

I. Pen-and-paper

1)

①

$$\gamma_k = p(c_k | x_i) = \frac{p(x_i | \text{cluster} = k) p(\text{cluster} = k)}{p(x_i)} = \frac{\pi_k \cdot \mathcal{N}(x_i | \mu_k, \Sigma_k)}{\sum_k \pi_k \cdot \mathcal{N}(x_i | \mu_k, \Sigma_k)}$$

$$N_k = \sum_{i=1}^n \gamma_k^{(i)} \quad \mu_k = \frac{1}{N_k} \sum_{i=1}^n \gamma_k^{(i)} \cdot x_i \quad \Sigma_k = \frac{1}{N_k} \sum_{i=1}^n \gamma_k^{(i)} (x_i - \mu_k)(x_i - \mu_k)^T$$

$$\pi_k = p(c_k) = \frac{N_k}{N}$$

$x_1 = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$:

$\mathcal{N}(\begin{bmatrix} 1 & 2 \end{bmatrix}^T | \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}, \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}) = \frac{1}{2\pi \cdot \sqrt{3}} \cdot e^{-\frac{1}{2} \left(\begin{bmatrix} 1 \\ 2 \end{bmatrix} - \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right)^T \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}^{-1} \left(\begin{bmatrix} 1 \\ 2 \end{bmatrix} - \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right)} = \frac{1}{2\pi \sqrt{3}} \cdot e^{-\frac{1}{2} \cdot (-1 \ 0) \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}^{-1} \begin{bmatrix} -1 \\ 1 \end{bmatrix}} = \frac{1}{2\pi \sqrt{3}} \cdot e^{-\frac{1}{2} \cdot 2 \cdot \frac{1}{3}} = 0.0658$

$\mathcal{N}(\begin{bmatrix} 1 & 2 \end{bmatrix}^T | \begin{bmatrix} 0 & 0 \\ 0 & 2 \end{bmatrix}, \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}) = \frac{1}{2\pi \cdot 2} \cdot e^{-\frac{1}{2} \left(\begin{bmatrix} 1 \\ 2 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right)^T \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}^{-1} \left(\begin{bmatrix} 1 \\ 2 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right)} = \frac{1}{4\pi} \cdot e^{-\frac{1}{2} \cdot (1 \ 2) \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}^{-1} \begin{bmatrix} 1 \\ 2 \end{bmatrix}} = \frac{1}{4\pi} \cdot e^{-\frac{1}{2} \cdot 10 \cdot \frac{1}{2}} = 0.0228$

$$\gamma_1 = p(\text{cluster} = 1 | x_1) = \frac{\pi_1 \cdot \mathcal{N}(x_1 | \mu_1, \Sigma_1)}{\sum_{k=1}^2 \pi_k \cdot \mathcal{N}(x_1 | \mu_k, \Sigma_k)} = \frac{0.5 \cdot 0.0658}{0.5 \cdot 0.0658 + 0.5 \cdot 0.0228} = 0.7428$$

$$\gamma_2 = p(\text{cluster} = 2 | x_1) = \frac{\pi_2 \cdot \mathcal{N}(x_1 | \mu_2, \Sigma_2)}{\sum_{k=1}^2 \pi_k \cdot \mathcal{N}(x_1 | \mu_k, \Sigma_k)} = \frac{0.5 \cdot 0.0228}{0.5 \cdot 0.0658 + 0.5 \cdot 0.0228} = 0.2572$$

$x_2 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$:

$\mathcal{N}(\begin{bmatrix} -1 & 1 \end{bmatrix}^T | \begin{bmatrix} 2 & 2 \\ 1 & 2 \end{bmatrix}, \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}) = \frac{1}{2\pi \cdot \sqrt{3}} \cdot e^{-\frac{1}{2} \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right)^T \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}^{-1} \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right)} = \frac{1}{2\pi \sqrt{3}} \cdot e^{-\frac{1}{2} \cdot (-3 \ -1) \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}^{-1} \begin{bmatrix} -3 \\ 0 \end{bmatrix}} = \frac{1}{2\pi \sqrt{3}} \cdot e^{-\frac{1}{2} \cdot 4 \cdot \frac{1}{3}} = 0.0089$

$\mathcal{N}(\begin{bmatrix} -1 & 1 \end{bmatrix}^T | \begin{bmatrix} 0 & 0 \\ 0 & 2 \end{bmatrix}, \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}) = \frac{1}{2\pi \cdot 2} \cdot e^{-\frac{1}{2} \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right)^T \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}^{-1} \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right)} = \frac{1}{4\pi} \cdot e^{-\frac{1}{2} \cdot (-1 \ 1) \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}^{-1} \begin{bmatrix} -1 \\ 1 \end{bmatrix}} = \frac{1}{4\pi} \cdot e^{-\frac{1}{2} \cdot 4 \cdot \frac{1}{2}} = 0.0483$

$$\gamma_1 = \frac{\pi_1 \cdot \mathcal{N}(x_2 | \mu_1, \Sigma_1)}{\sum_{k=1}^2 \pi_k \cdot \mathcal{N}(x_2 | \mu_k, \Sigma_k)} = \frac{0.5 \cdot 0.0089}{0.5 \cdot 0.0089 + 0.5 \cdot 0.0483} = 0.1558$$

$$\gamma_2 = \frac{\pi_2 \cdot \mathcal{N}(x_2 | \mu_2, \Sigma_2)}{\sum_{k=1}^2 \pi_k \cdot \mathcal{N}(x_2 | \mu_k, \Sigma_k)} = \frac{0.5 \cdot 0.0483}{0.5 \cdot 0.0089 + 0.5 \cdot 0.0483} = 0.8442$$

$$u_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad \sum_{i=1}^n u_i \quad \text{cluster} = 1 \quad \frac{1}{2\pi} \cdot \frac{1}{\sqrt{3}} \cdot e^{-\frac{1}{2} \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 2 \\ 2 \end{bmatrix} \right)^T \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 2 \\ 2 \end{bmatrix} \right) \cdot \frac{1}{2}}$$

$$= \frac{1}{2\pi\sqrt{3}} \cdot e^{-\frac{1}{2} \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 2 \\ 2 \end{bmatrix} \right)^T \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 2 \\ 2 \end{bmatrix} \right) \cdot \frac{1}{2}} = \frac{1}{2\pi\sqrt{3}} \cdot e^{-\frac{1}{2} \cdot 6 \cdot \frac{1}{2}} = 0.0338$$

$$u_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad \sum_{i=1}^n u_i \quad \text{cluster} = 2 \quad \frac{1}{2\pi} \cdot \frac{1}{2} \cdot e^{-\frac{1}{2} \left(\begin{bmatrix} 0 \\ 1 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right)^T \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \left(\begin{bmatrix} 0 \\ 1 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right) \cdot \frac{1}{4}}$$

$$= \frac{1}{4\pi} \cdot e^{-\frac{1}{2} \left(\begin{bmatrix} 0 \\ 1 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right)^T \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \left(\begin{bmatrix} 0 \\ 1 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right) \cdot \frac{1}{4}} = \frac{1}{4\pi} \cdot e^{-\frac{1}{2} \cdot 2 \cdot \frac{1}{4}} = 0.0620$$

$$\pi_1 = \frac{\pi_1 \cdot N(\mu_3 | u_1, \Sigma_1)}{\sum_{k=1}^2 \pi_k \cdot N(\mu_3 | u_k, \Sigma_k)} = \frac{0.5 \cdot 0.0338}{0.5 \cdot 0.0338 + 0.5 \cdot 0.0620} = 0.3528$$

$$\pi_2 = \frac{\pi_2 \cdot N(\mu_3 | u_2, \Sigma_2)}{\sum_{k=1}^2 \pi_k \cdot N(\mu_3 | u_k, \Sigma_k)} = \frac{0.5 \cdot 0.0620}{0.5 \cdot 0.0338 + 0.5 \cdot 0.0620} = 0.6472$$

Re-estimation: $N_1 = \sum_{i=1}^3 \pi_1^{(i)} = 0.7428 + 0.1558 + 0.3528 = 1.2514$

$$N_2 = \sum_{i=1}^3 \pi_2^{(i)} = 0.2572 + 0.8442 + 0.6472 = 1.7486$$

$$u_1 = \frac{1}{N_1} \sum_{i=1}^3 \pi_1^{(i)} \cdot u_i = \frac{1}{1.2514} \cdot (0.7428 \cdot \begin{bmatrix} 1 \\ 2 \end{bmatrix} + 0.1558 \cdot \begin{bmatrix} -1 \\ 1 \end{bmatrix} + 0.3528 \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix}) = \begin{bmatrix} 0.7510 \\ 1.3117 \end{bmatrix}$$

$$u_2 = \frac{1}{N_2} \sum_{i=1}^3 \pi_2^{(i)} \cdot u_i = \frac{1}{1.7486} \cdot (0.2572 \cdot \begin{bmatrix} 1 \\ 2 \end{bmatrix} + 0.8442 \cdot \begin{bmatrix} -1 \\ 1 \end{bmatrix} + 0.6472 \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix}) = \begin{bmatrix} 0.0344 \\ 0.7770 \end{bmatrix}$$

$$\Sigma_1 = \frac{1}{N_1} \sum_{i=1}^3 \pi_1^{(i)} (u_i - u_1)(u_i - u_1)^T = \frac{1}{1.2514} \cdot (0.7428 \left(\begin{bmatrix} 1 \\ 2 \end{bmatrix} - \begin{bmatrix} 0.7510 \\ 1.3117 \end{bmatrix} \right) \left(\begin{bmatrix} 1 \\ 2 \end{bmatrix} - \begin{bmatrix} 0.7510 \\ 1.3117 \end{bmatrix} \right)^T + 0.1558 \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0.7510 \\ 1.3117 \end{bmatrix} \right) \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0.7510 \\ 1.3117 \end{bmatrix} \right)^T + 0.3528 \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 0.7510 \\ 1.3117 \end{bmatrix} \right) \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 0.7510 \\ 1.3117 \end{bmatrix} \right)^T) = \begin{bmatrix} 0.4960 & 0.0776 \\ 0.0776 & 0.7784 \end{bmatrix}$$

$$\Sigma_2 = \frac{1}{N_2} \sum_{i=1}^3 \pi_2^{(i)} (u_i - u_2)(u_i - u_2)^T = \frac{1}{1.7486} \cdot (0.2572 \left(\begin{bmatrix} 1 \\ 2 \end{bmatrix} - \begin{bmatrix} 0.0344 \\ 0.7770 \end{bmatrix} \right) \left(\begin{bmatrix} 1 \\ 2 \end{bmatrix} - \begin{bmatrix} 0.0344 \\ 0.7770 \end{bmatrix} \right)^T + 0.8442 \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0.0344 \\ 0.7770 \end{bmatrix} \right) \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0.0344 \\ 0.7770 \end{bmatrix} \right)^T + 0.6472 \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 0.0344 \\ 0.7770 \end{bmatrix} \right) \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 0.0344 \\ 0.7770 \end{bmatrix} \right)^T) = \begin{bmatrix} 0.9988 & -0.2154 \\ -0.2154 & 0.4675 \end{bmatrix}$$

$$\pi_1 = \frac{N_1}{N} = \frac{1.2514}{1.2514 + 1.7486} = 0.4171$$

$$\pi_2 = \frac{N_2}{N} = \frac{1.7486}{1.2514 + 1.7486} = 0.5829$$

2)

a)

2a) $x_1 = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$; $x_2 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$; $x_3 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$

$P(c_k | x_n) = \frac{P(x_n | c_k) \cdot P(c_k)}{P(c_k)}$; Tendo em conta a MAP assumption
queremos $\underset{c_k}{\operatorname{argmax}} P(x_n | c_k) \cdot P(c_k)$

$\mu_1 = \begin{bmatrix} 0,7510 \\ 1,3112 \end{bmatrix}$; $\mu_2 = \begin{bmatrix} 0,0344 \\ 0,7770 \end{bmatrix}$; $\Sigma_1 = \begin{bmatrix} 0,4360 & 0,0776 \\ 0,0776 & 0,7784 \end{bmatrix}$; $\Sigma_2 = \begin{bmatrix} 0,9988 & -0,2454 \\ -0,2454 & 0,4675 \end{bmatrix}$

$\det(\Sigma_1) = 0,3334$; $\det(\Sigma_2) = 0,4205$; $\Sigma_1^{-1} = \begin{bmatrix} 2,3347 & -0,2328 \\ -0,2328 & 1,3077 \end{bmatrix}$;

$\Sigma_2^{-1} = \begin{bmatrix} 1,1118 & 0,5122 \\ 0,5122 & 2,3753 \end{bmatrix}$; $\bar{\pi}_1 = 0,4171$; $\bar{\pi}_2 = 0,5829$

x_1 :

$$P(x_1 | c=1) = N(x_1 | \mu_1, \Sigma_1) = \frac{1}{2\pi} \cdot \frac{1}{\sqrt{\det(\Sigma_1)}} \cdot \exp\left(-\frac{1}{2}(x_1 - \mu_1)^T \Sigma_1^{-1} (x_1 - \mu_1)\right) =$$

$$= \frac{1}{2\pi \cdot \sqrt{0,3334}} \cdot \exp\left(-\frac{1}{2} \left(\begin{bmatrix} 1 \\ 2 \end{bmatrix} - \begin{bmatrix} 0,7510 \\ 1,3112 \end{bmatrix}\right)^T \begin{bmatrix} 2,3347 & -0,2328 \\ -0,2328 & 1,3077 \end{bmatrix} \left(\begin{bmatrix} 1 \\ 2 \end{bmatrix} - \begin{bmatrix} 0,7510 \\ 1,3112 \end{bmatrix}\right)\right) =$$

$$= \frac{1}{2\pi \cdot 0,5774} \exp\left(-\frac{1}{2} \cdot 0,6853\right) = 0,1957$$

$P(x_1 | c=2) = N(x_1 | \mu_2, \Sigma_2) = \frac{1}{2\pi} \cdot \frac{1}{\sqrt{\det(\Sigma_2)}} \cdot \exp\left(-\frac{1}{2}(x_1 - \mu_2)^T \Sigma_2^{-1} (x_1 - \mu_2)\right) =$

$$= \frac{1}{2\pi \cdot \sqrt{0,4205}} \exp\left(-\frac{1}{2} \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0,0344 \\ 0,7770 \end{bmatrix}\right)^T \begin{bmatrix} 1,1118 & 0,5122 \\ 0,5122 & 2,3753 \end{bmatrix} \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0,0344 \\ 0,7770 \end{bmatrix}\right)\right) =$$

$$= \frac{1}{2\pi \cdot 0,6485} \exp\left(-\frac{1}{2} \cdot 5,7992\right) = 0,0135$$

$P(x_1, c=1) = P(x_1 | c=1) \cdot \bar{\pi}_1 = 0,1957 \cdot 0,4171 = 0,0816$

$P(x_1, c=2) = P(x_1 | c=2) \cdot \bar{\pi}_2 = 0,0135 \cdot 0,5829 = 0,0079$

$\operatorname{argmax}(P(x_1, c=1), P(x_1, c=2)) = P(x_1, c=1) \rightarrow x_1 \in \text{Cluster 1}$

x_2 :

$$P(x_2 | c=1) = N(x_2 | \mu_1, \Sigma_1) = \frac{1}{2\pi} \cdot \frac{1}{\sqrt{\det(\Sigma_1)}} \cdot \exp\left(-\frac{1}{2}(x_2 - \mu_1)^T \Sigma_1^{-1} (x_2 - \mu_1)\right) =$$

$$= \frac{1}{2\pi} \cdot \frac{1}{\sqrt{0,3334}} \cdot \exp\left(-\frac{1}{2} \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0,7510 \\ 1,3112 \end{bmatrix}\right)^T \begin{bmatrix} 2,3347 & -0,2328 \\ -0,2328 & 1,3077 \end{bmatrix} \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0,7510 \\ 1,3112 \end{bmatrix}\right)\right) =$$

$$= \frac{1}{2\pi \cdot 0,5774} \exp\left(-\frac{1}{2} \cdot 7,0311\right) = 0,0082$$

$P(x_2 | c=2) = N(x_2 | \mu_2, \Sigma_2) = \frac{1}{2\pi} \cdot \frac{1}{\sqrt{\det(\Sigma_2)}} \cdot \exp\left(-\frac{1}{2}(x_2 - \mu_2)^T \Sigma_2^{-1} (x_2 - \mu_2)\right) =$

$$= \frac{1}{2\pi} \cdot \frac{1}{\sqrt{0,4205}} \cdot \exp\left(-\frac{1}{2} \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0,0344 \\ 0,7770 \end{bmatrix}\right)^T \begin{bmatrix} 1,1118 & 0,5122 \\ 0,5122 & 2,3753 \end{bmatrix} \left(\begin{bmatrix} -1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0,0344 \\ 0,7770 \end{bmatrix}\right)\right) =$$

$$= \frac{1}{2\pi \cdot 0,6485} \exp\left(-\frac{1}{2} \cdot 1,0714\right) = 0,1436$$

$P(x_2, c=1) = P(x_2 | c=1) \cdot \bar{\pi}_1 = 0,0082 \cdot 0,4171 = 0,0034$

$P(x_2, c=2) = P(x_2 | c=2) \cdot \bar{\pi}_2 = 0,1436 \cdot 0,5829 = 0,0837$

$\operatorname{argmax}(P(x_2, c=1), P(x_2, c=2)) = P(x_2, c=2) \rightarrow x_2 \in \text{Cluster 2}$

x_3 :

$$P(x_3 | c=1) = N(x_3 | \mu_1, \Sigma_1) = \frac{1}{2\pi} \cdot \frac{1}{\sqrt{\det(\Sigma_1)}} \cdot \exp\left(-\frac{1}{2}(x_3 - \mu_1)^T \Sigma_1^{-1} (x_3 - \mu_1)\right) =$$

$$= \frac{1}{2\pi} \cdot \frac{1}{\sqrt{0,3334}} \cdot \exp\left(-\frac{1}{2} \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 0,7510 \\ 1,3112 \end{bmatrix}\right)^T \begin{bmatrix} 2,3347 & -0,2328 \\ -0,2328 & 1,3077 \end{bmatrix} \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 0,7510 \\ 1,3112 \end{bmatrix}\right)\right) =$$

$$= \frac{1}{2\pi \cdot 0,5774} \exp\left(-\frac{1}{2} \cdot 2,545\right) = 0,0772$$

$P(x_3 | c=2) = N(x_3 | \mu_2, \Sigma_2) = \frac{1}{2\pi} \cdot \frac{1}{\sqrt{\det(\Sigma_2)}} \cdot \exp\left(-\frac{1}{2}(x_3 - \mu_2)^T \Sigma_2^{-1} (x_3 - \mu_2)\right) =$

$$= \frac{1}{2\pi} \cdot \frac{1}{\sqrt{0,4205}} \cdot \exp\left(-\frac{1}{2} \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 0,0344 \\ 0,7770 \end{bmatrix}\right)^T \begin{bmatrix} 1,1118 & 0,5122 \\ 0,5122 & 2,3753 \end{bmatrix} \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 0,0344 \\ 0,7770 \end{bmatrix}\right)\right) =$$

$$= \frac{1}{2\pi \cdot 0,6485} \exp\left(-\frac{1}{2} \cdot 1,7021\right) = 0,1008$$

$P(x_3, c=1) = P(x_3 | c=1) \cdot \bar{\pi}_1 = 0,0772 \cdot 0,4171 = 0,0322$

$P(x_3, c=2) = P(x_3 | c=2) \cdot \bar{\pi}_2 = 0,1008 \cdot 0,5829 = 0,06109$

$\operatorname{argmax}(P(x_3, c=1), P(x_3, c=2)) = P(x_3, c=2) \rightarrow x_3 \in \text{Cluster 2}$

b)

2b) O maior cluster é C_2 , pois possui mais elementos.

$$x_1 = \begin{bmatrix} 1 \\ 2 \end{bmatrix}; x_2 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}; x_3 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}; \mu_2 = \begin{bmatrix} 0,0344 \\ 0,7770 \end{bmatrix}$$

$$x_1 \in C_1; x_2, x_3 \in C_2$$

$$x_2: d(x_2, x_3) = \sqrt{|x_{21} - x_{31}|^2 + |x_{22} - x_{32}|^2} = \sqrt{|-1 - 1|^2 + |1 - 0|^2} = \sqrt{5}$$

$$d(x_2, x_1) = \sqrt{|x_{21} - x_{11}|^2 + |x_{22} - x_{12}|^2} = \sqrt{|-1 - 1|^2 + |1 - 2|^2} = \sqrt{5}$$

$$s(x_2) = \frac{d(x_2, x_1)}{d(x_2, x_3)} - 1 = 0$$

$$x_3: d(x_2, x_3) = \sqrt{|x_{21} - x_{31}|^2 + |x_{22} - x_{32}|^2} = \sqrt{5}$$

$$d(x_3, x_1) = \sqrt{|x_{31} - x_{11}|^2 + |x_{32} - x_{12}|^2} = \sqrt{|1 - 1|^2 + |0 - 2|^2} = \sqrt{4} = 2$$

$$s(x_3) = \frac{d(x_3, x_1)}{d(x_2, x_3)} - 1 = \frac{2}{\sqrt{5}} - 1 = -0,1056$$

$$s(C_2) = \frac{s(x_2) + s(x_3)}{2} = \frac{0 - 0,1056}{2} = -0,0528$$

II. Programming and critical analysis

3)

Silhouette score of Solution 1: 0.1136;

Silhouette score of Solution 2: 0.1140;

Silhouette score of Solution 3: 0.1136;

Purity of Solution 1: 0.7672;

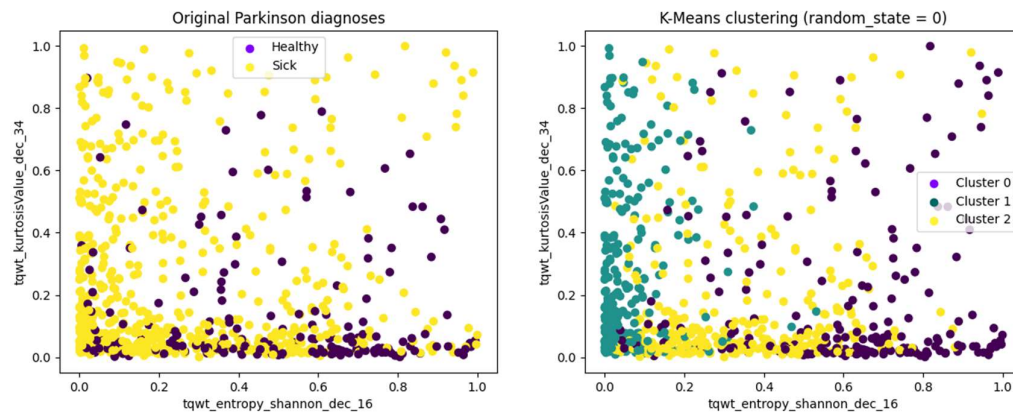
Purity of Solution 2: 0.7632;

Purity of Solution 3: 0.7672.

4)

A inicialização dos centróides é a principal causa de não determinismo presente neste método, daí a utilização de `random_state=n`, que tem como objetivo aplicar uma determinação transformação a `n` de forma a atribuir pseudo-aleatoriamente determinados valores como sendo os centros de cada cluster. Como o resto do algoritmo (k-means) pode ser considerado determinista, concluímos que esta é a única causa para o aparente não-determinismo.

5)



6)

Number of principal components: 31.

III. APPENDIX

```
##### Importing required libraries #####
import pandas as pd
from scipy.io.arff import loadarff
from sklearn.preprocessing import MinMaxScaler
from sklearn import metrics, cluster
import matplotlib.pyplot as plt
import numpy as np
from sklearn.decomposition import PCA

##### Defining Purity Function #####
def purity_score(y_true, y_pred):
    # compute contingency/confusion matrix
    confusion_matrix = metrics.cluster.contingency_matrix(y_true, y_pred)
    return round(np.sum(np.amax(confusion_matrix, axis=0)) /
np.sum(confusion_matrix), 4)

##### Reading the ARFF file #####
data = loadarff('pd_speech.arff')
df = pd.DataFrame(data[0])
df['class'] = df['class'].str.decode('utf-8')
X, y = df.drop('class', axis=1), df['class']

##### Normalizing #####
scaler = MinMaxScaler()
X_normalized = scaler.fit_transform(X)

##### K-Means #####
kmeans_algo0 = cluster.KMeans(n_clusters=3, random_state=0)
kmeans_algo1 = cluster.KMeans(n_clusters=3, random_state=1)
kmeans_algo2 = cluster.KMeans(n_clusters=3, random_state=2)

# learning the model
kmeans_model0 = kmeans_algo0.fit(X_normalized)
kmeans_model1 = kmeans_algo1.fit(X_normalized)
kmeans_model2 = kmeans_algo2.fit(X_normalized)

# getting the predicted labels
y_pred0 = kmeans_model0.labels_
y_pred1 = kmeans_model1.labels_
y_pred2 = kmeans_model2.labels_

##### Ex 1 #####
print("Silhouette score of Solution 1:", round(metrics.silhouette_score(X_normalized,
y_pred0), 4))
print("Purity of Solution 1:", purity_score(y, y_pred0))
```

```

print("Silhouette score of Solution 2:", round(metrics.silhouette_score(X_normalized,
y_pred1), 4))
print("Purity of Solution 2:", purity_score(y, y_pred1))
print("Silhouette score of Solution 3:", round(metrics.silhouette_score(X_normalized,
y_pred2), 4))
print("Purity of Solution 3:", purity_score(y, y_pred2))

#####          Ex 3          #####
# variance by feature of normalized data
variance = X_normalized.var(axis=0)
# get the two highest features based on variance
two_highest_variance = variance.argsort()[-2:][::-1]

# plotting
plt.figure(figsize=(14, 5))

plt.subplot(121)
y_values = np.array([int(i) for i in y.values])
plt.scatter(X_normalized[:, two_highest_variance[0]], X_normalized[:,
two_highest_variance[1]], c=y_values)
plt.legend(handles=[plt.scatter([], [], label='Healthy', c='#7F00FF'),
                    plt.scatter([], [], label='Sick', c='#FFF333')])
plt.title("Original Parkinson diagnoses")
plt.xlabel(X.columns[two_highest_variance[0]])
plt.ylabel(X.columns[two_highest_variance[1]])

plt.subplot(122)
plt.scatter(X_normalized[:, two_highest_variance[0]], X_normalized[:,
two_highest_variance[1]], c=y_pred0)
plt.legend(handles=[plt.scatter([], [], label='Cluster 0', c='#7F00FF'),
                    plt.scatter([], [], label='Cluster 1', c='#006666'),
                    plt.scatter([], [], label='Cluster 2', c='#FFF333')])
plt.title("K-Means clustering (random_state = 0)")
plt.xlabel(X.columns[two_highest_variance[0]])
plt.ylabel(X.columns[two_highest_variance[1]])

plt.show()

#####          Ex 4          #####
pca = PCA()
pca.fit(X_normalized)
i = 1
for var in np.cumsum(pca.explained_variance_ratio_):
    if var > 0.8:
        break
    i += 1
print("Number of principal components:", i)

```

END