

## EXERCISES FOR CHAPTER 3: UNCONSTRAINED PROBLEMS

**Exercises for everyone:** All exercises in parts A and B.

**A. Non-assessed Exercises (corrected in class):**

0.1.4; 0.1.9(a); 0.1.12; 0.1.15; 0.2.4; 0.2.10; 0.3.15; 0.3.20; 0.3.24; 0.3.25; 0.4.2.

**B. Assessed Assignments (to be submitted):**

0.1.1; 0.1.8; 0.1.9(b), (c); 0.1.10; 0.1.11; 0.1.14; 0.2.1; 0.2.3; 0.2.6; 0.2.7; 0.2.8;  
0.2.11; 0.2.13; 0.3.1; 0.3.2; 0.3.4; 0.3.5; 0.3.6; 0.3.7; 0.3.8; 0.3.10; 0.3.11;  
0.3.13; 0.3.14; 0.3.17; 0.3.23; 0.3.26; 0.4.1; 0.4.3.

**C. Bonus Exercises:** Remaining exercises.

### 0.1 PRELIMINARIES

**Exercise 0.1.1.** Let

$$\mathbf{A} = \begin{bmatrix} 4 & 2 & 3 \\ 2 & 3 & 2 \\ 3 & 2 & 4 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 2 & 2 & 2 \\ 2 & 2 & 2 \\ 2 & 2 & -1 \end{bmatrix}, \quad \mathbf{C} = \begin{bmatrix} -4 & 1 & 1 \\ 1 & -4 & 1 \\ 1 & 1 & -4 \end{bmatrix}.$$

Show that  $\mathbf{A}$  is positive definite,  $\mathbf{B}$  is indefinite, and  $\mathbf{C}$  is negative definite.

**Exercise 0.1.2.** Show that a matrix  $\mathbf{A}$  is positive definite if and only if its inverse is positive definite.

**Exercise 0.1.3.** Show that if  $\mathbf{A}$  is a symmetric matrix and if there exist positive and negative elements in the diagonal of  $\mathbf{A}$ , then  $\mathbf{A}$  is indefinite.

**Exercise 0.1.4.** Let  $\mathbf{x} \in \mathbb{R}^n$  and let  $\mathbf{A}$  be defined as

$$a_{ij} = x_i x_j, \quad i, j = 1, 2, \dots, n.$$

Show that  $\mathbf{A}$  is positive semidefinite and that it is *not* a positive definite matrix when  $n > 1$ .

**Exercise 0.1.5.** Show that the leading principal minors of the matrix

$$\mathbf{A} = \begin{bmatrix} 1 & -8 \\ 1 & 1 \end{bmatrix}$$

are positive, but that there are  $\mathbf{x} \neq \mathbf{0}$  in  $\mathbb{R}^2$  such that  $\mathbf{x}^T \mathbf{A} \mathbf{x} < 0$ .

**Exercise 0.1.6.** Let  $\mathbf{A}$  be a square  $n \times n$ -matrix.

- (a) Show that  $\mathbf{B} = \frac{1}{2}(\mathbf{A} + \mathbf{A}^T)$  is symmetric.
- (b) Show that  $\mathbf{x}^T \mathbf{A} \mathbf{x} = \mathbf{x}^T \mathbf{B} \mathbf{x}$  for all  $\mathbf{x} \in \mathbb{R}^n$
- (c) Conclude that  $\mathbf{x}^T \mathbf{A} \mathbf{x} \geq 0$  for all  $\mathbf{x}$  in  $\mathbb{R}^2$  iff  $\mathbf{B}$  is positive semidefinite;  
 $\mathbf{x}^T \mathbf{A} \mathbf{x} > 0$  for all  $\mathbf{x} \neq \mathbf{0}$  iff  $\mathbf{B}$  is positive definite.
- (d) Show that if  $\mathbf{A} = \begin{bmatrix} 3 & 4 \\ 2 & 7 \end{bmatrix}$ , then  $\mathbf{x}^T \mathbf{A} \mathbf{x} > 0$  for all  $\mathbf{x} \neq \mathbf{0}$  in  $\mathbb{R}^2$ .

**Exercise 0.1.7.** Let  $\mathbf{B}$  be an  $n \times k$  matrix and let  $\mathbf{A} = \mathbf{B} \mathbf{B}^T$ .

- (i) Prove  $\mathbf{A}$  is positive semidefinite.
- (ii) Prove that  $\mathbf{A}$  is positive definite if and only if  $\mathbf{B}$  has a full row rank.

**Exercise 0.1.8.** Let  $\mathbf{A}$  be an  $n \times n$  symmetric matrix. Show that  $\mathbf{A}$  is positive semidefinite if and only if there exists an  $n \times n$  matrix  $\mathbf{B}$  such that  $\mathbf{A} = \mathbf{B} \mathbf{B}^T$ .

**Exercise 0.1.9.** Write each of the quadratic forms in the form  $\mathbf{x}^T \mathbf{A} \mathbf{x}$  where  $\mathbf{A}$  is an appropriate symmetric matrix:

- (a)  $3x_1^2 - x_1x_2 + 2x_2^2$ .
- (b)  $x_1^2 + 2x_2^2 - 3x_3^2 + 2x_1x_2 - 4x_1x_3 + 6x_2x_3$ .
- (c)  $2x_1^2 - 4x_3^2 + x_1x_2 - x_2x_3$ .

**Exercise 0.1.10.** Suppose that  $f : \mathbb{R}^3 \rightarrow \mathbb{R}$  is defined by

$$f(\mathbf{x}) = c_1x_1^2 + c_2x_2^2 + c_3x_3^2 + c_4x_1x_2 + c_5x_1x_3 + c_6x_2x_3.$$

Show that  $f(\mathbf{x})$  is the quadratic form and find  $\frac{1}{2}\mathbf{F}(\mathbf{x})$ . Discuss generalizations to higher dimensions.

**Exercise 0.1.11.** Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be a continuous function defined over  $\mathbb{R}^n$ . The function  $f$  is called **coercive** if

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

This means that for any constant  $M$  there must be a positive number  $r$  such that  $f(\mathbf{x}) > M$  whenever  $|\mathbf{x}| > r$ .

Let  $\mathbf{A}$  be a positive definite  $n \times n$  matrix. Determine whether the function

$$f(\mathbf{x}) = \frac{\mathbf{x}^T \mathbf{A} \mathbf{x}}{|\mathbf{x}| + 1}$$

is coercive or not.

**Exercise 0.1.12.** Define  $f(x, y)$  on  $\mathbb{R}^2$  by  $f(x, y) = x^4 + y^4 - 32y^2$ .

- (a) Find a point in  $\mathbb{R}^2$  at which  $\nabla^2 f$  is indefinite.
- (b) Show that  $f(x, y)$  is coercive.
- (c) Minimize  $f(x, y)$  on  $\mathbb{R}^2$ .

**Exercise 0.1.13.** Find a function  $f : \mathbb{R}^2 \rightarrow \mathbb{R}$  which is not coercive and satisfies that for any  $\alpha \in \mathbb{R}$ ,

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

**Exercise 0.1.14.** Find the first three terms of the Taylor series for

$$f(\mathbf{x}) = 3x_1^4 - 2x_1^3x_2 - 4x_1^2x_2^2 + 5x_1x_2^3 + 2x_2^4.$$

at the point  $\mathbf{x}_0 = (1, -1)$ . Evaluate the series for  $\mathbf{d} = (0.1, 0.01)$  and compare with the value of  $f(\mathbf{x} + \mathbf{d})$ .

**Exercise 0.1.15.** Consider the quadratic function given by

$$f(\mathbf{x}) = \frac{1}{2}\mathbf{x}^T\mathbf{Q}\mathbf{x} + \mathbf{b}^T\mathbf{x} + c.$$

Show that  $\mathbf{Q}$  is the Hessian of  $f$  and that if  $\mathbf{x}_0$  is any point, then

$$f(\mathbf{x}) = f(\mathbf{x}_0) + \nabla f(\mathbf{x}_0)\mathbf{h} + \frac{1}{2}\mathbf{h}^T\mathbf{Q}\mathbf{h},$$

where  $\mathbf{h} = \mathbf{x} - \mathbf{x}_0$ . Hence  $f$  coincides with its Taylor expansion of second order about any point.

**Exercise 0.1.16.** Let  $V$  be a vector space. A function  $p : V \rightarrow \mathbb{R}$  is called a seminorm if it satisfies the following conditions:

- (a)  $p(x) \geq 0$  for all  $x \in V$ .
- (b) If  $x \in V$  and  $\alpha$  is a number, then  $p(\alpha x) = |\alpha|p(x)$ .
- (c)  $p(x + y) \leq p(x) + p(y)$  for all  $x, y \in V$ .

Show that every seminorm is convex. In particular, every norm is convex.

**Exercise 0.1.17.** Let  $\mathbf{Q}$  be an  $n \times n$  positive semidefinite matrix.

- (a) Use the fact that for fixed  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ , the quadratic functions  $\varphi(t) = (t\mathbf{x} + \mathbf{y})^T\mathbf{Q}(t\mathbf{x} + \mathbf{y})$  and  $\psi(t) = (\mathbf{x} + t\mathbf{y})^T\mathbf{Q}(\mathbf{x} + t\mathbf{y})$ ,  $t \in \mathbb{R}$ , are non-negative to show that

$$|\mathbf{x}^T\mathbf{Q}\mathbf{y}| \leq \sqrt{\mathbf{x}^T\mathbf{Q}\mathbf{x} \cdot \mathbf{y}^T\mathbf{Q}\mathbf{y}} \quad \text{for all } \mathbf{x}, \mathbf{y} \in \mathbb{R}^n. \quad (0.1.1)$$

- (b) Show that the function  $f(\mathbf{x}) = \sqrt{\mathbf{x}^T\mathbf{Q}\mathbf{x}}$  is convex.
- (c) Show that  $f(\mathbf{x})$  is a seminorm on  $\mathbb{R}^n$  (see Exercise 0.1.16).
- (d) Show that if  $\mathbf{Q}$  is positive definite, then  $f(\mathbf{x})$  is a norm on  $\mathbb{R}^n$ .

## 0.2 FIRST AND SECOND-ORDER CONDITIONS

**Exercise 0.2.1.** Let  $\Omega = \{\mathbf{x} \in \mathbb{R}^n : g_i(\mathbf{x}) \leq 0, i = 1, 2, \dots, m\}$  and assume that the functions  $g_i$  are all continuous. Prove that if  $g_i(\bar{\mathbf{x}}) < 0$  for all  $i$ , then  $\bar{\mathbf{x}}$  is an interior point of  $\Omega$ , that is,  $\{\mathbf{x} \in \mathbb{R}^n : |\mathbf{x} - \bar{\mathbf{x}}| < r\} \subset \Omega$  for some  $r > 0$ .

**Exercise 0.2.2.** Let  $S = \{\mathbf{x} : \mathbf{Ax} \leq \mathbf{b}\}$ . Derive the conditions that must be satisfied by a feasible direction at a point  $\mathbf{x}_0 \in S$ .

**Exercise 0.2.3.** Consider a linear program in standard form

$$\begin{aligned} & \text{minimize} && z = \mathbf{c}^T \mathbf{x} \\ & \text{subject to} && \mathbf{Ax} = \mathbf{b} \\ & && \mathbf{x} \geq \mathbf{0}. \end{aligned}$$

Suppose that  $\mathbf{x}^*$  is an optimal basic feasible solution. Show that if  $\mathbf{d}$  is a feasible direction at  $\mathbf{x}^*$ , then

$$\begin{aligned} \mathbf{c}^T \mathbf{d} &\geq 0 \\ \mathbf{Ad} &= \mathbf{0} \\ d_i &\geq 0 \text{ if } x_i^* = 0. \end{aligned}$$

These conditions can be use to derive the simplex method.

**Exercise 0.2.4.** Let  $f$  be a function defined on  $\Omega \subset \mathbb{R}^n$  and  $\mathbf{x} \in \Omega$ . We say that the vector  $\mathbf{d} \in \mathbb{R}^n$  is a **feasible descent direction** at a point  $\mathbf{x} \in \Omega$  if there exists a  $\delta > 0$  such that

$$\mathbf{x} + \alpha \mathbf{d} \in \Omega \quad \text{and} \quad f(\mathbf{x} + \alpha \mathbf{d}) < f(\mathbf{x}) \quad \text{for all } 0 < \alpha \leq \delta.$$

Assume that  $f$  is continuously differentiable on  $\Omega$  and  $\mathbf{x} \in \Omega$ . Show that if  $\nabla f(\mathbf{x})\mathbf{p} < 0$ , then  $\mathbf{p}$  is a descent direction with respect to  $f$  at  $\mathbf{x}$ .

**Exercise 0.2.5.** Consider the problem

$$\begin{aligned} & \text{minimize} && f(x_1, x_2) = -x_1 - x_2 \\ & \text{subject to} && x_1 + x_2 \leq 2 \\ & && x_1, x_2 \geq 0. \end{aligned}$$

- (i) Determine the feasible directions at  $(0, 0)$ ,  $(0, 1)$ ,  $(1, 1)$ , and  $(0, 2)$ .
- (ii) Determine whether there exist feasible descent directions at these points, and hence determine which (if any) of the points can be local minimizers.

**Exercise 0.2.6.** Show that the function  $f(x_1, x_2) = x_1^3 x_2^3$  satisfies two conditions

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

(ii)  $\mathbf{d}^T \nabla^2 f(\mathbf{x}^*) \mathbf{d} \geq 0$  for all  $\mathbf{d}$

at the point  $\mathbf{x}^* = (0, 0)$  but  $\mathbf{x}^*$  is not a local minimum point.

**Exercise 0.2.7.** Investigate the stationary points of the function

$$f(x, y) = \frac{x + y}{x^2 + y^2 + 1}.$$

**Exercise 0.2.8.** Find optimum point(s) of

$$f(\mathbf{x}) = x_1^2 + x_2^2 + x_3^2 + x_1x_2 + x_2x_3 + x_3x_1 + (x_1^2 + x_2^2 + x_3^2)^2.$$

**Exercise 0.2.9.** Find all the values of the parameter  $a$  such that  $(1, 0)$  is the minimizer or maximizer of the function

$$f(x_1, x_2) = a^3 x_1 e^{x_2} + 2a^2 \log(x_1 + x_2) - (a + 2)x_1 + 8ax_2 + 16x_1x_2.$$

**Exercise 0.2.10.** Consider the problem

$$\text{minimize } f(x_1, x_2) = (x_2 - x_1^2)(x_2 - 2x_1^2).$$

- (i) Show that the first- and second-order necessary conditions for optimality are satisfied at  $(0, 0)$ .
- (ii) Show that the origin is a local minimizer of  $f$  along any line passing through the origin (that is,  $x_2 = mx_1$ ).
- (iii) Show that the origin is not a local minimizer of  $f$  (consider, for example, curves of the form  $x_2 = kx_1^2$ ). What conclusions can you draw from this?

**Exercise 0.2.11.** Let

$$f(x_1, x_2) = cx_1^2 + x_2^2 - 2x_1x_2 - 2x_2,$$

where  $c$  is some constant.

- (i) Determine the stationary points of  $f$  for each value of  $c$ .
- (ii) For what values of  $c$  can  $f$  have a minimizer? For what values of  $c$  can  $f$  have a maximizer? Determine the minimizers/maximizers corresponding to such values of  $c$  and indicate what kind of minima or maxima (local, global, strict, etc.) they are.

**Exercise 0.2.12.** Consider the following unconstrained problem:

$$\text{minimize } f(x_1, x_2) = x_1^2 - x_1x_2 + 2x_2^2 - 2x_1 + e^{x_1+x_2}.$$

- (i) Write down the first-order necessary conditions for optimality.
- (ii) Is  $\mathbf{x} = (0, 0)$  a local optimum? If not, find a direction  $\mathbf{d}$  along which the function decreases.
- (iii) Attempt to minimize the function starting from  $\mathbf{x} = (0, 0)$  along the direction  $\mathbf{d}$  that you have chosen in part (ii).

[Hint: Consider  $\varphi(t) = f(\mathbf{x} + t\mathbf{d})$ .]

**Exercise 0.2.13.** Consider the quadratic function

$$f(\mathbf{x}) = \frac{1}{2}\mathbf{x}^T\mathbf{Q}\mathbf{x} - \mathbf{c}^T\mathbf{x}.$$

- (i) Write the first-order necessary condition. When does a stationary point exist?
- (ii) Under what conditions on  $\mathbf{Q}$  does a local minimizer exist?
- (iii) Under what conditions on  $\mathbf{Q}$  does  $f$  have a stationary point, but no local minima nor maxima?

**Exercise 0.2.14.** Consider the problem

$$\text{minimize } f(\mathbf{x}) = \|\mathbf{Ax} - \mathbf{b}\|^2,$$

where  $\mathbf{A}$  is an  $m \times n$  matrix with  $m \geq n$ , and  $\mathbf{b}$  is a vector of length  $m$ . Assume that the rank of  $\mathbf{A}$  is equal to  $n$ .

- (i) Write down the first-order necessary condition for optimality. Is this also a sufficient condition?
- (ii) Write down the optimal solution in closed form.

## 0.3 CONVEX FUNCTIONS AND OPTIMIZATION OF CONVEX FUNCTIONS

### 0.3.1 Convex Functions

**Exercise 0.3.1.** Let  $\mathbf{x}_0 \in \mathbb{R}^n$  and  $r > 0$ . Let  $\|\cdot\|$  be an arbitrary norm defined on  $\mathbb{R}^n$ .

- (a) Show that the function  $f(\mathbf{x}) = \|\mathbf{x} - \mathbf{x}_0\|$  is convex.
- (b) Show that the open ball  $B(\mathbf{x}_0, r) = \{\mathbf{x} : \|\mathbf{x} - \mathbf{x}_0\| < r\}$  and the closed ball  $\overline{B}(\mathbf{x}_0, r) = \{\mathbf{x} : \|\mathbf{x} - \mathbf{x}_0\| \leq r\}$  are convex.

*Application:* Let  $x_k, y_k \in \mathbb{R}$ ,  $1 \leq k \leq n$ , be such that  $x_k^2 + y_k^2 = 1$  for all  $k$ . Let  $c_1, \dots, c_n \in [0, 1]$  with  $\sum_{k=1}^n c_k = 1$ . Show that

$$\left( \sum_{k=1}^n c_k x_k \right)^2 + \left( \sum_{k=1}^n c_k y_k \right)^2 \leq 1.$$

**Exercise 0.3.2.** An **ellipsoid** is a set of the form

$$E = \{\mathbf{x} : \mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{b}^T \mathbf{x} + c \leq 0\},$$

where  $\mathbf{Q}$  is a positive semidefinite symmetric  $n \times n$  matrix,  $\mathbf{b} \in \mathbb{R}^n$ , and  $c \in \mathbb{R}$ . Show that every ellipsoid is convex.

Show that if  $\mathbf{Q}$  is positive definite, then the ellipsoid  $E$  is compact.

**Exercise 0.3.3.** Show that the set

$$K = \{\mathbf{x} \in \mathbb{R}^n : \mathbf{x}^T \mathbf{Q} \mathbf{x} \leq (\mathbf{a}^T \mathbf{x})^2, \mathbf{a}^T \mathbf{x} \geq 0\},$$

where  $\mathbf{Q}$  is an  $n \times n$  positive definite matrix and  $\mathbf{a} \in \mathbb{R}^n$  is a convex cone.

**Exercise 0.3.4.** Consider the function  $f(x, y) = ax^p y^q$ , defined on  $C = \{(x, y) \in \mathbb{R}^2 : x > 0, y > 0\}$ . For what values of  $\alpha$ ,  $p$ , and  $q$  is the function convex? Strictly convex? For what values is it concave? Strictly concave?

**Exercise 0.3.5.** Show that any norm on  $\mathbb{R}^n$  is convex.



**Exercise 0.3.6.** Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be a convex function, and let  $g : \mathbb{R} \rightarrow \mathbb{R}$  be a convex increasing function. Prove that the composite function  $h : \mathbb{R}^n \rightarrow \mathbb{R}$  defined by  $h(\mathbf{x}) = g(f(\mathbf{x}))$  is convex.

**Exercise 0.3.7.** Show that the function  $f(x) = x^4$  is strictly convex on  $\mathbb{R}$  and that  $g(x) = x^p$  for  $p > 1$  is strictly convex over  $[0, \infty)$ .

**Exercise 0.3.8.** Show that the following functions are convex over the given specified domain:

(i)  $f(x_1, x_2, x_3) = -\sqrt{x_1 x_2} + 2x_1^2 + 2x_2^2 + 3x_3^2 - 2x_1 x_2 - 2x_2 x_3$  over  $\{\mathbf{x} \in \mathbb{R}^3 : \mathbf{x} > \mathbf{0}\}$ .

(ii)  $f(\mathbf{x}) = |\mathbf{x}|^p$ ,  $p > 1$ , over  $\mathbb{R}^n$ .

(iii)  $f(\mathbf{x}) = \sum_{i=1}^n x_i \log(x_i) - (\sum_{i=1}^n x_i) \log(\sum_{i=1}^n x_i)$  over  $\{\mathbf{x} \in \mathbb{R}^n : \mathbf{x} > \mathbf{0}\}$ .

(iv)  $f(\mathbf{x}) = \sqrt{\mathbf{x}^T \mathbf{Q} \mathbf{x} + 1}$  over  $\mathbb{R}^n$ , where  $\mathbf{Q}$  is a semidefinite  $n \times n$  matrix.

(v)  $f(x_1, x_2) = (2x_1^2 + 3x_2^2) \left( \frac{1}{2}x_1^2 + \frac{1}{3}x_2^2 \right)$ .

**Exercise 0.3.9.** Let  $C = \{\mathbf{x} \in \mathbb{R}^n : \mathbf{x} > \mathbf{0}\}$  and  $\phi : C \rightarrow \mathbb{R}$  be a convex function. Then the function  $f : C \rightarrow \mathbb{R}$  defined by

$$f(x, y) = y\phi\left(\frac{x}{y}\right), \quad x, y > 0$$

is convex over  $C$ .

Application: Show that the function  $f(x, y) = -x^p y^{1-p}$ ,  $0 < p < 1$ , is convex on  $\{(x, y) \in \mathbb{R}^2 : x > 0, y > 0\}$ .

**Exercise 0.3.10.** Let  $f$  be a convex function defined on a convex set  $C$ . Suppose that  $f$  is not strictly convex on  $C$ . Prove that there exist  $\mathbf{x}, \mathbf{y} \in C$ ,  $\mathbf{x} \neq \mathbf{y}$ , such that  $f$  is affine over the segment  $[\mathbf{x}, \mathbf{y}]$ , that is,

$$f((1 - \lambda)\mathbf{x} + \lambda\mathbf{y}) = (1 - \lambda)f(\mathbf{x}) + \lambda f(\mathbf{y}), \quad \text{for all } \lambda \in [0, 1].$$

**Exercise 0.3.11.** Let  $C \subset \mathbb{R}^n$  be convex and  $f : C \rightarrow \mathbb{R}$ . Prove that  $f$  is convex if and only if for any  $\mathbf{x} \in \mathbb{R}^n$  and  $\mathbf{d} \neq \mathbf{0}$ , the one-dimensional function

$$\varphi_{\mathbf{x},\mathbf{d}}(t) := f(\mathbf{x} + t\mathbf{d})$$

is convex on  $I_{\mathbf{x}} := \{t \in \mathbb{R} : \mathbf{x} + t\mathbf{d} \in C\}$ .

**Exercise 0.3.12.** Let  $C \subset \mathbb{R}^n$  be a convex set. Let  $f$  be a convex function over  $C$ , and let  $g$  be a strictly convex function over  $C$ . Show that the sum function  $f + g$  is strictly convex over  $C$ .

**Exercise 0.3.13.** Show that any affine function  $f(\mathbf{x}) = \mathbf{a}^T \mathbf{x} + \alpha$ , where  $\mathbf{a} \in \mathbb{R}^n$  and  $\alpha \in \mathbb{R}$ , is convex.

**Exercise 0.3.14.** Show that  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is both convex and concave if and only if  $f$  is affine, that is, there exists  $\mathbf{a} \in \mathbb{R}^n$  and  $\alpha \in \mathbb{R}$  such that  $f(\mathbf{x}) = \mathbf{a}^T \mathbf{x} + \alpha$  for all  $\mathbf{x} \in \mathbb{R}^n$ .

**Exercise 0.3.15. (Jensen's Inequality)** Let  $f$  be a function on a convex set  $C \subset \mathbb{R}^n$ . Prove that  $f$  is convex if and only if

$$f\left(\sum_{i=1}^k \alpha_i \mathbf{x}_i\right) \leq \sum_{i=1}^k \alpha_i f(\mathbf{x}_i).$$

for all  $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k \in C$  and  $0 \leq \alpha_i \leq 1$ ,  $\sum_{i=1}^k \alpha_i = 1$ .

**Exercise 0.3.16.** Prove that if  $f$  and  $g$  are convex, twice differentiable, nondecreasing, and positive on  $\mathbb{R}$ , then the product  $fg$  is convex over  $\mathbb{R}$ . Show by an example that the positivity assumption is necessary to establish the convexity.

**Exercise 0.3.17.** Let  $f(\mathbf{x}) = \mathbf{x}^T \mathbf{A} \mathbf{x} + 2\mathbf{b} \mathbf{x} + c$  be a quadratic function over  $\mathbb{R}^n$ . Suppose that  $\mathbf{A}$  is positive definite. Determine the global minimizer and the minimal value of  $f$ .

**Exercise 0.3.18.** Let  $f(\mathbf{x}) = \mathbf{x}^T \mathbf{A} \mathbf{x} + 2\mathbf{b} \mathbf{x} + c$ , where  $\mathbf{A}$  is an  $n \times n$  symmetric matrix,  $\mathbf{b} \in \mathbb{R}^n$ , and  $c \in \mathbb{R}$ . Show that  $f$  is coercive if and only if  $\mathbf{A}$  is positive definite.

**Exercise 0.3.19.** Show that the functions  $f(\mathbf{x}) = |\mathbf{x}|^4$  and  $g(\mathbf{x}) = (|\mathbf{x}|^2 + 1)^2$  are strictly convex on  $\mathbb{R}^n$ .

**Exercise 0.3.20.** Let  $f : C \rightarrow \mathbb{R}$  be a convex function which is not constant over the convex set  $C \subset \mathbb{R}^n$ . Show that  $f$  does not attain a maximum at a point in  $\text{int}(C)$ .

**Exercise 0.3.21.** Let  $C \subset \mathbb{R}^n$  be a nonempty closed convex set and  $\mathbf{y} \in \mathbb{R}^n$ . Consider the problem

$$\begin{array}{ll} \text{minimize} & f(\mathbf{x}) = |\mathbf{x} - \mathbf{y}|^2 \\ \text{subject to} & \mathbf{x} \in C. \end{array}$$

- (a) Show that the problem has a unique solution.
- (b) Show that  $\mathbf{x}^* \in C$  is the solution of the problem if and only if

$$(\mathbf{y} - \mathbf{x}^*)^T(\mathbf{x} - \mathbf{x}^*) \leq 0 \quad \text{for any } \mathbf{x} \in C.$$

**Exercise 0.3.22.** Suppose that  $\Omega \subset \mathbb{R}^n$  is convex and that  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is convex and in  $C^1$  on  $\Omega$ . Then, the value of  $\nabla f(x)$  is constant on the optimal solution set  $\Gamma$ . Further, suppose that  $\mathbf{x}^* \in \Gamma$ . Then

$$\Gamma = \{\mathbf{x} \in \Omega : \nabla f(\mathbf{x}^*)(\mathbf{x} - \mathbf{x}^*) = 0 \quad \text{and} \quad \nabla f(\mathbf{x}) = \nabla f(\mathbf{x}^*)\}.$$

### 0.3.2 Use Convex Functions to Prove Inequalities

**Exercise 0.3.23.** (a) Prove that the function  $f(x) = \frac{1}{1+e^x}$  is strictly convex over  $[0, \infty)$ .

- (b) Prove that for any  $a_1, a_2, \dots, a_n \geq 1$  the inequality

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

holds.

### 0.3.3 Convex Optimization

**Exercise 0.3.24.** Given a nonempty closed convex set  $C \subset \mathbb{R}^n$ , the **orthogonal projection operator**  $P_C : \mathbb{R}^n \rightarrow C$  is defined by

$$P_C(\mathbf{x}) = \{\mathbf{z} \in C : |\mathbf{x} - \mathbf{z}|^2 \leq |\mathbf{x} - \mathbf{y}|^2 \text{ for all } \mathbf{y} \in C\}.$$

- (a) Show that  $P_C(\mathbf{x})$  is singleton for all  $\mathbf{x} \in \mathbb{R}^n$ .
- (b) Show that for  $\mathbf{x} \in \mathbb{R}^n$ ,  $\mathbf{z} = P_C(\mathbf{x})$  if and only if

$$(\mathbf{x} - \mathbf{z})^T(\mathbf{y} - \mathbf{z}) \leq 0 \quad \text{for any } \mathbf{y} \in C. \quad (0.3.1)$$

**Exercise 0.3.25.** Find the global minimizers of

$$(a) \quad f(x, y) = e^{x-y} + e^{y-x} \quad (b) \quad g(x, y, z) = e^{x-y} + e^{x+y}.$$

**Exercise 0.3.26.** Consider the problem

$$\begin{aligned} & \text{minimize} && f(\mathbf{x}) \\ & \text{subject to} && g(\mathbf{x}) \leq 0, \\ & && \mathbf{x} \in \Omega, \end{aligned}$$

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

$$\begin{aligned} & \text{minimize} && f(\mathbf{x}) \\ & \text{subject to} && \mathbf{x} \in \Omega. \end{aligned}$$

**Exercise 0.3.27.** Let  $f$  be a strictly convex function over  $\mathbb{R}^m$  and let  $g$  be a convex function over  $\mathbb{R}^n$ . Define the function

$$h(\mathbf{x}) = f(\mathbf{Ax}) + g(\mathbf{x}),$$

where  $\mathbf{A}$  is an  $m \times n$  matrix. Assume that  $\mathbf{x}^*$  and  $\mathbf{y}^*$  are optimal solutions of the unconstrained problem of minimizing  $h$ . Show that  $\mathbf{Ax}^* = \mathbf{Ay}^*$ .

## 0.4 NEWTON METHODS

**Exercise 0.4.1.** Use Newton's method to solve

$$\text{minimize } f(x_1, x_2) = 5x_1^4 + 6x_2^4 - 6x_1^2 + 2x_1x_2 + 5x_2^2 + 15x_1 - 7x_2 + 13.$$

Use the initial guess  $(1, 1)$ . Make sure that you have found a minimum and not a maximum.

**Exercise 0.4.2.** Construct the Newton's Method sequence  $\{\mathbf{x}_k\}$  for minimizing the function

$$f(x_1, x_2) = x_1^4 + 2x_1^2x_2^2 + x_2^4$$

with initial point  $\mathbf{x}_0 = (a, a)$ , where  $a \in \mathbb{R}$ .

$$\text{ANS. } \mathbf{x}_k = \left( \left(\frac{2}{3}\right)^k a, \left(\frac{2}{3}\right)^k a \right).$$

**Exercise 0.4.3.** Consider the problem

$$\text{minimize } f(\mathbf{x}) = \frac{1}{2}\mathbf{x}^T\mathbf{Q}\mathbf{x} - \mathbf{c}^T\mathbf{x},$$

where  $\mathbf{Q}$  is a positive-definite matrix. Prove that Newton's method will determine the minimizer of  $f$  in one iteration, regardless of the starting point.