

HW1 Solutions

October 1, 2019

1. We show that the four conditions are met:

- $\|\cdot\|_1$ is nonnegative: $\|x\|_1 \geq 0$, for all $x \in \mathbb{R}^n$.
 $\|x\|_1 = \sum_{i=1}^n |x_i| \geq \sum_{i=1}^n 0 = 0, \forall x \in \mathbb{R}^n$.
- f is definite: $\|x\|_1 = 0$ if and only if $x = 0$.
(\leftarrow) if $x_i = 0, \forall i = 1, 2, \dots, n \Rightarrow \|x\|_1 = \sum_{i=1}^n |x_i| = \sum_{i=1}^n 0 = 0$.
(\rightarrow) if $x_i \neq 0$ (i.e., $x \neq 0$) $\Rightarrow \sum_{i=1}^n |x_i| > 0 \neq 0 \Rightarrow \sum_{i=1}^n |x_i| = 0$ only if $x = 0$.
- $\|\cdot\|_1$ is homogeneous: $\|tx\|_1 = |t| \|x\|_1$, for all $x \in \mathbb{R}^n$ and $t \in \mathbb{R}$.
 $\|tx\|_1 = \sum_{i=1}^n |tx_i| = \sum_{i=1}^n |t| |x_i| = |t| \sum_{i=1}^n |x_i| = |t| \|x\|_1, \forall x \in \mathbb{R}^n, t \in \mathbb{R}$.
- $\|\cdot\|_1$ satisfies the triangle inequality: $\|x + y\|_1 \leq \|x\|_1 + \|y\|_1$, for all $x, y \in \mathbb{R}^n$.
$$\begin{aligned} \|x + y\|_1 &= \sum_{i=1}^n |x_i + y_i| \leq \sum_{i=1}^n (|x_i| + |y_i|) = \sum_{i=1}^n |x_i| + \sum_{i=1}^n |y_i| \\ &= \|x\|_1 + \|y\|_1, \forall x, y \in \mathbb{R}^n. \end{aligned}$$

Therefore, ℓ_1 -norm is a norm.

2. We use the definition of operator norm on $\mathbb{R}^{m \times n}$

$$\begin{aligned} \|X\|_{1,1} &= \sup\{\|Xu\|_1 : \|u\|_1 \leq 1\} = \sup\left\{\sum_{i=1}^m \left|\sum_{j=1}^n X_{i,j} u_j\right| : \sum_{j=1}^n |u_j| \leq 1\right\} \\ &\leq \sup\left\{\sum_{j=1}^n \sum_{i=1}^m |X_{i,j}| |u_j| : \sum_{j=1}^n |u_j| \leq 1\right\} \\ &\leq \sup\left\{\left[\max_j \left(\sum_{i=1}^m |X_{i,j}|\right)\right] \sum_{j=1}^n |u_j| : \sum_{j=1}^n |u_j| \leq 1\right\} \\ &\leq \sup\left\{\max_j \sum_{i=1}^m |X_{i,j}|\right\} \\ &= \max_j \sum_{i=1}^m |X_{i,j}|. \end{aligned}$$

This can be achieved by choosing u such that $u_j = 1$ for j that maximizes $\sum_{i=1}^m |X_{i,j}|$ and $u_j = 0$ otherwise.

$$\begin{aligned}
3. \quad \|z\|_* &= \sup\{z^T x : \|x\|_1 \leq 1\} \\
&\leq \sup\left\{\sum_{i=1}^n |z_i| |x_i| : \|x\|_1 \leq 1\right\} \\
&= \sup\left\{\sum_{i=1}^n |z_i| |x_i| : \sum_{i=1}^n |x_i| \leq 1\right\} \\
&\leq \sup\left\{\max_i |z_i| \sum_{i=1}^n |x_i| : \sum_{i=1}^n |x_i| \leq 1\right\} \\
&\leq \sup\{\max_i |z_i|\} \\
&= \max_i |z_i| = \|z\|_\infty.
\end{aligned}$$

This can be achieved by choosing x such that $x_i = 1$ for i that maximizes $|z_i|$ and $x_i = 0$ otherwise.

$$\begin{aligned}
4. \quad (a) \quad \text{tr}(AB) &= \sum_{i=1}^n \sum_{j=1}^n a_{ij} b_{ji} = \sum_{j=1}^n \sum_{i=1}^n b_{ji} a_{ij} = \text{tr}(BA). \\
(b) \quad \text{tr}(tA + B) &= \sum_{i=1}^n (ta_{ii} + b_{ii}) = t \sum_{i=1}^n a_{ii} + \sum_{i=1}^n b_{ii} = t \cdot \text{tr}(A) + \text{tr}(B). \\
5. \quad \|x - cy\|^2 &= \langle x - cy, x - cy \rangle \\
&= \langle x, x \rangle + \langle -cy, x \rangle + \langle x, -cy \rangle + \langle -cy, -cy \rangle \\
&= \langle x, x \rangle - c \langle y, x \rangle - c \langle x, y \rangle + c^2 \langle y, y \rangle \\
&= \langle x, x \rangle - 2c \langle x, y \rangle + c^2 \langle y, y \rangle, \quad \forall c \in \mathbb{R}.
\end{aligned}$$

Then we choose $c = \frac{\langle x, y \rangle}{\langle y, y \rangle}$.

$$\begin{aligned}
\Rightarrow \|x - cy\|^2 &= \langle x, x \rangle - 2 \frac{\langle x, y \rangle}{\langle y, y \rangle} \langle x, y \rangle + \left(\frac{\langle x, y \rangle}{\langle y, y \rangle} \right)^2 \langle y, y \rangle \\
&= \langle x, x \rangle - \frac{|\langle x, y \rangle|^2}{\langle y, y \rangle} \geq 0 \\
\Rightarrow |\langle x, y \rangle|^2 &\leq \langle x, x \rangle \langle y, y \rangle.
\end{aligned}$$

6. We show that the three conditions are met:

- Conjugate symmetry: $\langle X, Y \rangle_F = \overline{\langle Y, X \rangle_F}$.

$$\overline{\langle Y, X \rangle_F} = \text{tr}(\overline{Y^T X}) = \text{tr}(Y^T X) = \text{tr}(X^T Y) = \langle X, Y \rangle_F.$$

- Linearity in the first argument:

$$\langle cX, Y \rangle_F = c \langle X, Y \rangle_F, \text{ and } \langle X + Z, Y \rangle_F = \langle X, Y \rangle_F + \langle Z, Y \rangle_F.$$

$$\langle X + Z, Y \rangle_F = \text{tr}((X + Z)^T Y)$$

$$= \text{tr}((X^T + Z^T)Y)$$

$$= \text{tr}(X^T Y) + \text{tr}(Z^T Y) \quad (\text{Problem by 4,(b)})$$

$$= \langle X, Y \rangle_F + \langle Z, Y \rangle_F, \quad \forall Z \in \mathbb{R}^{m \times n}.$$

$$\langle cX, Y \rangle_F = \text{tr}(cX^T Y) = c \cdot \text{tr}(X^T Y) = c \langle X, Y \rangle, \quad \forall c \in \mathbb{R}. \quad (\text{Problem by 4,(b)})$$

- Positive-definite: $\langle X, X \rangle_F > 0$, if $X \neq 0$.

if $X \neq 0$, $\exists x_{i,j}$, then $\langle X, X \rangle_F = \text{tr}(X^T X) = \sum_{i=1}^m \sum_{j=1}^n x_{ij}^2 > 0$.

$$\begin{aligned}
 7. \quad (a) \quad f(x) &= \|Ax - b\|_2^2 = (Ax - b)^T (Ax - b) = (x^T A^T - b^T)(Ax - b) \\
 &= x^T A^T Ax - b^T Ax - x^T A^T b + b^T b = x^T A^T Ax - 2b^T Ax + b^T b. \\
 \nabla f(x) &= 2A^T Ax - 2A^T b = 2A^T (Ax - b).
 \end{aligned}$$

$$(b) \quad \nabla^2 f(x) = \nabla_x (2A^T Ax - 2A^T b) = 2A^T A.$$

$$8. \quad (a) \quad \text{tr}(A) = \text{tr}(Q\Lambda Q^T) = \text{tr}(Q^T Q\Lambda) = \text{tr}(I\Lambda) = \text{tr}(\Lambda) = \sum_{i=1}^n \lambda_i.$$

(b) (\rightarrow) suppose that λ is an eigenvalue of A . Then there exists a nonzero eigenvector $x \in \mathbb{R}^n$ s.t., $Ax = \lambda x$. So $0 \leq x^T Ax = \lambda x^T x$. Since $x^T x$ is positive for all nonzero x , this implies that λ is non-negative.

(\leftarrow) if $\lambda_i \geq 0 \quad \forall i = 1, 2, \dots, n$.

$$\Rightarrow x^T Ax = x^T Q\Lambda Q^T x = z^T \Lambda z = \sum_{i=1}^n \lambda_i (z_i)^2 \geq 0 \quad (\text{let } z = Q^T x).$$

(c) We set $z = Q^T x$.

$$\frac{x^T Ax}{x^T x} = \frac{x^T Q\Lambda Q^T x}{z^T Q Q^T z} = \frac{z^T \Lambda z}{z^T z} = \frac{\lambda_{\min}|z_1|^2 + \dots + \lambda_{\max}|z_n|^2}{|z_1|^2 + \dots + |z_n|^2} \leq \frac{\lambda_{\max}(|z_1|^2 + \dots + |z_n|^2)}{|z_1|^2 + \dots + |z_n|^2} = \lambda_{\max}$$

$$\Rightarrow x^T Ax \leq \lambda_{\max} x^T x.$$

$$\frac{x^T Ax}{x^T x} = \frac{z^T \Lambda z}{z^T z} = \frac{\lambda_{\min}|z_1|^2 + \dots + \lambda_{\max}|z_n|^2}{|z_1|^2 + \dots + |z_n|^2} \geq \frac{\lambda_{\min}(|z_1|^2 + \dots + |z_n|^2)}{|z_1|^2 + \dots + |z_n|^2} \geq \lambda_{\min} \Rightarrow x^T Ax \geq \lambda_{\min} x^T x$$

$$\Rightarrow \lambda_{\min} x^T x \leq x^T Ax \leq \lambda_{\max} x^T x.$$