

Lecture 11: Density Estimation with Gaussian Mixture Models

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Mathematics for Machine Learning
<https://yung-web.github.io/home/courses/mathml.html>
KAIST EE

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Please watch this tutorial video by Luis Serrano on Gaussian Mixture Model.

<https://www.youtube.com/watch?v=q71Niz856KE>

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- (1) Gaussian Mixture Model
- (2) Parameter Learning: MLE
- (3) Latent-Variable Perspective for Probabilistic Modeling
- (4) EM Algorithm

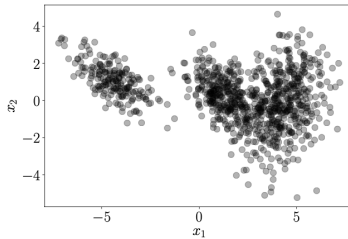
- (1) **Gaussian Mixture Model**
- (2) Parameter Learning: MLE
- (3) Latent-Variable Perspective for Probabilistic Modeling
- (4) EM Algorithm

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- Represent data compactly using a density from a parametric family, e.g., Gaussian or Beta distribution
- Parameters of those families can be found by MLE and MAPE
- However, there are many cases when simple distributions (e.g., just Gaussian) fail to approximate data.



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- More expressive family of distribution
- Idea: Let's mix! A **convex combination** of K "base" distributions

$$p(\mathbf{x}) = \sum_{k=1}^K \pi_k p_k(\mathbf{x}), \quad 0 \leq \pi_k \leq 1, \quad \sum_{k=1}^K \pi_k = 1$$

- Multi-modal distributions: Can be used to describe datasets with multiple clusters
- Our focus: Gaussian mixture models
- Want to finding the parameters using MLE, but **cannot have the closed form** solution (even with the mixture of Gaussians) → some iterative methods needed

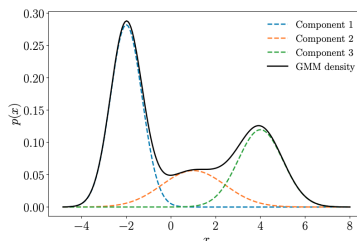
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$$p(\mathbf{x}|\boldsymbol{\theta}) = \sum_{k=1}^K \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k), \quad 0 \leq \pi_k \leq 1, \quad \sum_{k=1}^K \pi_k = 1,$$

where the parameters $\boldsymbol{\theta} := \{\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k, \pi_k : k = 1, \dots, K\}$

- **Example.** $p(x|\boldsymbol{\theta}) = 0.5\mathcal{N}(x|-2, 1/2) + 0.2\mathcal{N}(x|1, 2) + 0.3\mathcal{N}(x|4, 1)$



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- (1) Gaussian Mixture Model
- (2) **Parameter Learning: MLE**
- (3) Latent-Variable Perspective for Probabilistic Modeling
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- Given a iid dataset $\mathcal{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_n\}$, the log-likelihood is:

$$\mathcal{L}(\theta) = \log p(\mathcal{X}|\theta) = \sum_{n=1}^N \log p(\mathbf{x}_n|\theta) = \sum_{n=1}^N \log \sum_{k=1}^K \pi_k \mathcal{N}(\mathbf{x}_n|\mu_k, \Sigma_k)$$

- $\theta_{\text{ML}} = \arg \min_{\theta} (-\mathcal{L}(\theta))$
- Necessary condition for θ_{ML} : $\left. \frac{d\mathcal{L}}{d\theta} \right|_{\theta_{\text{ML}}} = 0$
- However, the closed-form solution of θ_{ML} does not exist, so we rely on an iterative algorithm (also called EM algorithm).
- We show the algorithm first, and then discuss how we get the algorithm.

- Definition. Responsibilities.** Given n -th data point \mathbf{x}_n and the parameters $(\mu_k, \Sigma_k, \pi_k : k = 1, \dots, K)$,

$$r_{nk} = \frac{\pi_k \mathcal{N}(\mathbf{x}_n|\mu_k, \Sigma_k)}{\sum_j \pi_j \mathcal{N}(\mathbf{x}_n|\mu_j, \Sigma_j)}$$

- How much is each component k responsible, if the data \mathbf{x}_n is sampled from the current mixture model?
- $\mathbf{r}_n = (r_{nk} : k = 1, \dots, K)$ is a probability distribution, so $\sum_{k=1}^K r_{nk} = 1$
- Soft assignment of \mathbf{x}_n to the K mixture components

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EM Algorithm: MLE in Gaussian Mixture Models

Example: EM Algorithm

EM for MLE in Gaussian Mixture Models

- S1.** Initialize μ_k, Σ_k, π_k
- S2. E-step:** Evaluate responsibilities r_{nk} for every data point \mathbf{x}_n using the current μ_k, Σ_k, π_k :

$$r_{nk} = \frac{\pi_k \mathcal{N}(\mathbf{x}_n|\mu_k, \Sigma_k)}{\sum_j \pi_j \mathcal{N}(\mathbf{x}_n|\mu_j, \Sigma_j)}, \quad N_k = \sum_{n=1}^N r_{nk}$$

- S3. M-step:** Reestimate parameters μ_k, Σ_k, π_k using the current responsibilities r_{nk} :

$$\mu_k = \frac{1}{N_k} \sum_{n=1}^N r_{nk} \mathbf{x}_n, \quad \Sigma_k = \frac{1}{N_k} \sum_{n=1}^N r_{nk} (\mathbf{x}_n - \mu_k)(\mathbf{x}_n - \mu_k)^T, \quad \pi_k = \frac{N_k}{N},$$

and go to **S2**.

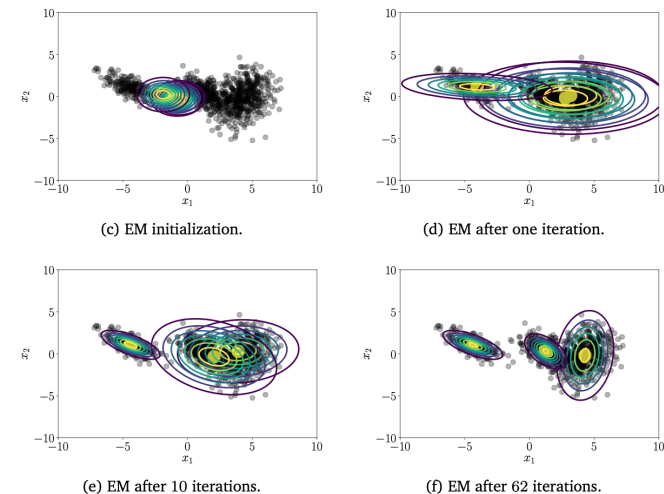
- The update equation in **M-step** is still mysterious, which will be covered later.

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- Given \mathcal{X} and r_{nk} from E-step, the new updates of μ_k , Σ_k , π_k should be made, such that the followings are satisfied:

$$\frac{\partial \mathcal{L}}{\partial \mu_k} = 0^T \iff \sum_{n=1}^N \frac{\partial \log p(\mathbf{x}_n | \theta)}{\partial \mu_k} = 0^T$$

$$\frac{\partial \mathcal{L}}{\partial \Sigma_k} = 0 \iff \sum_{n=1}^N \frac{\partial \log p(\mathbf{x}_n | \theta)}{\partial \Sigma_k} = 0$$

$$\frac{\partial \mathcal{L}}{\partial \pi_k} = 0 \iff \sum_{n=1}^N \frac{\partial \log p(\mathbf{x}_n | \theta)}{\partial \pi_k} = 0$$

- Nice thing: the new updates of μ_k , Σ_k , π_k are all expressed by the responsibilities $[r_{nk}]$
- Let's take a look at them one by one!

$$\mu_k^{\text{new}} = \frac{\sum_{n=1}^N r_{nk} \mathbf{x}_n}{\sum_{n=1}^N r_{nk}}, k = 1, \dots, K$$

•

$$\Sigma_k^{\text{new}} = \frac{1}{N_k} \sum_{n=1}^N r_{nk} (\mathbf{x}_n - \mu_k)(\mathbf{x}_n - \mu_k)^T, k = 1, \dots, K$$

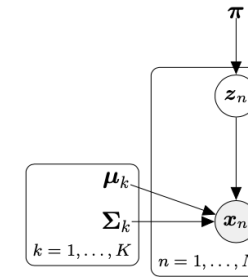
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$$\pi_k^{\text{new}} = \frac{\sum_{n=1}^N r_{nk}}{N}, k = 1, \dots, K$$

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- (1) Gaussian Mixture Model
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- Justify some ad hoc decisions made earlier
- Allow for a concrete interpretation of the responsibilities as **posterior distributions**
- Iterative algorithm for updating the model parameters can be derived in a principled manner



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Generative Process

- Latent variable \mathbf{z} :** One-hot encoding random vector $\mathbf{z} = [z_1, \dots, z_K]^T$ consisting of $K - 1$ many 0s and exactly one 1.
- An indicator rv $z_k = 1$ represents whether k -th component is used to generate the data sample \mathbf{x} or not.
- $p(\mathbf{x}|z_k = 1) = \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$
- Prior for \mathbf{z} with $\pi_k = p(z_k = 1)$

$$p(\mathbf{z}) = \boldsymbol{\pi} = [\pi_1, \dots, \pi_K]^T, \quad \sum_{k=1}^K \pi_k = 1$$

- Sampling procedure
 - Sample which component to use $z^{(i)} \sim p(\mathbf{z})$
 - Sample data according to i -th Gaussian $\mathbf{x}^{(i)} \sim p(\mathbf{x}|z^{(i)})$

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Joint Distribution, Likelihood, and Posterior (1)

- Joint distribution

$$p(\mathbf{x}, \mathbf{z}) = \begin{pmatrix} p(\mathbf{x}, z_1 = 1) \\ \vdots \\ p(\mathbf{x}, z_K = 1) \end{pmatrix} = \begin{pmatrix} p(\mathbf{x}|z_1 = 1)p(z_1 = 1) \\ \vdots \\ p(\mathbf{x}|z_K = 1)p(z_K = 1) \end{pmatrix} = \begin{pmatrix} \pi_1 \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_1, \boldsymbol{\Sigma}_1) \\ \vdots \\ \pi_K \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_K, \boldsymbol{\Sigma}_K) \end{pmatrix}$$

- Likelihood for an arbitrary single data \mathbf{x} : By summing out all latent variables¹,

$$p(\mathbf{x}|\boldsymbol{\theta}) = \sum_{\mathbf{z}} p(\mathbf{x}|\boldsymbol{\theta}, \mathbf{z})p(\mathbf{z}|\boldsymbol{\theta}) = \sum_{k=1}^K p(\mathbf{x}|\boldsymbol{\theta}, z_k = 1)p(z_k = 1|\boldsymbol{\theta}) = \sum_{k=1}^K \pi_k \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$$

- For all the data samples \mathcal{X} , the log-likelihood is:

$$\log p(\mathcal{X}|\boldsymbol{\theta}) = \sum_{n=1}^N \log p(\mathbf{x}_n|\boldsymbol{\theta}) = \sum_{n=1}^N \log \sum_{k=1}^K \pi_k \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$$

Compare: Page 7

¹In probabilistic PCA, \mathbf{z} was continuous, so we integrated them out.

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- Posterior for the k -th z_k , given an arbitrary single data \mathbf{x} :

$$p(z_k = 1|\mathbf{x}) = \frac{p(z_k = 1)p(\mathbf{x}|z_k = 1)}{\sum_{j=1}^K p(z_j = 1)p(\mathbf{x}|z_j = 1)} = \frac{\pi_k \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{j=1}^K \pi_j \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}$$

- Now, for all data samples \mathcal{X} , each data \mathbf{x}_n has $\mathbf{z}_n = [z_{n1}, \dots, z_{nK}]^T$, but with the same prior π .

$$p(z_{nk} = 1|\mathbf{x}_n) = \frac{p(z_{nk} = 1)p(\mathbf{x}_n|z_{nk} = 1)}{\sum_{j=1}^K p(z_{nj} = 1)p(\mathbf{x}_n|z_{nj} = 1)} = \frac{\pi_k \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{j=1}^K \pi_j \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)} = r_{nk}$$

- Responsibilities are mathematically interpreted as **posterior distributions**.

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Revisiting EM Algorithm for MLE

Other Issues

S1. Initialize $\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k, \pi_k$

S2. E-step:

$$r_{nk} = \frac{\pi_k \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_j \pi_j \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}$$

S3. M-step: Update $\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k, \pi_k$ using r_{nk} and go to **S2**.

- E-step. Expectation** over $\mathbf{z}|\mathbf{x}, \boldsymbol{\theta}^{(t)}$: Given the current $\boldsymbol{\theta}^{(t)} = (\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k, \pi_k)$, calculates the expected log-likelihood

$$\begin{aligned} Q(\boldsymbol{\theta}|\boldsymbol{\theta}^{(t)}) &= \mathbb{E}_{\mathbf{z}|\mathbf{x}, \boldsymbol{\theta}^{(t)}}[\log p(\mathbf{x}, \mathbf{z}|\boldsymbol{\theta})] \\ &= \int \log p(\mathbf{x}, \mathbf{z}|\boldsymbol{\theta}) p(\mathbf{z}|\mathbf{x}, \boldsymbol{\theta}^{(t)}) d\mathbf{z} \end{aligned}$$

- M-step. Maximization** of the computation results in E-step for the new model parameters.

- Only guarantee of just local-optimum because the original optimization is not necessarily a convex optimization.

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- Model selection for finding a good K , e.g., using nested cross-validation
- Application: Clustering
 - K-means: Treat the means in GMM as cluster centers and ignore the covariances.
 - K-means: hard assignment, GMM: soft assignment
- EM algorithm: Highly generic in the sense that it can be used for parameter learning in general latent-variable models
- Standard criticism for MLE exists such as overfitting. Also, fully-Bayesian approach assuming some priors on the parameters is possible, but not covered in this notes.
- Other density estimation methods
 - Histogram-based method: non-parametric method
 - Kernel-density estimation: non-parametric method

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Questions?

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