

Lec. #3 (09/20/2022)

Same
Example from last lecture

$$X = \begin{bmatrix} 2 & -1 & 0 \\ -1 & 2 & -1 \\ 0 & -1 & 2 \end{bmatrix} \in S^3$$

$$2 > 0, 3 > 0, \quad 2(4-1) + 1(-2-0) + 0 \\ = 6 - 2 = 4 > 0$$

$$\therefore X \in S_{++}^3$$

next pg.

Testing S_+^n via principal minors (needs to be ≥ 0)

From the square matrix, delete specific rows & columns such that the row and column indices being deleted are the same

→ principal minors are determinants of the resulting matrices.

Example: Consider $X = \begin{bmatrix} 1 & 2 & -1 \\ 2 & 4 & -2 \\ -1 & -2 & 1 \end{bmatrix} \in S^3$

delete nothing: $\det(X) = 1(4 - 4) - 2(2 - 2) - 1(-4 + 4)$
 $= 0$

delete one row-col. pair:

delete $(r_1, c_1) \rightarrow \det(\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}_{2 \times 2}) = 1 - 1 = 0$

" $(r_2, c_2) \rightarrow \det(\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}_{2 \times 2}) = 1 - 1 = 0$

" $(r_3, c_3) \rightarrow \det(\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}_{2 \times 2}) = 1 - 1 = 0$

delete two row-col. pairs:

delete $(r_1, c_1) \& (r_2, c_2) \rightarrow$ } main diag. entries
" $(r_2, c_2) \& (r_3, c_3) \rightarrow$ } $1 > 0, 1 > 0, 1 > 0.$
" $(r_3, c_3) \& (r_1, c_1) \rightarrow$ }

$$\boxed{\therefore X \in S_+^3}$$

End of
Example.

Application Example:

$$X \in S_+^2, \text{ we have } X = \begin{bmatrix} x & z \\ z & y \end{bmatrix}$$

$$\begin{aligned} \text{Principal minor condition: } & x \geq 0 \\ & y \geq 0 \\ & xy - z^2 \geq 0 \end{aligned}$$

$$\therefore S_+^2 = \left\{ (x, y, z) \in \mathbb{R}^3 \mid \begin{aligned} & x \geq 0, y \geq 0, \\ & xy \geq z^2 \end{aligned} \right\}$$

$\subset \mathbb{R}^3$

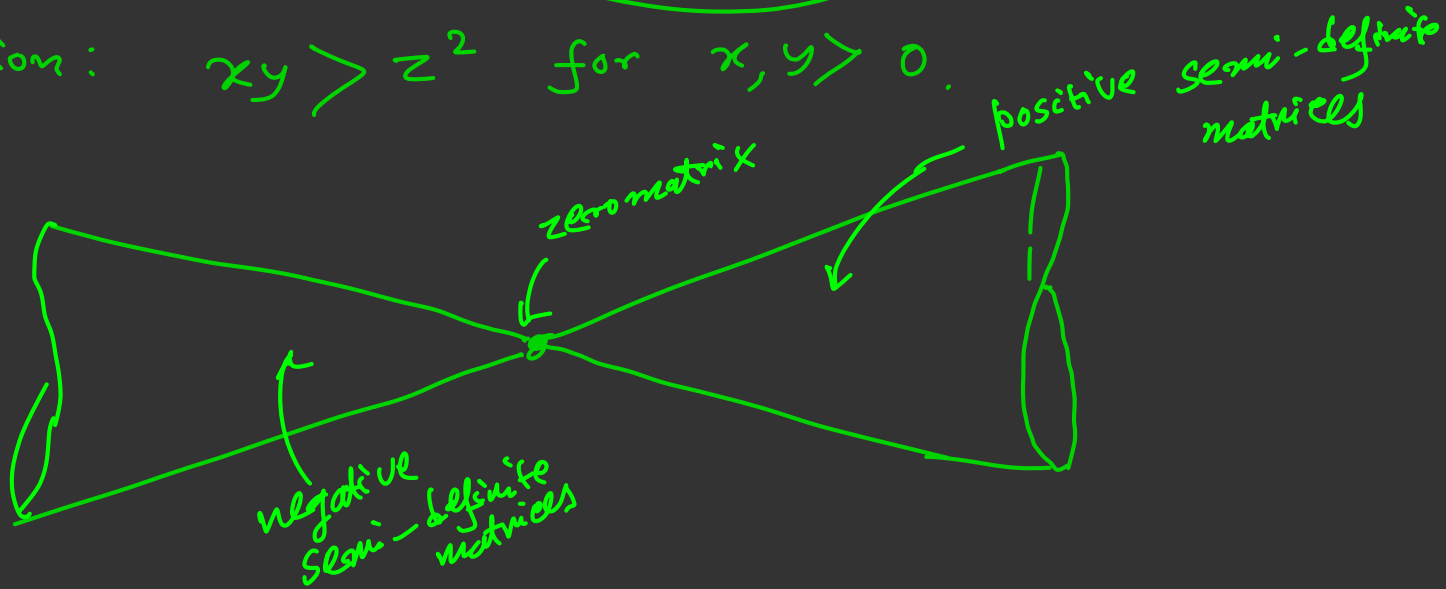
Visualize
this
set
(code in CANVAS)

$$\begin{aligned} \text{Boundary of this surface/set: } & z^2 = xy \\ \Leftrightarrow z &= \pm \sqrt{xy} \\ & x \geq 0, y \geq 0. \end{aligned}$$

\therefore Interior of S^2_+ is precisely S^2_{++}

\Leftrightarrow Boundary of S^2_+ comprises of rank deficient matrices

Interior satisfies the leading principal minor condition: $xy > z^2$ for $x, y > 0$.



Optimization nomenclature:

Optimization problem
looks like :

$$\begin{array}{ll} \min & f_0(\underline{x}) \\ \text{s.t.} & \underline{x} \in \mathcal{X} \end{array}$$

$$\min_{\underline{x} \in \mathcal{X}} f_0(\underline{x})$$

Decision variable

↪ Returns minimum value $f_0(\underline{x}^*)$

Here, $f_0 : \mathcal{X} \mapsto \overline{\mathbb{R}}$

↖ Objective function

"argmin" ↔ argument of the minimizer: \underline{x}^*

Set $\mathcal{X} \rightarrow$ feasible set
Similarly, we can do:

$$\begin{array}{ll} \min & f_0(X) \\ & X \in \mathcal{X} \end{array}$$

Examples of scalar functions of scalars :

linear function: ax , $a \neq 0$

affine function: $ax + b$, $a \neq 0, b \neq 0$

quadratic : $ax^2 + bx + c$, etc.

trig. functions: $\sin(x)$, $\cos(x)$ etc.

Scalar functions of vectors :

$$f(\underline{x}) = \langle \underline{a}, \underline{x} \rangle \quad (\text{linear function}), \quad \underline{a} \in \mathbb{R}^n \setminus \{0\}$$

\swarrow

$$\equiv \underline{a}^T \underline{x} \equiv \underline{a} \cdot \underline{x} = a_1 x_1 + a_2 x_2 + \dots + a_n x_n$$

inner product

$$f(\underline{x}) = \langle \underline{a}, \underline{x} \rangle + b \quad (\text{affine function})$$

$$f(\underline{x}) = \underline{x}^T A \underline{x} + \langle \underline{b}, \underline{x} \rangle + c,$$

↑ quadratic function.

$$A \in \mathbb{R}^{n \times n}, \underline{b} \in \mathbb{R}^n, c \in \mathbb{R}.$$

$$f(\underline{x}) = \|\underline{x}\|_p \leftarrow \text{vector } p \text{ norm. } 0 \leq p \leq +\infty.$$

$$:= \begin{cases} \text{Cardinality}(\underline{x}) & \text{for } p=0 \\ \left(\sum_{i=1}^n |x_i|^p \right)^{1/p} & \text{for } 0 < p < +\infty \\ \max_{i=1, \dots, n} |x_i| & \text{for } p = +\infty \end{cases}$$

e.g., $\|\underline{x}\|_2 = \sqrt{x_1^2 + x_2^2 + \dots + x_n^2}, \quad \|\underline{x}\|_1 = |x_1| + \dots + |x_n|$
 $\|\underline{x}\|_3 = (|x_1|^3 + \dots + |x_n|^3)^{1/3}$

$$f(\underline{x}) = \frac{\underline{x}^T P \underline{x} + \langle \underline{q}, \underline{x} \rangle + r}{\langle \underline{a}, \underline{x} \rangle + b} \quad (\text{quadratic over linear})$$

Scalar functions of matrix:

$$f(X) = \text{tr}(X), \quad X \in \mathbb{R}^{n \times n}$$

$$f(X) = \det(X), \quad X \in \mathbb{R}^{n \times n}$$

$$f(X) = \text{tr}(X^{-1}), \quad X \in GL(n)$$

$$f(X) = \langle A, X \rangle + b, \quad X \in \mathbb{R}^{m \times n}$$

↖ Affine function

where $\langle A, X \rangle := \text{tr}(A^T X)$

↖ matrix
Euclidean/
Frobenius
inner product

$$f(X) = \underbrace{\rho(X)}_{\text{spectral radius of matrix}} := \max_{i=1, \dots, n} |\lambda_i(X)|$$

$X \in \mathbb{R}^{n \times n}$

$$f(X) = \lambda_{\min}(X), \quad X \in S^n.$$

Matrix norm: $X \in \mathbb{R}^{m \times n}$

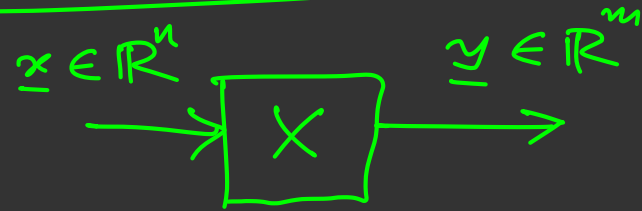
Frobenius or Hilbert-Schmidt norm:

$$\|X\|_F = \sqrt{\langle X, X \rangle} = \sqrt{\text{tr}(X^T X)} = \sqrt{\sum_{i=1}^m \sum_{j=1}^n X_{ij}^2}$$

next pg.

Induced Matrix Norms / Operator matrix norm:

$$\|X\|_p = \max_{\substack{\underline{x} \in \mathbb{R}^n \setminus \{0\} \\ \|\underline{x}\|_p}} \frac{\|\underline{y}\|_p}{\|\underline{x}\|_p}$$



$$= \max_{\|\underline{x}\|_p = 1} \|X \underline{x}\|_p$$

→ Special cases:

$$\|X\|_1 = \max_{j=1, \dots, n} \sum_{i=1}^m |X_{ij}| \rightarrow \text{maximum col. sum}$$

$$\|X\|_\infty = \max_{i=1, \dots, m} \sum_{j=1}^n |X_{ij}| \rightarrow \text{maximum row sum}$$

$$\|X\|_2 \leftarrow \text{spectral norm} = \sqrt{\lambda_{\max}(X^T X)} = \underline{\sigma_{\max}(X)}$$

maximum singular value

Singular values of $X \in \mathbb{R}^{m \times n}$:

$$\sigma_i(X) := \sqrt{\lambda_i(X^T X)}$$

$$\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n \geq 0 \quad \left. \vphantom{\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n \geq 0} \right\} \begin{array}{l} \text{order the} \\ \text{Singular} \\ \text{values of } X \end{array}$$

of nonzero singular values = rank(X)

$$\text{rank}(X) \leq \min\{m, n\}$$

↑ if equality then full rank.

Highly popular Misconceptions

#1 Function f is convex (Subtle!)

Convexity is a topological notion/idea, NOT a geometric notion. Convexity depends on BOTH f and $\boxed{\text{domain}(f)}$ (denoted as $\text{dom}(f)$)

By changing $\text{dom}(f)$, the same function f maybe convex or non-convex!!