EECS 349 Machine Learning

Instructor: Doug Downey

(some slides from Pedro Domingos, University of Washington)

Logistics

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Grading and Assignments

Assignment	Due Date	Points	
Homework 1	21-Jan-14	10	
Homework 2	28-Jan-14	20	
Project Proposal	6-Feb-14	10	
Homework 3	~13-Feb-14	10	
Project Status Report	18-Feb-14	10	
Homework 4	~6-Mar-14	10	
Project Video	21-Mar-14	20	
Project website	21-Mar-14	15	
	TOTAL POINTS	105	

Α	A-	B+	В	B-	C+	С	C-	Etc
93+	92-90	89-87	86-83	82-80	79-77	76-73	72-70	69

Homework

- Four homeworks (50 pts)
 - Submitted via e-mail according to hmwk instructions
 - Late assignments penalized 5% per day must be within 1 week of original deadline
 - Significant programming, some exercises
 - Any programming language
 - Program grading based on sample output, code, explanation
- Final Project (55 pts)
 - Teams of k
 - Define a task, create/acquire data for the task, train ML algorithm(s), evaluate & report

Prerequisites

- Significant Programming Experience
 - EECS 214/311, 325 or the equivalent
 - Example: implement decision trees (covered next Monday)
- Basics of probability
 - E.g. independence
- Basics of logic
 - E.g. DeMorgan's laws



Look at Homework #2 today

Source Materials

- T. Mitchell, *Machine Learning*, McGraw-Hill
- E. Alpaydin, *Introduction to Machine* Learning, MIT Press
- (both "required")
- Papers & Web pages

A Few Quotes

- "A breakthrough in machine learning would be worth ten Microsofts" (Bill Gates, Chairman, Microsoft)
- "Machine learning is the next Internet" (Tony Tether, Director, DARPA)
- "Machine learning is the hot new thing" (John Hennessy, President, Stanford)
- "Web rankings today are mostly a matter of machine learning" (Prabhakar Raghavan, Dir. Research, Yahoo)
- "Machine learning is going to result in a real revolution" (Greg Papadopoulos, CTO, Sun)
- "Machine learning is today's discontinuity" (Jerry Yang, CEO, Yahoo)

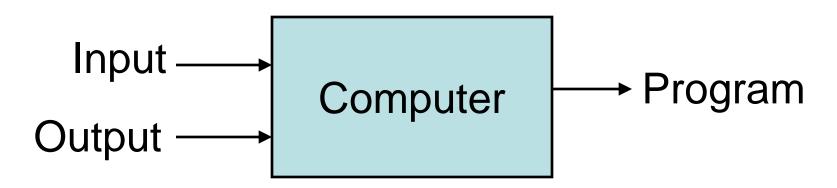
So What Is Machine Learning?

 "The study of computer programs that improve automatically with experience"
 T. Mitchell *Machine Learning*

- Automating automation
- Getting computers to program themselves
- Writing software is the bottleneck
- Let the data do the work instead!

Traditional Programming

Machine Learning



Magic?

No, more like gardening

- Seeds = Algorithms
- Nutrients = Data
- Gardener = You
- Plants = Programs



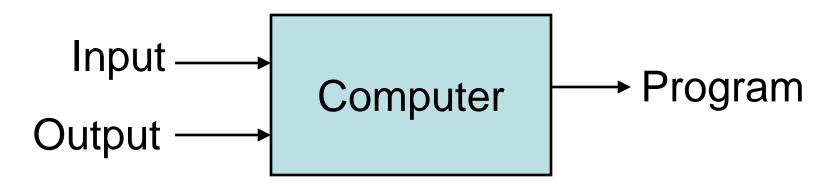
Case Study: Farecast

Search Flights Find cheap flights	and free airfare predictions
Round Trip One Way	Multi-City
Please enter a To city	
From: Chicago, IL (CHI) - All airports	To: Seattle, WA (SEA) - Seattle/Tacoma
Include Nearby Airports	Include Nearby 7-Day Low Fare Prediction Image: Confidence: Tip: Buy Fares Rising \$42 Confidence: 66% Details Applies to ORD>SEA only Saliy Low Fare History \$390 \$305 \$220 \$135 69 Days Ago Now

Sample Applications

- Web search
- Computational biology
- Finance
- E-commerce
- Space exploration

- Robotics
- Information extraction
- Social networks
- Finance
- Debugging
- [Your favorite area]



ML in a Nutshell

- Tens of thousands of machine learning algorithms
- Hundreds new every year
- Every machine learning algorithm has three components:
 - Representation
 - Evaluation
 - Optimization

Representation

- How do we represent the function from input to output?
 - Decision trees
 - Sets of rules / Logic programs
 - Instances
 - Graphical models (Bayes/Markov nets)
 - Neural networks
 - Support vector machines
 - Model ensembles

– Etc.

Evaluation

- Given some data, how can we tell if a function is "good"?
 - Accuracy
 - Precision and recall
 - Squared error
 - Likelihood
 - Posterior probability
 - Cost / Utility
 - Margin
 - Entropy
 - K-L divergence
 - Etc.

Optimization

- Given some data, how do we **find** the "best" function?
 - Combinatorial optimization
 - E.g.: Greedy search
 - Convex optimization
 - E.g.: Gradient descent
 - Constrained optimization
 - E.g.: Linear programming

Types of Learning

- Supervised (inductive) learning
 - Training data includes desired outputs
- Unsupervised learning
 - Training data does not include desired outputs
- Semi-supervised learning
 - Training data includes a few desired outputs
- Reinforcement learning

- Rewards from sequence of actions

Inductive Learning

- **Given** examples of a function (X, F(X))
- **Predict** function *F*(*X*) for new examples *X*
 - Discrete F(X): Classification
 - Continuous F(X): Regression
 - -F(X) = Probability(X): Probability estimation

What We'll Cover

Inductive learning

- Decision tree induction
- Instance-based learning
- Neural networks
- Genetic Algorithms
- Support vector machines
- Bayesian Learning
- Hidden Markov Models
- Learning theory
- Reinforcement Learning

Unsupervised learning

- Clustering
- Dimensionality reduction

What You'll Learn

- Where can I use ML?
- For a given problem, how do I:
 - Express it as an ML task
 - Choose the right ML algorithm
 - Evaluate the results
- What are the unsolved problems/new frontiers?

ML in Practice

- Understanding domain, prior knowledge, and goals
- Data integration, selection, cleaning, pre-processing, etc.
- Learning models
- Interpreting results
- Consolidating and deploying discovered knowledge
- Loop

Reading for This Week

• Wired data mining article, Forbes article (linked on course Web page)

- Recommended:
 - Mitchell, Chapters 1 & 2
 Alpaydin, Ch 1 & 2