

LINEAR DISCRIMINANT ANALYSIS (LDA)

Goal :- To project a feature space (N dimensional data) onto a smaller subspace k ($k \leq n-1$) while maintaining the class discriminatory info.

Example :-

Consider 2-D dataset with class information.

x_1	x_2	Y
4	1	C_1
2	4	C_2
2	3	C_1
3	6	C_1
4	4	C_1
9	10	C_2
6	8	C_2
9	5	C_2
8	7	C_2
10	8	C_2

Step 1 :- Compute within class scattered matrix (S_W)

$$S_W = S_1 + S_2$$

S_1 is the covariance matrix for class C_1 ,

S_2 is the covariance matrix for class C_2 .

So, let's compute the covariance matrices of each class

$$S_1 = \sum_{x \in C_1} (x - \mu_1) (x - \mu_1)^T$$

μ_1 is the mean of class C_1 , which is computed by

$$\mu_1 = \left\{ \frac{4+2+2+3+4}{5}, \frac{1+4+3+6+4}{5} \right\}$$
$$= [3.00, 3.60]$$

similarly $\mu_2 = \left\{ \frac{9+6+9+8+10}{5}, \frac{10+8+5+7+8}{5} \right\}$

$$= [8.4, 7.60]$$

Now Again, $S_1 = \sum_{x \in C_1} (x - \mu_1) (x - \mu_1)^T$

$$(x - \mu_1) = \begin{bmatrix} 4-3 & 2-3 & 2-3 & 3-3 & 4-3 \\ 1-3.6 & 4-3.6 & 3-3.6 & 6-3.6 & 4-3.6 \end{bmatrix}$$
$$= \begin{bmatrix} 1 & -1 & -1 & 0 & 1 \\ -2.6 & 0.4 & -0.6 & 2.4 & 0.4 \end{bmatrix}$$

Now, For each x , we are going to calculate $(x - \mu_1) (x - \mu_1)^T$. So, we will have 5 such matrices

we have to calculate one by one for each,

$$\begin{bmatrix} 1 \\ -2.6 \end{bmatrix} \begin{bmatrix} 1 & -2.6 \end{bmatrix} = \begin{bmatrix} 1 & -2.6 \\ -2.6 & 6.76 \end{bmatrix} \quad \text{--- ①}$$

↳ First matrix

Similarly, for rest we get

$$\begin{bmatrix} -1 \\ 0.4 \end{bmatrix} \begin{bmatrix} -1 & 0.4 \end{bmatrix} = \begin{bmatrix} 1 & -0.4 \\ -0.4 & 0.16 \end{bmatrix} \quad \text{--- (2)}$$

$$\begin{bmatrix} -1 \\ -0.6 \end{bmatrix} \begin{bmatrix} -1 & -0.6 \end{bmatrix} = \begin{bmatrix} 1 & 0.6 \\ 0.6 & 0.36 \end{bmatrix} \quad \text{--- (3)}$$

$$\begin{bmatrix} 0 \\ 2.4 \end{bmatrix} \begin{bmatrix} 0 & 2.4 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 5.76 \end{bmatrix} \quad \text{--- (4)}$$

$$\begin{bmatrix} 1 \\ 0.4 \end{bmatrix} \begin{bmatrix} 1 & 0.4 \end{bmatrix} = \begin{bmatrix} 1 & 0.4 \\ 0.4 & 0.16 \end{bmatrix} \quad \text{--- (5)}$$

Adding (1), (2), (3), (4), and (5) and taking average we get covariance matrix S_1 ,

$$S_1 = \begin{bmatrix} 0.8 & -0.4 \\ -0.4 & 2.6 \end{bmatrix}$$

Similarly, for the class 2, the covariance matrix is given by

$$S_2 = \begin{bmatrix} 1.84 & -0.04 \\ -0.04 & 2.64 \end{bmatrix}$$

$$\text{NOW, } S_W = S_1 + S_2$$

$$= \begin{bmatrix} 2.64 & -0.44 \\ -0.44 & 5.28 \end{bmatrix}$$

Step 2 :- Compute between class scattered matrix S_B

$$\begin{aligned} S_B &= (\mu_1 - \mu_2) (\mu_1 - \mu_2)^T \\ &= \begin{pmatrix} -5.4 \\ -4 \end{pmatrix} \begin{pmatrix} -5.4 & -4 \end{pmatrix} \\ &= \begin{pmatrix} 29.16 & 21.6 \\ 21.6 & 16.00 \end{pmatrix} \end{aligned}$$

Step 3 :- Find the best LDA projection vector.

Similar to PCA, we find this using eigen vectors having largest eigen value:

$$S_W^{-1} \cdot S_B V = \lambda \cdot V$$

↑ ↑ ↓
within class between class projection vector
scattered matrix scattered matrix

$$|S_W^{-1} \cdot S_B - \lambda I| = 0$$

$$\begin{vmatrix} 11.89 - \lambda & 8.81 \\ 5.08 & 3.76 - \lambda \end{vmatrix} = 0$$

Solving λ , we get $\lambda = 15.65$

substitute λ value and

$$\begin{bmatrix} 11.89 & 8.81 \\ 5.08 & 3.76 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = 15.65 \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$$

we get, $\begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} 0.91 \\ 0.39 \end{bmatrix}$

or we get directly by solving

$$\begin{aligned} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} &= S_w^{-1} (\mu_1 - \mu_2) \\ &= \begin{bmatrix} 0.1921 & -0.032 \\ -0.031 & 0.38 \end{bmatrix} \begin{bmatrix} -5.4 \\ -4 \end{bmatrix} \\ &= \begin{bmatrix} -0.91 & -0.39 \end{bmatrix}^T \end{aligned}$$

S_w^{-1} is found by using the formula,

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

Step 4 :- Dimension Reduction

$$y = \underset{\substack{\uparrow \\ \text{projection vector}}}{W^T} x \leftarrow \begin{matrix} \text{Input data} \\ \text{sample} \end{matrix}$$

$$= \begin{bmatrix} 4 & 1 \\ 2 & 4 \\ 2 & 3 \\ 3 & 6 \\ 4 & 4 \\ 9 & 10 \\ 6 & 8 \\ 9 & 5 \\ 8 & 7 \\ 10 & 8 \end{bmatrix} \cdot \begin{bmatrix} 0.91 \\ 0.39 \end{bmatrix} = \begin{bmatrix} 4.03 \\ 3.38 \\ 2.99 \\ 5.07 \\ 5.2 \\ 12.09 \\ 8.58 \\ 10.14 \\ 10.01 \\ 12.22 \end{bmatrix}$$