LEARNING FROM OBSERVATIONS

CHAPTER 18, SECTIONS 1–3
Outline

♦ Learning agents
♦ Inductive learning
♦ Decision tree learning
♦ Measuring learning performance
Learning

Learning is essential for unknown environments, i.e., when designer lacks omniscience

Learning is useful as a system construction method, i.e., expose the agent to reality rather than trying to write it down

Learning modifies the agent’s decision mechanisms to improve performance
Learning agents

Performance standard

Agent

Environment

Critic

Sensors

Performance element

Learning element

feedback

changes

knowledge

learning goals

experiments

Problem generator

Effectors

Chapter 18, Sections 1–3
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

Example scenarios:

<table>
<thead>
<tr>
<th>Performance element</th>
<th>Component</th>
<th>Representation</th>
<th>Feedback</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alpha–beta search</td>
<td>Eval. fn.</td>
<td>Weighted linear function</td>
<td>Win/loss</td>
</tr>
<tr>
<td>Logical agent</td>
<td>Transition model</td>
<td>Successor–state axioms</td>
<td>Outcome</td>
</tr>
<tr>
<td>Utility–based agent</td>
<td>Transition model</td>
<td>Dynamic Bayes net</td>
<td>Outcome</td>
</tr>
<tr>
<td>Simple reflex agent</td>
<td>Percept–action fn</td>
<td>Neural net</td>
<td>Correct action</td>
</tr>
</tbody>
</table>

Supervised learning: correct answers for each instance
Reinforcement learning: occasional rewards
Inductive learning (a.k.a. Science)

Simplest form: learn a function from examples (tabula rasa)

\( f \) is the target function

An example is a pair \( x, f(x) \), e.g.,

\[
\begin{array}{|c|c|c|}
\hline
O & O & X \\
\hline
X & X & X \\
\hline
\end{array}
\] , +1

Problem: find a(n) hypothesis \( h \)
such that \( h \approx f \)
given a training set of examples

(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

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 method

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($h$ is consistent if it agrees with $f$ on all examples)

E.g., curve fitting:

\[ f(x) \]

\[ x \]
Inductive learning method

Construct/adjust \( h \) to agree with \( f \) on training set
\( (h \text{ is consistent if it agrees with } f \text{ on all examples}) \)

E.g., curve fitting:

\[
\begin{align*}
&\text{\( f(x) \)} \\
&\text{\( x \)} \\
&\text{\( \)}
\end{align*}
\]
Inductive learning method

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f(x)
\]
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E.g., curve fitting:

Ockham’s razor: maximize a combination of consistency and simplicity
### Attribute-based representations

Examples described by **attribute values** (Boolean, discrete, continuous, etc.)

E.g., situations where I will/won’t wait for a table:

<table>
<thead>
<tr>
<th>Example</th>
<th>Alt</th>
<th>Bar</th>
<th>Fri</th>
<th>Hun</th>
<th>Pat</th>
<th>Price</th>
<th>Rain</th>
<th>Res</th>
<th>Type</th>
<th>Est</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>X₁</td>
<td>T</td>
<td>F</td>
<td>F</td>
<td>T</td>
<td>Some</td>
<td>$$$</td>
<td>F</td>
<td>T</td>
<td>French</td>
<td>0–10</td>
<td>T</td>
</tr>
<tr>
<td>X₂</td>
<td>T</td>
<td>F</td>
<td>F</td>
<td>T</td>
<td>Full</td>
<td>$</td>
<td>F</td>
<td>F</td>
<td>Thai</td>
<td>30–60</td>
<td>F</td>
</tr>
<tr>
<td>X₃</td>
<td>F</td>
<td>T</td>
<td>F</td>
<td>F</td>
<td>Some</td>
<td>$</td>
<td>F</td>
<td>F</td>
<td>Burger</td>
<td>0–10</td>
<td>T</td>
</tr>
<tr>
<td>X₄</td>
<td>T</td>
<td>F</td>
<td>T</td>
<td>T</td>
<td>Full</td>
<td>$</td>
<td>F</td>
<td>F</td>
<td>Thai</td>
<td>10–30</td>
<td>T</td>
</tr>
<tr>
<td>X₅</td>
<td>T</td>
<td>F</td>
<td>T</td>
<td>F</td>
<td>Full</td>
<td>$$$</td>
<td>F</td>
<td>T</td>
<td>French</td>
<td>&gt;60</td>
<td>F</td>
</tr>
<tr>
<td>X₆</td>
<td>F</td>
<td>T</td>
<td>F</td>
<td>T</td>
<td>Some</td>
<td>$$</td>
<td>T</td>
<td>T</td>
<td>Italian</td>
<td>0–10</td>
<td>T</td>
</tr>
<tr>
<td>X₇</td>
<td>F</td>
<td>T</td>
<td>F</td>
<td>F</td>
<td>None</td>
<td>$</td>
<td>T</td>
<td>F</td>
<td>Burger</td>
<td>0–10</td>
<td>F</td>
</tr>
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<td>X₈</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>T</td>
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<td>$$$</td>
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<td>F</td>
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<td>F</td>
<td>Burger</td>
<td>30–60</td>
<td>T</td>
</tr>
</tbody>
</table>

Classification of examples is positive (T) or negative (F)
Decision trees

One possible representation for hypotheses
E.g., here is the “true” tree for deciding whether to wait:

```
Patrons?
  None  Some  Full
    F     T
  WaitEstimate?
    >60  30−60  10−30  0−10
      F   F   F   F
    Alternate?  Hungry?
      No   Yes   No  Yes
      Reservation?  Fri/Sat?
        No   Yes   No   Yes
        Bar?
          No   Yes   No   Yes
            T   F   T   T
        Alternate?
          No  Yes
            Raining?
              No  Yes
                F  T
              F  T
```
Expressiveness

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

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>A xor B</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>F</td>
<td>F</td>
</tr>
<tr>
<td>F</td>
<td>T</td>
<td>T</td>
</tr>
<tr>
<td>T</td>
<td>F</td>
<td>T</td>
</tr>
<tr>
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</table>

Trivially, there is a consistent decision tree for any training set w/ one path to leaf for each example (unless $f$ nondeterministic in $x$) but it probably won’t generalize to new examples

Prefer to find more compact decision trees
Hypothesis spaces

How many distinct decision trees with $n$ Boolean attributes?
Hypothesis spaces

How many distinct decision trees with $n$ Boolean attributes?

= number of Boolean functions
Hypothesis spaces

How many distinct decision trees with \( n \) Boolean attributes?

= number of Boolean functions
= number of distinct truth tables with \( 2^n \) rows
Hypothesis spaces

How many distinct decision trees with $n$ Boolean attributes?

= number of Boolean functions
= number of distinct truth tables with $2^n$ rows = $2^{2^n}$
Hypothesis spaces

How many distinct decision trees with $n$ Boolean attributes??

= number of Boolean functions
= number of distinct truth tables with $2^n$ rows = $2^{2^n}$

E.g., with 6 Boolean attributes, there are 18,446,744,073,709,551,616 trees
Hypothesis spaces

How many distinct decision trees with \( n \) Boolean attributes??

\[ = \text{number of Boolean functions} \]
\[ = \text{number of distinct truth tables with } 2^n \text{ rows} = 2^{2^n} \]

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How many purely conjunctive hypotheses (e.g., \( \text{Hungry} \land \neg \text{Rain} \))??
Hypothesis spaces

How many distinct decision trees with \( n \) Boolean attributes??

\[
\text{number of Boolean functions} = \text{number of distinct truth tables with } 2^n \text{ rows} = 2^{2^n}
\]

E.g., with 6 Boolean attributes, there are 18,446,744,073,709,551,616 trees

How many purely conjunctive hypotheses (e.g., \( \text{Hungry} \land \neg \text{Rain} \))??

Each attribute can be in (positive), in (negative), or out

\[ \Rightarrow 3^n \text{ distinct conjunctive hypotheses} \]

More expressive hypothesis space

– increases chance that target function can be expressed

– increases number of hypotheses consistent w/ training set

\[ \Rightarrow \text{may get worse predictions} \]
Decision tree learning

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 ← 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

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

Patrons? is a better choice—gives information about the classification
Information

Information answers questions

The more clueless I am about the answer initially, the more information is contained in the answer

Scale: 1 bit = answer to Boolean question with prior \( \langle 0.5, 0.5 \rangle \)

Information in an answer when prior is \( \langle P_1, \ldots, P_n \rangle \) is

\[
H(\langle P_1, \ldots, P_n \rangle) = \sum_{i=1}^{n} - P_i \log_2 P_i
\]

(also called entropy of the prior)
Suppose we have \( p \) positive and \( n \) negative examples at the root
\[
\Rightarrow H\left(\frac{p}{p+n}, \frac{n}{p+n}\right) \text{ bits needed to classify a new example}
\]
E.g., for 12 restaurant examples, \( p = n = 6 \) so we need 1 bit

An attribute splits the examples \( E \) into subsets \( E_i \), each of which (we hope) needs less information to complete the classification

Let \( E_i \) have \( p_i \) positive and \( n_i \) negative examples
\[
\Rightarrow H\left(\frac{p_i}{p_i+n_i}, \frac{n_i}{p_i+n_i}\right) \text{ bits needed to classify a new example}
\]
\[
\Rightarrow \text{expected number of bits per example over all branches is}
\]
\[
\sum_i \frac{p_i + n_i}{p + n} H\left(\frac{p_i}{p_i+n_i}, \frac{n_i}{p_i+n_i}\right)
\]

For \textit{Patrons?}, this is 0.459 bits, for \textit{Type} this is (still) 1 bit
\[
\Rightarrow \text{choose the attribute that minimizes the remaining information needed}
\]
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

How do we know that $h \approx f$? (Hume’s Problem of Induction)

1) Use theorems of computational/statistical learning theory

2) Try $h$ on a new test set of examples
   (use same distribution over example space as training set)

Learning curve = % correct on test set as a function of training set size
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, and its representation

For supervised learning, the aim is to find a simple hypothesis that is approximately consistent with training examples

Decision tree learning using information gain

Learning performance = prediction accuracy measured on test set