CPSC 440: Advanced Machine Learning Convex Optimization

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Machine Learning and Optimization

- In machine learning, training is typically written as an optimization problem:
 - We optimize parameters w of model, given data.
- There are some exceptions:
 - Methods based on counting and distances (KNN, random forests).
 - See CPSC 340.
 - **2** Methods based on averaging and integration (Bayesian learning).
 - Later in course.
 - But even these models have parameters to optimize.
- Important class of optimization problems: convex optimization problems.

Convex Optimization

• Consider an optimization problem of the form

 $\min_{w \in \mathcal{C}} f(w).$

where we are minimizing a function f subject to w being in the set C.

- $\bullet\,$ For least squares we have $f(w)=\|Xw-y\|^2$ and $\mathcal{C}\equiv R^d$
- If we had non-negative constraints, we would have $\mathcal{C} \equiv \{w \mid w \ge 0\}$.

• Notation: when I write $w \ge 0$ for a vector w I mean inequality holds for each row.

- We say that this is a convex optimization problem if:
 - The set \mathcal{C} is a convex set.
 - The function f is a convex function.

• This lecture is boring, but convexity ideas will show up throughout the course.

Convex Optimization

- Key property of convex optimization problems:
 - All local optima are global optima.
- Convexity is usually a good indicator of tractability:
 - Minimizing convex functions is usually easy.
 - Minimizing non-convex functions is usually hard.
- Off-the-shelf software solves many classes of convex problems (*MathProgBase*).

Convex Sets and Functions

Definition of Convex Sets

• A set \mathcal{C} is convex if the line between any two points stays also in the set.



Definition of Convex Sets

- To formally define convex sets, we use the notion of convex combination:
 - A convex combination of two variables w and v is given by

 $\theta w + (1 - \theta) v$ for any $0 \le \theta \le 1$,

which characterizes the points on the line between w and v.

• A set C is convex if convex combinations of points in the set are also in the set:

• For all $w \in \mathcal{C}$ and $v \in \mathcal{C}$ we have $\theta w + (1 - \theta)v \in \mathcal{C}$ for $0 \le \theta \le 1$.

convex comb

• This definition allows us to prove the convexity of many simple sets.

- Real space \mathbb{R}^d .
- Positive orthant $\mathbb{R}^d_+: \{w \mid w \ge 0\}.$
- Hyper-plane: $\{w \mid a^{\top}w = b\}.$
- Half-space: $\{w \mid a^{\top}w \leq b\}.$
- Norm-ball: $\{w \mid ||w||_p \leq \tau\}.$
- Norm-cone: $\{(w, \tau) \mid ||w||_p \le \tau\}.$

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Loo-norm "ball" of radius 'r'

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Convex Sets and Functions

Summary

- Convex optimization problems are a class that we can usually efficiently solve.
- Next time: more about convexity than you ever wanted to know.