Optimization for Machine Learning

DSCC 435 / CSC 435 / ECE 412 Fall 2024

Meeting Information

Tuesday/Thursday 9:40-10:55 am
Hylan Building Room 203

Instructor

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Teaching Assistant

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Office Hours

4:00-5:00 pm, Wednesday, Wegmans Hall 2403 (Jiaming Liang)
4:00-5:00 pm, Friday, Wegmans Hall 1219 (Lin Zang)

Prerequisites

Students should be familiar with multivariate calculus, linear algebra, basic probability, and have good MATLAB or Python programming skills. Prior knowledge of optimization is helpful but not required.

Course Description

This course primarily focuses on algorithms for large-scale optimization problems arising in machine learning and data science applications. The first part will cover various first-order methods including gradient and subgradient methods, mirror descent, proximal gradient method, accelerated gradient method, Frank-Wolfe method, and dual methods. The second part will survey topics in machine learning from an optimization perspective, e.g., stochastic optimization, distributionally robust optimization, online learning, and reinforcement learning.

Topics (subject to change)

1. Introduction
    - Applications in ML
    - Convexity and complexity
2. First-order methods I: basic concepts
    - Gradient method
    - Subgradient method
    - Mirror descent

- Proximal gradient method
- Accelerated gradient method
- Frank-Wolfe method

3. First-order methods II: advanced topics
    - Dual methods
    - Operator splitting
    - Universal methods
    - Optimization in relative scale
4. Selected topics in machine learning
    - Stochastic optimization
    - Distributionally robust optimization
    - Distributed optimization
    - Online learning
    - Reinforcement learning
5. Beyond first-order methods
    - Second-order methods
    - Higher-order methods

Textbooks

1. Amir Beck. *First-order methods in optimization*. SIAM, 2017.
2. Yurii Nesterov. *Lectures on convex optimization*. Springer, 2018.

Recommended Readings

1. Guanghui Lan. *First-order and Stochastic Optimization Methods for Machine Learning*. Springer, 2020.
2. Benjamin Recht and Stephen Wright. *Optimization for Data Analysis*. Cambridge University Press, 2022.
3. Suvrit Sra, Sebastian Nowozin, and Stephen Wright, eds. *Optimization for Machine Learning*. MIT Press, 2011.

Assessments & Grading

- 30% homework (6 problem sets x 5% each)
- 45% midterm exam (Oct. 17)
- 5% project proposal (Nov. 5)
- 10% project presentation (Dec. 5)
- 10% project report (Dec. 10)

The final grade will be assigned as a letter grade according to the following scale:

A	90-100%
B	80-89%
C	70-79%
D	60-69%
F	0-59%

Project

The final course project is intended to give students the opportunity for in-depth exploration of a topic in modern optimization methods for machine learning and data science. Course projects could 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 data set or an engineering application. The application can be non-standard; in fact, proposing new applications for the material developed in class is encouraged. However, the methodology in the implementation needs to involve techniques that we discuss during the class.
- A conceptual (i.e., either theoretical or simulation-based) topic of novel research related to the class. Preliminary results and directions for future work are common outcomes.

Project proposals that do not neatly fall into one of these categories are also welcome. Students are encouraged to work in a group of **no more than two members**. Students will be asked to submit an abstract around mid-October (ungraded), submit a proposal on November 5 (5%), make a presentation on December 5 (10%), and submit a final report on December 10 (10%).

Academic Integrity

Academic integrity is a core value of the University of Rochester. 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/consisting of their own code. All assignments and activities associated with this course must be performed in accordance with the University of Rochester's Academic Honesty Policy. More information is available at: http://www.rochester.edu/college/honesty.

Absences/Late Submissions

Out of fairness to the entire class, late submission of homework 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.

Diversity, Equity, Inclusion, & Belonging

Instructors, teaching assistants, and students should work together to ensure that our class is a welcoming, inclusive, respectful, and vibrant place for all of its members to share, learn, and grow. Our class will not tolerate discrimination, prejudice, or harassment of any kind. More resources can be found at: https://www.rochester.edu/diversity/.

Accessibility

Students needing academic adjustments or accommodations because of a documented disability must contact the Disability Resource Coordinator for the school in which they are enrolled. I am happy to accommodate any and all accommodations, so long as they are documented with the Office of Disability Resources. I am glad to meet to discuss your specific situation or to help ensure you have the support you need. For additional information, please see: https://www.rochester.edu/college/disability/.