

# Abstract Linear Algebra: Homework 9

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**Problem 1.** Let  $V$  be a finite-dimensional inner product space over  $\mathbb{C}$ , and let  $T$  be a linear transformation on  $V$ . Prove that  $T$  is self-adjoint if and only if  $\langle \mathbf{x}, T\mathbf{x} \rangle$  is real for all  $\mathbf{x} \in V$ .

*Solution.* Assume  $T$  is self-adjoint. We need to show that  $\langle \mathbf{x}, T\mathbf{x} \rangle$  is real for all  $\mathbf{x} \in V$ . Since  $T$  is self-adjoint, we have

$$\langle T\mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{x}, T\mathbf{y} \rangle \quad \text{for all } \mathbf{x}, \mathbf{y} \in V.$$

Setting  $\mathbf{y} = \mathbf{x}$ , we obtain  $\langle T\mathbf{x}, \mathbf{x} \rangle = \langle \mathbf{x}, T\mathbf{x} \rangle$ . By the conjugate symmetry of the inner product, we know that

$$\langle \mathbf{x}, T\mathbf{x} \rangle = \overline{\langle T\mathbf{x}, \mathbf{x} \rangle}.$$

Thus, we have

$$\langle \mathbf{x}, T\mathbf{x} \rangle = \overline{\langle \mathbf{x}, T\mathbf{x} \rangle}.$$

This means that  $\langle \mathbf{x}, T\mathbf{x} \rangle$  is equal to its own complex conjugate, which implies that it is a real number.

Assume  $\langle \mathbf{x}, T\mathbf{x} \rangle$  is real for all  $\mathbf{x} \in V$ . We need to show that  $T$  satisfies  $\langle T\mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{x}, T\mathbf{y} \rangle$  for all  $\mathbf{x}, \mathbf{y} \in V$ . Define the function  $f : V \times V \rightarrow \mathbb{C}$  by

$$f(\mathbf{x}, \mathbf{y}) = \langle T\mathbf{x}, \mathbf{y} \rangle.$$

We need to show that  $f(\mathbf{x}, \mathbf{y}) = f(\mathbf{y}, \mathbf{x})$ , i.e.,

$$\langle T\mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{x}, T\mathbf{y} \rangle$$

Define the function  $g(\mathbf{x}, \mathbf{y})$  as

$$g(\mathbf{x}, \mathbf{y}) = \langle T\mathbf{x}, \mathbf{y} \rangle - \overline{\langle T\mathbf{y}, \mathbf{x} \rangle}.$$

Since the inner product satisfies conjugate symmetry, we get

$$\overline{\langle T\mathbf{y}, \mathbf{x} \rangle} = \langle \mathbf{x}, T\mathbf{y} \rangle.$$

Thus, we can rewrite  $g$  as

$$g(\mathbf{x}, \mathbf{y}) = \langle T\mathbf{x}, \mathbf{y} \rangle - \langle \mathbf{x}, T\mathbf{y} \rangle.$$

We need to show that  $g(\mathbf{x}, \mathbf{y}) = 0$  for all  $\mathbf{x}, \mathbf{y} \in V$ .

For any  $\mathbf{x}$ , define  $h(\mathbf{y}) = g(\mathbf{x}, \mathbf{y})$ . Notice that  $h$  is linear in  $\mathbf{y}$ . Taking  $\mathbf{y} = \mathbf{x}$ , we get

$$g(\mathbf{x}, \mathbf{x}) = \langle T\mathbf{x}, \mathbf{x} \rangle - \langle \mathbf{x}, T\mathbf{x} \rangle = 0,$$

since we assumed that  $\langle \mathbf{x}, T\mathbf{x} \rangle$  is real.

For any  $\mathbf{x}, \mathbf{y}$ , consider

$$g(\mathbf{x} + \mathbf{y}, \mathbf{x} + \mathbf{y}) = \langle T(\mathbf{x} + \mathbf{y}), \mathbf{x} + \mathbf{y} \rangle - \langle \mathbf{x} + \mathbf{y}, T(\mathbf{x} + \mathbf{y}) \rangle.$$

Since each term is real, we get

$$\langle T\mathbf{x}, \mathbf{x} \rangle + \langle T\mathbf{x}, \mathbf{y} \rangle + \langle T\mathbf{y}, \mathbf{x} \rangle + \langle T\mathbf{y}, \mathbf{y} \rangle - (\langle \mathbf{x}, T\mathbf{x} \rangle + \langle \mathbf{x}, T\mathbf{y} \rangle + \langle \mathbf{y}, T\mathbf{x} \rangle + \langle \mathbf{y}, T\mathbf{y} \rangle) = 0.$$

Canceling out terms, we obtain

$$\langle T\mathbf{x}, \mathbf{y} \rangle + \langle T\mathbf{y}, \mathbf{x} \rangle - \langle \mathbf{x}, T\mathbf{y} \rangle - \langle \mathbf{y}, T\mathbf{x} \rangle = 0.$$

Thus,  $\langle T\mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{x}, T\mathbf{y} \rangle$ . Since  $\mathbf{x}$  and  $\mathbf{y}$  were arbitrary,  $T$  is self-adjoint.

Thus,  $T$  is self-adjoint if and only if  $\langle \mathbf{x}, T\mathbf{x} \rangle$  is real for all  $\mathbf{x} \in V$ .  $\square$

**Problem 2.** Let  $A \in \mathbb{C}^{n \times n}$ . Prove that  $A$  is normal if and only if  $A$  can be written in the form of  $A = A_1 + iA_2$  where  $A_1$  and  $A_2$  are Hermitian and  $A_1A_2 = A_2A_1$ .

*Solution.* Assume  $A$  is normal. We want to show that  $A$  can be written as  $A_1 + iA_2$  with the given properties. Define

$$A_1 = \frac{A + A^*}{2} \quad \text{and} \quad A_2 = \frac{A - A^*}{2i}.$$

We first need to verify that  $A_1$  and  $A_2$  are Hermitian. The conjugate transpose of  $A_1$  is

$$A_1^* = \left( \frac{A + A^*}{2} \right)^* = \frac{A^* + (A^*)^*}{2} = \frac{A^* + A}{2} = A_1 \quad \text{and} \quad A_2^* = \left( \frac{A - A^*}{2i} \right)^* = \frac{A^* - A}{2i} = A_2.$$

Therefore,  $A_1$  and  $A_2$  are Hermitian. Since  $A_1$  and  $A_2$  are defined in terms of  $A$  and  $A^*$  respectively, we see that  $A = A_1 + iA_2$ .

Now, we need to show that  $A_1$  and  $A_2$  commute, i.e.,  $A_1A_2 = A_2A_1$ . Since  $A$  is normal, we have  $AA^* = A^*A$ . Substituting  $A = A_1 + iA_2$  and  $A^* = A_1 - iA_2$ , we compute

$$(A_1 + iA_2)(A_1 - iA_2) = A_1^2 - iA_1A_2 + iA_2A_1 + A_2^2 = A_1^2 + A_2^2 + i(A_2A_1 - A_1A_2).$$

Similarly,

$$(A_1 - iA_2)(A_1 + iA_2) = A_1^2 - iA_1A_2 + iA_2A_1 + A_2^2 = A_1^2 + A_2^2 + i(A_2A_1 - A_1A_2).$$

Since  $AA^* = A^*A$ , it follows that  $i(A_2A_1 - A_1A_2) = 0$ . Thus,  $A_1A_2 = A_2A_1$ . Hence, if  $A$  is normal, then it can be decomposed as  $A = A_1 + iA_2$ , where  $A_1, A_2$  are Hermitian and commute.

Assume  $A = A_1 + iA_2$  where  $A_1$  and  $A_2$  are Hermitian and commute. We need to show that  $AA^* = A^*A$ . We get  $A^* = (A_1 + iA_2)^* = A_1^* + iA_2^* = A_1 - iA_2$ . Now, compute  $AA^*$  and  $A^*A$  to get

$$\begin{aligned} AA^* &= A_1^2 - iA_1A_2 + iA_2A_1 + A_2^2 = A_1^2 + A_2^2 + i(A_2A_1 - A_1A_2) \\ \text{and } A^*A &= (A_1 - iA_2)(A_1 + iA_2) = A_1^2 - iA_1A_2 + iA_2A_1 + A_2^2 = A_1^2 + A_2^2 + i(A_2A_1 - A_1A_2). \end{aligned}$$

Since, by assumption, that  $A_1A_2 = A_2A_1$ , the term  $A_2A_1 - A_1A_2$  cancel, leaving  $AA^* = A_1^2 + A_2^2 = A^*A$ . Thus,  $A$  is normal.

Therefore,  $A$  is normal if and only if it can be decomposed in this form.  $\square$

**Problem 3.** Prove that a normal and nilpotent linear transformation is the zero linear transformation. (Note: A linear transformation  $T$  is nilpotent if there exists a positive integer  $r$  such that  $T^r = 0$ .)

*Solution.* Assume  $T$  is a normal and nilpotent linear transformation. We need to show that  $T = 0$ . Since  $T$  is normal, by the Spectral Theorem, we know that  $T$  is diagonalizable, i.e.,  $T = UDU^*$ , where  $D$  is a diagonal matrix of eigenvalues and  $U$  is a unitary matrix. Since it is diagonalizable, then there exists an eigenbasis, say  $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ , with corresponding eigenvalues, say  $\lambda_1, \dots, \lambda_n$ , so that  $T\mathbf{v}_i = \lambda_i\mathbf{v}_i$ , for  $i = 1, \dots, n$ . Since  $T$  is nilpotent, all its eigenvalues are zero. To show this, suppose  $T^k = 0$ , for some  $k$ . Applying this to an eigenvector, we have

$$T^k\mathbf{v}_i = \lambda_i^k\mathbf{v}_i \Rightarrow \mathbf{0} = \lambda_i^k\mathbf{v}_i \Rightarrow \lambda_i^k = 0 \Rightarrow \lambda_i = 0.$$

Since  $T$  is normal, it is diagonalizable, and all its eigenvalues are zero, giving us

$$D = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{pmatrix} \Rightarrow T = UDU^* = 0.$$

Therefore, a normal and nilpotent linear transformation is the zero linear transformation.  $\square$

**Problem 4.** Let  $A \in \mathbb{C}^{n \times n}$  be a Hermitian matrix. Prove that  $A$  is positive definite if and only if all the eigenvalues of  $A$  are positive.

*Solution.* Assume that  $A$  is a positive definite Hermitian matrix. We need to show that all the eigenvalues of  $A$  are positive. Since  $A$  is Hermitian, the spectral theorem states that  $A$  has an orthonormal basis of eigenvectors, and all its eigenvalues are real. Let  $\mathbf{v}$  be an eigenvector of  $A$  corresponding to eigenvalue  $\lambda$ , i.e.,  $A\mathbf{v} = \lambda\mathbf{v}$ . Consider the quadratic form for this eigenvector  $\mathbf{v}^*A\mathbf{v} = \mathbf{v}^*(\lambda\mathbf{v}) = \lambda(\mathbf{v}^*\mathbf{v})$ . Since  $\mathbf{v}^*\mathbf{v} = \|\mathbf{v}\|^2 > 0$  for any nonzero eigenvector, we have that  $\mathbf{v}^*A\mathbf{v} > 0$ . It follows that  $\lambda > 0$ . Thus, if  $A$  is positive definite, then all its eigenvalues are positive.

Assume that all the eigenvalues of  $A$  are positive and  $A$  is Hermitian. We need to show that  $A$  is positive definite. Again, by the spectral theorem, we can diagonalize  $A$  as  $A = UDU^*$ , where  $D$  is a diagonal matrix of eigenvalues,  $\lambda_1, \dots, \lambda_n$ , and  $U$  is a unitary matrix. For any nonzero vector,  $\mathbf{x}$ , write  $\mathbf{y} = U^*\mathbf{x}$ , so that  $\mathbf{x}^*A\mathbf{x}$  can be re-written as

$$\mathbf{x}^*A\mathbf{x} = \mathbf{x}^*UDU^*\mathbf{x} = (U^*\mathbf{x})^*D(U^*\mathbf{x}) = \mathbf{y}^*D\mathbf{y}.$$

Since  $D$  is diagonal, this simplifies to

$$\mathbf{y}^*D\mathbf{y} = \sum_{i=1}^n \lambda_i \|\mathbf{y}_i\|^2.$$

If all  $\lambda_i > 0$ , then each term in the sum is strictly positive for any nonzero  $\mathbf{y}$ , meaning

$$\mathbf{x}^*A\mathbf{x} = \sum_{i=1}^n \lambda_i \|\mathbf{y}_i\|^2 > 0.$$

Thus,  $A$  is positive definite.

Therefore,  $A$  is positive definite if and only if all its eigenvalues are positive.  $\square$

**Problem 5.** Let  $A \in \mathbb{C}^{n \times n}$  be a normal matrix. Prove that  $A$  is unitary if and only if every eigenvalue of  $A$  has magnitude (or absolute value) 1.

*Solution.* Assume  $A$  is a unitary square normal matrix. We want to show that every eigenvalue of  $A$  has magnitude 1. Since  $A$  is unitary, by definition, we have  $A^*A = I = AA^*$ . Let  $(\lambda, v)$  be an eigenpair of  $A$ , meaning that  $A\mathbf{v} = \lambda\mathbf{v}$ . Taking norms on both sides, we get

$$\|A\mathbf{v}\| = \|\lambda\mathbf{v}\| = |\lambda|\|\mathbf{v}\|.$$

Since  $A$  is unitary, it preserves norms, so  $\|A\mathbf{v}\| = \|\mathbf{v}\|$ . Thus, we obtain  $|\lambda|\|\mathbf{v}\| = \|\mathbf{v}\|$ . Since  $\mathbf{v} \neq 0$ , it follows that  $|\lambda| = 1$ . Therefore, if  $A$  is unitary, then every eigenvalue of  $A$  has magnitude 1.

Conversely, assume that every eigenvalue of  $A$  has magnitude 1 and that  $A$  is normal. We need to show that  $A$  is unitary. Since  $A$  is normal, it is unitarily diagonalizable, meaning that there exists a unitary matrix  $U$  such that  $U^*AU = D$ , where  $D$  is a diagonal matrix whose diagonal entries are the eigenvalues  $\lambda_1, \dots, \lambda_n$  of  $A$ . By assumption, each eigenvalue satisfies  $|\lambda_i| = 1$ . We compute

$$D^*D = \text{diag}(\overline{\lambda_1}, \dots, \overline{\lambda_n}) \text{diag}(\lambda_1, \dots, \lambda_n) = \text{diag}(|\lambda_1|^2, \dots, |\lambda_n|^2) = I.$$

Since unitary similarity preserves this property, we compute

$$\begin{aligned} A^*A &= (UDU^*)^*(UDU^*) \\ &= UD^*U^*UDU^* \\ &= UD^*DU^* \\ &= UIU^* \\ &= I. \end{aligned}$$

Similarly, we compute

$$\begin{aligned}
 AA^* &= (UDU^*)(UDU^*)^* \\
 &= UDU^*UD^*U^* \\
 &= UDD^*U^* \\
 &= UIU^* \\
 &= I.
 \end{aligned}$$

Thus, if every eigenvalue of  $A$  has magnitude 1, then  $A$  is unitary.

Therefore,  $A$  is unitary if and only if every eigenvalue of  $A$  has magnitude 1.  $\square$

**Problem 6.** Let  $A \in \mathbb{C}^{n \times n}$  be a Hermitian matrix. Suppose  $A$  is both positive definite and unitary. Prove that  $A = I$ . *Hint: You may use conclusions from the above two problems.*

*Solution.* Let  $\lambda$  be an eigenvalue of  $A$ . By problem 4 and 5,  $\lambda > 0$  and  $|\lambda| = 1$ . By the Spectral Theorem,  $A$  is diagonalizable with an orthonormal basis of eigenvectors. Because all of its eigenvalues are 1, the diagonalized form of  $A$  is simply the identity matrix  $I$ .  $\square$

**Problem 7.** Consider  $A = \begin{pmatrix} -1 & 0 & 1 \\ 1 & -1 & 0 \end{pmatrix}$

- (i) Find the singular value decomposition of  $A$ . (Show your computation work, do not use technology.)
- (ii) Find the generalized inverse  $A^+$ .

*Solution to (i).* Computing  $A^T A$ , we get

$$A^T A = \begin{pmatrix} -1 & 1 \\ 0 & -1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} -1 & 0 & 1 \\ 1 & -1 & 0 \end{pmatrix} = \begin{pmatrix} (-1)(-1) + (1)(1) & (1)(-1) & (-1)(1) \\ (-1)(1) & (-1)(-1) & 0 \\ (1)(-1) & 0 & (1)(1) \end{pmatrix} = \begin{pmatrix} 2 & -1 & -1 \\ -1 & 1 & 0 \\ -1 & 0 & 1 \end{pmatrix}.$$

Now, we need to find the eigenvalues and eigenvectors of  $A^T A$ . The characteristic polynomial of  $A^T A$  is given by

$$\det(A^T A - \lambda I) = \begin{vmatrix} 2 - \lambda & -1 & -1 \\ -1 & 1 - \lambda & 0 \\ -1 & 0 & 1 - \lambda \end{vmatrix} = -\lambda(\lambda - 3)(\lambda - 1) = 0,$$

giving us the eigenvalues  $\lambda_1 = 3$ ,  $\lambda_2 = 1$ , and  $\lambda_3 = 0$ . Next, we need to find the eigenvectors corresponding to each eigenvalue.

$$\begin{aligned}
 \underline{\lambda = 3}: A^T A - 3I &= \begin{pmatrix} -1 & -1 & -1 \\ -1 & -2 & 0 \\ -1 & 0 & -2 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 2 \\ 0 & 1 & -1 \\ 0 & 0 & 0 \end{pmatrix} \\
 \Rightarrow \begin{pmatrix} 1 & 0 & 2 \\ 0 & 1 & -1 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} &= \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \Rightarrow \mathbf{v}_1 = \begin{pmatrix} -2 \\ 1 \\ 1 \end{pmatrix}
 \end{aligned}$$

$$\begin{aligned}
\underline{\lambda = 1} : A^T A - I &= \begin{pmatrix} 1 & -1 & -1 \\ -1 & 0 & 0 \\ -1 & 0 & 0 \end{pmatrix} = \begin{pmatrix} 1 & -1 & -1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix} \\
\Rightarrow \begin{pmatrix} 1 & -1 & -1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} &= \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \Rightarrow \mathbf{v}_2 = \begin{pmatrix} 0 \\ -1 \\ 1 \end{pmatrix} \\
\underline{\lambda = 0} : A^T A &= \begin{pmatrix} 2 & -1 & -1 \\ -1 & 1 & 0 \\ -1 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 2 & -1 & -1 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix} \\
\Rightarrow \begin{pmatrix} 2 & -1 & -1 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} &= \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \Rightarrow \mathbf{v}_3 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}.
\end{aligned}$$

The matrix  $\Sigma$  is made up of the square roots of the eigenvalues of  $A^T A$  along the diagonal, giving us

$$\Sigma = \begin{pmatrix} \sqrt{\lambda_1} & 0 \\ 0 & \sqrt{\lambda_2} \end{pmatrix} = \begin{pmatrix} \sqrt{3} & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}.$$

The columns of the matrix  $V$  are the normalized vectors

$$\mathbf{v}_1 = \begin{pmatrix} -2 \\ 1 \\ 1 \end{pmatrix}, \quad \mathbf{v}_2 = \begin{pmatrix} 0 \\ -1 \\ 1 \end{pmatrix}, \quad \text{and} \quad \mathbf{v}_3 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}.$$

Normalizing each eigenvector gives us

$$\begin{aligned}
\hat{\mathbf{v}}_1 &= \frac{1}{\sqrt{6}} \cdot \begin{pmatrix} -2 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} -\frac{2}{\sqrt{6}} \\ \frac{1}{\sqrt{6}} \\ \frac{1}{\sqrt{6}} \end{pmatrix} = \begin{pmatrix} -\frac{\sqrt{6}}{3} \\ \frac{\sqrt{6}}{6} \\ \frac{\sqrt{6}}{6} \end{pmatrix} \\
\hat{\mathbf{v}}_2 &= \frac{1}{\sqrt{2}} \cdot \begin{pmatrix} 0 \\ -1 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{pmatrix} = \begin{pmatrix} 0 \\ -\frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{pmatrix} \\
\hat{\mathbf{v}}_3 &= \frac{1}{\sqrt{3}} \cdot \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \end{pmatrix} = \begin{pmatrix} \frac{\sqrt{3}}{3} \\ \frac{\sqrt{3}}{3} \\ \frac{\sqrt{3}}{3} \end{pmatrix}.
\end{aligned}$$

This gives us the matrix  $V$  as

$$V = \begin{pmatrix} -\frac{\sqrt{6}}{3} & 0 & \frac{\sqrt{3}}{3} \\ \frac{\sqrt{6}}{6} & -\frac{\sqrt{2}}{2} & \frac{\sqrt{3}}{3} \\ \frac{\sqrt{6}}{6} & \frac{\sqrt{2}}{2} & \frac{\sqrt{3}}{3} \end{pmatrix}.$$

The columns of the matrix  $U$  are the left singular vectors of the original matrix. Finding each  $\mathbf{u}_i$  gives us

$$\begin{aligned} \mathbf{u}_1 &= \frac{1}{\sigma_1} A \hat{\mathbf{v}}_1 = \frac{1}{\sqrt{3}} \cdot \begin{pmatrix} -1 & 0 & 1 \\ 1 & -1 & 0 \end{pmatrix} \cdot \begin{pmatrix} -\frac{\sqrt{6}}{3} \\ \frac{\sqrt{6}}{6} \\ \frac{\sqrt{6}}{6} \end{pmatrix} = \begin{pmatrix} \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{pmatrix} \\ \mathbf{u}_2 &= \frac{1}{\sigma_2} A \hat{\mathbf{v}}_2 = \frac{1}{\sqrt{1}} \cdot \begin{pmatrix} -1 & 0 & 1 \\ 1 & -1 & 0 \end{pmatrix} \cdot \begin{pmatrix} 0 \\ -\frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{pmatrix} = \begin{pmatrix} \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{pmatrix}. \end{aligned}$$

This gives us the matrix  $U$  as

$$U = \begin{pmatrix} \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} & -\frac{\sqrt{2}}{2} \end{pmatrix}.$$

Finally, we have the singular value decomposition of  $A$  as

$$A = U \Sigma V^* = \begin{pmatrix} \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} & -\frac{\sqrt{2}}{2} \end{pmatrix} \cdot \begin{pmatrix} \sqrt{3} & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \cdot \begin{pmatrix} -\frac{\sqrt{6}}{3} & \frac{\sqrt{6}}{6} & \frac{\sqrt{6}}{6} \\ 0 & -\frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} \\ \frac{\sqrt{3}}{3} & \frac{\sqrt{3}}{3} & \frac{\sqrt{3}}{3} \end{pmatrix}. \quad \square$$

*Solution to (ii).* Using the general formula for the general inverse, we have  $A^+ = A^T \cdot (AA^T)^{-1}$ . Computing  $AA^T$ , we get

$$A \cdot A^T = \begin{pmatrix} -1 & 0 & 1 \\ 1 & -1 & 0 \end{pmatrix} \cdot \begin{pmatrix} -1 & 1 \\ 0 & -1 \\ 1 & 0 \end{pmatrix} = \begin{pmatrix} 2 & -1 \\ -1 & 2 \end{pmatrix}.$$

The inverse of this matrix is

$$(AA^T)^{-1} = \frac{1}{\det(AA^T)} \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} = \frac{1}{3} \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} = \begin{pmatrix} \frac{2}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{2}{3} \end{pmatrix}.$$

Lastly, we multiply this by  $A^T$  to get

$$A^T \cdot (AA^T)^{-1} = \begin{pmatrix} -1 & 1 \\ 0 & -1 \\ 1 & 0 \end{pmatrix} \cdot \begin{pmatrix} \frac{2}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{2}{3} \end{pmatrix} = \begin{pmatrix} -\frac{1}{3} & \frac{1}{3} \\ -\frac{1}{3} & -\frac{2}{3} \\ \frac{2}{3} & \frac{1}{3} \end{pmatrix}.$$



Therefore, the generalized inverse of  $A$  is

$$A^+ = \begin{pmatrix} -\frac{1}{3} & \frac{1}{3} \\ -\frac{1}{3} & -\frac{2}{3} \\ \frac{2}{3} & \frac{1}{3} \end{pmatrix}. \quad \square$$

**Problem 8.** Let  $A \in \mathbb{C}^{n \times n}$  be a Hermitian and indefinite (i.e. not positive definite or positive semi-definite). Suppose  $A = PDP^*$  for some unitary matrix  $P$  and some diagonal matrix  $D \in \mathbb{R}^{n \times n}$ . Find the singular value decomposition of  $A = V\Sigma U^*$  by constructing  $V$ ,  $\Sigma$ , and  $U$  using some possible variations of the columns or entries of  $P$  and  $D$ .

*Solution.* The singular values of  $A$  are the absolute values of its eigenvalues, since  $A$  is Hermitian and diagonalizable. That is, if  $D = \text{diag}(\lambda_1, \dots, \lambda_n)$ , then the singular values of  $A$  are

$$\sigma_i = |\lambda_i|, \quad i = 1, \dots, n.$$

Thus, the singular value matrix  $\Sigma$  is given by

$$\Sigma = \text{diag}(|\lambda_1|, \dots, |\lambda_n|).$$

Since  $A = PDP^*$ , we consider how to transform this into an SVD. Firstly, choose  $U$  to align with the eigenvectors of  $A$ . Since the right singular vectors (columns of  $U$ ) correspond to the eigenvectors of  $A^*A = A^2$ , we observe that  $A^*A = A^2 = PD^2P^*$ .

Since  $P$  is unitary, it diagonalizes  $A^*A$  with eigenvalues  $\lambda_i^2$ , meaning the right singular vectors are also given by  $P$ . Thus, we set  $U = P$ .

The left singular vectors (columns of  $V$ ) are eigenvectors of  $AA^* = A^2$ , which is the same computation as  $A^*A$ , meaning we can also use  $P$  up to sign adjustments. Define a signature matrix  $S$  as  $S = \text{diag}(\text{sgn}(\lambda_1), \text{sgn}(\lambda_2), \dots, \text{sgn}(\lambda_n))$  where

$$\text{sgn}(\lambda_i) = \begin{cases} +1, & \lambda_i > 0 \\ -1, & \lambda_i < 0 \end{cases}.$$

Then, setting  $V = PS$  ensures that  $A = V\Sigma U^*$ .

Therefore, the singular value decomposition of  $A$  is  $A = V\Sigma U^*$  where  $U = P$ ,  $V = PS$ , where  $S$  is the signature matrix, and  $\Sigma$  is the diagonal matrix of singular values.  $\square$

**Problem 9.** Let  $A$  be an  $m \times n$  matrix, and let  $P$  and  $Q$  be  $m \times m$  and  $n \times n$  unitary matrices. Show that  $A$  and  $PAQ$  have the same singular values.

*Solution.* Consider the transformed matrix  $B = PAQ$ . Its Gram matrix is given by  $B^*B = (PAQ)^*(PAQ)$ . Using the properties of the conjugate transpose,  $B^* = (PAQ)^* = Q^*A^*P^*$ . Thus,  $B^*B = Q^*A^*P^*PAQ$ . Since  $P$  is unitary, we have  $P^*P = I_m$ , so this simplifies to  $B^*B = Q^*A^*AQ$ . Since  $Q$  is unitary, it preserves eigenvalues. That is,  $A^*A$  and  $Q^*A^*AQ$  have the same eigenvalues. Therefore, the eigenvalues of  $B^*B$  are the same as those of  $A^*A$ . Since the singular values are the square roots of the eigenvalues of  $A^*A$  (or equivalently  $B^*B$ ), we conclude that  $A$  and  $PAQ$  have the same singular values,

$$\sigma_i(A) = \sigma_i(PAQ) = \sigma_i(B), \quad \text{for all } i. \quad \square$$