

例 $A \in M_{m,n}(\mathbb{R})$, $\|A\|_F := (\text{trace}(A^T A))^{\frac{1}{2}}$. Frobenius 范数.

(1) $\text{trace}(A^T A) \geq 0$. $\|A\|_F = 0 \Leftrightarrow A = 0$.

Pf. 设 $A = [\vec{a}_1 \vec{a}_2 \cdots \vec{a}_n] = (a_{ij})_{m \times n}$

$$A^T A : n \times n, (A^T A)_{jj} = \vec{a}_j^T \vec{a}_j = \|\vec{a}_j\|^2, j=1, 2, \dots, n.$$

$$\therefore \text{trace}(A^T A) = \sum_{j=1}^n (A^T A)_{jj} = \sum_{j=1}^n \|\vec{a}_j\|^2 = \sum_{j=1}^n \sum_{i=1}^m (a_{ij})^2 \geq 0.$$

$$\|A\|_F = 0 \Leftrightarrow \text{trace}(A^T A) = 0 \Leftrightarrow a_{ij} = 0, \forall i, j \Leftrightarrow A = 0.$$

(2) $\forall B \in M_{n,k}(\mathbb{R})$. 证明: $\|AB\|_F \leq \|A\| \|B\|_F$. $\|AB\|_F \leq \|A\|_F \|B\|$

其中 $\|A\| = \max_{\vec{x} \neq 0} \frac{\|A\vec{x}\|}{\|\vec{x}\|} = \max_{\|\vec{x}\|=1} \|A\vec{x}\|$ 普通范数.

Pf. ① $AB = [A\vec{b}_1 \ A\vec{b}_2 \ \cdots \ A\vec{b}_k]$

$$\|AB\|_F^2 = \sum_{j=1}^k \|A\vec{b}_j\|^2 \leq \sum_{j=1}^k \|A\|^2 \|\vec{b}_j\|^2 = \|A\|^2 \left(\sum_{j=1}^k \|\vec{b}_j\|^2 \right) = \|A\|^2 \|B\|_F^2$$

$$\therefore \|AB\|_F \leq \|A\| \|B\|_F.$$

$$\text{② } \|A\|_F = \left(\sum_{i=1}^m \sum_{j=1}^n a_{ij}^2 \right)^{\frac{1}{2}} = \|A^T\|_F.$$

$\|B\| = B \text{ 的最大奇异值} = B^T \text{ 的最大奇异值} = \|B^T\|$.

$$\|AB\|_F = \|B^T A^T\|_F \leq \|B^T\| \|A^T\|_F = \|B\| \|A\|_F$$

(3) 若 C 是 n 阶半正定矩阵. 证明 $\|C\|_F \leq \text{trace}(C)$

Pf. Method 1 C 为半正定. $\therefore \exists$ 矩阵 A . s.t. $C = A^T A$.

$$\|C\|_F = \|A^T A\|_F \leq \|A\| \|A\|_F$$

而 $\|A\| = A \text{ 的最大奇异值}$

$$\|A\|_F^2 = \text{trace}(A^T A) = A^T A \text{ 特征值之和} = A \text{ 的所有奇异值的平方和}$$

$$\therefore \|C\|_F \leq \|A\|_F^2 = \text{trace}(A^T A) = \text{trace}(C).$$

Method 2 设 C 的特征值为 $\lambda_1, \lambda_2, \dots, \lambda_n \geq 0$ (半正定). 则 C^2 特征值为 $\lambda_1^2, \lambda_2^2, \dots, \lambda_n^2$

$$\begin{cases} \|C\|_F^2 = \text{trace}(C^T C) = \text{trace}(C^2) = \lambda_1^2 + \lambda_2^2 + \dots + \lambda_n^2. \end{cases}$$

$$\begin{cases} \text{trace}(C)^2 = (\lambda_1 + \lambda_2 + \dots + \lambda_n)^2 \end{cases}$$

$$\Rightarrow \|C\|_F \leq \text{trace}(C). \quad \#$$

$$\begin{cases} \therefore \|A\| \leq \|A\|_F \end{cases}$$

例 设 A 为实方阵. 证明 $A^T A$ 与 $A A^T$ 相似.

Pf. 取 A 的奇异值分解: $A = U \Sigma V^T$, Σ 为对称方阵 (A 为方阵)

$$\left\{ \begin{array}{l} A^T A = V \Sigma^T U^T U \Sigma V^T = V (\Sigma^T \Sigma) V^T = V \Sigma^2 V^T, \quad V^T = V^{-1} \\ A A^T = U \Sigma V^T V \Sigma^T U^T = U (\Sigma \Sigma^T) U^T = U \Sigma^2 U^T, \quad U^T = U^{-1} \end{array} \right.$$

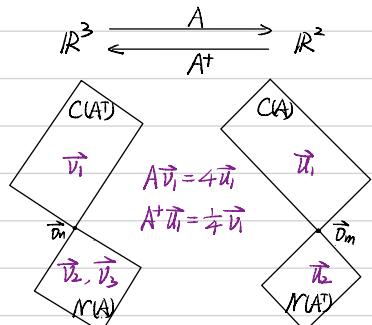
$$\therefore \Sigma^2 = U^T A A^T U$$

$$\therefore A^T A = V (U^T A A^T U) V^T = (U V^T)^{-1} (A A^T) (U V^T)$$

即 $A^T A$ 与 $A A^T$ 相似. #

例 设 $A \in M_{2,3}$ 有如下奇异值分解

$$A = U \Sigma V^T = \begin{bmatrix} \vec{u}_1 & \vec{u}_2 \end{bmatrix} \begin{bmatrix} 4 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \vec{v}_1^T \\ \vec{v}_2^T \\ \vec{v}_3^T \end{bmatrix}$$



(1) 求 $N(A)$ 的一组标准正交基.

(2) 写出 $A \vec{x} = \vec{u}_1$ 的通解.

(3) 求 $A \vec{x} = \vec{u}_1$ 的长度最短的解.

解 (1) $A = U \Sigma V^T \Rightarrow A V = U \Sigma$

$$\Rightarrow A \vec{v}_1 = 4 \vec{u}_1, \quad A \vec{v}_2 = A \vec{v}_3 = \vec{0}$$

V 为正交阵. $\therefore \vec{v}_1, \vec{v}_2$ 为 $N(A)$ -一组标准正交基.

$$\text{rank}(A) = 1$$

(2) $\because A \vec{u}_1 = 4 \vec{u}_1, \therefore$ 本 \vec{u}_1 为 $A \vec{x} = \vec{u}_1$ 的一个特解 (particular solution).

$$\text{通解: } \frac{1}{4} \vec{v}_1 + \underbrace{C_1 \vec{v}_2 + C_2 \vec{v}_3}_{\in N(A) \text{ 中任意向量}}. \quad \forall C_1, C_2 \in \mathbb{R}$$

(3) $A \vec{x} = \vec{u}_1$ 长度最短的解 = $A^+ \vec{u}_1 = \frac{1}{4} \vec{u}_1$.

$$\begin{aligned} \text{or. } \| \frac{1}{4} \vec{u}_1 + C_1 \vec{v}_2 + C_2 \vec{v}_3 \|^2 &= (\frac{1}{4} \vec{u}_1 + C_1 \vec{v}_2 + C_2 \vec{v}_3) \cdot (\frac{1}{4} \vec{u}_1 + C_1 \vec{v}_2 + C_2 \vec{v}_3) \\ &= \| \frac{1}{4} \vec{u}_1 \|^2 + \| C_1 \vec{v}_2 + C_2 \vec{v}_3 \|^2 \quad \because \vec{u}_1 \perp (C_1 \vec{v}_2 + C_2 \vec{v}_3) \\ &\geq \| \frac{1}{4} \vec{u}_1 \|^2. \end{aligned}$$

例 $A \in M_{3,2}(\mathbb{R})$ 且 $A = A^T$. 若 $1, 1, -2$ 是 A 的特征值. 且 $[1, 1, -1]^T$ 是属于 -2 的特征向量. 求 A .

解 A 为实对称阵 必可相似对角化.

\therefore 特征值 1 的几何重数为 2, $v_1 \oplus v_2 = \mathbb{R}^3$

A 为实对称阵, 必有 $v_1 \perp v_2$ (不同特征值的特征向量正交)

$$\therefore V_1 = V_2^\perp$$

↗ 矢量组

设 $\vec{x} = [\alpha \ \beta \ \gamma]^T \in V_1$, 则有 $\vec{x} \perp \begin{bmatrix} 1 \\ -1 \end{bmatrix}$, 那 $\alpha + \beta - \gamma = 0$.
 任取 V_1 -组基 $\vec{x}_1 = [0, 1, 1]^T$, $\vec{x}_2 = [1, 0, 1]^T$ (属于 V_1 的 2 个线性无关的特征向量)
 则有 $A[\vec{x}_1 \ \vec{x}_2 \ \vec{x}_3] = [\vec{x}_1 \ \vec{x}_2 \ \vec{x}_3] \begin{bmatrix} 1 & & \\ & 1 & \\ & & -2 \end{bmatrix}$
 由得 $A = \begin{bmatrix} 0 & 1 & 1 \\ -1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}$

例. $A, B \in M_n(\mathbb{R})$ 且 $AB = BA$. 令 $C = \begin{bmatrix} A \\ B \end{bmatrix}$. 证明: $\text{rank}(A) + \text{rank}(B) \geq \text{rank}(AB) + \text{rank}(C)$.

$$\text{pf. } \dim N(A) = n - \text{rank}(A) \quad \dim N(B) = n - \text{rank}(B)$$

$$\dim N(AB) = n - \text{rank}(AB) \quad \dim N(C) = n - \text{rank}(C)$$

$$\text{只需证明 } \dim N(A) + \dim N(B) \leq \dim N(AB) + \dim N(C). \quad (\#)$$

$$\because N(C) = N(A) \cap N(B)$$

$$\therefore \dim N(C) = \dim N(A) + \dim N(B) - \dim(N(A) \cap N(B))$$

$$(\#) \text{ 式等价 } \dim(N(A) + N(B)) \leq \dim N(AB). \quad (\#\#)$$

$$\begin{aligned} \text{而 } N(A) + N(B) &= N(BA) = N(AB) \\ N(B) &\subset N(AB) \end{aligned} \Rightarrow N(A) + N(B) \subset N(AB)$$

$\therefore (\#\#)$ 式成立. #.

例. 设 $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ 为 \mathbb{R}^n -组标准正交基. 且 $(\vec{w}_1, \vec{w}_2, \dots, \vec{w}_n) = (\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n)Q$, Q 为 $n \times n$ 方阵.

证明: $(\vec{w}_1, \vec{w}_2, \dots, \vec{w}_n)$ 为 \mathbb{R}^n -组标准正交基 $\Leftrightarrow Q$ 为正交阵.

Pf. 设 $A = [\vec{v}_1 \ \vec{v}_2 \ \dots \ \vec{v}_n]$, $Q = [\vec{q}_1 \ \vec{q}_2 \ \dots \ \vec{q}_n]$. 则 $\vec{w}_j = A \vec{q}_j$, $j=1, 2, \dots, n$

$$\vec{w}_i \cdot \vec{w}_j = (A \vec{q}_i)^T (A \vec{q}_j) = \vec{q}_i^T A^T A \vec{q}_j$$

$$\text{而 } \vec{v}_1, \dots, \vec{v}_n \text{ 为标准正交基} \quad \therefore (A^T A)_{ij} = \vec{v}_i \cdot \vec{v}_j = \delta_{ij}. \quad A^T A = I_n$$

$$\therefore \vec{w}_i \cdot \vec{w}_j = \vec{q}_i \cdot \vec{q}_j, \quad i, j = 1, 2, \dots, n$$

$$\vec{w}_1, \dots, \vec{w}_n \text{ 是标准正交基} \Leftrightarrow \vec{w}_i \cdot \vec{w}_j = \delta_{ij}, \forall i, j \Leftrightarrow \vec{q}_i \cdot \vec{q}_j = \delta_{ij}, \forall i, j \Leftrightarrow Q^T Q = I, \text{ 即 } Q \text{ 为正交阵.}$$

例 $A \in M_n(\mathbb{C})$. 证明.

(1) A 是相似于形如 $\begin{bmatrix} \lambda_1 & b_{12} & \cdots & b_{1n} \\ 0 & b_{22} & \cdots & b_{2n} \\ \vdots & & & \vdots \\ 0 & b_{n2} & \cdots & b_{nn} \end{bmatrix}$ 的矩阵.

(2) A 是与一个上三角阵相似.

Pf. (1) 取 A 的一个特征值 λ_1 及对应的一个特征向量 \vec{x}_1 , 有

$$A\vec{x}_1 = \lambda_1 \vec{x}_1$$

将 \vec{x}_1 扩充为 \mathbb{C}^n -组基: $\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n$

设 $A\vec{x}_j = b_{1j}\vec{x}_1 + b_{2j}\vec{x}_2 + \cdots + b_{nj}\vec{x}_n$, 则 $\quad \checkmark \quad B$

$$A[\vec{x}_1 \ \vec{x}_2 \ \cdots \ \vec{x}_n] = [\vec{x}_1 \ \vec{x}_2 \ \cdots \ \vec{x}_n]$$

$$\begin{bmatrix} \lambda_1 & b_{12} & \cdots & b_{1n} \\ 0 & b_{22} & \cdots & b_{2n} \\ \vdots & & & \vdots \\ 0 & b_{n2} & \cdots & b_{nn} \end{bmatrix}$$

$$\text{i.e. } A\vec{x} = \vec{x}B$$

而 $\vec{x}_1, \dots, \vec{x}_n$ 线性无关. $\therefore \vec{x}$ 可逆. $\therefore X^{-1}AX = B$. 即 A 相似于 B .

(2) 对 n 作数学归纳法.

① $n=1$ 时, 显然.

② 假设结论对 $n-1$ 阶方阵成立.

③ $A \in M_n(\mathbb{C})$. n 阶的情形.

由(1). \exists 可逆矩阵 X_1 , s.t. $X_1^{-1}AX_1 = \begin{bmatrix} \lambda_1 & b_{12} & \cdots & b_{1n} \\ 0 & b_{22} & \cdots & b_{2n} \\ \vdots & & & \vdots \\ 0 & b_{n2} & \cdots & b_{nn} \end{bmatrix}$

$\therefore C = \begin{bmatrix} b_{22} & \cdots & b_{2n} \\ \vdots & & \vdots \\ b_{n2} & \cdots & b_{nn} \end{bmatrix} \in M_{n-1}(\mathbb{C})$. 由归纳假设. $\exists n-1$ 阶可逆矩阵 X_2 , s.t.

$$X_2^{-1}CX_2 = \begin{bmatrix} c_1 & & & \\ c_2 & \ddots & & \\ \vdots & & \ddots & \\ c_{n-1} & & & c_n \end{bmatrix} \quad (C \text{ 相似于上三角阵})$$

$\therefore X = X_1 \begin{bmatrix} 1 & 0 \\ 0 & X_2 \end{bmatrix}$, X 可逆. 且

$$X^{-1}AX = \begin{bmatrix} 1 & & \\ & X_2^{-1} \end{bmatrix} X_1^{-1}AX_1 \begin{bmatrix} 1 & & \\ & X_2 \end{bmatrix} = \begin{bmatrix} 1 & & \\ & X_2^{-1} \end{bmatrix} \begin{bmatrix} \lambda_1 & * \\ & C \end{bmatrix} \begin{bmatrix} 1 & \\ & X_2 \end{bmatrix}$$

$$= \begin{bmatrix} \lambda_1 & * \\ & X_2^{-1}CX_2 \end{bmatrix} = \begin{bmatrix} \lambda_1 & c_1 & * \\ & c_2 & \ddots & \\ & \vdots & & c_{n-1} \end{bmatrix} \quad \#.$$