

# 1 BASICS OF SET CONSTRAINED AND UNCONSTRAINED OPTIMIZATION

## 1.1 INTRODUCTION

- We consider the **optimization problem**

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

- The function  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  that we wish to minimize is a real-valued function called the **objective function**.
- The vector  $\mathbf{x}$  is an  $n$ -vector of **independent variables**:  $\mathbf{x} = [x_1, \dots, x_n]^\top \in \mathbb{R}^n$ .
- The set  $\Omega$  is a subset of  $\mathbb{R}^n$  called the **constraint set**, which takes the form  $\Omega = \{\mathbf{x}: \mathbf{h}(\mathbf{x}) = \mathbf{0}, \mathbf{g}(\mathbf{x}) \leq \mathbf{0}\}$ , where  $\mathbf{h}$  and  $\mathbf{g}$  are given functions.
- The **minimizer** of  $f$  over  $\Omega$  is a vector  $\mathbf{x}$  which results in the smallest value of the objective function.
- Definition 1.1** Suppose that  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  is a real-valued function defined on some set  $\Omega \subset \mathbb{R}^n$ . A point  $x^* \in \Omega$  is a **local minimizer** of  $f$  over  $\Omega$  if there exists  $\varepsilon > 0$  such that  $f(x) \geq f^*(x)$  for all  $x \in \Omega \setminus \{x^*\}$  and  $\|x - x^*\| < \varepsilon$ . A point  $x^* \in \Omega$  is a **global minimizer** of  $f$  over  $\Omega$  if  $f(x) \geq f(x^*)$  for all  $x \in \Omega \setminus \{x^*\}$ .
- If  $x^*$  is a global minimizer of  $f$  over  $\Omega$ , we write  $f(x^*) = \min_{x \in \Omega} f(x)$  and  $x^* = \operatorname{argmin}_{x \in \Omega} f(x)$ .

**Example 1.1.1.** Suppose  $f: \mathbb{R} \rightarrow \mathbb{R}$  is given by  $f(x) = (x + 1)^2 + 3$ . Find  $\arg \min_{x \in \Omega} f(x)$  where  $\Omega = \{x: x \geq 0\}$ .

$$x^* = \arg \min_{x \in \Omega} f(x) = 0.$$

Note: If  $\Omega = \mathbb{R}$ , then  $x^* = \arg \min_{x \in \Omega} f(x) = -1$ .

## 1.2 CONDITIONS FOR LOCAL MINIMIZERS

- Global minimizers are, in general, **difficult** to find. Therefore, in practice, we often have to be **satisfied** with finding local minimizers.
- The **first-order derivative** of  $f: \mathbb{R}^n \rightarrow \mathbb{R}$ , denoted  $Df(\mathbf{x})$ , is

$$Df(\mathbf{x}) \triangleq \left[ \frac{\partial f(\mathbf{x})}{\partial x_1}, \dots, \frac{\partial f(\mathbf{x})}{\partial x_n} \right].$$

- The **gradient**  $\nabla f(\mathbf{x})$  is the transpose of  $Df(\mathbf{x})$ ; that is,  $\nabla f(\mathbf{x}) = (Df(\mathbf{x}))^\top$ .
- The **second derivative** of  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  (also called the Hessian of  $f$ ) is

$$D^2f(\mathbf{x}) \triangleq \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2}(\mathbf{x}) & \cdots & \frac{\partial^2 f}{\partial x_n \partial x_1}(\mathbf{x}) \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_1 \partial x_n}(\mathbf{x}) & \cdots & \frac{\partial^2 f}{\partial x_n^2}(\mathbf{x}) \end{bmatrix}.$$

**Example 1.2.1.** Let  $f(x_1, x_2) = 5x_1 + 8x_2 + x_1x_2 - x_1^2 - 2x_2^2$ . Find  $Df(\mathbf{x})$  and  $D^2f(\mathbf{x})$ .

$$Df(\mathbf{x}) = (\nabla f(\mathbf{x}))^\top = \left[ \frac{\partial f}{\partial x_1}(\mathbf{x}), \frac{\partial f}{\partial x_2}(\mathbf{x}) \right] = [5 + x_2 - 2x_1, 8 + x_1 - 4x_2]$$

and

$$D^2f(\mathbf{x}) = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2}(\mathbf{x}) & \cdots & \frac{\partial^2 f}{\partial x_n \partial x_1}(\mathbf{x}) \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_1 \partial x_n}(\mathbf{x}) & \cdots & \frac{\partial^2 f}{\partial x_n^2}(\mathbf{x}) \end{bmatrix} = \begin{bmatrix} -2 & 1 \\ 1 & -4 \end{bmatrix}.$$

- Given an optimization problem with constraint set  $\Omega$ , a minimizer may lie either in the **interior** or on the **boundary** of  $\Omega$ . To study the case where it lies on the boundary, we need the notion of **feasible directions**.
- **Definition 1.2** A vector  $\mathbf{d} \in \mathbb{R}^n$ ,  $\mathbf{d} \neq \mathbf{0}$ , is a **feasible direction** at  $\mathbf{x} \in \Omega$  if there exists  $\alpha_0 > 0$  such that  $\mathbf{x} + \alpha \mathbf{d} \in \Omega$  for all  $\alpha \in [0, \alpha_0]$ .
- Let  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  be a real-valued function and let  $\mathbf{d}$  be a feasible direction at  $\mathbf{x} \in \Omega$ . The **directional derivative** of  $f$  in the direction  $\mathbf{d}$ , denoted  $\partial f / \partial \mathbf{d}$ , is the real-valued function defined by

$$\frac{\partial f(\mathbf{x})}{\partial \mathbf{d}} = \lim_{\alpha \rightarrow 0} \frac{f(\mathbf{x} + \alpha \mathbf{d}) - f(\mathbf{x})}{\alpha} = \langle \nabla f(\mathbf{x}), \mathbf{d} \rangle = \mathbf{d}^\top \nabla f(\mathbf{x}).$$

- If  $\|\mathbf{d}\| = 1$ , then  $\partial f / \partial \mathbf{d}$  is the rate of increase of  $f$  at  $\mathbf{x}$  in the direction  $\mathbf{d}$ .

**Example 1.2.2.** Define  $f: \mathbb{R}^3 \rightarrow \mathbb{R}$  by  $f(\mathbf{x}) = x_1x_2x_3$ , and let  $\mathbf{d} = [1/2, 1/2, 1/\sqrt{2}]^\top$ . Find the directional derivative of  $f$  in the direction  $\mathbf{d}$ .

$$\frac{\partial f(\mathbf{x})}{\partial \mathbf{d}} = \nabla f(\mathbf{x})^\top \mathbf{d} = [x_2 x_3, x_1 x_3, x_1 x_2] \begin{bmatrix} 1/2 \\ 1/2 \\ 1/\sqrt{2} \end{bmatrix} = \frac{x_2 x_3 + x_1 x_3 + \sqrt{2} x_1 x_2}{2}.$$

Note that  $\|\mathbf{d}\| = \sqrt{(1/2)^2 + (1/2)^2 + (1/\sqrt{2})^2} = 1$ . The above is also the rate of increase of  $f$  at  $\mathbf{x}$  in the direction  $\mathbf{d}$ .

- **Theorem 1.1 First-Order Necessary Condition (FONC).** Let  $\Omega$  be a subset of  $\mathbb{R}^n$  and  $f \in C^1$  (i.e., the first derivative exists and is continuous) a real-valued function on  $\Omega$ . If  $\mathbf{x}^*$  is a local minimizer of  $f$  over  $\Omega$ , then for any feasible direction  $\mathbf{d}$  at  $\mathbf{x}^*$ , we have

$$\mathbf{d}^\top \nabla f(\mathbf{x}^*) \geq 0.$$

- **Corollary 1.1 Interior Case.** Let  $\Omega$  be a subset of  $\mathbb{R}^n$  and  $f \in C^1$  a real-valued function on  $\Omega$ . If  $\mathbf{x}^*$  is a local minimizer of  $f$  over  $\Omega$  and if  $\mathbf{x}^*$  is an interior point of  $\Omega$ , then

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

**Example 1.2.2.** Consider the problem

$$\text{minimize } x_1^2 + 0.5x_2^2 + 3x_2 + 4.5 \quad \text{subject to } x_1, x_2 \geq 0.$$

- Is the first-order necessary condition (FONC) for a local minimizer satisfied at  $\mathbf{x} = [1, 3]^\top$ ?
- Is the FONC for a local minimizer satisfied at  $\mathbf{x} = [0, 3]^\top$ ?
- Is the FONC for a local minimizer satisfied at  $\mathbf{x} = [1, 0]^\top$ ?
- Is the FONC for a local minimizer satisfied at  $\mathbf{x} = [1, 0]^\top$ ?

(a) At  $\mathbf{x} = [1, 3]^\top$ , we have  $\nabla f(\mathbf{x}) = [2x_1, x_2 + 3]^\top = [2, 6]^\top$ . The point  $\mathbf{x} = [1, 3]^\top$  is an interior point of  $\Omega = \{\mathbf{x}: x_1 \geq 0, x_2 \geq 0\}$ . Hence, the FONC requires that  $\nabla f(\mathbf{x}) = 0$ .

The point  $\mathbf{x} = [1, 3]^\top$  does not satisfy the FONC for a local minimizer.

(b) At  $\mathbf{x} = [0, 3]^\top$ , we have  $\nabla f(\mathbf{x}) = [2x_1, x_2 + 3]^\top = [0, 6]^\top$ , and hence  $\mathbf{d}^\top \nabla f(\mathbf{x}) = 6d_2$ , where  $\mathbf{d} = [d_1, d_2]^\top$ . For  $\mathbf{d}$  to be feasible at  $\mathbf{x}$ , we need  $d_1 \geq 0$  and  $d_2$  can take an arbitrary value in  $\mathbb{R}$ .

The point  $\mathbf{x} = [0, 3]^\top$  does not satisfy the FONC for a minimizer because  $d_2$  is allowed to be less than zero. For example,  $\mathbf{d} = [1, -1]^\top$  is a feasible direction, but  $\mathbf{d}^\top \nabla f(\mathbf{x}) = -6 < 0$ .

(c) At  $\mathbf{x} = [1, 0]^\top$ , we have  $\nabla f(\mathbf{x}) = [2x_1, x_2 + 3]^\top = [2, 3]^\top$ , and hence  $\mathbf{d}^\top \nabla f(\mathbf{x}) = 2d_1 + 3d_2$ , where  $\mathbf{d} = [d_1, d_2]^\top$ . For  $\mathbf{d}$  to be feasible at  $\mathbf{x}$ , we need  $d_2 \geq 0$  and  $d_1$  can take an arbitrary value in  $\mathbb{R}$ .

The point  $\mathbf{x} = [1, 0]^\top$  does not satisfy the FONC for a minimizer because  $d_1$  is allowed to be less than zero. For example,  $\mathbf{d} = [-5, 1]^\top$  is a feasible direction, but  $\mathbf{d}^\top \nabla f(\mathbf{x}) = -7 < 0$ .

(d) At  $\mathbf{x} = [0, 0]^\top$ , we have  $\nabla f(\mathbf{x}) = [2x_1, x_2 + 3]^\top = [0, 3]^\top$ , and hence  $\mathbf{d}^\top \nabla f(\mathbf{x}) = 3d_2$ , where  $\mathbf{d} = [d_1, d_2]^\top$ . For  $\mathbf{d}$  to be feasible at  $\mathbf{x}$ , we need  $d_1 \geq 0$  and  $d_2 \geq 0$ . The point  $\mathbf{x} = [1, 0]^\top$  satisfies the FONC because  $\mathbf{d}^\top \nabla f(\mathbf{x}) = 3d_2 \geq 0$ .

**Example 1.2.2.** Consider the set-constrained problem

$$\text{minimize } f(\mathbf{x}) \quad \text{subject to } \mathbf{x} \in \Omega = \{[x_1, x_2]^\top : x_1^2 + x_2^2 = 1\}.$$

(a) Consider a point  $\mathbf{x}^* \in \Omega$ . Specify all feasible directions at  $\mathbf{x}^*$ .

(b) Which points in  $\Omega$  satisfy the FONC for this set-constrained problem?

(c) Based on part (b), is the FONC for this set-constrained problem useful for eliminating local-minimizer candidates?

(d) Suppose that we use polar coordinates to parameterize points  $\mathbf{x} \in \Omega$  in terms of a single parameter  $\theta$ :

$$x_1 = \cos \theta \quad x_2 = \sin \theta.$$

Now use the FONC for unconstrained problems (with respect to  $\theta$ ) to derive a necessary condition of this sort: if  $\mathbf{x}^* \in \Omega$  is a local minimizer, then  $\mathbf{d}^\top \nabla f(\mathbf{x}^*) = 0$  for all  $\mathbf{d}$  satisfying a “certain condition.” Specify what this certain condition is.

(a) There are no feasible directions at any  $\mathbf{x}^*$ .

(b) Because of part a, all points in  $\Omega$  satisfy the FONC for this set-constrained problem.

(c) No, the FONC for this set-constrained problem is not useful for eliminating local-minimizer candidates.

(d) Write  $h(\theta) = f(g(\theta))$ , where  $g: \mathbb{R} \rightarrow \mathbb{R}^2$  is given by the equations relating  $\theta$  to  $\mathbf{x} = [x_1, x_2]^\top$ . Note that  $Dg(\theta) = [-\sin \theta, \cos \theta]^\top$ . Hence, by the chain rule,

$$h'(\theta) = Df(g(\theta))Dg(\theta) = Dg(\theta)^\top \nabla f(g(\theta)).$$

Notice that  $Dg(\theta)$  is **tangent** to  $\Omega$  at  $\mathbf{x} = g(\theta)$ . Alternatively, we could say that  $Dg(\theta)$  is orthogonal to  $\mathbf{x} = g(\theta)$ . Suppose that  $\mathbf{x}^* \in \Omega$  is a local minimizer. Write  $\mathbf{x}^* = g(\theta^*)$ . Then  $\theta^*$  is an unconstrained minimizer of  $h$ . By the FONC for unconstrained problems,  $h'(\theta^*) = 0$ , which implies that  $\mathbf{d}^\top \nabla f(\mathbf{x}^*) = 0$  for all  $\mathbf{d}$  tangent to  $\Omega$  at  $\mathbf{x}^*$  (or, alternatively, for all  $\mathbf{d}$  orthogonal to  $\mathbf{x}^*$ ).

- **Theorem 1.2 Second-Order Necessary Condition (SONC).** Let  $\Omega \subset \mathbb{R}^n$ ,  $f \in C^2$  a function on  $\Omega$ ,  $\mathbf{x}^*$  a local minimizer of  $f$  over  $\Omega$ , and  $\mathbf{d}$  a feasible direction at  $\mathbf{x}^*$ . If  $\mathbf{d}^\top \nabla f(\mathbf{x}^*) = 0$ , then

$$\mathbf{d}^\top \mathbf{F}(\mathbf{x}^*) \mathbf{d} \geq 0,$$

where  $\mathbf{F}$  is the Hessian of  $f$ .

- **Corollary 1.2 Interior Case.** Let  $\mathbf{x}^*$  be an interior point of  $\Omega \subset \mathbb{R}^n$ . If  $\mathbf{x}^*$  is a local minimizer of  $f: \Omega \rightarrow \mathbb{R}$ ,  $f \in C^2$ , then

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

and  $\mathbf{F}(\mathbf{x}^*)$  is positive semidefinite ( $\mathbf{F}(\mathbf{x}^*) \geq 0$ ); that is, for all  $\mathbf{d} \in \mathbb{R}^n$ ,

$$\mathbf{d}^\top \mathbf{F}(\mathbf{x}^*) \mathbf{d} \geq 0.$$

**Example 1.6** Consider a function of one variable  $f(x) = x^3$ ,  $f: \mathbb{R} \rightarrow \mathbb{R}$ . Does the point  $x = 0$  satisfy both the FONC and SONC?

$x = 0$  is an interior point. Then,  $\nabla f(x^*) = 3x^2$  and  $F(x^*) = 6x$ . Hence, both the FONC and SONC are satisfied:  $\nabla f(0) = 0$  and  $F(0) = 0$ .

**Example 1.7** Consider a function  $f: \mathbb{R}^2 \rightarrow \mathbb{R}$ , where  $f(\mathbf{x}) = x_1^2 - x_2^2$ . Does the point  $\mathbf{x} = [0, 0]^\top$  satisfy both the FONC and SONC?

The FONC requires that  $\nabla f(\mathbf{x}) = [2x_1, -2x_2]^\top = 0$ . Thus,  $\mathbf{x} = [0, 0]^\top$  satisfies the FONC.

The Hessian matrix of  $f$  is

$$\mathbf{F}(\mathbf{x}) = \begin{bmatrix} 2 & 0 \\ 0 & -2 \end{bmatrix}.$$

The Hessian matrix is indefinite; that is, for some  $\mathbf{d}_1 \in \mathbb{R}^2$  we have  $\mathbf{d}_1^\top \mathbf{F} \mathbf{d}_1 > 0$  (e.g.,  $\mathbf{d}_1 = [1, 0]^\top$ ); and, for some  $\mathbf{d}_2$ , we have  $\mathbf{d}_2^\top \mathbf{F} \mathbf{d}_2 < 0$  (e.g.,  $\mathbf{d}_2 = [0, 1]^\top$ ). Thus,  $\mathbf{x} = [0, 0]^\top$  does not satisfy the SONC, and hence it is not a minimizer.

- **Theorem 1.3 Second-Order Sufficient Condition (SOSC), Interior Case.** Let  $f \in C^2$  be defined on a region in which  $\mathbf{x}^*$  is an interior point. Suppose that

1.  $\nabla f(\mathbf{x}^*) = 0$ .
2.  $\mathbf{F}(\mathbf{x}^*) > 0$ .

Then,  $\mathbf{x}^*$  is a strict local minimizer of  $f$ .

**Example 1.8** Let  $f(\mathbf{x}) = x_1^2 + x_2^2$ . We have Consider a function  $f: \mathbb{R}^2 \rightarrow \mathbb{R}$ , where  $f(\mathbf{x}) = x_1^2 - x_2^2$ . Does the point  $\mathbf{x} = [0, 0]^\top$  satisfy the FONC, SONC, and SOSC?

We have  $\nabla f(\mathbf{x}) = [2x_1, 2x_2]^\top = 0$  if and only if  $\mathbf{x} = [0, 0]^\top$ . For all  $\mathbf{x} \in \mathbb{R}^2$ , we have

$$\mathbf{F}(\mathbf{x}) = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} > 0.$$

satisfies the FONC, SONC, and SOSC.

## APPENDIX

- **Theorem 1.1 First-Order Necessary Condition (FONC).** Let  $\Omega$  be a subset of  $\mathbb{R}^n$  and  $f \in C^1$  (i.e., the first derivative exists and is continuous) a real-valued function on  $\Omega$ . If  $\mathbf{x}^*$  is a local minimizer of  $f$  over  $\Omega$ , then for any feasible direction  $\mathbf{d}$  at  $\mathbf{x}^*$ , we have

$$\mathbf{d}^\top \nabla f(\mathbf{x}^*) \geq 0.$$

*Proof.* Define

$$\mathbf{x}(\alpha) = \mathbf{x}^* + \alpha \mathbf{d} \in \Omega.$$

Note that  $\mathbf{x}(0) = \mathbf{x}^*$ . Define the composite function

$$\phi(\alpha) = f(\mathbf{x}(\alpha)).$$

Then, by Taylor's theorem,

$$f(\mathbf{x}^* + \alpha \mathbf{d}) - f(\mathbf{x}^*) = \phi(\alpha) - \phi(0) = \phi'(0)\alpha + o(\alpha) = \alpha \mathbf{d}^\top \nabla f(\mathbf{x}(0)) + o(\alpha),$$

where  $\alpha \geq 0$ . Thus, if  $\phi(\alpha) \geq \phi(0)$ , that is,  $f(\mathbf{x}^* + \alpha \mathbf{d}) \geq f(\mathbf{x}^*)$  for sufficiently small values of  $\alpha > 0$ , then we have to have  $\mathbf{d}^\top \nabla f(\mathbf{x}(0)) \geq 0$ .

- **Corollary 1.1 Interior Case.** Let  $\Omega$  be a subset of  $\mathbb{R}^n$  and  $f \in C^1$  a real-valued function on  $\Omega$ . If  $\mathbf{x}^*$  is a local minimizer of  $f$  over  $\Omega$  and if  $\mathbf{x}^*$  is an interior point of  $\Omega$ , then

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

*Proof.* Suppose that  $f$  has a local minimizer  $\mathbf{x}^*$  that is an interior point of  $\Omega$ . Because  $\mathbf{x}^*$  is an interior point of  $\Omega$ , the set of feasible directions at  $\mathbf{x}^*$  is the whole of  $\mathbb{R}^n$ . Thus, for any  $\mathbf{d} \in \mathbb{R}^n$ ,  $\mathbf{d}^\top \nabla f(\mathbf{x}^*) \geq 0$  and  $-\mathbf{d}^\top \nabla f(\mathbf{x}^*) \geq 0$ . Hence,  $\mathbf{d}^\top \nabla f(\mathbf{x}^*) = 0$  for all  $\mathbf{d} \in \mathbb{R}^n$ , which implies that  $\nabla f(\mathbf{x}^*) = \mathbf{0}$ .

- **Theorem 1.2 Second-Order Necessary Condition (SONC).** Let  $\Omega \subset \mathbb{R}^n$ ,  $f \in C^2$  a function on  $\Omega$ ,  $\mathbf{x}^*$  a local minimizer of  $f$  over  $\Omega$ , and  $\mathbf{d}$  a feasible direction at  $\mathbf{x}^*$ . If  $\mathbf{d}^\top \nabla f(\mathbf{x}^*) = 0$ , then

$$\mathbf{d}^\top \mathbf{F}(\mathbf{x}^*) \mathbf{d} \geq 0,$$

where  $\mathbf{F}$  is the Hessian of  $f$ .

*Proof.* We prove the result by contradiction. Suppose there is a feasible direction  $\mathbf{d}$  at  $\mathbf{x}^*$  such that  $\mathbf{d}^\top \nabla f(\mathbf{x}^*) = 0$  and  $\mathbf{d}^\top \mathbf{F}(\mathbf{x}^*) \mathbf{d} < 0$ . Let  $\mathbf{x}(\alpha) = \mathbf{x}^* + \alpha \mathbf{d}$  and define the composite function  $\phi(\alpha) = f(\mathbf{x}^* + \alpha \mathbf{d}) = f(\mathbf{x}(\alpha))$ . Then, by Taylor's theorem,

$$\phi(\alpha) = \phi(0) + \phi''(0) \frac{\alpha^2}{2} + o(\alpha^2),$$

where by assumption,  $\phi'(0) = \mathbf{d}^\top \nabla F(\mathbf{x}^*) = 0$  and  $\phi''(0) = \mathbf{d}^\top \mathbf{F}(\mathbf{x}^*) \mathbf{d} < 0$ .

For sufficiently small  $\alpha$ ,

$$\phi(\alpha) - \phi(0) = \phi''(0) \frac{\alpha^2}{2} + o(\alpha^2) < 0,$$

that is,

$$f(\mathbf{x}^* + \alpha \mathbf{d}) < f(\mathbf{x}^*),$$

which contradicts the assumption that  $\mathbf{x}^*$  is a local minimizer. Thus,

$$\phi''(0) = \mathbf{d}^\top \mathbf{F}(\mathbf{x}^*) \mathbf{d} \geq 0.$$

- **Corollary 1.2 Interior Case.** Let  $\mathbf{x}^*$  be an interior point of  $\Omega \subset \mathbb{R}^n$ . If  $\mathbf{x}^*$  is a local minimizer of  $f: \Omega \rightarrow \mathbb{R}$ ,  $f \in C^2$ , then

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

and  $\mathbf{F}(\mathbf{x}^*)$  is positive semidefinite ( $\mathbf{F}(\mathbf{x}^*) \geq 0$ ); that is, for all  $\mathbf{d} \in \mathbb{R}^n$ ,

$$\mathbf{d}^\top \mathbf{F}(\mathbf{x}^*) \mathbf{d} \geq 0.$$

*Proof.* If  $\mathbf{x}^*$  is an interior point, then all directions are feasible. The result then follows from Corollary 1.1 and Theorem 1.2.

- **Theorem 1.3 Second-Order Sufficient Condition (SOSC), Interior Case.** Let  $f \in C^2$  be defined on a region in which  $\mathbf{x}^*$  is an interior point. Suppose that

1.  $\nabla f(\mathbf{x}^*) = \mathbf{0}$ .
2.  $\mathbf{F}(\mathbf{x}^*) > 0$ .

Then,  $\mathbf{x}^*$  is a strict local minimizer of  $f$ .

*Proof.* Because  $f \in C^2$ , we have  $\mathbf{F}(\mathbf{x}^*) = \mathbf{F}^\top(\mathbf{x}^*)$ . Using assumption 2 and Rayleigh's inequality it follows that if  $\mathbf{d} \neq \mathbf{0}$ , then  $0 < \lambda_{\min}(\mathbf{F}(\mathbf{x}^*)) \|\mathbf{d}\|^2 \leq \mathbf{d}^\top \mathbf{F}(\mathbf{x}^*) \mathbf{d}$ .

By Taylor's theorem and assumption 1,

$$f(\mathbf{x}^* + \mathbf{d}) - f(\mathbf{x}^*) = \frac{1}{2} \mathbf{d}^\top \mathbf{F}(\mathbf{x}^*) \mathbf{d} + o(\|\mathbf{d}\|^2) \geq \frac{\lambda_{\min}(\mathbf{F}(\mathbf{x}^*))}{2} \|\mathbf{d}\|^2 + o(\|\mathbf{d}\|^2).$$

Hence, for all  $\mathbf{d}$  such that  $\|\mathbf{d}\|$  is sufficiently small,

$$f(\mathbf{x}^* + \mathbf{d}) > f(\mathbf{x}^*),$$

which completes the proof.