MATP4820/6610 • Computational Optimization • Spring 2023

Time: 12:00pm-1:50pm TF   Location: DCC 337

Instructor:	Yangyang Xu
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Office:	Amos Eaton 310
Office hours:	Tuesday 4pm – 5pm and Friday 4pm – 5pm (in person)
Course page:	https://xu-yangyang.github.io/MATP6610.html

Course Objective and Topics

This course is to introduce optimization methods and applications. An emphasis will be placed on understanding and implementing optimization algorithms, including gradient-type methods, Newton-type methods, derivative free methods, primal-dual type methods. The following topics will be covered.

1. Concepts of numerical algorithm and convergence
2. Fundamentals of unconstrained optimization
3. Gradient type methods: steepest gradient descent, projected gradient, conjugate gradient, proximal gradient, and Nesterov's accelerated proximal gradient methods
4. Newton type methods: Newton's method, quasi-Newton method, and Gauss-Newton method
5. Derivative free methods: coordinate descent method
6. Theory of functional constrained optimization: Karush-Kuhn-Tucker (KKT) conditions and Lagrangian duality
7. Simplex method and Interior-point methods for linear programming
8. Penalty methods, barrier function methods, and augmented Lagrangian method
9. Alternating direction method of multipliers and application in imaging and statistics

Learning outcomes

After taking the course, **undergraduate students are expected to know:**

1. how to estimate the per-iteration complexity, namely, counting the number of arithmetic operations

2. how to find stationary points of a function by formulating the first-order optimality condition

3. how to analytically check local and/global optimality of a given point for an unconstrained problem

4. how to numerically implement each optimization method that is taught and verify if a computed point is approximately a local/global optimal solution

5. how to apply optimization methods to applications such as in imaging, finance, and machine learning

In addition to the above, **graduate students are expected to also know:**

1. how to analyze the convergence and/or convergence rate of certain iterative methods

2. how to formulate the KKT systems of a functional constrained problem

3. how to choose appropriate optimization methods depending on the structure of applications

Prerequisites

Multi-variable calculus, linear algebra, and experience of using MATLAB.

Textbooks

- *Numerical Optimization* by Jorge Nocedal and Stephen Wright, 2006
- *Lectures on Convex Optimization* by Yurii Nesterov, 2018
- *Constrained Optimization and Lagrange Multiplier Methods* by Dimitri P. Bertsekas, 1996.
- *Introduction to Mathematical Programming* by Michael Kupferschmid
- *An Introduction to Optimization* by Edwin K. P. Chong and Stanislaw H. Zak, 4th Edition, 2013

Homework and exams

- **Homework:** roughly once every 1.5 weeks and will be posted in LMS.
- **Exams:** two mid-term exams (tentative time: 12:00pm-1:50pm on February 24, 2023 and on April 25, 2023)

Evaluation and Grading Policy

All students will be evaluated and graded by the following policy.

1. **Evaluation:** homework 40%, the first mid-term exam 30%, and the second mid-term exam 30%.
2. **Grading of homework:**
   - For each homework, a random portion of assigned problems will be graded;
   - The score composes of two parts: completeness (40%, check if all problems are finished), and correctness (60%, check if graded problems are done correctly)
3. **Late homework:**
   - Homework that is late up to one day will be penalized by 20%;
   - Homework that is late between one day and two days will be penalized by 40%;
   - No homework will be accepted if it is late more than two days unless you have a special reason (like illness with doctor's note) and notified the instructor at least three days ahead of the due time.
4. **Exam:**
   - No early exam will be taken (more details on how to monitor the exam will be announced).
   - A make-up exam will be administered only at the discretion of the instructor in the event of a verifiable emergency. In the event of a verifiable emergency, the student must contact the instructor as soon as possible, and in any case, prior to the next regularly scheduled class.

Attendance

Attendance and participation in class is a vital part of the learning process. Regular class attendance is strongly encouraged. It is the students' responsibility to keep informed of any announcement, or policy changes made through LMS and/or Email.

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.