

Machine Learning Assignment3 - EM for GMM

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1 Derive the equations for learning parameters of a Gaussian mixture model

Responsibility can be written as follows:

$$\gamma(z_{nk}) \equiv p(z_k = 1|x_n) = \frac{p(x_n|z_k = 1)p(z_k = 1)}{\sum_{j=1}^K p(x_n|z_j = 1)p(z_j = 1)}$$

In the context of the Gaussian mixture model, the log of the likelihood function is as follows:

$$\ln p(X|\pi, \mu, \Sigma) = \sum_{n=1}^N \ln \left\{ \sum_{k=1}^K \pi_k \mathcal{N}(x_n|\mu_k, \Sigma_k) \right\}$$

As we want to maximize the log likelihood, take derivatives with respect to μ_k, Σ_k, π_k and set them to zero.

1.1 Take derivatives with respect to μ_k and setting to zero

$$\begin{aligned} 0 &= \sum_{n=1}^N \frac{\pi_k \mathcal{N}(x_n|\mu_k, \Sigma_k)}{\sum_{j=1}^K \pi_j \mathcal{N}(x_n|\mu_j, \Sigma_j)} \Sigma_k (x_n - \mu_k) \\ &= \sum_{n=1}^N \gamma(z_{nk}) \Sigma_k (x_n - \mu_k) \quad \left(\frac{\pi_k \mathcal{N}(x_n|\mu_k, \Sigma_k)}{\sum_{j=1}^K \pi_j \mathcal{N}(x_n|\mu_j, \Sigma_j)} = \gamma(z_{nk}) \right) \end{aligned}$$

Multiply both side by Σ_k^{-1}

$$\mu_k = \frac{\sum_{n=1}^N \gamma(z_{nk}) X_n}{\sum_{n=1}^N \gamma(z_{nk})}$$

1.2 Take derivatives with respect to Σ_k and setting to zero

$$\begin{aligned} 0 &= \sum_{n=1}^N \frac{\pi_k \mathcal{N}(x_n|\mu_k, \Sigma_k)}{\sum_{j=1}^K \pi_j \mathcal{N}(x_n|\mu_j, \Sigma_j)} \left\{ \frac{1}{2} \sum_k^{-1} (x_n - \mu_k)(x_n - \mu_k)^T \Sigma_k^{-1} - \frac{1}{2} \Sigma_k^{-1} \right\} \\ &\Leftrightarrow \sum_{n=1}^N \gamma(z_{nk}) \left\{ \sum_k^{-1} (x_n - \mu_k)(x_n - \mu_k)^T - 1 \right\} = 0 \\ \Sigma_k &= \frac{\sum_{n=1}^N \gamma(z_{nk}) (x_n - \mu_k)(x_n - \mu_k)^T}{\sum_{n=1}^N \gamma(z_{nk})} \end{aligned}$$

1.3 Take derivatives with respect to π_k and setting to zero

π_k can be obtained by Lagrangian multiplier because it is a constrained optimization

$$J(X; \theta, \lambda) = \sum_{n=1}^N \ln \sum_{k=1}^K \pi_k \mathcal{N}(x_n|\mu_k, \Sigma_k) + \lambda \left(1 - \sum_{k=1}^K \pi_k \right)$$

$$\begin{aligned}
\frac{\partial J(X; \theta, \lambda)}{\partial \pi_k} &= \sum_{n=1}^N \frac{N(x_n | \mu_k, \Sigma_k)}{\sum_{j=1}^K \pi_j N(x_n | \mu_j, \Sigma_j)} - \lambda = 0 \\
\leftrightarrow \sum_{k=1}^K \sum_{n=1}^N \frac{\pi_k N(x_n | \mu_k, \Sigma_k)}{\sum_{j=1}^K \pi_j N(x_n | \mu_j, \Sigma_j)} - \lambda \sum_{k=1}^K \pi_k &= 0 \\
\leftrightarrow \sum_{k=1}^K \sum_{n=1}^N \gamma(z_{nk}) - \lambda &= 0 \\
\lambda &= N
\end{aligned}$$

$$\begin{aligned}
\frac{\partial J(X; \theta, \lambda)}{\partial \pi_k} &= \sum_{n=1}^N \frac{N(x_n | \mu_k, \Sigma_k)}{\sum_{j=1}^K \pi_j N(x_n | \mu_j, \Sigma_j)} - N = 0 \\
\leftrightarrow \sum_{n=1}^N \frac{N(x_n | \mu_k, \Sigma_k)}{\sum_{j=1}^K \pi_j N(x_n | \mu_j, \Sigma_j)} - N \pi_k &= 0 \\
\pi_k &= \frac{1}{N} \sum_{n=1}^N \gamma(z_{nk})
\end{aligned}$$