

## **Machine Learning Homework 11**

**Author: Jesus Arturo Sol Navarro** 

### 1 Problem 5

• Expeted value

$$E[\mathbf{x}] = \int \mathbf{x} \sum_{k} \pi_{k} \mathcal{N}(\mathbf{x} \mid \boldsymbol{\mu}_{k}, \boldsymbol{\Sigma}_{k}) d\mathbf{x} = \sum_{k} \pi_{k} \int \mathbf{x} \mathcal{N}(\mathbf{x} \mid \boldsymbol{\mu}_{k}, \boldsymbol{\Sigma}_{k}) d\mathbf{x}$$

Expectation of a gaussian distribution is it's mean, thus

$$E[\mathbf{x}] = \sum_{k} \pi_k \mu_k$$

• Covariance

$$E[\mathbf{x}\mathbf{x}^T] = \int \mathbf{x}\mathbf{x}^T p(\mathbf{x}) d\mathbf{x}. = \sum_k \pi_k \int \mathbf{x}\mathbf{x}^T \mathcal{N}(\mathbf{x} \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) d\mathbf{x} = \sum_k \pi_k \left(\boldsymbol{\Sigma}_k + \boldsymbol{\mu}_k \boldsymbol{\mu}_k^T\right)$$

From the identity provided and the results from the expected value:

$$Cov[x] = \sum_{k} \pi_k \left( \mathbf{\Sigma}_k + \boldsymbol{\mu}_k \boldsymbol{\mu}_k^T \right) - \left( \sum_{k} \pi_k \mu_k \right) \left( \sum_{k} \pi_k \mu_k \right)^T$$

### 2 Problem 6

• E Step

$$\gamma_t(z_{ik}) = \frac{\pi_k^{(t)} \mathcal{N}(x_i | \mu_k^{(t)}, \sigma^2 I)}{\sum_{j=1}^K \pi_j^{(t)} \mathcal{N}(x_i | \mu_j^{(t)}, \sigma^2 I)}.$$

• M Step

$$\pi_k^{(t+1)} = \frac{N_k}{N} \quad \text{where} \quad N_k = \sum_{i=1}^N \gamma_t(z_{ik}).$$
 
$$\mu_k^{(t+1)} = \frac{1}{N_k} \sum_{i=1}^N \gamma_t(z_{ik}) x_i$$

• If  $\sigma^2 I$  is close to zero, then all the gaussian become peaky around the mean. Each point is asigned to the closest cluster with probability really close to 1, in other words  $\gamma_t(z_{ik}) \approx 1$  if the squared euclidean distance between the data point and the nearest centroid is the smallest in comparison to other centroids.

$$\gamma_t(z_{ik}) = z_{ik} = \begin{cases} 1 & \text{if } k = \arg\min_j \|x_i - \mu_j\|^2, \\ 0 & \text{else.} \end{cases}$$

$$\mu_k^{(t+1)} = \frac{1}{N_k} \sum_{i=1}^N z_{ik} x_i \quad \text{where} \quad N_k = \sum_{i=1}^N z_{ik}.$$

#### 3 Problem 7

• a)

- 1) Draw a one-hot cluster indicator  $z_x \sim \operatorname{Cat}(\pi_k^x)$ .
- 2) Draw a one-hot cluster indicator  $z_y \sim \text{Cat}(\pi_l^y)$ .
- 3) Sample  $x \sim \mathcal{N}(\mu_k^x, \Sigma_k^x)$  and  $y \sim \mathcal{N}(\mu_l^y, \Sigma_l^y)$ .
- -4)z = x + y

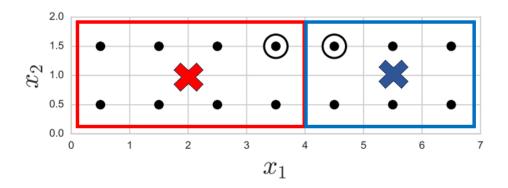


- b) The distribution  $p(z \mid \theta^x, \theta^y)$  remains a mixture of Gaussians because the sum of two independent Gaussian random variables is still Gaussian. The resulting Gaussian Mixture Model has  $K_xK_y$  individual gaussians distributions, where the mean and covariance of each new distribution is the sum of the respective means and covariances.
- c)

$$p(\mathbf{z} \mid \boldsymbol{\theta}^{x}, \boldsymbol{\theta}^{y}) = \sum_{k=1}^{K_{x}} \sum_{l=1}^{K_{y}} \pi_{k}^{x} \pi_{l}^{y} \mathcal{N}(\mathbf{z} \mid \boldsymbol{\mu}_{k}^{x} + \boldsymbol{\mu}_{l}^{y}, \boldsymbol{\Sigma}_{k}^{x} + \boldsymbol{\Sigma}_{l}^{y}).$$
(1)

# 4 Problem 8

• a) The K-Means algorithm converged in just one iteration to the centroids  $\mu_1=(2,1)$  and  $\mu_2=(5.5,1)$ .



• b) If the centroids are initialized as follow  $\mu_1 = (1.5,0)$  and  $\mu_2 = (6,2)$ . It takes two iterations to converge to the centroids found in the last section.

