## Package 'doMIsaul'

July 19, 2021

```
Learning
Version 1.0.0
Description Algorithms for (i) unsupervised learning for dataset with
      missing data and/or left-censored data, using multiple imputation and
      consensus clustering; (ii) semisupervised learning with a survival
      endpoint (right-censored) for complete or incomplete datasets, using
      multiple imputation and consensus clustering in the latter case.
License GPL (>= 3)
{\bf URL} \ {\tt https://github.com/LilithF/doMIsaul}
BugReports https://github.com/LilithF/doMIsaul/issues
Imports aricode,
      arules,
      clusterCrit,
      clusteval,
      dplyr,
      ggplot2,
      Gmedian,
      graphics,
      MASS,
      methods,
      mice,
      NbClust,
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```

Title Do Multiple Imputation-Based Semisupervised and Unsupervised

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igraph, mclust, parallel, RColorBrewer, reshape2, testthat (>= 3.0.0), timeROC, truncnorm Remotes cran/clusteval LinkingTo nevreg  $\textbf{Config/testthat/edition} \ \ 3$ **Encoding** UTF-8 Language en-US LazyData true **Roxygen** list(markdown = TRUE) RoxygenNote 7.1.1

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## Description

Remove small clusters (i.e. unclassified observations for which no consensus was obtained)

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#### Usage

```
cleanUp_partition(
  partition,
  min.cluster.size = 10,
  level.order = NULL,
  Unclassified = c(NA, "Unclassified")
)
```

#### **Arguments**

partition the partition to clean (vector). min.cluster.size

Minimum cluster size (i.e., smaller clusters will be discarded)

level.order optional. If you supply a variable the cluster levels will be ordinated according

to the mean values for the variable

Unclassified string for the label of the unclassified observations. defaults value is NA.

#### Value

The cleaned up partition (factor).

#### **Examples**

```
part <- factor(kmeans(iris[, 1:4], 8)$cluster)
summary(part)
part.clean <- cleanUp_partition(part, Unclassified = "Unclassified")</pre>
```

CVE\_LP

Cross-validation for cox regression using the linear predictor estimator with wrapper for warnings handling

#### **Description**

Cross-validation for cox regression using the linear predictor estimator with wrapper for warnings handling

## Usage

```
CVE_LP(x)
```

## Arguments

Χ

list of 3 named elements: data (data containing columns time and status), partition (dataframe with 1 column), nfolds (number of fold for cross-validation).

## Value

numeric, cross-validation error

#### **Examples**

```
data(cancer, package = "survival")
cancer$status <- cancer$status - 1
part <- data.frame(Cl= factor(cancer[, "sex"]), stringsAsFactors = TRUE)
CVE_LP(list(data = cancer, partition = part, nfolds = 10))</pre>
```

evaluate\_partition\_semisup

Evaluation of a semisupervised obtained partition in comparison to reference partitions

#### **Description**

Evaluate number of clusters, ARI, AUC difference, c-index and CPE, with Supervised, unsupervised and Semisupervised reference partitions

#### Usage

```
evaluate_partition_semisup(
  partition,
  ref.unsup,
  ref.sup,
  ref.semisup,
  data.surv,
  TMIN = 2,
  TMAX = 5
)
```

#### **Arguments**

```
partition Vector containing cluster ids of the partition to evaluate.

ref.unsup Vector: Unsupervised reference partition (i.e. data structure).

ref.sup Vector: Supervised reference partition (i.e. using survival parameters).

ref.semisup Vector: Semisupervised reference partition (i.e. combining both).

data.surv dataframe with variables time and status.

TMIN time point to start analyzing AUC.

TMAX time point to analyze AUC.
```

## Value

a list of named performances values

```
library(survival) # survival should be loaded in the environment
data(cancer, package = "survival")
cancer$status <- cancer$status - 1
res <- evaluate_partition_semisup (
  partition = factor(rep(c(1,2,3), each = 50)),
  ref.unsup = factor(rep(c(1,2,3), times = c(100, 25, 25))),</pre>
```

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```
ref.sup = factor(rep(c(1,2), times = c(50, 100))),
ref.semisup = factor(rep(c(3, 2, 1), times = c(120, 10, 20))),
data.surv = cancer[1:150, c("time", "status")])
```

```
evaluate_partition_unsup
```

Comparison of an unsupervised obtained partition to a reference partition.

#### **Description**

Compares partitions on number of cluster, ARI and percentage of unclassified observations.

#### Usage

```
evaluate_partition_unsup(
  partition,
  partition.ref,
  is.missing = NULL,
  is.cens = NULL
)
```

## Arguments

```
partition vector (factor): the partition to evaluate.

partition.ref reference partition 1 (ex partition on complete data or true partition if known).

is.missing boolean vector identifying observations with missing data (coded TRUE), from those without (coded FALSE).

is.cens the incomplete dataframe with NA for missing and left-censored data (or the complete datasets if all data were observed).
```

#### Value

A list containing the following elements: Nbclust: number of clusters of the partition; ARI: ARI value on cases classified by both partitions; ARI.cc: ARI value on cases complete AND classified by both partitions; ARI.nona; ARI on cases with no missing data AND classified by both partitions; ARI.nocens: ARI on cases with no censored data AND classified by both partitions; Per.Unclass: Percentage of observations unclassified in the partition; Per.Unclass.cc: Among complete cases, percentage of observations unclassified in the partition; Per.Unclass.na: Among cases with missing data, percentage of observations unclassified in the partition; Per.Unclass.cens: Among cases with censored data, percentage of observations unclassified in the partition; Per.Unclass.ic: Among incomplete cases, percentage of observations unclassified in the partition

```
res <- evaluate_partition_unsup(
  partition = factor(rep(c(1,2,3), each = 50)),
  partition.ref = factor(rep(c(1,2,3), times = c(100, 25, 25))))
## With missing data
res2 <- evaluate_partition_unsup(</pre>
```

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```
partition = factor(rep(c(1,2,3), each = 50)),
  partition.ref = factor(rep(c(1,2,3), times = c(100, 25, 25))),
  is.missing = sample(c(TRUE, FALSE), 150, replace = TRUE, prob = c(.2,.8)))
## With missing and censored data
  missing.indicator <- sample(c(TRUE, FALSE), 150,
  replace = TRUE, prob = c(.2,.8))
  Censor.indicator <- data.frame(</pre>
  X1 = runif(150, 1, 5),
  X2 = runif(150, 6, 8),
  X3 = runif(150, 3, 9))
  Censor.indicator$X1[missing.indicator] <- NA</pre>
  Censor.indicator$X1[
  sample(c(TRUE, FALSE), 150, replace = TRUE, prob = c(.1,.9))] <- NA
  Censor.indicator$X2[
  sample(c(TRUE, FALSE), 150, replace = TRUE, prob = c(.3, .7))] <- NA
  Censor.indicator$X3[
  sample(c(TRUE, FALSE), 150, replace = TRUE, prob = c(.05, .95))] <- NA
res3 <- evaluate_partition_unsup(</pre>
  partition = factor(rep(c(1,2,3), each = 50)),
  partition.ref = factor(rep(c(1,2,3), times = c(100, 25, 25))),
  is.missing = missing.indicator,
  is.cens = Censor.indicator)
## With missing and censored data and unclassifed observations
res4 <- evaluate_partition_unsup(</pre>
  partition = factor(rep(c(1,2, NA,3), times = c(50, 40, 20, 40))),
  partition.ref = factor(rep(c(1,2,3), times = c(100, 25, 25))),
  is.missing = missing.indicator,
  is.cens = Censor.indicator)
```

initiate\_centers

Initiate centers for clustering algorithm

#### **Description**

Initiate centers for clustering algorithm

#### Usage

```
initiate_centers(data, N = 1000, t = 1, k, algorithms = NULL, seeds.N = NULL)
```

#### Arguments

data	Dataset that clustering will be applied on
N	Integer. Number clustering initialization (set of centers) to generate
t	Numeric between 0 and 1. weight coefficient between only random centers (t=1) and only centers from clustering (t=0).
k	Vector of size N containing the number of centers for each initialization.
algorithms	list of algorithm(s) (size N $\star$ (1-t) to generate centers if t!=1, given as characters. Possible values are km for K-means, kmed for K-medians, hclust.mean, hclust.med for hierarchical clustering with mean or median position of the center.
seeds.N	(optional) vector of size N containing seeds for each initialization.

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#### Value

list of size N containing coordinates of centers for clustering initialization.

## **Examples**

mice.impute.cens

Impute left censored data with MICE

## Description

Function from Lapidus et al. for imputing left-censored data with mice

## Usage

```
mice.impute.cens(
   y,
   ry,
   x,
   lod.j,
   lod.name = "lod",
   REDRAW = FALSE,
   wy = NULL,
   ...
)
```

## **Arguments**

у	Vector to be imputed
ry	Logical vector of length length(y) indicating the the subset y[ry] of elements in y to which the imputation model is fitted. The ry generally distinguishes the observed (TRUE) and missing values (FALSE) in y.
X	Numeric design matrix with length(y) rows with predictors for y. Matrix $x$ may have no missing values.
lod.j	censoring value.
lod.name	suffix name used for the censored variable.
REDRAW	Boolean indicating whether values should be redrawn if some are over the censoring limit
wy	$\label{logical vector} Logical\ vector\ of\ length\ length\ (y).\ A\ TRUE\ value\ indicates\ locations\ in\ y\ for\ which\ imputations\ are\ created.$
	Other named arguments.

## Value

Vector with imputed data, same type as y, and of length sum(wy).

8 MImpute

MImpute

Wrapper functions for multivariate imputation with survival data or left-censored data

## Description

Performs imputation of the missing data using MICE and returns a list in the correct format for the unsupMI() and seMIsupcox()functions. MImpute performs imputation for datasets with missing data only. MImpute\_surv performs imputation for a dataset with survival data. The Nelson Aalen estimator is calculated and used as predictor in the imputation, Time is not used as predictor. MImpute\_lcens performs imputation for a dataset with left-censored data. Note that with MImpute\_lcens pmm imputation is performed for variables not affected by left-censoring.

## Usage

```
MImpute(
  data,
  mi.m,
  method = NULL,
  predMat = NULL,
  maxit = 10,
  return.midsObject = FALSE
MImpute_surv(
  data,
  mi.m,
  time.status.names = c("time", "status"),
  return.midsObject = FALSE
MImpute_lcens(
  data,
  data.lod,
  standards,
  mi.m,
  mice.log = 10,
  maxit = 10,
  return.midsObject = FALSE
)
```

## **Arguments**

data

Dataframe with incomplete data. (for MImpute\_lcens, with NA for both missing and left-censored data).

mi.m

Number of imputations to perform.

method

Optional. single string, or a vector of strings specifying the imputation method to be used for each column in data (passed to mice()). If NULL default mice setting are used.

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optional. supply a predictorMatrix (passed to mice()). If NULL default mice

setting are used.

maxit passed to mice().

return.midsObject

Boolean

time.status.names

Names of the variables for time and status (in that order).

data.lod

Dataframe containing indicators of which observation are left-censored (censoring value for such observations and any other values for not censored observations). The colnames should correspond to variables in data. The variables that are left-censored are thus given in data (with left-censored data as NA) and in data.lod with random values for observed data and the LOD for left-censored data. Note that if the data are to be logged (is.numeric(mice.log)), only the argument data will be logged, therefore, the LOD values given here should be given as log(LOD) with the correct number of decimals: round(log(LOD), mice.log).

standards

Dataframe of 1 row containing the LOD values (not logged, whatever the value

for mice.log).

mice.log

set to FALSE if the imputation should be performed on unlogged data. Otherwise, number of decimal to save after taking the log of data (should be 10 unless for specific reasons); in that case the data will be unlogged after imputation.

#### Value

If return.midsObject == FALSE a list of size mi.m, containing the imputed datasets. If return.midsObject == TRUE a list of 2, the first element (imputed.data) being the list of size mi.m as described in the previous sentence, the 2nd element (mids.obj) containing the mids object as returned by mice()

```
data(cancer, package = "survival")
cancer.imp <- MImpute(cancer[, -c(1:3)], 3)</pre>
## MImpute_surv
data(cancer, package = "survival")
cancer$status <- cancer$status - 1
cancer.imp <- MImpute_surv(cancer, 3)</pre>
## MImpute_lcens
toy <- iris[, 1:4]
# censor on variables 3 and 4, with LOD at quantile .1 and .2.
LODs <- toy[1, ]
LODs[1, ] \leftarrow c(NA, NA, quantile(toy[,3], .2), quantile(toy[,4], .1))
# Censor indicator
Censored <- data.frame(Petal.Length = runif(150, 50,60),</pre>
                        Petal.Width = runif(150, 50,60))
Censored[toy[,3] < LODs[1, 3], 1] \leftarrow LODs[1, 3]
Censored[toy[,4] < LODs[1, 4], 2] \leftarrow LODs[1, 4]
# NA for censored data
toy[toy[,3] < LODs[1, 3], 3] <- NA
toy[toy[,4] < LODs[1, 4], 4] <- NA
# Additional missing data
toy[sample(1:nrow(toy), 30), 1] <- NA
toy[sample(1:nrow(toy), 30), 3] <- NA
toy[sample(1:nrow(toy), 30), 4] <- NA
```

10 MultiCons

MultiCons

MultiCons Consensus Clustering Algorithm

## **Description**

Performs MultiCons clustering, from Al-Najdi et Al. For some reason, if you want to use mclust clustering the package needs to be loaded manually

## Usage

```
MultiCons(
   DB,
   Clust_entry = FALSE,
   Clustering_selection = c("kmeans", "pam", "OPTICS", "agghc", "AGNES", "DIANA",
        "MCLUST", "CMeans", "FANNY", "BaggedClust"),
   num_algo = 10,
   maxClust = 10,
   sim.indice = "jaccard",
   returnAll = FALSE,
   Plot = TRUE,
   verbose = FALSE
)
```

#### **Arguments**

DB Either data or dataframe of partitions.

Clust\_entry Is DB partitions (TRUE) or data (FALSE).

Clustering\_selection

If DB is data, clustering algorithm to select among. Must be included in default

value.

num\_algo Number of clustering algorithms to perform.

maxClust Maximum number of clusters.
sim.indice Index for defining best partition.

returnAll Should all partitions (TRUE) or only the best (FALSE) be returned.

Plot Should tree be plotted.

verbose Passed on to mclust and other functions.

## Value

A list of 2: performances and partitions. If returnAll is TRUE, both elements of the list contain results for all levels of the tree, else they only contain the results for the best level of the tree.

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#### **Examples**

 ${\tt partition\_generation} \quad \textit{Unsupervised partition with $K$ selection}$ 

#### **Description**

Generates a partition using clust.algo algorithm, with k.crit for selecting the number of clusters

## Usage

```
partition_generation(data, LOG, clust.algo, k.crit)
```

## Arguments

data	dataframe to cluster
LOG	logical. Should all columns of the dataset be logged before applying clustering algorithms?
clust.algo	vector of strings: name of clustering algorithms to use (use "km" for k-means, "kmed" for K-medians, "hc" for hclust and/or "mclust" for mclust).
k.crit	string. Criterion to select the optimal number of clusters (for each imputed dataset). Use "ch" for Calinski and Harabasz criterion (not available for mclust), "CritCF" for CritCF or bic for BIC (mclust only).

#### Value

a dataframe with one column for each algorithm in clust.algo, containing the cluster IDs.

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plot\_boxplot

ggplot type boxplots for each vars.cont by partition level.

#### **Description**

ggplot type boxplots for each vars.cont by partition level.

#### Usage

```
plot_boxplot(
  data,
  partition.name,
  vars.cont,
  vars.cont.names = NULL,
  unclass.name = "Unclassified",
  include.unclass = FALSE,
  add.n = FALSE,
  nc.facet = 10
)
```

## **Arguments**

The dataset. data partition.name string. Name of the partition (in data). The partition variable should be a factor. vector of strings. variables to plot (continuous only). vars.cont vars.cont.names Optional. Names for displaying the continuous variables. (given in the same order than vars.cont) If applicable, name for the unclassified observations in the partition. unclass.name include.unclass boolean, should boxplot be displayed for the unclassified or should they be excluded from the plot. add.n Boolean. Should the number of samples per cluster be indicated on the x axis and color legend. nc.facet integer. Number of columns in the facet\_wrap()

#### Value

ggplot object.

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plot\_frequency

ggplot type barplots representing frequencies for each vars.cat by partition level.

#### **Description**

ggplot type barplots representing frequencies for each vars.cat by partition level.

## Usage

```
plot_frequency(
  data,
  partition.name,
  vars.cat,
  vars.cat.names = NULL,
  binary.simplify = TRUE,
  unclass.name = "Unclassified",
  include.unclass = FALSE
)
```

## Arguments

data The dataset.

partition.name string. Name of the partition (in data). The partition variable should be a factor.

vars.cat vector of strings. variables to plot (categorical only).

vars.cat.names Optional. Names for displaying the categorical variables. (given in the same order than vars.cat)

binary.simplify boolean. Should only the 1st level be kept for binary variables in vars.cat?

unclass.name If applicable, name for the unclassified observations in the partition.

include.unclass

boolean, should boxplot be displayed for the unclassified or should they be excluded from the plot.

## Value

ggplot object.

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#### **Examples**

```
data(cancer, package = "survival")
cancer$status <- factor(cancer$status)</pre>
plot_frequency(data = cancer, partition.name = "status",
                   vars.cat = c("sex", "ph.ecog"))
## With unclassifieds
cancer$status.2 <- as.character(cancer$status)</pre>
cancer$status.2[sample(1:nrow(cancer), 30)] <- "Unclassif."</pre>
cancer$status.2 <- factor(cancer$status.2)</pre>
plot_frequency(data = cancer, partition.name = "status.2",
               vars.cat = c("sex", "ph.ecog"),
               unclass.name = "Unclassif.", include.unclass = TRUE)
## With unclassifieds (as NA)
cancer$status.3 <- cancer$status</pre>
cancer$status.3[sample(1:nrow(cancer), 30)] <- NA</pre>
plot_frequency(data = cancer, partition.name = "status.3",
               vars.cat = c("sex", "ph.ecog"),
               unclass.name = NA, include.unclass = TRUE)
plot_frequency(data = cancer, partition.name = "status.3",
               vars.cat = c("sex", "ph.ecog", "ph.karno"),
               binary.simplify = FALSE,
               unclass.name = NA, include.unclass = FALSE)
```

plot\_MIpca

Plot a PCA from a multiply imputed dataset.

## Description

plot\_MIpca plots only mean value while plot\_MIpca\_all plots all values for the selected observations.

#### Usage

```
plot_MIpca(
  data.list,
  obs.sel,
  color.var = NULL,
  pca.varsel = NULL,
  pc.sel = c(1, 2)
)

plot_MIpca_all(
  data.list,
  obs.sel,
  pca.varsel = NULL,
  color.var = NULL,
  pc.sel = c(1, 2),
  alpha = 0.4
)
```

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#### **Arguments**

data.list	The list of the imputed datasets.
obs.sel	The selection of observations to highlight. If NULL, no observations are selected; if numeric, the vector corresponds to the observations' row number to highlight, if character, the string should be of type a condition (TRUE/FALSE) on the dataset to select the observations, where the dataset is referred to as "DATA" (ex: obs.sel = "DATA\$X1>3").
color.var	Either NULL to color according to obs.sel, "none" to use no color, or a vector of size nrow(data.list[[1]]) (a factor).
pca.varsel	optional. A vector of strings containing the names of the variables to use for the PCA. If NULL all variables in the dataset will be used.
pc.sel	Numeric vector of size 2 containing the indexes of the principal components to plot. Default is PC1 and PC2.
alpha	Transparency level for plotting the point of the selected observations.

#### Value

A ggplot object.

#### **Examples**

seMIsupcox

Semisupervised learning for a right censored endpoint

#### **Description**

MultiCons consensus based method for MI-Semisupervised clustering. The final partition is a consensus of the Pareto-optimal solutions.

#### Usage

```
seMIsupcox(
   Impute = FALSE,
   Impute.m = 5,
   center.init = TRUE,
   center.init.N = 500,
   center.init.Ks = 2:7,
```

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```
X,
CVE.fun = "LP",
Y,
nfolds = 10,
save.path = NULL,
Unsup.Sup.relImp = list(relImp.55 = c(0.5, 0.5)),
plot.cons = FALSE,
cleanup.partition = TRUE,
min.cluster.size = 10,
level.order = NULL,
Unclassified = "Unclassified",
return.detail = FALSE
)
```

#### Arguments

Impute

Boolean. Default is FALSE to indicate that the user performed the imputation and provides the imputed data. If TRUE, the imputation will be performed within the call using the MImpute\_surv() function. Note that if Impute is TRUE, center.init is also forced to TRUE as the center coordinates may depend on the imputation.

Impute.m

Used only if Impute is TRUE; number of imputations to perform

center.init

Either a User supplied List of dataframe containing the cluster centers coordinates (for example as obtained with initiate\_centers(), Or TRUE to initiate the centers within the call of the function (performed with initiate\_centers()). Note that if TRUE a random initialization will be performed. For a finer tuning of the center initialization the user should generate and provide the list of centers coordinates.

center.init.N

Used only if center.init is TRUE. The number to initialization to produce. Default to 500.

center.init.Ks

Used only if center.init is TRUE. Vector of number of clusters to generate for the initialization. Default to 2 to 7 clusters.

Χ

Data, in the form of a list of data.frame(s). The list should be one length 1 if data are complete or if Impute is TRUE, of should be a list of imputed dataframes if data are incomplete. If columns named "time" and "status" are present they will be discarded for the clustering.

 $\mathsf{CVE}.\mathsf{fun}$ 

string indicating how to calculate the cross validation error: only LP is available and stands for linear predictor approach (using the ncvreg package).

Υ

Passed to CVE.fun, Outcome data: should be dataframe or matrix with 2 columns: "time" and "status".

nfolds

Number of folds for cross-validation.

save.path

Path indicating where objectives values for each iteration should be saved. If null the values are not saved.

Unsup.Sup.relImp

List of weights for the unsupervised and supervised objectives for the Pareto optimal solution. Default is to use only one set of weights: same weight.

plot.cons

Logical. Should the consensus tree be plotted?

cleanup.partition

should the partition be trimmed of small clusters. (The consensus may generate small clusters of observations for which there is no consensus on the cluster assignation)

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```
min.cluster.size

if cleanup.partition == TRUE: Minimum cluster size (i.e., smaller clusters will be discarded)

level.order

if cleanup.partition == TRUE: optional. If you supply a variable the cluster levels will be ordinated according to the mean values for the variable

Unclassified

if cleanup.partition == TRUE string for the label of the unclassified observations. defaults value is NA.

return.detail logical. Should the detail of imputation specific partition be returned, in supplement to the final consensus partition?
```

#### Value

A vector containing the final cluster IDs. Or if return.detail == TRUE, a list containing Consensus: the final cluster ID, Detail: the clusters obtained for each imputed dataset, Imputed.data a list containing the imputed datasets.

```
data(cancer, package = "survival")
cancer$status <- cancer$status - 1</pre>
cancer <- cancer[, -1]</pre>
## With imputation included
## not run ##
# res <- seMIsupcox(X = list(cancer), Y = cancer[, c("time", "status")],</pre>
                     Impute = TRUE, Impute.m = 3, center.init = TRUE,
#
#
                     nfolds = 10, center.init.N = 100)
### With imputation and center initialization not included
## 1 imputation
cancer.imp <- MImpute_surv(cancer, 3)</pre>
## 2 Center initialization
center.number <- sample(2:6, size = N, replace = TRUE)</pre>
the.seeds <- runif(N) * 10^9
sel.col <- which(!colnames(cancer) %in% c("time", "status"))</pre>
inits <- sapply(1:length(cancer.imp), function(mi.i) {</pre>
 initiate_centers(data = cancer.imp[[mi.i]][, sel.col],
                   N = N, t = 1, k = center.number,
                   seeds.N = the.seeds)},
                 USE.NAMES = TRUE, simplify = FALSE)
## 3 learning
## not run ##
# res1 <- seMIsupcox(X = cancer.imp, Y = cancer[, c("time", "status")],</pre>
                      Impute = FALSE, center.init = inits, nfolds = 10,
                      cleanup.partition = FALSE)
# res2 <- seMIsupcox(X = cancer.imp, Y = cancer[, c("time", "status")],</pre>
                     center.init = inits, nfolds = 10)
```

18 table\_categorical

table_categorical	Display table with comparison of the partition with categorical vari-
_ 0	ables.

## Description

Display table with comparison of the partition with categorical variables.

## Usage

```
table_categorical(
  data,
  partition.name,
  vars.cat,
  vars.cat.names = NULL,
  na.value = "",
  nb.dec = 1,
  text.pval = FALSE
)
```

## Arguments

data	The dataset.
partition.name	string. Name of the partition (in data). The partition variable should be a factor.
vars.cat	vector of strings. variables to compare to (categorical only).
vars.cat.names	Optional. Names for displaying the categorical variables. (in the same order than ${\tt vars.cat})$
na.value	Value to use for the empty cases (e.g. "" or NA).
nb.dec	digit. Number of decimals for the percentage.
text.pval	boolean. Set to TRUEto display "p=", to FALSE to display only the value.

#### Value

table with n and percentage values per level of the partition and chi square test p-values.

table\_continuous 19

table_continuous	Display table with comparison of the partition with continuous vari-
	ables.

#### **Description**

Display table with comparison of the partition with continuous variables.

#### Usage

```
table_continuous(
  data,
  partition.name,
  vars.cont,
  vars.cont.names = NULL,
  na.value = "",
  nb.dec = 1,
  text.pval = FALSE
)
```

#### **Arguments**

```
data The dataset.

partition.name string. Name of the partition (in data). The partition variable should be a factor.

vars.cont vector of strings. variables to compare to (continuous only).

vars.cont.names

Optional. Names for displaying the continuous variables. (in the same order than vars.cont)

na.value Value to use for the empty cases (e.g. "" or NA).

nb.dec digit. Number of decimals for the mean and quartile values.

text.pval boolean. Set to TRUEto display "p=", to FALSE to display only the value.
```

#### Value

table with mean and Q1 Q3 values per level of the partition and ANOVA test p-values.

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unsupMI

Unsupervised learning for incomplete dataset

## Description

Unsupervised clustering for multiply imputed datasets using MultiCons consensus (Faucheux et al. 2021 procedure)

## Usage

```
unsupMI(
  Impute = FALSE,
  Impute.m = 5,
  cens.data.lod = NULL,
  cens.standards = NULL,
  cens.mice.log = 10,
  data,
  log.data = FALSE,
  algo = "km",
  k.crit = "ch",
  comb.cons = FALSE,
  plot.cons = FALSE,
  return.detail = FALSE,
  not.to.use = c("time", "status"),
  cleanup.partition = TRUE,
  min.cluster.size = 10,
  level.order = NULL,
  Unclassified = "Unclassified"
)
```

#### **Arguments**

Impute	Default is FALSE to indicate that the user performed the imputation and provides the imputed data. Otherwise string ("MImpute", "MImpute_surv" or "MImpute_lcens" to perform the imputation within the call using the MImpute(), MImpute_surv() or MImpute_lcens() function.
Impute.m	Used only if Impute is not FALSE; number of imputations to perform
cens.data.lod	<pre>passed to MImpute_lcens() if Impute == MImpute_lcens</pre>
cens.standards	<pre>passed to MImpute_lcens() if Impute == MImpute_lcens</pre>
cens.mice.log	<pre>passed to MImpute_lcens() if Impute == MImpute_lcens</pre>
data	Data, in the form of a list of data.frame(s). The list should be one length 1 if data are complete or if Impute is not FALSE, it should be a list of imputed dataframes if data are incomplete and imputed. If some columns are in not.to.use, they will be discarded for the clustering.
log.data	logical. Should all columns of the dataset be logged before applying clustering algorithms?
algo	vector of strings: name of clustering algorithms to use (use "km" for k-means, "kmed" for K-medians, "hc" for hclust and/or "mclust" for mclust).

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k.crit	string. Criterion to select the optimal number of clusters (for each imputed dataset). Use "ch" for Calinski and Harabasz criterion (not available for mclust), "CritCF" for CritCF or "bic" for BIC (mclust only).					
comb.cons	logical. Forced to FALSE if length(algo)<2. Use TRUE to perform an additional consensus from all partitions generates, whatever the algorithm.					
plot.cons	logical. Use TRUE to print the MultiCons tree. Note that if all partitions are identical across the imputation no consensus will be performed and therefore not plot will be obtained even if plot.cons = TRUE.					
return.detail	logical. Should the detail of imputation specific partition and the imputed data be returned, in the supplement to the final consensus partition?					
not.to.use	vector of strings: names of the columns that should be discarded for the learning step.					
cleanup.partit	cleanup.partition					
	should the partition be trimmed of small clusters. (The consensus may generate small clusters of observations for which there is no consensus on the cluster assignation)					
min.cluster.si	ze					
	if cleanup.partition == TRUE: Minimum cluster size (i.e., smaller clusters will be discarded)					
level.order	if cleanup.partition == TRUE: optional. If you supply a variable the cluster levels will be ordinated according to the mean values for the variable					
Unclassified	if cleanup.partition == TRUE string for the label of the unclassified observations. defaults value is NA.					

#### Value

if length(algo)>1 a vector of final cluster ID; if length(algo)>1 a data.frame with each column being the final cluster ID for the corresponding algorithm. Or if return.detail == TRUE, a list containing Consensus: the final cluster ID (or data.frame), Detail: the clusters obtained for each imputed dataset, Imputed.data a list containing the imputed datasets.

```
## With imputation included
data(cancer, package = "survival")
cancer$status <- cancer$status - 1</pre>
res.0 <- unsupMI(data = list(cancer), Impute = "MImpute_surv",</pre>
                 cleanup.partition = FALSE)
### With imputation not included
## 1 imputation
cancer.imp <- MImpute_surv(cancer, 3)</pre>
## 2 learning
res <- unsupMI(data = cancer.imp, cleanup.partition = FALSE)</pre>
summary(factor(res))
res.1 <- unsupMI(data = cancer.imp)</pre>
summary(factor(res.1))
## 2.bis learning with several algorithms
res.2 <- unsupMI(data = cancer.imp, algo = c("km", "hc"), comb.cons = TRUE,</pre>
                  plot.cons = TRUE)
```

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```
## Alternative: perform imputation within
## not run ##
# res <- unsupMI(Impute = "MImpute_surv", data = list(cancer))</pre>
```

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