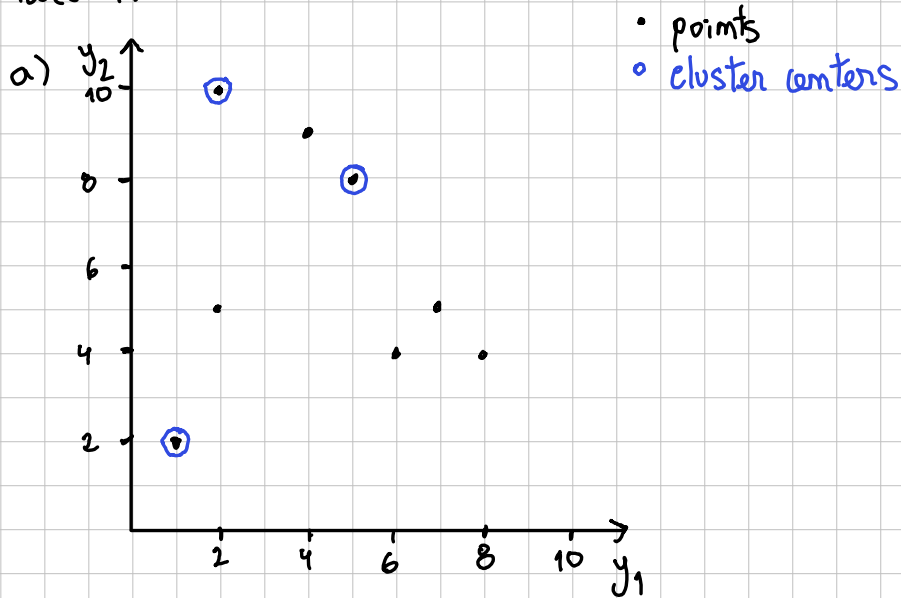


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Part A.



b) $\mu_1 = (2, 10)$ $\mu_2 = (5, 8)$ $\mu_3 = (1, 2)$

$$d(x_1, \mu_1) = \sqrt{(2-2)^2 + (10-10)^2} = 0 \quad \leftarrow$$

$$d(x_1, \mu_2) = \sqrt{13}$$

$$d(x_1, \mu_3) = \sqrt{65}$$

$$d(x_2, \mu_1) = 5$$

$$d(x_2, \mu_2) = 3\sqrt{2}$$

$$d(x_2, \mu_3) = \sqrt{10} \quad \leftarrow$$

$$d(x_3, \mu_1) = 6\sqrt{2}$$

$$d(x_3, \mu_2) = 5 \quad \leftarrow$$

$$d(x_3, \mu_3) = \sqrt{53}$$

$$\begin{aligned} d(x_4, \mu_1) &= \sqrt{13} \\ d(x_4, \mu_2) &= 0 \\ d(x_4, \mu_3) &= 2\sqrt{13} \end{aligned} \quad \leftarrow$$

$$\begin{aligned} d(x_5, \mu_1) &= 5\sqrt{2} \\ d(x_5, \mu_2) &= \sqrt{13} \\ d(x_5, \mu_3) &= 3\sqrt{5} \end{aligned} \quad \leftarrow$$

$$\begin{aligned} d(x_6, \mu_1) &= 2\sqrt{13} \\ d(x_6, \mu_2) &= \sqrt{17} \\ d(x_6, \mu_3) &= \sqrt{29} \end{aligned} \quad \leftarrow$$

$$\begin{aligned} d(x_7, \mu_1) &= \sqrt{65} \\ d(x_7, \mu_2) &= 2\sqrt{13} \\ d(x_7, \mu_3) &= 0 \end{aligned} \quad \leftarrow$$

$$\begin{aligned} d(x_8, \mu_1) &= \sqrt{5} \\ d(x_8, \mu_2) &= \sqrt{2} \\ d(x_8, \mu_3) &= \sqrt{58} \end{aligned} \quad \leftarrow$$

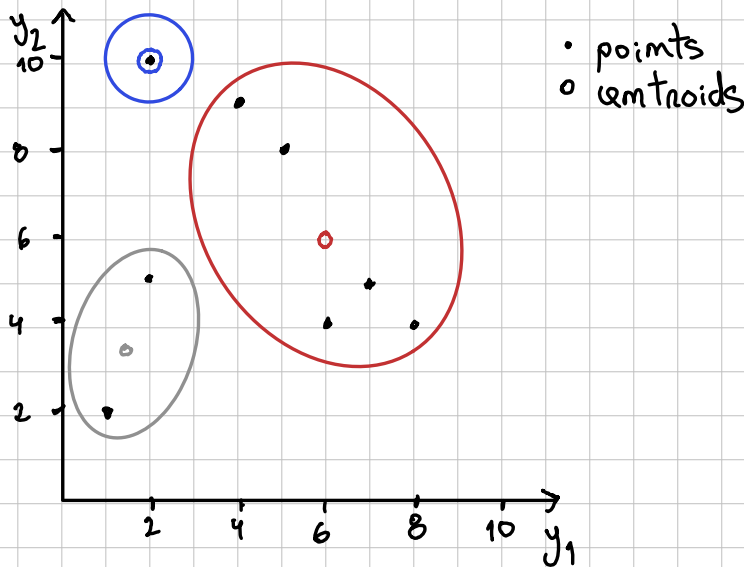
$$C_1 = \{x_1\} \quad C_2 = \{x_3, x_4, x_5, x_6, x_8\} \quad C_3 = \{x_2, x_7\}$$

$$\mu_1 = (2, 10)$$

$$\mu_2 = \left(\frac{8+5+7+6+4}{5}, \frac{4+8+5+4+9}{5} \right) = (6, 6)$$

$$\mu_3 = \left(\frac{2+1}{2}, \frac{5+2}{2} \right) = (1.5; 3.5)$$

c) $\mu_1 = (2, 10)$ $\mu_2 = (6, 6)$ $\mu_3 = (1.5, 3.5)$



d) The initialization of centroids in the k-means algorithm has a significant impact on both the convergence process, performance and the final results.

Because the k-means tries to minimize an objective function, different initializations can lead the algorithm to converge to different local minimums.

If the initial centroids are chosen well, the algorithm quickly converges to clusters that accurately represent the data structure resulting in lower within-cluster variance. However, poor initial centroids can slow convergence, resulting in a worst performance, produce empty or unbalanced clusters, and lead to suboptimal partitions that do not reflect the true relationships between data points. In some cases, two different initializations can yield completely different final cluster assignments.

Part B

$$a) \mu = \frac{1}{3} \left(\begin{bmatrix} 5 \\ 0 \\ 1 \end{bmatrix} + \begin{bmatrix} 0 \\ 5 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \right) = \begin{bmatrix} 2 \\ 5/3 \\ 0 \end{bmatrix}$$

$$x_1 - \mu = \begin{bmatrix} 5 \\ 0 \\ 1 \end{bmatrix} - \begin{bmatrix} 2 \\ 5/3 \\ 0 \end{bmatrix} = \begin{bmatrix} 3 \\ -5/3 \\ 1 \end{bmatrix}$$

$$x_2 - \mu = \begin{bmatrix} 0 \\ 5 \\ 0 \end{bmatrix} - \begin{bmatrix} 2 \\ 5/3 \\ 0 \end{bmatrix} = \begin{bmatrix} -2 \\ 10/3 \\ 0 \end{bmatrix}$$

$$x_3 - \mu = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} - \begin{bmatrix} 2 \\ 5/3 \\ 0 \end{bmatrix} = \begin{bmatrix} -1 \\ -5/3 \\ -1 \end{bmatrix}$$

$$\tilde{X} = \begin{bmatrix} 3 & -5/3 & 1 \\ -2 & 10/3 & 0 \\ -1 & -5/3 & -1 \end{bmatrix}$$

$$C = \frac{1}{n} \tilde{X}^T \tilde{X} = \frac{1}{3} \begin{bmatrix} 3 & -2 & -1 \\ -5/3 & 10/3 & -5/3 \\ 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} 3 & -5/3 & 1 \\ -2 & 10/3 & 0 \\ -1 & -5/3 & -1 \end{bmatrix}$$

$$= \begin{bmatrix} 14/3 & -10/3 & 4/3 \\ -10/3 & 50/9 & 0 \\ 4/3 & 0 & 2/3 \end{bmatrix}$$

$$b) \det(C - \lambda I) = 0$$

$$\Leftrightarrow \begin{vmatrix} 14/3 - \lambda & -10/3 & 4/3 \\ -10/3 & 50/9 - \lambda & 0 \\ 4/3 & 0 & 2/3 - \lambda \end{vmatrix} = 0$$

$$\Leftrightarrow \left(\frac{14}{3} - \lambda \right) \left(\frac{50}{9} - \lambda \right) \left(\frac{2}{3} - \lambda \right) + 0 + 0 - \left(\frac{4}{3} \times \frac{4}{3} \times \left(\frac{50}{9} - \lambda \right) + \right.$$

$$\left. \left(\frac{-10}{3} \times \frac{-10}{3} \times \left(\frac{2}{3} - \lambda \right) \right) \right) = 0$$

$$\Leftrightarrow \left(\frac{14}{3} - \lambda \right) \left(\frac{50}{9} - \lambda \right) \left(\frac{2}{3} - \lambda \right) - \left(\frac{800}{81} - \frac{16}{9} \lambda \right) - \left(\frac{200}{27} - \frac{100}{9} \lambda \right) = 0$$

$$\Leftrightarrow \left(\frac{700}{27} - \frac{14\lambda}{3} - \frac{50}{9} \lambda + \lambda^2 \right) \left(\frac{2}{3} - \lambda \right) - \left(\frac{800}{81} - \frac{16}{9} \lambda \right) - \left(\frac{200}{27} - \frac{100}{9} \lambda \right) = 0$$

$$\Leftrightarrow \frac{1400}{81} - \frac{700\lambda}{27} - \frac{28\lambda}{9} + \frac{14\lambda^2}{3} - \frac{100\lambda}{27} + \frac{50\lambda^2}{9} + \frac{2\lambda^2}{3} - \lambda^3 - \frac{800}{81} + \frac{16\lambda}{9} - \frac{200}{27} + \frac{100\lambda}{9} = 0$$

$$\Leftrightarrow -\lambda^3 + \frac{98}{9} \lambda^2 - \frac{536}{27} \lambda = 0 \Leftrightarrow \lambda \left(-\lambda^2 + \frac{98}{9} \lambda - \frac{536}{27} \right) = 0$$

$$\Leftrightarrow \lambda_3 = 0 \vee \lambda_1 = 8,5733 \vee \lambda_2 = 2,3155$$

$$\lambda_1: (C - \lambda_1 I) \mu_1 = 0$$

$$\begin{bmatrix} 14/3 - 8,5733 & -10/3 & 4/3 \\ -10/3 & 50/9 - 8,5733 & 0 \\ 4/3 & 0 & 2/3 - 8,5733 \end{bmatrix} \begin{bmatrix} \mu_{11} \\ \mu_{12} \\ \mu_{13} \end{bmatrix} = 0$$

$$\Rightarrow \begin{cases} -3,906 \mu_{11} - 10/3 \mu_{12} + 4/3 \mu_{13} = 0 \\ -10/3 \mu_{11} - 3,0177 \mu_{12} = 0 \\ 4/3 \mu_{11} - 7,9066 \mu_{13} = 0 \end{cases}$$

$$\mu_{12} = -1,104594 \mu_{11}$$

$$\mu_{13} = 0,16863548 \mu_{11}$$

$$\text{if } \mu_{11} = 1 \text{ then: } \mu_1 = \begin{bmatrix} 1 \\ -1,104594 \\ 0,16863548 \end{bmatrix}$$

$$\text{Normalizing: } \mu_1 = \begin{bmatrix} 0,6669 \\ -0,7366 \\ 0,1125 \end{bmatrix}$$

$$\lambda_2: (C - \lambda_2 I) \mu_2 = 0$$

$$\begin{bmatrix} 14/3 - 2,3155 & -10/3 & 4/3 \\ -10/3 & 30/9 - 2,3155 & 0 \\ 4/3 & 0 & 2/3 - 2,3155 \end{bmatrix} \begin{bmatrix} \mu_{21} \\ \mu_{22} \\ \mu_{23} \end{bmatrix} = 0$$

$$\Rightarrow \begin{cases} 2,35117 \mu_{21} - 10/3 \mu_{22} - 4/3 \mu_{23} \\ -10/3 \mu_{21} + 3,24 \mu_{22} = 0 \\ 4/3 \mu_{21} - 1,6488 \mu_{23} = 0 \end{cases}$$

$$\mu_{22} = 1,0288 \mu_{21}$$

$$\mu_{23} = 0,80867 \mu_{21}$$

$$\text{if } \mu_{21} = 1 \text{ then } \mu_2 = \begin{bmatrix} 1 \\ 1,0288 \\ 0,80867 \end{bmatrix}$$

$$\text{Normalizing: } \mu_2 = \begin{bmatrix} 0,6072 \\ 0,6247 \\ 0,4910 \end{bmatrix}$$

$$\text{Plano de projeção} = \text{Span} \{ \mu_1, \mu_2 \}$$

$$\text{where } \mu_1 = \begin{bmatrix} 0,6669 \\ -0,7366 \\ 0,1125 \end{bmatrix} \text{ and } \mu_2 = \begin{bmatrix} 0,6072 \\ 0,6247 \\ 0,4910 \end{bmatrix}$$

$$c) X' = \tilde{X} U$$

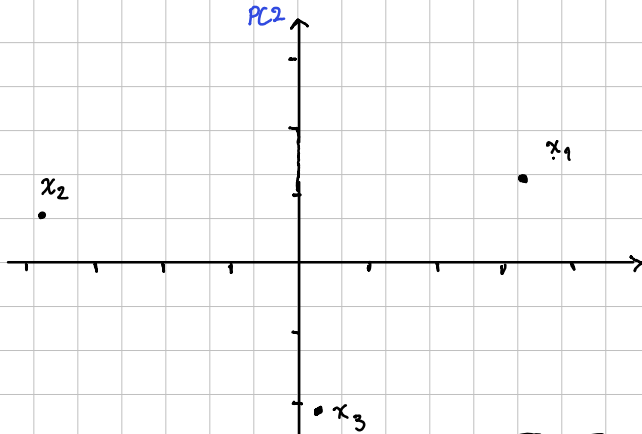
$$U = [u_1 \ u_2] = \begin{bmatrix} 0,6669 & 0,6072 \\ -0,7366 & 0,6247 \\ 0,1125 & 0,4910 \end{bmatrix}$$

$$\tilde{X} = \begin{bmatrix} 3 & -5/3 & 1 \\ -2 & 10/3 & 0 \\ -1 & -5/3 & -1 \end{bmatrix}$$

$$X' = \begin{bmatrix} 3 & -5/3 & 1 \\ -2 & 10/3 & 0 \\ -1 & -5/3 & -1 \end{bmatrix} \begin{bmatrix} 0,6669 & 0,6072 \\ -0,7366 & 0,6247 \\ 0,1125 & 0,4910 \end{bmatrix}$$

$$= \begin{bmatrix} 3,341 & 1,2714 \\ -3,789 & 0,8679 \\ 0,448 & -2,139 \end{bmatrix} \begin{matrix} \leftarrow x_1 (3,341 ; 1,2714) + \\ \leftarrow x_2 (-3,789 ; 0,8679) + \\ \leftarrow x_3 (0,448 ; -2,139) - \end{matrix}$$

PC1 PC2



This projection plane helps discriminate between the two classes.

Considering the positioning of the points in the graph we can conclude that: when the PC2 is positive the class is "+", and when

it is negative the class is "-". This shows that PC2, alone, can discriminate the classes