

6.25

$$\langle Px, Py \rangle = (Px)^t P y = x^t P^t P y = x^t y = \langle x, y \rangle.$$

■

6.26

$$(AB)^t AB = B^t A^t AB = B^t B = I$$

$\therefore (AB)^{-1} = (AB)^t$ no orthogonal mat.

$$(BA)^t (BA) = A^t B^t BA = A^t A = I$$

$\therefore (BA)^{-1} = (BA)^t$ no orthogonal mat.

■

6.33

$$P_6 = \begin{bmatrix} e_{6(1)}^t \\ \vdots \\ e_{6(n)}^t \end{bmatrix}$$

$$m P_6 P_6^t = \begin{bmatrix} e_{6(1)}^t \\ \vdots \\ e_{6(n)}^t \end{bmatrix} \cdot [e_{6(1)} \cdots e_{6(n)}]$$

$$= [\langle e_{6(i)}, e_{6(j)} \rangle]_{ij} = I.$$

$\therefore P_6$: orthogonal mat

■

6.34. $\exists u \in M_{m,1}(\mathbb{R}), v \in M_{n,1}(\mathbb{R})$.

$$(a). (u \otimes v)_{ij} = u_i v_j \rightsquigarrow u \otimes v = [uv_1 \cdots uv_n]$$

$$= u \cdot [v_1 \cdots v_n] = uv^t \in M_{m,n}(\mathbb{R})$$

$$(b) (u \otimes v) \cdot v = uv^t \cdot v = u \cdot \|u\|_2^2.$$

■

6.36 SVD: $\forall A \in M_{n \times n}(\mathbb{R})$, \exists orthogonal mat U, V and a diag matrix Σ , s.t. $A = U\Sigma V^t$.

$$(a) A^t A = V \Sigma U^t \cdot U \Sigma V^t = V \Sigma \cdot \Sigma V^t = V \Sigma^2 V^t.$$

(b) $\because A^t A$ is a sym mat, A is diagonalizable.

$$A^t A = V \Sigma^2 V^t \quad \text{as } \underbrace{\Sigma^2}_{\text{Equal}} = U^t (A^t A) V$$

\therefore equal of Σ^2 is square of diag. entries in Σ

■

(C), (d): coding prob.

6.40: coding prob.

7.2.

$$(a) A = \begin{bmatrix} 1 & 9 \\ -1 & 5 \end{bmatrix} \quad \|A\|_1 = \max_j \sum_i |a_{ij}| = 14$$

$$A^t A = \begin{bmatrix} 2 & 4 \\ 4 & 10 \end{bmatrix} \quad \|A\|_2 = \max_i \sqrt{s_i} = 10.303$$

$$\|A\|_\infty = \max_i \sum_j |a_{ij}| = 10$$

$$\|A\|_F = \sqrt{82+25} = 6\sqrt{3}$$

$$(b) A = \begin{bmatrix} 2 & 5 & 3 \\ 0 & 4 & 1 \end{bmatrix} \quad \|A\|_1 = \max_j \sum_i |a_{ij}| = 9$$

$$A^T A = \begin{bmatrix} 4 & 10 & 6 \\ 10 & 41 & 19 \\ 6 & 19 & 10 \end{bmatrix} \quad \|A\|_2 = \max_i \sqrt{s_i} = 7.2652$$

$$\|A\|_\infty = \max_i \sum_j |a_{ij}| = 10$$

$$\|A\|_F = \sqrt{38+19} = \sqrt{57}$$

$$7.5. \quad \|A\|_1 = \max_{1 \leq k \leq n} \sum_i |a_{ik}|$$

(proof)

$$\begin{aligned} \|A\|_1 &= \max_{x \neq 0} \frac{\|Ax\|_1}{\|x\|_1} = \max_{x \neq 0} \frac{\sum_i |\sum_j a_{ij} x_j|}{\sum_j |x_j|} \\ &\leq \max_{x \neq 0} \frac{\sum_j \sum_i |a_{ij}| \cdot |x_j|}{\sum_j |x_j|} = \max_{x \neq 0} \frac{\sum_j |x_j| \left(\sum_i |a_{ij}| \right)}{\sum_j |x_j|} \\ &\leq \max_{\substack{x \neq 0 \\ k}} \frac{\left(\sum_i |a_{ik}| \right) \cdot \sum_j |x_j|}{\sum_j |x_j|} = \max_{\substack{x \neq 0 \\ k}} \underbrace{\sum_i |a_{ik}|}_{\text{upper bound}} \quad (\text{upper bound}) \\ &\quad \downarrow \\ &x = e_k \rightarrow \frac{\|Ax\|_1}{\|x\|_1} = \sum_i |a_{ik}|. \end{aligned}$$

(exists x for equality)

$\exists x$ for upper bound. upper bound \Rightarrow maximum.

7.18

$$\|Ax\|_2^2 = \sum_i \left(\sum_j a_{ij} x_j \right)^2 \leq \sum_i \left(\sum_j a_{ij}^2 \right) \left(\sum_j x_j^2 \right) = \|A\|_F^2 \cdot \|x\|_2^2$$

C.F.
inequality

\therefore Euclidean norm is compatible with
Frobenius Norm. ■

7.19.

(a) Using the well known fact: $\|A\|_2 = \max_i \delta_i < \delta_n$: singular values of matrix)

$$\|A\|_{\infty, scale} := \lim_{p \rightarrow \infty} \left(\sum_{i=1}^n \delta_i^p \right)^{\frac{1}{p}} = \lim_{p \rightarrow \infty} \left(\sum_{i=1}^n \left(\frac{\delta_i}{\delta} \right)^p \right)^{\frac{1}{p}} \cdot \delta$$

(δ : $\max_i (\delta_i)$)

$$= \lim_{p \rightarrow \infty} \left(m_\delta \cdot 1 + \sum_{i=1}^n \left(\frac{\delta_i}{\delta} \right)^p \right)^{\frac{1}{p}} \cdot \delta = \delta$$

$\hookrightarrow \delta_i \neq \delta$

multiplicity

factor of δ

$$(b) \|A\|_{2, scale}^2 = \sum_{i=1}^n \delta_i^2 = \operatorname{tr}(A^T A) = \sum_{i=1}^n \sum_{j=1}^n a_{ij} a_{ij} = \|A\|_F^2$$

■

7.20.

(a) A : symmetric $\Rightarrow \|A\|_2 = \rho(A)$

(proof) singular value is equal of $A^T A$. \exists a very sym. matrix,

diagonalizable. $\Rightarrow (P \Lambda P^T) \cdot (P \Lambda P^T) = P \Lambda^2 P^T \Leftrightarrow \Lambda = \operatorname{diag}(\lambda_1, \dots, \lambda_n)$,

$$\therefore \|A\|_2 = \max_i \sqrt{s_i} = \max_i |\lambda_i| = \rho(A). \quad ■$$

(b) $\|A^{-1}\|_2$ is eigenvalue of $(A^{-1})^t A^{-1} \rightarrow$ singular value of A^{-1} .

Singular value of A is spectrum of $A^t A$.

Now $A^t A = P \Lambda P^t$ is diagonalizable, $(A^t A)^{-1} = P \Lambda^{-1} P^t$

Also, $A^t A$ is positive-semidefinite matrix, all diagonal

values of Λ are non-negative. ($\because x^t A^t A x = (Ax)^t Ax \geq 0$)

\therefore equal of $A^t A$ is same as equal of AA^t .

$$(A^t A)^{-1} = (A^{-1})(A^t)^{-1} = \underbrace{(A^{-1})(A^t)^{-1}}_{\text{some equal}} \longleftrightarrow \underbrace{(A^t)^{-1} A^{-1}}_{\text{some equal}}$$

some equal.

$$\therefore \|A^{-1}\|_2 = \max_i \sqrt{\lambda_i} = \sigma_{\max}. (\Lambda = \text{diag}(d_1, \dots, d_n))$$

$$\|A^{-1}\|_2 = \max_i \frac{1}{\sqrt{\lambda_i}} = \frac{1}{\min_i \sqrt{\lambda_i}} = \frac{1}{\sigma_{\min}}$$

$\therefore A$ is nonsingular, $\Rightarrow i.e. \lambda_i \neq 0$.

■

7.24. Coding Problem

7.31.

$$(a) \det(\lambda I - A) = (\lambda - 0.6)^4 \cdot \lambda + 0.7 = 0$$

$$\therefore \lambda = 0.6, -0.7$$

$$(b) \begin{pmatrix} 0.6 & 1 & 6 & -1 & 5 \\ 0 & 0.6 & 1 & 1 & 0 \\ 0 & 0 & 0.6 & 1 & 3 \\ 0 & 0 & 0 & 0.6 & 1 \\ 0 & 0 & 0 & 0 & -0.1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{pmatrix} = 0.6 \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{pmatrix}$$

$$\therefore x_5 = 0, x_4 = 0, x_3 = 0, x_2 = 0, \text{ and } [1, 0, 0, 0, 0]^T.$$

$$\begin{pmatrix} 0.6 & 1 & 6 & -1 & 5 \\ 0 & 0.6 & 1 & 1 & 0 \\ 0 & 0 & 0.6 & 1 & 3 \\ 0 & 0 & 0 & 0.6 & 1 \\ 0 & 0 & 0 & 0 & -0.1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{pmatrix} = -0.1 \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{pmatrix}$$

↓

$$(A + 0.1I)X = \begin{pmatrix} 1.3 & 1 & 6 & -1 & 5 \\ 0 & 1.3 & 1 & 1 & 0 \\ 0 & 0 & 1.3 & 1 & 3 \\ 0 & 0 & 0 & 1.3 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{pmatrix} = 0$$

↳ $\ker(A + 0.1I) = \mathcal{Y}$

$\rightarrow \dim \ker(A + 0.1I) = 5 - 4 = 1$

\therefore A basis for eigenvectors (\mathcal{V}) dim of eigenspace
is only 2)

(c) 0.1.

(d) ~ (g): code.

(h)

i) If A is symmetric, A is diagonalizable. ($P^{-1}AP = \Lambda$)

~ $A = P\Lambda P^T$. If $\rho(A) > 1$. \exists diagonal comp. of

Λ^n s.t. or $\Lambda \rightarrow \infty \Rightarrow$ such element $\rightarrow \infty$.

\therefore some elements in A tends to get larger.

∴ sym mat generated by random for probability

that all spectrum of A is smaller than 1 conv. to 0.

(\because Fixing orthogonal Mex p. chance that picking a real num from \mathbb{R} , with absolute value is smaller than 1 is trivially zero)

\therefore At (i), powers of sym matrix always tends to diverge.

ii) In non-symmetric case, using Schur's triangulation,

\exists orthogonal Mex p. s.t. $A = PTP^T$ (T : upper triangular Mex).

Then we can separate T into $T = \Lambda + T'$, where

Λ : diagonal Mex, T' : strictly upper triangular Mex.

\downarrow

$A^N = P T^N P^T = P (\Lambda + T')^N P^T$. $\because T'$ is nilpotent,

$\exists k \leq n \in \mathbb{N} \subset T' \in M_{n,n}(\mathbb{R})$ s.t. $(T')^k = 0$.

$$A^N = P \left(\sum_{i=0}^N \binom{N}{i} \Lambda^{N-i} T^i \right) P^T \dots (*)$$

If \exists spectrum of A , greater than 1, some components

in $(*)$ will diverge as $N \rightarrow \infty$

If all spectrum of A is smaller than 1, $(*)$ goes to

$$\text{zero. or } \lim_{N \rightarrow \infty} \frac{(k)^N}{r^k} = 0 \quad (\forall i \in \mathbb{N}).$$



(e). If $\exists q \in \mathbb{C}$

then

proposal: $\max_{1 \leq i, j \leq n} |a_{ij}|^{\alpha} \leq \|A\|$.

(proof)

i) Frobenius Norm

$$\max_{1 \leq i, j \leq n} |a_{ij}|^{\alpha} \leq \left(\sum_{i,j} a_{ij}^2 \right)^{\frac{1}{2}} = \|A\|_F.$$

ii) Induced Norms

Assume $\underbrace{|a_{\bar{i}\bar{j}}|}_{\sim} = \max_{1 \leq i, j \leq n} |a_{ij}|^{\alpha}$
 \hookrightarrow Maximum absolute value occurs at (\bar{i}, \bar{j}) .

$$\max_{x \neq 0} \frac{\|Ax\|}{\|x\|} \geq \frac{\|Ae_{\bar{j}}\|}{\|e_{\bar{j}}\|} = \| [a_{1\bar{j}} \ a_{2\bar{j}} \ \dots \ a_{n\bar{j}}] \|$$

$$\geq |a_{\bar{i}\bar{j}}| = \max_{1 \leq i, j \leq n} |a_{ij}|^{\alpha}$$

■

8.15.

$$(a) \left[\frac{\sum_{k=1}^n |x_k|}{\left| \sum_{k=1}^n x_k \right|} \right]. 17 \text{ epr.}$$

(b) (1.06). (9) epr.

8.11

$$b=10, p=4,$$

$$p = 0.5612 \times 10^2, \quad y = 0.1618 \times 10^2, \quad r = 0.9815 \times 10^2.$$

$$p \otimes (y \oplus r) = 0.5612 \times 10^2 \otimes (0.1618 \times 10^2 \oplus 0.9815 \times 10^2)$$

—————

$$\underline{1.1493},$$

$$= 0.5612 \times 10^2 \otimes 0.1147 \times 10^3$$

$$= \underline{0.6511 \times 10^4} \cdot (1)$$

$$p \otimes y + p \otimes r = 0.5612 \times 10^2 \otimes 0.1618 \times 10^2$$

$$\oplus 0.5612 \times 10^2 \otimes 0.9815 \times 10^2$$

$$= 0.9516 \times 10^3 + 0.5561 \times 10^4 = \underline{0.6519 \times 10^4} \quad (2)$$

$$(1) \neq (2).$$

■

8.16. $b=10, p=1$

$$x = 0.1526351 \times 10^{-4}, \quad y = 0.5258231 \times 10^2, \quad z = 0.3000000 \times 10^{-7}$$

$$(x \oplus y) \oplus z = 0.1516939 \times 10^{-4} \oplus 0.3000000 \times 10^{-7}$$

$$= 0.1516939 \times 10^{-4} \quad (1)$$

$$x \oplus (y \oplus z) = 0.1526351 \times 10^{-4} \oplus 0.5258231 \times 10^2.$$

$$= (0.1526351 + 0.0052583) \times 10^{-4} = 0.1516940 \times 10^{-4} \quad (2)$$

$$(1) \neq (2)$$

■

B.J2

(a), (b), (c) \rightarrow coding problem

(d) The term $\frac{A^n}{n!}$ gets very large before it conv. to 0.

\Rightarrow inaccuracy with large values.

(shown at code file)

B.J5.

$$(a) \frac{-15000 + \sqrt{15000^2 + 4(0.0001)^2}}{0.0002} = 9.094941011129282 \times 10^{-9}$$

(b) code

(c) sympy library also shows some errors!

