A Complete Solution Guide to Introduction to Nonlinear Optimization Theory, Algorithms, and Applications with MATLAB

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1 Chapter 1 Mathematical Preliminaries

1.1 Some important concepts

1.1.1 Induced matrix norm and several equivalent definitions

Here we introduce the definition of the induced matrix norm from the textbook. That is, the induced matrix norm $\|A\|_{a,b}$ is defined by

$$\|\mathbf{A}\|_{a,b} = \max_{\mathbf{x}} \{\|\mathbf{A}\mathbf{x}\|_b \colon \|\mathbf{x}\|_a \leq 1\}. \tag{1}$$

$\|\mathbf{A}\|_{a,b}$ can also be computed in the following alternative ways (Horn and Johnson, 2013, p. 343, Definition 5.6.1):

$$\|\mathbf{A}\|_{a,b} = \max_{\mathbf{x}}\{\|\mathbf{A}\mathbf{x}\|_b \colon \|\mathbf{x}\|_a = 1\} = \max_{\|\mathbf{x}\|_a \neq \mathbf{0}} \frac{\|\mathbf{A}\mathbf{x}\|_b}{\|\mathbf{x}\|_a}. \tag{2}$$

Now we show that they are valid alternatives of (1) by proving two lemmas. The first alternative is exactly the following lemma.

Lemma 1.1. *The maximum points* $\mathbf{x}^*$ *of the RHS of* (1) *must satisfy* $\|\mathbf{x}^*\|_a = 1$.

Proof. We will prove it by contradiction. Given $\mathbf{A} \neq \mathbf{0}$, it is obvious that $\mathbf{x}^* \neq \mathbf{0}$ must hold, otherwise $\|\mathbf{A}\mathbf{x}^*\|_b = 0$ which is the minimum value and it is easy to find an $\mathbf{x}$ such that $\|\mathbf{A}\mathbf{x}\|_b > 0$. Suppose that the maximum points satisfy $\|\mathbf{x}^*\|_a < 1$, then there exists real numbers k such that $\|k\mathbf{x}^*\|_a = 1$ in which $|k| = 1/\|\mathbf{x}^*\|_a > 1$. Let $\mathbf{y} = k\mathbf{x}^*$, then we get

$$\|\mathbf{A}\mathbf{y}\|_b = \|\mathbf{A}(k\mathbf{x}^*)\|_b = |k|\|\mathbf{A}\mathbf{x}^*\|_b > \|\mathbf{A}\mathbf{x}^*\|_b \tag{3}$$

which contradicts that $\mathbf{x}^*$ are the maximum points. Thus, $\|\mathbf{x}^*\|_a = 1$ holds. □

We directly present the second alternative as a lemma as follows and prove it through Lemma 1.1.

Lemma 1.2. *For any* $\mathbf{x} \in \mathbb{R}^n$,

$$\|\mathbf{A}\|_{a,b} = \max_{\|\mathbf{x}\|_a \neq \mathbf{0}} \frac{\|\mathbf{A}\mathbf{x}\|_b}{\|\mathbf{x}\|_a}. \tag{4}$$

Proof. An equivalent form of Lemma 1.1 is

$$\|\mathbf{A}\|_{a,b} = \max_{\mathbf{y}} \left\{ \frac{\|\mathbf{A}\mathbf{y}\|_b}{\|\mathbf{y}\|_a} : \|\mathbf{y}\|_a = 1 \right\} = \max_{\|\mathbf{y}\|_a = 1} \frac{\|\mathbf{A}\mathbf{y}\|_b}{\|\mathbf{y}\|_a}. \tag{5}$$

By letting $\mathbf{y} = k\mathbf{x}$ where $k \in \mathbb{R}\backslash\{0\}$, we have

$$\|\mathbf{A}\|_{a,b} = \max_{|k|\|\mathbf{x}\|_a = 1} \frac{|k|\|\mathbf{A}\mathbf{x}\|_b}{|k|\|\mathbf{x}\|_a} = \max_{\|\mathbf{x}\|_a = 1/|k|} \frac{\|\mathbf{A}\mathbf{x}\|_b}{\|\mathbf{x}\|_a} = \max_{\|\mathbf{x}\|_a \neq 0} \frac{\|\mathbf{A}\mathbf{x}\|_b}{\|\mathbf{x}\|_a} \tag{6}$$

where the last equality follows from that k is an *arbitrary* nonnegative real number. This completes our proof. □

The textbook gives a result about the induced matrix norm without a proof right after its definition. Here, we will present it as a proposition with a proof. The proof is an immediate result of Lemma 4.

Proposition 1.3. *For any* $\mathbf{x} \in \mathbb{R}^n$ *the inequality*

$$\|\mathbf{A}\mathbf{x}\|_b \leq \|\mathbf{A}\|_{a,b}\|\mathbf{x}\|_a \tag{7}$$

holds.

Proof. According to Lemma 4, for any $\mathbf{x} \neq \mathbf{0}$, it follows that

$$\frac{\|\mathbf{A}\mathbf{x}\|_b}{\|\mathbf{x}\|_a} \leq \|\mathbf{A}\|_{a,b} \Longleftrightarrow \|\mathbf{A}\mathbf{x}\|_b \leq \|\mathbf{A}\|_{a,b}\|\mathbf{x}\|_a \tag{8}$$

completing the proof. □

1.1.2 De Morgan's Law/Theorem

Here we present a generalized form of De Morgan's Law which is also known as De Morgan's Theorem from Wikipedia[1].

Theorem 1.4 (De Morgan's Law/Theorem).

$$\left(\bigcup_{i\in I} A_i\right)^c = \bigcap_{i\in I} A_i^c \tag{9}$$

$$\left(\bigcap_{i\in I} A_i\right)^c = \bigcup_{i\in I} A_i^c \tag{10}$$

where I is some, possibly countably or uncountably infinite, indexing set.

1.2 Exercises

Exercise 1.1

Show that $\|\cdot\|_{1/2}$ is not a norm.

Proof. To show that a function is not a norm, it suffices to find a counterexample which does not satisfy at least one of the three properties of a norm. For $\|\cdot\|_{1/2}$, we let

$$\mathbf{x} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \quad \mathbf{y} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}.$$

Then we have

$$\begin{aligned} \|\mathbf{x}+\mathbf{y}\|_{1/2} &= \| \begin{pmatrix} 1 \\ 1 \end{pmatrix} \|_{1/2} = (\sqrt{1}+\sqrt{1})^2 = 4 \\ \|\mathbf{x}\|_{1/2} &= (\sqrt{1}+\sqrt{0})^2 = 1 \\ \|\mathbf{y}\|_{1/2} &= (\sqrt{0}+\sqrt{1})^2 = 1 \end{aligned}$$

However,

$$\|\mathbf{x}+\mathbf{y}\|_{1/2} = 4 > \|\mathbf{x}\|_{1/2} + \|\mathbf{y}\|_{1/2} = 1+1 = 2.$$

Hence, $\|\cdot\|_{1/2}$ does not satisfy the triangle inequality. This completes the proof. □

In fact, when $0 < p < 1$, $\|\cdot\|_p$ satisfies the reverse of Minkowski's inequality within the domain of $\mathbb{R}^n_+$. Formally, we have the following theorem.

Theorem 1.5 (reversed Minkowski's inequality). *For any $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n_+$ and $0 < p < 1$, the following inequality*

$$\|\mathbf{x}+\mathbf{y}\|_p \geq \|\mathbf{x}\|_p + \|\mathbf{y}\|_p$$

holds.

The following proof largely follows Jax (2016) but in greater detail.

[1] https://en.wikipedia.org/wiki/De_Morgan%27s_laws

Proof. Obviously, the claim holds when either $\mathbf{x} = 0$ or $\mathbf{y} = 0$. We only need to consider the case when $\mathbf{x} \neq 0$ and $\mathbf{y} \neq 0$, which guarantees $\|\mathbf{x}+\mathbf{y}\|_p \neq 0$. Let $f(x) = x^p$ with $x > 0$ and $0 < p < 1$. Since $f''(x) = p(p-1)x^{p-2} < 0$ for any $x > 0$, $f(x)$ is concave. Thus, we have

$$\begin{aligned}(x_i + y_i)^p &= \left(t \cdot \frac{x_i}{t} + (1-t) \cdot \frac{y_i}{1-t}\right)^p, \quad 0 < t < 1, i \in \{1, 2, \ldots, n\} \\ &\geq t \cdot \frac{x_i^p}{t^p} + (1-t) \cdot \frac{y_i^p}{(1-t)^p}.\end{aligned}$$

Taking summation over i gives

$$\begin{aligned}\sum_{i=1}^n (x_i + y_i)^p &\geq t \sum_{i=1}^n \frac{x_i^p}{t^p} + \frac{y_i^p}{(1-t)^p} \\ \|\mathbf{x}+\mathbf{y}\|_p^p &\geq t \frac{\|\mathbf{x}\|_p^p}{t^p} + (1-t) \frac{\|\mathbf{y}\|_p^p}{(1-t)^p}\end{aligned}$$

47 Letting $t = \frac{\|\mathbf{x}\|_p}{\|\mathbf{x}\|_p + \|\mathbf{y}\|_p}$ yields

$$\begin{aligned}\|\mathbf{x}+\mathbf{y}\|_p^p &\geq t \frac{\|\mathbf{x}\|_p^p}{\frac{\|\mathbf{x}\|_p^p}{(\|\mathbf{x}\|_p + \|\mathbf{y}\|_p)^p}} + (1-t) \frac{\|\mathbf{y}\|_p^p}{\frac{\|\mathbf{y}\|_p^p}{(\|\mathbf{x}\|_p + \|\mathbf{y}\|_p)^p}} \\ &= t(\|\mathbf{x}\|_p + \|\mathbf{y}\|_p)^p + (1-t)(\|\mathbf{x}\|_p + \|\mathbf{y}\|_p)^p \\ &= (\|\mathbf{x}\|_p + \|\mathbf{y}\|_p)^p \\ \implies \quad \|\mathbf{x}+\mathbf{y}\|_p &\geq \|\mathbf{x}\|_p + \|\mathbf{y}\|_p,\end{aligned}$$

48 as desired. $\square$

Remark 1.6. You may observe that the reversed Minkowski's inequality does not hold when $\mathbf{x} = -\mathbf{y} \neq 0$. The reason is that in the above proof, the condition $x_i, y_i \geq 0, \forall i$ is required to ensure that $f(x)$ is concave and well defined. Concretely speaking, $\sqrt[3]{x}$ is convex on $\mathbb{R}_-$ and $\sqrt[4]{x}$ is not well defined on $\mathbb{R}_-$. Hence, the reversed Minkowski's inequality only works for both vectors with nonnegative entries. Note that Minkowski's inequality works not only for $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ but also for $\mathbf{x}, \mathbf{y} \in \mathbf{C}^n$.

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Extensions

Since $\|\cdot\|_0$ does not satisfy the positive homogeneity, it is not a true norm.

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Exercise 1.2

Prove that for any $\mathbf{x} \in \mathbb{R}^n$ one has

$$\|\mathbf{x}\|_\infty = \lim_{p\to\infty} \|\mathbf{x}\|_p.$$

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Proof. Since the definitions $\|\mathbf{x}\|_\infty \equiv \max_{i=1,2,\ldots,n} |x_i|$ and $\|\mathbf{x}\|_p \equiv \sqrt[p]{\sum_{i=1}^n |x_i|^p}$, we only need to show $\lim_{p\to\infty} \|\mathbf{x}\|_p = \max_{i=1,2,\ldots,n} |x_i|$. Given any $\mathbf{x} \in \mathbb{R}^n$ where n is a finite positive integer, we have

$$\lim_{p\to\infty} \sqrt[p]{\left(\max_{i=1,2,\ldots,n} |x_i|\right)^p} \leq \lim_{p\to\infty} \sqrt[p]{\sum_{i=1}^n |x_i|^p} \leq \lim_{p\to\infty} \sqrt[p]{\left(n \cdot \max_{i=1,2,\ldots,n} |x_i|\right)^p}$$

$$\Downarrow$$

$$\max_{i=1,2,\ldots,n}|x_i|\leq \lim_{p\to\infty}\sqrt[p]{\sum_{i=1}^{n}|x_i|^p}\leq \underbrace{\lim_{p\to\infty}\sqrt[p]{n}}_{=1}\cdot \max_{i=1,2,\ldots,n}|x_i|$$

$$\Downarrow$$

$$\max_{i=1,2,\ldots,n}|x_i|\leq \lim_{p\to\infty}\sqrt[p]{\sum_{i=1}^{n}|x_i|^p}\leq \max_{i=1,2,\ldots,n}|x_i|$$

$$\Downarrow$$

$$\lim_{p\to\infty}\sqrt[p]{\sum_{i=1}^{n}|x_i|^p}=\max_{i=1,2,\ldots,n}|x_i|.$$

52 □

53 This completes our proof.

Exercise 1.3

Show that for any $\mathbf{x},\mathbf{y},\mathbf{z}\in\mathbb{R}^n$

$$\|\mathbf{x}-\mathbf{z}\|\leq\|\mathbf{x}-\mathbf{y}\|+\|\mathbf{y}-\mathbf{z}\|.$$

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Proof. Here, $\|\cdot\|$ refers to the vector norm $\|\cdot\|_2$ whose subscript is frequently omitted for brevity. By the definition of the vector norm, $\|\cdot\|_2$ satisfies the triangle inequality as follows.

$$\begin{aligned}\|\mathbf{x}-\mathbf{z}\|_2&=\|\mathbf{x}-\mathbf{y}+\mathbf{y}-\mathbf{z}\|_2\\ &\leq\|\mathbf{x}-\mathbf{y}\|+\|\mathbf{y}-\mathbf{z}\|_2\end{aligned}$$

55 as desired. □

Exercise 1.4

Prove the Cauchy-Schwarz inequality (Lemma 1.5)

$$|\mathbf{x}^T\mathbf{y}|\leq\|\mathbf{x}\|_2\cdot\|\mathbf{y}\|_2,\quad\forall\mathbf{x},\mathbf{y}\in\mathbb{R}^n. \tag{11}$$

Show that equality holds if and only if the vectors $\mathbf{x}$ and $\mathbf{y}$ are linearly dependent.

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Proof. This lemma can be concisely proved via the following formula from geometry.

$$\mathbf{x}^T\mathbf{y}=\|\mathbf{x}\|_2\cdot\|\mathbf{y}\|_2\cdot\cos\theta \tag{12}$$

where θ denotes the angle between $\mathbf{x}$ and $\mathbf{y}$. Since $|\cos\theta|\leq 1$, it follows that

$$-\|\mathbf{x}\|_2\cdot\|\mathbf{y}\|_2\leq\mathbf{x}^T\mathbf{y}=\|\mathbf{x}\|_2\cdot\|\mathbf{y}\|_2\cdot\cos\theta\leq\|\mathbf{x}\|_2\cdot\|\mathbf{y}\|_2 \tag{13}$$

where the equality holds if and only if $|\cos\theta|=1$ which geometrically implies that $\mathbf{x}$ and $\mathbf{y}$ are parallel to each other, in other words, $\mathbf{x}$ and $\mathbf{y}$ are linearly dependent. If we express (13) in a compact way, then we get

$$|\mathbf{x}^T\mathbf{y}|\leq\|\mathbf{x}\|_2\cdot\|\mathbf{y}\|_2,\quad\forall\mathbf{x},\mathbf{y}\in\mathbb{R}^n. \tag{14}$$

57 This completes the proof. □

Exercise 1.5

Suppose that $\mathbb{R}^m$ and $\mathbb{R}^n$ are equipped with norms $\|\cdot\|_b$ and $\|\cdot\|_a$, respectively. Show that the induced matrix norm $\|\cdot\|_{a,b}$ satisfies the triangle inequality. That is, for any $\mathbf{A}, \mathbf{B} \in \mathbb{R}^{m\times n}$ the inequality

$$\|\mathbf{A}+\mathbf{B}\|_{a,b} \leq \|\mathbf{A}\|_{a,b} + \|\mathbf{B}\|_{a,b} \tag{15}$$

holds.

Proof. By the definition of the induced norm, namely (1),

$$\begin{aligned}
\|\mathbf{A}+\mathbf{B}\|_{a,b} &= \max_{\mathbf{x}}\{\|(\mathbf{A}+\mathbf{B})\mathbf{x}\|_b : \|\mathbf{x}\|_a \leq 1\} && (16)\\
&= \max_{\mathbf{x}}\{\|\mathbf{A}\mathbf{x}+\mathbf{B}\mathbf{x}\|_b : \|\mathbf{x}\|_a \leq 1\} && (17)\\
&\leq \max_{\mathbf{x}}\{\|\mathbf{A}\mathbf{x}\|_b + \|\mathbf{B}\mathbf{x}\|_b : \|\mathbf{x}\|_a \leq 1\} && (18)\\
&\leq \max_{\mathbf{x}}\{\|\mathbf{A}\mathbf{x}\|_b : \|\mathbf{x}\|_a \leq 1\} + \max_{\mathbf{x}}\{\|\mathbf{B}\mathbf{x}\|_b : \|\mathbf{x}\|_a \leq 1\} && (19)\\
&= \|\mathbf{A}\|_{a,b} + \|\mathbf{B}\|_{a,b} && (20)
\end{aligned}$$

where the first inequality follows from the triangle inequality. This completes the proof. □

Exercise 1.6

Let $\|\cdot\|$ be a norm on $\mathbb{R}^n$. Show that the norm function $f(\mathbf{x}) = \|\mathbf{x}\|$ is a continuous function over $\mathbb{R}^n$.

Proof. As we know, the continuity of $f(\mathbf{x})$ at a point $\mathbf{x}_0$ requires that, for any $\epsilon > 0$ and the point $\mathbf{x}_0$ in the domain $\mathcal{D}$ of f, there always exists a δ such that $|f(\mathbf{x}) - f(\mathbf{x}_0)| < \epsilon$ whenever $\mathbf{x} \in \mathcal{D}$ and $\|\mathbf{x}-\mathbf{x}_0\| < \delta$. Here, any nonnegative $\delta < \epsilon$ will satisfy this requirement. To see this, we need to analyze two cases. For the case when $\|\mathbf{x}\| > \|\mathbf{x}_0\|$,

$$\begin{aligned}
|f(\mathbf{x}) - f(\mathbf{x}_0)| &= \|\mathbf{x}\| - \|\mathbf{x}_0\| && (21)\\
&= \|\mathbf{x}-\mathbf{x}_0+\mathbf{x}_0\| - \|\mathbf{x}_0\| && (22)\\
&\leq \|\mathbf{x}-\mathbf{x}_0\| + \|\mathbf{x}_0\| - \|\mathbf{x}_0\| && (23)\\
&= \|\mathbf{x}-\mathbf{x}_0\| < \delta < \epsilon. && (24)
\end{aligned}$$

The case of $\|\mathbf{x}\| = \|\mathbf{x}_0\|$ is trivial. For the case when $\|\mathbf{x}\| < \|\mathbf{x}_0\|$,

$$\begin{aligned}
|f(\mathbf{x}) - f(\mathbf{x}_0)| &= \|\mathbf{x}_0\| - \|\mathbf{x}\| && (25)\\
&= \|\mathbf{x}_0-\mathbf{x}+\mathbf{x}\| - \|\mathbf{x}\| && (26)\\
&\leq \|\mathbf{x}-\mathbf{x}_0\| + \|\mathbf{x}\| - \|\mathbf{x}\| && (27)\\
&= \|\mathbf{x}-\mathbf{x}_0\| < \delta < \epsilon. && (28)
\end{aligned}$$

Since the above argument holds for any $\mathbf{x}_0 \in \mathbb{R}^n$, it follows that $f(\mathbf{x}) = \|\mathbf{x}\|$ is continuous over $\mathbb{R}^n$. This completes the proof. □

Exercise 1.7

(**attainment of the maximum in the induced norm definition**) Suppose that $\mathbb{R}^m$ and $\mathbb{R}^n$ are equipped with norms $\|\cdot\|_b$ and $\|\cdot\|_a$, respectively, and let $\mathbf{A} \in \mathbb{R}^{m\times n}$. Show that there exists $\mathbf{x} \in \mathbb{R}^n$ such that $\|\mathbf{x}\|_a \leq 1$ and $\|\mathbf{A}\mathbf{x}\|_b = \|\mathbf{A}\|_{a,b}$.

Proof. Define the set $C = \{\mathbf{x} \in \mathbb{R}^n | \|\mathbf{x}\|_a \leq 1\}$. It is easy to see that C contains all the limits of convergent sequences of points in C, so C is closed. We can find a positive number M, say 2, such that $C \subset B(\mathbf{0}, M)$, so C is bounded. Since $\mathbf{0} \in C$, C is nonempty. Thus, C is a nonempty and compact set. From Exercise 1.6, since $\|\cdot\|_b$ is a norm, $\|\mathbf{Ax}\|_b$ is continuous. According to Weierstrass theorem (see Theorem 2.30 in the textbook), there exists a global minimum of f and a global maximum of f over C. By the definition of the induced norm, the maximum is denoted $\|\mathbf{A}\|_{a,b}$. This completes our proof. □

Exercise 1.8

Suppose that $\mathbb{R}^m$ and $\mathbb{R}^n$ are equipped with norms $\|\cdot\|_b$ and $\|\cdot\|_a$, respectively. Show that the induced matrix norm $\|\cdot\|_{a,b}$ can be computed by the formula

$$\|\mathbf{A}\|_{a,b} = \max_{\mathbf{x}}\{\|\mathbf{Ax}\|_b : \|\mathbf{x}\|_a = 1\}. \tag{29}$$

Proof. By the definition of the induced norm, the claim is equivalent to proving that the maxima are achieved at $\mathbf{x}^*$ satisfying $\|\mathbf{x}^*\| = 1$, which has been shown in Lemma 1.1. □

Exercise 1.9

Suppose that $\mathbb{R}^m$ and $\mathbb{R}^n$ are equipped with norms $\|\cdot\|_b$ and $\|\cdot\|_a$, respectively. Show that the induced matrix norm $\|\cdot\|_{a,b}$ can be computed by the formula

$$\|\mathbf{A}\|_{a,b} = \max_{\mathbf{x} \neq \mathbf{0}} \frac{\|\mathbf{Ax}\|_b}{\|\mathbf{x}\|_a}. \tag{30}$$

Proof. This is exactly Lemma 2 which includes a proof. □

Exercise 1.10

Let $\mathbf{A} \in \mathbb{R}^{m \times n}, \mathbf{B} \in \mathbb{R}^{n \times k}$ and assume that $\mathbb{R}^m, \mathbb{R}^n, \mathbb{R}^k$ are equipped with the norms $\|\cdot\|_c$, $\|\cdot\|_b$, and $\|\cdot\|_a$, respectively. Prove that

$$\|\mathbf{AB}\|_{a,c} \leq \|\mathbf{A}\|_{b,c} \|\mathbf{B}\|_{a,b}. \tag{31}$$

Proof. From Exercise 1.9, we have

$$\|\mathbf{AB}\|_{a,c} \leq \frac{\|\mathbf{ABx}\|_c}{\|\mathbf{x}\|_a} \tag{32}$$

where $\mathbf{x} \neq \mathbf{0}$. For every $\mathbf{x} \neq \mathbf{0}$, if $\mathbf{Bx} = \mathbf{0}$, then $\mathbf{B} = \mathbf{0}$ must hold, in which case the claim is obviously true. When $\mathbf{Bx} \neq \mathbf{0}$, let $\mathbf{y} = \mathbf{Bx}$ and then,

$$\|\mathbf{AB}\|_{a,c} \leq \frac{\|\mathbf{Ay}\|_c}{\|\mathbf{y}\|_b} \frac{\|\mathbf{Bx}\|_b}{\|\mathbf{x}\|_a} \leq \|\mathbf{A}\|_{b,c} \|\mathbf{B}\|_{a,b}. \tag{33}$$

This completes the proof. □

Exercise 1.11

Prove the formula of the ∞-matrix norm given in Example 1.9 of the textbook. Specifically, given $\mathbf{A} \in \mathbb{R}^{m \times n}$,

$$\|\mathbf{A}\|_\infty = \max_{i=1,2,\ldots,m} \sum_{j=1}^{n} |A_{i,j}|. \tag{34}$$

Proof. From Exercise 1.8, the induced norm $\|\mathbf{A}\|_\infty$ can also be computed by

$$\|\mathbf{A}\|_\infty = \max_{\mathbf{x}}\{\|\mathbf{Ax}\|_\infty \colon \|\mathbf{x}\|_\infty = 1\} \tag{35}$$

$$= \max_{\mathbf{x}}\left\{\max_{i=1,\dots,m} \left| \sum_{j=1}^{n} A_{ij}x_j \right| \colon \max_{j=1,\dots,n}|x_j| = 1\right\} \tag{36}$$

$$= \max_{\mathbf{x}}\left\{\max_{i=1,\dots,m} \sum_{j=1}^{n} | A_{ij}x_j | \colon \max_{j=1,\dots,n}|x_j| = 1\right\} \tag{37}$$

$$= \max_{i=1,\dots,m} \sum_{j=1}^{n} | A_{ij}\text{sign}(A_{ij}) | = \max_{i=1,\dots,m} \sum_{j=1}^{n} | A_{ij} | \tag{38}$$

where $\text{sign}(A_{ij}) = 1$ if $A_{ij} \geq 0$ otherwise $\text{sign}(A_{ij}) = -1$. Note that, besides the last line, (37) also makes use of the constraint $|x_j| \leq 1$ for every $j \in \{1, \dots, n\}$. □

Exercise 1.12

Let $\mathbf{A} \in \mathbb{R}^{m\times n}$. Prove that

(i) $\frac{1}{\sqrt{n}}\|\mathbf{A}\|_\infty \leq \|\mathbf{A}\|_2 \leq \sqrt{m}\|\mathbf{A}\|_\infty$,

(ii) $\frac{1}{\sqrt{m}}\|\mathbf{A}\|_1 \leq \|\mathbf{A}\|_2 \leq \sqrt{n}\|\mathbf{A}\|_1$.

Proof. Before we prove the claimed 4 inequalities, we have

$$\|\mathbf{A}\|_2 = \max_{\|\mathbf{x}\|_2=1}\|\mathbf{Ax}\|_2 \qquad \text{(Definition of } \|\mathbf{A}\|_2) \tag{39}$$

$$= \max_{\|\mathbf{x}\|_2=1}\sqrt{\sum_{i=1}^{m}\left(\sum_{j=1}^{n} A_{ij}x_j\right)^2} \qquad \text{(Definition of } \|\mathbf{A}\|_2) \tag{40}$$

$$= \max_{\|\mathbf{x}\|_2=1}\sqrt{\sum_{i=1}^{m}\left(\sum_{j=1}^{n} |A_{ij}||x_j|\right)^2} \qquad (\forall j,\ \text{sgn}(x_j) \text{ does not change } \|\mathbf{x}\|_2) \tag{41}$$

Given this, for Part (i), we first show the second inequality.

$$\max_{\|\mathbf{x}\|_2=1}\sqrt{\sum_{i=1}^{m}\left(\sum_{j=1}^{n} |A_{ij}||x_j|\right)^2} \leq \max_{\|\mathbf{x}\|_\infty=1}\sqrt{\sum_{i=1}^{m}\left(\sum_{j=1}^{n} |A_{ij}||x_j|\right)^2} \qquad (\{\mathbf{x} \mid \|x\|_2 = 1\} \subset \{\mathbf{x} \mid \|x\|_\infty = 1\}) \tag{42}$$

$$= \sqrt{\sum_{i=1}^{m}\left(\sum_{j=1}^{n} |A_{ij}|\right)^2} \qquad (\text{Maximum is attained at } |x_i| = 1\ \forall i) \tag{43}$$

$$\leq \sqrt{\sum_{i=1}^{m}\left(\max_{i=1,\dots,m}\sum_{j=1}^{n} |A_{ij}|\right)^2} \qquad (u_i \leq \max_i |u_i|,\ \forall i) \tag{44}$$

$$= \sqrt{\sum_{i=1}^{m} (\|\mathbf{A}\|_\infty)^2} = \sqrt{m}\|\mathbf{A}\|_\infty \qquad \text{(Definition of } \|\mathbf{A}\|_\infty\text{)} \tag{45}$$

as desired. Now we prove the first inequality of Part (i).

$$\max_{\|\mathbf{x}\|_2=1} \sqrt{\sum_{i=1}^{m}\left(\sum_{j=1}^{n}|A_{ij}||x_j|\right)^2} \geq \sqrt{\sum_{i=1}^{m}\left(\sum_{j=1}^{n}|A_{ij}|\cdot\frac{1}{\sqrt{n}}\right)^2} \qquad \left(\sum_{j=1}^{n}\left(\frac{1}{\sqrt{n}}\right)^2 = 1\right) \tag{46}$$

$$= \sqrt{\frac{1}{n}\sum_{i=1}^{m}\left(\sum_{j=1}^{n}|A_{ij}|\right)^2} \qquad \left(\left(\frac{1}{\sqrt{n}}\right)^2 = \frac{1}{n}\right) \tag{47}$$

$$\geq \sqrt{\max_{i=1,\ldots,m}\frac{1}{n}\left(\sum_{j=1}^{n}|A_{ij}|\right)^2} \qquad \left(\sum_i |u_i| \geq \max_i |u_i| \;\forall i\right) \tag{48}$$

$$= \frac{1}{\sqrt{n}}\max_{i=1,\ldots,m}\sum_{j=1}^{n}|A_{ij}| = \frac{1}{\sqrt{n}}\|\mathbf{A}\|_\infty \qquad \text{(Definition of } \|\mathbf{A}\|_\infty\text{)} \tag{49}$$

For part (ii), we first consider the left inequality.

$$\max_{\|\mathbf{x}\|_2=1} \sqrt{\sum_{i=1}^{m}\left(\sum_{j=1}^{n}|A_{ij}||x_j|\right)^2} = \sqrt{m}\cdot\max_{\|\mathbf{x}\|_2=1}\frac{\sum_{i=1}^{m}\sum_{j=1}^{n}|A_{ij}||x_j|}{m} \qquad \text{(AM-QM inequality)} \tag{50}$$

$$= \frac{1}{\sqrt{m}}\cdot\max_{\|\mathbf{x}\|_2=1}\sum_{j=1}^{n}|x_j|\left(\sum_{i=1}^{m}|A_{ij}|\right) \qquad \left(\forall m, n < \infty, \sum_{i=1}^{m}\sum_{j=1}^{n} = \sum_{j=1}^{n}\sum_{i=1}^{m}\right) \tag{51}$$

$$= \frac{1}{\sqrt{m}}\cdot\max_{\|\mathbf{x}\|_2=1}\sqrt{\sum_{j=1}^{n}|x_j|^2}\sqrt{\sum_{j=1}^{n}\left(\sum_{i=1}^{m}|A_{ij}|\right)^2} \qquad \text{(Cauchy-Schwarz inequality)} \tag{52}$$

$$= \frac{1}{\sqrt{m}}\sqrt{\sum_{j=1}^{n}\left(\sum_{i=1}^{m}|A_{ij}|\right)^2} \qquad (\|\mathbf{A}\|_2 = 1) \tag{53}$$

$$\geq \frac{1}{\sqrt{m}}\sqrt{\max_{j=1,\ldots,n}\left(\sum_{i=1}^{m}|A_{ij}|\right)^2} \qquad \left(\sum_i |u_i| \geq \max_i |u_i| \;\forall i\right) \tag{54}$$

$$= \frac{1}{\sqrt{m}}\max_{j=1,\ldots,n}\sum_{i=1}^{m}|A_{ij}| = \frac{1}{\sqrt{m}}\|\mathbf{A}\|_1 \qquad \text{(Definition of } \|\mathbf{A}\|_1\text{)} \tag{55}$$

When applying the AM-GM inequality, the equality holds if and only if $\sum_{j=1}^{n}|A_{1j}x_j| = \cdots = \sum_{j=1}^{n}|A_{mj}x_j|$, which is attainable. For Cauchy-Schwarz inequality, the equality holds if and only if $\sum_{i=1}^{m}|A_{ij}| = k|x_j|$ for all $j = 1, \ldots, n$ where k is a constant, which is attainable too.

Now we show the inequality on the right hand side.

$$
\begin{aligned}
\max_{\|\mathbf{x}\|_2=1} \sqrt{\sum_{i=1}^{m}\left(\sum_{j=1}^{n}|A_{ij}||x_j|\right)^2} &\le \max_{\|\mathbf{x}\|_2=1} \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}A_{ij}^2\sum_{j=1}^{n}x_j^2} && \text{(Cauchy-Schwarz inequality)} && (56)\\
&= \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}A_{ij}^2} && (\|\mathbf{x}\|_2 = 1) && (57)\\
&= \sqrt{\sum_{j=1}^{n}\sum_{i=1}^{m}|A_{ij}|^2} && \left(\forall m, n < \infty, \sum_{i=1}^{m}\sum_{j=1}^{n} = \sum_{j=1}^{n}\sum_{i=1}^{m}\right) && (58)\\
&\le \sqrt{\sum_{j=1}^{n}\left(\sum_{i=1}^{m}|A_{ij}|\right)^2} && \left(\forall a_i \ge 0, \sum_{i=1}^{m} a_i^2 \le \left(\sum_{i=1}^{m} a_i\right)^2\right) && (59)\\
&\le \sqrt{\sum_{j=1}^{n}\left(\max_{j=1,\dots,n}\sum_{i=1}^{m}|A_{ij}|\right)^2} && (u_i \le \max_i |u_i|,\ \forall i) && (60)\\
&= \sqrt{n}\cdot \max_{j=1,\dots,n}\sum_{i=1}^{m}|A_{ij}| && \left(\sum_{j=1}^{n} c = nc\right) && (61)\\
&= \sqrt{n}\|\mathbf{A}\|_1 && \text{(Definition of } \|\mathbf{A}\|_1\text{)} && (62)
\end{aligned}
$$

where in the first line the equality holds if and only if $|A_{ij}| = k_i|x_j|$ for all $i = 1, \dots, m$ and $j = 1, \dots, n$, and k_i is a constant, which is not necessarily attainable. This completes the proof. □

Exercise 1.13

Let $\mathbf{A} \in \mathbb{R}^{m\times n}$. Show that

(i) $\|\mathbf{A}\| = \|\mathbf{A}^T\|$ (here $\|\cdot\|$ is the spectral norm),

(ii) $\|\mathbf{A}\|_F^2 = \sum_{i=1}^{n} \lambda_i(\mathbf{A}^T\mathbf{A})$.

Proof. For part (i), the spectral norm is defined by

$$\|\mathbf{A}\|_2 = \sqrt{\lambda_{\max}(\mathbf{A}^T\mathbf{A})} = \sigma_{\max}(\mathbf{A}) \tag{63}$$

where $\lambda_{\max}(\mathbf{A}^T\mathbf{A})$ is the maximum eigenvalue of $\mathbf{A}^T\mathbf{A}$, and $\sigma_{\max}(\mathbf{A})$ is the largest singular values of $\mathbf{A}$. Similarly,

$$\|\mathbf{A}^T\|_2 = \sqrt{\lambda_{\max}(\mathbf{A}\mathbf{A}^T)} = \sigma_{\max}(\mathbf{A}^T) \tag{64}$$

By the Theorem 2.6.3(a) in Horn and Johnson (2013), the singular values are supposed to be nonnegative. And by the Theorem 2.6.3(b) in Horn and Johnson (2013), the nonzero eigenvalues of $\mathbf{A}\mathbf{A}^T$ and $\mathbf{A}^T\mathbf{A}$ are identical. Thus,

$$\|\mathbf{A}\|_2 = \sqrt{\lambda_{\max}(\mathbf{A}^T\mathbf{A})} = \sqrt{\lambda_{\max}(\mathbf{A}\mathbf{A}^T)} = \|\mathbf{A}^T\|_2 \tag{65}$$

as desired.

Now we consider part (ii).

$$\begin{aligned}
\|\mathbf{A}\|_F^2 =& \sum_{i=1}^{m}\sum_{j=1}^{n} A_{ij}^2 && \text{(Definition of Frobenius norm)} && (66)\\
=& \mathrm{Tr}(\mathbf{A}^T\mathbf{A}) && \text{(Definition of trace)} && (67)\\
=& \sum_{n=1}^{n} \lambda_i(\mathbf{A}^T\mathbf{A}) && && (68)
\end{aligned}$$

where the last line follows from the following argument[2]. By definition, the characteristic polynomial of $\mathbf{A}^T\mathbf{A}$ is given by

$$\begin{aligned}
p(t) =& \det(t\mathbf{I} - \mathbf{A}^T\mathbf{A}) && && (69)\\
=& t^n - \mathrm{Tr}(\mathbf{A}^T\mathbf{A})t^{n-1} + \cdots + (-1)^n \det(\mathbf{A}^T\mathbf{A}) && \text{(Definition of determinant)} && (70)
\end{aligned}$$

Also, by the definition, eigenvalues are the roots of $p(t)$. Hence,

$$p(t) = (t-\lambda_1)(t-\lambda_2)\cdots(t-\lambda_n) \tag{71}$$

By comparing coefficients, we have

$$\mathrm{Tr}(\mathbf{A}^T\mathbf{A}) = \sum_{i=1}^{n} \lambda_i(\mathbf{A}^T\mathbf{A}) \tag{72}$$

which completes the proof. □

Exercise 1.14

Let $\mathbf{A} \in \mathbb{R}^{n\times n}$ be a symmetric matrix. Show that

$$\max_{\mathbf{x}}\{\mathbf{x}^T\mathbf{A}\mathbf{x} : \|\mathbf{x}\|^2 = 1\} = \lambda_{\max}(\mathbf{A}). \tag{73}$$

The inspiration of the following proof is from the proof of Lemma 1.11 in the textbook.

Proof. According to the spectral decomposition theorem there exists an orthogonal matrix $\mathbf{U} \in \mathbb{R}^{n\times n}$ and a diagonal matrix $\mathbf{D} = \mathrm{diag}(d_1, d_2, \ldots, d_n)$ such that $\mathbf{U}^T\mathbf{A}\mathbf{U} = \mathbf{D}$. Without the loss of generality, we can assume that the diagonal elements of $\mathbf{D}$, which are the eigenvalues of $\mathbf{A}$, are ordered nonincreasingly: $d_1 \geq d_2 \geq \cdots \geq d_n$, where $d_1 = \lambda_{\max}(\mathbf{A})$. Since $\mathbf{U}$ is an orthogonal matrix, we can make the change of variables $\mathbf{x} = \mathbf{U}\mathbf{y}$.

$$\begin{aligned}
\max_{\|\mathbf{x}\|_2^2=1} \mathbf{x}^T\mathbf{A}\mathbf{x} =& \max_{\|\mathbf{U}\mathbf{y}\|_2^2=1} (\mathbf{U}\mathbf{y})^T\mathbf{A}\mathbf{U}\mathbf{y} && && (74)\\
=& \max_{\|\mathbf{y}\|_2^2=1} \mathbf{y}^T\mathbf{U}^T\mathbf{A}\mathbf{U}\mathbf{y} && (\|\mathbf{U}\mathbf{y}\|_2^2 = \|\mathbf{y}\|_2^2) && (75)\\
=& \max_{\|\mathbf{y}\|_2^2=1} \mathbf{y}^T\mathbf{D}\mathbf{y} && (\mathbf{U}^T\mathbf{A}\mathbf{U} = \mathbf{D}) && (76)\\
=& \max_{\|\mathbf{y}\|_2^2=1} \sum_{i=1}^{n} d_i y_i^2 \leq d_1 \max_{\|\mathbf{y}\|_2^2=1} \sum_{i=1}^{n} y_i^2 && (d_1 \geq d_2 \geq \cdots \geq d_n) && (77)\\
=& d_1 = \lambda_{\max}(\mathbf{A}) && && (78)
\end{aligned}$$

□

[2] https://math.stackexchange.com/questions/546155/proof-that-the-trace-of-a-matrix-is-the-sum-of-its-eigenvalues

Exercise 1.15

Prove that a set $U \subseteq R^n$ is closed if and only if its complement U^c is open.

For better presenting the proof of Exercise 1.15, we introduce the definitions of accumulation points and closed sets.

Definition 1.7 (accumulation points). *If any open ball of a point x contains infinitely many points of a set S, then x is called an accumulation point of S. The set of all accumulation points of S is denoted by S'.*

Now we describe the definition of closed sets in a slightly different way than the textbook. However, in essence, they are the same thing.

Definition 1.8 (closed sets). *If a set S contains all of its accumulation points, then we call S a closed set.*

Proof. We first prove the sufficiency. Given U^c is open, we suppose that U is not closed. Then there must exist at least one accumulation point of U, say x, such that $x \notin U$, i.e., $x \in U^c$. Since U^c is open, then there exists an open ball $B(x,r) \subseteq U^c$ with $r > 0$, which contradicts $x \in U'$ where U' denotes the set of accumulation points of U. Specifically, since $x \in U'$, by Definition 1.7, there are infinitely many points of $B(x,r)$ belonging to U, which is impossible for $B(x,r) \subseteq U^c$.

Now we show the necessity. Given any point $x \in U^c$, it suffices to show that x is an interior point of U^c. Obviously, $x \notin U$. Since U is closed, x is not an accumulation point of U. By Definition 1.8, this implies that there exists an open ball $B(x,r)$ such that $B(x,r) \bigcap U = \emptyset$. Thus, $B(x,r) \subseteq U^c$. This completes our proof. $\square$

Exercise 1.16

1. Let $\{A_i\}_{i \in I}$ be a collection of open sets where I is a given index set. Show that $\bigcup_{i \in I} A_i$ is an open Set. Show that if I is finite, then $\bigcap_{i \in I} A_i$ is open.

2. Let $\{A_i\}_{i \in I}$ be a collection of closed sets where I is a given index set. Show that $\bigcap_{i \in I} A_i$ is a closed Set. Show that if I is finite, then $\bigcup_{i \in I} A_i$ is closed.

The following proof is taken from the proof of Theorem 11.1.5 in Chen et al. (2019).

Proof.

1. For any $\mathbf{x} \in \bigcup_{i \in I} A_i$, then there exists at least an $i \in I$ such that $\mathbf{x} \in A_i$. Since A_i is an open set, then $\mathbf{x}$ is an interior point of A_i. Also, $\mathbf{x}$ is an interior point of $\bigcup_{i \in I} A_i$. Thus, $\bigcup_{i \in I} A_i$ is an open set.

   Since I is finite, suppose there are k sets in total. For any $\mathbf{x} \in \bigcap_{i \in I} A_i$, $x \in A_i$ for arbitrary $i = 1, \ldots, k$. Thus, for any $i \in I$, there exists an $r_i > 0$ such that $B(\mathbf{x}, r_i) \subset A_i$. Let $r = \min_{i \in I} r_i$, then $B(\mathbf{x}, r) \subset \bigcap_{i \in I} A_i$. Therefore, $\bigcap_{i \in I} A_i$ is open.

2. By De Morgan's Theorem (see Theorem 1.4), $(\bigcap_{i \in I} A_i)^c = \bigcup_{i \in I} A_i^c$. Since A_i is closed, its complement A_i^c is open. From the first part of this proof, $\bigcup_{i \in I} A_i^c$ is open. Thus, its complement $\bigcap_{i \in I} A_i$ is closed.

If each A_i is closed, then A_i^c is open. If I is finite, by the first part of this proof, $\bigcap_{i\in I} A_i^c$ is open. According to De Morgan's Theorem, its complement is $\bigcup_{i\in I} A_i$ which is closed. This completes the proof.

$\square$

Exercise 1.17

Give an example of open sets A_i, $i \in I$ for which $\bigcap_{i\in I} A_i$ is not open.

Solution: Let I be $\mathbb{Z}_+$ where $\mathbb{Z}_+$ denotes the set of positive integers. When A_i is defined as

$$A_i = (1 - \frac{1}{i}, 2 + \frac{1}{i}), \quad i \in I,$$

the intersection

$$\bigcap_{i\in I} A_i = [1, 2]$$

is not open. However, it is a closed set. $\square$

Extensions

Likewise, we can construct an example of closed sets A_i, $i \in I$ for which $\bigcup_{i\in I} A_i$ is not closed. For example, the union of the closed sets $A_i = [\frac{1}{i}, 2 - \frac{1}{i}], \forall i \in I$ is $(0, 2)$ which is an open set.

2 Chapter 2 Optimality Conditions for Unconstrained Optimization

Exercise 2.1

Find the global minimum and maximum points of the function $f(x, y) = x^2 + y^2 + 2x - 3y$ over the unit ball $S = B[0, 1] = \{(x, y) : x^2 + y^2 \leq 1\}$.

Solution: By applying Cauchy-Swcharz inequality on $2x - 3y$, we get

$$|2x - 3y| = \left| \begin{pmatrix} x & y \end{pmatrix} \begin{pmatrix} 2 \\ -3 \end{pmatrix} \right| \leq \sqrt{2^2 + (-3)^2}\sqrt{x^2 + y^2} = \sqrt{13}\sqrt{x^2 + y^2}$$

$$\Downarrow$$

$$-\sqrt{13}\sqrt{x^2 + y^2} \leq 2x - 3y \leq \sqrt{13}\sqrt{x^2 + y^2}$$

where the equalities hold when $-3x = 2y$. Thus,

$$x^2 + y^2 - \sqrt{13}\sqrt{x^2 + y^2} \leq x^2 + y^2 + 2x - 3y \leq x^2 + y^2 + \sqrt{13}\sqrt{x^2 + y^2}$$

Since $x^2 + y^2 \leq 1$, when $x^2 + y^2 = 1$, the RHS reaches its maximum $1 + \sqrt{13}$. Combining with $-3x = 2y$ gives $x = 2/\sqrt{13}$ and $y = -3/\sqrt{13}$. When $\sqrt{x^2 + y^2} = 1$, the LHS achieves its minimum $1 - \sqrt{13}$. Similar calculations give $x = -2/\sqrt{13}$ and $y = 3/\sqrt{13}$.

To sum up, the global minimum and maximum points are $(x, y) = (2/\sqrt{13}, -3/\sqrt{13})$ and $(x, y) = (-2/\sqrt{13}, 3/\sqrt{13})$, respectively. $\square$

Exercise 2.2

Let $\mathbf{a} \in \mathbb{R}^n$ be a nonzero vector. Show that the maximum of $\mathbf{a}^T\mathbf{x}$ over $B[0,1] = \{\mathbf{x} \in \mathbb{R}^n : \|\mathbf{x}\| \leq 1\}$ is attained at $x^* = \frac{\mathbf{a}}{\|\mathbf{a}\|}$ and that the maximal value is $\|\mathbf{a}\|$.

3 Chapter 3 Least Squares

Exercise 3.1

Let $\mathbf{A} \in \mathbb{R}^{m\times n}, \mathbf{b} \in \mathbb{R}^m, \mathbf{L} \in \mathbb{R}^{p\times n}$, and $\lambda \in \mathbb{R}_{++}$. Consider the regularized least squares problem

$$\min_{\mathbf{x}\in\mathbb{R}^n} \|\mathbf{A}\mathbf{x} - \mathbf{b}\|^2 + \lambda\|\mathbf{L}\mathbf{x}\|^2. \tag{RLS}$$

Show that (RLS) has a unique solution if and only if $\mathrm{Null}(\mathbf{A}) \cap \mathrm{Null}(\mathbf{L}) = \{\mathbf{0}\}$, where here for a matrix $\mathbf{B}$, $\mathrm{Null}(\mathbf{B})$ is the null space of $\mathbf{B}$ given by $\{\mathbf{x} : \mathbf{B}\mathbf{x} = \mathbf{0}\}$.

Note that it is supposed to be $\mathbf{b} \in \mathbb{R}^m$ instead of $\mathbf{b} \in \mathbb{R}^n$. In the textbook, this is a typo which is not yet mentioned at `http://www.siam.org/books/mo19/mo19_err.pdf`.

Proof. Since the Hessian of the objective function is $2(\mathbf{A}^T\mathbf{A} + \lambda\mathbf{L}^T\mathbf{L}) \succeq \mathbf{0}$, it follows by Lemma 2.41 of the textbook that any stationary point is a global minimum point. Then, we have

$$\text{(RLS) has a unique solution} \iff \mathbf{A}^T\mathbf{A} + \lambda\mathbf{L}^T\mathbf{L} \succ \mathbf{0}$$
$$\Updownarrow$$
$$\mathbf{x}^T(\mathbf{A}^T\mathbf{A} + \lambda\mathbf{L}^T\mathbf{L})\mathbf{x} > 0, \forall\mathbf{x} \neq \mathbf{0} \iff \|\mathbf{A}\mathbf{x}\|^2 + \lambda\|\mathbf{L}\mathbf{x}\|^2 > 0, \forall\mathbf{x} \neq \mathbf{0}$$
$$\Updownarrow$$
$$\text{There exists no nonzero } \mathbf{x} \text{ such that } \mathbf{A}\mathbf{x} = \mathbf{0} \text{ and } \mathbf{L}\mathbf{x} = \mathbf{0} \text{ hold simultaneously.}$$
$$\Updownarrow$$
$$\mathrm{Null}(\mathbf{A}) \cap \mathrm{Null}(\mathbf{L}) = \{\mathbf{0}\}.$$

This completes the proof. □

4 Chapter 4 The Gradient Method

Before working on the exercises of Chapter 4, we first introduce the notation of $f \in C_L^{k,p}(D)$. We write $f \in C_L^{k,p}(D)$ if

1. $f^{(k)}$ exists and is continuous on D.
2. $f^{(p)}$ is Lipschitz continuous with a constant L, namely,

$$\|f^{(p)}(y_1) - f^{(p)}(y_2)\| \leq L\|y_1 - y_2\|, \quad \forall y_1, y_2 \in D.$$

Exercise 4.1

Let $f \in C_L^{1,1}(\mathbb{R}^n)$ and let $\{\mathbf{x}^k\}_{k\geq 0}$ be the sequence generated by the gradient method with a constant stepsize $t_k = \frac{1}{L}$. Assume that $\mathbf{x}_k \to \mathbf{x}^*$. Show that if $\nabla f(\mathbf{x}_k) \neq \mathbf{0}$ for all $k \geq 0$, then $\mathbf{x}^*$ is not a local maximum point.

Proof. Suppose $\mathbf{x}^*$ is a local maximum point, then there exists a ball $B(\mathbf{x}^*, r)$ with any $r > 0$ such that

$$f(\mathbf{x}^*) \geq f(\mathbf{x}_k), \quad \forall \mathbf{x}_k \in B(\mathbf{x}^*, r)$$

Since $t_k = \frac{1}{L}$, by the descent lemma (Lemma 4.22 in the textbook), we have

$$\begin{aligned}
f(\mathbf{x}^*) &\leq f(\mathbf{x}_k) + \nabla f(\mathbf{x}_k)^T(\mathbf{x}^* - \mathbf{x}_k) + \frac{L}{2}\|\mathbf{x}^* - \mathbf{x}_k\|^2 \\
&= f(\mathbf{x}_k) + \nabla f(\mathbf{x}_k)^T(-\frac{1}{L}\nabla f(\mathbf{x}_k)) + \frac{L}{2}\|-\frac{1}{L}\nabla f(\mathbf{x}_k)\|^2 \\
&= f(\mathbf{x}_k) - \frac{1}{2L}\|\nabla f(\mathbf{x}_k)\|^2 \\
&< f(\mathbf{x}_k)
\end{aligned}$$

where the last line follows from that $\nabla f(\mathbf{x}_k) \neq \mathbf{0}$ for all $k \geq 0$. This contradicts the supposition, which implies that $\mathbf{x}^*$ is not a local maximum point. This completes the proof. ☐

5 Chapter 5 Newton's Method

6 Chapter 6 Convex Sets

7 Chapter 7 Convex Functions

Exercise 7.36

Prove that for any $x_1, x_2, \ldots, x_n \in \mathbb{R}_+$ the following inequality holds:

$$\frac{\sum_{i=1}^n x_i}{n} \leq \sqrt{\frac{\sum_{i=1}^n x_i^2}{n}}$$

Proof. According to Cauchy-Schwartz inequality which says that given two vectors $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, $\|\mathbf{x}\|_2\|\mathbf{y}\|_2 \geq |\mathbf{x}^T\mathbf{y}|$, we have

$$\begin{aligned}
\sqrt{\frac{\sum_{i=1}^n x_i^2}{n}} &= \sqrt{\sum_{i=1}^n (\frac{|x_i|}{\sqrt{n}})^2} \cdot \overbrace{\sqrt{\sum_{i=1}^n (\frac{1}{\sqrt{n}})^2}}^{=1} \\
&\geq \frac{\sum_{i=1}^n |x_i|}{n} \geq \frac{\sum_{i=1}^n x_i}{n},
\end{aligned}$$

where the equalities in the first and second inequalities hold if and only if $|x_1| = |x_2| = \cdots = |x_n|$ and $x_1 = x_2 = \cdots = x_n$, respectively. This completes the proof. ☐

Exercise 7.37

Prove that for any $x_1, x_2, \ldots, x_n \in \mathbb{R}_{++}$ the following inequality holds:

$$\frac{\sum_{i=1}^n x_i^2}{\sum_{i=1}^n x_i} \leq \sqrt{\frac{\sum_{i=1}^n x_i^3}{\sum_{i=1}^n x_i}}$$

Proof. Let $f(x) = x^2$ and then $f''(x) = 2 > 0$ implying that f is convex. Furthermore, given $\lambda_1, \lambda_2, \ldots, \lambda_n \in [0,1]$ satisfying $\sum_{i=1}^n \lambda_i = 1$, we have

$$\left(\sum_{i=1}^n \lambda_i x_i\right)^2 \le \sum_{i=1}^n \lambda_i x_i^2$$

By letting $\lambda_i = \frac{x_i}{\sum_{i=1}^n x_i}$, we have

$$\left(\sum_{i=1}^n \frac{x_i}{\sum_{i=1}^n x_i} x_i\right)^2 \le \sum_{i=1}^n \frac{x_i}{\sum_{i=1}^n x_i} x_i^2 \iff \left(\frac{\sum_{i=1}^n x_i^2}{\sum_{i=1}^n x_i}\right)^2 \le \frac{\sum_{i=1}^n x_i^3}{\sum_{i=1}^n x_i} \iff \frac{\sum_{i=1}^n x_i^2}{\sum_{i=1}^n x_i} \le \sqrt{\frac{\sum_{i=1}^n x_i^3}{\sum_{i=1}^n x_i}}.$$

Note that the condition $\lambda_i \in [0,1]$ is satisfied automatically since $x_i > 0, \forall i = 1, 2, \ldots, n$. This completes our proof. ☐

Exercise 7.38

Let $x_1, x_2, \ldots, x_n > 0$ satisfy $\sum_{i=1}^n x_i = 1$. Prove that

$$\sum_{i=1}^n \frac{x_i}{\sqrt{1 - x_i}} \ge \sqrt{\frac{n}{n-1}}.$$

Proof. Define $f(x) = 1/\sqrt{1-x}$ and then $f''(x) = \frac{3}{4}(1-x)^{-5/2} > 0$. So $f(x)$ is convex. Since $\sum_{i=1}^n x_i = 1$, then we have

$$\begin{aligned}
\sum_{i=1}^n x_i f(x_i) \ge & f\Big(\sum_{i=1}^n x_i \cdot x_i\Big) = f\Big(\sum_{i=1}^n x_i^2\Big) \\
= & 1/\sqrt{1 - \sum_{i=1}^n x_i^2} \\
\ge & 1/\sqrt{1 - \frac{(\sum_{i=1}^n x_i)^2}{n}} \\
= & 1/\sqrt{1 - \frac{1}{n}} = 1/\sqrt{\frac{n-1}{n}} \\
= & \sqrt{\frac{n}{n-1}}
\end{aligned}$$

where the second inequality follows from the result given in Exercise 7.36. ☐

Exercise 7.39

Prove that for any $a, b, c > 0$ the following inequality holds:

$$\frac{9}{a+b+c} \le 2\left(\frac{1}{a+b} + \frac{1}{b+c} + \frac{1}{c+a}\right)$$

To simplify the proof of Exercise 7.39, we introduce the following theorem which says that the **harmonic mean** (HM) is less than or equal to the **geometric mean** (GM).

Theorem 7.1 (HM≤GM). *For any $x_1, x_2, \cdots, x_n > 0$ the following inequality holds:*

$$\frac{n}{\sum_{i=1}^{n} \frac{1}{x_i}} \le \sqrt[n]{\prod_{i=1}^{n} x_i}$$

Proof. According to AGM inequality, for any $a_1, a_2, \cdots, a_n \ge 0$, we have

$$\frac{1}{n}\sum_{i=1}^{n} a_i \ge \sqrt[n]{\prod_{i=1}^{n} a_i}.$$

Replacing a_i with $\frac{1}{x_i}$ where $x_i > 0$ for $i \in \{1, 2, \dots, n\}$, we get

$$\frac{1}{n}\sum_{i=1}^{n} \frac{1}{x_i} \ge \sqrt[n]{\prod_{i=1}^{n} \frac{1}{x_i}}.$$

Since both sides are positive, taking reciprocals and reversing the inequality yield

$$\frac{1}{\frac{1}{n}\sum_{i=1}^{n} \frac{1}{x_i}} \le \frac{1}{\sqrt[n]{\prod_{i=1}^{n} \frac{1}{x_i}}}$$

$$\frac{n}{\sum_{i=1}^{n} \frac{1}{x_i}} \le \sqrt[n]{\prod_{i=1}^{n} \frac{1}{x_i}},$$

as desired. □

Naturally, we get the following corollary in which AM is short for the arithmetic mean.

Corollary 7.2 (HM≤GM≤AM). *For any $x_1, x_2, \cdots, x_n > 0$ the following inequality holds:*

$$\frac{n}{\sum_{i=1}^{n} \frac{1}{x_i}} \le \sqrt[n]{\prod_{i=1}^{n} x_i} \le \frac{1}{n}\sum_{i=1}^{n} \frac{1}{x_i}$$

Proof. The first inequality and the second inequality are exactly Theorem 7.1 and AGM inequality, respectively. □

Now we prove Exercise 7.39 using Corollary 7.2.

Proof. Since HM≤AM, letting $x_1 = \frac{2}{a+b}$, $x_2 = \frac{2}{b+c}$ and $x_3 = \frac{2}{c+a}$ yields

$$\frac{3}{\frac{1}{\frac{2}{a+b}} + \frac{1}{\frac{2}{b+c}} + \frac{1}{\frac{2}{c+a}}} \le \frac{\frac{2}{a+b} + \frac{2}{b+c} + \frac{2}{c+a}}{3}$$

$$\frac{3}{a+b+c} \le \frac{2}{3}\left(\frac{1}{a+b} + \frac{1}{b+c} + \frac{1}{c+a}\right)$$

$$\frac{9}{a+b+c} \le 2\left(\frac{1}{a+b} + \frac{1}{b+c} + \frac{1}{c+a}\right),$$

as desired. □

Exercise 7.40

(i) Prove that the function $f(x) = \frac{1}{1+e^x}$ is strictly convex over $[0, \infty)$.

(ii) Prove that for any $a_1, a_2, \ldots, a_n \geq 1$ the equality

$$\sum_{i=1}^{n} \frac{1}{1+a_i} \geq \frac{n}{1+\sqrt[n]{a_1 a_2 \cdots a_n}}$$

holds.

Proof. (i) The second derivative is given by

$$f''(x) = \frac{e^x(e^x-1)}{(1+e^x)^3} > 0, \quad x > 0$$

Thus, $f(x)$ is strictly convex on $(0, +\infty)$. By Theorem 7.13 in the textbook, $f''(x) > 0$ is a sufficient, not necessary, condition for strict convexity. Even though $f''(x) = 0$ at the unique boundary point $x = 0$, this does not alter the strict convexity of $f(x)$. To see this, recall the definition of strict convexity, i.e. Definition 7.2, that is, for any $\underline{x \neq y \in C, \lambda \in (0,1)}$,

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

It is easy to see that for any $y > x = 0$, the above always holds for any $\lambda \in (0,1)$. Thus, $\frac{1}{1+e^x}$ is strictly convex over $[0, +\infty]$.

(ii) Let $a_i = e^{x_i}, i = 1, \ldots, n$. Then for any $a_i \geq 1$, $x_i \geq 0$. Since $f(x) = \frac{1}{1+e^x}$ is strictly convex, then

$$\begin{aligned}
\sum_{i=1}^{n} \frac{1}{n} \cdot \frac{1}{1+a_i} = \sum_{i=1}^{n} \frac{1}{n} \cdot \frac{1}{1+e^{x_i}} &\geq \frac{1}{1+e^{1/n * \sum_{i=1}^{n} x_i}} \\
&= \frac{1}{1+(e^{\sum_{i=1}^{n} x_i})^{1/n}} \\
&= \frac{1}{1+(\prod_{i=1}^{n} e^{x_i})^{1/n}} \\
&= \frac{1}{1+(\prod_{i=1}^{n} a_i)^{1/n}} = \frac{1}{1+\sqrt[n]{a_1 a_2 \cdots a_n}}
\end{aligned}$$

Multiplying both sides by n gives the claim, namely,

$$\sum_{i=1}^{n} \frac{1}{1+a_i} \geq \frac{n}{1+\sqrt[n]{a_1 a_2 \cdots a_n}}$$

Since $\frac{1}{1+e^x}$ is strictly convex, the equality holds if and only if $a_1 = a_2 = \cdots = a_n = 1$. This completes our proof.

$\square$

8 Chapter 8 Convex Optimization

Exercise 8.1

Consider the problem

$$\begin{aligned} \min \quad & f(\mathbf{x}) \\ \text{s.t.} \quad & g(\mathbf{x}) \leq 0 \\ & \mathbf{x} \in X \end{aligned} \tag{P}$$

where f and g are convex functions over $\mathbb{R}^n$ and $X \subseteq \mathbb{R}^n$ is a convex set. Suppose that $\mathbf{x}^*$ is an optimal solution of (P) that satisfies $g(\mathbf{x}^*) < 0$. Show that $\mathbf{x}^*$ is also an optimal solution of the problem

$$\begin{aligned} \min \quad & f(\mathbf{x}) \\ \text{s.t.} \quad & \mathbf{x} \in X \end{aligned}$$

Proof. We denote the feasible sets of (P) and the second problem by C_p and C, respectively. Since $f(\mathbf{x}), g(\mathbf{x})$ and X are convex, both C_p and C are convex sets with $C_p \subseteq C$. Since $g(\mathbf{x}^*) < 0$, $\mathbf{x}^* \in \text{int}(C_p)$. This indicates that the second problem has a local optimal solution on C_p, i.e. $\mathbf{x}^*$. By Theorem 8.1, we know that a local minimum is also a global minimum in terms of convex optimization. Hence, $\mathbf{x}^*$ is also an optimal solution of the problem without the constraint of $g(\mathbf{x}) \leq 0$. □

Exercise 8.2

Let $C = B[\mathbf{x}_0, r]$, where $\mathbf{x}_0 \in \mathbb{R}^n$ and $r > 0$ are given. Find a formula for the orthogonal projection operator P_C.

Solution: Given $\mathbf{x} \in \mathbb{R}^n$, we want to find its projection onto the closed ball $B[\mathbf{x}_0, r]$. Then the optimization problem associated with the computation of $P_C(\mathbf{x})$ is given by

$$\min_{\mathbf{y}} \{\|\mathbf{y} - \mathbf{x}\|^2 | \ \|\mathbf{y} - \mathbf{x}_0\|^2 \leq r^2\}.$$

If $\|\mathbf{x} - \mathbf{x}_0\| \leq r$, then obviously $\mathbf{y} = \mathbf{x}$ since it corresponds to the optimal value 0. When $\|\mathbf{x} - \mathbf{x}_0\| > r$, then the optimal solution must belong to the boundary of the ball due to Theorem 2.6 in the textbook. Specifically, Theorem 2.6 says that for a differentiable function $f(\mathbf{x})$, if $\mathbf{x}^*$ is a local optimum point, then $\nabla f(\mathbf{x}^*) = 0$. Accordingly,

$$2(\mathbf{y} - \mathbf{x}) = 0 \Longleftrightarrow \mathbf{y} = \mathbf{x},$$

which is impossible since $\mathbf{x} \notin C$. Thus, we conclude that in the case of $\|\mathbf{x} - \mathbf{x}_0\| > r$, the projection problem is equivalent to

$$\begin{aligned} & \min_{\mathbf{y}} \{\|\mathbf{y} - \mathbf{x}\|^2 | \ \|\mathbf{y} - \mathbf{x}_0\|^2 = r^2\} \\ \Longleftrightarrow & \min_{\mathbf{y}} \{\|\mathbf{y} - \mathbf{x}_0 + \mathbf{x}_0 - \mathbf{x}\|^2 | \ \|\mathbf{y} - \mathbf{x}_0\|^2 = r^2\} \\ \Longleftrightarrow & \min_{\mathbf{y}} \{\|\mathbf{y} - \mathbf{x}_0\|^2 + 2\langle \mathbf{y} - \mathbf{x}_0, \mathbf{x}_0 - \mathbf{x}\rangle + \|\mathbf{x}_0 - \mathbf{x}\|^2 | \ \|\mathbf{y} - \mathbf{x}_0\|^2 = r^2\} \\ \Longleftrightarrow & \min_{\mathbf{y}} \{r^2 + 2\langle \mathbf{y} - \mathbf{x}_0, \mathbf{x}_0 - \mathbf{x}\rangle + \|\mathbf{x}_0 - \mathbf{x}\|^2 | \ \|\mathbf{y} - \mathbf{x}_0\|^2 = r^2\}. \end{aligned}$$

After dropping those terms that are not depend on $\mathbf{y}$, we get the equivalent form as follows.

$$\operatorname*{argmin}_{\mathbf{y}} \{\langle \mathbf{y}, \mathbf{x}_0 - \mathbf{x}\rangle \mid \|\mathbf{y} - \mathbf{x}_0\|^2 = r^2\}$$

By the Cauchy-Schwarz inequality, the objective function can be lower bounded by

$$\langle \mathbf{y}, \mathbf{x}_0 - \mathbf{x} \rangle \geq -\|\mathbf{y}\| \|\mathbf{x}_0 - \mathbf{x}\| = -r\|\mathbf{x}_0 - \mathbf{x}\|,$$

and this lower bound can be attained at $\mathbf{y} = r\frac{\mathbf{x}-\mathbf{x}_0}{\|\mathbf{x}-\mathbf{x}_0\|}$. Therefore, the orthogonal projection operator P_C is

$$P_{B[\mathbf{x}_0, r]} = \begin{cases} \mathbf{x}, & \text{if } \|\mathbf{x}\| \leq r \\ r\frac{\mathbf{x}-\mathbf{x}_0}{\|\mathbf{x}-\mathbf{x}_0\|}, & \text{if } \|\mathbf{x}\| > r. \end{cases}$$

□

9 Chapter 9 Optimization over a Convex Set

Exercise 9.1

Let f be a continuously differentiable convex function over a closed and convex set $C \subseteq \mathbb{R}^n$. Show that $x^* \in C$ is an optimal solution of the problem

$$\min \{f(\mathbf{x}) : \mathbf{x} \in C\} \tag{P}$$

if and only if

$$\langle \nabla f(\mathbf{x}), \mathbf{x}^* - \mathbf{x} \rangle \leq 0 \text{ for all } \mathbf{x} \in C.$$

The necessity is easy to show, but proving the sufficiency is hard. On Math StackExchange, Parasseux Nguyen provides a beautiful proof for the sufficiency[3].

Proof. We first show the necessity. Since $x^* \in C$ is an optimal solution of (P), then we have

$$f(\mathbf{x}^*) - f(\mathbf{x}) \leq 0.$$

By the convexity of f, we have

$$f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{x}^* - \mathbf{x} \rangle \leq f(\mathbf{x}^*) \iff \langle \nabla f(\mathbf{x}), \mathbf{x}^* - \mathbf{x} \rangle \leq f(\mathbf{x}^*) - f(\mathbf{x}) \leq 0.$$

Proving the sufficiency is not trivial. For all $\mathbf{x} \in C$, let $\mathbf{v} = \mathbf{x} - \mathbf{x}^*$ and then $\mathbf{x}^* + t\mathbf{v} = (1-t)\mathbf{x}^* + t\mathbf{x} \in C$. Define $g(t) = f(\mathbf{x}^* + t\mathbf{v})$ on $t \in [0, 1]$. Since f is continuously differentiable over C, then $g(t)$ is also continuously differentiable on $[0, 1]$. Furthermore,

$$\begin{aligned} g'(t) &= \langle \nabla f(\mathbf{x}^* + t\mathbf{v}), \mathbf{v} \rangle \\ &= \frac{1}{t} \langle \nabla f(\mathbf{x}^* + t\mathbf{v}), t\mathbf{v} \rangle \\ &= \frac{1}{t} \langle \nabla f(\mathbf{x}^* + t\mathbf{v}), (\mathbf{x}^* + t\mathbf{v}) - \mathbf{x}^* \rangle \\ &= -\frac{1}{t} \langle \nabla f(\mathbf{x}^* + t\mathbf{v}), \mathbf{x}^* - (\mathbf{x}^* + t\mathbf{v}) \rangle \\ &\geq 0 \end{aligned}$$

where the inequality follows from the premise of $\langle \nabla f(\mathbf{x}), \mathbf{x}^* - \mathbf{x} \rangle \leq 0$ for all $\mathbf{x} \in C$. □

Note. It is interesting to note that from the above proof, we can see that the convexity of f is not required for the sufficiency and we only used the convexity of C.

[3] https://math.stackexchange.com/questions/4178673/if-nabla-fxt-x-x-leq-0-for-all-x-in-c-then-x-is-optimal-so?

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