Package ‘dataPreparation’

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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.
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adult

Adult for UCI repository

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

Automatic data_set aggregation by key

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

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

Arguments
data_set: Matrix, data.frame or data.table (with only numeric, integer, factor, logical, character columns)
key: Name of a column of data_set according to which the set should be aggregated (character)
verbose: Should the algorithm talk? (logical, default to TRUE)
thresh: Number of max values for frequencies count (numerical, default to 53)
aggregate_by_key

... Optional argument: functions: aggregation functions for numeric columns (vector of function names (character), optional, if not set we use: c("mean", "min", "max", "sd"))

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

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

data("adult")

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

# Example 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

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")

build_bins

Compute bins

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(tiny_messy_adult)
head(tiny_messy_adult)

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

build_date_factor  Date Factor

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**

```r
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")
```

---

### Description

Build a list of one hot encoding for each `cols`.

### Usage

```r
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 out-layers 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

```r
# 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**

*Compute scales*

**Description**

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

**Usage**

```r
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**

```r
# Get a data set
data(adult)
scales <- build_scales(adult, cols = "auto", verbose = TRUE)
print(scales)
```
**build_target_encoding**  
*Build target encoding*

---

**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**

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

```r
# 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 \( \frac{P(\text{most freq element})}{1 - P(\text{most freq element})} \).

**Usage**

\[
\text{compute\_probability\_ratio}(x)
\]

**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**

```r
# Build example list
eexample_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**

\[
\text{compute\_weight\_of\_evidence}(x)
\]

**Examples**

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

# Compute weight of evidence
compute_weight_of_evidence(example_list)
```
Arguments
   x    A list of categorical elements

Details
   To be more generic, the library compute \( P(\text{most freq element}) \) inplace 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)

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

Describe data set

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(tiny_messy_adult)

# Describe it
description(tiny_messy_adult)
Discretization

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 function build_bins, (list, default to NULL).
To perform the same discretization on train and test, it is recommended to compute build_bins before. If it is kept to NULL, build_bins 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(tiny_messy_adult)
head(tiny_messy_adult)

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

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

# Control
head(tiny_messy_adult)

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

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

Usage

```r
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

```r
# First let's build a data.frame with 3 columns: a constant column, and a column in double
## Not run:
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:
def <- fast_filter_variables(df)
head(df)

### End(Not run)
# Don't run for CRAN, you can run example

---

**fast_handle_na**  
*Handle NA values*

## Description

Handle NAs values depending on the class of the column.

## Usage

```r
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 Fast checks of equality

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(tiny_messy_adult, messy_adult)

---

fast_round Fast round

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

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

# And use our function
M_rounded <- 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**

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

**Arguments**

- `data_set`: Matrix, data.frame or data.table
- `scales`: Result of function `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 useful for some machine learning algorithm such as logistic regression or neural networks.
Unscaling numeric values can be very useful for most post-model analysis to do so set way to "unscale".
This implementation of scale will be faster than `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

```r
# 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 uses a bunch of default formats, and you can also add your own formats.

**Usage**

```r
find_and_transform_dates(
  data_set,  # Matrix, data.frame or data.table
  cols = "auto",  # 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 = NULL,  # List of additional Date formats to check (see strftime)
  n_test = 30,    # (integer, default to 30)
  ambiguities = "IGNORE",  # (character, default to "IGNORE")
  verbose = TRUE  # (logical, default to 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 strftime)
find_and_transform_dates

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 its 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(tiny_messy_adult)
head(tiny_messy_adult)
# using the find_and_transform_dates
find_and_transform_dates(tiny_messy_adult, n_test = 5)
head(tiny_messy_adult)

# Example with ambiguities
## Not run:
require(data.table)
data(tiny_messy_adult) # reload data
# Add an ambiguity by sorting date1
tiny_messy_adult$date1 = sort(tiny_messy_adult$date1, na.last = TRUE)
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", "1", "1", "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

data_set  
Matrix, data.frame or data.table

cols  
List of date column(s) name(s) of data_set to commute difference on. To transform all dates, set it to "auto". (character, default to "auto")

analysis_date  
Static date (Date or POSIXct, optional)

units  
Unit of difference between too dates (string, default to 'years')

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 ".")

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)
generate_from_character

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(tiny_messy_adult)
tiny_messy_adult <- find_and_transform_dates(tiny_messy_adult, verbose = FALSE)

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

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

generate_from_character

Rcode 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, 
... 
)
generate_from_factor

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(tiny_messy_adult)
tiny_messy_adult <- un_factor(tiny_messy_adult, verbose = FALSE) # un factor ugly factors

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

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

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,
  ...
)
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

Value

The most frequent element
Examples

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

# Compute most frequent element
get_most_frequent_element(example_list)

identify_dates

### Identify date columns

**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**

```r
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

```r
# Load exemple set
data(tiny_messy_adult)
head(tiny_messy_adult)
# using the find_and_transform_dates
identify_dates(tiny_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(tiny_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

Description

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

Usage

```r
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 function `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

```r
data(tiny_messy_adult)

# Compute encoding
encoding <- build_encoding(tiny_messy_adult, cols = c("marital", "occupation"), verbose = TRUE)

# Apply it
tiny_messy_adult <- one_hot_encoder(tiny_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**

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

**Arguments**

- `data_set` Matrix, data.frame or data.table
- `final_form` "data.table" or "numerical_matrix" (default to data.table)
- `verbose` Should the algorithm talk? (logical, default to TRUE)
- `...` 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 factor, 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`)
prepare_set

- **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**

```r
# Load ugly set
## Not run:
data(tiny_messy_adult)

# Have a look to set
head(tiny_messy_adult)

# Compute full pipeline
clean_adult <- prepare_set(tiny_messy_adult)

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

# Add aggregation by country
adult_agg <- prepare_set(tiny_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(tiny_messy_adult, analysis_date = as.Date("2017-01-01"), key = "country", functions = c("min", "max", "mean", "power"))

## End(Not run)
```

## 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 n-th and 100 - n-th 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 extreme values from first element of cols are removed, then extreme values from second element of cols are removed, ...
So if filtering is performed on too many column, there ia 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 extreme value is no longer in set
remove_rare_categorical

Filter rare categories

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 extreme values from first element of cols are removed, then extreme 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
remove_sd_outlier

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 mean - sd * n_sigmas and mean + sd * 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 (integer, default to 3)
verbose  Should the algorithm talk? (logical, default to TRUE)

Details

Filtering is made column by column, meaning that extreme values from first element of cols are removed, then extreme values from second element of cols are removed, ...
So if filtering is performed on too many column, there ia 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)
extreme_val <- col_mean + 6 * col_sd
data_set <- data.table(num_col = c(col_vals, extreme_val))

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

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

---

**same_shape**

Give same shape

---

**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**

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

**Arguments**

- `data_set`: Matrix, data.frame or data.table to transform
- `reference_set`: Matrix, data.frame or data.table
- `verbose`: 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

```r
## Not run:
# Build a train and a test
data(tiny_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**  

### Description

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

### Usage

```r
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

Set columns as POSIXct

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)
set_col_as_date

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

```r
# 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**

**Set columns as factor**

**Description**

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

**Usage**

```r
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**

```r
# Load messy_adult
data(tiny_messy_adult)

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

sapply(tiny_messy_adult[, .(education)], class)
# education is now a factor
```
Description
Set columns as numeric

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\n")

# 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**

```r
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**

*Target encode*

**Description**

Target encoding is the process of replacing a categorical value with the aggregation of 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**

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

data_set: Matrix, data.frame or data.table

target_encoding: result of function `build_target_encoding` (list)

drop: Should col_to_encode be dropped after generation (logical, default to FALSE)

verbose: 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

```r
# 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)
```

tiny_messy_adult  
*First 500 rows of messy_adult*

Description

First 500 rows of `messy_adult`

Usage

data(tiny_messy_adult)

Format

A data.table with 500 rows and 24 variables.
Description

To un-factorize all columns that have more than a given amount of various values. This function will be usefully 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 un-factored.
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, expect 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 identifies 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(tiny_messy_adult)

# Let's try our function
which_are_constant(tiny_messy_adult)
# Indeed it return constant the name of the constant column.
which_are_included  Identify columns that are included in others

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(tiny_messy_adult)

# Check for included columns
which_are_included(tiny_messy_adult)

# Return columns that are also constant, double and bijection
# Let's add a truly just included column
tiny_messy_adult$are50OrMore <- tiny_messy_adult$age > 50
which_are_in_double(tiny_messy_adult[, .(age, are50OrMore)])

# 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:
tiny_messy_adult$id = seq_len(nrow(tiny_messy_adult)) # build id
which_are_included(tiny_messy_adult)

---

which_are_in_double  Identify double columns

### Description

Find all the columns that are in double.

### Usage

```r
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

```r
# 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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