

CMSE890 Homework#1

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1.

If \mathbf{x} is optimal, for all feasible \mathbf{y} , $\mathbf{y}_k = \frac{k}{k+1}\mathbf{x} + \frac{1}{k+1}\mathbf{y}$, we have $f(\mathbf{y}_k) - f(\mathbf{x}) \geq 0, \forall k$. So

$$\frac{f(\mathbf{y}_k) - f(\mathbf{x})}{\frac{1}{k+1}} = \frac{f(\mathbf{x} + \frac{1}{k+1}(\mathbf{y} - \mathbf{x})) - f(\mathbf{x})}{\frac{1}{k+1}} \geq 0$$

Let $k \rightarrow \infty$, we get $\nabla f(\mathbf{x})^T(\mathbf{y} - \mathbf{x}) \geq 0$

2.

Because $\mathbf{x}^T W \mathbf{x}$ is a scalar. $(\mathbf{x}^T W \mathbf{x})^T = \mathbf{x}^T W \mathbf{x} = \mathbf{x}^T \frac{W+W^T}{2} \mathbf{x}$. So we always assume W is symmetric. Symmetric positive definite matrix has the real and positive eigenvalue and eigenvector is orthogonal, which means $P^{-1} = P^T$.

Suppose

$$\begin{aligned} W_1 &= P^{-1} \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n) P \\ &= (P^{-1} \text{diag}(\sqrt{\lambda_1}, \sqrt{\lambda_2}, \dots, \sqrt{\lambda_n}) P)^T (P^{-1} \text{diag}(\sqrt{\lambda_1}, \sqrt{\lambda_2}, \dots, \sqrt{\lambda_n}) P) \\ &\triangleq S^T S \end{aligned}$$

In the same way, we define $W_2 = R^T R$.

$$\begin{aligned} \|\mathbf{x}\|_{W_1} &= \sqrt{\mathbf{x}^T W_1 \mathbf{x}} = \sqrt{\mathbf{x}^T S^T S \mathbf{x}} \\ &= \|S \mathbf{x}\|_2 = \|S R^{-1} R \mathbf{x}\|_2 \\ &\leq \|S R^{-1}\|_2 \cdot \|R \mathbf{x}\|_2 = \|S R^{-1}\|_2 \cdot \|\mathbf{x}\|_{W_2} \end{aligned}$$

In the same way, we get $\|\mathbf{x}\|_{W_2} \leq \|R S^{-1}\|_2 \cdot \|\mathbf{x}\|_{W_1}$, so $m = \|S R^{-1}\|_2^{-1}$ and $M = \|R S^{-1}\|_2$.

3.

Suppose $f(\mathbf{x}) = \|\mathbf{x}\|_1 + \mathbf{x}^T \mathbf{b}$, $\mathbf{b} = (b_1, b_2, \dots, b_n)^T$.

Case 1: $|b_i| \leq 1, \forall i \in \{1, 2, \dots, n\}$.

Then

$$\begin{aligned} f(\mathbf{x}) &= \sum_{i=1}^n (|x_i| + b_i x_i) \\ &\geq \sum_{i=1}^n (|x_i| - |b_i| |x_i|) \\ &= \sum_{i=1}^n (1 - |b_i|) |x_i| \\ &\geq 0 \end{aligned}$$

However, $f(\mathbf{x}^*) = 0$ when $\mathbf{x}^* = \mathbf{0}$, So

$$\begin{aligned} \min_{\|\mathbf{x}\|_2 \leq 1} f(\mathbf{x}) &= 0 \\ \arg \min_{\|\mathbf{x}\|_2 \leq 1} f(\mathbf{x}) &= \mathbf{0} \end{aligned}$$

Case 2: $\exists i \in \{1, 2, \dots, n\}$ that makes $|b_i| > 1$.

In this case, we suppose that $|b_1| \geq |b_2| \geq \dots \geq |b_k| > 1 \geq |b_{k+1}| \geq \dots \geq |b_n|$. (In other words, we sort $|b_i|$)

Then, for $\|\mathbf{x}\|_2 \leq 1$,

$$\begin{aligned} f(\mathbf{x}) &= \sum_{i=1}^n (|x_i| + b_i x_i) \\ &\geq \sum_{i=1}^n (|x_i| - |b_i| |x_i|) \\ &= \sum_{i=1}^k (1 - |b_i|) |x_i| + \sum_{i=k+1}^n (1 - |b_i|) |x_i| \\ &\geq \sum_{i=1}^k (1 - |b_i|) |x_i| \\ &= (\mathbf{b}^*)^T \text{sgn}(\mathbf{x}) \end{aligned}$$

where $\mathbf{b}^* = (1 - |b_1|, 1 - |b_2|, \dots, 1 - |b_k|, 0, \dots, 0)^T$ and $\text{sgn}(\mathbf{x}) = (|x_1|, |x_2|, \dots, |x_n|)^T$. We have $\{\text{sgn}(\mathbf{x}) : \|\mathbf{x}\|_2 \leq 1\} \subset \{\mathbf{x} : \|\mathbf{x}\|_2 \leq 1\}$.

So

$$\begin{aligned} f(\mathbf{x}) &\geq (\mathbf{b}^*)^T \text{sgn}(\mathbf{x}) \\ &\geq \inf_{\|\mathbf{x}\|_2 \leq 1} (\mathbf{b}^*)^T \text{sgn}(\mathbf{x}) \\ &\geq \inf_{\|\mathbf{x}\|_2 \leq 1} (\mathbf{b}^*)^T \mathbf{x} \\ &= (\mathbf{b}^*)^T \left(-\frac{\mathbf{b}^*}{\|\mathbf{b}^*\|_2} \right) \\ &= -\|\mathbf{b}^*\|_2 \\ &= -\sqrt{\sum_{i=1}^k (1 - |b_i|)^2} \end{aligned}$$

However, let $\mathbf{x}^* = \left(\frac{(1 - |b_1|)\text{sgn}(b_1)}{\sqrt{\sum_{i=1}^k (1 - |b_i|)^2}}, \frac{(1 - |b_2|)\text{sgn}(b_2)}{\sqrt{\sum_{i=1}^k (1 - |b_i|)^2}}, \dots, \frac{(1 - |b_k|)\text{sgn}(b_k)}{\sqrt{\sum_{i=1}^k (1 - |b_i|)^2}}, 0, \dots, 0 \right)^T$

Then

$$\begin{aligned} f(\mathbf{x}^*) &= \sum_{i=1}^k \left(\frac{|\text{sgn}(b_i)(1 - |b_i|)|}{\sqrt{\sum_{j=1}^k (1 - |b_j|)^2}} + \frac{b_i \text{sgn}(b_i)(1 - |b_i|)}{\sqrt{\sum_{j=1}^k (1 - |b_j|)^2}} \right) \\ &= \sum_{i=1}^k \left(\frac{(|b_i| - 1)}{\sqrt{\sum_{j=1}^k (1 - |b_j|)^2}} + \frac{|b_i|(1 - |b_i|)}{\sqrt{\sum_{j=1}^k (1 - |b_j|)^2}} \right) \\ &= \sum_{i=1}^k \frac{-(1 - |b_i|)^2}{\sqrt{\sum_{j=1}^k (1 - |b_j|)^2}} \\ &= -\sqrt{\sum_{i=1}^k (1 - |b_i|)^2} \end{aligned}$$

So

$$\min_{\|\mathbf{x}\|_2 \leq 1} f(\mathbf{x}) = -\sqrt{\sum_{i=1}^k (1 - |b_i|)^2}$$

$$\arg \min_{\|\mathbf{x}\|_2 \leq 1} f(\mathbf{x}) = \left(\frac{(1 - |b_1|)\text{sgn}(b_1)}{\sqrt{\sum_{i=1}^k (1 - |b_i|)^2}}, \frac{(1 - |b_2|)\text{sgn}(b_2)}{\sqrt{\sum_{i=1}^k (1 - |b_i|)^2}}, \dots, \frac{(1 - |b_k|)\text{sgn}(b_k)}{\sqrt{\sum_{i=1}^k (1 - |b_i|)^2}}, 0, \dots, 0 \right)^T$$

4.

Let $p = 1/\theta$, $q = 1/(1 - \theta)$. Then $1/p + 1/q = 1$

$$\begin{aligned} f(\theta \mathbf{x} + (1 - \theta) \mathbf{y}) &= \sum_{i=1}^n \log \left(1 + e^{\mathbf{a}_i^T (\theta \mathbf{x} + (1 - \theta) \mathbf{y})} \right) \\ &= \sum_{i=1}^n \log \left(1^\theta \cdot 1^{1-\theta} + e^{\theta \mathbf{a}_i^T \mathbf{x}} \cdot e^{(1-\theta) \mathbf{a}_i^T \mathbf{y}} \right) \\ &\leq \sum_{i=1}^n \log \left(\left((1^\theta)^p + (e^{\theta \mathbf{a}_i^T \mathbf{x}})^p \right)^{1/p} \cdot \left((1^{1-\theta})^q + (e^{(1-\theta) \mathbf{a}_i^T \mathbf{y}})^q \right)^{1/q} \right) \\ &= \frac{1}{p} \sum_{i=1}^n \log(1 + e^{\mathbf{a}_i^T \mathbf{x}}) + \frac{1}{q} \sum_{i=1}^n \log(1 + e^{\mathbf{a}_i^T \mathbf{y}}) \\ &= \theta f(\mathbf{x}) + (1 - \theta) f(\mathbf{y}) \end{aligned}$$

so f is convex.

5.

(1)

$$\begin{aligned} (F(\mathbf{x}) - F(\mathbf{y}))^T (\mathbf{x} - \mathbf{y}) &\geq 0 \Leftrightarrow (\mathbf{x} - \mathbf{y})^T A^T (\mathbf{x} - \mathbf{y}) \geq 0 \\ &\Leftrightarrow A \text{ is positive semi-definite.} \end{aligned}$$

(2)

$$\begin{aligned} (F(\mathbf{x}) - F(\mathbf{y}))^T (\mathbf{x} - \mathbf{y}) &> 0 \Leftrightarrow (\mathbf{x} - \mathbf{y})^T A^T (\mathbf{x} - \mathbf{y}) > 0 \\ &\Leftrightarrow A \text{ is positive definite.} \end{aligned}$$

(3)

$$\begin{aligned} (F(\mathbf{x}) - F(\mathbf{y}))^T (\mathbf{x} - \mathbf{y}) &\geq m \|\mathbf{x} - \mathbf{y}\|^2 \Leftrightarrow (\mathbf{x} - \mathbf{y})^T (A - mI)^T (\mathbf{x} - \mathbf{y}) \geq 0 \\ &\Leftrightarrow A - mI \text{ is positive semi-definite.} \end{aligned}$$

(4)

$$\begin{aligned} \|F(\mathbf{x}) - F(\mathbf{y})\| &\leq L \|\mathbf{x} - \mathbf{y}\| \Leftrightarrow (\mathbf{x} - \mathbf{y})^T A^T A (\mathbf{x} - \mathbf{y}) \leq L^2 (\mathbf{x} - \mathbf{y})^T (\mathbf{x} - \mathbf{y}) \\ &\Leftrightarrow L^2 I - A^T A \text{ is positive semi-definite.} \end{aligned}$$

(5)

$$\begin{aligned} (F(\mathbf{x}) - F(\mathbf{y}))^T (\mathbf{x} - \mathbf{y}) &\geq \frac{1}{L} \|F(\mathbf{x}) - F(\mathbf{y})\|^2 \Leftrightarrow (\mathbf{x} - \mathbf{y})^T A^T (\mathbf{x} - \mathbf{y}) \geq \frac{1}{L} (\mathbf{x} - \mathbf{y})^T A^T A (\mathbf{x} - \mathbf{y}) \\ &\Leftrightarrow A^T - \frac{1}{L} A^T A \text{ is positive semi-definite.} \end{aligned}$$