

# Package ‘missMethods’

October 13, 2022

**Title** Methods for Missing Data

**Version** 0.4.0

**Description** Supply functions for the creation and handling of missing data as well as tools to evaluate missing data methods. Nearly all possibilities of generating missing data discussed by Santos et al. (2019) <[doi:10.1109/ACCESS.2019.2891360](https://doi.org/10.1109/ACCESS.2019.2891360)> and some additional are implemented. Functions are supplied to compare parameter estimates and imputed values to true values to evaluate missing data methods. Evaluations of these types are done, for example, by Cetin-Berber et al. (2019) <[doi:10.1177/0013164418805532](https://doi.org/10.1177/0013164418805532)> and Kim et al. (2005) <[doi:10.1093/bioinformatics/bth499](https://doi.org/10.1093/bioinformatics/bth499)>.

**License** GPL-3

**URL** <https://github.com/torockel/missMethods>

**BugReports** <https://github.com/torockel/missMethods/issues>

**Imports** mvtnorm, stats, utils

**Suggests** ggplot2, knitr, lpSolve, norm, rmarkdown, testthat (>= 2.1.0), tibble

**VignetteBuilder** knitr

**Encoding** UTF-8

**RoxygenNote** 7.2.1

**NeedsCompilation** no

**Author** Tobias Rockel [aut, cre]

**Maintainer** Tobias Rockel <[Rockel.To@gmail.com](mailto:Rockel.To@gmail.com)>

**Repository** CRAN

**Date/Publication** 2022-09-16 15:16:10 UTC

## R topics documented:

apply_imputation . . . . .	2
count_NA . . . . .	4

delete_MAR_1_to_x . . . . .	5
delete_MAR_censoring . . . . .	8
delete_MAR_one_group . . . . .	11
delete_MAR_rank . . . . .	13
delete_MCAR . . . . .	15
delete_MNAR_1_to_x . . . . .	17
delete_MNAR_censoring . . . . .	19
delete_MNAR_one_group . . . . .	20
delete_MNAR_rank . . . . .	22
evaluate_imputation_parameters . . . . .	23
evaluate_imputed_values . . . . .	25
evaluate_parameters . . . . .	28
impute_EM . . . . .	29
impute_expected_values . . . . .	30
impute_hot_deck_in_classes . . . . .	31
impute_in_classes . . . . .	33
impute_LS_adaptive . . . . .	34
impute_LS_array . . . . .	36
impute_LS_combined . . . . .	38
impute_LS_gene . . . . .	39
impute_mean . . . . .	41
impute_median . . . . .	42
impute_mode . . . . .	43
impute_sRHD . . . . .	44
median.factor . . . . .	46
<b>Index</b>	<b>48</b>

---

apply_imputation	<i>Apply a function for imputation</i>
------------------	--

---

## Description

Apply a function for imputation over rows, columns or combinations of both

## Usage

```
apply_imputation(
  ds,
  FUN = mean,
  type = "columnwise",
  convert_tibble = TRUE,
  ...
)
```

## Arguments

ds	A data frame or matrix with missing values.
FUN	The function to be applied for imputation.
type	A string specifying the values used for imputation; one of: "columnwise", "rowwise", "total", "Two-Way" or "Winer" (see details).
convert_tibble	If ds is a tibble, should it be converted (see section A note for tibble users).
...	Further arguments passed to FUN.

## Details

The functionality of `apply_imputation` is inspired by the `apply` function. The function applies a function `FUN` to impute the missing values in `ds`. `FUN` must be a function, which takes a vector as input and returns exactly one value. The argument `type` is comparable to `apply`'s `MARGIN` argument. It specifies the values that are used for the calculation of the imputation values. For example, `type = "columnwise"` and `FUN = mean` will impute the mean of the observed values in a column for all missing values in this column. In contrast, `type = "rowwise"` and `FUN = mean` will impute the mean of the observed values in a row for all missing values in this row.

List of all implemented types:

- "columnwise" (the default): imputes column by column; all observed values of a column are given to `FUN` and the returned value is used as the imputation value for all missing values of the column.
- "rowwise": imputes row by row; all observed values of a row are given to `FUN` and the returned value is used as the imputation value for all missing values of the row.
- "total": All observed values of `ds` are given to `FUN` and the returned value is used as the imputation value for all missing values of `ds`.
- "Winer": The mean value from "columnwise" and "rowwise" is used as the imputation value.
- "Two-Way": The sum of the values from "columnwise" and "rowwise" minus "total" is used as the imputation value.

If no value can be given to `FUN` (for example, if no value in a column is observed and `type = "columnwise"`), then a warning will be issued and no value will be imputed in the corresponding column or row.

## Value

An object of the same class as `ds` with imputed missing values.

## A note for tibble users

If you use tibbles and `convert_tibble` is `TRUE` the tibble is first converted to a data frame, then imputed and converted back. If `convert_tibble` is `FALSE` no conversion is done. However, depending on the tibble and the package version of tibble you use, imputation may not be possible and some errors will be thrown.

## References

Beland, S., Pichette, F., & Jolani, S. (2016). Impact on Cronbach's  $\alpha$  of simple treatment methods for missing data. *The Quantitative Methods for Psychology*, 12(1), 57-73.

## See Also

A convenient interface exists for common cases like mean imputation: [impute\\_mean](#), [impute\\_median](#), [impute\\_mode](#). All these functions call `apply_imputation`.

## Examples

```
ds <- data.frame(X = 1:20, Y = 101:120)
ds_mis <- delete_MCAR(ds, 0.2)
ds_imp_app <- apply_imputation(ds_mis, FUN = mean, type = "total")
# the same result can be achieved via impute_mean():
ds_imp_mean <- impute_mean(ds_mis, type = "total")
all.equal(ds_imp_app, ds_imp_mean)
```

---

count\_NA

*Count the number of NAs*

---

## Description

Count the number of NA values in a vector, matrix or data frame

## Usage

```
count_NA(x, type = "default")
```

## Arguments

- |      |  |
|------|--|
| x    | a vector, matrix or data frame, in which NA values are counted   |
| type | How to count the NA values. Possible choices: <ul style="list-style-type: none"> <li>"default": If x is a matrix or a data frame, the number of missing values per column is returned. If x is something else, the total number of missing values in x is returned.</li> <li>"all": The number of all missing values in x is returned.</li> <li>"cols": The number of missing values per column is returned.</li> <li>"rows": The number of missing values per row is returned.</li> </ul> |

## Value

The number of missing values.

**Examples**

```
count_NA(c(1, NA, 3, NA, 5, NA))
test_df <- data.frame(X1 = rep(c(1, NA), 5), X2 = c(1:9, NA))
count_NA(test_df)
count_NA(test_df, "cols") # the default
count_NA(test_df, "rows")
count_NA(test_df, "all")
```

---

```
delete_MAR_1_to_x      Create MAR values using MARI:x
```

---

**Description**

Create missing at random (MAR) values using MARI:x in a data frame or a matrix

**Usage**

```
delete_MAR_1_to_x(
  ds,
  p,
  cols_mis,
  cols_ctrl,
  x,
  cutoff_fun = median,
  prop = 0.5,
  use_lpSolve = TRUE,
  ordered_as_unordered = FALSE,
  n_mis_stochastic = FALSE,
  x_stochastic = FALSE,
  add_realized_x = FALSE,
  ...,
  miss_cols,
  ctrl_cols,
  stochastic
)
```

**Arguments**

<code>ds</code>	A data frame or matrix in which missing values will be created.
<code>p</code>	A numeric vector with length one or equal to length <code>cols_mis</code> ; the probability that a value is missing.
<code>cols_mis</code>	A vector of column names or indices of columns in which missing values will be created.
<code>cols_ctrl</code>	A vector of column names or indices of columns, which controls the creation of missing values in <code>cols_mis</code> . Must be of the same length as <code>cols_mis</code> .

<code>x</code>	Numeric with length one ( $0 < x < \text{Inf}$ ); odds are 1 to $x$ for the probability of a value to be missing in group 1 against the probability of a value to be missing in group 2 (see details).
<code>cutoff_fun</code>	Function that calculates the cutoff values in the <code>cols_ctrl</code> .
<code>prop</code>	Numeric of length one; (minimum) proportion of rows in group 1 (only used for unordered factors).
<code>use_lpSolve</code>	Logical; should <code>lpSolve</code> be used for the determination of groups, if <code>cols_ctrl[i]</code> is an unordered factor.
<code>ordered_as_unordered</code>	Logical; should ordered factors be treated as unordered factors.
<code>n_mis_stochastic</code>	Logical, should the number of missing values be stochastic? If <code>n_mis_stochastic = TRUE</code> , the number of missing values for a column with missing values <code>cols_mis[i]</code> is a random variable with expected value $\text{nrow}(ds) * p[i]$ . If <code>n_mis_stochastic = FALSE</code> , the number of missing values will be deterministic. Normally, the number of missing values for a column with missing values <code>cols_mis[i]</code> is $\text{round}(\text{nrow}(ds) * p[i])$ . Possible deviations from this value, if any exists, are documented in Details.
<code>x_stochastic</code>	Logical; should the odds be stochastic or deterministic.
<code>add_realized_x</code>	Logical; if <code>TRUE</code> the realized odds for <code>cols_mis</code> will be returned (as attribute).
<code>...</code>	Further arguments passed to <code>cutoff_fun</code> .
<code>miss_cols</code>	Deprecated, use <code>cols_mis</code> instead.
<code>ctrl_cols</code>	Deprecated, use <code>cols_ctrl</code> instead.
<code>stochastic</code>	Deprecated, use <code>n_mis_stochastic</code> instead.

## Details

This function creates missing at random (MAR) values in the columns specified by the argument `cols_mis`. The probability for missing values is controlled by `p`. If `p` is a single number, then the overall probability for a value to be missing will be `p` in all columns of `cols_mis`. (Internally `p` will be replicated to a vector of the same length as `cols_mis`. So, all `p[i]` in the following sections will be equal to the given single number `p`.) Otherwise, `p` must be of the same length as `cols_mis`. In this case, the overall probability for a value to be missing will be `p[i]` in the column `cols_mis[i]`. The position of the missing values in `cols_mis[i]` is controlled by `cols_ctrl[i]`. The following procedure is applied for each pair of `cols_ctrl[i]` and `cols_mis[i]` to determine the positions of missing values:

At first, the rows of `ds` are divided into two groups. Therefore, the `cutoff_fun` calculates a cutoff value for `cols_ctrl[i]` (via `cutoff_fun(ds[, cols_ctrl[i]], ...)`). The group 1 consists of the rows, whose values in `cols_ctrl[i]` are below the calculated cutoff value. If the so defined group 1 is empty, the rows that have a value equal to the cutoff value will be added to this group (otherwise, these rows will belong to group 2). The group 2 consists of the remaining rows, which are not part of group 1. Now the probabilities for the rows in the two groups are set in the way that the odds are 1: $x$  against a missing value in `cols_mis[i]` for the rows in group 1 compared to the rows in group 2. That means, the probability for a value to be missing in group 1 divided by the probability for a value to be missing in group 2 equals 1 divided by  $x$ . For example, for two equal

sized groups 1 and 2, ideally the number of NAs in group 1 divided by the number of NAs in group 2 should equal 1 divided by  $x$ . But there are some restrictions, which can lead to some deviations from the odds 1: $x$  (see below).

If `x_stochastic` and `n_mis_stochastic` are false (the default), then exactly  $\text{round}(\text{nrow}(\text{ds}) * p[i])$  values will be set NA in column `cols_mis[i]`. To achieve this, it is possible that the true odds differ from 1: $x$ . The number of observations that are deleted in group 1 and group 2 are chosen to minimize the absolute difference between the realized odds and 1: $x$ . Furthermore, if  $\text{round}(\text{nrow}(\text{ds}) * p[i]) == 0$ , then no missing value will be created in `cols_mis[i]`.

If `x_stochastic` is true, the rows from the two groups will get sampling weights proportional to 1 (group 1) and  $x$  (group 2). If `n_mis_stochastic` is false, these weights are given to `sample` via the argument `prob` and exactly  $\text{round}(\text{nrow}(\text{ds}) * p[i])$  values will be set NA. If `n_mis_stochastic` is true, the sampling weights will be scaled and compared to uniform random numbers. The scaling is done in such a way to get expected  $\text{nrow}(\text{ds}) * p[i]$  missing values in `cols_mis[i]`.

If  $p$  is high and  $x$  is too high or too low, it is possible that the odds 1: $x$  and the proportion of missing values  $p$  cannot be realized together. For example, if  $p[i] = 0.9$ , then a maximum of  $x = 1.25$  is possible (assuming that exactly 50 % of the values are below and 50 % of the values are above the cutoff value in `cols_ctrl[i]`). If a combination of  $p$  and  $x$  that cannot be realized together is given to `delete_MAR_1_to_x`, then a warning will be generated and  $x$  will be adjusted in such a way that  $p$  can be realized as given to the function. The warning can be silenced by setting the option `missMethods.warn.too.high.p` to false.

The argument `add_realized_x` controls whether the  $x$  of the realized odds are added to the return value or not. If `add_realized_x = TRUE`, then the realized  $x$  values for all `cols_mis` will be added as an attribute to the returned object. For `x_stochastic = TRUE` these realized  $x$  will differ from the given  $x$  most of the time and will change if the function is rerun without setting a seed. For `x_stochastic = FALSE`, it is also possible that the realized odds differ (see above). However, the realized odds will be constant over multiple runs.

## Value

An object of the same class as `ds` with missing values.

## Treatment of factors

If `ds[, cols_ctrl[i]]` is an unordered factor, then the concept of a cutoff value is not meaningful and cannot be applied. Instead, a combinations of the levels of the unordered factor is searched that

- guarantees at least a proportion of `prop` rows are in group 1
- minimize the difference between `prop` and the proportion of rows in group 1.

This can be seen as a binary search problem, which is solved by the solver from the package `lpSolve`, if `use_lpSolve = TRUE`. If `use_lpSolve = FALSE`, a very simple heuristic is applied. The heuristic only guarantees that at least a proportion of `prop` rows are in group 1. The choice `use_lpSolve = FALSE` is not recommend and should only be considered, if the solver of `lpSolve` fails.

If `ordered_as_unordered = TRUE`, then ordered factors will be treated like unordered factors and the same binary search problem will be solved for both types of factors. If `ordered_as_unordered = FALSE` (the default), then ordered factors will be grouped via `cutoff_fun` as described in Details.

## References

Santos, M. S., Pereira, R. C., Costa, A. F., Soares, J. P., Santos, J., & Abreu, P. H. (2019). Generating Synthetic Missing Data: A Review by Missing Mechanism. *IEEE Access*, 7, 11651-11667

## See Also

[delete\\_MNAR\\_1\\_to\\_x](#)

Other functions to create MAR: [delete\\_MAR\\_censoring\(\)](#), [delete\\_MAR\\_one\\_group\(\)](#), [delete\\_MAR\\_rank\(\)](#)

## Examples

```
ds <- data.frame(X = 1:20, Y = 101:120)
delete_MAR_1_to_x(ds, 0.2, "X", "Y", 3)
# beware of small datasets and x_stochastic = FALSE
attr(delete_MAR_1_to_x(ds, 0.4, "X", "Y", 3, add_realized_x = TRUE), "realized_x")
attr(delete_MAR_1_to_x(ds, 0.4, "X", "Y", 4, add_realized_x = TRUE), "realized_x")
attr(delete_MAR_1_to_x(ds, 0.4, "X", "Y", 5, add_realized_x = TRUE), "realized_x")
attr(delete_MAR_1_to_x(ds, 0.4, "X", "Y", 7, add_realized_x = TRUE), "realized_x")
# p = 0.4 and 20 values -> 8 missing values, possible combinations:
# either 6 above 2 below (x = 3) or
# 7 above and 1 below (x = 7)
# Too high combination of p and x:
tryCatch(delete_MAR_1_to_x(ds, 0.9, "X", "Y", 3), warning = function(w) w)
```

---

delete\_MAR\_censoring *Create MAR values using a censoring mechanism*

---

## Description

Create missing at random (MAR) values using a censoring mechanism in a data frame or a matrix

## Usage

```
delete_MAR_censoring(
  ds,
  p,
  cols_mis,
  cols_ctrl,
  n_mis_stochastic = FALSE,
  where = "lower",
  sorting = TRUE,
  miss_cols,
  ctrl_cols
)
```



**Arguments**

<code>ds</code>	A data frame or matrix in which missing values will be created.
<code>p</code>	A numeric vector with length one or equal to length <code>cols_mis</code> ; the probability that a value is missing.
<code>cols_mis</code>	A vector of column names or indices of columns in which missing values will be created.
<code>cols_ctrl</code>	A vector of column names or indices of columns, which controls the creation of missing values in <code>cols_mis</code> . Must be of the same length as <code>cols_mis</code> .
<code>n_mis_stochastic</code>	Logical, should the number of missing values be stochastic? If <code>n_mis_stochastic = TRUE</code> , the number of missing values for a column with missing values <code>cols_mis[i]</code> is a random variable with expected value $nrow(ds) * p[i]$ . If <code>n_mis_stochastic = FALSE</code> , the number of missing values will be deterministic. Normally, the number of missing values for a column with missing values <code>cols_mis[i]</code> is $round(nrow(ds) * p[i])$ . Possible deviations from this value, if any exists, are documented in Details.
<code>where</code>	Controls where missing values are created; one of "lower", "upper" or "both" (see details).
<code>sorting</code>	Logical; should sorting be used or a quantile as a threshold.
<code>miss_cols</code>	Deprecated, use <code>cols_mis</code> instead.
<code>ctrl_cols</code>	Deprecated, use <code>cols_ctrl</code> instead.

**Details**

This function creates missing at random (MAR) values in the columns specified by the argument `cols_mis`. The probability for missing values is controlled by `p`. If `p` is a single number, then the overall probability for a value to be missing will be `p` in all columns of `cols_mis`. (Internally `p` will be replicated to a vector of the same length as `cols_mis`. So, all `p[i]` in the following sections will be equal to the given single number `p`.) Otherwise, `p` must be of the same length as `cols_mis`. In this case, the overall probability for a value to be missing will be `p[i]` in the column `cols_mis[i]`. The position of the missing values in `cols_mis[i]` is controlled by `cols_ctrl[i]`. The following procedure is applied for each pair of `cols_ctrl[i]` and `cols_mis[i]` to determine the positions of missing values:

The default behavior (`sorting = TRUE`) of this function is to first sort the column `cols_ctrl[i]`. Then missing values in `cols_mis[i]` are created in the rows with the  $round(nrow(ds) * p[i])$  smallest values. This censors approximately the proportion of `p[i]` rows of smallest values in `cols_ctrl[i]` in `cols_mis[i]`. Hence, the name of the function.

If `where = "upper"`, instead of the rows with the smallest values, the rows with the highest values will be selected. For `where = "both"`, the one half of the  $round(nrow(ds) * p[i])$  rows with missing values will be the rows with the smallest values and the other half will be the rows with the highest values. So the censoring rows are divided to the highest and smallest values of `cols_ctrl[i]`. For odd  $round(nrow(ds) * p[i])$  one more value is set NA among the smallest values.

If `n_mis_stochastic = TRUE` and `sorting = TRUE` the procedure is slightly altered. In this case, at first the  $floor(nrow(ds) * p[i])$  rows with the smallest values (`where = "lower"`) are set NA. If  $nrow(ds) * p[i] > floor(nrow(ds) * p[i])$ , the row with the next greater value will be set

NA with a probability to get expected  $nrow(ds) * p[i]$  missing values. For where = "upper" this "random" missing value will be the next smallest. For where = "both" this "random" missing value will be the next greatest of the smallest values.

If `sorting = FALSE`, the rows of `ds` will not be sorted. Instead, a quantile will be calculated (using [quantile](#)). If where = "lower", the `quantile(ds[, cols_ctrl[i]], p[i])` will be calculated and all rows with values in `ds[, cols_ctrl[i]]` below this quantile will have missing values in `cols_mis[i]`. For where = "upper", the `quantile(ds[, cols_ctrl[i]], 1 - p[i])` will be calculated and all rows with values above this quantile will have missing values. For where = "both", the `quantile(ds[, cols_ctrl[i]], p[i] / 2)` and `quantile(ds[, cols_ctrl[i]], 1 - p[i] / 2)` will be calculated. All rows with values in `cols_ctrl[i]` below the first quantile or above the second quantile will have missing values in `cols_mis[i]`.

For `sorting = FALSE` only `n_mis_stochastic = FALSE` is implemented at the moment.

The option `sorting = TRUE` with `n_mis_stochastic = FALSE` will always create exactly  $round(nrow(ds) * p[i])$  missing values in `cols_mis[i]`. With `n_mis_stochastic = TRUE` `sorting` will result in  $floor(nrow(ds) * p[i])$  or  $ceiling(nrow(ds) * p[i])$  missing values in `cols_mis[i]`. For `sorting = FALSE`, the number of missing values will normally be close to  $nrow(ds) * p[i]$ . But for `cols_ctrl` with many duplicates the choice `sorting = FALSE` can be problematic, because of the calculation of `quantile(ds[, cols_ctrl[i]], p[i])` and setting values NA below this threshold (see examples). So, in most cases `sorting = TRUE` is recommended.

## Value

An object of the same class as `ds` with missing values.

## References

Santos, M. S., Pereira, R. C., Costa, A. F., Soares, J. P., Santos, J., & Abreu, P. H. (2019). Generating Synthetic Missing Data: A Review by Missing Mechanism. *IEEE Access*, 7, 11651-11667

## See Also

[delete\\_MNAR\\_censoring](#)

Other functions to create MAR: [delete\\_MAR\\_1\\_to\\_x\(\)](#), [delete\\_MAR\\_one\\_group\(\)](#), [delete\\_MAR\\_rank\(\)](#)

## Examples

```
ds <- data.frame(X = 1:20, Y = 101:120)
delete_MAR_censoring(ds, 0.2, "X", "Y")
# many duplicated values can be problematic for sorting = FALSE:
ds_many_dup <- data.frame(X = 1:20, Y = c(rep(0, 10), rep(1, 10)))
delete_MAR_censoring(ds_many_dup, 0.2, "X", "Y") # 4 NAs as expected
quantile(ds_many_dup$Y, 0.2) # 0
# No value is BELOW 0 in ds_many_dup$Y, so no missing values will be created:
delete_MAR_censoring(ds_many_dup, 0.2, "X", "Y", sorting = FALSE) # No NA!
```

---

delete\_MAR\_one\_group *Create MAR values by deleting values in one of two groups*

---

### Description

Create missing at random (MAR) values by deleting values in one of two groups in a data frame or a matrix

### Usage

```
delete_MAR_one_group(
  ds,
  p,
  cols_mis,
  cols_ctrl,
  cutoff_fun = median,
  prop = 0.5,
  use_lpSolve = TRUE,
  ordered_as_unordered = FALSE,
  n_mis_stochastic = FALSE,
  ...,
  miss_cols,
  ctrl_cols,
  stochastic
)
```

### Arguments

<code>ds</code>	A data frame or matrix in which missing values will be created.
<code>p</code>	A numeric vector with length one or equal to length <code>cols_mis</code> ; the probability that a value is missing.
<code>cols_mis</code>	A vector of column names or indices of columns in which missing values will be created.
<code>cols_ctrl</code>	A vector of column names or indices of columns, which controls the creation of missing values in <code>cols_mis</code> . Must be of the same length as <code>cols_mis</code> .
<code>cutoff_fun</code>	Function that calculates the cutoff values in the <code>cols_ctrl</code> .
<code>prop</code>	Numeric of length one; (minimum) proportion of rows in group 1 (only used for unordered factors).
<code>use_lpSolve</code>	Logical; should lpSolve be used for the determination of groups, if <code>cols_ctrl[i]</code> is an unordered factor.
<code>ordered_as_unordered</code>	Logical; should ordered factors be treated as unordered factors.
<code>n_mis_stochastic</code>	Logical, should the number of missing values be stochastic? If <code>n_mis_stochastic = TRUE</code> , the number of missing values for a column with missing values <code>cols_mis[i]</code>

is a random variable with expected value  $nrow(ds) * p[i]$ . If `n_mis_stochastic = FALSE`, the number of missing values will be deterministic. Normally, the number of missing values for a column with missing values `cols_mis[i]` is  $round(nrow(ds) * p[i])$ . Possible deviations from this value, if any exists, are documented in Details.

... Further arguments passed to `cutoff_fun`.

`miss_cols` Deprecated, use `cols_mis` instead.

`ctrl_cols` Deprecated, use `cols_ctrl` instead.

`stochastic` Deprecated, use `n_mis_stochastic` instead.

### Details

This function creates missing at random (MAR) values in the columns specified by the argument `cols_mis`. The probability for missing values is controlled by `p`. If `p` is a single number, then the overall probability for a value to be missing will be `p` in all columns of `cols_mis`. (Internally `p` will be replicated to a vector of the same length as `cols_mis`. So, all `p[i]` in the following sections will be equal to the given single number `p`.) Otherwise, `p` must be of the same length as `cols_mis`. In this case, the overall probability for a value to be missing will be `p[i]` in the column `cols_mis[i]`. The position of the missing values in `cols_mis[i]` is controlled by `cols_ctrl[i]`. The following procedure is applied for each pair of `cols_ctrl[i]` and `cols_mis[i]` to determine the positions of missing values:

At first, the rows of `ds` are divided into two groups. Therefore, the `cutoff_fun` calculates a cutoff value for `cols_ctrl[i]` (via `cutoff_fun(ds[, cols_ctrl[i]], ...)`). The group 1 consists of the rows, whose values in `cols_ctrl[i]` are below the calculated cutoff value. If the so defined group 1 is empty, the rows that are equal to the cutoff value will be added to this group (otherwise, these rows will belong to group 2). The group 2 consists of the remaining rows, which are not part of group 1. Now one of these two groups is chosen randomly. In the chosen group, values are deleted in `cols_mis[i]`. In the other group, no missing values will be created in `cols_mis[i]`.

If `p` is too high, it is possible that a group contains not enough objects to reach  $nrow(ds) * p$  missing values. In this case, `p` is reduced to the maximum possible value (given the (random) group with missing data) and a warning is given. Obviously this case will occur regularly, if  $p > 0.5$ . Therefore, this function should normally not be called with  $p > 0.5$ . However, this can occur for smaller values of `p`, too (depending on the grouping). The warning can be silenced by setting the option `missMethods.warn.too.high.p` to `false`.

### Value

An object of the same class as `ds` with missing values.

### Treatment of factors

If `ds[, cols_ctrl[i]]` is an unordered factor, then the concept of a cutoff value is not meaningful and cannot be applied. Instead, a combinations of the levels of the unordered factor is searched that

- guarantees at least a proportion of `prop` rows are in group 1
- minimize the difference between `prop` and the proportion of rows in group 1.

This can be seen as a binary search problem, which is solved by the solver from the package `lpSolve`, if `use_lpSolve = TRUE`. If `use_lpSolve = FALSE`, a very simple heuristic is applied. The heuristic only guarantees that at least a proportion of prop rows are in group 1. The choice `use_lpSolve = FALSE` is not recommend and should only be considered, if the solver of `lpSolve` fails.

If `ordered_as_unordered = TRUE`, then ordered factors will be treated like unordered factors and the same binary search problem will be solved for both types of factors. If `ordered_as_unordered = FALSE` (the default), then ordered factors will be grouped via `cutoff_fun` as described in Details.

## References

Santos, M. S., Pereira, R. C., Costa, A. F., Soares, J. P., Santos, J., & Abreu, P. H. (2019). Generating Synthetic Missing Data: A Review by Missing Mechanism. *IEEE Access*, 7, 11651-11667

## See Also

[delete\\_MNAR\\_one\\_group](#)

Other functions to create MAR: [delete\\_MAR\\_1\\_to\\_x\(\)](#), [delete\\_MAR\\_censoring\(\)](#), [delete\\_MAR\\_rank\(\)](#)

## Examples

```
ds <- data.frame(X = 1:20, Y = 101:120)
delete_MAR_one_group(ds, 0.2, "X", "Y")
```

---

delete_MAR_rank	<i>Create MAR values using a ranking mechanism</i>
-----------------	--

---

## Description

Create missing at random (MAR) values using a ranking mechanism in a data frame or a matrix

## Usage

```
delete_MAR_rank(
  ds,
  p,
  cols_mis,
  cols_ctrl,
  n_mis_stochastic = FALSE,
  ties.method = "average",
  miss_cols,
  ctrl_cols
)
```

**Arguments**

<code>ds</code>	A data frame or matrix in which missing values will be created.
<code>p</code>	A numeric vector with length one or equal to length <code>cols_mis</code> ; the probability that a value is missing.
<code>cols_mis</code>	A vector of column names or indices of columns in which missing values will be created.
<code>cols_ctrl</code>	A vector of column names or indices of columns, which controls the creation of missing values in <code>cols_mis</code> . Must be of the same length as <code>cols_mis</code> .
<code>n_mis_stochastic</code>	Logical, should the number of missing values be stochastic? If <code>n_mis_stochastic = TRUE</code> , the number of missing values for a column with missing values <code>cols_mis[i]</code> is a random variable with expected value <code>nrow(ds) * p[i]</code> . If <code>n_mis_stochastic = FALSE</code> , the number of missing values will be deterministic. Normally, the number of missing values for a column with missing values <code>cols_mis[i]</code> is <code>round(nrow(ds) * p[i])</code> . Possible deviations from this value, if any exists, are documented in Details.
<code>ties.method</code>	How ties are handled. Passed to <a href="#">rank</a> .
<code>miss_cols</code>	Deprecated, use <code>cols_mis</code> instead.
<code>ctrl_cols</code>	Deprecated, use <code>cols_ctrl</code> instead.

**Details**

This function creates missing at random (MAR) values in the columns specified by the argument `cols_mis`. The probability for missing values is controlled by `p`. If `p` is a single number, then the overall probability for a value to be missing will be `p` in all columns of `cols_mis`. (Internally `p` will be replicated to a vector of the same length as `cols_mis`. So, all `p[i]` in the following sections will be equal to the given single number `p`.) Otherwise, `p` must be of the same length as `cols_mis`. In this case, the overall probability for a value to be missing will be `p[i]` in the column `cols_mis[i]`. The position of the missing values in `cols_mis[i]` is controlled by `cols_ctrl[i]`. The following procedure is applied for each pair of `cols_ctrl[i]` and `cols_mis[i]` to determine the positions of missing values:

At first, the probability for a value to be missing is calculated. This probability for a missing value in a row of `cols_mis[i]` is proportional to the rank of the value in `cols_ctrl[i]` in the same row. If `n_mis_stochastic = FALSE` these probabilities are given to the `prob` argument of [sample](#). If `n_mis_stochastic = TRUE`, they are scaled to sum up to `nrow(ds) * p[i]`. Then for each probability a uniformly distributed random number is generated. If this random number is less than the probability, the value in `cols_mis[i]` is set NA.

The ranks are calculated via [rank](#). The argument `ties.method` is directly passed to this function. Possible choices for `ties.method` are documented in [rank](#).

For high values of `p` it is mathematically not possible to get probabilities proportional to the ranks. In this case, a warning is given. This warning can be silenced by setting the option `missMethods.warn.too.high.p` to false.

**Value**

An object of the same class as `ds` with missing values.

## References

Santos, M. S., Pereira, R. C., Costa, A. F., Soares, J. P., Santos, J., & Abreu, P. H. (2019). Generating Synthetic Missing Data: A Review by Missing Mechanism. *IEEE Access*, 7, 11651-11667

## See Also

[rank](#), [delete\\_MNAR\\_rank](#)

Other functions to create MAR: [delete\\_MAR\\_1\\_to\\_x\(\)](#), [delete\\_MAR\\_censoring\(\)](#), [delete\\_MAR\\_one\\_group\(\)](#)

## Examples

```
ds <- data.frame(X = 1:20, Y = 101:120)
delete_MAR_rank(ds, 0.2, "X", "Y")
```

---

delete\_MCAR

*Create MCAR values*

---

## Description

Create missing completely at random (MCAR) values in a data frame or a matrix

## Usage

```
delete_MCAR(
  ds,
  p,
  cols_mis = seq_len(ncol(ds)),
  n_mis_stochastic = FALSE,
  p_overall = FALSE,
  miss_cols,
  stochastic
)
```

## Arguments

<code>ds</code>	A data frame or matrix in which missing values will be created.
<code>p</code>	A numeric vector with length one or equal to length <code>cols_mis</code> ; the probability that a value is missing.
<code>cols_mis</code>	A vector of column names or indices of columns in which missing values will be created.
<code>n_mis_stochastic</code>	Logical, should the number of missing values be stochastic? If <code>n_mis_stochastic = TRUE</code> , the number of missing values for a column with missing values <code>cols_mis[i]</code> is a random variable with expected value <code>nrow(ds) * p[i]</code> . If <code>n_mis_stochastic = FALSE</code> , the number of missing values will be deterministic. Normally, the number of missing values for a column with missing values <code>cols_mis[i]</code> is <code>round(nrow(ds) * p[i])</code> . Possible deviations from this value, if any exists, are documented in Details.

<code>p_overall</code>	Logical; see details.
<code>miss_cols</code>	Deprecated, use <code>cols_mis</code> instead.
<code>stochastic</code>	Deprecated, use <code>n_mis_stochastic</code> instead.

## Details

This function creates missing completely at random (MCAR) values in the dataset `ds`. The proportion of missing values is specified with `p`. The columns in which missing values are created can be set via `cols_mis`. If `cols_mis` is not specified, then missing values are created in all columns of `ds`.

The probability for missing values is controlled by `p`. If `p` is a single number, then the overall probability for a value to be missing will be `p` in all columns of `cols_mis`. (Internally `p` will be replicated to a vector of the same length as `cols_mis`. So, all `p[i]` in the following sections will be equal to the given single number `p`.) Otherwise, `p` must be of the same length as `cols_mis`. In this case, the overall probability for a value to be missing will be `p[i]` in the column `cols_mis[i]`.

If `n_mis_stochastic = FALSE` and `p_overall = FALSE` (the default), then exactly  $\text{round}(\text{nrow}(\text{ds}) * p[i])$  values will be set NA in column `cols_mis[i]`. If `n_mis_stochastic = FALSE` and `p_overall = TRUE`, then `p` must be of length one and exactly  $\text{round}(\text{nrow}(\text{ds}) * p * \text{length}(\text{cols\_mis}))$  values will be set NA (over all columns in `cols_mis`). This can result in a proportion of missing values in every `miss_col` unequal to `p`, but the proportion of missing values in all columns together will be close to `p`.

If `n_mis_stochastic = TRUE`, then each value in column `cols_mis[i]` has probability `p[i]` to be missing (independently of all other values). Therefore, the number of missing values in `cols_mis[i]` is a random variable with a binomial distribution  $B(\text{nrow}(\text{ds}), p[i])$ . This can (and will most of the time) lead to more or less missing values than  $\text{round}(\text{nrow}(\text{ds}) * p[i])$  in column `cols_mis[i]`. If `n_mis_stochastic = TRUE`, then the argument `p_overall` is ignored because it is superfluous.

## Value

An object of the same class as `ds` with missing values.

## References

Santos, M. S., Pereira, R. C., Costa, A. F., Soares, J. P., Santos, J., & Abreu, P. H. (2019). Generating Synthetic Missing Data: A Review by Missing Mechanism. *IEEE Access*, 7, 11651-11667

## Examples

```
ds <- data.frame(X = 1:20, Y = 101:120)
delete_MCAR(ds, 0.2)
```



---

delete\_MNAR\_1\_to\_x      *Create MNAR values using MNAR1:x*

---

## Description

Create missing not at random (MNAR) values using MNAR1:x in a data frame or a matrix

## Usage

```
delete_MNAR_1_to_x(
  ds,
  p,
  cols_mis,
  x,
  cutoff_fun = median,
  prop = 0.5,
  use_lpSolve = TRUE,
  ordered_as_unordered = FALSE,
  n_mis_stochastic = FALSE,
  x_stochastic = FALSE,
  add_realized_x = FALSE,
  ...,
  miss_cols,
  stochastic
)
```

## Arguments

ds	A data frame or matrix in which missing values will be created.
p	A numeric vector with length one or equal to length cols_mis; the probability that a value is missing.
cols_mis	A vector of column names or indices of columns in which missing values will be created.
x	Numeric with length one ( $0 < x < \text{Inf}$ ); odds are 1 to x for the probability of a value to be missing in group 1 against the probability of a value to be missing in group 2 (see details).
cutoff_fun	Function that calculates the cutoff values in the cols_ctrl.
prop	Numeric of length one; (minimum) proportion of rows in group 1 (only used for unordered factors).
use_lpSolve	Logical; should lpSolve be used for the determination of groups, if cols_ctrl[i] is an unordered factor.
ordered_as_unordered	Logical; should ordered factors be treated as unordered factors.

<code>n_mis_stochastic</code>	Logical, should the number of missing values be stochastic? If <code>n_mis_stochastic = TRUE</code> , the number of missing values for a column with missing values <code>cols_mis[i]</code> is a random variable with expected value <code>nrow(ds) * p[i]</code> . If <code>n_mis_stochastic = FALSE</code> , the number of missing values will be deterministic. Normally, the number of missing values for a column with missing values <code>cols_mis[i]</code> is <code>round(nrow(ds) * p[i])</code> . Possible deviations from this value, if any exists, are documented in Details.
<code>x_stochastic</code>	Logical; should the odds be stochastic or deterministic.
<code>add_realized_x</code>	Logical; if TRUE the realized odds for <code>cols_mis</code> will be returned (as attribute).
<code>...</code>	Further arguments passed to <code>cutoff_fun</code> .
<code>miss_cols</code>	Deprecated, use <code>cols_mis</code> instead.
<code>stochastic</code>	Deprecated, use <code>n_mis_stochastic</code> instead.

## Details

The functions `delete_MNAR_1_to_x` and `delete_MAR_1_to_x` are sisters. The only difference between these two functions is the column that controls the generation of missing values. In `delete_MAR_1_to_x` a separate column `cols_ctrl[i]` controls the generation of missing values in `cols_mis[i]`. In contrast, in `delete_MNAR_1_to_x` the generation of missing values in `cols_mis[i]` is controlled by `cols_mis[i]` itself. All other aspects are identical for both functions. Therefore, further details can be found in `delete_MAR_1_to_x`.

## Value

An object of the same class as `ds` with missing values.

## References

Santos, M. S., Pereira, R. C., Costa, A. F., Soares, J. P., Santos, J., & Abreu, P. H. (2019). Generating Synthetic Missing Data: A Review by Missing Mechanism. *IEEE Access*, 7, 11651-11667

## See Also

[delete\\_MAR\\_1\\_to\\_x](#)

Other functions to create MNAR: [delete\\_MNAR\\_censoring\(\)](#), [delete\\_MNAR\\_one\\_group\(\)](#), [delete\\_MNAR\\_rank\(\)](#)

## Examples

```
ds <- data.frame(X = 1:20, Y = 101:120)
delete_MNAR_1_to_x(ds, 0.2, "X", x = 3)
```

---

delete\_MNAR\_censoring *Create MNAR values using a censoring mechanism*

---

### Description

Create missing not at random (MNAR) values using a censoring mechanism in a data frame or a matrix

### Usage

```
delete_MNAR_censoring(
  ds,
  p,
  cols_mis,
  n_mis_stochastic = FALSE,
  where = "lower",
  sorting = TRUE,
  miss_cols
)
```

### Arguments

ds	A data frame or matrix in which missing values will be created.
p	A numeric vector with length one or equal to length cols_mis; the probability that a value is missing.
cols_mis	A vector of column names or indices of columns in which missing values will be created.
n_mis_stochastic	Logical, should the number of missing values be stochastic? If n_mis_stochastic = TRUE, the number of missing values for a column with missing values cols_mis[i] is a random variable with expected value nrow(ds) * p[i]. If n_mis_stochastic = FALSE, the number of missing values will be deterministic. Normally, the number of missing values for a column with missing values cols_mis[i] is round(nrow(ds) * p[i]). Possible deviations from this value, if any exists, are documented in Details.
where	Controls where missing values are created; one of "lower", "upper" or "both" (see details).
sorting	Logical; should sorting be used or a quantile as a threshold.
miss_cols	Deprecated, use cols_mis instead.

### Details

The functions `delete_MNAR_censoring` and `delete_MAR_censoring` are sisters. The only difference between these two functions is the column that controls the generation of missing values. In `delete_MAR_censoring` a separate column `cols_ctrl[i]` controls the generation of missing values in `cols_mis[i]`. In contrast, in `delete_MNAR_censoring` the generation of missing values in

cols\_mis[i] is controlled by cols\_mis[i] itself. All other aspects are identical for both functions. Therefore, further details can be found in [delete\\_MAR\\_censoring](#).

### Value

An object of the same class as ds with missing values.

### References

Santos, M. S., Pereira, R. C., Costa, A. F., Soares, J. P., Santos, J., & Abreu, P. H. (2019). Generating Synthetic Missing Data: A Review by Missing Mechanism. *IEEE Access*, 7, 11651-11667

### See Also

[delete\\_MAR\\_censoring](#)

Other functions to create MNAR: [delete\\_MNAR\\_1\\_to\\_x\(\)](#), [delete\\_MNAR\\_one\\_group\(\)](#), [delete\\_MNAR\\_rank\(\)](#)

### Examples

```
ds <- data.frame(X = 1:20, Y = 101:120)
delete_MNAR_censoring(ds, 0.2, "X")
```

---

delete\_MNAR\_one\_group *Create MNAR values by deleting values in one of two groups*

---

### Description

Create missing not at random (MNAR) values by deleting values in one of two groups in a data frame or a matrix

### Usage

```
delete_MNAR_one_group(  
  ds,  
  p,  
  cols_mis,  
  cutoff_fun = median,  
  prop = 0.5,  
  use_lpSolve = TRUE,  
  ordered_as_unordered = FALSE,  
  n_mis_stochastic = FALSE,  
  ...,  
  miss_cols,  
  stochastic  
)
```

**Arguments**

ds	A data frame or matrix in which missing values will be created.
p	A numeric vector with length one or equal to length cols_mis; the probability that a value is missing.
cols_mis	A vector of column names or indices of columns in which missing values will be created.
cutoff_fun	Function that calculates the cutoff values in the cols_ctrl.
prop	Numeric of length one; (minimum) proportion of rows in group 1 (only used for unordered factors).
use_lpSolve	Logical; should lpSolve be used for the determination of groups, if cols_ctrl[i] is an unordered factor.
ordered_as_unordered	Logical; should ordered factors be treated as unordered factors.
n_mis_stochastic	Logical, should the number of missing values be stochastic? If n_mis_stochastic = TRUE, the number of missing values for a column with missing values cols_mis[i] is a random variable with expected value nrow(ds) * p[i]. If n_mis_stochastic = FALSE, the number of missing values will be deterministic. Normally, the number of missing values for a column with missing values cols_mis[i] is round(nrow(ds) * p[i]). Possible deviations from this value, if any exists, are documented in Details.
...	Further arguments passed to cutoff_fun.
miss_cols	Deprecated, use cols_mis instead.
stochastic	Deprecated, use n_mis_stochastic instead.

**Details**

The functions `delete_MNAR_one_group` and `delete_MAR_one_group` are sisters. The only difference between these two functions is the column that controls the generation of missing values. In `delete_MAR_one_group` a separate column `cols_ctrl[i]` controls the generation of missing values in `cols_mis[i]`. In contrast, in `delete_MNAR_one_group` the generation of missing values in `cols_mis[i]` is controlled by `cols_mis[i]` itself. All other aspects are identical for both functions. Therefore, further details can be found in `delete_MAR_one_group`.

**Value**

An object of the same class as ds with missing values.

**References**

Santos, M. S., Pereira, R. C., Costa, A. F., Soares, J. P., Santos, J., & Abreu, P. H. (2019). Generating Synthetic Missing Data: A Review by Missing Mechanism. *IEEE Access*, 7, 11651-11667

**See Also**

`delete_MAR_one_group`

Other functions to create MNAR: `delete_MNAR_1_to_x()`, `delete_MNAR_censoring()`, `delete_MNAR_rank()`

**Examples**

```
ds <- data.frame(X = 1:20, Y = 101:120)
delete_MNAR_one_group(ds, 0.2, "X")
```

---

delete_MNAR_rank	<i>Create MNAR values using a ranking mechanism</i>
------------------	---

---

**Description**

Create missing not at random (MNAR) values using a ranking mechanism in a data frame or a matrix

**Usage**

```
delete_MNAR_rank(
  ds,
  p,
  cols_mis,
  n_mis_stochastic = FALSE,
  ties.method = "average",
  miss_cols
)
```

**Arguments**

<code>ds</code>	A data frame or matrix in which missing values will be created.
<code>p</code>	A numeric vector with length one or equal to length <code>cols_mis</code> ; the probability that a value is missing.
<code>cols_mis</code>	A vector of column names or indices of columns in which missing values will be created.
<code>n_mis_stochastic</code>	Logical, should the number of missing values be stochastic? If <code>n_mis_stochastic = TRUE</code> , the number of missing values for a column with missing values <code>cols_mis[i]</code> is a random variable with expected value $nrow(ds) * p[i]$ . If <code>n_mis_stochastic = FALSE</code> , the number of missing values will be deterministic. Normally, the number of missing values for a column with missing values <code>cols_mis[i]</code> is $round(nrow(ds) * p[i])$ . Possible deviations from this value, if any exists, are documented in Details.
<code>ties.method</code>	How ties are handled. Passed to <a href="#">rank</a> .
<code>miss_cols</code>	Deprecated, use <code>cols_mis</code> instead.

## Details

The functions `delete_MNAR_rank` and `delete_MAR_rank` are sisters. The only difference between these two functions is the column that controls the generation of missing values. In `delete_MAR_rank` a separate column `cols_ctrl[i]` controls the generation of missing values in `cols_mis[i]`. In contrast, in `delete_MNAR_rank` the generation of missing values in `cols_mis[i]` is controlled by `cols_mis[i]` itself. All other aspects are identical for both functions. Therefore, further details can be found in `delete_MAR_rank`.

## Value

An object of the same class as `ds` with missing values.

## References

Santos, M. S., Pereira, R. C., Costa, A. F., Soares, J. P., Santos, J., & Abreu, P. H. (2019). Generating Synthetic Missing Data: A Review by Missing Mechanism. *IEEE Access*, 7, 11651-11667

## See Also

`delete_MAR_rank`

Other functions to create MNAR: `delete_MNAR_1_to_x()`, `delete_MNAR_censoring()`, `delete_MNAR_one_group()`

## Examples

```
ds <- data.frame(X = 1:20, Y = 101:120)
delete_MNAR_rank(ds, 0.2, "X")
```

---

evaluate\_imputation\_parameters

*Evaluate estimated parameters after imputation*

---

## Description

Compares estimated parameters after imputation to true parameters or estimates based on the original dataset

## Usage

```
evaluate_imputation_parameters(
  ds_imp,
  ds_orig = NULL,
  pars_true = NULL,
  parameter = "mean",
  criterion = "RMSE",
  cols_which = seq_len(ncol(ds_imp)),
  tolerance = sqrt(.Machine$double.eps),
  ...,
```

```

    imp_ds,
    true_pars,
    which_cols
)

```

### Arguments

<code>ds_imp</code>	A data frame or matrix with imputed values.
<code>ds_orig</code>	A data frame or matrix with original (true) values.
<code>pars_true</code>	True parameters, normally a vector or a matrix.
<code>parameter</code>	A string specifying the estimated parameters for comparison.
<code>criterion</code>	A string specifying the used criterion for comparing the imputed and original values.
<code>cols_which</code>	Indices or names of columns used for evaluation.
<code>tolerance</code>	Numeric, only used for <code>criterion = "precision"</code> : numeric differences smaller than tolerance are treated as zero/equal.
<code>...</code>	Further arguments passed to the function for parameter estimation.
<code>imp_ds</code>	Deprecated, renamed to <code>ds_imp</code> .
<code>true_pars</code>	Deprecated, renamed to <code>pars_true</code> .
<code>which_cols</code>	Deprecated, renamed to <code>cols_which</code> .

### Details

Either `ds_orig` or `pars_true` must be supplied and the other one must be NULL (default: both are NULL, just supply one, see examples). The following parameters are implemented: "mean", "median", "var", "sd", "quantile", "cov", "cov\_only", "cor", "cor\_only". Some details follow:

- "var", "cov" and "cov\_only": For "var" only the variances of the columns (the diagonal elements of the covariance matrix) are compared. For "cov" the whole covariance matrix is compared. For "cov\_only" only the upper triangle (excluding the diagonal) of the covariance matrix is compared.
- "cor", "cor\_only": For "cor" the whole correlation matrix is compared. For "cor\_only" only the upper triangle (excluding the diagonal) of the correlation matrix is compared.
- "quantile": the quantiles can be set via the additional argument `probs` (see examples). Otherwise, the default quantiles from [quantile](#) will be used.

The argument `cols_which` allows the selection of columns for comparison (see examples). If `pars_true` is used, it is assumed that only relevant parameters are supplied (see examples).

Possible choices for the argument `criterion` are documented in [evaluate\\_imputed\\_values](#)

### Value

A numeric vector of length one.



## References

Cetin-Berber, D. D., Sari, H. I., & Huggins-Manley, A. C. (2019). Imputation Methods to Deal With Missing Responses in Computerized Adaptive Multistage Testing. *Educational and psychological measurement*, 79(3), 495-511.

## See Also

Other evaluation functions: [evaluate\\_imputed\\_values\(\)](#), [evaluate\\_parameters\(\)](#)

## Examples

```
# only ds_orig known
ds_orig <- data.frame(X = 1:10, Y = 101:101)
ds_imp <- impute_mean(delete_MCAR(ds_orig, 0.4))
evaluate_imputation_parameters(ds_imp, ds_orig = ds_orig)

# true parameters known
ds_orig <- data.frame(X = rnorm(100), Y = rnorm(100, mean = 10))
ds_imp <- impute_mean(delete_MCAR(ds_orig, 0.3))
evaluate_imputation_parameters(ds_imp, pars_true = c(0, 10), parameter = "mean")
evaluate_imputation_parameters(ds_imp, pars_true = c(1, 1), parameter = "var")

# set quantiles
evaluate_imputation_parameters(ds_imp,
  pars_true = c(qnorm(0.3), qnorm(0.3, mean = 10)),
  parameter = "quantile", probs = 0.3
)

# compare only column Y
evaluate_imputation_parameters(ds_imp,
  pars_true = c(Y = 10), parameter = "mean",
  cols_which = "Y"
)
```

---

evaluate\_imputed\_values

*Evaluate imputed values*

---

## Description

Compare imputed to true values

## Usage

```
evaluate_imputed_values(
  ds_imp,
  ds_orig,
  criterion = "RMSE",
  M = NULL,
```

```

cols_which = seq_len(ncol(ds_imp)),
tolerance = sqrt(.Machine$double.eps),
imp_ds,
orig_ds,
which_cols
)

```

### Arguments

<code>ds_imp</code>	A data frame or matrix with imputed values.
<code>ds_orig</code>	A data frame or matrix with original (true) values.
<code>criterion</code>	A string specifying the used criterion for comparing the imputed and original values.
<code>M</code>	NULL (the default) or a missing data indicator matrix. The missing data indicator matrix is normally created via <code>is.na(ds_mis)</code> , where <code>ds_mis</code> is the dataset after deleting values from <code>ds_orig</code> .
<code>cols_which</code>	Indices or names of columns used for evaluation.
<code>tolerance</code>	Numeric, only used for <code>criterion = "precision"</code> : numeric differences smaller than <code>tolerance</code> are treated as zero/equal.
<code>imp_ds</code>	Deprecated, renamed to <code>ds_imp</code> .
<code>orig_ds</code>	Deprecated, renamed to <code>ds_orig</code> .
<code>which_cols</code>	Deprecated, renamed to <code>cols_which</code> .

### Details

The following criteria are implemented to compare the imputed values to the true values:

- "RMSE" (the default): The Root Mean Squared Error between the imputed and true values
- "bias": The mean difference between the imputed and the true values
- "cor": The correlation between the imputed and true values
- "MAE": The Mean Absolute Error between the imputed and true values
- "MSE": The Mean Squared Error between the imputed and true values
- "NRMSE\_col\_mean": For every column the RMSE divided by the mean of the true values is calculated. Then these columnwise values are squared and averaged. Finally, the square root of this average is returned.
- "NRMSE\_col\_mean\_sq": For every column the RMSE divided by the square root of the mean of the squared true values is calculated. Then these columnwise values are squared and averaged. Finally, the square root of this average is returned.
- "NRMSE\_col\_sd": For every column the RMSE divided by the standard deviation of all true values is calculated. Then these columnwise values are squared and averaged. Finally, the square root of this average is returned.
- "NRMSE\_tot\_mean": RMSE divided by the mean of all true values
- "NRMSE\_tot\_mean\_sq": RMSE divided by the square root of the mean of all squared true values

- "NRMSE\_tot\_sd": RMSE divided by the standard deviation of all true values
- "nr\_equal": number of imputed values that are equal to the true values
- "nr\_NA": number of values in ds\_imp that are NA (not imputed)
- "precision": proportion of imputed values that are equal to the true values

Additionally there are relative versions of bias and MAE implemented. In the relative versions, the differences are divided by the absolute values of the true values. These relative versions can be selected via "bias\_rel" and "MAE\_rel". The "NRMSE\_tot\_" and "NRMSE\_col\_" are equal, if the columnwise normalization values are equal to the total normalization value (see examples).

The argument cols\_which allows the selection of columns for comparison (see examples).

If M = NULL (the default), then all values of ds\_imp and ds\_orig will be used for the calculation of the evaluation criterion. If a missing data indicator matrix is given via M, only the truly imputed values (values that are marked as missing via M) will be used for the calculation. If you want to provide M, M must be a logical matrix of the same dimensions as ds\_orig and missing values must be coded as TRUE. This is the standard behavior, if you use `is.na` on a dataset with missing values to generate M (see examples). It is possible to combine M and cols\_which.

### Value

A numeric vector of length one.

### References

Kim, H., Golub, G. H., & Park, H. (2005). Missing value estimation for DNA microarray gene expression data: local least squares imputation. *Bioinformatics*, 21(2), 187-198.

### See Also

Other evaluation functions: `evaluate_imputation_parameters()`, `evaluate_parameters()`

### Examples

```
ds_orig <- data.frame(X = 1:10, Y = 101:110)
ds_mis <- delete_MCAR(ds_orig, 0.3)
ds_imp <- impute_mean(ds_mis)
# compare all values from ds_orig and ds_imp
evaluate_imputed_values(ds_imp, ds_orig)
# compare only the imputed values
M <- is.na(ds_mis)
evaluate_imputed_values(ds_imp, ds_orig, M = M)
# compare only the imputed values in column X
evaluate_imputed_values(ds_imp, ds_orig, M = M, cols_which = "X")

# NRMSE_tot_mean and NRMSE_col_mean are equal, if columnwise means are equal
ds_orig <- data.frame(X = 1:10, Y = 10:1)
ds_mis <- delete_MCAR(ds_orig, 0.3)
ds_imp <- impute_mean(ds_mis)
evaluate_imputed_values(ds_imp, ds_orig, "NRMSE_tot_mean")
evaluate_imputed_values(ds_imp, ds_orig, "NRMSE_col_mean")
```

---

evaluate\_parameters    *Evaluate estimated parameters*

---

### Description

Compare estimated parameters to true parameters

### Usage

```
evaluate_parameters(  
  pars_est,  
  pars_true,  
  criterion = "RMSE",  
  tolerance = sqrt(.Machine$double.eps),  
  est_pars,  
  true_pars  
)
```

### Arguments

pars_est	A vector or matrix of estimated parameters.
pars_true	True parameters, normally a vector or a matrix.
criterion	A string specifying the used criterion for comparing the imputed and original values.
tolerance	Numeric, only used for criterion = "precision": numeric differences smaller than tolerance are treated as zero/equal.
est_pars	Deprecated, renamed to pars_est.
true_pars	Deprecated, renamed to pars_true.

### Details

The same criterions are implemented for `evaluate_parameters` and `evaluate_imputed_values`. The possible choices are documented in `evaluate_imputed_values`.

### Value

A numeric vector of length one.

### References

Cetin-Berber, D. D., Sari, H. I., & Huggins-Manley, A. C. (2019). Imputation Methods to Deal With Missing Responses in Computerized Adaptive Multistage Testing. *Educational and psychological measurement*, 79(3), 495-511.

### See Also

Other evaluation functions: `evaluate_imputation_parameters()`, `evaluate_imputed_values()`

**Examples**

```
evaluate_parameters(1:4, 2:5, "RMSE")
```

---

impute_EM	<i>EM imputation</i>
-----------	----------------------

---

**Description**

Impute missing values in a data frame or a matrix using parameters estimated via EM

**Usage**

```
impute_EM(
  ds,
  stochastic = TRUE,
  maxits = 1000,
  criterion = 1e-04,
  verbose = FALSE
)
```

**Arguments**

ds	A data frame or matrix with missing values.
stochastic	Logical; see details.
maxits	Maximum number of iterations for the EM, passed to <code>norm::em.norm()</code> .
criterion	If maximum relative difference in parameter estimates is below this threshold, the EM algorithm stops. Argument is directly passed to <code>norm::em.norm()</code> .
verbose	Should messages be given for special cases (see details)?

**Details**

At first parameters are estimated via `norm::em.norm()`. Then these parameters are used in regression like models to impute the missing values. If `stochastic = FALSE`, the expected values (given the observed values and the estimated parameters via EM) are imputed for the missing values of an object. If `stochastic = TRUE`, residuals from a multivariate normal distribution are added to these expected values.

If all values in a row are NA or the required part of the covariance matrix for the calculation of the expected values is not invertible, parts of the estimated mean vector will be imputed. If `stochastic = TRUE`, residuals will be added to these values. If `verbose = TRUE`, a message will be given for these rows.

**Value**

An object of the same class as `ds` with imputed missing values.

The number of EM iterations are added as an attribute (`iterations`).

**See Also**

- `norm::em.norm()`, which estimates the parameters
- `impute_expected_values()`, which calculates the imputation values

**Examples**

```
ds_orig <- mvtnorm::rmvnorm(100, rep(0, 7))
ds_mis <- delete_MCAR(ds_orig, p = 0.2)
ds_imp <- impute_EM(ds_mis, stochastic = FALSE)
```

---

impute\_expected\_values

*Impute expected values*

---

**Description**

Impute the missing values with expected values given the observed values and estimated parameters assuming a multivariate normal distribution

**Usage**

```
impute_expected_values(
  ds,
  mu,
  S,
  stochastic = FALSE,
  M = is.na(ds),
  verbose = FALSE
)
```

**Arguments**

ds	A data frame or matrix with missing values.
mu	Vector of means for the variables.
S	Covariance matrix of the variables.
stochastic	Logical, should residuals be added to the expected values.
M	Missing data indicator matrix.
verbose	Should messages be given for special cases (see details)?

## Details

Normally, this function is called by other imputation function and should not be called directly. The function imputes the missing values assuming a multivariate normal distribution. This is equivalent to imputing the least squares estimate of the missing values in some kind of way.

If no values is observed in a row or a relevant submatrix of the covariance matrix (S\_22) is not invertible, the missing values are imputed with (parts of) mu (plus a residuum, if stochastic = TRUE). If verbose = TRUE, these cases will be listed in a message. Otherwise, they will be imputed silently.

## Value

An object of the same class as ds with imputed missing values.

## Examples

```
ds_orig <- rmvnorm::rmvnorm(100, rep(0, 2))
ds_mis <- delete_MCAR(ds_orig, p = 0.2)
# impute using true parameters:
ds_imp <- impute_expected_values(ds_mis, mu = c(0, 0), diag(1, 2))
```

---

impute\_hot\_deck\_in\_classes

*Hot deck imputation in imputation classes*

---

## Description

Impute missing values in a data frame or a matrix using a hot deck within imputation classes

## Usage

```
impute_hot_deck_in_classes(
  ds,
  cols_class,
  type = "cols_seq",
  breaks = Inf,
  use_quantiles = FALSE,
  min_objs_in_class = 1,
  min_obs_comp = 0,
  min_obs_per_col = 1,
  donor_limit = Inf,
  add_imputation_classes = FALSE
)
```

**Arguments**

<code>ds</code>	A data frame or matrix with missing values.
<code>cols_class</code>	Columns that are used for constructing the imputation classes.
<code>type</code>	The type of hot deck (for details, see <a href="#">impute_sRHD()</a> ).
<code>breaks</code>	Number of intervals / levels a column is broken into (see <a href="#">cut()</a> , which is used internally for cutting numeric columns). If <code>breaks = Inf</code> (the default), every unique value of a column can be in a separate class (if no other restrictions apply).
<code>use_quantiles</code>	Should quantiles be used for cutting numeric vectors? Normally, <a href="#">cut()</a> divides the range of an vector into equal spaced intervals. If <code>use_quantiles = TRUE</code> , the classes will be of roughly equal content.
<code>min_objs_in_class</code>	Minimum number of objects (rows) in an imputation class.
<code>min_obs_comp</code>	Minimum number of completely observed objects (rows) in an imputation class.
<code>min_obs_per_col</code>	Minimum number of observed values in every column of an imputation class.
<code>donor_limit</code>	Minimum odds between incomplete and complete values in a column, if <code>type = cols_seq</code> . If <code>type = sim_comp</code> , minimum odds between incomplete and complete rows. For <code>type = sim_part</code> the donor limit option is not implemented and <code>donor_limit</code> should be <code>Inf</code> .
<code>add_imputation_classes</code>	Should imputation classes be added as attributes to the imputed dataset?

**Details**

This function is a combination of [impute\\_in\\_classes\(\)](#) and [impute\\_sRHD\(\)](#). It applies [impute\\_sRHD\(\)](#) inside of imputation classes (adjustment cells), which are constructed via [impute\\_in\\_classes\(\)](#). More details can be found in these two functions.

**Value**

An object of the same class as `ds` with imputed missing values.

**References**

Andridge, R.R. and Little, R.J.A. (2010), A Review of Hot Deck Imputation for Survey Non-response. *International Statistical Review*, 78: 40-64. doi:10.1111/j.1751-5823.2010.00103.x

**See Also**

[impute\\_in\\_classes\(\)](#), which is used for the construction of the imputation classes.

[impute\\_sRHD\(\)](#), which is used for the imputation.



**Examples**

```

impute_hot_deck_in_classes(data.frame(
  X = c(rep("A", 10), rep("B", 10)),
  Y = c(rep(NA, 5), 106:120)
),
"X",
donor_limit = 1
)

```

---

impute\_in\_classes      *Impute in classes*

---

**Description**

Apply an imputation function inside imputation classes

**Usage**

```

impute_in_classes(
  ds,
  cols_class,
  FUN,
  breaks = Inf,
  use_quantiles = FALSE,
  min_objs_in_class = 1,
  min_obs_comp = 0,
  min_obs_per_col = 1,
  donor_limit = Inf,
  dl_type = "cols_seq",
  add_imputation_classes = FALSE,
  ...
)

```

**Arguments**

ds	A data frame or matrix with missing values.
cols_class	Columns that are used for constructing the imputation classes.
FUN	An imputation function that is applied to impute the missing values.
breaks	Number of intervals / levels a column is broken into (see <code>cut()</code> , which is used internally for cutting numeric columns). If <code>breaks = Inf</code> (the default), every unique value of a column can be in a separate class (if no other restrictions apply).
use_quantiles	Should quantiles be used for cutting numeric vectors? Normally, <code>cut()</code> divides the range of an vector into equal spaced intervals. If <code>use_quantiles = TRUE</code> , the classes will be of roughly equal content.

<code>min_objs_in_class</code>	Minimum number of objects (rows) in an imputation class.
<code>min_obs_comp</code>	Minimum number of completely observed objects (rows) in an imputation class.
<code>min_obs_per_col</code>	Minimum number of observed values in every column of an imputation class.
<code>donor_limit</code>	Minimum odds between incomplete and complete values in a column, if <code>dl_type = cols_seq</code> . If <code>dl_type = sim_comp</code> , minimum odds between incomplete and complete rows.
<code>dl_type</code>	See <code>donor_limit</code> .
<code>add_imputation_classes</code>	Should imputation classes be added as attributes to the imputed dataset?
<code>...</code>	Arguments passed to FUN.

### Details

Imputation classes (sometimes also called adjustment cells) are build using cross-validation of all `cols_class`. The classes are collapsed, if they do not satisfy all of the criteria defined by `min_objs_in_class`, `min_obs_comp`, `min_obs_per_col` and `donor_limit`. Collapsing starts from the last value of `cols_class`. Internally, a mixture of collapsing and early stopping is used for the construction of the classes.

### Value

An object of the same class as `ds` with imputed missing values.

### References

Andridge, R.R. and Little, R.J.A. (2010), A Review of Hot Deck Imputation for Survey Non-response. *International Statistical Review*, 78: 40-64. doi:10.1111/j.1751-5823.2010.00103.x

### Examples

```
# Mean imputation in classes
impute_in_classes(data.frame(X = 1:5, Y = c(NA, 12:15)), "X",
  impute_mean,
  min_obs_per_col = 2
)
```

---

`impute_LS_adaptive`      *LSimpute\_adaptive*

---

### Description

Perform `LSimpute_adaptive` as described by Bo et al. (2004)

**Usage**

```

impute_LS_adaptive(
  ds,
  k = 10,
  eps = 1e-06,
  min_common_obs = 5,
  r_max_min = 100,
  p_mis_sim = 0.05,
  warn_r_max = FALSE,
  verbose_gene = FALSE,
  verbose_array = FALSE,
  verbose_gene_p = FALSE,
  verbose_array_p = FALSE
)

```

**Arguments**

ds	A data frame or matrix with missing values.
k	Directly passed to <code>impute_LS_gene()</code> .
eps	Directly passed to <code>impute_LS_gene()</code> .
min_common_obs	Directly passed to <code>impute_LS_gene()</code> .
r_max_min	Minimum number of nearest genes used for imputation. The default value (100) corresponds to the choice of Bo et al. (2004).
p_mis_sim	Percentage of observed values that are set NA to estimate the mixing coefficient $p$ . The default value (0.05) corresponds to the choice of Bo et al. (2004).
warn_r_max	Should a warning be given, if r_max_min is set too high?
verbose_gene	Should <code>impute_LS_gene()</code> be verbose?
verbose_array	Should <code>impute_LS_array()</code> be verbose?
verbose_gene_p	Should <code>impute_LS_gene()</code> be verbose while estimating $p$ ?
verbose_array_p	Should <code>impute_LS_array()</code> be verbose while estimating $p$ ?

**Details**

This function performs `LSimpute_adaptive` as described by Bo et al. (2004). The function assumes that the genes are the rows of `ds`.

`LSimpute_adaptive` combines imputation values from `impute_LS_gene()` and `impute_LS_array()` using a local (adaptive) approach for the mixing coefficient  $p$ .

If the dataset is too small or has too many missing values, there are some fallback systems implemented. First, if `ncol(ds) <= min_common_obs` (normally, this should not be the case!), values are imputed through `impute_LS_array()`. Second, `r_max_min` is automatically adjusted, if it is too high. In this case, a warning will be given, if `warn_r_max = TRUE`. Third, if there are not enough observed values in a row (less than `min_common_obs`), the calculation of the mixing coefficient is not possible and missing values of these rows are imputed with the values from `impute_LS_array()`.

The amount of feedback given from `impute_LS_gene()` and `impute_LS_array()` is controlled via `verbose_gene`, `verbose_array`, `verbose_gene_p` and `verbose_array_p`. The last two control the amount of feedback while estimating  $p$  and the first two the amount of feedback during the estimation of the values that are mixed with  $p$ . Internally, the imputed dataset from `impute_LS_gene()` is passed on to `impute_LS_array()`. Therefore, all messages from `impute_LS_gene()` are truly from `impute_LS_gene()` and not a part of `impute_LS_array()`, which never calls `impute_LS_gene()` in this case. Furthermore, all messages from `impute_expected_values()` belong to `impute_LS_array()`.

## Value

An object of the same class as `ds` with imputed missing values.

## References

Bo, T. H., Dysvik, B., & Jonassen, I. (2004). LSImpute: accurate estimation of missing values in microarray data with least squares methods. *Nucleic acids research*, 32(3), e34

## See Also

Other LSImpute functions: `impute_LS_array()`, `impute_LS_combined()`, `impute_LS_gene()`

## Examples

```
set.seed(123)
ds_mis <- delete_MCAR(mvtnorm::rmvnorm(100, rep(0, 10)), 0.1)
ds_imp <- impute_LS_adaptive(ds_mis)
```

---

<code>impute_LS_array</code>	<i>LSimpute_array</i>
------------------------------	-----------------------

---

## Description

Perform `LSimpute_array` as described by Bo et al. (2004)

## Usage

```
impute_LS_array(
  ds,
  k = 10,
  eps = 1e-06,
  min_common_obs = 5,
  ds_impute_LS_gene = NULL,
  verbose_gene = FALSE,
  verbose_expected_values = FALSE
)
```

**Arguments**

ds	A data frame or matrix with missing values.
k	Directly passed to <code>impute_LS_gene()</code> .
eps	Directly passed to <code>impute_LS_gene()</code> .
min_common_obs	Directly passed to <code>impute_LS_gene()</code> .
ds_impute_LS_gene	Result of imputing ds with <code>ds_impute_LS_gene()</code> , if this already exists (see details).
verbose_gene	Should <code>impute_LS_gene()</code> be verbose?
verbose_expected_values	Should <code>impute_expected_values()</code> be verbose?

**Details**

This function performs `LSimpute_array` as described by Bo et al. (2004). The function assumes that the genes are the rows of ds.

The mean vector and covariance matrix for the imputation in `LSimpute_array` is based on a imputed dataset from `LSimpute_gene`. This dataset can be supplied directly via `ds_impute_LS_gene` or will automatically be created with `impute_LS_gene()` (if `ds_impute_LS_gene` is NULL). The imputation values are the expected values given the estimated parameters and the observed values. They are calculated via `impute_expected_values()`. The amount of feedback from these two functions is controlled via `verbose_gene` and `verbose_expected_values`. The values of these two arguments are passed on to the argument `verbose` from `impute_LS_gene()` and `impute_expected_values()`.

**Value**

An object of the same class as ds with imputed missing values.

**References**

Bo, T. H., Dysvik, B., & Jonassen, I. (2004). `LSimpute`: accurate estimation of missing values in microarray data with least squares methods. *Nucleic acids research*, 32(3), e34

**See Also**

Other `LSimpute` functions: `impute_LS_adaptive()`, `impute_LS_combined()`, `impute_LS_gene()`

**Examples**

```
set.seed(123)
ds_mis <- delete_MCAR(mvtnorm::rmvnorm(100, rep(0, 10)), 0.1)
ds_imp <- impute_LS_array(ds_mis)
```

---

impute\_LS\_combined      *LSimpute\_combined*

---

## Description

Perform `LSimpute_combined` as described by Bo et al. (2004)

## Usage

```
impute_LS_combined(
  ds,
  k = 10,
  eps = 1e-06,
  min_common_obs = 5,
  p_mis_sim = 0.05,
  verbose_gene = FALSE,
  verbose_array = FALSE,
  verbose_gene_p = FALSE,
  verbose_array_p = FALSE
)
```

## Arguments

<code>ds</code>	A data frame or matrix with missing values.
<code>k</code>	Directly passed to <code>impute_LS_gene()</code> .
<code>eps</code>	Directly passed to <code>impute_LS_gene()</code> .
<code>min_common_obs</code>	Directly passed to <code>impute_LS_gene()</code> .
<code>p_mis_sim</code>	Percentage of observed values that are set NA to estimate the mixing coefficient $p$ . The default value (0.05) corresponds to the choice of Bo et al. (2004).
<code>verbose_gene</code>	Should <code>impute_LS_gene()</code> be verbose?
<code>verbose_array</code>	Should <code>impute_LS_array()</code> be verbose?
<code>verbose_gene_p</code>	Should <code>impute_LS_gene()</code> be verbose while estimating $p$ ?
<code>verbose_array_p</code>	Should <code>impute_LS_array()</code> be verbose while estimating $p$ ?

## Details

This function performs `LSimpute_combined` as described by Bo et al. (2004). The function assumes that the genes are the rows of `ds`.

`LSimpute_combined` combines imputation values from `impute_LS_gene()` and `impute_LS_array()` using a global approach for the mixing coefficient  $p$ . The amount of feedback given from these underlying functions is controlled via `verbose_gene`, `verbose_array`, `verbose_gene_p`, `verbose_array_p`. The last two control the amount of feedback while estimating  $p$  and the first two the amount of feedback during the estimation of the values that are mixed with  $p$ . Internally, the imputed

dataset from `impute_LS_gene()` is passed on to `impute_LS_array()`. Therefore, all messages from `impute_LS_gene()` are truly from `impute_LS_gene()` and not a part of `impute_LS_array()`, which never calls `impute_LS_gene()` in this case. Furthermore, all messages from `impute_expected_values()` belong to `impute_LS_array()`.

## Value

An object of the same class as `ds` with imputed missing values.

## References

Bo, T. H., Dysvik, B., & Jonassen, I. (2004). LSimpute: accurate estimation of missing values in microarray data with least squares methods. *Nucleic acids research*, 32(3), e34

## See Also

Other LSimpute functions: `impute_LS_adaptive()`, `impute_LS_array()`, `impute_LS_gene()`

## Examples

```
set.seed(123)
ds_mis <- delete_MCAR(mvtnorm::rmvnorm(100, rep(0, 10)), 0.1)
ds_imp <- impute_LS_combined(ds_mis)
```

---

<code>impute_LS_gene</code>	<i>LSimpute_gene</i>
-----------------------------	----------------------

---

## Description

Perform `LSimpute_gene` as described by Bo et al. (2004)

## Usage

```
impute_LS_gene(  
  ds,  
  k = 10,  
  eps = 1e-06,  
  min_common_obs = 5,  
  return_r_max = FALSE,  
  verbose = FALSE  
)
```

## Arguments

<code>ds</code>	A data frame or matrix with missing values.
<code>k</code>	Number of most correlated genes used for the imputation of a gene.
<code>eps</code>	Used in the calculation of the weights (Bo et al. (2004) used $\text{eps} = 1\text{e-}6$ ).
<code>min_common_obs</code>	A row can only take part in the imputation of another row, if both rows share at least <code>min_common_obs</code> columns with no missing values.
<code>return_r_max</code>	Logical; normally, this should be FALSE. TRUE is used inside of <code>impute_LS_adaptive()</code> to speed up some computations.
<code>verbose</code>	Should messages be given for special cases (see details)?

## Details

This function performs `LSimpute_gene` as described by Bo et al. (2004). The function assumes that the genes are the rows of `ds`.

Bo et al. (2004) seem to have chosen `min_common_obs = 5`. However, they did not document this behavior. This value emerged from inspecting imputation results from the original jar-file, which is provided by Bo et al. (2004).

If there are less than `min_common_obs` observed values in a row and at least one observed value, the mean of the observed row values is imputed. If no value is observed in a row, the observed column means are imputed for the missing row values. This is the only known difference between this function and the original one from Bo et al. (2004). The original function would not impute such a row and return a dataset with missing values in this row. There is one more case that needs a special treatment: If no suitable row can be found to impute a row, the mean of the observed values is imputed, too. If `verbose = TRUE`, a message will be given for the encountered instances of the described special cases. If `verbose = FALSE`, the function will deal with these cases silently.

## Value

An object of the same class as `ds` with imputed missing values.

If `return_r_max = TRUE`, a list with the imputed dataset and `r_max`.

## References

Bo, T. H., Dysvik, B., & Jonassen, I. (2004). `LSimpute`: accurate estimation of missing values in microarray data with least squares methods. *Nucleic acids research*, 32(3), e34

## See Also

Other `LSimpute` functions: [impute\\_LS\\_adaptive\(\)](#), [impute\\_LS\\_array\(\)](#), [impute\\_LS\\_combined\(\)](#)

## Examples

```
set.seed(123)
ds_mis <- delete_MCAR(mvtnorm::rmvnorm(100, rep(0, 10)), 0.1)
ds_imp <- impute_LS_gene(ds_mis)
```



---

impute_mean	<i>Mean imputation</i>
-------------	------------------------

---

## Description

Impute an observed mean for the missing values

## Usage

```
impute_mean(ds, type = "columnwise", convert_tibble = TRUE)
```

## Arguments

ds	A data frame or matrix with missing values.
type	A string specifying the values used for imputation; one of: "columnwise", "rowwise", "total", "Two-Way" or "Winer" (see details).
convert_tibble	If ds is a tibble, should it be converted (see section A note for tibble users).

## Details

For every missing value the mean of some observed values is imputed. The observed values to be used are specified via type. For example, type = "columnwise" (the default) imputes the mean of the observed values in a column for all missing values in the column. This is normally meant, if someone speaks of "imputing the mean" or "mean imputation".

Other options for type are: "rowwise", "total", "Winer" and "Two-way". The option "rowwise" imputes all missing values in a row with the mean of the observed values in the same row. "total" will impute every missing value with the mean of all observed values in ds. "Winer" imputes the mean of the rowwise and columnwise mean. Beland et al. (2016) called this method "Winer" and they attributed the method to Winer (1971). "Two-way" imputes the sum of rowwise and columnwise mean minus the total mean. This method was suggested by D.B Rubin to Bernaards & Sijtsma, K. (2000).

## Value

An object of the same class as ds with imputed missing values.

## A note for tibble users

If you use tibbles and convert\_tibble is TRUE the tibble is first converted to a data frame, then imputed and converted back. If convert\_tibble is FALSE no conversion is done. However, depending on the tibble and the package version of tibble you use, imputation may not be possible and some errors will be thrown.

## References

- Beland, S., Pichette, F., & Jolani, S. (2016). Impact on Cronbach's  $\alpha$  of simple treatment methods for missing data. *The Quantitative Methods for Psychology*, 12(1), 57-73.
- Bernaards, C. A., & Sijtsma, K. (2000). Influence of imputation and EM methods on factor analysis when item nonresponse in questionnaire data is nonignorable. *Multivariate Behavioral Research*, 35(3), 321-364.
- Winer, B. J. (1971). *Statistical principles in experimental design (2ed ed.)* New York: McGraw-Hill

## See Also

[apply\\_imputation](#) the workhorse for this function.

Other location parameter imputation functions: [impute\\_median\(\)](#), [impute\\_mode\(\)](#)

## Examples

```
ds <- data.frame(X = 1:20, Y = 101:120)
ds_mis <- delete_MCAR(ds, 0.2)
ds_imp <- impute_mean(ds_mis)
# completely observed columns can be of any type:
ds_mis_char <- cbind(ds_mis, letters[1:20])
ds_imp_char <- impute_mean(ds_mis_char)
```

---

impute\_median

*Median imputation*

---

## Description

Impute an observed median value for every missing value

## Usage

```
impute_median(
  ds,
  type = "columnwise",
  ordered_low = FALSE,
  convert_tibble = TRUE
)
```

## Arguments

- |                |  |
|----------------|--|
| ds             | A data frame or matrix with missing values.  |
| type           | A string specifying the values used for imputation; one of: "columnwise", "row-wise", "total", "Two-Way" or "Winer" (see details). |
| ordered_low    | Logical; used for the calculation of the median from ordered factors (for details see: <a href="#">median.factor</a> ).            |
| convert_tibble | If ds is a tibble, should it be converted (see section A note for tibble users).   |

## Details

This function behaves exactly like [impute\\_mean](#). The only difference is that it imputes a median instead of a mean. All types from [impute\\_mean](#) are also implemented for [impute\\_median](#). They are documented in [impute\\_mean](#) and [apply\\_imputation](#). The function [median](#) is used for the calculation of the median values for imputation.

## Value

An object of the same class as `ds` with imputed missing values.

## A note for tibble users

If you use tibbles and `convert_tibble` is `TRUE` the tibble is first converted to a data frame, then imputed and converted back. If `convert_tibble` is `FALSE` no conversion is done. However, depending on the tibble and the package version of tibble you use, imputation may not be possible and some errors will be thrown.

## References

Beland, S., Pichette, F., & Jolani, S. (2016). Impact on Cronbach's  $\alpha$  of simple treatment methods for missing data. *The Quantitative Methods for Psychology*, 12(1), 57-73.

## See Also

[apply\\_imputation](#) the workhorse for this function.

[median](#), [median.factor](#)

Other location parameter imputation functions: [impute\\_mean\(\)](#), [impute\\_mode\(\)](#)

## Examples

```
ds <- data.frame(X = 1:20, Y = ordered(LETTERS[1:20]))
ds_mis <- delete_MCAR(ds, 0.2)
ds_imp <- impute_median(ds_mis)
# completely observed columns can be of any type:
ds_mis_char <- cbind(ds_mis, letters[1:20])
ds_imp_char <- impute_median(ds_mis_char)
```

---

impute\_mode

*Mode imputation*

---

## Description

Impute an observed mode value for every missing value

## Usage

```
impute_mode(ds, type = "columnwise", convert_tibble = TRUE)
```

**Arguments**

- `ds` A data frame or matrix with missing values.
- `type` A string specifying the values used for imputation; one of: "columnwise", "rowwise", "total", "Two-Way" or "Winer" (see details).
- `convert_tibble` If `ds` is a tibble, should it be converted (see section A note for tibble users).

**Details**

This function behaves exactly like [impute\\_mean](#). The only difference is that it imputes a mode instead of a mean. All types from [impute\\_mean](#) are also implemented for `impute_mode`. They are documented in [impute\\_mean](#) and [apply\\_imputation](#).

A mode value of a vector  $x$  is a most frequent value of  $x$ . If this value is not unique, the first occurring mode value in  $x$  will be used as imputation value.

**Value**

An object of the same class as `ds` with imputed missing values.

**References**

Beland, S., Pichette, F., & Jolani, S. (2016). Impact on Cronbach's  $\alpha$  of simple treatment methods for missing data. *The Quantitative Methods for Psychology*, 12(1), 57-73.

**See Also**

[apply\\_imputation](#) the workhorse for this function.

Other location parameter imputation functions: [impute\\_mean\(\)](#), [impute\\_median\(\)](#)

**Examples**

```
ds <- data.frame(X = c(1:12, rep(8, 8)), Y = 101:120)
ds_mis <- delete_MCAR(ds, 0.2)
ds_imp <- impute_mode(ds_mis)
```

---

impute\_sRHD

*Simple random hot deck imputation*

---

**Description**

Impute missing values in a data frame or a matrix using a simple random hot deck

**Usage**

```
impute_sRHD(ds, type = "cols_seq", donor_limit = Inf)
```

**Arguments**

<code>ds</code>	A data frame or matrix with missing values.
<code>type</code>	The type of hot deck; the default (" <code>cols_seq</code> ") is a random hot deck that imputes each column separately. Other choices are " <code>sim_comp</code> " and " <code>sim_part</code> ". Both impute all missing values in an object (row) simultaneously using a single donor object. The difference between the two types is the choice of objects that can act as donors. " <code>sim_comp</code> :" only completely observed objects can be donors. " <code>sim_part</code> ": all objects that have no missing values in the missing parts of a recipient can be donors.
<code>donor_limit</code>	Numeric of length one or " <code>min</code> "; how many times an object can be a donor. Default is <code>Inf</code> (no restriction).

**Details**

There are three types of simple random hot decks implemented. They can be selected via `type`:

- "`cols_seq`" (the default): Each variable (column) is handled separately. If an object (row) has a missing value in a variable (column), then one of the observed values in the same variable is chosen randomly and the missing value is replaced with this chosen value. This is done for all missing values.
- "`sim_comp`": All missing variables (columns) of an object are imputed together ("simultaneous"). For every object with missing values (such an object is called a recipient in hot deck terms), one complete object is chosen randomly and all missing values of the recipient are imputed with the values from the complete object. A complete object used for imputation is called a donor.
- "`sim_part`": All missing variables (columns) of an object are imputed together ("simultaneous"). For every object with missing values (recipient) one donor is chosen. The donor must have observed values in all the variables that are missing in the recipient. The donor is allowed to have unobserved values in the non-missing parts of the recipient. So, in contrast to "`sim_comp`", the donor can be partly incomplete.

The parameter `donor_limit` controls how often an object can be a donor. This parameter is only implemented for types "`cols_seq`" and "`sim_comp`". If `type = "sim_part"` and `donor_limit` is not `Inf`, then an error will be thrown. For "`sim_comp`" the default value (`Inf`) allows every object to be a donor for an infinite number of times (there is no restriction on the times an object can be a donor). If a numeric value less than `Inf` is chosen, then every object can be a donor at most `donor_limit` times. For example `donor_limit = 1` ensures that every object donates at most one time. If there are only few complete objects and `donor_limit` is set too low, then an imputation might not be possible with the chosen `donor_limit`. In this case, the `donor_limit` will be adjusted (see examples). Setting `donor_limit = "min"` chooses automatically the minimum value for `donor_limit` that allows imputation of all missing values. For `type = "cols_seq"` the donor limit is applied for every column separately.

**Value**

An object of the same class as `ds` with imputed missing values.

## References

Andridge, R. R., & Little, R. J. (2010). A review of hot deck imputation for survey non-response. *International statistical review*, 78(1), 40-64.

## Examples

```
ds <- data.frame(X = 1:20, Y = 101:120)
ds_mis <- delete_MCAR(ds, 0.2)
ds_imp <- impute_sRHD(ds_mis)

# Warning: donor limit to low
ds_mis_one_donor <- ds
ds_mis_one_donor[1:19, "X"] <- NA
impute_sRHD(ds_mis_one_donor, donor_limit = 3)
```

---

median.factor	<i>Median for ordered factors</i>
---------------	-----------------------------------

---

## Description

Compute the median of an ordered factor

## Usage

```
## S3 method for class 'factor'
median(x, na.rm = FALSE, ordered_low = FALSE, ...)
```

## Arguments

x	An ordered factor (for unordered factors an error will be thrown).
na.rm	Logical; should NA be removed before computation?
ordered_low	Logical; only used if the length of x is even and the two middle values are unequal (see details).
...	Not used in this function.

## Details

Currently, the median for an ordered factor is not implemented in base R. This function is a remedy for this. It allows the computation of “a median” for ordered factors (see below) and overwrites the error message for unordered factors from [median.default](#) (hence, the function name is `median.factor` and not `median.ordered`).

If the length of x is odd, then the median will be the middle value of the sorted list of elements from x. If the length of x is even and the two middle values of the sorted list of elements from x are equal, then the median is one of these (equal) middle values. The only problematic case is an even length x with unequal middle values. In this case, the median of a numeric vector is normally defined as the

mean of the two middle values. However, for ordered factors the mean is not defined. The argument `ordered_low` cures this problem. If `ordered_low = FALSE` (the default), then the larger of the two middle values is returned (this value is called ‘hi-median’ in `mad`). If `ordered_low = TRUE`, then the smaller of the two middle values is returned (this value is called ‘low-median’ in `mad`).

**Value**

a length-one factor

**Examples**

```
ord_factor_odd <- ordered(letters[1:5])
median(ord_factor_odd) # calls median.factor, if package is loaded

# If only base R is loaded, median.default will be called
# and will throw an error:
tryCatch(median.default(ord_factor_odd), error = function(e) e)

ord_factor_even <- ordered(letters[1:4])
median(ord_factor_even, ordered_low = FALSE)
median(ord_factor_even, ordered_low = TRUE)
```

# Index

- \* **LSimpute functions**
    - impute\_LS\_adaptive, 34
    - impute\_LS\_array, 36
    - impute\_LS\_combined, 38
    - impute\_LS\_gene, 39
  - \* **evaluation functions**
    - evaluate\_imputation\_parameters, 23
    - evaluate\_imputed\_values, 25
    - evaluate\_parameters, 28
  - \* **functions to create MAR**
    - delete\_MAR\_1\_to\_x, 5
    - delete\_MAR\_censoring, 8
    - delete\_MAR\_one\_group, 11
    - delete\_MAR\_rank, 13
  - \* **functions to create MNAR**
    - delete\_MNAR\_1\_to\_x, 17
    - delete\_MNAR\_censoring, 19
    - delete\_MNAR\_one\_group, 20
    - delete\_MNAR\_rank, 22
  - \* **location parameter imputation functions**
    - impute\_mean, 41
    - impute\_median, 42
    - impute\_mode, 43
- apply, 3
- apply\_imputation, 2, 42–44
- count\_NA, 4
- cut(), 32, 33
- delete\_MAR\_1\_to\_x, 5, 10, 13, 15, 18
- delete\_MAR\_censoring, 8, 8, 13, 15, 19, 20
- delete\_MAR\_one\_group, 8, 10, 11, 15, 21
- delete\_MAR\_rank, 8, 10, 13, 13, 23
- delete\_MCAR, 15
- delete\_MNAR\_1\_to\_x, 8, 17, 20, 21, 23
- delete\_MNAR\_censoring, 10, 18, 19, 21, 23
- delete\_MNAR\_one\_group, 13, 18, 20, 20, 23
- delete\_MNAR\_rank, 15, 18, 20, 21, 22
- evaluate\_imputation\_parameters, 23, 27, 28
- evaluate\_imputed\_values, 24, 25, 25, 28
- evaluate\_parameters, 25, 27, 28
- impute\_EM, 29
- impute\_expected\_values, 30
- impute\_expected\_values(), 30, 36, 37, 39
- impute\_hot\_deck\_in\_classes, 31
- impute\_in\_classes, 33
- impute\_in\_classes(), 32
- impute\_LS\_adaptive, 34, 37, 39, 40
- impute\_LS\_array, 36, 36, 39, 40
- impute\_LS\_array(), 35, 38
- impute\_LS\_combined, 36, 37, 38, 40
- impute\_LS\_gene, 36, 37, 39, 39
- impute\_LS\_gene(), 35, 37, 38
- impute\_mean, 4, 41, 43, 44
- impute\_median, 4, 42, 42, 44
- impute\_mode, 4, 42, 43, 43
- impute\_sRHD, 44
- impute\_sRHD(), 32
- is.na, 27
- mad, 47
- median, 43
- median.default, 46
- median.factor, 42, 43, 46
- norm::em.norm(), 29, 30
- quantile, 10, 24
- rank, 14, 15, 22
- sample, 7, 14