EE381K-18: Convex Optimization (Unique Number: 17990)
CS395T: Convex Optimization (Unique Number: 53128)

Fall 2022

Aryan Mokhtari

Course Description:

This course focuses on the theory of Convex Optimization. The first part of the class focuses on the theory of Linear Programming (LP) and its applications, as well as the analysis of Simplex Algorithm for solving LPs. The second part of the class focuses on the basics of Convex Optimization and covers some important classes of convex programs such as semidefinite programing (SDP), second order cone programing (SOCP), and geometric programing (GP), as well as duality in linear programming and general convex and conic optimization problems. In the third part of the course, we will focus on applications of convex optimization in engineering, statistics and operations research. The applications range from systems and control theory to estimation, data fitting, information theory, statistics and machine learning. Finally, in the last part of the course we discuss some basic optimization algorithms for solving convex programming as well as their complexity analysis. It is intended to be a first year graduate class, but assumes good familiarity and ability with linear algebra, and a relatively strong mathematical background.

Instructor:

Aryan Mokhtari (https://sites.utexas.edu/mokhtari/)
Email: mokhtari@austin.utexas.edu
Lectures: 10:30am-12:00pm MW, ECJ 1.312.
Office Hours: 1:30pm-2:30pm, Mondays, EER 6.826.

TA and their Office Hours:

Name: Jiaxun Cui
Email: cuijiaxun@utexas.edu
Office Hours: TBA

Course Expectations:

The course will use several online tools:

- *Canvas:* Announcements, scanned class notes, assignments, grades for homework and exams.

- *Piazza:* this facilitates discussion between students in the class. It is primarily a venue to get basic help from your student peers. Office hours are the best way to get guidance on solutions from the TAs and the instructors. The TAs will answer questions on Piazza to the best of their bandwidth. Emailed questions about the homework will not be answered; email should be restricted to logistical issues.

- *Gradescope:* Electronic homework submission and homework/exam grading platform.

Course Material:

The class will primarily be taught in person. The class includes material from several sources, but the primary textbook is Convex Optimization by Boyd and Vandenberghe. This is available for purchase, and also for download at http://web.stanford.edu/~boyd/cvxbook/

Homework:

There will be homework due approximately once every week, and **will be assigned on Canvas**. **Homework needs to be scanned and submitted via Gradescope before 11:59pm** on the day it is due. Solutions will be released the day after when the homework was due.

Submissions outside of Gradescope, and late submissions, will not be accepted.

** *One homework (the one with lowest score) will be dropped from the final grading*.

** *Discussing homework problems is encouraged*. *Copying is considered cheating*. Be absolutely certain to submit your own independent homework solutions, e.g., copying or letting someone else copy your homework is unacceptable.

Grading:

Homework: 35%, Midterm: 25%, Final: 40%

Regrade request policy: If you feel we have made a mistake in the way a certain problem has been graded, you will have one week - from the date the grades are returned - to inform the relevant person (TAs for homework sets, instructors for exams) about the discrepancy. Requests should be made via Gradescope.

Exams:

Midterm exam: TBD.
Final exam will be on Friday, December 9, 10:20 am-12:30pm.

University Honor Code:

"The core values of The University of Texas at Austin are learning, discovery, freedom, leadership, individual opportunity, and responsibility. Each member of the University is expected to uphold these values through integrity, honesty, trust, fairness, and respect toward peers and community."

College of Engineering Drop/Add Policy

The Dean must approve adding or dropping courses after the fourth class day of the semester.

Students with Disabilities

UT provides upon request appropriate academic accommodations for qualified students with disabilities. Please contact the Office of Dean of Students at 4716259 or ssd@uts.cc.utexas.edu.

Emergency Preparedness

Every member of the university community must take appropriate and deliberate action when an emergency strikes a building, a portion of the campus, or entire campus community. Emergency preparedness means we are all ready to act for our own safety and the safety of others during a crisis. Students requiring assistance in evacuation must inform the instructor in writing of their needs during the first week of class. This information must then be provided to the Fire Prevention Services office by fax (5122322759), with "Attn. Mr. Roosevelt Easley" written in the subject line.

You may want to bookmark the emergency Web site http://www.utexas.edu/emergency/ because it is updated with information during actual emergencies or campus closures.
The university collects cell phone numbers from members of the campus community for emergency text messages. You can sign up for campus text alerts online. If you would like more information regarding emergency preparedness, visit http://www.utexas.edu/safety/preparedness

Tentative Course Lecture Schedule:

Lecture 1: Basic formulation of LP, hyperplane, half-space, affine set, polyhedron, lineality space, pointed polyhedron

Lecture 2: Face, minimal face, extreme point, vertex, basic feasible solution, active constraints, rank test for an extreme point

Lecture 3: Extreme points and optimality, Theorem of alternatives

Lecture 4: Farkas' Lemma (statement, proof, and geometric interpretation), Different forms of LP, Dual problems for LPs, Weak duality.

Lecture 5: Strong duality of LPs Part I, examples of dual problems.

Lecture 6: Complementary slackness Strict complementary, Geometric interpretation of complementary slackness, introduction of Max Flow and Min Cut problems.

Lecture 7: Totally UniModular (TUM) matrices, Proving Max Flow = Min Cut by using strong duality of LPs.

Lecture 8: Simplex method and its analysis.

Lecture 9: Convex set definition, examples of convex sets and proving their convexity (convex cone, hyperplane, polyhedron, ball, ellipsoid, norm cone, …), Operations that preserve convexity for sets.

Lecture 10: Convex functions (zeroth, 1st- and 2nd-order definitions) and their properties, sublevel sets and epigraphs

Lecture 11: Operations that preserve convexity for functions, conjugate function and its properties

Lecture 12: Quasi-convex and log-concave functions

Lecture 13: Convex programs, local min, global min, optimality conditions (constrained & unconstrained)

Lecture 14: Quasi-convex optimization, linear-fractional program

Lecture 15: QP, QCQP, SOCP, Robust Linear Programming

Lecture 16: Geometric Programming (GP), SDP, Schur complement, and connection between SOCP and SDP

Lecture 17: Proper cone, generalized inequalities and their properties, minimum and minimal elements, convexity via generalized inequalities, vector optimization

Lecture 18: Dual cones and generalized inequalities, minimum and minimal elements via dual inequalities, scalarization.

Lecture 19: Lagrangian, dual function, dual problem, connection between dual function and conjugate function, minimum volume covering ellipsoid

Lecture 20: Weak and strong duality, Slater's condition, complementary slackness, KKT conditions

Lecture 21: Solving primal problem via its dual problem, Dual of SOCP, Dual of SDP

Lecture 22: Approximation & fitting (Norm approximation, Least-norm problems, Regularized approximation, Robust approximation)

Lecture 23: Maximum Likelihood Estimation, experiment design

Lecture 24: Classification, linear classification, SVMs

Lecture 25: Strong convexity and smoothness, their important inequalities

Lecture 26: Gradient Descent, Convergence of gradient descent (GD) for smooth and strongly convex functions, convergence of GD for smooth (possibly nonconvex functions)

Lecture 27: Convergence of GD with exact line-search, Convergence of GD with backtracking line-search

Lecture 28: Newton's method and its convergence properties