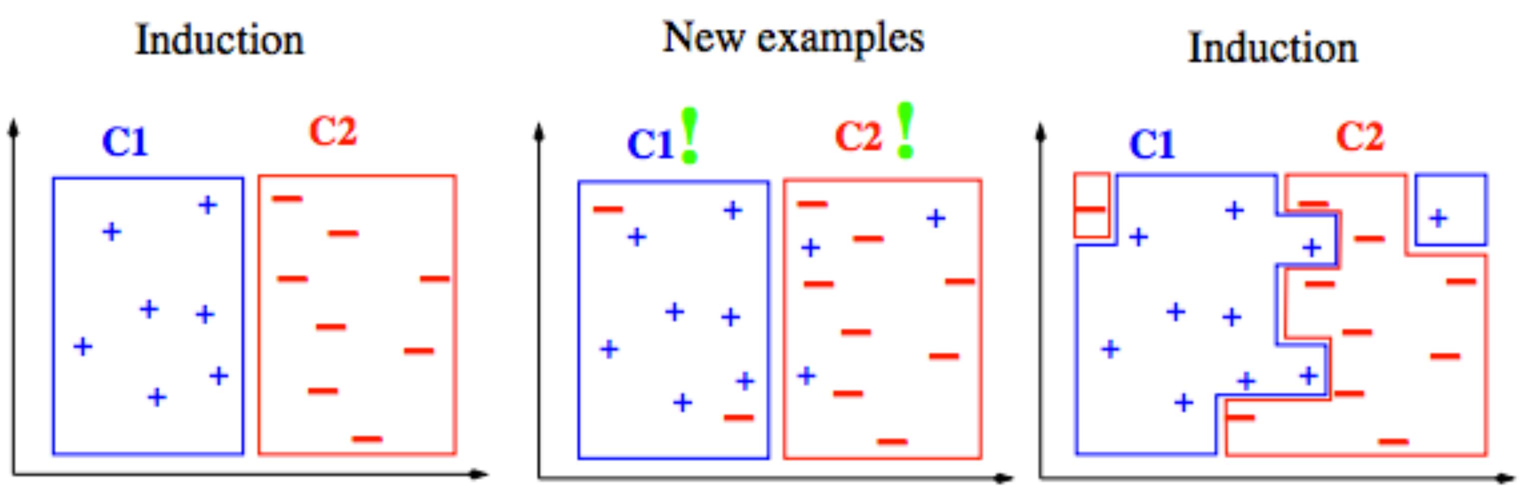


Given labeled examples, you find features that are common within each class.

Supervised Learning - Inductive

- Inductive: goes from specific to general

- tries to obtain new knowledge.
- new data points may force you to change old hypothesis.



Inductive vs Deductive

- Deductive: uses given premises and logical arguments to infer conclusions.
- tries to obtain knowledge that is implicit in original knowledge.
- Classic example:

 * All men are mortal. (major premise)

 * Socrates is a man. (minor premise)

 * Socrates is mortal. (conclusion)

Inductive vs Deductive

- In this class, we will focus on <u>inductive</u> learning.
- Can you see any <u>issues</u> with inductive approach?
  - What do you expect the data to be?
  - How do you expect the learner to behave?
  - When you make a conclusion, are you 100% sure or are you probably sure?
  - Is it even possible to obtain 100% accuracy on training and test data?
  - …

Learning

- Inductive learning is supervised learning because the training data has the class labels.
  => That's what you are trying to learn.
  => So you create an algorithm that separates the two classes based on features.
- What if you just want to find patterns in data i.e. how can you find similar items based on their attributes. => Unsupervised learning
  => No labeling provided or you don't care for labels.
  => You want to create a natural grouping of people based on shared interests on FB.

Types of learning task

- Supervised: correct output known for each training example
  - Learn to predict output when given an input vector
    - Classification: 1-of-N output (speech recognition, object recognition, medical diagnosis)
    - Regression: real-valued output (predicting market prices, customer rating)

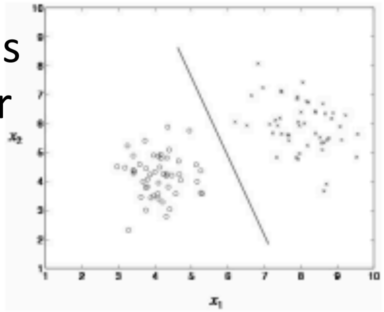
- Unsupervised learning
  - Create an internal representation of the input, capturing regularities/structure in data
  - Examples: form clusters; extract features
    - How do we know if a representation is good?

- Reinforcement learning
  - Learn action to maximize payoff

Supervised Learning

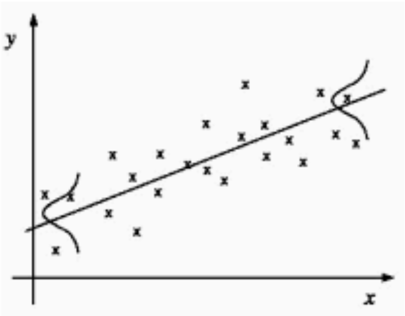
- Classification
  - Outputs are categorical (1-of-N)
  - Inputs are anything
  - Goal: select correct class for new inputs
  - Ex: speech, object recognition, medical diagnosis

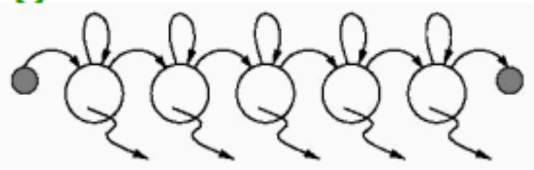
You have N choices for output, learner needs to find best 1



- Regression
  - Outputs are continuous
  - Inputs are anything (typically continuous)
  - Goal: predict outputs accurately for new inputs
  - Ex: predicting market prices, customer rating of movie

You have infinite output choices.





- Temporal Prediction
  - Goal: perform classification/regression on new input sequences values at future time points
  - Given input values and corresponding class labels/outputs at some previous time points

Machine Learning------------------------------Statistics

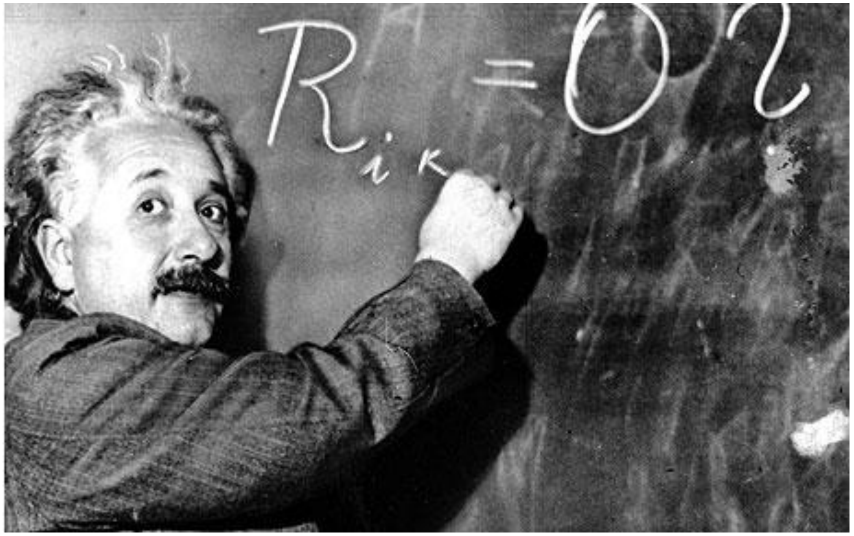
- network, graphs
- weights
- learning
- generalization
- supervised learning
- unsupervised learning.
- large grant: $1,000,000
- conference location: Snowbird, French Alps

- model
- parameters
- fitting
- test set performance
- regression/classification
- density estimation, clustering
- large grant: $50,000
- conference location: Las Vegas in August

Applications of ML

- Pattern Identification:
  - facial, fingerprint, gene sequence
- Differentiation:
  spam or non-spam
  cancerous or non-cancerous cells
  normal traffic or hacker traffic
- Finding association rules
- Recommender Systems
- … Many more

Let’s do some theory



Formal notation of learning

- You own a credit card company.
- You get a lot of applicants, your job is to design the best classifier for approving them.
- You have <u>some</u> historical data to rely upon.

$$x^j = (x_1, x_2, \ldots, x_n)^T$$

Input vector for customer x^j

$$X = \{x^1, x^2, \ldots, x^N\}$$

set of all customers

$$y = \{0,1\}$$

Binary Output

$$f : X -> Y$$

Ideal target function i.e. if you had <u>entire</u> data in front of you

Formal notation of learning

$(x^1, y^1), (x^2, y^2), \ldots, (x^n, y^n)$

You have this data

$H = \{h_1, h_2, \ldots, h_N\}$

The set of all possible hypothesis. Doesn't matter if they are meaningful or not

$g : X -> Y,$

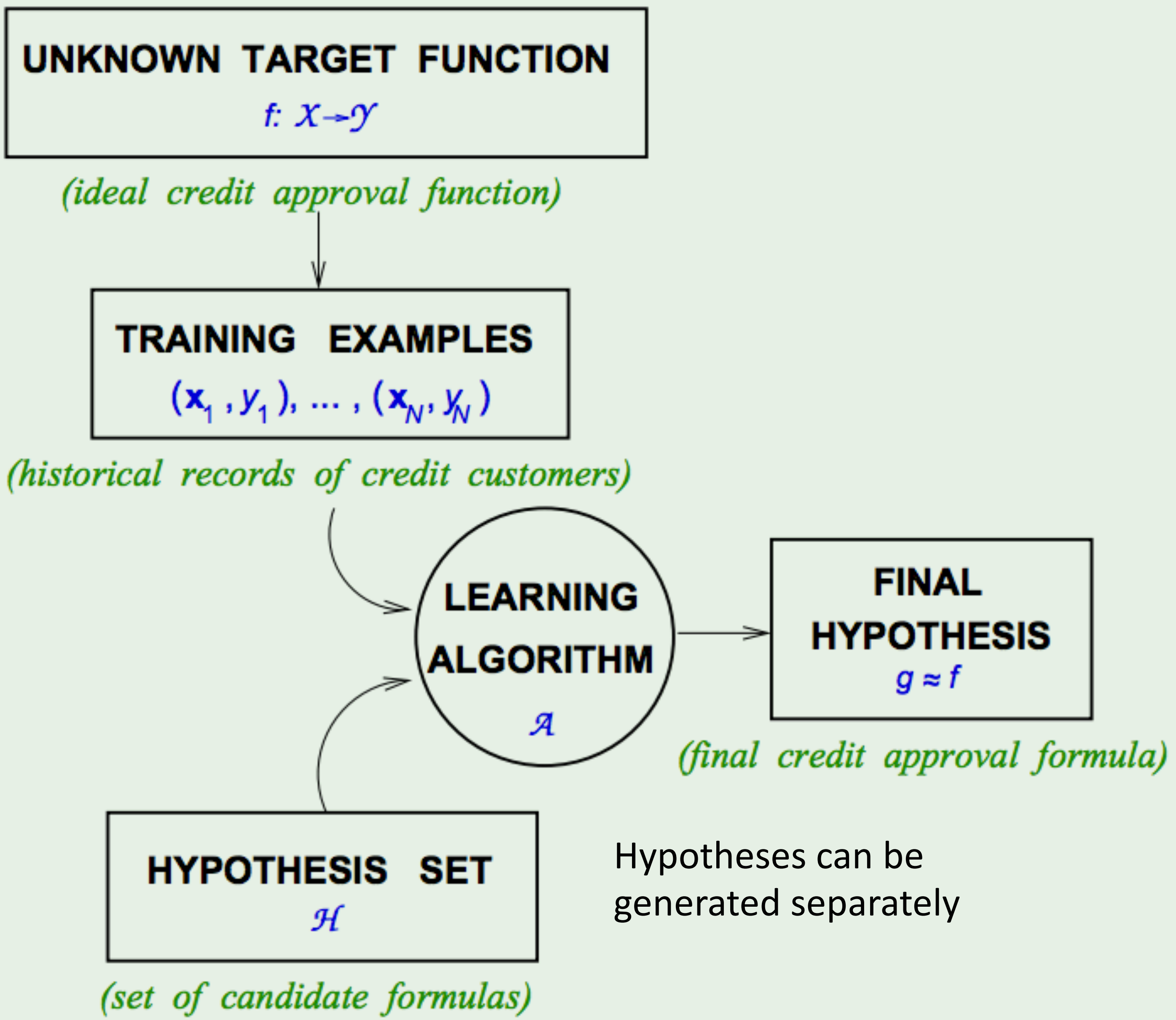
$g \in H$

The best hypothesis you can come up with given the data

Can you really know f?

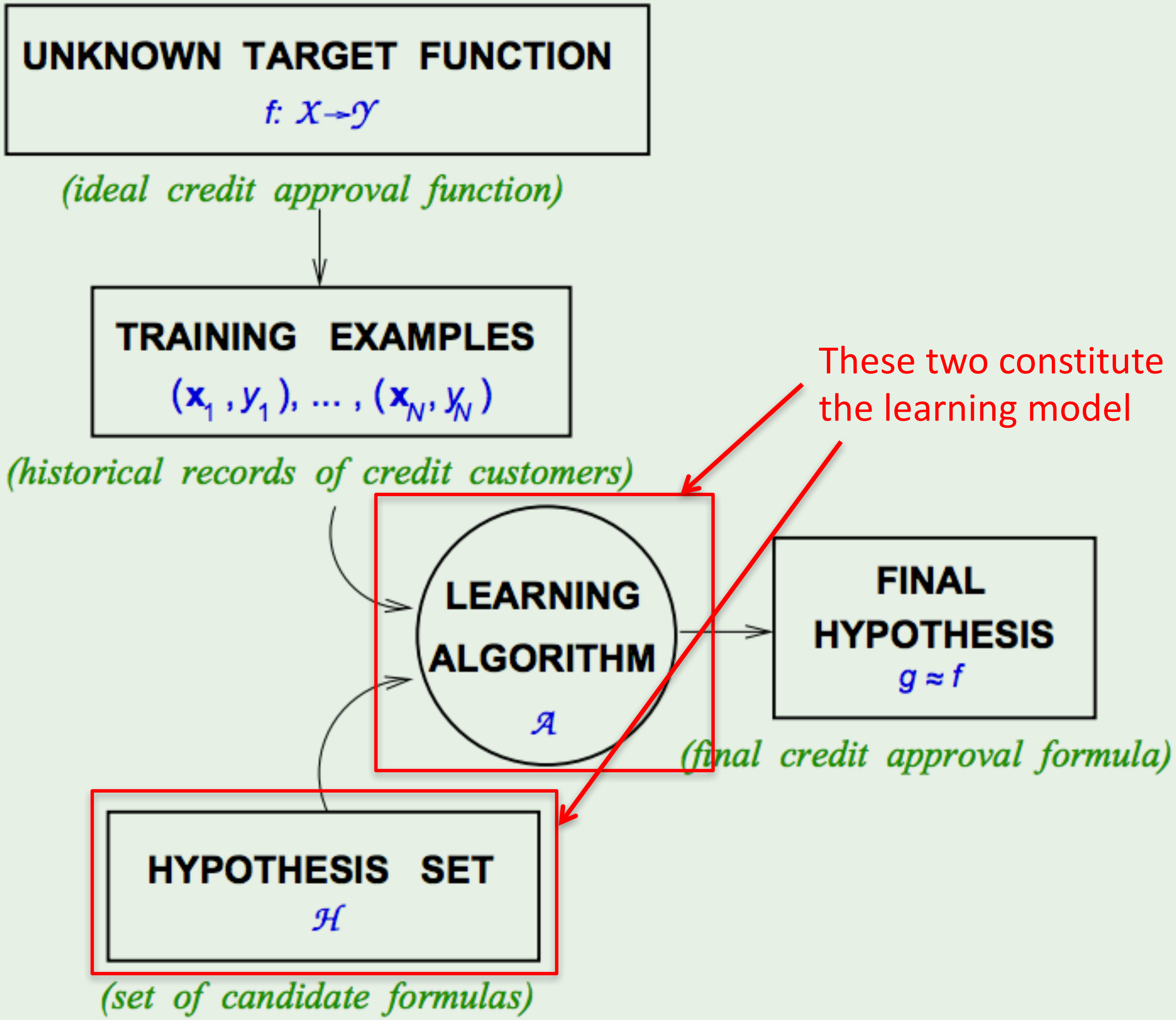
- No, you can only try to approximate it by g
- Your approximation is only as good as the data that you see.

Formal notation of learning



Hypotheses can be generated separately

Formal notation of learning



Really simple, right?

- All you have to worry about is the type of learning model and how to generate (and eliminate hypotheses)

- In this class, we will focus on these types:

- Linear separators (Perceptron)
- Extension of linear to non-linear (SVM, ANN, etc)
- Tree-based classifiers (Starting with decision trees)

Linearly Separable Data

- Suppose you have following data:
  (This is a toy example ☺)

GPA	Internship
4.0	1
3.0	0
3.4	0
3.6	1
3.8	1
2.5	0

What can you infer?

Linearly Separable Data

- Suppose you have following data:
  (This is a toy example ☺)

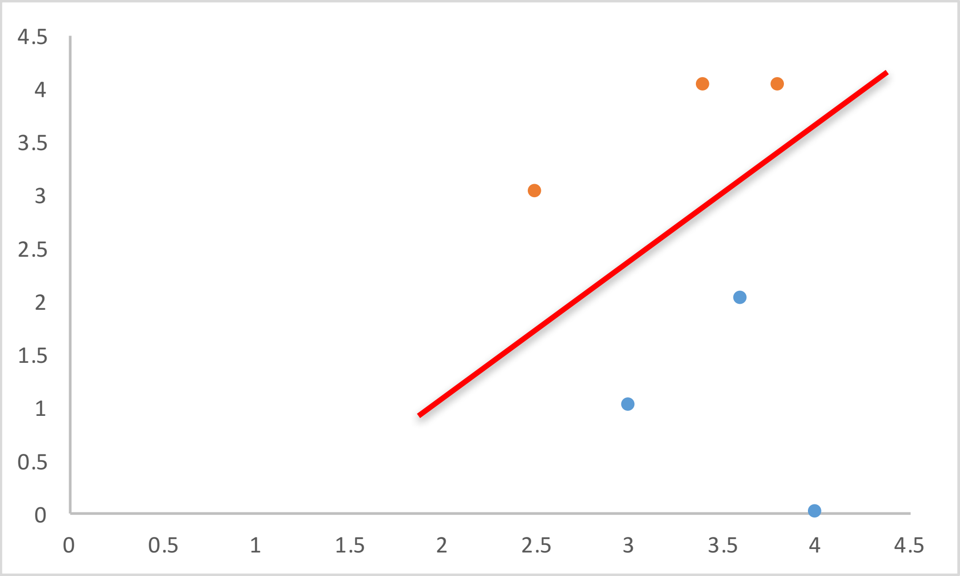
GPA	Internship
4.0	1
3.0	0
3.4	0
3.6	1
3.8	1
2.5	0

GPA=3.5 can separate the points.
Actually, it's one of many possible hypothesis.

Linearly Separable Data

- 2-D case

GPA	Years Exp	Internship
4.0	0	0
3.0	1	0
3.4	4	1
3.6	2	0
3.8	4	1
2.5	3	1



Perceptron

- It's a simple linear classifier -> straight line in 2-D and a plane in higher dimensions.
- Suppose each instance is represented by the vector x^j $$x^j = (x_1, x_2, \ldots, x_d)^T$$
  Example of instance can be a student, a customer, etc. Attributes are x_1, x_2, …, x_d
- Each attribute can have different weights w_1, w_2, …, w_d

Perceptron

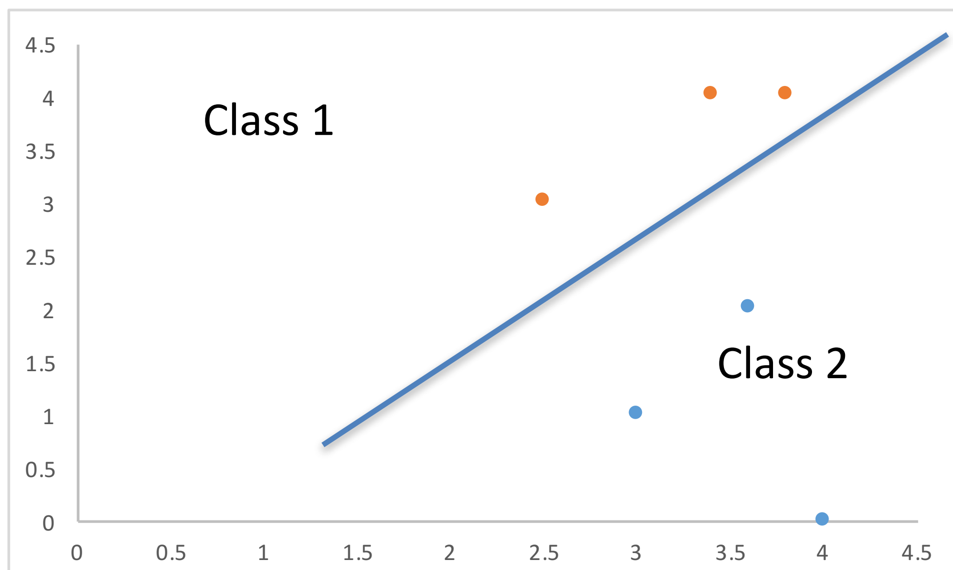
- Equation of separator is:

$$y = \sum_i w_i x_i$$

An easy way to separate classes is:

If $\sum_i w_i x_i > threshold$ assign class1

else assign class 2.



Perceptron

- An easier way to present this is:

This linear formula $h \in \mathcal{H}$ can be written as

$$h(\mathbf{x}) = \text{sign}\left(\left(\sum_{i=1}^{d} w_i x_i\right) - \text{threshold}\right)$$

In vector form, the perceptron implements

$$h(\mathbf{x}) = \text{sign}(\mathbf{w}^{\mathsf{T}}\mathbf{x})$$

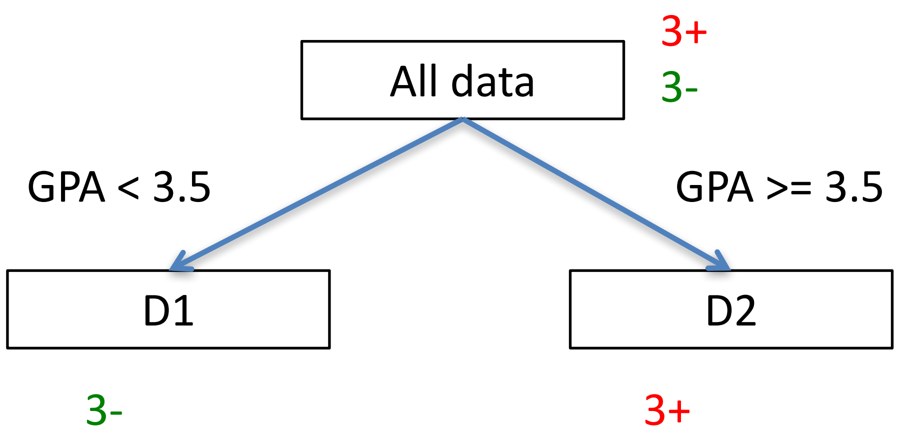
Learning

- Let us look at another way of classification.
- Decision Trees.

Decision Tree

- Toy example again

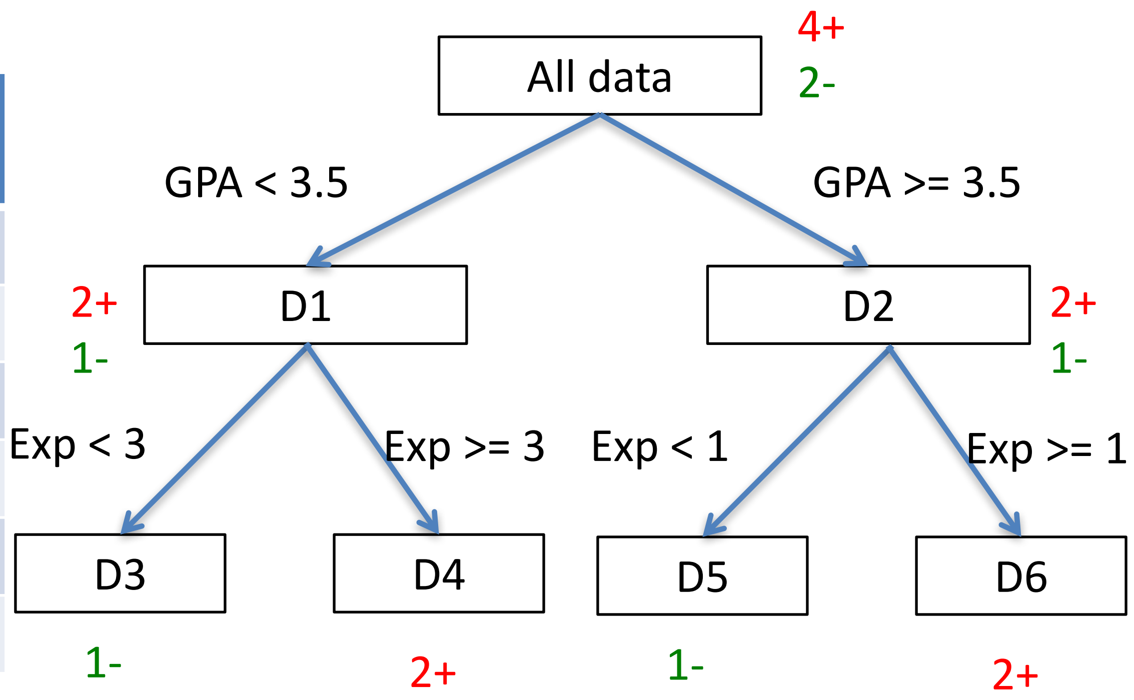
GPA	Internship
4.0	1
3.0	0
3.4	0
3.6	1
3.8	1
2.5	0



Decision Tree

- 2-D case

GPA	Years Exp	Internship
4.0	0	0
3.0	1	0
3.4	4	1
3.6	2	1
3.8	4	1
2.5	3	1



Decision Tree

- What can you infer?
- Think about decision trees as a way to learn classification function.
- Can also be thought of as rules:
  eg: X1 ^ X2 -> 0
  where x1 is boolean GPA<3.5
  and x2 is boolean exp<3
- OK…but which attribute should I choose to be at the top i.e. how do I choose attibutes??

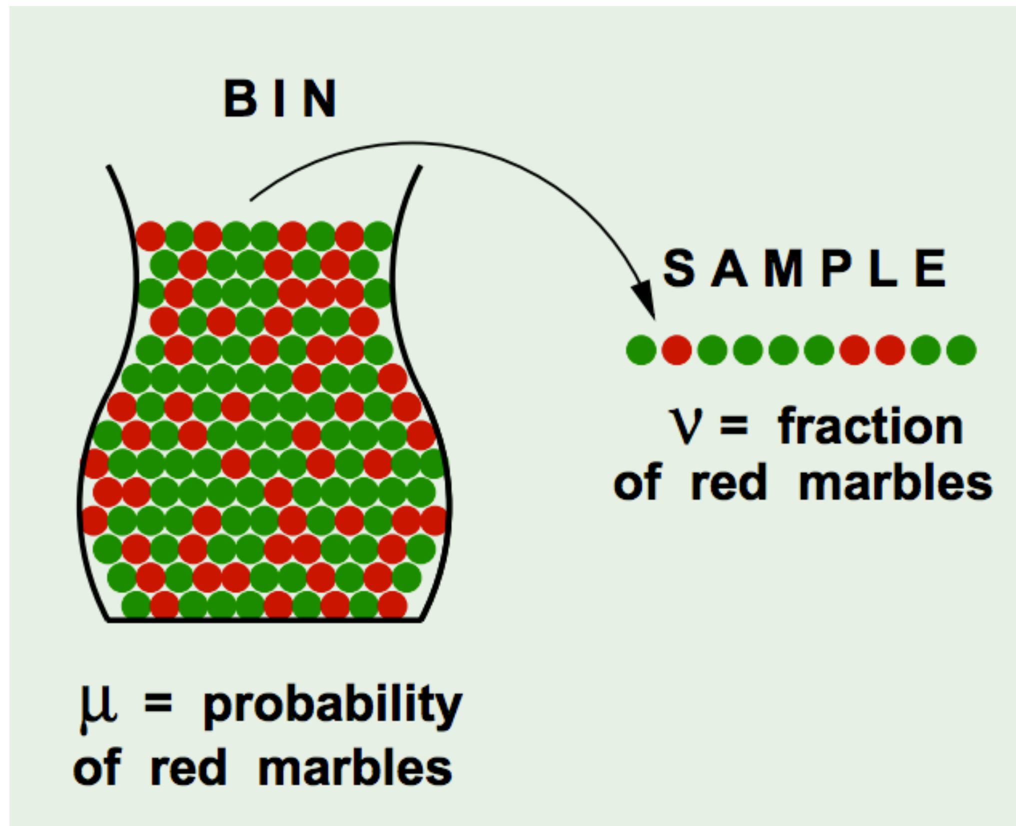
Sounds great, but …

- Can you make some guarantee about the the <u>unknown</u> data / parameters?

Let's do an experiment. You have a bin and want to estimate the probability of red marbles (μ).

You draw N samples and observe fraction of red marbles = ν

Is there any relation between μ, ν, and N?



Hoeffding's Inequality

- It turns out there is a relation:

$$\mathbb{P}\left[\,|\nu - \mu| > \epsilon\,\right] \le 2e^{-2\epsilon^2 N}$$

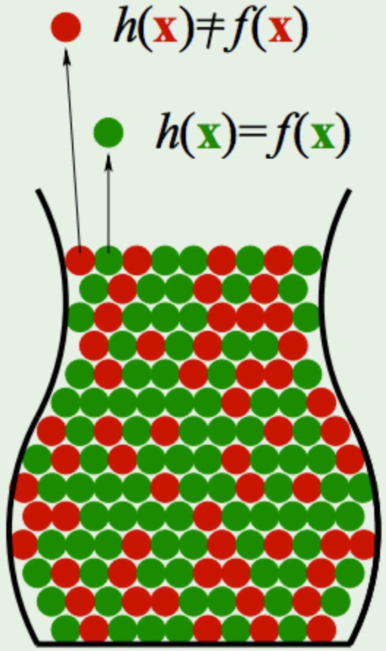
For large values of N, the probability of large error (difference) between ν and μ is bounded.

Think:
What happens when N becomes large, and when N is small?

Connection to learning

Bin: The unknown is a number μ

Learning: The unknown is a function $f : \mathcal{X} \to \mathcal{Y}$



Each marble ● is a point $\mathbf{x} \in \mathcal{X}$

- ● : Hypothesis got it right $h(\mathbf{x}) = f(\mathbf{x})$
- ● : Hypothesis got it wrong $h(\mathbf{x}) \neq f(\mathbf{x})$