

Fig 1. Plot of 1-(c)-(iii)

The horizontal axis denotes x_1 , the vertical axis denotes x_2 ,
The red, blue, green circle denote $d_M^2(\underline{x}, \underline{m}_1) = 1$, $d_M^2(\underline{x}, \underline{m}_2) = 1$, $d_M^2(\underline{x}, \underline{m}_3) = 1$ respectively,
The purple, cyan, yellow region denote decision regions of $\Gamma_1, \Gamma_2, \Gamma_3$ respectively,
The cyan, white, purple line denote decision boundaries for class 1 and 2, class 1 and 3, class 2 and 3 respectively.

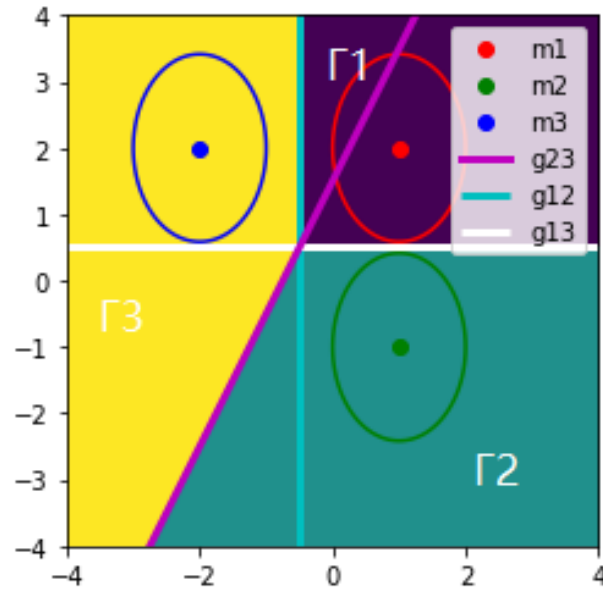


Fig 2. Plot of 2-(c)-(iii)

The horizontal axis denotes x_1 , the vertical axis denotes x_2 ,
The red, blue, green circle denote $d_M^2(\underline{x}, \underline{m}_1) = 1$, $d_M^2(\underline{x}, \underline{m}_2) = 1$, $d_M^2(\underline{x}, \underline{m}_3) = 1$ respectively,
The purple, cyan, yellow region denote decision regions of $\Gamma_1, \Gamma_2, \Gamma_3$ respectively,
The cyan, white, purple line denote decision boundaries for class 1 and 2, class 1 and 3, class 2 and 3 respectively.

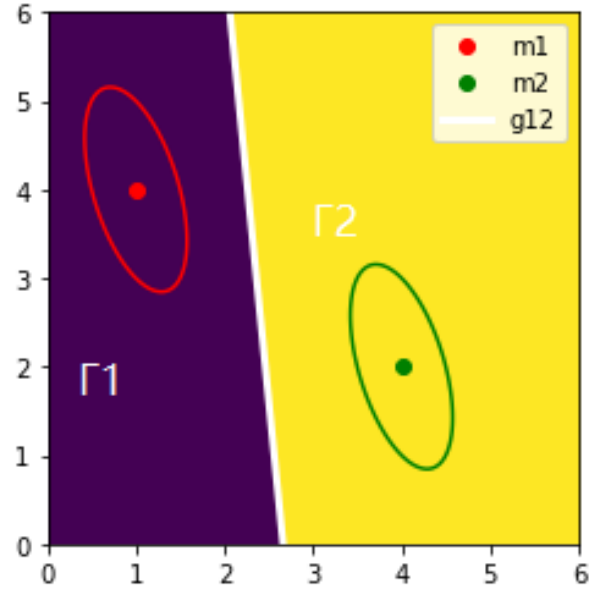


Fig 3. Plot of 3-(d)

The horizontal axis denotes x_1 , the vertical axis denotes x_2 ,
The red, green circle denote $d_M^2(\underline{x}, \underline{m}_1) = 1$, $d_M^2(\underline{x}, \underline{m}_2) = 1$ respectively,
The purple, yellow region denote decision regions of Γ_1 , Γ_2 respectively,
The white line denotes decision boundaries for class 1 and 2.

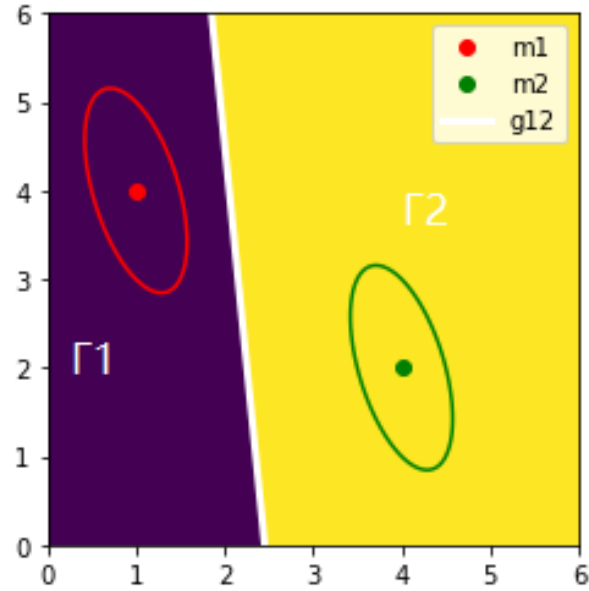


Fig 4. Plot of 3-(e)

The horizontal axis denotes x_1 , the vertical axis denotes x_2 ,
The red, green circle denote $d_M^2(\underline{x}, \underline{m}_1) = 1$, $d_M^2(\underline{x}, \underline{m}_2) = 1$ respectively,
The purple, yellow region denote decision regions of Γ_1 , Γ_2 respectively,
The white line denotes decision boundaries for class 1 and 2.

$$1. (a) (i). g_i(x) = -\frac{1}{2} \ln |\Sigma_i| - \frac{1}{2} (x - m_i)^T \Sigma_i^{-1} (x - m_i) + \ln P(S_i).$$

$$= -\frac{1}{2} d_m^2(x, m_i) - \frac{1}{2} \ln |\Sigma_i| + \ln \pi_i.$$

$$(ii) g_i(x) = -\frac{1}{2} \ln |\Sigma_i| + \ln \pi_i - \frac{1}{2} (x^T \Sigma_i^{-1} - m_i^T \Sigma_i^{-1}) (x - m_i).$$

$$= -\frac{1}{2} \ln |\Sigma_i| + \ln \pi_i - \frac{1}{2} (x^T \Sigma_i^{-1} x - 2 m_i^T \Sigma_i^{-1} x + m_i^T \Sigma_i^{-1} m_i).$$

$$= x^T (-\frac{1}{2} \Sigma_i^{-1}) x + (m_i^T \Sigma_i^{-1}) x - \frac{1}{2} m_i^T \Sigma_i^{-1} m_i - \frac{1}{2} \ln |\Sigma_i| + \ln \pi_i.$$

$$w_i = -\frac{1}{2} \Sigma_i^{-1}, \quad w_i = m_i^T \Sigma_i^{-1}, \quad w_i^{(0)} = -\frac{1}{2} m_i^T \Sigma_i^{-1} m_i - \frac{1}{2} \ln |\Sigma_i| + \ln \pi_i.$$

$$(b) \text{ decision rule: } \begin{cases} \text{if } g_1(x) > g_2(x), g_1(x) > g_3(x), & x \in S_1 \\ \text{if } g_2(x) > g_1(x), g_2(x) > g_3(x), & x \in S_2 \\ \text{if } g_3(x) > g_1(x), g_3(x) > g_2(x), & x \in S_3 \end{cases}$$

if $\Sigma_1 = \Sigma_2 = \Sigma_3$, it is linear classifier, else, it is quadratic classifier

$$(c) (i) \text{ Because } \Sigma_1 = \Sigma_2 = \Sigma_3, g_i(x) \text{ could be simplified to } g_i(x) = (m_i^T \Sigma_i^{-1}) x - \frac{1}{2} m_i^T \Sigma_i^{-1} m_i + \ln \pi_i.$$

$$\text{So } \Sigma_i^{-1} = \begin{bmatrix} 1 & -1 \\ 1 & 2 \end{bmatrix}^{-1} = \begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix}$$

$$\text{So } g_1(x) = [1, 2] \begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix} x - \frac{1}{2} [1, 2] \begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} + \ln \pi_1.$$

$$= 4x_1 + 3x_2 - 5 + \ln \pi_1.$$

$$g_2(x) = [1, -1] \begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix} x - \frac{1}{2} [1, -1] \begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} + \ln \pi_2$$

$$= x_1 - \frac{1}{2} + \ln \pi_2$$

$$g_3(x) = [-2, 2] \begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix} x - \frac{1}{2} [-2, 2] \begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} -2 \\ 2 \end{bmatrix} + \ln \pi_3$$

$$= -2x_1 - 2 + \ln \pi_3$$

This is a linear classifier

$$(ii) \text{ decision boundary: } 1, 2: g_1(x) = g_2(x) \Rightarrow x_1 + x_2 - \frac{3}{2} = 0$$

$$1, 3: g_1(x) = g_3(x) \Rightarrow 2x_1 + x_2 - 1 = 0$$

$$2, 3: g_2(x) = g_3(x) \Rightarrow x_1 + \frac{1}{2} = 0$$

$$(iii) d_m^2(x, m_1) = 1 \Rightarrow 2(x_1 - m_1)^2 + 2(x_1 - m_1)(x_2 - m_2) + (x_2 - m_2)^2 = 1$$

$$d_m^2(x, m_1) = 1 \Rightarrow 2(x_1 - 1)^2 + 2(x_1 - 1)(x_2 - 2) + (x_2 - 2)^2 = 1$$

$$d_m^2(x, m_2) = 1 \Rightarrow 2(x_1 - 1)^2 + 2(x_1 - 1)(x_2 + 1) + (x_2 + 1)^2 = 1$$

$$d_m^2(x, m_3) = 1 \Rightarrow 2(x_1 + 2)^2 + 2(x_1 + 2)(x_2 - 2) + (x_2 - 2)^2 = 1$$

Plot is shown in Fig. 1.

$$2. (a). g_i(x) = -\frac{1}{2} \ln |\Sigma_i| - \frac{1}{2} (x - m_i)^T \Sigma_i^{-1} (x - m_i) + \ln P(\zeta_i).$$

$$|\Sigma_i| = (\sigma_1^{(i)})^2 (\sigma_2^{(i)})^2. \quad \Sigma_i^{-1} = \text{diag} \left(\frac{1}{(\sigma_1^{(i)})^2}, \frac{1}{(\sigma_2^{(i)})^2} \right). \quad -\frac{1}{2} \ln |\Sigma_i| = -\ln \sigma_1^{(i)} \sigma_2^{(i)}$$

$$g_i(x) = -\ln(\sigma_1^{(i)} \sigma_2^{(i)}) + \ln \pi_i - \frac{1}{2(\sigma_1^{(i)})^2} (x_1 - m_1^{(i)})^2 - \frac{1}{2(\sigma_2^{(i)})^2} (x_2 - m_2^{(i)})^2$$

$$= -\frac{1}{2(\sigma_1^{(i)})^2} x_1^2 + \frac{1}{(\sigma_1^{(i)})^2} m_1^{(i)} x_1 - \frac{1}{2(\sigma_2^{(i)})^2} x_2^2 + \frac{1}{(\sigma_2^{(i)})^2} m_2^{(i)} x_2 + \ln \pi_i - \ln(\sigma_1^{(i)} \sigma_2^{(i)}) - \frac{m_1^{(i)2}}{2(\sigma_1^{(i)})^2} - \frac{m_2^{(i)2}}{2(\sigma_2^{(i)})^2}$$

$$\text{So } w_{11}^{(i)} = -\frac{1}{2(\sigma_1^{(i)})^2} \quad w_{12}^{(i)} = 0 \quad w_{22}^{(i)} = -\frac{1}{2(\sigma_2^{(i)})^2}$$

$$w_{1i}^{(i)} = \frac{m_1^{(i)}}{(\sigma_1^{(i)})^2} \quad w_{2i}^{(i)} = \frac{m_2^{(i)}}{(\sigma_2^{(i)})^2} \quad w_0^{(i)} = \ln \pi_i - \ln(\sigma_1^{(i)} \sigma_2^{(i)}) - \frac{m_1^{(i)2}}{2(\sigma_1^{(i)})^2} - \frac{m_2^{(i)2}}{2(\sigma_2^{(i)})^2}$$

(b). if $\Sigma_i = \Sigma_j$ it is linear. else, it is quadratic.

$$(c) (i) g_i(x) = \frac{m_1^{(i)}}{(\sigma_1^{(i)})^2} x_1 + \frac{m_2^{(i)}}{(\sigma_2^{(i)})^2} x_2 + \ln \pi_i - \frac{m_1^{(i)2}}{2(\sigma_1^{(i)})^2} - \frac{m_2^{(i)2}}{2(\sigma_2^{(i)})^2}$$

$$g_1(x) = x_1 + x_2 - \frac{3}{2} + \ln \pi_1$$

$$g_2(x) = x_1 - \frac{1}{2} x_2 - \frac{3}{4} + \ln \pi_2$$

$$g_3(x) = -2x_1 + x_2 - 3 + \ln \pi_3$$

This is a linear classifier

$$(ii). \text{decision boundary: } 1, 2: g_1(x) = g_2(x) \Rightarrow x_2 - \frac{1}{2} = 0$$

$$1, 3: g_1(x) = g_3(x) \Rightarrow x_1 + \frac{1}{2} = 0$$

$$2, 3: g_2(x) = g_3(x) \Rightarrow x_1 - \frac{1}{2} x_2 + \frac{3}{4} = 0$$

$$(iii). d m^2(x, m_i) = 1 \Rightarrow (x_1 - m_1)^2 + \frac{1}{2} (x_2 - m_2)^2 = 1$$

$$d m^2(x, m_1) = 1 \Rightarrow (x_1 - 1)^2 + \frac{1}{2} (x_2 - 2)^2 = 1$$

$$d m^2(x, m_2) = 1 \Rightarrow (x_1 - 1)^2 + \frac{1}{2} (x_2 + 1)^2 = 1$$

$$d m^2(x, m_3) = 1 \Rightarrow (x_1 + 2)^2 + \frac{1}{2} (x_2 - 2)^2 = 1$$

Plot is shown in Fig. 2.

(d). Both decision boundaries in 2(c)(iii) and 1(c)(iii) are linear.

From 2(c)(iii) we could see that the Naive Bayes makes the axis of the oval denoting $d m^2(x, m_i) = 1$ parallel to the coordinates. ~~Because the form of decision boundaries is not changed~~ so it make a substantial difference in decision boundaries and regions.

3(a). decision rule: $R(x_1|x) \stackrel{S_1}{\geq} R(x_2|x)$

$$R(x_1|x) = \lambda_{11} P(S_1|x) + \lambda_{12} P(S_2|x) = \lambda_{11} \frac{P(x|S_1)P(S_1)}{P(x)} + \lambda_{12} \frac{P(x|S_2)P(S_2)}{P(x)}$$

$$R(x_2|x) = \lambda_{21} P(S_1|x) + \lambda_{22} P(S_2|x) = \lambda_{21} \frac{P(x|S_1)P(S_1)}{P(x)} + \lambda_{22} \frac{P(x|S_2)P(S_2)}{P(x)}$$

In both side of the inequality, multiple by $P(x)$,

$$\Rightarrow \lambda_{11} P(x|S_1)P(S_1) + \lambda_{12} P(x|S_2)P(S_2) \stackrel{S_1}{\geq} \lambda_{21} P(x|S_1)P(S_1) + \lambda_{22} P(x|S_2)P(S_2)$$

$$\Rightarrow (\lambda_{21} - \lambda_{11}) P(x|S_1)P(S_1) \stackrel{S_1}{\geq} (\lambda_{22} - \lambda_{12}) P(x|S_2)P(S_2)$$

$$\Rightarrow \ln(\lambda_{21} - \lambda_{11}) + \ln P(x|S_1) + \ln P(S_1) \stackrel{S_1}{\geq} \ln(\lambda_{22} - \lambda_{12}) + \ln P(x|S_2) + \ln P(S_2)$$

$$\Rightarrow \ln(\lambda_{21} - \lambda_{11}) + \ln P(S_1) - \frac{1}{2} \ln |\Sigma_1| - \frac{1}{2} d_M^2(x, m_1) \stackrel{S_1}{\geq} \ln(\lambda_{22} - \lambda_{12}) + \ln P(S_2) - \frac{1}{2} \ln |\Sigma_2| - \frac{1}{2} d_M^2(x, m_2)$$

(b) $P(S_1) = 0.8$ $P(S_2) = 0.2$

(c) $\Sigma_1^{-1} = \frac{2}{3} \begin{pmatrix} 4 & 1 \\ 1 & 1 \end{pmatrix}$

$$d_M^2(x, m_1) = (x_1 - 1, x_2 - 4) \cdot \frac{2}{3} \begin{pmatrix} 4 & 1 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} x_1 - 1 \\ x_2 - 4 \end{pmatrix} = \frac{2}{3} [4(x_1 - 1)^2 + 2(x_1 - 1)(x_2 - 4) + (x_2 - 4)^2]$$

$$= \frac{2}{3} (4x_1^2 - 8x_1 + 4 + 2x_1x_2 - 8x_1 - 2x_2 + 8 + x_2^2 - 8x_2 + 16)$$

$$d_M^2(x, m_2) = (x_1 - 4, x_2 - 2) \cdot \frac{2}{3} \begin{pmatrix} 4 & 1 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} x_1 - 4 \\ x_2 - 2 \end{pmatrix} = \frac{2}{3} [4(x_1 - 4)^2 + 2(x_1 - 4)(x_2 - 2) + (x_2 - 2)^2]$$

$$= \frac{2}{3} (4x_1^2 - 32x_1 + 64 + 2x_1x_2 - 4x_1 - 8x_2 + 16 + x_2^2 - 4x_2 + 4)$$

$$\ln(1-0) + \ln 0.8 - \frac{1}{3} (-16x_1 - 10x_2 + 28) \stackrel{S_1}{\geq} \ln(0-0) + \ln 0.2 - \frac{1}{3} (-36x_1 - 12x_2 + 84)$$

$$\Rightarrow g_1(x) = \ln 1 + \ln 0.8 - \frac{1}{3} (-16x_1 - 10x_2 + 28)$$

$$g_2(x) = \ln 0 + \ln 0.2 - \frac{1}{3} (-36x_1 - 12x_2 + 84)$$

Decision boundary $g_{12}(x) = \ln 1 + \ln 0.8 - \ln 0 - \ln 0.2 - \frac{1}{3} (-16x_1 - 10x_2 + 28) + \frac{1}{3} (-36x_1 - 12x_2 + 84)$

$$= -\frac{20}{3}x_1 - \frac{2}{3}x_2 + \frac{56}{3} + \ln 0.4$$

$$\approx -\frac{20}{3}x_1 - \frac{2}{3}x_2 + 17.75$$

So, decision boundary is $-\frac{20}{3}x_1 - \frac{2}{3}x_2 + \frac{56}{3} + \ln 0.4 = 0$

decision rule: if $-\frac{20}{3}x_1 - \frac{2}{3}x_2 + \frac{56}{3} + \ln 0.4 > 0$, $x \in S_1$

if $-\frac{20}{3}x_1 - \frac{2}{3}x_2 + \frac{56}{3} + \ln 0.4 < 0$, $x \in S_2$

(d). See Fig. 3

(e). See Fig. 4, the decision boundary moves slightly towards m_1 , and in the same range, as Fig. 3, the area of decision region of S_1 become smaller