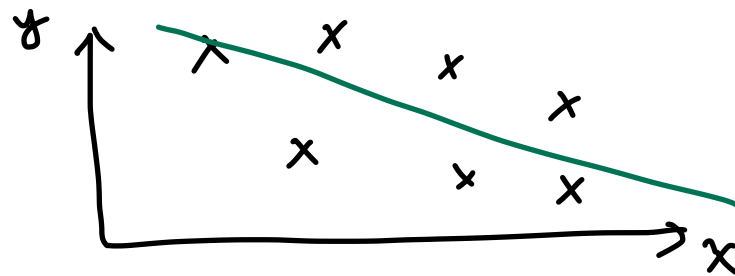
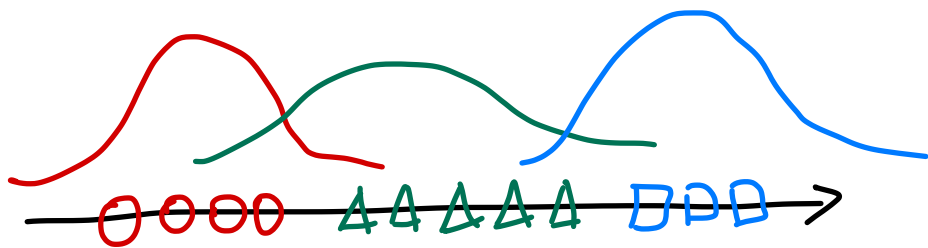


Multivariate methods



⇒ multiple measurements from each data point

$$x_i \in \mathbb{R}^D$$

$$x_i = \begin{bmatrix} x_{i1} & x_{i2} & \dots & x_{iD} \end{bmatrix}^T$$

$\xleftarrow{\text{ith data point}}$
 $\xrightarrow{\text{first feature}}$
 $\xrightarrow{D^{\text{th}} \text{ feature}}$

$y_i \Rightarrow$ class label
classification

$$X = \{ (x_i, y_i) \}_{i=1}^N \quad x_i \in \mathbb{R}^D$$

$y_i \Rightarrow$ target value
regression

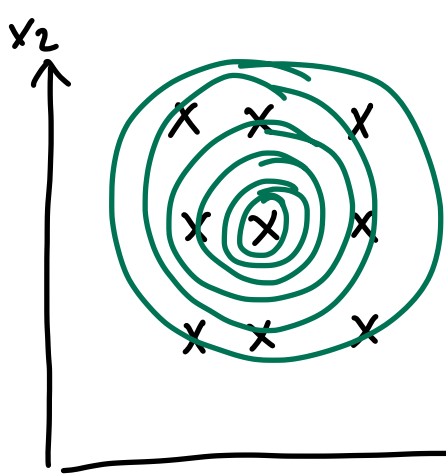
$$y_i \in \{1, 2, \dots, K\}$$

$$y_i \in \mathbb{R}$$

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1D} \\ x_{21} & x_{22} & \dots & x_{2D} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \dots & x_{ND} \end{bmatrix}$$

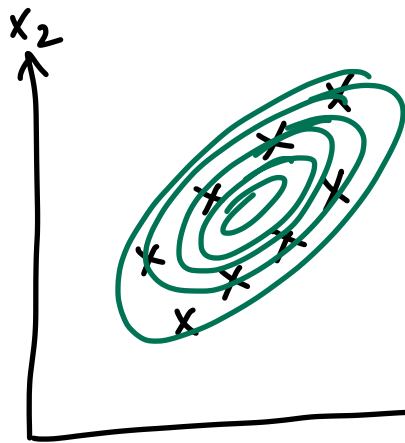
$\rightarrow x_1$
 $\rightarrow x_2$
 $\rightarrow x_N$
 $N \times D$

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix}_{N \times 1}$$



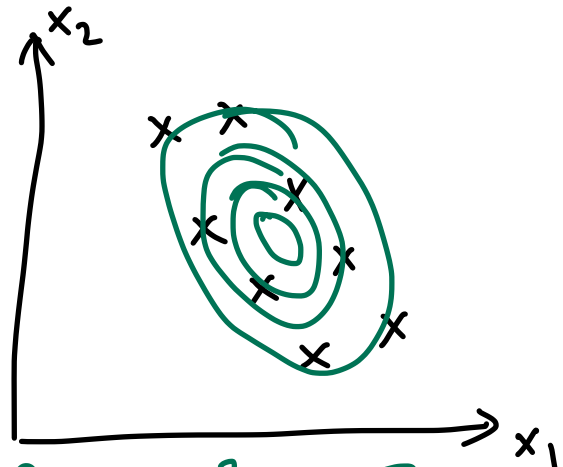
$$\begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}$$

$$\sigma_{12} = \sigma_{21} \approx 0$$



$$\begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}$$

$$\sigma_{12} = \sigma_{21} > 0$$



$$\begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}$$

$$\sigma_{12} = \sigma_{21} < 0$$

univariate
multivariate

$$x \sim N(x; \mu, \sigma^2)$$

$$x \sim N(x; \mu, \Sigma)$$

variance matrix $(D \times D)$
mean vector $(D \times 1)$

sample mean

$$\hat{\mu}_{1 \times 1} = \frac{\sum_{i=1}^N x_i}{N}$$

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^N (x_i - \hat{\mu})^2}{N}$$

sample variance

sample mean vector

$$\hat{\mu}_{D \times 1} = \frac{\sum_{i=1}^N x_i_{D \times 1}}{N}$$

$$\begin{bmatrix} 1 \\ 2 \end{bmatrix} \begin{bmatrix} 1 & 2 \end{bmatrix} = \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}$$

sample covariance matrix

$$\hat{\Sigma}_{D \times D} = \frac{\sum_{i=1}^N (x_i - \hat{\mu})_{D \times 1} (x_i - \hat{\mu})_{1 \times D}^T}{N}$$

$$N(x; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]$$

$$N(\mathbf{x}; \mu, \Sigma) = \frac{1}{\sqrt{(2\pi)^D |\Sigma|}} \exp\left[-\frac{1}{2} \underbrace{(\mathbf{x}-\mu)^T}_{1 \times D} \underbrace{\Sigma^{-1}}_{D \times D} \underbrace{(\mathbf{x}-\mu)}_{D \times 1}\right]$$

determinant
1x1

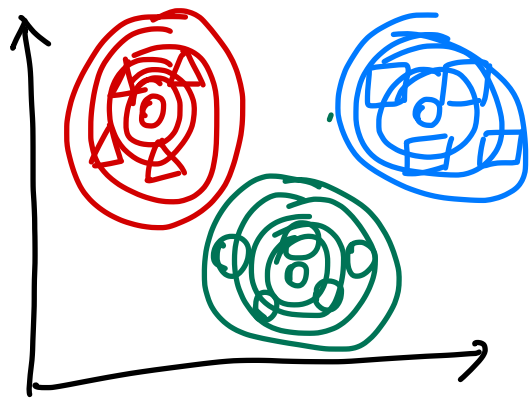
When $D=1$

$$\Sigma = [\sigma^2]_{1 \times 1}$$

$$= \frac{1}{\sqrt{(2\pi)^1 \cdot \sigma^2}} \cdot \exp\left[-\frac{1}{2} (\mathbf{x}-\mu)^T \left[\frac{1}{\sigma^2}\right] (\mathbf{x}-\mu)\right]$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} \cdot \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]$$

Multivariate Parametric Classification



$$p(x|y=c) \sim N(x; \mu_c, \Sigma_c)$$

$$\frac{1}{\sqrt{(2\pi)^D |\Sigma_c|}} \exp\left[-\frac{1}{2}(x-\mu_c)^T \Sigma_c^{-1} (x-\mu_c)\right]$$

$$g_c(x) = \log[p(x|y=c)] + \log[Pr(y=c)]$$

$$= -\frac{D}{2} \log(2\pi) - \frac{1}{2} \log(|\hat{\Sigma}_c|) - \frac{1}{2} (x - \hat{\mu}_c)^T \hat{\Sigma}_c^{-1} (x - \hat{\mu}_c) + \log[\hat{Pr}(y=c)]$$

Model parameters

$\hat{\mu}_1 \rightarrow D \times 1$
 $\hat{\Sigma}_1 \rightarrow D \times D$
 $\hat{Pr}(y=1) \rightarrow 1 \times 1$

$\hat{\mu}_2 \rightarrow D \times 1$
 $\hat{\Sigma}_2 \rightarrow D \times D$
 $\hat{Pr}(y=2) \rightarrow 1 \times 1$

$\hat{\mu}_3 \rightarrow D \times 1$
 $\hat{\Sigma}_3 \rightarrow D \times D$
 $\hat{Pr}(y=3) \rightarrow 1 \times 1$



total # of parameters

$$\Rightarrow \underbrace{K \cdot D}_{\text{mean vectors}} + K \cdot \underbrace{\left[\frac{D \cdot [D+1]}{2} \right]}_{\text{covariance matrices}} + \underbrace{K-1}_{\text{prior probabilities}}$$

$$-\frac{1}{2} (x-a)^T B (x-a) = -\frac{1}{2} x^T B x + x^T B a - \frac{1}{2} a^T B a$$

$$-\frac{1}{2} x^T \hat{\Sigma}_c^{-1} x + x^T \hat{\Sigma}_c^{-1} \hat{\mu}_c - \frac{1}{2} \hat{\mu}_c^T \hat{\Sigma}_c^{-1} \hat{\mu}_c$$

quadratic

$$a^T X b = b^T X a$$

if X is square & symmetric

$$\hat{\mu}_c = \frac{\sum_{i=1}^N [x_i \mathbb{1}(y_i=c)]}{\sum_{i=1}^N \mathbb{1}(y_i=c)}$$

$N_c = \# \text{ of data points from class } c.$

$$= a \cdot x^2 + b x + c$$

$$= x^T A \cdot x + b^T x + c$$

$$\hat{\Sigma}_c = \frac{\sum_{i=1}^N [(x_i - \hat{\mu}_c)(x_i - \hat{\mu}_c)^T \mathbb{1}(y_i=c)]}{\sum_{i=1}^N \mathbb{1}(y_i=c)}$$

$$\boxed{(A^T B)^T = B^T A}$$

$$\hat{\Pr}(y=c) = \frac{\sum_{i=1}^N \mathbb{1}(y_i=c)}{N} = \frac{N_c}{N}$$

frequency of class $c.$

$$g_c(x) = x^T W_c \cdot x + \underbrace{W_c^T}_{W_{c0}} \cdot x + W_{c0}$$

$$= -\frac{1}{2} x^T \hat{\Sigma}_c^{-1} \cdot x + \hat{\mu}_c^T \hat{\Sigma}_c^{-1} \cdot x$$

$$-\frac{1}{2} \hat{\mu}_c^T \hat{\Sigma}_c^{-1} \cdot \hat{\mu}_c - \frac{D}{2} \cdot \log(2\pi) - \frac{1}{2} \log(|\hat{\Sigma}_c|)$$

$$+ \log(\hat{\Pr}(y=c))$$

$$W_c = ? \cdot \frac{1}{2} \cdot \hat{\Sigma}_c^{-1}$$

$$W_c = ? \cdot \hat{\Sigma}_c^{-1} \cdot \hat{\mu}_c$$

$$W_{c0} = ?$$

$$g_1(x) = x^T W_1 \cdot x + w_1^T \cdot x + w_{10}$$

$$g_2(x) = x^T W_2 \cdot x + w_2^T \cdot x + w_{20}$$

$$\vdots$$

$$g_k(x) = x^T W_k \cdot x + w_k^T \cdot x + w_{k0}$$

Pick the maximum one.

when $k=2$

$$g_1(x) = x^T W_1 \cdot x + w_1^T \cdot x + w_{10}$$

$$g_2(x) = x^T W_2 \cdot x + w_2^T \cdot x + w_{20}$$

$$\underbrace{g_1(x) - g_2(x)}_{g(x)} = x^T \underbrace{(W_1 - W_2)}_W x + \underbrace{(w_1 - w_2)}_w^T \cdot x + \underbrace{(w_{10} - w_{20})}_{w_0}$$

$g(x) > 0 \Rightarrow$ pick 1st class

$g(x) < 0 \Rightarrow$ pick 2nd class