

# Linear Discriminant Analysis

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# LDA

- Find the function that better predicts the class of an object
- Based on Factorial methods

# LDA

## ■ Given

- A data matrix  $X$  ( $n \times p$ ) centered
  - $n$  individuals
  - $p$  variables
- $Y$  categorical variable ( $m$  modalities)



	Workload	Distance to work	Salary	Y
Smith	1.0	0.2	1.2	A
Johnson	2.0	0.0	0.3	A
Williams	-1.0	0.1	-1.0	B
Jones	-2.0	0.2	-0.1	A
Davis	0.0	-0.4	-0.4	B

## ■ Total Variability of $X$ :

–  $T_{pp} = X'PX$

–  $P = \text{diagonal}(1/n)$        $T_{pp} = V(X) = \frac{(X - \bar{X})^2}{n}$

Matricial notation. Care, centered data means  $\bar{X}=0$

# LDA

## ■ Variability decomposition

- Total variability  $T_{pp} = X^t P X$

- $T = E + D$

- $E = G^t H G$

- G centroids matrix

- $H = \text{diag}(n_k/n)$

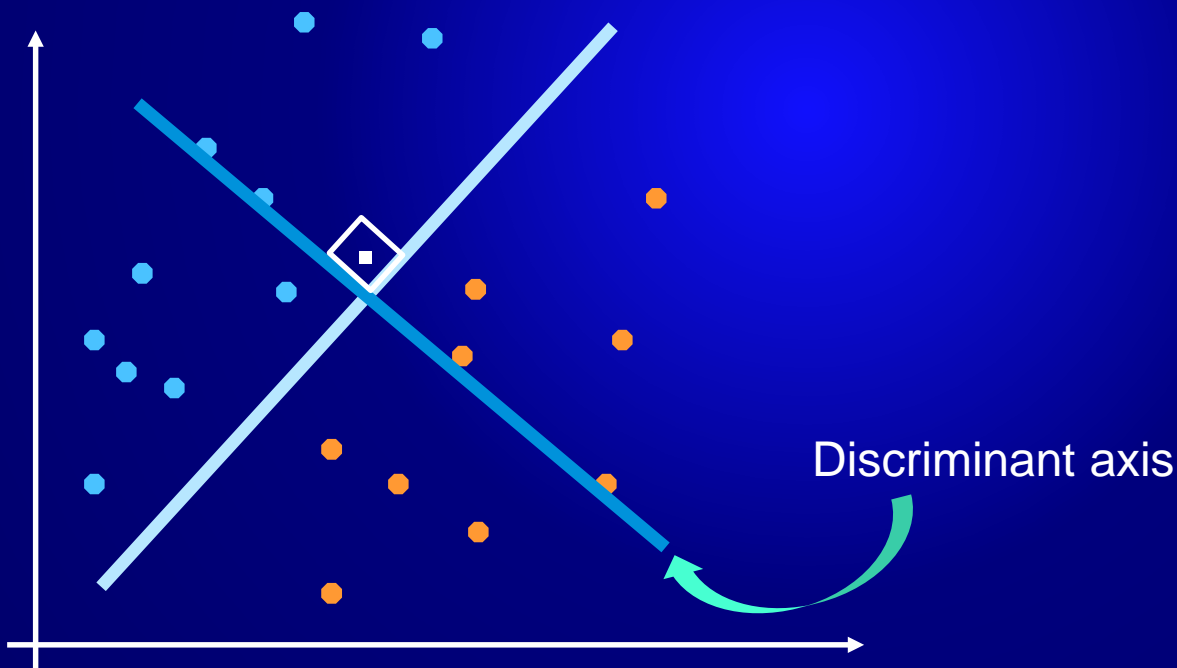
- $D = X'^t P X$

- $X' = (x_{ij} - g_{kj})$

- $P = \text{diag}(1/n)$

# Linear Discriminant Analysis

- Find the axis that better discriminates



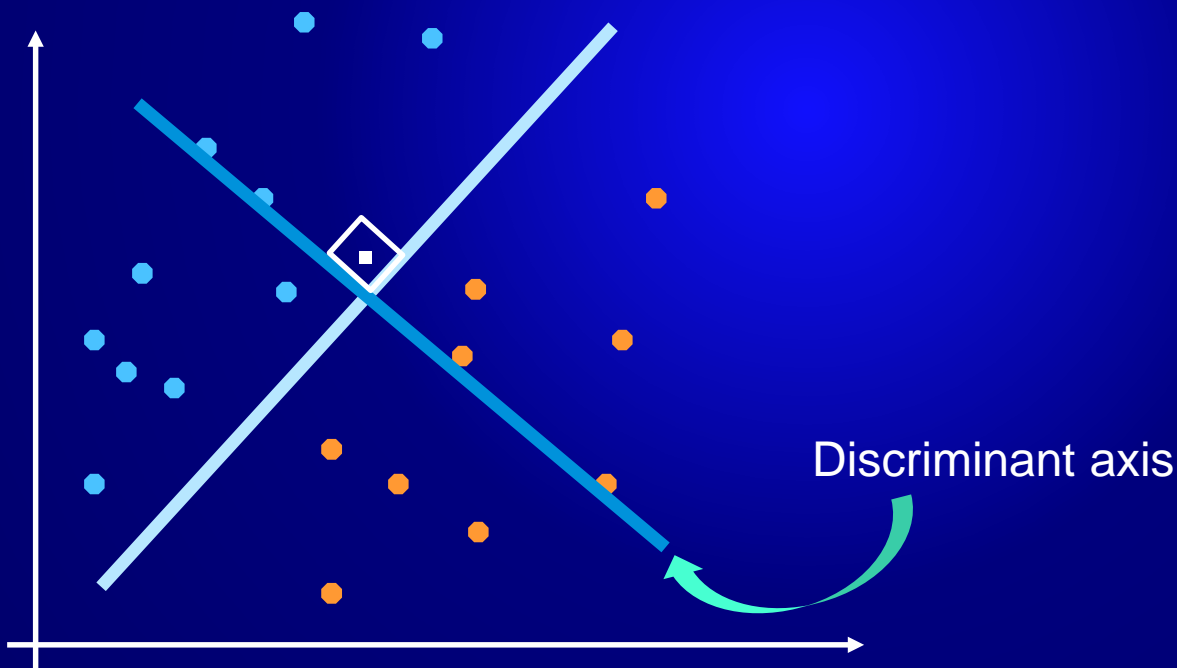
# LDA

## ■ Factorial spaces

- $\langle X_{n \times p}, I_p, P_{n \times n} \rangle$
- $\langle G_{m \times p}, I_p, H_{m \times m} \rangle$
- $\langle G_{m \times p}, D_{p \times p}, H_{m \times m} \rangle$
- *Projected variabilities on direction  $\vec{w}$*
- *Total variability projected  $\vec{w}^t T \vec{w}$*
- *Between Classes variability projected  $\vec{w}^t E \vec{w}$*
- *Within Classes variability projected  $\vec{w}^t D \vec{w}$*

# Linear Discriminant Analysis

- Find the axis that better discriminates
- Find the axis that maximizes  $\vec{w}^t E \vec{w}$



# LDA

- $\langle G, D^{-1}, H \rangle$
- Search direction  $\vec{w}$  such that  $\vec{w}^t E \vec{w}$  is maximized
- Diagonalization of
$$\vec{u}^t D^{-1} G^t H G D^{-1} \vec{u}$$
subject to  $\vec{u}^t D \vec{u} = 1$
- The first eigen value points to an eigen vector that gives solution