CSE291 Convex Optimization  
(CSE203B Pending)

CK Cheng  
Dept. of Computer Science and Engineering  
University of California, San Diego
Outlines

• Staff
  – Instructor: CK Cheng, TA: Po-Ya Hsu

• 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+291@ucsd.edu
- Office: Room CSE2130
- Office hour will be posted on the course website
  - 2-250PM Th
- Websites
  - http://cseweb.ucsd.edu/~kuan
  - http://cseweb.ucsd.edu/classes/fa17/cse291-a
Staff

Teaching Assistant

• Po-Ya Hsu, p8hsu@ucsd.edu
Logistics: Textbooks

Required text:

• Convex Optimization, Stephen Boyd and Lieven Vandenberghe, Cambridge, 2004

References


Logistics: Grading

Home Works (25%)
- Exercises (Grade by completion)
- Assignments (Grade by content)

Project (40%)
- Theory or applications of convex optimization
- Survey of the state of the art approaches
- Outlines, references (W4)
- Presentation (W9,10)
- Report (W11)

Exams
- Midterm (35%)
Classification: Brief history of convex optimization

theory (convex analysis): 1900–1970

algorithms
• 1947: simplex algorithm for linear programming (Dantzig)
• 1970s: ellipsoid method and other subgradient methods
• 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

Boyd
## Classification

### Tradition

<table>
<thead>
<tr>
<th>Linear Programming</th>
<th>Nonlinear Programming</th>
<th>Discrete Integer Programming</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simplex</td>
<td>Lagrange multiplier</td>
<td>Trial and error</td>
</tr>
<tr>
<td>Primal/Dual</td>
<td>Gradient descent</td>
<td>Cutting plane</td>
</tr>
<tr>
<td>Interior point method</td>
<td>Newton’s iteration</td>
<td>Relaxation</td>
</tr>
</tbody>
</table>

### This class

<table>
<thead>
<tr>
<th>Convex Optimization</th>
<th>Nonconvex, Discrete Problems</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primal/Dual, Lagrange multiplier</td>
<td></td>
</tr>
<tr>
<td>Gradient descent</td>
<td></td>
</tr>
<tr>
<td>Newton’s iteration</td>
<td></td>
</tr>
<tr>
<td>Interior point method</td>
<td></td>
</tr>
</tbody>
</table>
Scope of Convex Optimization

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

Problem Statement (Key word: convexity)
• Convex Sets (Ch2)
• Convex Functions (Ch3)
• Formulations (Ch4)

Tools (Key word: mechanism)
• Duality (Ch5)
• Optimal Conditions (Ch5)

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

Algorithms (Key words: Taylor’s expansion)
• Unconstrained (Ch9)
• Equality constraints (Ch10)
• Interior method (Ch11)