CS 2416 Machine Learning Theory
Fall 2005
Location: MS 2173
Time: Thursdays 12-2pm

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Course Web Site: http://www.cs.toronto.edu/ toni/Courses/MLTheory/ML.html
Refer to this site periodically for important announcements and other information. All handouts will be available on the site in postscript form.

Course Materials: The text for this course is **An Introduction to Comptutational Learning Theory** by Kearns and Vazirani, plus papers and notes for topics not in the book. I will try to make most of the supplementary material available on the webpage for this course.

Prerequisites:

The only prerequisite for this course is the equivalent of CS364 (undergraduate complexity theory). A very related course (but not a prerequisite) is Machine Learning, CS2515. This course (Learning Theory) will cover the foundations of computational learning theory, and will complement the existing Machine Learning graduate courses.

Course Description

The goal of creating programs or computers that learn with experience is one of the most intriguing problems in computer science. It is of practical value since we want programs that will adapt to change, that can adapt to the needs of their users, and that can find useful information in extremely large amounts of data. It is also closely connected to understanding human perception, since humans are the ideal model of how we would like many of these types of programs to act.

In this course, we will study mathematical frameworks and foundations of machine learning. These mathematical models should capture key aspects of machine learning systems. A good framework will allow us to study problems and algorithms, allowing us to analyze the algorithms with respect to different measures, such as runtime efficiency, and accuracy. We will analyze how hard it is to learn various problems and will mathematically analyze general issues such as Occam's Razor.

Most of the course will focus on the problem of concept learning. Given data (for example, pictures of hippos and other zoo animals), we want to be able to learn from this data to classify future examples (new unlabelled pictures) well. This seems like a restricted form of learning, but it turns out that most methods for other kinds of learning end up solving this sort of problem at their core.

Here is an outline of specific topics that we hope to cover in this course. The first 8 items are core topics, and a selection of the remaining items will be chosen.

(1.) Introduction to machine learning theory, basic definitions.

(2.) The consistency model, the mistake-bound model.

(3.) Decision lists, Perceptron Algorithm

(4.) Weighted Majority Algorithm, Winnow Algorithm

(5.) Introduction to the PAC model

(6.) VC dimension and uniform convergence

(7.) Boosting: Weak and strong learning, Shapire's theorem, Adaboost, connection to hard-core distributions.

(8.) Algorithmic hardness results for learning and connections with cryptography.

(9.) Learning with noise, and the Statistical Query model, and Fourier analysis.

(10.) State-of-the-art algorithms for learning decision trees and DNF, and connection to automatizability of Resolution.

(11.) Bayesian inference: definition and applications, complexity issues, exact and approximate algorithms.

Grading and Assignments

Grading will be based on 4 assignments which will be handed out during the semester. You will have at least one week to turn in each assignment. Extra challenging questions will be marked with a (*). For each homework assignment, you may work on your own, or with one other partner. If you work with a partner, please submit only one copy of the assignment, with both of your names on it. You should work and discuss the problems with only your partner. In exceptional circumstances you may be allowed to work in groups of three. You must get my permission ahead of time to work in a group of three. Please do not consult the web or any other sources for solutions to homework problems. Class attendence is manditory and you are encouraged to ask many questions in class. You will additionally be asked to do one of the following: prepare lectures notes for one class lecture, or to give a short (20 minute) presentation on a current research paper in the area, or submit a short research project from a list of possible topics.