

Math, Inner Product Space#3

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1. (4.2)

D should take the form of $\begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix}$

$p_D(z) = \det(zI - D) = z^3$. If $p_D(z) = 0$, it indicates that eigenvalue of D is 0 with the algebraic multiplicity of 3. Also $\mathcal{N}(0I - D) = \mathcal{N}(-D) = \text{span}\{[x, 0, 0]^T\}$. The geometric multiplicity is 1, since $\dim(\mathcal{N}(-D)) = 1$.

2. (4.4)

Using 4.3, we could show if $(\text{tr}(A)^2 - 4\det(A))$ is non-negative, then the matrix only got real eigenvalues, otherwise, it only gets imaginary eigenvalues.

i. If the matrix is Hermitian, the $A = \begin{bmatrix} a & b \\ b & d \end{bmatrix}$, then $(\text{tr}(A)^2 - 4\det(A)) = (a - d)^2 + 4b^2 \geq 0$

ii. If the matrix is skew-Hermitian, then $\begin{bmatrix} 0 & b \\ -b & 0 \end{bmatrix}$. Therefore, $(\text{tr}(A)^2 - 4\det(A)) = -4b^2 < 0$ for $b \neq 0$

3. (4.6)

Let $A_{n \times n}$ be an upper triangular matrix. $\det(\lambda I - A) = 0 \implies \prod_{i=1}^n (\lambda_i - a_{ii}) = 0$. Therefore, the eigenvalues of matrix A are its diagonal elements.

4. (4.8)

i. To prove $\{\sin(x), \cos(x), \sin(2x), \cos(2x)\}$ is the basis for V , we need to prove they are linearly independent. This is equivalent to prove that for $\forall x \in \mathbb{R}, a\sin(x) + b\cos(x) + c\sin(2x) + d\cos(2x) = 0$ only when $a = b = c = d = 0$. When $x = 0, b + d = 0$. When $x = \pi, -b + d = 0$. Therefore, $b = d = 0$. Also, when $x = \frac{\pi}{2}, a - d = 0 \implies a = 0$. Then $\forall x \in \mathbb{R}, d\cos(2x) = 0 \implies d = 0$. This completes the proof that S is a basis for V .

ii. $(a\sin(x) + b\cos(x) + c\sin(2x) + d\cos(2x))' = (-b)\sin(x) + a\cos(x) + (-2d)\sin(2x) +$

$2ccos(x)$. So the matrix representation of D is $\begin{bmatrix} 0 & -1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -2 \\ 0 & 0 & 2 & 0 \end{bmatrix}$

iii. $\text{span}\{[1, 0, 0, 0], [0, 1, 0, 0]\}$ and $\text{span}\{[0, 0, 1, 0], [0, 0, 0, 1]\}$

5. (4.13)

Let $B = P^{-1}AP$, where B is a diagonal matrix. Since P is a non-singular matrix, it indicates that A is diagonalizable. According to the Theorem 4.3.7, A is also semisimple. Then columns of P are just the eigenvectors of A and B is a diagonal matrix with eigenvalues on its diagonal. $\lambda = 1$ and 0.4 . Therefore, we let $P = \begin{bmatrix} 2 & 1 \\ 1 & -1 \end{bmatrix}$

6. (4.15)

We will use Theorem 4.3.7 and Proposition 4.3.10 to prove this. According to Theorem 4.3.7, A is semisimple, therefore diagonalizable. We could write $D = P^{-1}AP$ where D is a diagonalizable matrix with eigenvalues of A on its diagonal. And columns of P form the eigenspace of A . According to Proposition 4.3.10, we know that for $i = 1, 2, \dots, n, D^i = P^{-1}A^iP$. Also, because P is a linear operator, we have $P^{-1}f(A)P = a_0I + a_1P^{-1}AP + \dots + a_nP^{-1}A^nP =$

$$a_0I + a_1D + \dots + a_nD^n. \text{ Since we know that } D^i = \begin{bmatrix} \lambda_1^i & & \\ & \ddots & \\ & & \lambda_n^i \end{bmatrix}, \text{ Then}$$

$$P^{-1}f(A)P = \begin{bmatrix} \sum_{i=0}^n a_i \lambda_1^i & & \\ & \ddots & \\ & & \sum_{i=0}^n a_i \lambda_n^i \end{bmatrix} = \begin{bmatrix} f(\lambda_1) & & \\ & \ddots & \\ & & f(\lambda_n) \end{bmatrix}$$

7. (4.16)

i. We have in 4.13 that $D = P^{-1}AP$, where $D = \begin{bmatrix} 1 & 0 \\ 0 & 0.4 \end{bmatrix}$ and $P = \begin{bmatrix} 2 & 1 \\ 1 & -1 \end{bmatrix}$.

According to proposition 4.3.10, $A^n = PD^nP^{-1}$. So $\lim_{n \rightarrow \infty} A^n = \lim_{n \rightarrow \infty} PD^nP^{-1} = P(\lim_{n \rightarrow \infty} D^n)P^{-1} = P \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} P^{-1} = \begin{bmatrix} \frac{2}{3} & \frac{2}{3} \\ \frac{1}{3} & \frac{1}{3} \end{bmatrix}$

ii. It doesn't matter.

iii. Since the eigenvalues of A are 1 and 0.4, according to Theorem 4.3.12, the eigenvalues are $3 + 5 * 1 + 1^3 = 9$ and $3 + 5 * 0.4 + 0.4^3 = 5.064$.

8. (4.18)

Since the characteristic polynomial of A and A^T is the same, therefore, A and A^T have the same eigenvalues. If λ is a eigenvalue of A , it's Also an eigenvalue of A^T . Therefore, \exists non-zero x , such that $A^T X = \lambda x \implies x^T A = \lambda x^T$.

9. (4.20)

Since A is Hermitian, $B = U^H A U \implies B^H = (U^H A U)^H = (U^H A^H U) = (U^H A U) = B$.

10. (4.24)

- i. If A is Hermitian, according to Corollary 4.4.9, it must have an orthonormal eigen basis V . We represent x in V as $x = Va$, where a is the coefficient vector of x in basis V . Then $\rho(x) = \frac{\langle x, Ax \rangle}{\|x\|^2}$
- $$= \frac{a^H V^H A V a}{a^H a}$$
- $$= \frac{a^H D a}{a^H a} \text{ (where } D \text{ is a diagonal matrix, the diagonal elements of which are real eigenvalues of } A \text{)}$$
- $$= \frac{\sum_{i=1}^n \lambda_i |a_i|^2}{\sum_{i=1}^n |a_i|^2} \text{ (which has to be real given all its elements are real value)}$$
- Since all eigenvalues of a skew-Hermitian matrix are all imaginary, we could use the same proof techniques above, therefore omitted.

11. (4.25)

- i. Since $X = [x_1 \ \dots \ x_n]$ is orthonormal, therefore, $XX^H = I \implies \sum_{i=1}^n x_i x_i^H$
- ii. Given the result in i., left-multiplying both side by A will give us that $A = \sum_i A x_i x_i^H = \sum_i \lambda_i x_i x_i^H$

12. (4.27)

Since A is positive definite, it's also Hermitian. Therefore, all its diagonal elements are real. If any of its diagonal element is not positive, W.L.O.G., we assume $a_{ii} \leq 0$. Then, we let $y = e_i$. $\langle y, Ay \rangle = y^H Ay = a_{ii} \leq 0$, contradicting the fact that A is a positive definite matrix.

13. (4.28)

Since Cauchy Schwartz need to hold for any inner product space, we have

$$tr(AB) \leq \sqrt{tr(A^2)tr(B^2)}$$

$$= \sqrt{(\sum_{i=1}^n \lambda_{a,i}^2)(\sum_{i=1}^n \lambda_{b,i}^2)}$$

$$\leq \sqrt{(\sum_{i=1}^n \lambda_{a,i})^2 (\sum_{i=1}^n \lambda_{b,i})^2}$$

$$= tr(A)tr(B)$$

14. (4.31)

- i. $\|A\|_2 = \sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2}$
- $$= \sup_{x \neq 0} \frac{\|U \Sigma V^H x\|_2}{\|x\|_2}$$
- $$= \sup_{x \neq 0} \frac{\|\Sigma V^H x\|_2}{\|x\|_2} \text{ (invariant under multiplication by orthonormal matrix)}$$
- $$= \sup_{x \neq 0} \frac{\|\Sigma y\|_2}{\|V y\|_2} \text{ (let } y = V^H x \text{)}$$
- $$= \sup_{x \neq 0} \frac{\|\Sigma y\|_2}{\|y\|_2} \text{ (invariant under multiplication by orthonormal matrix)}$$
- $$= \sup_{x \neq 0} \frac{(\sum_{i=1}^n |\sigma_i y_i|^2)^{\frac{1}{2}}}{(\sum_{i=1}^n |y_i|^2)^{\frac{1}{2}}}$$

We let $y = [1, 0, \dots, 0]^H$, then $\|A\|_2 = \sigma_1$

- ii. Since, based on singular value decomposition, $A^{-1} = (U \Sigma V^H)^{-1} = V \Sigma^{-1} U^H$. The diagonal elements of Σ^{-1} are $\frac{1}{\sigma_1}, \frac{1}{\sigma_2}, \dots, \frac{1}{\sigma_n}$, the biggest of which will be $\frac{1}{\sigma_n}$.

Therefore, according to the result of i., we know that $\|A^{-1}\|_2 = \frac{1}{\sigma_n}$.

iii. It's easy to prove that $\|A\|_2^H = \|A\|_2^T = \|A\|_2$ since the Σ of their SVD is the same. $A^H A = V \Sigma^H U^H U \Sigma V^H = V \Sigma^H \Sigma V^H$. Since the diagonal elements of $\Sigma^H \Sigma$ are $\sigma_1^2, \sigma_2^2, \dots, \sigma_n^2$. By using the results of i., we could know that $\|A^H A\| = \sigma_1^2$.

iv. $\|UAV\|_2^2 = \|UAVV^H A^H U^H\|_2 = \|U A A^H U^H\|_2 = \|A A^H U^H\|_2 = \|(A A^H U^H)^H\|_2 = \|U A A^H\|_2 = \|A A^H\|_2 = \|A\|_2^2$

15. (4.32)

i. $\|UAV\|_F = (tr((UAV)^H UAV))^{\frac{1}{2}} = (tr(V^H A^H AV))^{\frac{1}{2}} = (tr(VV^H A^H A))^{\frac{1}{2}} = (tr(A^H A))^{\frac{1}{2}} = \|A\|_F$

ii. According to SVD Theorem, let $A = U \Sigma V^H$, so $\|A\|_F = tr(A^H A)^{\frac{1}{2}} = tr(V \Sigma^H \Sigma V^H)^{\frac{1}{2}} = tr(V^H V \Sigma^H \Sigma)^{\frac{1}{2}} = tr(\Sigma^H \Sigma)^{\frac{1}{2}} = (\sum_{i=1}^r \sigma_i^2)^{\frac{1}{2}}$

16. (4.33)

By 4.31, we know that $\|A\|_2 = \sigma_1$. According to SVD Theorem, let $A = U \Sigma V^H$. Let $x = \sum_{i=1}^n a_i v_i = Va$, where we expressed x in the orthonormal basis of V . Similarly, we let $y = Ub$. Since $x^H x, y^H y = 1 \implies a^H V^H V a = 1 \implies a^H a = 1$ and $b^H b = 1$.

$$\begin{aligned} & \sup_{\|x\|_2=1, \|y\|_2=1} |y^H Ax| \\ &= \sup_{\|a\|=1, \|b\|=1} |b^H U^H U \Sigma V^H Va| \\ &= \sup_{\|a\|=1, \|b\|=1} |b^H \Sigma a| \\ &= \sup_{\|a\|=1, \|b\|=1} \left| \sum_{i=1}^n \sigma_i a_i b_i \right| \\ &= \sigma_1 \text{ (According to Cauchy Schwartz inequality)} \\ &= \|A\|_2 \end{aligned}$$

17. (4.36)

$$A = \begin{bmatrix} 4 & 1 \\ 0 & 4 \end{bmatrix}$$

18. (4.38)

Let $A = U_1 \Sigma_1 V_1^H$

i. $AA^\dagger A$

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

ii. $A^\dagger A A^\dagger$

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

iii. $(AA^\dagger)^H$

$$\begin{aligned} &= (V_1 \Sigma_1^{-1} U_1^H)^H (U_1 \Sigma_1 V_1^H)^H \\ &= U_1 \Sigma_1 V_1^H V_1 \Sigma_1^{-1} U_1^H \\ &= AA^\dagger \end{aligned}$$

iv. $(A^\dagger A)^H$

$$\begin{aligned}
&= (U_1 \Sigma_1 V_1^H)^H (V_1 \Sigma_1^{-1} U_1^H)^H \\
&= V_1 \Sigma_1^{-1} U_1^H U_1 \Sigma_1 V_1^H \\
&= A^\dagger A
\end{aligned}$$