

IOE 611: Homework 1

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Problem 1

For a vector $x \in \mathbf{R}^n$, its ℓ_∞ -norm is defined as $\|x\|_\infty = \max_{1 \leq i \leq n} |\alpha_i|$. Consider the following two optimization problems:

$$(P1) \min_x \|Ax - b\|_\infty$$
$$\text{s.t. } x \succeq 0$$

$$(P2) \min_{y,t} t$$
$$\text{s.t. } a_i^\top y - t \leq b_i,$$
$$-a_i^\top y - t \leq -b_i, \forall i = 1, \dots, k,$$
$$y \succeq 0.$$

where $x \in \mathbf{R}^n$, and a_i^\top is the i th row of A . Note that $(P2)$ is a linear program. Show that $(P1)$ and $(P2)$ are equivalent by showing that:

(a) For every feasible solution x of $(P1)$, there exists a feasible solution (y, t) of $(P2)$ such that $t \leq \|Ax - b\|_\infty$

Proof. Notice that

$$\|Ax - b\|_\infty = \max_{i=1, \dots, k} |(Ax - b)_i|$$
$$= \max_{i=1, \dots, k} |a_i^\top x - b_i|$$

For any feasible solution $x \succeq 0$ of $(P1)$, let

$$\begin{cases} \hat{y} = x \succeq 0 \\ \hat{t} = \|Ax - b\|_\infty = \max_i |a_i^\top \hat{y} - b_i| \end{cases}$$

For any $i = 1, \dots, k$,

$$\begin{cases} \hat{t} \geq |a_i^\top \hat{y} - b_i| \\ \hat{t} \geq a_i^\top x - b_i \Leftrightarrow b_i \geq a_i^\top x - \hat{t}, \\ \hat{t} \geq b_i - a_i^\top x \Leftrightarrow -b_i \geq -a_i^\top x - \hat{t}, \end{cases}$$

which implies (\hat{y}, \hat{t}) is a feasible solution of $(P2)$. □

(b) For every feasible solution (y, t) of $(P2)$, there exists a feasible solution x of $P1$ such that $\|Ax - b\|_\infty \leq t$

Proof. For any feasible solution (y, t) of $(P2)$, let $\hat{x} = y$. By definition

$$\begin{aligned} y &\succeq 0 \\ a_i^\top y - t &\leq b_i, \forall i = 1, \dots, k \\ -a_i^\top y - t &\leq -b_i, \forall i = 1, \dots, k \end{aligned}$$

For any $i = 1, \dots, k$

$$\begin{aligned} -t &\leq a_i^\top y - b_i \leq t \\ t &\geq |a_i^\top y - b_i| \\ t &\geq \max_{i=1, \dots, k} |a_i^\top y - b_i| \\ t &\geq \|Ay - b\|_\infty \\ t &\geq \|A\hat{x} - b\|_\infty \end{aligned}$$

which implies \hat{x} is a feasible solution of $(P1)$. □

Problem 2

Derive a linear program equivalent to

$$\min_x \|Ax - b\|_\infty + \rho \|x\|_1$$

where $\rho \geq 0$.

Solution.

$$\begin{aligned} \min_{t,y,z} \quad & t + \rho \sum_{j=1}^n z_j \\ \text{s.t.} \quad & a_i^\top - t \leq b_i \\ & -a_i^\top - t \leq -b_i \\ & y_j \leq z_j \\ & -y_j \leq z_j \\ & i = 1, \dots, k \\ & j = 1, \dots, n \end{aligned}$$

■

Problem 3

Let $C \subseteq \mathbf{R}^n$ be a convex set, with $x_1, \dots, x_k \in C$, and let $\theta_1, \dots, \theta_k \in \mathbf{R}$ satisfy $\theta_i \geq 0$, $\theta_1 + \dots + \theta_k = 1$. Show that $\theta_1 x_1 + \dots + \theta_k x_k \in C$.

Proof. By induction, for $k = 2$, $\theta_1 x_1 + \theta_2 x_2 \in C$ holds by the definition of convexity.

Assume this holds for $k = m$, $m \geq 2$.

$$\theta_1 x_1 + \dots + \theta_m x_m \in C$$

For $k = m + 1$, $x_1, \dots, x_m, x_{m+1} \in C$, and $\theta_1, \dots, \theta_m, \theta_{m+1} \in \mathbf{R}$ satisfy $\theta_i \geq 0$, $\sum_{i=1}^{m+1} \theta_i = 1$.

$$\begin{aligned} & \sum_{i=1}^{m+1} \theta_i x_i \\ &= \sum_{i=1}^m \theta_i x_i + \theta_{m+1} x_{m+1} \\ &= (1 - \theta_{m+1}) \sum_{i=1}^m \frac{\theta_i}{1 - \theta_{m+1}} x_i + \theta_{m+1} x_{m+1} \end{aligned}$$

Since $\sum_{i=1}^m \frac{\theta_i}{1 - \theta_{m+1}} x_i \in C$ by the induction hypothesis, and

$$\begin{aligned} & \sum_{i=1}^{m+1} \theta_i = 1 \\ & \sum_{i=1}^m \theta_i = 1 - \theta_{m+1} \\ & \sum_{i=1}^m \frac{\theta_i}{1 - \theta_{m+1}} = 1 \end{aligned}$$

Original proposition holds for arbitrary k . □

Problem 4

(a) Show that if a matrix is symmetric and has non-negative eigenvalues, then it must be PSD.

Proof. Suppose $A \in \mathbb{R}^{n \times n}$ is a symmetric matrix and has non-negative eigenvalues, we can decompose A as

$$A = \sum_{i=1}^n \lambda_i v_i v_i^\top, i = 1, \dots, n$$

where $\lambda_i \geq 0$ are eigenvalues of A and v_i is the corresponding eigenvectors. Note that $\{v_i\}_{i \in [n]}$ is an orthonormal basis of \mathbb{R}^n , i.e.

$$v_i^\top v_j = \begin{cases} 0 & i \neq j \\ 1 & i = j \end{cases}$$

For any $x \in \mathbb{R}^n$, $\exists \alpha_i \in \mathbb{R}, i = 1, \dots, n$, we can represent it as

$$x = \sum_{i=1}^n \alpha_i v_i$$

and then

$$\begin{aligned} Ax &= \left(\sum_{i=1}^n \lambda_i v_i v_i^\top \right) \left(\sum_{j=1}^n \alpha_j v_j \right) \\ &= \sum_{i,j=1}^n \lambda_i \alpha_j (v_i^\top v_j) v_j \\ &= \sum_{i=1}^n \lambda_i \alpha_i v_i, \\ x^\top Ax &= \left(\sum_{i=1}^n \alpha_i v_i^\top \right) \left(\sum_{j=1}^n \lambda_j \alpha_j v_j \right) \\ &= \sum_{i,j=1}^n \lambda_j \alpha_i \alpha_j (v_i^\top v_j) \\ &= \sum_{i=1}^n \lambda_i \alpha_i^2 \geq 0. \end{aligned}$$

Therefore, A is PSD.

□

(b) Show that a symmetric matrix X is PSD if and only if it can be written as $X = VV^\top$, for some matrix V .

Proof. \Rightarrow : If a symmetric matrix X is PSD, it can be decomposed as

$$\begin{aligned} X &= \sum_{i=1}^n \lambda_i v_i v_i^\top \\ &= Q \Lambda Q^\top \end{aligned}$$

where $\lambda_i \geq 0$ are eigenvalues of A ; v_i is the corresponding eigenvectors; $Q = [v_1, \dots, v_n]$ is an orthogonal matrix and $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$ is a diagonal matrix.

Let $V = Q\sqrt{\Lambda}$, where $\sqrt{\Lambda} = \text{diag}(\sqrt{\lambda_1}, \dots, \sqrt{\lambda_n})$, we have

$$\begin{aligned} X &= Q\sqrt{\Lambda}\sqrt{\Lambda}^\top Q^\top \\ &= (Q\sqrt{\Lambda})(Q\sqrt{\Lambda})^\top \\ &= VV^\top \end{aligned}$$

\Leftarrow : If a symmetric matrix $X = VV^\top$, for any $z \in \mathbb{R}^n$, we have

$$\begin{aligned} z^\top X z &= z^\top V V^\top z \\ &= (V^\top z)^\top (V^\top z) \\ &= \|V^\top z\|^2 \geq 0 \end{aligned}$$

Therefore, X is PSD. □

Problem 5

Show that the PSD cone is self-dual, that is, $(\mathbb{S}_+^n)^* = \mathbb{S}_+^n$.

Proof. By the definition of dual cone, we have

$$(\mathbb{S}_+^n)^* = \{B \in \mathbb{S}_+^n \mid \langle A, B \rangle \geq 0, \forall A \in \mathbb{S}_+^n\}$$

where $\langle A, B \rangle = \text{tr}(AB)$.

We now show that $\forall A \in \mathbb{S}_+^n$, $\langle A, B \rangle \geq 0$ if and only if $B \in \mathbb{S}_+^n$.

\Rightarrow : Suppose $B \notin \mathbb{S}_+^n$, then there exists $z \in \mathbb{R}^n$, such that $z^\top B z = \text{tr}(zz^\top B) < 0$.

Let $A = zz^\top$ is PSD, then

$$\langle A, B \rangle = \text{tr}(AB) = \text{tr}(zz^\top B) < 0$$

which shows $B \notin (\mathbb{S}_+^n)^*$

\Leftarrow : Since $A \in \mathbb{S}_+^n$, A can be decomposed as

$$A = \sum_{i=1}^n \lambda_i z_i z_i^\top$$

where $\lambda_i \geq 0$ are eigenvalues. Then,

$$\begin{aligned} \langle A, B \rangle &= \text{tr}(AB) \\ &= \text{tr}\left(B \sum_{i=1}^n \lambda_i z_i z_i^\top\right) \\ &= \sum_{i=1}^n \lambda_i z_i^\top B z_i \geq 0 \end{aligned}$$

which shows $B \in (\mathbb{S}_+^n)^*$

□

Problem 6

The second-order cone is defined as $C = \{(x, t) : \|x\|_2 \leq t, t \geq 0\}$.

(a) Prove that C is a cone and it is convex.

Proof. To show C is a cone, for any $\lambda > 0, (x, t) \in C$ we have

$$\|\lambda x\|_2 = \lambda \|x\|_2 \leq \lambda t$$

which implies $\lambda(x, t) = (\lambda x, \lambda t) \in C$ is a cone.

To show C is convex, for any $(x_1, t_1), (x_2, t_2) \in C, \theta \in [0, 1]$, we have

$$\begin{aligned} \|\theta x_1 + (1 - \theta)x_2\|_2 &\leq \theta \|x_1\|_2 + (1 - \theta) \|x_2\|_2 \\ &\leq \theta t_1 + (1 - \theta)t_2 \end{aligned}$$

which implies $\theta(x_1, t_1) + (1 - \theta)(x_2, t_2) = (\theta x_1 + (1 - \theta)x_2, \theta t_1 + (1 - \theta)t_2) \in C$ is convex. \square

(b) Let P be a PSD matrix. Prove that the set $C = \{x | x^\top P x \leq (a^\top x)^2, a^\top x \geq 0\}$ is a cone and it is convex. This cone is called hyperbolic cone.

Proof. To show C is a cone, for any $\lambda > 0, x \in C$,

$$\begin{aligned} (\lambda x)^\top P (\lambda x) &= \lambda^2 (x^\top P x) \\ &\leq \lambda^2 (a^\top x)^2 \\ &= (a^\top (\lambda x))^2 \end{aligned}$$

Since $a^\top \lambda x = \lambda a^\top x \geq 0, \lambda x \in C$. C is a cone. \square