

# Homework 5

Total 40 points

**Problem 1.** (8 points) Compute the subdifferentials of the following functions

(a)  $f(\mathbf{x}) = \|\mathbf{x}\|_2$

(b) Given a closed convex set  $\mathcal{C}$ , define

$$f(\mathbf{x}) = \begin{cases} 0 & \text{if } \mathbf{x} \in \mathcal{C} \\ +\infty & \text{otherwise.} \end{cases}$$

**Solution.**

(a)

$$\partial f(\mathbf{x}) = \begin{cases} \frac{\mathbf{x}}{\|\mathbf{x}\|_2} & \text{if } \mathbf{x} \neq 0 \\ \{\mathbf{g} \mid \|\mathbf{g}\|_2 \leq 1\} & \text{if } \mathbf{x} = 0 \end{cases}$$

(b)

$$\partial f(\mathbf{x}) = \begin{cases} \emptyset & \text{if } \mathbf{x} \notin \mathcal{C} \\ \{\mathbf{g} \mid \langle \mathbf{g}, \mathbf{y} - \mathbf{x} \rangle \leq 0, \forall \mathbf{y} \in \mathcal{C}\} & \text{if } \mathbf{x} \in \partial \mathcal{C} \\ 0 & \text{if } \mathbf{x} \in \mathcal{C}^\circ \end{cases}$$

**Problem 2.** (8 points) If function  $f$  is convex, Show that  $\partial f(\mathbf{x}) \neq \emptyset$  for all  $\mathbf{x} \in \text{int}(\text{dom } f)$ .

**Solution.** Notice that  $(\mathbf{x}, f(\mathbf{x}))$  is on the boundary of  $\text{epi } f$ . The hyperplane supporting theorem say there exists  $(\mathbf{a}, b)$  with  $\mathbf{a} \neq \mathbf{0}$  such that

$$\left\langle \begin{bmatrix} \mathbf{a} \\ b \end{bmatrix}, \begin{bmatrix} \mathbf{y} - \mathbf{x} \\ t - f(\mathbf{x}) \end{bmatrix} \right\rangle \leq 0$$

for any  $(\mathbf{y}, t) \in \text{epi } f$ , which means

$$S \triangleq \langle \mathbf{a}, \mathbf{y} - \mathbf{x} \rangle + b(t - f(\mathbf{x})) \leq 0.$$

We can conclude  $b \leq 0$ , otherwise, let  $t \rightarrow +\infty$ , then  $S$  goes to  $+\infty$ .

Since  $\mathbf{x}$  is in the interior, we can find some  $\epsilon > 0$  such that  $\mathbf{y} = \mathbf{x} + \epsilon \mathbf{a} \in \text{dom } f$ , which leads to  $S = \epsilon \|\mathbf{a}\|_2^2 + b(t - f(\mathbf{x}))$ . Let  $t > f(\mathbf{x})$ , then we know  $b \neq 0$ . Hence we can say  $b < 0$ . Thus,  $\langle \mathbf{a}/b, \mathbf{y} - \mathbf{x} \rangle + (t - f(\mathbf{x})) \geq 0$ , i.e.,  $t \geq f(\mathbf{x}) + \langle -\mathbf{a}/b, \mathbf{y} - \mathbf{x} \rangle$ .

Take  $t = f(\mathbf{y})$  means  $\mathbf{g} = -\mathbf{a}/b$  is a subgradient at  $\mathbf{x}$ .

**Remark.**  $\partial f(\mathbf{x})$  may be empty if  $\mathbf{x}$  is on the boundary of  $\text{dom } f$ . For example, suppose the function is  $f(\mathbf{x}) = -\sqrt{\mathbf{x}}$  for  $\mathbf{x} \geq 0$ , then  $\partial f(\mathbf{0}) = \emptyset$ .

**Problem 3.** (6 points) If function  $f$  is  $\mu$ -strongly convex, and  $\mathbf{g}$  is a subgradient of  $f$  at  $\mathbf{x}$ . Show that for any  $\mathbf{y} \in \text{dom } f$ ,

$$f(\mathbf{y}) \geq f(\mathbf{x}) + \langle \mathbf{g}, \mathbf{y} - \mathbf{x} \rangle + \frac{\mu}{2} \|\mathbf{y} - \mathbf{x}\|_2^2.$$

**Solution.** Let  $h(\mathbf{x}) = f(\mathbf{x}) - \frac{\mu}{2} \|\mathbf{x}\|_2^2$ . Then  $h(\mathbf{x})$  is convex and  $\mathbf{g} - \mu\mathbf{x}$  is a subgradient of  $h$  at  $\mathbf{x}$ . Thus we have

$$h(\mathbf{y}) \geq h(\mathbf{x}) + \langle \mathbf{g} - \mu\mathbf{x}, \mathbf{y} - \mathbf{x} \rangle,$$

which means

$$\begin{aligned} f(\mathbf{y}) &\geq f(\mathbf{x}) + \frac{\mu}{2} (\|\mathbf{y}\|_2^2 - \|\mathbf{x}\|_2^2) + \langle \mathbf{g} - \mu\mathbf{x}, \mathbf{y} - \mathbf{x} \rangle \\ &= f(\mathbf{x}) + \langle \mathbf{g}, \mathbf{y} - \mathbf{x} \rangle + \frac{\mu}{2} \|\mathbf{y} - \mathbf{x}\|_2^2. \end{aligned}$$

**Problem 4.** (6 points) Suppose  $f$  is convex and  $G$ -Lipschitz continuous over the constraint  $\mathcal{C}$ , which is bounded and convex with diameter  $D > 0$ . If we run projected subgradient descent method for  $T$  rounds with  $\eta_t = \frac{D}{G\sqrt{T}}$ , then we have

$$f(\bar{\mathbf{x}}_t) - f^* \leq \frac{DG}{\sqrt{T}},$$

where  $\bar{\mathbf{x}}_t = \frac{1}{T} \sum_{t=1}^T \mathbf{x}_t$ .

**Solution.** In the class, we have shown

$$f(\bar{\mathbf{x}}_t) - f^* \leq \frac{\|\mathbf{x}_0 - \mathbf{x}^*\|_2^2 + \sum_{k=0}^t \eta_k^2 \|\mathbf{g}_k\|^2}{2 \sum_{k=0}^t \eta_k}.$$

Since  $\|\mathbf{x}_0 - \mathbf{x}^*\|_2 \leq D$  and  $\|\mathbf{g}_k\| \leq G$ , we have

$$f(\bar{\mathbf{x}}_t) - f^* \leq \frac{DG}{\sqrt{T}}.$$

**Problem 5.** (12 points) Let  $f$  be  $\mu$ -strongly convex and  $G$ -Lipschitz continuous over the constraint  $\mathcal{C}$ . Let  $\eta_t = \frac{2}{\mu(t+1)}$  and  $\bar{\mathbf{x}}_t = \sum_{k=1}^t \frac{2k}{t(t+1)} \mathbf{x}_k$ . Prove that the projected subgradient descent obeys

(a)

$$f(\bar{\mathbf{x}}_t) - f^* \leq \frac{2G^2}{\mu(t+1)};$$

(b)

$$\|\bar{\mathbf{x}}_t - \mathbf{x}^*\|_2 \leq \frac{2G}{\mu\sqrt{t+1}}.$$

**Solution.**

(a) In the class, we have shown that

$$\sum_{k=0}^t k(f(\mathbf{x}_k) - f^*) \leq \frac{tG^2}{\mu}.$$

By Jensen inequality, we have

$$\sum_{k=0}^t k(f(\mathbf{x}_k) - f^*) = \frac{t(t+1)}{2} \left( \sum_{k=1}^t \frac{2k}{t(t+1)} f(\mathbf{x}_k) - f^* \right) \geq \frac{t(t+1)}{2} (f(\bar{\mathbf{x}}_t) - f^*).$$

Thus we can get

$$f(\bar{\mathbf{x}}_t) - f^* \leq \frac{2G^2}{\mu(t+1)}.$$

(b) By strong convexity and (a), we have

$$\frac{\mu}{2} \|\bar{\mathbf{x}}_t - \mathbf{x}^*\|_2^2 \leq \langle \nabla f(\mathbf{x}^*), \bar{\mathbf{x}}_t - \mathbf{x}^* \rangle + \frac{\mu}{2} \|\bar{\mathbf{x}}_t - \mathbf{x}^*\|_2^2 \leq f(\bar{\mathbf{x}}_t) - f^* \leq \frac{2G^2}{\mu(t+1)}.$$