

Linear Discriminant Analysis

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Discussion Points

- Linear Discriminant Analysis
 - Objective
 - Steps
 - Use Case – Face Recognition

Objective

- Used to reduce the dimension of multivariate data, while preserving as much of the relevant information as possible.
 - If we have samples represented in the m dimensional space, $\{x_1, x_2, x_3, x_4, x_5, x_6, \dots, x_M\}$, our intension is to find out k features, such that $k \leq m$ that preserve most of the variance present in the data.
- However, we want to preserve as much of the class discriminatory information as possible.

Derivation

- In many physical, biological, and statistical convention it is desirable to represent a system of points with the help of a line or plane.
- Therefore, we can represent the equation of line with the linear combination of these points(variables).

$$y_k = \sum_{i=1}^m a_{ki} x_i \quad \text{Where } K=1,2,3, \dots, p$$

C_1	y_1		$a1_1$	$a1_2$	$a1_3$.	$a1_m$		x_1
	y_2		$a2_1$	$a2_2$	$a2_3$.	$a2_m$		x_2
C_2	y_3	=	$a3_1$	$a3_2$	$a3_3$.	$a3_m$	*	x_3

C_n	y_p		ap_1	ap_2	ap_3	.	ap_m		x_m

Steps used in LDA: [Step-1: Mean Calculation]

- Calculate mean of each class ($\mu_1, \mu_2, \dots, \mu_n$) and global mean (μ):

Let us assume, we have samples having m features. We have stored all these in a matrix called training samples T having N rows and M columns (where N represents the population and M represents the Features). So in that regard we have data like.

μ_1	$a1_1$	$a1_2$	$a1_3$.	$a1_m$
	$a2_1$	$a2_2$	$a2_3$.	$a2_m$
μ_2	$a3_1$	$a3_2$	$a3_3$.	$a3_m$

μ_n	ap_1	ap_2	ap_3	.	ap_m

Step-1: Calculate Between Class and Within Class Scatter Matrix

- Between Class Scatter Matrix
 - Represents the distance between the mean of two/n classes.

$$SB = \sum_{i=1}^n N_i (\mu_i - \mu) * (\mu_i - \mu)^T$$

- Within Class Scatter Matrix
 - Represents the variance of each class.

$$SW = \sum_{i=1}^n (s_i - \mu_i) * (s_i - \mu_i)^T$$

$a1_1$	$a1_2$	$a1_3$.	$a1_m$
$a2_1$	$a2_2$	$a2_3$.	$a2_m$
$a3_1$	$a3_2$	$a3_3$.	$a3_m$
.
ap_1	ap_2	ap_3	.	ap_m

Step-3: Calculate Cost Function

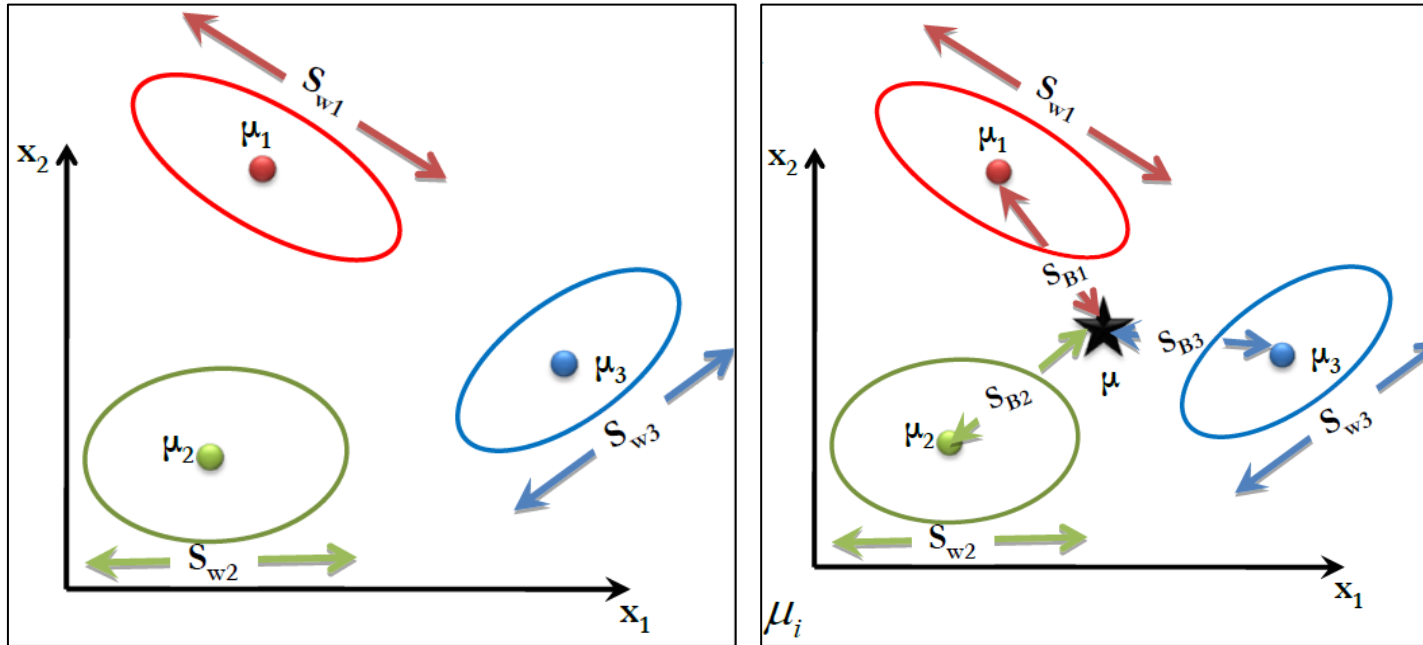


Sir Ronald Aylmer Fisher

■ Cost Function:

- Minimize the within class scatter matrix while maximize the between class scatter matrix.

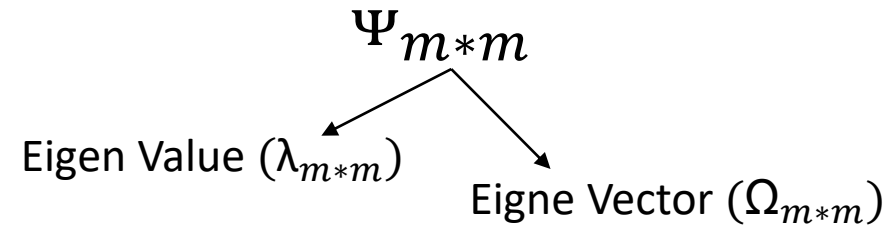
$$Cost(\Psi) = \frac{SB}{SW}$$



https://en.wikipedia.org/wiki/Ronald_Fisher

Step-4: Eigen Vector and Eigen Value Decomposition

- Linear discriminant components are the Eigen values and Eigen vectors, those are computed on the basis of cost function (Ψ), calculated in the previous step.



Step:4 Eigen Vector Selection

- Sort the eigen values in the descending order and the eigen vector as well.
- Select the k components out of m based on how much variance you want to preserve.

$$W = \begin{array}{|c|c|c|c|c|} \hline w1_1 & w1_2 & w1_3 & & w1_m \\ \hline w2_1 & w2_2 & w2_3 & & w2_m \\ \hline w3_1 & w3_2 & w3_3 & & w3_m \\ \hline . & . & . & & . \\ \hline wm_1 & wm_2 & wm_3 & & wm_m \\ \hline \end{array}$$

$m \times m$

$$W_k = \begin{array}{|c|c|c|} \hline w1_1 & w1_2 & w1_3 \\ \hline w2_1 & w2_2 & w2_3 \\ \hline w3_1 & w3_2 & w3_3 \\ \hline . & . & . \\ \hline wm_1 & wm_2 & wm_3 \\ \hline \end{array}$$

$m \times k$

Step 5: Projecting the data to principal directions

$$\text{ProjectedSamples}_{p \times k} = D_{p \times m} * W_{m \times k}$$

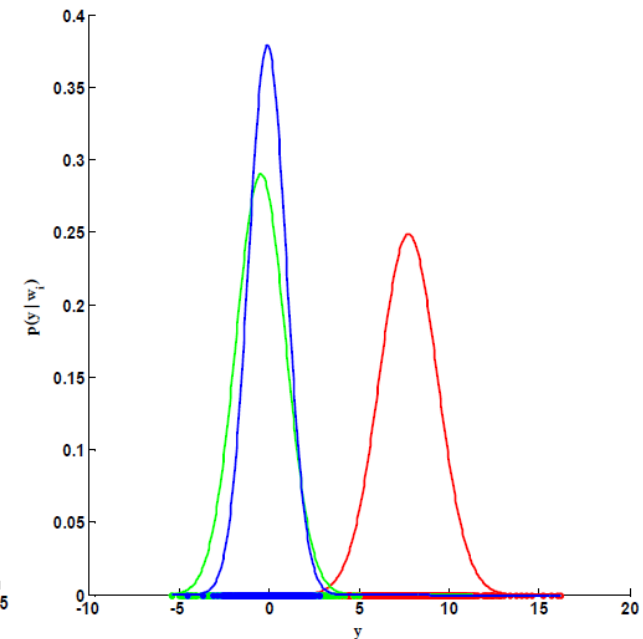
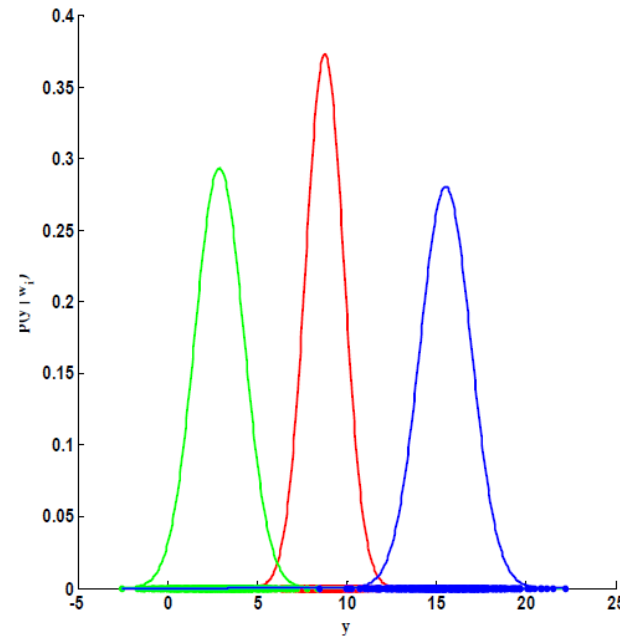
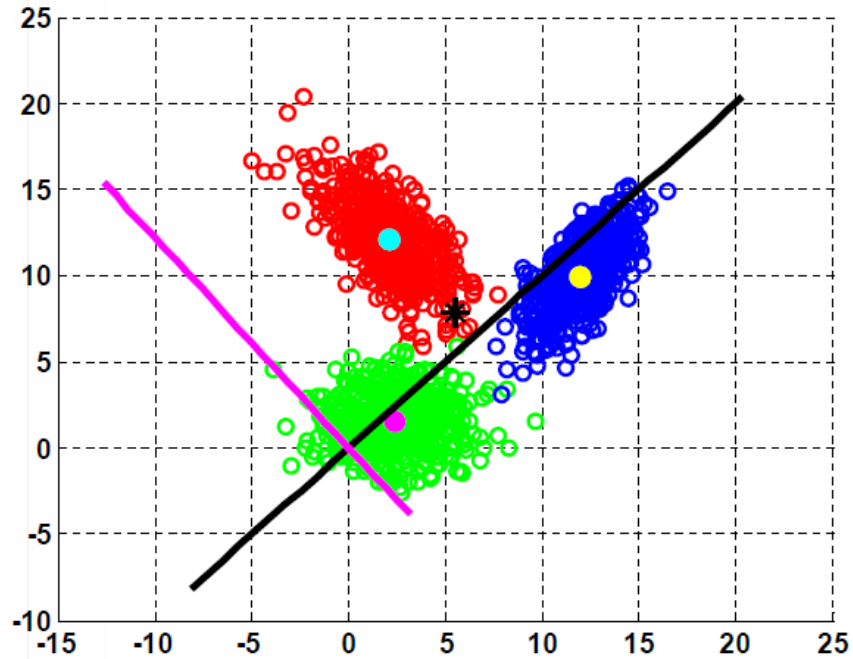
$a1_1$	$a1_2$	$a1_3$.	$a1_m$
$a2_1$	$a2_2$	$a2_3$.	$a2_m$
$a3_1$	$a3_2$	$a3_3$.	$a3_m$
.
ap_1	ap_2	ap_3	.	ap_m

 \times

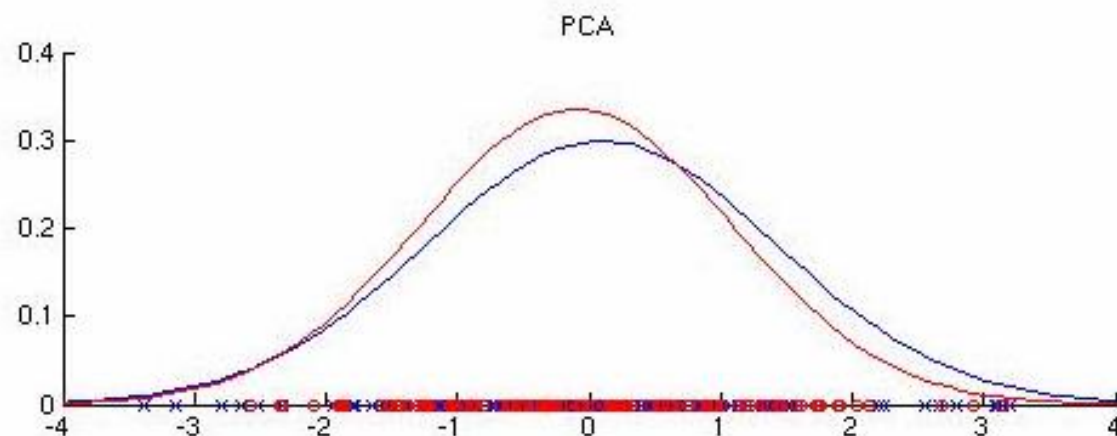
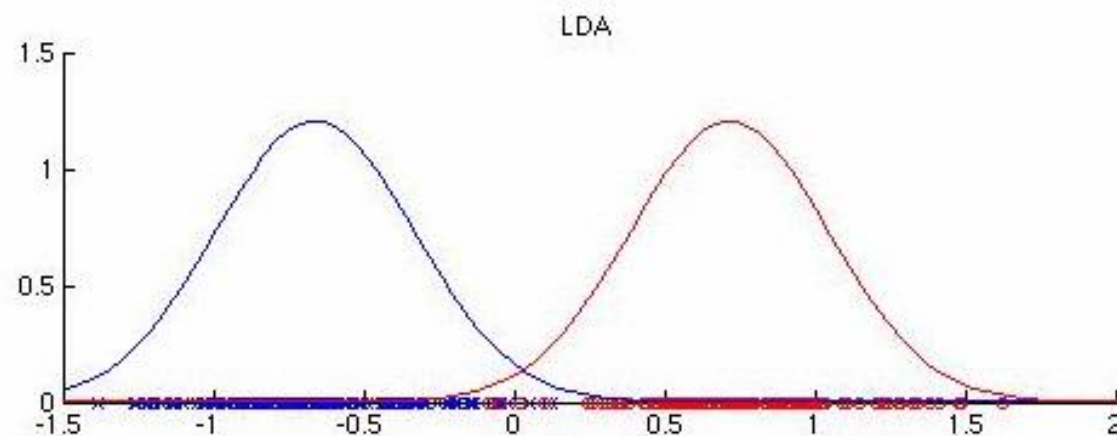
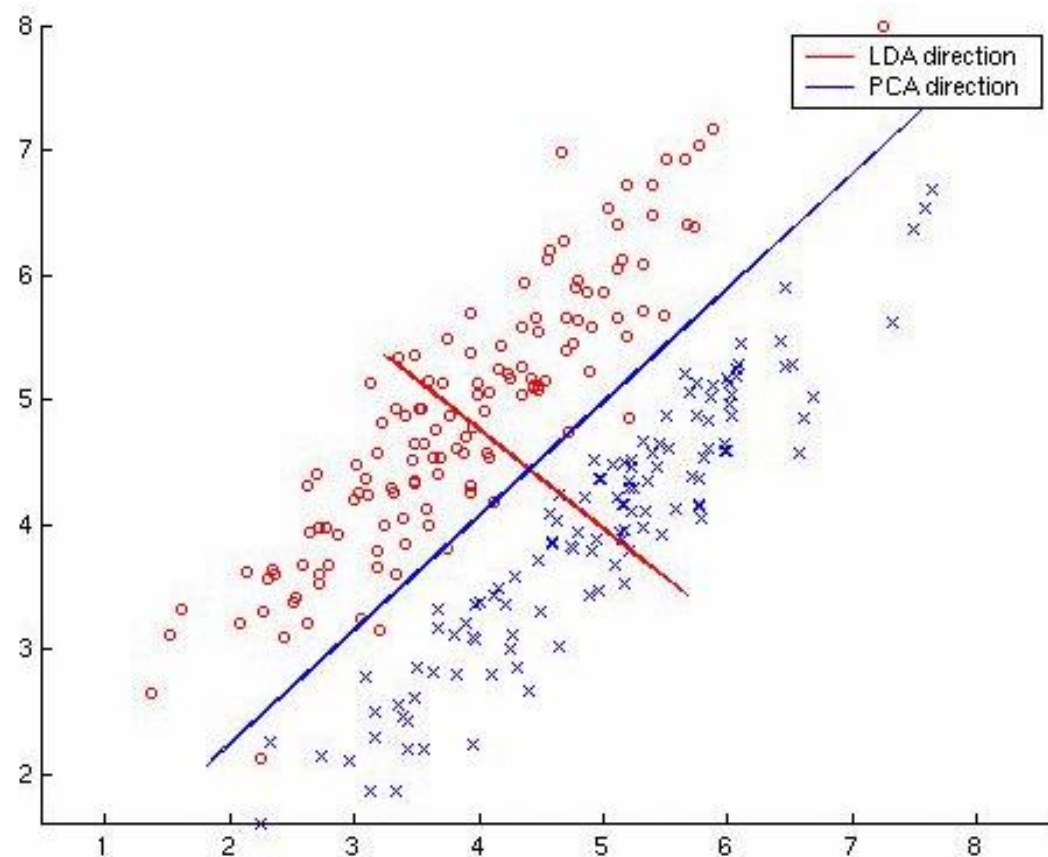
$w1_1$	$w1_2$	$w1_3$
$w2_1$	$w2_2$	$w2_3$
$w3_1$	$w3_2$	$w3_3$
.	.	.
wm_1	wm_2	wm_3

LDA : Another use case

$$\lambda = \begin{bmatrix} 4508.2089 \\ 1878.8511 \end{bmatrix}$$

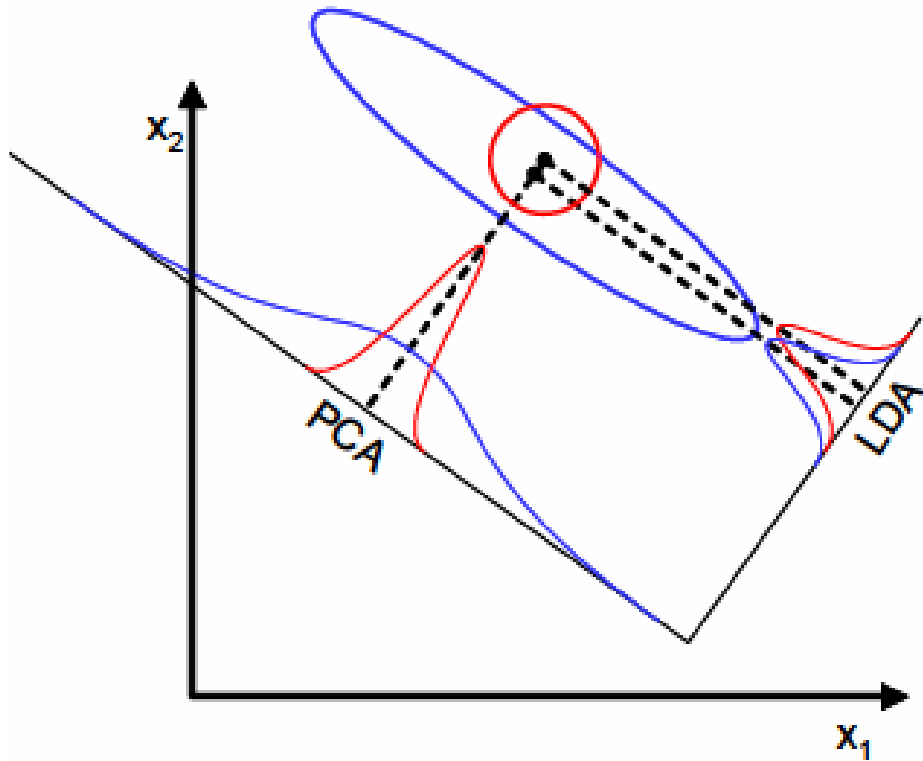


PCA VS LDA



When to use LDA and When PCA

- LDA will fail when the discriminatory information is not in the mean but rather in the variance of the data



Limitation

