THE CHINESE UNIVERSITY OF HONG KONG Department of Mathematics MATH4230 2024-25 Lecture 1 January 7, 2025 (Tuesday)

1 Introduction

Usually, we want to solve some problems related to maximum or minimum, and subject to some constraints, such as the following:

$$\min_{x} f(x) \quad \text{subject to } x \in K \subseteq \mathbb{R}^n$$
 (P)

In this course, we will mainly learn the following topics:

- Existence of solution
- Characterization of the optimizer
- Convex optimization or duality
- Numerical method and applications

Let us first focus on "Existence of solution", and it is natural to ask the following questions:

- 1. When is the existence of the minimizer x^* ?
- 2. If x^* exists, which properties that it has to satisfy?
- 3. How to find the minimizer x^* and the optimal value $f(x^*) = \min_{x \in V} f(x)$ numerically?

In the first lesson, we will focus on the section of "existence of optimal solution". The main reference for the first part of our course is:

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D. Michael Patricksson:
An introduction to continuous optimization Foundations and
Fundamental Algorithms (Section 4)
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2 Existence of Optimal Solution

Definition 1. Let $f : \mathbb{R}^n \to \mathbb{R}$ be a function and $K \subseteq \mathbb{R}^n$ be a non-empty set. We call the value $\ell \in [-\infty, +\infty)$ the **infimum** of f(x) on K if ℓ satisfies

- 1. $\ell \leq f(x)$, for all $x \in K$,
- 2. there exists a sequence $(x_n)_{n\geq 1} \subseteq K$ such that $\lim_{n\to\infty} f(x_n) = \ell$.

Then, we denote

$$\inf_{x \in K} f(x) := \ell$$

Definition 2. If $\inf_{x \in K} f(x) > -\infty$ and there exists $x^* \in K$ such that $f(x^*) = \inf_{x \in K} f(x)$, we say

- 1. $f^* := f(x^*)$ is the minimum value of the problem $\inf_{x \in K} f(x)$, denoted as $\min_{x \in K} f(x)$ (P)
- 2. x^* is a solution to the minimization problem (P).

Definition 3. A function $f : \mathbb{R}^n \to \mathbb{R}$ is called **coercive** if

$$\lim_{\|x\| \to +\infty} f(x) = +\infty$$

Example 1. Let $f(\mathbf{x}) = \mathbf{x}^T A \mathbf{x} + \mathbf{b}^T \mathbf{x} + c$, where $\mathbf{b} \in \mathbb{R}^n$ is a vector, $c \in \mathbb{R}$ is a constant and A is an $n \times n$ symmetric positive-definite matrix. Then $f(\mathbf{x})$ is coercive.

Proof. As A is positive-definite matrix, so we have $\mathbf{x}^T A \mathbf{x} > 0$ for any $\mathbf{x} \in \mathbb{R}^n$. Moreover, if λ is an eigenvalue of A, then we have

$$\mathbf{x}^T A \mathbf{x} = \lambda \mathbf{x}^T \mathbf{x} = \lambda \|\mathbf{x}\|^2 > 0$$

So, any eigenvalues of A must be strictly positive. Denote

$$\lambda_{\min} := \min \left\{ \lambda : A\mathbf{x} = \lambda \mathbf{x}, \ \mathbf{x} \neq \mathbf{0} \right\} > 0$$

then we have

$$\mathbf{x}^T A \mathbf{x} \ge \lambda_{\min} \| \mathbf{x} \|^2.$$

Moreover, as b and c are constants, so we have

$$f(\mathbf{x}) \ge \underbrace{\lambda_{\min} \|\mathbf{x}\|^2}_{\text{Dominated}} + \mathbf{b}^T \mathbf{x} + c \to +\infty$$

as $\|\mathbf{x}\| \to +\infty$. This proves that f is corecive.

Proposition 1. Let $f_i : \mathbb{R} \to \mathbb{R}$ be bounded below and coercive functions for each i = 1, 2, ..., n. Then

$$f(\mathbf{x}) = \sum_{i=1}^{n} f_i(x_i)$$

is also coercive for all $\mathbf{x} = (x_1, x_2, \dots, x_n) \in \mathbb{R}^n$.

Proof. Without loss of generality, we may assume $f_i(x_i) \ge 0$ for all $x_i \in \mathbb{R}$, i = 1, 2, ..., n. As f_i is bounded below, that is, there exists some $m \in \mathbb{R}$ such that $f_i \ge m$ for all i, we may replace

$$g = f_i - m \ge 0$$

if necessarily. Then, using this fact, we have

$$f(\mathbf{x}) = \sum_{i=1}^{n} f_i(x_i) \ge \max_{1 \le i \le n} f_i(x_i) \quad (\because f_i \ge 0, \ \forall i)$$

On the other hand, if $\|\mathbf{x}\| \to +\infty$, then $\max_{1 \le i \le n} |x_i| \to +\infty$. Now, it remains to show $f(\mathbf{x}) \to +\infty$ to conclude that f is coercive. Suppose on contradictory that $\lim_{\|\mathbf{x}\|\to+\infty} f(\mathbf{x}) \ne +\infty$, then there exists a sequence of points $(\mathbf{x}^m)_{m>1}$ such that

$$\lim_{m \to +\infty} f(\mathbf{x}^m) < +\infty \quad \text{as} \quad \|\mathbf{x}^m\| \to +\infty$$

Since $f \ge \max_{1\le i\le n} f_i$, so this follows that $\overline{\lim_{m\to+\infty}} f_i(x_i^m) < +\infty$ for all $i = 1, \ldots, n$. As $\|\mathbf{x}^m\| \to +\infty$, there exists a subsequence $(m_k)_{m\ge 1}$ and i so that $|x_i^{m_k}| \to +\infty$. Using the given fact that f_i are coercive for all $i = 1, 2, \ldots, n$, so

$$\overline{\lim_{m \to +\infty}} f_i(x_i) \ge \lim_{k \to +\infty} f_i(x_i^{m_k}) = +\infty > \lim f(\mathbf{x}^m)$$

Contradiction occurs, so we have $\lim_{\|\mathbf{x}\| \to +\infty} f(\mathbf{x}) = +\infty$, i.e. f is also coercive.

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Theorem 2. Let $f : \mathbb{R}^n \to \mathbb{R}$ be a continuous function, and $K \subseteq \mathbb{R}^n$ be a non-empty subset. Then

- *1.* If K is compact, then (P) has an optimal solution $\mathbf{x}^* \in K$
- 2. If K is closed, and $f(\mathbf{x})$ is coercive, then (P) has an optimal solution $\mathbf{x}^* \in K$.
- *Proof.* 1. If K is compact, consider a sequence $(\mathbf{x}_n)_{n\geq 1} \subseteq K$ be a minimizing sequence of (P), that is

$$\lim_{n \to +\infty} f(\mathbf{x}_n) = \inf_{\mathbf{x} \in K} f(\mathbf{x})$$

Then there exists a subsequence $(\mathbf{x}_{n_k})_{k\geq 1}$ such that $\lim_{k\to +\infty} \mathbf{x}_{n_k} = \mathbf{x}^* \in K$ (by closeness), and

$$f(\mathbf{x}^*) = \lim_{k \to +\infty} f(\mathbf{x}_{n_k}) = \inf_{\mathbf{x} \in K} f(\mathbf{x})$$

(this step aims to concretely define x^* .)

Alternative Proof: Applying Extreme-Value Theorem for f over compact K, then prove the existence by intermediate value theorem.

2. If $f(\mathbf{x})$ is coercive, so by definition we have

$$\lim_{\|\mathbf{x}\| \to +\infty} f(\mathbf{x}) = +\infty$$

Then, we have

$$\inf_{\mathbf{x}\in K} f(\mathbf{x}) = \inf_{\mathbf{x}\in K_n} f(\mathbf{x})$$

where $K_n := {\mathbf{x} \in K : ||\mathbf{x}|| \le n}$ for sufficiently large enough $n \in \mathbb{N}$. Since K_n is closed (as its complement is open), and bounded in \mathbb{R}^n , hence it is compact. Therefore, there exists $\mathbf{x}^* \in K_n \subseteq K$ such that

$$f(\mathbf{x}^*) = \inf_{\mathbf{x}\in K_n} f(\mathbf{x}) = \inf_{\mathbf{x}\in K} f(\mathbf{x}).$$

Example 2. The set

 $K = \{ \mathbf{x} \in \mathbb{R}^n : g(\mathbf{x}) \le 0, \ h(\mathbf{x}) = 0 \}$

is closed if g and h are continuous.

Proof. It suffices to prove its complement is open, that is

$$K' := \mathbb{R}^n \setminus K = \{ \mathbf{x} \in \mathbb{R}^n : g(\mathbf{x}) > 0 \text{ or } h(\mathbf{x}) \neq 0 \}$$

Now, we aim to find open balls of all \mathbf{x} contained in K'.

Let $\varepsilon > 0$ be arbitrary. By the continuity of g, if $g(\mathbf{x}) > 0$, there exists some $\delta > 0$ such that for any y satisfying $\|\mathbf{y} - \mathbf{x}\| < \delta$, then we have

$$|g(\mathbf{y}) - g(\mathbf{x})| < \varepsilon$$

i.e. $g(\mathbf{y}) > g(\mathbf{x}) - \varepsilon > 0$, so there exists an open ball $B_{\delta}(\mathbf{x}) \subseteq K'_1 := {\mathbf{x} \in \mathbb{R}^n : g(\mathbf{x}) > 0}$. Moreover, by continuity of h as well, there exists some $\delta' > 0$ such that for any $\mathbf{y} \in B_{\delta'}(\mathbf{x})$, then

$$|h(\mathbf{y}) - h(\mathbf{x})| < \varepsilon$$

By choosing $\varepsilon = |h(\mathbf{x})|/2 > 0$, we have $|h(\mathbf{y})| > |h(\mathbf{x})|/2 > 0$, so this proves there exists an open ball $B_{\delta'}(\mathbf{x}) \subseteq K'_2 := {\mathbf{x} \in \mathbb{R}^n : h(\mathbf{x}) \neq 0}$. Since $K' = K'_1 \cup K'_2$, and from the above, there exists $\delta^* := \min{\{\delta, \delta'\}}$ such that $B_{\delta^*}(\mathbf{x}) \subseteq K'$. This proves that K' is open, that is equivalently showing that K is closed.

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Proposition 3. Let $K \subseteq \mathbb{R}^n$ be a bounded and open subset, and $f : \mathbb{R}^n \to \mathbb{R}$ be a continuous function on \overline{K} (the closure of K). If there exists $\mathbf{x}_0 \in K$ such that $f(\mathbf{x}_0) \leq f(\mathbf{x})$, for all $\mathbf{x} \in \partial K = \overline{K} \setminus K$, then (P) has an optimal solution $\mathbf{x}^* \in K$.

Proof. Since there exists such $\mathbf{x}_0 \in K$ such that $f(\mathbf{x}_0) \leq f(\mathbf{x})$, for all $\mathbf{x} \in \partial K$, so it follows that

$$\inf_{\mathbf{x}\in K} f(\mathbf{x}) = \inf_{\mathbf{x}\in\bar{K}} f(\mathbf{x})$$

As \bar{K} is closed set (after taking closure), and bounded (given), so it is compact. Moreover, as f is continuous on \bar{K} , so by the Extreme-Value Theorem, there exists $\mathbf{x}^* \in \bar{K}$ such that

$$f(\mathbf{x}^*) = \inf_{\mathbf{x} \in \bar{K}} f(\mathbf{x})$$

Now, it remains to conclude that $\mathbf{x}^* \in K$ but not on ∂K . We consider the following cases:

• Case 1: $\mathbf{x}^* \in \partial K$ From $f(\mathbf{x}_0) \leq f(\mathbf{x})$ for all $\mathbf{x} \in \partial K$ consequences

$$f(\mathbf{x}_0) \le f(\mathbf{x}^*) = \inf_{\mathbf{x}\in\bar{K}} f(\mathbf{x})$$

this implies that $\mathbf{x}_0 \in K$ is a solution to (P).

• Case 2: $\mathbf{x}^* \in K$ From the above $f(\mathbf{x}^*) = \inf_{\mathbf{x} \in \overline{K}} f(\mathbf{x})$, it follows that $\mathbf{x}^* \in K$ is a solution to (P).

In any case, there exists $\mathbf{x}^* \in K$ is a solution to (P).

3 First order necessary condition of the optimizer x^*

After discussing the existence of optimal solution to (P), it is natural to ask what properties that optimizers have. So, we introduce the following theorem:

Theorem 4. If $f(\mathbf{x})$ is continuously differentiable, $\emptyset \neq K$ is an open set in \mathbb{R}^n and $\mathbf{x}^* \in K$ is an optimal solution to (P), then

$$\nabla f(\mathbf{x}^*) = \mathbf{0}$$

This is called the **Euler's first order condition**.

Proof. We will prove by contradiction. Suppose that $\nabla f(\mathbf{x}^*) = \begin{pmatrix} \partial_{x_1} f(\mathbf{x}^*) \\ \vdots \\ \partial_{x_n} f(\mathbf{x}^*) \end{pmatrix} \neq \mathbf{0}$, then there exists

some $\mathbf{v} \in \mathbb{R}^n$ such that

$$\langle \mathbf{v}, \nabla f(\mathbf{x}^*) \rangle > 0.$$

Let $\varepsilon > 0$. Define $\mathbf{x}_{\varepsilon} := \mathbf{x}^* - \varepsilon \mathbf{v}$, then applying the taylor-expansion of f about \mathbf{x}_{ε} , we have

$$f(\mathbf{x}_{\varepsilon}) = f(\mathbf{x}^*) + \langle \mathbf{x}_{\varepsilon} - \mathbf{x}^*, \nabla f(\mathbf{x}^*) \rangle + O(\varepsilon^2)$$
$$= f(\mathbf{x}^*) - \varepsilon \langle \mathbf{v}, \nabla f(\mathbf{x}^*) \rangle + O(\varepsilon^2)$$

Since $\varepsilon > 0$ is arbitrary, taking $\varepsilon \to 0^+$ yields $f(\mathbf{x}_{\varepsilon}) < f(\mathbf{x}^*)$ and $\mathbf{x}_{\varepsilon} \in K$. This contradicts the fact that \mathbf{x}^* is an optimal solution because $f(\mathbf{x}^*) \neq \inf_{\mathbf{x} \in K} f(\mathbf{x})$.

— End of Lesson 1 —