Package ‘imp4p’

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Introduction to the IMP4P package

Description

This package provides functions to analyse missing value mechanisms in the context of bottom-up MS-based quantitative proteomics.

It allows estimating a mixture model of missing completely-at-random (MCAR) values and missing not-at-random (MNAR) values.

It also contains functions allowing the imputation of missing values under hypotheses of MCAR and/or MNAR values.

The main functions of this package are the `estim.mix` (estimation of a model of MCAR and MNAR (left-censored) values), `impute.mi` (multiple imputation) and `impute.mix` (imputation based on a decision rule). It provides also several imputation algorithms for MS-based data. They can be used to impute matrices containing peptide intensities (as Maxquant outputs for instance).

Missing values has to be indicated with NA and a log-2 transformation of the intensities has to be applied before using these functions. An example for using this package from MaxQuant outputs is provided in Giai Gianetto Q. (2021).

More explanations and details on the functions of this package are available in Giai Gianetto Q. et al. (2020) (doi: doi: 10.1101/2020.05.29.122770).

Author(s)

Maintainer: Quentin Giai Gianetto <quentin2g@yahoo.fr>
References
Giai Gianetto, Q. (2021) Statistical analysis of post-translational modifications quantified by label-free proteomics across multiple biological conditions with R: illustration from SARS-CoV-2 infected cells. (pasteur-03243433)

estim.bound

Estimation of lower and upper bounds for missing values.

Description
This function allows estimating lower and upper bounds for missing values of an input matrix. It can be used before to use the functions prob.mcar and prob.mcar.tab.

Usage
estim.bound(tab, conditions, q=0.95)

Arguments
- tab: A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to the intensities measured in an experimental sample, and each row to the ones of an identified peptide.
- conditions: A vector of factors indicating the biological condition to which each sample belongs.
- q: A numeric value allowing to define confidence intervals for missing values (see Details).

Details
In each condition, this function estimates lower and upper bounds for missing values of row i by:
upper(i) = max(tab[i,]);
lower(i) = max(tab[i,]) - quant_diff(q);
where quant_diff(q) corresponds to a quantile value of the differences between the maximum and the minimum of the observed values for all the peptides in the condition. As a result, if q is close to 1, quant_diff(q) represents an extrem value between the maximum and the minimum of the intensity values in a condition for a peptide.

Value
A list composed of:
- tab.lower: A matrix with the lower bounds for each missing value in tab.
- tab.upper: A matrix with the upper bounds for each missing value in tab.
estim.mix

Estimation of a mixture model of MCAR and MNAR values in each column of a data matrix.

Description

This function allows estimating a mixture model of MCAR and MNAR values in each column of data sets similar to the ones which can be studied in MS-based quantitative proteomics. Such data matrices contain intensity values of identified peptides.

Usage

estim.mix(tab, tab.imp, conditions, x.step.mod=150, x.step.pi=150, nb.rei=200)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>tab</td>
<td>A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.</td>
</tr>
<tr>
<td>tab.imp</td>
<td>A matrix where the missing values of tab have been imputed under the assumption that they are all MCAR. For instance, such a matrix can be obtained by using the function <code>impute.slsa</code> of this package.</td>
</tr>
<tr>
<td>conditions</td>
<td>A vector of factors indicating the biological condition to which each column (experimental sample) belongs.</td>
</tr>
</tbody>
</table>
The number of points in the intervals used for estimating the cumulative distribution functions of the mixing model in each column.

The number of points in the intervals used for estimating the proportion of MCAR values in each column.

The number of initializations of the minimization algorithm used to estimate the proportion of MCAR values (see Details).

This function aims to estimate the following mixture model in each column:

\[ F_{\text{tot}}(x) = \pi_{na} \times F_{na}(x) + (1 - \pi_{na}) \times F_{obs}(x) \]

\[ F_{na}(x) = \pi_{mcar} \times F_{\text{tot}}(x) + (1 - \pi_{mcar}) \times F_{mnar}(x) \]

where \( \pi_{na} \) is the proportion of missing values, \( \pi_{mcar} \) is the proportion of MCAR values, \( F_{\text{tot}} \) is the cumulative distribution function (cdf) of the complete values, \( F_{na} \) is the cdf of the missing values, \( F_{obs} \) is the cdf of the observed values, and \( F_{mnar} \) is the cdf of the MNAR values.

To estimate this model, a first step consists of computing a rough estimate of \( F_{na} \) by assuming that all missing values are MCAR (thanks to the argument \( \text{tab.imp} \)). This rough estimate is noted \( \hat{F}_{na} \).

In a second step, the proportion of MCAR values is estimated. To do so, the ratio

\[ \hat{\pi}(x) = (1 - \hat{F}_{na}(x))/(1 - \hat{F}_{\text{tot}}(x)) \]

is computed for different \( x \), where

\[ \hat{F}_{\text{tot}}(x) = \pi_{na} \times \hat{F}_{na}(x) + (1 - \pi_{na}) \times \hat{F}_{obs}(x) \]

with \( \hat{F}_{obs} \) the empirical cdf of the observed values.

Next, the following minimization is performed:

\[ \min_{k>0,a>0,d>0} f(k, a, d) \]

where

\[ f(k, a, d) = \sum_x \frac{1}{s(x)^2} \times \left[ \hat{\pi}(x) - k - (1 - k) \frac{\exp(-a \times |x - \text{lower}_x| d)}{1 - \hat{F}_{\text{tot}}(x)} \right]^2 \]

where \( s(x)^2 \) is an estimate of the asymptotic variance of \( \hat{\pi}(x) \), \( \text{lower}_x \) is an estimate of the minimum of the complete values. To perform this minimization, the function \( \text{optim} \) with the method "L-BFGS-B" is used. Because it is function of its initialization, it is possible to reinitialize a number of times the minimisation algorithm with the argument \( \text{nb.rei} \): the parameters leading to the lowest minimum are next kept.

Once \( k, a \) and \( d \) are estimated, one can use several methods to estimate \( \pi_{mcar} \): it is estimated by \( k \).

A list composed of:

- \( \text{abs.pi} \) A numeric matrix containing the intervals used for estimating the ratio
  \( (1-F_{na}(x))/(1-F_{\text{tot}}(x)) \)
  in each column.

- \( \text{pi.init} \) A numeric matrix containing the estimated ratios
  \( (1-F_{na}(x))/(1-F_{\text{tot}}(x)) \)
  where \( x \) belongs to \( \text{abs.pi}[,j] \) for each sample \( j \).
var.pi.init  A numeric matrix containing the estimated asymptotic variances of pi.init.
trend.pi.init  A numeric matrix containing the estimated trend of the model used in the minimization algorithm.
abs.mod  A numeric vector containing the interval used for estimating the mixture models in each column.
pi.na  A numeric vector containing the proportions of missing values in each column.
F.na  A numeric matrix containing the estimated cumulative distribution functions of missing values in each column on the interval abs.mod.
F.tot  A numeric matrix containing the estimated cumulative distribution functions of complete values in each column on the interval abs.mod.
F.obs  A numeric matrix containing the estimated cumulative distribution functions of observed values in each column on the interval abs.mod.
pi.mcar  A numeric vector containing the estimations of the proportion of MCAR values in each column.
MinRes  A numeric matrix containing the three parameters of the model used in the minimization algorithm (three first rows), and the value of minimized function.

Author(s)
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See Also
impute.slsa

Examples

#Simulating data
res.sim=sim.data(nb.pept=2000,nb.miss=600);

#Imputation of missing values with a MCAR-devoted algorithm: here the slsa algorithm
dat.slsa=impute.slsa(tab=res.sim$dat.obs,conditions=res.sim$condition,repbio=res.sim$repbio);

#Estimation of the mixture model
res=estim.mix(tab=res.sim$dat.obs, tab.imp=dat.slsa, conditions=res.sim$condition);

---

fast_apply_nb_na  Function similar to the function apply(X,dim,function(x)sum(is.na(x))).

Description
This function is similar to the function apply(X,dim,function(x)sum(is.na(x))) but written thanks to the Rcpp package and therefore faster than apply(X,dim,function(x)sum(is.na(x))).
**Usage**

`fast_apply_nb_na(X, dim)`

**Arguments**

- **X**: A data matrix containing numeric and missing values.
- **dim**: A numeric value: 1 if the number of missing values has to be computed for each row of `X`, or 2 if it has to be computed for each column of `X`.

**Value**

A numeric vector containing the number of missing values in either each row or each column of `X`.

**Author(s)**

Quentin Giai Gianetto <quentin2g@yahoo.fr>

**Examples**

```r
## The function is currently defined as
##function (X, dim)
##{
##  .Call("imp4p_fast_apply_nb_na", PACKAGE = "imp4p", X, dim)
##}
##
## You can compare the execution time with a traditional apply function by
##library(rbenchmark)
##res.sim=sim.data(nb.pept=2000,nb.miss=600);
##benchmark(fast_apply_nb_na(res.sim$dat.obs, 1),
##  apply(res.sim$dat.obs,1,function(x)sum(is.na(x))))
##
## fast_apply_nb_not_na
```

---

**Description**

This function is similar to the function `apply(X, dim, function(x) sum(!is.na(x)))` but written thanks to the Rcpp package and therefore faster than `apply(X, dim, function(x) sum(!is.na(x)))`.

**Usage**

`fast_apply_nb_not_na(X, dim)`
Arguments

X  A data matrix containing numeric and missing values.
dim A numeric value: 1 if the number of observed values has to be computed for each row of X, or 2 if it has to be computed for each column of X.

Value

A numeric vector containing the number of observed values in either each row or each column of X.

Author(s)

Quentin Giai Gianetto <quentin2g@yahoo.fr>

Examples

## The function is currently defined as
##function (X, dim)
##{
##  .Call("imp4p_fast_apply_nb_not_na", PACKAGE = "imp4p", X,
##  dim)
## }
##
## You can compare the execution time with a traditional apply function by
## library(rbenchmark)
## res.sim=sim.data(nb.pept=2000,nb.miss=600);
## benchmark(fast_apply_nb_not_na(res.sim$dat.obs, 1),
## apply(res.sim$dat.obs,1,function(x)sum(!is.na(x))))

---

**fast_apply_sd_na_rm_T**  Function similar to the function apply(X, dim, sd, na.rm=TRUE).

Description

This function is similar to the function apply(X, dim, sd, na.rm=TRUE) but written thanks to the Rcpp package and therefore faster than apply(X, dim, sd, na.rm=TRUE).

Usage

fast_apply_sd_na_rm_T(X, dim)

Arguments

X  A data matrix containing numeric and missing values.
dim  A numeric value: 1 if the standard deviation has to be computed for each row of X, or 2 if the standard deviation has to be computed for each column of X.
Value

A numeric vector containing the standard deviation of observed values in either each row or each column of X.

Author(s)

Quentin Giai Gianetto <quentin2g@yahoo.fr>

Examples

```r
## The function is currently defined as
##function (X, dim)
##{
##  .Call("imp4p_fast_apply_sd_na_rm_T", PACKAGE = "imp4p", X,
##           dim)
##  }
##
## You can compare the execution time with a traditional apply function by
## library(rbenchmark)
## res.sim=sim.data(nb.pept=2000,nb.miss=600);
## benchmark(fast_apply_sd_na_rm_T(res.sim$dat.obs, 1),
##           apply(res.sim$dat.obs,1,sd,na.rm=TRUE))
```

Description

This function is similar to the function `apply(X, dim, sum, na.rm=TRUE)` but written thanks to the Rcpp package and therefore faster than `apply(X, dim, sum, na.rm=TRUE)`.

Usage

`fast_apply_sum_na_rm_T(X, dim)`

Arguments

- `X`  
  A data matrix containing numeric and missing values.

- `dim`  
  A numeric value: 1 if the sum has to be computed for each row of X, or 2 if the sum has to be computed for each column of X.

Value

A numeric vector containing the sum of observed values in either each row or each column of X.

Author(s)

Quentin Giai Gianetto <quentin2g@yahoo.fr>
Examples

```r
## The function is currently defined as
## function (X, dim)
##{
##   .Call("imp4p_fast_apply_sum_na_rm_T", PACKAGE = "imp4p",
##         X, dim)
## }
##
## You can compare the execution time with a traditional apply function by
## library(rbenchmark)
## res.sim=sim.data(nb.pept=2000,nb.miss=600);
## benchmark(fast_apply_sum_na_rm_T(res.sim$dat.obs, 1),
##          apply(res.sim$dat.obs,1,sum,na.rm=TRUE))
```

---

**fast_sim**

*Function to compute similarity measures between a vector and each row of a matrix.*

---

**Description**

This function allows computing a similarity measure between a vector and each row of a matrix. The similarity measure is defined by $d^2$ where $d$ is the Euclidean distance between the vector and each row. It is implemented thanks to the RCpp package.

**Usage**

```r
fast_sim(prot, mat)
```

**Arguments**

- **prot**
  - A numeric vector containing numeric and missing values.

- **mat**
  - A data matrix containing numeric and missing values.

**Value**

A numeric vector containing the values of the similarity measures between the `prot` vector and each row of the `mat` matrix.

**Author(s)**

Quentin Giai Gianetto <quentin2g@yahoo.fr>
Examples

```r
#Simulating data
res.sim=sim.data(nb.pept=20000,nb.miss=1000);

#Fast computation of similarities
fast_sim(res.sim$dat.obs[1,],res.sim$dat.obs);
```

---

**Function allowing to create a vector indicating the membership of each sample to a condition.**

**Description**

This function creates a vector of factors where each element refers to a condition to which a sample belongs.

**Usage**

```r
gen.cond(nb_cond=2,nb_sample=5)
```

**Arguments**

- `nb_cond` Number of biological conditions.
- `nb_sample` Number of samples in each condition.

**Value**

A vector of factors of length `nb_cond*nb_sample`.

**Author(s)**

Quentin Giai Gianetto <quentin2g@yahoo.fr>
**Description**

This function allows imputing missing values under the assumption that the distribution of complete values has to be Gaussian in each column.

Note that the imputed values are not necessary small values (compared to observed values).

**Usage**

```r
impute.igcda(tab, tab.imp, conditions, q=0.95)
```

**Arguments**

- `tab`: A numeric vector or matrix with observed and missing values.
- `tab.imp`: A matrix where the missing values of `tab` have been imputed under the assumption that they are all MCAR. For instance, such a matrix can be obtained by using the function `impute.slsa` of this package.
- `conditions`: A vector of factors indicating the biological condition to which each column (experimental sample) belongs.
- `q`: A quantile value (see Details).

**Details**

The mean and variance of the Gaussian distribution are determined using a linear regression between the quantiles of the observed values $q_{\text{obs}}$ and the ones of the standard normal distribution $q_{\text{N}(0,1)}$.

The quantile value is used for determining the minimum of imputed values. This minimum is determined by the minimum observed value in the dataset minus `quant_diff(q)` where `quant_diff(q)` corresponds to a quantile value of the differences between the maximum and the minimum of the observed values for all the peptides in the condition. As a result, if $q$ is close to 1, `quant_diff(q)` represents an extrem value between the maximum and the minimum of the intensity values in a condition for a peptide.

**Value**

The numeric input matrix with imputed values. The distribution of the intensity values in each of its columns is supposed to be Gaussian.

**Author(s)**

Quentin Giai Gianetto <quentin2g@yahoo.fr>
Examples

#Simulating data
res.sim=sim.data(nb.pept=2000,nb.miss=600);

#Imputation of missing values with a MCAR-devoted algorithm: here the slsa algorithm
dat.slsa=impute.slsa(tab=res.sim$dat.obs,conditions=res.sim$condition,repbio=res.sim$repbio);

#Imputation of missing values under a Gaussian assumption
dat.gauss=impute.igcda(tab=res.sim$dat.obs, tab.imp=dat.slsa, conditions=res.sim$conditions);

impute.mi

Imputation of data sets containing peptide intensities with a multiple imputation strategy.

Description

This function allows imputing data sets containing peptide intensities with a multiple imputation strategy distinguishing MCAR and MNAR values. For details, see Giai Gianetto Q. et al. (2020) (doi: doi: 10.1101/2020.05.29.122770).

Usage

impute.mi(tab, conditions, repbio=NULL, reptech=NULL, nb.iter=3, nknn=15, selec=1000, siz=900, weight=1, ind.comp=1, progress.bar=TRUE, x.step.mod=300, x.step.pi=300, nb.rei=100, q=0.95, methodMCAR="mle",ncp.max=5, maxiter = 10, ntree = 100, variablewise = FALSE, decreasing = FALSE, verbose = FALSE, mtry = floor(sqrt(ncol(tab))), replace = TRUE, classwt = NULL, cutoff = NULL, strata = NULL, sampsize = NULL, nodesize = NULL, maxnodes = NULL, xtrue = NA, parallelize = c("variables", 'forests'), methodMNAR="igcda",q.min = 0.025, q.norm = 3, eps = 0, distribution = "unif", param1 = 3, param2 = 1, R.q.min=1);

Arguments

tab
A data matrix containing only numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.

conditions
A vector of factors indicating the biological condition to which each column (experimental sample) belongs.

repbio
A vector of factors indicating the biological replicate to which each column belongs. Default is NULL (no experimental design is considered).

reptech
A vector of factors indicating the technical replicate to which each column belongs. Default is NULL (no experimental design is considered).
<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>nb.iter</code></td>
<td>The number of iterations used for the multiple imputation method (see <code>mi.mix</code>).</td>
</tr>
<tr>
<td><code>methodMCAR</code></td>
<td>The method used for imputing MCAR data. If <code>methodMCAR</code>=&quot;mle&quot; (default), then the <code>impute.mle</code> function is used (imputation using an EM algorithm). If <code>methodMCAR</code>=&quot;pca&quot;, then the <code>impute.PCA</code> function is used (imputation using Principal Component Analysis). If <code>methodMCAR</code>=&quot;rf&quot;, then the <code>impute.RF</code> function is used (imputation using Random Forest). Else, the <code>impute.slsa</code> function is used (imputation using Least Squares on nearest neighbours).</td>
</tr>
<tr>
<td><code>methodMNAR</code></td>
<td>The method used for imputing MNAR data. If <code>methodMNAR</code>=&quot;igcda&quot; (default), then the <code>impute.igcda</code> function is used. Else, the <code>impute.pa</code> function is used.</td>
</tr>
<tr>
<td><code>nknn</code></td>
<td>The number of nearest neighbours used in the SLSA algorithm (see <code>impute.slsa</code>).</td>
</tr>
<tr>
<td><code>selec</code></td>
<td>A parameter to select a part of the dataset to find nearest neighbours between rows. This can be useful for big data sets (see <code>impute.slsa</code>).</td>
</tr>
<tr>
<td><code>siz</code></td>
<td>A parameter to select a part of the dataset to perform imputations with the MCAR-devoted algorithm. This can be useful for big data sets (see <code>mi.mix</code>).</td>
</tr>
<tr>
<td><code>weight</code></td>
<td>The way of weighting in the algorithm (see <code>impute.slsa</code>).</td>
</tr>
<tr>
<td><code>ind.comp</code></td>
<td>If <code>ind.comp</code>=1, only nearest neighbours without missing values are selected to fit linear models (see <code>impute.slsa</code>). Else, they can contain missing values.</td>
</tr>
<tr>
<td><code>progress.bar</code></td>
<td>If TRUE, a progress bar is displayed.</td>
</tr>
<tr>
<td><code>x.step.mod</code></td>
<td>The number of points in the intervals used for estimating the cumulative distribution functions of the mixing model in each column (see <code>estim.mix</code>).</td>
</tr>
<tr>
<td><code>x.step.pi</code></td>
<td>The number of points in the intervals used for estimating the proportion of MCAR values in each column (see <code>estim.mix</code>).</td>
</tr>
<tr>
<td><code>nb.rei</code></td>
<td>The number of initializations of the minimization algorithm used to estimate the proportion of MCAR values (see Details) (see <code>estim.mix</code>).</td>
</tr>
<tr>
<td><code>q</code></td>
<td>A quantile value (see <code>impute.igcda</code>).</td>
</tr>
<tr>
<td><code>ncp.max</code></td>
<td>parameter of the <code>impute.PCA</code> function.</td>
</tr>
<tr>
<td><code>maxiter</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>ntree</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>variablewise</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>decreasing</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>verbose</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>mtry</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>replace</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>classwt</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>cutoff</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>strata</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>sampsize</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>nodesize</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>maxnodes</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
<tr>
<td><code>xtrue</code></td>
<td>parameter of the <code>impute.RF</code> function.</td>
</tr>
</tbody>
</table>
parallelize parameter of the `impute.RF` function.
q.min parameter of the `impute.pa` function.
q.norm parameter of the `impute.pa` function.
eps parameter of the `impute.pa` function.
distribution parameter of the `impute.pa` function.
param1 parameter of the `impute.pa` function.
param2 parameter of the `impute.pa` function.
R.q.min parameter of the `impute.pa` function.

Details

First, a mixture model of MCAR and MNAR values is estimated in each column of `tab`. This model is used to estimate probabilities that each missing value is MCAR. Then, these probabilities are used to perform a multiple imputation strategy (see `mi.mix`). Rows with no value in a condition are imputed using the `impute.pa` function. More details and explanations can be found in Giai Gianetto (2020).

Value

The input matrix `tab` with imputed values instead of missing values.

Author(s)

Quentin Giai Gianetto <quentin2g@yahoo.fr>

References


Examples

```r
#Simulating data
data=sim.data(nb.pept=2000,nb.miss=600,nb.cond=2);

#Imputation of the dataset noting the conditions to which the samples belong.
result=impute.mi(tab=data$dat.obs, conditions=data$conditions);

#Imputation of the dataset noting the conditions to which the samples belong
#and also their biological replicate, and using the SLSA method for the MCAR values
result=impute.mi(tab=data$dat.obs, conditions=data$conditions, repbio=data$repbio, methodMCAR = "slsa");

#For large data sets, the SLSA imputation can be accelerated thanks to the selec parameter
#and the siz parameter (see impute.slsa and mi.mix)
#but it may result in a less accurate data imputation. Note that selec has to be greater than siz.
#Here, nb.iter is fixed to 3
```
result1=impute.mi(tab=res.sim$dat.obs, conditions=res.sim$conditions, progress.bar=TRUE, 
selec=400, siz=300, nb.iter=3, methodMCAR = "slsa", methodMNAR = "igcda");

---

`impute.mix`  
*Imputation using a decision rule under an assumption of a mixture of MCAR and MNAR values.*

**Description**

This function allows imputing data sets with a MCAR-devoted algorithm and a MNAR-devoted algorithm using probabilities that missing values are MCAR. If such a probability is superior to a chosen threshold, then the MCAR-devoted algorithm is used, otherwise it is the MNAR-devoted algorithm. For details, see Giai Gianetto, Q. et al. (2020) (doi: 10.1101/2020.05.29.122770).

**Usage**

```r
impute.mix(tab, prob.MCAR, threshold, conditions, repbio=NULL, reptech=NULL, 
methodMCAR="mle", nknn=15, weight=1, selec="all", ind.comp=1, progress.bar=TRUE, q=0.95, 
ncp.max=5, maxiter = 10, ntree = 100, variablewise = FALSE, decreasing = FALSE, 
verbose = FALSE, mtry = 10, ntree = 100, variablewise = FALSE, decreasing = FALSE, 
repbio=NULL, reptech=NULL, methodMNAR="igcda", q.min = 0.025, q.norm = 3, eps = 0, distribution = "unif", 
param1 = 3, param2 = 1, R.q.min=1)
```

**Arguments**

- **tab**: A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.
- **prob.MCAR**: A matrix of probabilities that each missing value is MCAR. For instance such a matrix can be obtained from the function `prob.mcar.tab` of this package.
- **threshold**: A value such that if the probability that a missing value is MCAR is superior to it, then a MCAR-devoted algorithm is used, otherwise it is a MNAR-devoted algorithm that is used.
- **conditions**: A vector of factors indicating the biological condition to which each column (experimental sample) belongs.
- **repbio**: A vector of factors indicating the biological replicate to which each column belongs. Default is NULL (no experimental design is considered).
- **reptech**: A vector of factors indicating the technical replicate to which each column belongs. Default is NULL (no experimental design is considered).
- **methodMCAR**: The method used for imputing MCAR data. If `methodi="mle"` (default), then the `impute.mle` function is used (imputation using an EM algorithm). If `methodi="pca"`, then the `impute.PCA` function is used (imputation using Principal Component Analysis). If `methodi="rf"`, then the `impute.RF` function is used (imputation...
using Random Forest). Else, the **impute.slsa** function is used (imputation using Least Squares on nearest neighbours).

**methodMNAR**

The method used for imputing MNAR data. If `methodMNAR="igcda"` (default), then the **impute.igcda** function is used. Else, the **impute.pa** function is used.

**nknn**

The number of nearest neighbours used in the SLSA algorithm (see **impute.slsa**).

**weight**

The way of weighting in the algorithm (see **impute.slsa**).

**selec**

A parameter to select a part of the dataset to find nearest neighbours between rows. This can be useful for big data sets (see **impute.slsa**).

**ind.comp**

If `ind.comp=1`, only nearest neighbours without missing values are selected to fit linear models (see **impute.slsa**). Else, they can contain missing values.

**progress.bar**

If TRUE, a progress bar is displayed.

**q**

A quantile value (see **impute.igcda**).

**ncp.max**

Parameter of the **impute.PCA** function.

**maxiter**

Parameter of the **impute.RF** function.

**ntree**

Parameter of the **impute.RF** function.

**variablewise**

Parameter of the **impute.RF** function.

**decreasing**

Parameter of the **impute.RF** function.

**verbose**

Parameter of the **impute.RF** function.

**mtry**

Parameter of the **impute.RF** function.

**replace**

Parameter of the **impute.RF** function.

**classwt**

Parameter of the **impute.RF** function.

**cutoff**

Parameter of the **impute.RF** function.

**strata**

Parameter of the **impute.RF** function.

**sampsize**

Parameter of the **impute.RF** function.

**nodesize**

Parameter of the **impute.RF** function.

**maxnodes**

Parameter of the **impute.RF** function.

**xtrue**

Parameter of the **impute.RF** function.

**parallelize**

Parameter of the **impute.RF** function.

**q.min**

Parameter of the **impute.pa** function.

**q.norm**

Parameter of the **impute.pa** function.

**eps**

Parameter of the **impute.pa** function.

**distribution**

Parameter of the **impute.pa** function.

**param1**

Parameter of the **impute.pa** function.

**param2**

Parameter of the **impute.pa** function.

**R.q.min**

Parameter of the **impute.pa** function.

---

**Details**

The missing values for which prob.MCAR is superior to a chosen threshold are imputed with one of the MCAR-devoted imputation methods (**impute.mle**, **impute.RF**, **impute.PCA** or **impute.slsa**). The other missing values are considered MNAR and imputed with **impute.igcda**. More details and explanations can be bound in Giai Gianetto (2020).
Value

The input matrix `tab` with imputed values instead of missing values.

Author(s)

Quentin Giai Gianetto <quentin2g@yahoo.fr>

References


Examples

```r
#Simulating data
res.sim=sim.data(nb.pept=2000,nb.miss=600);

#Fast imputation of missing values with the impute.rand algorithm
dat.rand=impute.rand(tab=res.sim$dat.obs,conditions=res.sim$condition);

#Estimation of the mixture model
res=estim.mix(tab=res.sim$dat.obs, tab.imp=dat.rand, conditions=res.sim$condition);

#Computing probabilities to be MCAR
born=estim.bound(tab=res.sim$dat.obs,conditions=res.sim$condition);
proba=prob.mcar.tab(born$tab.upper,res);

#Imputation under the assumption of MCAR and MNAR values
tabi=impute.mix(tab=res.sim$dat.obs, prob.MCAR=proba, threshold=0.5, conditions=res.sim$conditions, repbio=res.sim$repbio, methodMCAR="slsa", methodMNAR="igcda", nknn=15, weight=1, selec="all", ind.comp=1, progress.bar=TRUE);
```

**impute.mle**  
*Imputing missing values using a maximum likelihood estimation (MLE).*

Description

Imputing missing values using the EM algorithm proposed in section 5.4.1 of Schafer (1997). The function is based on the imp.norm function of the R package norm.

Usage

```r
impute.mle(tab, conditions)
```
Arguments

- **tab**: A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.

- **conditions**: A vector of factors indicating the biological condition to which each sample belongs.

Details

See section 5.4.1 of Schafer (1997) for the theory. It is built from functions proposed in the R package norm.

Value

The input matrix **tab** with imputed values instead of missing values.

Author(s)

Quentin Giai Gianetto <quentin2g@yahoo.fr>

References


Examples

```r
# Simulating data
res.sim = sim.data(nb.pept=2000, nb.miss=600, nb.cond=2);

# Imputation of missing values with the mle algorithm
dat.mle = impute.mle(tab=res.sim$dat.obs, conditions=res.sim$condition);
```

Description

This function imputes missing values by small values.

Usage

```r
impute.pa(tab, conditions, q.min = 0.025, q.norm = 3, eps = 0,
    distribution = "unif", param1 = 3, param2 = 1, R.q.min=1)
```
Arguments

**tab**
A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.

**conditions**
A vector of factors indicating the biological condition to which each column (experimental sample) belongs.

**q.min**
A quantile value of the observed values allowing defining the maximal value which can be generated. This maximal value is defined by the quantile \( q \text{.min} \) of the observed values distribution minus \( \text{eps} \). Default is 0.025 (the maximal value is the 2.5 percentile of observed values minus \( \text{eps} \)).

**q.norm**
A quantile value of a normal distribution allowing defining the minimal value which can be generated. Default is 3 (the minimal value is the maximal value minus \( qn \text{*median}(sd(\text{observed values})) \) where \( sd \) is the standard deviation of a row in a condition).

**eps**
A value allowing defining the maximal value which can be generated. This maximal value is defined by the quantile \( q \text{.min} \) of the observed values distribution minus \( \text{eps} \). Default is 0.

**distribution**
Distribution used to generated missing values. You have the choice between "unif" for the uniform distribution, "beta" for the Beta distribution or "dirac" for the Dirac distribution. Default is "unif".

**param1**
Parameter shape1 of the Beta distribution.

**param2**
Parameter shape2 of the Beta distribution.

**R.q.min**
Parameter used for the Dirac distribution. In this case, all the missing values are imputed by a single value which is equal to \( R \text{.q.min*quantile(tab[,j], probs=q.min, na.rm=T) \). Default is 1 : } \) the imputed value is the \( q\text{min} \) quantile of observed values.

Details

This function replaces the missing values in a column by random draws from a specified distribution. The value of \( \text{eps} \) can be interpreted as a minimal fold-change value above which the present/absent peptides appear.

Value

A list composed of:

- **tab.imp**: the input matrix \( \text{tab} \) with imputed values instead of missing values.
- **para**: the parameters of the distribution which has been used to impute.

Author(s)

Quentin Giai Gianetto <quentin2g@yahoo.fr>
impute.PCA

Examples

#Simulating data
res.sim=sim.data(nb.pept=2000,nb.miss=600);

#Imputation of the simulated data set with small values
data.small.val=impute.pa(res.sim$dat.obs,res.sim$conditions);

impute.PCA

Imputing missing values using Principal Components Analysis.

Description

Imputing missing values using the algorithm proposed by Josse and Husson (2013). The function is based on the imputePCA function of the R package missMDA.

Usage

impute.PCA(tab, conditions, ncp.max=5)

Arguments

tab: A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.

conditions: A vector of factors indicating the biological condition to which each sample belongs.

ncp.max: integer corresponding to the maximum number of components to test (used in the estim_ncpPCA function of R package missMDA).

Details

See Josse and Husson (2013) for the theory. It is built from functions proposed in the R package missMDA.

Value

The input matrix tab with imputed values instead of missing values.

Author(s)

Quentin Giai Gianetto <quentin2g@yahoo.fr>

References

Examples

```r
# Simulating data
res.sim = sim.data(nb.pept = 2000, nb.miss = 600, nb.cond = 2);

# Imputation of missing values with PCA
dat.pca = impute.PCA(tab = res.sim$data, conditions = res.sim$condition);
```

---

### impute.rand

**Imputation of peptides with a random value.**

**Description**

For each row (peptide), this function imputes missing values by random values following a Gaussian distribution.

**Usage**

```r
impute.rand(tab, conditions)
```

**Arguments**

- `tab`: A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.
- `conditions`: A vector of factors indicating the biological condition to which each column (experimental sample) belongs.

**Details**

For each row (peptide), this function imputes missing values by random values following a Gaussian distribution centered on the mean of the observed values in the condition for the specific peptide and with a standard deviation equal to the first quartile of the distribution of the standard deviation the values observed for all the peptides. Rows with only missing values in a condition are not imputed (the `impute.pa` function can be used for this purpose).

**Value**

The input matrix `tab` with imputed values instead of missing values.

**Author(s)**

Quentin Giai Gianetto <quentin2g@yahoo.fr>
Examples

```r
# Simulating data
res.sim = sim.data(nb.pept = 2000, nb.miss = 600);

# Imputation of the simulated data set with random values
data.rand = impute.rand(res.sim$dat.obs, res.sim$conditions);
```

**Description**

Imputing missing values using the algorithm proposed by Stekhoven and Buehlmann (2012). The function is based on the `missForest` function of the R package `missForest`.

**Usage**

```r
impute.RF(tab, conditions,
          maxiter = 10, ntree = 100, variablewise = FALSE,
          decreasing = FALSE, verbose = FALSE,
          mtry = floor(sqrt(ncol(tab))), replace = TRUE,
          classwt = NULL, cutoff = NULL, strata = NULL,
          sampsize = NULL, nodesize = NULL, maxnodes = NULL,
          xtrue = NA, parallelize = c('no', 'variables', 'forests'))
```

**Arguments**

- `tab`: A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.
- `conditions`: A vector of factors indicating the biological condition to which each sample belongs.
- `maxiter`: Parameter of the `missForest` function (missForest R package).
- `ntree`: Parameter of the `missForest` function (missForest R package).
- `variablewise`: Parameter of the `missForest` function (missForest R package).
- `decreasing`: Parameter of the `missForest` function (missForest R package).
- `verbose`: Parameter of the `missForest` function (missForest R package).
- `mtry`: Parameter of the `missForest` function (missForest R package).
- `replace`: Parameter of the `missForest` function (missForest R package).
- `classwt`: Parameter of the `missForest` function (missForest R package).
- `cutoff`: Parameter of the `missForest` function (missForest R package).
- `strata`: Parameter of the `missForest` function (missForest R package).
Imputing missing values using an adaptation of the LSImpute algorithm (Bo et al. (2004)) to experimental designs. This algorithm is named "Structured Least Squares Algorithm" (SLSA).

This function is an adaptation of the LSImpute algorithm (Bo et al. (2004)) to experimental designs usually met in MS-based quantitative proteomics.

Usage

impute.slsa(tab, conditions, repbio=NULL, reptech=NULL, nknn=30, selec="all", weight="o", ind.comp=1, progress.bar=TRUE)
Arguments

- **tab**: A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.
- **conditions**: A vector of factors indicating the biological condition to which each sample belongs.
- **repbio**: A vector of factors indicating the biological replicate to which each sample belongs. Default is NULL (no experimental design is considered).
- **reptech**: A vector of factors indicating the technical replicate to which each sample belongs. Default is NULL (no experimental design is considered).
- **nknn**: The number of nearest neighbours used in the algorithm (see Details).
- **selec**: A parameter to select a part of the dataset to find nearest neighbours between rows. This can be useful for big data sets (see Details).
- **weight**: The way of weighting in the algorithm (see Details).
- **ind.comp**: If ind.comp=1, only nearest neighbours without missing values are selected to fit linear models (see Details). Else, they can contain missing values.
- **progress.bar**: If TRUE, a progress bar is displayed.

Details

This function imputes the missing values condition by condition. The rows of the input matrix are imputed when they have at least one observed value in the considered condition. For the rows having only missing values in a condition, you can use the `impute.pa` function.

For each row, a similarity measure between the observed values of this row and the ones of the other rows is computed. The similarity measure which is used is the absolute pairwise correlation coefficient if at least three side-by-side values are observed, and the inverse of the euclidean distance between side-by-side observed values in the other cases.

For big data sets, this step can be time consuming and that is why the input parameter selec allows to select random rows in the data set. If selec="all", then all the rows of the data set are considered; while if selec is a numeric value, for instance selec=100, then only 100 random rows are selected in the data set for computing similarity measures with each row containing missing values.

Once similarity measures are computed for a specific row, then the nknn rows with the highest similarity measures are considered to fit linear models and to predict several estimates for each missing value (see Bo et al. (2004)). If ind.comp=1, then only nearest neighbours without missing values in the condition are considered. However, unlike the original algorithm, our algorithm allows to consider the design of experiments that are specified in input through the vectors conditions, repbio and reptech. Note that conditions has to get a lower number of levels than repbio; and repbio has to get a lower number of levels than reptech.

In the original algorithm, several predictions of each missing value are done from the estimated linear models and, then, they are weighted in function of their similarity measure and summed (see Bo et al. (2004)). In our algorithm, one can use the original weighting function of Bo et al. (2004) if weight="o", i.e. \((\text{sim}^2/(1-\text{sim}^2+1e-06))^2\) where sim is the similarity measure; or the weighting function sim^weight if weight is a numeric value.
**Value**

The input matrix `tab` with imputed values instead of missing values.

**Author(s)**

Quentin Giai Gianetto <quentin2g@yahoo.fr>

**References**


**Examples**

```r
#Simulating data
res.sim=sim.data(nb.pept=2000,nb.miss=600);

#Imputation of missing values with the slsa algorithm
dat.slsa=impute.slsa(tab=res.sim$dat.obs,conditions=res.sim$condition,repbio=res.sim$repbio);
```

---

**mi.mix**

*Multiple imputation from a matrix of probabilities of being MCAR for each missing value.*

---

**Description**

This function allows imputing data sets with a multiple imputation strategy. For details, see Giai Gianetto Q. et al. (2020) (doi: 10.1101/2020.05.29.122770).

**Usage**

```r
mi.mix(tab, tab.imp, prob.MCAR, conditions, repbio=NULL, reptech=NULL, nb.iter=3, nknn=15,
weight=1, selec="all", siz=500, ind.comp=1, methodMCAR="mle", q=0.95,
progress.bar=TRUE, details=FALSE, ncp.max=5, maxiter = 10, ntree = 100,
variablewise = FALSE, decreasing = FALSE, verbose = FALSE, mtry = floor(sqrt(ncol(tab))))
```

**Arguments**

- `tab` A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.
A matrix where the missing values of `tab` have been imputed under the assumption that they are all MCAR. For instance, such a matrix can be obtained from the function `impute.slsa` of this package.

A matrix of probabilities that each missing value is MCAR. For instance such a matrix can be obtained from the function `prob.mcar.tab` of this package.

A vector of factors indicating the biological condition to which each column (experimental sample) belongs.

A vector of factors indicating the biological replicate to which each column belongs. Default is NULL (no experimental design is considered).

A vector of factors indicating the technical replicate to which each column belongs. Default is NULL (no experimental design is considered).

The number of iterations used for the multiple imputation method.

The number of nearest neighbours used in the SLSA algorithm (see `impute.slsa`).

A parameter to select a part of the dataset to find nearest neighbours between rows. This can be useful for big data sets (see `impute.slsa`).

A parameter to select a part of the dataset to perform imputations with a MCAR-devoted algorithm. This can be useful for big data sets. Note that `siz` needs to be inferior to `selec`.

The way of weighting in the algorithm (see `impute.slsa`).

If `ind.comp=1`, only nearest neighbours without missing values are selected to fit linear models (see `impute.slsa`). Else, they can contain missing values.

The method used for imputing MCAR data. If `methodi="mle"` (default), then the `impute.mle` function is used (imputation using an EM algorithm). If `methodi="pca"`, then the `impute.PCA` function is used (imputation using Principal Component Analysis). If `methodi="rf"`, then the `impute.RF` function is used (imputation using Random Forest). Else, the `impute.slsa` function is used (imputation using Least Squares on nearest neighbours).

The method used for imputing MNAR data. If `methodMNAR="igcda"` (default), then the `impute.igcda` function is used. Else, the `impute.pa` function is used.

A quantile value (see `impute.igcda`).

If `TRUE`, a progress bar is displayed.

If `TRUE`, the function gives a list of three values: `imputed.matrix` a matrix with the average of imputed values for each missing value, `sd.imputed.matrix` a matrix with the standard deviations of imputed values for each missing value, `all.imputed.matrices` an array with all the `nb.iter` matrices of imputed values that have been generated.

Parameter of the `impute.PCA` function.

Parameter of the `impute.RF` function.

Parameter of the `impute.RF` function.

Parameter of the `impute.RF` function.

Parameter of the `impute.RF` function.
mtry parameter of the `impute.RF` function.
replace parameter of the `impute.RF` function.
classwt parameter of the `impute.RF` function.
cutoff parameter of the `impute.RF` function.
strata parameter of the `impute.RF` function.
sampsize parameter of the `impute.RF` function.
nodesize parameter of the `impute.RF` function.
maxnodes parameter of the `impute.RF` function.
xtrue parameter of the `impute.RF` function.
parallelize parameter of the `impute.RF` function.
q.min parameter of the `impute.pa` function.
q.norm parameter of the `impute.pa` function.
eps parameter of the `impute.pa` function.
distribution parameter of the `impute.pa` function.
param1 parameter of the `impute.pa` function.
param2 parameter of the `impute.pa` function.
R.q.min parameter of the `impute.pa` function.

Details

At each iteration, a matrix indicating the MCAR values is generated by Bernoulli distributions having parameters given by the matrix `prob.MCAR`. The generated MCAR values are next imputed thanks to the matrix `tab.imp`. For each row containing MNAR values, the other rows are imputed thanks to the function `impute.igcda` and, next, the considered row is imputed thanks to one of the MCAR-devoted imputation methods (`impute.mle`, `impute.RF`, `impute.PCA` or `impute.slsa`). So, the function `impute.igcda` allows to deform the correlation structure of the dataset in view to be closer to that of the true values, while the MCAR-devoted imputation method will impute by taking into account this modified correlation structure.

Value

The input matrix `tab` with average imputed values instead of missing values if `details=FALSE` (default). If `details=TRUE`, a list of three values: `imputed.matrix` a matrix with the average of imputed values for each missing value, `sd.imputed.matrix` a matrix with the standard deviations of imputed values for each missing value, `all.imputed.matrices` an array with all the `nb.iter` matrices of imputed values that have been generated.

Author(s)

Quentin Giai Gianetto <quentin2g@yahoo.fr>

References

miss.mcar.process

Estimating the MCAR mechanism in a sample.

Description

This function allows estimating the MCAR data mechanism, i.e. the probability to be MCAR given that the value is missing in function of the intensity level, from an estimation of a mixture model of MNAR and MCAR values (see estim.mix function).

Usage

miss.mcar.process(abs,pi_mcar,F_tot,F_na)

Arguments

abs The interval on which is estimated the MCAR data mechanism.
pi_mcar An estimation of the proportion of MCAR values.
F_tot An estimation of the cumulative distribution function of the complete values on the interval abs.
F_na An estimation of the cumulative distribution function of the missing values on the interval abs.

Value

A list composed of:

abs The interval on which is estimated the MCAR data mechanism.
p The estimated probability to be MCAR given that the value is missing on the interval abs.
miss.total.process

Estimating the missing data mechanism in a sample.

Description

This function allows estimating the missing data mechanism, i.e. the probability to be missing in function of the intensity level, from an estimation of a mixture model of MNAR and MCAR values (see estim.mix function).

Usage

miss.total.process(abs, pi_na, F_na, F_tot)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>abs</td>
<td>The interval on which is estimated the missing data mechanism.</td>
</tr>
<tr>
<td>pi_na</td>
<td>The proportion of missing values.</td>
</tr>
<tr>
<td>F_na</td>
<td>An estimation of the cumulative distribution function of the missing values on the interval abs.</td>
</tr>
<tr>
<td>F_tot</td>
<td>An estimation of the cumulative distribution function of the complete values on the interval abs.</td>
</tr>
</tbody>
</table>
Value

A list composed of:

abs  The interval on which is estimated the missing data mechanism.
p    The estimated probability to be missing in function of the intensity level.

Author(s)

Quentin Giai Gianetto <quentin2g@yahoo.fr>

See Also

estim.mix

Examples

# Simulating data
res.sim=sim.data(nb.pept=2000,nb.miss=600);

# Imputation of missing values with the slsa algorithm
dat.slsa=impute.slsa(tab=res.sim$dat.obs,conditions=res.sim$condition,repbio=res.sim$repbio);

# Estimation of the mixture model
res=estim.mix(tab=res.sim$dat.obs,tab.imp=dat.slsa,conditions=res.sim$condition);

# Estimating the missing mechanism in the first replicate
mtp=miss.total.process(res$abs.mod,res$pi.na[,1],res$F.na[,1],res$F.tot[,1])
plot(mtp$abs,mtp$p,ty="l",xlab="Intensity values",ylab="Estimated probability to be missing")

pi.mcar.karpievitch  Estimating the proportion of MCAR values in biological conditions using the method of Karpievitch (2009).

Description

This function allows estimating the proportion of MCAR values in biological conditions using the method of Karpievitch (2009).

Usage

pi.mcar.karpievitch(tab,conditions)
pi.mcar.logit

Arguments

- **tab**: A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.
- **conditions**: A vector of factors indicating the biological condition to which each column (experimental sample) belongs.

Value

A list composed of:

- **pi.mcar**: The proportion of MCAR values in each biological condition.
- **prop.na**: The proportion of missing values for each peptide in each condition.
- **moy**: The average of observed values for each peptide in each condition.

Author(s)

Quentin Giai Gianetto <quentin2g@yahoo.fr>

References


See Also

- estim.mix

Examples

```r
#Simulating data
res.sim=sim.data(nb.pept=2000,nb.miss=600);

#Proportion of MCAR values in each condition
pi.mcar.karpievitch(tab=as.data.frame(res.sim$dat.obs),conditions=res.sim$conditions)
```

---

**pi.mcar.logit**: *Estimating the proportion of MCAR values in a sample using a logit model.*

Description

This function allows estimating the proportion of MCAR values in a sample using a logit model.
Usage

`pi.mcar.logit(tab, conditions)`

Arguments

- `tab`: A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.
- `conditions`: A vector of factors indicating the biological condition to which each column (experimental sample) belongs.

Value

A list composed of:

- `pi.mcar`: The estimated proportion of MCAR values.
- `coef1`: The estimated intercept of each logit model estimated in a sample.
- `coef2`: The estimated coefficient of each logit model estimated in a sample.

Author(s)

Quentin Giai Gianetto <quentin2g@yahoo.fr>

See Also

`estim.mix`

Examples

```r
#Simulating data
res.sim=sim.data(nb.pept=2000, nb.miss=600);

#Proportion of MCAR values in each sample
pi.mcar.logit(tab=res.sim$dat.obs, conditions=res.sim$conditions)
```

---

`pi.mcar.probit`  
*Estimating the proportion of MCAR values in a sample using a probit model.*

Description

This function allows estimating the proportion of MCAR values in a sample using a probit model.

Usage

`pi.mcar.probit(tab, conditions)`
prob.mcar

Arguments

- `tab`: A data matrix containing numeric and missing values. Each column of this matrix is assumed to correspond to an experimental sample, and each row to an identified peptide.
- `conditions`: A vector of factors indicating the biological condition to which each column (experimental sample) belongs.

Value

A list composed of:

- `pi.mcar`: The estimated proportion of MCAR values.
- `coef1`: The estimated intercept of each probit model estimated in a sample.
- `coef2`: The estimated coefficient of each probit model estimated in a sample.

Author(s)

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See Also

- `estim.mix`

Examples

```R
# Simulating data
res.sim = sim.data(nb.pept = 2000, nb.miss = 600);

# Proportion of MCAR values in each sample
pi.mcar.probit(tab = res.sim$dat.obs, conditions = res.sim$condition);
```

<table>
<thead>
<tr>
<th>prob.mcar</th>
<th>Estimation of a vector of probabilities that missing values are MCAR.</th>
</tr>
</thead>
</table>

Description

This function returns a vector of probabilities that each missing value is MCAR from specified confidence intervals.

Usage

`prob.mcar(b.u, absc, pi.na, pi.mcar, F.tot, F.obs)`
**Arguments**

- **b.u**
  A numeric vector of upper bounds for missing values.
- **absc**
  The interval on which is estimated the MCAR data mechanism.
- **pi.na**
  The estimated proportion of missing values.
- **pi.mcar**
  The estimated proportion of MCAR values among missing values.
- **F.tot**
  An estimation of the cumulative distribution function of the complete values on the interval absc.
- **F.obs**
  An estimation of the cumulative distribution function of the missing values on the interval absc.

**Value**

A numeric vector of estimated probabilities to be MCAR for missing values assuming upper bounds for them (b.u). The input arguments absc, pi.mcar, pi.na, F.tot and F.obs can be estimated thanks to the function `estim.mix`.

**Author(s)**

Quentin Giai Gianetto <quentin2g@yahoo.fr>

**See Also**

`estim.mix`

**Examples**

```r
#Simulating data
res.sim=sim.data(nb.pept=2000,nb.miss=600);

#Imputation of missing values with the slsa algorithm
dat.slsa=impute.slsa(tab=res.sim$dat.obs,conditions=res.sim$condition,repbio=res.sim$repbio);

#Estimation of the mixture model
res=estim.mix(tab=res.sim$dat.obs, tab.imp=dat.slsa, conditions=res.sim$condition);

#Computing probabilities to be MCAR
born=estim.bound(tab=res.sim$dat.obs,conditions=res.sim$condition);

#Computing probabilities to be MCAR in the first column of result$tab.mod
prob=prob.mcar(b.u=born$tab.upper[,1],absc=res$abs.mod,pi.na=res$pi.na[1],
    pi.mcar=res$pi.mcar[1], F.tot=res$F.tot[,1], F.obs=res$F.obs[,1]);
```
prob.mcar.tab

Estimation of a matrix of probabilities that missing values are MCAR.

Description
This function returns a matrix of probabilities that each missing value is MCAR from specified confidence intervals.

Usage
prob.mcar.tab(tab.u,res)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>tab.u</td>
<td>A numeric matrix of upper bounds for missing values.</td>
</tr>
<tr>
<td>res</td>
<td>An output list resulting from the function estim.mix.</td>
</tr>
</tbody>
</table>

Value
A numeric matrix of estimated probabilities to be MCAR for missing values assuming upper bounds for them (tab.u).

Author(s)
Quentin Giai Gianetto <quentin2g@yahoo.fr>

See Also
estim.mix

Examples

#Simulating data
res.sim=sim.data(nb.pept=2000,nb.miss=600,para=5);

#Imputation of missing values with a MCAR-devoted algorithm: here the slsa algorithm
dat.slsa=impute.slsa(tab=res.sim$dat.obs,conditions=res.sim$condition,repbio=res.sim$repbio);

#Estimation of the mixture model
res=estim.mix(tab=res.sim$dat.obs, tab.imp=dat.slsa, conditions=res.sim$condition);

#Computing probabilities to be MCAR
born=estim.bound(tab=res.sim$dat.obs,conditions=res.sim$condition);
proba=prob.mcar.tab(born$tab.upper,res);

#Histogram of probabilities to be MCAR associated to generated MCAR values
hist(proba[res.sim$link.MCAR[[1]],1],
sim.data

Simulation of data sets by controlling the proportion of MCAR values and the distribution of MNAR values.

Description

This function simulates data sets similar to MS-based bottom-up proteomic data sets.

Usage

```r
sim.data(nb.pept=15000, nb.miss=5000, pi.mcar=0.2, para=3, nb.cond=1, nb.repbio=3,
  nb.sample=3, m.c=25, sd.c=2, sd.rb=0.5, sd.r=0.2)
```

Arguments

- `nb.pept` The number of rows (identified peptides) of the generated data set.
- `nb.miss` The number of missing values to generate in each column.
- `pi.mcar` The proportion of MCAR values in each column.
- `para` Parameter used for simulating MNAR values in columns (see Details).
- `nb.cond` The number of studied biological conditions.
- `nb.repbio` The number of biological samples in each condition.
- `nb.sample` The number of samples coming from each biological sample.
- `m.c` The mean of the average values in each condition.
- `sd.c` The standard deviation of the average values in each condition.
- `sd.rb` The standard deviation of the average values in each biological sample.
- `sd.r` The standard deviation of values in each row among the samples coming from a same biological sample.

Details

First, the average of intensities of a peptide \(i\) in a condition is generated by a Gaussian distribution \(m_{\text{cond}} \sim N(m.c, sd.c)\). Second, the effect of a biological sample is generated by \(m_{\text{bio}} \sim N(0, sd.rb)\). The value of a peptide \(i\) in the sample \(j\) belonging to a specific biological sample and a specific condition is finally generated by \(x_{ij} \sim N(m_{\text{cond}} + m_{\text{bio}}, sd.r)\).

Next, the MCAR values are generated in each column by random draws without replacement among the indexes of rows. The MNAR values are generated in the remaining indexes of rows by random draws without replacement and by respecting the following probabilities:

\[
P(x_{ij} \text{isMNAR}) = 1 - \frac{(x_{ij} - \min_i(x_{ij}))}{(\max_i(x_{ij}) - \min_i(x_{ij}))} \times (\text{para})
\]

where `para` allows adjusting the distribution of MNAR values. If `para = 0`, then the MNAR values are uniformly distributed among intensity level. More `para` is high and more the MNAR values arise for small intensity levels and not for high intensity levels.
translatedRandomBeta

Function to generated values following a translated Beta distribution

Description

Function to generate values following a translated Beta distribution

Usage

translatedRandomBeta(n, min, max, param1 = 3, param2 = 1)
### Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>n</td>
<td>Number of values to generate.</td>
</tr>
<tr>
<td>min</td>
<td>Minimum of the values to be generated.</td>
</tr>
<tr>
<td>max</td>
<td>Maximum of the values to be generated.</td>
</tr>
<tr>
<td>param1</td>
<td>Parameter of the Beta distribution.</td>
</tr>
<tr>
<td>param2</td>
<td>Parameter of the Beta distribution.</td>
</tr>
</tbody>
</table>

### Value

A vector of values following a translated Beta distribution.
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