

# Package ‘MsCoreUtils’

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**Title** Core Utils for Mass Spectrometry Data

**Version** 1.2.0

**Description** MsCoreUtils defines low-level functions for mass spectrometry data and is independent of any high-level data structures. These functions include mass spectra processing functions (noise estimation, smoothing, binning), quantitative aggregation functions (median polish, robust summarisation, ...), missing data imputation, data normalisation (quantiles, vsn, ...) as well as misc helper functions, that are used across high-level data structure within the R for Mass Spectrometry packages.

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aggregate_by_vector	<i>Aggregate quantitative features.</i>
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**Description**

This function takes a matrix of quantitative features  $x$  and a factor (of length equal to  $nrow(x)$ ) defining subsets, and applies a user-defined function to aggregate each subset into a vector of quantitative values.

User-defined functions must thus return a vector of length equal to  $ncol(x)$ . Examples thereof are

- `medianPolish()` to fits an additive model (two way decomposition) using Tukey's median polish\_ procedure using `stats::medpolish()`;
- `robustSummary()` to calculate a robust aggregation using `MASS::rlm()`;
- `base::colMeans()` to use the mean of each column;
- `base::colSums()` to use the sum of each column;
- `matrixStats::colMedians()` to use the median of each column.

**Usage**

```
aggregate_by_vector(x, INDEX, FUN, ...)
```

**Arguments**

x	A matrix of mode numeric.
INDEX	A factor of length nrow(x).
FUN	A function to be applied to the subsets of x.
...	Additional arguments passed to FUN.

**Value**

A new matrix of dimensions ncol(x) and length(INDEX) with dimnames equal to colnames(x) and INDEX.

**Author(s)**

Laurent Gatto

**See Also**

Other Quantitative feature aggregation: [colCounts\(\)](#), [medianPolish\(\)](#), [robustSummary\(\)](#)

**Examples**

```
x <- structure(c(10.3961935744407, 17.1663715212693, 14.1027587989326,
  12.850349037785, 10.6379251053134, 7.52885076885599,
  3.91816118984218, 11.1339832690524, 16.5321471730746,
  14.1787908569268, 11.9422579479634, 11.5154097311056,
  7.69906817878979, 3.97092153807337, 11.9394664781386,
  15.3791100898935, 14.2409281956285, 11.2106867261254,
  12.2958526883634, 9.00858488668671, 3.83120129974963,
  12.9033445520186, 14.375814954807, 14.1617803596661,
  10.1237981632645, 13.3390344671153, 9.75719265786117,
  3.81046169359919),
  .Dim = c(7L, 4L),
  .Dimnames = list(c("X1", "X27", "X41", "X47", "X52",
    "X53", "X55"),
    c("iTRAQ4.114", "iTRAQ4.115",
    "iTRAQ4.116", "iTRAQ4.117"))))

x

k <- factor(c("B", "E", "X", "E", "B", "B", "E"))

aggregate_by_vector(x, k, colMeans)
aggregate_by_vector(x, k, robustSummary)
aggregate_by_vector(x, k, medianPolish)
```

---

between                      *Range helper functions*

---

### Description

These functions help to work with numeric ranges.

### Usage

```
between(x, range)
```

```
x %between% range
```

### Arguments

x                      numeric, input values.

range                 numeric(2), range to compare against.

### Value

logical vector of length length(x).

### Author(s)

Sebastian Gibb

### See Also

Other helper functions for developers: [isPeaksMatrix\(\)](#), [rbindFill\(\)](#), [validPeaksMatrix\(\)](#), [vapply1c\(\)](#)

### Examples

```
between(1:4, 2:3)
1:4 %between% 2:3
```

---

bin                      *Binning*

---

### Description

Aggregate values in x for bins defined on y: all values in x for values in y falling into a bin (defined on y) are aggregated with the provided function FUN.

**Usage**

```
bin(  
  x,  
  y,  
  size = 1,  
  breaks = seq(floor(min(y)), ceiling(max(y)), by = size),  
  FUN = max  
)
```

**Arguments**

x	numeric with the values that should be aggregated/binned.
y	numeric with same length than x with values to be used for the binning.
size	numeric(1) with the size of a bin.
breaks	numeric defining the breaks (bins).
FUN	function to be used to aggregate values of x falling into the bins defined by breaks.

**Value**

list with elements x (aggregated values of x) and mids (the bin mid points).

**Author(s)**

Johannes Rainer, Sebastian Gibb

**See Also**

Other grouping/matching functions: [closest\(\)](#)

**Examples**

```
## Define example intensities and m/z values  
ints <- abs(rnorm(20, mean = 40))  
mz <- seq(1:length(ints)) + rnorm(length(ints), sd = 0.001)  
  
## Bin intensities by m/z bins with a bin size of 2  
bin(ints, mz, size = 2)  
  
## Repeat but summing up intensities instead of taking the max  
bin(ints, mz, size = 2, FUN = sum)
```

closest

*Relaxed Value Matching***Description**

These functions offer relaxed matching of one vector in another. In contrast to the similar `match()` and `%in%` functions they just accept numeric arguments but have an additional tolerance argument that allows relaxed matching.

**Usage**

```
closest(
  x,
  table,
  tolerance = Inf,
  ppm = 0,
  duplicates = c("keep", "closest", "remove"),
  nomatch = NA_integer_,
  .check = TRUE
)

common(
  x,
  table,
  tolerance = Inf,
  ppm = 0,
  duplicates = c("keep", "closest", "remove"),
  .check = TRUE
)

join(
  x,
  y,
  tolerance = 0,
  ppm = 0,
  type = c("outer", "left", "right", "inner"),
  .check = TRUE,
  ...
)
```

**Arguments**

<code>x</code>	numeric, the values to be matched. In contrast to <code>match()</code> <code>x</code> has to be sorted in increasing order and must not contain any NA.
<code>table</code>	numeric, the values to be matched against. In contrast to <code>match()</code> <code>table</code> has to be sorted in increasing order and must not contain any NA.
<code>tolerance</code>	numeric, accepted tolerance. Could be of length one or the same length as <code>x</code> .
<code>ppm</code>	numeric(1) representing a relative, value-specific parts-per-million (PPM) tolerance that is added to tolerance.

duplicates	character(1), how to handle duplicated matches. Has to be one of c("keep", "closest", "remove") No abbreviations allowed.
nomatch	integer(1), if the difference between the value in x and table is larger than tolerance nomatch is returned.
.check	logical(1) turn off checks for increasingly sorted x and y. This should just be done if it is ensured by other methods that x and y are sorted, see also <a href="#">closest()</a> .
y	numeric, the values to be joined. Should be sorted.
type	character(1), defines how x and y should be joined. See details for <a href="#">join</a> .
...	ignored.

### Details

For `closest/common` the tolerance argument could be set to 0 to get the same results as for [match\(\)/%in%](#). If it is set to Inf (default) the index of the closest values is returned without any restriction.

It is not guaranteed that there is a one-to-one matching for neither the x to table nor the table to x matching.

If multiple elements in x match a single element in table all their corresponding indices are returned if `duplicates="keep"` is set (default). This behaviour is identical to [match\(\)](#). For `duplicates="closest"` just the closest element in x gets the corresponding index in table and for `duplicates="remove"` all elements in x that match to the same element in table are set to `nomatch`.

If a single element in x matches multiple elements in table the *closest* is returned for `duplicates="keep"` or `duplicates="closest"` (*keeping* multiple matches isn't possible in this case because the return value should be of the same length as x). If the differences between x and the corresponding matches in table are identical the lower index (the smaller element in table) is returned. There is one exception: if the lower index is already returned for another x with a smaller difference to this index the higher one is returned for `duplicates = "closer"` (but only if there is no other x that is closer to the higher one). For `duplicates="remove"` all multiple matches are returned as `nomatch` as above.

`.checks = TRUE` tests among other input validation checks for increasingly sorted x and table arguments that are mandatory assumptions for the `closest` algorithm. These checks require to loop through both vectors and compare each element against its precursor. Depending on the length and distribution of x and table these checks take equal/more time than the whole `closest` algorithm. If it is ensured by other methods that both arguments x and table are sorted the tests could be skipped by `.check = FALSE`. In the case that `.check = FALSE` is used and one of x and table is not sorted (or decreasingly sorted) the output would be incorrect in the best case and result in infinity loop in the average and worst case.

`join`: joins two numeric vectors by mapping values in x with values in y and *vice versa* if they are similar enough (provided the tolerance and ppm specified). The function returns a matrix with the indices of mapped values in x and y. Parameter `type` allows to define how the vectors will be joined: `type = "left"`: values in x will be mapped to values in y, elements in y not matching any value in x will be discarded. `type = "right"`: same as `type = "left"` but for y. `type = "outer"`: return matches for all values in x and in y. `type = "inner"`: report only indices of values that could be mapped.

### Value

`closest` returns an integer vector of the same length as x giving the closest position in table of the first match or `nomatch` if there is no match.

common returns a logical vector of length x that is TRUE if the element in x was found in table. It is similar to `%in%`.

join returns a matrix with two columns, namely x and y, representing the index of the values in x matching the corresponding value in y (or NA if the value does not match).

### Note

join is based on `closest(x, y, tolerance, duplicates = "closest")`. That means for multiple matches just the closest one is reported.

### Author(s)

Sebastian Gibb, Johannes Rainer

### See Also

`match()`

`%in%`

Other grouping/matching functions: `bin()`

### Examples

```
## Define two vectors to match
x <- c(1, 3, 5)
y <- 1:10

## Compare match and closest
match(x, y)
closest(x, y)

## If there is no exact match
x <- x + 0.1
match(x, y) # no match
closest(x, y)

## Some new values
x <- c(1.11, 45.02, 556.45)
y <- c(3.01, 34.12, 45.021, 46.1, 556.449)

## Using a single tolerance value
closest(x, y, tolerance = 0.01)

## Using a value-specific tolerance accepting differences of 20 ppm
closest(x, y, ppm = 20)

## Same using 50 ppm
closest(x, y, ppm = 50)

## Sometimes multiple elements in `x` match to `table`
x <- c(1.6, 1.75, 1.8)
y <- 1:2
closest(x, y, tolerance = 0.5)
closest(x, y, tolerance = 0.5, duplicates = "closest")
closest(x, y, tolerance = 0.5, duplicates = "remove")
```



```
## Are there any common values?
x <- c(1.6, 1.75, 1.8)
y <- 1:2
common(x, y, tolerance = 0.5)
common(x, y, tolerance = 0.5, duplicates = "closest")
common(x, y, tolerance = 0.5, duplicates = "remove")

## Join two vectors
x <- c(1, 2, 3, 6)
y <- c(3, 4, 5, 6, 7)

jo <- join(x, y, type = "outer")
jo
x[jo$x]
y[jo$y]

jl <- join(x, y, type = "left")
jl
x[jl$x]
y[jl$y]

jr <- join(x, y, type = "right")
jr
x[jr$x]
y[jr$y]

ji <- join(x, y, type = "inner")
ji
x[ji$x]
y[ji$y]
```

---

coerce

*Coerce functions*

---

### Description

- `asInteger`: convert `x` to an integer and throw an error if `x` is not a numeric.

### Usage

```
asInteger(x)
```

### Arguments

`x`                   input argument.

### Author(s)

Johannes Rainer

**Examples**

```
## Convert numeric to integer
asInteger(3.4)

asInteger(3)
```

---

**colCounts***Counts the number of features*

---

**Description**

Returns the number of non-NA features in a features by sample matrix.

**Usage**

```
colCounts(x, ...)
```

**Arguments**

**x** A matrix of mode numeric.  
**...** Currently ignored.

**Value**

A numeric vector of length identical to `ncol(x)`.

**Author(s)**

Laurent Gatto

**See Also**

Other Quantitative feature aggregation: [aggregate\\_by\\_vector\(\)](#), [medianPolish\(\)](#), [robustSummary\(\)](#)

**Examples**

```
m <- matrix(c(1, NA, 2, 3, NA, NA, 4, 5, 6),
            nrow = 3)
colCounts(m)
m <- matrix(rnorm(30), nrow = 3)
colCounts(m)
```



`navdist`: the normalized absolute values distance is described in Stein and Scott 1994 as:  $NED = (1 + \frac{\sum(|W_1 - W_2|)}{\sum(W_2)})^{-1}$ ; where  $W_i = x^m * y^n$ , where  $x$  and  $y$  are the m/z and intensity values, respectively. See the details section about `ndotproduct` for an explanation how to set  $m$  and  $n$ .

`nspectraangle`: the normalized spectra angle is described in Toprak et al 2014 as:  $NSA = 1 - \frac{2 * \cos^{-1}(W_1 \cdot W_2)}{\pi}$ ; where  $W_i = x^m * y^n$ , where  $x$  and  $y$  are the m/z and intensity values, respectively. The weighting was not originally proposed by Toprak et al. 2014. See the details section about `ndotproduct` for an explanation how to set  $m$  and  $n$ .

### Value

double(1) value between 0:1, where 0 is completely different and 1 identically.

### Note

These methods are implemented as described in Stein and Scott 1994 (`navdist`, `ndotproduct`, `neuclidean`) and Toprak et al. 2014 (`nspectraangle`) but because there is no reference implementation available we are unable to guarantee that the results are identical. Please see also the corresponding discussion at the github pull request linked below. If you find any problems or reference implementation please open an issue at <https://github.com/rformassspectrometry/MsCoreUtils/issues>.

### Author(s)

`navdist`, `neuclidean`, `nspectraangle`: Sebastian Gibb

`ndotproduct`: Sebastian Gibb and Thomas Naake, <thomasnaake@googlemail.com>

### References

Stein, S. E., and Scott, D. R. (1994). Optimization and testing of mass spectral library search algorithms for compound identification. *Journal of the American Society for Mass Spectrometry*, 5(9), 859–866. doi: [10.1016/10440305\(94\)870098](https://doi.org/10.1016/10440305(94)870098).

Horai et al. (2010). MassBank: a public repository for sharing mass spectral data for life sciences. *Journal of mass spectrometry*, 45(7), 703–714. doi: [10.1002/jms.1777](https://doi.org/10.1002/jms.1777).

Toprak et al. (2014). Conserved peptide fragmentation as a benchmarking tool for mass spectrometers and a discriminating feature for targeted proteomics. *Molecular & Cellular Proteomics : MCP*, 13(8), 2056–2071. doi: [10.1074/mcp.O113.036475](https://doi.org/10.1074/mcp.O113.036475).

Pull Request for these distance/similarity measurements: <https://github.com/rformassspectrometry/MsCoreUtils/pull/33>

### Examples

```
x <- matrix(c(1:5, 1:5), ncol = 2, dimnames = list(c(), c("mz", "intensity")))
y <- matrix(c(1:5, 5:1), ncol = 2, dimnames = list(c(), c("mz", "intensity")))
```

```
ndotproduct(x, y)
ndotproduct(x, y, m = 2, n = 0.5)
ndotproduct(x, y, m = 3, n = 0.6)
```

```
neuclidean(x, y)
```

```
navdist(x, y)
```

```
nspectraangle(x, y)
```

---

group	<i>Grouping of numeric values by similarity</i>
-------	---

---

### Description

The group function groups numeric values by first ordering and then putting all values into the same group if their difference is smaller defined by parameters tolerance (a constant value) and ppm (a value-specific relative value expressed in parts-per-million).

### Usage

```
group(x, tolerance = 0, ppm = 0)
```

### Arguments

x	increasingly ordered numeric with the values to be grouped.
tolerance	numeric(1) with the maximal accepted difference between values in x to be grouped into the same entity.
ppm	numeric(1) defining a value-dependent maximal accepted difference between values in x expressed in parts-per-million.

### Value

integer of length equal to x with the groups.

### Note

Since grouping is performed on pairwise differences between consecutive values (after ordering x), the difference between the smallest and largest value in a group can be larger than tolerance and ppm.

### Author(s)

Johannes Rainer, Sebastin Gibb

### Examples

```
## Define a (sorted) numeric vector
x <- c(34, 35, 35, 35 + ppm(35, 10), 56, 56.05, 56.1)

## With `ppm = 0` and `tolerance = 0` only identical values are grouped
group(x)

## With `tolerance = 0.05`
group(x, tolerance = 0.05)

## Also values 56, 56.05 and 56.1 were grouped into a single group,
## although the difference between the smallest 56 and largest value in
## this group (56.1) is 0.1. The (pairwise) difference between the ordered
## values is however 0.05.
```

```
## With ppm
group(x, ppm = 10)

## Same on an unsorted vector
x <- c(65, 34, 65.1, 35, 66, 65.2)
group(x, tolerance = 0.1)

## Values 65, 65.1 and 65.2 have been grouped into the same group.
```

---

i2index

*Input parameter check for subsetting operations*


---

### Description

i2index is a simple helper function to be used in subsetting functions. It checks and converts the parameter `i`, which can be of type integer, logical or character to integer vector that can be used as index for subsetting.

### Usage

```
i2index(i, length = length(i), names = NULL)
```

### Arguments

<code>i</code>	character logical or integer used in <code>[i]</code> for subsetting.
<code>length</code>	integer representing the length of the object to be subsetted.
<code>names</code>	character with the names (rownames or similar) of the object. This is only required if <code>i</code> is of type character.

### Value

integer with the indices

### Author(s)

Johannes Rainer

### Examples

```
## With `i` being an `integer`
i2index(c(4, 1, 3), length = 10)

## With `i` being a `logical`
i2index(c(TRUE, FALSE, FALSE, TRUE, FALSE), length = 5)

## With `i` being a `character`
i2index(c("b", "a", "d"), length = 5, names = c("a", "b", "c", "d", "e"))
```

---

`impute_matrix`*Quantitative mass spectrometry data imputation*

---

## Description

The `impute_matrix` function performs data imputation on `matrix` objects instance using a variety of methods (see below).

Users should proceed with care when imputing data and take precautions to assure that the imputation produce valid results, in particular with naive imputations such as replacing missing values with 0.

## Usage

```
impute_matrix(x, method, ...)
```

```
imputeMethods()
```

```
impute_neighbour_average(x, k = min(x, na.rm = TRUE))
```

```
impute_knn(x, ...)
```

```
impute_mle(x, ...)
```

```
impute_bpca(x, ...)
```

```
impute_mixed(x, randna, mar, mmar, ...)
```

```
impute_min(x)
```

## Arguments

<code>x</code>	A matrix with missing values to be imputed.
<code>method</code>	character(1) defining the imputation method. See <code>imputeMethods()</code> for available ones.
<code>...</code>	Additional parameters passed to the inner imputation function.
<code>k</code>	numeric(1) providing the imputation value used for the first and last samples if they contain an NA. The default is to use the smallest value in the data.
<code>randna</code>	logical of length equal to <code>nrow(object)</code> defining which rows are missing at random. The other ones are considered missing not at random. Only relevant when <code>method</code> is <code>mixed</code> .
<code>mar</code>	Imputation method for values missing at random. See <code>method</code> above.
<code>mmar</code>	Imputation method for values missing not at random. See <code>method</code> above.

## Details

There are two types of mechanisms resulting in missing values in LC/MSMS experiments.

- Missing values resulting from absence of detection of a feature, despite ions being present at detectable concentrations. For example in the case of ion suppression or as a result from the stochastic, data-dependent nature of the MS acquisition method. These missing value are expected to be randomly distributed in the data and are defined as missing at random (MAR) or missing completely at random (MCAR).
- Biologically relevant missing values resulting from the absence of the low abundance of ions (below the limit of detection of the instrument). These missing values are not expected to be randomly distributed in the data and are defined as missing not at random (MNAR).

MNAR features should ideally be imputed with a left-censor method, such as QRILC below. Conversely, it is recommended to use host deck methods such nearest neighbours, Bayesian missing value imputation or maximum likelihood methods when values are missing at random.

Currently, the following imputation methods are available.

- *MLE*: Maximum likelihood-based imputation method using the EM algorithm. Implemented in the `norm::imp.norm()` function. See `norm::imp.norm()` for details and additional parameters. Note that here, `...` are passed to the `[norm::em.norm()]` function, rather to the actual imputation function `imp.norm()`.
- *bpca*: Bayesian missing value imputation are available, as implemented in the `pcaMethods::pca()` function. See `pcaMethods::pca()` for details and additional parameters.
- *knn*: Nearest neighbour averaging, as implemented in the `impute::impute.knn` function. See `impute::impute.knn()` for details and additional parameters.
- *QRILC*: A missing data imputation method that performs the imputation of left-censored missing data using random draws from a truncated distribution with parameters estimated using quantile regression. Implemented in the `imputeLCMD::impute.QRILC` function. `imputeLCMD::impute.QRILC()` for details and additional parameters.
- *MinDet*: Performs the imputation of left-censored missing data using a deterministic minimal value approach. Considering a expression data with  $n$  samples and  $p$  features, for each sample, the missing entries are replaced with a minimal value observed in that sample. The minimal value observed is estimated as being the  $q$ -th quantile (default  $q = 0.01$ ) of the observed values in that sample. Implemented in the `imputeLCMD::impute.MinDet` function. See `imputeLCMD::impute.MinDet()` for details and additional parameters.
- *MinProb*: Performs the imputation of left-censored missing data by random draws from a Gaussian distribution centred to a minimal value. Considering an expression data matrix with  $n$  samples and  $p$  features, for each sample, the mean value of the Gaussian distribution is set to a minimal observed value in that sample. The minimal value observed is estimated as being the  $q$ -th quantile (default  $q = 0.01$ ) of the observed values in that sample. The standard deviation is estimated as the median of the feature standard deviations. Note that when estimating the standard deviation of the Gaussian distribution, only the peptides/proteins which present more than 50 are considered. Implemented in the `imputeLCMD::impute.MinProb` function. See `imputeLCMD::impute.MinProb()` for details and additional parameters.
- *min*: Replaces the missing values with the smallest non-missing value in the data.
- *zero*: Replaces the missing values with 0.
- *mixed*: A mixed imputation applying two methods (to be defined by the user as `mar` for values missing at random and `mna` for values missing not at random, see example) on two MCAR/MNAR subsets of the data (as defined by the user by a `randna` logical, of length equal to `nrow(object)`).
- *nbavg*: Average neighbour imputation for fractions collected along a fractionation/separation gradient, such as sub-cellular fractions. The method assumes that the fraction are ordered along the gradient and is invalid otherwise.



Continuous sets NA value at the beginning and the end of the quantitation vectors are set to the lowest observed value in the data or to a user defined value passed as argument k. Then, when a missing value is flanked by two non-missing neighbouring values, it is imputed by the mean of its direct neighbours.

- *with*: Replaces all missing values with a user-provided value.
- *none*: No imputation is performed and the missing values are left untouched. Implemented in case one wants to only impute value missing at random or not at random with the *mixed* method.

The `imputeMethods()` function returns a vector with valid imputation method arguments.

### Author(s)

Laurent Gatto

### References

Olga Troyanskaya, Michael Cantor, Gavin Sherlock, Pat Brown, Trevor Hastie, Robert Tibshirani, David Botstein and Russ B. Altman, Missing value estimation methods for DNA microarrays *Bioinformatics* (2001) 17 (6): 520-525.

Oba et al., A Bayesian missing value estimation method for gene expression profile data, *Bioinformatics* (2003) 19 (16): 2088-2096.

Cosmin Lazar (2015). `imputeLCMD`: A collection of methods for left-censored missing data imputation. R package version 2.0. <http://CRAN.R-project.org/package=imputeLCMD>.

Lazar C, Gatto L, Ferro M, Bruley C, Burger T. Accounting for the Multiple Natures of Missing Values in Label-Free Quantitative Proteomics Data Sets to Compare Imputation Strategies. *J Proteome Res.* 2016 Apr 1;15(4):1116-25. doi: 10.1021/acs.jproteome.5b00981. PubMed PMID:26906401.

### Examples

```
## test data
set.seed(42)
m <- matrix(rlnorm(60), 10)
dimnames(m) <- list(letters[1:10], LETTERS[1:6])
m[sample(60, 10)] <- NA

## available methods
imputeMethods()

impute_matrix(m, method = "zero")

impute_matrix(m, method = "min")

impute_matrix(m, method = "knn")

## same as impute_zero
impute_matrix(m, method = "with", val = 0)

## impute with half of the smallest value
impute_matrix(m, method = "with",
              val = min(m, na.rm = TRUE) * 0.5)

## all but third and fourth features' missing values
```

```
## are the result of random missing values
randna <- rep(TRUE, 10)
randna[c(3, 9)] <- FALSE

impute_matrix(m, method = "mixed",
              randna = randna,
              mar = "knn",
              mnar = "min")
```

---

isPeaksMatrix

*Check functions*

---

## Description

These functions are used to check input arguments.

## Usage

```
isPeaksMatrix(x)
```

## Arguments

x                    object to test.

## Details

isPeaksMatrix: test for a numeric matrix with two columns named "mz" and "intensity". The "mz" column has to be sorted increasingly.

## Value

logical(1), TRUE if checks are successful otherwise FALSE.

## Author(s)

Sebastian Gibb

## See Also

Other helper functions for developers: [between\(\)](#), [rbindFill\(\)](#), [validPeaksMatrix\(\)](#), [vapply1c\(\)](#)

## Examples

```
isPeaksMatrix(1:2)
isPeaksMatrix(cbind(mz = 2:1, intensity = 1:2))
isPeaksMatrix(cbind(mz = 1:2, intensity = 1:2))
```

---

localMaxima	<i>Local Maxima</i>
-------------	---------------------

---

**Description**

This function finds local maxima in a numeric vector. A local maximum is defined as maximum in a window of the current index +/- hws.

**Usage**

```
localMaxima(x, hws = 1L)
```

**Arguments**

x	numeric, vector that should be searched for local maxima.
hws	integer(1), half window size, the resulting window reaches from (i -hws) : (i + hws).

**Value**

A logical of the same length as x that is TRUE for each local maxima.

**Author(s)**

Sebastian Gibb

**See Also**

Other extreme value functions: [.peakRegionMask\(\)](#), [refineCentroids\(\)](#), [valleys\(\)](#)

**Examples**

```
x <- c(1:5, 4:1, 1:10, 9:1, 1:5, 4:1)
localMaxima(x)
localMaxima(x, hws = 10)
```

---

medianPolish	<i>Return the Median Polish (Robust Twoway Decomposition) of a matrix</i>
--------------	---

---

**Description**

Fits an additive model (two way decomposition) using Tukey's median polish procedure using [stats::medpolish\(\)](#).

**Usage**

```
medianPolish(x, verbose = FALSE, ...)
```

**Arguments**

`x` A matrix of mode numeric.  
`verbose` Default is FALSE.  
`...` Additional arguments passed to `stats::medpolish()`.

**Value**

A numeric vector of length identical to `ncol(x)`.

**Author(s)**

Laurent Gatto

**See Also**

Other Quantitative feature aggregation: `aggregate_by_vector()`, `colCounts()`, `robustSummary()`

**Examples**

```
x <- matrix(rnorm(30), nrow = 3)
medianPolish(x)
```

---

noise

*Noise Estimation*

---

**Description**

This functions estimate the noise in the data.

**Usage**

```
noise(x, y, method = c("MAD", "SuperSmoother"), ...)
```

**Arguments**

`x` numeric, x values for noise estimation (e.g. *mz*)  
`y` numeric, y values for noise estimation (e.g. *intensity*)  
`method` character(1) used method. Currently MAD (median absolute deviation) and Friedman's SuperSmoother are supported.  
`...` further arguments passed to `method`.

**Value**

A numeric of the same length as `x` with the estimated noise.

**Author(s)**

Sebastian Gibb

**See Also**

[stats::mad\(\)](#), [stats::supsmu\(\)](#)

Other noise estimation and smoothing functions: [smooth\(\)](#)

**Examples**

```
x <- 1:20
y <- c(1:10, 10:1)
noise(x, y)
noise(x, y, method = "SuperSmoother", span = 1 / 3)
```

---

normalizeMethods

*Quantitative data normalisation*

---

**Description**

Function to normalise a matrix of quantitative omics data. The nature of the normalisation is controlled by the method argument, described below.

**Usage**

```
normalizeMethods()
```

```
normalize_matrix(x, method, ...)
```

**Arguments**

x	A matrix to be normalised.
method	character(1) defining the normalisation method. See <a href="#">normalizeMethods()</a> for available ones.
...	Additional parameters passed to the inner normalisation function.

**Details**

The method parameter can be one of "sum", "max", "center.mean", "center.median", "div.mean", "div.median", "diff.meda", "quantiles", "quantiles.robust" or "vsn". The [normalizeMethods\(\)](#) function returns a vector of available normalisation methods.

- For "sum" and "max", each feature's intensity is divided by the maximum or the sum of the feature respectively. These two methods are applied along the features (rows).
- "center.mean" and "center.median" center the respective sample (column) intensities by subtracting the respective column means or medians. "div.mean" and "div.median" divide by the column means or medians.
- "diff.median" centers all samples (columns) so that they all match the grand median by subtracting the respective columns medians differences to the grand median.
- Using "quantiles" or "quantiles.robust" applies (robust) quantile normalisation, as implemented in [preprocessCore::normalize.quantiles\(\)](#) and [preprocessCore::normalize.quantiles.robust\(\)](#). "vsn" uses the [vsn::vsn2\(\)](#) function. Note that the latter also log-transforms the intensities. See respective manuals for more details and function arguments.

**Value**

A normalised matrix of dimensions  $\dim(x)$ .

**Author(s)**

Laurent Gatto

**See Also**

The `scale()` function that centers (like `center.mean` above) and scales.

**Examples**

```
normalizeMethods()

## test data
set.seed(42)
m <- matrix(rlnorm(60), 10)

normalize_matrix(m, method = "sum")

normalize_matrix(m, method = "max")

normalize_matrix(m, method = "quantiles")

normalize_matrix(m, method = "center.mean")
```

---

ppm

*PPM - Parts per Million*

---

**Description**

ppm is a small helper function to determine the parts-per-million for a user-provided value and ppm.

**Usage**

```
ppm(x, ppm)
```

**Arguments**

x	numeric, value(s) used for ppm calculation, e.g. mz value(s).
ppm	numeric, parts-per-million (ppm) value(s).

**Value**

numeric: parts-per-million of x

**Author(s)**

Sebastian Gibb

**Examples**

```
ppm(c(1000, 2000), 5)
```

---

`rbindFill`*Combine R Objects by Row*

---

### Description

This function combines instances of `matrix`, `data.frame` or `DataFrame` objects into a single instance adding eventually missing columns (filling them with NAs).

### Usage

```
rbindFill(...)
```

### Arguments

... 2 or more: `matrix`, `data.frame` or `DataFrame`.

### Value

Depending on the input a single `matrix`, `data.frame` or `DataFrame`.

### Note

`rbindFill` might not work if one of the columns contains S4 classes.

### Author(s)

Johannes Rainer, Sebastian Gibb

### See Also

Other helper functions for developers: [between\(\)](#), [isPeaksMatrix\(\)](#), [validPeaksMatrix\(\)](#), [vapply1c\(\)](#)

### Examples

```
## Combine matrices
a <- matrix(1:9, nrow = 3, ncol = 3)
colnames(a) <- c("a", "b", "c")
b <- matrix(1:12, nrow = 3, ncol = 4)
colnames(b) <- c("b", "a", "d", "e")
rbindFill(a, b)
rbindFill(b, a, b)
```

---

refineCentroids	<i>Refine Peak Centroids</i>
-----------------	------------------------------

---

### Description

This function refines the centroided values of a peak by weighting the y values in the neighbourhood that belong most likely to the same peak.

### Usage

```
refineCentroids(x, y, p, k = 2L, threshold = 0.33, descending = FALSE)
```

### Arguments

x	numeric, i.e. m/z values.
y	numeric, i.e. intensity values.
p	integer, indices of identified peaks/local maxima.
k	integer(1), number of values left and right of the peak that should be considered in the weighted mean calculation.
threshold	double(1), proportion of the maximal peak intensity. Just values above are used for the weighted mean calculation.
descending	logical, if TRUE just values between the nearest valleys around the peak centroids are used.

### Details

For descending = FALSE the function looks for the k nearest neighbouring data points and use their x for weighted mean with their corresponding y values as weights for calculation of the new peak centroid. If k are chosen too large it could result in skewed peak centroids, see example below. If descending = TRUE is used the k should be general larger because it is trimmed automatically to the nearest valleys on both sides of the peak so the problem with skewed centroids is rare.

### Author(s)

Sebastian Gibb, Johannes Rainer

### See Also

Other extreme value functions: [.peakRegionMask\(\)](#), [localMaxima\(\)](#), [valleys\(\)](#)

### Examples

```
ints <- c(5, 8, 12, 7, 4, 9, 15, 16, 11, 8, 3, 2, 3, 9, 12, 14, 13, 8, 3)
mzs <- seq_along(ints)

plot(mzs, ints, type = "h")

pidx <- as.integer(c(3, 8, 16))
points(mzs[pidx], ints[pidx], pch = 16)

## Use the weighted average considering the adjacent mz
```



```

mzs1 <- refineCentroids(mzs, ints, pidx,
                        k = 2L, descending = FALSE, threshold = 0)
mzs2 <- refineCentroids(mzs, ints, pidx,
                        k = 5L, descending = FALSE, threshold = 0)
mzs3 <- refineCentroids(mzs, ints, pidx,
                        k = 5L, descending = TRUE, threshold = 0)
points(mzs1, ints[pidx], col = "red", type = "h")
## please recognize the artificial moved centroids of the first peak caused
## by a too large k, here
points(mzs2, ints[pidx], col = "blue", type = "h")
points(mzs3, ints[pidx], col = "green", type = "h")
legend("topright",
      legend = paste0("k = ", c(2, 5, 5),
                      ", descending =", c("FALSE", "FALSE", "TRUE")),
      col = c("red", "blue", "green"), lwd = 1)

```

---

rla	<i>Calculate relative log abundances</i> rla calculates the relative log abundances (RLA, see reference) on a numeric vector. rowRla performs row-wise RLA calculations on a numeric matrix.
-----	--

---

## Description

Calculate relative log abundances

rla calculates the relative log abundances (RLA, see reference) on a numeric vector. rowRla performs row-wise RLA calculations on a numeric matrix.

## Usage

```

rla(
  x,
  f = rep_len(1, length(x)),
  transform = c("log2", "log10", "identity"),
  na.rm = TRUE
)

```

```
rowRla(x, f = rep_len(1, ncol(x)), transform = c("log2", "log10", "identity"))
```

## Arguments

x	numeric (for rla) or matrix (for rowRla) with the abundances (in natural scale) on which the RLA should be calculated.
f	factor, numeric or character with the same length than x (or, for rowRla equal to the number of columns of x) allowing to define the grouping of values in x. If omitted all values are considered to be from the same group.
transform	character(1) defining the function to transform x. Defaults to transform = "log2" which log2 transforms x prior to calculation. If x is already in log scale use transform = "identity" to avoid transformation of the values.
na.rm	logical(1) whether NA values should be removed prior to calculation of the group-wise medians.

**Details**

The RLA is defined as the (log2) abundance of an analyte relative to the median across all abundances of that analyte in samples of the same group. The grouping of values can be defined with parameter *f*.

**Value**

numeric with the relative log abundances (in log2 scale) with the same length than *x* (for *r1a*) or matrix with the same dimensions than *x* (for *rowR1a*).

**Author(s)**

Johannes Rainer

**References**

De Livera AM, Dias DA, De Souza D, Rupasinghe T, Pyke J, Tull D, Roessner U, McConville M, Speed TP. Normalizing and integrating metabolomics data. *Anal Chem* 2012 Dec 18;84(24):10768-76.

**Examples**

```
x <- c(3, 4, 5, 1, 2, 3, 7, 8, 9)
grp <- c(1, 1, 1, 2, 2, 2, 3, 3, 3)
r1a(x, grp)

x <- rbind(c(324, 4542, 3422, 3232, 5432, 6535, 3321, 1121),
           c(12, 3341, 3034, 6540, 34, 4532, 56, 1221))
grp <- c("a", "b", "b", "b", "a", "b", "a", "b")

## row-wise RLA values
rowR1a(x, grp)
```

---

robustSummary

*Return the Robust Expression Summary of a matrix*


---

**Description**

This function calculates the robust summarisation for each feature (protein). Note that the function assumes that the intensities in input *e* are already log-transformed.

**Usage**

```
robustSummary(x, ...)
```

**Arguments**

*x* A feature by sample matrix containing quantitative data with mandatory colnames and rownames.

... Additional arguments passed to `MASS::rlm()`.

**Value**

numeric() vector of length `ncol(x)` with robust summarised values.

**Author(s)**

Adriaan Sticker, Sebastian Gibb and Laurent Gatto

**See Also**

Other Quantitative feature aggregation: [aggregate\\_by\\_vector\(\)](#), [colCounts\(\)](#), [medianPolish\(\)](#)

**Examples**

```
x <- matrix(rnorm(30), nrow = 3)
colnames(x) <- letters[1:10]
rownames(x) <- LETTERS[1:3]
robustSummary(x)
```

---

smooth

*Smoothing*

---

**Description**

This function smoothes a numeric vector.

**Usage**

```
smooth(x, cf)
```

```
coefMA(hws)
```

```
coefWMA(hws)
```

```
coefSG(hws, k = 3L)
```

**Arguments**

<code>x</code>	numeric, i.e. m/z values.
<code>cf</code>	matrix, a coefficient matrix generated by <code>coefMA</code> , <code>coefWMA</code> or <code>coefSG</code> .
<code>hws</code>	integer(1), half window size, the resulting window reaches from $(i - hws) : (i + hws)$ .
<code>k</code>	integer(1), set the order of the polynomial used to calculate the coefficients.

**Details**

For the Savitzky-Golay-Filter the `hws` should be smaller than *FWHM* of the peaks (full width at half maximum; please find details in Bromba and Ziegler 1981).

In general the `hws` for the (weighted) moving average (`coefMA`/`coefWMA`) has to be much smaller than for the Savitzky-Golay-Filter to conserve the peak shape.

**Value**

smooth: A numeric of the same length as x.  
 coefMA: A matrix with coefficients for a simple moving average.  
 coefWMA: A matrix with coefficients for a weighted moving average.  
 coefSG: A matrix with *Savitzky-Golay-Filter* coefficients.

**Functions**

- coefMA: Simple Moving Average  
This function calculates the coefficients for a simple moving average.
- coefWMA: Weighted Moving Average  
This function calculates the coefficients for a weighted moving average with weights depending on the distance from the center calculated as  $1/2^{\text{abs}(-\text{hws}:\text{hws})}$  with the sum of all weights normalized to 1.
- coefSG: Savitzky-Golay-Filter  
This function calculates the Savitzky-Golay-Coefficients. The additional argument k controls the order of the used polynomial. If k is set to zero it yield a simple moving average.

**Note**

The hws depends on the used method ((weighted) moving average/Savitzky-Golay).

**Author(s)**

Sebastian Gibb, Sigurdur Smarason (weighted moving average)

**References**

A. Savitzky and M. J. Golay. 1964. Smoothing and differentiation of data by simplified least squares procedures. *Analytical chemistry*, 36(8), 1627-1639.  
 M. U. Bromba and H. Ziegler. 1981. Application hints for Savitzky-Golay digital smoothing filters. *Analytical Chemistry*, 53(11), 1583-1586.  
 Implementation based on: Steinier, J., Termonia, Y., & Deltour, J. (1972). Comments on Smoothing and differentiation of data by simplified least square procedure. *Analytical Chemistry*, 44(11), 1906-1909.

**See Also**

Other noise estimation and smoothing functions: [noise\(\)](#)

**Examples**

```
x <- c(1:10, 9:1)
plot(x, type = "b", pch = 20)
cf <- list(MovingAverage = coefMA(2),
          WeightedMovingAverage = coefWMA(2),
          SavitzkyGolay = coefSG(2))
for (i in seq_along(cf)) {
  lines(smooth(x, cf[[i]]), col = i + 1, pch = 20, type = "b")
}
legend("bottom", legend = c("x", names(cf)), pch = 20,
      col = seq_len(length(cf) + 1))
```

---

validPeaksMatrix	<i>Validation functions</i>
------------------	-----------------------------

---

### Description

These functions are used to validate input arguments. In general they are just wrapper around their corresponding `is*` function with an error message.

### Usage

```
validPeaksMatrix(x)
```

### Arguments

`x` object to test.

### Details

`validPeaksMatrix`: see [isPeaksMatrix](#).

### Value

`logical(1)`, TRUE if validation are successful otherwise an error is thrown.

### Author(s)

Sebastian Gibb

### See Also

Other helper functions for developers: [between\(\)](#), [isPeaksMatrix\(\)](#), [rbindFill\(\)](#), [vapply1c\(\)](#)

### Examples

```
try(validPeaksMatrix(1:2))
validPeaksMatrix(cbind(mz = 1:2, intensity = 1:2))
```

---

valleys	<i>Find Peak Valleys</i>
---------	--------------------------

---

### Description

This function finds the valleys around peaks.

### Usage

```
valleys(x, p)
```

**Arguments**

x	numeric, e.g. intensity values.
p	integer, indices of identified peaks/local maxima.

**Value**

A matrix with three columns representing the index of the left valley, the peak centroid, and the right valley.

**Note**

The detection of the valleys is based on `localMaxima`. It returns the *first* occurrence of a local maximum (in this specific case the minimum). For plateaus, e.g. `c(0, 0, 0, 1:3, 2:1, 0)` this results in a wrongly reported left valley index of 1 (instead of 3, see the example section as well). In real data this should not be a real problem. `x[x == min(x)] <- -Inf` could be used before running `valleys` to circumvent this specific problem but it is not really tested and could cause different problems.

**Author(s)**

Sebastian Gibb

**See Also**

Other extreme value functions: `.peakRegionMask()`, `localMaxima()`, `refineCentroids()`

**Examples**

```
ints <- c(5, 8, 12, 7, 4, 9, 15, 16, 11, 8, 3, 2, 3, 2, 9, 12, 14, 13, 8, 3)
mzs <- seq_along(ints)
peaks <- which(localMaxima(ints, hws = 3))
cols <- seq_along(peaks) + 1

plot(mzs, ints, type = "h", ylim = c(0, 16))
points(mzs[peaks], ints[peaks], col = cols, pch = 20)

v <- valleys(ints, peaks)
segments(mzs[v[, "left"]], 0, mzs[v[, "right"]], col = cols, lwd = 2)

## Known limitations for plateaus
y <- c(0, 0, 0, 0, 0, 1:5, 4:1, 0)
valleys(y, 10L) # left should be 5 here but is 1

## a possible workaround that may cause other problems
y[min(y) == y] <- Inf
valleys(y, 10L)
```

---

`vapply1c`*vapply wrappers*

---

**Description**

These functions are short wrappers around typical `vapply` calls for easier development.

**Usage**

```
vapply1c(X, FUN, ..., USE.NAMES = FALSE)
```

```
vapply1d(X, FUN, ..., USE.NAMES = FALSE)
```

```
vapply1l(X, FUN, ..., USE.NAMES = FALSE)
```

**Arguments**

<code>X</code>	a vector (atomic or list).
<code>FUN</code>	the function to be applied to each element of <code>X</code> .
<code>...</code>	optional arguments to <code>FUN</code> .
<code>USE.NAMES</code>	logical, should the return value be named.

**Value**

`vapply1c` returns a vector of characters of length `X`.

`vapply1d` returns a vector of doubles of length `X`.

`vapply1l` returns a vector of logicals of length `X`.

**Author(s)**

Sebastian Gibb

**See Also**

Other helper functions for developers: [between\(\)](#), [isPeaksMatrix\(\)](#), [rbindFill\(\)](#), [validPeaksMatrix\(\)](#)

**Examples**

```
l <- list(a=1:3, b=4:6)
vapply1d(l, sum)
```

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