1 BASICS OF SET CONTSTRAINED AND UNCONSTRAINED OPTIMIZATION

1.1 INTRODUCTION

• Consider the optimization problem

minimize f(x) subject to $x \in \Omega$.

- The function $f: \mathbb{R}^n \to \mathbb{R}$ 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**: $\mathbf{x} = [x_1, ..., x_n]^{\mathsf{T}} \in \mathbb{R}^n$.
- The set Ω is a subset of \mathbb{R}^n called the **constraint set** or **feasible set**, which takes the form $\Omega = \{x: h(x) = 0, g(x) \leq 0\}$, where h and g are given functions.
- The **minimizer** of f over Ω is a vector \mathbf{x} which results in the smallest value of the objective function.
- **Definition 1.1.1** Suppose that $f: \mathbb{R}^n \to \mathbb{R}$ 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 Ω if there exists $\varepsilon > 0$ such that $f(x) \ge f(x^*)$ for all $x \in \Omega \setminus \{x^*\}$ and $||x x^*|| < \varepsilon$. A point $x^* \in \Omega$ is a **global minimizer** of f over Ω if $f(x) \ge f(x^*)$ for all $x \in \Omega \setminus \{x^*\}$.
- If x^* is a global minimizer of f over Ω , we write $f(x^*) = \min_{x \in \Omega} f(x)$ and $x^* = \underset{x \in \Omega}{\operatorname{argmin}} f(x)$.

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

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

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 $f: \mathbb{R}^n \to \mathbb{R}$, denoted Df(x), is

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

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

$$D^{2}f(\mathbf{x}) \triangleq \begin{bmatrix} \frac{\partial^{2}f}{\partial x_{1}^{2}}(\mathbf{x}) & \cdots & \frac{\partial^{2}f}{\partial x_{n}\partial x_{1}}(\mathbf{x}) \\ \vdots & \ddots & \vdots \\ \frac{\partial^{2}f}{\partial x_{1}\partial x_{n}}(\mathbf{x}) & \cdots & \frac{\partial^{2}f}{\partial x_{n}^{2}}(\mathbf{x}) \end{bmatrix}.$$

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(x) and $D^2f(x)$.

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

and

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

- Given an optimization problem with constraint set Ω , a minimizer may lie either in the **interior** or on the **boundary** of Ω . To study the case where it lies on the boundary, we need the notion of **feasible directions**.
- **Definition 1.2.1** 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 $f: \mathbb{R}^n \to \mathbb{R}$ be a real-valued function and let d be a feasible direction at $x \in \Omega$. The **directional derivative** of f in the direction d, denoted $\partial f/\partial d$, is the real-valued function defined by

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

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

Example 1.2.2. Define $f: \mathbb{R}^3 \to \mathbb{R}$ by $f(x) = x_1 x_2 x_3$, and let $\mathbf{d} = \begin{bmatrix} 1/2, 1/2, 1/\sqrt{2} \end{bmatrix}^\mathsf{T}$. Find the directional derivative of f in the direction \mathbf{d} .

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

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

• Theorem 1.2.2 First-Order Necessary Condition (FONC). Let Ω 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 Ω . If x^* is a local minimizer of f over Ω , then for any feasible direction d at x^* , we have

$$\boldsymbol{d}^{\mathsf{T}} \nabla f(\boldsymbol{x}^*) \geq 0.$$

• Corollary 1.2.3 Interior Case. Let Ω be a subset of \mathbb{R}^n and $f \in C^1$ a real-valued function on Ω . If x^* is a local minimizer of f over Ω and if x^* is an interior point of Ω , then

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

Example 1.2.3. Consider the problem

minimize
$$x_1^2 + 0.5x_2^2 + 3x_2 + 4.5$$
 subject to $x_1, x_2 \ge 0$.

- (a) Is the first-order necessary condition (FONC) for a local minimizer satisfied at $x = [1,3]^T$?
- (b) Is the FONC for a local minimizer satisfied at $x = [0,3]^{T}$?
- (c) Is the FONC for a local minimizer satisfied at $x = [1, 0]^T$?
- (d) Is the FONC for a local minimizer satisfied at $x = [0, 0]^{\mathsf{T}}$?
- (a) At $\boldsymbol{x} = [1,3]^{\mathsf{T}}$, we have $\nabla f(\boldsymbol{x}) = [2x_1,x_2+3]^{\mathsf{T}} = [2,6]^{\mathsf{T}}$. The point $\boldsymbol{x} = [1,3]^{\mathsf{T}}$ is an interior point of $\Omega = \{\boldsymbol{x}: x_1 \geq 0, x_2 \geq 0\}$. Hence, the FONC requires that $\nabla f(\boldsymbol{x}) = 0$.

The point $x = [1, 3]^T$ does not satisfy the FONC for a local minimizer.

(b) At $\mathbf{x} = [0,3]^{\mathsf{T}}$, we have $\nabla f(\mathbf{x}) = [2x_1, x_2 + 3]^{\mathsf{T}} = [0,6]^{\mathsf{T}}$, and hence $\mathbf{d}^{\mathsf{T}} \nabla f(\mathbf{x}) = 6d_2$, where $\mathbf{d} = [d_1, d_2]^{\mathsf{T}}$. 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 $\mathbf{x} = [0,3]^{\mathsf{T}}$ does not satisfy the FONC for a minimizer because d_2 is allowed to be less than zero. For example, $\mathbf{d} = [1,-1]^{\mathsf{T}}$ is a feasible direction, but $\mathbf{d}^{\mathsf{T}} \nabla f(\mathbf{x}) = -6 < 0$.

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(c) At $\mathbf{x} = [1,0]^{\mathsf{T}}$, we have $\nabla f(\mathbf{x}) = [2x_1, x_2 + 3]^{\mathsf{T}} = [2,3]^{\mathsf{T}}$, and hence $\mathbf{d}^{\mathsf{T}} \nabla f(\mathbf{x}) = 2d_1 + 3d_2$, where $\mathbf{d} = [d_1, d_2]^{\mathsf{T}}$. 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 $\mathbf{x} = [1, 0]^{\mathsf{T}}$ does not satisfy the FONC for a minimizer because d_1 is allowed to be less than zero. For example, $\mathbf{d} = [-5, 1]^{\mathsf{T}}$ is a feasible direction, but $\mathbf{d}^{\mathsf{T}} \nabla f(\mathbf{x}) = -7 < 0$.

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

• Theorem 1.2.4 Second-Order Necessary Condition (SONC). Let $\Omega \subset \mathbb{R}^n$, $f \in C^2$ a function on Ω , x^* a local minimizer of f over Ω , and d a feasible direction at x^* . If $d^T \nabla f(x^*) = 0$, then

$$\boldsymbol{d}^{\mathsf{T}}\boldsymbol{F}(\boldsymbol{x}^*)\boldsymbol{d}\geq 0,$$

where F is the Hessian of f.

• Corollary 1.2.5 Interior Case. Let x^* be an interior point of $\Omega \subset \mathbb{R}^n$. If x^* is a local minimizer of $f: \Omega \to \mathbb{R}$, $f \in C^2$, then $\nabla f(x^*) = \mathbf{0}$, and $F(x^*)$ is positive semidefinite $(F(x^*) \geq 0)$; that is, for all $d \in \mathbb{R}^n$, $d^T F(x^*) d \geq 0$.

Example 1.2.4 Consider a function of one variable $f(x) = x^3$, $f: \mathbb{R} \to \mathbb{R}$. 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 1.2.5 Consider a function $f: \mathbb{R}^2 \to \mathbb{R}$, where $f(x) = x_1^2 - x_2^2$. Does the point $x = [0,0]^T$ satisfy both the FONC and SONC?

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

The Hessian matrix of f is

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

The Hessian matrix is indefinite; that is, for some $d_1 \in \mathbb{R}^2$ we have $d_1^T F d_1 > 0$ (e.g., $d_1 = [1,0]^T$); and, for some d_2 , we have $d_2^T F d_2 < 0$ (e.g., $d_2 = [0,1]^T$). Thus, $x = [0,0]^T$ does not satisfy the SONC, and hence it is not a minimizer.

- Theorem 1.2.6 Second-Order Sufficient Condition (SOSC), Interior Case. Let $f \in C^2$ be defined on a region in which x^* is an interior point. Suppose that
 - 1. $\nabla f(\mathbf{x}^*) = 0$.
 - 2. $F(x^*) > 0$.

Then, x^* is a strict local minimizer of f.

Example 1.2.6 Consider a function $f: \mathbb{R}^2 \to \mathbb{R}$, where $f(x) = x_1^2 + x_2^2$. Does the point $x = [0,0]^T$ satisfy the FONC, SONC, and SOSC?

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

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

satisfies the FONC, SONC, and SOSC.

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• Theorem 1.2.2 First-Order Necessary Condition (FONC). Let Ω 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 Ω . If x^* is a local minimizer of f over Ω , then for any feasible direction d at x^* , we have

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

Proof. Define $x(\alpha) = x^* + \alpha d \in \Omega$. Note that $x(0) = x^*$. Define the composite function

$$\phi(\alpha) = f(x(\alpha)).$$

Then, by Taylor's theorem,

$$f(\mathbf{x}^* + \alpha \mathbf{d}) - f(\mathbf{x}^*) = \phi(\alpha) - \phi(0) = \phi'(0)\alpha + o(\alpha) = \alpha \mathbf{d}^{\mathsf{T}} \nabla f(\mathbf{x}(0)) + o(\alpha),$$

where $\alpha \geq 0$ and $o(\alpha)$ means that $\lim_{\alpha \to 0} o(\alpha)/\alpha = 0$. 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 $d^{\mathsf{T}} \nabla f(\mathbf{x}(0)) \geq 0$.

• Corollary 1.2.3 Interior Case. Let Ω be a subset of \mathbb{R}^n and $f \in C^1$ a real-valued function on Ω . If x^* is a local minimizer of f over Ω and if x^* is an interior point of Ω , then

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

Proof. Suppose that f has a local minimizer \mathbf{x}^* that is an interior point of Ω . Because \mathbf{x}^* is an interior point of Ω , 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 $d \in \mathbb{R}^n$, which implies that $\nabla f(\mathbf{x}^*) = \mathbf{0}$.

• Theorem 1.2.4 Second-Order Necessary Condition (SONC). Let $\Omega \subset \mathbb{R}^n$, $f \in C^2$ a function on Ω , x^* a local minimizer of f over Ω , and d a feasible direction at x^* . If $d^{\mathsf{T}}\nabla f(x^*) = 0$, then

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

where F is the Hessian of f.

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

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

where, by assumption, $\phi'(0) = \mathbf{d}^{\mathsf{T}} \nabla F(\mathbf{x}^*) = 0$ and $\phi''(0) = \mathbf{d}^{\mathsf{T}} F(\mathbf{x}^*) \mathbf{d} < 0$. For sufficiently small α ,

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

that is,

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

which contradicts the assumption that x^* is a local minimizer. Thus,

$$\phi''(0) = \mathbf{d}^{\mathsf{T}} \mathbf{F}(\mathbf{x}^*) \mathbf{d} \ge 0.$$

• Corollary 1.2.5 Interior Case. Let x^* be an interior point of $\Omega \subset \mathbb{R}^n$. If x^* is a local minimizer of $f: \Omega \to \mathbb{R}$, $f \in C^2$, then

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

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

$$\boldsymbol{d}^{\mathsf{T}}\boldsymbol{F}(\boldsymbol{x}^*)\boldsymbol{d}\geq 0.$$

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

- Theorem 1.2.6 Second-Order Sufficient Condition (SOSC), Interior Case. Let $f \in C^2$ be defined on a region in which x^* is an interior point. Suppose that
 - 1. $\nabla f(\mathbf{x}^*) = 0$.
 - 2. $F(x^*) > 0$.

Then, x^* is a strict local minimizer of f.

Proof. Because $f \in C^2$, we have $F(x^*) = F^{\mathsf{T}}(x^*)$. Using assumption 2 and Rayleigh's inequality it follows that if $d \neq 0$, then $0 < \lambda_{\min}(F(x^*)) ||d||^2 \le d^{\mathsf{T}} F(x^*) d$.

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By Taylor's theorem and assumption 1,

$$f(x^* + d) - f(x^*) = \frac{1}{2}d^{\mathsf{T}}F(x^*)d + o(\|d\|^2) \ge \frac{\lambda_{\min}(F(x^*))}{2}\|d\|^2 + o(\|d\|^2).$$

Hence, for all d such that ||d|| is sufficiently small,

$$f(x^* + d) > f(x^*),$$

which completes the proof.