Module 6

Q. **Principal Component Analysis (PCA) for Dimension Reduction**

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1. Principal Component Analysis (PCA) is a **statistical technique used to reduce dimensions** in large datasets.
2. It helps in converting many **correlated variables** into a smaller number of **uncorrelated components**.
3. The main purpose of PCA is to simplify the data while keeping most of the important information.
4. It helps in **reducing data complexity** without losing much of the variation present in it.
5. PCA is mainly used in **machine learning and data science** for data preprocessing and feature reduction.
6. Example – In a dataset containing 100 features, PCA can reduce it to 10 important features while maintaining 90–95% of the information.

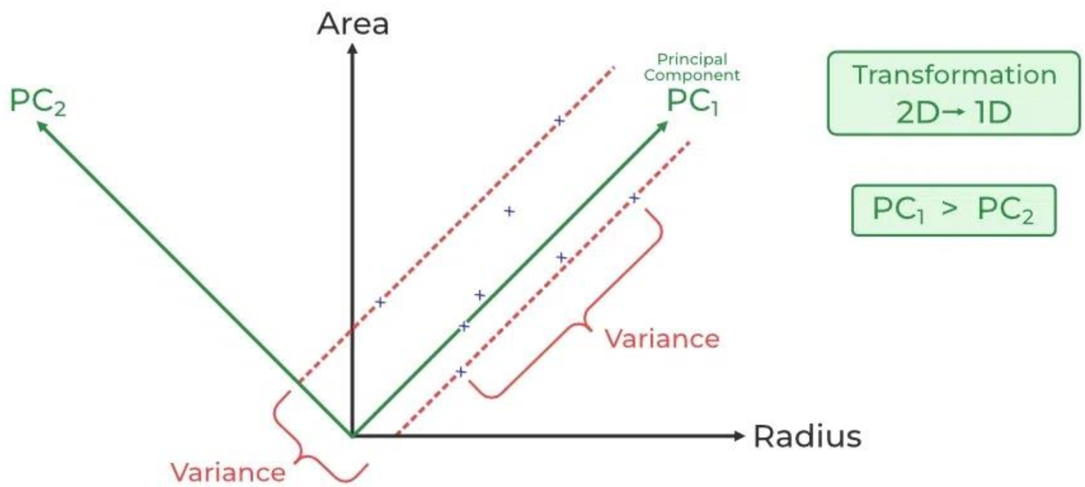
2. Concept and Working of PCA

1. PCA works by finding new axes or directions that **capture the highest variance** in the data.
2. Each new axis is called a **Principal Component (PC)**.
3. The **first principal component** captures the maximum variance in the data.
4. The **second component** captures the next most variance and is **perpendicular (uncorrelated)** to the first.
5. The process continues to find more components until all significant variations are captured.
6. The components are arranged in decreasing order of importance, based on how much variance they explain.
7. PCA changes the coordinate system of the data but not the actual information.

3. Mathematical Steps Involved

1. **Step 1 – Standardization:**
   The data is standardized so that all features have equal weight (mean = 0, variance = 1).
2. **Step 2 – Covariance Matrix:**
   A covariance matrix is computed to study how variables are related to one another.
3. **Step 3 – Eigenvalues and Eigenvectors:**
   PCA calculates eigenvalues and eigenvectors from the covariance matrix.
4. **Step 4 – Selecting Principal Components:**
   Eigenvalues show the importance of each component. The top ones are selected.

5. **Step 5 – Formation of New Dataset:**
   A new dataset is formed using the selected principal components.
6. **Example:**
   If a dataset has 5 features, and the first 2 components explain 95% of the total variance, PCA will keep only those 2 for further analysis.



4. Applications of PCA

1. **Image Processing:**
   PCA reduces thousands of pixel values into a few main image features.
   Example – Face recognition systems use PCA to extract key facial patterns.
2. **Finance:**
   PCA helps to identify main financial indicators from many correlated market variables.
3. **Genetics:**
   PCA is used to find key patterns in thousands of gene expression data points.
4. **Education:**
   PCA can combine several test scores into a few major academic performance factors.
5. **Machine Learning:**
   It is used for **feature extraction** before applying algorithms like K-Means or SVM.

Q. Linear Discriminant Analysis (LDA)

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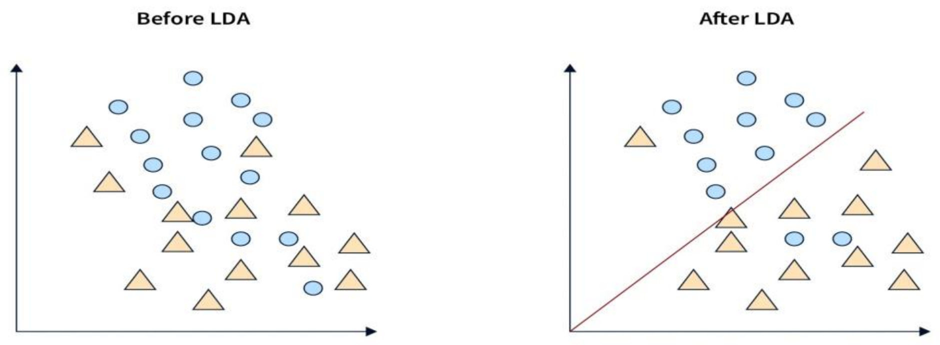
1. Introduction

1. **Linear Discriminant Analysis (LDA)** is a **supervised dimensionality reduction** technique used in machine learning.
2. It helps to **reduce the number of features** in the dataset while keeping the **class-separating information**.
3. Unlike PCA (which is unsupervised), LDA uses **class labels** to maximize separation between multiple classes.
4. LDA finds a new axis (or line) that best separates different classes in the data.
5. It is commonly used in **classification problems** to improve model accuracy and reduce complexity.
6. Example – LDA can separate email data into "spam" and "not spam" categories using fewer features.

2. Basic Concept of LDA

1. The main goal of LDA is to **maximize the distance between different classes** and **minimize the spread within the same class**.
2. It projects high-dimensional data onto a **lower-dimensional space** where the separation between classes is most visible.
3. It helps in improving the **decision boundary** of classification algorithms such as Logistic Regression, SVM, or KNN.
4. LDA assumes that each class's data points follow a **normal (Gaussian) distribution**.
5. It also assumes that each class has the **same covariance matrix**, which simplifies calculations.



3. Mathematical Steps in LDA

1. **Step 1 – Compute Mean Vectors:**
   Find the mean (average) of each class.
   Example – Mean of "spam" emails and mean of "non-spam" emails.
2. **Step 2 – Compute Scatter Matrices:**
   a. **Within-Class Scatter (SW):** Measures how data points vary inside each class.
   b. **Between-Class Scatter (SB):** Measures how far apart the means of classes are.
3. **Step 3 – Compute Projection Matrix:**
   The algorithm finds a matrix that maximizes the ratio of SB to SW.
   This ensures better separation between classes.
4. **Step 4 – Compute Eigenvalues and Eigenvectors:**
   Eigenvectors corresponding to the largest eigenvalues are selected.
   These vectors form the new axes (discriminant functions).
5. **Step 5 – Project Data:**
   The data is projected onto these new axes to get reduced-dimensional data.
6. Example – If data has 5 features but only 2 classes, LDA can reduce it to **1 feature** that best separates the classes.

4. Applications of LDA

1. **Face Recognition:**
   LDA is used to identify faces by reducing image pixels into class-separating features.
   Example – The **Fisherfaces method** for face recognition uses LDA.

2. **Text Classification:**
   LDA helps in separating documents into different categories like "sports," "politics," or "technology."
3. **Medical Diagnosis:**
   It helps doctors classify patients as "healthy" or "diseased" based on clinical features.
4. **Finance:**
   Used to classify customers into "high risk" or "low risk" groups for loan approval.
5. **Speech Recognition:**
   LDA reduces the number of features from voice signals while keeping class information.

5. Example for Better Understanding

1. Suppose we have a dataset of **students' marks** in Mathematics and English.
2. Each student is classified as either **"Passed"** or **"Failed."**
3. The marks of both subjects are plotted on a graph with two axes (Math and English).
4. LDA finds a **line (discriminant axis)** that best separates "Passed" and "Failed" students.
5. This line becomes the **new 1D feature**, reducing 2D data into 1D while preserving class information.