mixedClust: an R package for mixed data classification, clustering and co-clustering

Margot Selosse, Julien Jacques, Christophe Biernacki

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mixedClust: an R package for mixed data classification, clustering and co-clustering

Package functionalities
The package provides model-based algorithm for clustering, co-clustering and classification with mixed-type data.

Principal functions are:
mixedClust # to perform clustering
mixedClassif # to perform classification, in a parsimonious way or not predictions # use the result from mixedClassif for predictions

Notations
- \(x\): N rows and \(J_1 + \ldots + J_d + \ldots + J_D\) columns
- \(x\) composed of several matrices: \(x^1, \ldots, x^D\)
- \(x^d\): N \(\times J_d\) matrix
- \(x^d\) is made of variables from one of 5 different types: Continuous, Nominal, Ordinal or Integer.
- In unsupervised methods: \(G\) clusters in line, \(H_1\ldots H_D\) clusters in column

\[
x = \begin{bmatrix} x^1 \ldots \ldots x^D \end{bmatrix}, x^d = (x^d_{ij})_{1 \leq i \leq N, 1 \leq j \leq J_d}
\]

Models (for \(D = 2\))

Legend: -Observed partitions -Latent partitions

- Clustering:
  \[p(x; \Theta) = \sum_{z \in \Omega} p(z; \Theta) \times p(x^1|z; \Theta)p(x^2|z; \Theta)\]

- Co-clustering:
  \[p(x; \Theta) = \sum_{w, w', \Theta} p(w; \Theta)p(w'; \Theta)p(x^1|w; \Theta)p(x^2|w'; \Theta)p(x^1|w'; \Theta)p(x^2|w; \Theta)\]

- Classification without parsimony:
  \[p(x; \Theta) = p(z; \Theta) \times p(x^1|z; \Theta)p(x^2|z; \Theta)\]

- Classification with parsimony (obtained by clustering the features):
  \[p(x; \Theta) = \sum_{w, w', \Theta} p(w; \Theta)p(w'; \Theta)p(x^1|w, \Theta)p(x^2|w', \Theta)p(x^1|w', \Theta)p(x^2|w, \Theta)\]

The parameters we want to estimate are:
\[
\Theta = (\alpha_{gh}, \beta_{gh}, \gamma_{gh}, \delta_{gh}, \rho_{gh})_{1 \leq g \leq 2, 1 \leq h \leq D}
\]
- \(\alpha_{gh}\): parameters of distribution of \(g^{th}\) row-cluster and \(h^{th}\) column-cluster of \(x^d\). It will depend on the type of \(x^d\).
- \(\beta_{gh}\): mixing proportion of \(g^{th}\) row-cluster
- \(\gamma_{gh}\): mixing proportion of \(h^{th}\) column-cluster for \(x^d\)

Inference
EM and BIC not tractable in co-clustering, due to the double missing structure. Consequently, we use:
- Stochastic EM algorithm, with a Gibbs sampler for the latent variables simulation
- ICL-BIC criterion for model selection

Results for classification on real dataset

Dataset
- Trauma-survey: 823 persons answered to 88 psychological questions about anxiety, depression, anger and possibly traumatizing life events. 307 of them were diagnosed with trauma, and 516 were declared not traumatized.
- \(x^1\): Categorical data from 17 questions about traumatizing life events.
- \(x^2\): Ordinal data from 71 questions about anger, depression and anxiety.
- 2/3 of the dataset was used to train the model. The last 1/3 was then used for prediction.

Results

<table>
<thead>
<tr>
<th></th>
<th>precision</th>
<th>recall</th>
<th>specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>not parsimonious</td>
<td>0.75</td>
<td>0.80</td>
<td>0.83</td>
</tr>
<tr>
<td>((H_1, H_2) = (1.3))</td>
<td>0.78</td>
<td>0.88</td>
<td>0.85</td>
</tr>
<tr>
<td>((H_1, H_2) = (2.5))</td>
<td>0.82</td>
<td>0.92</td>
<td>0.88</td>
</tr>
</tbody>
</table>

Table: Precision, recall and specificity for different \(k_c\).

On classification with parsimony:
- Better results are obtained on predictions when we introduce parsimony than when we don’t.
- Parsimony training result gives less parameters, which makes easier the interpretation.

Features clusters for parsimonious classification

![Figure: Patients classification and features clusters. Categorical answers about life events on the left. Ordinal answers about Anger/Angry/Depression on the right.](image)

R code

```r
# Defining the dataset properties
distrib = c("Multinomial", "Box") # defining the distribution types
# Defining the SEM-Gibbs algorithm configuration
nbSEM = 250 # total number of iterations
nbSEMburn = 200 # burn-in period
nbblock = 10 # minimum number of elements in one block
init = "kmeans" # initialization type
# Defining the number of classes
kr = 2 # Two classes : Traumatized/Not Traumatized
k_c = c(2, 5) # Introducing parsimony (put to 0 for no parsimony)
# Running the classification function
classification = mixedClassif(x.train, y.train, list, k = kr, k_c = k_c, init, distrib, nbSEM, nbSEMburn, nbblock, init)
prediction = predictions(classification, Mtest)
# Printing predicted labels
prediction$ER$t.predict;
```

References