

# **Study Notes of Numerical Optimization**

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# Update progress

- writing [ch1](#)...

2023.10.20

# Preface

Notes mainly refer to the following resources:

- [lecture notes from class Matrix and tensor factorization techniques for machine learning](#)

all the codes in the notes are completed by python. You can get the codes in the following website:

- -

## **Part I**

# **Fundamental Concepts of Optimization**

# Chapter 1

## Convex Optimization

*”The great watershed in Optimization is not between linearity and nonlinearity, but convexity and nonconvexity. ”*

### 1.1 General Convex Optimization Problems

#### Definition 1.1 (Convex Set)

a set  $\Omega \in \mathbb{R}^n$  is convex if

$$\forall x, y \in \Omega, t \in [0, 1] : x + t(y - x) \in \Omega. \quad (1.1)$$

**Remark.** This definition is equivalent to saying that all connecting lines lie inside set.

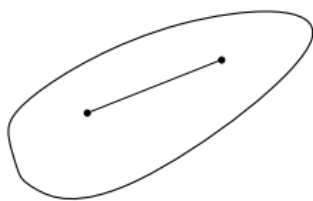


Figure 1.1: an example of a convex set

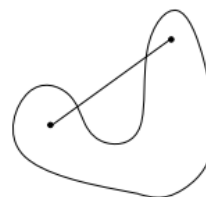


Figure 1.2: an example of a non convex set

#### Definition 1.2 (Convex Function)

a function  $f : \Omega \rightarrow \mathbb{R}$  is convex, if  $\Omega$  is convex and if

$$\forall x, y \in \Omega, t \in [0, 1] : f(x + t(y - x)) \leq f(x) + t(f(y) - f(x)). \quad (1.2)$$

**Remark.** This definition is equivalent to saying that all secants are above graph.

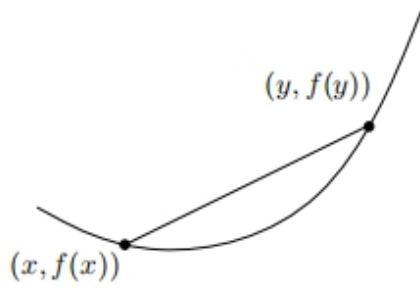


Figure 1.3: For a convex function, the line segment between any two points on the graph lies above the graph

#### Definition 1.3 (Convex Optimizaition Problem)

an optimization problem with

- a convex feasible set  $\Omega$  and
- a convex objective function  $f : \Omega \rightarrow \mathbb{R}$

is called a "convex Optimization problem"

#### Theorem 1.1 (Local Implies Global Optimality for Convex Problems)

for a convex Optimization problem, every local minimum is also a global one.

*Proof.* Consider a local minimum  $x^*$  of the convex optimization problem

$$\begin{aligned} \min_{x \in \mathbb{R}^n} f(x) \\ \text{s.t. } x \in \Omega \end{aligned}$$

We will show that for each  $y \in \Omega$  it holds  $f(y) \geq f(x^*)$ .

Suppose that  $x^*$  is not the global minimum, that is  $\exists \tilde{x} \in \Omega$  s.t.  $f(\tilde{x}) < f(x^*)$ .

Consider the line segment  $x(t) = tx^* + (1-t)\tilde{x}$ ,  $t \in [0, 1]$ , noting that  $x(t) \in \Omega$  by the convexity of  $\Omega$ . By the convexity of  $f$ ,

$$f(x(t)) \leq tf(x^*) + (1-t)f(\tilde{x}) < tf(x^*) + (1-t)f(x^*) = f(x^*), \forall t \in [0, 1]$$

As  $x^*$  is a local minimum, we know that  $\exists N$  ( $N$  is a neighbourhood of  $x^*$ ),  $\forall x \in N$ ,  $f(x) \geq f(x^*)$ . We can pick  $t$  sufficiently close to 1 such that  $x(t) \in N$ . Then  $f(x(t)) < f(x^*)$ . This is a contradiction as  $f(x(t)) < f(x^*)$  by the above inequality.

Hence,  $x^*$  is the global minimum.  $\square$

## 1.2 How to Check Convexity of Functions?

**Theorem 1.2** (Local Implies Global Optimality for Convex Problems)

for a convex Optimization problem, every local minimum is also a global one.

## 1.3 convex optimization problems



# Chapter 2

## Linear Programming

### 2.1 Introduction to LP

### 2.2 LP Relaxation

### 2.3 Algorithms Solving LP