Consensus clustering for Bayesian mixture models: Supplementary materials

Stephen Coleman, Paul DW Kirk and Chris Wallace September 11, 2020

Abstract

- 1 Algorithms
- 2 The model
- 3 Additional results
- 3.1 Simulations
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Input: Distance between means \Delta_{\mu}
A common standard deviation \sigma^2
A number of clusters K
The number of items to generate in total N
The number of features to generate in total P
An indicator vector of feature relevance \phi = (\phi_1, \dots, \phi_P)
The expected proportion of items in each cluster \pi = (\pi_1, \dots, \pi_K)
A method for sampling x times from the array y, with weights \pi:
Sample(y, x, \pi)
A method for permuting a vector x: Permute(x)
A method for generating a value from a univariate Gaussian
distribution with mean \mu and standard deviation \sigma^2: Gaussian(\mu, \sigma^2)
Output: A dataset, X
The generating cluster labels c = (c_1, \ldots, c_N)
begin
    /* initialise the empty data matrix
   X \leftarrow 0_{N \times P};
   /* create a matrix of K means
   \mu \leftarrow (\Delta_{\mu}, \ldots, K\Delta_{\mu});
    /* generate the allocation vector
   c \leftarrow Sample(1:K,N,\pi);
   \mathbf{M} \leftarrow \mathbf{0}_{N \times N};
   for p = 1 to P do
       /* Test if the feature is relevant, if relevant
           generate data from a mixture of univariate
           Gaussians, otherwise draw all items from the same
           distribution
       if \phi_p = 1 then
           \nu \leftarrow Permute(\mu);
           for n = 1 to N do
            X(n,p) \leftarrow Gaussian(\nu_{c_n}, \sigma^2)
           end
       end
       if \phi_p = 0 then
           for n = 1 to N do
            X(n,p) \leftarrow Gaussian(0,\sigma^2)
           end
       end
   /* Mean centre and scale the data
                                                                            */
   X \leftarrow Normalise(X)
end
```

Algorithm 1: Data generation for a mixture of Gaussian with independent features. This algorithm is implemented in the generateSimulationDataset function from the mdiHelpR package available at www.github.com/stcolema/mdiHelpR.

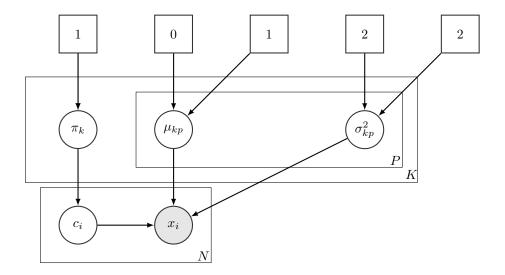


Figure 1: Directed acyclic graph for the Bayesian mixture of Gaussians used.

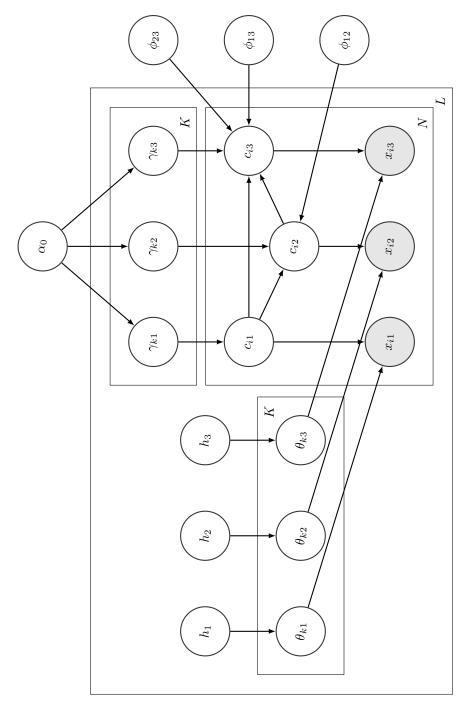
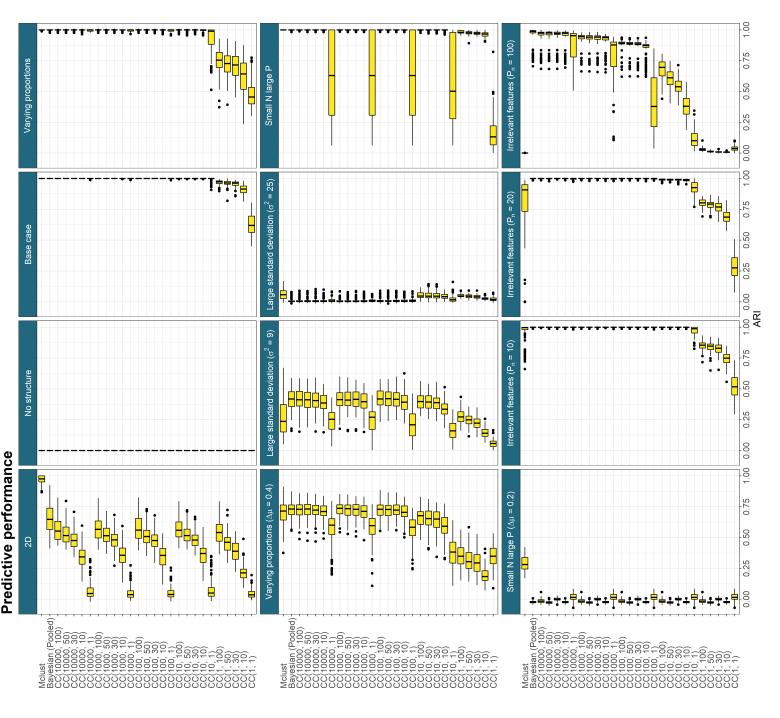


Figure 2: Directed acyclic graph for the Multiple Dataset Integration model for 3 datasets.



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Figure 4: Frobenius norm across simulations. CC(R,S) denotes consensus clustering using the R^{th} sample from S different chains. Lower values are better.

 $./{\tt Imag} {\color{red}\mathsf{es}} / {\tt Yeast/GloverRepresentationBayesChains.png}$

Figure 5: The GO enrichment is very similar across chains.