

Problem Set 3.

4.2 pf: We should have the matrix representation of D

$$D = \begin{bmatrix} 0 & 0 & 0 \\ 2 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

Now we have

$$\lambda E - D = \begin{bmatrix} \lambda & 0 & 0 \\ -2 & \lambda & 0 \\ 0 & -1 & \lambda \end{bmatrix}$$

$$\Rightarrow \det(\lambda E - D) = \lambda^3 = 0$$

$$\Rightarrow \lambda = 0$$

$$\Rightarrow \lambda E - D = \begin{bmatrix} 0 & 0 & 0 \\ -2 & 0 & 0 \\ 0 & -1 & 0 \end{bmatrix}$$

Then there are one linearly independent eigenvector of D with respect to λ .

\Rightarrow the algebraic multiplicity is 3 and geometric multiplicity is one.

4.4. 7) pf: denote $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$ since $A = A^H$.

\Rightarrow a and d are real numbers since $a = \bar{a}$ and $d = \bar{d}$

$$b = \bar{c}.$$

$$\Rightarrow \lambda E - A = \begin{bmatrix} \lambda - a & -b \\ -c & \lambda - d \end{bmatrix}$$

$$\begin{aligned} \Rightarrow \det(\lambda E - A) &= \lambda^2 - (a+d)\lambda + ad - bc \\ &= \lambda^2 - (a+d)\lambda + ad - \|b\|^2 \\ &= 0 \end{aligned}$$

$$\lambda = \frac{a+d \pm \sqrt{(a+d)^2 - 4ad + 4\|b\|^2}}{2}$$

$$\Rightarrow (a+d)^2 - 4ad + 4\|b\|^2 \\ = (a-d)^2 + 4\|b\|^2 \geq 0$$

$\Rightarrow \lambda$ must be real.

ii) Now suppose $A = -A^H$

and denote $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$

$$\Rightarrow \bar{a} = -a. \quad \bar{b} = -b.$$

$\Rightarrow a$ and b only have imaginary part.

$$\bar{b} = -c \quad \text{and} \quad \bar{c} = -b \Rightarrow b = -\bar{c}.$$

$$\lambda E - A = \begin{bmatrix} \lambda - a & -b \\ -c & \lambda - d \end{bmatrix}$$

$$\det(\lambda E - A) = \lambda^2 - (a+d)\lambda + ad - bc$$

$$\text{Consider } (a+d)^2 - 4ad + 4bc$$

$$= (a-d)^2 + 4bc$$

Since $a-d$ only has imaginary part

$$\Rightarrow (a-d)^2 \leq 0$$

$$4bc = -4\|c\|^2 \leq 0$$

$$\Rightarrow (a+d)^2 - 4ad + 4bc \leq 0$$

\Rightarrow it can only have imaginary eigenvalue.

4.6.

pf: denote the upper triangular matrix $A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ 0 & a_{22} & & \\ \vdots & & \ddots & \\ 0 & \dots & & a_{nn} \end{bmatrix}$

$$\Rightarrow \lambda E - A = \begin{bmatrix} \lambda - a_{11} & -a_{12} & \dots & -a_{1n} \\ & \lambda - a_{22} & & \\ & & \ddots & \\ 0 & & & \lambda - a_{nn} \end{bmatrix}$$

$$\Rightarrow \det(\lambda E - A) = (\lambda - a_{11})(\lambda - a_{22}) \dots (\lambda - a_{nn}) = 0$$

\Rightarrow The characteristic polynomial implies.

$$\lambda_1 = a_{11}, \lambda_2 = a_{22}, \dots, \lambda_n = a_{nn}$$

4.8.

i). Now we just have to prove that $\{\sin(x), \cos(x), \sin(2x), \cos(2x)\}$ are linearly independent.

$$\begin{aligned} \text{Now consider } & a \sin(x) + b \cos(x) + c \sin(2x) + d \cos(2x) \\ &= a \sin(x) + b \cos(x) + 2c \sin(x) \cos(x) + d \cos^2(x) - d \sin^2(x). \\ &= 0. \end{aligned}$$

$$\text{When } x=0: a \sin(x) + b \cos(x) + c \sin(2x) + d \cos(2x) = b + d = 0$$

$$\text{When } x=\frac{\pi}{2}: a \sin(x) + b \cos(x) + c \sin(2x) + d \cos(2x) = a - d = 0$$

$$\text{When } x=\pi: a \sin(x) + b \cos(x) + c \sin(2x) + d \cos(2x) = -b + d = 0$$

$$\text{Now we know that } a = b = d = 0$$

$$\Rightarrow c = 0$$

$$\Rightarrow a = b = c = d = 0$$

$\Rightarrow \{\sin(x), \cos(x), \sin(2x), \cos(2x)\}$ are linearly independent.

$$i). \sin'(x) = \cos(x)$$

$$\cos'(x) = -\sin(x)$$

$$\sin'(2x) = 2\cos(2x)$$

$$\cos'(2x) = -2\sin(2x)$$

$$\text{then } D = \begin{bmatrix} 0 & -1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -2 \\ 0 & 0 & 2 & 0 \end{bmatrix}$$

ii) The two D -invariant subspaces are $\{\sin(x), \cos(x)\}$ and

$$\{\sin(2x), \cos(2x)\}.$$

$$\text{For } \{\sin(x), \cos(x)\}. \text{ consider } v \in \{\sin(x), \cos(x)\} = \begin{bmatrix} a \\ b \\ 0 \\ 0 \end{bmatrix}.$$

$$\text{then } D.v = \begin{bmatrix} -b \\ a \\ 0 \\ 0 \end{bmatrix} \in \{\sin(x), \cos(x)\}.$$

$$\text{For } \{\sin(2x), \cos(2x)\}. \text{ consider } w \in \{\sin(2x), \cos(2x)\} = \begin{bmatrix} 0 \\ 0 \\ c \\ d \end{bmatrix}$$

$$\text{then } D.w = \begin{bmatrix} 0 \\ 0 \\ -2d \\ 2c \end{bmatrix} \in \{\sin(2x), \cos(2x)\}.$$

Then we know that they are two D -invariant subspaces.

$$4.13. \text{ Now consider } \lambda E - A = \begin{bmatrix} \lambda - 0.8 & -0.4 \\ -0.2 & \lambda - 0.6 \end{bmatrix}$$

$$\det(\lambda E - A) = \lambda^2 - 1.4\lambda + 0.48 - 0.08.$$

$$= \lambda^2 - 1.4\lambda + 0.4$$

$$= (\lambda - 1)(\lambda - 0.4)$$

$$\Rightarrow \lambda_1 = 1, \lambda_2 = 0.4.$$

$$\lambda_1 E - A = \begin{bmatrix} 0.2 & -0.4 \\ -0.2 & 0.4 \end{bmatrix}$$

$$\text{then } \begin{bmatrix} 0.2 & -0.4 \\ -0.2 & 0.4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0.2x_1 - 0.4x_2 \\ -0.2x_1 + 0.4x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\Rightarrow \begin{cases} 0.2x_1 - 0.4x_2 = 0 \\ -0.2x_1 + 0.4x_2 = 0 \end{cases} \Rightarrow x_1 = 2x_2 \quad \text{then } \begin{bmatrix} 2 \\ 1 \end{bmatrix} \text{ is an eigenvector.}$$

$$\lambda_2 E - A = \begin{bmatrix} -0.4 & -0.4 \\ -0.2 & -0.2 \end{bmatrix}$$

$$\begin{bmatrix} -0.4 & -0.4 \\ -0.2 & -0.2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} -0.4x_1 - 0.4x_2 \\ -0.2x_1 - 0.2x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\Rightarrow \begin{cases} -0.4x_1 - 0.4x_2 = 0 \\ -0.2x_1 - 0.2x_2 = 0 \end{cases} \Rightarrow x_1 = -x_2 \quad \text{then } \begin{bmatrix} 1 \\ -1 \end{bmatrix} \text{ is an eigenvector}$$

with respect to $\lambda_2 = 0.4$.

$$\text{Then construct } P = \begin{bmatrix} 2 & 1 \\ 1 & -1 \end{bmatrix}$$

$$\det(P) = -2 - 1 = -3.$$

$$\text{then } P^{-1} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & -\frac{2}{3} \end{bmatrix}$$

$$\Rightarrow P^{-1}AP = \begin{bmatrix} 1 & 0 \\ 0 & 0.4 \end{bmatrix}$$

4.15

Pf: Now firstly we try to prove $\{f(\lambda_i)\}_{i=1}^n$ are the eigenvalues.
for arbitrary λ_i , denote the ^{corresponding} eigenvector as x_i .

$$\begin{aligned} \text{then } f(A) \cdot x_i &= a_0 I x_i + a_1 A x_i + \dots + a_n A^n x_i \\ &= (a_0 + a_1 \lambda_i + \dots + a_n \lambda_i^n) \cdot x_i \\ &= f(\lambda_i) x_i \end{aligned}$$

$\Rightarrow f(\lambda_i)$ is an eigenvalue of $f(A)$

Then we prove that there are no other eigenvalues.

Suppose there are other eigenvalues λ' .

Since A is a semi-simple matrix. then we can form a set of eigenvectors $\{x_1, x_2, \dots, x_n\}$ that forms a basis of \mathbb{F}^n .

Then since there is another eigenvalue λ' , then there is another eigenvector x' . And these are distinct eigenvalues, then x_1, \dots, x_n, x' are linearly independent. But the dimension of \mathbb{F}^n is n . Contradiction

$\Rightarrow \{f(\lambda_i)\}_{i=1}^n$ are the eigenvalues of $f(A)$.

4.16.

i) from 4.13, we know

$$P^{-1} A P = \begin{bmatrix} 1 & 0 \\ 0 & 0.4 \end{bmatrix} \Rightarrow A = P \begin{bmatrix} 1 & 0 \\ 0 & 0.4 \end{bmatrix} P^{-1}$$

$$\Rightarrow A^n = P \begin{bmatrix} 1 & 0 \\ 0 & 0.4^n \end{bmatrix} P^{-1}$$

$$\Rightarrow \lim_{n \rightarrow \infty} A^n = P \lim_{n \rightarrow \infty} \begin{bmatrix} 1 & 0 \\ 0 & 0.4^n \end{bmatrix} P^{-1} = P \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} P^{-1} = \begin{bmatrix} 2 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{2} & -1 \\ 1 & 2 \end{bmatrix}$$

$$\Rightarrow \lim_{n \rightarrow \infty} A^n = \begin{bmatrix} 2 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & -\frac{2}{3} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{2}{3} & \frac{2}{3} \\ \frac{1}{3} & \frac{1}{3} \end{bmatrix}$$

$$\text{Then } A^k = \begin{bmatrix} 2 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 0.4^k \end{bmatrix} \begin{bmatrix} \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & -\frac{2}{3} \end{bmatrix}$$

$$= \begin{bmatrix} 2 & 0.4^k \\ 1 & -0.4^k \end{bmatrix} \begin{bmatrix} \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & -\frac{2}{3} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{2}{3} + \frac{0.4^k}{3} & \frac{2}{3} - \frac{2}{3} \cdot 0.4^k \\ \frac{1}{3} - \frac{1}{3} \cdot 0.4^k & \frac{1}{3} + \frac{2}{3} \cdot 0.4^k \end{bmatrix}$$

$$\Rightarrow A^k - \begin{bmatrix} \frac{2}{3} & \frac{2}{3} \\ \frac{1}{3} & \frac{1}{3} \end{bmatrix} = \begin{bmatrix} \frac{0.4^k}{3} & -\frac{2}{3} \cdot 0.4^k \\ -\frac{1}{3} \cdot 0.4^k & \frac{2}{3} \cdot 0.4^k \end{bmatrix}$$

The 1 norm is maximum column sum,

$$\Rightarrow \|A^k - \begin{bmatrix} \frac{2}{3} & \frac{2}{3} \\ \frac{1}{3} & \frac{1}{3} \end{bmatrix}\|_1 = 2 \cdot \left| \frac{2}{3} \cdot 0.4^k \right| = \frac{4}{3} \cdot 0.4^k.$$

Then $\forall \epsilon > 0$, $\exists N = \left\lceil \log_{0.4} \frac{3}{4\epsilon} \right\rceil$ s.t. $\forall k > N$

$$\|A^k - \begin{bmatrix} \frac{2}{3} & \frac{2}{3} \\ \frac{1}{3} & \frac{1}{3} \end{bmatrix}\|_1 < \epsilon.$$

Then $B = \begin{bmatrix} \frac{2}{3} & \frac{2}{3} \\ \frac{1}{3} & \frac{1}{3} \end{bmatrix}$ is the $\lim_{n \rightarrow \infty} A^n$ under 1 norm

ii) Now consider

$$\begin{aligned} \|A^k - \begin{bmatrix} \frac{2}{3} & \frac{2}{3} \\ \frac{1}{3} & \frac{1}{3} \end{bmatrix}\|_{\infty} &= \left\| \begin{bmatrix} \frac{0.4^k}{3} & -\frac{2}{3} 0.4^k \\ -\frac{0.4^k}{3} & \frac{2}{3} 0.4^k \end{bmatrix} \right\|_{\infty} \\ &= \left| \frac{1}{3} 0.4^k \right| + \left| -\frac{2}{3} 0.4^k \right| \\ &= 0.4^k. \end{aligned}$$

then $\forall \epsilon > 0$, $\exists N = \lceil \log_{0.4} \epsilon \rceil$ s.t. $\forall k > N$.

$$\|A^k - \begin{bmatrix} \frac{2}{3} & \frac{2}{3} \\ \frac{1}{3} & \frac{1}{3} \end{bmatrix}\|_{\infty} < \epsilon.$$

iii) By theorem 4.3.12

$$\lambda_1 = f(1) = 3 + 5 \times 1 + 1^3 = 9.$$

$$\begin{aligned} \lambda_2 = f(0.4) &= 3 + 5 \times 0.4 + 0.4^3 = 3 + 2 + 0.064 \\ &= 5.064. \end{aligned}$$

$$\Rightarrow \lambda_1 = 9 \quad \lambda_2 = 5.064.$$

4.18. pt: Consider the eigenvalues of A^T .

$$\Rightarrow |\lambda E - A^T| = |(\lambda E - A^T)^T| = |\lambda E - A|.$$

\Rightarrow the eigenvalues of A are the eigenvalues of A^T .

$$\Rightarrow \text{for } \lambda, \exists \text{ eigenvector } x \text{ s.t. } A^T x = \lambda x.$$

$$\Rightarrow (A^T x)^T = (\lambda x)^T \Rightarrow x^T A = \lambda x^T.$$

$\Rightarrow \exists$ a non zero row vector x^T st. $x^T A = \lambda x^T$.

4.20.

Pf: Since A and B are orthogonally similar.

then \exists an orthogonal matrix U s.t.

$$B = U^H A U.$$

$$\Rightarrow B^H = (U^H A U)^H = U^H A^H (U^H)^H = U^H A U = B.$$

$\Rightarrow B$ is hermitian.

4.24.

Pf. ① Suppose A is hermitian matrix

$$\text{then } \langle x, Ax \rangle = x^H A x.$$

\Rightarrow Consider $\langle x, Ax \rangle$ as a 1×1 matrix

$$\text{then } \langle x, Ax \rangle^H = \overline{\langle x, Ax \rangle}$$

$$\Rightarrow \langle x, Ax \rangle^H = x^H A^H x = x^H A x$$

$$\Rightarrow \langle x, Ax \rangle = \overline{\langle x, Ax \rangle}$$

Then $\langle x, Ax \rangle$ takes on only real values.

$\Rightarrow P(x) = \frac{\langle x, Ax \rangle}{\|x\|^2}$ takes only real values if A is hermitian

② Suppose A is skew matrix

$$\text{then } \langle x, Ax \rangle = x^H A x$$

$$\langle x, Ax \rangle^H = x^H A^H x = -x^H A x = -\langle x, Ax \rangle$$

$$\Rightarrow \overline{\langle x, Ax \rangle} = -\langle x, Ax \rangle$$

$\Rightarrow \langle x, Ax \rangle$ takes on only imaginary parts

$$\Rightarrow \rho(x) = \frac{\langle x, Ax \rangle}{\|x\|^2} \text{ takes } \overset{\text{on}}{\vee} \text{ only imaginary values}$$

When A is a skew matrix.

4.25.

$$\begin{aligned} \text{i) Consider } (x_1 x_1^H + \dots + x_n x_n^H) \cdot x_j \\ = x_1 x_1^H x_j + \dots + x_j x_j^H x_j + \dots + x_n x_n^H x_j \end{aligned}$$

Since $\{x_1, \dots, x_n\}$ is orthonormal eigenvectors.

$$\text{Then } (x_1 x_1^H + \dots + x_n x_n^H) \cdot x_j$$

$$= x_j x_j^H x_j$$

$$= x_j.$$

This is true for $\forall j \in \{1, \dots, n\}$.

Since $\{x_1, \dots, x_n\}$ is a basis in \mathbb{C}^n .

$$\Rightarrow \forall x \in \mathbb{C}^n. (x_1 x_1^H + \dots + x_n x_n^H) x = x.$$

$$\Rightarrow I = x_1 x_1^H + \dots + x_n x_n^H$$

$$\begin{aligned} \text{ii) Consider } (\lambda_1 x_1 x_1^H + \dots + \lambda_n x_n x_n^H) x_j \\ = \lambda_j x_j \end{aligned}$$

This is true for $\forall j \in \{1, \dots, n\}$.

$\Rightarrow \lambda_1 x_1 x_1^H + \dots + \lambda_n x_n x_n^H$ has eigenvalues $\lambda_1, \dots, \lambda_n$ and corresponding eigenvectors x_1, \dots, x_n .

\Rightarrow denote $P = [x_1 \dots x_n]$

$$B = \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix}$$

then $\lambda_1 x_1 x_1^H + \dots + \lambda_n x_n x_n^H$

$$= P^H B P$$

$$= A$$

4.2].

Pf: denote $A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ \vdots & \ddots & & \vdots \\ a_{n1} & \dots & \dots & a_{nn} \end{bmatrix}$

Now consider e_j .

$$e_j^H A e_j = a_{jj} > 0 \quad \text{by definition of positive definite matrix.}$$

This is true for $\forall j \in \{1, 2, \dots, n\}$

Then all diagonal entries are real positive

4.28. $AB = \begin{bmatrix} \sum_{i=1}^n a_{1i} b_{i1} & & \\ & \ddots & \\ & & \sum_{i=1}^n a_{ni} b_{in} \end{bmatrix}$

$$\Rightarrow \text{tr}(AB) = \sum_{j=1}^n \sum_{i=1}^n a_{ji} b_{ij}$$

$$\text{tr}(A) = \sum_{i=1}^n a_{ii} \quad \text{tr}(B) = \sum_{j=1}^n b_{jj} \quad \rightarrow \text{tr}(A) \text{tr}(B) = \sum_{i=1}^n \sum_{j=1}^n a_{ii} b_{jj}$$

Since A and B are positive semi-definite.

then $\exists X, Y \in M_n(\mathbb{C})$ s.t. $A = X^H X$ $B = Y^H Y$.

$$\Rightarrow \text{tr}(AB) = \text{tr}(X^H X Y^H Y) = \text{tr}(\dots)$$
$$= \text{tr}((X Y^H)^H X Y^H)$$

denote $X Y^H = Z$ then

$$\text{tr}(AB) = \text{tr}(Z^H Z)$$
$$= \sum_{i=1}^n \sum_{j=1}^n \bar{z}_{ij} z_{ij}$$
$$= \sum_{i=1}^n \sum_{j=1}^n \|z_{ij}\|^2$$
$$\geq 0$$

We know that $\langle A, B \rangle = \text{tr}(A^H B)$

~~$$1 = \text{tr}(B) = \text{tr}(X^H X) \cdot \text{tr}(Y^H Y)$$~~

~~By Cauchy Schwarz inequality~~

~~$$\text{tr}(X^H Y)^2 \leq \text{tr}(X^H X) \text{tr}(Y^H Y)$$~~

~~$$\text{tr}((Y X^H)^H (Y X^H)) \leq \sqrt{\text{tr}(Y X^H)}$$~~

Now we have.

$$\text{tr}(AB) \leq \sqrt{\text{tr}(A^2) \text{tr}(B^2)} = \sqrt{\left(\sum_{i=1}^n \lambda_i^2\right) \left(\sum_{i=1}^n \eta_i^2\right)}$$

Since A and B are positive semi-definite $\Rightarrow \lambda_i \geq 0$ $\eta_i \geq 0 \forall i$.

$$\Rightarrow \text{tr}(AB) \leq \sqrt{\left(\sum_{i=1}^n \lambda_i^2\right) \left(\sum_{i=1}^n \eta_i^2\right)}$$
$$\leq \sqrt{\left(\sum_{i=1}^n \lambda_i\right)^2 \left(\sum_{i=1}^n \eta_i\right)^2}$$
$$= \text{tr}(A) \text{tr}(B)$$

$$\Rightarrow \text{tr}(AB) \leq \text{tr}(A) \text{tr}(B)$$

To sum up $0 \leq \text{tr}(AB) \leq \text{tr}(A) \text{tr}(B)$

4.31.

$$i). \|A\|_2 = \sup_{\|x\|=1} \|Ax\|_2 = \sup_{\|x\|=1} \sqrt{x^H A^H A x}.$$

$A^H A$ is symmetric $\Rightarrow A^H A$ is normal

Hence it's orthonormally diagonalizable.

Then let $\{x_1, x_2, \dots, x_n\}$ be a set of orthonormal eigenvectors of $A^H A$

then for $\forall x \in F^n$ with $\|x\|_2 = 1$ $x = a_1 x_1 + a_2 x_2 + \dots + a_n x_n$

$$\Rightarrow \|x\|_2^2 = a_1^2 + a_2^2 + \dots + a_n^2 = 1$$

$$\Rightarrow x^H A^H A x = \lambda_1 a_1^2 + \dots + \lambda_n a_n^2.$$

Then since $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n \geq 0$

then $\sup x^H A^H A x = \lambda_1$.

$$\Rightarrow \sup_{\|x\|=1} \|Ax\|_2 = \sqrt{\lambda_1} = \sigma_1.$$

$$\Rightarrow \|A\|_2 = \sigma_1.$$

$$ii) \|A^{-1}\|_2 = \sup_{\|x\|=1} \sqrt{x^H (A^H A)^{-1} x}.$$

with B being symmetric.

For $\forall B \in M_n(F)$ suppose B has eigenvalues $\lambda_1, \dots, \lambda_n$. then

B^{-1} has eigenvalues $\lambda_1^{-1}, \dots, \lambda_n^{-1}$

Then for $A^H A$, since $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n \geq 0$

$$\Rightarrow \lambda_1^{-1} \leq \lambda_2^{-1} \leq \dots \leq \lambda_n^{-1}$$

$$\Rightarrow \sigma_1^{-1} \leq \sigma_2^{-1} \leq \dots \leq \sigma_n^{-1}$$

By the result in i) we have $\|A^{-1}\|_2 = \sigma_n^{-1}$

iii) Firstly prove $\|A_2\|_2^2 = \|A^H A\|_2$.

$$\|A_2\|^2 = \left(\sup_x \sqrt{x^H A^H A x} \right)^2 = \sup x^H A^H A x = \sigma_1^2 = d_1$$

$$\|A^H A\|_2 = \sup_x \sqrt{x^H A^H A A^H A x}$$

$$\text{Now } A^H A A^H A = (A^H A)^2$$

$\Rightarrow A^H A A^H A$ has eigenvalues $d_1^2, d_2^2, \dots, d_n^2$

$$\Rightarrow d_1^2 \geq d_2^2 \geq \dots \geq d_n^2$$

$$\Rightarrow \|A^H A\|_2 = \sqrt{d_1^2} = d_1 = \|A_2\|^2$$

iv) Since U and V are orthonormal

$$\Rightarrow \forall x, y \in \mathbb{R}^n \langle x, y \rangle = \langle Ux, Uy \rangle$$

$$\forall v, w \in \mathbb{R}^n, \langle v, w \rangle = \langle Vx, Vy \rangle$$

$$\Rightarrow \|UAV\|_2 = \sup_{\|x\|=1} \|UAVx\|_2 = \sup_{\|x\|=1} \sqrt{\langle UAVx, UAVx \rangle} = \sup_{\|x\|=1} \sqrt{\langle AVx, AVx \rangle}$$

Since V is orthonormal, $V(\mathbb{F}^n) = \mathbb{R}(V) = \mathbb{F}^n$.

additionally for $\forall x \in \mathbb{F}^n$ with $\|x\|_2 = 1$ $\langle Vx, Vx \rangle = \langle x, x \rangle = 1$

$\Rightarrow \forall x = y$ and $\|y\|_2 = 1$

$$\Rightarrow \|UAV\|_2 = \sup_{\|x\|_2=1} \sqrt{\langle AVx, AVx \rangle} = \sup_{\|y\|_2=1} \sqrt{\langle Ay, Ay \rangle} = \|A\|_2.$$

4.32.

i). We know $\|A\|_F = \sqrt{\text{tr}(A^H A)}$.

$$\begin{aligned} \Rightarrow \|UAV\|_F &= \sqrt{\text{tr}(V^H A^H U^H U A V)} \\ &= \sqrt{\text{tr}(V^H A^H A V)} \\ &= \sqrt{\text{tr}(A^H A V V^H)} \\ &= \sqrt{\text{tr}(A^H A)} \\ &= \|A\|_F. \end{aligned}$$

ii) Now apply Singular value decomposition to A .

Suppose $A = U \Sigma V$ where U and V are orthonormal and

$$\Sigma = \begin{bmatrix} \sigma_1 & & & 0 \\ & \sigma_2 & & \\ & & \ddots & \\ 0 & & & \sigma_r & & 0 \\ & & & & \ddots & \\ & & & & & 0 \end{bmatrix}$$

according to i), $\|A\|_F = \|U \Sigma V\|_F = \|\Sigma\|_F$

$$\Rightarrow \|\Sigma\|_F = (\sigma_1^2 + \sigma_2^2 + \dots + \sigma_r^2)^{\frac{1}{2}}$$

$$\Rightarrow \|A\|_F = \|\Sigma\|_F = (\sigma_1^2 + \dots + \sigma_r^2)^{\frac{1}{2}}.$$

4.33

Pf: Now for $\forall x, y$. Since U and V are orthonormal matrix.

$$\exists v, w \text{ s.t. } Uv = y \quad Vw = x.$$

and. $|v| = 1, |w| = 1$ by definition of orthonormal transformation

$$\Rightarrow \sup_{|x|=1, |y|=1} |y^H A x| = \sup_{|v|=1, |w|=1} |v^H U^H U \Sigma V^H V w|.$$

$$= \sup_{|v|=1, |w|=1} |v^H \Sigma w|.$$

$$= \sup_{|v|=1, |w|=1} \left| \sum_{i=1}^n \sigma_i \bar{v}_i w_i \right|.$$

Since $|v| = 1$ and $|w| = 1$, then $\bar{v}_i w_i \leq 1$.

$$\Rightarrow \sup_{|x|=1, |y|=1} |y^H A x| = \sigma_1 \quad \text{where we set } v_i = w_i = 1$$

$$\Rightarrow \sup_{|x|=1, |y|=1} |y^H A x| = \sigma_1 = \|A\|_2.$$

4.36.

Consider $A = \begin{bmatrix} 2 & 2 \\ 1 & 2 \end{bmatrix}$

$$\begin{aligned} \text{Then } A^H A &= \begin{bmatrix} 2 & 1 \\ 2 & 2 \end{bmatrix} \begin{bmatrix} 2 & 2 \\ 1 & 2 \end{bmatrix} \\ &= \begin{bmatrix} 5 & 6 \\ 6 & 8 \end{bmatrix} \end{aligned}$$

$$\det(\lambda E - A) = \det \left(\begin{bmatrix} \lambda - 2 & -2 \\ -1 & \lambda - 2 \end{bmatrix} \right) = (\lambda - 2)^2 - 2 = \lambda^2 - 4\lambda + 2.$$

$$\Rightarrow \lambda_1 = \frac{4 + \sqrt{8}}{2} = 2 + \sqrt{2}$$

$$\lambda_2 = \frac{4 - \sqrt{8}}{2} = 2 - \sqrt{2}$$

$$\det(\eta E - A^H A) = \det \left(\begin{bmatrix} \eta - 5 & -6 \\ -6 & \eta - 8 \end{bmatrix} \right) = \eta^2 - 13\eta + 4$$

$$\eta_1 = \frac{13 + \sqrt{153}}{2} \quad \eta_2 = \frac{13 - \sqrt{153}}{2}$$

$$\text{and } \eta_1 \neq \lambda_1^2 \neq \lambda_2^2$$

$$\eta_2 \neq \lambda_1^2 \neq \lambda_2^2.$$

\Rightarrow singular values are not equal to any of A 's eigenvalues.

Additionally $\det(A) = 2 \neq 0$

4.38.

$$\Rightarrow AA^H A = A.$$

$$\begin{aligned} A &= U \Sigma V^H \quad \Rightarrow \quad A^H A = V \Sigma^H U^H U \Sigma V^H \\ A^H &= V \Sigma^H U^H \\ &= V V^H = E. \end{aligned}$$

$$\Rightarrow AA^H A = AE = A.$$

$$i) A^T A A^T$$

from i) we know $A^T A = E$

$$\Rightarrow A^T A A^T = E A^T = A^T.$$

$$ii) (A A^T)^H = A A^T$$

$$A A^T = U, \Sigma, V,^H V, \Sigma^{-1} U,^H = U, \Sigma, \Sigma^{-1} U,^H = U, \Sigma, \Sigma^{-1} U,^H$$

$$\Rightarrow (A A^T)^H = U, (\Sigma^{-1})^H V,^H V, \Sigma, U,^H.$$

$$= U, \Sigma^{-1} V,^H V, \Sigma, U,^H.$$

$$= U, \Sigma^{-1} \Sigma, U,^H$$

$$= A A^T.$$

$$iv) (A^T A)^H = A^T A.$$

$$A^T A = V, \Sigma^{-1} U,^H U, \Sigma, V,^H$$

$$(A^T A)^H = V, \Sigma, U,^H U, (\Sigma^{-1})^H V,^H$$

$$= V, \Sigma, U,^H U, \Sigma^{-1} V,^H$$

$$= V, \Sigma, \Sigma^{-1} V,^H$$

$$= V, \Sigma^{-1} \Sigma, V,^H$$

$$= V, \Sigma^{-1} U,^H U, \Sigma, V,^H$$

$$= A^T A.$$

v). We know $R(A) = N(A^H)^\perp$.

$$\begin{aligned} AA^T &= A \cdot V_1 \Sigma_1^{-1} U_1^H \\ &= A V_1 \Sigma_1^{-1} (\Sigma_1^{-1})^H V_1^H A^H. \end{aligned}$$

$$\Rightarrow \forall x \in N(A^H).$$

$$\begin{aligned} AA^T x &= A V_1 \Sigma_1^{-1} (\Sigma_1^{-1})^H V_1^H (A^H x) \\ &= 0 \end{aligned}$$

$$\forall y \in N(A^H)^\perp$$

$$\begin{aligned} AA^T x &= U_1 \Sigma_1 V_1^H V_1 \Sigma_1^{-1} (\Sigma_1^{-1})^H V_1^H (A^H y) \\ &= U_1^H U_1 x \\ &= x. \end{aligned}$$

$$\Rightarrow AA^T = \text{Proj}_{N(A^H)^\perp} = \text{Proj}_{R(A)}$$

iv) We know $R(A^H) = N(A)^\perp$

then $\forall x \in N(A)$

$$A^T A x = A^T (Ax) = A^T 0 = 0.$$

$$\forall y \in N(A)^\perp$$

$$\begin{aligned} A^T A y &= V_1 \Sigma_1^{-1} U_1^H U_1 \Sigma_1 V_1^H y \\ &= y. \end{aligned}$$

$$\Rightarrow A^T A = \text{Proj}_{N(A)^\perp} = \text{Proj}_{R(A^H)}$$