

1. (a)

$$\begin{aligned} \text{RHS} &= f^* + \frac{1}{2t_k} (\|x^k - x^*\|^2 - \|x^{k+1} - x^*\|^2) + (e^k)^T (x^{k+1} - x^k) + (e^k)^T (x^k - x^*) \\ &= f^* + \frac{1}{2t_k} (\|x^k\|^2 - \|x^{k+1}\|^2 - 2x^k x^{*T} + 2x^{k+1} x^{*T}) + (e^k)^T (x^{k+1} - x^*) \end{aligned}$$

$$\because e^k = \nabla f(x^k) + \frac{1}{t_k} (x^{k+1} - x^k)$$

$$\begin{aligned} \therefore \text{RHS} &= f^* + \frac{1}{2t_k} (\|x^k\|^2 - \|x^{k+1}\|^2 - 2x^k x^{*T} + 2x^{k+1} x^{*T}) + \nabla f(x^k)^T (x^{k+1} - x^*) + \frac{1}{t_k} (x^{k+1} - x^k)^T (x^{k+1} - x^*) \\ &= f^* + \frac{1}{2t_k} \|x^k\|^2 + \frac{1}{2t_k} \|x^{k+1}\|^2 - \frac{1}{t_k} x^k x^{*T} + \nabla f(x^k)^T (x^{k+1} - x^*) \\ &= f^* + \nabla f(x^k)^T (x^{k+1} - x^*) + \frac{1}{2t_k} \|x^{k+1} - x^k\|^2 \end{aligned}$$

$$\text{LHS} = f(x^{k+1})$$

$$\leq f(x^k) + \nabla f(x^k)^T (x^{k+1} - x^k) + \frac{L}{2} \|x^{k+1} - x^k\|^2$$

$\because f(x)$  is convex

$$\therefore f(x^*) \geq f(x^k) + \nabla f(x^k)^T (x^* - x^k)$$

$$\therefore f(x^k) \leq f^* + \nabla f(x^k)^T (x^k - x^*)$$

$$\begin{aligned} \therefore \text{LHS} &\leq f^* + \nabla f(x^k)^T (x^k - x^*) + \nabla f(x^k)^T (x^{k+1} - x^k) + \frac{L}{2} \|x^{k+1} - x^k\|^2 \\ &= f^* + \nabla f(x^k)^T (x^{k+1} - x^*) + \frac{L}{2} \|x^{k+1} - x^k\|^2 \end{aligned}$$

$$\because t_k \leq \frac{1}{L}$$

$$\therefore L \leq \frac{1}{t_k}$$

$$\therefore \text{LHS} \leq f^* + \nabla f(x^k)^T (x^{k+1} - x^*) + \frac{1}{2t_k} \|x^{k+1} - x^k\|^2 = \text{RHS}$$

(b) multiply both sides <sup>of (a)</sup> with  $t_k$

$$t_k (f(x^{k+1}) - f^*) \leq \frac{1}{2} (\|x^k - x^*\|^2 - \|x^{k+1} - x^*\|^2) - t_k^2 (e^k)^T \tilde{g}^k + t_k (e^k)^T (x^k - x^*)$$

$$\sum_{i=0}^k t_i (f(x^{i+1}) - f^*) \leq \frac{1}{2} \sum_{i=0}^k (\|x^i - x^*\|^2 - \|x^{i+1} - x^*\|^2) - \sum_{i=0}^k [t_i (e^i)^T \tilde{g}^i + t_i (e^i)^T (x^i - x^*)]$$

$$\leq \frac{1}{2} \|x^0 - x^*\|^2 - \sum_{i=0}^k [t_i (e^i)^T \tilde{g}^i + t_i (e^i)^T (x^i - x^*)]$$

$$\text{LHS} \geq k \cdot t_{\min} (\min_{0 \leq i \leq k} f(x^i) - f^*)$$

$$\therefore \min_{0 \leq i \leq k} f(x^i) - f^* \leq \frac{1}{k t_{\min}} \cdot \frac{D^2}{2} - \frac{1}{k t_{\min}} \sum_{i=0}^k [t_i^2 (e^i)^T \tilde{g}^i + t_i (e^i)^T (x^i - x^*)]$$



§ 2 (a)  $\text{prox}_h(a) = \underset{u}{\text{argmin}} \left( h(u) + \frac{1}{2} \|u-a\|_2^2 \right) = \underset{u}{\text{argmin}} \left( \lambda \|u\|_0 + \frac{1}{2} \|u-a\|_2^2 \right)$

$$0 \in \lambda \|u^*\|_0 + \frac{1}{2} \|u^*-a\|_2^2$$

$$\Rightarrow 0 \in \lambda \partial \|u^*\|_0 + u^* - a$$

$$\partial \|u\|_0 = \begin{cases} v \in \mathbb{R}^n & | v_i = 0 \\ & \in \mathbb{R} \end{cases} \quad \begin{matrix} u_i \neq 0 \\ u_i = 0 \end{matrix}$$

$\therefore$  if  $u_i \neq 0$  then

$$u_i^* = a_i$$

if  $u_i = 0$  then

$$0 \in \mathbb{R} + 0 - a_i$$

$$\Rightarrow a_i \in \mathbb{R}$$

$$\therefore \text{prox}_h(a)_i = \{0, a_i\}$$

(b)  $0 \in \lambda \partial \|u^*\|_1 + u^* - a$

$$\partial \|u\|_1 = \begin{cases} \text{sign}(u) & u \neq 0 \\ [-1, 1] & u = 0 \end{cases}$$

if  $u_i \neq 0$  then

$$0 \in \text{sign}(u_i) \cdot \lambda + u_i^* - a_i \Rightarrow u_i^* = \begin{cases} a_i - \lambda & a_i > \lambda \\ a_i + \lambda & a_i < -\lambda \end{cases}$$

if  $u_i = 0$  then

$$0 \in [-\lambda, \lambda] + u_i^* - a_i \Rightarrow |a_i| \leq \lambda$$

$$\therefore \text{prox}_h(a)_i \in \begin{cases} a_i - \lambda & a_i > \lambda \\ 0 & |a_i| \leq \lambda \\ a_i + \lambda & a_i < -\lambda \end{cases}$$

$$(c) \quad 0 \in \lambda \|u^*\|_* + u^* - A$$

$$0 \in \lambda \{y : \text{tr}((u^*)^T y) = \|u^*\|_*, \|y\| \leq 1\} + u^* - A$$

$$\therefore u^* = A - \lambda y$$

$$\therefore \text{tr}((A - \lambda y)^T y) = \|A - \lambda y\|_*, \|y\| \leq 1$$

$$\therefore \text{prox}_h(A) = A - \lambda y \quad \text{where } y \text{ can be obtained by solving}$$

§3. (a) let  $t_k^i = \rho^i t_k^0$  where  $i = 1, 2, 3, \dots$

$i$  denotes  $i^{\text{th}}$  step in backtracking step. and  $t_k^i$  is the corresponding stepsize  $t$

$$\text{Assume at step } i, t_k^i \geq \frac{1}{L} > t_{\min}, t_k^i \leq \frac{1}{\rho L}$$

$$\text{If } g(x^k - t_k^i G_t(x^k)) \leq g(x^k) - t_k^i \nabla g(x^k)^T G_t(x^k) + \frac{t_k^i}{2} \|G_t(x^k)\|^2 \text{ satisfies}$$

$$\text{then } t_k = t_k^i > t_{\min}$$

Else:

$$\text{then } t_k^{i+1} = \rho t_k^i \text{ and } t_k^{i+1} \in \left[\frac{\rho}{L}, \frac{1}{L}\right]$$

from the upper bound of  $g(\cdot)$

$$g(x - t_k^{i+1} G_t(x)) \leq g(x) + t_k^{i+1} \nabla g(x)^T G_t(x) + \frac{L t_k^{i+1 2}}{2} \|G_t(x)\|_2^2$$

$$\leq g(x) + t_k^{i+1} \nabla g(x)^T G_t(x) + \frac{t_k^{i+1}}{2} \|G_t(x)\|_2^2$$

$$\text{then } t_k = t_k^{i+1} \geq \frac{\rho}{L} \geq t_{\min}$$

$$\therefore t_k \geq t_{\min} \quad \forall k$$



(b) From (4) in slides 9-10, we have

$$f(x^k - t_k G(x^k)) \leq f(z) + G_t(x^k)^T (x^k - z) - \frac{t_k}{2} \|G_t(x^k)\|_2^2 - \frac{\eta}{2} \|x^k - z\|_2^2$$

let  $z = x^k$ , then

$$f(x^k - t_k G(x^k)) \leq f(x^k) - \frac{t_k}{2} \|G_t(x^k)\|_2^2 \leq f(x^k)$$

$$\Rightarrow f(x^{k+1}) \leq f(x^k) \Rightarrow \{f(x^k)\} \text{ is nonincreasing}$$

let  $z = x^*$  then

$$\cancel{f(x^{k+1})} f(x^{k+1}) - f(x^*) \leq G_t(x^k)^T (x^k - x^*) - \frac{t_k}{2} \|G_t(x^k)\|_2^2 - \frac{\eta}{2} \|x^k - x^*\|_2^2$$

$$\text{RHS} = \frac{1}{2t_k} (\|x^k - x^*\|_2^2 - \|x^k - x^* - t_k G_t(x^k)\|_2^2) - \frac{\eta}{2} \|x^k - x^*\|_2^2 \quad (1)$$

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

$$\therefore f(x^{k+1}) - f(x^*) \leq \frac{1}{2t_k} (\|x^k - x^*\|_2^2 - \|x^{k+1} - x^*\|_2^2) \quad \forall k \geq 0$$

$$\begin{aligned} (c) \sum_{i=0}^k (f(x^{i+1}) - f(x^*)) &\leq \frac{1}{2t_k} \sum_{i=0}^k (\|x^i - x^*\|_2^2 - \|x^{i+1} - x^*\|_2^2) \\ &= \frac{1}{2t_k} (\|x^0 - x^*\|_2^2 - \|x^{k+1} - x^*\|_2^2) \\ &\leq \frac{1}{2t_k} \|x^0 - x^*\|_2^2 \end{aligned}$$

$$\sum_{i=0}^k (f(x^{i+1}) - f(x^*)) \geq \cancel{0} k (f(x^k) - f(x^*)) \Leftarrow \text{from (b), } f(x^k) \text{ nonincreasing}$$

$$\begin{aligned} \therefore f(x^k) - f(x^*) &\leq \frac{1}{2t_k \cdot k} \|x^0 - x^*\|_2^2 \\ &\leq \frac{1}{2t_{\min} k} \|x^0 - x^*\|_2^2 \end{aligned}$$

$$\text{since } D = \min (\|x^0 - x\| \mid x \in X^*)$$

$$\therefore f(x^k) - f(x^*) \leq \frac{D^2}{2t_{\min} k} \quad \forall k \geq 1$$

(d) use (4) from slides 9-10, and (i) from (b)

let  $m = \sigma$  then

$$\begin{aligned} f(x^{k+1}) - f^* &\leq G_t(x^k)^T(x^k - x^*) - \frac{t_k}{2} \|G_t(x^k)\|^2 - \frac{\sigma}{2} \|x^k - x^*\|^2 \\ &= \frac{1}{2t_k} ((1 - \sigma t_k) \|x^k - x^*\|^2 - \|x^{k+1} - x^*\|^2) \\ &= \frac{1 - \sigma t_k}{2t_k} \|x^k - x^*\|^2 - \frac{1}{2t_k} \|x^{k+1} - x^*\|^2 \quad \forall k \geq 0 \end{aligned}$$

(e) if  $g$  is strongly convex, then  $f$  is also strongly convex

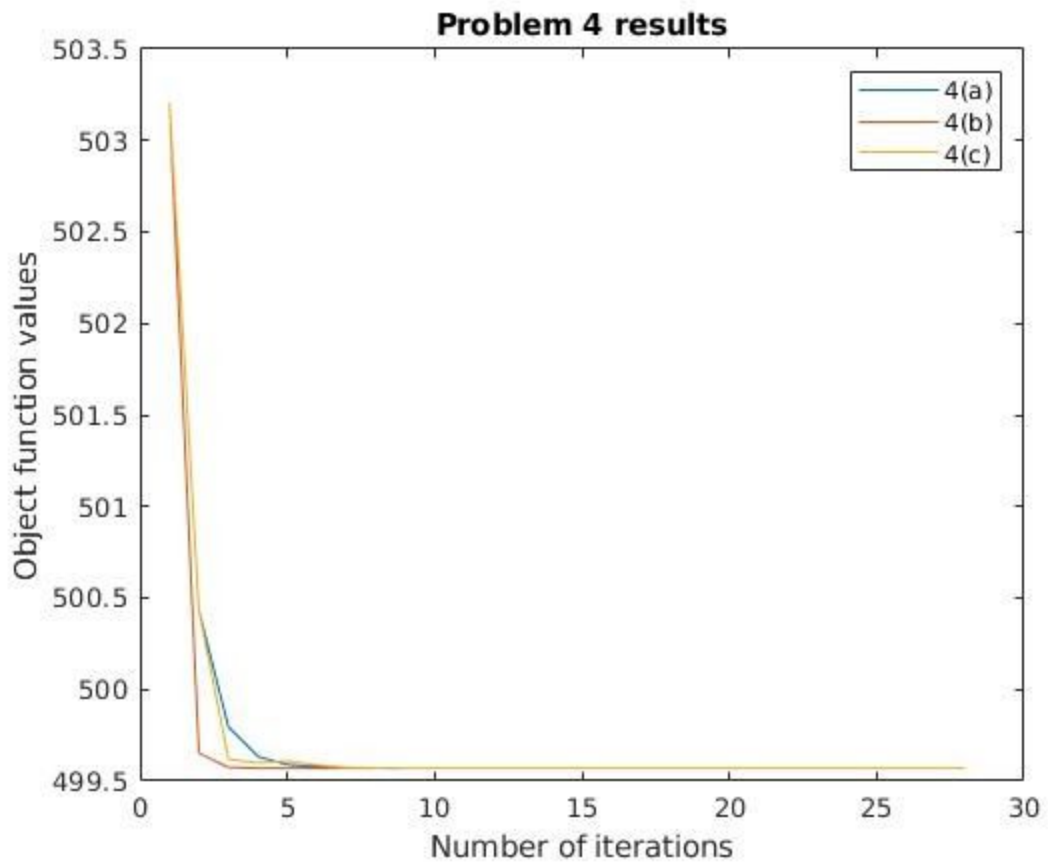
$$\therefore f(x^{k+1}) \geq f(x^*) + \frac{\sigma}{2} \|x^{k+1} - x^*\|^2$$

1° from (d)

$$\begin{aligned} \frac{\sigma}{2} \|x^{k+1} - x^*\|^2 &\leq \frac{1 - \sigma t_k}{2t_k} \|x^k - x^*\|^2 - \frac{1}{2t_k} \|x^{k+1} - x^*\|^2 \\ \frac{\sigma}{2} \|x^{k+1} - x^*\|^2 &\leq \frac{1 - \sigma t_{\min}}{2t_{\min}} \|x^k - x^*\|^2 - \frac{1}{2t_{\min}} \|x^{k+1} - x^*\|^2 \\ \therefore \|x^{k+1} - x^*\|^2 &\leq \frac{1 - \sigma t_{\min}}{1 + \sigma t_{\min}} \|x^k - x^*\|^2 \\ \therefore \|x^k - x^*\|^2 &\leq \left( \frac{1 - \sigma t_{\min}}{1 + \sigma t_{\min}} \right)^k \|x^0 - x^*\|^2 = \left( \frac{1 - 2\sigma t_{\min}}{1 + \sigma t_{\min}} \right)^k \|x^0 - x^*\|^2 \end{aligned}$$

2° from (d) and (e) 1°

$$\begin{aligned} f(x^k) - f^* &\leq \frac{1 - \sigma t_{\min}}{2t_{\min}} \|x^{k-1} - x^*\|^2 \\ &\leq \frac{1 - \sigma t_{\min}}{2t_{\min}} \left( \frac{1 - 2\sigma t_{\min}}{1 + \sigma t_{\min}} \right)^{k-1} \|x^0 - x^*\|^2 \\ &= \frac{1 - \sigma t_{\min}}{2t_{\min}} \left( \frac{1 - 2\sigma t_{\min}}{1 + \sigma t_{\min}} \right)^{k-1} D^2 \end{aligned}$$



	4(a)	4(b)	4(c)
final object value	499.5697	499.5697	499.5697
number of proximal gradient evaluations	46	92	56
number of outer iterations	23	8	28
CPU time	0.08s	0.09s	0.04s