mixedClust: an R package for mixed data classification, clustering and co-clustering
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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, Integer or Functional.
- In unsupervised methods: \( G \) clusters in line, \( H_1 \ldots H_D \) clusters in column

\[
x = \begin{bmatrix}
x^1 & \ldots & x^D 
\end{bmatrix}, \quad x^d = (x^d)_{i \in S(N), j \in S(J)}
\]

Models (for \( D = 2 \))

Legend: -Observed partitions -Latent partitions

- Clustering:
  \[
p(x; \Theta) = \sum_{v \in V} p(v; \Theta) \times p(x^1|v \Theta)p(x^2|v \Theta)
\]
- Co-clustering:
  \[
p(x; \Theta) = \sum_{v,w \in V \times W} p(v; \Theta)p(w; \Theta)p(x^1|v \Theta)p(x^2|w \Theta)
\]
- Classification without parsimony:
  \[
p(x; \Theta) = p(v; \Theta) \times p(x^1|v \Theta)p(x^2|v \Theta)
\]
- Classification with parsimony (obtained by clustering the features):
  \[
p(x; \Theta) = \sum_{v,w \in V \times W} p(v; \Theta)p(w; \Theta)p(x^1|v \Theta)p(x^2|w \Theta)
\]

The parameters we want to estimate are:

\[
\Theta = \{ \alpha^d, \beta^d, \gamma, \rho^g, \rho^h \} \quad \text{where} \quad 1 \leq g \leq D \text{ and } 1 \leq h \leq D
\]
- \( \alpha^d \): parameters of distribution of \( g^d \) row-cluster and \( h^k \) column-cluster of \( x^d \). It will depend on the type of \( x^d \).
- \( \gamma \): \( g^k \) mixing proportion of \( g^k \) row-cluster
- \( \rho^h \): \( h^k \) mixing proportion of \( h^k \) 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.

<table>
<thead>
<tr>
<th>Results</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/Anger/Depression on the right.

R code

```r
# Defining the dataset properties
# dist = c(0,17) # defining where each type begins in the complete dataset
distrib = c("Multinomial","Bos") # defining the distribution types
# defining the SEM-Gibbs algorithm configuration
# nbSEM = 250 # total number of iterations
# nbSEMburn = 200 # burn-in period
# nbindmini = 10 # minimum number of elements in one block
# init = "kmeans" # initialization type

# defining the number of clusters
# k = 2 # Two classes : Traumatized/Not Traumatized
# kc = c(2,5) # Introducing parsimony (put to 0 for no parsimony)

# running the classification function
# classif = mixedClassifM.train, y.train, dist, k = kr, kc = kc, init = distrib, nbSEM, nbSEMburn, nbindmini)
prediction <- predictions(classif, M.test)

# printing predicted labels
prediction@zr@topredict;
```

References


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