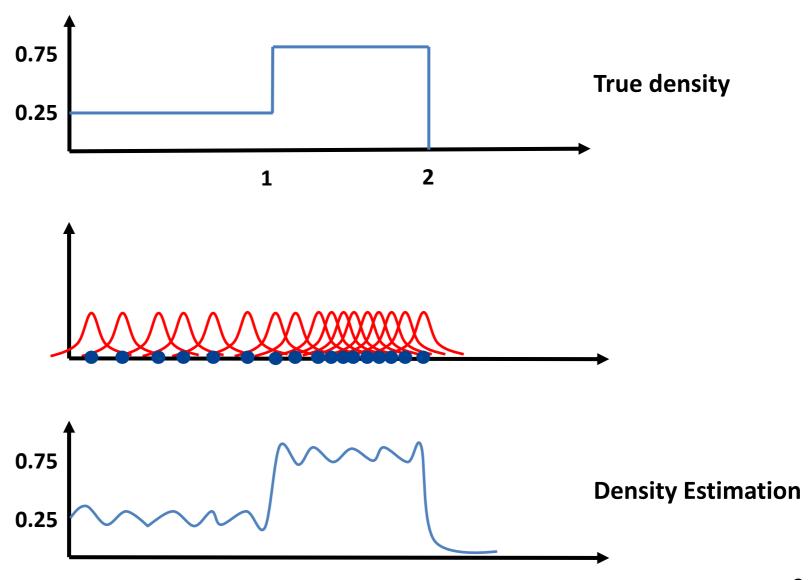
Pattern Classification 08. Gaussian Mixture Model

AbdElMoniem Bayoumi, PhD

Recap: Kernel Density Estimator



Gaussian Mixture Model (GMM)

 Assume we have a small data set → not possible to estimate class conditionals using kernel density estimator

 Instead, we model each class conditional as a sum of multivariate Gaussian densities

Gaussian Mixture Model (GMM)

 The parameters, i.e., the mean vectors & covariance matrices, are determined so that this sum approximates as good as possible the given class conditional density

$$\widehat{P}(\underline{X}) = \sum_{j=1}^{K} w_j \frac{e^{-\frac{1}{2}(\underline{X} - \underline{\mu}_j)^T \Sigma_j^{-1}(\underline{X} - \underline{\mu}_j)}}{(2\pi)^{\frac{N}{2}} det^{\frac{1}{2}}(\Sigma_j)}$$

$$= \sum_{j=1}^{K} w_j N(\underline{X}, \underline{\mu}_j, \Sigma_j)$$

 $w_j \equiv$ represents the probability of each mixture component $N(\underline{X}, \mu_j, \Sigma_j) \equiv$ multi-variate Gaussian density with mean μ_j and covariance Σ_j

Gaussian Mixture Model (GMM)

$$\widehat{P}(\underline{X}) = \sum_{j=1}^{K} w_j N(\underline{X}, \underline{\mu}_j, \Sigma_j)$$

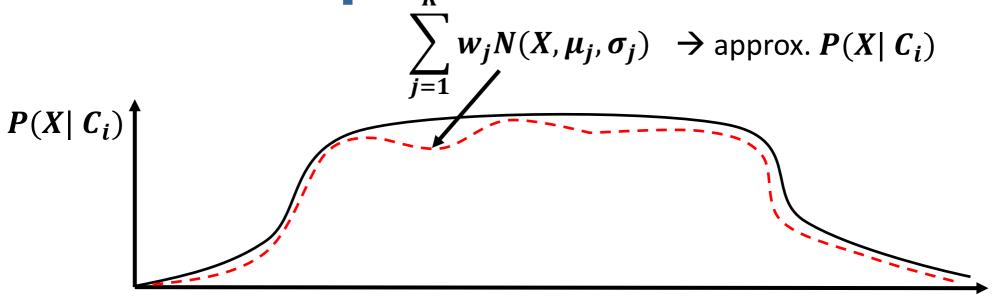
Condition:

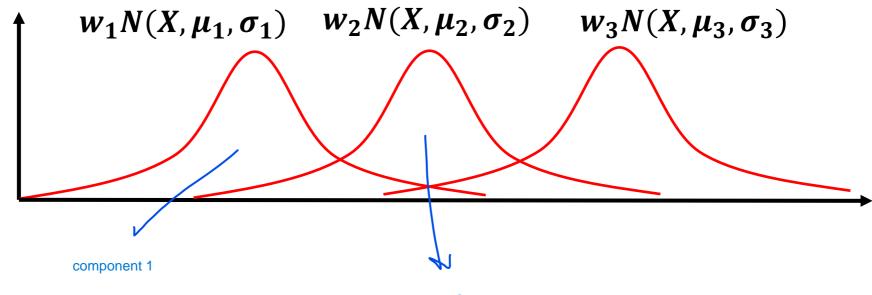
$$\sum_{j=1}^K w_j = 1$$

Because we need:

$$\int_{-\infty}^{\infty} \widehat{P}(\underline{X}) = \sum_{j=1}^{K} w_j \left(\int_{-\infty}^{\infty} N(\underline{X}, \underline{\mu}_j, \Sigma_j) \right) = 1$$

1-D Example





Expectation-Maximization (EM)

- Apply EM algorithm, which is an iterative algorithm, to estimate the parameters of the GMM components
- For simplicity assume 2-component case ,i.e.,

$$\widehat{P}(\underline{X}|C_i) = w N(\underline{X}, \underline{\mu}_1, \Sigma_1) + (1 - w) N(\underline{X}, \underline{\mu}_2, \Sigma_2)$$

Expectation-Maximization (EM)

- 1. Take initial guesses for the parameters: $w, \underline{\mu}_1, \Sigma_1, \underline{\mu}_2$ and Σ_2
- 2. Expectation step: compute the responsibilities:

$$\widehat{\gamma}_{m} = \frac{\widehat{w}N\left(\underline{X}(m), \underline{\widehat{\mu}}_{1}, \widehat{\Sigma}_{1}\right)}{\widehat{w}N\left(\underline{X}(m), \underline{\widehat{\mu}}_{1}, \widehat{\Sigma}_{1}\right) + (1 - \widehat{w})N\left(\underline{X}(m), \underline{\widehat{\mu}}_{2}, \widehat{\Sigma}_{2}\right)}$$

 $\hat{\gamma}_m$ represents the probability that $\underline{X}(m)$ is generated from component 1

3. Maximization step: compute the weighted means & covariance matrices:

$$\begin{split} \hat{\underline{\mu}}_1 &= \frac{\sum_{m=1}^M \widehat{\gamma}_m \underline{X}(m)}{\sum_{m=1}^M \widehat{\gamma}_m}, \ \hat{\underline{\mu}}_2 = \frac{\sum_{m=1}^M (1-\widehat{\gamma}_m) \, \underline{X}(m)}{\sum_{m=1}^M (1-\widehat{\gamma}_m)} \\ \hat{\Sigma}_1 &= \frac{\sum_{m=1}^M \widehat{\gamma}_m \left(\underline{X}(m) - \hat{\underline{\mu}}_1\right) \left(\underline{X}(m) - \hat{\underline{\mu}}_1\right)^T}{\sum_{m=1}^M \widehat{\gamma}_m} \quad , \ \hat{\Sigma}_2 &= \frac{\sum_{m=1}^M (1-\widehat{\gamma}_m) \left(\underline{X}(m) - \hat{\underline{\mu}}_2\right) \left(\underline{X}(m) - \hat{\underline{\mu}}_2\right)^T}{\sum_{m=1}^M (1-\widehat{\gamma}_m)} \\ \hat{w} &= \frac{\sum_{m=1}^M \widehat{\gamma}_m}{M} \end{split}$$

4. Iterate steps 2 & 3 until convergence

Expectation-Maximization (EM)

$$\begin{split} \gamma_{m} &= P\big(\underline{X}(m) \in \text{component 1}\big) \\ &= \frac{P(comp.\ 1)\ P\big(\underline{X}(m)|comp.\ 1\big)}{P\left(\underline{X}(m)\right)} \quad \text{apply Bayes rule} \\ &= \frac{P(comp.\ 1)\ P\big(\underline{X}(m)|comp.\ 1\big)}{P(comp.\ 1)\ P\big(\underline{X}(m)|comp.\ 1\big) + P(comp.\ 2)\ P\big(\underline{X}(m)|comp.\ 2\big)} \\ &\equiv \frac{w\ N\big(\underline{X}(m),\underline{\mu_{1},\Sigma_{1}}\big)}{w\ N\big(\underline{X}(m),\underline{\mu_{1},\Sigma_{1}}\big) + (1-w)\ N\big(\underline{X}(m),\underline{\mu_{2},\Sigma_{2}}\big)} \end{split}$$

Issues with GMM

- Initialization:
 - EM is an iterative algorithm which is very sensitive to initial conditions:
 - Start from trash → end up with trash
 - Usually, we use the K-Means to get a good initialization

- Number of Gaussian Components:
 - Try different number of Gaussian components and choose the best based on validation set.

Midterm

Midterm will be up to this slide, i.e., GMM is included

Acknowledgment

 These slides have been created relying on lecture notes of Amir Atiya and Mohand Saïd Allili