8803 RLDM

CS 8803 Reinforcement Learning and Decision Making
Spring 2016

Instructor of Record:
Charles Isbell, isbell@cc.gatech.edu
259, College of Computing Building

Creators of Online Material:
Prof. Charles Isbell, isbell@cc.gatech.edu
Prof. Michael Littman, littman@cs.brown.edu

TAs:
Timothy Bail, timbail@gatech.edu
Miguel Morales, mimoralea@gatech.edu
Pushkar Kolhe, pushkar@cc.gatech.edu

Piazza:
Piazza will be our main discussion platform.

Office Hours:
Office Hours will be on Hangouts on Air. To get invites:

- Join our Google+ Community at https://plus.google.com/communities/103271501464593879536
- Look out for T-sq announcements. You will get a new link for every office hours.

General Information

Reinforcement Learning and Decision Making is a three-credit course on, well, Reinforcement Learning and Decision Making. Reinforcement Learning is a subarea of Machine Learning, that area of Artificial Intelligence that is concerned with computational artifacts that modify and improve their performance through experience. This course focuses on automated computational decision making through a combination of classic papers and more recent work. It examines efficient algorithms, where they exist, for single agent and multiagent planning as well as approaches to learning near-optimal decisions from experience. Topics include: Markov decision processes; stochastic and repeated games; partially observable Markov decision processes; reinforcement learning; and interactive reinforcement learning. The class is particularly interested in issues of generalization, exploration, and representation.

Objectives

There are four primary objectives for the course:

- To provide a broad survey of approaches and techniques in RLDM
- To develop a deeper understanding of several major topics in RLDM
- To develop the design and programming skills that will help you to build RLDM systems
- To develop the basic skills necessary to pursue research in RLDM

As you will see in the next section, we assume that you are already familar with machine learning techniques and have some comfort with doing empirical work in machine learning. As a result, we emphasize the more computational aspects of developing decison-making systems. Having said that, our concern with research is expressed by having students replicate a result in a published paper in the area.

Prerequisites

The official prerequisite for this course is an introductory course in machine learning at the graduate level. While having taken such a course is not strictly necessary, you will find that the lectures make constant call-backs to material covered in graduate machine learning courses (and the course offered by the creators of this material in particular). Of course, having said all that, the most important prerequisite for enjoying and doing well in this class is your interest in the material. I say that every semester and in every course, but it's true. In the end it will be your own motivation to understand the material that gets you through it more than anything else. If you are not sure whether this class is for you, please talk to me.

Resources

- **Readings.** This class being more of a seminar, there is no required textbook; however, Sutton and Barto's Reinforcement Learning is an awesome resource we strongly support (see: http://webdocs.cs.ualberta.ca/~sutton/book/the-book.html). We use research paper readings as well, but those will be provided for you.
- **Computing.** You will have access to CoC clusters for your programming assignments, I suppose, but you won't need them. We use BURLAP as our programming environment, so that means Java! Weekly Assignments will be submitted using Udacity's quiz mechanisms.
- **Web.** We will use the class web page to post last minute announcements, so check it early and often.

Statement of Academic honesty

At this point in your academic careers, I feel that it would be impolite to harp on cheating, so I won't. You are all adults, more or less, and are expected to follow the university's code of academic conduct (you know, the honor code). Furthermore, at least some of you are researchers-in-training, and I expect that you understand proper attribution and the importance of intellectual honesty.

Please note that unauthorized use of any previous semester course materials, such as tests, quizzes, homework, projects, videos, and any other coursework, is prohibited in this course. In particular, you are not allowed to use old exams. Using these materials will be considered a direct violation of academic policy and will be dealt with according to the GT Academic Honor Code. Furthermore, I do not allow copies of my exams out in the ether (so there should not be any out there for you to use anyway). Just as you are not to use previous material you are not to share current material—including lecture material—with others either now or in the future. My policy on that is strict. If you violate the policy in any shape, form or fashion you will be dealt with according to the GT Academic Honor Code. I also have several... friends... from Texas who will help me personally deal with you. They are on retainer from my Machine Learning course and they've tasted blood.

Readings and Lectures

The online lectures are meant to summarize the readings and stress the important points. You are expected to critically read any assigned material. Your active participation in the material, the lectures, and various forums are crucial in making the course successful. This is less about my teaching than about your learning. My role is merely to assist you in the process of learning more about the area.

To help you to pace yourself, I have provided a nominal schedule (see the Schedule link on the left) that tells you when we would be covering material if we were meeting once a week for three hours during the term. I recommend you try to keep that pace. More to the point, there are weekly assignments that correspond to the reading material and it will be difficult to do those without at least passing familiarity with the material.

Grading

Your final grade is divided into three components: assignments, a semester project, and a final exam.

- **Assignments.** There will be eight short assignments, some involving programming, some not.
- **Projects.** Students will be asked to replicate results from relevant papers from the literature. Each of the two projects will consist of a short write up and a short video presentation of the work.
- **Exams.** There will be two written, closed-book exams. The first will be about halfway through the term, and the last will be at whatever time is scheduled for our class' final exam. Although I'm told I have a reputation for creative exams, these exams are meant to be a walk in the park if you follow and read the material.

Due Dates

All graded assignments are due by the time and date indicated. I will not accept late assignments or make up exams. You will get zero credit for any late assignment. The only exceptions will require: a **note** from an appropriate authority and **immediate notification** of the problem when it arises. Naturally, your excuse must be acceptable. If an alien parasite that thrives on electronic assignments gets into your computer and erases all copies of your work from existence, I will need a signed note from the relevant galactic authorities who have investigated... in English.

Numbers

Component	
Assignments (8)	46%
Projects (2)	30%
Exams (2)	24%

In the spirit of mechanism design, the grading scheme is set up so that one can't blow off reading the material and still earn an A. Similarly, one can't blow off a project either. Not that you would do either of those things, but it's all about incentives, people.

Disclaimer

I reserve the right to modify any of these plans as need be during the course of the class; however, I won't do anything capriciously, anything I do change won't be too drastic, and you'll be informed as far in advance as possible.