

CSE203B Convex Optimization: Chapter 4: Problem Statement

CK Cheng

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

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Convex Optimization Formulation

1. Introduction
 - I. Eliminating equality constants
 - II. Slack variables
 - III. Absolute values, softmax
2. Optimality Conditions
 - I. Local vs. global optimum
 - II. Optimality criterion for differentiable f_0
 - i. Optimization without constraints
 - ii. Opt. with inequality constraints
 - iii. Opt. with equality constraints
 - III. Quasi-convex optimization
3. Linear Optimization
4. Quadratic Optimization
5. Geometric Programming
6. Generalized Inequality Constraints

variations → *Dual Problems*
Same original problems

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1. Introduction

Formulation: One of the most critical processes to conduct a project.

$$\begin{aligned} \min & f_0(x) \\ \text{s.t.} & f_i(x) \leq 0 \quad i = 1, \dots, m \\ & h_i(x) = 0 \quad i = 1, \dots, p \quad (Ax = b \text{ Affine set}) \\ & x \in R^n \\ & D_{f_0} f_0: R^n \rightarrow R \\ & D_{f_i} f_i: R^n \rightarrow R \\ & D_{h_i} h_i: R^n \rightarrow R \\ & f_0, f_i, \dots, f_m \text{ are convex} \end{aligned}$$

$D = \bigcap_{i=0,m} D_{f_i} \cap \bigcap_{i=0,p} D_{h_i}$ **Domain of functions**, but not the feasible set.

Feasible Set: The set which satisfies the constraints (is convex for convex problems).

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1.1 Introduction: Eliminating Equality Constraints

$$\begin{aligned} \min & f_0(x) \\ \text{s.t.} & f_i(x) \leq 0 \quad i = 1, \dots, m \\ & Ax = b \end{aligned} \quad \{x | Ax \leq b\} \Rightarrow \{U \theta | \mathbb{1} \theta = 1, \theta \geq 0\}$$

(note that this is equality relation)

a. Convert $\{x | Ax = b\}$ to $\{Fz + x_0 | z \in R^k\}$ $Ax_0 = b$

b. We have a equivalent problem

$$\begin{aligned} \min & f_0(Fz + x_0) \\ \text{s.t.} & f_i(Fz + x_0) \leq 0 \end{aligned}$$

Remark: Matrix F contains columns of null space basis

$$\begin{array}{ccc} \begin{matrix} p \\ n \end{matrix} \begin{bmatrix} A \\ I \end{bmatrix} \begin{matrix} n \\ n \times n \end{matrix} & \begin{matrix} P \\ n \times n \end{matrix} = \begin{bmatrix} B \\ C \end{bmatrix} & \xrightarrow{\text{elimination}} \begin{matrix} A \\ p \times n \end{matrix} z = 0 \\ & \begin{matrix} \rightarrow F \\ AP = B \\ IP = C \Rightarrow P = C \end{matrix} & \downarrow h = Fz + x_0 \\ & & \rightarrow AC = B \end{array}$$

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1.2 Introduction: Slack Variables

$$\begin{aligned} \min & f_0(x) \\ \text{s. t.} & f_i(x) \leq 0, i = 1, \dots, m \\ & Ax = b \end{aligned}$$

Add slack variables to convert to an equivalent problem

a. Convert the objective function with variable t

$$\begin{aligned} \min & t \\ \text{s. t.} & f_0(x) - t \leq 0 \\ & f_i(x) \leq 0, i = 1, \dots, m \\ & A^T x = b \end{aligned}$$

b. Convert the inequality with variables s_i

$$\begin{aligned} \min & f_0(x) \\ \text{s. t.} & f_i(x) + s_i = 0 \\ & A^T x = b \\ & s_i \in R_+, i = 1, \dots, m \end{aligned}$$

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1.3 Introduction: Absolute values and Softmax

a. Absolute values

$$\begin{aligned} |f_i(x)| &\leq b \\ \Rightarrow f_i(x) &\leq b \text{ and} \\ &-f_i(x) \leq b \end{aligned}$$

b. Maximum values

$$\max\{f_1, f_2, \dots, f_m\}$$

$$\text{Softmax: } \frac{1}{\alpha} \log (e^{\alpha f_1} + e^{\alpha f_2} + \dots + e^{\alpha f_m})$$

Example: $\max\{1, 5, 10, 2, 3\} \Rightarrow \text{Softmax}$

$$\frac{1}{\alpha} \log(e^{\alpha} + e^{5\alpha} + e^{10\alpha} + e^{2\alpha} + e^{3\alpha}) \approx 10$$

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2.1 Optimality Conditions: Local vs. Global Optima

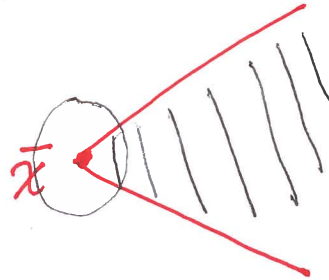
Definition: Local Optima

Given a convex optimization problem and a point $\bar{x} \in R^n$

If there exists a $r > 0$

s. t. $f_0(z) \geq f_0(\bar{x})$ for all $z \in \text{Feasible Set}$, and $\|z - \bar{x}\|_2 \leq r$

Then \bar{x} is a local optimum.



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2.2 Optimality Conditions

Theorem: Given a convex opt. problem

If \bar{x} is a local optimum, then \bar{x} is a global optimum

Proof: By contradiction

Suppose that $\exists y \in \text{Feasible Set}$

s. t. $f_0(\bar{x}) > f_0(y)$

We have $f_0(\bar{x}) > (1 - \theta)f_0(\bar{x}) + \theta f_0(\bar{y})$ (by assumption) I

$> f_0((1 - \theta)\bar{x} + \theta\bar{y})$ (f_0 is convex) II

And $(1 - \theta)\bar{x} + \theta\bar{y}$ is feasible (Feasible set is convex)

The inequality contradicts to the assumption of local optima.

$(1 - \theta) + \theta$



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Null space

$$A = \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}$$

$$\begin{bmatrix} A \\ I \end{bmatrix} P = \begin{bmatrix} B \\ C \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 \\ 2 & 4 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} P$$

$$= \begin{bmatrix} 1 & 0 \\ 2 & 0 \\ 1 & -2 \\ 0 & 1 \end{bmatrix}$$

$$AC = B$$

$$A \begin{bmatrix} 1 & -2 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 2 & 0 \end{bmatrix}$$

$$C_1 \quad C_2 \\ C_2 - 2 \times C_1$$

$$\Rightarrow \text{Null space } \left\{ \begin{bmatrix} -2 \\ 1 \end{bmatrix} \theta \mid \theta \in \mathbb{R} \right\}$$

A4

