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## **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
mixedCoClust # to perform co-clustering
mixedClassif # to perform classification, in a parsimonious way or not
predictions # use the result from mixedClassif for predictions
```

## Notations

- ▶  $\mathbf{x}$ :  $N$  rows and  $J = J_1 + \dots + J_d + \dots + J_D$  columns
- ▶  $\mathbf{x}$  composed of several matrices:  $\mathbf{x}^1, \dots, \mathbf{x}^D$
- ▶  $\mathbf{x}^d$ :  $N \times J_d$  matrix
- ▶  $\mathbf{x}^d$  is made of variables from one of 5 different types: **Continuous**, **Nominal**, **Ordinal**, **Integer** or **Functional**.
- ▶ In unsupervised methods:  $G$  clusters in line,  $H_1 \dots H_D$  clusters in column

$$\mathbf{x} = \left[ \begin{array}{c|c|c} \mathbf{x}^1 & \dots & \mathbf{x}^D \end{array} \right], \mathbf{x}^d = (x_{ij}^d)_{1 \leq i \leq N; 1 \leq j \leq J_d}$$

## Models (for $D = 2$ )

Legend: -Observed partitions -Latent partitions

- ▶ Clustering:

$$p(\mathbf{x}; \Theta) = \sum_{\mathbf{v} \in V} p(\mathbf{v}; \Theta) \times p(\mathbf{x}^1 | \mathbf{v}; \Theta) p(\mathbf{x}^2 | \mathbf{v}; \Theta)$$

- ▶ Co-clustering:

$$p(\mathbf{x}; \Theta) = \sum_{\mathbf{v}, \mathbf{w}^1, \mathbf{w}^2} p(\mathbf{v}; \Theta) p(\mathbf{w}^1; \Theta) p(\mathbf{w}^2; \Theta) \times p(\mathbf{x}^1 | \mathbf{v}, \mathbf{w}^1; \Theta) p(\mathbf{x}^2 | \mathbf{v}, \mathbf{w}^2; \Theta)$$

- ▶ Classification without parsimony:

$$p(\mathbf{x}; \Theta) = p(\mathbf{v}; \Theta) \times p(\mathbf{x}^1 | \mathbf{v}; \Theta) p(\mathbf{x}^2 | \mathbf{v}; \Theta)$$

- ▶ Classification with parsimony (obtained by clustering the features):

$$p(\mathbf{x}; \Theta) = \sum_{\mathbf{w}^1, \mathbf{w}^2} p(\mathbf{v}; \Theta) p(\mathbf{w}^1; \Theta) p(\mathbf{w}^2; \Theta) \times p(\mathbf{x}^1 | \mathbf{v}, \mathbf{w}^1; \Theta) p(\mathbf{x}^2 | \mathbf{v}, \mathbf{w}^2; \Theta)$$

The parameters we want to estimate are:

$$\Theta = (\alpha_{gh}^d, \gamma_g, \rho_h^d)_{1 \leq h \leq H_d \text{ and } 1 \leq d \leq D}$$

- ▶  $\alpha_{gh}^d$ : parameters of distribution of  $g^{th}$  row-cluster and  $h^{th}$  column-cluster of  $\mathbf{x}^d$ . It will depend on the type of  $\mathbf{x}^d$ .
- ▶  $\gamma_g$ : mixing proportion of  $g^{th}$  row-cluster
- ▶  $\rho_h^d$ : mixing proportion of  $h^{th}$  column cluster for  $\mathbf{x}^d$

## 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.
- ▶  $\mathbf{x}^1$ : Categorical data from 17 questions about traumatizing life events.
- ▶  $\mathbf{x}^2$ : 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

	precision	recall	specificity
not parsimonious	0.75	0.80	0.83
$(H_1, H_2) = (3, 8)$	0.78	0.88	0.85
$(H_1, H_2) = (2, 5)$	<b>0.82</b>	<b>0.92</b>	<b>0.88</b>

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

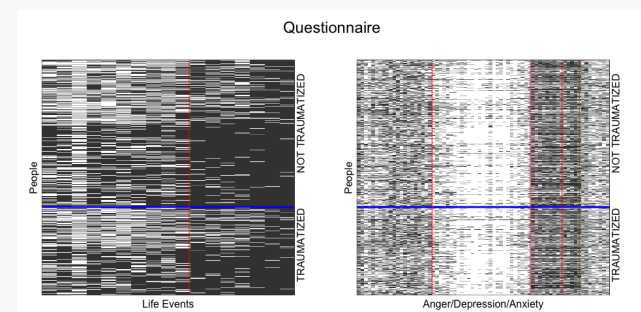


Figure: Patients classification and features clusters. Categorical answers about life events on the left. Ordinal answers about Anger/Anxiety/Depression on the right.

## R code

```
##### Defining the dataset properties #####
2 dlist = c(0,17) # defining where each type begins in the complete
  dataset
distrib = c("Multinomial", "Bos") # defining the distribution types
4
##### defining the SEM-Gibbs algorithm configuration #####
6 nbSEM = 250 # total number of iterations
nbSEMburn = 200 # burn-in period
8 nbindmini = 10 # minimum number of elements in one block
init = "kmeans" # initialization type
10
##### defining the number of clusters #####
12 kr = 2 # Two classes : Traumatized/Not Traumatized
kc = c(2,5) # Introducing parsimony (put to 0 for no parsimony)
14
##### running the classification function #####
16 classif = mixedClassif(M.train, y.train, dlist, kr = kr, kc = kc, init,
  distrib, nbSEM, nbSEMburn, nbindmini)
18 prediction <- predictions(classif, M.test)
20
##### printing predicted labels #####
prediction@zr_topredict;
```

## References

- [1] V. Robert. Classification et détection de signaux de pharmacovigilance dans des bases de données de grandes dimensions. PhD Thesis, Université Paris Sud, 2017.
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- [3] C. Keribin, G. Govaert, and G. Celeux. Estimation d'un modèle à blocs latents par l'algorithme SEM. 42èmes Journées de Statistique, 2010.