Machine Learning

CS 486/686: Introduction to Artificial Intelligence

Outline

- Forms of Learning
- Inductive Learning
  - Decision Trees

What is Machine Learning

- Definition:
  - A computer program is said to **learn** from **experience** E with respect to some class of **tasks** T and **performance measures** P, if its performance at tasks in T, as measured by P, improves with experience E.

[T Mitchell, 1997]

Examples

- A checkers learning problem
  - T: playing checkers
  - P: percent of games won against an opponenet
  - E: playing practice games against itself
- Handwriting recognition
  - T: recognize and classify handwritten words within images
  - P: percent of words correctly classified
  - E: database of handwritten words with given classifications

Examples

- Autonomous driving:
  - T: driving on a public four-lane highway using vision sensors
  - P: average distance traveled before an error was made (as judged by human overseer)
  - E: sequence of images and steering commands recorded while observing a human driver

Types of Learning

- Supervised Learning
  - Learn a function from examples of its inputs and outputs
  - Example scenario:
    - Handwriting recognition
  - Techniques:
    - Decision trees
    - Support Vector Machines

Types of Learning

- Unsupervised learning
  - Learn patterns in the input when no specific output is given
  - Example scenario:
    - Cluster web log data to discover groups of similar access patterns
  - Techniques
    - Clustering

Type of Learning

- Reinforcement learning
  - Agents learn from feedback (rewards and punishments)
  - Example scenario:
    - Checker playing agent
  - Techniques:
    - TD learning
    - Q-learning

Representation

- Representation of learned information is important
  - Determines how the learning algorithm will work
- Common representations:
  - Linear weighted polynomials
  - Propositional logic
  - First order logic
  - Bayes nets
  - ...

Special case for neural nets

Today's lecture

Inductive Learning (aka concept learning)

- Given a **training set** of examples of the form (x,f(x))
  - x is the input, f(x) is the output
- Return a function h that approximates f
  - h is the **hypothesis**

attribute

Sky	AirTemp	Humidity	Wind	Water	Forecast	EnjoySport
Sunny	Warm	Normal	Strong	Warm	Same	Yes
Sunny	Warm	High	Strong	Warm	Same	Yes
Sunny	Warm	High	Strong	Warm	Change	No
Sunny	Warm	High	Strong	Cool	Change	Yes

x

f(x)

Inductive Learning

- We need a hypothesis representation for the problem
  - A reasonable candidate for our example is a conjunction of constraints
  - Vector of 6 constraints specifying the values of the 6 attributes
    - ? to denote that any value is acceptable
    - Specify a single required value (e.g. Warm)
    - 0 to specify that no value is acceptable
- If some instance satisfies all constraints of hypothesis h, then h classifies x as a positive example (h(x)=1)
- h=<?,Cold,High,?,?,?> represents a hypothesis that someone enjoys her favorite sport only on cold days with high humidity

Inductive Learning

- Most general hypothesis
  - <?,?,?,?,?,?> (every day is a positive example)
- Most specific hypothesis
  - <0,0,0,0,0,0> (no day is a positive example)
- **Hypothesis space,** H
  - Set of all possible hypothesis that the learner may consider regarding the target concept
- Can think of learning as a space through a hypothesis space

Inductive Learning

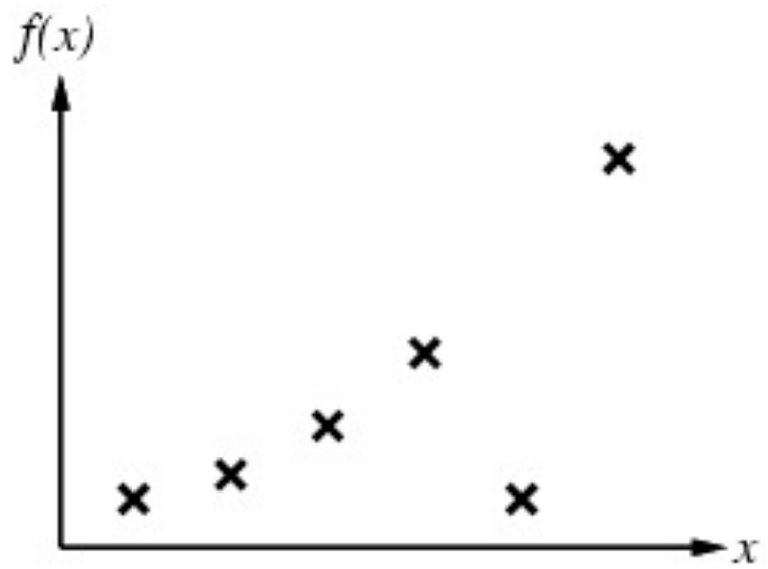
- Our goal is to find a good hypothesis
- What does this mean?
  - It is as close to the real function f as possible
    - This is hard to determine since all we have is input and output
- A good hypothesis will generalize well
  - Predict unseen examples correctly

Inductive Learning Hypothesis

- Any hypothesis found to approximate the target function well ***over a sufficiently large set of training examples*** will also approximate the target function well over any unobserved examples

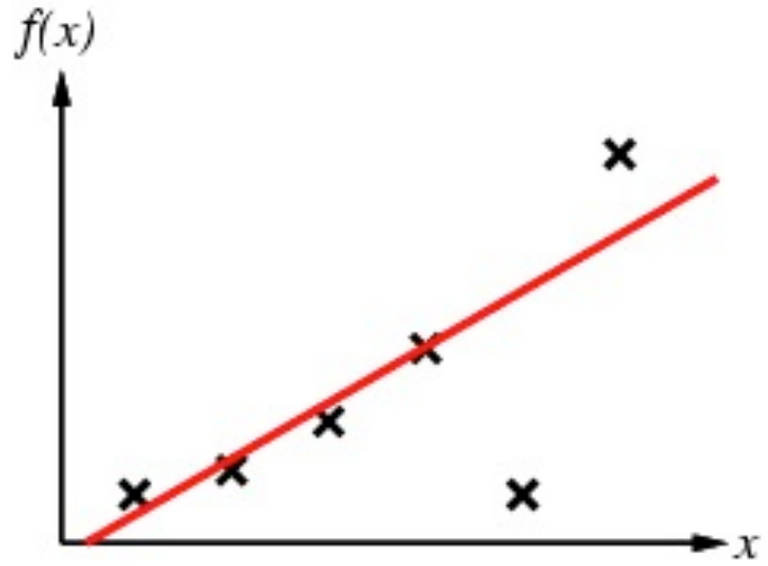
Inductive Learning

- Construct/adjust h to agree with f on training set
  - h is **consistent** if it agrees with f on all examples
  - e.g. curve fitting



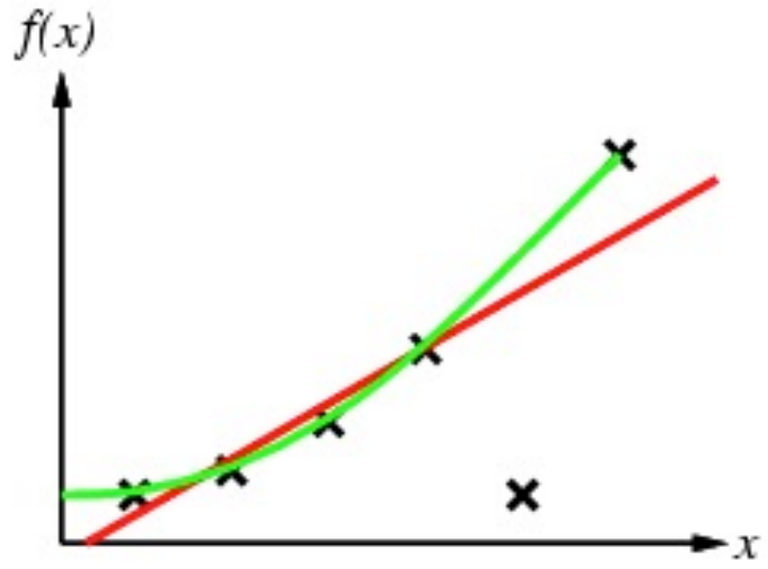
Inductive Learning

- Construct/adjust h to agree with f on training set
  - h is **consistent** if it agrees with f on all examples
  - e.g. curve fitting



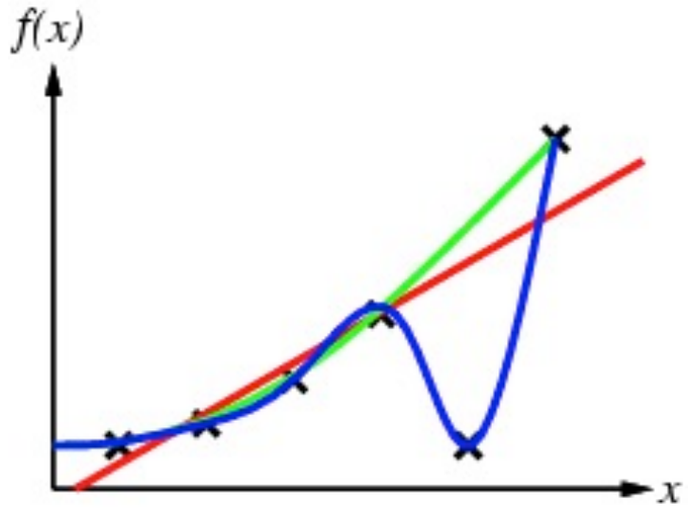
Inductive Learning

- Construct/adjust h to agree with f on training set
  - h is **consistent** if it agrees with f on all examples
  - e.g. curve fitting



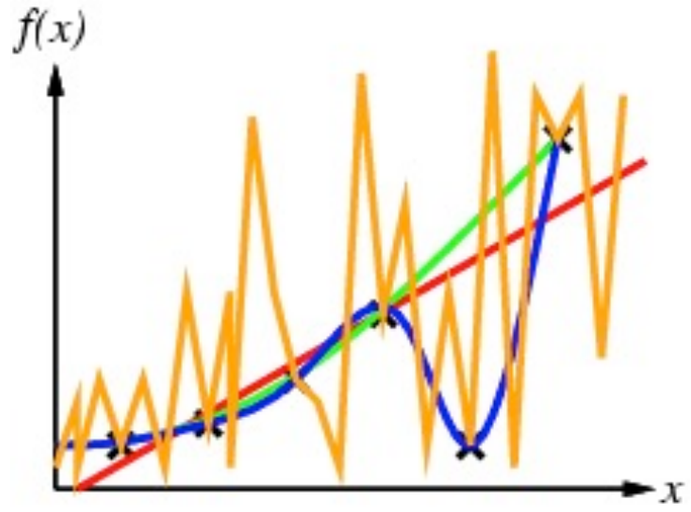
Inductive Learning

- Construct/adjust h to agree with f on training set
  - h is **consistent** if it agrees with f on all examples
  - e.g. curve fitting



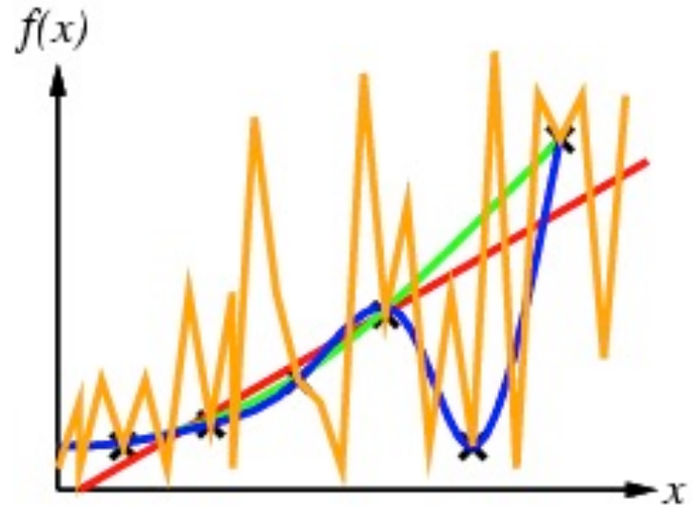
Inductive Learning

- Construct/adjust h to agree with f on training set
  - h is **consistent** if it agrees with f on all examples
  - e.g. curve fitting



Inductive Learning

- Construct/adjust h to agree with f on training set
  - h is **consistent** if it agrees with f on all examples
  - e.g. curve fitting



Ockham's Razor: Prefer the simplest hypothesis consistent with the data

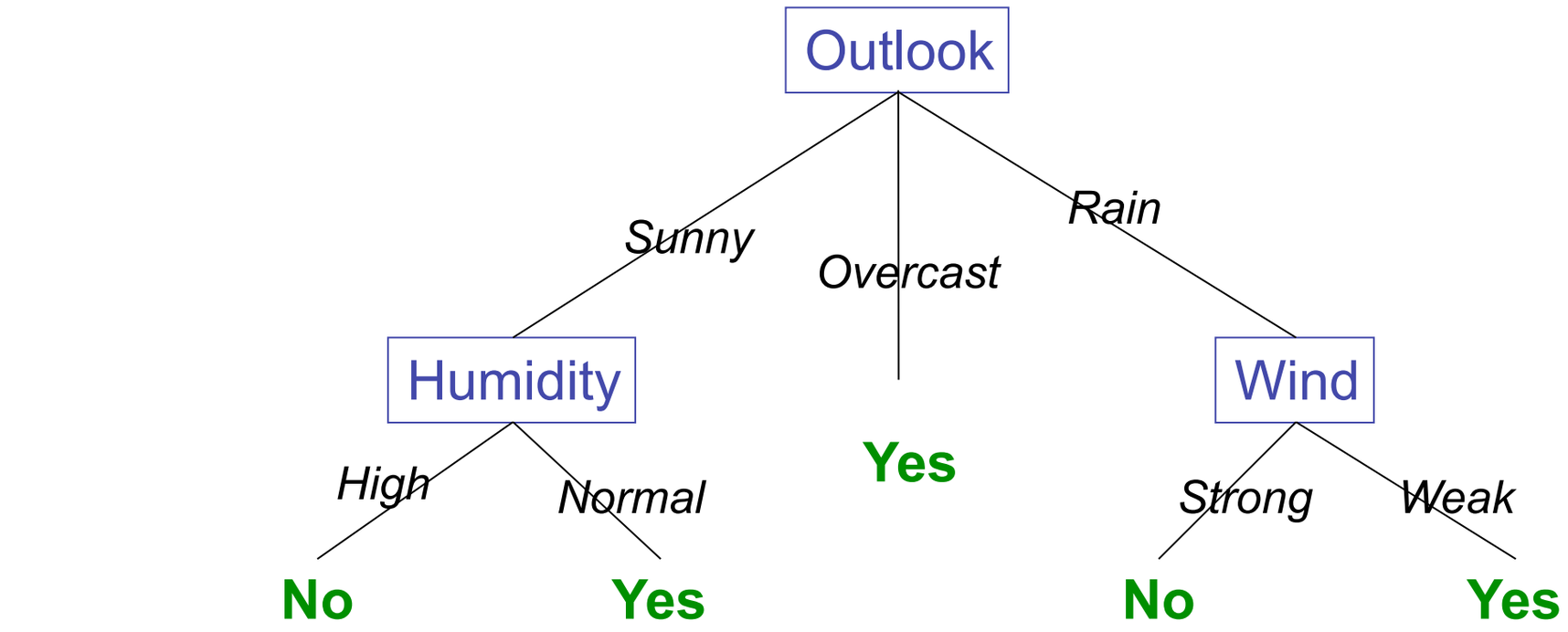
Inductive Learning

- Possibility of finding a single consistent hypothesis depends on the hypothesis space
  - **Realizable**: hypothesis space contains the true function
- Can use large hypothesis space (e.g. space of all Turing machines)
  - Tradeoff between expressiveness and complexity of finding a simple consistent hypothesis

Decision Tree

- Decision trees classify instances by sorting them down the tree from root to leaf
  - Nodes correspond with a test of some attribute
  - Each branch corresponds to some value an attribute can take
- Classification algorithm
  - Start at root, test attribute specified by root
  - Move down the branch corresponding to value of the attribute
  - Continue until you reach leaf (classification)

Decision Tree



An instance

<Outlook=Sunny, Temp=Hot, Humidity=High, Wind=Strong>

Classification: No

Note: Decision trees represent disjunctions of conjunctions of constraints on attribute values

Decision-Tree Representation

- Decision trees are fully expressive within the class of propositional languages
- Any Boolean function can be written as a decision tree
  - Trivially by allowing each row in a truth table correspond with a path in the tree
  - Often can use smaller trees to represent the function
  - Some functions require an exponential sized tree (majority function, parity function)
- No representation is efficient for all functions

Inducing a Decision Tree

- **Aim**: Find a small tree consistent with the training examples
- **Idea**: (recursively) choose "most significant" attribute as root of (sub)tree

function DTL(*examples, attributes, default*) **returns** a decision tree

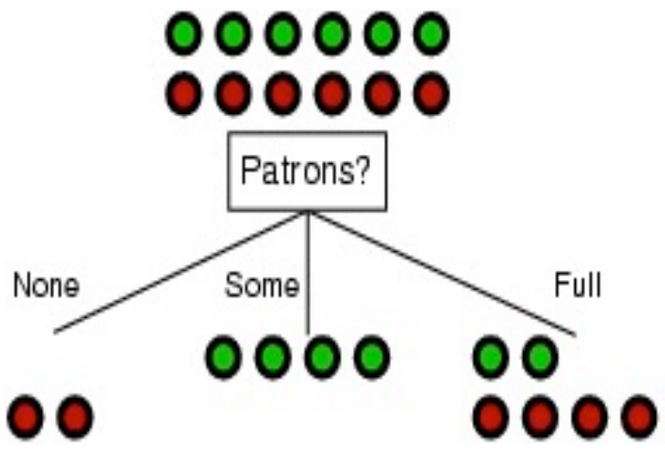
  if *examples* is empty **then return** *default*
  else if all *examples* have the same classification **then return** the classification
  else if *attributes* is empty **then return** MODE(*examples*)
  else
    $best \leftarrow$ CHOOSE-ATTRIBUTE(*attributes, examples*)
    $tree \leftarrow$ a new decision tree with root test *best*
    for each value v_i of *best* **do**
      $examples_i \leftarrow$ {elements of *examples* with $best = v_i$}
      $subtree \leftarrow$ DTL($examples_i, attributes - best,$ MODE(*examples*))
      add a branch to *tree* with label v_i and subtree *subtree*
    return *tree*

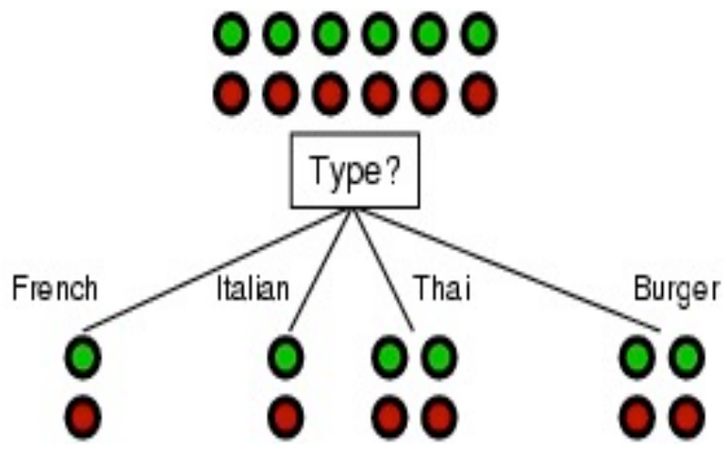
Example: Restaurant

Example	Attributes										Target
	Alt	*Bar*	*Fri*	*Hun*	*Pat*	*Price*	*Rain*	*Res*	*Type*	*Est*	*Wait*
X_1	T	F	F	T	Some	$$$	F	T	French	0–10	T
X_2	T	F	F	T	Full	$	F	F	Thai	30–60	F
X_3	F	T	F	F	Some	$	F	F	Burger	0–10	T
X_4	T	F	T	T	Full	$	F	F	Thai	10–30	T
X_5	T	F	T	F	Full	$$$	F	T	French	>60	F
X_6	F	T	F	T	Some	$$	T	T	Italian	0–10	T
X_7	F	T	F	F	None	$	T	F	Burger	0–10	F
X_8	F	F	F	T	Some	$$	T	T	Thai	0–10	T
X_9	F	T	T	F	Full	$	T	F	Burger	>60	F
X_{10}	T	T	T	T	Full	$$$	F	T	Italian	10–30	F
X_{11}	F	F	F	F	None	$	F	F	Thai	0–10	F
X_{12}	T	T	T	T	Full	$	F	F	Burger	30–60	T

Choosing an Attribute

- A good attribute splits the examples into subsets that are (ideally) “all positive” or “all negative”





Using Information Theory

- Information content (Entropy):

$$I(P(v_1),\ldots,P(v_2))=\sum -P(v_i)\log_2 P(v_i)$$

- For a training set containing p positive examples and n negative examples

$$I(\frac{p}{p+n},\frac{n}{p+n}) = -\frac{p}{p+n}\log_2\frac{p}{p+n} - \frac{n}{p+n}\log_2\frac{n}{p+n}$$

Information Gain

- Chosen attribute A divides the training set E into subsets $E_1,...,E_v$ according to their values for A, where A has v distinct values

$$remainder(A) = \sum_{i=1}^{v} \frac{p_i + n_i}{p + n} I(\frac{p_i}{p_i + n_i}, \frac{n_i}{p_i + n_i})$$

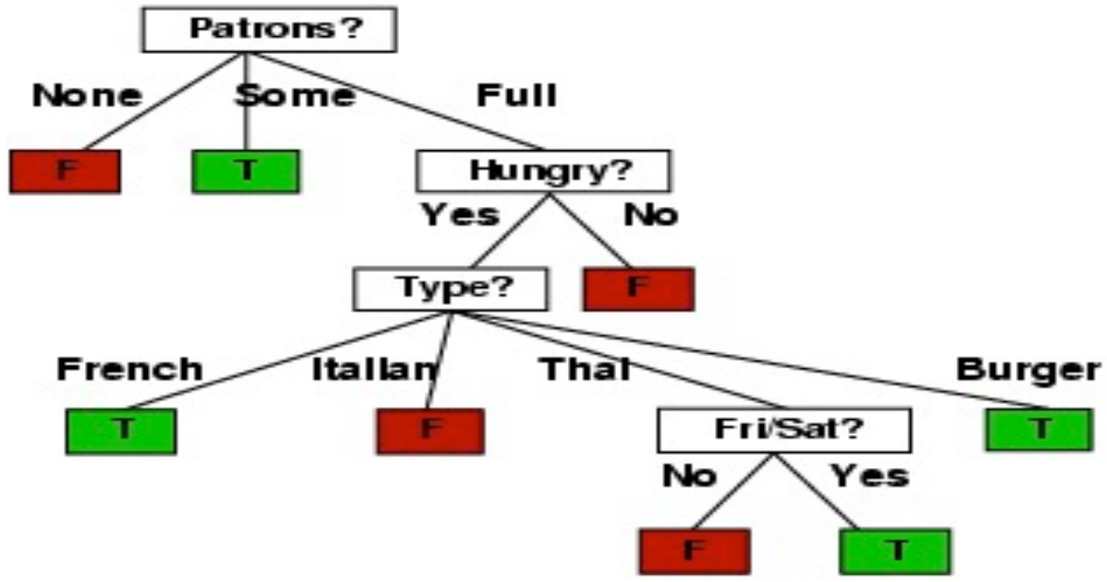
- Information Gain (IG) or reduction in entropy from the attribute test:

$$IG(A) = I(\frac{p}{p + n}, \frac{n}{p + n}) - remainder(A)$$

Information Gain Example

Decision Tree Example

- Decision tree learned from 12 examples



- Substantially simpler than “true” tree
  - A more complex hypothesis isn’t justified by the small amount of data

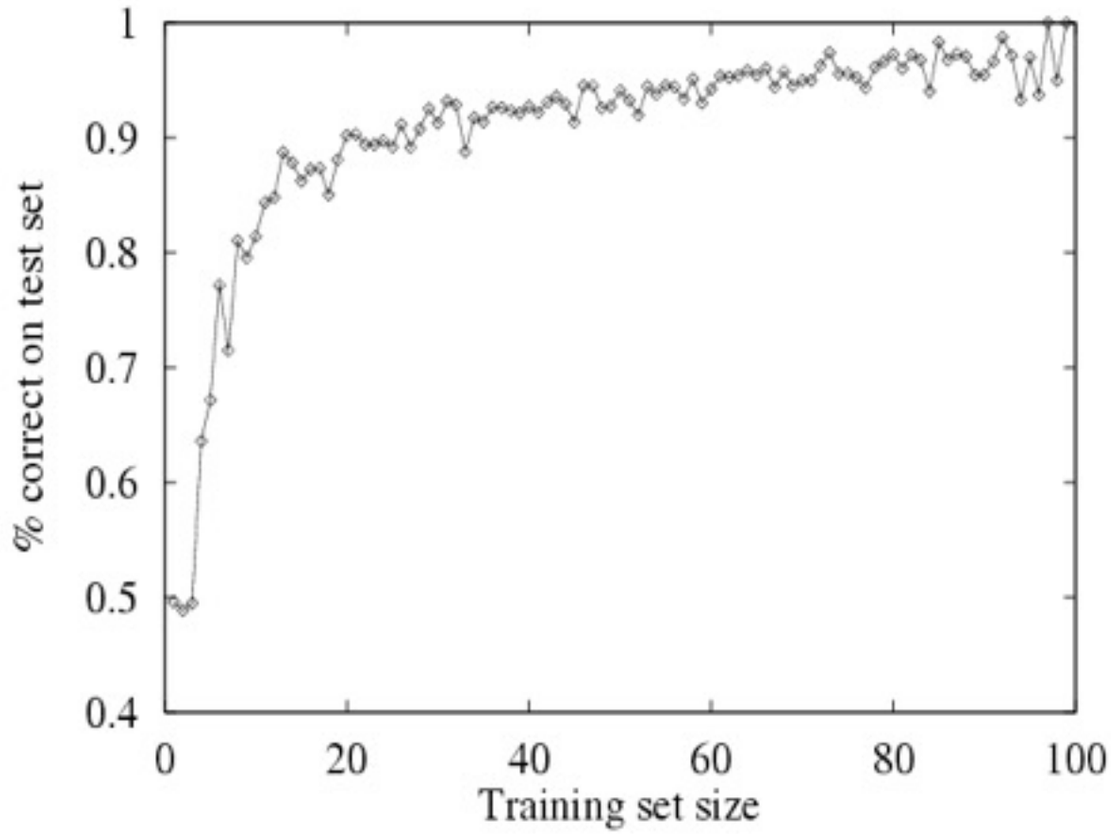
Assessing Performance of a Learning Algorithm

- A learning algorithm is good if it produces a hypothesis that does a good job of predicting classifications of unseen examples
- There are theoretical guarantees (learning theory)
- Can also test this

Assessing Performance of a Learning Algorithm

- Test set
  - Collect a large set of examples
  - Divide them into 2 disjoint sets: training set and test set
  - Apply learning algorithm to the training set to get h
  - Measure percentage of examples in the test set that are correctly classified by h
  - Repeat for different sizes of training sets and different randomly selected test sets for each size

Learning Curves



As the training set grows, accuracy increases

No Peeking at the Test Set!

- A learning algorithm should not be allowed to see the test set data before the hypothesis is tested on it
  - ***No Peeking!!***
- Every time you want to compare performance of a hypothesis on a test set ***you should use a new test set***!

Overfitting

- Decision tree algorithm grows each branch of the tree just deep enough to perfectly classify the training examples
- Sometimes a good idea
- Sometimes a bad idea
  - Noise in the data
  - Training set too small to get a representative sample of the true target function
- Overfitting
  - Problem with all learning algorithms

Overfitting

- Given a hypothesis space H, a hypothesis h in H is said to overfit the training data if there exists some alternative hypothesis h' in H such that h has smaller error than h' on the training examples, but h' has smaller error than h over the entire distribution of instances
  - h in H overfits if there exists h' in H such that $error_{Tr}(h) < error_{Tr}(h')$ but $error_{Te}(h') < error_{Te}(h)$

- Overfitting has been found to decrease accuracy of decision trees by 10-25%

Avoiding Overfitting

- Pruning
  - Assume there is no pattern in the data (null hypothesis)
    - Attribute is irrelevant and so info gain would be 0 for an infinitely large sample
    - Compute probability that (under null hypothesis) a sample size v would exhibit observed deviation

$$\hat{p}_i = p\frac{p_i + n_i}{p + n} \qquad \hat{n}_i = n\frac{p_i + n_i}{p + n}$$

$$D = \sum_{i=1}^{v} \frac{(p_i - \hat{p}_i)^2}{\hat{p}_i} + \frac{(n_i - \hat{n}_i)^2}{\hat{n}_i}$$

$$\text{compare to } \chi^2 \text{ table}$$

Cross Validation

- Split the training set into two parts, one for training and one for choosing the hypothesis with highest accuracy
  - K-fold cross validation means you run k experiments, each time putting aside 1/k of the data to test on
  - Leave-one-out cross validation

Summary

- Types of machine learning
- Supervised Learning
  - Decision Trees
- Overfitting
- Cross Validation