Proposed Syllabus for ECE6xxx: Online Decision Making in Machine Learning

February 8, 2021

Summary of course

In many applications of machine learning, data is collected sequentially; moreover, decisions can impact performance both in the present and the future. This class will deal with the design of machine learning algorithms for real-time decision making, including reinforcement learning. Classical applications in engineering, and modern applications in the ML pipeline will both be discussed.

Prerequisites

An introductory course in linear algebra and multivariable calculus (MATH2551 or equivalent), and an upper-division probability course (ECE3077 or equivalent) are mandatory prerequisites to take this course. Much of the course will be in the language of matrices and vectors, and will assume that students are comfortable with the use of matrices in equations and taking gradients of functions of several variables. The course will also assume familiarity with basic topics in probability and statistics such as working with Bayes' rule, and understanding what a confidence interval means. Finally, students should have basic Python programming skills (CS1301 or equivalent). We will organize a review session on these concepts at the start of the semester to help students refresh their memory on these concepts. This will, however, *not* constitute a substitute for having taken these courses.

Additionally, prior background in optimization (ECE3xxx or equivalent) is not mandatory, but recommended. The course will use concepts from convex analysis and dynamic programming. We will also organize a review session on optimization at the start of the semester to cover these concepts at a rudimentary level. Finally, this course is a complementary offering to graduate-level machine learning courses such as ECE6254. While a prior background in ML is not needed to understand the topics covered in this course, it would enrich a student's experience and appreciation of this course material.

Instructor

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Office hours: TBD. Additional availability by appointment.

Grading

The course will be graded on the following components:

- **Homeworks (**45%**)**: Homework will be biweekly, and there will be approx. 6 homework assignments. Further details on homework are listed below.

- **Midterm** (25%): There will be one midterm exam, that will test conceptual and technical knowledge of the first two parts of the course material (online learning and bandits).

- **Course project** (30%): In lieu of a final exam, we will have a project in which students study in depth a topic of their choosing related to the course. Students can form groups of upto 3, or work alone on this project. Grading for the project will be based on two components: a) a poster presentation (if instruction is in-person) or a submitted video presentation (if instruction is remote), and b) a short report due by the end of finals week. More details on these are provided below.

Note: some adjustments may be made to this break-up if the course is offered with remote instruction depending on logistics of organizing a midterm exam. An alternate grading make-up will be 70% *homeworks (weekly, not biweekly) and* 30% *course project.*

The students' final grade will be assigned as a letter grade according to the scale:
A: $90 - 100\%$ B: $80 - 89\%$ C: $70 - 79\%$ D: $60 - 69\%$ F: $\leq 59\%$
The instructor may exercise the option to "curve" midterm scores if determined that midterm was more difficult than intended. This would result in grades being adjusted *higher* for all students, if at all.

Homework and project

Homework will be assigned approximately biweekly. *Homework will be turned in via Canvas. Late submissions will result in zero credit unless you have made prior arrangements with the instructor.* Each homework assignment has a maximum of 100 points, and the best $N - 1$ out of the N homeworks will be evaluated. Thus, *the maximum number of homework points you can earn is equal to* $(N-1) \cdot 100$. *This also means that you can drop one out of the N homeworks if you like, or alternatively, give yourself some breathing room to submit a partially completed one!*

This is a largely mathematical class, and each homework assignment will have a significant ($\sim 70\%$) mathematical component. Homework problems will build on lecture material in substantive ways, and help students understand how and why the algorithms developed in class work. The remaining $\sim 30\%$ of the homework will use Jupyter notebooks and evaluations on datasets. These will take students through real-world scenarios where the algorithms developed in class are applicable. *Students will need coding familiarity with Python to do the homework. Students will need a working Jupyter notebook installation as well as capability to install additional open-source Python packages as needed.*

The final course project is intended to give students a bird's-eye view of what doing research in online decision making in ML is like. Most course projects would look like one of the following:

- An in-depth survey of one of the topics covered in the class. A survey consists of a rigorous academic review of the literature related to the topic interpreted *in the student's own words*, and a possible discussion of future areas of research.

- An application of the algorithms discussed in class on a ML dataset or an engineering application. *The application can be non-standard for this type of algorithm; in fact, proposing new applications for the material developed in class is encouraged.* However, the methodology in the implementation needs to involve an online decision-making or reinforcement learning algorithm.

- A mathematical topic of novel research related to algorithms covered in the class. *This does not need to constitute a publishable paper; initial results and directions for future work are a much more common outcome of a short course project.* Students who are interested in conducting research after the completion of this course are welcome to contact the instructor at the end of the semester.

Project proposals that do not neatly fall into one of these categories are also welcome. Students will be asked to submit a short abstract on their course project topic around the middle of the semester to allow the instructor to determine validity based on the criterion of sufficiently involving course material.

Course materials

A course webpage will be made publicly available. This page will provide general course information, links to lecture notes and videos, and links to homework assignments. Homework assignments and solutions will also be posted in canvas as they are made available.

The instructor and TAs will make exclusive use of Piazza to make announcements and answer questions. Piazza is a great problem to discuss problems, find study groups, etc. Please direct any questions you might have about the course to Piazza. Unless your questions are personal in nature, please do not make private posts: if you have a question you are probably not the only one, and other students may benefit from seeing the discussion!

Textbook: Each of the parts of this course (online learning/optimization, multi-armed bandits, RL and game theory) are deep fields of study and each by itself could make up an entire course. This course is designed as a introductory gateway to these areas of research. As a result, we will not be using a single "required" textbook, but drawing from multiple references. The main reference for the class will be the instructor's self-contained course notes. If students are interested in diving deeper into any of these topics, the books listed below are all highly recommended (but optional reading). Some lectures will draw on material from these references and we will point it out as and when done so.

- Cesa-Bianchi and Lugosi: "Prediction, Learning and Games"

- Shalev-Schwartz: "Online learning and online convex optimization"

- Elad Hazan: "Introduction to online convex optimization"

- Szepesvari and Lattimore: "Bandit algorithms"

- Bertsekas: "Reinforcement Learning and Optimal Control"

- Sutton and Barto: "Reinforcement Learning: An Introduction"

- Nisan et al: "Algorithmic game theory"

- Myerson: "Game Theory: An Analysis of Conflict"

Course expectations and guidelines

Academic integrity Georgia Tech aims to cultivate a community based on trust, academic integrity, and honor. Students are expected to act according to the highest ethical standards. For information on Georgia Tech's Academic Honor Code, please visit `www.catalog.gatech.edu/policies/honor-code`. Any student suspected of cheating or plagiarizing on a quiz, exam, or assignment will be reported to the Office of Student Integrity, who will investigate the incident and identify the appropriate penalty for violations.

Redistributing materials for this course and/or using external sites for assistance (e.g. contributing to test banks, CourseHero, Chegg, or similar sites) is prohibited.

Collaboration and group work Students are strongly encouraged to discuss homework problems with one another. However, *each student must write up and turn in their own solutions written in their own words. Cases where solutions appear to be identical or nearly identical will be immediately referred to the Office of Student Integrity.*

Absences/late submissions Out of fairness to the entire class, *late submission of homework, or absence at the midterm exam, will not be accepted in the absence of a prior agreement between the student and instructor*. In particular, *excused absences* include illnesses, religious observations, career fairs and job interviews. In the event than an excused absence such as above prevents a student from submitting an assignment, their homework grade will be calculated on a prorated basis. A student who expects to miss the midterm due to an excused absence should contact the instructor as soon as possible so that the instructor can make alternate arrangements. Such arrangements could be taking the midterm at an alternate time or adjust the grading allocation depending on the circumstances.

Accommodations for students with disabilities If you are a student with learning needs that require special accommodation, contact the Office of Disability Services at (404) 894-2563 or disabilityservices.gatech.edu, as soon as possible, to make an appointment to discuss your special needs and to obtain an accommodations letter. Please also email the instructor as soon as possible in order to set up a time to discuss your learning needs.

Student-faculty expetations agreement At Georgia Tech, we believe that it is important to strive for an atmosphere of mutual respect, acknowledgement, and responsibility between faculty members and the student body. In the end, simple respect for knowledge, hard work, and cordial interactions will help build the environment we seek. Therefore, I encourage you to remain committed to the ideals of Georgia Tech while in this class. See www.catalog.gatech.edu/rules/22 for an articulation of some basic expectation that we can have of each other.

Outline of course

NOTE: Instructor may choose to cover only one of Parts III and IV depending on student progress and understanding of material.

Part I: Online learning and optimization

- Motivation: Prediction from adversarial/time-varying data

- The multiplicative weights method

- Online convex optimization

- An application: adaptive online gradient descent (AdaGrad) in training of neural networks

Part II: Multi-armed bandits

- Motivation: Learning from limited data

- Bandit algorithms: Exploration-vs-exploitation

- Contextual decision processes

- An application: Cognitive radio OR A/B testing)

Part III: Reinforcement learning (RL)

- Basics: Dynamic programming and optimal control

- Reinforcement learning from simulation

- RL from batch/online data

- An application: Power grid optimization OR mobile healthcare

Part IV: Game theory/multi-agent systems

- Basics: Nash and correlated equilibrium in finite-player games

- Convergence to equilibrium of online learning algorithms

- A well-understood application: Selfish routing in networks OR auction design

- A nascent application: Training of generative adversarial networks