

1) Coding: find the implementation in the jupyter notebook.

### Theory

2) (ignore  $r_{ij} > 0$  constraint)

$$(i) \quad L = \sum_{i=1}^N \sum_{j=1}^K r_{ij}^2 \|x_i - u_j\|^2 + \sum_{i=1}^N \lambda_i \left[ 1 - \sum_{j=1}^K r_{ij} \right]$$

$$\frac{\partial L}{\partial u} = 0$$

$$(ii) \Rightarrow \frac{\partial L}{\partial u} = -2 \sum_{j=1}^K r_{ij}^2 (x_i - u_j) = 0$$

$$\Rightarrow u_j = \frac{\sum_{i=1}^N r_{ij}^2 x_i}{\sum_{i=1}^N r_{ij}^2}$$

$$\frac{\partial L}{\partial r_{ij}} = 2 r_{ij} \|x_i - u_j\|^2 - \lambda_i = 0$$

$$\lambda_i = 2 r_{ij} \|x_i - u_j\|^2$$

$$\therefore \sum_{j=1}^K r_{ij} = \sum_{j=1}^K \frac{\lambda_i}{2 \|x_i - u_j\|^2} = 1$$

$$\lambda_i = \frac{1}{\sum_{j=1}^K \frac{1}{2 \|x_i - u_j\|^2}}$$

$$r_i = \frac{1}{\sum_{j=1}^K \frac{1}{2 \|x_i - \mu_j\|^2}}$$

$$\therefore r_{ij} = \frac{\frac{1}{\|x_i - \mu_j\|^2}}{\sum_{j=1}^K \frac{1}{\|x_i - \mu_j\|^2}} > 0 \quad (\text{positively constraint satisfied})$$

(ii) set;  $r_{ij}^{(0)} = \frac{1}{K}$  and  $\mu^{(0)}$  randomly.

Iterate until convergence:

$$\mu_j^{(t+1)} = \frac{\sum_{i=1}^N r_{ij}^{(t)} x_i}{\sum_{i=1}^N r_{ij}^{(t)}}$$

$$r_{ij}^{(t+1)} = \frac{\left( \frac{1}{\|x_i - \mu_j^{(t+1)}\|_2^2} \right)}{\sum_{j=1}^K \frac{1}{\|x_i - \mu_j^{(t+1)}\|_2^2}}$$

(d) At every step take the argmax  $r_{ij}^{(t)} = \begin{cases} 1 & \text{if } r_{ij} > r_{ik} \quad \forall k \neq j \\ 0 & \text{otherwise.} \end{cases}$

This would make the above algorithm equivalent to K-means:-

3)

$$\log P_\theta(x) = \log \sum_{i=1}^n P_\theta(x | z = z_i) \underbrace{P_\theta(z = z_i)}_{\mu_i}$$

$$= \log \sum_{i=1}^n \lambda_i e^{-\lambda_i x} \cdot \mu_i$$

Consider the ELBO:

$$\begin{aligned} \log P_{\theta}(x) &\geq F_{\theta}(q) \\ &= \log P_{\theta}(x) - \mathbb{D}_{KL}[q(z|x) \| P_{\theta}(z|x)] \end{aligned}$$

(i)

Expectation Step: (E-Step)

$$\begin{aligned} q^{(t+1)}(z_j | x_i) &= q_{ji}^{(t+1)} \propto P_{\theta}(x_i | z_j) P_{\theta}(z_j) \\ &\propto \lambda_j e^{-\lambda_j x_i} \cdot \mu_j \end{aligned}$$

we know,

$$\sum_{j=1}^K q_{ji}^{(t+1)} = 1 \quad \forall i$$

$$q_{ji}^{(t+1)} = \frac{\mu_j \lambda_j e^{-\lambda_j x_i}}{\sum_{j=1}^K \mu_j \lambda_j e^{-\lambda_j x_i}}$$

(ii) Maximization Step:

$$\theta^{(t+1)} = \underset{\theta}{\operatorname{argmax}} F_{\theta}(q^{(t+1)}) \quad \text{s.t.}$$

$$= \mathbb{E}_{x_i \sim P_x} \mathbb{E}_{z_j \sim q(z|x_i)} \frac{\log P_{\theta}(x|z) \cdot P_{\theta}(z)}{\underbrace{q^{(t+1)}(z|x)}_{(\text{const})}}$$

$$= \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^K q_{ji}^{(t+1)} \left[ \log P_{\theta=\{\mu_j, \lambda_j\}}(x_i | z_j) + \log P_{\theta}(z_j) \right]$$

$$\text{s.t.} \quad \sum_{j=1}^K u_j = 1$$

$$\mathcal{L}(\lambda, u) = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^K q_{ji}^{(t+1)} \left[ \log \lambda_j e^{-\lambda_j x_i} + \log u_j \right] + \lambda \left[ 1 - \sum_{j=1}^K u_j \right]$$

$$\frac{\partial \mathcal{L}}{\partial u_j} = \frac{1}{N} \sum_{i=1}^N q_{ji}^{(t+1)} / u_j - \lambda = 0$$

$$\Rightarrow \sum_{j=1}^K (\lambda u_j) = \sum_{j=1}^K \frac{1}{N} \sum_{i=1}^N q_{ji}^{(t+1)}$$

$$\text{w.s. } \sum_j u_j = 1$$

$$\Rightarrow \lambda = \frac{1}{N} \sum_{i=1}^N \underbrace{\sum_{j=1}^K q_{ji}^{(t+1)}}_1 = 1$$

$$\therefore \left[ u_j^{(t+1)} = \frac{1}{N} \sum_{i=1}^N q_{ji}^{(t+1)} \right] \quad \forall j$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_j} = \frac{1}{N} \sum_{i=1}^N q_{ji}^{(t+1)} \left[ \frac{\partial \log \lambda_j}{\partial \lambda_j} - \frac{\partial \lambda_j x_i}{\partial \lambda_j} \right] = 0$$

$$\Rightarrow \sum_{i=1}^N q_{ji}^{(t+1)} \left[ \frac{1}{\lambda_j} - x_i \right] = 0$$

$$\Rightarrow \sum_{i=1}^N q_{ji}^{(t+1)} x_i = \frac{1}{\lambda_j} \sum_{i=1}^N q_{ji}^{(t+1)}$$

$$\sum_{i=1}^N q_{ji}^{(t+1)} x_i = \frac{\sum_{i=1}^N q_{ji}^{(t+1)}}{\lambda_j}$$

$$\Rightarrow \lambda_j^{(t+1)} = \frac{\sum_{i=1}^N q_{ji}^{(t+1)}}{\sum_{i=1}^N q_{ji}^{(t+1)} x_i} \rightarrow$$

$$\Rightarrow \lambda_j^{(t+1)} = \frac{N \mu_j^{(t+1)}}{\sum_{i=1}^N q_{ji}^{(t+1)} x_i}$$