Finite Mixture Model

Introduction

Imagine we randomly choose a distribution to sample from. Let k denote which distribution we choose.

- Distribution 1
 - Parameter Ω_1
 - Probability of choosing distribution 1 is π_1
 - $-x|k=1,\Omega_1 \sim \Pr(x|k=1,\Omega_1)$
- Distribution 2
 - Parameter Ω_2
 - Probability of choosing distribution 2 is π_2
 - $-x|k=2,\Omega_2 \sim \Pr(x|k=2,\Omega_2)$

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- Distribution C
 - Parameter Ω_C
 - Probability of choosing distribution C is π_C
 - $-x|k=C,\Omega_C \sim \Pr(x|k=C,\Omega_C)$

In general we have data $\mathbf{x} = \{x_1, x_2, ... x_n\}$. Suppose we know which distribution each sample was sampled from $\mathbf{k} = \{k_1, k_2, ... k_n\}$. We know the parameters of each distribution $\mathbf{\Omega} = \{\Omega_1, \Omega_2, ... \Omega_C\}$. Finally we know the probability of choosing each distribution $\mathbf{\pi} = \{\pi_1, \pi_2, ... \pi_C\}$. We can represent each sample as:

$$x_i|k_i, \mathbf{\Omega}| \sim \Pr(x_i|k_i, \mathbf{\Omega})$$

Bayes Theorm

$$\Pr(\mathbf{k}, \mathbf{\Omega} | \mathbf{x}) \propto \Pr(\mathbf{x} | \mathbf{k}, \mathbf{\Omega}) \Pr(\mathbf{k}, \mathbf{\Omega}, \boldsymbol{\pi})$$

Prior

We often times assume independence between the some of the parameters

$$\Pr(\mathbf{k}, \mathbf{\Omega}, \boldsymbol{\pi}) = \Pr(\mathbf{k} | \boldsymbol{\pi}) \Pr(\boldsymbol{\pi}) \Pr(\mathbf{\Omega})$$

$$\begin{aligned} \Pr(\mathbf{k}, \mathbf{\Omega}, \boldsymbol{\pi}) &= \Pr(\mathbf{k}, \boldsymbol{\pi}) \Pr(\mathbf{\Omega}) \\ &\propto \Pr(\mathbf{k} | \boldsymbol{\pi}) \Pr(\boldsymbol{\pi}) \Pr(\mathbf{\Omega}) \end{aligned}$$

Prior $Pr(\pi)$

We typically sample π from a Dirichlet Distribution. If so we have the following:

$$\pi \sim \text{Dirichlet}(\alpha) \mid \alpha \in [0, \infty)^C$$

using the PDF of the Dirichlet Distribution we can get:

$$\Pr(\boldsymbol{\pi}) = \frac{1}{B(\boldsymbol{\alpha})} \prod_{j=1}^{C} \pi_j^{\alpha_j - 1}$$

The normalization constant is found using this B function. In this $\Gamma(x)$ denotes the Gamma function.

$$B(\boldsymbol{\alpha}) = \frac{\prod_{j=1}^{C} \Gamma(\alpha_j)}{\Gamma(\sum_{j=1}^{C} \alpha_j)}$$

Prior $Pr(k|\pi)$

for a single sample k_i the probability is just the associated π

$$\Pr(k_i|\boldsymbol{\pi}) = \pi_{k_i}$$

We can represent in a diffrent way were we product over all the π

$$\Pr(k_i|\boldsymbol{\pi}) = \prod_{j=1}^{C} \pi_j^{\delta_{k_i j}}$$

 $\delta_{k_i j}$ Is the Kronecker delta function $\delta_{ij} = \begin{cases} 0 & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases}$. Lets see what this looks like for when $k_i = 2$

$$\Pr(k_i = 2 | \boldsymbol{\pi}) = \prod_{j=1}^{C} \pi_j^{\delta_{2j}}$$

$$= \pi_1^{\delta_{21}} \pi_2^{\delta_{22}} \pi_2^{\delta_{23}} \dots \pi_C^{\delta_{2C}}$$

$$= \pi_1^0 \pi_2^1 \pi_2^0 \dots \pi_C^0$$

$$= \pi_2$$

We can see that this product is another way to represent the math. Going back to finding $\Pr(\mathbf{k}|\boldsymbol{\pi})$ we can assume that k_i are independent of each other

$$\begin{aligned} \Pr(\mathbf{k}|\boldsymbol{\pi}) &= \prod_{i=1}^{n} \Pr(k_i|\boldsymbol{\pi}) \\ &= \prod_{i=1}^{n} \prod_{j=1}^{C} \pi_j^{\delta_{k_i j}} \\ &= \prod_{i=1}^{n} \pi_j^{n_j} \; \bigg| \; n_j \; \text{is number of samples in category j} \end{aligned}$$

$\mathbf{Prior}\ \mathbf{Pr}(\Omega)$

if we assume independent parameters:

$$\Pr(\mathbf{\Omega}) = \prod_{j=1}^{C} \Pr(\Omega_j)$$

Likelihood

We can look at a single sample and do a smilar thing that we did for $\Pr(\mathbf{k}|\boldsymbol{\pi})$

$$\Pr(x_i|k_i, \mathbf{\Omega}) = \prod_{i=1}^{C} \Pr(x_i|k_i = j, \Omega_j)^{\delta_{k_i j}}$$

Looking at all samples we get

$$\Pr(\mathbf{x}|\mathbf{k}, \mathbf{\Omega}) = \prod_{i=1}^{n} \Pr(x_i|k_i, \mathbf{\Omega})$$

$$= \prod_{i=1}^{n} \prod_{j=1}^{C} \Pr(x_i|k_i = j, \Omega_j)^{\delta_{k_i j}}$$

$$= \prod_{j=1}^{C} \prod_{i \mid k_i = j} \Pr(x_i|k_i = j, \Omega_j)$$