

Proof:

Since $\hat{\mathbf{x}} \notin \text{int}(C)$, there is a sequence $\{\mathbf{x}_k\}$ which does not belong to the closure of C , \bar{C} , and converges to $\hat{\mathbf{x}}$. Now, denote by $p(\mathbf{x}_k)$ the orthogonal projection of \mathbf{x}_k into \bar{C} by a standard norm. One can see that by the convexity of \bar{C} [Bertsekas]

$$(p(\mathbf{x}_k) - \mathbf{x}_k)^T(\mathbf{x} - p(\mathbf{x}_k)) \geq 0, \quad \forall \mathbf{x} \in \bar{C}.$$

Hence,

$$(p(\mathbf{x}_k) - \mathbf{x}_k)^T \mathbf{x} \geq (p(\mathbf{x}_k) - \mathbf{x}_k)^T p(\mathbf{x}_k) = (p(\mathbf{x}_k) - \mathbf{x}_k)^T (p(\mathbf{x}_k) - \mathbf{x}_k) + (p(\mathbf{x}_k) - \mathbf{x}_k)^T \mathbf{x}_k \geq (p(\mathbf{x}_k) - \mathbf{x}_k)^T \mathbf{x}_k.$$

Now, since $\mathbf{x}_k \notin \bar{C}$, calling $\mathbf{d}_k = \frac{p(\mathbf{x}_k) - \mathbf{x}_k}{\|p(\mathbf{x}_k) - \mathbf{x}_k\|}$,

$$\mathbf{d}_k^T \mathbf{x} \geq \mathbf{d}_k^T \mathbf{x}_k, \quad \forall \mathbf{x} \in \bar{C}.$$

Since $\|\mathbf{d}_k\| = 1$, it has a converging subsequence which will converge to let us say \mathbf{d} . Taking the same indices for this subsequence for \mathbf{x}_k , we have the desired result. \blacksquare

Theorem 2.2 (Separation Theorem for Convex Sets) Let C_1 and C_2 nonempty non-intersecting convex subsets of \mathbb{R}^n . Then, $\exists \mathbf{d} \in \mathbb{R}^n$, $\mathbf{d} \neq \mathbf{0}$ such that

$$\sup_{\mathbf{x}_1 \in C_1} \mathbf{d}^T \mathbf{x}_1 \leq \inf_{\mathbf{x}_2 \in C_2} \mathbf{d}^T \mathbf{x}_2.$$

Proof:

Consider the set

$$C := \{\mathbf{x}_2 - \mathbf{x}_1 \in \mathbb{R}^n \mid \mathbf{x}_2 \in C_2, \mathbf{x}_1 \in C_1\}$$

which is convex by Propositions 1.10 and 1.11.

Since C_1 and C_2 are disjoint, the origin $\mathbf{0}$ does not belong to the interior of C . From Proposition 2.1, there is $\mathbf{d} \neq \mathbf{0}$ such that $\mathbf{d}^T \mathbf{x} \geq \mathbf{0}$, $\forall \mathbf{x} \in C$. Therefore

$$\mathbf{d}^T \mathbf{x}_1 \leq \mathbf{d}^T \mathbf{x}_2, \quad \forall \mathbf{x}_1 \in C_1 \text{ and } \mathbf{x}_2 \in C_2.$$

Finally, since both C_1 and C_2 are nonempty, it follows the result. \blacksquare

Remark 2.3 The Separation Theorem for Convex Sets is an essential result to show the strong duality theorem in convex optimization problems (see for example [Bertsekas]).

3 Lipschitz Continuous Differentiable Functions

Definition 3.1 Let $\mathbf{x} \in \mathbb{R}^n$ and $\mathbf{s} \in \mathbb{R}^n$ be a direction (vector) in \mathbb{R}^n . Then the one-sided *directional derivative* of a function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ in the direction \mathbf{s} is defined as

$$f'(\mathbf{x}; \mathbf{s}) := \lim_{\alpha \downarrow 0} \frac{f(\mathbf{x} + \alpha \mathbf{s}) - f(\mathbf{x})}{\alpha}.$$

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a differentiable function on \mathbb{R}^n . Then for any $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, we have

$$f(\mathbf{y}) = f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle + o(\|\mathbf{y} - \mathbf{x}\|_2),$$

where $o(r)$ is some function of $r > 0$ such that

$$\lim_{r \rightarrow 0} \frac{1}{r} o(r) = 0, \quad o(0) = 0.$$

We say that the function is continuously differentiable if the function $\nabla f : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is continuous.

Hereafter, we define for $\mathbf{a}, \mathbf{b} \in \mathbb{R}^n$, the standard inner product $\langle \mathbf{a}, \mathbf{b} \rangle := \sum_{i=1}^n a_i b_i$, and the associated norm $\|\mathbf{a}\|_2 := \sqrt{\langle \mathbf{a}, \mathbf{a} \rangle}$ to it.

Definition 3.2 Let Q be a subset of \mathbb{R}^n . We denote by $\mathcal{C}_L^{k,p}(Q)$ the class of functions with the following properties:

- Any $f \in \mathcal{C}_L^{k,p}(Q)$ is k times continuously differentiable on Q ;
- Its p th derivative is Lipschitz continuous on Q with the constant $L \geq 0$:

$$\|\mathbf{f}^{(p)}(\mathbf{x}) - \mathbf{f}^{(p)}(\mathbf{y})\|_2 \leq L\|\mathbf{x} - \mathbf{y}\|_2, \quad \forall \mathbf{x}, \mathbf{y} \in Q.$$

In particular, $\mathbf{f}^{(1)}(\mathbf{x}) = \nabla \mathbf{f}(\mathbf{x})$ and $\mathbf{f}^{(2)}(\mathbf{x}) = \nabla^2 \mathbf{f}(\mathbf{x})$. Observe that if $f_1 \in \mathcal{C}_{L_1}^{k,p}(Q)$, $f_2 \in \mathcal{C}_{L_2}^{k,p}(Q)$, and $\alpha, \beta \in \mathbb{R}$, then for $L_3 = |\alpha|L_1 + |\beta|L_2$ we have $\alpha f_1 + \beta f_2 \in \mathcal{C}_{L_3}^{k,p}(Q)$.

Lemma 3.3 Let $f \in \mathcal{C}^2(\mathbb{R}^n)$. Then $f \in \mathcal{C}_L^{2,1}(\mathbb{R}^n)$ if and only if $\|\nabla^2 \mathbf{f}(\mathbf{x})\|_2 \leq L, \quad \forall \mathbf{x} \in \mathbb{R}^n$.

Proof:

For $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$,

$$\begin{aligned} \nabla \mathbf{f}(\mathbf{y}) &= \nabla \mathbf{f}(\mathbf{x}) + \int_0^1 \nabla^2 \mathbf{f}(\mathbf{x} + \tau(\mathbf{y} - \mathbf{x}))(\mathbf{y} - \mathbf{x}) d\tau \\ &= \nabla \mathbf{f}(\mathbf{x}) + \left(\int_0^1 \nabla^2 \mathbf{f}(\mathbf{x} + \tau(\mathbf{y} - \mathbf{x})) d\tau \right) (\mathbf{y} - \mathbf{x}). \end{aligned}$$

Since $\|\nabla^2 \mathbf{f}(\mathbf{x})\|_2 \leq L$,

$$\begin{aligned} \|\nabla \mathbf{f}(\mathbf{y}) - \nabla \mathbf{f}(\mathbf{x})\|_2 &\leq \left\| \int_0^1 \nabla^2 \mathbf{f}(\mathbf{x} + \tau(\mathbf{y} - \mathbf{x})) d\tau \right\|_2 \|\mathbf{y} - \mathbf{x}\|_2 \\ &\leq \int_0^1 \|\nabla^2 \mathbf{f}(\mathbf{x} + \tau(\mathbf{y} - \mathbf{x}))\|_2 d\tau \|\mathbf{y} - \mathbf{x}\|_2 \\ &\leq L\|\mathbf{y} - \mathbf{x}\|_2. \end{aligned}$$

On the other hand, for $\mathbf{s} \in \mathbb{R}^n$, and $\alpha \in \mathbb{R}, \alpha \neq 0$,

$$\|\nabla \mathbf{f}(\mathbf{x} + \alpha \mathbf{s}) - \nabla \mathbf{f}(\mathbf{x})\|_2 \leq |\alpha|L\|\mathbf{s}\|_2.$$

Dividing both sides by $|\alpha|$ and taking the limit to zero,

$$\|\nabla^2 \mathbf{f}(\mathbf{x})\mathbf{s}\|_2 \leq L\|\mathbf{s}\|_2, \quad \mathbf{s} \in \mathbb{R}^n.$$

Therefore, $\|\nabla^2 \mathbf{f}(\mathbf{x})\|_2 \leq L$. ■

Example 3.4

1. The linear function $f(\mathbf{x}) = \alpha + \langle \mathbf{a}, \mathbf{x} \rangle \in \mathcal{C}_0^{2,1}(\mathbb{R}^n)$ since

$$\nabla \mathbf{f}(\mathbf{x}) = \mathbf{a}, \quad \nabla^2 \mathbf{f}(\mathbf{x}) = \mathbf{O}.$$

2. The quadratic function $f(\mathbf{x}) = \alpha + \langle \mathbf{a}, \mathbf{x} \rangle + 1/2 \langle \mathbf{A}\mathbf{x}, \mathbf{x} \rangle$ with $\mathbf{A} = \mathbf{A}^T$ belongs to $\mathcal{C}_L^{2,1}(\mathbb{R}^n)$ where

$$\nabla \mathbf{f}(\mathbf{x}) = \mathbf{a} + \mathbf{A}\mathbf{x}, \quad \nabla^2 \mathbf{f}(\mathbf{x}) = \mathbf{A}, \quad L = \|\mathbf{A}\|_2.$$

3. The function $f(x) = \sqrt{1+x^2} \in \mathcal{C}_1^{2,1}(\mathbb{R})$ since

$$\nabla f(x) = \frac{x}{\sqrt{1+x^2}}, \quad \nabla^2 f(x) = \frac{1}{(1+x^2)^{3/2}} \leq 1.$$

Lemma 3.5 Let $f \in \mathcal{C}_L^{1,1}(\mathbb{R}^n)$. Then for any $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, we have

$$|f(\mathbf{y}) - f(\mathbf{x}) - \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle| \leq \frac{L}{2} \|\mathbf{y} - \mathbf{x}\|_2^2.$$

Proof:

For any $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, we have

$$\begin{aligned} f(\mathbf{y}) &= f(\mathbf{x}) + \int_0^1 \langle \nabla f(\mathbf{x} + \tau(\mathbf{y} - \mathbf{x})), \mathbf{y} - \mathbf{x} \rangle d\tau \\ &= f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle + \int_0^1 \langle \nabla f(\mathbf{x} + \tau(\mathbf{y} - \mathbf{x})) - \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle d\tau. \end{aligned}$$

Therefore,

$$\begin{aligned} |f(\mathbf{y}) - f(\mathbf{x}) - \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle| &= \left| \int_0^1 \langle \nabla f(\mathbf{x} + \tau(\mathbf{y} - \mathbf{x})) - \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle d\tau \right| \\ &\leq \int_0^1 |\langle \nabla f(\mathbf{x} + \tau(\mathbf{y} - \mathbf{x})) - \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle| d\tau \\ &\leq \int_0^1 \|\nabla f(\mathbf{x} + \tau(\mathbf{y} - \mathbf{x})) - \nabla f(\mathbf{x})\|_2 \|\mathbf{y} - \mathbf{x}\|_2 d\tau \\ &\leq \int_0^1 \tau L \|\mathbf{y} - \mathbf{x}\|_2^2 d\tau = \frac{L}{2} \|\mathbf{y} - \mathbf{x}\|_2^2. \end{aligned}$$

Consider a function $f \in \mathcal{C}_L^{1,1}(\mathbb{R}^n)$. Let us fix $\mathbf{x}_0 \in \mathbb{R}^n$, and define two quadratic functions:

$$\begin{aligned} \phi_1(\mathbf{x}) &= f(\mathbf{x}_0) + \langle \nabla f(\mathbf{x}_0), \mathbf{x} - \mathbf{x}_0 \rangle - \frac{L}{2} \|\mathbf{x} - \mathbf{x}_0\|_2^2, \\ \phi_2(\mathbf{x}) &= f(\mathbf{x}_0) + \langle \nabla f(\mathbf{x}_0), \mathbf{x} - \mathbf{x}_0 \rangle + \frac{L}{2} \|\mathbf{x} - \mathbf{x}_0\|_2^2. \end{aligned}$$

Then the graph of the function f is located between the graphs of ϕ_1 and ϕ_2 :

$$\phi_1(\mathbf{x}) \leq f(\mathbf{x}) \leq \phi_2(\mathbf{x}), \quad \mathbf{x} \in \mathbb{R}^n.$$

Lemma 3.6 Let $f \in \mathcal{C}_M^{2,2}(\mathbb{R}^n)$. Then for all $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, we have

$$\begin{aligned} \|\nabla f(\mathbf{y}) - \nabla f(\mathbf{x}) - \nabla^2 f(\mathbf{x})(\mathbf{y} - \mathbf{x})\|_2 &\leq \frac{M}{2} \|\mathbf{y} - \mathbf{x}\|_2^2, \\ |f(\mathbf{y}) - f(\mathbf{x}) - \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle - \frac{1}{2} \langle \nabla^2 f(\mathbf{x})(\mathbf{y} - \mathbf{x}), \mathbf{y} - \mathbf{x} \rangle| &\leq \frac{M}{6} \|\mathbf{y} - \mathbf{x}\|_2^3. \end{aligned}$$

Lemma 3.7 Let $f \in \mathcal{C}_M^{2,2}(\mathbb{R}^n)$, with $\|\nabla^2 f(\mathbf{x}) - \nabla^2 f(\mathbf{y})\|_2 \leq M \|\mathbf{x} - \mathbf{y}\|_2$. Then

$$\nabla^2 f(\mathbf{x}) - M \|\mathbf{y} - \mathbf{x}\|_2 \mathbf{I} \preceq \nabla^2 f(\mathbf{y}) \preceq \nabla^2 f(\mathbf{x}) + M \|\mathbf{y} - \mathbf{x}\|_2 \mathbf{I}.$$

Proof:

Since $f \in \mathcal{C}_M^{2,2}(\mathbb{R}^n)$, $\|\nabla^2 f(\mathbf{y}) - \nabla^2 f(\mathbf{x})\|_2 \leq M \|\mathbf{y} - \mathbf{x}\|_2$. This means that the eigenvalues of the symmetric matrix $\nabla^2 f(\mathbf{y}) - \nabla^2 f(\mathbf{x})$ satisfy:

$$|\lambda_i(\nabla^2 f(\mathbf{y}) - \nabla^2 f(\mathbf{x}))| \leq M \|\mathbf{y} - \mathbf{x}\|_2, \quad i = 1, 2, \dots, n.$$

Therefore,

$$-M \|\mathbf{y} - \mathbf{x}\|_2 \mathbf{I} \preceq \nabla^2 f(\mathbf{y}) - \nabla^2 f(\mathbf{x}) \preceq M \|\mathbf{y} - \mathbf{x}\|_2 \mathbf{I}.$$