

Problem Set #3

OSM

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Exercise 2

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

All eigenvalues of D are 0 because D is upper triangular. Therefore, the algebraic multiplicity is 3. Because D has 1 eigenvector for eigenvalue of 0 and the eigenspace of 0 is $\text{span}(1)$, the geometric multiplicity is 1.

Exercise 4

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$$\text{Let } A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

So $\det(A) = ad - bc$ and if $A^H = A$, then $a = \bar{a}, b = \bar{c}, d = \bar{d}$, which means a and d are real. Because $bc = \bar{c}c = \|c\|^2$ is also real.

$$p(\lambda) = \lambda^2 - \text{tr}(A)\lambda + \det(A) = \lambda^2 - (a + d)\lambda + ad - \|c\|^2$$

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

Because $(a - d)^2 + \|c\|^2 \geq 0$, λ is real.

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$$\text{Let } A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

Because $a = -\bar{a}, b = -\bar{c}, d = -\bar{d}$, a and d are imaginary. Because $bc = -\bar{c}c = -\|c\|^2$, a and d are also negative.

$$p(\lambda) = \lambda^2 - \text{tr}(A)\lambda + \det(A) = \lambda^2 - (a + d)\lambda + ad - \|c\|^2$$

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

Because $(a - d)^2 + \|c\|^2 < 0$, λ is imaginary.

Exercise 6

If matrix A is upper triangular, $\det(A) = \prod_{i=1}^n a_{ii}$ and its eigenvalues are such that $\det(\lambda I - A) = 0$.

$$\det(\lambda I - A) = \prod_{i=1}^n a_{ii} = 0$$

This implies that the eigenvalues are given by the diagonal elements of matrix A .

Exercise 8

- Because this set is orthonormal given the inner product $\frac{1}{\pi} \int_{-\pi}^{\pi} f(t)g(t)dt$, each element is independent and forms a basis for V.
- $D\sin(x) = \cos(x)$, $D\cos(x) = -\sin(x)$, $D\cos(2x) = -2\sin(2x)$, $D\sin(2x) = 2\cos(2x)$,
so

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

- $\text{span}(\sin(x), \cos(x))$ and $\text{span}(\sin(2x), \cos(2x))$

Exercise 13

$\det(\lambda I - A) = \lambda^2 - 1.4\lambda + 0.4$ which means the roots and eigenvalues are 1 and 0.4,
and

$$\begin{bmatrix} -0.2 & 0.4 \\ 0.2 & -0.4 \end{bmatrix}$$

has a solution of $[2 \ 1]^T$. The eigenvector for $\lambda = 0.4$ has a null space

$$\begin{bmatrix} 0.4 & 0.4 \\ 0.2 & 0.2 \end{bmatrix}$$

with a solution of $[1 \ -1]^T$, which means

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

Exercise 15

Let $(\lambda_i)_{i=1}^n$ be the eigenvalues of matrix $A \in M_n(\mathbb{F})$ and $f(x) = a_0 + a_1x + a_2x^2 + \dots + a_nx^n$. Because A can be diagonalized as PBP^{-1}

$$f(A) = a_0I + a_1A + a_2A^2 + \dots + a_nA^n = a_0PP^{-1} + a_1PBP^{-1} + a_2PB^2P^{-1} + \dots + a_nPB^nP^{-1} = Pf(B)$$

Because each term in $f(B)$ is a diagonal matrix, the eigenvalues are $(f(\lambda_i))_{i=1}^n$

Exercise 16

- $A^n = PC^nP^{-1}$

$$C^n = \begin{bmatrix} 1^n & 0 \\ 0 & 0.4^n \end{bmatrix}$$

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

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

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

where each term converges with respect to the 1-norm.

- $-0.4^k + 2 * 0.4^k \rightarrow 0$ as $k \rightarrow \infty$ and the ∞ norm is the largest row sum, so

$$\begin{aligned} \|A^k - B\|_F &= \sqrt{\text{tr}\left(\begin{bmatrix} 2 * 0.4^{2k} & -4 * 0.4^{2k} \\ -4 * 0.4^{2k} & 8 * 0.4^{2k} \end{bmatrix}\right)} \\ &= \sqrt{10 * 0.4^{2k}} \rightarrow 0 \text{ as } k \rightarrow \infty \end{aligned}$$

Because $\|A^k - B\|_F \rightarrow 0$, the answer doesn't depend on the norm.

- $f(A) = 3I + 5A + A^3$ where $f(1) = 3 + 5 + 1 = 9$ and $f(0.4) = 3 + 5 * 0.4 + 0.4^3 = 5.06$

Exercise 18

Let λ be an eigenvalue of $A \in M_n(\mathbb{F})$. Because A and A^T have the same characteristic polynomial, λ is an eigenvalue of A^T , which means $A^T x = \lambda x \rightarrow (A^T x)^T = (\lambda x)^T$. Therefore, $x^T A = \lambda x^T$

Exercise 20

If A is Hermitian and orthonormally similar to B ,

$$B = PAP^H = PA^H P^H = (PAP^H)^H = B^H$$

Exercise 24

If A is Hermitian,

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

. Because the numerator is real, the Rayleigh quotient takes real values. If A is skew Hermitian,

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

Because the numerator is imaginary, the Rayleigh quotient takes imaginary values.

Exercise 25

- Because $\langle x_j, x_j \rangle = x_j^H x_j = 1$, and $\langle x_i, x_j \rangle = x_i^H x_j = 0$, $(x_1 x_1^H + \dots + x_n x_n^H) x_j = x_j x_j^H x_j = I x_j$, so $I = x_1 x_1^H + \dots + x_n x_n^H$.

- Because $(\lambda_1 x_1 x_1^H + \dots + \lambda_n x_n x_n^H)x_j = \lambda x_j x_j^H x_j = \lambda x_j = Ax_j$, so $A = \lambda_1 x_1 x_1^H + \dots + \lambda_n x_n x_n^H$

Exercise 27

Let e_i be the i th vector of the standard basis. Because $\langle x, Ax \rangle = x^H Ax > 0$ for all $x \neq 0$, $0 < e_i^H A e_i = a_{ii}$ must be real and positive.

Exercise 31

- Let $A = U \Sigma V^H$, $y = V^H x$

$$\begin{aligned} \|A\|_2 &= \sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} = \sup_{x \neq 0} \frac{\|U \Sigma V^H x\|_2}{\|x\|_2} = \sup_{x \neq 0} \frac{\|\Sigma V^H x\|_2}{\|x\|_2} = \sup_{y \neq 0} \frac{\|\Sigma y\|_2}{\|V y\|_2} = \\ &= \sup_{y \neq 0} \frac{\|\Sigma y\|_2}{\|y\|_2} = \sup_{y=1} \|\Sigma y\|_2 = \sigma_1 \end{aligned}$$

- Let $A = U \Sigma V^H$ so $A^{-1} = V \Sigma^{-1} U^H$. Because $\frac{1}{\sigma_1}, \dots, \frac{1}{\sigma_n}$ are the diagonal entries of Σ^{-1} , $\frac{1}{\sigma_n}$ is the largest singular value of A^{-1} and $\|A^{-1}\|_2 = \frac{1}{\sigma_n}$
- Let $A = U \Sigma V^H$ so $A^T = V \Sigma^T U^T$ and $A^H = V \Sigma^H U^H$.

$$\|A\|_2^2 = \|A^T\|_2^2 = \|A^H\|_2^2 = \sigma_1^2$$

$$A^H A = V \Sigma^H U^H U \Sigma V^H = V \Sigma^H \Sigma V^H = V \Sigma^2 V^H$$

$$\|A^H A\|_2 = \sigma_1^2 = \|A\|_2^2$$

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$$\|UAV\|_2^2 = \|(UAV)^H UAV\|_2 = \|V^H A^H AV\|_2 = \|A^H AV V^H\|_2 = \|A^H A\|_2 = \|A\|_2^2$$

Exercise 32

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$$\|UAV\|_F = \sqrt{\text{tr}(V^H A^H U^H U A V)} = \sqrt{\text{tr}(V^H A^H A V)} = \sqrt{\text{tr}(A^H A V V^H)} = \sqrt{\text{tr}(A^H A)} = \|A\|_F$$

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$$\|A\|_F = \|U \Sigma V^H\|_F = \|\Sigma\|_F = \sqrt{\text{tr}(\Sigma^H \Sigma)} = \left(\sum_{i=1}^r \sigma_i^2 \right)^{\frac{1}{2}} = (\sigma_1^2 + \sigma_2^2 + \dots + \sigma_r^2)^{\frac{1}{2}}$$

Exercise 33

Because $\|A\|_2 = \sigma_1$ with σ_1 being the largest singular value of A,

$$\sup_{\|x\|_2=1, \|y\|_2=1} |y^H Ax| \leq \sup_{\|x\|_2=1, \|y\|_2=1} \|y\|_2 \|\Sigma x\|_2$$

$$= \sup_{\|x\|_2=1} \|\Sigma x\|_2 \leq \sigma_1$$

$$\sup_{\|x\|_2=1, \|y\|_2=1} |y^H Ax| \geq |y^H Ax| = \sigma_1$$

Exercise 36

$$\text{Let } A = \begin{bmatrix} 0 & 2 \\ 1 & 0 \end{bmatrix}$$

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

where $\det(A) = -2$ and the singular values are 1 and 2 with eigenvalues $\pm\sqrt{2}$.

Exercise 38

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$$AA^\dagger A = U_1 V_1 \Sigma_1 V_1^H V_1 \Sigma_1^{-1} U_1^H U_1 \Sigma_1 V_1^H = U_1 \Sigma_1 \Sigma_1^{-1} \Sigma_1 V_1^H = U_1 \Sigma_1 V_1^H = A$$

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$$A^\dagger A A^\dagger = V_1 \Sigma_1^{-1} U_1^H U_1 \Sigma_1 V_1^H V_1 \Sigma_1^{-1} U_1^H = V_1 \Sigma_1^{-1} \Sigma_1 \Sigma_1^{-1} U_1^H = V_1 \Sigma_1^{-1} U_1^H = A^\dagger$$

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

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

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$$(AA^\dagger A)A^\dagger = A^\dagger A \rightarrow (AA^\dagger)(AA^\dagger) = A^\dagger A$$

Let $U_1 = [u_1, \dots, u_n]$ where U_1 is an orthonormal basis for $\mathbb{R}(A)$.

$$AA^\dagger = U_1 U_1^H x = U_1 [u_1^H x, \dots, u_n^H x] = \sum_{i=1}^n u_i^H x u_i = \sum_{i=1}^n \langle u_i, x \rangle u_i = \text{proj}_{\mathbb{R}(A)} x$$

• Let $V_1 = [v_1, \dots, v_n]$ where V_1 is an orthonormal basis for $\mathbb{R}(A^H)$.

$$A^\dagger A x = V_1 V_1^H x = V_1 [v_1^H x, \dots, v_n^H x] = \sum_{i=1}^n v_i^H x v_i = \sum_{i=1}^n \langle v_i, x \rangle v_i = \text{proj}_{\mathbb{R}(A^H)} x$$