Introduction to Artificial Intelligence

Learning from Oberservations

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Outline

- Learning agents
- Inductive learning
- Decision tree learning

Learning

Reasons for learning

- **Learning is essential for unknown environments,**

  – when designer lacks omniscience –

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- **Learning is essential for unknown environments,**

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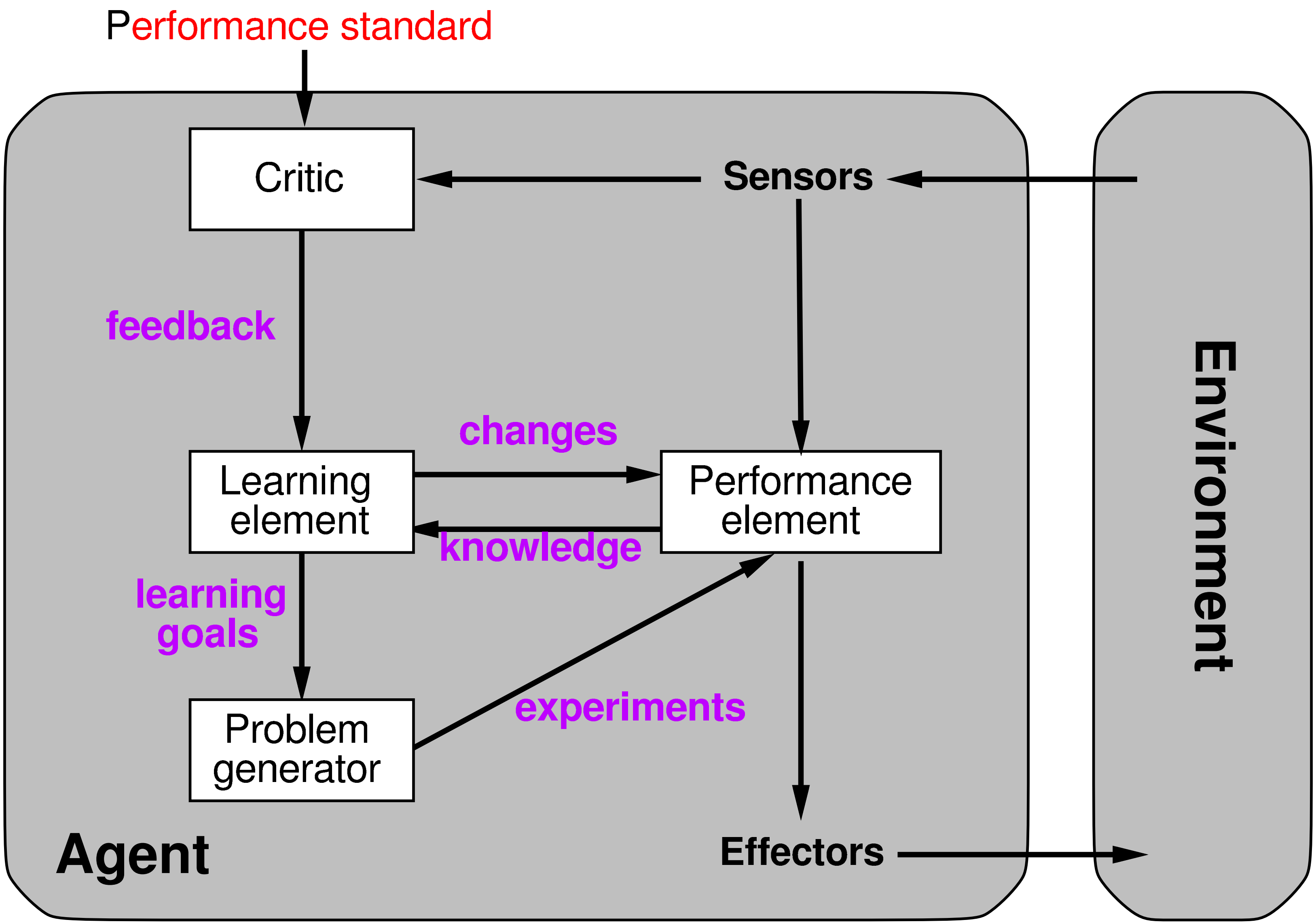
- **Learning is useful as a system construction method,**

  – expose the agent to reality rather than trying to write it down –

- **Learning modifies the agent's decision mechanisms to improve performance**

Learning Agents



Learning Element

Design of learning element is dictated by

- what type of performance element is used
- which functional component is to be learned
- how that functional component is represented
- what kind of feedback is available

Types of Learning

Supervised learning

Correct answers for each example instance known

Requires “teacher”

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Reinforcement learning

Occasional rewards

Learning is harder

Requires no teacher

Inductive Learning (a.k.a. Science)

Simplest form

**Learn a function f from examples (tabula rasa), i.e.,
find an hypothesis h such that $h \approx f$ given a training set of examples**

f is the target function

An example is a pair $x, f(x)$

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Example (for an example)

$$\begin{array}{c|c|c} O & O & X \\ \hline & X & \\ \hline X & & \end{array} \quad , \quad +1$$

Inductive Learning Method

This is a highly simplified model of real learning

- **Ignores prior knowledge**
- **Assumes a deterministic, observable environment**
- **Assumes examples are given**
- **Assumes that the agent wants to learn f (why?)**

Inductive Learning Method

Idea

Construct/adjust h to agree with f on training set

h is consistent if it agrees with f on all examples

Example: Curve fitting

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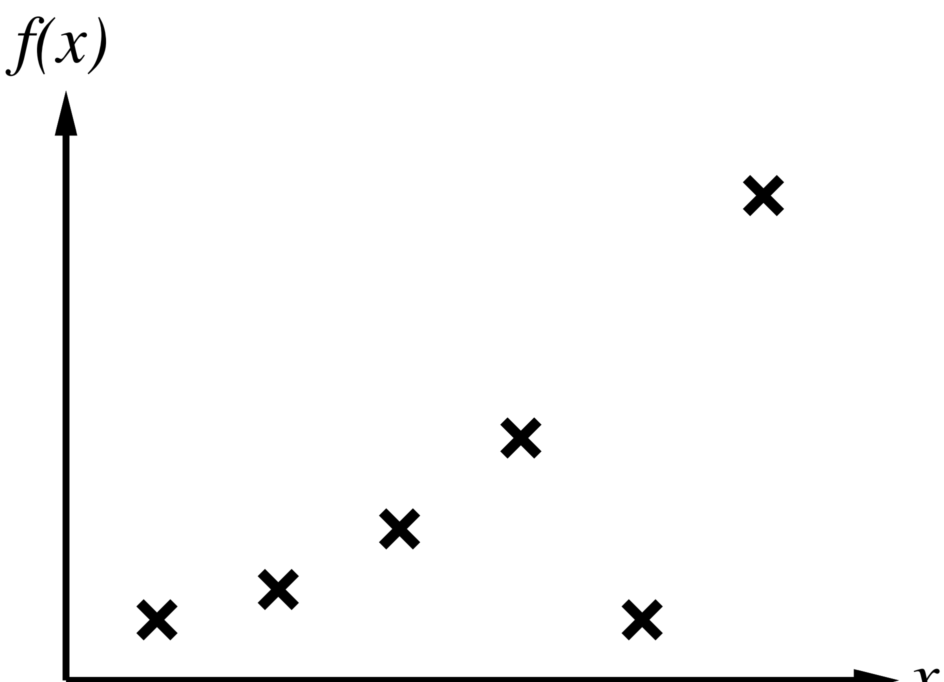

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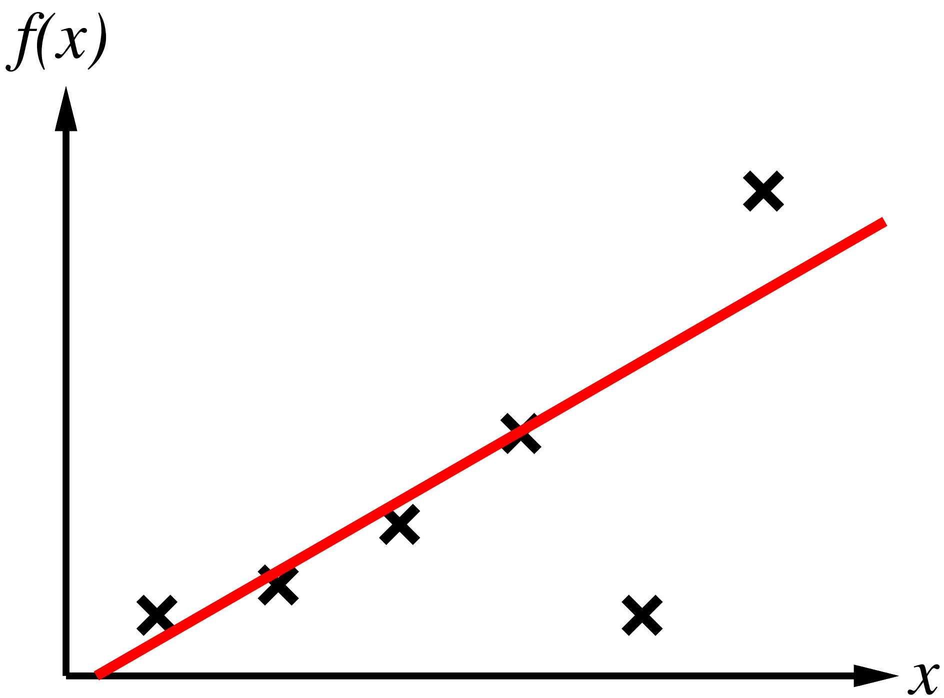

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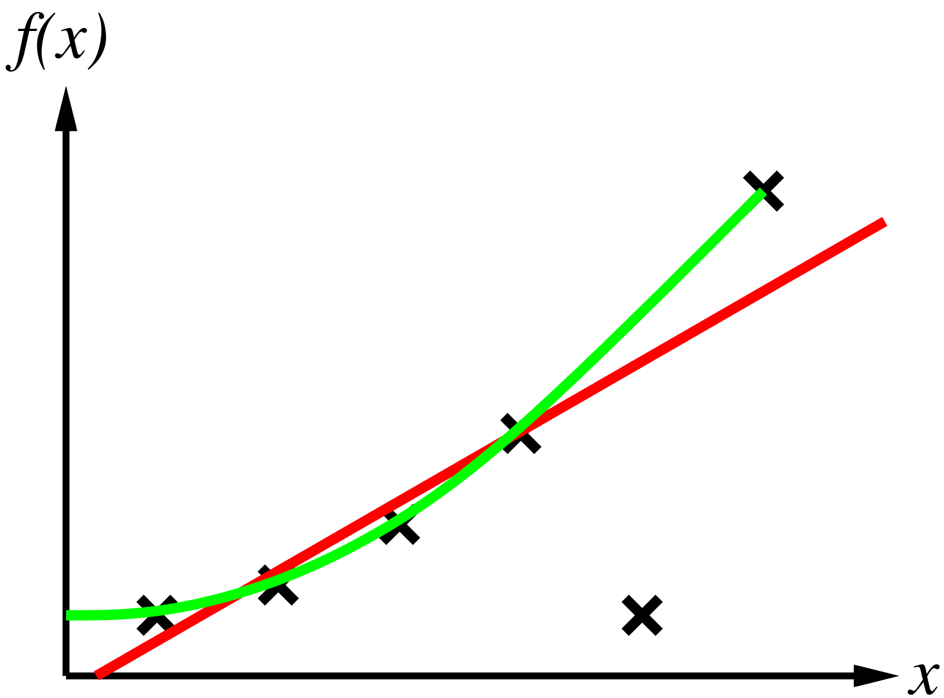

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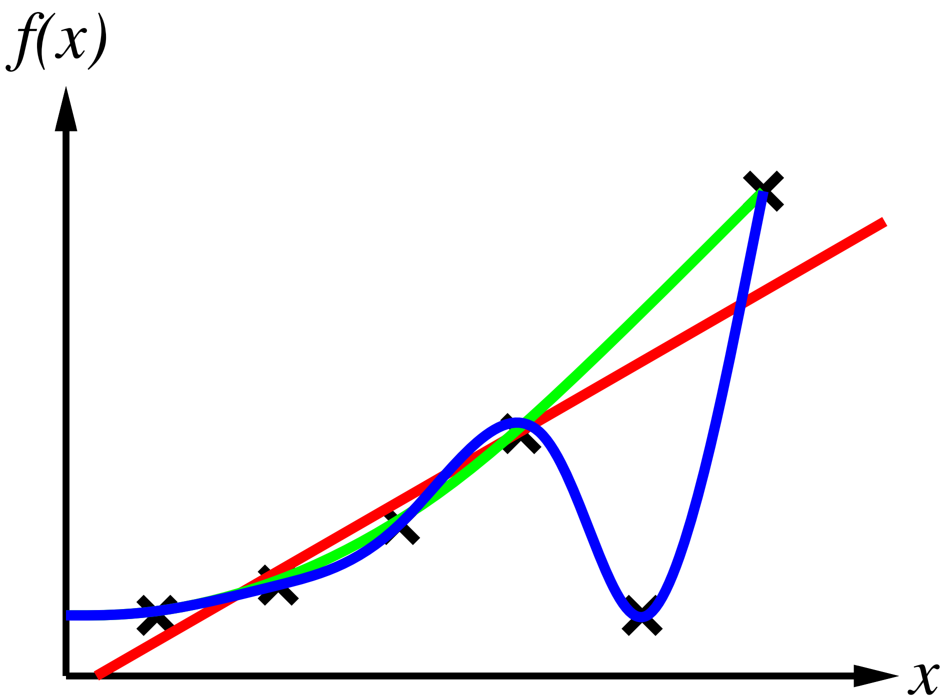

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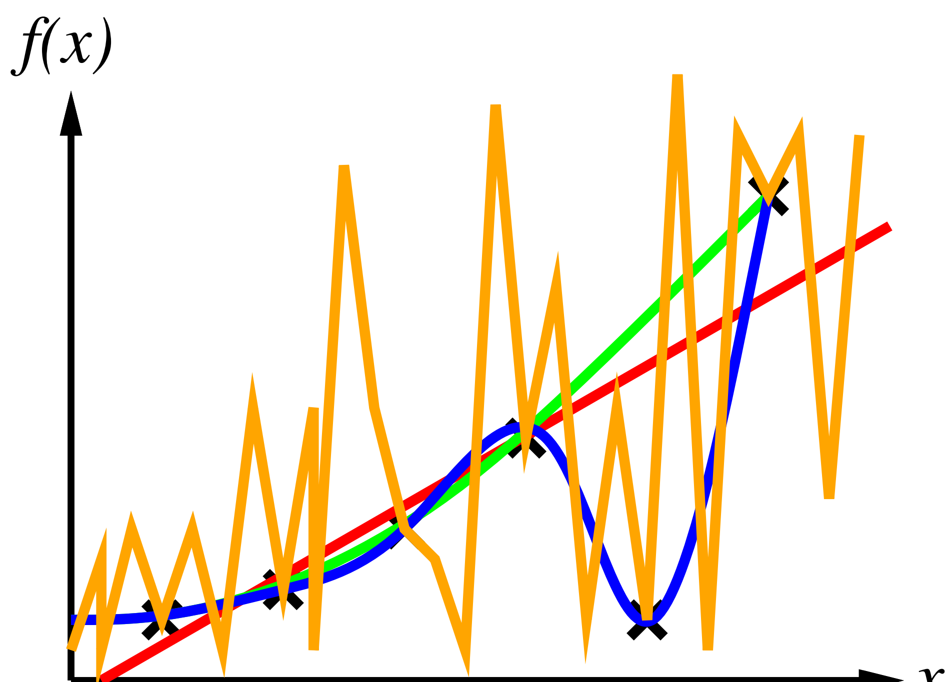

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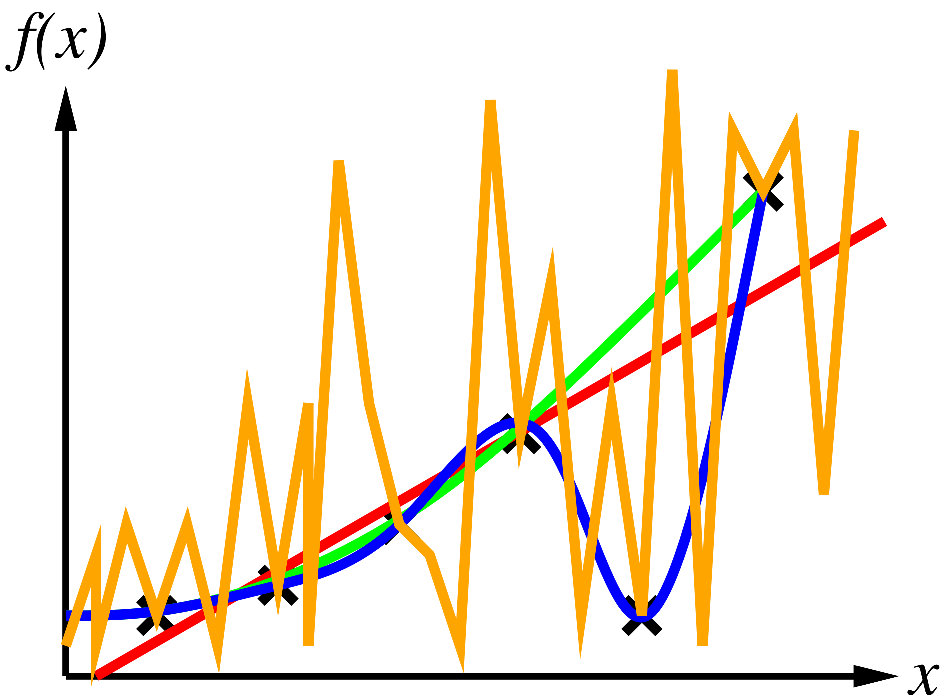


Ockham's razor

Maximize a combination of consistency and simplicity

Attribute-based Representations

Example description consists of

- **Attribute values (boolean, discrete, continuous, etc.)**
- **Target value**

Attribute-based Representations

Example

Situations where I will/won't wait for a table in a restaurant

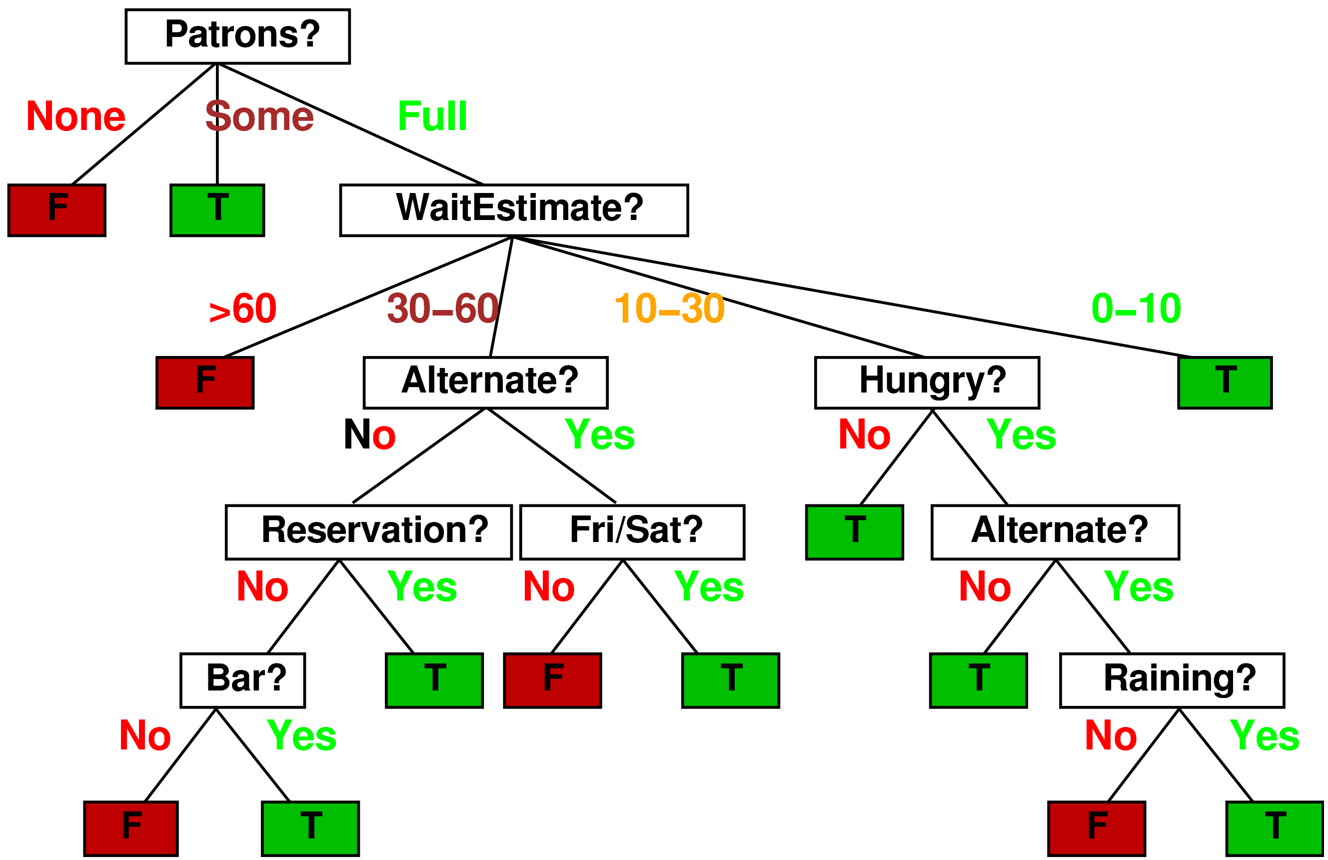
Exmpl.	Attributes										Target
	Alt	*Bar*	*Fri*	*Hun*	*Pat*	*Price*	*Rain*	*Res*	*Type*	*Est*	WillWait
X_1	T	F	F	T	Some	$$$	F	T	French	0–10	T
X_2	T	F	F	T	Full	$	F	F	Thai	30–60	F
X_3	F	T	F	F	Some	$	F	F	Burger	0–10	T
X_4	T	F	T	T	Full	$	F	F	Thai	10–30	T
X_5	T	F	T	F	Full	$$$	F	T	French	$>$60	F
X_6	F	T	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

Decision Trees

A possible representation for hypotheses

Example

The “correct” tree for deciding whether to wait



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Properties

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- Decision tree for training examples probably won't generalize to new examples
- Compact decision trees are preferable
- More expressive hypothesis space
  - increases chance that target function can be expressed
  - increases number of hypotheses consistent with training set

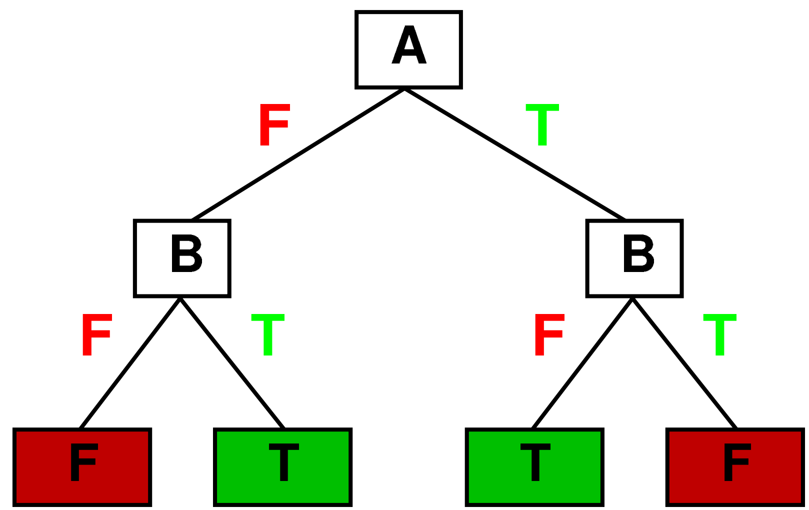
    $\Rightarrow$ may get worse predictions

Decision Trees

Example

For Boolean functions: truth-table row = path to leaf in decision tree

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



Hypothesis Spaces

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= 2^{2^n}

Example

With 6 Boolean attributes, there are

$18{,}446{,}744{,}073{,}709{,}551{,}616$ **trees**

Decision Tree Learning

Aim

Find a small tree consistent with the training examples

Idea

(Recursively) choose "most significant" attribute as root of (sub)tree

Choosing an Attribute

Idea

A good attribute splits the examples into subsets that are (ideally) "all positive" or "all negative", i.e.,

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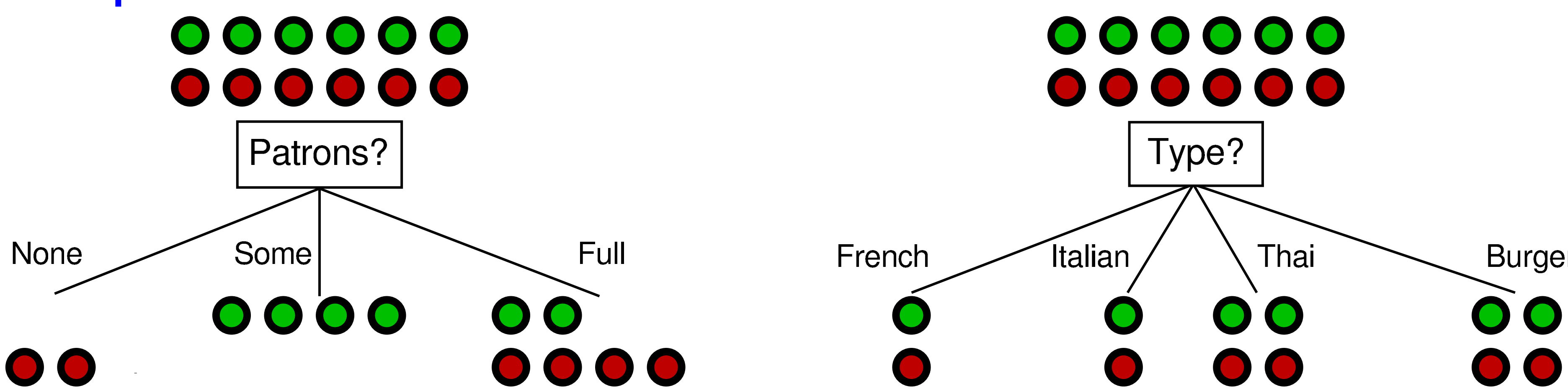


Patrons **is a better choice**

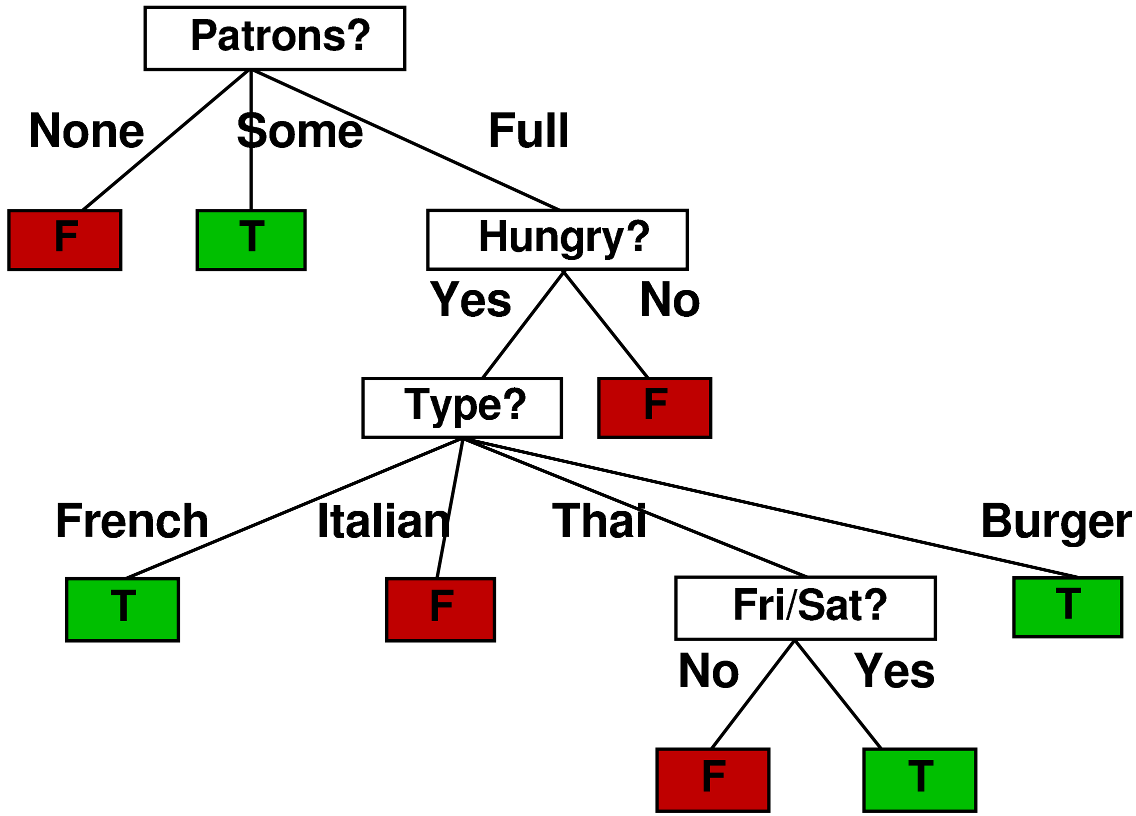
Decision Tree Learning: Algorithm

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** MAJORITY-VALUE(*examples*)
    else
        best $\leftarrow$ CHOOSE-ATTRIBUTE(*attributes*,*examples*)
        tree $\leftarrow$ a new decision tree with root test *best*
        m $\leftarrow$ MAJORITY-VALUE(*examples*)
        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*,*m*)
            add a branch to *tree* with label v_i and subtree *subtree*
        return *tree*

Example

Decision tree learned from the 12 examples



Substantially simpler than “true” tree

A more complex hypothesis isn’t justified by small amount of data

Performance Measurement

Hume's *Problem of Induction*

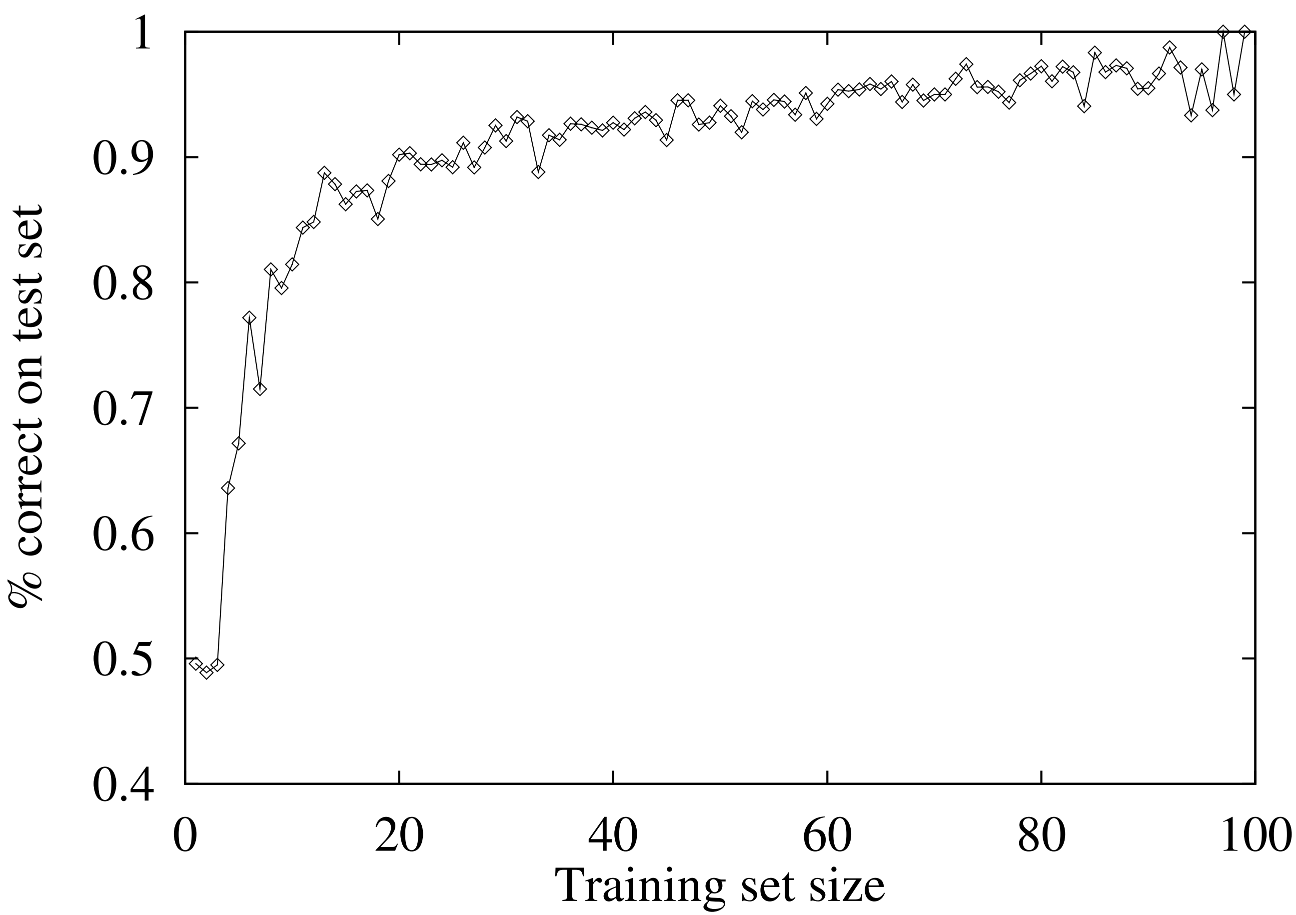
How do we know that $h \approx f$?

- **Use theorems of computational/statistical learning theory**
- **Try h on a new test set of examples**
  (use same distribution over example space as training set)

Performance Measurement

Learning curve

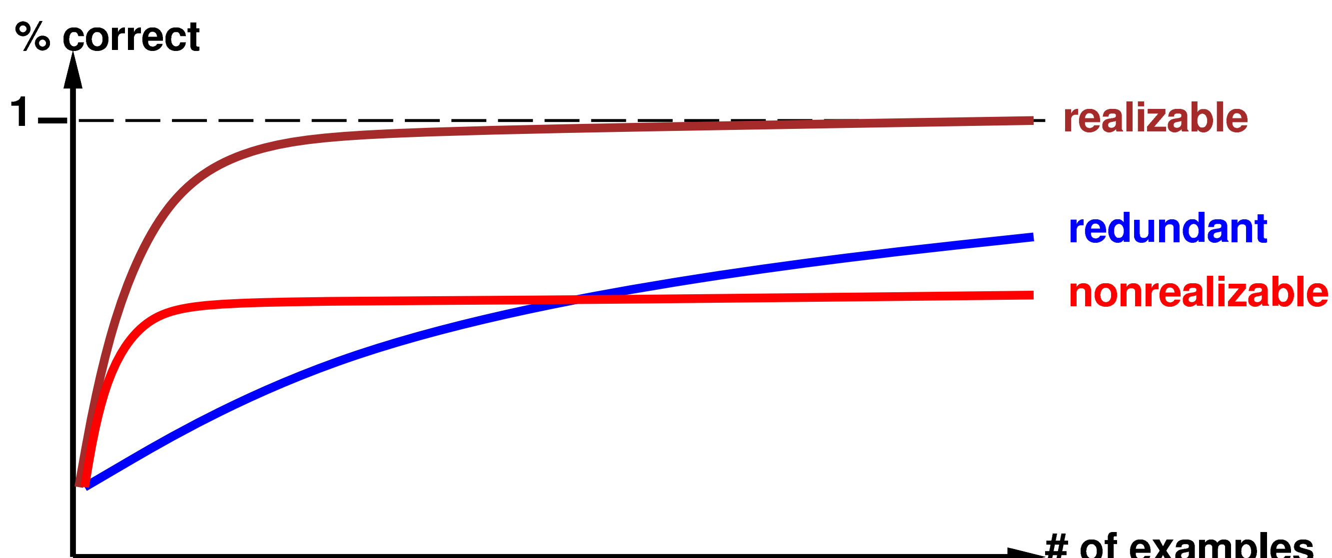
% correct on test set as a function of training set size



Performance Measurement (cont.)

Learning curve depends on

- realizable (can express target function) vs. non-realizable
  Non-realizability can be due to
  - missing attributes, or
  - restricted hypothesis class (e.g., thresholded linear function)
- redundant expressiveness (e.g., loads of irrelevant attributes)



Summary

- Learning needed for unknown environments, lazy designers
- Learning agent = performance element + learning element
- Learning method depends on type of performance element, available feedback, type of component to be improved
- For supervised learning, the aim is to find a simple hypothesis approximately consistent with training examples
- Decision tree learning using information gain
- Learning performance = prediction accuracy measured on test set