

Implementation of Bayesian Hierarchical Clustering

Lina Yang, Xiaodi Qin

April 29, 2017

1 Abstract

Hierarchical clustering is commonly used in unsupervised learning. There are several limitations to the traditional hierarchical clustering, including no guide to pre-specify number of clusters, difficult to choose suitable distance metric, and lack of probability based criterion for model evaluation. To overcome these limitations, Heller and Ghahramani (2005) developed a Bayesian hierarchical clustering based on Dirichlet process mixtures. It uses marginal likelihoods and Bayesian hypothesis testing as criteria for merging cluster.

2 Background

3 Algorithm

4 Optimization

5 Application

5.1 Simulated data sets

5.2 Real data sets

6 Comparative analysis

7 Discussion

8 Code

The repository can be found at <https://github.com/qxxxd/Bayesian-Hierarchical-Clustering>.

Algorithm 1: Bayesian Hierarchical Clustering

Input: Data $X = (X_0, X_1, \dots, X_N)$, $family \in \{niw\}$, hyperparameter α , scaling factor on the prior precision of the mean r .

Output: A linkage matrix Z

```
1 Set  $\mathbb{S} = \emptyset$ 
2 For  $l \in \{0, 1, \dots, N - 1\}$ :
3    $n_l^0 = 1, d_l^0 = \alpha, X_l^0 = X_l, ml_l = \text{FAMILY}(X_l^0)$ 
4    $\mathbb{S} = \mathbb{S} \cup \{l\}$ 
5 Set  $t = 0, \mathbb{P} = \emptyset$ 
6 For  $i \in \{0, 1, \dots, N - 2\}$ :
7   For  $j \in \{i + 1, \dots, N - 1\}$ :
8      $c_{1,t} = i, c_{2,t} = j, n_t = n_i^0 + n_j^0$ 
9      $X_t = (X_i^0, X_j^0)^T, d_t = \alpha\Gamma(n_t) + d_i^0 d_j^0$ 
10     $P_{1,t} = \text{FAMILY}(X_t)\alpha\Gamma(n_t)/d_t, P_{2,t} = ml_i ml_j (d_i^0 d_j^0 / d_t)$ 
11     $logodds_t = \log P_{1,t} - \log P_{2,t}$ 
12     $\mathbb{P} = \mathbb{P} \cup \{t\}, t = t + 1$ 
13 Set  $p = 0, Z = []$ 
14 While 1:
15    $idx = \arg \max_{idx \in \mathbb{P}} logodds$ 
16    $Z.\text{APPEND}([c_{1,idx}, c_{2,idx}, logodds_{idx}, n_{idx}])$ 
17    $n_{N+p}^0 = n_{idx}, X_{N+p}^0 = X_{idx}, d_{N+p}^0 = d_{idx}, ml_{N+p} = P_{1,idx} + P_{2,idx}$ 
18    $rm = \{c_{1,idx}, c_{2,idx}\}, \mathbb{S} = \mathbb{S} \setminus rm$ 
19   If  $\mathbb{S} = \emptyset$ :
20     break
21   For  $q \in \mathbb{S}$ :
22      $c_{1,t} = N + p, c_{2,t} = q, n_t = n_{N+p}^0 + n_q^0$ 
23      $X_t = (X_{N+p}^0, X_q^0)^T, d_t = \alpha\Gamma(n_t) + d_{N+p}^0 d_q^0$ 
24      $P_{1,t} = \text{FAMILY}(X_t)\alpha\Gamma(n_t)/d_t, P_{2,t} = ml_{N+p} ml_q (d_{N+p}^0 d_q^0 / d_t)$ 
25      $logodds_t = \log P_{1,t} - \log P_{2,t}$ 
26      $\mathbb{P} = \mathbb{P} \cup \{t\}, t = t + 1$ 
27    $\mathbb{P} = \mathbb{P} \setminus \{r : c_{1,r} \in rm \vee c_{2,r} \in rm\}$ 
28    $\mathbb{S} = \mathbb{S} \cup \{N + p\}, p = p + 1$ 
29 return  $Z$ 
```

9 References

Heller, K. A. and Z. Ghahramani (2005). Bayesian Hierarchical Clustering. In *Proceedings of the 22Nd International Conference on Machine Learning*, ICML '05, New York, NY, USA, pp. 297–304. ACM.