Continuous

linear
polynomial
Rational

Convex Prob | Nonconvex Prob

Continuous
Discrete

CSE203B Convex Optimization

Theory Applications Algorithms.

exp
log

CK Cheng
Dept. of Computer Science and Engineering
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Duality

Outlines

- Staff
  - Instructor: CK Cheng
  - TAs: Po-Ya Hsu, Chester Holtz, James Lin
- Logistics
  - Websites, Textbooks, References, Grading Policy
- Classification
  - History and Category
- Scope
  - Coverage

Information about the Instructor

- Instructor: CK Cheng
- Education: Ph.D. in EECS UC Berkeley
- Industrial Experiences: Engineer of AMD, Mentor Graphics, Bellcore; Consultant for technology companies
- Research: Design Automation, Brain Computer Interface
- Email: ckcheng+203B@ucsd.edu, Office: Room CSE2130
- Office hour will be posted on the course website
- Websites
  - http://cseweb.ucsd.edu/~kuan
  - http://cseweb.ucsd.edu/classes/wi21/cse203B

VLSI Moore's law
3D layout
Simulation →
Wearable Sensor
Dehydration PepsiCo

Staff

Teaching Assistant

- Po-Ya Hsu, p8hsu@ucsd.edu
- Chester Holtz, chholtz@ucsd.edu
- James Lin, til002@ucsd.edu

Logistics: Class Schedule

Class Time: 2-320 PM TTH,

Discussion Session: 2-250 PM F (Separate zoom link) W1- W6

Class website: http://cseweb.ucsd.edu/classes/wi21/cse203B

Piazza link: piazza.com/ucsd/winter2021/cse203b/home

Gradescope link: https://www.gradescope.com/courses/221286

Zoom lecture:

https://ucsd.zoom.us/j/98033436384?pwd=Y3UrMDlIY0pyOTRmTGovVENQSXpvdz09

For access code of the links, check with TAs or the instructor

Logistics: Grading

1. Homeworks (40%) · H0- H3 -Web search is permitted
   - 40 50 45 Exercises (Grade by completion) -Group discussion is encourage
   - Assignments (Grade by content) → Work by oneself
2. Project (25%) Team 2-4
   - Theory or applications of convex optimization
   - 30 25 25 Survey of the state of the art approaches { Convexity, Duality
   - Outlines, references (W4)
   - Report (6PM 3/18/2021, W11)
3. ~~Exams~~ Exam (35%) Open book 48 hrs
   - 30 25 30 Midterm, 2/16/2021, T (W7)

Due

Logistics: Textbooks

Required text:

- Convex Optimization, Stephen Boyd and Lieven Vandenberghe, Cambridge, 2004 Classic / Worth the money
- Review appendix A in the first week HW0

References

- Numerical Recipes: The Art of Scientific Computing, Third Edition, W.H. Press, S.A. Teukolsky, W.T. Vetterling, and B.P. Flannery, Cambridge University Press, 2007.
- Functions of Matrices: Theory and Computation, N.J. Higham, SIAM, 2008.
- Fall 2016, Convex Optimization by R. Tibshirani, http://www.stat.cmu.edu/~ryantibs/convexopt/
- EE364a: Convex Optimization I, S. Boyd, http://stanford.edu/class/ee364a/

Classification: Brief history of convex optimization

Theory (convex analysis): 1900–1970

Algorithms

- 1947: simplex algorithm for linear programming (Dantzig) Army
- 1970s: ellipsoid method and other subgradient methods
- 1980s & 90s: polynomial-time interior-point methods for convex Optimization (Karmarkar 1984, Nesterov & Nemirovski 1994)
- since 2000s: many methods for large-scale convex optimization

Applications

- before 1990: mostly in operations research, a few in engineering
- since 1990: many applications in engineering (control, signal processing, communications, circuit design, . . .)
- since 2000s: machine learning and statistics

Classification

Tradition

Linear Programming	Nonlinear Programming	Discrete Integer Programming
Simplex	Lagrange multiplier	Trial and error
Primal/Dual	Gradient descent	Cutting plane
Interior point method	Newton's iteration	Relaxation

This class

Convex Optimization	Nonconvex, Discrete Problems
Primal/Dual, Lagrange multiplier	Local Optimal Solution Search, SA (Simulated Annealing), ILP (Integer Linear Programming), MLP (Mixed Integer Programming), SAT (Satisfiability), SMT (Satisfiability Modulo Theories), etc.
Gradient descent	
Newton's iteration	
Interior point method	

Mechanism Ch1-5

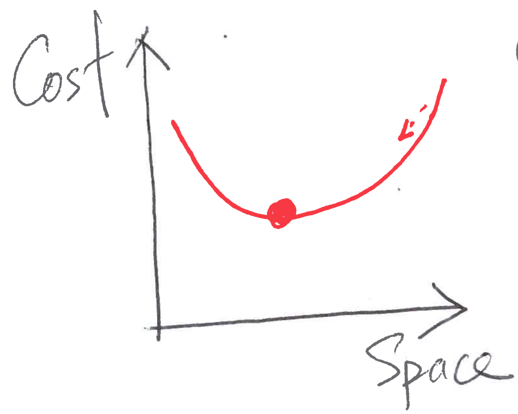
Algorithms Ch9-11

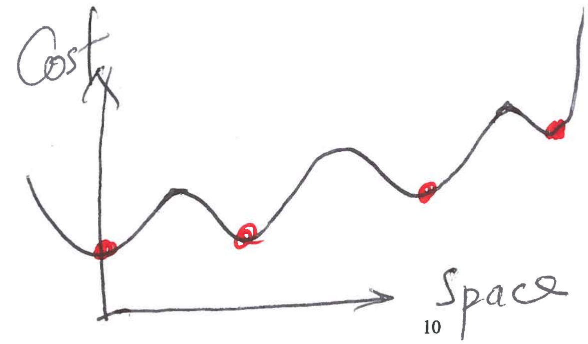
Ch6-8 applications

Trial & Errors

Scope of Convex Optimization

For a convex problem, a local optimal solution is also a global optimum solution.





Scope

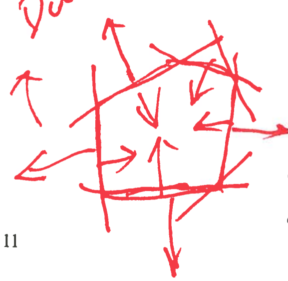
1. Problem Statement (Key word: **convexity**)
   - Convex Sets (Ch2)
   - Convex Functions (Ch3) $f(x) \leq 0$
   - Formulations (Ch4)
2. Tools (Key word: **mechanism**)
   - Duality (Ch5)
   - Optimal Conditions (Ch5) K.K.T.

   Midterm

3. Applications (Ch6,7,8) (Key words: complexity, optimality)

   Coverage depends upon class schedule
4. Algorithms (Key words: **Taylor's expansion**)
   - Unconstrained (Ch9)
   - Equality constraints (Ch10)
   - Interior method (Ch11)

Duality



Scope

$x \in R^n \to$ Matrix

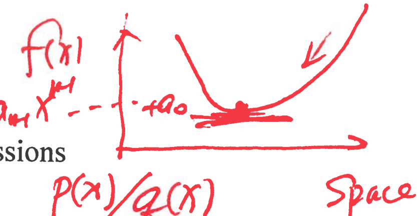
$f(x)$, $f'(x)=0$, $f'' > 0$

CSE203B Convex Optimization

- Optimization of convex function with constraints which form convex domains.

Background

- Linear algebra $p(x) = a_n x^n + a_{n-1} x^{n-1} \cdots + a_0$
- Polynomial and fractional expressions
- HW0 Log and exponential functions $p(x)/q(x)$
- Optimality of continuously differentiable functions



Concepts and Techniques to Master in CSE203B

- Convexity
- Hyperplane $x^n \in R^n$
- Duality
- KKT optimality conditions

$$\frac{d \det A}{dA}$$