

Package ‘dataPreparation’

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Title Automated Data Preparation

Version 1.0.5

Description Do most of the painful data preparation for a data science project with a minimum amount of code; Take advantages of 'data.table' efficiency and use some algorithmic trick in order to perform data preparation in a time and RAM efficient way.

Depends R (>= 3.3.0), lubridate, stringr, Matrix, progress

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LazyData true

Encoding UTF-8

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Suggests testthat (>= 2.0.0)

Imports data.table

BugReports <https://github.com/ELToulemonde/dataPreparation/issues>

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Description

For examples and tutorials, and in order to build `messy_adult`, UCI adult data set is used.

Data Set Information:

Extraction was done by Barry Becker from the 1994 Census database. A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AFNL-WGT>1)&& (HRSWK>0))

Prediction task is to determine whether a person makes over 50K a year.

Usage

```
data("adult")
```

Format

A data.frame with 32561 rows and 15 variables.

References

<https://archive.ics.uci.edu/ml/datasets/adult>

aggregate_by_key	<i>Automatic data_set aggregation by key</i>
------------------	--

Description

Automatic aggregation of a `data_set` set according to a key.

Usage

```
aggregate_by_key(data_set, key, verbose = TRUE, thresh = 53, ...)
```

Arguments

<code>data_set</code>	Matrix, data.frame or data.table (with only numeric, integer, factor, logical, character columns)
<code>key</code>	Name of a column of <code>data_set</code> according to which the set should be aggregated (character)
<code>verbose</code>	Should the algorithm talk? (logical, default to TRUE)
<code>thresh</code>	Number of max values for frequencies count (numerical, default to 53)
<code>...</code>	Optional argument: functions: aggregation functions for numeric columns (vector of function names (character), optional, if not set we use: <code>c("mean", "min", "max", "sd")</code>)

Details

Perform aggregation depending on column type:

- If column is numeric functions are performed on the column. So 1 numeric column give length(functions) new columns,
- If column is character or factor and have less than thresh different values, frequency count of values is performed,
- If column is character or factor with more than thresh different values, number of different values for each key is performed,
- If column is logical, number of TRUE is computed.

In all cases, if the set as more rows than unique key, a number of lines will be computed.

Be careful using functions argument, given functions should be an aggregation function, meaning that for multiple values it should only return one value.

Value

A `data.table` with one line per key elements and multiple new columns.

Examples

```
## Not run:
# Get generic dataset from R
data("adult")

# Aggregate it using aggregate_by_key, in order to extract characteristics for each country
adult_aggregated <- aggregate_by_key(adult, key = 'country')

# Exmple with other functions
power <- function(x) {sum(x^2)}
adult_aggregated <- aggregate_by_key(adult, key = 'country', functions = c("power", "sqrt"))

# sqrt is not an aggregation function, so it wasn't used.

## End(Not run)
# "##NOT RUN:" mean that this example hasn't been run on CRAN since its long. But you can run it!
```

as.POSIXct_fast

Faster date transformation

Description

Based on the trick that often dates are repeated in a column, we make date transformation faster by computing date transformation only on uniques.

Usage

```
as.POSIXct_fast(x, ...)
```

Arguments

x An object to be converted
 ... other argument to pass to `as.POSIXct`

Details

The more

Value

`as.POSIXct` and `as.POSIXlt` return an object of the appropriate class. If `tz` was specified, `as.POSIXlt` will give an appropriate "tzone" attribute. Date-times known to be invalid will be returned as NA.

Examples

```
# Work the same as as.POSIXct
as.POSIXct_fast("2018-01-01", format="%Y-%m-%d")
```

<code>build_bins</code>	<i>Compute bins</i>
-------------------------	---------------------

Description

Compute bins for discretization of numeric variable (either `equal_width` or `equal_fred`).

Usage

```
build_bins(
  data_set,
  cols = "auto",
  n_bins = 10,
  type = "equal_width",
  verbose = TRUE
)
```

Arguments

`data_set` Matrix, `data.frame` or `data.table`
`cols` List of numeric column(s) name(s) of `data_set` to transform. To transform all characters, set it to "auto". (character, default to "auto")
`n_bins` Number of group to compute (numeric, default to 10)
`type` Type of discretization ("equal_width" or "equal_freq")
`verbose` Should the algorithm talk? (Logical, default to TRUE)

Details

Using equal freq first bin will start at `-Inf` and last bin will end at `+Inf`.

Value

A list where each element name is a column name of data set and each element contains bins to discretize this column.

Examples

```
# Load data
data(messy_adult)
head(messy_adult)

# Compute bins
bins <- build_bins(messy_adult, cols = "auto", n_bins = 5, type = "equal_freq")
print(bins)
```

build_date_factor	<i>Date Factor</i>
-------------------	--------------------

Description

Map a vector of dates to a factor at one of these levels "yearmonth", "yearquarter", "quarter", "month"

Usage

```
build_date_factor(data_set, type = "yearmonth")
```

Arguments

data_set	A vector of date values
type	One of "year", "yearquarter", "yearmonth", "quarter", "month"

Details

The resulting vector is an ordered factor of the specified type (e.g. yearmonth)

Examples

```
library(data.table)
data_set <- as.Date(c("2014-01-01", "2015-01-01", "2015-06-01"))
build_date_factor(data_set, type = "yearmonth")
build_date_factor(data_set, type = "yearquarter")
build_date_factor(data_set, type = "yearquarter")
```

build_encoding	<i>Compute encoding</i>
----------------	-------------------------

Description

Build a list of one hot encoding for each cols.

Usage

```
build_encoding(data_set, cols = "auto", verbose = TRUE, min_frequency = 0, ...)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of numeric column(s) name(s) of data_set to transform. To transform all characters, set it to "auto". (character, default to "auto")
verbose	Should the algorithm talk? (Logical, default to TRUE)
min_frequency	The minimal share of lines that a category should represent (numeric, between 0 and 1, default to 0)
...	Other arguments such as name_separator to separate words in new columns names (character, default to ".")

Details

To avoid creating really large sparse matrices, one can use param min_frequency to be sure that only most representative values will be used to create a new column (and not outliers or mistakes in data).

Setting min_frequency to something greater than 0 may cause the function to be slower (especially for large data_set).

Value

A list where each element name is a column name of data set and each element new_cols and values the new columns that will be built during encoding.

Examples

```
# Get a data set
data(adult)
encoding <- build_encoding(adult, cols = "auto", verbose = TRUE)

print(encoding)

# To limit the number of generated columns, one can use min_frequency parameter:
build_encoding(adult, cols = "auto", verbose = TRUE, min_frequency = 0.1)
# Set to 0.1, it will create columns only for values that are present 10% of the time.
```

build_scales	<i>Compute scales</i>
--------------	-----------------------

Description

Build a list of means and standard deviation for each cols.

Usage

```
build_scales(data_set, cols = "auto", verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of numeric column(s) name(s) of data_set to transform. To transform all characters, set it to "auto". (character, default to "auto")
verbose	Should the algorithm talk? (Logical, default to TRUE)

Value

A list where each element name is a column name of data set and each element contains means and sd.

Examples

```
# Get a data set
data(adult)
scales <- build_scales(adult, cols = "auto", verbose = TRUE)

print(scales)
```

build_target_encoding	<i>Build target encoding</i>
-----------------------	------------------------------

Description

Target encoding is the process of replacing a categorical value with the aggregation of the target variable. build_target_encoding is used to compute aggregations.

Usage

```
build_target_encoding(
  data_set,
  cols_to_encode,
  target_col,
  functions = "mean",
  verbose = TRUE
)
```


Arguments

data_set	Matrix, data.frame or data.table
cols_to_encode	columns to aggregate according to (list)
target_col	column to aggregate (character)
functions	functions of aggregation (list or character, default to "mean"). Functions compute_probability_ratio and compute_weight_of_evidence are classically used functions
verbose	Should the algorithm talk? (Logical, default to TRUE)

Value

A list of `data.table` a `data.table` for each `cols_to_encode` each `data.table` containing a line by unique value of column and `len(functions) + 1` columns.

Examples

```
# Build a data set
require(data.table)
data_set <- data.table(student = c("Marie", "Marie", "Pierre", "Louis", "Louis"),
                      grades = c(1, 1, 2, 3, 4))

# Perform target_encoding construction
build_target_encoding(data_set, cols_to_encode = "student", target_col = "grades",
                    functions = c("mean", "sum"))
```

```
compute_probability_ratio
```

Compute probability ratio

Description

Probability ratio is an aggregation function that can be used for `build_target_encoding`. Probability ratio is the $P(\text{most freq element}) / (1 - P(\text{most freq element}))$.

Usage

```
compute_probability_ratio(x)
```

Arguments

x A list of categorical elements

Details

To be more generic, the library compute $P(\text{most freq element})$ inplace of traditional formula $P(1)/P(0)$

Value

$P(\text{most freq element}) / (1 - P(\text{most freq element}))$

Examples

```
# Build example list
example_list <- c(1, 1, 1, 2, 2, 3)

# Compute probability ratio
compute_probability_ratio(example_list)
```

```
compute_weight_of_evidence
      Compute weight of evidence
```

Description

Weight of evidence is an aggregation function that can be used for `build_target_encoding`.
Weight of evidence is the $\ln(P(\text{most freq element}) / (1 - P(\text{most freq element})))$.

Usage

```
compute_weight_of_evidence(x)
```

Arguments

x A list of categorical elements

Details

To be more generic, the library compute `P(most freq element)` in place of traditional formula $\ln(P(1)/P(0))$

Value

Weight of evidence

Examples

```
# Build example list
example_list <- c(1, 1, 1, 2, 2, 3)

# Compute weight of evidence
compute_weight_of_evidence(example_list)
```

data_preparation_news *Show the NEWS file*

Description

Show the NEWS file of the dataPreparation package.

Usage

```
data_preparation_news()
```

date_format_unifier *Unify dates format*

Description

Unify every column in a date format to the same date format.

Usage

```
date_format_unifier(data_set, format = "Date")
```

Arguments

data_set	Matrix, data.frame or data.table
format	Desired target format: Date, POSIXct or POSIXlt, (character, default to Date)

Details

This function only handle Date, POSIXct and POSIXlt dates.
POSIXct format is a bit slower than Date but can keep hours-min.

Value

The same data_set set but with dates column with the desired format.

Examples

```
# build a data.table
require(data.table)
data_set <- data.table( column1 = as.Date("2016-01-01"), column2 = as.POSIXct("2017-01-01") )

# Use the function
data_set = date_format_unifier(data_set, format = "Date")

# Control result
sapply(data_set, class)
# return Date for both columns
```

description	<i>Describe data set</i>
-------------	--------------------------

Description

Generate extensive description of a data set.

Usage

```
description(data_set, level = 1, path_to_write = NULL, verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
level	Level of description (0: generic, 1: column by column) (numeric, default to 1)
path_to_write	Path where the report should be written (character, default to NULL)
verbose	Should the algorithm talk? (Logical, default to TRUE)

Examples

```
# Load exemple set
data(messy_adult)

# Describe it
description(messy_adult)
```

fast_discretization	<i>Discretization</i>
---------------------	-----------------------

Description

Discretization of numeric variable (either equal_width or equal_fred).

Usage

```
fast_discretization(data_set, bins = NULL, verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
bins	Result of funcion <code>build_bins</code> , (list, default to NULL). To perform the same discretization on train and test, it is recommended to compute <code>build_bins</code> before. If it is kept to NULL, <code>build_bins</code> will be called. bins could also be carefully hand written.
verbose	Should the algorithm talk? (Logical, default to TRUE)

Details

NAs will be putted in an NA category.

Value

Same dataset discretized by **reference**.

If you don't want to edit by reference please provide set `data_set = copy(data_set)`.

Examples

```
# Load data
data(messy_adult)
head(messy_adult)

# Compute bins
bins <- build_bins(messy_adult, cols = "auto", n_bins = 5, type = "equal_freq")

# Discretize
messy_adult <- fast_discretization(messy_adult, bins = bins)

# Control
head(messy_adult)

# Example with hand written bins
data("adult")
adult <- fast_discretization(adult, bins = list(age = c(0, 40, +Inf)))
print(table(adult$age))
```

fast_filter_variables *Filtering useless variables*

Description

Delete columns that are constant or in double in your `data_set` set.

Usage

```
fast_filter_variables(
  data_set,
  level = 3,
  keep_cols = NULL,
  verbose = TRUE,
  ...
)
```

Arguments

data_set	Matrix, data.frame or data.table
level	which columns do you want to filter (1 = constant, 2 = constant and doubles, 3 = constant doubles and bijections, 4 = constant doubles bijections and included)(numeric, default to 3)
keep_cols	List of columns not to drop (list of character, default to NULL)
verbose	Should the algorithm talk (logical or 1 or 2, default to TRUE)
...	optional parameters to be passed to the function when called from another function

Details

verbose can be set to 2 have full details from which functions, otherwise they don't log. (verbose = 1 is equivalent to verbose = TRUE).

Value

The same data_set but with fewer columns. Columns that are constant, in double, or bijection of another have been deleted.

Examples

```
# First let's build a data.frame with 3 columns: a constant column, and a column in double
df <- data.frame(col1 = 1, col2 = rnorm(1e6), col3 = sample(c(1, 2), 1e6, replace = TRUE))
df$col4 <- df$col2
df$col5[df$col3 == 1] = "a"
df$col5[df$col3 == 2] = "b" # Same info than in col1 but with a for 1 and b for 2
head(df)

# Let's filter columns:
df <- fast_filter_variables(df)
head(df)
```

fast_handle_na

Handle NA values

Description

Handle NAs values depending on the class of the column.

Usage

```
fast_handle_na(
  data_set,
  set_num = 0,
  set_logical = FALSE,
  set_char = "",
  verbose = TRUE
)
```

Arguments

data_set	Matrix, data.frame or data.table
set_num	NAs replacement for numeric column, (numeric or function, default to 0)
set_logical	NAs replacement for logical column, (logical or function, default to FALSE)
set_char	NAs replacement for character column, (character or function, default to "")
verbose	Should the algorithm talk (logical, default to TRUE)

Details

To preserve RAM this function edits data_set by **reference**. To keep object unchanged, please use [copy](#).

If you provide a function, it will be applied to the full column. So this function should handle NAs. For factor columns, it will add NA to list of values.

Value

data_set as a [data.table](#) with NAs replaced.

Examples

```
# Build a useful data_set set for example
require(data.table)
data_set <- data.table(numCol = c(1, 2, 3, NA),
                      charCol = c("", "a", NA, "c"),
                      booleanCol = c(TRUE, NA, FALSE, NA))

# To set NAs to 0, FALSE and "" (respectively for numeric, logical, character)
fast_handle_na(copy(data_set))

# In a numeric column to set NAs as "missing"
fast_handle_na(copy(data_set), set_char = "missing")

# In a numeric column, to set NAs to the minimum value of the column#'
fast_handle_na(copy(data_set), set_num = min) # Won't work because min(c(1, NA)) = NA so put back NA
fast_handle_na(copy(data_set), set_num = function(x)min(x,na.rm = TRUE)) # Now we handle NAs

# In a numeric column, to set NAs to the share of NAs values
rateNA <- function(x) {
  sum(is.na(x)) / length(x)
}
fast_handle_na(copy(data_set), set_num = rateNA)
```

fast_is_equal	<i>Fast checks of equality</i>
---------------	--------------------------------

Description

Performs quick check if two objects are equal.

Usage

```
fast_is_equal(object1, object2)
```

Arguments

object1	An element, a vector, a data.frame, a data.table
object2	An element, a vector, a data.frame, a data.table

Details

This function uses exponential search trick, so it is fast for very large vectors, data.frame and data.table. This function is also very robust; you can compare a lot of stuff without failing.

Value

Logical (TRUE or FALSE) if the two objects are equals.

Examples

```
# Test on a character
fast_is_equal("a", "a")
fast_is_equal("a", "b")

# Test on a vector
myVector <- rep(x = "a", 10000)
fast_is_equal(myVector, myVector)

# Test on a data.table
fast_is_equal(messy_adult, messy_adult)
```

fast_round	<i>Fast round</i>
------------	-------------------

Description

Fast round of numeric columns in a data.table. Will only round numeric, so don't worry about characters. Also, it computes it column by column so your RAM is safe too.

Usage

```
fast_round(data_set, cols = "auto", digits = 2, verbose = TRUE)
```

Arguments

data_set	matrix, data.frame or data.table
cols	List of numeric column(s) name(s) of data_set to transform. To transform all numerics columns, set it to "auto" (characters, default to "auto")
digits	The number of digits after comma (numeric, default to 2)
verbose	Should the algorithm talk? (logical, default to TRUE)

Details

It is performing round by **reference** on data_set, column by column, only on numerical columns. So that it avoid copying data_set in RAM.

Value

The same datasets but as a data.table and with numeric rounded.

Examples

```
# First let's build a very large data.table with random numbers
require(data.table)
M <- as.data.table(matrix(runif(3e4), ncol = 10))

M_rouded <- fast_round(M, 2)
# Lets add some character
M[, stringColumn := "a string"]

# And use our function
M_rouded <- fast_round(M, 2)
# It still work :) and you don't have to worry about the string.
```

fast_scale

scale

Description

Perform efficient scaling on a data set.

Usage

```
fast_scale(data_set, scales = NULL, way = "scale", verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
scales	Result of funcion build_scales , (list, default to NULL). To perform the same scaling on train and test, it is recommended to compute build_scales before. If it is kept to NULL, build_scales will be called.
way	should scaling or unscaling be performed? (character either "scale" or "unscale", default to "scale")
verbose	Should the algorithm talk? (Logical, default to TRUE)

Details

Scaling numeric values is usefull for some machine learning algorithm such as logistic regression or neural networks.

Unscaling numeric values can be very usefull for most post-model analysis to do so set way to "unscale".

This implementation of scale will be faster that [scale](#) for large data sets.

Value

data_set with columns scaled (or unscaled) by **reference**. Scaled means that each column mean will be 0 and each column standard deviation will be 1.

Examples

```
# Load data
data(adult)

# compute scales
scales <- build_scales(adult, cols = "auto", verbose = TRUE)

# Scale data set
adult <- fast_scale(adult, scales = scales, verbose = TRUE)

# Control
print(mean(adult$age)) # Almost 0
print(sd(adult$age)) # 1
```

```
# To unscale it:
adult <- fast_scale(adult, scales = scales, way = "unscale", verbose = TRUE)

# Control
print(mean(adult$age)) # About 38.6
print(sd(adult$age)) # About 13.6
```

find_and_transform_dates
Identify date columns

Description

Find and transform dates that are hidden in a character column.
It use a bunch of default formats, and you can also add your own formats.

Usage

```
find_and_transform_dates(  
  data_set,  
  cols = "auto",  
  formats = NULL,  
  n_test = 30,  
  ambiguities = "IGNORE",  
  verbose = TRUE  
)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of column(s) name(s) of data_set to look into. To check all all columns, set it to "auto". (characters, default to "auto")
formats	List of additional Date formats to check (see strptime)
n_test	Number of non-null rows on which to test (numeric, default to 30)
ambiguities	How ambiguities should be treated (see details in ambiguities section) (character, default to IGNORE)
verbose	Should the algorithm talk? (Logical, default to TRUE)

Details

This function is using [identify_dates](#) to find formats. Please see it's documentation. In case [identify_dates](#) doesn't find wanted formats you can either provide format in param formats or use [set_col_as_date](#) to force transformation.

Value

data_set set (as a data.table) with identified dates transformed by **reference**.

Ambiguity

Ambiguities are often present in dates. For example, in date: 2017/01/01, there is no way to know if format is YYYY/MM/DD or YYYY/DD/MM.

Some times ambiguity can be solved by a human. For example 17/12/31, a human might guess that it is YY/MM/DD, but there is no sure way to know.

To be safe, find_and_transform_dates doesn't try to guess ambiguities.

To answer ambiguities problem, param ambiguities is now available. It can take one of the following values

- IGNORE function will then take the first format which match (fast, but can make some mistakes)
- WARN function will try all format and tell you - via prints - that there are multiple matches (and won't perform date transformation)
- SOLVE function will try to solve ambiguity by going through more lines, so will be slower. If it is able to solve it, it will transform the column, if not it will print the various acceptable formats.

If there are some columns that have no chance to be a match think of removing them from cols to save some computation time.

Examples

```
# Load exemple set
data(messy_adult)
head(messy_adult)
# using the find_and_transform_dates
find_and_transform_dates(messy_adult, n_test = 5)
head(messy_adult)

# Example with ambiguities
## Not run:
require(data.table)
data(messy_adult) # reload data
# Add an ambiguity by sorting date1
messy_adult$date1 = sort(messy_adult$date1, na.last = TRUE)
# Try all three methods:
result_1 = find_and_transform_dates(copy(messy_adult))
result_2 = find_and_transform_dates(copy(messy_adult), ambiguities = "WARN")
result_3 = find_and_transform_dates(copy(messy_adult), ambiguities = "SOLVE")

## End(Not run)
# "##NOT RUN:" mean that this example hasn't been run on CRAN since its long. But you can run it!
```

```
find_and_transform_numerics
```

Identify numeric columns in a data_set set

Description

Function to find and transform characters that are in fact numeric.

Usage

```
find_and_transform_numerics(  
  data_set,  
  cols = "auto",  
  n_test = 30,  
  verbose = TRUE  
)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of column(s) name(s) of data_set to look into. To check all all columns, set it to "auto". (characters, default to "auto")
n_test	Number of non-null rows on which to test (numeric, default to 30)
verbose	Should the algorithm talk? (logical, default to TRUE)

Details

This function is looking for perfect transformation. If there are some mistakes in data_set, consider setting them to NA before.

If there are some columns that have no chance to be a match think of removing them from cols to save some computation time.

Value

The data_set set (as a data.table) with identified numeric transformed.

Warning

All these changes will happen **by reference**.

Examples

```
# Let's build a data_set set  
data_set <- data.frame(ID = seq_len(5),  
  col1 = c("1.2", "1.3", "1.2", "1", "6"),  
  col2 = c("1,2", "1,3", "1,2", "1", "6")  
)
```

```
# using the find_and_transform_numerics
find_and_transform_numerics(data_set, n_test = 5)
```

generate_date_diffs *Date difference*

Description

Perform the differences between all dates of the `data_set` set and optionally with a static date.

Usage

```
generate_date_diffs(
  data_set,
  cols = "auto",
  analysis_date = NULL,
  units = "years",
  drop = FALSE,
  verbose = TRUE,
  ...
)
```

Arguments

<code>data_set</code>	Matrix, <code>data.frame</code> or <code>data.table</code>
<code>cols</code>	List of date column(s) name(s) of <code>data_set</code> to compute difference on. To transform all dates, set it to "auto". (character, default to "auto")
<code>analysis_date</code>	Static date (Date or POSIXct, optional)
<code>units</code>	Unit of difference between two dates (string, default to 'years')
<code>drop</code>	Should <code>cols</code> be dropped after generation (logical, default to FALSE)
<code>verbose</code>	should the function log (logical, default to TRUE)
<code>...</code>	Other arguments such as <code>name_separator</code> to separate words in new column names (character, default to ".")

Details

`units` is the same as `difftime` units, but with one more possibility: years.

Value

`data_set` (as a `data.table`) with more columns. A numeric column has been added for every couple of Dates. The result is in years.

Examples

```
# First build a useful data_set set
require(data.table)
data_set <- data.table(ID = seq_len(100),
  date1 = seq(from = as.Date("2010-01-01"),
    to = as.Date("2015-01-01"),
    length.out = 100),
  date2 = seq(from = as.Date("1910-01-01"),
    to = as.Date("2000-01-01"),
    length.out = 100)
)

# Now let's compute
data_set <- generate_date_diffs(data_set, cols = "auto", analysis_date = as.Date("2016-11-14"))
```

```
generate_factor_from_date
```

Generate factor from dates

Description

Taking Date or POSIXct columns, and building factor columns from them.

Usage

```
generate_factor_from_date(
  data_set,
  cols = "auto",
  type = "yearmonth",
  drop = FALSE,
  verbose = TRUE,
  ...
)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of date column(s) name(s) of data_set to transform into factor. To transform all dates, set it to "auto". (characters, default to "auto")
type	"year", "yearquarter", "yearmonth", "quarter" or "month", way to aggregate a date, (character, default to "yearmonth")
drop	Should cols be dropped after generation (logical, default to FALSE)
verbose	Should the function log (logical, default to TRUE)
...	Other arguments such as name_separator to separate words in new columns names (character, default to ".")

Value

data_set with new columns. data_set is edited by **reference**.

Examples

```
# Load set, and find dates
data(messy_adult)
messy_adult <- find_and_transform_dates(messy_adult, verbose = FALSE)

# Generate new columns
# Generate year month columns
messy_adult <- generate_factor_from_date(messy_adult, cols = c("date1", "date2", "num1"))
head(messy_adult[, .(date1.yearmonth, date2.yearmonth)])

# Generate quarter columns
messy_adult <- generate_factor_from_date(messy_adult, cols = c("date1", "date2"), type = "quarter")
head(messy_adult[, .(date1.quarter, date2.quarter)])
```

generate_from_character

Recode character

Description

Recode character into 3 new columns:

- was the value not NA, "NA", "",
- how often this value occurs,
- the order of the value (ex: M/F => 2/1 because F comes before M in alphabet).

Usage

```
generate_from_character(
  data_set,
  cols = "auto",
  verbose = TRUE,
  drop = FALSE,
  ...
)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of character column(s) name(s) of data_set to transform. To transform all characters, set it to "auto". (character, default to "auto")

verbose	Should the function log (logical, default to TRUE)
drop	Should cols be dropped after generation (logical, default to FALSE)
...	Other arguments such as name_separator to separate words in new columns names (character, default to ".")

Value

data_set with new columns. data_set is edited by **reference**.

Examples

```
# Load data set
data(messy_adult)
messy_adult <- un_factor(messy_adult, verbose = FALSE) # un factor ugly factors

# transform column "mail"
messy_adult <- generate_from_character(messy_adult, cols = "mail")
head(messy_adult)

# To transform all characters columns:
messy_adult <- generate_from_character(messy_adult, cols = "auto")
```

generate_from_factor *Recode factor*

Description

Recode factors into 3 new columns:

- was the value not NA, "NA", "",
- how often this value occurs,
- the order of the value (ex: M/F => 2/1 because F comes before M in alphabet).

Usage

```
generate_from_factor(
  data_set,
  cols = "auto",
  verbose = TRUE,
  drop = FALSE,
  ...
)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	list of character column(s) name(s) of data_set to transform. To transform all factors, set it to "auto". (character, default to "auto")
verbose	Should the function log (logical, default to TRUE)
drop	Should cols be dropped after generation (logical, default to FALSE)
...	Other arguments such as name_separator to separate words in new columns names (character, default to ".")

Value

data_set with new columns. data_set is edited by **reference**.

Examples

```
# Load data set
data(messy_adult)

# transform column "type_employer"
messy_adult <- generate_from_factor(messy_adult, cols = "type_employer")
head(messy_adult)

# To transform all factor columns:
messy_adult <- generate_from_factor(messy_adult, cols = "auto")
```

get_most_frequent_element

Get most frequent element

Description

Provide most frequent element in a list, a data.frame or data.table column

Usage

```
get_most_frequent_element(x)
```

Arguments

x A list, data.frame or data.table column

Examples

```
# Build example list
example_list <- c(1, 1, 2, 3, 1, 4, 1)

# Compute most frequent element
get_most_frequent_element(example_list)
```

identify_dates	<i>Identify date columns</i>
----------------	------------------------------

Description

Function to identify dates columns and give there format. It use a bunch of default formats. But you can also add your own formats.

Usage

```
identify_dates(  
  data_set,  
  cols = "auto",  
  formats = NULL,  
  n_test = 30,  
  ambiguities = "IGNORE",  
  verbose = TRUE  
)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of column(s) name(s) of data_set to look into. To check all all columns, set it to "auto". (characters, default to "auto")
formats	List of additional Date formats to check (see strptime)
n_test	Number of non-null rows on which to test (numeric, default to 30)
ambiguities	How ambiguities should be treated (see details in ambiguities section) (character, default to IGNORE)
verbose	Should the algorithm talk? (Logical, default to TRUE)

Details

This function is looking for perfect transformation. If there are some mistakes in data_set, consider setting them to NA before.

In the unlikely case where you have numeric higher than `as.numeric(as.POSIXct("1990-01-01"))` they will be considered as timestamps and you might have some issues. On the other side, if you have timestamps before 1990-01-01, they won't be found, but you can use [set_col_as_date](#) to force transformation.

Value

A named list with names being col names of data_set and values being formats.

Ambiguity

Ambiguities are often present in dates. For example, in date: 2017/01/01, there is no way to know if format is YYYY/MM/DD or YYYY/DD/MM.

Some times ambiguity can be solved by a human. For example 17/12/31, a human might guess that it is YY/MM/DD, but there is no sure way to know.

To be safe, `find_and_transform_dates` doesn't try to guess ambiguities.

To answer ambiguities problem, param `ambiguities` is now available. It can take one of the following values

- IGNORE function will then take the first format which match (fast, but can make some mistakes)
- WARN function will try all format and tell you - via prints - that there are multiple matches (and won't perform date transformation)
- SOLVE function will try to solve ambiguity by going through more lines, so will be slower. If it is able to solve it, it will transform the column, if not it will print the various acceptable formats.

Examples

```
# Load exemple set
data(messy_adult)
head(messy_adult)
# using the find_and_transform_dates
identify_dates(messy_adult, n_test = 5)
```

`messy_adult`

Adult with some ugly columns added

Description

For examples and tutorials, `messy_adult` has been built using UCI `adult`.

Usage

```
data("messy_adult")
```

Format

A `data.table` with 32561 rows and 24 variables.

Details

We added 9 really ugly columns to the data set:

- 4 dates with various formats and time stamp, containing NAs
- 1 constant column
- 3 numeric with different decimal separator
- 1 email address

one_hot_encoder	<i>One hot encoder</i>
-----------------	------------------------

Description

Transform factor column into 0/1 columns with one column per values of the column.

Usage

```
one_hot_encoder(  
  data_set,  
  encoding = NULL,  
  type = "integer",  
  verbose = TRUE,  
  drop = FALSE  
)
```

Arguments

data_set	Matrix, data.frame or data.table
encoding	Result of funcion build_encoding , (list, default to NULL). To perform the same encoding on train and test, it is recommended to compute build_encoding before. If it is kept to NULL, build_encoding will be called.
type	What class of columns is expected? "integer" (0L/1L), "numeric" (0/1), or "logical" (TRUE/FALSE), (character, default to "integer")
verbose	Should the function log (logical, default to TRUE)
drop	Should cols be dropped after generation (logical, default to FALSE)

Details

If you don't want to edit your data set consider sending `copy(data_set)` as an input.
Please **be careful** using this function, it will generate as many columns as there different values in your column and might use a lot of RAM. To be safe, you can use parameter `min_frequency` in [build_encoding](#).

Value

data_set edited by **reference** with new columns.

Examples

```
data(messy_adult)  
  
# Compute encoding  
encoding <- build_encoding(messy_adult, cols = c("marital", "occupation"), verbose = TRUE)  
  
# Apply it
```

```

messy_adult <- one_hot_encoder(messy_adult, encoding = encoding, drop = TRUE)

# Apply same encoding to adult
data(adult)
adult <- one_hot_encoder(adult, encoding = encoding, drop = TRUE)

# To have encoding as logical (TRUE/FALSE), pass it in type argument
data(adult)
adult <- one_hot_encoder(adult, encoding = encoding, type = "logical", drop = TRUE)

```

```
prepare_set
```

```
Preparation pipeline
```

Description

Full pipeline for preparing your `data_set` set.

Usage

```
prepare_set(data_set, final_form = "data.table", verbose = TRUE, ...)
```

Arguments

<code>data_set</code>	Matrix, data.frame or data.table
<code>final_form</code>	"data.table" or "numerical_matrix" (default to data.table)
<code>verbose</code>	Should the algorithm talk? (logical, default to TRUE)
<code>...</code>	Additional parameters to tune pipeline (see details)

Details

Additional arguments are available to tune pipeline:

- `key` Name of a column of `data_set` according to which `data_set` should be aggregated (character)
- `analysis_date` A date at which the `data_set` should be aggregated (differences between every date and `analysis_date` will be computed) (Date)
- `n_unfactor` Number of max value in a facotr, set it to -1 to disable `un_factor` function. (numeric, default to 53)
- `digits` The number of digits after comma (optional, numeric, if set will perform `fast_round`)
- `dateFormats` List of format of Dates in `data_set` (list of characters)
- `name_separator` character to separate parts of new column names (character, default to ".")
- `functions` Aggregation functions for numeric columns, see `aggregate_by_key` (list of functions names (character))
- `factor_date_type` Aggregation level to factorize date (see `generate_factor_from_date`) (character, default to "yearmonth")
- `target_col` A target column to perform target encoding, see `target_encode` (character)
- `target_encoding_functions` Functions to perform target encoding, see `build_target_encoding`, if `target_col` is not given will not do anything, (list, default to "mean")

Value

A data.table or a numerical matrix (according to final_form).

It will perform the following steps:

- Correct set: unfactor factor with many values, id dates and numeric that are hidden in character
- Transform set: compute differences between every date, transform dates into factors, generate features from character..., if key is provided, will perform aggregate according to this key
- Filter set: filter constant, in double or bijection variables. If 'digits' is provided, will round numeric
- Handle NA: will perform [fast_handle_na](#))
- Shape set: will put the result in asked shape (final_form) with acceptable columns format.

Examples

```
# Load ugly set
## Not run:
data(messy_adult)

# Have a look to set
head(messy_adult)

# Compute full pipeline
clean_adult <- prepare_set(messy_adult)

# With a reference date
adult_agg <- prepare_set(messy_adult, analysis_date = as.Date("2017-01-01"))

# Add aggregation by country
adult_agg <- prepare_set(messy_adult, analysis_date = as.Date("2017-01-01"), key = "country")

# With some new aggregation functions
power <- function(x) {sum(x^2)}
adult_agg <- prepare_set(messy_adult, analysis_date = as.Date("2017-01-01"), key = "country",
                        functions = c("min", "max", "mean", "power"))

## End(Not run)
# "##NOT RUN:" mean that this example hasn't been run on CRAN since its long. But you can run it!
```

remove_percentile_outlier

Percentile outlier filtering

Description

Remove outliers based on percentiles.

Only values within nth and 100 - nth percentiles are kept.

Usage

```
remove_percentile_outlier(
  data_set,
  cols = "auto",
  percentile = 1,
  verbose = TRUE
)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of numeric column(s) name(s) of data_set to transform. To transform all numeric columns, set it to "auto". (character, default to "auto")
percentile	percentiles to filter (numeric, default to 1)
verbose	Should the algorithm talk? (logical, default to TRUE)

Details

Filtering is made column by column, meaning that extrem values from first element of cols are removed, then extrem values from second element of cols are removed, ...
So if filtering is performed on too many column, there is high risk that a lot of rows will be dropped.

Value

Same dataset with less rows, edited by **reference**.
If you don't want to edit by reference please provide set data_set = copy(data_set).

Examples

```
# Given
library(data.table)
data_set <- data.table(num_col = seq_len(100))

# When
data_set <- remove_percentile_outlier(data_set, cols = "auto", percentile = 1, verbose = TRUE)

# Then extrem value is no longer in set
1 %in% data_set[["num_col"]] # Is false
2 %in% data_set[["num_col"]] # Is true
```

```
remove_rare_categorical
```

Filter rare categoricals

Description

Filter rows that have a rare occurrences

Usage

```
remove_rare_categorical(  
  data_set,  
  cols = "auto",  
  threshold = 0.01,  
  verbose = TRUE  
)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of column(s) name(s) of data_set to transform. To transform all columns, set it to "auto". (character, default to "auto")
threshold	share of occurrences under which row should be removed (numeric, default to 0.01)
verbose	Should the algorithm talk? (logical, default to TRUE)

Details

Filtering is made column by column, meaning that extrem values from first element of cols are removed, then extrem values from second element of cols are removed, ...
So if filtering is performed on too many column, there is a high risk that a lot of rows will be dropped.

Value

Same dataset with less rows, edited by **reference**.
If you don't want to edit by reference please provide set data_set = copy(data_set).

Examples

```
# Given a set with rare "C"  
library(data.table)  
data_set <- data.table(cat_col = c(sample(c("A", "B"), 1000, replace=TRUE), "C"))  
  
# When calling function  
data_set <- remove_rare_categorical(data_set, cols = "cat_col",  
                                   threshold = 0.01, verbose = TRUE)  
  
# Then there are no "C"  
unique(data_set[["cat_col"]])
```

remove_sd_outlier *Standard deviation outlier filtering*

Description

Remove outliers based on standard deviation thresholds.
 Only values within $\text{mean} - \text{sd} * \text{n_sigmas}$ and $\text{mean} + \text{sd} * \text{n_sigmas}$ are kept.

Usage

```
remove_sd_outlier(data_set, cols = "auto", n_sigmas = 3, verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of numeric column(s) name(s) of data_set to transform. To transform all numeric columns, set it to "auto". (character, default to "auto")
n_sigmas	number of times standard deviation is accepted (interger, default to 3)
verbose	Should the algorithm talk? (logical, default to TRUE)

Details

Filtering is made column by column, meaning that extrem values from first element of cols are removed, then extrem values from second element of cols are removed, ...
 So if filtering is performed on too many column, there is a high risk that a lot of rows will be dropped.

Value

Same dataset with less rows, edited by **reference**.
 If you don't want to edit by reference please provide `set data_set = copy(data_set)`.

Examples

```
# Given
library(data.table)
col_vals <- runif(1000)
col_mean <- mean(col_vals)
col_sd <- sd(col_vals)
extrem_val <- col_mean + 6 * col_sd
data_set <- data.table(num_col = c(col_vals, extrem_val))

# When
data_set <- remove_sd_outlier(data_set, cols = "auto", n_sigmas = 3, verbose = TRUE)

# Then extrem value is no longer in set
extrem_val %in% data_set[["num_col"]] # Is false
```

same_shape	<i>Give same shape</i>
------------	------------------------

Description

Transform `data_set` into the same shape as `reference_set`. Especially this function will be useful to make your test set have the same shape as your train set.

Usage

```
same_shape(data_set, reference_set, verbose = TRUE)
```

Arguments

<code>data_set</code>	Matrix, data.frame or data.table to transform
<code>reference_set</code>	Matrix, data.frame or data.table
<code>verbose</code>	Should the algorithm talk? (logical, default to TRUE)

Details

This function will make sure that `data_set` and `reference_set`

- have the same class
- have exactly the same columns
- have columns with exactly the same class
- have factor factor with exactly the same levels

You should always use this function before applying your model on a new data set to make sure that everything will go smoothly. But if this function change a lot of stuff you should have a look to your preparation process, there might be something wrong.

Value

Return `data_set` transformed in order to make it have the same shape as `reference_set`

Examples

```
## Not run:  
# Build a train and a test  
data("messy_adult")  
data("adult")  
train <- messy_adult  
test <- adult # So test will have missing columns  
  
# Prepare them  
train <- prepare_set(train, verbose = FALSE, key = "country")  
test <- prepare_set(test, verbose = FALSE, key = "country")
```

```

# Give them the same shape
test <- same_shape(test, train)
# As one can see in log, a lot of small change had to be done.
# This is an extreme case but you get the idea.

## End(Not run)
# "##NOT RUN:" mean that this example hasn't been run on CRAN since its long. But you can run it!

```

set_as_numeric_matrix *Numeric matrix preparation for Machine Learning.*

Description

Prepare a numeric matrix from a data.table. This matrix is suitable for machine learning purposes, since factors are binarized. It may be sparsed, include an intercept, and drop a reference column for each factor if required (when using `lm()`, for instance)

Usage

```

set_as_numeric_matrix(
  data_set,
  intercept = FALSE,
  all_cols = FALSE,
  sparse = FALSE
)

```

Arguments

data_set	data.table
intercept	Should a constant column be added? (logical, default to FALSE)
all_cols	For each factor, should we create all possible dummies, or should we drop a reference dummy? (logical, default to FALSE)
sparse	Should the resulting matrix be of a (sparse) Matrix class? (logical, default to FALSE)

set_col_as_character *Set columns as character*

Description

Set as character a column (or a list of columns) from a data.table.

Usage

```

set_col_as_character(data_set, cols = "auto", verbose = TRUE)

```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of column(s) name(s) of data_set to transform into characters. To transform all columns, set it to "auto". (characters, default to "auto")
verbose	Should the function log (logical, default to TRUE)

Value

data_set (as a [data.table](#)), with specified columns set as character.

Examples

```
# Build a fake data.frame
data_set <- data.frame(numCol = c(1, 2, 3), factorCol = as.factor(c("a", "b", "c")))

# Set numCol and factorCol as character
data_set <- set_col_as_character(data_set, cols = c("numCol", "factorCol"))
```

set_col_as_date	<i>Set columns as POSIXct</i>
-----------------	-------------------------------

Description

Set as POSIXct a character column (or a list of columns) from a data.table.

Usage

```
set_col_as_date(data_set, cols = NULL, format = NULL, verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of column(s) name(s) of data_set to transform into dates
format	Date's format (function will be faster if the format is provided) (character or list of character, default to NULL). For timestamps, format need to be provided ("s" or "ms" or second or millisecond timestamps)
verbose	Should the function log (logical, default to TRUE)

Details

set_col_as_date is way faster when format is provided. If you want to identify dates and format automatically, have a look to [identify_dates](#).

If input column is a factor, it will be returned as a POSIXct column.

If cols is kept to default (NULL) set_col_as_date won't do anything.

Value

data_set (as a [data.table](#)), with specified columns set as Date. If the transformation generated only NA, the column is set back to its original value.

Examples

```
# Lets build a data_set set
data_set <- data.frame(ID = seq_len(5),
  date1 = c("2015-01-01", "2016-01-01", "2015-09-01", "2015-03-01", "2015-01-31"),
  date2 = c("2015_01_01", "2016_01_01", "2015_09_01", "2015_03_01", "2015_01_31")
)

# Using set_col_as_date for date2
data_transformed <- set_col_as_date(data_set, cols = "date2", format = "%Y_%m_%d")

# Control the results
lapply(data_transformed, class)

# With multiple formats:
data_transformed <- set_col_as_date(data_set, format = list(date1 = "%Y-%m-%d", date2 = "%Y_%m_%d"))
lapply(data_transformed, class)

# It also works with timestamps
data_set <- data.frame(time_stamp = c(1483225200, 1485990000, 1488495600))
set_col_as_date(data_set, cols = "time_stamp", format = "s")
```

set_col_as_factor	<i>Set columns as factor</i>
-------------------	------------------------------

Description

Set columns as factor and control number of unique element, to avoid having too large factors.

Usage

```
set_col_as_factor(data_set, cols = "auto", n_levels = 53, verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of column(s) name(s) of data_set to transform into factor. To transform all columns set it to "auto", (characters, default to auto).
n_levels	Max number of levels for factor (integer, default to 53) set it to -1 to disable control.
verbose	Should the function log (logical, default to TRUE)

Details

Control number of levels will help you to distinguish true categorical columns from just characters that should be handled in another way.

Value

data_set(as a [data.table](#)), with specified columns set as factor or logical.

Examples

```
# Load messy_adult
data("messy_adult")

# we wil change education
messy_adult <- set_col_as_factor(messy_adult, cols = "education")

sapply(messy_adult[, .(education)], class)
# education is now a factor
```

set_col_as_numeric *Set columns as numeric*

Description

Set as numeric a character column (or a list of columns) from a data.table.

Usage

```
set_col_as_numeric(data_set, cols, strip_string = FALSE, verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of column(s) name(s) of data_set to transform into numerics
strip_string	should I change "," to "." in the string? (logical, default to FALSE) If set to TRUE, computation will be a bit longer
verbose	Should the function log (logical, default to TRUE)

Value

data_set (as a [data.table](#)), with specified columns set as numeric.

Examples

```
# Build a fake data.table
data_set <- data.frame(charCol1 = c("1", "2", "3"),
  charCol2 = c("4", "5", "6"))

# Set charCol1 and charCol2 as numeric
data_set <- set_col_as_numeric(data_set, cols = c("charCol1", "charCol2"))

# Using strip string when spaces or wrong decimal separator is used
data_set <- data.frame(charCol1 = c("1", "2", "3"),
  charCol2 = c("4, 1", "5, 2", "6, 3"))

# Set charCol1 and charCol2 as numeric
set_col_as_numeric(data_set, cols = c("charCol1", "charCol2"))
# generate mistakes
set_col_as_numeric(data_set, cols = c("charCol1", "charCol2"), strip_string = TRUE)
# Doesn't generate any mistake (but is a bit slower)
```

 shape_set

Final preparation before ML algorithm

Description

Prepare a data.table by:

- transforming numeric variables into factors whenever they take less than thresh unique variables
- transforming characters using [generate_from_character](#)
- transforming logical into binary integers
- dropping constant columns
- Sending the data.table to [set_as_numeric_matrix](#) (when final_form == "numerical_matrix") will then allow you to get a numerical matrix usable by most Machine Learning Algorithms.

Usage

```
shape_set(data_set, final_form = "data.table", thresh = 10, verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
final_form	"data.table" or "numerical_matrix" (default to data.table)
thresh	Threshold such that a numerical column is transformed into a factor whenever its number of unique modalities is smaller or equal to thresh (numeric, default to 10)
verbose	Should the algorithm talk? (logical, default to TRUE)

Warning

All these changes will happen **by reference**.

target_encode	<i>Target encode</i>
---------------	----------------------

Description

Target encoding is the process of replacing a categorical value with the aggregation of the target variable. the target variable. `target_encode` is used to apply this transformations on a data set. Function `build_target_encoding` must be used first to compute aggregations.

Usage

```
target_encode(data_set, target_encoding, drop = FALSE, verbose = TRUE)
```

Arguments

<code>data_set</code>	Matrix, data.frame or data.table
<code>target_encoding</code>	result of function <code>build_target_encoding</code> (list)
<code>drop</code>	Should <code>col_to_encode</code> be dropped after generation (logical, default to FALSE)
<code>verbose</code>	Should the algorithm talk? (Logical, default to TRUE)

Value

`data_set` with new cols of `target_encoding` merged to `data_set` using `target_encoding` names as merging key. `data_set` is edited by **reference**.

Examples

```
# Build a data set
require(data.table)
data_set <- data.table(student = c("Marie", "Marie", "Pierre", "Louis", "Louis"),
                      grades = c(1, 1, 2, 3, 4))

# Construct encoding
target_encoding <- build_target_encoding(data_set, cols_to_encode = "student",
                                       target_col = "grades", functions = c("mean", "sum"))

# Apply them
target_encode(data_set, target_encoding = target_encoding)
```

un_factor	<i>Unfactor factor with too many values</i>
-----------	---

Description

To unfactorize all columns that have more than a given amount of various values. This function will be usefull after using some reading functions that put every string as factor.

Usage

```
un_factor(data_set, cols = "auto", n_unfactor = 53, verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
cols	List of column(s) name(s) of data_set to look into. To check all all columns, set it to "auto". (characters, default to "auto")
n_unfactor	Number of max element in a factor (numeric, default to 53)
verbose	Should the algorithm talk? (logical, default to TRUE)

Details

If a factor has (strictly) more than n_unfactor values it is unfactored.

It is recommended to use [find_and_transform_numerics](#) and [find_and_transform_dates](#) after this function.

If n_unfactor is set to -1, nothing will be performed.

If there are a lot of column that have been transformed, you might want to look at the documentation of your data reader in order to stop transforming everything into a factor.

Value

Same data_set (as a data.table) with less factor columns.

Examples

```
# Let's build a data_set
data_set <- data.frame(true_factor = factor(rep(c(1,2), 13)),
                      false_factor = factor(LETTERS))

# Let's un factorize all factor that have more than 5 different values
data_set <- un_factor(data_set, n_unfactor = 5)
sapply(data_set, class)
# Let's un factorize all factor that have more than 5 different values
data_set <- un_factor(data_set, n_unfactor = 0)
sapply(data_set, class)
```

which_are_bijection *Identify bijections*

Description

Find all the columns that are bijections of another column.

Usage

```
which_are_bijection(data_set, keep_cols = NULL, verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
keep_cols	List of columns not to drop (list of character, default to NULL)
verbose	Should the algorithm talk (logical, default to TRUE)

Details

Bijection, meaning that there is another column containing the exact same information (but maybe coded differently) for example col1: Men/Women, col2 M/W.

This function is performing search by looking to every couple of columns. It computes numbers of unique elements in each column, and number of unique tuples of values.

Computation is made by exponential search, so that the function is faster.

If verbose is TRUE, the column logged will be the one returned.

Ex: if column i and column j (with $j > i$) are bijections it will return j, except if j is a character then it return i.

Value

A list of index of columns that have an exact bijection in the data_set set.

Examples

```
# First let's get a data set
data("adult")

# Now let's check which columns are equals
which_are_in_double(adult)
# It doesn't give any result.

# Let's look of bijections
which_are_bijection(adult)
# Return education_num index because education_num and education which
# contain the same info
```

which_are_constant *Identify constant columns*

Description

Find all the columns that are constant.

Usage

```
which_are_constant(data_set, keep_cols = NULL, verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
keep_cols	List of columns not to drop (list of character, default to NULL)
verbose	Should the algorithm talk (logical, default to TRUE)

Details

Algorithm is performing exponential search: it check constancy on row 1 to 10, if it's not constant it stops, if it's constant then on 11 to 100 ...

If you have a lot of columns than aren't constant, this function is way faster than a simple `length(unique())!`
The larger the data_set set is, the more interesting it is to use this function.

Value

List of column's indexes that are constant in the data_set set.

Examples

```
# Let's load our data_set
data("messy_adult")

# Let's try our function
which_are_constant(messy_adult)
# Indeed it return constant the name of the constant column.
```

which_are_included	<i>Identify columns that are included in others</i>
--------------------	---

Description

Find all the columns that don't contain more information than another column. For example if you have a column with an amount and another with the same amount but rounded, the second column is included in the first.

Usage

```
which_are_included(data_set, keep_cols = NULL, verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
keep_cols	List of columns not to drop (list of character, default to NULL)
verbose	Should the algorithm talk (logical, default to TRUE)

Details

This function is performing exponential search and is looking to every couple of columns. Be very careful while using this function:

- if there is an id column, it will say everything is included in the id column;
- the order of columns will influence the result.

For example if you have a column with an amount and another with the same amount but rounded, the second column is included in the first.

And last but not least, with some machine learning algorithm it's not always smart to drop columns even if they don't give more info: the extreme example is the id example.

Value

A list of index of columns that have an exact duplicate in the data_set.

Examples

```
# Load toy data set
require(data.table)
data(messy_adult)

# Reduce set size to save time (you can run it on full set)
messy_adult = messy_adult[seq_len(100), ]

# Check for included columns
which_are_included(messy_adult)
```

```
# Return columns that are also constant, double and bijection
# Let's add a truly just included column
messy_adult$are500rMore <- messy_adult$age > 50
which_are_included(messy_adult[, .(age, are500rMore)])

# As one can, see this column that doesn't have additional info than age is spotted.

# But you should be careful, if there is a column id, every column will be dropped:
messy_adult$id = seq_len(nrow(messy_adult)) # build id
which_are_included(messy_adult)
```

which_are_in_double *Identify double columns*

Description

Find all the columns that are in double.

Usage

```
which_are_in_double(data_set, keep_cols = NULL, verbose = TRUE)
```

Arguments

data_set	Matrix, data.frame or data.table
keep_cols	List of columns not to drop (list of character, default to NULL)
verbose	Should the algorithm talk (logical, default to TRUE)

Details

This function is performing search by looking to every couple of columns. First it compares the first 10 lines of both columns. If they are not equal then the columns aren't identical, else it compares lines 11 to 100; then 101 to 1000... So this function is fast with data_set set with a large number of lines and a lot of columns that aren't equals.

If verbose is TRUE, the column logged will be the one returned.

Value

A list of index of columns that have an exact duplicate in the data_set set. Ex: if column i and column j (with j > i) are equal it will return j.

Examples

```
# First let's build a matrix with 3 columns and a lot of lines, with 1's everywhere
M <- matrix(1, nrow = 1e6, ncol = 3)

# Now let's check which columns are equals
which_are_in_double(M)
```

```
# It return 2 and 3: you should only keep column 1.

# Let's change the column 2, line 1 to 0. And check again
M[1, 2] <- 0
which_are_in_double(M)
# It only returns 3

# What about NA? NA vs not NA => not equal
M[1, 2] <- NA
which_are_in_double(M)
# It only returns 3

# What about NA? Na vs NA => yep it's the same
M[1, 1] <- NA
which_are_in_double(M)
# It only returns 2
```

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