

# Problem 1

Tuesday, 29 January 2019 11:22

**Problem 1:** Consider a mixture of  $K$  Gaussians

$$p(\mathbf{x}) = \sum_k \pi_k \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) = \sum_{k=1}^K p(z=k) p(\mathbf{x}|z=k)$$

Derive the expected value  $\mathbb{E}[\mathbf{x}]$  and the covariance  $\text{Cov}[\mathbf{x}]$ .

Hint: it is helpful to remember the identity  $\text{Cov}[\mathbf{x}] = \mathbb{E}[\mathbf{x}\mathbf{x}^T] - \mathbb{E}[\mathbf{x}]\mathbb{E}[\mathbf{x}]^T$ .

$$\begin{aligned} \mathbb{E}[\mathbf{x}] &= \int \mathbf{x} p(\mathbf{x}) d\mathbf{x} = \int \mathbf{x} \sum_{k=1}^K \pi_k \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}_k) d\mathbf{x} = \\ &= \sum_{k=1}^K \pi_k \int \mathbf{x} \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}_k) d\mathbf{x} = \sum_{k=1}^K \pi_k \boldsymbol{\mu}_k = \boldsymbol{\mu} \\ \mathbb{E}[\mathbf{x} | z=k] &= \boldsymbol{\mu}_k \end{aligned}$$

Remark:  $\mathbb{E}[g(\mathbf{x})] = \mathbb{E}_z[\mathbb{E}_{\mathbf{x}|z}[g(\mathbf{x})|z]]$

$$\int g(\mathbf{x}) p(\mathbf{x}) d\mathbf{x} = \sum_k \pi_k \cdot \mathbb{E}[g(\mathbf{x}) | z=k]$$

$$\text{Cov}(\mathbf{x}) = \mathbb{E}[\mathbf{x}\mathbf{x}^T] - \underbrace{\mathbb{E}[\mathbf{x}]}_{\boldsymbol{\mu}} \cdot \underbrace{\mathbb{E}[\mathbf{x}]^T}_{\boldsymbol{\mu}^T}$$

$$\mathbb{E}_{\mathbf{x}}[\mathbf{x}\mathbf{x}^T] = \mathbb{E}_z[\mathbb{E}_{\mathbf{x}|z}[\mathbf{x}\mathbf{x}^T|z]] = \sum_{k=1}^K \pi_k (\boldsymbol{\Sigma}_k + \boldsymbol{\mu}_k \boldsymbol{\mu}_k^T)$$

$$\rightarrow \boldsymbol{\Sigma}_k = \mathbb{E}[\mathbf{x}\mathbf{x}^T | z=k] - \underbrace{\mathbb{E}[\mathbf{x} | z=k]}_{\boldsymbol{\mu}_k} \cdot \underbrace{\mathbb{E}[\mathbf{x} | z=k]^T}_{\boldsymbol{\mu}_k^T}$$

$$\begin{aligned}
 \text{Cov}(x) &= \sum_k \pi_k (\Sigma_k + \mu_k \mu_k^T) - \underbrace{\sum_k \sum_j \pi_k \pi_j \mu_k \mu_j^T}_{\mu \mu^T} = \\
 &= \sum_k \pi_k \Sigma_k - \sum_k \sum_j \pi_k (\pi_j - 1_{k=j}) \mu_k \mu_j^T
 \end{aligned}$$

## Problem 2

Tuesday, 29 January 2019 11:24

**Problem 2:** Consider a mixture of  $K$  isotropic Gaussians, all with the same *known* covariances  $\Sigma_k = \sigma^2 I$ . Derive the EM algorithm for the case when  $\sigma^2 \rightarrow 0$ , and show that it's equivalent to Lloyd's algorithm for  $K$ -means.

Z-update step for k-means (Reminder)

$$z_{i,k} = \begin{cases} 1 & \text{if } k = \arg \max_j \|x_i - \mu_j\|^2 \\ 0 & \text{else} \end{cases}$$

GMM, E-step:

$$y(z_{i,k}) = \frac{\pi_k N(x_i | \mu_k, \Sigma_k)}{N} = \frac{\pi_k \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\|x_i - \mu_k\|^2}{2\sigma^2}\right)}{\sum_{j=1}^K \pi_j \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\|x_i - \mu_j\|^2}{2\sigma^2}\right)}$$

$$= \frac{1}{\sum_{j=1}^K \frac{\pi_j}{\pi_k} \exp\left(\frac{-\|x_i - \mu_j\|^2 + \|x_i - \mu_k\|^2}{2\sigma^2}\right)}$$

Case 1: for all  $j$   $\|x_i - \mu_k\| \leq \|x_i - \mu_j\| \Rightarrow$

$$0 \geq \frac{-\|x_i - \mu_j\|^2 + \|x_i - \mu_k\|^2}{2\sigma^2} \xrightarrow{\sigma \rightarrow 0} -\infty \Rightarrow$$

$$\exp\left(\frac{-\|x_i - \mu_j\|^2 + \|x_i - \mu_k\|^2}{2\sigma^2}\right) \xrightarrow{\sigma \rightarrow 0} 0$$

$$\Rightarrow y(z_{i,k}) \xrightarrow{\sigma \rightarrow 0} 1$$

Case 2: for some  $j$   $\|x_i - \mu_j\| < \|x_i - \mu_k\| \Rightarrow$

$$0 < \frac{-\|x_i - \mu_j\|^2 + \|x_i - \mu_k\|^2}{2\sigma^2} \xrightarrow{\sigma \rightarrow 0} +\infty \Rightarrow$$

$$\exp\left(-\frac{\|x_i - \mu_k\|^2}{2\sigma^2}\right) \xrightarrow{\sigma \rightarrow 0} 0 \Rightarrow$$

$$g(z_{ik}) \xrightarrow{\sigma \rightarrow 0} 0$$

M-step:

$$N_k = \sum_{i=1}^N g(z_{ik}) \rightarrow \# \text{ samples } i, \text{ st. } g(z_{ik}) = 1$$

$$\mu_k^{\text{new}} = \frac{1}{N_k} \sum_{i=1}^N g(z_{ik}) x_i \rightarrow \text{mean of } \{x_i \mid g(z_{ik}) = 1\}$$

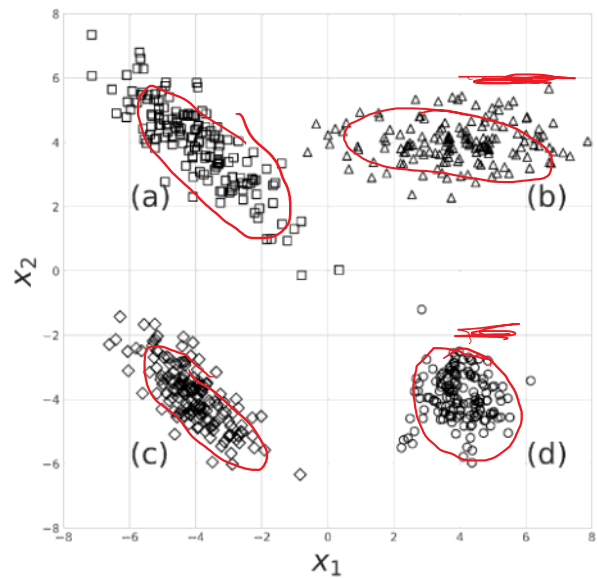
### Problem 3

Tuesday, 29 January 2019 11:24

**Problem 3:** The dataset displayed on the right has been generated using a Gaussian mixture model with  $K = 4$  components, each with its own mean  $\mu_k$  and covariance matrix  $\Sigma_k$ .

Match the covariance matrices in the table on the left with their corresponding Gaussian components in the plot on the right. Explain each of the answers with 1 sentence.

$\Sigma_k$	Cluster
$\begin{bmatrix} 2 & -1.7 \\ -1.7 & 2 \end{bmatrix}$	a
$\begin{bmatrix} 0.9 & -0.8 \\ -0.8 & 1.2 \end{bmatrix}$	c
$\begin{bmatrix} 3 & 0 \\ 0 & 0.5 \end{bmatrix}$	b
$\begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix}$	d



## Problem 4

Tuesday, 29 January 2019 11:24

### Problem 4:

- a) Given is the dataset displayed in the figure below. Apply the K-means algorithm to this data using  $K = 2$  and using the circled points as initial centroids.

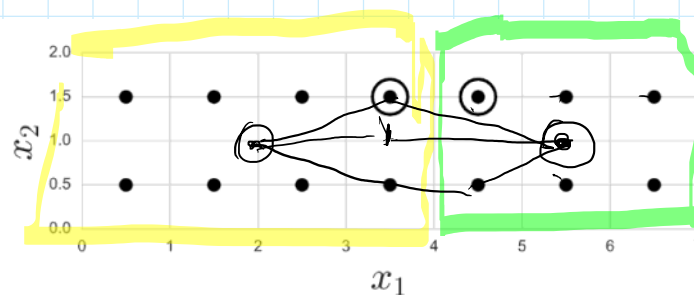


Figure 1: K-Means Dataset

What are the clusters after K-Means converges? Draw your solution in the figure above, i.e. mark the location of the centroids with  $\times$ 's and show the clusters by drawing two bounding boxes around the points assigned to each cluster.

How many iterations did it take for K-Means to converge in the above problem?

- b) Provide a different initialization, for which the algorithm will take **more** iterations to converge to the **same** solution. Make sure that your initialization does not lead to ties. Draw your initialization in the figure below.

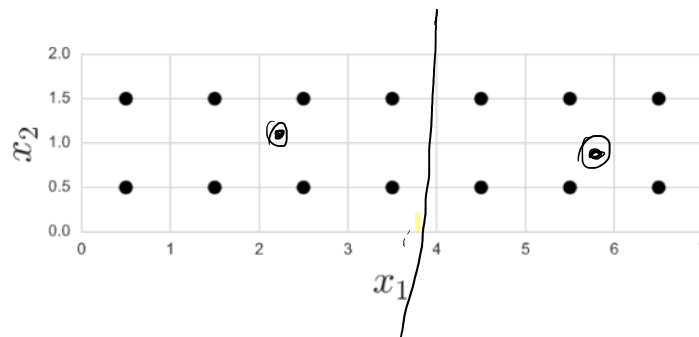


Figure 2: Provide your initialization