CS 391L: Machine Learning Introduction

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What is Learning?

- Herbert Simon: “Learning is any process by which a system improves performance from experience.”
- What is the task?
  - Classification
  - Problem solving / planning / control

Classification

- Assign object/event to one of a given finite set of categories.
  - Medical diagnosis
  - Credit card applications or transactions
  - Fraud detection in e-commerce
  - Worm detection in network packets
  - Spam filtering in email
  - Recommended articles in a newspaper
  - Recommended books, movies, music, or jokes
  - Financial investments
  - DNA sequences
  - Spoken words
  - Handwritten letters
  - Astronomical images

Problem Solving / Planning / Control

- Performing actions in an environment in order to achieve a goal.
  - Solving calculus problems
  - Playing checkers, chess, or backgammon
  - Balancing a pole
  - Driving a car or a jeep
  - Flying a plane, helicopter, or rocket
  - Controlling an elevator
  - Controlling a character in a video game
  - Controlling a mobile robot

Measuring Performance

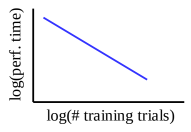
- Classification Accuracy
- Solution correctness
- Solution quality (length, efficiency)
- Speed of performance

Why Study Machine Learning? Engineering Better Computing Systems

- Develop systems that are too difficult/expensive to construct manually because they require specific detailed skills or knowledge tuned to a specific task (***knowledge engineering bottleneck***).
- Develop systems that can automatically adapt and customize themselves to individual users.
  - Personalized news or mail filter
  - Personalized tutoring
- Discover new knowledge from large databases (***data mining***).
  - Market basket analysis (e.g. diapers and beer)
  - Medical text mining (e.g. migraines to calcium channel blockers to magnesium)

Why Study Machine Learning? Cognitive Science

- Computational studies of learning may help us understand learning in humans and other biological organisms.
  - Hebbian neural learning
    - "Neurons that fire together, wire together."
  - Human's relative difficulty of learning disjunctive concepts vs. conjunctive ones.
  - Power law of practice



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Why Study Machine Learning? The Time is Ripe

- Many basic effective and efficient algorithms available.
- Large amounts of on-line data available.
- Large amounts of computational resources available.

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Related Disciplines

- Artificial Intelligence
- Data Mining
- Probability and Statistics
- Information theory
- Numerical optimization
- Computational complexity theory
- Control theory (adaptive)
- Psychology (developmental, cognitive)
- Neurobiology
- Linguistics
- Philosophy

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Defining the Learning Task

Improve on task, T, with respect to performance metric, P, based on experience, E.

T: Playing checkers
P: Percentage of games won against an arbitrary opponent
E: Playing practice games against itself

T: Recognizing hand-written words
P: Percentage of words correctly classified
E: Database of human-labeled images of handwritten words

T: Driving on four-lane highways using vision sensors
P: Average distance traveled before a human-judged error
E: A sequence of images and steering commands recorded while observing a human driver.

T: Categorize email messages as spam or legitimate.
P: Percentage of email messages correctly classified.
E: Database of emails, some with human-given labels

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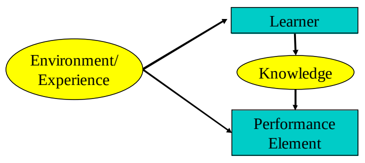
Designing a Learning System

- Choose the training experience
- Choose exactly what is too be learned, i.e. the ***target function***.
- Choose how to represent the target function.
- Choose a learning algorithm to infer the target function from the experience.



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Sample Learning Problem

- Learn to play checkers from self-play
- We will develop an approach analogous to that used in the first machine learning system developed by Arthur Samuels at IBM in 1959.

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Training Experience

- Direct experience: Given sample input and output pairs for a useful target function.
  - Checker boards labeled with the correct move, e.g. extracted from record of expert play
- Indirect experience: Given feedback which is ***not*** direct I/O pairs for a useful target function.
  - Potentially arbitrary sequences of game moves and their final game results.
- Credit/Blame Assignment Problem: How to assign credit blame to individual moves given only indirect feedback?

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Source of Training Data

- Provided random examples outside of the learner's control.
  - Negative examples available or only positive?
- Good training examples selected by a "benevolent teacher."
  - "Near miss" examples
- Learner can query an oracle about class of an unlabeled example in the environment.
- Learner can construct an arbitrary example and query an oracle for its label.
- Learner can design and run experiments directly in the environment without any human guidance.

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Training vs. Test Distribution

- Generally assume that the training and test examples are independently drawn from the same overall distribution of data.
  - IID: Independently and identically distributed
- If examples are not independent, requires ***collective classification***.
- If test distribution is different, requires ***transfer learning***.

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Choosing a Target Function

- What function is to be learned and how will it be used by the performance system?
- For checkers, assume we are given a function for generating the legal moves for a given board position and want to decide the best move.
  - Could learn a function:
    ChooseMove(board, legal-moves) → best-move
  - Or could learn an ***evaluation function***, *V*(board) → $\mathcal{R}$, that gives each board position a score for how favorable it is. *V* can be used to pick a move by applying each legal move, scoring the resulting board position, and choosing the move that results in the highest scoring board position.

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Ideal Definition of *V*(*b*)

- If *b* is a final winning board, then *V*(*b*) = 100
- If *b* is a final losing board, then *V*(*b*) = –100
- If *b* is a final draw board, then *V*(*b*) = 0
- Otherwise, then *V*(*b*) = *V*(*b*´), where *b*´ is the highest scoring final board position that is achieved starting from *b* and playing optimally until the end of the game (assuming the opponent plays optimally as well).
  - Can be computed using complete mini-max search of the finite game tree.

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Approximating *V*(*b*)

- Computing *V*(*b*) is intractable since it involves searching the complete exponential game tree.
- Therefore, this definition is said to be ***non-operational***.
- An ***operational*** definition can be computed in reasonable (polynomial) time.
- Need to learn an operational *approximation* to the ideal evaluation function.

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Representing the Target Function

- Target function can be represented in many ways: lookup table, symbolic rules, numerical function, neural network.
- There is a trade-off between the expressiveness of a representation and the ease of learning.
- The more expressive a representation, the better it will be at approximating an arbitrary function; however, the more examples will be needed to learn an accurate function.

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Linear Function for Representing *V*(*b*)

- In checkers, use a linear approximation of the evaluation function.

$$\hat{V}(b) = w_0 + w_1 \cdot bp(b) + w_2 \cdot rp(b) + w_3 \cdot bk(b) + w_4 \cdot rk(b) + w_5 \cdot bt(b) + w_6 \cdot rt(b)$$

  - *bp*(*b*): number of black pieces on board b
  - *rp*(*b*): number of red pieces on board b
  - *bk*(*b*): number of black kings on board b
  - *rk*(*b*): number of red kings on board b
  - *bt*(*b*): number of black pieces threatened (i.e. which can be immediately taken by red on its next turn)
  - *rt*(*b*): number of red pieces threatened

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Obtaining Training Values

- Direct supervision may be available for the target function.
  - < <*bp*=3,*rp*=0,*bk*=1,*rk*=0,*bt*=0,*rt*=0>, 100> (win for black)
- With indirect feedback, training values can be estimated using ***temporal difference learning*** (used in ***reinforcement learning*** where supervision is ***delayed reward***).

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Temporal Difference Learning

- Estimate training values for intermediate (non-terminal) board positions by the estimated value of their successor in an actual game trace.

$$V_{train}(b) = \hat{V}(\text{successor}(b))$$

  where successor(*b*) is the next board position where it is the program's move in actual play.
- Values towards the end of the game are initially more accurate and continued training slowly "backs up" accurate values to earlier board positions.

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Learning Algorithm

- Uses training values for the target function to induce a hypothesized definition that fits these examples and hopefully generalizes to unseen examples.
- In statistics, learning to approximate a continuous function is called ***regression***.
- Attempts to minimize some measure of error (***loss function***) such as ***mean squared error***:

$$E = \frac{\sum_{b \in B} [V_{train}(b) - \hat{V}(b)]^2}{|B|}$$

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Least Mean Squares (LMS) Algorithm

- A gradient descent algorithm that incrementally updates the weights of a linear function in an attempt to minimize the mean squared error

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Until weights converge :
  For each training example b do :
    1) Compute the absolute error :
         $error(b) = V_{train}(b) - \hat{V}(b)$
    2) For each board feature, $f_i$, update its weight, $w_i$ :
         $w_i = w_i + c \cdot f_i \cdot error(b)$
       for some small constant (learning rate) c
```

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LMS Discussion

- Intuitively, LMS executes the following rules:
  - If the output for an example is correct, make no change.
  - If the output is too high, lower the weights proportional to the values of their corresponding features, so the overall output decreases
  - If the output is too low, increase the weights proportional to the values of their corresponding features, so the overall output increases.
- Under the proper weak assumptions, LMS can be proven to eventetually converge to a set of weights that minimizes the mean squared error.

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Lessons Learned about Learning

- Learning can be viewed as using direct or indirect experience to approximate a chosen target function.
- Function approximation can be viewed as a search through a space of hypotheses (representations of functions) for one that best fits a set of training data.
- Different learning methods assume different hypothesis spaces (representation languages) and/or employ different search techniques.

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Various Function Representations

- Numerical functions
  - Linear regression
  - Neural networks
  - Support vector machines
- Symbolic functions
  - Decision trees
  - Rules in propositional logic
  - Rules in first-order predicate logic
- Instance-based functions
  - Nearest-neighbor
  - Case-based
- Probabilistic Graphical Models
  - Naïve Bayes
  - Bayesian networks
  - Hidden-Markov Models (HMMs)
  - Probabilistic Context Free Grammars (PCFGs)
  - Markov networks

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Various Search Algorithms

- Gradient descent
  - Perceptron
  - Backpropagation
- Dynamic Programming
  - HMM Learning
  - PCFG Learning
- Divide and Conquer
  - Decision tree induction
  - Rule learning
- Evolutionary Computation
  - Genetic Algorithms (GAs)
  - Genetic Programming (GP)
  - Neuro-evolution

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Evaluation of Learning Systems

- Experimental
  - Conduct controlled cross-validation experiments to compare various methods on a variety of benchmark datasets.
  - Gather data on their performance, e.g. test accuracy, training-time, testing-time.
  - Analyze differences for statistical significance.
- Theoretical
  - Analyze algorithms mathematically and prove theorems about their:
    - Computational complexity
    - Ability to fit training data
    - Sample complexity (number of training examples needed to learn an accurate function)

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History of Machine Learning

- 1950s
  - Samuel's checker player
  - Selfridge's Pandemonium
- 1960s:
  - Neural networks: Perceptron
  - Pattern recognition
  - Learning in the limit theory
  - Minsky and Papert prove limitations of Perceptron
- 1970s:
  - Symbolic concept induction
  - Winston's arch learner
  - Expert systems and the knowledge acquisition bottleneck
  - Quinlan's ID3
  - Michalski's AQ and soybean diagnosis
  - Scientific discovery with BACON
  - Mathematical discovery with AM

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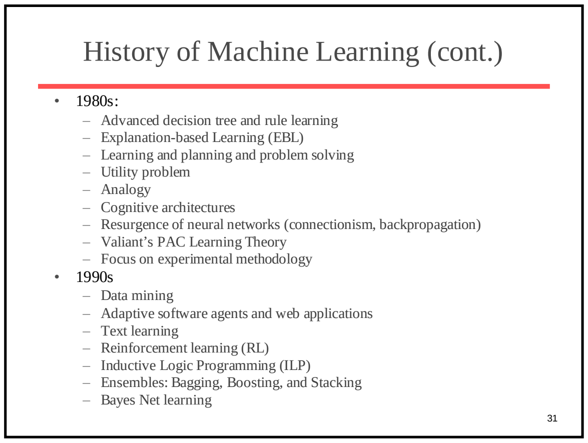
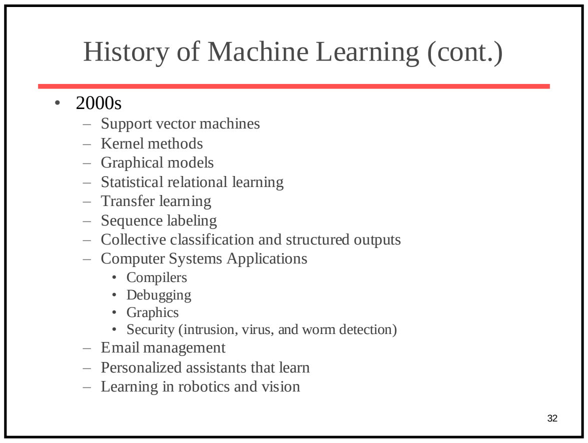


History of Machine Learning (cont.)

- 1980s:
  - Advanced decision tree and rule learning
  - Explanation-based Learning (EBL)
  - Learning and planning and problem solving
  - Utility problem
  - Analogy
  - Cognitive architectures
  - Resurgence of neural networks (connectionism, backpropagation)
  - Valiant’s PAC Learning Theory
  - Focus on experimental methodology
- 1990s
  - Data mining
  - Adaptive software agents and web applications
  - Text learning
  - Reinforcement learning (RL)
  - Inductive Logic Programming (ILP)
  - Ensembles: Bagging, Boosting, and Stacking
  - Bayes Net learning



History of Machine Learning (cont.)

- 2000s
  - Support vector machines
  - Kernel methods
  - Graphical models
  - Statistical relational learning
  - Transfer learning
  - Sequence labeling
  - Collective classification and structured outputs
  - Computer Systems Applications
    - Compilers
    - Debugging
    - Graphics
    - Security (intrusion, virus, and worm detection)
  - Email management
  - Personalized assistants that learn
  - Learning in robotics and vision