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.

- 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

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

### Models (for \( D = 2 \))

Legend: Observed partitions - Latent partitions

- **Clustering:**
  \[
p(x; \Theta) = \sum_{i \in I} p(v; \Theta) \times p(x^1 | v; \Theta)p(x^2 | v; \Theta)
\]

- **Co-clustering:**
  \[
p(x; \Theta) = \sum_{i \in I} p(v; \Theta)p(w^1; \Theta)p(w^2; \Theta) \times p(x^1 | i, w^1; \Theta)p(x^2 | i, w^2; \Theta)
\]

- **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):**
  \[
p(x; \Theta) = \sum_{i \in I} p(v; \Theta)p(w^1; \Theta)p(w^2; \Theta) \times p(x^1 | i, w^1; \Theta)p(x^2 | i, w^2; \Theta)
\]

The parameters we want to estimate are:

\[
\Theta = \{ \alpha^d, \rho^d, p^d \}_{1 \leq d \leq D} \quad \{ \alpha^d : \text{parameters of distribution of } g^d \text{th row-cluster and } h^d \text{th column-cluster of } x^d \}; \quad \text{it will depend on the type of } x^d.
\]

\[
\{ P^d_h : \text{mixing proportion of } g^d \text{th row-cluster} \}
\]

\[
\{ p^d_h : \text{mixing proportion of } h^d \text{th column cluster for } x^d \}
\]

### 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>( k_c )</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>0.76</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/Anxiety/Depression on the right.

### R code

```r
# Defining the dataset properties
distri = c("Multinomial", "Boo") # defining the distribution types
# Defining the SEM-Gibbs algorithm configuration
nbSEM = 250 # total number of iterations
nbindmini = 10 # minimum number of elements in one block
init = "kmeans" # initialization type
# Defining the number of clusters
kr = 2 # Two classes : Traumatized/Not Traumatized
# Introducing parsimony (put to 0 for no parsimony)
kc = c(2.5)
# Running the classification function
classif = mixedClassif(x.train, y.train, distri, kr = kr, kc = kc, init, distrib, nbSEM, nbindmini)
prediction <- predictions(classif, M.test)
# Printing predicted labels
prediction@z@predict;
```

### References