633-600 Machine Learning

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Textbook

- Ethem Alpaydin (2010) "Introduction to Machine Learning", 2nd edition. MIT Press.
- Book webpage: http://www.cmpe.boun.edu.tr/~ethem/i2ml2e/
- Tom M. Mitchell (1997) "Machine Learning", McGraw-Hill.
- Book webpage: http://www.cs.cmu.edu/~tom/mlbook.html
- Text and figures, etc. will be quoted from the textbook without repeated acknowledgment. Instructor's perspective will be indicated by "YC" where appropriate.

Course Info

- Grading, academic policy, students with disabilities, lecture notes, computer accounts, programming languages.
- See course web page.

Relation to Other Courses

Some overlaps:

- Neural Networks: perceptrons, backpropagation, etc.
- Pattern analysis: Bayesian learning, instance-based learning
- Artificial intelligence: decision trees (in some courses)
- Statistics: hypothesis testing
- (Relatively) unique to this course: concept learning, computational learning theory, genetic algorithms, reinforcement learning, decision trees (in depth treatment)

ML Overview (I)

- How can machines (computers) learn?
  How can machines **improve automatically with experience**?
- Benefits:
  - Improved performance
  - Automated optimization
  - New uses of computers
  - Reduced programming (YC)
  - Insights into human learning and learning disabilities

ML Overview (II)

- Current status: Yet unsolved problem.
  - Theoretical insights emerging.
  - Practical applications.
  - Huge data volume demands ML, and provides opportunity to ML (datamining).
- State of the art:
  - speech recognition
  - medical predictions
  - fraud detection
  - drive autonomous vehicles (highway and desert)
  - board games (backgammon, chess)
  - theoretical bounds on error, number of inputs needed, etc.

ML Overview (III)

Multidisciplinary roots:

- AI
- probability and statistics
- computational complexity theory
- control theory
- information theory
- philosophy
- psychology
- neurobiology

Well-Posed Learning Problem

A program is said to **learn** from

- experience E with respect to
- task T and
- performance measure P,
- P in T increase with E.

Examples: Playing checkers, Handwriting recognition, Robot driving, etc.

Goal of ML: "define precisely a class of problems that encompasses interesting forms of learning [but not all: YC], to explore algorithms that solve such problems, and to understand the fundamental structure of learning problems and processes" (Mitchell, 1997)

Designing a Learning System (I)

Training experience:

- direct vs. indirect (problem of credit assignment)
- degree of control over training examples (teacher-dependent or learner-generated)
- closeness of training example distribution to true distribution over which P is measured: in many cases, ML algorithms assume that both distributions are similar, which may not be the case in practice.

Designing a Learning System (II)

Remaining design choices:

- Exact type of knowledge to be learned.
- A representation for this target knowledge.
- A learning mechanism.
- functional/operational principle giving rise to the learning mechanism (YC)

Design: Target Function (I)

Type of knowledge to be learned: for example, we want to learn **best move** in a board game.

- Can represent as a function (B: board states, M: moves):

  $$ChooseMove : B \rightarrow M,$$

  but it is hard to learn directly.

Design: Target Function (II)

- Another function (B: board states, $\mathcal{R}$: real numbers):

  $$V : B \rightarrow \mathcal{R},$$

  which gives the **evaluation** of each board state.
  - $V(b = win) = 100$
  - $V(b = lose) = -100$
  - $V(b = draw) = 0$
  - $V(b = otherwise) = V(b')$, where b' is the best final board state that can be reached from b.
  - However, this is not **efficiently computable**, i.e., it is a **nonoperational** definition.
  - Goal of ML is to find an **operational** description of V, however, in practice, an **approximation** is all we can get.

Design: Representation for Target Function

Given an ideal target function V, we want to learn an approximate function $\hat{V}$:

- Trade-off between rich and parsimonious representation.
- Example: $\hat{V}$ as a linear combination of number of pieces, number of particular relational situations in the board (e.g., threatened), etc. (represented as x_i) in board configuration b:

$$\hat{V}(b) = w_0 + \sum_{i=1}^{n} w_i x_i,$$

  where w_i are the weight values **to be learned**.
- Advantage of the above representation: **reduction of scope (or dimensionality)** from the original problem.

Design: Function Approximation Algorithm

Given **board state and true** V, we want to learn the **weights** w_i that specify $\hat{V}$.

- Start with a set of a large number of input-target pairs $< b, V_{train}(b) >$.
- Problem: cannot come up with a full set of $< b, V_{train}(b) >$ pairs.
- Solution: If $V_{train}(b)$ is unknown, set it to the **estimated** $\hat{V}$ of its successor board state:

$$V_{train}(b) = \hat{V}_{train}(Successor(b)).$$

Design: Adjusting Weights (I)

Last component in defining a learning algorithm: adjustment of weights.

- Want to learn weights w_i that **best fit** the set of training samples $\{< b, V_{train}(b) >\}$.
- How to define best fit? Once we have $\hat{V}$ we can calculate all $\hat{V}(b)$ for all b in the training set, and calculate the error.

$$E \equiv \sum_{<b, V_{train}(b)> \in training\ set} \left(V_{train}(b) - \hat{V}(b) \right)^2$$

- How to reduce E?

Design: Adjusting Weights (II)

Least Mean Squares (LMS) learning rule: For each training example $< b, V_{train}(b) >$,

- Use the current weights to calculate $\hat{V}(b)$.
- For each weight w_i, update it as

$$w_i \leftarrow w_i + \eta (V_{train}(b) - \hat{V}(b)) x_i,$$

  where η is a small **learning rate** constant.
- The error $V_{train}(b) - \hat{V}(b)$ and the input x_i both contribute to the weight update.

Final Design

Putting together the system (checker player):

- Performance system: input = problem, output = solution trace = game history (using what is learned so far)
- Critic: input = solution trace, output = training examples (estimated $V_{train}(b)$)
- Generalizer: input = training examples, output = estimated hypothesis $\hat{V}$ (i.e., learned weights w_i)
- Experiment generator: input = hypothesis $\hat{V}$, output = new problem (new initial condition, to explore particualar regions)

Alternatives (I)

- Training experience: against experts, against self, table of correct moves, ...
- Target function: board $\longrightarrow$ move, board $\longrightarrow$ value, ...
- Representation of target function: polynomial, linear function of small number of features, artificial neural network
- Learning algorithm: gradient descent, linear programming, ...

Alternatives (II)

- Memorize (instance-based learning)
- Spawn a population and make them compete with each other (genetic algorithms)
- Analyze and reason about things

Perspectives on ML: Hypothesis Space Search

- Useful to think of ML as **searching** a very large space of **possible hypotheses** to **best fit** the data and the learner's prior knowledge.
- For example, the hypothesis space for $\hat{V}$ would be all possible $\hat{V}$s with different weight assignment.
- Useful concepts regarding hypothesis space search:
  - Size of hypothesis space
  - Number of training examples available/needed.
  - Confidence in generalizing to new unseen data.

Issues in ML

- What algorithms exist for generalizable learners given specific training set? Requirements for convergence? Which algorithms are best for a particular domain?
- How much training data needed? Bounds on confidence, based on data size? How long to train?
- Use of prior knowledge?
- How to choose best training experience? Impact of the choice?
- How to reduce ML problem to function approximation?
- How can learner **alter** the representation itself?

Classification of learning algorithms (YC)

- Supervised learning: input-target pairs given.
- Unsupervised learning: only input distribution is given.
- Reinforcement learning: sparse reward signal is given for action based on sensory input; environment-altering actions.

Broader questions (YC)

- Can machines themselves formulate their own learning tasks?
  - Can they come up with their own representations?
  - Can they come up with their own learning strategy?
  - Can they come up with their own motivation?
  - Can they come up with their own questions/problems?
- What if the machines are faced with multiple, possibly conflicting tasks? Can there be a meta learning algorithm?
- What if performance is hard to measure (i.e., hard to quantify, or even worse, subjective)?
- Lesson: think outside the box; question the questions themselves.