

## Suggested Solutions to A.2

1. Consider the unconstrained optimization problem

$$\min f(x) \quad \text{s.t.} \quad x \in \mathbb{R}^n, \quad (\text{P})$$

where  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is convex and  $L_f$ -smooth. Assume  $X^* \subset \mathbb{R}^n$ , the optimal set of (P), is nonempty. Let  $f^*$  be the optimal value. Recall that the following useful details on GD method (convex case).

- (1). the iterative process:

$$x^{k+1} = x^k - \frac{1}{L_k} \nabla f(x^k),$$

- (2).  $1/L_k$  is the  $k$ -th stepsize chosen by the constant-stepsize or the backtracking procedure.

- (3).  $L_k$  satisfies for any  $x, y \in \mathbb{R}^n$ ,

$$f(x) - f(T_{L_k}(y)) \geq \frac{L_k}{2} \|x - T_{L_k}(y)\|^2 - \frac{L_k}{2} \|x - y\|^2 + f(x) - f(y) - \langle \nabla f(y), x - y \rangle.$$

- (4). the bounds on  $L_k$  (independent with  $k$ ) is

$$\beta L_f \leq L_k \leq \alpha L_f.$$

- (5). the theorem on sequence convergence under Fejér monotonicity.

Show that

- (a)  $\{f(x^k)\}_{k \geq 0}$  is nonincreasing.
- (b)  $\{\|x^k - x^*\|\}_{k \geq 0}$  is nonincreasing for any  $x^* \in X^*$ .
- (c)  $f(x^k) - f^* \leq \frac{\alpha L_f \|x^0 - x^*\|^2}{2k}$  for any  $k \geq 1$  and  $x^* \in X^*$ .
- (d)  $\{x^k\}_{k \geq 0}$  converges to some optimal solution as  $k \rightarrow \infty$ .
- (e)  $\min_{n=0,1,\dots,k} \|\nabla f(x^n)\| \leq \frac{2\alpha^{1.5} L_f \|x^0 - x^*\|}{\sqrt{\beta k}}$  for any  $k \geq 1$  and  $x^* \in X^*$ .
- (f) Under the constant stepsize rule in which  $L_k \equiv L_f$  and  $\alpha = \beta = 1$ ,

$$\|\nabla f(x^k)\| \leq \frac{2L_f \|x^0 - x^*\|}{k}$$

for any  $k \geq 1$  and  $x^* \in X^*$ .

Hint: prove the norm of the gradient  $\{\|\nabla f(x^k)\|\}_{k \geq 0}$  is nonincreasing.

*Proof.* (a) Let  $x = y = x^k$  in (detail 3),

$$f(x^k) - f(x^{k+1}) \geq \frac{L_k}{2} \|x^k - x^{k+1}\|^2 = \frac{L_k}{2L_k^2} \|\nabla f(x^k)\|^2 \geq 0. \quad (\text{Inq1})$$

(b) Let  $x = x^*$ ,  $y = x^k$  in (detail 3),

$$0 \geq f(x^*) - f(x^{k+1}) \geq \frac{L_k}{2} \|x^* - x^{k+1}\|^2 - \frac{L_k}{2} \|x^* - x^k\|^2. \quad (\text{Inq2.1})$$

Then

$$\|x^* - x^{k+1}\| \leq \|x^* - x^k\|. \quad (\text{Inq2.2})$$

(c) By (Inq2.1) and (detail 4),

$$f(x^k) - f^* \leq \frac{\alpha L_f}{2} \|x^* - x^k\|^2 - \frac{\alpha L_f}{2} \|x^* - x^{k-1}\|^2 \text{ for } k \geq 1.$$

Hence,

$$k[f(x^k) - f^*] \leq \sum_{n=1}^k [f(x^n) - f^*] \leq \frac{\alpha L_f}{2} \|x^* - x^k\|^2 \quad (\text{Inq3})$$

where the first inequality in (Inq3) holds by (Inq1).

(d)  $\dots$

(e) By (Inq1) and (detail 4),

$$f(x^n) - f(x^{n+1}) \geq \frac{\beta}{2\alpha^2 L_f} \|\nabla f(x^n)\|^2. \quad (\text{Inq5.1})$$

Summing (Inq5.1) over  $n = k, k+1, \dots, 2k-1$  yields

$$f(x^k) - f^* \geq f(x^{2k}) - f^* + \frac{\beta}{2\alpha^2 L_f} \sum_{n=k}^{2k-1} \|\nabla f(x^n)\|^2.$$

By (Inq3),

$$\frac{\alpha^3 L_f^2}{\beta k} \|x^* - x^k\| \geq \sum_{n=k}^{2k-1} \|\nabla f(x^n)\|^2 \geq k \min_{n=k, \dots, 2k-1} \|\nabla f(x^n)\|^2 \geq k \min_{n=0, \dots, 2k} \|\nabla f(x^n)\|^2.$$

So

$$\min_{n=0, \dots, 2k-1} \|\nabla f(x^n)\|^2 \leq \frac{\alpha^3 L_f^2}{\beta k^2} \|x^* - x^k\|^2. \quad (\text{Inq5.2})$$

$$\min_{n=0, \dots, 2k} \|\nabla f(x^n)\|^2 \leq \frac{\alpha^3 L_f^2}{\beta k^2} \|x^* - x^k\|^2. \quad (\text{Inq5.3})$$

For any  $p = 1, 2, \dots$ , if  $p$  is odd, then  $\frac{p+1}{2}$  is an integer and

$$\min_{n=0, \dots, p} \|\nabla f(x^n)\|^2 = \min_{n=0, \dots, 2\frac{p+1}{2}-1} \|\nabla f(x^n)\|^2 \leq \frac{\alpha^3 L_f^2}{\beta \left(\frac{p+1}{2}\right)^2} \|x^* - x^{\frac{p+1}{2}}\|^2 \leq \frac{4\alpha^3 L_f^2}{\beta p^2} \|x^* - x^p\|^2.$$

If  $p$  is even, then

$$\min_{n=0, \dots, p} \|\nabla f(x^n)\|^2 = \min_{n=0, \dots, 2\frac{p}{2}} \|\nabla f(x^n)\|^2 \leq \frac{\alpha^3 L_f^2}{\beta \left(\frac{p}{2}\right)^2} \|x^* - x^{\frac{p}{2}}\|^2 \leq \frac{4\alpha^3 L_f^2}{\beta p^2} \|x^* - x^p\|^2.$$

(f) Recall that

$$\langle \nabla f(x) - \nabla f(y), x - y \rangle \geq \frac{1}{L} \|\nabla f(x) - \nabla f(y)\|^2.$$

Let  $x = x^k, y = x^{k+1}$ ,

$$\langle \nabla f(x^k) - \nabla f(x^{k+1}), \nabla f(x^k) \rangle \geq \|\nabla f(x^k) - \nabla f(x^{k+1})\|^2.$$

Set  $a = \nabla f(x^k), b = \nabla f(x^{k+1})$ , we have

$$(a - b)^T a \geq (a - b)^T (a - b).$$

Then

$$\begin{aligned} b^T b - a^T a &= (b - a + a)^T (b - a + a) - a^T a = (b - a)^T (b - a) - 2(a - b)^T a + a^T a - a^T a \\ &\leq (b - a)^T (b - a) - 2(a - b)^T (a - b) \leq 0. \end{aligned}$$

□

2.

3. (a) Notice that

$$f''(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ -2x & \text{if } x > 0. \end{cases}$$

Hence the Newton's method is not well-defined if initial point  $x^0 \leq 0$ . We set  $\sqrt{c} \neq x^0 > 0$ , the iterative formula is

$$x^{k+1} := x^k - \frac{f'(x^k)}{f''(x^k)} = \frac{1}{2} \left( x^k + \frac{c}{x^k} \right).$$

It's easy to show that  $x^n \geq \sqrt{c}$  for  $n = 1, 2, \dots$  and  $\{x^n\}_{n \geq 1}$  is decreasing, so  $\{x^n\}_{n \geq 1}$  converges to  $\sqrt{c}$  noticing the fixed points of the iterative equation are  $\pm \sqrt{c}$ .

(b) Let

$$f_i(x) = \frac{1}{1 + \exp(-b_i a_i^T x)}.$$

Then

$$\begin{aligned} \nabla l(x) &= -\frac{1}{m} \sum_{i=1}^m (1 - f_i(x)) b_i a_i + 2\lambda x \\ \nabla^2 l(x) &= -\frac{1}{m} \sum_{i=1}^m (1 - f_i(x)) f_i(x) b_i^2 a_i a_i^T + 2\lambda I. \end{aligned}$$

4. (a) Because  $\Omega$  is bounded, there exists  $M \in \mathbf{R}$  such that  $\sup\{\|w\| \mid w \in \Omega\} < M$ . Hence

$$\mu_\Omega(x) \leq \sup\{\|x\| + \|w\| \mid w \in \Omega\} = \|x\| + \sup\{\|w\| \mid w \in \Omega\} \leq \|x\| + M < \infty.$$

(b) Let  $x, y \in \mathbf{R}^n$  and  $0 \leq \lambda \leq 1$ , set  $z := \lambda x + (1 - \lambda)y$ . For any  $\varepsilon > 0$ , there exists  $w_z \in \Omega$  such that

$$\mu_\Omega(z) - \varepsilon \leq \|z - w_z\| \leq \lambda \|x - w_z\| + (1 - \lambda) \|y - w_z\| \leq \lambda \mu_\Omega(x) + (1 - \lambda) \mu_\Omega(y).$$

The arbitrariness of  $\varepsilon$  implies that  $\mu_\Omega$  is convex.

5. (a)

$$\begin{aligned}
g_1(\lambda x + (1-\lambda)y) &= f(\lambda x + (1-\lambda)y) - \frac{\sigma}{2} \|\lambda x + (1-\lambda)y\|^2 \\
&\leq \lambda f(x) + (1-\lambda)f(y) - \frac{\sigma}{2} \left( \lambda(1-\lambda) \|x-y\|^2 + \|\lambda x + (1-\lambda)y\|^2 \right) \\
&= \lambda f(x) + (1-\lambda)f(y) - \lambda \frac{\sigma}{2} \|x\|^2 - (1-\lambda) \|y\|^2 \\
&= \lambda g_1(x) + (1-\lambda)g_1(y)
\end{aligned}$$

(b) Notice that  $g_2(x) = g_1(x) + \frac{\sigma}{2} (\|x^*\|^2 - 2x^{*T}x)$ . The result can be obtained by using the definition of convex functions.

(c) The result can be obtained by using the definition of strongly convex functions.

6. For any  $x \in \mathbf{R}^n$ , we have

(a)  $d_\Omega(x)$  is well-defined.

Just notice that the real subset  $\{\|x-z\| \mid z \in \Omega\}$  is lower bounded.

(b)  $P_\Omega(x)$  is nonempty.

By the definition of  $d_\Omega(x)$ , we have  $z_n \in \Omega$  satisfying  $\|x - z_n\| \leq d_\Omega(x) + \frac{1}{n}$ . On the other hand, the boundedness and closeness of  $\Omega$  implies that there exists a limiting point  $w \in \Omega$  of  $(z_n)_{n \geq 1}$ . Hence  $\|x - w\| = d_\Omega(x)$ .

In fact, just notice that the distance operator  $\|x - \cdot\|$  is continuous and  $\Omega$  is compact for any fixed  $x \in \mathbf{R}^n$ . Hence the distance operator attains its infimum over  $\Omega$  at some point.

(c)  $P_\Omega(x)$  is a singleton.

Suppose there exist  $w_1 \neq w_2$  with  $w_1, w_2 \in P_\Omega(x)$ , noticing  $\frac{w_1+w_2}{2} \in \Omega$  since that  $\Omega$  is convex. Then

$$d_\Omega(x) \leq \left\| x - \frac{w_1 + w_2}{2} \right\| < \frac{1}{2} \|x - w_1\| + \frac{1}{2} \|x - w_2\| = d_\Omega(x).$$

It's a contradiction noticing that the second inequality is strict.

In fact,

$$\left\| x - \frac{w_1 + w_2}{2} \right\|^2 = \left( \frac{1}{2} \|x - w_1\| + \frac{1}{2} \|x - w_2\| \right)^2 \Rightarrow \|w_1 - w_2\|^2 = 0.$$

7. *Proof.* (a) Pick  $\bar{v} \in \partial f(\bar{x})$ . (By the way, Theorem 5.2.4 guarantees the nonemptiness of  $\partial f(\bar{x})$ ). Then we have

$$f(x) \geq f(\bar{x}) + \langle \bar{v}, x - \bar{x} \rangle \text{ for all } x \in \mathbf{R}^n. \quad (1)$$

Moreover, the conclusion condition  $0 \in \partial f(\bar{x}) + N_\Omega(\bar{x})$  shows that  $-\bar{v} \in N_\Omega(\bar{x})$ , or equivalently,

$$\langle -\bar{v}, x - \bar{x} \rangle \leq 0 \text{ for all } x \in \Omega. \quad (2)$$

Combining (1) and (2), we derive

$$f(x) \geq f(\bar{x}) + \langle \bar{v}, x - \bar{x} \rangle \text{ for all } x \in \Omega.$$

(b) By second-order Taylor expansion, we have

$$f(\bar{x} + \alpha(x - \bar{x})) = f(\bar{x}) + \alpha(x - \bar{x})^T \nabla f(\bar{x}) + \frac{(x - \bar{x})^T \nabla^2 f(\bar{x})(x - \bar{x})}{2} \alpha^2 + o(\alpha^2).$$

If we choose  $x \in \Omega$  and  $\alpha > 0$  sufficiently small, then the convexity of  $\Omega$  implies that  $\bar{x} + \alpha(x - \bar{x}) \in \Omega$ . Considering Condition (a) and (b), we have

$$f(\bar{x} + \alpha(x - \bar{x})) \geq f(\bar{x}) + \frac{(x - \bar{x})^T \nabla^2 f(\bar{x})(x - \bar{x})}{2} \alpha^2 > f(\bar{x})$$

for sufficiently small  $\alpha > 0$ . Hence  $\bar{x}$  is a strictly minimizer of  $f$  over  $\Omega$ .

□

8. *Proof.* Define

$$\mathcal{D}(\bar{x}) = \{\alpha(x - \bar{x}) \mid \forall \alpha \geq 0 \text{ and } x \in \Omega\}.$$

First, we show  $\mathcal{D}(\bar{x}) \subset T(\bar{x})$ . For any  $0 \neq d \in \mathcal{D}(\bar{x})$ , i.e.,  $\exists \alpha_d > 0, x_d \in \Omega$  with  $d = \alpha_d(x_d - \bar{x})$ , then  $d$  is a feasible direction of  $\Omega$  at  $\bar{x}$  (think of why) and hence  $d \in T(\bar{x})$  (think of why).

Secondly, we show  $T(\bar{x}) \subset \text{cl}(\mathcal{D})$ . Actually, for any  $d \in T(\bar{x})$ ,  $\exists t_k \downarrow 0, d^k \rightarrow d$  with  $\bar{x} + t_k d^k \in \Omega$ . Notice that

$$d^k = \frac{1}{t_k} (\bar{x} + t_k d^k - \bar{x}),$$

i.e.,  $d^k \in \mathcal{D}(\bar{x})$ . Then  $d \in \text{cl}(\mathcal{D})$ . □

**more details:** Is  $\mathcal{D}(\bar{x}) / \{0\}$  the collection of feasible directions to  $\Omega$  at  $\bar{x}$ ? Is  $\mathcal{D}(\bar{x})$  closed?

9. *Proof.*  $\supset$ : For any  $d$  satisfying  $\langle d, x - \bar{x} \rangle \leq 0, \forall x \in \Omega$ , we have

$$\limsup_{x \xrightarrow{\Omega} \bar{x}} \frac{\langle d, x - \bar{x} \rangle}{\|x - \bar{x}\|} \leq 0,$$

i.e.,  $d \in N(\bar{x})$ .

$\subset$ : Pick  $d \in N(\bar{x})$  arbitrarily, for any  $\bar{x} \neq x \in \Omega$ , define

$$x^k = \frac{1}{k}x + \left(1 - \frac{1}{k}\right)\bar{x},$$

noticing that  $x^k \in \Omega$ , (the convexity of  $\Omega$ ),  $x^k \rightarrow \bar{x}$  and  $d \in N(\bar{x})$ , we have

$$0 \geq \limsup_{k \rightarrow \infty} \frac{\langle d, x^k - \bar{x} \rangle}{\|x^k - \bar{x}\|} = \frac{\langle d, x - \bar{x} \rangle}{\|x - \bar{x}\|},$$

that is to say,  $\langle d, x - \bar{x} \rangle \leq 0$ . □

10. *Proof.* (a)

(b)

(c) Let

$$\Omega = \{(x_1, x_2) \in \mathbb{R}^2 \mid \forall x_1 \in \mathbb{R}^n, x_2 \geq e^{x_1}\}$$

and

$$D = \mathbb{R} \times \{0\}.$$

Then for any  $p = (p_1, p_2) \in \mathbb{R}^2$ , we have

$$\inf_{x \in D} \langle p, x \rangle = \inf_{x_1 \in \mathbb{R}} p_1 x_1 = -\infty.$$

□