10. Conclusions

- main ideas of the course
- further topics

Modeling

inverse problem formulation of machine learning models:

- as mathematical optimization problems
- say what you want and how to evaluate a candidate
- incorporate prior knowledge and requirements

tractability

- roughly speaking, requires convexity
- surprisingly many inverse problems can be formulated as convex
- heuristics (local solutions) for nonconvex problems via (sequential) convex optimization, often works quite well

Consequences of convexity

theoretical consequences

- local optima are global
- systematic way of deriving lower bounds on optimal value
- certificates of optimality, unboundedness, or infeasibility

practical consequences

- (most) convex problems can be solved globally and efficiently
- high quality implementations of numerical algorithms
- many hight level symbolic modeling languages enable fast prototyping

Further topics

- convex optimization
  - subgradient calculus, convex analysis
  - algorithms for convex optimization
  - methods for very large scale problems
  - distributed optimization
- numerical linear algebra
  - preconditioning
  - iterative methods
- domain specific languages for optimization
  - symbolic modeling, verification, and canonicalization
  - differentiating through optimization problems
  - embedded code generation