

1. Problem 1

E-step:

$$\tau_{nj} = P(z_n = j | x_n, \theta) = \frac{P(x_n | z_n = j, \theta) \cdot P(z_n = j | \theta)}{P(x_n | \theta)} = \frac{\pi_j P(x_n | u_j)}{\sum_{i=1}^K \pi_i P(x_n | u_i)}$$

$$\text{denote } U_j = \prod_{s=1}^M u_j(s) x_n(s)$$

$$\text{so } \tau_{nj} = \frac{\pi_j U_j}{\sum_{i=1}^K \pi_i U_i}$$

M-step:

$$P(x_n, z = j | \theta) = P(x_n | z = j, \theta) \cdot P(z = j | \theta) = \pi_j U_j$$

$$\text{so } \theta := \arg \max_{\theta} \sum_{n=1}^N \sum_{j=1}^K \tau_{nj} \log \frac{P(x_n, z = j | \theta)}{\tau_{nj}}$$

$$= \arg \max_{\theta} \sum_{n=1}^N \sum_{j=1}^K \tau_{nj} (\log \pi_j + \log U_j) \quad \text{s.t. } \sum_{s=1}^M u_j(s) = 1, \sum_{j=1}^K \pi_j = 1$$

Applying Lagrangian:

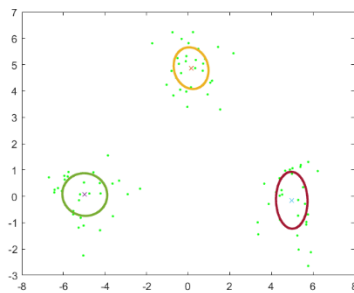
$$L(\pi, \alpha, \beta) = \sum_{n=1}^N \sum_{j=1}^K \tau_{nj} (\log \pi_j + \log U_j) - \alpha \left(\sum_{j=1}^K \pi_j - 1 \right) - \sum_{j=1}^K \beta_j \left(\sum_{s=1}^M u_j(s) - 1 \right)$$

$$\frac{\partial L}{\partial \pi_j} = 0 \Rightarrow \pi_j = \frac{1}{\alpha} \sum_{n=1}^N \tau_{nj} \Rightarrow \pi_j = \frac{1}{N} \sum_{n=1}^N \tau_{nj}$$

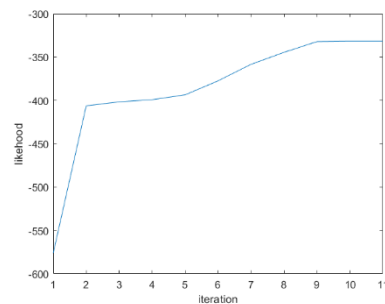
$$\frac{\partial L}{\partial u_j(s)} = 0 \Rightarrow u_j(s) = \frac{1}{\beta_j} \sum_{n=1}^N \tau_{nj} x_n(s) \Rightarrow u_j(s) = \frac{\sum_{n=1}^N x_{nj}(s)}{\sum_{p=1}^K \tau_{pj}}$$

2. Problem 2

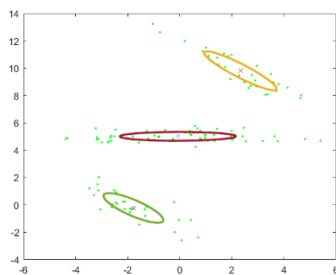
Part A



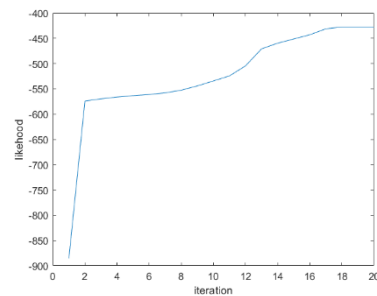
Dataset A



iteration result

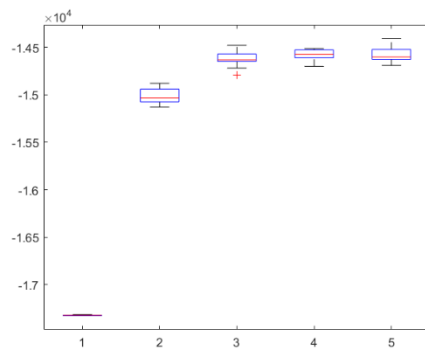


Dataset B

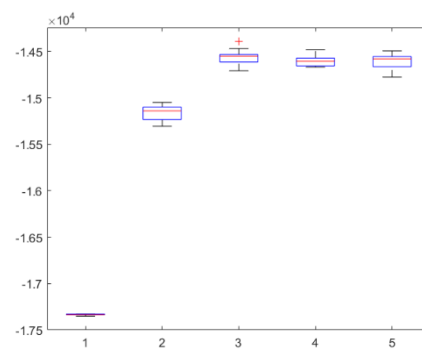


iteration result

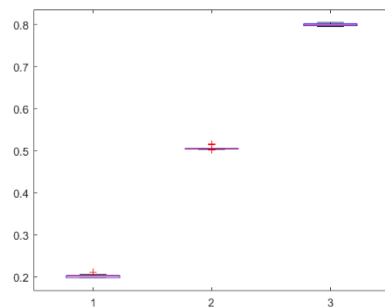
Part B



train log-likelihood average and std



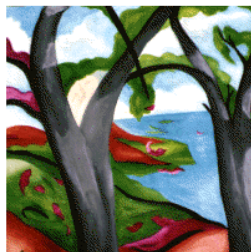
test log-likelihood average and std



Optimal coefficients average and std

The Bernoulli coefficients are [0.2, 0.5, 0.8] in average

3. Problem 3



Original picture



k = 3



K = 4



k = 5

For randomly initialized K means, some values might be too far away from data points thus lead to it is not closest mean to any point, this explains the inconsistencies.

To improve, we should calculate a range according to the given dataset for the initial means. Also, we

should make sure that every initial mean will not be too close to each other.

4. Problem 4

(a)

$$\text{We are proving } \frac{1}{n} \sum_{i=1}^n x_i \geq \left(\prod_{i=1}^n x_i \right)^{1/n}$$

applying Jensen's inequality

$$\log \left(\frac{\sum x_i}{n} \right) \geq \frac{1}{n} \sum \log(x_i) = \frac{1}{n} \log(\prod x_i) = \log(\prod x_i)^{1/n}$$

so proved.

(b)

$$\sum_{i=1}^m \exp(\theta^T f_i) = \sum_{i=1}^m \alpha_i \frac{\exp(\theta^T f_i)}{\alpha_i}, \text{ where } \sum \alpha_i = 1$$

so applying Jensen's inequality:

$$\begin{aligned} \ln \left[\sum_{i=1}^m \alpha_i \frac{\exp(\theta^T f_i)}{\alpha_i} \right] &\geq \sum_{i=1}^m \alpha_i \ln \left[\frac{\exp(\theta^T f_i)}{\alpha_i} \right] = \theta^T \sum_{i=1}^m \alpha_i f_i - \sum_{i=1}^m \alpha_i \ln \alpha_i \\ &= \ln \left[\exp \left(\theta^T \sum_{i=1}^m \alpha_i f_i - \sum_{i=1}^m \alpha_i \ln \alpha_i \right) \right] \end{aligned}$$

$$\Rightarrow \sum_{i=1}^m \exp(\theta^T f_i) \geq \exp \left(\theta^T \sum_{i=1}^m \alpha_i f_i - \sum_{i=1}^m \alpha_i \ln \alpha_i \right)$$