CSE 473

Chapter 18
Machine Learning: Decision Trees

Why Learning?

- Learning is essential for unknown environments
  e.g., when designer lacks omniscience
- Learning is necessary in dynamic environments
  Agent can adapt to changes in environment not foreseen at design time
- Learning is useful as a system construction method
  Expose the agent to reality rather than trying to approximate it through equations etc.
- Learning modifies the agent's decision mechanisms to improve performance

Types of Learning

- Supervised learning: correct answers for each input is provided
  E.g., decision trees, backprop neural networks
- Unsupervised learning: correct answers not given, must discover patterns in input data
  E.g., clustering, principal component analysis
- Reinforcement learning: occasional rewards (or punishments) given
  E.g., Q learning, MDPs

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Inductive learning

A form of Supervised Learning:
Learn a function from examples

f is the target function. Examples are pairs (x, $f(x)$)

Problem: learn a function ("hypothesis") h
such that $h \approx f$ (h approximates f as best as possible)
given a training set of examples

(This is a highly simplified model of real learning:
Ignores prior knowledge
Assumes examples are given)

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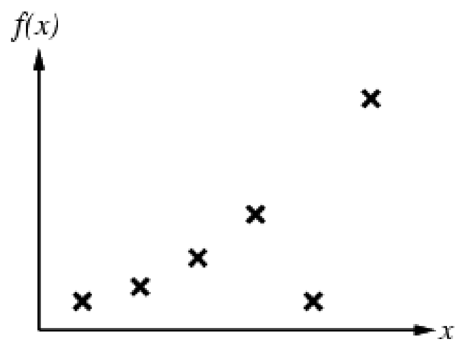
Inductive learning example

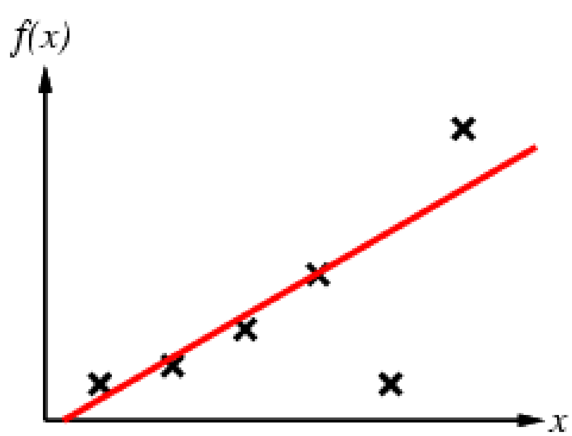
- Construct *h* to agree with *f* on training set
  h is consistent if it agrees with *f* on all training examples
- E.g., curve fitting (regression):



× = Input data point (a training example)

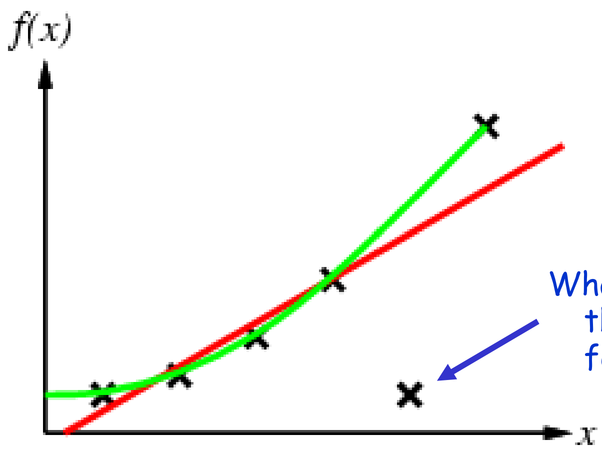
Inductive learning example

h = Straight line?



Inductive learning example

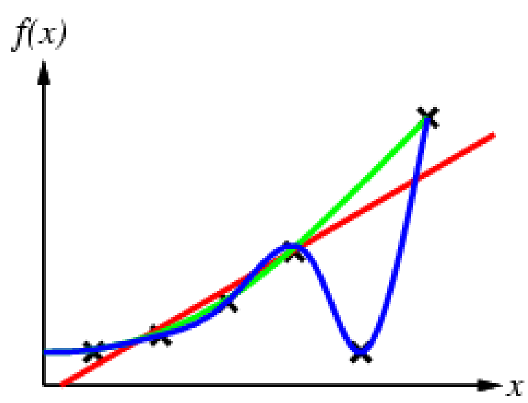
What about a quadratic function?



What about
this little
fella?

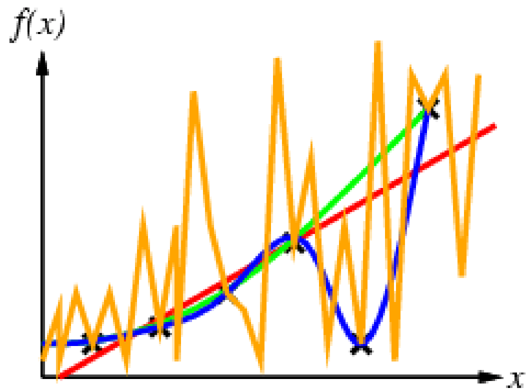
Inductive learning example

Finally, a function that satisfies all!

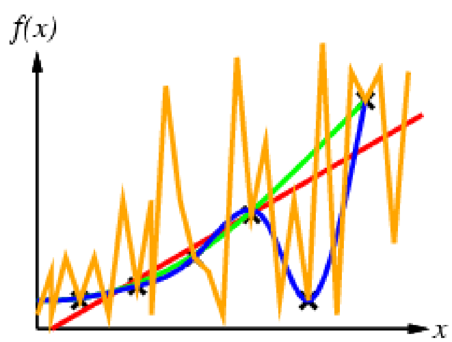


Inductive learning example

But so does this one…



Ockham's razor principle



- Ockham's razor: prefer the simplest hypothesis consistent with data
  - Related to KISS principle ("keep it simple stupid")
  - Smooth blue function preferable over wiggly yellow one
  - If noise known to exist in this data, even linear might be better (the lowest x might be due to noise)

Example data for learning the concept "Good day for tennis"

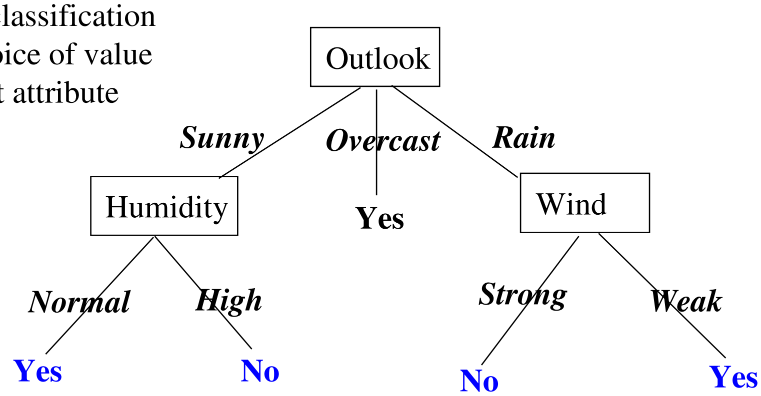
Day	Outlook	Humid	Wind	**PlayTennis?**
d1	s	h	w	n
d2	s	h	s	n
d3	o	h	w	y
d4	r	h	w	y
d5	r	n	w	y
d6	r	n	s	y
d7	o	n	s	y
d8	s	h	w	n
d9	s	n	w	y
d10	r	n	w	y
d11	s	n	s	y
d12	o	h	s	y
d13	o	n	w	y
d14	r	h	s	n

- Outlook = sunny, overcast, rain
- Humidity = high, normal
- Wind = weak, strong

A Decision Tree for the Same Data

PlayTennis?

Leaves = classification
Arcs = choice of value for parent attribute



Decision tree is equivalent to logic in disjunctive normal form

PlayTennis $\Leftrightarrow$ (Sunny $\wedge$ Normal) $\vee$ Overcast $\vee$ (Rain $\wedge$ Weak)

Decision Trees

Input: Description of an object or a situation through a set of **attributes**

Output: a **decision** that is the predicted output value for the input

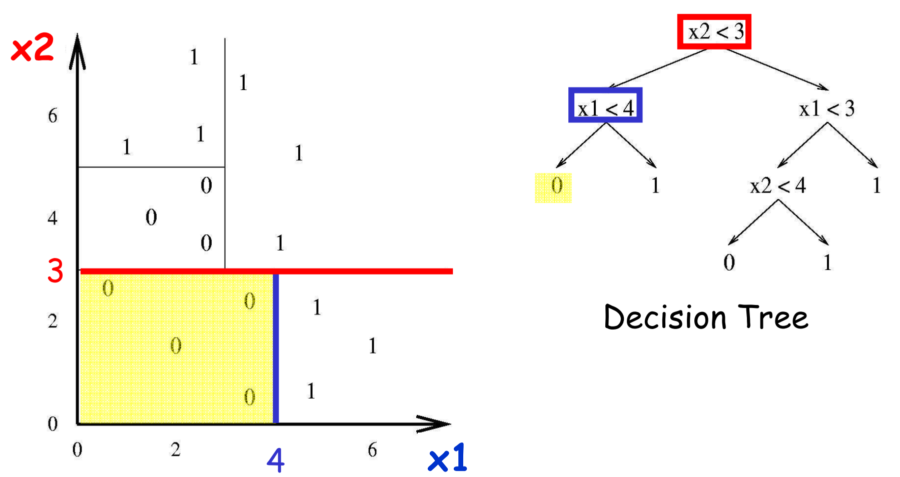
Both **input and output can be discrete or continuous**

Discrete-valued functions lead to **classification problems**

Learning a **continuous function** is called **regression**

Example: Classification of Continuous Valued Inputs

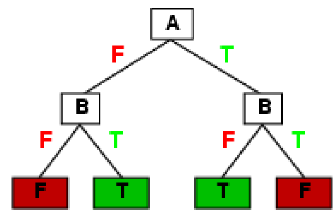
Decision trees divide the feature space into axis-parallel rectangles, and label each rectangle with one of the K classes.



Expressiveness

- Decision trees can express any function of the input attributes.
- E.g., for Boolean functions, truth table row → path to leaf:

A	B	A xor B
F	F	F
F	T	T
T	F	T
T	T	F



- Trivially, there is a consistent decision tree for any training set with one path to leaf for each example

  But most likely won't generalize to new examples

- Prefer to find more compact decision trees

Learning Decision Trees

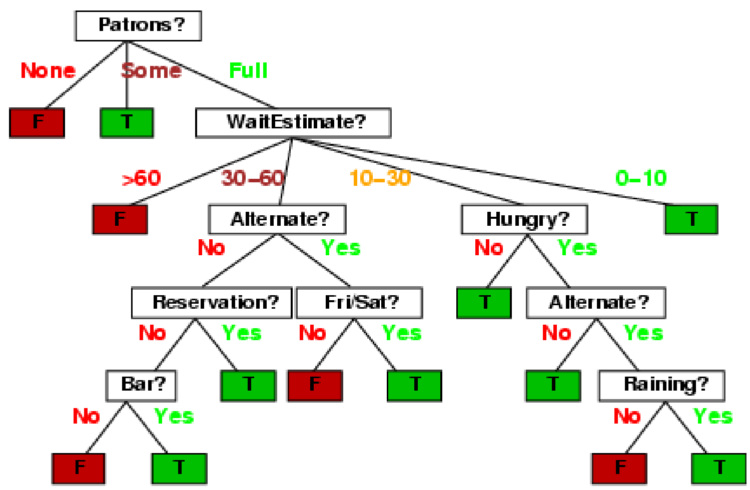
Example: When should I wait for a table at a restaurant?

Attributes (features) relevant to *Wait?* decision:

1. Alternate: is there an alternative restaurant nearby?
2. Bar: is there a comfortable bar area to wait in?
3. Fri/Sat: is today Friday or Saturday?
4. Hungry: are we hungry?
5. Patrons: number of people in the restaurant (None, Some, Full)
6. Price: price range ($, $$, $$$)
7. Raining: is it raining outside?
8. Reservation: have we made a reservation?
9. Type: kind of restaurant (French, Italian, Thai, Burger)
10. WaitEstimate: estimated waiting time (0-10, 10-30, 30-60, >60)

Example Decision tree

A decision tree for *Wait?* based on personal "rules of thumb":



Input Data for Learning

- Past examples where I did/did not wait for a table:

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

- Classification of examples is positive (T) or negative (F)

Decision Tree Learning

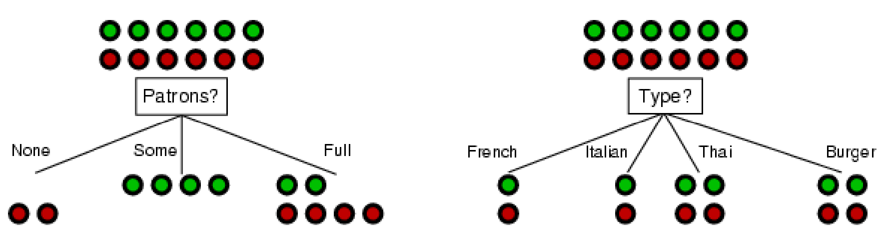
- Aim: find a small tree consistent with training examples
- Idea: (recursively) choose "most significant" attribute as root of (sub)tree

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 ← CHOOSE-ATTRIBUTE(*attributes*, *examples*)
    tree ← a new decision tree with root test *best*
    for each value v_i of *best* **do**
      $examples_i$ ← {elements of *examples* with *best* $= v_i$}
      subtree ← DTL($examples_i$, *attributes* − *best*, MODE(*examples*))
      add a branch to *tree* with label v_i and subtree *subtree*
    return *tree*

Choosing an attribute to split on

- Idea: a good attribute splits the examples into subsets that are (ideally) "all positive" or "all negative"



- *Patrons?* is a better choice

Next Time

- How to choose attributes to split on?
  - Using information theory and entropy
- The more, the merrier (and better) – combining classifiers
  - Ensemble learning via boosting