

Homework assignment 2

1. (100 + 40 points) Consider the following Mixture of Gaussians (MOG) model defined on \mathbb{R}^d .

$$p(x|\theta) = \sum_{k=1}^K \pi_k \mathcal{N}(x|\mu_k, \Sigma_k), \quad \sum_{k=1}^K \pi_k = 1. \quad (1)$$

We assume that the covariance matrix Σ_k for each component is decomposed as

$$\Sigma_k = \lambda_k I_d + v_k v_k^\top, \quad (2)$$

where $\lambda_k > 0$, $v \in \mathbb{R}^d$, and I_d is the $d \times d$ identity matrix. The set of parameters θ is defined as

$$\theta = \{\pi \in \mathbb{R}^K, \{\mu_k \in \mathbb{R}^d, \lambda_k \in \mathbb{R}_+, v_k \in \mathbb{R}^d\}_{k=1}^K\}. \quad (3)$$

Assume the following priors,

$$p(\theta) = \text{Dir}(\pi; \mathbf{1}_K) \prod_{k=1}^K \mathcal{N}(\mu_k; \mathbf{0}_d, 5.0 \cdot I_d) \cdot \log \mathcal{N}(\lambda_k; 0.1, 0.1) \cdot \mathcal{N}(v_k; \mathbf{0}_d, 0.25 \cdot I_d), \quad (4)$$

where $\mathbf{1}_K = \underbrace{[1, \dots, 1]}_K^\top$, $\mathbf{0}_d = \underbrace{[0, \dots, 0]}_d^\top$ and $\log \mathcal{N}(x; \mu, \sigma^2)$ is the log-normal distribution with density

$$\log \mathcal{N}(x; \mu, \sigma^2) = \frac{1}{x\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(\log x - \mu)^2}{2\sigma^2}\right). \quad (5)$$

Let $X = \{x_i\}_{i=1}^n$ be a set of observed data. For the ease of implementation, we introduce a set of latent variables $Z = \{z_i\}_{i=1}^n$ where $z_i \in \{1, \dots, K\}$. $z_i = k$ indicates that the observation x_i was generated from k th component. The joint likelihood is then written as,

$$p(X, Z, \theta) = p(\theta) \cdot \prod_{i=1}^n \prod_{k=1}^K \left(\pi_k \mathcal{N}(x_i|\mu_k, \lambda_k I_d + v_k v_k^\top) \right)^{\mathbf{1}_{\{z_i=k\}}}, \quad (6)$$

where $\mathbf{1}_{\{z_i=k\}} = 1$ only if $z_i = k$ and zero otherwise. Your goal is to implement a sampler conducting the posterior inference for $p(\theta, Z|X)$.

- (a) (5 points) Derive the conditional distribution

$$p(z_i|Z \setminus \{z_i\}, X, \theta), \quad (7)$$

and explain how to sample from it.

- (b) (5 points) Derive the conditional distribution

$$p(\pi|X, Z, \theta \setminus \{\pi\}), \quad (8)$$

and explain how to sample from it.

- (c) (10 points) The posterior for (μ_k, λ_k, v_k) is not easily simulated via Gibbs sampling, so we will use the Metropolis-Hastings algorithm. Consider the following random-walk proposal distribution,

$$q(\mu'_k, \lambda'_k, v'_k | \mu_k, \lambda_k, v_k) = \mathcal{N}(\mu'_k; \mu_k, \sigma_q^2 I_d) \log \mathcal{N}(\lambda'_k; \log \lambda_k, \sigma_q^2) \mathcal{N}(v'_k; v_k, \sigma_q^2 I). \quad (9)$$

Compute the acceptance probability for updating (μ_k, λ_k, v_k) .

- (d) (80 points) Download the file `X.txt` attached. Set X to be the 2D data ($d = 2$) written in `X.txt`. Write a sampler simulating $p(\theta, Z | X)$ via the Gibbs + Metropolis-Hastings with the sampling strategies described above, while fixing the number of components $K = 3$. You can use any scientific programming language you like. Along with the code, you should submit a report describing your implementation and explaining the result. Especially, your report should convince that your sampler works properly. You may show the trace plots of $\log p(X, Z, \theta)$, the clustering induced by the mixture assignments Z after convergence, or the estimated parameters.