# Mixture Models and EM Algorithm

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Clustering problems could be solved by applying model-based approach, which consists in using certain models for clusters and attempting to optimize the fit between the data and the model. Each cluster (component) can be mathematically represented by a parametric distribution, for eg, Gaussian (continuous) or a poisson (discrete). The entire data set is therefore modelled by a mixture of these distributions. An individual distribution used to model a specific cluster is often referred to as a component distribution.

Let there be k clusters. Let the random variable C denote the component with values 1,..k. Here we are considering Gaussian mixture models. So  $x_j/(C = i) \sim N(\mu_i, \sum_i)$  where  $\mu_i$  and  $\Sigma_i$  are the mean and covariance matrix of the  $i^{th}$  class.

A data point is generated by first choosing a component and then generating a sample from that component. By total probability theorem,

$$p(x) = \sum_{i=1}^{k} p(C=i)p(x/C=i)$$
(1)

[p(C = i) is analogous to p(y = i) in Gaussian discriminant analysis.]

To determine in which cluster each  $x_j$  belongs,  $p(C = i/x_j)$  has to be found. Now

$$p(C = i/x_j) = p_{ij} = \frac{p(C = i)p(x_j/C = i)}{p(x_j)}, i = 1, 2, \dots, k, j = 1, 2, \dots, N$$
(2)

Hence  $\sum_{i=1}^{k} p_{ij} = 1$ . Let  $w_i = p(C = i), i = 1, 2, \dots, k$ . Therefore the unknown parameters of a mixture of Gaussians are  $w_i, \mu_i$  and  $\Sigma_i$ .

The EM algorithm can be applied to determine the unknown parameters. The EM algorithm has two main steps: E step & M step. In the E-step, it assumes the values of the model (that is  $w_i, \mu_i$  and  $\Sigma_i$ ) and find  $P(C = i/x_j), i = 1, 2, ..., k, j = 1, 2, ..., N$ . In the M-step, it updates the parameters of the model. The process iterates until convergence.

## E step

In the E step, compute the probabilities  $p_{ij}$ , i = 1, 2, ..., k, j = 1, 2, ..., N.

# M step

Compute the new mean, covariance and component weights as follows:

$$\mu_{i} = \frac{\sum_{j=1}^{N} p_{ij} x_{j}}{\sum_{j=1}^{N} p_{ij}}$$

[For sure event,  $\mu_i = \frac{\sum_j 1\{x_j \in C = i\}x_j}{\sum_j 1.\{x_j \in C = i\}}$ . Here, we don't know whether  $x_j$  is in component *i*. We only know  $p(C = i/x_j)$ .]

$$\Sigma_{i} = \frac{\sum_{j} p_{ij} (x_{j} - \mu_{i}) (x_{j} - \mu_{i})^{T}}{\sum_{j=1}^{N} p_{ij}}$$
$$w_{i} = \frac{\sum_{j=1}^{N} p_{ij}}{N}$$

[Compare these formulas with those of Gaussian discriminant analysis] The algorithm can be summarized as follows:

#### Algorithm 1 EM algorithm

Initialize  $\mu_i$ ,  $\Sigma_i$ ,  $w_i$ , i = 1, 2, ..., kIterate until covergence: E Stepfor i = 1 to k do for j = 1 to N do calculate  $p(x_j/C = i) = \frac{1}{(2\pi)^{n/2} |\Sigma_i|^{1/2}} \exp{-\frac{1}{2}(x_j - \mu_i)^T \Sigma_i^{-1}(x_j - \mu_i)}$ calculate  $p_{ij} = \frac{p(x_j/C = i)w_i}{\sum_{i=1}^k p(x_j/C = i)w_i}$ end for  $p_i = \sum_{j=1}^N p_{ij}$ end for M Stepfor i = 1 to k do calculate  $\mu_i = \frac{\sum_{j=1}^N p_{ij}x_j}{p_i}$ calculate  $\Sigma_i = \frac{\sum_{j=1}^N p_{ij}(x_j - \mu_i)(x_j - \mu_i)^T}{p_i}$ set  $w_i = \frac{p_i}{N}$ end for end

### References

- (1) Artificial Intelligence by Stuart Russel and Peter Norwig(2) Andrew Ng's Lecture Note