

2. (a)

$$f(y) = f(x) + \nabla f(x)^T (y-x)$$

$$f(x^+) = f(x) + \nabla f(x)^T (x^+ - x) \quad (1)$$

$$x^+ - x = -t \nabla f(x) \quad (2)$$

由 $\| \nabla f(x) - \nabla f(y) \|_2 \leq L \|x-y\|_2$ 得 $f(y) \leq f(x) + \nabla f(x)^T (y-x) + \frac{L}{2} \|y-x\|_2^2$ Homework 2

$$\therefore f(x^+) \leq f(x) + \nabla f(x)^T (x^+ - x) + \frac{L}{2} \|x^+ - x\|_2^2 \quad (3)$$

$$\text{②/③} \quad f(x^+) \leq f(x) + \nabla f(x)^T (x^+ - x) + \frac{L}{2} t^2 \|\nabla f(x)\|_2^2$$

$$t \leq \frac{1}{L} \quad \therefore \frac{L}{2} t^2 \leq \frac{t}{2}$$

$$\therefore \text{得 } f(x^+) \leq f(x) + \underbrace{\nabla f(x)^T (x^+ - x)}_{-t \|\nabla f(x)\|_2^2} + \frac{t}{2} \|\nabla f(x)\|_2^2 \quad (4) \quad \text{得 } f(x^+) \leq f(x) - \frac{t}{2} \|\nabla f(x)\|_2^2 \quad (5) \quad (\text{题解})$$

$$f^* = f(x) + \nabla f(x)^T (x^* - x)$$

$$f(x) \leq f^* + \nabla f(x)^T (x^* - x) \quad (6)$$

$$\text{⑤⑥: } f(x^+) \leq f^* + \nabla f(x)^T (x - x^*) - \frac{t}{2} \|\nabla f(x)\|_2^2 \quad \text{得证}$$

$$(b) \text{ 已知 } f(x^+) \leq f^* + \nabla f(x)^T (x - x^*) - \frac{t}{2} \|\nabla f(x)\|_2^2 \quad (1) \quad \begin{matrix} \nearrow \frac{1}{2} \|x^+ - x\|_2^2 \\ x^+ - x = -t \nabla f(x) \end{matrix}$$

$$\|x^+ - x^*\|_2^2 = \|x - t \nabla f(x) - x^*\|_2^2 = \|x - x^*\|_2^2 + t^2 \|\nabla f(x)\|_2^2 - 2t \nabla f(x)^T (x - x^*)$$

$$\therefore -2t \nabla f(x)^T (x - x^*) = \|x^+ - x^*\|_2^2 - \|x - x^*\|_2^2 - t^2 \|\nabla f(x)\|_2^2 \quad (2)$$

\therefore ①② 结合

$$f(x^+) \leq f^* + \frac{1}{2t} (\|x - x^*\|_2^2 - \|x^+ - x^*\|_2^2)$$

(c) 无需求

$$(d) \sum_{i=1}^k (f(x^{(i)}) - f^*) \leq \frac{1}{2k} \|x^{(0)} - x^*\|^2 \quad (1)$$

$$\square f \text{ 满足 } f\left(\frac{1}{k} \sum_{i=1}^k x^{(i)}\right) \leq \frac{1}{k} \sum_{i=1}^k f(x^{(i)})$$

$$\bar{x}^{(k)} = \frac{1}{k} \sum_{i=1}^k x^{(i)}$$

$$f(\bar{x}^{(k)}) - f^* \leq \frac{1}{k} \sum_{i=1}^k (f(x^{(i)}) - f^*)$$

\therefore 函数值 $f(x^{(i)})$ 是单调下降的

$$f(x^{(1)}) \geq f(x^{(2)}) \geq \dots \geq f(x^{(k)})$$

$$\therefore f(x^{(k)}) - f^* \leq f(\bar{x}^{(k)}) - f^*$$

$$\therefore \text{由 (1) 得 } f(\bar{x}^{(k)}) - f^* \leq \frac{1}{2k} \|x^{(0)} - x^*\|^2$$

\downarrow

$$f(x^{(k)}) - f^* \leq \frac{1}{2k} \|x^{(0)} - x^*\|^2$$

3.

(a) 若 h 是适当的凸函数, 假设 h 至少在定义域一点处存在次梯度

$$m(u) = h(u) + \frac{1}{2} \|u - x_0\|^2$$

h 凸函数, 且至少在一点处存在次梯度, $\therefore h$ 有全局解

$$h(v) \geq h(u) + \theta^T(u-v) \quad \theta \in \partial h(u)$$

$$m(u) = h(u) + \frac{1}{2} \|u - x_0\|^2 \geq h(v) + \theta^T(u-v) + \frac{1}{2} \|u - x_0\|^2$$

$\therefore m(u)$ 有次下界, 当 $\|u\| \rightarrow +\infty$, $m(u) \rightarrow +\infty$ $\therefore m(u)$ 有最小值

有最小值 (Homework 2)

唯一性: $m(u)$ 强凸, $m(u)$ 有最小值

(由 f 为强凸且存在最小值, $\therefore f$ 有最小值)

(b)

$$\min_z \left\{ \frac{1}{2\epsilon} \|x - z\|^2 + \frac{1}{2} z^T A z - b^T z \right\}$$

$$x^{(k+1)} = \arg \min_z \left\{ \frac{1}{2\epsilon} \|x^{(k)} - z\|^2 + \frac{1}{2} z^T A z - b^T z \right\}$$

$$\frac{\partial}{\partial z} \leftarrow \frac{1}{\epsilon} (z - x^{(k)}) + A z - b = 0$$

$$\text{得 } z = \left(\frac{1}{\epsilon} I + A \right)^{-1} \left(\frac{1}{\epsilon} x^{(k)} + b \right)$$

$$\therefore x^{(k+1)} = \left(\frac{1}{\epsilon} I + A \right)^{-1} \left(\frac{1}{\epsilon} x^{(k)} + b \right)$$

$$\epsilon = \frac{1}{\epsilon} \text{ 得}$$

$$\begin{aligned} x^{(k+1)} &= (A + \epsilon I)^{-1} (b - A x^{(k)} + A x^{(k)} + \epsilon x^{(k)}) \\ &= x^{(k)} + (A + \epsilon I)^{-1} (b - A x^{(k)}) \end{aligned}$$

(b) 证