

$$L_p = \left( \sum_{i=1}^D |x_i - y_i|^p \right)^{1/p} \quad p=2 \text{ generally}$$

$$d_2^2(x, y) = \sum_{i=1}^D |x_i - y_i|^2 \quad \text{euclidean distance}$$

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_D \end{bmatrix} \quad y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_D \end{bmatrix}$$

$$d_2^2(x, y) = (x - y)^T (x - y)$$

height = x	weight = y		$x_i - \mu_x$	$y_i - \mu_y$
70	40		5	0
67	45	→	2	5
65	50		0	10
58	35		-7	-5
60	30		-5	-10

$$\mu_x = \frac{1}{n} \sum_{i=1}^n x_i = \sum_{i=1}^n p_i x_i$$

$$\text{var}(x) = \frac{1}{n} \sum_{i=1}^n (x_i - \mu_x)^2$$

$$\text{covariance}(x, y) = \frac{1}{n} \sum_{i=1}^n (x_i - \mu_x)(y_i - \mu_y)$$

$$\left. \begin{array}{l} \sum x_i y_i > 0 \\ \text{cov}(x, y) > 0 \end{array} \right\} x \text{ increases} \rightarrow y \text{ increases}$$

$$\left. \begin{array}{l} \sum x_i y_i < 0 \\ \text{cov}(x, y) < 0 \end{array} \right\} \rightarrow x \text{ increases} \rightarrow y \text{ decreases}$$

$$\text{cov}(x, y) = 0 \rightarrow \text{cant say anything.}$$

→ correlation value.

$$\rho(x, y) = \frac{\text{cov}(x, y)}{\sqrt{\text{var}(x) \text{var}(y)}}$$

$$-1 \leq \rho(x, y) \leq 1$$

$$\sum_{i,j=1}^n f_i \begin{bmatrix} f_1 & f_2 & f_3 & \dots \\ \text{cov}(f_1, f_1) & \text{cov}(f_1, f_2) & \text{cov}(f_1, f_3) & \dots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

$$\text{cov}(f_i, f_j) = \text{cov}(f_j, f_i)$$

$$\text{cov}(f_i, f_i) = \text{var}(f_i)$$

$\Sigma$  is real, positive, symmetric definite matrix.

positive definite  $\rightarrow x'Ax > 0$  for any vector  
 $\rightarrow$  then  $|\Sigma| > 0$   $\Sigma^{-1}$  is also positive definite.

$$d_M^2(c_1, x) = (x - \mu_1)' \Sigma^{-1} (x - \mu_1)$$

$$d_M^2(c_1, c_2) = (\mu_2 - \mu_1)' \Sigma^{-1} (\mu_2 - \mu_1)$$

$$\Sigma = \frac{\Sigma_1 + \Sigma_2}{2}$$

$$\cos \theta = \frac{x \cdot y}{|x| |y|} \rightarrow \frac{x^T y}{\sqrt{\sum_{i=1}^n x_i^2} \sqrt{\sum_{i=1}^n y_i^2}}$$

eigenvalues and eigenvector

$$Ax = \lambda x$$

$$A_{D \times D} \quad x_{D \times 1}$$

$$|A - \lambda I| = 0$$

$$\lambda_1, \lambda_2, \dots, \lambda_D \rightarrow \text{eigenvalue}$$

$$v_1, v_2, \dots, v_D \rightarrow \text{corresponding eigenvector}$$

calculate dispersion matrix  $\Sigma$ :

a) subtract mean from each data in the dataset

$$b) \Sigma_{D \times D} = X^T X \quad X = \mu \text{ subtracted dataset}$$

c) calculate eigenvalues and eigenvectors of  $\Sigma$

$$\text{trace}(\Sigma) = \sum \lambda_i \quad \lambda_i \geq 0$$

if arrange  $\lambda_1 > \lambda_2 > \dots > \lambda_D$

$$\begin{matrix} v_1 & v_2 & \dots & v_D \\ \hline & d < D \end{matrix}$$

$$\frac{\sum_{i=1}^d \lambda_i}{\sum_{i=1}^D \lambda_i}$$

$\geq 97\% \rightarrow$  not all dimensions are equally important in terms of spread of data.

$$|\Sigma| = \lambda_1 \cdot \lambda_2 \cdot \lambda_3 \cdot \dots \cdot \lambda_D$$

$$W_{D \times D} = \begin{bmatrix} v_1 & v_2 & \dots & v_D \end{bmatrix}$$

$$Y_{D \times N} = W_{D \times D}^T X_{D \times N}^T$$

eg  $X = \begin{bmatrix} 2 & 1 \\ 3 & 5 \\ 4 & 3 \\ 5 & 6 \\ 6 & 7 \\ 7 & 8 \end{bmatrix}$   
 $\mu_1 = 4.5 \quad \mu_2 = 5$

$$X' = \begin{bmatrix} -2.5 & -4 \\ -1.5 & 0 \\ -0.5 & -2 \\ 0.5 & 1 \\ 1.5 & 2 \\ 2.5 & 3 \end{bmatrix}$$

$$\Sigma = \frac{1}{n} X'^T X' = \frac{1}{6} \begin{bmatrix} 17.5 & 22 \\ 22 & 34 \end{bmatrix} = \begin{bmatrix} 2.92 & 3.67 \\ 3.67 & 5.67 \end{bmatrix}$$

$$\lambda_1 = 8.22 \quad \lambda_2 = 0.37$$



$V_1$ 

$$W_k = \begin{bmatrix} 2.55 \\ 3.67 \end{bmatrix}$$

$$w^T = [2.55 \quad 3.67]$$

$$Y = w^T X^T = \begin{bmatrix} 8.77 \\ 2.6 \\ 21.21 \\ 34.77 \\ 40.92 \\ 47.21 \end{bmatrix}$$

$$= [8.77 | 2.6 | 21.21 | 34.77 | 40.92 | 47.21]$$

Intra class distance should be small (within)  
 Inter class distance should be large (between)

## # Machine Learning

### Classification

1. Supervised
2. Given an unknown pattern and assign into predefined classes
3. Generate and train a classification model with the help of training data.

### Clustering

- Unsupervised
- Based on similarity measure among patterns, develop an algo to find natural grouping

## Classification

- Probabilistic (Baye's)
- similarity based (MDC, KAN, LDC, QDC)
- SVM

## Bayes' Rule

$$f(x) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp \left\{ -\frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu) \right\}$$

multidimensional gaussian function.

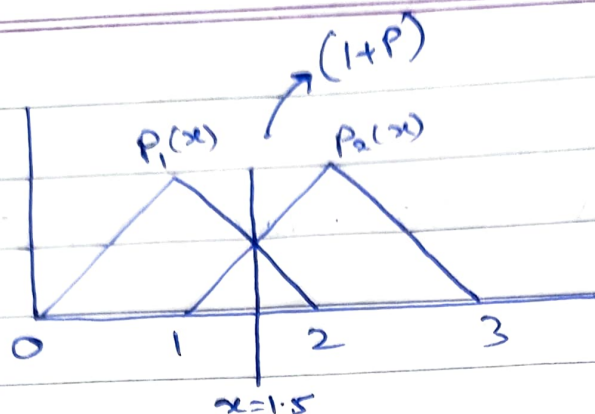
Let there be  $M$  classes ( $M \geq 2$ ), prior probability be  $P_1, P_2, \dots, P_M$ . Where  $0 \leq P_i \leq 1$  and  $\sum_{i=1}^M P_i = 1$ .  
Let  $P_1(x), P_2(x), \dots, P_M(x)$  be the conditional probability density function.

Given an unknown pattern  $x_0$ ,  $x_0$  be in class  $i$  if  $P_i P_i(x_0) \geq P_j P_j(x_0) \quad \forall i \neq j$ .

eg let  $M=2$  Prior prob  $P, (1-P)$

$$P_1(x) = \begin{cases} x & 0 \leq x \leq 1 \\ 2-x & 1 \leq x \leq 2 \\ 0 & \text{otherwise} \end{cases}$$

$$P_2(x) = \begin{cases} x-1 & 1 \leq x \leq 2 \\ 3-x & 2 \leq x \leq 3 \\ 0 & \text{o.t.h.} \end{cases}$$


 $1.5 \geq \text{class 1}$ 
 $1.5 \leq \text{class 2}$ 

0 to 1

$$P_1 = P \quad P_2 = 1 - P$$

$$P_1(x) = x \quad P_2(x) = 0$$

$$P_1 P_1(x) \geq P_2 P_2(x) \Rightarrow x \text{ should be in class 1}$$

case 2 2 to 3

$$P_1 = P \quad P_2 = 1 - P$$

$$P_1(x) = 0 \quad P_2(x) = 3 - x$$

$$P_2 P_2(x) \geq P_1 P_1(x) \Rightarrow x \text{ should be class 2}$$

case 3 1 to 2

$$P_1 = P \quad P_2 = 1 - P$$

$$P_1(x) = 2 - x \quad P_2(x) = x - 1$$

4

$$P_1 P_1(x) \geq P_2 P_2(x)$$

$$P(2-x) \geq (1-P)(x-1)$$

$$2P - xP \geq x - xP + P - 1$$

$$\boxed{x \leq 1+P} \quad \text{for class 1}$$

$$\boxed{x \geq 1+P} \quad \text{for class 2}$$