Conditional Distributions of a Gaussian Mixture Model

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1 Introduction

Gaussian Mixture Models are a classic clustering technique, that can easily be generalised to, for example, semi-supervised learning. Sometimes we need to compute closed-form expressions for the conditional distributions. Finding this a bit more difficult that expected, these notes and code were created as a way of making sure that I'd done it properly...

2 Conditional of a Gaussian Mixture Model

Say we have the following Gaussian Mixture Model:

$$p(\boldsymbol{x}_1, \boldsymbol{x}_2) = \sum_{c} \Pr(c) \mathcal{N} \left(\begin{pmatrix} \boldsymbol{x}_1 \\ \boldsymbol{x}_2 \end{pmatrix}; \begin{pmatrix} \boldsymbol{\mu}_1^{(c)} \\ \boldsymbol{\mu}_2^{(c)} \end{pmatrix}, \begin{bmatrix} \boldsymbol{\Sigma}_{1,1}^{(c)} & \boldsymbol{\Sigma}_{1,2}^{(c)} \\ \boldsymbol{\Sigma}_{2,1}^{(c)} & \boldsymbol{\Sigma}_{2,2}^{(c)} \end{bmatrix} \right)$$
(1)

where $\mathbf{x}_1 \in \mathbb{R}^{D_1}$, $\mathbf{x}_2 \in \mathbb{R}^{D_2}$, c indexes each Gaussian in the mixture and Pr(c) is the mixture proportion associated with the cth Gaussian. Our aim is to derive an expression for $p(\mathbf{x}_1 \mid \mathbf{x}_2)$.

We begin by noting that

$$p(\boldsymbol{x}_1 \mid \boldsymbol{x}_2) = \sum_{c} \Pr(c \mid \boldsymbol{x}_2) \mathcal{N}\left(\boldsymbol{x}_1; \boldsymbol{\mu}_{1|2}^{(c)}, \boldsymbol{\Sigma}_{1|2}^{(c)}\right)$$
(2)

where, using standard properties of Gaussian distributions, we know that:

$$\mu_{1|2}^{(c)} = \mu_1^{(c)} + \Sigma_{1,1}^{(c)} \left(\Sigma_{2,2}^{(c)}\right)^{-1} (x_2 - \mu_2^{(c)})$$
(3)

and

$$\Sigma_{1|2}^{(c)} = \Sigma_{1,1}^{(c)} - \Sigma_{1,2}^{(c)} \left(\Sigma_{2,2}^{(c)}\right)^{-1} \Sigma_{2,1}^{(c)}$$
(4)

Note that the mixture proportions in equation (??) are now conditional on x_2 and that, in general, we cannot say that Pr(c) will be equal to $Pr(c|x_2)$. To evaluate $Pr(c|x_2)$ we use Bayes' theorem to obtain:

$$\Pr(c|\mathbf{x}_2) = \frac{p(\mathbf{x}_2|c)\Pr(c)}{\sum_{c'} p(\mathbf{x}_2|c')\Pr(c')}$$
(5)

$$= \frac{\mathcal{N}(\boldsymbol{x}_{2} \mid \boldsymbol{\mu}_{2}^{(c)}, \boldsymbol{\Sigma}_{2,2}^{(c)}) \Pr(c)}{\sum_{c'} \mathcal{N}(\boldsymbol{x}_{2} \mid \boldsymbol{\mu}_{2}^{(c')}, \boldsymbol{\Sigma}_{2,2}^{(c')}) \Pr(c')}$$
(6)

Example code is implemented in Python 3.