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 \( J_1 + \ldots + J_d \) 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 columns

\[
x = \left[ \begin{array}{c}
x^1 \\
\vdots \\
\vdots \\
x^D \\
\end{array} \right], x^d = (x^d_{ij})_{1 \leq i \leq N; 1 \leq j \leq J_d}
\]

Models (for \( D = 2 \))

Legend: -Observed partitions -Latent partitions

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

The parameters we want to estimate are:

\[
\Theta = (\gamma_1, \ldots, \gamma_D, \Theta_{V})^{T} \in \mathcal{L} \times H_d \quad 1 \leq d \leq D
\]

- \( \gamma_d \): parameters of distribution of the \( g^{th} \) row-cluster and \( h^{th} \) column-cluster of \( x^d \). It will depend on the type of \( x^d \).
- \( Y_l \): mixing proportion of \( g^{th} \) row-cluster
- \( \eta_{hl} \): 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>prediction, recall and specificity</th>
<th>not parsimonious</th>
<th>0.75</th>
<th>0.80</th>
<th>0.83</th>
</tr>
</thead>
<tbody>
<tr>
<td>(H_1, H_2) = (1,3)</td>
<td>0.78</td>
<td>0.88</td>
<td>0.85</td>
<td></td>
</tr>
<tr>
<td>(H_1, H_2) = (2,5)</td>
<td>0.82</td>
<td>0.92</td>
<td>0.88</td>
<td></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/anxiety/depression on the right.

R code

```
# defining the dataset properties
cl.dist = c(0.07) # defining where each type begins in the complete dataset
distrib = c("Multinomial", "Bos") # defining the distribution types

# defining the SEM-Gibbs algorithm configuration
nSEM = 250 # total number of iterations
nSEMburn = 200 # burn-in period
nbindmini = 10 # minimum number of elements in one block
init = "kmeans" # initialization type

# defining the number of clusters
nc = 2 # Two classes : Traumatized/Not Traumatized

# running the classification function
predicted = predict(mixedClassif(x = x_train, y = y_train, dist = cl.dist, kr = nc, kc = kc, init = init, distrib = distrib, nSEM = nSEM, nbindmini = nbindmini))

# printing predicted labels
prediction = predict(mixedClust(data, nclasses = nc, init = init, kr = kr, kc = kc), newdata = x_test)
```