13. Conclusions

- main ideas of the course
- importance of modeling in optimization

Modeling

mathematical optimization

- problems in engineering design, data analysis and statistics, economics, management, . . . , can often be expressed as mathematical optimization problems
- techniques exist to take into account multiple objectives or uncertainty in the data

tractability

- roughly speaking, tractability in optimization requires convexity
- algorithms for nonconvex optimization find local (suboptimal) solutions, or are very expensive
- surprisingly many applications can be formulated as convex problems

Theoretical consequences of convexity

- local optima are global
- extensive duality theory
  - systematic way of deriving lower bounds on optimal value
  - necessary and sufficient optimality conditions
  - certificates of infeasibility
  - sensitivity analysis
- solution methods with polynomial worst-case complexity theory (with self-concordance)

Practical consequences of convexity

(most) **convex problems can be solved globally and efficiently**

- interior-point methods require $20 - 80$ steps in practice
- basic algorithms ($e.g.$, Newton, barrier method, . . .) are easy to implement and work well for small and medium size problems (larger problems if structure is exploited)
- more and more high-quality implementations of advanced algorithms and modeling tools are becoming available
- high level modeling tools like `cvx` ease modeling and problem specification

How to use convex optimization

to use convex optimization in some applied context

- use rapid prototyping, approximate modeling
  - start with simple models, small problem instances, inefficient solution methods
  - if you don't like the results, no need to expend further effort on more accurate models or efficient algorithms

- work out, simplify, and interpret optimality conditions and dual

- even if the problem is quite nonconvex, you can use convex optimization
  - in subproblems, *e.g.*, to find search direction
  - by repeatedly forming and solving a convex approximation at the current point

Further topics

some topics we didn't cover:

- methods for very large scale problems
- subgradient calculus, convex analysis
- localization, subgradient, and related methods
- distributed convex optimization
- applications that build on or use convex optimization

What's next?

- EE364B — convex optimization II (Spr 13–14)
- MATH301 — advanced topics in convex optimization
- MS&E314 — linear and conic optimization
- EE464 — semidefinite optimization and algebraic techniques