

### Solution to Final Examination

1. (a) False. Let  $\mathbf{A} = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 2 \end{bmatrix}$ . Consider

$$\det(\mathbf{A} - \lambda \mathbf{I}) = (1 - \lambda)^2(2 - \lambda) = 0.$$

We can then obtain that the eigenvalues of  $\mathbf{A}$  are 1, 1, and 2. For  $\lambda = 1$ , its AM is 2. Since

$$\mathbf{A} - 1 \cdot \mathbf{I} = \begin{bmatrix} 0 & 1 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}$$

the GM of eigenvalue 1 is 1, which is smaller than its AM. Therefore,  $\mathbf{A}$  is not diagonalizable.

- (b) Let

$$\mathbf{B} = \frac{1}{2}(\mathbf{A} + \mathbf{A}^T) = \begin{bmatrix} -4 & -2 & 2 \\ -2 & -10 & -2 \\ 2 & -2 & -5 \end{bmatrix}$$

which is a symmetric matrix. Then we can obtain  $\mathbf{x}^T \mathbf{A} \mathbf{x} = \mathbf{x}^T \mathbf{B} \mathbf{x}$ . Hence  $\mathbf{x}^T \mathbf{A} \mathbf{x} = \mathbf{x}^T \mathbf{B} \mathbf{x} < 0$  for every nonzero vector  $\mathbf{x}$  if and only if  $\mathbf{B}$  is negative definite, or equivalently,

$$-\mathbf{B} = \begin{bmatrix} 4 & 2 & -2 \\ 2 & 10 & 2 \\ -2 & 2 & 5 \end{bmatrix}$$

is positive definite. Since the upper left determinants of  $-\mathbf{B}$  are 4, 36, 108, which are all positive,  $-\mathbf{B}$  is positive definite. As a result,  $\mathbf{x}^T \mathbf{A} \mathbf{x} < 0$  for every nonzero vector  $\mathbf{x}$ .

- (c) True. Since

$$\begin{bmatrix} 4 & 0 & 0 \\ 0 & -2 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} -2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 4 \end{bmatrix} \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}^{-1}$$

$$\begin{bmatrix} 4 & 0 & 0 \\ 0 & -2 & 0 \\ 0 & 0 & 1 \end{bmatrix} \text{ is similar to } \begin{bmatrix} -2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 4 \end{bmatrix}.$$

- (d) False. Let  $p(x) = 1$ . Since

$$\begin{aligned} T(cp(x)) &= T(c) = x^2 + c \\ cT(p(x)) &= cT(1) = c(x^2 + 1) = cx^2 + c \end{aligned}$$

we have  $T(cp(x)) \neq cT(p(x))$  as long as  $c \neq 1$ . Therefore,  $T$  is not linear.

(e) True. For every  $\mathbf{b} \in \mathbb{R}^m$ , we can have

$$\mathbf{b} = \mathbf{p} + \mathbf{e}$$

where  $\mathbf{p} \in \mathcal{C}(\mathbf{A})$  and  $\mathbf{e} \in \mathcal{N}(\mathbf{A}^T)$ . We can then have, for all  $\mathbf{b} \in \mathbb{R}^m$ ,

$$\begin{aligned} \mathbf{A}^+ \mathbf{A} \mathbf{A}^+ \mathbf{b} &= \mathbf{A}^+ \mathbf{A} \mathbf{A}^+ (\mathbf{p} + \mathbf{e}) \\ &= \mathbf{A}^+ \mathbf{A} \mathbf{A}^+ \mathbf{p} + \mathbf{A}^+ \mathbf{A} \mathbf{A}^+ \mathbf{e} \\ &= \mathbf{A}^+ (\mathbf{p}) + \mathbf{A}^+ \mathbf{A} \mathbf{0} \\ &= \mathbf{A}^+ \mathbf{p} \\ &= \mathbf{A}^+ (\mathbf{p} + \mathbf{e}) \\ &= \mathbf{A}^+ \mathbf{b} \end{aligned}$$

since  $\mathbf{A} \mathbf{A}^+$  is the projection matrix onto  $\mathcal{C}(\mathbf{A})$  and  $\mathbf{A}^+ \mathbf{e} = \mathbf{0}$ . Therefore,  $\mathbf{A}^+ \mathbf{A} \mathbf{A}^+ = \mathbf{A}^+$ .

2. (a) Consider

$$\det(\mathbf{A} - \lambda \mathbf{I}) = \begin{vmatrix} -\lambda & -1 \\ 1 & -\lambda \end{vmatrix} = \lambda^2 + 1 = 0.$$

Hence, the eigenvalues of  $\mathbf{A}$  are  $i$  and  $-i$ .

(b) Let  $\lambda$  be an eigenvalue of  $\mathbf{A}$  and  $\mathbf{x}$  be the corresponding unit eigenvector. Since  $\mathbf{A}$  is real, we can have

$$\begin{aligned} \mathbf{A} \mathbf{x} &= \lambda \mathbf{x} \\ \implies \bar{\mathbf{A}} \bar{\mathbf{x}} &= \bar{\lambda} \bar{\mathbf{x}} \\ \implies \mathbf{A} \bar{\mathbf{x}} &= \bar{\lambda} \bar{\mathbf{x}}. \end{aligned}$$

Consider  $\bar{\mathbf{x}}^T \mathbf{A} \mathbf{x}$ . We can then have:

$$\begin{aligned} \text{(i)} \quad \bar{\mathbf{x}}^T \mathbf{A} \mathbf{x} &= \bar{\mathbf{x}}^T (\lambda \mathbf{x}) = \lambda \bar{\mathbf{x}}^T \mathbf{x} = \lambda \|\mathbf{x}\|^2 = \lambda \\ \text{(ii)} \quad \bar{\mathbf{x}}^T \mathbf{A} \mathbf{x} &= (\mathbf{A}^T \bar{\mathbf{x}})^T \mathbf{x} = (-\mathbf{A} \bar{\mathbf{x}})^T \mathbf{x} = (-\bar{\lambda} \bar{\mathbf{x}})^T \mathbf{x} = -\bar{\lambda} \bar{\mathbf{x}}^T \mathbf{x} = -\bar{\lambda} \|\mathbf{x}\|^2 \\ &= -\bar{\lambda}. \end{aligned}$$

Hence, we can obtain  $\lambda = -\bar{\lambda}$ , which means that  $\lambda$  is pure imaginary.

(c) We can have

$$\mathbf{x}^T \mathbf{A} \mathbf{x} = (\mathbf{x}^T \mathbf{A} \mathbf{x})^T = \mathbf{x}^T \mathbf{A}^T \mathbf{x} = \mathbf{x}^T (-\mathbf{A}) \mathbf{x} = -\mathbf{x}^T \mathbf{A} \mathbf{x}.$$

Hence,  $\mathbf{x}^T \mathbf{A} \mathbf{x} = 0$  for every real vector  $\mathbf{x}$ .

3. Let  $\mathbf{A} = \begin{bmatrix} 0.4 & 0.2 \\ 0.6 & 0.8 \end{bmatrix}$ . Since the eigenvalues of  $\mathbf{A}$  are 1, 0.2, and  $\begin{bmatrix} 1 \\ 3 \end{bmatrix}$ ,  $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$  are their corresponding eigenvectors, respectively, we can have

$$\mathbf{A} = \mathbf{S} \mathbf{\Lambda} \mathbf{S}^{-1}$$

where

$$\mathbf{S} = \begin{bmatrix} 1 & 1 \\ 3 & -1 \end{bmatrix} \quad \text{and} \quad \mathbf{\Lambda} = \begin{bmatrix} 1 & 0 \\ 0 & 0.2 \end{bmatrix}.$$

Hence, we can have

$$\begin{aligned} \mathbf{A}^k &= \mathbf{S}\mathbf{\Lambda}^k\mathbf{S}^{-1} = \begin{bmatrix} 1 & 1 \\ 3 & -1 \end{bmatrix} \begin{bmatrix} 1^k & 0 \\ 0 & 0.2^k \end{bmatrix} \begin{bmatrix} 1/4 & 1/4 \\ 3/4 & -1/4 \end{bmatrix} \\ \implies \lim_{k \rightarrow \infty} \mathbf{A}^k &= \begin{bmatrix} 1 & 1 \\ 3 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1/4 & 1/4 \\ 3/4 & -1/4 \end{bmatrix} = \begin{bmatrix} 1/4 & 1/4 \\ 3/4 & 3/4 \end{bmatrix}. \end{aligned}$$

Therefore,

$$\begin{aligned} \lim_{k \rightarrow \infty} \mathbf{A}^k \begin{bmatrix} 1 \\ 0 \end{bmatrix} &= \begin{bmatrix} 1/4 \\ 3/4 \end{bmatrix} \\ \lim_{k \rightarrow \infty} \mathbf{A}^k \begin{bmatrix} 0 \\ 1 \end{bmatrix} &= \begin{bmatrix} 1/4 \\ 3/4 \end{bmatrix}. \end{aligned}$$

4. Let

$$\mathbf{B} = \frac{1}{2}(\mathbf{A} + \mathbf{A}^T) = \frac{1}{2} \left( \begin{bmatrix} 2 & 5 \\ -7 & 2 \end{bmatrix} + \begin{bmatrix} 2 & -7 \\ 5 & 2 \end{bmatrix} \right) = \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix}$$

which is a symmetric matrix, and  $\mathbf{x}^T \mathbf{A} \mathbf{x} = \mathbf{x}^T \mathbf{B} \mathbf{x}$ . The eigenvalues of  $\mathbf{B}$  can be found as:

$$\begin{aligned} \det(\mathbf{B} - \lambda \mathbf{I}) &= \begin{vmatrix} 2 - \lambda & -1 \\ -1 & 2 - \lambda \end{vmatrix} = \lambda^2 - 4\lambda + 3 = 0 \\ \implies \lambda &= 1 \text{ or } 3. \end{aligned}$$

From class, we can have

$$\lambda_{\min} \leq R(\mathbf{x}) = \frac{\mathbf{x}^T \mathbf{A} \mathbf{x}}{\mathbf{x}^T \mathbf{x}} = \frac{\mathbf{x}^T \mathbf{B} \mathbf{x}}{\mathbf{x}^T \mathbf{x}} \leq \lambda_{\max}$$

where  $\lambda_{\min}$  and  $\lambda_{\max}$  are the minimum and maximum eigenvalues of  $\mathbf{B}$ , respectively. Since  $\lambda_{\min} = 1$ , we have

$$\min_{\mathbf{x} \neq \mathbf{0}} R(\mathbf{x}) = 1.$$

Besides,  $\mathbf{x}$  achieves  $\min_{\mathbf{x} \neq \mathbf{0}} R(\mathbf{x})$  if  $\mathbf{x}$  belongs to the eigenspace corresponding to  $\lambda_{\min}$ . Since

$$\mathbf{B} - \lambda_{\min} \mathbf{I} = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$$

we can choose  $\mathbf{x} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$  or any nonzero scalar multiple of  $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$ .

5. (a) We have  $\gamma = \{\mathbf{e}_1, \mathbf{e}_2\}$ , where

$$\mathbf{e}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad \mathbf{e}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}.$$

Let  $\beta = \{\mathbf{V}_1, \mathbf{V}_2, \mathbf{V}_3, \mathbf{V}_4\}$ , where

$$\mathbf{V}_1 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \quad \mathbf{V}_2 = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \quad \mathbf{V}_3 = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \quad \mathbf{V}_4 = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}.$$

Since

$$\begin{aligned} T(\mathbf{V}_1) &= \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} = 1 \cdot \mathbf{e}_1 + 0 \cdot \mathbf{e}_2 \\ T(\mathbf{V}_2) &= \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 3 \\ 0 \end{bmatrix} = 3 \cdot \mathbf{e}_1 + 0 \cdot \mathbf{e}_2 \\ T(\mathbf{V}_3) &= \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = 0 \cdot \mathbf{e}_1 + 1 \cdot \mathbf{e}_2 \\ T(\mathbf{V}_4) &= \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 0 \\ 3 \end{bmatrix} = 0 \cdot \mathbf{e}_1 + 3 \cdot \mathbf{e}_2 \end{aligned}$$

we can have

$$[T]_{\beta}^{\gamma} = \begin{bmatrix} 1 & 3 & 0 & 0 \\ 0 & 0 & 1 & 3 \end{bmatrix}.$$

(b) From (a), we can find that  $\left\{ \begin{bmatrix} -3 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ -3 \\ 1 \end{bmatrix} \right\}$  forms a basis for  $\mathcal{N}([T]_{\beta}^{\gamma})$ .

Therefore, the kernel of  $T$  is given by the span of  $-3\mathbf{V}_1 + \mathbf{V}_2$  and  $-3\mathbf{V}_3 + \mathbf{V}_4$ .

(c) Let  $\omega = \{\mathbf{w}_1, \mathbf{w}_2\}$ , where

$$\mathbf{w}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \quad \mathbf{w}_2 = \begin{bmatrix} 1 \\ 2 \end{bmatrix}.$$

Since

$$\begin{aligned} T(\mathbf{V}_1) &= \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} = 2 \cdot \mathbf{w}_1 + (-1) \cdot \mathbf{w}_2 \\ T(\mathbf{V}_2) &= \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 3 \\ 0 \end{bmatrix} = 6 \cdot \mathbf{w}_1 + (-3) \cdot \mathbf{w}_2 \\ T(\mathbf{V}_3) &= \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = (-1) \cdot \mathbf{w}_1 + 1 \cdot \mathbf{w}_2 \\ T(\mathbf{V}_4) &= \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 0 \\ 3 \end{bmatrix} = (-3) \cdot \mathbf{w}_1 + 3 \cdot \mathbf{w}_2 \end{aligned}$$

we can have

$$[T]_{\beta}^{\omega} = \begin{bmatrix} 2 & 6 & -1 & -3 \\ -1 & -3 & 1 & 3 \end{bmatrix}.$$

6. (a) Perform the singular value decomposition, and we can have

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T = \begin{bmatrix} -\sqrt{6}/6 & -\sqrt{2}/2 & \sqrt{3}/3 \\ \sqrt{6}/3 & 0 & \sqrt{3}/3 \\ -\sqrt{6}/6 & \sqrt{2}/2 & \sqrt{3}/3 \end{bmatrix} \begin{bmatrix} \sqrt{3} & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \sqrt{2}/2 & -\sqrt{2}/2 \\ \sqrt{2}/2 & \sqrt{2}/2 \end{bmatrix}.$$

(b) Since there are 2 nonzero singular values of  $\mathbf{A}$ , the rank of  $\mathbf{A}$  is 2. The dimension of the column space of  $\mathbf{A}$  is 2, and an orthonormal basis for the column space of  $\mathbf{A}$  can be obtained as the first two columns of  $\mathbf{U}$ , i.e.,

$$\begin{bmatrix} -\sqrt{6}/6 \\ \sqrt{6}/3 \\ -\sqrt{6}/6 \end{bmatrix}, \begin{bmatrix} -\sqrt{2}/2 \\ 0 \\ \sqrt{2}/2 \end{bmatrix}.$$

(c) Since  $\mathbf{A}$  has full column rank, there is a left inverse for  $\mathbf{A}$ . We can have

$$\mathbf{A}^+ \mathbf{A} = \mathbf{I}$$

and hence the pseudoinverse

$$\begin{aligned} \mathbf{A}^+ &= \mathbf{V}\mathbf{\Sigma}^+\mathbf{U}^T \\ &= \begin{bmatrix} -2/3 & 1/3 & 1/3 \\ -1/3 & -1/3 & 2/3 \end{bmatrix} \end{aligned}$$

is a left inverse for  $\mathbf{A}$ .

(d) The shortest least squares solution is

$$\mathbf{A}^+ \mathbf{b} = \begin{bmatrix} 1/3 \\ -1/3 \end{bmatrix}.$$

(e) We can have

$$\mathbf{x}_r = \mathbf{A}^+ \mathbf{b} = \begin{bmatrix} 1/3 \\ -1/3 \end{bmatrix}.$$