Learning Intro

CPS 170
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Why Study Learning?

- Considered a hallmark of intelligence
- Viewed as way to reduce programming burden
- Many algorithms assume parameters that are difficult to determine exactly a priori

Formalizing Learning

- Learning Element
  - Changes due to information or stimuli
- Performance Element
  - Objective measure of change
- Learning is simply an increase in the ability of the learning element over time to achieve the task specified by the performance element

Types of Learning

- Inductive Learning
  - Acquiring new information that previously was not available
  - Learning concepts
- Speedup learning
  - Learning to do something you already “know” faster or better

Feedback in Learning

- Supervised Learning
  - Given examples of correct behavior
- Unsupervised Learning
  - No external notion of what is correct
  - Is this well-defined?
- Reinforcement Learning
  - Indirect indication of effectiveness

Learning Methodology

- Distinction between training and testing is crucial
- Correct performance on training set is just memorization!
- Researcher should ***never*** look at the test data
- Raises some troubling issues for “benchmark” learning problems

Computational Learning Theory

- Formal study of what can be learned from data
- Need to make some assumptions:
  - Training examples must be representative
  - Algorithm needn't always work, but should scale well
  - Number of training samples or run time needed should have polynomial relationship to inverse probability of error and percentage of misclassifications
- Probably Approximately Correct (PAC) learning
- Goal: Algorithms that have a low error rate with high probability

COLT

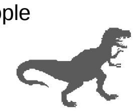
- Learning theory is elegant and mathematically rich. However,
  - It sometimes isn't constructive
  - It sometimes tells us how many data are needed, but not how to manipulate the data efficiently
- Until recently, learning theory has been disconnected from practical learning algorithms
- New advances are leading to a rapprochement
  - Support vector machines
  - Boosting

Supervised Learning

- Classical framework
- Target concept, e.g., green
- Learner is presented with labeled instances
  - True: Green cones, green cubes, green spheres
  - False: Red cones, red cubes, red spheres, blue cones, blue cubes, blue spheres
- Learner must correctly identify the target concept from the training data

Performance Measure

- Training set won't have all possible objects
- Test set will contain novel objects
  - Blue cylinders, yellow tetrahedra
- To learn successfully, learner must have good performance even when confronted with novel objects
  - This is what we would expect from people
  - A blue dinosaur is still blue



Examples

- Distinguish healthy/diseased tissue
- Predict good/bad credit risks
- Drilling sites likely to have oil
- Document categorization
- Predict failures in physical systems
- Predict if mushrooms are safe to eat
- Good/bad moves in a game
- Public database of learning problems:
  - http://www.ics.uci.edu/~mlearn/MLSummary.html

Why Learning Is Tricky

- Suppose we have seen:
  - Red tetrahedron (f), Blue sphere (**T**), Blue cone (**T**), green cube (f)
- Possible concepts:
  - Blue
  - (Blue Sphere) or (Blue Cone)
  - Objects a prime number from start
  - Objects with a circular cross-section
- What if some data are mislabeled?

Learning and Representation

- Learning is very sensitive to representation
- Every learning algorithm can be viewed as a search procedure through a space of concepts
- Space of concepts determines
  - Difficulty of task
  - Appropriate algorithm
  - Restricting too aggressively can trivialize problem
- Space: Conjunctions of colors and shapes
  - Eliminates primes and (possibly) cross sections