

$$A \in \mathbb{R}^{m \times n}$$

Problem 1:

$$\|A\|_2 = \max_{\|x\|_2=1} \|Ax\|_2$$

a) $m=1 \rightarrow A=[a] \in \mathbb{R}^m$

$$\|A\|_2 = \max_{\|x\|_2=1} \|Ax\|_2 = \max_{\substack{\|x\|_2=1 \\ x \in \mathbb{R}}} \{ \|a\|_2 \} = \|a\|_2$$

$$\Rightarrow \|x\|_2 = \sqrt{x^2} = |x| = 1 \Leftrightarrow x \in \{-1, 1\}$$

$n=1 \rightarrow A=[a^T] \in \mathbb{R}^{1 \times n}$

$$\|A\|_2 = \max_{\|x\|_2=1} \|Ax\|_2 = \max_{\|x\|_2=1} \|a^T x\|_2$$

$$= \max_{\|x\|_2=1} |\langle a, x \rangle| \leq \max_{\|x\|_2=1} \|a\|_2 \|x\|_2 = \|a\|_2$$

Cauchy-Schwarz

$$x = \frac{a}{\|a\|_2} \rightarrow |\langle a, \frac{a}{\|a\|_2} \rangle| = \|a\|_2 \Rightarrow \max_{\|x\|_2=1} |\langle a, x \rangle| = \|a\|_2$$

$$\Rightarrow \|A\|_2 = \|a\|_2$$

b) $\|\text{diag}(\lambda_1, \dots, \lambda_n)\|_2 = \max_{\|x\|_2=1} \left\| \begin{bmatrix} \lambda_1 x_1 \\ \vdots \\ \lambda_n x_n \end{bmatrix} \right\|_2 =$

$$= \max_{\|x\|_2=1} \sqrt{\lambda_1^2 x_1^2 + \dots + \lambda_n^2 x_n^2} \leq \max_{\|x\|_2=1} \sqrt{\lambda_{\max}^2 x_1^2 + \dots + \lambda_{\max}^2 x_n^2}$$

$$= |\lambda_{\max}| \max_{\|x\|_2=1} \sqrt{x_1^2 + \dots + x_n^2} = |\lambda_{\max}|$$

$$\lambda_{\max} = \max_{i=1, \dots, n} |\lambda_i| \rightarrow \|\text{diag}(\lambda_1, \dots, \lambda_n)\|_2 = \left\| \begin{bmatrix} 0 \\ \vdots \\ \lambda_{\max} \\ \vdots \\ 0 \end{bmatrix} \right\|_2 = |\lambda_{\max}|$$

Problem 2: $A \in \mathbb{R}^{m \times n}$, $m \geq n$

$\rightarrow \sigma_1(A), \dots, \sigma_n(A)$ singular values

• $X = \begin{pmatrix} A & I_m \end{pmatrix} \quad m \times (m+n)$

$$XX^T = \begin{pmatrix} A & I_m \end{pmatrix} \begin{pmatrix} A^T \\ I_m \end{pmatrix} = AA^T + I_m$$

$$\begin{aligned} \sigma_i(X) &= \sqrt{\lambda_i(XX^T)} = \sqrt{\lambda_i(AA^T + I_m)} = \sqrt{\lambda_i(AA^T) + 1} \\ &= \sqrt{\sigma_i^2(A) + 1} \quad , i = 1, 2, \dots, m \end{aligned}$$

(for $i = n+1, \dots, m \rightarrow \sigma_i(X) = \sqrt{1} = 1$)

• $X = \begin{pmatrix} A \\ I_n \end{pmatrix} \quad (m+n) \times n$

$$X^T X = \begin{pmatrix} A^T & I_n \end{pmatrix} \begin{pmatrix} A \\ I_n \end{pmatrix} = A^T A + I_n$$

again, $\sigma_i(X) = \sqrt{\sigma_i^2(A) + 1} \quad , i = 1, 2, \dots, n$

• $X = \begin{pmatrix} A & I_m \\ I_m & 0 \end{pmatrix} \quad (m+n) \times (m+n)$

$$X^T X = \begin{pmatrix} A^T & I_m \\ I_m & 0 \end{pmatrix} \begin{pmatrix} A & I_m \\ I_m & 0 \end{pmatrix} = \begin{pmatrix} A^T A + I_m & A^T \\ A & I_m \end{pmatrix}$$

$$X^T X \begin{bmatrix} y \\ z \end{bmatrix} = \lambda \begin{bmatrix} y \\ z \end{bmatrix} \rightarrow \begin{pmatrix} A^T A + I_m & A^T \\ A & I_n \end{pmatrix} \begin{pmatrix} y \\ z \end{pmatrix} = \lambda \begin{pmatrix} y \\ z \end{pmatrix}$$

$$\rightarrow A^T A y + y + A^T z = \lambda y$$

$$\underline{A y + z = \lambda z}$$

$$(\lambda - 1) A^T z + y + A^T z = \lambda y \Rightarrow A^T z = \frac{\lambda - 1}{\lambda} y$$

$$\Rightarrow A^T A y + y + \frac{\lambda - 1}{\lambda} y = \lambda y$$

$$A^T A y = \frac{(\lambda - 1)^2}{\lambda} y$$

$$\lambda \neq 0 \text{ eigenvalue of } X^T X \Rightarrow \frac{(\lambda - 1)^2}{\lambda} \text{ eigenvalue of } A^T A \quad (\lambda \rightarrow 0 \Rightarrow \begin{bmatrix} y \\ z \end{bmatrix} = 0)$$

$$\Rightarrow \mu \text{ eigenvalue of } A^T A \Rightarrow \mu = \frac{(\lambda - 1)^2}{\lambda}, \text{ for } \lambda \neq 0 \text{ eigenvalue of } X^T X$$

$$\Rightarrow \lambda \mu = \lambda^2 - 2\lambda + 1 \Rightarrow \lambda^2 - (\mu + 2)\lambda + 1 = 0$$

$$\lambda_{1,2} = \frac{(\mu + 2) \pm \sqrt{(\mu + 2)^2 - 4}}{2} = \frac{(\mu + 2) \pm \sqrt{\mu^2 + 4\mu}}{2}$$

$\rightarrow$ singular values of X are given by:

$$\sqrt{\frac{1}{2}(\sigma_i^2(A) + 2 \pm \sqrt{\sigma_i^4(A) + 4\sigma_i^2(A)})}, \quad i = 1, 2, \dots, n$$

$\uparrow$
 $2n$ of them

+ additional $\sqrt{\frac{1}{2} \cdot 2} = 1$ $(n - n)$ of them

Problem 3: $A, B \in \mathbb{R}^{m \times n}$

prove: $\text{tr}(B^T A) = \text{tr}(AB^T) = \text{vec}(B)^T \text{vec}(A)$

$$A = [a_1 \dots a_n] \quad \left. \begin{array}{l} \\ \\ \end{array} \right\} \text{column partitions}$$

$$B = [b_1 \dots b_n]$$

$$\rightarrow B^T = \begin{bmatrix} b_1^T \\ \vdots \\ b_n^T \end{bmatrix}$$

$$\text{tr}(B^T A) = b_1^T a_1 + \dots + b_n^T a_n$$

$$\text{vec}(B)^T \text{vec}(A) = [b_1^T \dots b_n^T] \begin{bmatrix} a_1 \\ \vdots \\ a_n \end{bmatrix} = b_1^T a_1 + \dots + b_n^T a_n$$

$$\underbrace{\text{tr}(AB^T)}_{\text{m} \times \text{m}} = \sum_{i=1}^m (AB^T)_{ii} = \sum_{i=1}^m \sum_{j=1}^n a_{ij} b_{ij} = \sum_{j=1}^n \sum_{i=1}^m b_{ij} a_{ij} =$$

$$= \sum_{j=1}^n (B^T A)_{jj} = \text{tr}(B^T A)$$

Problem 4 : $A \in \mathbb{R}^{n \times n}$

PROVE : $\text{tr}(A) = n$ and $\|A\|_2 \leq 1 \Rightarrow A = I_n$

$$\text{tr}(A) = n \Rightarrow a_{11} + a_{22} + \dots + a_{nn} = n$$

$$a_{ii} = \langle e_i, A e_i \rangle \leq \underbrace{\|e_i\|_2}_{=1} \|A e_i\|_2 \leq \|A\|_2 \leq 1, \quad \forall i = 1, 2, \dots, n$$

$$\Rightarrow a_{ii} = 1, \quad \forall i = 1, 2, \dots, n$$

Suppose $a_{ij} \neq 0$, for some $j \in \{1, \dots, n\} \Rightarrow$

$$\|A e_j\|_2 = \sqrt{a_{ij}^2 + 1} > 1, \quad \Rightarrow \text{wh } \|A\|_2 \leq 1 \Rightarrow a_{ij} = 0, \quad \forall i \neq j$$

↓

e.g. $\begin{bmatrix} 1 & a \\ & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} a \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} > \begin{bmatrix} 1 & 0 \\ a & 1 \\ & & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ a \\ \vdots \\ 0 \end{bmatrix}$

Problem 5 : $A, B \in \mathbb{R}^{u \times v}$, $u \geq v$

$$\max_d \left\{ \text{tr}(P^T M Q) \mid P \in \mathbb{R}^{u \times k}, Q \in \mathbb{R}^{u \times k}, P^T P = Q^T Q = I_k \right\} = \sigma_1 + \dots + \sigma_k$$

PROVE: $\sigma_1(A+B) + \dots + \sigma_k(A+B) \leq \sigma_1(A) + \dots + \sigma_k(A) + \sigma_1(B) + \dots + \sigma_k(B)$

$$\sum_{i=1}^k \sigma_i(A+B) = \max_d \left\{ \text{tr}(P^T (A+B) Q) \mid P \in \mathbb{R}^{u \times k}, Q \in \mathbb{R}^{u \times k}, P^T P = Q^T Q = I_k \right\}$$

$$= \max_d \left\{ \text{tr}(P^T A Q + P^T B Q) \mid \text{---} \right\}$$

$$= \max_d \left\{ \text{tr}(P^T A Q) + \text{tr}(P^T B Q) \mid \text{---} \right\}$$

$$\leq \max_d \left\{ \text{tr}(P^T A Q) \mid \dots \right\} + \max_d \left\{ \text{tr}(P^T B Q) \mid \dots \right\}$$

$$= \sigma_1(A) + \dots + \sigma_k(A) + \sigma_1(B) + \dots + \sigma_k(B)$$

Problem 6 : $A, B \in \mathbb{R}^{m \times n}$

$$C = A * B$$

Prove : $\text{rank}(C) \leq \text{rank}(A) \cdot \text{rank}(B)$

$$r_A = \text{rank}(A) \Rightarrow A = \sum_{i=1}^{r_A} p_i q_i^T$$

$$\begin{matrix} m \times r_A & r_A \times n \\ (A = P Q^T) \end{matrix}$$

$$r_B = \text{rank}(B) \rightarrow B = \sum_{j=1}^{r_B} s_j t_j^T$$

$$\begin{matrix} m \times r_B & r_B \times n \\ (B = S T^T) \end{matrix}$$

$$A * B = \left(\sum_{i=1}^{r_A} p_i q_i^T \right) * \left(\sum_{j=1}^{r_B} s_j t_j^T \right)$$

$$= \sum_{i=1}^{r_A} \sum_{j=1}^{r_B} (p_i q_i^T) * (s_j t_j^T)$$

$$= \sum_{i=1}^{r_A} \sum_{j=1}^{r_B} (p_i * s_j) (q_i * t_j)^T$$

$\Rightarrow A * B$ is a sum of $r_A \cdot r_B$ rank-one matrices $\Rightarrow$

$$\text{rank}(A * B) \leq \text{rank}(A) \cdot \text{rank}(B)$$