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### Exercise 3

$D : V \rightarrow V$  can be represented in matrix form as

$$\begin{bmatrix} 0 & 2 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix},$$

which is upper triangular with all diagonal elements zero. Thus, all eigenvalues are 0, with algebraic multiplicity 3. However, if  $x$  is an eigenvector of  $D$  corresponding to  $\lambda = 0$ , then  $Dx = 0$ . Given the form of  $D$  we conclude that  $x_2 = x_3 = 0$  and so the eigenspace of  $\lambda = 0$  is  $\text{span}\{1\}$ . Therefore,  $\lambda = 0$  has geometric multiplicity 1.

### Exercise 4

(i) Let

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

Since  $A$  is hermitian, we know that  $a = \bar{a}$ ,  $d = \bar{d}$  and  $b = \bar{c}$ . Then

$$\begin{aligned} \det A &= ad - cb = ad - c\bar{c} = ad - \|c\|^2 = \\ &\bar{a}\bar{d} - \|c\|^2 = \overline{ad - \|c\|^2} = \overline{\det A} \end{aligned}$$

and

$$\text{Tr}(A) = a + d = \bar{a} + \bar{d} = \overline{a + d} = \overline{\text{Tr}(A)}.$$

Thus both the determinant and the trace of  $A$  are real. Notice that using Exercise 3 we have

$$\lambda_{1,2} = \frac{(a + d) \pm \sqrt{(a + d)^2 - 4(ad - \|c\|^2)}}{2}$$

and the discriminant becomes  $(a - d)^2 + 4\|c\|^2$ , which is real and nonnegative, therefore  $A$  has only real eigenvalues.

(ii) If  $A$  is skew-symmetric, then  $a = -\bar{a}$  and  $d = -\bar{d}$ , so they are imaginary, and  $b = -\bar{c}$ . Thus  $bc = -\|c\|^2$ , and

$$\lambda_{1,2} = \frac{(a + d) \pm \sqrt{(a - d)^2 - 4\|c\|^2}}{2}.$$

Let  $a = \alpha i$  and  $d = \beta i$ . Then  $(a - d)^2 = i^2(\alpha - \beta)^2$  is clearly negative. Therefore the discriminant is negative and the eigenvalues are all imaginary.

### Exercise 6

Let  $R \in \mathbb{M}_n(\mathbb{F})$  be an upper-triangular matrix with diagonal entries  $r_{ii}$ . Then  $\lambda I - R$  is also upper-triangular and so  $\det R = \prod_{i=1}^n (\lambda_i - r_{ii})$ . Since  $r_{ii}$  are the roots of the characteristic polynomials,  $\lambda_i = r_{ii}$ .

### Exercise 8

(i) We know that  $V$  is the span of  $S$ . If the vectors in  $S$  are linearly independent, then  $S$  is a basis for  $V$ . From Problem Set 2 we noticed that the vectors in  $S$  are orthonormal under the inner product  $\langle a, b \rangle := \frac{1}{\pi} \int_{-\pi}^{\pi} a(x)b(x)dx$ . Therefore they are independent and are thus a basis of  $V$ .

(ii) Since  $d \sin(x)/dx = \cos(x)$ ,  $d \cos(x)/dx = -\sin(x)$ ,  $d \sin(2x)/dx = 2 \cos(2x)$  and  $d \cos(2x)/dx = -2 \sin(2x)$ , we have that

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

(iii) Two complementary  $D$ -invariant subspaces are  $\text{span}\{\sin(x), \cos(x)\}$  and  $\text{span}\{\sin(2x), \cos(2x)\}$ .

### Exercise 13

Since  $\det(\lambda I - A) = \lambda^2 - 1.4\lambda + 0.4$ , the eigenvalues are 1 and 0.4, with corresponding eigenvectors  $(2, 1)$ , and  $(1, -1)$ . Therefore

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

### Exercise 15

$A$  is semisimple, thus there exist matrices  $\Lambda$  and  $P$  such that  $A = P\Lambda P^{-1}$ . Then

$$f(A) = a_0 P P^{-1} + a_1 P \Lambda P^{-1} + \dots + a_n P \Lambda^n P^{-1} = P f(\Lambda) P^{-1},$$

where  $f(\Lambda)$  is diagonal with elements  $(f(\lambda_i))_{i=1}^n$ . Since  $f(A)$  is similar to  $f(\Lambda)$ , they have the same eigenvalues.

### Exercise 16

(i) By Proposition 4.3.10,

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

Consider the matrix

$$B = \frac{1}{3} \begin{bmatrix} 2 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 1 & -1 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 2 & 2 \\ 1 & 1 \end{bmatrix}.$$

Their difference is

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

and its 1-norm is  $4/3 \times 0.4^k$ , which converges to 0.

(ii) The  $\infty$ -norm of  $A^k - B$  is  $0.4^k$ , whereas the Frobenius norm is

$$\sqrt{\text{tr} \left( (A^k - B)^T (A^k - B) \right)} = \sqrt{10 \times 0.4^{2k}}$$

and both of them converge to zero.

(iii) By theorem 4.3.12, the eigenvalues of  $3I + 5A + A^3$  are given by  $f(\lambda_i) = 3 + 5\lambda_i + \lambda_i^3$ , where  $\lambda_i$ 's are the eigenvalues of  $A$ . So the eigenvalues are  $f(1) = 9$  and  $f(0.4) = 5.064$ .

## Exercise 18

Let  $\lambda$  be an eigenvalue of  $A$ , then it is also an eigenvalue of  $A^T$ . Then there exists a nonzero vector  $x$  such that  $A^T x = \lambda x$ . Transposing both the RHS and the LHS we get the desired result.

## Exercise 20

Since  $A$  is orthonormally similar to  $B$ , we know that there exists an orthonormal  $P$  such that  $B = PAP^H$ . Since  $A$  is hermitian,

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

## Exercise 24

First notice that the denominator is real nonnegative. Also, notice that if  $A$  is hermitian, then

$$x^H A x = x^H A^H x = (x^H A x)^H = \overline{x^H A x}.$$

Thus  $\langle x, Ax \rangle = \overline{\langle x, Ax \rangle}$ , and so it is real. On the other hand, if  $A$  is skew-hermitian, then

$$x^H A x = -x^H A^H x = -(x^H A x)^H = -\overline{x^H A x}.$$

Thus  $\langle x, Ax \rangle = -\overline{\langle x, Ax \rangle}$ , and is therefore imaginary.

### Exercise 25

(i) Take an arbitrary vector  $x$  in  $\mathbb{C}^n$ , then there exist coefficients  $a_i$ 's such that  $x = \sum_i a_i x_i$ , since  $\{x_i\}_i$  is a basis. Then

$$\left( \sum_j x_j x_j^H \right) \sum_i a_i x_i = \sum_j x_j x_j^H a_j x_j + \sum_j \sum_{i \neq j} x_j x_j^H a_i x_i = \sum_j a_j x_j$$

because  $x_j^H x_j = 1$  for any  $j$  and  $x_j^H x_i = 0$  for any  $i \neq j$ . Thus  $(\sum_j x_j x_j^H)x = x$  for any  $x$  in  $\mathbb{C}^n$ . It must then be that  $\sum_j x_j x_j^H = I$ .

(ii) Notice that

$$Ax = \sum_j A a_j x_j = \sum_j a_j \lambda_j x_j$$

and

$$\left( \sum_j \lambda_j x_j x_j^H \right) \left( \sum_i a_i x_i \right) = \sum_j \lambda_j x_j x_j^H a_j x_j + \sum_j \sum_{i \neq j} \lambda_j x_j x_j^H a_i x_i = \sum_j a_j \lambda_j x_j,$$

shows that  $A = \sum_j \lambda_j x_j x_j^H$ .

### Exercise 27

Since  $A$  is positive definite, it is hermitian, hence its diagonal elements are reals. Also, let  $e_i$  denote  $i^{\text{th}}$  standard basis vector of  $\mathbb{F}^n$ . Then we have that, for any  $i$ :

$$a_{ii} = e_i^H A e_i = \langle e_i, A e_i \rangle > 0.$$

### Exercise 28

By proposition 4.5.7, There exist matrices  $S_A$  and  $S_B$  such that  $A = S_A^H A_A$  and  $B = S_B^H S_B$ . Then

$$\text{Tr}(AB) = \text{Tr}(S_A^H S_A S_B^H S_B) = \text{Tr}(S_B S_A^H S_A S_B^H) = \text{Tr}((S_A S_B^H)^H S_A S_B^H) = \|S_A S_B^H\|_F^2 \geq 0.$$

By Proposition 4.5.6  $A = Q_A D_A Q_A^H$  and  $B = Q_B D_B Q_B^H$ , where  $Q_A$  and  $Q_B$  are orthonormal and  $D_A$ ,  $D_B$  are diagonal matrices containing the eigenvalues of  $A$  and  $B$  respectively. Since the trace is invariant under orthonormal transformations we have

$$\text{Tr}(AB) = \text{Tr}(D_A D_B) = \sum_i \lambda_i^A \lambda_i^B \leq \left( \sum_i \lambda_i^A \right) \left( \sum_i \lambda_i^B \right) = \text{Tr}(A) \text{Tr}(B),$$

which concludes the proof.

### Exercise 31

(i) Let  $B = A^H A$ , then  $B$  is hermitian. Then by Corollary 4.4.8  $B$  has an orthonormal eigenbasis, say  $\{b_i\}_{i=1}^n$ , which spans  $\mathbb{F}^n$ , and real eigenvalues  $\{\sigma_i\}_{i=1}^n$ . Take an arbitrary  $x \in \mathbb{F}^n$  and real  $(a_i)_{i=1}^n$  such that  $x = \sum_i a_i b_i$ . We have

$$\|x\|_2 = \left\langle \sum_i a_i b_i, \sum_i a_i b_i \right\rangle^{1/2} = \sqrt{\sum_i a_i^2}$$

since the  $b_i$ 's are orthonormal. Also

$$Bx = B \left( \sum_i a_i b_i \right) = \sum_i a_i \sigma_i b_i.$$

Let  $\sigma_1$  be the largest eigenvalue of  $B$ . Then

$$\begin{aligned} \|Ax\| &= \langle Ax, Ax \rangle = \langle x, A^H A x \rangle = \langle x, Bx \rangle = \\ &= \left\langle \sum_i a_i b_i, \sum_i \sigma_i a_i b_i \right\rangle = \sqrt{\sum_i a_i \sigma_i a_i} \leq \|x\| \max_i \sqrt{|\sigma_i|}. \end{aligned}$$

So  $\|A\| = \sup\{\|Ax\| : \|x\| = 1\} \leq \max_i \sqrt{|\sigma_i|}$ .

If we pick  $x = b_1$ , then

$$\|A\| \geq \langle b_1, Bb_1 \rangle = \langle b_1, \sigma_1 b_1 \rangle = \sqrt{|\sigma_1|},$$

which proves the result.

(ii) Let  $A = U\Sigma V^H$  be the singular value decomposition of  $A$ . Then,  $A^{-1} = (V^H)^{-1}\Sigma^{-1}U^{-1}$ . This is also a singular value decomposition, since  $(V^H)^{-1} = V$  and  $U^{-1} = U^H$ , because  $U$  and  $V$  are orthonormal matrices, and  $\Sigma^{-1}$  is diagonal. The largest singular value of  $\Sigma^{-1}$  is  $\frac{1}{\sigma_n}$ , where  $\sigma_n$  is the smallest one of  $A$ . Therefore, by (i) we have that  $\|A^{-1}\|_2 = \sigma_n^{-1}$ .

(iii) Let  $A = U\Sigma V^H$ . Then,

$$A^H = V\Sigma^H U^H A^T = \bar{V}\Sigma U^T A^H A = (V\Sigma^H U^H)(U\Sigma V^H) = V(\Sigma^H \Sigma)V^H$$

All of these are singular value decompositions. Now, consider the singular values of each of these decompositions (where  $\Sigma^H = \Sigma$  because singular values are reals). Thus,  $A^H$ ,  $A^T$  and  $A$  all have the same singular values. So by (i) we have that  $\|A^H\|_2^2 = \|A^T\|_2^2 = \|A\|_2^2 = \sigma_1^2$ . Also, notice that the diagonal elements of  $(\Sigma^H \Sigma)$  are the singular values squared. We conclude that  $\|A^H A\|_2 = \sigma_1^2$ .

### Exercise 36

$-I$  has both eigenvalues  $-1$  and both singular values  $1$ .

### Exercise 38

I will prove (1) and (5), the other proofs follow a similar logic.

(1)

Let  $A = U_1 \Sigma_1 V_1^H$  be the compact SVD of  $A$ . The Moore-Penrose pseudoinverse of  $A$  is  $A^\dagger = V_1 \Sigma_1^{-1} U_1^H$ . Notice that,

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

Therefore,  $AA^\dagger A = A$ .

(5)

First, notice that by (1),  $AA^\dagger AA^\dagger = AA^\dagger$ , so that  $AA^\dagger$  is idempotent. Then, notice that  $AA^\dagger = U_1 U_1^H$  where  $U_1$  is an orthonormal basis for the range of  $A$ . Let  $u_i$  denote the  $m$ -dimensional  $i^{th}$  column of  $U_1$ . Then

$$U_1 U_1^H x = U_1 (u_1^H x, \dots, u_r^H x)^T = \sum_i u_i u_i^H x = \sum_i u_i^H x u_i = \sum_i \langle u_i, x \rangle u_i,$$

which is the projection of  $x$  on the range of  $A$ .