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3. Introduction to Mixture Models

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3. Introduction to Mixture Models

Gaussian Mixture Model: Definitions



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Gaussian Mixture Model: Definitions

1/1 point (graded)

Assume a Gaussian mixture model with K Gaussians such that we know all the means and variances. Assume that we also know the mixture weights p_1, \dots, p_K . Let \mathbf{x} be an observation obtained from the Gaussian mixture model. Let all of the parameters of the Gaussian mixture model be collectively represented as θ .

Which of the following are true?

☒ We should be able to compute the probability density function (likelihood) $p(\mathbf{x}|\theta)$ given the information that we know.

☒ We should be able to compute the probability that \mathbf{x} belongs to each Gaussian component $j = 1, \dots, K$ given the information that we know.



Solution:

Both the statements are true. The generative Gaussian mixture model means that if we know all of the parameters of the K Gaussians and the mixture weights, the probability density function $p(\mathbf{x}|\theta)$ can be computed using the law of total probability as

$$p(\mathbf{x}|\theta) = \sum_{j=1}^K p_j \mathcal{N}(\mathbf{x}; \mu^{(j)}, \sigma_j^2).$$

The posterior probability that \mathbf{x} belongs to a Gaussian component j can then be computed using Bayes rule.

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Likelihood of Gaussian Mixture Model



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Gaussian Mixture Model: Definitions

A **Gaussian Mixture Model (GMM)**, which is a generative model for data $\mathbf{x} \in \mathbb{R}^d$, is defined by the following set of parameters:

1. K : Number of mixture components
2. A d -dimensional Gaussian $\mathcal{N}(\mu^{(j)}, \sigma_j^2)$ for every $j = 1, \dots, K$
3. p_1, \dots, p_K : Mixture weights

The parameters of a K -component GMM can be collectively represented as $\theta = \{p_1, \dots, p_K, \mu^{(1)}, \dots, \mu^{(K)}, \sigma_1^2, \dots, \sigma_K^2\}$. Note that we have assumed the same variance σ_j^2 across all components of the j^{th} Gaussian mixture component for $j = 1, \dots, K$. Further, every Gaussian component is assumed to have a

diagonal covariance matrix. These are two assumptions that are made only for simplicity and the methodology presented can be extended to the setting of a general covariance matrix. Also, note that $\mu^{(j)}$ is a d -dimensional vector for every $j = 1, \dots, K$.

The **likelihood** of a point \mathbf{x} in a GMM is given as

$$p(\mathbf{x} \mid \theta) = \sum_{j=1}^K p_j \mathcal{N}(\mathbf{x}, \mu^{(j)}, \sigma_j^2).$$

The generative model can be thought of first selecting the component $j \in \{1, \dots, K\}$, which is modeled using the multinomial distribution with parameters p_1, \dots, p_K , and then selecting a point \mathbf{x} from the Gaussian component $\mathcal{N}(\mu^{(j)}, \sigma_j^2)$.

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| <p>? <u>Difference between some terms</u></p> <p><u>What is the difference between "mixture components" and Clusters ? what is the difference b...</u></p> | 3 |

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