# Package 'miceFast'

July 22, 2025

Title Fast Imputations Using 'Rcpp' and 'Armadillo'

Version 0.8.5

**Description** Fast imputations under the object-oriented programming paradigm.

Moreover there are offered a few functions built to work with popular R packages such as 'data.table' or 'dplyr'.

The biggest improvement in time performance could be achieve for a calculation where a grouping variable have to be used.

A single evaluation of a quantitative model for the multiple imputations is another major enhancement.

A new major improvement is one of the fastest predictive mean matching in the R world because of presorting and binary search.

**Depends** R (>= 3.6.0)

**License** GPL (>= 2)

URL https://github.com/Polkas/miceFast

BugReports https://github.com/Polkas/miceFast/issues

**Encoding UTF-8** 

Imports methods, Rcpp (>= 0.12.12), data.table

**Suggests** knitr, rmarkdown, pacman, testthat, mice, magrittr, ggplot2, UpSetR, dplyr

VignetteBuilder knitr

LinkingTo Rcpp, RcppArmadillo

RcppModules miceFast, corrData

NeedsCompilation yes

LazyData true

RoxygenNote 7.3.2

Author Maciej Nasinski [aut, cre]

Maintainer Maciej Nasinski <nasinski.maciej@gmail.com>

Repository CRAN

**Date/Publication** 2025-02-03 22:20:02 UTC

2 miceFast-package

# **Contents**

miceFast-package	
air_miss	3
compare_imp	4
fill_NA	5
fill_NA_N	11
naive_fill_NA	17
neibo	18
Rcpp_corrData-class	19
Rcpp_miceFast-class	19
upset_NA	21
VIF	22
	<b>2</b> 4
Fast-package miceFast package for fast multiple imputations.	
	air_miss compare_imp fill_NA fill_NA_N naive_fill_NA neibo Rcpp_corrData-class Rcpp_miceFast-class upset_NA VIF

## **Description**

Fast imputations under the object-oriented programming paradigm. There was used quantitative models with a closed-form solution. Thus package is based on linear algebra operations. The biggest improvement in time performance could be achieve for a calculation where a grouping variable have to be used. A single evaluation of a quantitative model for the multiple imputations is another major enhancement. Moreover there are offered a few functions built to work with popular R packages such as 'data.table'.

## **Details**

Please read the vignette for additional information

# Author(s)

Maciej Nasinski

#### References

https://github.com/Polkas/miceFast

air\_miss 3

air\_miss

airquality dataset with additional variables

# Description

airquality dataset with additional variables

#### Usage

air\_miss

#### **Format**

A data frame and data table with 154 observations on 11 variables.

Ozone numeric Ozone (ppb) - Mean ozone in parts per billion from 1300 to 1500 hours at Roosevelt Island

**Solar.R** numeric Solar R (lang) - Solar radiation in Langleys in the frequency band 4000–7700 Angstroms from 0800 to 1200 hours at Central Park

Wind numeric Wind (mph) - Average wind speed in miles per hour at 0700 and 1000 hours at LaGuardia Airport

**Temp** numeric Temperature (degrees F) - Maximum daily temperature in degrees Fahrenheit at La Guardia Airport.

**Day** numeric Day of month (1–31)

Intercept numeric a constant

index numeric id

weights numeric positive values weights

**groups** factor Month (1–12)

x\_character character discrete version of Solar.R (5-levels)

Ozone\_chac character discrete version of Ozone (7-levels)

Ozone\_f factor discrete version of Ozone (7-levels)

Ozone\_high logical Ozone higher than its mean

#### **Details**

Daily readings of the following air quality values for May 1, 1973 (a Tuesday) to September 30, 1973.

#### Source

The data were obtained from the New York State Department of Conservation (ozone data) and the National Weather Service (meteorological data).

4 compare\_imp

#### References

Chambers, J. M., Cleveland, W. S., Kleiner, B. and Tukey, P. A. (1983) Graphical Methods for Data Analysis. Belmont, CA: Wadsworth.

## **Examples**

```
## Not run:
library(data.table)
data(airquality)
data <- cbind(as.matrix(airquality[, -5]),</pre>
 Intercept = 1, index = 1:nrow(airquality),
 # a numeric vector - positive values
 weights = rnorm(nrow(airquality), 1, 0.01),
 # months as groups
 groups = airquality[, 5]
# data.table
air_miss <- data.table(data)</pre>
air_miss$groups <- factor(air_miss$groups)</pre>
# Distribution of Ozone - close to log-normal
# hist(air_miss$0zone)
# Additional vars
# Make a character variable to show package capabilities
air_miss$x_character <- as.character(cut(air_miss$Solar.R, seq(0, 350, 70)))</pre>
# Discrete version of dependent variable
air_miss$0zone_chac <- as.character(cut(air_miss$0zone, seq(0, 160, 20)))</pre>
air_miss$0zone_f <- cut(air_miss$0zone, seq(0, 160, 20))</pre>
air_miss$0zone_high <- air_miss$0zone > mean(air_miss$0zone, na.rm = T)
## End(Not run)
```

compare\_imp

Comparing imputations and original data distributions

#### **Description**

ggplot2 visualization to support which imputation method to choose

#### Usage

```
compare_imp(df, origin, target)
```

## **Arguments**

df data.frame with origin variable and the new one with imputations
origin character value - the name of origin variable with values before any imputations
target character vector - names of variables with applied imputations

#### Value

ggplot2 object

#### **Examples**

```
library(miceFast)
library(ggplot2)
data(air_miss)
air_miss$Ozone_imp <- fill_NA(
  x = air_miss,
  model = "lm_bayes",
  posit_y = 1,
  posit_x = c(4, 6),
  logreg = TRUE
)
air_miss$Ozone_imp2 <- fill_NA_N(</pre>
  x = air_miss,
  model = "pmm",
 posit_y = 1,
  posit_x = c(4, 6),
  logreg = TRUE
)
compare_imp(air_miss, origin = "Ozone", "Ozone_imp")
compare_imp(air_miss, origin = "Ozone", c("Ozone_imp", "Ozone_imp2"))
```

fill\_NA

fill\_NA function for the imputations purpose.

#### **Description**

Regular imputations to fill the missing data. Non missing independent variables are used to approximate a missing observations for a dependent variable. Quantitative models were built under Rcpp packages and the C++ library Armadillo.

#### Usage

```
fill_NA(x, model, posit_y, posit_x, w = NULL, logreg = FALSE, ridge = 1e-06)
## S3 method for class 'data.frame'
fill_NA(x, model, posit_y, posit_x, w = NULL, logreg = FALSE, ridge = 1e-06)
```

```
## S3 method for class 'data.table'
fill_NA(x, model, posit_y, posit_x, w = NULL, logreg = FALSE, ridge = 1e-06)
## S3 method for class 'matrix'
fill_NA(x, model, posit_y, posit_x, w = NULL, logreg = FALSE, ridge = 1e-06)
```

## Arguments

Х	a numeric matrix or data.frame/data.table (factor/character/numeric/logical) - variables
model	a character - posibble options ("lda","lm_pred","lm_bayes","lm_noise")
posit_y	an integer/character - a position/name of dependent variable
posit_x	an integer/character vector - positions/names of independent variables
W	a numeric vector - a weighting variable - only positive values, Default:NULL
logreg	a boolean - if dependent variable has log-normal distribution (numeric). If TRUE log-regression is evaluated and then returned exponential of results., Default: FALSE
ridge	a numeric - a value added to diagonal elements of the x'x matrix, Default:1e-5

#### Value

load imputations in a numeric/logical/character/factor (similar to the input type) vector format

# Methods (by class)

fill\_NA(data.frame): S3 method for data.frame
fill\_NA(data.table): s3 method for data.table
fill\_NA(matrix): S3 method for matrix

#### Note

There is assumed that users add the intercept by their own. The miceFast module provides the most efficient environment, the second recommended option is to use data.table and the numeric matrix data type. The lda model is assessed only if there are more than 15 complete observations and for the lms models if number of independent variables is smaller than number of observations.

#### See Also

```
fill_NA_N VIF
```

```
library(miceFast)
library(dplyr)
library(data.table)
### Data
# airquality dataset with additional variables
```

```
data(air_miss)
### Intro: dplyr
# IMPUTATIONS
air_miss <- air_miss %>%
 # Imputations with a grouping option (models are separately assessed for each group)
 # taking into account provided weights
 group_by(groups) %>%
 do(mutate(., Solar_R_imp = fill_NA(
   x = .,
   model = "lm_pred",
   posit_y = "Solar.R",
   posit_x = c("Wind", "Temp", "Intercept"),
   w = .[["weights"]]
 ))) %>%
 ungroup() %>%
 # Imputations - discrete variable
 mutate(x_character_imp = fill_NA(
   x = .,
   model = "lda",
   posit_y = "x_character",
   posit_x = c("Wind", "Temp")
 )) %>%
 # logreg was used because almost log-normal distribution of Ozone
 # imputations around mean
 mutate(Ozone_imp1 = fill_NA(
   x = .,
   model = "lm_bayes",
   posit_y = "Ozone",
   posit_x = c("Intercept"),
   logreg = TRUE
 )) %>%
 # imputations using positions - Intercept, Temp
 mutate(Ozone_imp2 = fill_NA(
   x = .,
   model = "lm_bayes",
   posit_y = 1,
   posit_x = c(4, 6),
   logreg = TRUE
 )) %>%
 # multiple imputations (average of x30 imputations)
 # with a factor independent variable, weights and logreg options
 mutate(Ozone_imp3 = fill_NA_N(
   x = .,
   model = "lm_noise",
   posit_y = "Ozone",
   posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
   w = .[["weights"]],
   logreg = TRUE,
   k = 30
 )) %>%
 mutate(Ozone_imp4 = fill_NA_N(
   x = .,
   model = "lm_bayes",
```

```
posit_y = "Ozone",
   posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
   w = .[["weights"]],
   logreg = TRUE,
   k = 30
 )) %>%
 group_by(groups) %>%
 do(mutate(., Ozone_imp5 = fill_NA(
   x = .,
   model = "lm_pred",
   posit_y = "Ozone",
   posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
   w = .[["weights"]],
   logreg = TRUE
 ))) %>%
 do(mutate(., Ozone_imp6 = fill_NA_N(
   x = .,
   model = "pmm",
   posit_y = "Ozone",
   posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
   w = .[["weights"]],
   logreg = TRUE,
   k = 20
 ))) %>%
 ungroup() %>%
 # Average of a few methods
 mutate(Ozone_imp_mix = rowMeans(select(., starts_with("Ozone_imp")))) %>%
 # Protecting against collinearity or low number of observations - across small groups
 # Be carful when using a grouping option
 \# because of lack of protection against collinearity or low number of observations.
 # There could be used a tryCatch(fill_NA(...),error=function(e) return(...))
 group_by(groups) %>%
 do(mutate(., Ozone_chac_imp = tryCatch(
   fill_NA(
     x = .,
     model = "lda",
     posit_y = "Ozone_chac",
     posit_x = c(
        "Intercept",
        "Month",
       "Day",
       "Temp",
        "x_character_imp"
     ),
     w = .[["weights"]]
   ),
   error = function(e) .[["Ozone_chac"]]
 ))) %>%
 ungroup()
# Sample of results
air_miss[which(is.na(air_miss[, 1]))[1:5], ]
```

```
### Intro: data.table
# IMPUTATIONS
# Imputations with a grouping option (models are separately assessed for each group)
# taking into account provided weights
data(air_miss)
setDT(air_miss)
air_miss[, Solar_R_imp := fill_NA_N(
 x = .SD,
 model = "lm_bayes",
 posit_y = "Solar.R";
 posit_x = c("Wind", "Temp", "Intercept"),
 w = .SD[["weights"]],
 k = 100
), by = .(groups)] %>%
 # Imputations - discrete variable
  .[, x_character_imp := fill_NA(
   x = .SD,
   model = "lda",
   posit_y = "x_character",
   posit_x = c("Wind", "Temp", "groups")
 )] %>%
 # logreg was used because almost log-normal distribution of Ozone
 # imputations around mean
  .[, Ozone_imp1 := fill_NA(
   x = .SD,
   model = "lm_bayes",
   posit_y = "Ozone",
   posit_x = c("Intercept"),
   logreg = TRUE
 )] %>%
 # imputations using positions - Intercept, Temp
  .[, Ozone_imp2 := fill_NA(
   x = .SD,
   model = "lm_bayes",
   posit_y = 1,
   posit_x = c(4, 6),
   logreg = TRUE
 )] %>%
 # model with a factor independent variable
 # multiple imputations (average of x30 imputations)
 # with a factor independent variable, weights and logreg options
  .[, Ozone_imp3 := fill_NA_N(
   x = .SD,
   model = "lm_noise",
   posit_y = "Ozone",
   posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
   w = .SD[["weights"]],
   logreg = TRUE,
   k = 30
 )] %>%
  .[, Ozone_imp4 := fill_NA_N(
   x = .SD,
   model = "lm_bayes",
```

```
posit_y = "Ozone",
   posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
   w = .SD[["weights"]],
   logreg = TRUE,
   k = 30
 )] %>%
  .[, Ozone_imp5 := fill_NA(
   x = .SD,
   model = "lm_pred",
   posit_y = "Ozone",
   posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
   w = .SD[["weights"]],
   logreg = TRUE
 ), .(groups)] %>%
  .[, Ozone_imp6 := fill_NA_N(
   x = .SD,
   model = "pmm",
   posit_y = "Ozone",
   posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
   w = .SD[["weights"]],
   logreg = TRUE,
   k = 10
 ), .(groups)] %>%
 # Average of a few methods
  .[, Ozone_imp_mix := apply(.SD, 1, mean), .SDcols = Ozone_imp1:Ozone_imp6] %>%
 # Protecting against collinearity or low number of observations - across small groups
 # Be carful when using a data.table grouping option
 # because of lack of protection against collinearity or low number of observations.
 # There could be used a tryCatch(fill_NA(...),error=function(e) return(...))
  .[, Ozone_chac_imp := tryCatch(
   fill_NA(
     x = .SD,
     model = "lda",
     posit_y = "Ozone_chac",
     posit_x = c(
        "Intercept",
        "Month",
        "Day",
       "Temp",
        "x_character_imp"
     ),
     w = .SD[["weights"]]
   ),
   error = function(e) .SD[["Ozone_chac"]]
 ), .(groups)]
# Sample of results
air_miss[which(is.na(air_miss[, 1]))[1:5], ]
```

 $fill_NA_N$ 

fill\_NA\_N function for the multiple imputations purpose

#### **Description**

Multiple imputations to fill the missing data. Non missing independent variables are used to approximate a missing observations for a dependent variable. Quantitative models were built under Rcpp packages and the C++ library Armadillo.

# Usage

```
fill_NA_N(
  х,
 model,
 posit_y,
 posit_x,
 w = NULL,
  logreg = FALSE,
 k = 10,
 ridge = 1e-06
)
## S3 method for class 'data.frame'
fill_NA_N(
  Х,
 model,
  posit_y,
  posit_x,
  w = NULL,
  logreg = FALSE,
  k = 10,
  ridge = 1e-06
)
## S3 method for class 'data.table'
fill_NA_N(
  х,
 model,
  posit_y,
  posit_x,
 w = NULL,
  logreg = FALSE,
  k = 10,
  ridge = 1e-06
)
## S3 method for class 'matrix'
```

```
fill_NA_N(
    x,
    model,
    posit_y,
    posit_x,
    w = NULL,
    logreg = FALSE,
    k = 10,
    ridge = 1e-06
)
```

## **Arguments**

X	a numeric matrix or data.frame/data.table (factor/character/numeric/logical) - variables
model	a character - posibble options ("lm_bayes", "lm_noise", "pmm")
posit_y	an integer/character - a position/name of dependent variable
posit_x	an integer/character vector - positions/names of independent variables
W	a numeric vector - a weighting variable - only positive values, Default: NULL
logreg	a boolean - if dependent variable has log-normal distribution (numeric). If TRUE log-regression is evaluated and then returned exponential of results., Default: FALSE
k	an integer - a number of multiple imputations or for pmm a number of closest points from which a one random value is taken, Default:10
ridge	a numeric - a value added to diagonal elements of the x'x matrix, Default:1e-5

#### Value

load imputations in a numeric/character/factor (similar to the input type) vector format

#### Methods (by class)

```
fill_NA_N(data.frame): s3 method for data.frame
fill_NA_N(data.table): S3 method for data.table
fill_NA_N(matrix): S3 method for matrix
```

#### Note

There is assumed that users add the intercept by their own. The miceFast module provides the most efficient environment, the second recommended option is to use data.table and the numeric matrix data type. The lda model is assessed only if there are more than 15 complete observations and for the lms models if number of variables is smaller than number of observations.

#### See Also

```
fill_NA VIF
```

```
library(miceFast)
library(dplyr)
library(data.table)
### Data
# airquality dataset with additional variables
data(air_miss)
### Intro: dplyr
# IMPUTATIONS
air_miss <- air_miss %>%
  # Imputations with a grouping option (models are separately assessed for each group)
  # taking into account provided weights
  group_by(groups) %>%
  do(mutate(., Solar_R_imp = fill_NA(
   x = .,
   model = "lm_pred",
   posit_y = "Solar.R",
   posit_x = c("Wind", "Temp", "Intercept"),
   w = .[["weights"]]
  ))) %>%
  ungroup() %>%
  # Imputations - discrete variable
  mutate(x_character_imp = fill_NA(
   x = .,
   model = "lda",
   posit_y = "x_character",
   posit_x = c("Wind", "Temp")
  )) %>%
  # logreg was used because almost log-normal distribution of Ozone
  # imputations around mean
  mutate(Ozone_imp1 = fill_NA(
   x = .,
   model = "lm_bayes",
   posit_y = "Ozone",
   posit_x = c("Intercept"),
   logreg = TRUE
  )) %>%
  \# imputations using positions - Intercept, Temp
  mutate(Ozone_imp2 = fill_NA(
   x = .,
   model = "lm_bayes",
   posit_y = 1,
   posit_x = c(4, 6),
   logreg = TRUE
  )) %>%
  # multiple imputations (average of x30 imputations)
  # with a factor independent variable, weights and logreg options
  mutate(Ozone_imp3 = fill_NA_N(
   x = .,
    model = "lm_noise",
   posit_y = "Ozone",
    posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
```

```
w = .[["weights"]],
 logreg = TRUE,
 k = 30
)) %>%
mutate(Ozone_imp4 = fill_NA_N(
 x = .,
 model = "lm_bayes",
 posit_y = "Ozone",
 posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
 w = .[["weights"]],
 logreg = TRUE,
 k = 30
)) %>%
group_by(groups) %>%
do(mutate(., Ozone_imp5 = fill_NA(
  x = .,
 model = "lm_pred",
 posit_y = "Ozone",
 posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
 w = .[["weights"]],
 logreg = TRUE
))) %>%
do(mutate(., Ozone_imp6 = fill_NA_N(
 x = .,
 model = "pmm",
 posit_y = "Ozone",
 posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
 w = .[["weights"]],
 logreg = TRUE,
 k = 20
))) %>%
ungroup() %>%
# Average of a few methods
mutate(Ozone_imp_mix = rowMeans(select(., starts_with("Ozone_imp")))) %>%
# Protecting against collinearity or low number of observations - across small groups
# Be carful when using a grouping option
# because of lack of protection against collinearity or low number of observations.
 \begin{tabular}{llll} \tt \# There could be used a tryCatch(fill\_NA(...),error=function(e) return(...)) \\ \end{tabular} 
group_by(groups) %>%
do(mutate(., Ozone_chac_imp = tryCatch(
  fill_NA(
    x = .,
    model = "lda",
    posit_y = "Ozone_chac",
    posit_x = c(
      "Intercept",
      "Month",
      "Day",
      "Temp",
      "x\_character\_imp"
    ),
    w = .[["weights"]]
  ),
```

```
error = function(e) .[["Ozone_chac"]]
 ))) %>%
 ungroup()
# Sample of results
air_miss[which(is.na(air_miss[, 1]))[1:5], ]
### Intro: data.table
# IMPUTATIONS
# Imputations with a grouping option (models are separately assessed for each group)
# taking into account provided weights
data(air_miss)
setDT(air_miss)
air_miss[, Solar_R_imp := fill_NA_N(
 x = .SD,
 model = "lm_bayes",
 posit_y = "Solar.R",
 posit_x = c("Wind", "Temp", "Intercept"),
 w = .SD[["weights"]],
 k = 100
), by = .(groups)] \%
 # Imputations - discrete variable
  .[, x_character_imp := fill_NA(
   x = .SD,
   model = "lda",
   posit_y = "x_character",
   posit_x = c("Wind", "Temp", "groups")
 )] %>%
 # logreg was used because almost log-normal distribution of Ozone
 # imputations around mean
  .[, Ozone_imp1 := fill_NA(
   x = .SD,
   model = "lm_bayes",
   posit_y = "Ozone",
   posit_x = c("Intercept"),
   logreg = TRUE
 )] %>%
 # imputations using positions - Intercept, Temp
  .[, Ozone_imp2 := fill_NA(
   x = .SD,
   model = "lm_bayes",
   posit_y = 1,
   posit_x = c(4, 6),
   logreg = TRUE
 )] %>%
 # model with a factor independent variable
 # multiple imputations (average of x30 imputations)
 # with a factor independent variable, weights and logreg options
  .[, Ozone_imp3 := fill_NA_N(
   x = .SD,
   model = "lm_noise",
   posit_y = "Ozone",
   posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
```

```
w = .SD[["weights"]],
 logreg = TRUE,
 k = 30
)] %>%
.[, Ozone_imp4 := fill_NA_N(
 x = .SD,
 model = "lm_bayes",
 posit_y = "Ozone",
 posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
 w = .SD[["weights"]],
 logreg = TRUE,
 k = 30
)] %>%
.[, Ozone_imp5 := fill_NA(
 x = .SD,
 model = "lm_pred",
 posit_y = "Ozone",
 posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
 w = .SD[["weights"]],
 logreg = TRUE
), .(groups)] %>%
.[, Ozone_imp6 := fill_NA_N(
 x = .SD,
 model = "pmm",
 posit_y = "Ozone",
 posit_x = c("Intercept", "x_character_imp", "Wind", "Temp"),
 w = .SD[["weights"]],
 logreg = TRUE,
 k = 10
), .(groups)] %>%
# Average of a few methods
.[, Ozone_imp_mix := apply(.SD, 1, mean), .SDcols = Ozone_imp1:Ozone_imp6] %>%
# Protecting against collinearity or low number of observations - across small groups
# Be carful when using a data.table grouping option
# because of lack of protection against collinearity or low number of observations.
# There could be used a tryCatch(fill_NA(...),error=function(e) return(...))
.[, Ozone_chac_imp := tryCatch(
  fill_NA(
    x = .SD,
    model = "lda",
    posit_y = "Ozone_chac",
    posit_x = c(
      "Intercept",
      "Month",
      "Day",
      "Temp",
      "x_character_imp"
   ),
   w = .SD[["weights"]]
  error = function(e) .SD[["Ozone_chac"]]
), .(groups)]
```

naive\_fill\_NA

```
# Sample of results
air_miss[which(is.na(air_miss[, 1]))[1:5], ]
```

naive\_fill\_NA

naive\_fill\_NA function for the simple and automatic imputation

## **Description**

Automatically fill the missing data with a simple imputation method, impute with sampling the non missing values. It is recommended to use this function for each categorical variable separately.

## Usage

```
naive_fill_NA(x)
## S3 method for class 'data.frame'
naive_fill_NA(x)
## S3 method for class 'data.table'
naive_fill_NA(x)
## S3 method for class 'matrix'
naive_fill_NA(x)
```

## Arguments

X

a numeric matrix or data.frame/data.table (factor/character/numeric/logical variables)

#### Value

object with a similar structure to the input but without missing values.

#### Methods (by class)

- naive\_fill\_NA(data.frame): S3 method for data.frame
- naive\_fill\_NA(data.table): S3 method for data.table
- naive\_fill\_NA(matrix): S3 method for matrix

#### Note

this is a very simple and fast solution but not recommended, for more complex solutions please check the vignette.

18 neibo

## See Also

```
fill_NA fill_NA_N VIF
```

# **Examples**

```
## Not run:
library(miceFast)
data(air_miss)
naive_fill_NA(air_miss)
# Could be useful to run it separately for each group level
do.call(rbind, Map(naive_fill_NA, split(air_miss, air_miss$groups)))
## End(Not run)
```

neibo

Finding in random manner one of the k closets points in a certain vector for each value in a second vector

## Description

this function using pre-sorting of a y and the binary search the one of the k closest value for each miss is returned.

# Usage

```
neibo(y, miss, k)
```

# Arguments

k

y numeric vector values to be look up
miss numeric vector a values to be look for

integer a number of values which should be taken into account during sampling

one of the k closest point

#### Value

a numeric vector

Rcpp\_corrData-class 19

```
Rcpp_corrData-class Class "Rcpp_corrData"
```

#### **Description**

This C++ class could be used to build a corrData object by invoking new(corrData,...) function.

#### Methods

```
initialize(...): ~~
finalize(): ~~
fill(...): generating data
```

#### Note

This is only frame for building C++ object which could be used to implement certain methods. Check the vignette for more details of implementing methods.

```
Vigniette: https://CRAN.R-project.org/package=miceFast
```

#### References

See the documentation for Rcpp modules for more details of how this class was built. vignette("Rcpp-modules", package = "Rcpp")

#### **Examples**

```
#showClass("Rcpp_corrData")
show(corrData)
```

```
Rcpp_miceFast-class Class "Rcpp_miceFast"
```

#### **Description**

This C++ class could be used to build a miceFast objects by invoking new(miceFast) function.

#### Methods

20 Rcpp\_miceFast-class

```
get_data(...): retrieving the data
get_w(...): retrieving the weighting variable
get_g(...): retireiving the grouping variable
get_ridge(...): retireiving the ridge disturbance
get_index(...): getting the index
impute(...): impute data under characteristics from the object like a optional grouping or weight-
     ing variable
impute_N(...): multiple imputations - impute data under characteristics from the object like a
     optional grouping or weighting variable
update_var(...): permanently update the variable at the object and data. Use it only if you are
     sure about model parameters
get_models(...): get possible quantitative models for a certain type of dependent variable
get_model(...): get a recommended quantitative model for a certain type of dependent variable
which_updated(...): which variables at the object was modified by update_var
sort_byg(...): sort data by the grouping variable
is_sorted_byg(...): check if data is sorted by the grouping variable
vifs(...): Variance inflation factors (VIF) - helps to check when the predictor variables are not
     linearly related
initialize(...): ...
finalize(): ...
```

#### Note

This is only frame for building C++ object which could be used to implement certain methods. Check the vignette for more details of implementing these methods.

```
Vigniette: https://CRAN.R-project.org/package=miceFast
```

## References

See the documentation for Rcpp modules for more details of how this class was built. vignette("Rcpp-modules", package = "Rcpp")

```
#showClass("Rcpp_miceFast")
show(miceFast)
new(miceFast)
```

upset\_NA 21

upset\_NA

upset plot for NA values

#### Description

wrapper around UpSetR::upset for vizualization of NA values Visualization of set intersections using novel UpSet matrix design.

#### Usage

```
upset_NA(...)
```

#### **Arguments**

all arguments accepted by UpSetR::upset where the first one is expected to be a data.

#### **Details**

Visualization of set data in the layout described by Lex and Gehlenborg in https://www.nature.com/articles/nmeth.3033. UpSet also allows for visualization of queries on intersections and elements, along with custom queries queries implemented using Hadley Wickham's apply function. To further analyze the data contained in the intersections, the user may select additional attribute plots to be displayed alongside the UpSet plot. The user also has the the ability to pass their own plots into the function to further analyze data belonging to queries of interest. Most aspects of the UpSet plot are customizable, allowing the user to select the plot that best suits their style. Depending on how the features are selected, UpSet can display between 25-65 sets and between 40-100 intersections.

#### Note

Data set must be formatted as described on the original UpSet github page: https://github.com/ VCG/upset/wiki.

#### References

Lex et al. (2014). UpSet: Visualization of Intersecting Sets IEEE Transactions on Visualization and Computer Graphics (Proceedings of InfoVis 2014), vol 20, pp. 1983-1992, (2014).

Lex and Gehlenborg (2014). Points of view: Sets and intersections. Nature Methods 11, 779 (2014). https://www.nature.com/articles/nmeth.3033

```
library(miceFast)
library(UpSetR)
upset_NA(airquality)
upset_NA(air_miss, 6)
```

22 VIF

VIF

VIF function for assessing VIF.

## **Description**

VIF measure how much the variance of the estimated regression coefficients are inflated. It helps to identify when the predictor variables are linearly related. You have to decide which variable should be delete. Usually values higher than 10 (around), mean a collinearity problem.

#### Usage

```
VIF(x, posit_y, posit_x, correct = FALSE)
## S3 method for class 'data.frame'
VIF(x, posit_y, posit_x, correct = FALSE)
## S3 method for class 'data.table'
VIF(x, posit_y, posit_x, correct = FALSE)
## S3 method for class 'matrix'
VIF(x, posit_y, posit_x, correct = FALSE)
```

## **Arguments**

Х	a numeric matrix or data.frame/data.table (factor/character/numeric) - variables
posit_y	an integer/character - a position/name of dependent variable. This variable is taken into account only for getting complete cases.
posit_x	an integer/character vector - positions/names of independent variables
correct	a boolean - basic or corrected - Default: FALSE

#### Value

load a numeric vector with VIF for all variables provided by posit\_x

## Methods (by class)

```
• VIF(data.frame):
```

- VIF(data.table):
- VIF(matrix):

## Note

The corrected VIF is obtained by raising the basic VIF to the power of one divided by two times the degrees of freedom.

VIF 23

## See Also

```
fill_NA fill_NA_N
```

```
## Not run:
library(miceFast)
library(data.table)
airquality2 <- airquality</pre>
airquality2$Temp2 <- airquality2$Temp**2</pre>
airquality2$Month <- factor(airquality2$Month)</pre>
data_DT <- data.table(airquality2)</pre>
data_DT[, .(vifs = VIF(
  x = .SD,
  posit_y = "Ozone",
  posit_x = c("Solar.R", "Wind", "Temp", "Month", "Day", "Temp2"),
  correct = FALSE
))][["vifs.V1"]]
data_DT[, .(vifs = VIF(
  x = .SD,
  posit_y = 1,
  posit_x = c(2, 3, 4, 5, 6, 7),
  correct = TRUE
))][["vifs.V1"]]
## End(Not run)
```

# **Index**

```
* classes
    Rcpp_corrData-class, 19
    Rcpp_miceFast-class, 19
\ast datasets
    air_miss, 3
air_miss, 3
compare_imp, 4
corrData(Rcpp_corrData-class), 19
fill_NA, 5, 12, 18, 23
fill_NA_N, 6, 11, 18, 23
miceFast (Rcpp_miceFast-class), 19
\verb|miceFast-package|, 2
naive_fill_NA, 17
{\tt neibo, 18}
Rcpp_corrData-class, 19
Rcpp_miceFast-class, 19
upset_NA, 21
VIF, 6, 12, 18, 22
```