

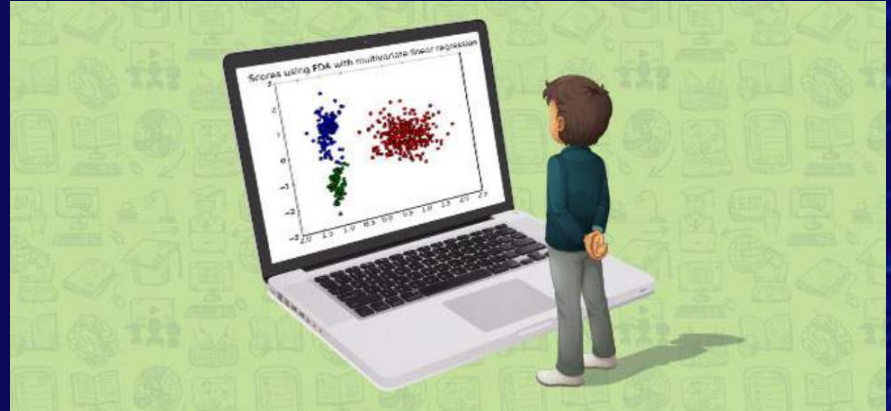
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## Unit 3.5

# Linear Discriminant Analysis in Machine Learning



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## Disclaimer

The content is curated from online/offline resources and used for educational purpose only

## Exam Score Analysis

**Scenario:** Imagine you are a teacher assessing the performance of your students in two subjects: Mathematics and English.

**Data Collection:** You have collected the scores of each student in both subjects for a class of 30 students.

**Scenario Description:** Upon plotting the scores of students in both subjects on a scatter plot, you notice that the data points are clustered in a way that suggests that the two subjects are correlated. However, it's not clear how well the scores distinguish high-performing students from low-performing ones.

## Learning Objectives

- Introduction
- What is Linear Discriminant Analysis?
- Assumptions of Linear Discriminant Analysis
- How LDA works and Steps Involved?
- Hands On
- PCA vs LDA
- Applications of LDA
- Disadvantages of LDA
- Hands On



## Introduction

- PCA aims to find the most accurate data representation in a lower dimensional space spanned by the maximum variance directions.
- However, such directions might not work well for tasks like classification.
- Here we present a new data reduction method that tries to preserve the discriminatory information between different classes of the dataset.

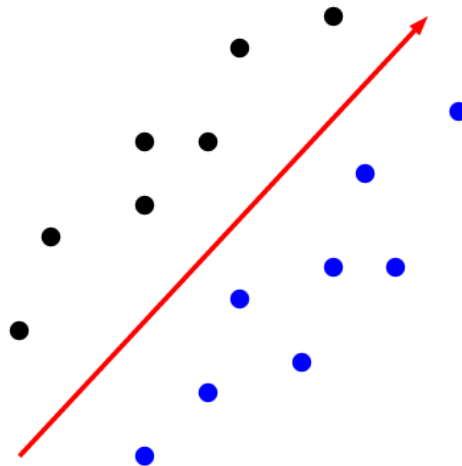


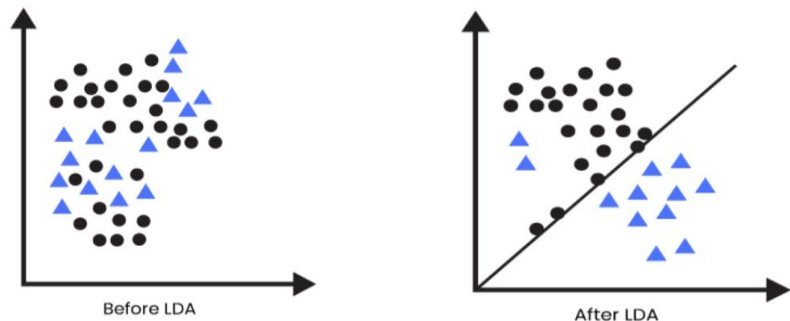
Image: Representative but not discriminative

## What is Linear Discriminant Analysis (LDA)?

- Linear Discriminant Analysis (LDA) is most commonly used as dimensionality reduction technique in the pre-processing step for pattern-classification and machine learning applications.
- The goal is to project a dataset onto a lower-dimensional space with good class-separability in order avoid overfitting (“curse of dimensionality”) and reduce computational costs.
- LDA was developed as early as 1936 by Ronald A. Fisher.
- The original Linear discriminant applied to only a 2-class problem.
- It was only in 1948 that C.R. Rao generalized it to apply to multi-class problems.

## What is Linear Discriminant Analysis (LDA).....?

- The main purpose of LDA is to find the line (or plane) that best separates data points belonging to different classes.
- The key idea behind LDA is that the decision boundary should be chosen such that it maximizes the distance between the means of the two classes.
- While maximizing distance LDA simultaneously minimizing the variance within each classes data or within-class scatter.
- This criterion is known as the Fisher criterion



[Image: LDA](#)

## Linear Discriminant Analysis Example

- For example: Consider a situation where you have plotted the relationship between two variables where each color represents a different class. One is shown with a red color and the other with blue in Image a.
- Suppose you want to reduce number of dimensions from 2 to 1, you can just project everything to the x-axis as shown below in Image b:

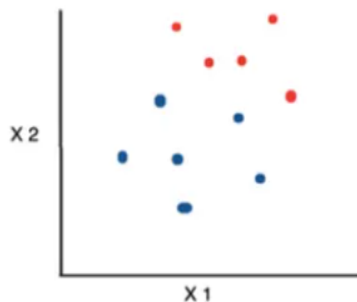


Image a

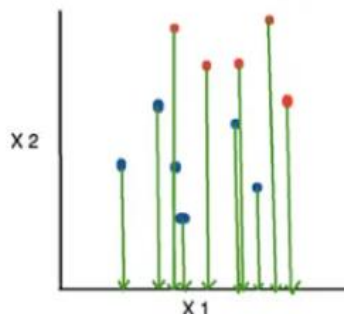


Image b

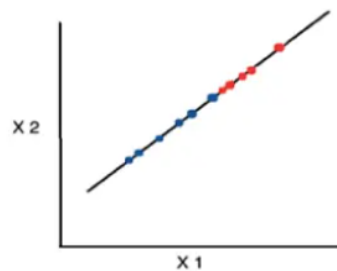
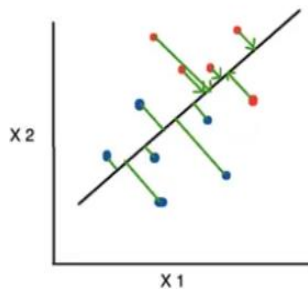


Result of projection to X axis



## Linear Discriminant Analysis Example....

- This approach neglects any helpful information provided by the second feature. However, you can use LDA to plot it.
- The advantage of LDA is that it uses information from both the features to create a new axis which in turn minimizes the variance and maximizes the class distance of the two variables.



[Image: LDA](#)

## Assumptions of Linear Discriminant Analysis

- Each feature (variable or dimension or attribute) in the dataset is a gaussian distribution. In other words, each feature in the dataset is shaped like a bell-shaped curve.
- Each feature has the same variance, the value of each feature varies around the mean with the same amount on average.
- Each feature is assumed to be randomly sampled.
- Lack of multicollinearity in independent features. Increase in correlations between independent features and the power of prediction decreases.

## How LDA works and Steps involved?

1. Calculate the separability between different classes. This is also known as between-class variance and is defined as the distance between the mean of different classes.

“Between-class scatter matrix”

$$S_b = \sum_{i=1}^g N_i (\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})^T$$

Overall mean

Sample size of class  $i$

Sample mean of class  $i$

The diagram shows the formula for the between-class scatter matrix,  $S_b$ . The term  $S_b$  is highlighted in a yellow box and labeled "Between-class scatter matrix" with a yellow arrow. The summation symbol  $\sum$  has a subscript  $i=1$  and a superscript  $g$ . The term  $N_i$  is highlighted in a green box and labeled "Sample size of class  $i$ " with a green arrow. The term  $\bar{x}_i$  is highlighted in a blue box and labeled "Sample mean of class  $i$ " with a blue arrow. The term  $\bar{x}$  is highlighted in a red box and labeled "Overall mean" with a red arrow. The term  $(\bar{x}_i - \bar{x})^T$  is highlighted in an orange box and labeled "Sample mean of class  $i$ " with an orange arrow.

[Image: Between class variance](#)

## How LDA works and Steps involved?

2. Calculate the within-class variance. This is the distance between the mean and the sample of every class.

“Within-class scatter matrix”

Sample size

$$S_w = \sum_{i=1}^g (N_i - 1) S_i = \sum_{i=1}^g \sum_{j=1}^{N_i} (x_{i,j} - \bar{x}_i)(x_{i,j} - \bar{x}_i)^T$$

The diagram illustrates the formula for the within-class scatter matrix  $S_w$ . It shows the summation over  $g$  classes of  $(N_i - 1) S_i$ , which is equivalent to the summation over all samples  $i$  and  $j$  of the product of the deviation of the sample from the class mean and its transpose. The terms  $S_i$  and  $N_i$  are highlighted with colored boxes and labeled with arrows.

[Image: within class variance](#)

## How LDA works and Steps involved?

3. Construct the lower-dimensional space that maximizes Step1 (between-class variance) and minimizes Step 2 (within-class variance). In the equation below  $P$  is the lower-dimensional space projection. This is also known as Fisher's criterion.

$$P_{lda} = \arg \max_P \frac{|P^T S_b P|}{|P^T S_w P|}$$

[Image: Fisher's criterion](#)

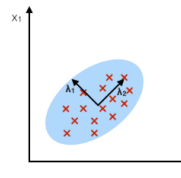
## Lab 1 Implementation of LDA in Python using scikit-learn

## Principal Component Analysis (PCA) vs. Linear Discriminant Analysis (LDA)

- PCA ignores class labels and focuses on finding the principal components that maximizes the variance in a given data. Thus it is an unsupervised algorithm.
- LDA is a supervised algorithm that intends to find the linear discriminants that represents those axes which maximize separation between different classes.
- LDA performs better multi-class classification tasks than PCA. However, PCA performs better when the sample size is comparatively small.

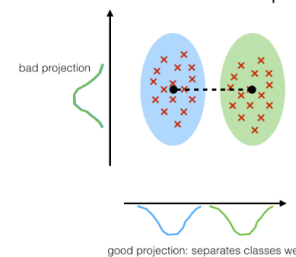
### PCA:

component axes that maximize the variance



### LDA:

maximizing the component axes for class-separation



## Applications of Linear Discriminant Analysis

- **Face Recognition:** LDA is used in face recognition to reduce the number of attributes to a more manageable number before the actual classification.
- **Medical:** You can use LDA to classify the patient disease as mild, moderate or severe. The classification is done upon the various parameters of the patient and his medical trajectory.
- **Customer Identification:** LDA helps in identifying and selecting which describes the properties of a group of customers who are most likely to buy a particular item in a shopping mall.
- **For predictions:** LDA is firmly used for prediction and hence in decision making, “will you read a book” gives you a predicted result through one or two possible class as a reading book or not.



## Disadvantages of LDA

- LDA is used specifically in solving supervised classification problems for multiple classes; something impossible if using logistic regression. But LDA does not work in cases when the mean of the distributions is shared.
- In such a situation, LDA can not produce a new axis that can linearly separate both classes. To solve this problem, non-linear discriminant analysis is used in machine learning.
- One of the primary disadvantages of LDA is its sensitivity to the assumptions it relies on.
- LDA requires a sufficient number of data points compared to the number of features.

## Lab 2 Comparison of PCA and LDA Using Wine Dataset

## Summary

- Linear Discriminant Analysis (LDA) is a dimensionality reduction technique that focuses on enhancing class separability.
- It aims to maximize the distance between class means and minimize within-class variance.
- LDA is particularly useful for classification tasks where class distinctions are important.
- The steps of LDA involve computing class means, within-class scatter matrix, between-class scatter matrix, eigenvalue decomposition, and projection.
- LDA assumes normal distribution, equal covariance matrices, and independence of features within classes.
- Despite its advantages, LDA can be sensitive to small sample sizes and non-linear relationships.

## Quiz

**Question 1: Which step in LDA involves performing eigenvalue decomposition?**

- A) Calculating class means
- B) Creating the projection matrix
- C) Selecting top eigenvectors
- D) Computing the between-class scatter matrix

**Answer: B)** Creating the projection matrix

## Quiz

**Question 2: LDA is most suitable for which type of data analysis tasks?**

- A) Clustering
- B) Dimensionality reduction
- C) Regression
- D) Visualization

**Answer: B)** Dimensionality reduction

## Quiz

**Question 3: What is a key disadvantage of Linear Discriminant Analysis (LDA)?**

- A) Sensitivity to outliers
- B) Inability to handle large datasets
- C) No assumptions required
- D) Works only for binary classification

**Answer: A) Sensitivity to outliers**

## Quiz

**Question 4: What is the primary goal of Linear Discriminant Analysis (LDA)?**

- A) Maximizing within-class variance
- B) Minimizing between-class separation
- C) Enhancing class separability
- D) Reducing overall data variance

**Answer: C)** Enhancing class separability

## Quiz

**Question 5: In LDA, the within-class scatter matrix measures:**

- A) Separation between class means
- B) Total variance within each class
- C) Similarity between class centroids
- D) Between-class distance

**Answer: B)** Total variance within each class



Thank you ...!