CS 181 – Machine Learning

Instructor:	Prof. Ryan P. Adams
Teaching Fellows:	TBD
Lectures:	Monday and Wednesday, 1-2:30pm
Location:	Jefferson 250
Section:	TBD
Office Hours:	Monday 2:30-4:00pm in MD 233 (Adams)
URL:	`http://isites.harvard.edu/k100309`
Contact:	`cs181-s14-staff@seas.harvard.edu`

Course Description

This course provides a broad and rigorous introduction to machine learning, probabilistic reasoning and decision making in uncertain environments. The course should be of interest to undergraduate students in computer science, applied mathematics, sciences and engineering, and lower-level graduate students looking to gain an introduction to the tools of machine learning and probabilistic reasoning with applications to data-intensive problems in the applied sciences, natural sciences and social sciences.

For students with interests in the fundamentals of machine learning and probabilistic artificial intelligence, this course will address three central, related questions in the design and engineering of intelligent systems. How can a system process its perceptual inputs in order to obtain a reasonable picture of the world? How can we build programs that learn from experience? And how can we design systems to deal with the inherent uncertainty in the real world?

Our approach to these questions will be both theoretical and practical. We will develop a mathematical underpinning for the methods of machine learning and probabilistic reasoning. We will look at a variety of successful algorithms and applications. We will also discuss the motivations behind the algorithms, and the properties that determine whether or not they will work well for a particular task.

Discussion Board

Most questions about the course, lecture or section material, or the assignments should be addressed via Piazza at `https://piazza.com/harvard/spring2014/cs181`. The course instructors will regularly check this discussion board and post responses. Students taking the class are also encouraged to post responses. Code examples can be posted, but don't post anything you wouldn't be expected to share with other students in the class as per the collaboration policy. Long, detailed questions are probably best answered during office hours. Questions that are not appropriate for the discussion board may be sent to the staff via email. Use your judgement.

Sections

There will be a recommended weekly section led by the teaching staff. Sections will be interactive and contain discussion of questions and examples related to the course. They will include discussion of homework assignments, and worked out examples of questions that might be good preparation for the midterms.

Textbooks and References

The following book is required for the course:

Pattern Recognition and Machine Learning Christopher M. Bishop, Springer, 2006.
`http://research.microsoft.com/en-us/um/people/cmbishop/PRML/`.

This book will be supplemented with lecture notes when the book does not cover a relevant topic. In addition, there are other optional books you may wish to read:

Artificial Intelligence: A Modern Approach Stuart J. Russell and Peter Norvig, Prentice Hall, Third Edition, 2009. The classic "must own" book on artificial intelligence. Be sure to buy the third edition.

Machine Learning Tom Mitchell, McGraw–Hill, 1997. A general introduction to the topic of machine learning.

Information Theory, Inference, and Learning Algorithms David J.C. MacKay, Cambridge University Press, 2003. A very well-written book with excellent explanations of many machine learning topics. Freely available online at
`http://www.inference.phy.cam.ac.uk/mackay/itila/`.

Machine Learning: A Probabilistic Perspective Kevin P. Murphy, MIT Press, 2012. A brand new book that overs a very wide range of important topics. It is a little rough around the edges.

Bayesian Reasoning and Machine Learning David Barber, Cambridge University Press, 2012. Freely available online at
`http://web4.cs.ucl.ac.uk/staff/D.Barber/pmwiki/pmwiki.php?n=Brml.Online`.

Elements of Statistical Learning Trevor Hastie, Robert Tibshirani, and Jerome Friedman, Springer 2009. Freely available at
`http://statweb.stanford.edu/~tibs/ElemStatLearn/`.

Reinforcement Learning: An Introduction Richard S. Sutton and Andrew G. Barto, MIT Press, 1998. An easy-to-read book by pioneers in reinforcement learning.

Prerequisites

Students should be comfortable with writing non-trivial programs (e.g. CS 51 or equivalent). We provide support code in Python and strongly discourage, but don't preclude, that assignments are completed in a different programming language. This is not a class about coding style, but a class about testing methods of machine learning and reasoning under uncertainty.

Students should have a background in basic probability theory (e.g. STAT 110 or equivalent), and some level of mathematical sophistication, including calculus and linear algebra (e.g. Math 21a and 21b or equivalent).

Requirements and Grading

There are four practicals (open-ended homeworks), making up 40% of the final grade. There are two midterms, each counting for 15% of the final grade. The second midterm will occur on the last day of class and will focus on the material in the second half of the course. There is also a final project, which you will complete on your own. This project will involve the development of an intelligent agent that will compete against other agents in a virtual world; your agents will operate alongside the agents from the Harvard College version of the course. The design, analysis, evaluation and, to some extent, performance of your agent will count for 25% of the final grade. There will also be online mini-quizzes on the readings, to be completed before lecture; these count for 5% of the final grade. In order to pass the course, students must receive a passing grade within each major component of the course: practicals, midterms, and final project.

Practicals

Practicals will be done in teams of three. The course staff can help you to find partners. The goal of the practicals in the course is twofold: to help you master the technical material, and to show you how the techniques we are learning can be used to build powerful and cool applications. We call them "practicals" rather than "homeworks" to make the point that they are meant to be open-ended and encourage creativity. Each practical will usually be due two weeks after being handed out. Each practical will generally be centered around a particular methodology and task and involve programming. You will need to consider some theoretical issues, write a program to solve the task, and evaluate your program through experiments to compare the performance of different algorithms and methods. This may involve uploading your predictions to a course-wide leaderboard. You'll be assessed on effort, the sophistication of your technical approach, the clarity of your explanations, the evidence that you present to support your evaluative claims, and the performance of your implementation.

Online Mini-Quizzes

You will be expected to complete a short online quiz before each lecture, via iSites. These are short, multiple-choice quizzes to help you keep motivated to come to class prepared. They will be due at the start of lecture and will determine 5% of your grade.

Collaboration Policy

We want you to be able to discuss the class material with each other, but we want the homework you submit to be your group's work. More specifically:

- Outside of your group, you may never:
  - Share code
  - Share writeups
- You may always:
  - Discuss the related concepts and the high-level approach
  - Discuss the results of your experiments at a high level, e.g., "We got 90% test accuracy."
- You should be wary of discussing details of proofs, your code, or results at an implementation level, rather than at the "big idea" level.

Late Policy

All homework should be submitted electronically by 23:59 on the due date, via the iSites dropbox at `http://isites.harvard.edu/k100309`. Only one submission is required for each team of students. Homework may be turned in up to one week late with a 50% penalty. Start early.

Final Project

The final project for this class will take the form of a challenge problem. This problem will require many of the techniques discussed in class as well as additional creativity. The project will be done in teams of three. You'll be designing and analyzing an agent in a virtual world!