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 column

Models (for \( D = 2 \))

Legend : Observed partitions - Latent partitions

- Clustering:
  \[
  p(x; \Theta) = \sum_{z \in Z} p(z; \Theta) \prod_{i=1}^{D} p(x^i | z^i; \Theta)
  \]
- Co-clustering:
  \[
  p(x; \Theta) = \sum_{i=1}^{N} p(v; \Theta) \prod_{i=1}^{D} p(x^i | v^i; \Theta) \prod_{i=1}^{D} p(x^i | v^i; \Theta)
  \]
- Classification without parsimony:
  \[
  p(x; \Theta) = \prod_{i=1}^{N} p(x_i; \Theta)
  \]
- Classification with parsimony (obtained by clustering the features):
  \[
  p(x; \Theta) = \prod_{i=1}^{N} p(x_i; \Theta)
  \]

The parameters we want to estimate are:

- \( \Theta = (\alpha, \gamma, \delta_1, \ldots, \delta_D) \): \( N \times D \) and \( 1 \leq d \leq D \)
- \( \alpha_d \): parameters of distribution of \( g^d \)-th row-cluster and \( h^d \)-th column-cluster of \( x^d \). It will depend on the type of \( x^d \).
- \( \gamma_d \): mixing proportion of \( g^d \)-th row-cluster
- \( \delta_d \): mixing proportion of \( h^d \)-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>kc</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) = (1.8))</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 \( kc \).

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/Angor/Axiety/Depression on the right.

R code

```r
#### Defining the dataset properties ####
dist = c("Multinomial","Bos") # defining the distribution types
nSEMburn = 200 # burn-in period
nbindmini = 10 # minimum number of elements in one block
init = "kmeans" # initialization type

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

#### running the classification function ####
classif = mixedClassifM(train, y.train, dist, kr = kr, kc = kc, init = init, distri = dist, nSEM = nSEMburn, nbindmini)
prediction <- predictions(classif, M.test)

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

References