MATP6960 • Stochastic Optimization and Reinforcement Learning • Fall 2022

Time: 2:00-3:50pm TF; Location: Carnegie 208

Instructor: Yangyang Xu
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Office hours (in person): 3:50pm – 4:50pm on Tuesday and Friday
Course page: https://xu-yangyang.github.io/MATP6960.html

Course Objective

This course is intended to talk several special topics in stochastic optimization and reinforcement learning. The focus will be on modeling and algorithmic design. Convergence and complexity analysis will be covered. Topics include stochastic approximation methods, chance-constrained and robust optimization, Markov decision process, dynamical programming, temporal difference, Q-learning, policy gradient, and primal-dual methods.

Prerequisites

MATP6600/ISYE6780 or MATP6610 or MATH6800

Textbooks

- *Lectures on Stochastic Programming* by Alexander Shapiro, Darinka Dentcheva, Andrzej Ruszczynski (**recommended**)
- *Reinforcement Learning: an introduction* by Richard S. Sutton and Andrew G. Barto (**recommended**)
- *Reinforcement Learning and Optimal Control* by Dimitri P. Bertsekas (**recommended**)
- *Optimization for Machine Learning* by Suvrit Sra, Sebastian Nowozin, Stephen Wright. (**recommended**)
- *Introductory Lectures on Stochastic Optimization* by John C. Duchi (**recommended**)
- *Numerical Optimization* by Jorge Nocedal and Stephen Wright (**recommended**)

Topics to cover

1. Stochastic approximation methods: stochastic (sub)gradient method, momentum-accelerated stochastic gradient, adaptive stochastic (sub)gradient method
2. Chance-constrained and robust optimization
3. Augmented Lagrangian method, (adaptive) primal-dual stochastic method
4. Algorithms for reinforcement learning: dynamical programming, temporal difference, Q-learning, policy gradient

Assignments and grading policy

- Assignments: 4 homework (programming and/or theory questions) will be assigned; for each assignment, a report by LaTex is required to include theoretical solutions, code, numerical results, and observations/discussions

- Grades: 25% for each of the 4 homework

Attendance

Attendance and participation in class is a vital part of the learning process. Notes will be shared in LMS, but regular class attendance is strongly encouraged. It is the students' responsibility to keep informed of any announcement, or policy changes made during scheduled classes.

Academic Integrity

Intellectual integrity and credibility are the foundation of all academic work. A violation of Academic Integrity policy is, by definition, considered a flagrant offense to the educational process. It is taken seriously by students, faculty, and Rensselaer and will be addressed in an effective manner.

If found responsible for committing academic dishonesty, a student may be subject to one or both types of penalties: an academic (grade) penalty administered by the professor and/or disciplinary action through the Rensselaer judicial process described in the Student Rights and Responsibilities Handbook.

Academic dishonesty is a violation of the Grounds for Disciplinary Action as described in the handbook. A student may be subject to any of the following types of disciplinary action should disciplinary action be pursued by the instructor: disciplinary warning; disciplinary probation; disciplinary suspension, expulsion and/or alternative actions as agreed on by the student and hearing officer. It should be noted that no student who allegedly commits academic dishonesty will be able to drop or change the grade option for the course in question and is not eligible to request an F examination for the course.

The academic integrity policy applies to all students, undergraduate and graduate, and to scholarly pursuits and research. Additionally, attempts to commit academic dishonesty or to assist in the commission or attempt of such an act are also violations of this policy.