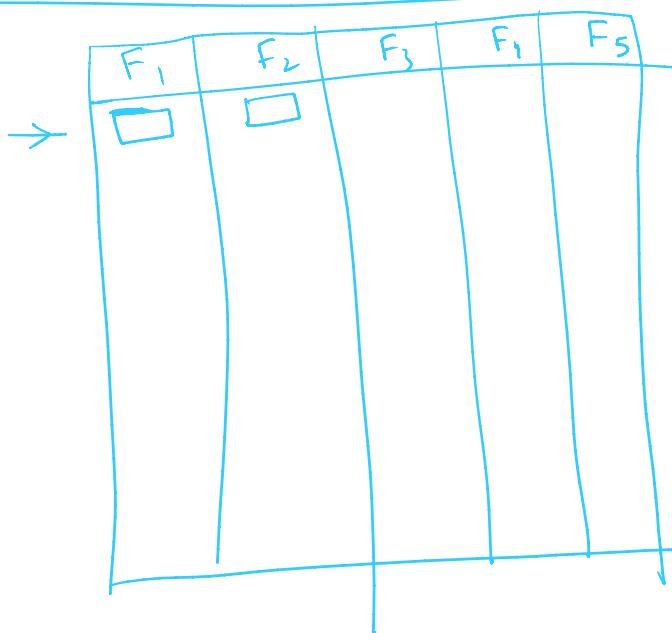
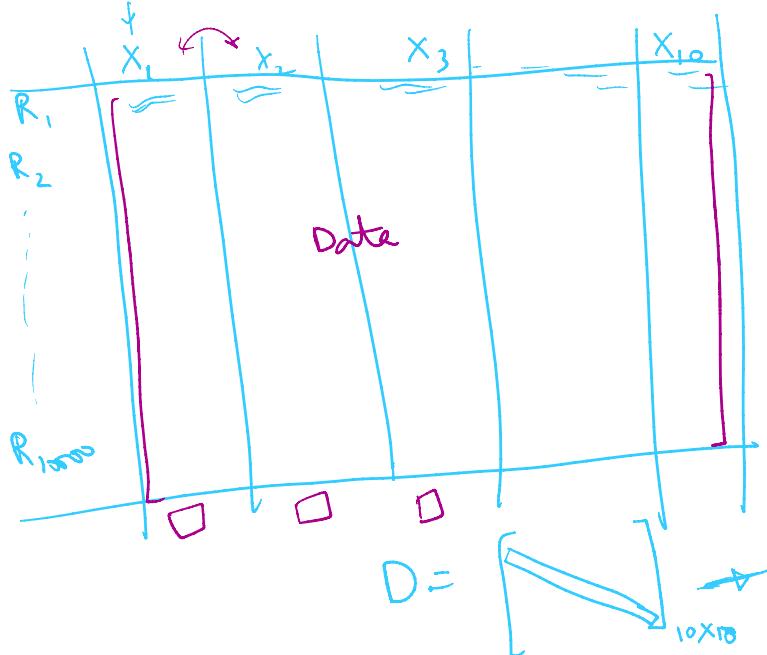


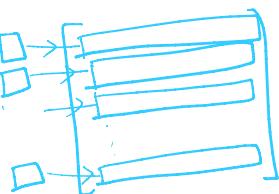
10000 data points  
~ 8000 data points →  
Build the model

~ 2000 data points



$$\lambda_1 + \lambda_2 + \dots + \lambda_{10} = \text{Sum of Variances}$$

$$\frac{(\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5)}{(\lambda_1 + \lambda_2 + \dots + \lambda_{10})}$$



$$A = \begin{bmatrix} & \\ & \\ & \\ & \\ & \end{bmatrix}$$

$$\frac{A^T A}{n}$$

~~Matrices~~  

$$\begin{matrix} \text{Data} & \xrightarrow{\text{Trans}} & \text{Data} \\ \downarrow & & \\ 10 \times 10000 & & 10000 \times 10 \end{matrix}$$

① SVD - Singular Value Decomposition

② LDA → Linear Discriminant

## ① SVD - Singular Value Decomposition

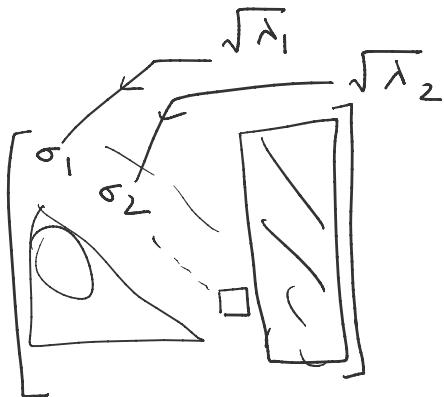
$$A = \underset{(m \times n)}{U} \underset{(m \times m)}{\Sigma} \underset{(n \times n)}{V^T}$$

$U = \text{orthogonal eigenvectors of } [A^T A]$

$V = \text{orthogonal eigenvectors of } [A^T A]$

## ② LDA → Linear Discriminant Analysis

**Singular Values**



$$\underset{m \times n}{[A]} = \left[ \begin{array}{c|c} & \text{Orthogonal basis } U \\ \hline & \sigma_1 \ \sigma_2 \ \dots \ \sigma_n \\ & \sqrt{\lambda_1} \ \sqrt{\lambda_2} \ \dots \ \sqrt{\lambda_n} \end{array} \right] \begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix}$$

## Concept of Rank of a Matrix

$$\begin{aligned} v_1 &\rightarrow \begin{bmatrix} 1 & -1 \\ 2 & 2 \end{bmatrix} \\ v_2 &\rightarrow \begin{bmatrix} 1 & -1 \\ 0 & 0 \end{bmatrix} \end{aligned}$$

$$2v_1 - v_2 = \begin{bmatrix} 0 & 0 \end{bmatrix}$$

Rank = 1

$$\begin{aligned} R_i &= R_i - k R_j \\ R_2 &= R_2 - 2 R_1 \end{aligned} \quad \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}$$

$$\begin{aligned} v_1 &\left[ \begin{array}{ccc} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{array} \right] \\ v_2 & \\ v_3 & \end{aligned}$$

$$\alpha_1 v_1 + \alpha_2 v_2 + \alpha_3 v_3 = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}$$

$$\alpha_1 = \alpha_2 = \alpha_3$$

Rank = 3

**"Column Rank = Row Rank = Rank of a Matrix"**

No. of non-zero eigenvalues =  
Rank of the matrix.

$$A = \sum_{m+n} U \Sigma V^T$$

$$\begin{bmatrix} u_1 & u_2 & \dots & u_m \\ \vdots & \vdots & \ddots & \vdots \end{bmatrix} \begin{bmatrix} \sigma_1 & & & \\ & \sigma_2 & & \\ & & \ddots & \\ & & & \sigma_n \end{bmatrix} \begin{bmatrix} v_1^T & v_2^T & \dots & v_n^T \\ \vdots & \vdots & \ddots & \vdots \end{bmatrix}$$

$$= \underbrace{\sigma_1 u_1 v_1^T}_{\substack{(m \times 1) \\ (1 \times n)}} + \underbrace{\sigma_2 u_2 v_2^T}_{\substack{+ \\ \vdots}} + \dots + \underbrace{\sigma_n u_n v_n^T}_{\substack{+ \\ \vdots}}$$

$$A = \underline{200 \times 300} \\ \approx \underline{60000}$$

$$\text{rank}(A) = \cancel{30} + \cancel{150}$$

$$(m+n+1) \times n \\ 501 \times \cancel{150} = \frac{15030}{75150}$$

$$\begin{bmatrix} a & c & \begin{bmatrix} e \\ f \end{bmatrix} \\ b & d & \begin{bmatrix} g \\ h \end{bmatrix} \end{bmatrix}_{2 \times 3} \rightarrow \begin{bmatrix} \begin{smallmatrix} \downarrow & \downarrow \\ 1 & 0 \end{smallmatrix} & \begin{smallmatrix} \downarrow \\ 0 \end{smallmatrix} & \begin{smallmatrix} \downarrow \\ 1 \end{smallmatrix} \\ \begin{bmatrix} 1 \\ 0 \end{bmatrix} & \begin{bmatrix} 0 \\ 1 \end{bmatrix} & \begin{bmatrix} 1 \\ 1 \end{bmatrix} \end{bmatrix}$$

$$605 \times 806$$

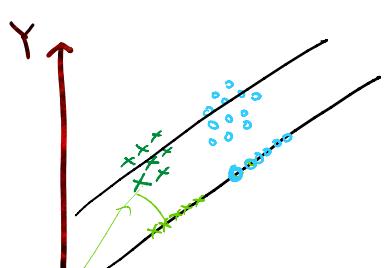
$$\approx \underline{480000}$$

50 singular values

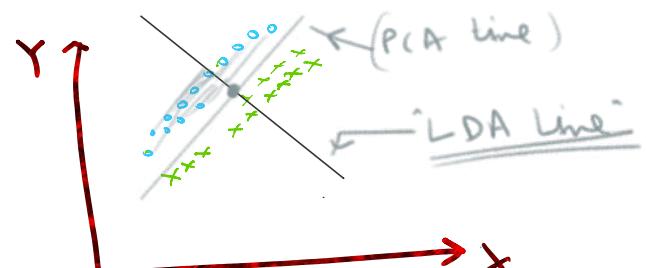
$$\underbrace{\sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \dots + \sigma_n u_n v_n^T}_{(50)} \\ \substack{(605 \times 1) \\ (806 \times 1)}$$

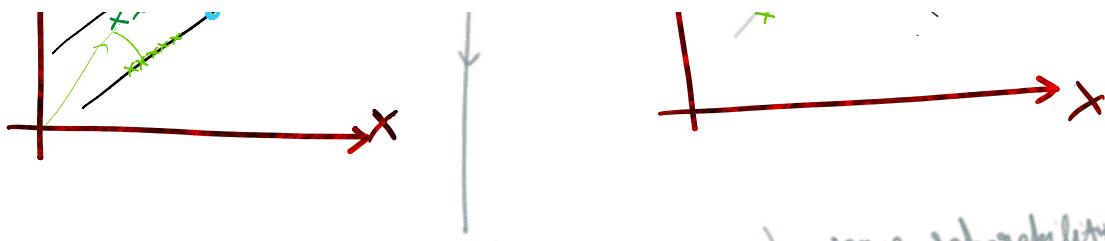
$$(605+806+1) \approx 1412$$

$$1412 \times 50 \approx \underline{70600}$$



LDA

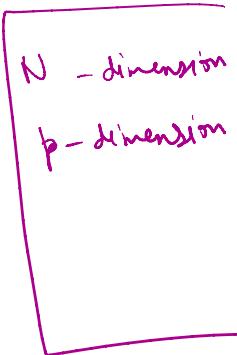
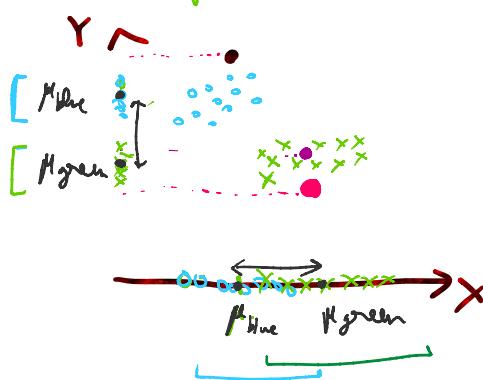
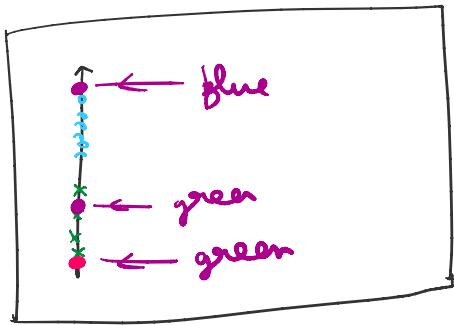




Lower the number of dimensions + preserve separability in the lower dimension.



Objective: ① Max the mean distance of the classes



② Min the scatter:

$$S_{\text{blue}}^2 = \sum_{\text{blue}} (y_{pi} - \mu_{p,\text{blue}})^2$$

$$S_{\text{green}}^2 = \sum_{\text{green}} (y_{pi} - \mu_{p,\text{green}})^2$$

$$\textcircled{1} \text{ Max: } (\mu_{p,\text{blue}} - \mu_{p,\text{green}})^T (\mu_{p,\text{blue}} - \mu_{p,\text{green}}) = (\mu_1 - \mu_2)^2$$

$$\textcircled{2} \text{ Min: } S_{\text{blue}}^2 + S_{\text{green}}^2 \Rightarrow \text{Max: } \frac{1}{S_{\text{blue}}^2 + S_{\text{green}}^2}$$

$$\left( \text{Max: } \left[ \frac{(\mu_1 - \mu_2)^2}{S_{\text{blue}}^2 + S_{\text{green}}^2} \right] \right)$$

$$S_w = S_{\text{blue}}^2 + S_{\text{green}}^2$$

$$v = S_w^{-1} (\mu_2 - \mu_1)$$