

## Math, Problem Set #3, Spectral Theory

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### Solutions

**4.2** The matrix  $D = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix}$ . Solving  $\det(D - \lambda I) = 0$ , we get  $\lambda^3 = 0$  and see that the only eigenvalue is 0. Solving  $(D - \lambda I)x = 0$ , we see that the eigenspace consists of all vectors of the form  $\begin{bmatrix} k \\ 0 \\ 0 \end{bmatrix}$ , where  $k \in \mathbb{R}$ . The eigenvalue 0 has algebraic multiplicity 3, and geometric multiplicity is 1 because the eigenspace is spanned by 1 nonzero eigenvector.

**4.4i** Let  $x$  be an arbitrary nonzero eigenvector, and  $\lambda$  be its eigenvalue. First note that  $x^H Ax = x^H \lambda x = \lambda x^H x$ . Then note that  $x^H Ax = x^H A^H x = (Ax)^H x = (\lambda x)^H x = x^H \lambda^H x = \lambda^H x^H x$ . Since  $x \neq 0$ , it follows that  $\lambda = \lambda^H$ . Because the hermitian conjugate of a scalar is simply its conjugate and the scalar equals its conjugate, it follows that the eigenvalue  $\lambda$  is a real number.

**4.4ii** Let  $x$  be an arbitrary nonzero eigenvector, and  $\lambda$  be its eigenvalue. First note that  $\langle Ax, x \rangle = \langle \lambda x, x \rangle = \lambda \langle x, x \rangle$ . Then note that  $\langle Ax, x \rangle = \langle x, A^H x \rangle = \langle x, -Ax \rangle = \langle x, -\lambda x \rangle = -\lambda \langle x, x \rangle$ . Since  $x$  is nonzero, we know that  $\lambda = -\lambda$  for any arbitrary eigenvalue  $\lambda$ . This can only be true if  $\lambda$  is purely imaginary with no real component.

**4.6** We want to prove that the diagonal entries of any triangular matrix are its eigenvalues. Without loss of generality, suppose that the  $n \times n$  matrix  $A$  is upper triangular, with entries  $a_{ij}$ . To find the eigenvalues, we need to set the determinant of the follow-

ing matrix to 0 and solve for the eigenvalues  $\lambda$ :

$$\begin{bmatrix} a_{1,1} - \lambda & \cdots & \cdots & \cdots & a_{1,n} \\ & a_{2,2} - \lambda & \cdots & \cdots & a_{2,n} \\ & & \ddots & \cdots & \vdots \\ & & & \ddots & \vdots \\ & & & & \ddots \\ & & & & & a_{n,n} - \lambda \end{bmatrix}.$$

This reduces to the characteristic polynomial equation  $(a_{1,1} - \lambda)(a_{2,2} - \lambda) \cdots (a_{n-2,n-2} - \lambda) \det \begin{bmatrix} d_{n-1,n-1} - \lambda & d_{n-1,n} \\ 0 & d_{n,n} \end{bmatrix} = (a_{1,1} - \lambda)(a_{2,2} - \lambda) \cdots (a_{n-2,n-2} - \lambda)(a_{n-1,n-1} - \lambda)(a_{n,n} - \lambda) = 0$  because the 0's in the lower diagonal nullify the off-diagonal terms at each step. It is then easy to see that the roots to the equation above (eigenvalues) are simply  $a_{1,1}, a_{2,2}, \dots, a_{n,n}$  which are the diagonal terms of the matrix  $A$ .

**4.8i** To show that  $S$  is a basis for  $V$ , we have to show that the functions in  $S$  are linearly independent. That is,  $a_1 \sin x + a_2 \cos x + a_3 \sin(2x) + a_4 \cos(2x) = 0$  only if  $a_1 = a_2 = a_3 = a_4 = 0$ . To solve for the coefficients, we let  $x = 0, \frac{\pi}{2}, \frac{\pi}{3}, \pi$  to get 4 equations to solve for the 4 unknowns. This results in the 4 equations:

$$a_1 - a_4 = 0$$

$$a_2 + a_4 = 0$$

$$a_4 - a_2 = 0$$

$$\frac{\sqrt{3}}{2}a_1 - 0.5a_2 + \frac{\sqrt{3}}{2}a_3 + 0.5a_4 = 0. \text{ Solving these, we obtain } a_2 = a_4 = a_1 = a_3 = 0.$$

Therefore, the elements of the set  $S$  are linearly independent. Since  $V$  is also the span of the set  $S$ , it follows that  $S$  forms a basis for  $V$ .

**4.8ii** Noting that  $D(\sin x) = \cos x = [0 \ 1 \ 0 \ 0]$ ,

$$D(\cos x) = -\sin x = [-1 \ 0 \ 0 \ 0],$$

$$D(\sin 2x) = 2\cos 2x = [0 \ 0 \ 0 \ 2],$$

$$D(\cos 2x) = -2\sin 2x = [0 \ 0 \ -2 \ 0]$$

, the matrix representation of  $D$  with respect to the basis  $[\sin x \ \cos x \ \sin 2x \ \cos 2x]$  is

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

**4.8iii** Let the subspaces be  $U = \{\sin x, \cos x\}$  and  $W = \{\sin 2x, \cos 2x\}$ . Then,  $U$  and  $W$  are complementary subspaces because for any basis  $\{u_1, u_2\}$  of  $U$  and  $\{w_1, w_2\}$  of  $W$ ,  $\{u_1, u_2, w_1, w_2\}$  forms a basis for the space spanned by  $V = \{\sin x, \cos x, \sin 2x, \cos 2x\}$ . Moreover,  $U$  and  $W$  are  $D$ -invariant because  $D(U) = \{\cos x, -\sin x\} \subset U$  and  $D(W) = \{2\cos 2x, -2\sin 2x\} \subset W$ .

**4.13** The matrix  $A$  can be diagonalized as  $A = \begin{bmatrix} 2 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 0.4 \end{bmatrix} \begin{bmatrix} \frac{1}{3} & \frac{1}{3} \\ -\frac{1}{3} & \frac{2}{3} \end{bmatrix}$ , where

$P = \begin{bmatrix} 2 & -1 \\ 1 & 1 \end{bmatrix}$  whose columns are the eigenvectors of  $A$ , and the matrix in the middle is a diagonal matrix with the eigenvalues of  $A$  as its diagonal entries, and the matrix on the right is  $P^{-1}$ .

**4.15** Suppose  $(\lambda_i)_{i=1}^n$  are eigenvalues of a semisimple matrix  $A$ . Then  $A$  is diagonalizable and can be rewritten as  $A = PDP^{-1}$ . Then,  $f(A) = a_0I + a_1A + \dots + a_nA^n = a_0I + a_1PDP^{-1} + \dots + a_nPD^nP^{-1} = P(a_0I + a_1D + a_2D^2 + \dots + a_nD^n)P^{-1} = P \begin{bmatrix} a_0 + a_1\lambda_1 + \dots + a_n\lambda_1^n & & \\ & \ddots & \\ & & a_0 + a_1\lambda_n + \dots + a_n\lambda_n^n \end{bmatrix} P^{-1}$  because the diagonal entries of  $D$  are just the eigenvalues  $\lambda_i, i \in \{1, 2, \dots, n\}$  of  $A$ . As such, we have diagonalized  $f(A)$ , and so the diagonal entries of the resulting matrix in the middle are the eigenvalues of  $f(A)$ , where  $f(\lambda_i) = a_0 + a_1\lambda_1 + \dots + a_n\lambda_n$ , as desired.

**4.16 i and ii** By diagonalization, we can rewrite  $A^k = PD^kP^{-1} = \begin{bmatrix} 2 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 0.4 \end{bmatrix}^k \begin{bmatrix} \frac{1}{3} & \frac{1}{3} \\ -\frac{1}{3} & \frac{2}{3} \end{bmatrix} =$

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

Then,  $B = \lim_{k \rightarrow \infty} A^k = \begin{bmatrix} \frac{2}{3} & \frac{2}{3} \\ \frac{1}{3} & \frac{1}{3} \end{bmatrix}$ . Then,  $A^k - \bar{A} = \begin{bmatrix} \frac{1}{3}0.4^k & -\frac{2}{3}0.4^k \\ -\frac{1}{3}0.4^k & \frac{2}{3}0.4^k \end{bmatrix}$ . The norms are as follows:

$$\|A\|_1 = \frac{2}{3}0.4^k, \|A\|_2 = 0.4^k, \|A\|_F = \sqrt{\text{tr}(A^H A)} = \sqrt{\text{tr} \begin{bmatrix} \frac{1}{9}0.4^{2k} + \frac{1}{9}0.4^{2k} & 0 \\ 0 & \frac{4}{9}0.4^{2k} + \frac{4}{9}0.4^{2k} \end{bmatrix}} = \sqrt{\frac{10}{9}0.4^{2k}},$$

all of which evidently converge to 0. Therefore, the choice of norm does not matter.

**4.16 iii** Using Theorem 4.3.12, we know  $f(x) = 3+5x+x^3$ , so  $f(0.4) = 3+2+(0.4)^3 = 5 + (0.4)^3$ .

**4.18** Let  $x$  be an eigenvector of  $A^T$ . We first claim that the eigenvalues of  $A$  and  $A^T$  are equal. To see why, note that the characteristic equation for  $A$  and  $A^T$  are  $\det(A - \lambda I) = 0$  and  $\det(A^T - \lambda I) = 0$ , but  $(A^T - \lambda I) = (A - \lambda I)^T$ . Therefore, if we let  $Q = (A - \lambda I)$ , the two equations reduce to  $\det(Q) = 0$  and  $\det(Q)^T = 0$ . By Theorem 2.8.21, we know that for all matrices  $Q$ ,  $\det(Q) = \det(Q^T)$ . Therefore, the characteristic equations are equal and have the same roots. Therefore, both  $A$  and  $A^T$  have the same eigenvalues. Let  $\lambda$  be an eigenvalue of  $A$ . Then, we know  $A^T x = \lambda x$  by our earlier claim. Taking the transpose of both sides, we obtain  $x^T A = \lambda x^T$ , as desired.

**4.20** Since  $A$  is Hermitian,  $A = A^H$ . Since  $A$  is orthonormally similar to  $B$ , there exists  $U$  such that  $B = U^H A U$ .  $B^H = (U^H A U)^H = U^H A^H U = U^H A U = B$ .

**4.24i** We aim to show that  $\rho = \rho^H$  because this is true if and only if  $\rho$  is a real number. We know  $A = A^H$ . Then,  $\rho = \frac{\langle x, Ax \rangle}{\|x\|^2} = \frac{\langle x, A^H x \rangle}{\|x\|^2} = \left( \frac{x^H A^H x}{x^H x} \right)^H = \left( \frac{\langle x, Ax \rangle}{\|x\|^2} \right)^H = \rho^H$ .

**4.24ii** We aim to show that  $-\rho = \rho^H$  because this is true if and only if  $\rho$  is an imag-

inary number. We know  $A = A^H$ . Then,  $-\rho = -\frac{\langle x, Ax \rangle}{\|x\|^2} = \frac{\langle x, -A^H x \rangle}{\|x\|^2} = -\left(\frac{x^H A^H x}{x^H x}\right)^H = -\left(\frac{\langle x, Ax \rangle}{\|x\|^2}\right)^H = -\rho^H$ .

**4.25i** Suppose  $A$  is a normal matrix with eigenvalues  $(\lambda_1, \dots, \lambda_n)$  and orthonormal eigenvectors  $(x_1, \dots, x_n)$  which forms an eigenbasis for the space. We know that  $I$  is an identity matrix if and only if  $Ix = x$  for any vector  $x \in \mathbb{F}$ . Since we have an eigenbasis,  $x$  can be rewritten as  $x = \alpha_1 x_1 + \dots + \alpha_n x_n$ . Then,  $(x_1 x_1^H + \dots + x_n x_n^H)x = (x_1 x_1^H + \dots + x_n x_n^H)(\alpha_1 x_1 + \dots + \alpha_n x_n) = (\alpha_1 x_1 x_1^H x_1 + \dots + \alpha_n x_n x_n^H x_n) = \alpha_1 x_1 + \dots + \alpha_n x_n$  because the vectors are orthonormal so  $x_j^H x_i = 0 \forall j \neq i$  and  $x_j^H x_i = 1 \forall j = i$ .

**4.25ii** Because  $(x_1 x_1^H + \dots + x_n x_n^H) = I$ , we can write  $A = A(x_1 x_1^H + \dots + x_n x_n^H) = (Ax_1 x_1^H + \dots + Ax_n x_n^H) = (\lambda_1 x_1 x_1^H + \dots + \lambda_n x_n x_n^H)$ , as desired.

**4.27** Suppose  $A$  is positive definite and  $\langle x, Ax \rangle \geq 0 \forall x \neq 0$ . Let  $e_j$  be the  $j$ th standard basis vector. Since  $x^T Ax \geq 0$ , it follows that  $e^T A e \geq 0$ . Then note that  $e^T A e = 0 + \dots + 0 + 1 \cdot a_{jj} + 0 \dots + 0 = a_{jj} \geq 0$ , where  $a_{jj}$  is the  $j$ th diagonal entry of the matrix  $A$ . Positive definiteness also implies  $A^H = A$ , such that  $a_{jj} = (e_j)^T A e_j = \langle e_j, A e_j \rangle = \langle A^H e_j, e_j \rangle = \langle A e_j, e_j \rangle = \overline{\langle e_j, A e_j \rangle} = \overline{(e_j)^T A e_j} = \overline{a_{jj}}$  which is true if and only if its diagonal entries are real.

**4.28** Since  $A$  is positive semidefinite,  $x^H A x \geq 0$ . From 4.27, we know the diagonal elements of  $A$  and  $B$  are non-negative. Then it follows that  $tr(AB) = \sum_{i=1}^n a_{ii} b_{ii} \geq 0$  as desired for the first inequality. For the second inequality, consider  $tr(A)tr(B) = \sum_{i=1}^n a_{ii} \sum_{j=1}^n b_{jj} = \sum_{i=1}^n \sum_{j=1}^n a_{ii} b_{jj} = \sum_{i=1}^n \sum_{j \neq i}^n a_{ii} b_{jj} + \sum_{i=1}^n a_{ii} b_{ii} = \sum_{i=1}^n \sum_{j \neq i}^n a_{ii} b_{jj} + tr(AB) \geq tr(AB)$ .

**4.31i**  $\|A\|_2 = \sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} = \sup_{x \neq 0} \frac{\|U \Sigma V^H x\|_2}{\|x\|_2} = \sup_{x \neq 0} \frac{\|\Sigma V^H x\|_2}{\|V V^H x\|_2}$  because  $U$  and  $V$  are orthonormal, such that  $\|U\| = 1$  and  $V V^H = I$ . Letting  $y = V^H x$ , we obtain  $\sup_{y \neq 0} \frac{\|\Sigma y\|_2}{\|y\|_2} = \sup_{y \neq 0} \left( \frac{\sum_{i=1}^r \sigma_i^2 |y_i|^2}{\sum_{i=1}^r |y_i|^2} \right)^{0.5}$ , where  $\sigma_i$  are the singular values of  $A$ , decreasing in  $i$ , such that  $\sigma_i$  is the largest singular value. Therefore, taking the supremum with

respect to  $y$  gives us  $y = (1 \ 0 \ \dots \ 0)^T$ , such that  $\|A\|_2 = \sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} = \sigma_1$ .

**4.31ii** Suppose  $A$  is invertible. Then  $A^{-1}$  exists.  $\|A^{-1}\|_2 = \sup_{x \neq 0} \frac{\|A^{-1}x\|_2}{\|x\|_2} = \sup_{x \neq 0} \frac{\|V\Sigma^{-1}U^Hx\|}{\|x\|_2} = \sup_{x \neq 0} \frac{\|V\Sigma^{-1}U^Hx\|}{\|UU^Hx\|} = \sup_{x \neq 0} \frac{\|\Sigma^{-1}U^Hx\|}{\|UU^Hx\|} = \sup_{x \neq 0} \frac{\|V\Sigma^{-1}y\|}{\|Uy\|} = \sup_{y \neq 0} \left( \frac{\sum_{i=1}^r \sigma_i^{-2} |y_i|^2}{\sum_{i=1}^r |y_i|^2} \right)^{0.5}$ , where  $\sigma_i$  are the singular values of  $A$ , decreasing in  $i$ , such that  $\sigma_i$  is the largest singular value. Therefore, taking the supremum with respect to  $y$  gives us  $y = (1 \ 0 \ \dots \ 0)^T$ , such that  $\|A\|_2 = \sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} = \sigma_1^{-1}$ .

**4.32i** Suppose  $U$  and  $V$  are orthonormal. Then,  $\|UAV\|_F = \sqrt{\text{tr}[(UAV)^H UAV]} = \sqrt{\text{tr}[V^H A^H U^H U A V]} = \sqrt{\text{tr}[V^H A^H A V]} = \sqrt{\text{tr}[V V^H A^H A]} = \sqrt{\text{tr}[A^H A]} = \|A\|_F$ .

**4.32ii**  $\|A\|_F = \|UAV\|_F = \|UU\Sigma V^H V\|_F = \|UU\Sigma\|_F = \sqrt{\text{tr}[(UU\Sigma)^H UU\Sigma]} = \sqrt{\text{tr}[\Sigma^H U^H U \Sigma]} = \sqrt{\text{tr}[\Sigma^H \Sigma]} = \text{tr} \left( \begin{bmatrix} \sigma_1^2 & & \\ & \ddots & \\ & & \sigma_r^2 \end{bmatrix} \right) = \sqrt{\sigma_1^2 + \dots + \sigma_r^2}$ .

**4.33**  $LHS = \|A\|_2 = \sigma_1$  by 31i.

$RHS = \sup_{\|x\|_2=1, \|y\|_2=1} |y^H A x|$   
 $= \sup_{\|x\|_2=1, \|y\|_2=1} |y^H U \Sigma V^H x|$   
 $= \sup_{\|a\|_2=1, \|b\|_2=1} |a^H U^H U \Sigma V^H V b|$  by rewriting  $x = Ua$  and  $y = vb$ . Note that  $\|x\|_2 = \|Ua\|_2 = \|a\|_2$  and  $\|y\|_2 = \|Vb\|_2 = \|b\|_2$  because  $U$  and  $V$  are orthonormal.  
 $= \sup_{\|a\|_2=1, \|b\|_2=1} |a^H \Sigma b|$   
 $= \sup_{\|a\|_2=1, \|b\|_2=1} \left| \sum_{i=1}^r a_i \sigma_i b_i \right|$ .

To get the supremum with respect to  $a$  and  $b$  such that their 2-norms each equal one, we let  $a = b = (1, 0, 0, \dots, 0)^T$  because the maximum occurs when we put all the

weight on the largest eigenvalue,  $\sigma_1$ . Thus,  $RHS = (1, 0, \dots, 0) \begin{bmatrix} \sigma_1^2 & & \\ & \ddots & \\ & & \sigma_r^2 \end{bmatrix} (1, 0, \dots, 0)^T = |\sigma_1| = \sigma_1 = \|A\|_2 = LHS$ .

**4.36**  $A = \begin{bmatrix} i & 0 \\ 0 & i \end{bmatrix}$ . Then,  $A^H A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ .

Then, the eigenvalues of A are i, but the singular value of A is 1, and the determinant is -1, which is nonzero.

**4.38**  $A^\dagger = V_1 \Sigma_1^{-1} U_1^H$  of the matrix  $A = U_1 \Sigma_1 V_1^H$  where  $U_1$  and  $V_1$  are orthonormal:

$$\begin{aligned} \text{i) } AA^\dagger A &= U_1 \Sigma_1 V_1^H V_1 \Sigma_1^{-1} U_1^H U_1 \Sigma_1 V_1^H = U_1 \Sigma_1 \Sigma_1^{-1} \Sigma_1 V_1^H = U_1 \Sigma_1 V_1^H = A \\ \text{ii) } A^\dagger AA^\dagger &= V_1 \Sigma_1^{-1} U_1^H U_1 \Sigma_1 V_1^H V_1 \Sigma_1^{-1} U_1^H = V_1 \Sigma_1^{-1} \Sigma_1 \Sigma_1^{-1} U_1^H = V_1 \Sigma_1^{-1} U_1^H = A^\dagger \\ \text{iii) } (AA^\dagger)^H &= (U_1 \Sigma_1 V_1^H V_1 \Sigma_1^{-1} U_1^H)^H = (U_1 \Sigma_1 \Sigma_1^{-1} U_1^H)^H = U_1 (\Sigma_1^{-1})^H (\Sigma_1)^H U_1^H = \\ &U_1 (\Sigma_1^H)^{-1} (\Sigma_1)^H U_1^H = U_1 \Sigma_1 (\Sigma_1)^{-1} U_1^H = U_1 \Sigma_1 V_1^H V_1 \Sigma_1^{-1} U_1^H = AA^\dagger. \\ \text{iv) } (A^\dagger A)^H &= (V_1 \Sigma_1^{-1} U_1^H U_1 \Sigma_1 V_1^H)^H = (V_1 \Sigma_1^{-1} \Sigma_1 V_1^H)^H = V_1 (\Sigma_1^{-1} \Sigma_1)^H V_1^H = \\ &V_1 \Sigma_1^H (\Sigma_1^H)^{-1} V_1^H = V_1 \Sigma_1^{-1} \Sigma_1 V_1^H = V_1 \Sigma_1^{-1} U_1^H U_1 \Sigma_1 V_1^H = A^\dagger A. \end{aligned}$$