

Convex Opt 球状化 HW11 王奕博 2100011025

$$1. (a) \quad \text{Prox}_c(x) = \inf_w \left\{ f(w) + \frac{1}{2c} \|w - x\|^2 \right\}, \quad c > 0$$

$$= \inf_w \left\{ \|w\|_2 + \frac{1}{2c} \|w - x\|_2^2 \right\}$$

direct computation:

取最小值时, $0 \in \partial \left[\|w\|_2 + \frac{1}{2c} \|w - x\|_2^2 \right]$

设 $w^* = \arg\min \{\dots\}$, ① $w^* \neq 0$, 则有: $0 = \frac{\vec{w}}{\|w\|_2} + \frac{1}{c} (\vec{w} - \vec{x})$

$$\therefore \vec{x} = \vec{w} \left(\frac{c}{\|w\|_2} + 1 \right), \quad \|x\|_2 = \left\| \frac{\vec{w}}{\|w\|_2} \right\| (c + \|w\|_2)$$

$$\|w\|_2 + \frac{1}{2c} \|w - x\|_2^2 = c + \|w\|_2$$

$$= \|w\|_2 + \frac{1}{2c} \cdot c^2 = \frac{c}{2} + \|w\|_2 = (c + \|w\|_2) - \frac{c}{2}$$

$$= \|x\|_2 - \frac{c}{2}$$

② $w^* = 0$, 有: $0 \in \partial \left[\|w\|_2 + \frac{1}{2c} \|w - x\|_2^2 \right] \Rightarrow \partial \|w\|_2 \Big|_{w=0} \ni \frac{\vec{x}}{c}$

则 $\frac{\vec{x}}{c} \in \{g \mid \|g\|_2 \leq 1\}$, $\text{Env}_c(x) = \frac{\|x\|_2^2}{2}$

$$\therefore \text{Prox}_c(x) = \begin{cases} 0, & \|x\|_2 \leq c \\ \vec{x} - \frac{c}{\|x\|_2} \vec{x}, & \|x\|_2 > c. \end{cases}$$

Moreau Decomposition:

$$\vec{x} = \text{Prox}_c(f(x)) + \text{Prox}_{c^{-1}} f^*(c^{-1}x) \cdot c$$

$$f(x) = \|x\|_2, \quad f^*(y) = \begin{cases} 0, & \|y\|_2 \leq 1 \\ +\infty, & \|y\|_2 > 1 \end{cases}$$

$$\text{Env}_{\frac{1}{c}} f^*\left(\frac{x}{c}\right) = \inf_w \left\{ f(w) + \frac{c}{2} \|w - \frac{x}{c}\|^2 \right\}$$

$$= \inf_{\substack{\|w\|_2 \leq 1 \\ \|w\|_2 \leq 1}} \left\{ \frac{c}{2} \|w - \frac{x}{c}\|^2 \right\} = \begin{cases} 0, & \|x\|_2 \leq c \\ \frac{c}{2} \left(\left\| \frac{x}{c} \right\|_2^2 - 1 \right), & \|x\|_2 > c \end{cases}$$

$$\therefore \text{Prox}_c(f(x)) = \vec{x} - c \cdot \text{Prox}_{\frac{1}{c}} f^*\left(\frac{x}{c}\right) \quad \therefore \text{Prox}_{\frac{1}{c}} f^*\left(\frac{x}{c}\right) = \begin{cases} \vec{x}, & \|x\|_2 \leq c \\ \frac{x}{\|x\|_2}, & \|x\|_2 > c \end{cases}$$

$$= \begin{cases} 0, & \|x\|_2 \leq c \\ \vec{x} - \frac{c}{\|x\|_2} \vec{x}, & \|x\|_2 > c \end{cases}$$

$$\text{lb)} \quad \text{Pro}_{X_C} f(x) = \underset{\vec{y}}{\arg\min} \left\{ \frac{1}{2} \vec{y}^T A \vec{y} + \vec{b}^T \vec{y} + c_0 + \frac{1}{2C} (\vec{y} - \vec{x})^T (\vec{y} - \vec{x}) \right\}$$

$$= \underset{\vec{y}}{\arg\min} \left\{ \frac{1}{2} \vec{y}^T (A + \frac{1}{C} I) \vec{y} + (\vec{b} - \frac{1}{C} \vec{x})^T \vec{y} + c_0 + \frac{1}{2C} \vec{x}^T \vec{x} \right\}$$

其存在最小值，当且仅当 $A + \frac{1}{C} I \succeq 0$ ，当此条件成立时，

$$\text{Pro}_{X_C} f(x) = \vec{y}, \text{ 其中 } \vec{y} \text{ 满足 } (A + \frac{1}{C} I) \vec{y} = \frac{1}{C} \vec{x} - \vec{b}$$

$$\text{若有 } A + \frac{1}{C} I > 0, \text{ 则有: } \text{Pro}_{X_C} f(x) = (A + \frac{1}{C} I)^{-1} (\frac{1}{C} \vec{x} - \vec{b})$$

$$\text{lc)} \quad \text{Pro}_{X_C} g(x) = \underset{\vec{w}}{\arg\min} \left\{ g(\vec{w}) + \frac{1}{2C} (\vec{w} - \vec{x})^2 \right\}, \text{ 认为 } \vec{x} \geq 0.$$

$$= \underset{\vec{w} \geq 0}{\arg\min} \left\{ \lambda \vec{w}^3 + \frac{1}{2C} (\vec{w} - \vec{x})^2 \right\}, \text{ 当 } \lambda < 0 \text{ 时其不存在.}$$

$$\text{当 } \lambda = 0 \text{ 时, } \text{Pro}_{X_C} g(x) = \vec{x}.$$

$$\text{当 } \lambda > 0 \text{ 时, } \frac{d}{d\vec{w}} (\lambda \vec{w}^3 + \frac{1}{2C} (\vec{w} - \vec{x})^2) = 0 \Rightarrow \text{Pro}_{X_C} g(x) = \frac{\sqrt[3]{1+12\lambda Cx}}{6\lambda C}$$

2. 对于 $d(x)$, 由前知 $d(x)$ is convex, $\therefore \frac{1}{2} d^2(x)$ is convex

$$\text{Pro}_{X_C} d(x) = \underset{\vec{w}}{\arg\min} \left\{ d(\vec{w}) + \frac{1}{2C} \|\vec{w} - \vec{x}\|_2^2 \right\}$$

$$1. \quad \vec{x} \in C, \text{ 则 } \partial d(\vec{w}) = 0, \quad \text{Pro}_{X_C} d(x) = \vec{x}.$$

$$2. \quad \vec{x} \notin C, \text{ 则令 } \vec{w}_0 = \underset{\substack{\vec{w} \in C \\ \|\vec{w} - \vec{x}\|_2}}{\arg\min} \|\vec{w} - \vec{x}\|_2, \text{ 易知 } \vec{w}_0 \text{ 唯一.}$$

$$\begin{aligned} \text{(讲义结论) 故易知, } \partial d(\vec{w}) &= \frac{\vec{w} - \vec{w}_0}{\|\vec{w} - \vec{w}_0\|_2} = (\vec{w} - P_C(\vec{w})) / \|\vec{w} - P_C(\vec{w})\|_2 \\ \text{则 } d(\vec{w}) &= \|\vec{w} - \vec{w}_0\|_2 \text{ 且 } d(\vec{w} + t \cdot (\vec{w} - \vec{w}_0)) = \|\vec{w} - \vec{w}_0\|_2 + t \|\vec{w} - \vec{w}_0\|_2 \end{aligned}$$

$$\therefore \frac{\vec{w} - P_C(\vec{w})}{\|\vec{w} - P_C(\vec{w})\|_2} + \frac{1}{C} (\vec{w} - \vec{x}) = 0 \Rightarrow \vec{w} = P_C(x) + t \cdot (x - P_C(x)) \quad \{t \geq 0\}$$

$$\text{则 } d(\vec{w}) + \frac{1}{2C} \|\vec{w} - \vec{x}\|_2^2 = \left[t \|\vec{x} - P_C(x)\|_2 + \frac{\|\vec{x} - P_C(x)\|_2^2}{2C} (t-1)^2 \right]$$

$$\textcircled{1} \quad d(x) \leq C, \text{ 则 } t^* = 0, \quad \text{Pro}_{X_C} d(x) = P_C(x).$$

$$\textcircled{2} \quad d(x) > C, \text{ 则 } t^* = 1 - \frac{C}{\|\vec{x} - P_C(x)\|_2}, \quad \text{Pro}_{X_C} d(x) = P_C(x) + \left(1 - \frac{C}{\|\vec{x} - P_C(x)\|_2}\right) \cdot (x - P_C(x))$$

故綫上, $\text{Prox}_c d(x) = \begin{cases} P_c(x), & d(x) \leq c \\ x + c \cdot \frac{P_c(x) - x}{\|P_c(x) - x\|_2}, & d(x) > c. \end{cases}$

对于 $\frac{1}{2}d_C^2$, 其为:

$$\text{prox}_{C,\frac{1}{2}d_C^2} = \underset{u}{\operatorname{argmin}} \left\{ \frac{1}{2} \cdot d_C^2(u) + \frac{1}{2C} \|u - x\|^2 \right\}$$

$$= \underset{u}{\operatorname{argmin}} \cdot \inf_{v \in C} \left\{ \frac{1}{2} \|u - v\|^2 + \frac{1}{2C} \|u - x\|^2 \right\}$$

$$= \underset{u}{\operatorname{argmin}} \inf_{v \in C} \left\{ \frac{1}{2} \left((1 + \frac{1}{C}) u^T u - 2(v^T + \frac{x^T}{C}) u \right) \right\}$$

则 u 与 v 满足: $u = \frac{c}{c+1}v + \frac{1}{c+1}x$

又有: $v = d_C(u)$, 即 $v = \underset{v \in C}{\operatorname{argmin}} \|u - v\|_2$

则 $v = \underset{v \in C}{\operatorname{argmin}} \left\| \frac{c}{c+1}v + \frac{1}{c+1}x - v \right\|_2 = \underset{v \in C}{\operatorname{argmin}} \frac{1}{c+1} \|x - v\|_2$

故: $v = d_C(x)$

故有: $\text{prox}_{C,\frac{1}{2}d_C^2}(x) = \frac{c}{c+1} d_C(x) + \frac{1}{c+1} x$

$$\begin{aligned}
 3. (a) \text{Prox}_C f(x) &= \underset{w}{\operatorname{argmin}} \left\{ g(w) + a^T w + \frac{1}{2C} \|w - x\|_2^2 \right\} \\
 &= \underset{w}{\operatorname{argmin}} \left\{ g(w) + a^T w + \frac{1}{2C} (w^T w - 2x^T w) \right\} \\
 &= \underset{w}{\operatorname{argmin}} \left\{ g(w) + \frac{1}{2C} (w^T w - 2(x - ca)^T w) \right\} \\
 &= \underset{w}{\operatorname{argmin}} \left\{ g(w) + \frac{1}{2C} \|w - (x - ca)\|_2^2 \right\} \\
 &= \text{Prox}_{Cg}(x - ca)
 \end{aligned}$$

$$\begin{aligned}
 (b) \text{Prox}_C f(x) &= \underset{w}{\operatorname{argmin}} \left\{ g(w) + \frac{1}{2\mu} \|w - a\|^2 + \frac{1}{2C} \|w - x\|_2^2 \right\} \quad (\text{舍去常数项}) \\
 &= \underset{w}{\operatorname{argmin}} \left\{ g(w) + \left(\frac{1}{2\mu} + \frac{1}{2C}\right) w^T w - \left(\frac{1}{\mu} a + \frac{1}{C} x\right)^T w \right\} \\
 &= \underset{w}{\operatorname{argmin}} \left\{ g(w) + \frac{\mu^{-1} + C^{-1}}{2} \|w - \frac{1}{\mu^{-1} + C^{-1}} \left(\frac{a}{\mu} + \frac{x}{C}\right)\|_2^2 \right\} \\
 &= \text{Prox}_{\lambda} g \left(\lambda \left(\frac{x}{C} + \frac{a}{\mu} \right) \right), \quad \lambda = \mu^{-1} + C^{-1}.
 \end{aligned}$$

4.

$$x_k = \underset{x}{\operatorname{argmin}} \left\{ g(x) + \frac{1}{2\eta} \|x - y_k + \eta \nabla f(y_k)\|_2^2 \right\}$$

∴ 有:

$$g(x_k) + \frac{1}{2\eta} \|x_k - y_k + \eta \nabla f(y_k)\|_2^2 \leq g(y_k) + \frac{1}{2\eta} \|\eta \nabla f(y_k)\|_2^2$$

移项, 得

$$g(x_k) \leq g(y_k) - \langle \nabla f(y_k), x_k - y_k \rangle - \frac{1}{2\eta} \|x_k - y_k\|^2$$

$$\left\{ \begin{array}{l} \leq \|x - w\| \frac{1}{2\varepsilon} + w^\top \alpha + (w^\top \beta) \min_{\omega} \omega = \text{soft, non} \\ (\text{未解}) \end{array} \right.$$

$$\left\{ \begin{array}{l} (w^\top x) \leq -w^\top w \frac{1}{2\varepsilon} + w^\top \alpha + (w^\top \beta) \min_{\omega} \omega = \\ \end{array} \right.$$

$$\left\{ \begin{array}{l} ((w^\top (x_0 - x)) \leq -w^\top x_0) \frac{1}{2\varepsilon} + (w^\top \beta) \min_{\omega} \omega = \\ \end{array} \right.$$

$$\left\{ \begin{array}{l} \leq \|x_0 - x\| \frac{1}{2\varepsilon} + (w^\top \beta) \min_{\omega} \omega = \\ (x_0 - x)^\top \alpha = \end{array} \right.$$

$$\left\{ \begin{array}{l} \leq \|x - w\| \frac{1}{2\varepsilon} \left\{ \|x_0 - w\| \frac{1}{2\varepsilon} + (w^\top \beta) \min_{\omega} \omega \right\} = \text{soft, non} \\ (\text{未解}) \end{array} \right.$$

$$\left\{ \begin{array}{l} w^\top \left(x_0 + \frac{\alpha}{2\varepsilon} \right) - w^\top w \left(\frac{1}{2\varepsilon} + \frac{1}{M\varepsilon} \right) + (w^\top \beta) \min_{\omega} \omega = \\ \end{array} \right.$$

$$\left\{ \begin{array}{l} \leq \left(\|x_0 + \frac{\alpha}{2\varepsilon}\| + \|w\| \right) \frac{\|x_0 + \frac{\alpha}{2\varepsilon}\|}{\varepsilon} + (w^\top \beta) \min_{\omega} \omega = \\ \end{array} \right.$$

$$\left\{ \begin{array}{l} \leq \left(\|x_0 + \frac{\alpha}{2\varepsilon}\| + \|w\| \right) \frac{\|x_0 + \frac{\alpha}{2\varepsilon}\|}{\varepsilon} + (w^\top \beta) \min_{\omega} \omega = \\ \end{array} \right.$$

年 月 日

5. 令 $f(x) = \begin{cases} 0, & x \in L \\ +\infty, & \text{otherwise} \end{cases}$

则 $f^*(y) = \sup_x \{ y^T x - f(x) \} = \sup_{x \in L} y^T x$

若 $y^T x \neq 0$, 则 $\lim_{t \rightarrow +\infty} y^T (tx)$ 与 $\lim_{t \rightarrow -\infty} y^T (tx)$ 中一定有一个为 $+\infty$

$\therefore y \in L^\perp$, $\therefore f^*(y) = \begin{cases} 0, & y \in L^\perp \\ +\infty, & \text{otherwise} \end{cases}$

故 $P_L(x) = \text{Prox}_c f(x)$, $P_{L^\perp}(x) = \text{Prox}_c f^*(x)$, $\forall c$.

由 Moreau 分解, $x = P_c f(x) + c P_{c^{-1}} f^*(c^{-1} x)$. 取 $c=1$,

有 $x = P_L(x) + P_{L^\perp}(x)$