

Emory University
MATH 347 Non Linear Optimization
Learning Notes

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1 Math Preliminaries

1.1 Introduction to Optimization

Definition 1.1.1 (Optimization Problem). The main optimization problem can be stated as follows

$$\min_{x \in S} f(x), \quad (1)$$

where

- x is the *optimization variable*,
- S is the *feasible set*, and
- f is the *objective function*.

Remark 1.1 $\max_{x \in S} f(x) = -\min_{x \in S} -f(x)$. Hence, we will only study minimization problems.

Theorem 1.1.2 Solving an Optimization Problem

- Theoretical Analysis: analytic solution
- Numerical solution/optimization

Definition 1.1.3 (Solution Methods depend on the type of x , S , and f).

- When x is continuous (e.g., \mathbb{R} , \mathbb{R}^n , $\mathbb{R}^{m \times n}$, \dots), then the optimization problem stated in Eq. (1) is a *continuous optimization problem*. It will also be the focus of this class.

Opposite to continuous optimization problems, we have *discrete optimization problem* if x is discrete.

If x has both types of components, then we call the problem *mixed*.

- Depending on S , we can have
 - *Unconstrained problems*: where $S = \mathbb{R}^n$, $S = \mathbb{R}^{m \times n}$, \dots (m, n are fixed).
 - *Constrained problems*: where $S \subsetneq \mathbb{R}^n$, $S \subsetneq \mathbb{R}^{m \times n}$, \dots

Both types of problems will be studied.

- Depending on f , we have
 - *Smooth optimization problems*: f has first and/or second order derivatives.
Only smooth optimization problems will be studied.
 - *Non-smooth optimization problems*: f is not differentiable.

Definition 1.1.4 (Linear Optimization/Program). If f is linear and S consists of linear constraints, then the optimization problem is called a *linear problem/program*.

Example 1.1.5 Classification of Optimization Problems

1. Consider the following problem

$$\min_{x_1, x_2, x_3} x_1^2 - 4x_1x_2 + 3x_2x_3 + \sin x_3$$

Solution 1.

- Optimization variable: $x = (x_1, x_2, x_3) \in \mathbb{R}^3$. \rightarrow continuous.
- Feasible set: $S = \mathbb{R}^3$. \rightarrow unconstrained.
- Objective function: $f(x_1, x_2, x_3) = x_1^2 - 4x_1x_2 + 3x_2x_3 + \sin x_3$. \rightarrow smooth but non-linear.

□

2. Consider the following problem

$$\max_{\substack{4x_1+7x_2+3x_3 \leq 1 \\ x_1, x_2, x_3 \geq 0}} x_1 + 2x_2 + 3x_3$$

Solution 2.

- Optimization variable: $x = (x_1, x_2, x_3) \in \mathbb{R}^3$. \rightarrow continuous.
- Feasible set: $S = \{(x_1, x_2, x_3) : x_1, x_2, x_3 \geq 0, 4x_1 + 7x_2 + 3x_3 \leq 1\} \subsetneq \mathbb{R}^3$. \rightarrow constrained.
- Objective function: $f(x_1, x_2, x_3) = x_1 + 2x_2 + 3x_3$. \rightarrow smooth and linear.

□

Remark 1.2 *This problem can be considered as the budget constrained optimization problem in Economics.*

3. Consider the following problem

$$\min_{x_1, x_2 \geq 0} 4x_1 - 3|x_2| + \sin(x_1^2 - 2x_2)$$

Solution 3.

- Optimization variable: $x = (x_1, x_2) \in \mathbb{R}^2$. \rightarrow continuous.

- Feasible set: $S = \{(x_1, x_2) : x_1, x_2 \geq 0\} \subsetneq \mathbb{R}^2$. \rightarrow constrained.
- Objective function: $f(x_1, x_2) = 4x_1 - 3|x_2| + \sin(x_1^2 - 2x_2)$. \rightarrow non-smooth and non-linear.

□

Remark 1.3 *In this particular problem, $x_2 \geq 0$, and so $f(x_1, x_2) = 4x_1 - 3x_2 + \sin(x_1^2 - 2x_2)$ on the feasible set. Hence, this problem can be equivalently written as*

$$\min_{x_1, x_2 \geq 0} 4x_1 - 3x_2 + \sin(x_1^2 - 2x_2),$$

which is a smooth optimization problem.

1.2 Linear Algebra Review

Example 1.2.1 Why linear algebra for optimization?

Consider $\min_{x \in \mathbb{R}} f(x)$, where $f(x) = c + bx + ax^2$, $a, b, c \in \mathbb{R}$.

- $a > 0$: $x^* = -\frac{b}{2a}$ is a global minimum and $f(x^*) = c - \frac{b^2}{4a}$.
- $a < 0$: no minimum exists.
- $a = 0$: $f(x) = c + bx$.
 - $b \neq 0$: no minimum exists.
 - $b = 0$: $f(x) = c$, and every x is a minimum point.

We can approximate any smoothing function using Taylor's approximation and make them simple into the case discussed above.

Theorem 1.2.2 Taylor's Approximation

$$f(x) = \underbrace{f(x_0) + f'(x_0)(x - x_0) + \frac{f''(x_0)}{2}(x - x_0)^2}_{q(x)} + \underbrace{\varepsilon(x - x_0)(x - x_0)^2}_{\text{error}},$$

where $\lim_{x \rightarrow x_0} \varepsilon(x - x_0) = 0$.

Remark 1.4 *The hope is that the quadratic approximation will inform us on the behavior of f near x_0 and be useful for instance in referring x_0 on the subject of optimality.*

Definition 1.2.3 (Quadratic Approximation in Higher Dimensions). When $d > 1$, we consider $\min_{x \in \mathbb{R}^d} f(x)$. Then, the *quadratic approximation* of f is defined as

$$q(x) := c + \langle b, x \rangle + \langle x, Ax \rangle,$$

where $c \in \mathbb{R}$, $b \in \mathbb{R}^d$, $A \in \mathbb{R}^{d \times d}$.

Remark 1.5 Then, to know if a minimum exists, we need information on the matrix A and the vector b .

Definition 1.2.4 (Vector, \mathbb{R}^d). We define a *vector* in \mathbb{R}^d as a column vector.

$$x = \begin{pmatrix} x_1 \\ \vdots \\ x_d \end{pmatrix} \in \mathbb{R}^d, \quad x_i \in \mathbb{R}.$$

On \mathbb{R}^d , we also have the following operations defined

- Addition:

$$\begin{pmatrix} x_1 \\ \vdots \\ x_d \end{pmatrix} + \begin{pmatrix} y_1 \\ \vdots \\ y_d \end{pmatrix} = \begin{pmatrix} x_1 + y_1 \\ \vdots \\ x_d + y_d \end{pmatrix}, \quad x_i, y_i \in \mathbb{R}$$

- Scalar multiplication:

$$\alpha \begin{pmatrix} x_1 \\ \vdots \\ x_d \end{pmatrix} = \begin{pmatrix} \alpha x_1 \\ \vdots \\ \alpha x_d \end{pmatrix}, \quad \alpha, x_i \in \mathbb{R}$$

Definition 1.2.5 (Basis of \mathbb{R}^d). A collection of vectors $v_1, \dots, v_d \in \mathbb{R}^d$ is a *basis* in \mathbb{R}^d if $\forall x \in \mathbb{R}^d$, $\exists! \alpha_1, \dots, \alpha_d \in \mathbb{R}$ s.t. $x = \alpha_1 v_1 + \dots + \alpha_d v_d$.

Example 1.2.6 The Standard Basis

The *standard basis* is defined as

$$e_i = \begin{pmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{pmatrix},$$

where 1 is at the i -th position for $1 \leq i \leq d$. Note that $\forall x \in \mathbb{R}^d$, $x = x_1 e_1 + \dots + x_d e_d$.

Notation 1.7.

$$0_d = \begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}.$$

Definition 1.2.8 (Inner Product). $\langle \cdot, \cdot \rangle : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$ is an *inner product* if

- (symmetry) $\langle x, y \rangle = \langle y, x \rangle \quad \forall x, y \in \mathbb{R}^d$
- (additivity) $\langle x, y + z \rangle = \langle x, y \rangle + \langle x, z \rangle \quad \forall x, y, z \in \mathbb{R}^d$
- (homogeneity) $\langle \lambda x, y \rangle = \lambda \langle x, y \rangle \quad \forall x, y \in \mathbb{R}^d, \lambda \in \mathbb{R}$
- (positive definiteness) $\langle x, x \rangle \geq 0 \quad \forall x \in \mathbb{R}^d$ and $\langle x, x \rangle = 0 \iff x = 0$

Example 1.2.9 Examples of Inner Products

1. **Definition 1.2.10 (Dot Product).** The *dot product* of $x, y \in \mathbb{R}^d$ is defined as

$$\langle x, y \rangle = x_1 y_1 + \cdots + x_d y_d = \sum_{i=1}^d x_i y_i \quad \forall x, y \in \mathbb{R}^d.$$

It is also referred as the *standard inner product*, and we often use the notation $x \cdot y$ to denote it.

2. **Definition 1.2.11 (Weighted Dot Product).** The *weighted dot product* of $x, y \in \mathbb{R}^d$ with some weight w is defined as

$$\langle x, y \rangle_w = \sum_{i=1}^d w_i x_i y_i,$$

where $w_1, \dots, w_d > 0$ are called *weights*.

Remark 1.6 When $d = 2$, then $\langle x, y \rangle = |x||y| \cos \angle(x, y)$. Dot product measure how correlated are two vectors (with respect to their directions).

Definition 1.2.12 (Vector Norm). $\|\cdot\| : \mathbb{R}^d \rightarrow \mathbb{R}$ is a *norm* if

- (non-negativity) $\|x\| \geq 0 \quad \forall x \in \mathbb{R}^d$ and $\|x\| = 0 \iff x = 0$
- (positive homogeneity) $\|\lambda x\| = |\lambda| \|x\| \quad \forall \lambda \in \mathbb{R}, x \in \mathbb{R}^d$
- (triangular inequality) $\|x + y\| \leq \|x\| + \|y\| \quad \forall x, y \in \mathbb{R}^d$.

Remark 1.7 Vector norm introduces the notion of length of vectors in \mathbb{R}^d .

Example 1.2.13 Examples of Vector Norms

- If $\langle \cdot, \cdot \rangle$ is an inner product on \mathbb{R}^d , then

$$\|x\| = \sqrt{\langle x, x \rangle} \quad \forall x \in \mathbb{R}^d$$

is a norm. For instance,

$$\|x\|_2 = \sqrt{x \cdot x} = \left(\sum_{i=1}^d x_i^2 \right)^{\frac{1}{2}}.$$

This norm is called the *standard (Euclidean)* or ℓ_2 norm in \mathbb{R}^d .

- **Definition 1.2.14 (ℓ_p Norms).** Suppose $p \geq 1$, then

$$\|x\|_p := \left(\sum_{i=1}^d x_i^p \right)^{\frac{1}{p}}.$$

- **Definition 1.2.15 (∞ -Norms).**

$$\|x\|_\infty := \max_{1 \leq i \leq d} |x_i| \quad \forall x \in \mathbb{R}^d.$$

Remark 1.8 $\lim_{p \rightarrow \infty} \|x\|_p = \|x\|_\infty$.

Theorem 1.2.16 Cauchy-Schwarz Inequality

Assume that $\langle \cdot, \cdot \rangle : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$ is an inner product, then

$$|\langle x, y \rangle|^2 \leq \langle x, x \rangle \cdot \langle y, y \rangle \quad \forall x, y \in \mathbb{R}^d.$$

In particular, if $\|x\| = \sqrt{\langle x, x \rangle}$, then

$$|\langle x, y \rangle| \leq \|x\| \cdot \|y\| \quad \forall x, y \in \mathbb{R}^d.$$

For the standard inner product, we have

$$\left| \sum_{i=1}^n x_i y_i \right| \leq \|x\|_2 \cdot \|y\|_2 \quad \forall x, y \in \mathbb{R}^d.$$

The equality holds when x and y are linearly dependent.

Definition 1.2.17 (Matrix). Let $d, m \in \mathbb{N}$. We say that $A \in \mathbb{R}^{d \times m}$ is a $d \times m$ *matrix* if

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{d1} & a_{d2} & \cdots & a_{dm} \end{pmatrix} = (a_{ij})_{i=1, j=1}^{d, m}$$

Definition 1.2.18 (Operations with Matrices).

- Let $A, B \in \mathbb{R}^{d \times m}$, then $(A + B)_{i,j} = a_{ij} + b_{ij} \quad \forall i, j$.
- Let $A \in \mathbb{R}^{d \times m}$ and $\alpha \in \mathbb{R}$, then $(\alpha A)_{ij} = \alpha a_{ij} \quad \forall i, j$.
- Let $A \in \mathbb{R}^{d \times m}$ and $B \in \mathbb{R}^{m, n}$, then $AB \in \mathbb{R}^{d \times n}$, and $(AB)_{ij} = \sum_{k=1}^m a_{ik} b_{kj} \quad \forall i, j$.

Remark 1.9 *Matrix multiplication is not commutative. In fact, if $A \in \mathbb{R}^{d \times m}$ and $B \in \mathbb{R}^{m \times n}$, then BA is defined if and only if $n = d$. In that case, $AB \in \mathbb{R}^{d \times d}$ and $BA \in \mathbb{R}^{m \times m}$, and so if $m \neq d$, AB and BA have different sizes. Finally, even if $m = d = n$, $AB \neq BA$ in general.*

Definition 1.2.19 (Linear Transformation). The mapping $\mathcal{L} : \mathbb{R}^m \rightarrow \mathbb{R}^d$ is called *linear* if $\mathcal{L}(\alpha x_1 + \beta x_2) = \alpha \mathcal{L}(x_1) + \beta \mathcal{L}(x_2)$.

Theorem 1.2.20 Matrices and Linear Transformation

$\forall A \in \mathbb{R}^{d \times m}$, $\mathcal{L}_A(x) = Ax$ is a linear mapping from \mathbb{R}^m to \mathbb{R}^d . Moreover, $\forall \mathcal{L} : \mathbb{R}^m \rightarrow \mathbb{R}^d$ linear, $\exists! A \in \mathbb{R}^{d \times m}$ s.t. $\mathcal{L} = \mathcal{L}_A$.

Proof 1. Here, we offer an intuition on why this is true. Suppose $A \in \mathbb{R}^{d \times m}$ and $x \in \mathbb{R}^m$ s.t.

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{d1} & \cdots & a_{dm} \end{pmatrix} \quad \text{and} \quad x \in \begin{pmatrix} x_1 \\ \vdots \\ x_m \end{pmatrix} \in \mathbb{R}^{m \times 1}.$$

Then, $Ax \in \mathbb{R}^{d \times 1}$ is the following

$$Ax = \begin{pmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{d1} & \cdots & a_{dm} \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_m \end{pmatrix} = \begin{pmatrix} a_{11}x_1 + \cdots + a_{1m}x_m \\ \vdots \\ a_{d1}x_1 + \cdots + a_{dm}x_m \end{pmatrix} \in \mathbb{R}^{d \times 1}.$$

So, if $\mathcal{L}_A(x) = Ax$ for $x \in \mathbb{R}^m$, then $\mathcal{L}_A : \mathbb{R}^m \rightarrow \mathbb{R}^d$ is linear. ■

Theorem 1.2.21 Matrix Multiplication as Composite Linear Transformations

Suppose $\mathcal{L}_A : \mathbb{R}^m \rightarrow \mathbb{R}^d$ and $\mathcal{L}_B : \mathbb{R}^n \rightarrow \mathbb{R}^m$, where $A \in \mathbb{R}^{d \times m}$ and $B \in \mathbb{R}^{m \times n}$. Define $\mathcal{L}(x) = \mathcal{L}_A \circ \mathcal{L}_B(x) = \mathcal{L}_A(\mathcal{L}_B(x)) \quad \forall x \in \mathbb{R}^n$. Then, $\mathcal{L} : \mathbb{R}^n \rightarrow \mathbb{R}^d$. Since \mathcal{L}_A and \mathcal{L}_B are linear, we found that \mathcal{L} is also linear. Hence, $\mathcal{L} = \mathcal{L}_C$ f.s. $C \in \mathbb{R}^{d \times n}$. It turns out that $C = AB$.

Definition 1.2.22 (Transpose of Matrix). Let $A \in \mathbb{R}^{d \times m}$, then its transpose $A^T \in \mathbb{R}^{m \times d}$, and

$$(A^T)_{ij} = a_{ji}.$$

Corollary 1.2.23 : If $x, y \in \mathbb{R}^d$, then $\langle x, y \rangle = \sum_{i=1}^d x_i y_i = x^T y = xy^T$.

Proof 2. Suppose $x = \begin{pmatrix} x_1 \\ \vdots \\ x_d \end{pmatrix}$, then $x^T = (x_1 \quad \cdots \quad x_d)$.

$$x^T y = (x_1 \quad \cdots \quad x_d) \begin{pmatrix} y_1 \\ \vdots \\ y_d \end{pmatrix} = x_1 y_1 + \cdots + x_d y_d.$$

■

Corollary 1.2.24 Cauchy-Schwarz: $|x^T y| \leq \|x\|_2 \|y\|_2$.

Definition 1.2.25 (Trace of a Matrix). Assume that $A \in \mathbb{R}^{d \times d}$, the *trace* of A , denoted as $\text{Tr}(A)$, is defined as

$$\text{Tr}(A) = \sum_{i=1}^d a_{ii}.$$

Definition 1.2.26 (Determinant of a Matrix). Assume that $A \in \mathbb{R}^{d \times d}$, the *determinant* of A , denoted as $\det(A)$, is defined as

$$\det(A) = \sum_{\sigma \in S_d} (-1)^{i(\sigma)} a_{1\sigma(1)} a_{2\sigma(2)} \cdots a_{d\sigma(d)},$$

where S_d is the set of all possible permutation of size d and $i(\sigma)$ denotes the sign of the permutation.

Definition 1.2.27 (Eigenvalue and Eigenvector). Assume that $A \in \mathbb{R}^{d \times d}$. We say that λ is an *eigenvalue* for A if $\exists x \in \mathbb{R}^d \setminus \{0\}$ s.t. $Ax = \lambda x$. In this case, x is called an *eigenvector*.

Definition 1.2.28 (Diagonalizability). A matrix $A \in \mathbb{R}^{d \times d}$ is called *diagonalizable* if \exists basis v_1, \dots, v_d s.t. $Av_i = \lambda v_i \quad \forall 1 \leq i \leq d$.

Theorem 1.2.29 Diagonalization, Singular Value Decomposition (SVD) of Squared Matrices

Assume that A is diagonalizable and

$$V = \begin{pmatrix} v_1 & v_2 & \cdots & v_d \end{pmatrix}.$$

Then, $A = VDV^{-1}$, where D is a diagonal matrix such that

$$D = \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_d \end{pmatrix}.$$

Example 1.2.30 Application of Diagonalization

$$A^2 = (VDV^{-1})(VDV^{-1}) = VD \underbrace{V^{-1}V}_I DV^{-1} = VD^2V^{-1}.$$

Generally,

$$A^n = VD^nV^{-1} = V \begin{pmatrix} \lambda_1^n & & 0 \\ & \ddots & \\ 0 & & \lambda_d^n \end{pmatrix} V^{-1}.$$

Remark 1.10 Remarks on Diagonalization

- *There might be repeating eigenvalues. Typically, we enumerate λ 's s.t. $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_d$.*
- *In general, it is hard to decide whether A is diagonalizable. For example, rotation matrices have no eigenvectors nor eigenvalues.*
- *If A is symmetric; that is $A = A^T$, then A is diagonalizable. Moreover, we can choose basis v_1, \dots, v_d s.t.*

$$v_i^T v_j = \begin{cases} 0, & i \neq j \\ 1, & i = j \end{cases}.$$

Such bases are called orthonormal. In matrix form, if $V = \begin{pmatrix} v_1 & v_2 & \cdots & v_d \end{pmatrix}$, then

$$V^T V = \begin{pmatrix} v_1^T \\ \vdots \\ v_d^T \end{pmatrix} \begin{pmatrix} v_1 & \cdots & v_d \end{pmatrix} = I.$$

That is, $V^T = V^{-1}$, and hence $A = VDV^{-1} = VDV^T$.

1.3 Basic Topology

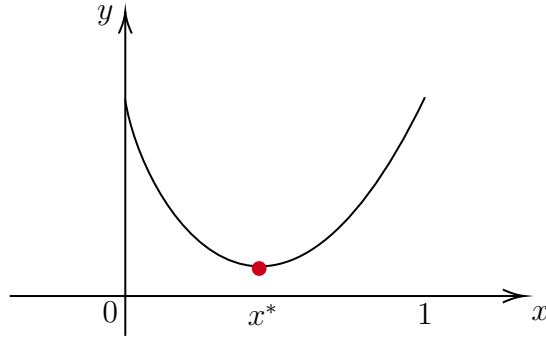
Example 1.3.1 Introduction

Consider the optimization problem $\min_{x \in [0,1]} f(x)$. Suppose that $x^* \in [0, 1]$ is a solution for this problem, then we have

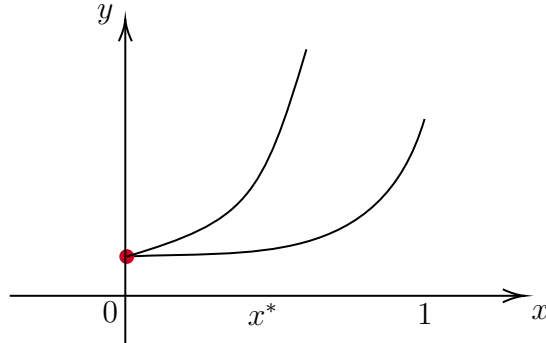
$$f(x) \geq f(x^*) \quad \forall x \in [0, 1].$$

Then, we can conduct a case study on the necessary condition we need to have on $f'(x)$.

1. $x^* \in (0, 1) \implies f'(x^*) = 0.$



2. $x^* = 0 \implies f'(x^*) \geq 0$



3. $x^* = 1 \implies f'(x^*) \leq 0.$

Definition 1.3.2 (Open/Closed Ball). The *open ball* with center $c \in \mathbb{R}^n$ and radius $r > 0$ is the set

$$B(c, r) := \{x \in \mathbb{R}^n : \|x - c\| < r\}.$$

The *closed ball* with center $c \in \mathbb{R}^n$ and radius $r > 0$ is the set

$$B[c, r] := \{x \in \mathbb{R}^n : \|x - c\| \leq r\}.$$

Remark 1.11 *The boundary is not included in an open ball.*

Definition 1.3.3 (Interior Point). Assume that $U \subseteq \mathbb{R}^n$. We say that $x \in U$ is an *interior point* if $\exists r > 0$ s.t. $B(x, r) \subseteq U$. The set of all interior points of U is denoted by $\text{int}(U)$

Example 1.3.4 Interior Point Example

Suppose $U = [0, 1]$. Prove that $\text{int}(U) = (0, 1)$.

Proof 1. To prove this, we have to show $\text{int}(U) \subseteq (0, 1)$ and $(0, 1) \subseteq \text{int}(U)$.

(\supseteq) : Let $x \in (0, 1)$. WTS: $x \in \text{int}(U)$. Take $r = \min\{x, 1 - x\}$, then the open ball $B(x, r) \subseteq U$. *proof omitted.* So, $x \in \text{int}(U)$, and thus $(0, 1) \subseteq \text{int}(U)$. \square

(\subseteq) : Let $x \in \text{int}(U)$. WTS: $x \in (0, 1)$. *omitted.* ■

Definition 1.3.5 (Open Set). A set $U \subseteq \mathbb{R}^n$ is called *open* if $\text{int}(U) = U$.

Example 1.3.6 Open Set Counterexample

$U = [0, 1]$ in Example 1.3.4 is not an open set.

Remark 1.12 *When f is defined over an open set U , then we can define differentiability on f on U .*

Definition 1.3.7 (Closed Set). A set $F \subseteq \mathbb{R}^n$ is called a *closed set* if $\forall (x_n)_{n=1}^{\infty} \subseteq F$ such that $\lim_{n \rightarrow \infty} x_n = x \implies x \in F$.

Example 1.3.8 Closed Set

- Take $F = \mathbb{R}^n$, then F is a closed set because we have taken everything into the set.
- $F = [0, 1]$ is closed.

Proof 2. Take $x_1, x_2, \dots, x_n, \dots \in [0, 1]$. That is, $0 \leq x_n \leq 1, \forall n \geq 1$. Then, set $x = \lim_{n \rightarrow \infty} x_n$. It must be that $0 \leq x \leq 1$, or $x \in [0, 1]$. ■

- $F = (0, 1]$ is not closed.

Proof 3. Take $x_1, \dots, x_n, \dots \in (0, 1]$, where $x_n = \frac{1}{n} \forall n \geq 1$. Then, $0 \leq x_n \leq 1$. However, notice that $x = \lim_{n \rightarrow \infty} x_n = \lim_{n \rightarrow \infty} \frac{1}{n} = 0 \notin (0, 1]$. Hence, F is not closed. ■

Remark 1.13 *In general, optimization problems are set on closed sets for otherwise, we cannot guarantee, in general, existence of optimal solutions.*

Example 1.3.9 Optimization Problem on a Set that is not Cloased

Suppose $f(x) = x$ and consider the optimization problem

$$\min_{0 < x \leq 1} f(x) = \min_{0 < x \leq 1} x.$$

Then we know that this problem does not have a solution.

Remark 1.14 *A set can be neither open nor closed.*

Definition 1.3.10 (Boundary Points). A point x is a *boundary point* for U if $\forall r > 0$, $B(x, r)$ contains points from both U and its complement. The set of all boundary points of U is denoted by $\text{bd}(U)$.

Example 1.3.11 Boundary Pooints

- $U = [0, 1] \implies \text{bd}(U) = \{0, 1\}.$
- $U = (0, 1] \implies \text{bd}(U) = \{0, 1\}.$

Definition 1.3.12 (Compact Set). A set $C \in \mathbb{R}^n$ is called *compact* if it is **closed** and **bounded**. The latter means that $\exists M > 0$ s.t. $\|x\| \leq M \quad \forall x \in C$.

1.4 Continuity and Differentiability

Definition 1.4.1 (Continuity). Let $S \subseteq \mathbb{R}^n$, $f : S \rightarrow \mathbb{R}$, $x \in S$. We say that f is *continuous at x* if

$$\lim_{\substack{z \rightarrow x \\ z \in S}} f(z) = f(x).$$

If f is continuous at all points $x \in S$, we simply say f is *continuous on S* . We also use the notation $f \in \mathcal{C}(S)$.

Theorem 1.4.2 Weierstrass Theorem

Assume that $S \subseteq \mathbb{R}^n$ is a compact set, and $f : S \rightarrow \mathbb{R}$ is a continuous function. Then $\exists x_{\min}, x_{\max} \in S$ s.t.

$$f(x) \geq f(x_{\min}) \quad \forall x \in S \quad \text{and} \quad f(x) \leq f(x_{\max}) \quad \forall x \in S.$$

In other words, $\min_{x \in S} f(x)$ and $\max_{x \in S} f(x)$ problems are guaranteed to have solutions.

Example 1.4.3 Classes of Continuous Functions

1. Polynomials.
2. $\sin(x)$ and $\cos(x)$; $\tan(x)$ and $\cot(x)$ at certain domain.
3. Exponents: e^{ax} , $a \in \mathbb{R}$.
4. Logarithm: $\ln x$, $x > 0$.
- 5.

Theorem 1.4.4 Building Continuous Functions

- If f and g are continuous, then $f \cdot g$, $f + g$, and af are continuous $\forall a \in \mathbb{R}$.
- If f and g are continuous, then $\frac{f}{g}$ is continuous for x s.t. $g(x) \neq 0$.
- If f, g are continuous and $h = f \circ g$ makes sense, then h is continuous.

Definition 1.4.5 (Differentiability). Let $S \subseteq \mathbb{R}^n$, $x \in \text{int}(S)$, and $f : S \rightarrow \mathbb{R}$. Then, the i -th partial derivative of f at x is the limit (if it exists)

$$\frac{\partial f(x)}{\partial x_i} = \lim_{t \rightarrow 0} \frac{f(x + te_i) - f(x)}{t}, \quad \text{where } e_i \text{ is the standard basis.}$$

If all partial derivatives exist, then we assemble them in a column vector called *gradient*.

$$\nabla f(x) = \left(\frac{\partial f(x)}{\partial x_1} \quad \dots \quad \frac{\partial f(x)}{\partial x_n} \right)^T$$

We say that f is *continuously differentiable* on S if $\exists U$ open set s.t. $S \subseteq U$ and $\nabla f(x)$ exists $\forall x \in U$ and is continuous. In this case, we write $f \in C^1(S)$.

Example 1.4.6 Continuous Function that is not Continuously Differentiable

Consider $f(x) = |x|$. Then we know its derivative

$$f'(x) = \begin{cases} 1 & x > 0 \\ -1 & x < 0 \\ \text{undefined} & x = 0. \end{cases}$$

So, $f \in C(\mathbb{R})$ but $f \notin C^1(\mathbb{R})$.

Definition 1.4.7 (Directional Derivative). Let $f \in \mathbb{R}^n \setminus \{0\}$. Then, the *directional derivative of f at x* is the limit (if it exists)

$$f'(x; d) = \lim_{t \rightarrow 0^+} \frac{f(x + td) - f(x)}{t}.$$

Remark 1.15 If $f \in \mathcal{C}^1(S)$, then

$$f'(x; d) = \nabla f(x)^T \cdot d.$$

However, the converse is not true in general. Indeed, for $f(x) = |x|$, we have that $f'(0; 1) = 1$ (the positive direction), and $f'(0; -1) = -1$ (the negative direction). But $f'(0)$ does not exist.

Definition 1.4.8 (Second-Order Differentiability). The (i, j) -th partial derivative of f at x is

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial}{\partial x_i} \left(\frac{\partial f(x)}{\partial x_j} \right).$$

If all second order partial derivatives exist and are continuous on S , we say that f is *twice continuously differentiable* on S and write $f \in \mathcal{C}^2(S)$.

If $f \in \mathcal{C}^2(S)$, then

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i} \quad \forall i, j.$$

If f has all second-order partial derivatives at x , then we denote the *Hessian of f at x* by the matrix

$$\nabla^2 f(x) = \left(\frac{\partial^2 f}{\partial x_i \partial x_j} \right)_{i,j=1}^n$$

If $f \in \mathcal{C}^2(S)$, then $\nabla^2 f(x)$ is *symmetric* for all $x \in S$.

Definition 1.4.9 (Small-O Notation). $o(r)$ is the *small-o notation* and means that this quantity is much smaller than r . For example, $o(\|y - x\|)$ is any quantity *s.t.*

$$\lim_{y \rightarrow x} \frac{o(\|y - x\|)}{\|y - x\|} = 0.$$

Theorem 1.4.10 Taylor Approximation I

If f is differentiable at x , then

$$f(y) = f(x) + \nabla f(x)^T (y - x) + o(\|y - x\|).$$

Theorem 1.4.11 Taylor Approximation II

If f is twice differentiable at x , then

$$f(y) = f(x) + \nabla f(x)^T (y - x) + \frac{1}{2} (y - x)^T \nabla^2 f(x) (y - x) + \underbrace{o(\|y - x\|^2)}_{\text{small error}}.$$

Theorem 1.4.12 Taylor Approximation III

If f is twice differentiable at x , then

$$f(y) = f(x) + \nabla f(x)^T(y - x) + \frac{1}{2}(y - x)^T \nabla^2 f(c)(y - x) \text{ for some } c(x, y, f \dots),$$

where the point c is dependent on x , y , and f , but we do not know exactly what c is.

Remark 1.16 *From Taylor Approximation II to III, we improve our approximation from an expression with a small error, to an exact equation. However, the trade-off here is that we have to introduce a new constant c , which we do not have any information about.*

2 Unconstrained Optimization

2.1 Global and Local Optima

Definition 2.1.1 (Global Minimum and Maximum). Let $f : S \rightarrow \mathbb{R}$ be defined on a set $S \subseteq \mathbb{R}^n$. Then, $x^* \in S$ is called a

- *global minimum point* of f over S if $f(x) \geq f(x^*)$ for any $x \in S$.
- *strict global minimum point* of f over S if $f(x) > f(x^*)$ for any $x^* \neq x \in S$.
- *global maximum point* of f over S if $f(x) \leq f(x^*)$ for any $x \in S$.
- *strict global maximum point* of f over S if $f(x) < f(x^*)$ for any $x^* \neq x \in S$.

Definition 2.1.2 (Feasible Set and Feasible Solution). The set S on which the optimization of f is performed is called the *feasible set*, and any only $x \in S$ is called a *feasible solution*.

Definition 2.1.3 (Minimizer and Maximizer). We refer to a global minimum point as a *minimizer* or a *global minimizer*, and a global maximum point as a *maximizer* or a *global maximizer*. A vector $x^* \in S$ is called a *global optimum* of f over S if it is either a global minimum or a global maximum.

Definition 2.1.4 (Maximal and Minimal Value). The *maximal value* of f over S is defined as the supremum of f over S :

$$\max \{f(x) : x \in S\} = \sup \{f(x) : x \in S\}.$$

If $x^* \in S$ is a global maximum of f over S , then the maximum value of f over S is $f(x^*)$. The *minimal value* of f over S is the infimum of f over S ,

$$\min \{f(x) : x \in S\} = \inf \{f(x) : x \in S\},$$

and is equal to $f(x^*)$ when x^* is a global minimizer of f over S .

Remark 2.1 (Difference between min and inf) For $A \subseteq \mathbb{R}$, $\min A = y^*$ if $y^* \in A$, and $y^* \leq y \quad \forall y \in A$. On the other hand, $\inf A = y^*$ if $y^* \leq y \quad \forall y \in A$, and any $y' > y^*$ is NOT a lower bound for A .

Remark 2.2 There could be several global minimum points, but there could be only one minimal value.

Definition 2.1.5 (Set of Global Minimizers and Global Maximizers). The set of *all global minimizers* of f over S is denoted by

$$\arg \min \{f(x) : x \in S\}$$

and the set of all global maximizers of f over S is denoted by

$$\arg \max \{f(x) : x \in S\}.$$

Definition 2.1.6 (Local Minima and Maxima). Let $f : S \rightarrow \mathbb{R}$ be defined on a set $S \subseteq \mathbb{R}^n$. Then, $x^* \in S$ is called a

- *local minimum point* of f over S if there exists $r > 0$ for which $f(x^*) \leq f(x)$ for any $x \in S \cap B(x^*, r)$.
- *strict local minimum point* of f over S if there exists $r > 0$ for which $f(x^*) < f(x)$ for any $x^* \neq x \in S \cap B(x^*, r)$.
- *local maximum point* of f over S if there exists $r > 0$ for which $f(x^*) \geq f(x)$ for any $x \in S \cap B(x^*, r)$.
- *strict local maximum point* of f over S if there exists $r > 0$ for which $f(x^*) > f(x)$ for any $x^* \neq x \in S \cap B(x^*, r)$.

Lemma 2.1.7 Fermat's Theorem: For a one-dimensional function f defined and differentiable over an interval (a, b) , if a point $x^* \in (a, b)$ is a local maximum or minimum, then $f'(x^*) = 0$.

Remark 2.3 *Moving into multidimensional extension of this Lemma, the result states that the gradient is zero at local optimum points. We refer to such an optimality condition as a first order optimality condition .*

Theorem 2.1.8 First Order Optimality Condition for Local Optima Points

Let $f : U \rightarrow \mathbb{R}$ be a function defined on a set $U \subseteq \mathbb{R}^n$. Suppose that $x^* \in \text{int}(U)$ is a local optimum point and that all the partial derivatives of f exist at x^* . Then, $\nabla f(x^*) = 0$.

Proof 1. Let $i \in \{1, 2, \dots, n\}$ and consider the one-dimensional function $g(t) = f(x^* + te_i)$, where e_i is the standard basis. Note that g is differentiable at $t = 0$ and that $g'(0) = \frac{\partial f}{\partial x_i}(x^*)$. Since x^* is a local optimum point of f , it follows that $t = 0$ is a local optimum of g , which immediately implies that $g'(0) = 0$. The latter equality is exactly the same as $\frac{\partial f}{\partial x_i}(x^*) = 0$. Since this is true for any $i \in \{1, 2, \dots, n\}$, the result $\nabla f(x^*) = 0$ follows. ■

Remark 2.4 *Our proof of the multidimensional First Order Condition relies on the first order optimality condition for one-dimensional functions.*

Remark 2.5 *Theorem 2.1.8 presents a necessary optimality condition: the gradient vanishes at all local optimum points, which are interior points of the domain of the function; however, the reverse claim is not true since there could be points which are not local optimum points whose gradient is zero.*

Definition 2.1.9 (Stationary Points). Let $f : U \rightarrow \mathbb{R}$ be a function defined on a set $U \subseteq \mathbb{R}^n$. Suppose that $x^* \in \text{int}(U)$ and that f is differentiable over some neighborhood of x^* . Then, x^* is called a *stationary point* of f if $\nabla f(x^*) = 0$.

Remark 2.6 *Theorem 2.1.8 essentially states that local optimum points are necessarily stationary points. However, again, stationary points are not necessarily local optimum points.*

2.2 Classification of Matrices

Definition 2.2.1 (Positive Definiteness, Negative Definiteness). A symmetric matrix $A \in \mathbb{R}^{n \times n}$ is called

- *positive semidefinite*, denoted by $A \succeq 0$, if $x^T A x \geq 0$ for every $x \in \mathbb{R}^n$.
- *positive definite*, denoted by $A \succ 0$, if $x^T A x > 0$ for every $x \neq 0 \in \mathbb{R}^n$.
- *negative semidefinite*, denoted by $A \preceq 0$, if $x^T A x \leq 0$ for every $x \in \mathbb{R}^n$.
- *negative definite*, denoted by $A \prec 0$, if $x^T A x < 0$ for every $x \neq 0 \in \mathbb{R}^n$.
- *indefinite* if there exist x and $y \in \mathbb{R}^n$ such that $x^T A x > 0$ and $y^T A y < 0$.

Remark 2.7 *A matrix is negative (semi)definite if and only if $-A$ is positive (semi)definite.*

Lemma 2.2.2 Necessary Condition for Definiteness of Matrices: If $A \in \mathbb{R}^{n \times n}$ is a positive definite matrix, then its diagonal elements are positive. If $A \in \mathbb{R}^{n \times n}$ is a semidefinite matrix, then its diagonal elements are nonnegative. Similarly, if A is a negative definite matrix, then its diagonal elements are negative. If A is a negative semidefinite matrix, then its diagonal elements are nonpositive.

Remark 2.8 *Note that Lemma 2.2.2 gives a necessary condition for a positive definite matrix. It is not sufficient. That is, one can easily generate a matrix with positive diagonal entries that is not positive definite.*

Lemma 2.2.3: Let A be a symmetric $n \times n$ matrix. If there exists positive and negative elements in the diagonal of A , then A is indefinite.

Theorem 2.2.4 Eigenvalue Characterization Theorem

Let A be a symmetric $n \times n$ matrix. Then,

- A is positive definite if and only if all its eigenvalues are positive.
- A is positive semidefinite if and only if all its eigenvalues are nonnegative.
- A is negative definite if and only if all its eigenvalues are negative.
- A is negative semidefinite if and only if all its eigenvalues are nonpositive.
- A is indefinite if and only if it has both positive and negative eigenvalues.

Corollary 2.2.5 : Let A be a positive semidefinite (definite) matrix. Then, $\text{tr}(A)$ and $\det(A)$ are nonnegative (positive).

Lemma 2.2.6 : Let $D = \text{diag}(d_1, d_2, \dots, d_n)$. Then, D is

- positive definite if and only if $d_i > 0 \quad \forall i$.
- positive semidefinite if and only if $d_i \geq 0 \quad \forall i$.
- negative definite if and only if $d_i < 0 \quad \forall i$.
- negative semidefinite if and only if $d_i \leq 0 \quad \forall i$.
- indefinite if and only if $\exists i, j \text{ s.t. } d_i > 0, d_j < 0$.

Proposition 2.2.7 : Let A be a symmetric 2×2 matrix. Then, A is positive semidefinite (definite) if and only if both $\text{tr}(A) \geq 0$ and $\det(A) \geq 0$ ($\text{tr}(A) > 0$ and $\det(A) > 0$).

Example 2.2.8 Square Root of Matrices

For any positive semidefinite matrix A , we can define the square root of matrix $A^{1/2}$. Let $A = UDU^T$ by the spectral decomposition. Then, $D = \text{diag}(d_1, d_2, \dots, d_n)$, where d_i 's are eigenvalues of A . Since A is positive semidefinite, we have $d_1, \dots, d_n \geq 0$. Now, define

$$A^{1/2} = UEU^T,$$

where $E = \text{diag}(\sqrt{d_1}, \dots, \sqrt{d_n})$. Then

$$A^{1/2}A^{1/2} = UEU^TUEU^T = UEEU^T = UDU^T = A.$$

The matrix $A^{1/2}$ is also known as the *positive semidefinite square root*.

Definition 2.2.9 (Principal Minor). Given an $n \times n$ matrix, the determinant of the upper left $k \times k$ sub-matrix is called the k -th *principal minor* and is denoted by $D_k(A)$.

Example 2.2.10 Principal Minor

Consider a 3×3 matrix

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}.$$

Then the principal minors are

$$D_1(A) = a_{11}, \quad D_2(A) = \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix}, \quad D_3(A) = \begin{vmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{vmatrix}.$$

Theorem 2.2.11 Principal Minors Criterion

Let A be an $n \times n$ symmetric matrix. Then, A is positive definite if and only if all its principal minors are positive. That is, $D_1(A) > 0, \dots, D_n(A) > 0$.

Remark 2.9 When the matrix becomes large, computing its determinant will be hard. So, other method to determine the definiteness of a matrix shall be introduced.

Definition 2.2.12 (Diagonally Dominant Matrices). Let A be a symmetric $n \times n$ matrix. Then,

- A is *diagonally dominant* if

$$|A_{ii}| \geq \sum_{j \neq i} |A_{ij}|, \quad \text{for } i = 1, 2, \dots, n.$$

- A is called *strictly diagonally dominant* if

$$|A_{ii}| > \sum_{j \neq i} |A_{ij}|, \quad \text{for } i = 1, 2, \dots, n.$$

Theorem 2.2.13 Positive (Semi)Definiteness of Diagonally Dominant Matrices

- Let A be a symmetric $n \times n$ diagonally dominant matrix whose diagonal elements are nonnegative. Then, A is positive semidefinite.
- Let A be a symmetric $n \times n$ strictly diagonally dominant matrix whose diagonal elements are positive. Then, A is positive definite.

2.3 Second Order Optimality Conditions**Theorem 2.3.1 Necessary Second Order Optimality Condition**

Let $f : U \rightarrow \mathbb{R}$ be a function defined on an open set $U \subseteq \mathbb{R}^n$. Suppose that f is twice continuously differentiable over U and that x^* is a stationary point. Then, the following hold:

- If x^* is a local minimum point of f over U , then $\nabla^2 f(x^*) \succeq 0$.
- If x^* is a local maximum point of f over U , then $\nabla^2 f(x^*) \preceq 0$.

Proof 1. Proving the second condition, we just need to employ the result from the first condition on the function $-f$. So, we will only prove the first condition here.

Since x^* is a local minimum point, \exists a ball $B(x^*, r) \subseteq U$ for which $f(x) \geq f(x^*)$ for all $x \in B(x^*, r)$. Let $d \in \mathbb{R}^n$ be a nonzero vector. For any $0 < \alpha < \frac{r}{\|d\|}$, we have $x_\alpha^* = x^* + \alpha d \in B(x^*, r)$, and hence for any such α ,

$$f(x_\alpha^*) \geq f(x^*). \quad (2)$$

On the other hand, by the linear approximation theorem (Taylor's approximation), it follows that \exists a vector $z_\alpha \in [x^*, x_\alpha^*]$ such that

$$f(x_\alpha^*) - f(x^*) = \nabla f(x^*)^\top (x_\alpha^* - x^*) + \frac{1}{2}(x_\alpha^* - x^*)^\top \nabla^2 f(z_\alpha)(x_\alpha^* - x^*).$$

Since x^* is a stationary point of f , and by the definition of x_α^* , the equation can be reduced to

$$f(x_\alpha^*) - f(x^*) = \frac{\alpha^2}{2} d^\top \nabla^2 f(z_\alpha) d. \quad (3)$$

Combining Eq. (2) and Eq. (3), it follows that for any $\alpha \in \left(0, \frac{r}{\|d\|}\right)$, the following inequality holds:

$$d^\top \nabla^2 f(z_\alpha) d \geq 0.$$

Finally, using the fact that $z_\alpha \rightarrow x^*$ as $\alpha \rightarrow 0^+$, and the continuity of the Hessian, we obtain that $d^\top \nabla^2 f(x^*) d \geq 0$. Since the inequality holds for any $d \in \mathbb{R}^n$, the desired result is established. ■

Theorem 2.3.2 Sufficient Second Order Optimal Condition

Let $f : U \rightarrow \mathbb{R}$ be a function defined on an open set $U \subseteq \mathbb{R}^n$. Suppose that f is twice continuously differentiable over U and that x^* is a stationary point. The following hold:

- If $\nabla^2 f(x^*) \succ 0$, then x^* is a strict local minimum point of f over U .
- If $\nabla^2 f(x^*) \prec 0$, then x^* is a strict local maximum point of f over U .

Definition 2.3.3 (Saddle Point). Let $f : U \rightarrow \mathbb{R}$ be a function defined on an open set $U \subseteq \mathbb{R}^n$. Suppose that f is continuously differentiable over U . A stationary point x^* is called a *saddle point* of f over U if it is neither a local minimum point nor a local maximum point of f over U .

Theorem 2.3.4 Sufficient Condition for a Saddle Point

Let $f : U \rightarrow \mathbb{R}$ be a function defined on an open set $U \subseteq \mathbb{R}^n$. Suppose that f is twice continuously differentiable over U and that x^* is a stationary point. If $\nabla^2 f(x^*)$ is an indefinite matrix, then x^* is a saddle point of f over U .

Remark 2.10 Recall the Weierstrass Theorem (Theorem 1.4.2), which states that a function defined over a compact set must attain its maximum and minimum value at some point. However, if we loose the condition on the compact set, we will not get this nice property. Therefore,

we wonder if we can come up with some condition on the objective function to ensure the maximum and minimum values are attained. This motivates the following definition of coerciveness.

Definition 2.3.5 (Coerciveness). Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a continuous function defined over \mathbb{R}^n . The function f is called *coercive* if

$$\lim_{\|x\| \rightarrow \infty} f(x) = \infty.$$

Theorem 2.3.6 Attainment Under Coerciveness

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a continuous and coercive function and let $S \subseteq \mathbb{R}^n$ be a nonempty closed set. Then, f has a global minimum point over S .

2.4 Global Optimality Condition and Quadratic Functions

Theorem 2.4.1 Global Optimality Condition

Let f be a twice continuously differentiable function defined over \mathbb{R}^n . Suppose that $\nabla^2 f(x) \succeq 0$ for any $x \in \mathbb{R}^n$. Let $x^* \in \mathbb{R}^n$ be a stationary point of f . Then, x^* is a global minimum point of f .

Proof 1. By the linear approximation theorem, it follows that for any $x \in \mathbb{R}^n$, there exists a vector $z_x \in [x^*, x]$ for which

$$f(x) - f(x^*) = \frac{1}{2}(x - x^*)^\top \nabla^2 f(z_x)(x - x^*).$$

Since $\nabla^2 f(z_x) \succeq 0$, we have that $f(x) \geq f(x^*)$, establishing the fact that x^* is a global minimum point of f . ■

Definition 2.4.2 (Quadratic Function). A *quadratic function* over \mathbb{R}^n is a function of the form

$$f(x) = x^\top A x + 2b^\top x + c,$$

where $A \in \mathbb{R}^{n \times n}$ is symmetric, $b \in \mathbb{R}^n$, and $c \in \mathbb{R}$. The matrix A will be referred as the matrix *associated* with the quadratic function f . The gradient and Hessian of a quadratic function have simple analytic formulas:

$$\nabla f(x) = 2Ax + 2b; \quad \nabla^2 f(x) = 2A.$$

Lemma 2.4.3 : Let $f(x) = x^\top A x + 2b^\top x + c$, where $A \in \mathbb{R}^{n \times n}$ is symmetric, $b \in \mathbb{R}^n$, and $c \in \mathbb{R}$. Then,

- x is a stationary point of f if and only if $Ax = -b$.

- if $A \succeq 0$, then x is a global minimum point of f if and only if $Ax = -b$.
- if $A \succ 0$, then $x = -A^{-1}b$ is a strict global minimum point of f .

Lemma 2.4.4 Coerciveness of Quadratic Functions: Let $f(x) = x^\top Ax + 2b^\top x + c$, where $A \in \mathbb{R}^{n \times n}$ symmetric, $b \in \mathbb{R}^n$, and $c \in \mathbb{R}$. Then, f is coercive if and only if $A \succ 0$.

Theorem 2.4.5 Characterization of the non-negativity of quadratic functions

Let $f(x) = x^\top Ax + 2b^\top x + c$, where $A \in \mathbb{R}^{n \times n}$ symmetric, $b \in \mathbb{R}^n$, and $c \in \mathbb{R}$. Then, the following two claims are equivalent:

- $f(x) \equiv x^\top Ax + 2b^\top x + c \geq 0$ for all $x \in \mathbb{R}^n$.
- $\begin{pmatrix} A & b \\ b^\top & c \end{pmatrix} \succeq 0$.

3 Least Square

3.1 “Solution” of Overdetermined Systems

Definition 3.1.1 (Least Square Problem). Suppose that we are given a linear system of the form $Ax = b$, where $A \in \mathbb{R}^{m \times n}$ and $b \in \mathbb{R}^m$. Assume that the system is *overdetermined*, meaning that $m > n$. Assume that A has a full column rank; that is, $\text{rank}(A) = n$. Then, the system is usually *inconsistent* (has no solution) and a common approach of finding an approximate solution is to pick the solution resulting with the minimal squared norm of the residual $r = Ax - b$:

$$\min_{x \in \mathbb{R}^n} \|Ax - b\|^2. \quad (\text{LS})$$

Solution 1.

To solve the Problem (LS), we can rewrite the objective function as

$$f(x) = x^\top A^\top Ax - 2b^\top Ax + \|b\|^2.$$

Since A is of full column rank, it follows that for any $x \in \mathbb{R}^n$, it holds that $\nabla^2 f(x) = 2A^\top A \succ 0$. Hence, the unique stationary point

$$x_{\text{LS}} = (A^\top A)^{-1} A^\top b$$

is the optimal solution of problem (LS). □

Definition 3.1.2 (The Least Square Solution/Normal System). The vector x_{LS} we found is called the *least squares solution* or the *least squares estimate* of the system $Ax = b$. It is also common to write the explicit expression for x_{LS} associated with the *normal system*:

$$(A^\top A)x_{\text{LS}} = A^\top b.$$

3.2 Data Fitting

Definition 3.2.1 (Linear Fitting). Suppose that we are given a set of data points (s_i, t_i) , $i = 1, 2, \dots, m$, where $s_i \in \mathbb{R}^n$ and $t_i \in \mathbb{R}$, and assume that a linear relation of the form

$$t_i = s_i^\top x, \quad i = 1, 2, \dots, m,$$

approximately holds.

Solution 1.

In the least square approach, the objective is to find the parameters vector $x \in \mathbb{R}^n$ that solves the problem

$$\min_{x \in \mathbb{R}^n} \sum_{i=1}^m (x_i^\top x - t_i)^2.$$

We can alternatively write the problem as

$$\min_{x \in \mathbb{R}^n} \|Sx - t\|^2,$$

where

$$S = \begin{pmatrix} -s_1^\top - \\ -s_2^\top - \\ \vdots \\ -s_m^\top - \end{pmatrix}, \quad t = \begin{pmatrix} t_1 \\ t_2 \\ \vdots \\ t_m \end{pmatrix}.$$

□

Definition 3.2.2 (Nonlinear Fitting). The least square approach can be used also in nonlinear fitting. Suppose, for example, that we are given a set of points in \mathbb{R}^2 : (u_i, y_i) , $i = 1, 2, \dots, m$, and that we know a priori that these points are approximately related via a polynomial of degree at most d ; i.e., there exists a_0, \dots, a_d such that

$$\sum_{j=0}^d a_j u_i^j \approx y_i, \quad i = 1, \dots, m.$$

The least squares approach to this problem seeks a_0, a_1, \dots, a_d that are the least squares solution to the linear system

$$\underbrace{\begin{pmatrix} 1 & u_1 & u_1^2 & \cdots & u_1^d \\ 1 & u_2 & u_2^2 & \cdots & u_2^d \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & u_m & u_m^2 & \cdots & u_m^d \end{pmatrix}}_U \begin{pmatrix} a_0 \\ a_1 \\ \vdots \\ a_d \end{pmatrix} = \begin{pmatrix} y_0 \\ y_1 \\ \vdots \\ y_m \end{pmatrix}.$$

Note that, the matrix U is also called the *Vandermonde matrix*.

Data Fitting

```

1 d = linspace(0, 1, 30)';
2 e = 2 * d + 1 + 0.1 * randn(30, 1);
3 plot(d, e, "*");
4 u = [d, ones(30,1)]\e;
5 a = u(1), b = u(2);
6 >>> a =
7     2.0616
8 >>> b =
9     0.9725

```

3.3 Regularized Least Squares

When A is underdetermined, that is, when there are fewer equations than variables, there are several optimal solutions to the least squares problem, and it is unclear which of these optimal solutions is the one that should be considered.

Example 3.3.1

Consider $A = \begin{pmatrix} 0 & | & | & | \\ \vdots & | & | & \dots & | \\ 0 & | & | & | \end{pmatrix}$. Then, consider

$$Ax = \begin{pmatrix} 0 & | & | & | \\ \vdots & | & | & \dots & | \\ 0 & | & | & | \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} = b.$$

There will be no x_1 in b . Therefore, changing x_1 will not alter the value $\|Ax - b\|^2$.

Theorem 3.3.2

Suppose that $b = Ax_0$. Consider all $x \neq x_0$ s.t. $Ax = Ax_0$, then $A(x - x_0) = 0$. So, $x - x_0 \in \text{null}(A)$, $x \in x_0 + \text{null}(A)$.

Definition 3.3.3 (Regularized Least Square). Consider a penalized problem in which a *regularization function* $R(\cdot)$ is added to the objective function. The *regularized least square (RLS)* problem has the form

$$\min_x \|Ax - b\|^2 + \lambda R(x). \quad (\text{RLS})$$

The positive constant λ is the *regularization parameter*. As λ gets larger, more weight is given to the regularization function.

In many cases, the regularization is taken to be *quadratic*. In particular, $R(x) = \|Dx\|^2$, where $D \in \mathbb{R}^{p \times n}$ is a given matrix. Then, (RLS) can be written as

$$\min_x \|Ax - b\|^2 + \lambda \|Dx\|^2.$$

To find the optimal solution, we can equivalently write the problem as

$$\min_x \{f_{\text{RLS}}(x) \equiv x^\top (A^\top A + \lambda D^\top D)x - 2b^\top Ax + \|b\|^2\}.$$

Since the Hessian of the objective function $\nabla^2 f_{\text{RLS}}(x) = 2(A^\top A + \lambda D^\top D) \succeq 0$, any stationary point is a global minimum point. The stationary points are those satisfying $\nabla f_{\text{RLS}}(x) = 0$, that is

$$(A^\top A + \lambda D^\top D)x = A^\top b.$$

Therefore, if $A^\top A + \lambda D^\top D \succ 0$, then the RLS solution is given by

$$x_{\text{RLS}} = (A^\top A + \lambda D^\top D)^{-1} A^\top b.$$

If we control the norm of the solution, we add the quadratic regularization function $\|x\|^2$, then

$$x_{\text{RLS}} = (A^\top A + \lambda I)^{-1} A^\top b.$$

Remark 3.1 *The regularization is to find the smallest norm possible. That is, x_{RLS} is the one orthogonal to the null space of A .*

Example 3.3.4

Suppose $B \in \mathbb{R}^{2 \times 3}$. Then, $A = B^\top B$ is rank deficient:

$$\text{rank}(A) = \text{rank}(B^\top) \text{rank}(B) \leq \min \{ \text{rank}(B^\top), \text{rank}(B) \}.$$

As $\text{rank}(B) \leq 2$, $\dim(\text{null}(A)) = 3 - \dim(\text{rank}(B)) \geq 1$.

Example 3.3.5

Suppose A is invertible. $Ax_{\text{true}} = b_{\text{true}}$ and $Ax_{\text{noisy}} = b_{\text{noisy}}$. Then,

$$\begin{aligned} A(x_{\text{true}} - x_{\text{noisy}}) &= b_{\text{true}} - b_{\text{noisy}} \\ x_{\text{true}} - x_{\text{noisy}} &= A^{-1}(b_{\text{true}} - b_{\text{noisy}}). \end{aligned}$$

Suppose $A = \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{pmatrix}$ with $\lambda_i > 0$. Then,

$$A^{-1} = \begin{pmatrix} 1/\lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & 1/\lambda_3 \end{pmatrix}.$$

If λ_3 is small, $A^{-1}(b_{\text{true}} - b_{\text{noisy}})$ will still be large.

3.4 Denoising

One application of regularization is *denoising*. Suppose that a noisy measurement of a signal $x \in \mathbb{R}^n$ is given as

$$b = x + w.$$

Here x is an unknown signal, w is an unknown noise vector, and b is the known measurements vector.

Denoising Problem: Given b , find a “good” estimate of x . The least squares problem associated with the approximate equation $x \approx b$ is

$$\min \|x - b\|^2.$$

In this case, though $x = b$ is the obvious solution of the problem, it is meaningless.

Solution: Considering the signal is smooth, we can add a penalty on the problem. That is,

$$\int_a^b [x'(t)]^2 dt < \infty \xrightarrow{\text{Discretization}} \sum_{i=1}^{n-1} (x_i - x_{i+1})^2, \quad \text{using } x'(t) \approx \frac{x_{i+1} - x_i}{\Delta t}.$$

This penalty is equivalent as using the matrix representation $R(x) = \|Lx\|^2$, where $L \in \mathbb{R}^{(n-1) \times n}$ is given by

$$L = \begin{pmatrix} 1 & -1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 1 & -1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 1 & -1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 1 & -1 \end{pmatrix}.$$

The resulting RLS problem is

$$\min_x \underbrace{\|x - b\|^2}_{\text{fidelity}} + \underbrace{\lambda \sum_{i=1}^{n-1} (x_i - x_{i+1})^2}_{\text{regularity}},$$

and the optimal solution is given by

$$x_{\text{RLS}}(\lambda) = (I + \lambda L^\top L)^{-1} b.$$

Remark 3.2 λ controls how smooth we want and how noisy we want. However, note that there is a trade-off between smoothness and accuracy.

3.5 Nonlinear Least Squares

Problem Assume that we have data $\{(x_1, y_1), \dots, (x_n, y_n)\}$, where $x_i \in \mathbb{R}^d, y \in \mathbb{R}$.

Goal Find f s.t. $y_i \approx f(x_i) \quad \forall i$ we are searching a function. Mathematically, we solve this problem as follows:

$$\min_{f \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^n (y_i - f(x_i))^2, \tag{4}$$

where \mathcal{H} is the hypothesis set, and $\frac{1}{n} \sum_{i=1}^n (y_i - f(x_i))^2$ is the loss function.

\mathcal{H} is linear

Suppose \mathcal{H} is a linear space: $\mathcal{H} \in \text{span} \{\varphi_1, \varphi_2, \dots, \varphi_m\}$. We know that $\forall f \in \mathcal{H}, \exists \alpha_1, \dots, \alpha_m \in \mathbb{R}$ s.t. $\alpha_1 \varphi_1 + \alpha_2 \varphi_2 + \dots + \alpha_m \varphi_m$. Hence, (4) is reduced to

$$\min_{\alpha_1, \dots, \alpha_m} \frac{1}{n} \sum_{i=1}^n \left(y_i - \underbrace{\sum_{j=1}^m \alpha_j \varphi_j(x_j)}_{f(x_i)} \right)^2 \quad (5)$$

In terms of least square:

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}, \quad \Phi = \begin{pmatrix} \varphi_1(x_1) & \cdots & \varphi_m(x_1) \\ \varphi_1(x_2) & \cdots & \varphi_m(x_2) \\ \vdots & \ddots & \vdots \\ \varphi_1(x_n) & \cdots & \varphi_m(x_n) \end{pmatrix}, \quad \alpha = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_m \end{pmatrix}.$$

Then, (5) reduces to

$$\min_{\alpha} \|y - \Phi \alpha\|^2, \quad (6)$$

where $\varphi_1, \dots, \varphi_n$ are called *features*, and Φ is called a *feature matrix*. *Example of features: polynomials, trigonometric polynomials, etc.*

\mathcal{H} is nonlinear

Suppose \mathcal{H} is not a linear subspace: $\mathcal{H} = \{\varphi(\cdot; \alpha) : \alpha \in \mathbb{R}^n\}$. So, $f(x) = \varphi(x; \alpha)$, which is a set of parametric function. Once α is fixed, we can evaluate $f(x)$. Note, generally, $\alpha \mapsto \varphi(x; \alpha)$ is not linear. When \mathcal{H} is a linear space with features $\varphi_1, \dots, \varphi_m$, then

$$\varphi(x; \alpha) = \alpha_1 \varphi_1(x) + \alpha_2 \varphi_2(x) + \dots + \alpha_m \varphi_m(x),$$

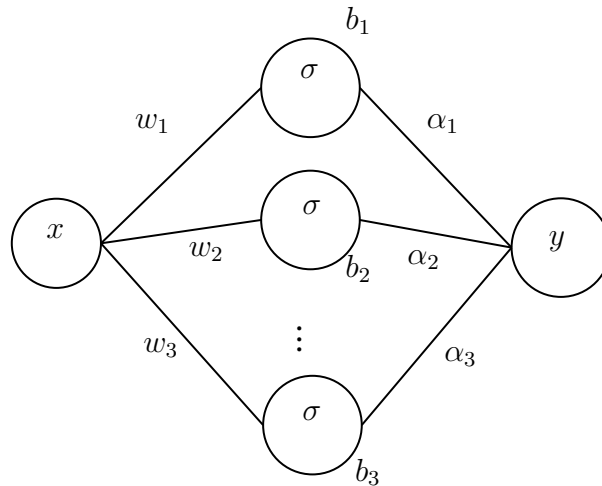
and then we are back into the \mathcal{H} is linear case.

For example, we can have a one-layer Neural Network as follows, where $\sigma : \mathbb{R} \rightarrow \mathbb{R}$ is called the *activation function*. Then,

$$\varphi(x; \underbrace{w_1, \dots, w_m, \overbrace{b_1, \dots, b_m}^{\text{biases}}, \alpha_1, \dots, \alpha_m}_{\text{weights}}) = \alpha_1 \underbrace{\sigma(x \cdot w_1 + b_1)}_{\varphi_1(x)} + \alpha_2 \underbrace{\sigma(x \cdot w_2 + b_2)}_{\varphi_2(x)} + \dots + \alpha_m \underbrace{\sigma(x \cdot w_m + b_m)}_{\varphi_m(x)}.$$

Compare with the case when \mathcal{H} is a linear subspace, we are now having $\varphi_i(x)$ is also dependent on w_i and b_i . We let the machine to learn the most efficient basis for the problem. So, this

approach will be more adaptable in different contexts.



More generally, the least square problem when \mathcal{H} is nonlinear can be written as

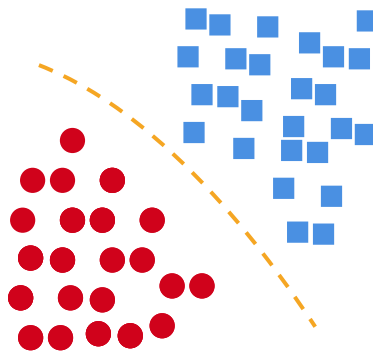
$$\min_{\alpha} \frac{1}{n} \sum_{i=1}^n \left(y_i - \underbrace{\varphi(x_i; \alpha)}_{\text{nonlinear}} \right) \quad (7)$$

As $\varphi(x; \alpha)$ is nonlinear, we cannot write it as a matrix-vector product as given in (6).

(7) is called a *nonlinear least square problem*.

Remark 3.3 We obtain nonlinear least square problems when we fit data with square loss and nonlinear model.

Problem: Data Classification Given $(x_1, y_1), \dots, (x_n, y_n)$, find $\varphi(x; \alpha)$ s.t. $\varphi(x_i; \alpha) \approx y_i \quad \forall i$.



Measuring Error: What does $\varphi(x; \alpha) \approx y_i$ mean?

- Distance – MSE: $\frac{1}{n} \sum_{i=1}^n (y_i - \varphi(x; \alpha))^2$. Or, more generally, $\frac{1}{n} \sum_{i=1}^n |y_i - \varphi(x_i; \alpha)|^p$.

- **Sign:** $\frac{1}{n} \sum_{i=1}^n (y_i - \text{sign}(\varphi(x_i; \alpha)))^2$, where

$$\text{sign}(x) = \begin{cases} 1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0. \end{cases}$$

- *Alternatively, softmax, then the output will be $\varphi(x; \alpha) \in \mathbb{R}^n$, where n is the number of classes, with $\varphi_i(x; \alpha)$ is the probability of x in class i . For example, take $n = 2$, then*

$$\varphi(x; \alpha) = (\varphi_1(x; \alpha), \varphi_2(x; \alpha))$$

where $(1, 0)$ means 100% in class 1 and $(0, 1)$ means 100% in class 2. Turning everything into positive and probability values, we get

$$\left(\frac{e^{\varphi_1(x; \alpha)}}{e^{\varphi_1(x; \alpha)} + e^{\varphi_2(x; \alpha)}}, \frac{e^{\varphi_2(x; \alpha)}}{e^{\varphi_1(x; \alpha)} + e^{\varphi_2(x; \alpha)}} \right).$$

Linear Least Square to Solve: Suppose there exists some lines dividing the classes. Those lines are called hyperplanes with equation

$$w \cdot x + \nu = 0.$$

Goal Find w, ν such that $w \cdot x + \nu > 0$ for x_i in **red** and $w \cdot x + \nu < 0$ for x_i in **blue**.

However, we can have multiple choices of the hyperplane. Which one is better? We will evaluate them using the concept of margin.

Definition 3.5.1 (Margin). We define the margin of the hyperplane defined by $w \cdot x + \nu = 0$ as follows

$$\rho(w) = \min_i \frac{|w \cdot w_i + \nu|}{\|w\|}.$$

If the classification is successful, we should have $w \cdot x_i + \nu$ and y_i to have the same sign, so $(w \cdot x_i + \nu) \cdot y_i \geq 0$. Therefore, we want the hyperplane that

$$\begin{aligned} \max_{(w \cdot x_i + \nu) \cdot y_i \geq 0} \rho(w) &= \max_{(w \cdot x_i + \nu) \cdot y_i \geq 0} \min_i \frac{|w \cdot w_i + \nu|}{\|w\|} \\ &= \max_{(w \cdot x_i + \nu) \cdot y_i \geq 0} \frac{1}{\|w\|} \end{aligned} \quad \text{by homogeneity of } w \text{ and } \nu$$

We can further show that the optimization problem can be written as the following least

square problem with respect to w and ν :

$$\min_{(w \cdot x_i + \nu) \cdot y_i \geq 0} \frac{\|w\|^2}{2}. \quad (8)$$

Proof 1. In this proof, let's get a sense why we are having a least square problem. Suppose $w \in \mathbb{R}^{d \times 1}$. Define

$$A = \left(\begin{array}{cc|c} 1 & & 0 \\ & \ddots & \\ 0 & & 1 \\ \hline & & 0 \end{array} \right) = \begin{pmatrix} I_d & 0 \\ 0 & 0 \end{pmatrix}.$$

Then,

$$A \begin{pmatrix} w \\ \nu \end{pmatrix} = \begin{pmatrix} I_d & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} w \\ \nu \end{pmatrix} = \begin{pmatrix} w \\ 0 \end{pmatrix}, \quad b = \begin{pmatrix} 0_d \\ 0 \end{pmatrix}.$$

Therefore, we get

$$A \begin{pmatrix} w \\ \nu \end{pmatrix} - b = \begin{pmatrix} w \\ 0 \end{pmatrix} \Rightarrow \left\| A \begin{pmatrix} w \\ \nu \end{pmatrix} - b \right\|^2 = \left\| \begin{pmatrix} w \\ 0 \end{pmatrix} \right\|^2 = \|w\|^2.$$

■

Nonlinear Least Square to Solve We can form the following nonlinear least square problem

$$\min_{w, \nu} \frac{1}{n} \sum_{i=1}^n (y_i - \text{sign}(w \cdot x_i + \nu))^2 + \lambda_1 \|w\|^2 + \lambda_2 \|\nu\|^2 \quad (9)$$

This is a nonlinear least square because $\text{sign}(w \cdot x_i + \nu)$ does not form a linear relationship with w and ν . This nonlinear least square will fail, in fact. To ensure (9) works, we have to add the constrain $(w \cdot x_i + \nu) \cdot y_i \geq 1$.

Nonlinearly Separable Classification If the classes are not linearly separable, neither (8) nor (9) will work. We need to transform them into a higher dimension. For example, consider the following mapping: $(x, y) \mapsto (x, y, x^2 + y^2)$. The map that makes data linearly separable is the *feature mapping*. Find a feature mapping can be very difficult.

4 Constrained Optimization

Goal: Constrained Optimal Problem

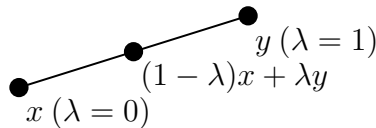
- figure out necessary conditions for optimality
- figure out sufficient conditions for optimality
- existence
- MATLAB function `fmincon`

We will mostly discuss: $\min_{x \in C} f(x)$, where C is closed and convex, and f can be either convex or non-convex.

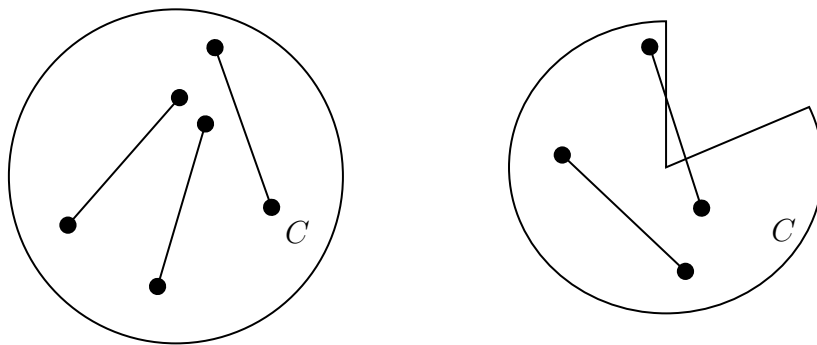
4.1 Convexity

Definition 4.1.1 (Convex Set). A set $C \subseteq \mathbb{R}^d$ is *convex* if $\forall x, y \in C$ and $\lambda \in (0, 1)$, we have that $(1 - \lambda)x + \lambda y \in C$.

Remark 4.1 *Convexity essentially means that if we know two points are in the set, then everything on the line connecting the two points is also in the set.*



Example 4.1.2 Example of convex and non-convex sets



Example 4.1.3 Show that $C = \{x : \|x - x_0\| \leq r\} = B_{x_0}(r)$ **is convex.**

Proof 1. Let $x, y \in C$ and $\lambda \in (0, 1)$.

We have: $\|x - x_0\| \leq r$ *and* $\|y - x_0\| \leq r$. *We want:* $\|(1 - \lambda)x + \lambda y - x_0\| \leq r$.

Note that

$$\begin{aligned}
 \|(1-\lambda)x + \lambda y - x_0\| &= \left\| \underbrace{(1-\lambda)(x-x_0)}_a + \underbrace{\lambda(y-x_0)}_b \right\| \\
 &= \|(1-\lambda)(x-x_0)\| + \|\lambda(y-x_0)\| && \text{triangular inequality} \\
 &= (1-\lambda)\|x-x_0\| + \lambda\|y-x_0\| && \text{homogeneity} \\
 &\leq (1-\lambda)r + \lambda r = r
 \end{aligned}$$

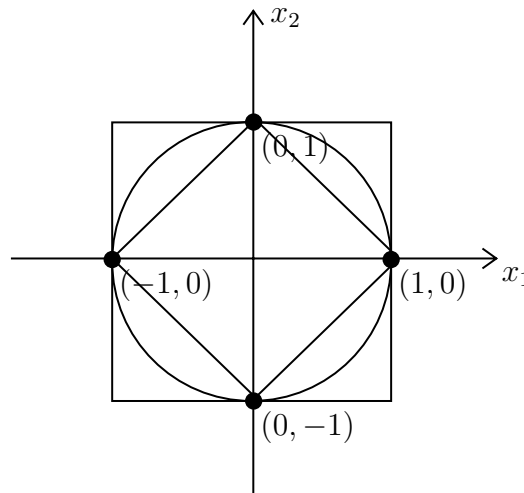
We've shown $\|(1-\lambda)x + \lambda y - x_0\| \leq r$, implying C is convex. ■

Remark 4.2 In this example, $\|\cdot\|$ is an arbitrary norm. So, any $B_{x_0}(r)$ defined with an arbitrary norm is convex.

Example 4.1.4 Unit Balls are Convex

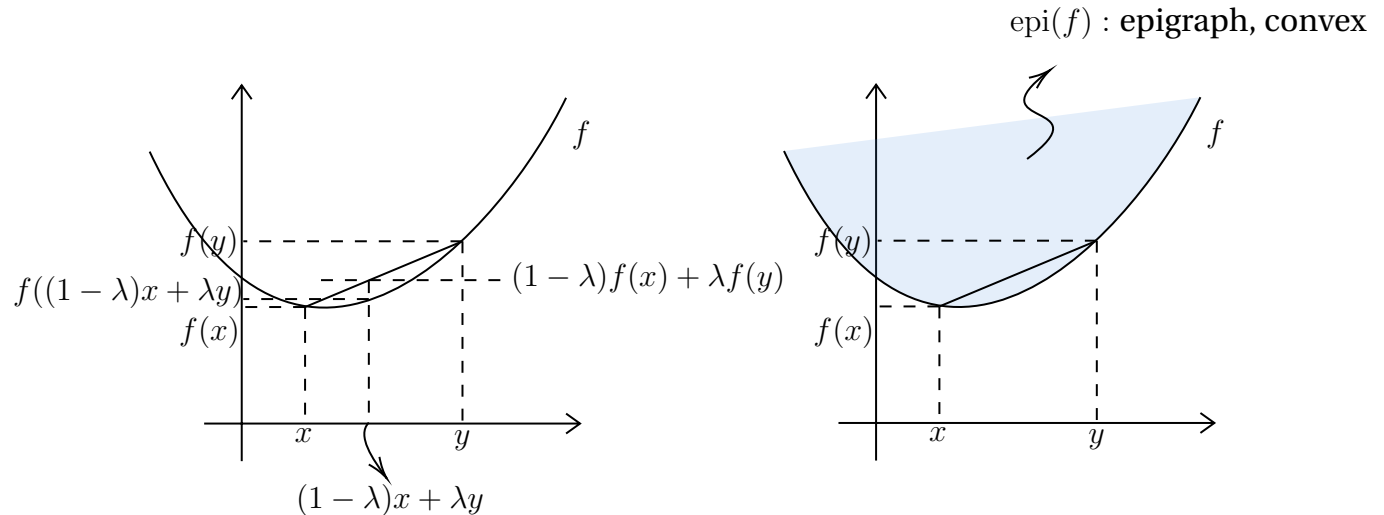
- $\|x\|_1 = \sum_{i=1}^d |x_i|$, $x_0 = (0, \dots, 0)$, $r = 1$, then the ℓ_1 unit ball is defined by the following convex set $C = \{(x_1, x_2) : |x_1| + |x_2| \leq 1\}$.
- $\|x\|_2 = \left(\sum_{i=1}^d x_i^2 \right)^{1/2}$, $x_0 = (0, \dots, 0)$, $r = 1$, and the ℓ_2 unit ball (also known as the unit circle) is defined by $C = \{(x_1, x_2) : x_1^2 + x_2^2 \leq 1\}$ convex.
- $\|x\|_\infty = \max_{1 \leq i \leq n} |x_i|$, $x_0 = (0, \dots, 0)$, $r = 1$. The ℓ_∞ unit ball is defined by the following set $C = \{(x_1, x_2) : \max\{|x_1|, |x_2|\} \leq 1\}$.

If we put the unit balls together, ℓ_1 -ball is the smallest and ℓ_∞ -ball is the largest.



Remark 4.3 When solving the regularization problem $\min_{x \in C} f(x) + \|x\|^\alpha$, we can choose different types of norms. The shape of the unit ball of the norms will inform which solution is selected. Usually, the solution will be on the boundary of the unit ball. ℓ_1 -ball gives sparse solution and using ℓ_1 -norm is called the LASSO method.

Definition 4.1.5 (Convex Function). A function $f : \mathbb{R}^d \rightarrow \mathbb{R}$ is called *convex* if $\forall x, y \in \mathbb{R}^d$ and $\lambda \in (0, 1)$, we have that $f((1 - \lambda)x + \lambda y) \leq (1 - \lambda)f(x) + \lambda f(y)$. Note that this condition is equivalent to saying that f has positive second order derivatives.



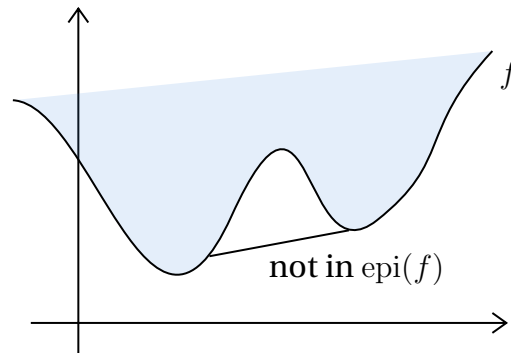
Remark 4.4 The definition of a convex function is to say that the graph of the function is below the straight line of connecting any two points on the graph.

Definition 4.1.6 (Epigraph of f). Define $\text{epi}(f) := \{(x, z) \in \mathbb{R}^{d+1} : z \geq f(x)\}$. Note that “epi” means “up” in greek.

Theorem 4.1.7 Duality of Convexity

A function $f : \mathbb{R}^d \rightarrow \mathbb{R}$ is convex if and only if $\text{epi}(f)$ is convex.

Example 4.1.8 A Nonexample



Proof 2. (\Rightarrow) Suppose f is convex. Let $(x, z), (y, w) \in \text{epi}(f)$ and $\lambda \in (0, 1)$. Our goal is to show that $(1 - \lambda)(x, z) + \lambda(y, w) \in \text{epi}(f)$ as well. Note that

$$(1 - \lambda)(x, z) + \lambda(y, w) = ((1 - \lambda)x + \lambda y, (1 - \lambda)z + \lambda w).$$

Since $(x, z), (y, w) \in \text{epi}(f)$, we have $z \geq f(x)$ and $w \geq f(y)$. Therefore

$$\begin{aligned} (1 - \lambda)z + \lambda w &\geq (1 - \lambda)f(x) + \lambda f(y) \\ &\geq f((1 - \lambda)x + \lambda y) \end{aligned} \quad \text{by convexity of } f \quad \square$$

(\Leftarrow) Suppose $\text{epi}(f)$ is a convex set. Note that $\forall x, y \in \mathbb{R}^d$, by definition of $\text{epi}(f)$, we have $(x, f(x)) \in \text{epi}(f)$ and $(y, f(y)) \in \text{epi}(f)$. Then, by convexity, we know

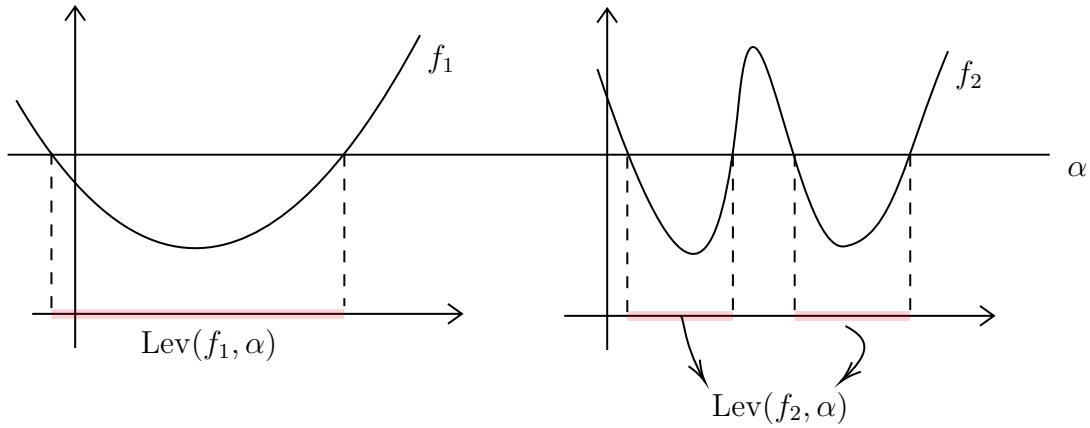
$$(1 - \lambda)(x, f(x)) + \lambda(y, f(y)) = ((1 - \lambda)x + \lambda y, (1 - \lambda)f(x) + \lambda f(y)) \in \text{epi}(f).$$

Again, by definition of $\text{epi}(f)$, we have

$$f((1 - \lambda)x + \lambda y) \leq (1 - \lambda)f(x) + \lambda f(y).$$

Therefore, f is convex. ■

Definition 4.1.9 (α -Level Set). Let $f : \mathbb{R}^d \rightarrow \mathbb{R}$ be an arbitrary function and $\alpha \in \mathbb{R}$. Then, the α -level set of f is $\text{Lev}(f, \alpha) := \{x \in \mathbb{R}^d : f(x) \leq \alpha\}$.



Theorem 4.1.10

If f is convex, then $\text{Lev}(f, \alpha)$ are convex $\forall \alpha \in \mathbb{R}$.

Remark 4.5 By convention, we consider empty set as convex as well

Proof 3. Let $x, y \in \text{Lev}(f, \alpha)$ and $\lambda \in (0, 1)$.

WTS: $(1 - \lambda)x + \lambda y \in \text{Lev}(f, \alpha) \iff f((1 - \lambda)x + \lambda y) \leq \alpha$.

As $x, y \in \text{Lev}(f, \alpha)$, then $f(x) \leq \alpha$ and $f(y) \leq \alpha$. So,

$$(1 - \lambda)f(x) + \lambda f(y) \leq (1 - \lambda)\alpha + \lambda\alpha = \alpha.$$

By convexity of f , we know

$$f((1 - \lambda)x + \lambda y) \leq (1 - \lambda)f(x) + \lambda f(y) \leq \alpha.$$

So, $(1 - \lambda)x + \lambda y \in \text{Lev}(f, \alpha)$. ■

Remark 4.6 Often, we have $\min_{f(x) \leq \alpha} g(x)$. In this case, $C = \{x : f(x) \leq \alpha\} = \text{Lev}(f, \alpha)$. In fact, every $\text{Lev}(f, \alpha)$ is corresponding to a certain convex function. Therefore, Theorem 4.1.10 can be strengthened into an if-and-only-if statement.

Example 4.1.11 Example 4.1.3 Revisit

Consider $B_r(x_0) = \{x \in \mathbb{R}^d : \|x - x_0\| \leq r\}$. If $f(x) = \|x - x_0\|$, $x \in \mathbb{R}^d$, then $B_r(x_0) = \text{Lev}(f, r)$. Show that $B_r(x_0)$ is convex.

Proof 4. To prove the statement, we first consider the convexity of $f(x)$:

Claim. f is convex.

Proof. Let $x, y \in \mathbb{R}^d$ and $\lambda \in (0, 1)$. WTS: $\|(1 - \lambda)x + \lambda y\| \leq (1 - \lambda)\|x\| + \lambda\|y\|$.

Note that

$$\begin{aligned} \|(1 - \lambda)x + \lambda y\| &\leq \|(1 - \lambda)x\| + \|\lambda y\| && \text{triangular inequality} \\ &= (1 - \lambda)\|x\| + \lambda\|y\| && \text{homogeneity} \end{aligned}$$

So, f is convex. □

As f is convex and $B_r(x_0) = \text{Lev}(f, r)$, by Theorem 4.1.10, $B_r(x_0)$ is convex. ■

Remark 4.7 Example 4.1.11 offers another approach to prove a set is convex other than applying the definition: proving it is the level set of a convex function. This is a more powerful approach and can be applied into different types of questions.

Theorem 4.1.12 Operations Preserving Convexity I

Assume that f_1, f_2, \dots, f_p are convex functions. Then,

1. $\alpha_1 f_1 + \alpha_2 f_2 + \dots + \alpha_p f_p$ is convex $\forall \alpha_1, \dots, \alpha_p \geq 0$.
2. $f(x) = \max \{f_1(x), f_2(x), \dots, f_p(x)\}$ is a convex function.

Proof 5. Here, we will offer a proof of Theorem 4.1.12 (2). Let $x, y \in \mathbb{R}^d$ and $\lambda \in (0, 1)$. We

want to show $f((1 - \lambda)x + \lambda y) \leq (1 - \lambda)f(x) + \lambda f(y)$. Note that

$$\begin{aligned} f_i((1 - \lambda)x + \lambda y) &\leq (1 - \lambda)f_i(x) + \lambda f_i(y) && \text{convexity of } f_i \\ &\leq (1 - \lambda)f(x) + \lambda f(y), \quad \forall i && \text{definition of } f : f_i(x) \leq f(x) \end{aligned}$$

So,

$$\max_i f_i((1 - \lambda)x + \lambda y) \leq (1 - \lambda)f(x) + \lambda f(y).$$

By definition of f , that is, $f((1 - \lambda)x + \lambda y) \leq (1 - \lambda)f(x) + \lambda f(y)$. ■

Theorem 4.1.13 Operations Preserving Convexity II

Let f be a convex function. Then, $g(y) = f(Ay + b)$ is also convex, where A is a matrix and b is a vector.

Proof 6. Let $y, z \in \text{dom}(g)$, the domain of g . Then,

$$\begin{aligned} g((1 - \lambda)y + \lambda z) &= f(A((1 - \lambda)y + \lambda z) + b) \\ &= f((1 - \lambda)Ay + \lambda Az + (1 - \lambda)b + \lambda b) && \text{linearity of } A \\ &= f((1 - \lambda)(Ay + b) + \lambda(Az + b)) \\ &\leq (1 - \lambda)f(Ay + b) + \lambda f(Az + b) && \text{convexity of } f \\ &= (1 - \lambda)g(y) + \lambda g(z) && \text{definition of } g \end{aligned}$$

As $g((1 - \lambda)y + \lambda z) \leq (1 - \lambda)g(y) + \lambda g(z)$, g is convex. ■

Theorem 4.1.14 Operations Preserving Convexity III

Assume $f : \mathbb{R}^d \rightarrow \mathbb{R}$ is convex and $g : \mathbb{R} \rightarrow \mathbb{R}$ is an increasing convex function. Then, $h(x) = (g \circ f)(x) = g(f(x))$ is also convex.

Proof 7. Let $x, y \in \mathbb{R}^d$ and $\lambda \in (0, 1)$. Then, by the convexity of f , we have

$$f((1 - \lambda)x + \lambda y) \leq (1 - \lambda)f(x) + \lambda f(y).$$

Further, due to g being monotonically increasing,

$$g(f((1 - \lambda)x + \lambda y)) \leq g((1 - \lambda)f(x) + \lambda f(y)).$$

Therefore,

$$\begin{aligned} h((1 - \lambda)x + \lambda y) &= g(f((1 - \lambda)x + \lambda y)) \leq g((1 - \lambda)f(x) + \lambda f(y)) \\ &\leq (1 - \lambda)g(f(x)) + \lambda g(f(y)) && \text{convexity of } g \\ &= (1 - \lambda)h(x) + \lambda h(y) && \text{definition of } h \end{aligned}$$

As $h((1 - \lambda)x + \lambda y) \leq (1 - \lambda)h(x) + \lambda h(y)$, h is convex. ■

Claim 4.15 Let C_1, C_2, \dots, C_p be convex sets. Then, $C = \bigcap_{i=1}^p C_i = C_1 \cap C_2 \cap \dots \cap C_p$ is also convex.

Remark 4.8 The union of convex sets, $C = \bigcup_{i=1}^p C_i = C_1 \cup C_2 \cup \dots \cup C_p$ might not be a convex set.

Corollary 4.1.16: Let f_1, f_2, \dots, f_p be convex functions and $\alpha_1, \alpha_2, \dots, \alpha_p \in \mathbb{R}$. Then,

$$\begin{aligned} C &= \{x : f_1(x) \leq \alpha_1, f_2(x) \leq \alpha_2, \dots, f_p(x) \leq \alpha_p\} \\ &= \text{Lev}(f_1, \alpha_1) \cap \text{Lev}(f_2, \alpha_2) \cap \dots \cap \text{Lev}(f_p, \alpha_p) \\ &= \bigcap_{i=1}^p \text{Lev}(f_i, \alpha_i) \end{aligned}$$

is also convex.

Remark 4.9 Consider an optimization problem $\min_{\substack{f_1(x) \leq \alpha_1 \\ f_2(x) \leq \alpha_2 \\ \vdots \\ f_p(x) \leq \alpha_p}} g(x)$. If f_i are convex, then the constraint set of this problem is also convex as a result of Corollary 4.1.16.

Example 4.1.17 Techniques to Prove Convexity I: Turn “ \geq ” into “ \leq ”

Consider $\min_{\substack{x_1^2 + x_2^2 \leq 1 \\ 2x_1 - x_2 \geq 0}} L(x_1, x_2)$. The constraint set $C = C_1 \cap C_2$ s.t.

$$C_1 = \{(x_1, x_2) : x_1^2 + x_2^2 \leq 1\} \quad \text{and} \quad C_2 = \{(x_1, x_2) : 2x_1 - x_2 \geq 0\}.$$

Find the convexity of C .

Solution 8.

Define $f_1(x_1, x_2) = x_1^2 + x_2^2$. Then, C_1 is a level set:

$$C_1 = \{(x_1, x_2) : f_1(x_1, x_2) \leq 1\}.$$

Note that $\nabla^2 f_1(x_1, x_2) = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \succ 0$, so $f_1(x_1, x_2)$ is convex and so is C_1 .

Define $f_2(x_1, x_2) = -2x_1 + x_2$. Then, C_2 is also a level set:

$$C_2 = \{(x_1, x_2) : -2x_1 + x_2 \leq 0\} = \{(x_1, x_2) : f_2(x_1, x_2) \leq 0\} \quad [a \geq 0 \iff -a \leq 0]$$

Note that $\nabla^2 f_2(x_1, x_2) = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \succeq 0$. Thus, $f_2(x_1, x_2)$ is convex and so is C_2 .

Hence, $C = C_1 \cap C_2$ is also convex. □

Remark 4.10 Every linear function $f(x) = c_0 + c_1x_1 + c_2x_2 + \cdots + c_dx_d$ always has Hessian semidefinite, and so they are all convex. Having a strict positive definite Hessian implies a strict convexity.

Example 4.1.18 Techniques to Prove Convexity II: Turn “=” into “≤”

Consider $\min_{\substack{e^{x_1} + x_2 - x_3 \leq 1 \\ 4x_1 - 2x_2 + 7x_3 = 2}} L(x_1, x_2, x_3).$

Let C be the constrain set. Determine the convexity of C .

Solution 9.

Note that $C = C_1 \cap C_2$ s.t.

$$C_1 = \{(x_1, x_2, x_3) : f_1(x_1, x_2, x_3) \leq 1\} \quad \text{where } f_1(x_1, x_2, x_3) = e^{x_1} + x_2 - x_3$$

and

$$C_2 = \{(x_1, x_2, x_3) : f_2(x_1, x_2, x_3) = 2\} \quad \text{where } f_2(x_1, x_2, x_3) = 4x_1 - 2x_2 + 7x_3.$$

In fact, we can decompose C_2 into the following conditions:

$$C_2 = \{(x_1, x_2, x_3) : f_2(x_1, x_2, x_3) \leq 2\} \quad \text{where } f_2(x_1, x_2, x_3) = 4x_1 - 2x_2 + 7x_3.$$

and

$$C_3 = \{(x_1, x_2, x_3) : f_3(x_1, x_2, x_3) \leq -2\} \quad \text{where } f_3(x_1, x_2, x_3) = -4x_1 + 2x_2 - 7x_3.$$

Therefore, $C = C_1 \cap C_2 \cap C_3$, with C_1, C_2, C_3 both level sets.

For C_1 , note that

$$\nabla^2 f_1(x_1, x_2, x_3) = \begin{bmatrix} e^{x_1} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \succeq 0.$$

So, f_1 is convex and so is C_1 .

Alternatively, e^{x_1} is convex and $x_2 - x_3$ is also convex. So, $f_1(x_1, x_2, x_3)$ is a sum of two convex functions.

For C_2 and C_3 , f_2 is linear, and so f_2 and $f_3 = -f_2$ are both linear and so convex. Then, C_2 and C_3 are convex.

Therefore, $C = C_1 \cap C_2 \cap C_3$ is convex. □

4.2 Conditions for Constrained Optimal Problems

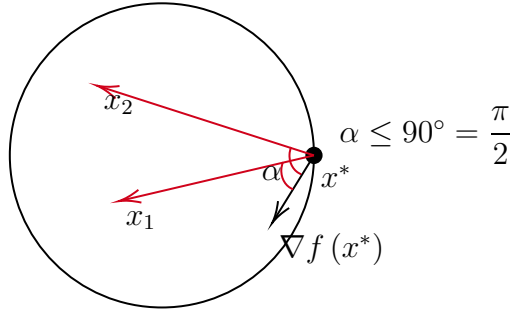
Problem

Consider $\min_{x \in C} f(x)$, where $C \subseteq \mathbb{R}^d$ is a convex set.

(P)

Definition 4.2.1 (Stationary Point). A point $x^* \in C$ is called a *stationary point* for (P) if

$$\nabla f(x^*)^\top (x - x^*) \geq 0 \quad \forall x \in C.$$



Theorem 4.2.2 Necessary Condition for Constrained Optimization

If x^* is a solution of (P), then x^* is a stationary point.

Proof 1. Assume that x^* is a solution of (P), but $\exists x \in C$ s.t. $\nabla f(x^*)^\top (x - x^*) < 0$. Consider $\varphi(t) = f(x^* + t(x - x^*))$. Note that

$$\begin{aligned} \varphi'(0) &= \lim_{t \rightarrow 0} \frac{\varphi(t) - \varphi(0)}{t} = \lim_{t \rightarrow 0} \frac{f(x^* + t(x - x^*)) - f(x^*)}{t} \\ [Directional \text{ derivative of } f \text{ in direction of } x - x^*] &= f'(x^*; x - x^*) \\ &= \nabla f(x^*)^\top \cdot (x - x^*) < 0. \end{aligned}$$

So, $\varphi'(0) = \nabla f(x^*)^\top \cdot (x - x^*) < 0$ by our assumption. So, $\exists t^* \in (0, 1)$ s.t. $\varphi(t^*) < \varphi(0)$. That is,

$$\begin{aligned} f(x^* + t^*(x - x^*)) &< f(x^*) \\ f((1 - t^*)x^* + t^*x) &< f(x^*) \end{aligned}$$

Denote $(1 - t^*)x^* + t^*x = x'$, we know $x' \in C$ by convexity of C . So, we've found a $x' \in C$ s.t.

$$f(x') < f(x^*).$$

✱ This contradicts with our assumption that x^* is a solution of (P). Hence, our assumption is incorrect, and the proof is complete. ■

Remark 4.11 When $x^* \in \text{int}(C)$, then x^* is stationary if and only if $\nabla f(x^*) = 0$. In particular, when $C = \mathbb{R}^d$, all $x^* \in \text{int}(C)$ and stationary means $\nabla f(x^*) = 0$.

Example 4.2.3 Use the Necessary Condition to Derive a KKT Condition

Consider $C = \mathbb{R}_+^d = \{(x_1, \dots, x_d) : x_i \geq 0 \quad \forall i\}$. Show that x^* is a stationary point if and only if $\forall i$,

$$\frac{\partial f}{\partial x_i}(x^*) \geq 0, \quad x_i^* \geq 0, \quad \frac{\partial f}{\partial x_i}(x^*)x_i^* = 0.$$

Proof2. The necessary condition for $x^* \in C$ to be stationary is given by

$$\begin{aligned}\nabla f(x^*)^\top (x - x^*) &\geq 0 \quad \forall x \in \mathbb{R}_+^d \\ \nabla f(x^*)^\top x - \nabla f(x^*)^\top x^* &\geq 0.\end{aligned}$$

Claim. $a^\top x + b \geq 0 \quad \forall x \in \mathbb{R}_+^d$ if and only if $a \geq 0$ and $b \geq 0$.

Using the Claim, we have that x^* is a stationary point if and only if

$$\frac{\partial f}{\partial x_i}(x^*) \geq 0 \quad \forall i$$

and

$$\nabla f(x^*)^\top x^* = \sum_{i=1}^d \frac{\partial f}{\partial x_i}(x^*) x_i^* \leq 0.$$

Hence, x^* is a stationary point if and only if

$$\forall i, \quad \frac{\partial f}{\partial x_i}(x^*) \geq 0, \quad x_i^* \geq 0, \quad \frac{\partial f}{\partial x_i}(x^*) x_i^* = 0.$$

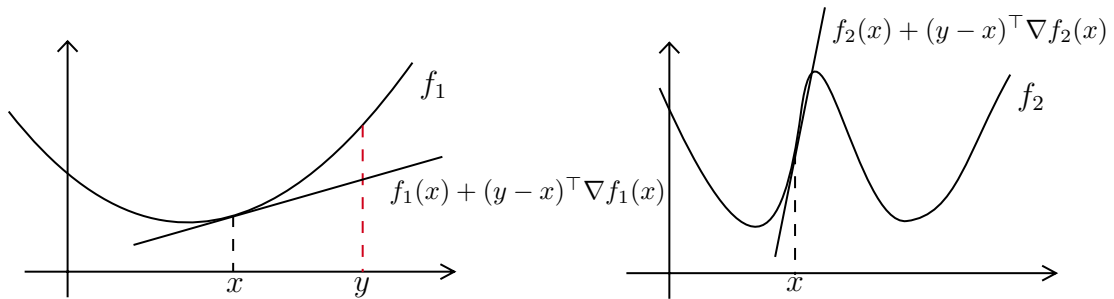
The three conditions, altogether, is called the *Karush–Kuhn–Tucker (KKT) Condition* for $C = \mathbb{R}_+^d$. The last condition, $\frac{\partial f}{\partial x_i}(x^*) x_i^* = 0 \quad \forall i$ is called the *Complementary Slackness Condition*, which indicates that for each i , either

$$\frac{\partial f}{\partial x_i}(x^*) = 0 \quad \longrightarrow \quad x^* \in \text{int}(C) \quad \text{or} \quad x_i^* = 0 \quad \longrightarrow \quad x^* \text{ is on the boundary}$$

■

Theorem 4.2.4 First-Order Characterization of a Convex Function

$f \in \mathcal{C}^1(\mathbb{R}^d)$ is convex if and only if $f(y) \geq \underbrace{f(x) + \nabla f(x)^\top (y - x)}_{\text{first-order approximation}}, \quad \forall x, y \in \mathbb{R}^d.$



Proof3. (\Rightarrow) Suppose $f \in \mathcal{C}^1(\mathbb{R}^d)$ is convex. Fix some $x, y \in \mathbb{R}^d$.

If $x = y$, then $f(y) \geq f(x) + \nabla f(x)^\top (y - x)$ is trivially true. So, WLOG, we can assume $x \neq y$. By convexity,

$$\begin{aligned}
f((1 - \lambda)x + \lambda y) &\leq (1 - \lambda)f(x) + \lambda f(y) && \forall \lambda \in (0, 1) \\
f(x + \lambda(y - x)) &\leq f(x) + \lambda(f(y) - f(x)) \\
f(y) - f(x) &\geq \frac{f(x + \lambda(y - x)) - f(x)}{\lambda} && \forall \lambda \in (0, 1) \\
\underbrace{\lim_{\lambda \rightarrow 0^+} \frac{f(x + \lambda(y - x)) - f(x)}{\lambda}}_{\text{Direction derivative along } y-x} &\leq f(y) - f(x) \\
f'(x; y - x) &\leq f(y) - f(x) \\
\nabla f(x)^\top (y - x) &\leq f(y) - f(x) && f \text{ is smooth} \\
f(y) &\geq f(x) + \nabla f(x)^\top (y - x). \quad \square
\end{aligned}$$

(\Leftarrow) Assume $f(y) \geq f(x) + \nabla f(x)^\top (y - x)$ is true. WTS: $f((1 - \lambda)x + \lambda y) \leq (1 - \lambda)f(x) + \lambda f(y)$. Denote $z := (1 - \lambda)x + \lambda y$, then by assumption,

$$f(x) \geq f(z) + \nabla f(z)^\top (x - z) \quad (10)$$

and

$$f(y) \geq f(z) + \nabla f(z)^\top (y - z) \quad (11)$$

Then, $(1 - \lambda)(10) + \lambda(11)$ for some $\lambda \in (0, 1)$ gives us

$$\begin{aligned}
(1 - \lambda)f(x) + \lambda f(y) &\geq (1 - \lambda)f(z) + (1 - \lambda)\nabla f(z)^\top (x - z) + \lambda f(z) + \lambda \nabla f(z)^\top (y - z) \\
(1 - \lambda)f(x) + \lambda f(y) &\geq f(z) + \nabla f(z)^\top ((1 - \lambda)(x - z) + \lambda(y - z)).
\end{aligned}$$

Note that

$$\begin{aligned}
(1 - \lambda)(x - z) + \lambda(y - z) &= (1 - \lambda)(x - (1 - \lambda)x - \lambda y) + \lambda(y - (1 - \lambda)x - \lambda y) \\
&= (1 - \lambda)\lambda(x - y) + \lambda(1 - \lambda)(y - x) \\
&= (1 - \lambda)\lambda(x - y) - (1 - \lambda)\lambda(x - y) \\
&= 0
\end{aligned}$$

So,

$$(1 - \lambda)f(x) + \lambda f(y) \geq f(z) + 0 = f((1 - \lambda)x + \lambda y).$$

■

Remark 4.12 The zero-order characterization of the convex function is the definition

$$f((1 - \lambda)x + \lambda y) \leq (1 - \lambda)f(x) + \lambda f(y).$$

The second-order characterization of a convex function is the Hessian being semidefinite. These three characterizations are equivalent.

Theorem 4.2.5 Sufficient Condition for Constrained Optimization

Assume that C is convex, f is convex, and $x^* \in C$ is a stationary point for (P). Then, x^* is a minimum point or solution.

Proof 4. Let $x \in C$. By convexity, we have that

$$f(x) \geq f(x^*) + \nabla f(x^*)^\top (x - x^*).$$

Since x^* is a stationary point, we have that, by definition,

$$\nabla f(x^*)^\top (x - x^*) \geq 0.$$

So,

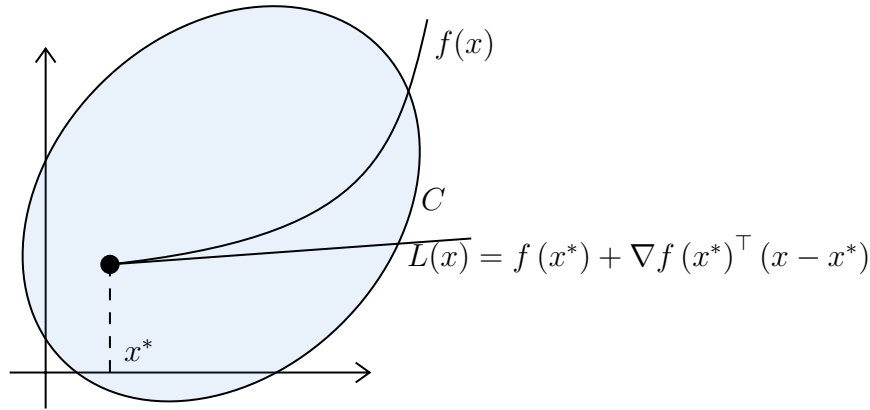
$$f(x) \geq f(x^*) + \nabla f(x^*)^\top (x - x^*) \geq f(x^*).$$

■

Remark 4.13 (View Convexity from Another Perspective) If f is linear (affine), stationary points satisfy:

$$\nabla f(x^*)^\top (x - x^*) = f(x) - f(x^*) \geq 0 \implies x^* \text{ is minimum.}$$

If f is nonlinear,



Let $L(x)$ be the affine function s.t. $L(x^*) = f(x^*)$ and $\nabla L(x^*) = \nabla f(x^*)$.

Now, consider $\min_{x \in C} L(x)$:

$$\nabla L(x^*)^\top (x - x^*) \geq 0 \quad \forall x \in C$$

$$\nabla f(x^*)^\top (x - x^*) \geq 0 \quad \forall x \in C.$$

So, x^* is the minimum of f if and only if it is also the minimum of L ,

Further, as x^* is a minimum of L ,

$$\nabla L(x^*)^\top (x - x^*) = L(x) - L(x^*) \geq 0 \implies L(x) \geq L(x^*) \quad \forall x \in C.$$

Now, the convexity of f guarantees that $f(x) \geq L(x)$. So, we have

$$f(x) \geq L(x) \geq L(x^*) = f(x^*).$$

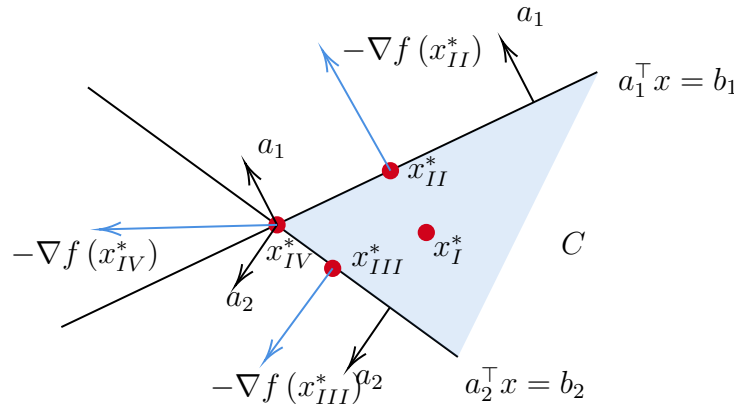
4.3 The Karush-Kuhn-Tucker (KKT) Conditions

4.3.1 KKT Conditions for Linear Inequality Constrains

Constrain Set: $C = \{x \in \mathbb{R}^d : a_i^\top x \leq b_i, \quad i = 1, 2, \dots, m\}.$

Example 4.3.1 Informal Discussion

Let's consider $C = \{x \in \mathbb{R}^d : a_1^\top x \leq b_1, a_2^\top x \leq b_2\}.$



Case I $a_1^\top x_I^* < b_1$ and $a_2^\top x_I^* < b_2$.

Recall that the gradient should form all acute angles with all possible directions such that we can move from x^* . So, the possible way is to take gradient = 0. So, stationary means

$$\nabla f(x_I^*) = 0.$$

Case II $a_1^\top x_{II}^* = b_1$ and $a_2^\top x_{II}^* < b_2$.

Again, the only possible way for the gradient to form acute angles is to take gradient orthogonal to the hyperplane $a_1^\top x = b_1$. Note that a_1 is also orthogonal to the hyperplane. So, stationary means a_1 and $-\nabla f(x_{II}^*)$ are collinear,

$$-\nabla f(x_{II}^*) = \lambda_1 a_1, \quad \lambda_1 \geq 0.$$

Case III $a_1^\top x_{III}^* < b_1$ and $a_2^\top x_{III}^* = b_2$.

Similar to Case II, we have $-\nabla f(x_{III}^*) = \lambda_2 a_2, \quad \lambda_2 \geq 0.$

Case IV $a_1^\top x_{III}^* = b_1$ and $a_2^\top x_{III}^* = b_2$.

Being stationary means:

$$-\nabla f(x_{IV}^*) = \lambda_1 a_1 + \lambda_2 a_2, \quad \lambda_1, \lambda_2 \geq 0.$$

In call cases, we have

KKT Conditions

$$-\nabla f(x^*) = \lambda_1 a_1 + \lambda_2 a_2, \quad \lambda_1, \lambda_2 \geq 0.$$

$$\lambda_1 (b_1 - a_1^\top x^*) = \lambda_2 (b_2 - a_2^\top x^*) = 0$$

Complementary Slackness Condition

This indicates that whichever inequality is strict, its coefficient (λ) should be 0.

$$b_1 - a_1^\top x^* \geq 0, \quad b_2 - a_2^\top x^* \geq 0.$$

Definition 4.3.2 (Active Constrain). If $a_i^\top x = b_i$, we say that this constrain is *active*.

Problem: We consider the following optimization problem:

$$\min_{x \in C} f(x), \quad C = \{x \in \mathbb{R}^d : a_i^\top x \leq b_i, i = 1, \dots, m\} \quad (\text{P})$$

We know that if x^* is a solution of (P), then x^* is a stationary point satisfying:

$$\nabla f(x^*)^\top (x - x^*) \geq 0 \quad \forall x \in C. \quad (\text{S})$$

Goal: Simply (S) for linear inequality constrains.

Example 4.3.3 Intuition of Farkas' Lemma

Consider the set of inequalities $\begin{cases} x_1 + 5x_2 \leq 0 \\ -x_1 + 2x_2 \leq 0 \end{cases}$. Does it imply $-x_1 + 9x_2 \leq 0$?

Solution 1.

It does. Noe that

$$(x_1 + 5x_2) + 2(-x_1 + 2x_2) = -x_1 + 9x_2 \leq 0.$$

In another perspective, let's denote $a_1 = \begin{bmatrix} 1 \\ 5 \end{bmatrix}$, $a_2 = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$, $c = \begin{bmatrix} -1 \\ 9 \end{bmatrix}$, $x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$. Then, we can rewrite the problem into:

Problem: “Do $a_1^\top x \leq 0$ and $a_2^\top x \leq 0$ imply $c^\top x \leq 0$?”

Our previous work show that it does since

$$c = a_1 + 2a_2 = \begin{bmatrix} 1 \\ 5 \end{bmatrix} + 2 \begin{bmatrix} -1 \\ 2 \end{bmatrix} = \begin{bmatrix} -1 \\ 9 \end{bmatrix}.$$

So, it seems that if $c = \lambda_1 a_1 + \lambda_2 a_2$, with λ_1, λ_2 positive, then $a_1^\top x \leq 0$ and $a_2^\top x \leq 0$ imply $c^\top x \leq 0$. We can extend this conclusion and form the Farkas' Lemma. \square

Lemma 4.3.4 Farkas' Lemma: Let $a_1, \dots, a_m, c \in \mathbb{R}^d$. Then, exactly one of the following statement is true:

- $c = \lambda_1 a_1 + \lambda_2 a_2 + \dots + \lambda_m a_m, \quad \lambda_i > 0 \quad \forall i = 1, 2, \dots, m.$
- $\exists x \in \mathbb{R}^d \text{ s.t. } a_i^\top x \leq 0 \quad \forall i = 1, 2, \dots, m \text{ and } c^\top x > 0.$

Remark 4.14 Farkas' Lemma does not impose any condition on a_i 's. If the first statement is true, then $a_i^\top x \leq 0 \quad \forall 1, 2, \dots, m \implies c^\top x \leq 0$. If the second statement is true, then we know c is not a linear combination of a_i 's with positive coefficients.

Remark 4.15 With Farkas's Lemma, we can regard (S) as a series of inequalities imply another:

$$a_i^\top x \leq b_i \quad (x \in C) \implies \nabla f(x^*)^\top (x - x^*) \geq 0.$$

Theorem 4.3.5 KKT Conditions for Linear Inequality Constrains

Let $x^* \in \mathbb{R}^d$ be a solution of (P). Then, $\exists \lambda_1, \lambda_2, \dots, \lambda_m \geq 0$ s.t.

KKT Conditions

$$-\nabla f(x^*) = \sum_{i=1}^m \lambda_i a_i,$$

$$(a_i^\top x^* - b_i) \lambda_i = 0 \quad \forall i = 1, 2, \dots, m, \quad (\text{Complementary Slackness Conditions})$$

$$\lambda_1, \lambda_2, \dots, \lambda_m \geq 0,$$

$$a_i^\top x^* - b_i \leq 0.$$

In this case, we say that i -th constraint is *active* if $a_i^\top x^* = b_i$. Hence, $-\nabla f(x^*)$ is a linear combination of a_i 's corresponding to activated constraints.

Proof2. We know that x^* must be a stationary point; that is,

$$\nabla f(x^*)^\top (x - x^*) \geq 0 \quad \forall x \text{ s.t. } a_i^\top x \leq b_i \quad \forall i = 1, \dots, m.$$

Define $y = x - x^*$. (Change of variable so Farkas' Lemma is applicable). Then,

$$-\nabla f(x^*)^\top y \leq 0 \quad \forall y \text{ s.t. } a_i^\top y \leq b_i - a_i^\top x^* \quad \forall i = 1, \dots, m.$$

Denote $I(x^*) = \{i : b_i - a_i^\top x^* = 0\}$. So, if $i \notin I(x^*)$, $b_i - a_i^\top x^* > 0$. When $i \in I(x^*)$, then $a_i^\top y \leq b_i - a_i^\top x^*$ means $a_i^\top y \leq 0$. Summarizing, we have that

$$\begin{cases} a_i^\top y \leq 0, & \forall i \in I(x^*) \\ a_i^\top y \leq b_i - a_i^\top x^*, & \forall i \notin I(x^*) \end{cases} \implies -\nabla f(x^*)^\top y \leq 0.$$

Claim 4.6 $a_i^\top y \leq 0 \quad \forall i \in I(x^*) \implies -\nabla f(x^*)^\top y \leq 0$.

This claim is asserting that we only need those $i \in I(x^*)$ to attain $-\nabla f(x^*)^\top y \leq 0$. Once this claim is proved, we can apply Farkas' Lemma to conclude that $-\nabla f(x^*)$ is a linear combinations of a_i 's.

Proof. (of the claim). Let y be such that $a_i^\top y \leq 0 \quad \forall i \in I(x^*)$.

Since $b_i - a_i^\top x^* > 0 \quad \forall i \notin I(x^*)$, we know that $\exists \alpha > 0$ s.t.

$$a_i^\top (\alpha y) \leq b_i - a_i^\top x^*, \quad \forall i \notin I(x^*).$$

So, for $\alpha > 0$ small enough, we have that

$$a_i^\top (\alpha y) \leq 0 \quad \forall i \in I(x^*) \quad \text{and} \quad a_i^\top (\alpha y) \leq b_i - a_i^\top x^* \quad \forall i \notin I(x^*).$$

But then, $-\nabla f(x^*)^\top (\alpha y) \leq 0 \implies -\nabla f(x^*)^\top y \leq 0$. \square

Thus, by Farkas' Lemma, $\exists \lambda_i > 0, \quad \forall i \in I(x^*)$ s.t.

$$-\nabla f(x^*) = \sum_{i \in I(x^*)} \lambda_i a_i.$$

For $i \notin I(x^*)$, simply take $\lambda_i = 0$. Hence,

$$-\nabla f(x^*) = \sum_{i=1}^m \lambda_i a_i.$$

This is the first condition in KKT.

By construction, we have that $\lambda_i \geq 0, \quad \forall i = 1, \dots, m$, which is the third condition in KKT.

If $i \in I(x^*)$, then $a_i^\top x^* - b_i = 0$, and so $\lambda_i(a_i^\top x^* - b_i) = 0$. If $i \notin I(x^*)$, then $\lambda_i = 0$, and $\lambda_i(a_i^\top x^* - b_i) = 0$ as well. Hence, $\lambda_i(a_i^\top x^* - b_i) = 0, \quad \forall i = 1, \dots, m$. This is the second condition in KKT.

Finally, the fourth condition is just the feasibility condition of x^* . This means that $x^* \in C$. We hereby complete the proof. \blacksquare

Remark 4.16 *Those λ_i 's are also called the Lagrange Multipliers.*