

DAI-101 Tutorial – 1 (5 February)

Instructions:

- Total Time: 25 minutes
- Total Marks: 20 marks
- Attempt all questions
- No negative marking

[**1 × 10 = 10 marks**]

1. What is the correct interpretation of the standard deviation of a dataset?
 - (A) It is the square of the mean
 - (B) It measures the asymmetry of the distribution
 - (C) It represents the spread of data around the mean
 - (D) It is always equal to the variance
2. According to Chebyshev's inequality, for any dataset (not necessarily normal), at least what percentage of values lie within $k = 2$ standard deviations from the mean?
 - (A) 50%
 - (B) 75%
 - (C) 88.89%
 - (D) 95%
3. Which of the following matrices is always symmetric?
 - (A) Covariance matrix
 - (B) Confusion matrix
 - (C) Min-max scaled matrix
 - (D) One-hot encoded matrix
4. Which of the following measures is most affected by extreme values (outliers)?
 - (A) Mean
 - (B) Median
 - (C) Mode
 - (D) Interquartile range
5. The eigenvectors of a real symmetric matrix are:
 - (A) Always real and orthogonal
 - (B) Always complex

- (C) Always linearly dependent
 - (D) Not guaranteed to exist
6. Which of the following properties is true for a matrix to be positive semi-definite?
- (A) All eigenvalues are negative
 - (B) All eigenvalues are non-negative
 - (C) It must be a diagonal matrix
 - (D) It must be orthogonal
7. The trace of a matrix is equal to:
- (A) The sum of all elements in the matrix
 - (B) The sum of all eigenvalues
 - (C) The product of the diagonal elements
 - (D) The determinant of the matrix
8. A matrix is orthogonal if:
- (A) Its determinant is 0
 - (B) Its inverse is equal to its transpose
 - (C) All rows are equal
 - (D) It has complex eigenvalues
9. In the context of PCA, the eigenvector corresponding to the largest eigenvalue represents:
- (A) The direction of minimum variance
 - (B) A redundant feature
 - (C) The principal component with the most variance
 - (D) The mean of the dataset
10. Which of the following is not a valid reason for using PCA?
- (A) Dimensionality reduction
 - (B) Noise reduction
 - (C) Improving classification accuracy directly
 - (D) Visualizing high-dimensional data

[2 marks]

Q11. What is the geometric intuition behind Principal Component Analysis (PCA)? Explain why the first principal component is important.

[4 marks]

Q12. Perform the spectral decomposition of the following symmetric matrix:

$$A = \begin{pmatrix} 4 & 1 \\ 1 & 3 \end{pmatrix}$$

[2 marks]

Q13. Given a NumPy array X of shape (n_samples, n_features), center the data and compute the covariance matrix manually (do not use `np.cov`).

```
import numpy as np

X = np.array([[1, 2], [3, 4], [5, 6]])

# TODO: Your code after this line
```

[2 marks]

Q14. Using pandas, load the following DataFrame and perform: Min-max scaling on "age", Z-score standardization on "income", and one-hot encoding on "city".

```
import pandas as pd

data = pd.DataFrame({
    'age': [22, 25, 47, 52],
    'income': [20000, 25000, 47000, 52000],
    'city': ['Delhi', 'Mumbai', 'Delhi', 'Chennai']
})

# TODO: Your code after this line
```

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Tutorial-02

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Q1. MCQ: In the SVD factorization $A = U\Sigma V^T$, which of the following is true?

- (A) U and V are diagonal
- (B) The columns of U are orthonormal
- (C) Σ must be square
- (D) V is upper triangular

Q2. MCQ: What are the singular values of the diagonal matrix

$$D = \begin{pmatrix} 3 & 0 \\ 0 & 5 \end{pmatrix} ?$$

- (A) 3, 5
- (B) 5, 3
- (C) $\sqrt{3}, \sqrt{5}$
- (D) 3, 0, 0, 5

Q3. Numerical: Suppose the eigenvalues of a covariance matrix (sorted descending) are:

$$\lambda_1 = 4.5, \lambda_2 = 2.0, \lambda_3 = 1.0, \lambda_4 = 0.5.$$

What is the minimum number of principal components needed to explain at least 90% of the variance?

Q4. Numerical: A centred data matrix $X \in \mathbb{R}^{100 \times 50}$ has rank 40. Keeping the first $k = 20$ singular values yields

$$\sum_{i=1}^{20} \sigma_i^2 = 8000, \quad \sum_{i=1}^{40} \sigma_i^2 = 9600.$$

Compute the fraction of total variance retained.

Q5. True/False: If you keep all non-zero singular values of X in its SVD, the reconstruction error (in Frobenius norm) is zero.

Q6. MCQ: In PCA, we compute the covariance matrix C . Which of the following is not a property of C ?

- (A) C is symmetric
- (B) All eigenvalues of C are real
- (C) C is orthogonal
- (D) C is positive semi-definite

Q7. MCQ: Given an $m \times n$ matrix A with SVD $A = U\Sigma V^T$, which holds?

- (A) Columns of U are eigenvectors of A
- (B) Columns of V are eigenvectors of $A^T A$
- (C) Σ is an orthogonal matrix
- (D) U and V are diagonal matrices

Q8. Numerical: For

$$X = \begin{pmatrix} 2 & 0 \\ 0 & 2 \\ 3 & 1 \end{pmatrix},$$

- (a) Compute the mean.

Q9. MCQ: If eigenvalues $\lambda_1 \geq \dots \geq \lambda_n$, then variance retained by first k PCs is

- (A) $\frac{\sum_{i=1}^k \lambda_i}{n}$
- (B) $\frac{\sum_{i=1}^k \lambda_i}{\sum_{j=1}^n \lambda_j}$
- (C) $\sum_{i=1}^k \lambda_i$
- (D) λ_k

Q10. Numerical: Given $\sigma_1 = 5$, $\sigma_2 = 3$, $\sigma_3 = 1$, what fraction of total energy is in first two?

Q11. MCQ: Which of the following is **NOT** an application of Singular Value Decomposition (SVD)?

- (A) Image compression via low-rank approximation
- (B) Collaborative filtering in recommender systems
- (C) Topic modeling in text analysis (Latent Semantic Analysis)
- (D) Efficient sorting of numerical arrays

Q12. Coding: Compute the SVD of a simple 2×2 matrix and reconstruct it.

- (1) Let

$$A = \begin{pmatrix} 1 & 2 \\ 3 & 4 \end{pmatrix}.$$

- (2) Compute its SVD: $A = U\Sigma V^T$.
- (3) Reconstruct $\hat{A} = U\Sigma V^T$ and print the Frobenius-norm error $\|A - \hat{A}\|_F$.

Q13. Coding: Use scikit-learn's PCA to reduce a small random dataset and report explained variance.

- (1) Generate a random array X of shape $(10, 3)$.
- (2) Fit `PCA(n_components=2)` on X and print explained variance ratio.

Starter Code (Optional)

Q12 (NumPy SVD):

```

import numpy as np

A = np.array([[1, 2],
              [3, 4]], dtype=float)

U, s, VT = np.linalg.svd(A, full_matrices=False)
Sigma = np.diag(s)

A_hat = U @ Sigma @ VT
err = np.linalg.norm(A - A_hat, ord='fro')

print("U=\n", U)
print("Sigma=\n", Sigma)
print("VT=\n", VT)
print("Frobenius error =", err)

```

Q13 (scikit-learn PCA):

```

import numpy as np
from sklearn.decomposition import PCA

np.random.seed(0)
X = np.random.randn(10, 3)

pca = PCA(n_components=2)
Z = pca.fit_transform(X)

print("Explained variance ratio:", pca.explained_variance_ratio_)

```