Lecture 22: Learning 1

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Today's Lecture

- The structure of a learning agent
- Basic problems: bias, Ockham's razor, expressiveness
- Decision-tree algorithms for Classification

Commonsense Definition

Learning is change within a system that improves its performance

This admits a lot of different behaviors, but identifies the basic preconditions of learning:

- Learning systems must be capable of change
- Learning systems must do something differently as a result of the change

Why Should Systems Learn?

- Learning can simplify the complexity of problem solving.
  - Replace procedural/declarative knowledge, inferencing, and search with learned functions and policies
- Learning increases efficiency, robustness, survivability, and autonomy of system.
  - Key to operating in "open" environments
  - Re-evaluate key assumptions in light of what is happening
- A learning program can become better than its teacher.

*A viable alternative to problem solving***.**

Types of Learned Knowledge*

- A direct mapping from conditions on the current state to actions.
- Weighting of parameters of multi-attribute decision process
- A means to infer relevant properties of the world from the percept sequence.
- Information about the way the world evolves.
  - Allow prediction of future events

How Does this Relate to Systems We Have Studied?

Types of Learned Knowledge cont.

- Information about the results of possible actions the agent can take
- Utility information indicating the desirability of world states.
- Action-value information indicating the desirability of particular actions in particular states.
- Goals that describe classes of states whose achievement maximizes the agent's utility.

How Does this Relate to Systems We Have Studied?

Examples from My Lab

- Meta-level Control
  - Learning policy for balancing thinking/coordinating and acting in a sophisticated agent
- Agent Plans - SRTA
  - Learned often used agent plans; avoided planning overhead
- Agent Behavior Statistics -- SRTA
  - Learned statistical distribution of performance of agent actions then used in planning and scheduling of agent activities
- Information Gathering -- BIG
  - Learned text extraction strategy
- Agent Coordination
  - Learned new coordination rules
  - Learned situation specific context for applying coordination rules
  - Learning routing policies in a peer-to-peer IR
  - Learning distributed task allocation policy
- BlackBoard control
  - Learned tactical control for when to invoke specific KSs
- Model Acquistion for Sound Understanding -- IPUS
  - Learned models for characterizing never before heard sounds

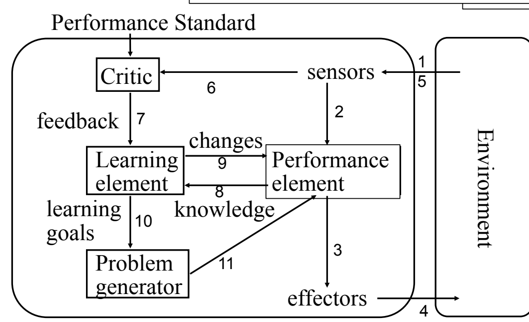
Characterizing Learning Systems

- What changes as a result of learning?
- How does the system find out change is needed?
- How does the system localize the problem to find out what changes are necessary?
- What is the mechanism of change?

Available Feedback

- Supervised learning
  - Is told by a “teacher” what action is best in a specific situation
  - *Learning to brake*
- Reinforcement Learning
  - Gets feedback about the consequences of a specific sequence of actions in a certain situation
  - *Can also be thought of as supervised learning with a less informative feedback signal.*
  - *Training a dog*
- Unsupervised Learning
  - No feedback about actions
  - Learns to predict future precepts given its previous precepts
  - Can’t learn what to do unless it already has a *utility function that defines appropriateness of a given situation (built-in feedback signal)*
  - *Learning traffic patterns*

A Model of Learning Agents



Model of Learning Agent

- Critic — tells learning element how well agent is doing
  - Fixed standard of performance
- Learning element — modifies performance element (usually its knowledge) in response to feedback
- Problem generator — suggests actions that will lead to new and informative experiences also called exploration
  - Related to decision to acquire information

Design of Learning Element

Goals:

- *Learn better actions that lead to higher long-term utility*
- *Speed up performance element*

- Which *components* of the performance element are to be improved.
- What *representation* is used for those components.
- What *feedback* is available
- What *prior information* is available.

Dimensions of Learning

- *The type of training instances*
  - *the beginning data for the learning task.*
- *The language used to represent knowledge.*
  - Specific training instances must be translated into this representation language
  - In some programs the training instances are in the same language as the internal knowledge base and this step is unnecessary.
- *A set of operations on representations.*
  - Typical operations generalize or specialize existing knowledge, combine units of knowledge, or otherwise modify the program's existing knowledge or the representation of the training instances.

Dimensions of Learning cont.

- *The concept space.*
  - The operations that define a space of possible knowledge structures that is searched to find the appropriate characterization of the training instances and similar problems.
    - *Learning as Search?*
- *The learning algorithms and heuristics employed to search the concept space.*
  - The order of the search and the use of heuristics to guide the search.

Types of Knowledge Representations for Learning

- numerical parameters
- decision trees
- formal grammars
- production rules
- logical theories
- graphs and networks
- frames and schemas
- computer programs (procedural encoding)

Learning Functions

All learning can be seen as learning the representation of a function/mapping

- Choice of representation of a function
  - Trade-off between expressiveness and efficiency
    - Is what you want representable?
    - Is what you want learnable (# of examples, cost of search)?
- Choice of training data
  - Correctly reflects past experiences
  - Correctly predicts future experiences
- How to judge the goodness of the learned function

Some Additional Thoughts

- Importance of Prior Knowledge
  - Prior knowledge (e.g., first principles) can significantly speed up learning process
  - EBL: Explanation-Based Learning
- Learning as a search process
  - Finding the “best” function
- Incremental Process (on-line) vs. off-line

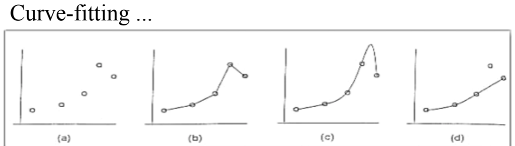
Inductive (Supervised) Learning

Let an example be *(x, f(x))*

- Give a collection of examples of *f*, return a function *h* that approximates *f*.
- This function *h* is called a hypothesis:
  - Feedback is relation between *f(x)* and *h(x)*
  - *(x, f(x))* could only be approximately correct
    - Noise – observation of *f(x)* not always accurate
    - Missing components of x – ambiguity of whether missing component is key to decision (output of *f(x))*

Problems

- Many hypotheses *h’s* are approximately consistent with the training set
- Curve-fitting ...



In (a) we have some example (input, output) pairs. In (b), (c), and (d) we have three hypotheses for functions from which these examples could be drawn.

- A preference for one hypothesis over another beyond consistency is called Bias

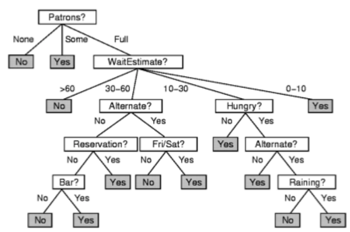
Ockham’s Razor

- “Simple” hypotheses that are consistent with data are preferred
- We want to maximize some metric of *consistency* and *simplicity* in the choice of the most appropriate function

Learning Classification Decision Trees

- Restricted representation of logical sentences
  - Boolean functions
- Takes as input situation described by a set of properties and outputs a "yes/no" decision
- Tree of property value tests
  - Terminals are decisions
- Not all attributes of situation need to be used
- Decision tree as a performance element

Learn, based on conditions of the situation, whether to wait at a restaurant for a table



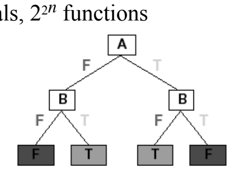
Decision trees

- A (classification) decision tree takes as input a situation described by a set of attributes and returns a "decision."
  - Reaches it decision by performing a sequence of incremental tests
  - Each internal node corresponds to a test of one of the attributes of the situation
- Can express any boolean function of the input attributes.
- How to choose between equally consistent trees

Expressions of Decision Tree

- Any Boolean function can be written as a decision tree
  - $\forall r$ *Patrons(r,Full)* Λ *WaitEstimate(r,10-30)* Λ *Hungry(r,N)* $\Rightarrow$ *WillWait(r)*
  - Row of truth table path in decision tree
  - 2^n rows given n literals, 2^{2^n} functions

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



Limits on Expressability

- Cannot use decision tree to represent tests that refer to two or more different objects
- $\exists r_2$ *Nearby*(r_2,r) Λ *Price(r,p)* Λ *Price*(r_2,p_2) Λ *Cheaper*(p_2,p)
- New Boolean attribute: *CheaperRestaurantNearby* but intractable to add all such attributes
- Some truth tables cannot be compactly represented in decision tree -- analagous to Baysean Joint Distribution
  - Parity function
    - **returns 1 if and only if an even number of inputs are 1**
    - **exponentially large decision tree will be needed.**
  - Majority function
    - **which returns 1 if more than half of its inputs are 1**

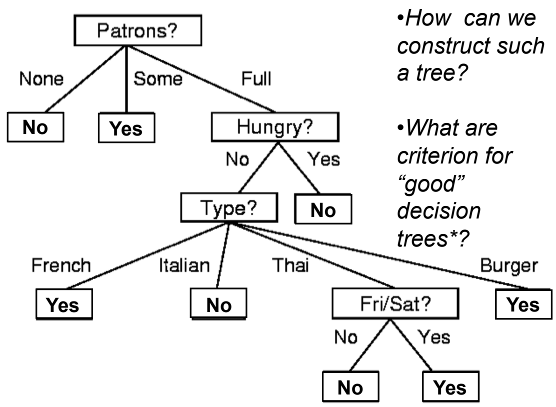
Example: Waiting for a Table

- Alternate restaurant exists
- Bar that you can wait
- Fri/Sat
- Hungry
- Patrons (None, Some, Full)
- Price ($, $$, $$$)
- Raining
- Reservation
- Type (French, Italian, Thai, Burger)
- WaitEstimate (0-10, 10-30, 30-60, >60)

Data available for decision whether to wait for a table

Inducing Decision Trees from Examples

Example	Attributes										Goal
	Alt	*Bar*	*Fri*	*Hun*	*Pat*	*Price*	*Rain*	*Res*	*Type*	*Est*	*WillWait*
X_1	Yes	No	No	Yes	Some	$$$	No	Yes	French	0–10	Yes
X_2	Yes	No	No	Yes	Full	$	No	No	Thai	30–60	No
X_3	No	Yes	No	No	Some	$	No	No	Burger	0–10	Yes
X_4	Yes	No	Yes	Yes	Full	$	No	No	Thai	10–30	Yes
X_5	Yes	No	Yes	No	Full	$$$	No	Yes	French	>60	No
X_6	No	Yes	No	Yes	Some	$$	Yes	Yes	Italian	0–10	Yes
X_7	No	Yes	No	No	None	$	Yes	No	Burger	0–10	No
X_8	No	No	No	Yes	Some	$$	Yes	Yes	Thai	0–10	Yes
X_9	No	Yes	Yes	No	Full	$	Yes	No	Burger	>60	No
X_{10}	Yes	Yes	Yes	Yes	Full	$$$	No	Yes	Italian	10–30	No
X_{11}	No	No	No	No	None	$	No	No	Thai	0–10	No
X_{12}	Yes	Yes	Yes	Yes	Full	$	No	No	Burger	30–60	Yes



- *How can we construct such a tree?*
- *What are criterion for "good" decision trees*?*

Next Lecture

- Continuation of Decision Trees
- Neural Networks