Package ‘mice’

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appendbreak

Appends specified break to the data

Description

A custom function to insert rows in long data with new pseudo-observations that are being done on the specified break ages. There should be a column called first in data with logical data that codes whether the current row is the first for subject id. Furthermore, the function assumes that columns age, occ, hgt.z, wgt.z and bmi.z are available. This function is used on the tbc data in FIMD chapter 9. Check that out to see it in action.

Usage

appendbreak(data, brk, warp.model = warp.model, id = NULL, typ = "pred")

Arguments

data A data frame in the long long format
brk A vector of break ages
warp.model A time warping model
id The subject identifier
typ Label to signal that this is a newly added observation

Value

A long data frame with additional rows for the break ages

as.mids

Converts an multiply imputed dataset (long format) into a mids object

Description

This function converts imputed data stored in long format into an object of class mids. The original incomplete data set needs to be available so that we know where the missing data are. The function is useful to convert back operations applied to the imputed data back in a mids object. It may also be used to store multiply imputed data sets from other software into the format used by mice.

Usage

as.mids(data, .imp=1, .id=2)


**as.mira**

Create a mira object from repeated analyses

**Description**

The `as.mira()` function takes the results of repeated complete-data analysis stored as a list, and turns it into a mira object that can be pooled. Pooling requires that `coef()` and `vcov()` methods are available for fitted object.

**Usage**

`as.mira(fitlist)`

---

**Arguments**

- `data` A multiply imputed data set in long format
- `.imp` Mandatory column indicator for the multiple imputation stream, where 0 indicates the incomplete data and 1 through m indicate the m multiple imputation streams. Default is 1.
- `.id` Optional column indicator for the row numbers. Default is 2.

**Details**

If `.id` is specified, row names from the original data (if supplied) will be copied to the `mids` object.

**Value**

An object of class `mids`

**Author(s)**

Gerko Vink, 2012

**Examples**

```r
# nhanes example without .id
imp <- mice(nhanes, print = FALSE)
X <- complete(imp, action = "long", include = TRUE)[, -2]
test <- as.mids(X, .id = NULL)
is.mids(test)
test.dat <- complete(test, action = "long", include = TRUE)

# Test on boys data
imp <- mice(boys, print = FALSE, maxit = 1)
X <- complete(imp, action = "long", include = TRUE)
test <- as.mids(X)
is.mids(test)
test.dat <- complete(test, action = "long", include = TRUE)
# original rownumbers are automatically copied from .id
```
Arguments

fitlist A list containing fitted analysis objects

Value

An S3 object of class mira.

Author(s)

Stef van Buuren, 2011

See Also

mira

boys  
\textit{Growth of Dutch boys}

Description

Height, weight, head circumference and puberty of 748 Dutch boys.

Format

A data frame with 748 rows on the following 9 variables:

\begin{itemize}
  \item \textbf{age} Decimal age (0-21 years)
  \item \textbf{hgt} Height (cm)
  \item \textbf{wgt} Weight (kg)
  \item \textbf{bmi} Body mass index
  \item \textbf{hc} Head circumference (cm)
  \item \textbf{gen} Genital Tanner stage (G1-G5)
  \item \textbf{phb} Pubic hair (Tanner P1-P6)
  \item \textbf{tv} Testicular volume (ml)
  \item \textbf{reg} Region (north, east, west, south, city)
\end{itemize}

Details

Random sample of 10\% from the cross-sectional data used to construct the Dutch growth references 1997. Variables gen and phb are ordered factors. reg is a factor.
Examples

# create two imputed data sets
imp <- mice(boys, m=1, maxit=2)
z <- complete(imp, 1)

# create imputations for age <8yrs
plot(z$age, z$gen, col=mdc(1:2)[1+is.na(boys$gen)],
xlab = "Age (years)", ylab = "Tanner Stage Genital")

# figure to show that the default imputation method does not impute BMI consistently
plot(z$bmi, z$wgt/(z$hgt/100)^2, col=mdc(1:2)[1+is.na(boys$bmi)],
xlab = "Imputed BMI", ylab="Calculated BMI")

# also, BMI distributions are somewhat different
require(MASS)
oldpar <- par(mfrow=c(1,2))
truehist(z$bmi[is.na(boys$bmi)],h=1,xlim=c(10,30),ymax=0.25,
        col=mdc(1),xlab="BMI observed")
truehist(z$bmi[is.na(boys$bmi)],h=1,xlim=c(10,30),ymax=0.25,
        col=mdc(2),xlab="BMI imputed")
par(oldpar)

# repair the inconsistency problem by passive imputation
meth <- imp$meth
meth["bmi"] <- "1/(wgt/(hgt/100)^2)"
pred <- imp$predictorMatrix
pred["hgt","bmi"] <- 0
pred["wgt","bmi"] <- 0
imp2 <- mice(boys, m=1, maxit=2, meth=meth, pred=pred)
z2 <- complete(imp2, 1)

# show that new imputations are consistent
plot(z2$bmi, z2$wgt/(z2$hgt/100)^2, col=mdc(1:2)[1+is.na(boys$bmi)],
ylab="Calculated BMI")

# and compare distributions
oldpar <- par(mfrow=c(1,2))
truehist(z2$bmi[is.na(boys$bmi)],h=1,xlim=c(10,30),ymax=0.25,col=mdc(1),
xlab="BMI observed")
truehist(z2$bmi[is.na(boys$bmi)],h=1,xlim=c(10,30),ymax=0.25,col=mdc(2),

Source


bwplot.mids

Box-and-whisker plot of observed and imputed data

Description

Plotting methods for imputed data using lattice. bwplot produces box-and-whisker plots. The function automatically separates the observed and imputed data. The functions extend the usual features of lattice.

Usage

```r
## S3 method for class 'mids'
bwplot(x, data, na.groups = NULL, groups = NULL,
       as.table = TRUE, theme = mice.theme(), mayreplicate = TRUE,
       allow.multiple = TRUE, outer = TRUE,
       drop.unused.levels = lattice.getOption("drop.unused.levels"), ...,
       subscripts = TRUE, subset = TRUE)
```

Arguments

- **x**: A mids object, typically created by mice() or mice.mids().
- **data**: Formula that selects the data to be plotted. This argument follows the lattice rules for formulas, describing the primary variables (used for the per-panel display) and the optional conditioning variables (which define the subsets plotted in different panels) to be used in the plot.

  The formula is evaluated on the complete data set in the long form. Legal variable names for the formula include names(x$data) plus the two administrative factors .imp and .id.

  **Extended formula interface**: The primary variable terms (both the LHS y and RHS x) may consist of multiple terms separated by a '+' sign, e.g., y1 + y2 ~ x | a * b. This formula would be taken to mean that the user wants to plot both y1 ~ x | a * b and y2 ~ x | a * b, but with the y1 ~ x and y2 ~ x in separate panels. This behavior differs from standard lattice. *Only combine terms of the same type*, i.e. only factors or only numerical variables. Mixing numerical and categorical data occasionally produces odds labeling of vertical axis.

  For convenience, in stripplot() and bwplot the formula y~.imp may be abbreviated as y. This applies only to a single y, and does not (yet) work for y1+y2~.imp.

- **na.groups**: An expression evaluating to a logical vector indicating which two groups are distinguished (e.g. using different colors) in the display. The environment in which this expression is evaluated is the response indicator is.na(x$data).

  The default na.group = NULL constrasts the observed and missing data in the LHS y variable of the display, i.e. groups created by is.na(y). The expression y creates the groups according to is.na(y). The expression y1 & y2
creates groups by `is.na(y1) & is.na(y2)`, and `y1 | y2` creates groups as
`is.na(y1) | is.na(y2)`, and so on.

**groups**
This is the usual groups arguments in *lattice*. It differs from `na.groups` because
it evaluates in the completed data `data.frame(complete(x, "long", inc=TRUE))`
(as usual), whereas `na.groups` evaluates in the response indicator. See `xyplot`
for more details. When both `na.groups` and `groups` are specified, `na.groups`
takes precedence, and `groups` is ignored.

**theme**
A named list containing the graphical parameters. The default function `mice.theme`
produces a short list of default colors, line width, and so on. The extensive list
may be obtained from `trellis.par.get()`. Global graphical parameters like
`col` or `cex` in high-level calls are still honored, so first experiment with the
global parameters. Many setting consists of a pair. For example, `mice.theme`
deﬁnes two symbol colors. The ﬁrst is for the observed data, the second for the
imputed data. The theme settings only exist during the call, and do not affect
the trellis graphical parameters.

**mayreplicate**
A logical indicating whether color, line widths, and so on, may be replicated.
The graphical functions attempt to choose "intelligent" graphical parameters.
For example, the same color can be replicated for different element, e.g. use all
reds for the imputed data. Replication may be switched off by setting the flag to
`FALSE`, in order to allow the user to gain full control.

**as.table**
See `xyplot`.

**outer**
See `xyplot`.

**allow.multiple**
See `xyplot`.

**drop.unused.levels**
See `xyplot`.

**subscripts**
See `xyplot`.

**subset**
See `xyplot`.

**...**
Further arguments, usually not directly processed by the high-level functions
documented here, but instead passed on to other functions.

**Details**

The argument `na.groups` may be used to specify (combinations of) missingness in any of the vari-
ables. The argument `groups` can be used to specify groups based on the variable values themselves.
Only one of both may be active at the same time. When both are specified, `na.groups` takes prece-
dence over `groups`.

Use the `subset` and `na.groups` together to plots parts of the data. For example, select the ﬁrst
imputed data set by by `subset=im1`.

Graphical parameters like `col`, `pch` and `cex` can be speciﬁed in the arguments list to alter the plotting
symbols. If `length(col)==2`, the color speciﬁcation to deﬁne the observed and missing groups.
`col[1]` is the color of the ‘observed’ data, `col[2]` is the color of the missing or imputed data.
A convenient color choice is `col=mdc(1:2)`, a transparent blue color for the observed data, and a
transparent red color for the imputed data. A good choice is `col=mdc(1:2)`, `pch=20`, `cex=1.5`.
These choices can be set for the duration of the session by running `mice.theme()`.
Value

The high-level functions documented here, as well as other high-level Lattice functions, return an object of class "trellis". The update method can be used to subsequently update components of the object, and the print method (usually called by default) will plot it on an appropriate plotting device.

Note

The first two arguments (x and data) are reversed compared to the standard Trellis syntax implemented in lattice. This reversal was necessary in order to benefit from automatic method dispatch.

In mice the argument x is always a mids object, whereas in lattice the argument x is always a formula.

In mice the argument data is always a formula object, whereas in lattice the argument data is usually a data frame.

All other arguments have identical interpretation.

Author(s)

Stef van Buuren

References


See Also

mice, xyplot, densityplot, stripplot, Lattice for an overview of the package, as well as bwplot, panel.bwplot, print.trellis, trellis.par.set

Examples

require(lattice)

imp <- mice(boys, maxit=1)

### box-and-whisker plot per imputation of all numerical variables
bwplot(imp)

### tv (testicular volume), conditional on region
bwplot(imp, tv~.imp|reg)

### same data, organized in a different way
bwplot(imp, tv=reg|imp, theme=list())
cbind.mids

Columnwise combination of a mids object.

Description
This function combines two mids objects columnwise into a single object of class mids, or combines a mids object with a vector, matrix, factor or data.frame columnwise into an object of class mids. The number of rows in the (incomplete) data x$data and y (or y$data if y is a mids object) should be equal. If y is a mids object then the number of imputations in x and y should be equal. Note: If y is a vector or factor its original name is lost and it will be denoted with y in the mids object.

Usage
cbind.mids(x, y, ...)

Arguments
x
A mids object.
y
A mids object or a data.frame, matrix, factor or vector.
...
Additional data.frame, matrix, vector or factor. These can be given as named arguments.

Value
An S3 object of class mids

Note
Component call is a vector, with first argument the mice() statement that created x and second argument the call to cbind.mids(). Component data is the codebind of the (incomplete) data in x$data and y$data. Component m is the number of imputations. Component nmis is an array containing the number of missing observations per column. Component imp is a list of nvar components with the generated multiple imputations. Each part of the list is a nmis[j] by m matrix of imputed values for variable j. The original data of y will be copied into this list, including the missing values of y then y is not imputed. Component method is a vector of strings of length(nvar) specifying the elementary imputation method per column. If y is a mids object this vector is a combination of x$method and y$method, otherwise this vector is x$method and for the columns of y the method is set to ''. Component predictorMatrix is a square matrix of size ncol(data) containing integer data specifying the predictor set. If x and y are mids objects then the predictor matrices of x and y are combined with zero matrices on the off-diagonal blocks. Otherwise the variables in y are included in the predictor matrix of x such that y is not used as predictor(s) and not imputed as well. Component visitSequence is the sequence in which columns are visited. The same as x$visitSequence. Component seed is the seed value of the solution, x$seed. Component iteration is the last Gibbs sampling iteration number, x$iteration. Component lastSeedValue is the most recent seed value, x$lastSeedValue Component chainMean is the combination of x$chainMean and y$chainMean. If y$chainMean does not exist this element equals x$chainMean.
Component `chainVar` is the combination of `x$chainVar` and `y$chainVar`. If `y$chainVar` does not exist this element equals `x$chainVar`. Component `pad` is a list containing various settings of the padded imputation model, i.e. the imputation model after creating dummy variables. This list is defined by combining `x$pad` and `y$pad` if `y` is a `mids` object. Otherwise, it is defined by the settings of `x` and the combination of the data `x$data` and `y`. Component `loggedEvents` is set to `x$loggedEvents`. If a column of `y` is categorical this is ignored in the padded model since that column is not used as predictor for another column.

Author(s)

Karin Groothuis-Oudshoorn, Stef van Buuren, 2009

See Also

`rbind.mids`, `ibind.mids`

Examples

```r
# append 'forgotten' variable `bmi` to `imp`
temp <- boys[,c(1:3,5:9)]
imp <- mice(temp,maxit=1,m=2)
imp2 <- cbind.mids(imp, data.frame(bmi=boys$bmi))

# append maturation score to `imp` (numerical)
mat <- (as.integer(temp$gen) + as.integer(temp$phb)
       + as.integer(cut(temp$tv,breaks=c(0,3,6,10,15,20,25))))
imp2 <- cbind.mids(imp, as.data.frame(mat))

# append maturation score to `imp` (factor)
# known issue: new column name is 'y', not 'mat'
mat <- as.factor(mat)
imp2 <- cbind.mids(imp, mat)

# append data frame with two columns to `imp`
temp2 <- data.frame(bmi=boys$bmi,mat=as.factor(mat))
imp2 <- cbind.mids(imp, temp2)

# combine two `mids` objects
impa <- mice(temp, maxit=1, m=2)
impb <- mice(temp2, maxit=2, m=2)

# first a then b
impab <- cbind.mids(impa, impb)

# first b then a
impba <- cbind.mids(impb, impa)
```
**cc**

**Complete cases**

**Description**

Extracting complete cases is also known as 'listwise deletion' or 'complete case analyses'. \( cc(x) \) is equivalent to \( \text{na.omit}(x) \). Missing values in \( x \) are coded as \( \text{NA} \). The companion function for selecting the incomplete cases is \( \text{ic()} \).

**Usage**

\[
\text{cc}(x, \text{drop} = \text{TRUE})
\]

**Arguments**

- **x**: An R object. Currently supported are methods for the following classes: \text{mids}, \text{mira}, \text{mipo}, \text{data.frame} and \text{matrix}. In addition, \( x \) can be a vector of any kind.

- **drop**: A logical flag for matrices and arrays. If \( \text{drop}=\text{TRUE} \) the result is coerced to the lowest possible dimension.

**Value**

A vector, matrix of \text{data.frame} containing the data of the complete cases.

**Author(s)**

Stef van Buuren, 2010.

**See Also**

\text{na.omit, ic, cci, ici, ccn, icn}

**Examples**

\[
\begin{align*}
\text{cc(nhanes)} & \quad \# \text{get the 13 complete cases} \\
\text{cc(nhanes[,2,drop=FALSE], drop=FALSE)} & \quad \# \text{extract complete bmi as column}
\end{align*}
\]
cci

Complete case indicator

Description

This array is useful for extracting the subset of complete cases. The function cci(x) is equivalent to complete.cases(x). Missing values in x are coded as NA. The companion function for selecting the incomplete cases is ici().

Usage

cci(x)

Arguments

x

An R object. Currently supported are methods for the following classes: mids, data.frame and matrix. In addition, x can be a vector of any kind.

Value

Logical vector indicating the complete cases. If x is a data.frame or matrix the length is nrow(x). In other cases, the length is length(x).

Author(s)

Stef van Buuren, 2010.

See Also

complete.cases, ici cc, ic, ccn, icn

Examples

cci(nhanes) # indicator for 13 complete cases
f <- cci(nhanes[,c("bmi","hyp")]) # complete data for bmi and hyp
nhanes[f,] # obtain all data from those with complete bmi and hyp
**ccn**

### Complete cases n

**Description**

Calculates the number of complete cases. The companion function for calculating the number of incomplete cases is icn().

**Usage**

```r
ccn(x)
```

**Arguments**

- `x` An R object. Currently supported are methods for the following classes: mids, data.frame and matrix. In addition, `x` can be a vector of any kind.

**Value**

An integer with the number of elements in `x` with complete data.

**Author(s)**

Stef van Buuren, 2010.

**See Also**

icn, cc, ic, cci, ici

**Examples**

```r
ccn(nhanes) # 13 complete cases
```

---

**complete**

### Creates imputed data sets from a mids object

**Description**

Takes an object of class mids, fills in the missing data, and returns the completed data in a specified format.

**Usage**

```r
complete(x, action = 1, include = FALSE)
```
Arguments

x An object of class mids as created by the function mice().

action If action is a scalar between 1 and x$m, the function returns the data with imputation number action filled in. Thus, action=1 returns the first completed data set, action=2 returns the second completed data set, and so on. The value of action can also be one of the following strings: "long", "broad", "repeated". See 'Details' for the interpretation.

include Flag to indicate whether the original data with the missing values should be included. This requires that action is specified as 'long', 'broad' or 'repeated'.

Details

The argument action can also be a string, which is partially matched as follows:

list("\'long\'") produces a long data frame of vertically stacked imputed data sets with nrow(x$data) * x$m rows and ncol(x$data)+2 columns. The two additional columns are labeled .id containing the row names of x$data, and .imp containing the imputation number. If include=TRUE then nrow(x$data) additional rows with the original data are appended with .imp set equal to 0.

list("\'broad\'") produces a broad data frame with nrow(x$data) rows and ncol(x$data) * x$m columns. Columns are ordered such that the first ncol(x$data) columns corresponds to the first imputed data matrix. The imputation number is appended to each column name. If include=TRUE then ncol(x$data) additional columns with the original data are appended. The number .0 is appended to the column names.

list("\'repeated\'") produces a broad data frame with nrow(x$data) rows and ncol(x$data) * x$m columns. Columns are ordered such that the first x$m columns correspond to the x$m imputed versions of the first column in x$data. The imputation number is appended to each column name. If include=TRUE then ncol(x$data) additional columns with the original data are appended. The number .0 is appended to the column names.

Value

A data frame with the imputed values filled in. Optionally, the original data are appended.

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2009

See Also

mice, mids

Examples

# do default multiple imputation on a numeric matrix
imp <- mice(nhanes)

# obtain first imputated matrix
mat <- complete(imp)
# fill in the third imputation
mat <- complete(imp, 3)

# long matrix with stacked complete data
mat <- complete(imp, 'long')

# long matrix with stacked complete data, including the original data
mat <- complete(imp, 'long', inc=TRUE)

# repeated matrix with complete data
mat <- complete(imp, 'r')

# for numeric data, produces a blocked correlation matrix, where
# each block contains of the same variable pair over different
# multiple imputations.
cor(mat)

densityplot.mids  
Density plot of observed and imputed data

Description
Plotting methods for imputed data using lattice. densityplot produces plots of the densities. The function automatically separates the observed and imputed data. The functions extend the usual features of lattice.

Usage
## S3 method for class 'mids'
densityplot(x, data, na.groups = NULL, groups = NULL,
             as.table = TRUE, plot.points = FALSE, theme = mice.theme(),
             mayreplicate = TRUE, thicker = 2.5, allow.multiple = TRUE,
             outer = TRUE,
             drop.unused.levels = lattice.getOption("drop.unused.levels"),
             panel = lattice.getOption("panel.densityplot"),
             default.prepanel = lattice.getOption("prepanel.default.densityplot"), ...,
             subscripts = TRUE, subset = TRUE)

Arguments

x          A mids object, typically created by mice() or mice.mids().
data       Formula that selects the data to be plotted. This argument follows the lattice
           rules for formulas, describing the primary variables (used for the per-panel display) and the optional conditioning variables (which define the subsets plotted in different panels) to be used in the plot.
           The formula is evaluated on the complete data set in the long form. Legal variable names for the formula include names(x$data) plus the two administrative factors .imp and .id.
Extended formula interface: The primary variable terms (both the LHS \( y \) and RHS \( x \)) may consist of multiple terms separated by a `+` sign, e.g., \( y_1 + y_2 \sim x | a + b \). This formula would be taken to mean that the user wants to plot both \( y_1 \sim x | a + b \) and \( y_2 \sim x | a + b \), but with the \( y_1 \sim x \) and \( y_2 \sim x \) in separate panels. This behavior differs from standard lattice. Only combine terms of the same type, i.e. only factors or only numerical variables. Mixing numerical and categorical data occasionally produces odds labeling of vertical axis.

The function densityplot does not use the \( y \) terms in the formula. Density plots for \( x_1 \) and \( x_2 \) are requested as \( \sim x_1 + x_2 \).

na.groups An expression evaluating to a logical vector indicating which two groups are distinguished (e.g. using different colors) in the display. The environment in which this expression is evaluated is the response indicator \( \text{is.na(x$\text{data})} \).

The default \( \text{na.group} = \text{NULL} \) constrasts the observed and missing data in the LHS \( y \) variable of the display, i.e. groups created by \( \text{is.na(y)} \). The expression \( y \) creates the groups according to \( \text{is.na(y)} \). The expression \( y_1 \ & \ y_2 \) creates groups by \( \text{is.na(y1)} \ & \ \text{is.na(y2)} \), and \( y_1 \ | \ y_2 \) creates groups as \( \text{is.na(y1)} \ | \ \text{is.na(y2)} \), and so on.

groups This is the usual groups arguments in lattice. It differs from \( \text{na.groups} \) because it evaluates in the completed data \( \text{data.frame(complete(x, "long", inc=TRUE))} \) (as usual), whereas \( \text{na.groups} \) evaluates in the response indicator. See \( \text{xyplot} \) for more details. When both \( \text{na.groups} \) and \( \text{groups} \) are specified, \( \text{na.groups} \) takes precedence, and \( \text{groups} \) is ignored.

plot.points A logical used in densityplot that signals whether the points should be plotted.

theme A named list containing the graphical parameters. The default function \( \text{mice.theme} \) produces a short list of default colors, line width, and so on. The extensive list may be obtained from \( \text{trellis.par.get()} \). Global graphical parameters like \( \text{col} \) or \( \text{cex} \) in high-level calls are still honored, so first experiment with the global parameters. Many setting consists of a pair. For example, \( \text{mice.theme} \) defines two symbol colors. The first is for the observed data, the second for the imputed data. The theme settings only exist during the call, and do not affect the trellis graphical parameters.

mayreplicate A logical indicating whether color, line widths, and so on, may be replicated. The graphical functions attempt to choose “intelligent” graphical parameters. For example, the same color can be replicated for different element, e.g. use all reds for the imputed data. Replication may be switched off by setting the flag to \( \text{FALSE} \), in order to allow the user to gain full control.

thicker Used in densityplot. Multiplication factor of the line width of the observed density. \( \text{thicker}=1 \) uses the same thickness for the observed and imputed data.

as.table See \( \text{xyplot} \).

panel See \( \text{xyplot} \).

default.prepanel See \( \text{xyplot} \).

outer See \( \text{xyplot} \).

allow.multiple See \( \text{xyplot} \).
densityplot.mids

drop.unused.levels
    See xyplot.
subscripts
    See xyplot.
subset
    See xyplot.

... Further arguments, usually not directly processed by the high-level functions
documented here, but instead passed on to other functions.

Details

The argument na.groups may be used to specify (combinations of) missingness in any of the variables. The argument groups can be used to specify groups based on the variable values themselves. Only one of both may be active at the same time. When both are specified, na.groups takes precedence over groups.

Use the subset and na.groups together to plots parts of the data. For example, select the first imputed data set by by subset=imp==1.

Graphical parameters like col, pch and cex can be specified in the arguments list to alter the plotting symbols. If length(col)==2, the color specification to define the observed and missing groups. col[1] is the color of the ’observed’ data, col[2] is the color of the missing or imputed data. A convenient color choice is col=mdc(1:2), a transparent blue color for the observed data, and a transparent red color for the imputed data. A good choice is col=mdc(1:2), pch=20, cex=1.5. These choices can be set for the duration of the session by running mice.theme().

Value

The high-level functions documented here, as well as other high-level Lattice functions, return an object of class "trellis". The update method can be used to subsequently update components of the object, and the print method (usually called by default) will plot it on an appropriate plotting device.

Note

The first two arguments (x and data) are reversed compared to the standard Trellis syntax implemented in lattice. This reversal was necessary in order to benefit from automatic method dispatch.

In mice the argument x is always a mids object, whereas in lattice the argument x is always a formula.

In mice the argument data is always a formula object, whereas in lattice the argument data is usually a data frame.

All other arguments have identical interpretation.

densityplot.errs on empty groups, which occurs if all observations in the subgroup contain NA. The relevant error message is: Error in density.default: ... need at least 2 points to select a bandwidth automatically. There is yet no workaround for this problem. Use the more robust bwplot or stripplot as a replacement.

Author(s)

Stef van Buuren
extractBS

References


See Also

mice, xyplot, stripplot, bwplot, Lattice for an overview of the package, as well as densityplot, panel.densityplot, print.trellis, trellis.par.set

Examples

require(lattice)

imp <- mice(boys, maxit=1)

### density plot of head circumference per imputation
### blue is observed, red is imputed
densityplot(imp, ~hc|imp)

### All combined in one panel.
densityplot(imp, ~hc)

---

extractBS  
Extract broken stick estimates from a lmer object

Description

Extract broken stick estimates from a lmer object

Usage

eextractBS(fit)

Arguments

fit  
An object of class lmer

Value

A matrix containing broken stick estimates

Author(s)

Stef van Buuren, 2012
**Description**

Multiple outcomes of a randomized study to reduce post-traumatic stress.

**Format**

fdd is a data frame with 52 rows and 65 columns:

- **id**  Client number
- **trt**  Treatment (E=EMDR, C=CBT)
- **pp**  Per protocol (Y/N)
- **trtp**  Number of parental treatments
- **sex**  Sex: M/F
- **etn**  Ethnicity: NL/OTHER
- **age**  Age (years)
- **trauma**  Trauma count (1-5)
- **prop1**  PROPS total score T1
- **prop2**  PROPS total score T2
- **prop3**  PROPS total score T3
- **crop1**  CROPS total score T1
- **crop2**  CROPS total score T2
- **crop3**  CROPS total score T3
- **masc1**  MASC score T1
- **masc2**  MASC score T2
- **masc3**  MASC score T3
- **cbcl1**  CBCL T1
- **cbcl3**  CBCL T3
- **prs1**  PRS total score T1
- **prs2**  PRS total score T2
- **prs3**  PRS total score T3
- **ypa1**  PTSD-R1 B intrusive recollection parent T1
- **ypb1**  PTSD-R1 C avoidant/numbing parent T1
- **ypc1**  PTSD-R1 D hyper-arousal parent T1
- **yp1**  PTSD-R1 B+C+D parent T1
- **ypa2**  PTSD-R1 B intrusive recollection parent T2
- **ypb2**  PTSD-R1 C avoidant/numbing parent T2
fdd. pred is the 65 by 65 binary predictor matrix used to impute fdd.
Details

Data from a randomized experiment to reduce post-traumatic stress by two treatments: Eye Movement Desensitization and Reprocessing (EMDR) (experimental treatment), and cognitive behavioral therapy (CBT) (control treatment). 52 children were randomized to one of these two treatments. Outcomes were measured at three time points: at baseline (pre-treatment, T1), post-treatment (T2, 4-8 weeks), and at follow-up (T3, 3 months). For more details, see de Roos et al (2011). Some person covariates were reshuffled. The imputation methodology is explained in Chapter 9 of van Buuren (2012).

Source


Examples

data <- fdd
md.pattern(fdd)

<table>
<thead>
<tr>
<th>fdgs</th>
<th>Fifth Dutch growth study 2009</th>
</tr>
</thead>
</table>

Description

Age, height, weight and region of 10030 children measured within the Fifth Dutch Growth Study 2009

Format

*fdgs* is a data frame with 10030 rows and 8 columns:

<table>
<thead>
<tr>
<th>id</th>
<th>Person number</th>
</tr>
</thead>
<tbody>
<tr>
<td>reg</td>
<td>Region (factor, 5 levels)</td>
</tr>
<tr>
<td>age</td>
<td>Age (years)</td>
</tr>
<tr>
<td>sex</td>
<td>Sex (boy, girl)</td>
</tr>
<tr>
<td>hgt</td>
<td>Height (cm)</td>
</tr>
<tr>
<td>wgt</td>
<td>Weight (kg)</td>
</tr>
<tr>
<td>hgt.z</td>
<td>Height Z-score</td>
</tr>
<tr>
<td>wgt.z</td>
<td>Weight Z-score</td>
</tr>
</tbody>
</table>
Details

The data set contains data from children of Dutch descent (biological parents are born in the Netherlands). Children with growth-related diseases were excluded. The data were used to construct new growth charts of children of Dutch descent (Schonbeck 2013), and to calculate overweight and obesity prevalence (Schonbeck 2011).

Some groups were underrepresented. Multiple imputation was used to create synthetic cases that were used to correct for the nonresponse. See Van Buuren (2012), chapter 8 for details.

Source


Examples

data <- data(fdgs)
summary(data)

---

fico  
Fraction of incomplete cases among cases with observed

Description

FICO is an outbound statistic defined by the fraction of incomplete cases among cases with $y_j$ observed (White and Carlin, 2010).

Usage

fico(data)

Arguments

data  
A data frame or a matrix containing the incomplete data. Missing values are coded as NA's.

Value

A vector of length ncol(data) of FICO statistics.
Author(s)
Stef van Buuren, 2012

References

See Also
fluxplot, flux, md.pattern

---

**flux**

Influx and outflux of multivariate missing data patterns

Description

Influx and outflux are statistics of the missing data pattern. These statistics are useful in selecting predictors that should go into the imputation model.

Usage

```r
flux(data, local = names(data))
```

Arguments

- `data` A data frame or a matrix containing the incomplete data. Missing values are coded as NA's.
- `local` A vector of names of columns of `data`. The default is to include all columns in the calculations.

Details

Influx and outflux have been proposed by Van Buuren (2012), chapter 4.

Influx is equal to the number of variable pairs \((Y_j, Y_k)\) with \(Y_j\) missing and \(Y_k\) observed, divided by the total number of observed data cells. Influx depends on the proportion of missing data of the variable. Influx of a completely observed variable is equal to 0, whereas for completely missing variables we have influx = 1. For two variables with the same proportion of missing data, the variable with higher influx is better connected to the observed data, and might thus be easier to impute.

Outflux is equal to the number of variable pairs with \(Y_j\) observed and \(Y_k\) missing, divided by the total number of incomplete data cells. Outflux is an indicator of the potential usefulness of \(Y_j\) for imputing other variables. Outflux depends on the proportion of missing data of the variable. Outflux of a completely observed variable is equal to 1, whereas outflux of a completely missing variable is equal to 0. For two variables having the same proportion of missing data, the variable with higher...
outflux is better connected to the missing data, and thus potentially more useful for imputing other variables.

FICO is an outbound statistic defined by the fraction of incomplete cases among cases with $y_j$ observed (White and Carlin, 2010).

Value

A data frame with ncol(data) rows and six columns: pobs = Proportion observed, influx = Influx outflux = Outflux ainb = Average inbound statistic aout = Average outbound statistic fico = Fraction of incomplete cases among cases with $y_j$ observed

Author(s)

Stef van Buuren, 2012

References


See Also

fluxplot, md.pattern, fico

--

fluxplot

*Fluxplot of the missing data pattern*

Description

Influx and outflux are statistics of the missing data pattern. These statistics are useful in selecting predictors that should go into the imputation model.

Usage

fluxplot(data, local = names(data), plot = TRUE, labels = TRUE, xlim = c(0, 1), ylim = c(0, 1), las = 1, xlab = "Influx", ylab = "Outflux", main = paste("Influx-outflux pattern for", deparse(substitute(data))), eqscplot = TRUE, pty = "s", ...)
**Arguments**

- **data**: A data frame or a matrix containing the incomplete data. Missing values are coded as NA's.
- **local**: A vector of names of columns of data. The default is to include all columns in the calculations.
- **plot**: Should a graph be produced?
- **labels**: Should the points be labeled?
- **xlim**: See `par`.
- **ylim**: See `par`.
- **las**: See `par`.
- **xlab**: See `par`.
- **ylab**: See `par`.
- **main**: See `par`.
- **eqscplot**: Should a square plot be produced?
- **pty**: See `par`.
- **...**: Further arguments passed to `plot()` or `eqscplot()`.

**Details**

Infux and outflux have been proposed by Van Buuren (2012), chapter 4.

Infux is equal to the number of variable pairs $(Y_j, Y_k)$ with $Y_j$ missing and $Y_k$ observed, divided by the total number of observed data cells. Infux depends on the proportion of missing data of the variable. Infux of a completely observed variable is equal to 0, whereas for completely missing variables we have infux = 1. For two variables with the same proportion of missing data, the variable with higher infux is better connected to the observed data, and might thus be easier to impute.

Outflux is equal to the number of variable pairs with $Y_j$ observed and $Y_k$ missing, divided by the total number of incomplete data cells. Outflux is an indicator of the potential usefulness of $Y_j$ for imputing other variables. Outflux depends on the proportion of missing data of the variable. Outflux of a completely observed variable is equal to 1, whereas outflux of a completely missing variable is equal to 0. For two variables having the same proportion of missing data, the variable with higher outflux is better connected to the missing data, and thus potentially more useful for imputing other variables.

**Value**

An invisible data frame with `ncol(data)` rows and six columns: pobs = Proportion observed, infux = Infux outflux = Outflux ainb = Average inbound statistic aout = Average outbound statistic fico = Fraction of incomplete cases among cases with $Y_j$ observed

**Author(s)**

Stef van Buuren, 2012
References

See Also
*flux, md.pattern, fico*

---

**getfit**

*Extracts fit objects from mira object*

**Description**

`getfit` returns the list of objects containing the repeated analysis results, or optionally, one of these fit objects.

**Usage**

`getfit(x, i = -1, simplify = FALSE)`

**Arguments**

- **x**
  An object of class `mira`, typically produced by a call to `with()`.  
- **i**
  An integer between 1 and `x$m` signalling the number of the repeated analysis. The default `i = -1` return a list with all analyses.  
- **simplify**
  Should the return value be unlisted?

**Details**

This function is shorthand notation for `x$analyses` and `x$analyses[[i]]`.  

**Value**

If `i = -1` an object containing all analyses, otherwise it returns the fittd object of the i’th repeated analysis.

**Author(s)**

Stef van Buuren, March 2012.

**See Also**

*mira, with.mids*
Examples

```r
imp <- mice(nhanes)
fit <- with.imp, lm(bmi~chl+hyp))
getfit(fit)
getfit(fit, 2)
```

### glm.mids

**Generalized linear model for mids object**

### Description

Applies glm() to a multiply imputed data set

### Usage

```r
glm.mids(formula, family = gaussian, data, ...)
```

### Arguments

- `formula`: a formula expression as for other regression models, of the form response ~ predictors. See the documentation of `lm` and `formula` for details.
- `family`: The family of the glm model
- `data`: An object of type mids, which stands for 'multiply imputed data set', typically created by function mice().
- `...`: Additional parameters passed to glm.

### Details

This function is included for backward compatibility with V1.0. The function is superseeded by `with.mids`.

### Value

An objects of class `mira`, which stands for 'multiply imputed repeated analysis'. This object contains data$m distinct glm.objects, plus some descriptive information.

### Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000

### References


### See Also

`with.mids, glm.mids, mira`
Examples

```r
imp <- mice(nhanes)

# logistic regression on the imputed data
fit <- glm.mids(hyp==2~bmi+chl, data=imp, family = binomial)
fit
```

```{r}
ibind(x, y)
```

Description

This function combines two `mids` objects `x` and `y` into a single `mids` object. The two `mids` objects should have the same underlying multiple imputation model and should be fitted on exactly the same dataset. If the number of imputations in `x` is `m(x)` and in `y` is `m(y)` then the combination of both objects contains `m(x)+m(y)` imputations.

Usage

```{r}
ibind(x, y)
```

Arguments

- `x` A `mids` object.
- `y` A `mids` object.

Value

An S3 object of class `mids`

Author(s)

Karin Groothuis-Oudshoorn, Stef van Buuren, 2009

See Also

`mids`, `rbind.mids`, `cbind.mids`
ic

Incomplete cases

Description

Extracts incomplete cases from a data set. Missing values in \textit{x} are coded as \texttt{NA}. The companion function for selecting the complete cases is \texttt{cc()}. 

Usage

\begin{verbatim}
ic(x, drop = TRUE)
\end{verbatim}

Arguments

\begin{itemize}
\item \texttt{x} An \texttt{R} object. Currently supported are methods for the following classes: \texttt{mids}, \texttt{mira}, \texttt{mipo}, \texttt{data.frame} and \texttt{matrix}. In addition, \texttt{x} can be a vector of any kind.
\item \texttt{drop} A logical flag for matrices and arrays. If \texttt{drop}=\texttt{TRUE} the result is coerced to the lowest possible dimension.
\end{itemize}

Value

A vector, matrix of \texttt{data.frame} containing the data of the incomplete cases.

Author(s)

Stef van Buuren, 2010.

See Also

\begin{verbatim}
na.omit, cc, cci, ici, ccn, icn
\end{verbatim}

Examples

\begin{verbatim}
ic(nhanes)  # get the 12 rows with incomplete cases
ic(nhanes[1:10,])  # incomplete cases within the first ten rows
ic(nhanes[,2:3])  # restrict extraction to variables bmi and hyp
\end{verbatim}
ici

Incomplete case indicator

Description

This array is useful for extracting the subset of incomplete cases. Missing values in x are coded as NA. The companion function for selecting the complete cases is cci().

Usage

ici(x)

Arguments

x

An R object. Currently supported are methods for the following classes: mids, data.frame and matrix. In addition, x can be a vector of any kind.

Value

Logical vector indicating the incomplete cases. If x is a data.frame or matrix the length is nrow(x). In other cases, the length is length(x).

Author(s)

Stef van Buuren, 2010.

See Also

ci cc, ic, ccn, icn

Examples

ici(nhanes) # indicator for 12 rows with incomplete cases

icn

Incomplete cases n

Description

Calculates the number of incomplete cases. The companion function for calculating the number of complete cases is ccn().

Usage

icn(x)
is.mids

Arguments
x  An R object. Currently supported are methods for the following classes: mids, data.frame and matrix. In addition, x can be a vector of any kind.

Value
An integer with the number of elements in x with incomplete data.

Author(s)
Stef van Buuren, 2010.

See Also
ccn, cc, ic, cci, ici

Examples
icn(nhanes) # the remaining 12 rows
icn(nhanes[,c("bmi","hyp")]) # number of cases with incomplete bmi and hyp

Description
Check for mids object

Usage
is.mids(x)

Arguments
x  An object

Value
A logical indicating whether x is an object of class mids
is.mipo

Check for mipo object

Description

Check for mipo object

Usage

is.mipo(x)

Arguments

x An object

Value

A logical indicating whether x is an object of class mipo

is.mira

Check for mira object

Description

Check for mira object

Usage

is.mira(x)

Arguments

x An object

Value

A logical indicating whether x is an object of class mira
leiden85

**Description**

Subset of data from the Leiden 85+ study

**Format**

leiden85 is a data frame with 956 rows and 336 columns.

**Details**

The data set concerns of subset of 956 members of a very old (85+) cohort in Leiden.

Multiple imputation of this data set has been described in Boshuizen et al (1998), Van Buuren et al (1999) and Van Buuren (2012), chapter 7.

The data set is not available as part of mice.

**Source**


---

**lm.mids**

*Linear regression for mids object*

**Description**

Applies lm() to multiply imputed data set

**Usage**

`lm.mids(formula, data, ...)`
**mammalsleep**

**Arguments**

- `formula`: A formula object, with the response on the left of a ~ operator, and the terms, separated by + operators, on the right. See the documentation of `lm` and `formula` for details.
- `data`: An object of type 'mids', which stands for 'multiply imputed data set', typically created by a call to function `mice()`.
- `...`: Additional parameters passed to `lm`

**Details**

This function is included for backward compatibility with V1.0. The function is superseeded by `with.mids`.

**Value**

An objects of class `mira`, which stands for 'multiply imputed repeated analysis'. This object contains data$m$ distinct `lm` objects, plus some descriptive information.

**Author(s)**

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000

**References**


**See Also**

`lm`, `mids`, `mira`

**Examples**

```r
imp <- mice(nhanes)
fit <- lm.mids(bmi~hyp+chl, data = imp)
fit
```

---

**mammalsleep**

*Mammal sleep data*

**Description**

Dataset from Allison and Cicchetti (1976) of 62 mammal species on the interrelationship between sleep, ecological, and constitutional variables. The dataset contains missing values on five variables.
Format

mammalsleep is a data frame with 62 rows and 11 columns:

- **species**: Species of animal
- **bw**: Body weight (kg)
- **brw**: Brain weight (g)
- **sws**: Slow wave ("nondreaming") sleep (hrs/day)
- **ps**: Paradoxical ("dreaming") sleep (hrs/day)
- **ts**: Total sleep (hrs/day) (sum of slow wave and paradoxical sleep)
- **mls**: Maximum life span (years)
- **gt**: Gestation time (days)
- **pi**: Predation index (1-5), 1 = least likely to be preyed upon
- **sei**: Sleep exposure index (1-5), 1 = least exposed (e.g. animal sleeps in a well-protected den), 5 = most exposed
- **odi**: Overall danger index (1-5) based on the above two indices and other information, 1 = least danger (from other animals), 5 = most danger (from other animals)

Details

Allison and Cicchetti (1976) investigated the interrelationship between sleep, ecological, and constitutional variables. They assessed these variables for 39 mammalian species. The authors concluded that slow-wave sleep is negatively associated with a factor related to body size. This suggests that large amounts of this sleep phase are disadvantageous in large species. Also, paradoxical sleep (REM sleep) was associated with a factor related to predatory danger, suggesting that large amounts of this sleep phase are disadvantageous in prey species.

Source


Examples

```r
sleep <- data(mammalsleep)
```

---

**md.pairs**

*Missing data pattern by variable pairs*

**Description**

Number of observations per variable pair.

**Usage**

```r
md.pairs(data)
```
Arguments

data

A data frame or a matrix containing the incomplete data. Missing values are coded as NA.

Details

The four components in the output value have the following interpretation:

- `list('rr')` response-response, both variables are observed
- `list('rm')` response-missing, row observed, column missing
- `list('mr')` missing-response, row missing, column observed
- `list('mm')` missing-missing, both variables are missing

Value

A list of four components named `rr`, `rm`, `mr` and `mm`. Each component is a square numerical matrix containing the number of observations within four missing data patterns.

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2009

References


Examples

```r
pat <- md.pairs(nhanes)
pat

# show that these four matrices decompose the total sample size
# for each pair
pat$rr + pat$rm + pat$mr + pat$mm

# percentage of usable cases to impute row variable from column variable
round(100*pat$mr/(pat$mr+pat$mm))
```

MD-PATTERN

Description

Display missing-data patterns.
**md.pattern**

Usage

```r
md.pattern(x)
```

Arguments

- `x` A data frame or a matrix containing the incomplete data. Missing values are coded as NA's.

Details

This function is useful for investigating any structure of missing observation in the data. In specific case, the missing data pattern could be (nearly) monotone. Monotonicity can be used to simplify the imputation model. See Schafer (1997) for details. Also, the missing pattern could suggest which variables could potentially be useful for imputation of missing entries.

Value

A matrix with `ncol(x)+1` columns, in which each row corresponds to a missing data pattern (1=observed, 0=missing). Rows and columns are sorted in increasing amounts of missing information. The last column and row contain row and column counts, respectively.

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000

References


Examples

```r
md.pattern(nhanes)
#     age hyp bmi chl
# 13   1  1  1  1  1  0
#  1   1  1  0  1  1
#  3   1  1  1  0  1
#  1   1  0  0  1  2
#  7   1  0  0  0  3
#  0   8  9 10 12
```
Graphical parameter for missing data plots.

**Description**

`mdc` returns colors used to distinguish observed, missing and combined data in plotting. `mice.theme` return a partial list of named objects that can be used as a theme in `stripplot`, `bwplot`, `densityplot` and `xyplot`.

**Usage**

```r
mdc(r = "observed", s = "symbol", transparent = TRUE, cso = hcl(240, 100, 40, 0.7), csi = hcl(0, 100, 40, 0.7), csc = "gray50", clo = hcl(240, 100, 40, 0.8), cli = hcl(0, 100, 40, 0.8), clc = "gray50")
```

**Arguments**

- `r` A numerical or character vector. The numbers 1-6 request colors as follows: 1=cso, 2=csi, 3=csc, 4=clo, 5=cli and 6=clc. Alternatively, `r` may contain the strings 'observed', 'missing', or 'both', or abbreviations thereof.
- `s` A character vector containing the strings 'symbol' or 'line', or abbreviations thereof.
- `transparent` A logical indicating whether alpha-transparancy is allowed. The default is `TRUE`.
- `cso` The symbol color for the observed data. The default is a transparent blue.
- `csi` The symbol color for the missing or imputed data. The default is a transparent red.
- `csc` The symbol color for the combined observed and imputed data. The default is a grey color.
- `clo` The line color for the observed data. The default is a slightly darker transparent blue.
- `cli` The line color for the missing or imputed data. The default is a slightly darker transparent red.
- `clc` The line color for the combined observed and imputed data. The default is a grey color.

**Details**

This function eases consistent use of colors in plots. The default follows the Abayomi convention, which uses blue for observed data, red for missing or imputed data, and black for combined data.

**Value**

`mdc()` returns a vector containing color definitions. The length of the output vector is calculated from the length of `r` and `s`. Elements of the input vectors are repeated if needed.
**mice**

**Author(s)**

Stef van Buuren, sept 2012.

**References**


**See Also**

hcl, rgb, xypplot.mids, xypplot, trellis.par.set

**Examples**

```r
# all six colors
mdc(1:6)

# lines color for observed and missing data
mdc(c('obs', 'mis', 'lin'))
```

---

**mice**

*Multivariate Imputation by Chained Equations (MICE)*

**Description**

Generates Multivariate Imputations by Chained Equations (MICE)

**Usage**

```r
mice(data, m = 5, method = vector("character", length = ncol(data)),
      predictorMatrix = (1 - diag(1, ncol(data))),
      visitSequence = (1:ncol(data))[apply(is.na(data), 2, any)],
      form = vector("character", length = ncol(data)),
      post = vector("character", length = ncol(data)),
      defaultMethod = c("pmm", "logreg", "polyreg", "polr"),
      maxit = 5, diagnostics = TRUE,
      printFlag = TRUE, seed = NA, imputationMethod = NULL,
      defaultImputationMethod = NULL, data.init = NULL, ...)
```

**Arguments**

- **data**
  A data frame or a matrix containing the incomplete data. Missing values are coded as NA.

- **m**
  Number of multiple imputations. The default is m=5.
method  Can be either a single string, or a vector of strings with length `ncol(data)`, specifying the elementary imputation method to be used for each column in data. If specified as a single string, the same method will be used for all columns. The default imputation method (when no argument is specified) depends on the measurement level of the target column and are specified by the `defaultMethod` argument. Columns that need not be imputed have the empty method `''`. See details for more information.

predictorMatrix  A square matrix of size `ncol(data)` containing 0/1 data specifying the set of predictors to be used for each target column. Rows correspond to target variables (i.e. variables to be imputed), in the sequence as they appear in data. A value of `1` means that the column variable is used as a predictor for the target variable (in the rows). The diagonal of `predictorMatrix` must be zero. The default for `predictorMatrix` is that all other columns are used as predictors (sometimes called massive imputation). Note: For two-level imputation codes `2` and `-2` are also allowed.

visitSequence  A vector of integers of arbitrary length, specifying the column indices of the visiting sequence. The visiting sequence is the column order that is used to impute the data during one pass through the data. A column may be visited more than once. All incomplete columns that are used as predictors should be visited, or else the function will stop with an error. The default sequence `1:ncol(data)` implies that columns are imputed from left to right. It is possible to specify one of the keywords `roman` (left to right), `arabic` (right to left), `monotone` (sorted in increasing amount of missingness) and `revmonotone` (reverse of monotone). The keyword should be supplied as a string and may be abbreviated.

post  A vector of strings with length `ncol(data)`, specifying expressions. Each string is parsed and executed within the `sampler()` function to postprocess imputed values. The default is to do nothing, indicated by a vector of empty strings `''`.

form  A vector of strings with length `ncol(data)`, specifying formulae. Each string is parsed and executed within the `sampler()` function to create terms for the predictor. The default is to do nothing, indicated by a vector of empty strings `''`. The main value lies in the easy specification of interaction terms. The user must ensure that the set of variables in the formula match those in `predictors`.

defaultMethod  A vector of three strings containing the default imputation methods for numerical columns, factor columns with 2 levels, and columns with (unordered or ordered) factors with more than two levels, respectively. If nothing is specified, the following defaults will be used: `pmm`, predictive mean matching (numeric data) `logreg`, logistic regression imputation (binary data, factor with 2 levels) `polyreg`, polytomous regression imputation for unordered categorical data (factor $\geq 2$ levels) `polr`, proportional odds model for (ordered, $\geq 2$ levels)

maxit  A scalar giving the number of iterations. The default is 5.

diagnostics  A Boolean flag. If `TRUE`, diagnostic information will be appended to the value of the function. If `FALSE`, only the imputed data are saved. The default is `TRUE`.

printFlag  If `TRUE`, `mice` will print history on console. Use `print=False` for silent computation.

seed  An integer that is used as argument by the `set.seed()` for offsetting the random number generator. Default is to leave the random number generator alone.
imputationMethod
Same as method argument. Included for backwards compatibility.

defaultImputationMethod
Same as defaultMethod argument. Included for backwards compatibility.

data.init
A data frame of the same size and type as data, without missing data, used to initialize imputations before the start of the iterative process. The default NULL implies that starting imputation are created by a simple random draw from the data. Note that specification of data.init will start the m Gibbs sampling streams from the same imputations.

... Named arguments that are passed down to the elementary imputation functions.

Details
Generates multiple imputations for incomplete multivariate data by Gibbs sampling. Missing data can occur anywhere in the data. The algorithm imputes an incomplete column (the target column) by generating ‘plausible’ synthetic values given other columns in the data. Each incomplete column must act as a target column, and has its own specific set of predictors. The default set of predictors for a given target consists of all other columns in the data. For predictors that are incomplete themselves, the most recently generated imputations are used to complete the predictors prior to imputation of the target column.

A separate univariate imputation model can be specified for each column. The default imputation method depends on the measurement level of the target column. In addition to these, several other methods are provided. You can also write their own imputation functions, and call these from within the algorithm.

The data may contain categorical variables that are used in a regressions on other variables. The algorithm creates dummy variables for the categories of these variables, and imputes these from the corresponding categorical variable. The extended model containing the dummy variables is called the padded model. Its structure is stored in the list component pad.

Built-in elementary imputation methods are:

pmm_pred Predictive mean matching (any)

norm_Bayesian linear regression (numeric)

norm.nob_Linear regression ignoring model error (numeric)

norm.boot_Linear regression using bootstrap (numeric)

norm.predict_Linear regression, predicted values (numeric)

mean_Unconditional mean imputation (numeric)

2l.norm_Two-level normal imputation (numeric)

2l.pan_Two-level normal imputation using pan (numeric)

2lonly.mean_Imputation at level-2 of the class mean (numeric)

2lonly.norm_Imputation at level-2 by Bayesian linear regression (numeric)

2lonly.pmm_Imputation at level-2 by Predictive mean matching (any)

quadratic_Imputation of quadratic terms (numeric)

logreg_Logistic regression (factor, 2 levels)
logreg.boot  Logistic regression with bootstrap
polyreg  Polytomous logistic regression (factor, >= 2 levels)
polr  Proportional odds model (ordered, >=2 levels)
lda  Linear discriminant analysis (factor, >= 2 categories)
cart  Classification and regression trees (any)
rf  Random forest imputations (any)
ri  Random indicator method for nonignorable data (numeric)
sample  Random sample from the observed values (any)
fastpmm  Experimental: Fast predictive mean matching using C++ (any)

These corresponding functions are coded in the mice library under names mice.impute.method, where method is a string with the name of the elementary imputation method name, for example norm. The method argument specifies the methods to be used. For the j'th column, mice() calls the first occurrence of paste('mice.impute.', method[j], sep='') in the search path. The mechanism allows uses to write customized imputation function, mice.impute.myfunc. To call it for all columns specify method='myfunc'. To call it only for, say, column 2 specify method=c('norm','myfunc','logreg',...).

Passive imputation: mice() supports a special built-in method, called passive imputation. This method can be used to ensure that a data transform always depends on the most recently generated imputations. In some cases, an imputation model may need transformed data in addition to the original data (e.g. log, quadratic, recodes, interaction, sum scores, and so on).

Passive imputation maintains consistency among different transformations of the same data. Passive imputation is invoked if ~ is specified as the first character of the string that specifies the elementary method. mice() interprets the entire string, including the ~ character, as the formula argument in a call to model.frame(formula=data[,r[,j]],). This provides a simple mechanism for specifying deterministic dependencies among the columns. For example, suppose that the missing entries in variables data$height and data$weight are imputed. The body mass index (BMI) can be calculated within mice by specifying the string '~I(weight/height^2)' as the elementary imputation method for the target column data$bmi. Note that the ~ mechanism works only on those entries which have missing values in the target column. You should make sure that the combined observed and imputed parts of the target column make sense. An easy way to create consistency is by coding all entries in the target as NA, but for large data sets, this could be inefficient. Note that you may also need to adapt the default predictorMatrix to evade linear dependencies among the predictors that could cause errors like Error in solve.default() or Error: system is exactly singular. Though not strictly needed, it is often useful to specify visitSequence such that the column that is imputed by the ~ mechanism is visited each time after one of its predictors was visited. In that way, deterministic relation between columns will always be synchronized.

Value

Returns an S3 object of class mids (multiply imputed data set)

Author(s)

Stef van Buuren <stef.vanbuuren@tno.nl>, Karin Groothuis-Oudshoorn <c.g.m.oudshoorn@utwente.nl>, 2000-2010, with contributions of Alexander Robitzsch, Gerko Vink, Shahab Jolani, Roel de Jong, Jason Turner, Lisa Doove, John Fox, Frank E. Harrell, and Peter Malewski.
mice.impute.2l.norm

References


See Also

mids, with.mids, set.seed, complete

Examples

```r
# do default multiple imputation on a numeric matrix
imp <- mice(nhanes)
imp

# list the actual imputations for BMI
imp$imputations$bmi

# first completed data matrix
complete(imp)

# imputation on mixed data with a different method per column
mice(nhanes2, meth=c('sample','pmm','logreg','norm'))
```

---

**mice.impute.2l.norm  Imputation by a two-level normal model**

**Description**

Imputes univariate missing data using a two-level normal model

**Usage**

```r
mice.impute.2l.norm(y, ry, x, type, intercept = TRUE, ...)
```
Arguments

- **y**: Incomplete data vector of length n
- **ry**: Vector of missing data pattern (FALSE=missing, TRUE=observed)
- **x**: Matrix (n x p) of complete covariates.
- **type**: Vector of length ncol(x) identifying random and class variables. Random variables are identified by a ’2’. The class variable (only one is allowed) is coded as ’-2’. Random variables also include the fixed effect.
- **intercept**: Logical determining whether the intercept is automatically added.
- **...**: Other named arguments.

Details

Implements the Gibbs sampler for the linear multilevel model with heterogeneous within-class variance (Kasim and Raudenbush, 1998). Imputations are drawn as an extra step to the algorithm. For simulation work see Van Buuren (2011).

The random intercept is automatically added in mice.impute.2L.norm(). A model within a random intercept can be specified by mice(..., intercept = FALSE).

Value

A vector of length nmis with imputations.

Note

Added June 25, 2012: The currently implemented algorithm does not handle predictors that are specified as fixed effects (type=1). When using mice.impute.2L.norm(), the current advice is to specify all predictors as random effects (type=2).

Warning: The assumption of heterogeneous variances requires that in every class at least one observation has a response in y.

Author(s)

Roel de Jong, 2008

References


**mice.impute.2l.pan**

**Imputation by a two-level normal model using pan**

**Description**

Imputes univariate missing data using a two-level normal model with homogeneous within group variances. Aggregated group effects (i.e. group means) can be automatically created and included as predictors in the two-level regression (see argument type). This function needs the pan package.

**Usage**

```r
mice.impute.2l.pan(y, ry, x, type[, intercept = TRUE, paniter = 500,
               groupcenter.slope = FALSE, ...])
```

**Arguments**

- `y` Incomplete data vector of length \( n \)
- `ry` Vector of missing data pattern (FALSE=missing, TRUE=observed)
- `x` Matrix \((n \times p)\) of complete covariates.
- `type` Vector of length \( ncol(x) \) identifying random and class variables. Random effects are identified by a ‘2’. The group variable (only one is allowed) is coded as ‘-2’. Random effects also include the fixed effect. If for a covariate \( X_1 \) group means shall be calculated and included as further fixed effects choose ‘3’. In addition to the effects in ‘3’, specification ‘4’ also includes random effects of \( X_1 \).
- `intercept` Logical determining whether the intercept is automatically added.
- `paniter` Number of iterations in pan. Default is 500.
- `groupcenter.slope` If TRUE, in case of group means (type is ‘3’ or ‘4’) group mean centering for these predictors are conducted before doing imputations. Default is FALSE.
- `...` Other named arguments.

**Details**

Implements the Gibbs sampler for the linear two-level model with homogeneous within group variances which is a special case of a multivariate linear mixed effects model (Schafer & Yucel, 2002). For a two-level imputation with heterogeneous within-group variances see \texttt{mice.impute.2l.norm}. The random intercept is automatically added in \texttt{mice.impute.2l.norm()}

**Value**

A vector of length \( nmis \) with imputations.
Author(s)

Alexander Robitzsch (Federal Institute for Education Research, Innovation, and Development of the Austrian School System, Salzburg, Austria), <a.robitzsch@bifie.at>

References


See Also

`mice.impute.2l.pan`

Examples

# simulate some data
# two-level regression model with fixed slope

```r
# number of groups
G <- 250
# number of persons
n <- 20
# regression parameter
beta <- .3
# intraclass correlation
rho <- .30
# correlation with missing response
rho.miss <- .10
# missing proportion
missrate <- .50

y1 <- rep( rnorm( G, sd = sqrt( rho ) ), each=n ) + rnorm(G*n , sd = sqrt( 1 - rho ) )
x <- rnorm( G*n )
y <- y1 + beta * x
dfr0 <- data.frame( "group" = rep(1:G , each=n ) , "x" = x , "y" = y )
dfr[ rho.miss * x + rnorm( G*n , sd = sqrt( 1 - rho.miss ) ) < qnorm( missrate ) , "y" ] <- NA

#... # empty imputation in mice
imp0 <- mice( as.matrix(dfr0) , maxit=0 )
predM <- imp0$predictorMatrix
impM <- imp0$method

#... # specify predictor matrix and imputationMethod
predM1 <- predM
predM1["y","group"] <- -2
predM1["y","x"] <- 1  # fixed x effects imputation
impM1 <- impM
```
mice.impute.2lonly.mean

Imputation of the mean within the class

Description
Imputes the mean of within the class

Usage
mice.impute.2lonly.mean(y, ry, x, type, ...)

Arguments
- `y`: Incomplete data vector of length n
- `ry`: Vector of missing data pattern (FALSE=missing, TRUE=observed)
- `x`: Matrix (n x p) of complete covariates.
- `type`: Vector of length ncol(x) identifying random and class variables. The class variable (only one is allowed) is coded as '-2'.
- `...`: Other named arguments.

Details
Observed values in y are averaged within the class, and replicated to the missing y within that class. If there are no observed data in the class, all entries of the class are set to NaN. This function is primarily useful for repairing incomplete data that are constant within the class, but that vary over the classes.
Value

A vector of length nmis with imputations.

Author(s)

Gerko Vink, Stef van Buuren, 2013

Imputation at level 2 by Bayesian linear regression

mice.impute.2lonly.norm

Usage

mice.impute.2lonly.norm(y, ry, x, type, ...)
References


See Also

`mice.impute.norm, mice.impute.2lonly.pmm, mice.impute.2l.pan`

Examples

```
# simulate some data
# x,y ... level 1 variables
# v,w ... level 2 variables

G <- 250          # number of groups
n <- 20           # number of persons
beta <- .3        # regression coefficient
rho <- .30        # residual intraclass correlation
rho.miss <- .10   # correlation with missing response
missrate <- .50   # missing proportion

y1 <- rep( rnorm(G, sd = sqrt(rho) ), each=n ) + rnorm(G*n, sd = sqrt(1-rho) )
w <- rep( round( rnorm(G ), 2 ), each=n )
v <- rep( round( runif( G, 0, 3 ) ), each=n )
x <- rnorm( G*n )

y <- y1 + beta * x + .2 * w + .1 * v

dfr0 <- dfr <- data.frame("group" = rep(1:G, each=n ), "x" = x, "y" = y, "w" = w, "v" = v )

dfr[ rho.miss * x + rnorm( G*n, sd = sqrt(1-rho.miss) ) < qnorm( missrate ), "y" ] <- NA
dfr[ rep( rnorm(G), each=n ) < qnorm( missrate ), "w" ] <- NA
dfr[ rep( rnorm(G), each=n ) < qnorm( missrate ), "v" ] <- NA

#....
# empty mice imputation
imp0 <- mice( as.matrix(dfr), maxit=0 )

# multilevel imputation
predM <- imp0$predictorMatrix
impM <- imp0$method

#....
# fixed x effects imputation

impM1 <- impM

impM1[c("w","y","v"),"group"] <- -2
impM1["y","x"] <- 1

# y ... imputation using pan
impM1[c("y","w","v")]<- c("2l.pan", "2lonly.norm", "2lonly.pmm")

# y ... imputation using norm
# w ... imputation at level 2 using norm
# v ... imputation at level 2 using pmm
```
mice.impute.2lonely.pmm

Imputation at level 2 by predictive mean matching

Description

Imputes univariate missing data at level 2 using predictive mean matching. Variables are level 1 are aggregated at level 2. The group identifier at level 2 must be indicated by type=-2 in the predictorMatrix.

Usage

mice.impute.2lonely.pmm(y, ry, x, type, ...)

Arguments

y  Incomplete data vector of length n
ry  Vector of missing data pattern (FALSE=missing, TRUE=observed)
x  Matrix (n x p) of complete covariates. Only numeric variables are permitted for usage of this function.
type  Group identifier must be specified by '-2'. Predictors must be specified by '1'.
...  Other named arguments.

Details

This function allows in combination with mice.impute.21.pan switching regression imputation between level 1 and level 2 as described in Yucel (2008) or Gelman and Hill (2007, p. 541).

Value

A vector of length nmis with imputations.

Author(s)

Alexander Robitzsch (Federal Institute for Education Research, Innovation, and Development of the Austrian School System, Salzburg, Austria), <a.robitzsch@bifie.at>

References


mice.impute.cart

See Also

mice.impute.pmm, mice.impute.2lonly.norm, mice.impute.2lonly.pmm

Examples

# simulate some data
# x,y ... level 1 variables
# v,w ... level 2 variables

G <- 250  # number of groups
n <- 20   # number of persons
beta <- .3 # regression coefficient
rho <- .3  # residual intraclass correlation
rho.miss <- .10  # correlation with missing response
missrate <- .50  # missing proportion

y1 <- rep( rnorm( G , sd = sqrt( rho ) ) , each=n ) + rnorm(G*n , sd = sqrt( 1 - rho ) )
w <- rep( round( rnorm(G ) , 2 ) , each=n )
v <- rep( round( runif( G , 0 , 3 ) ) , each=n )
x <- rnorm( G*n )

y <- y1 + beta * x + .2 * w + .1 * v
dfr0 <- dfr <- data.frame( "group" = rep(1:G , each=n ) , "x" = x , "y" = y , "w" = w , "v" = v )
dfr[ rho.miss * x + rnorm( G*n , sd = sqrt( 1 - rho.miss ) ) < qnorm( missrate ) , "y" ] <- NA
dfr[ rep( rnorm(G ) , each=n ) < qnorm( missrate ) , "w" ] <- NA
dfr[ rep( rnorm(G ) , each=n ) < qnorm( missrate ) , "v" ] <- NA

# empty mice imputation
imp0 <- mice( as.matrix(dfr) , maxit=0 )

# multilevel imputation
predM <- imp0$predictorMatrix
impM <- imp0$method

# y ... imputation using pan
# w ... imputation at level 2 using norm
# v ... imputation at level 2 using pmm

imp1 <- mice( as.matrix( dfr ) , m = 1 , predictorMatrix = predM , imputationMethod = impM , maxit=1 , paniter=500)

mice.impute.cart

Imputation by classification and regression trees
Description

Imputes univariate missing data using classification and regression trees.

Usage

mice.impute.cart(y, ry, x, minbucket = 5, cp = 1e-04, ...)

Arguments

y
Numeric vector with incomplete data

ry
Response pattern of y (TRUE = observed, FALSE = missing)

x
Design matrix with length(y) rows and p columns containing complete covariates.

minbucket
The minimum number of observations in any terminal node used. See rpart.control for details.

cp
Complexity parameter. Any split that does not decrease the overall lack of fit by a factor of cp is not attempted. See rpart.control for details.

... Other named arguments passed down to rpart().

Details

Imputation of y by classification and regression trees. The procedure is as follows:

1. Fit a classification or regression tree by recursive partitioning;
2. For each ymis, find the terminal node they end up according to the fitted tree;
3. Make a random draw among the member in the node, and take the observed value from that draw as the imputation.

Value

Numeric vector of length sum(!ry) with imputations

Author(s)

Lisa Doove, Stef van Buuren, Elise Dusseldorp, 2012

References


See Also

mice, mice.impute.rf, rpart, rpart.control
mice.impute.fastpmm

Examples

```r
require(randomForest)
require(lattice)

imp <- mice(nhanes2, meth = "cart", minbucket = 4)
plot(imp)
```

mice.impute.fastpmm Imputation by fast predictive mean matching

Description

Imputes univariate missing data using fast predictive mean matching

Usage

```r
mice.impute.fastpmm(y, ry, x, donors = 5, type = 1, ridge = 1e-05,
version = "", ...)```

Arguments

- `y` Numeric vector with incomplete data
- `ry` Response pattern of `y` (TRUE=observed, FALSE=missing)
- `x` Design matrix with length(`y`) rows and `p` columns containing complete covariates.
- `donors` The size of the donor pool among which a draw is made. The default is `donors = 5`. Setting `donors = 1` always selects the closest match. Values between 3 and 10 provide the best results. Note: The default was changed from 3 to 5 in version 2.19, based on simulation work by Tim Morris.
- `type` Type of matching distance. The default choice `type = 1` calculates the distance between the predicted value of `yobs` and the drawn values of `ymis`. Other choices are `type = 0` (distance between predicted values) and `type = 2` (distance between drawn values). The current version supports only `type = 1`.
- `ridge` The ridge penalty applied in `norm.draw()` to prevent problems with multicollinearity. The default is `ridge = 1e-05`, which means that 0.01 percent of the diagonal is added to the cross-product. Larger ridges may result in more biased estimates. For highly noisy data (e.g. many junk variables), set `ridge = 1e-06` or even lower to reduce bias. For highly collinear data, set `ridge = 1e-04` or higher.
- `version` A character variable indicating the version. Currently unused.
- `...` Other named arguments.
Details

Imputation of y by predictive mean matching, based on Rubin (1987, p. 168, formulas a and b). The procedure is as follows:

1. Estimate beta and sigma by linear regression
2. Draw beta* and sigma* from the proper posterior
3. Compute predicted values for yobs beta and ymis beta*
4. For each ymis, find donors observations with closest predicted values, randomly sample one of these, and take its observed value in y as the imputation.
5. Ties are broken by making a random draw among ties. Note: The matching is done on predicted y, NOT on observed y.

Value

Numeric vector of length sum(!!ry) with imputations

Note

The mice.impute.fastpmm() function is an experimental version of the standard mice.impute.pmm() function. In mice 2.22 both are equivalent. In future versions of mice the mice.impute.fastpmm() function may be subject to additional optimizations. This is an experimental feature.

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000, 2012

References


See Also

mice.impute.pmm
mice.impute.lda  

Imputation by linear discriminant analysis

Description

Imputes univariate missing data using linear discriminant analysis

Usage

mice.impute.lda(y, ry, x, ...)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>y</td>
<td>Incomplete data vector of length n</td>
</tr>
<tr>
<td>ry</td>
<td>Vector of missing data pattern (FALSE=missing, TRUE=observed)</td>
</tr>
<tr>
<td>x</td>
<td>Matrix (n x p) of complete covariates.</td>
</tr>
<tr>
<td>...</td>
<td>Other named arguments.</td>
</tr>
</tbody>
</table>

Details

Imputation of categorical response variables by linear discriminant analysis. This function uses the Venables/Ripley functions lda() and predict.lda() to compute posterior probabilities for each incomplete case, and draws the imputations from this posterior.

Value

A vector of length nmis with imputations.

Warning

The function does not incorporate the variability of the discriminant weight, so it is not 'proper' in the sense of Rubin. For small samples and rare categories in the y, variability of the imputed data could therefore be somewhat underestimated.

Note

This function can be called from within the Gibbs sampler by specifying 'lda' in the method argument of mice(). This method is usually faster and uses fewer resources than calling the function mice.impute.polyreg.

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000
mice.impute.logreg

References


See Also

mice, link{mice.impute.polyreg}, lda

---

**mice.impute.logreg  Imputation by logistic regression**

**Description**

Imputes univariate missing data using logistic regression.

**Usage**

```r
mice.impute.logreg(y, ry, x, ...)
```

**Arguments**

- `y`: Incomplete data vector of length n
- `ry`: Vector of missing data pattern of length n (FALSE=missing, TRUE=observed)
- `x`: Matrix (n x p) of complete covariates.
- `...`: Other named arguments.

**Details**

Imputation for binary response variables by the Bayesian logistic regression model (Rubin 1987, p. 169-170). The Bayesian method consists of the following steps:

1. Fit a logit, and find (bhat, V(bhat))
2. Draw BETA from N(bhat, V(bhat))
3. Compute predicted scores for m.d., i.e. logit-1(X BETA)
4. Compare the score to a random (0,1) deviate, and impute.

The method relies on the standard glm.fit function. Warnings from glm.fit are suppressed. Perfect prediction is handled by the data augmentation method.
Value

A vector of length nmis with imputations (0 or 1).

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000, 2011

References


See Also

mice, glm, glm.fit

---

**mice.impute.logreg.boot**

*Imputation by logistic regression using the bootstrap*

Description

Imputes univariate missing data using logistic regression by a bootstrapped logistic regression model. The bootstrap method draws a simple bootstrap sample with replacement from the observed data y[ry] and x[ry,]. Perfect prediction is handled by the data augmentation method.

Usage

mice.impute.logreg.boot(y, ry, x, ...)

Arguments

- **y**  
  Incomplete data vector of length n
- **ry**  
  Vector of missing data pattern of length n (FALSE=missing, TRUE=observed)
- **x**  
  Matrix (n x p) of complete covariates.
- **...**  
  Other named arguments.
mice.impute.mean

Value
A vector of length nmis with imputations (0 or 1).

Author(s)
Stef van Buuren, Karin Groothuis-Oudshoorn, 2000, 2011

References

See Also
mice, glm, glm.fit

Description
Imputes the arithmetic mean of the observed data

Usage
mice.impute.mean(y, ry, x = NULL, ...)

Arguments
y Incomplete data vector of length n
ry Vector of missing data pattern (FALSE=missing, TRUE=observed)
x Matrix (n x p) of complete covariates.
... Other named arguments.

Value
A vector of length nmis with imputations.
mice.impute.norm

Warning

Imputing the mean of a variable is almost never appropriate. See Little and Rubin (1987).

Author(s)
Stef van Buuren, Karin Groothuis-Oudshoorn, 2000

References

See Also
mice, mean

Description
Imputes univariate missing data using Bayesian linear regression analysis

Usage
mice.impute.norm(y, ry, x, ...)

Arguments
y incomplete data vector of length n
ry Vector of missing data pattern (FALSE=missing, TRUE=observed)
x Matrix (n x p) of complete covariates.
... Other named arguments.

Details
Draws values of beta and sigma for Bayesian linear regression imputation of y given x according to Rubin p. 167.

Value
A vector of length n*mis with imputations.
Note

Using `mice.impute.norm` for all columns is similar to Schafer's NORM method (Schafer, 1997).

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000

References


---

`mice.impute.norm.boot`  *Imputation by linear regression, bootstrap method*

Description

Imputes univariate missing data using linear regression with bootstrap

Usage

```r
mice.impute.norm.boot(y, ry, x, ridge = 1e-05, ...)
```

Arguments

- `y`  Incomplete data vector of length `n`
- `ry`  Vector of missing data pattern (FALSE=missing, TRUE=observed)
- `x`  Matrix (n x p) of complete covariates.
- `ridge`  Ridge parameter
- `...`  Other named arguments.

Details

Draws a bootstrap sample from `x[ry,]` and `y[ry]`, calculates regression weights and imputes with normal residuals. The `ridge` parameter adds a penalty term `ridge*diag(xtx)` to the variance-covariance matrix `xtx`.

Value

A vector of length `nmis` with imputations.
**mice.impute.norm.nob**

**Author(s)**
Stef van Buuren, 2011

**References**

---

**mice.impute.norm.nob  Imputation by linear regression (non Bayesian)**

**Description**
Imputes univariate missing data using linear regression analysis (non Bayesian version)

**Usage**
```r
mice.impute.norm.nob(y, ry, x, ...)
```

**Arguments**
- `y`  Incomplete data vector of length `n`
- `ry`  Vector of missing data pattern (FALSE=missing, TRUE=observed)
- `x`  Matrix (n x p) of complete covariates.
- `...`  Other named arguments.

**Details**
This creates imputation using the spread around the fitted linear regression line of `y` given `x`, as fitted on the observed data.

**Value**
A vector of length `nmis` with imputations.

**Warning**
The function does not incorporate the variability of the regression weights, so it is not 'proper' in the sense of Rubin. For small samples, variability of the imputed data is therefore underestimated.

**Note**
This function is provided mainly to allow comparison between proper and improper norm methods. Also, it may be useful to impute large data containing many rows.
mice.impute.norm.predict

Author(s)
Stef van Buuren, Karin Groothuis-Oudshoorn, 2000

References

See Also
mice, mice.impute.norm

---

mice.impute.norm.predict

*Imputation by linear regression, prediction method*

Description
Imputes univariate missing data using the predicted value from a linear regression

Usage
mice.impute.norm.predict(y, ry, x, ridge = 1e-05, ...)

Arguments
- **y**: Incomplete data vector of length \(n\)
- **ry**: Vector of missing data pattern (FALSE=missing, TRUE=observed)
- **x**: Matrix (\(n \times p\)) of complete covariates.
- **ridge**: Ridge parameter
- **...**: Other named arguments.

Details
Calculates regression weights from the observed data and and return predicted values to as imputations. The ridge parameter adds a penalty term \(\text{ridge} \times \text{diag}(\text{xtx})\) to the variance-covariance matrix \(\text{xtx}\).

Value
A vector of length \(\text{nmiss}\) with imputations.
mice.impute.passive

Author(s)
Stef van Buuren, 2011

References

mice.impute.passive  Passive imputation

Description
Derive a new variable based on the imputed data

Usage
mice.impute.passive(data, func)

Arguments
data  A data frame
func  A formula specifying the transformations on data

Details
Passive imputation is a special internal imputation function. Using this facility, the user can specify, at any point in the mice Gibbs sampling algorithm, a function on the imputed data. This is useful, for example, to compute a cubic version of a variable, a transformation like \( Q = \frac{w}{h^2} \) based on two variables, or a mean variable like \( (x_1 + x_2 + x_3) / 3 \). The so derived variables might be used in other places in the imputation model. The function allows to dynamically derive virtually any function of the imputed data at virtually any time.

Value
The result of applying formula

Author(s)
Stef van Buuren, Karin Groothuis-Oudshoorn, 2000

References

See Also
mice
mice.impute.pmm  
Imputation by predictive mean matching

Description
Imputes univariate missing data using predictive mean matching

Usage
mice.impute.pmm(y, ry, x, donors = 5, type = 1, ridge = 1e-05, version = "", ...)

Arguments
- **y**: Numeric vector with incomplete data
- **ry**: Response pattern of y (TRUE=observed, FALSE=missing)
- **x**: Design matrix with length(y) rows and p columns containing complete covariates.
- **donors**: The size of the donor pool among which a draw is made. The default is donors = 5. Setting donors = 1 always selects the closest match. Values between 3 and 10 provide the best results. Note: The default was changed from 3 to 5 in version 2.19, based on simulation work by Tim Morris.
- **type**: Type of matching distance. The default choice type = 1 calculates the distance between the predicted value of yobs and the drawn values of ymis. Other choices are type = 0 (distance between predicted values) and type = 2 (distance between drawn values). The current version supports only type = 1.
- **ridge**: The ridge penalty applied in norm.draw() to prevent problems with multicollinearity. The default is ridge = 1e-05, which means that 0.01 percent of the diagonal is added to the cross-product. Larger ridges may result in more biased estimates. For highly noisy data (e.g. many junk variables), set ridge = 1e-06 or even lower to reduce bias. For highly collinear data, set ridge = 1e-04 or higher.
- **version**: A character variable indicating the version to be used. Specifying version = "2.21" calls .pmm.match() instead of the default matcher() function.
- **...**: Other named arguments.

Details
Imputation of y by predictive mean matching, based on Rubin (1987, p. 168, formulas a and b). The procedure is as follows:
1. Estimate beta and sigma by linear regression
2. Draw beta* and sigma* from the proper posterior
3. Compute predicted values for yobs beta and ymis beta*
4. For each ymis, find donors observations with closest predicted values, randomly sample one of these, and take its observed value in y as the imputation.

5. Ties are broken by making a random draw among ties. Note: The matching is done on predicted y, NOT on observed y.

Value

Numeric vector of length sum(!ry) with imputations

Note

Since mice 2.22 the standard mice.impute.pmm() calls the much faster matcher() function instead of .pmm.match(). Since matcher() uses its own random generator, results cannot be exactly reproduced. In case where you want the old .pmm.match(), specify mice(..., version = "2.21").

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000, 2012

References


mice.impute.polr  Imputation by polytomous regression - ordered

Description

Imputes missing data in a categorical variable using polytomous regression

Usage

mice.impute.polr(y, ry, x, nnet.maxit = 100, nnet.trace = FALSE, nnet.maxNWts = 1500, ...)

Arguments

- `y`: Incomplete data vector of length `n`.
- `ry`: Vector of missing data pattern (FALSE=missing, TRUE=observed).
- `x`: Matrix (`n` x `p`) of complete covariates.
- `nnet.maxit`: Tuning parameter for `nnet()`.
- `nnet.trace`: Tuning parameter for `nnet()`.
- `nnet.maxNWts`: Tuning parameter for `nnet()`.
- `...`: Other named arguments.

Details

By default, ordered factors with more than two levels are imputed by `mice.impute.polr`.

The function `mice.impute.polr()` imputes for ordered categorical response variables by the proportional odds logistic regression (`polr`) model. The function repeatedly applies logistic regression on the successive splits. The model is also known as the cumulative link model.

The algorithm of `mice.impute.polr` uses the function `polr()` from the MASS package.

In order to avoid bias due to perfect prediction, the algorithm augment the data according to the method of White, Daniel and Royston (2010).

The call to `polr` might fail, usually because the data are very sparse. In that case, `multinom` is tried as a fallback, and a record is written to the `loggedEvents` component of the `mids` object.

Value

A vector of length `nmis` with imputations.

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000-2010

References


See Also

`mice.impute.polr`, `multinom`, `polr`
mice.impute.polyreg  Imputation by polytomous regression - unordered

Description
Imputes missing data in a categorical variable using polytomous regression

Usage
mice.impute.polyreg(y, ry, x, nnet.maxit = 100, nnet.trace = FALSE, nnet.maxNWts = 1500, ...)

Arguments
y  Incomplete data vector of length n
ry  Vector of missing data pattern (FALSE=missing, TRUE=observed)
x  Matrix (n x p) of complete covariates.
nnet.maxit  Tuning parameter for nnet().
nnet.trace  Tuning parameter for nnet().
nnet.maxNWts  Tuning parameter for nnet().
...  Other named arguments.

Details
By default, unordered factors with more than two levels are imputed by mice.impute.polyreg(). The function mice.impute.polyreg() imputes categorical response variables by the Bayesian polytomous regression model. See J.P.L. Brand (1999), Chapter 4, Appendix B.

The method consists of the following steps:
1. Fit categorical response as a multinomial model
2. Compute predicted categories
3. Add appropriate noise to predictions.

The algorithm of mice.impute.polyreg uses the function multinom() from the nnet package.

In order to avoid bias due to perfect prediction, the algorithm augment the data according to the method of White, Daniel and Royston (2010).

Value
A vector of length nmis with imputations.

Author(s)
Stef van Buuren, Karin Groothuis-Oudshoorn, 2000-2010
mice.impute.quadratic

References


See Also

mice, multinom, polr

mice.impute.quadratic

**Imputation of quadratic terms**

Description

Imputes univariate missing data of incomplete variable that appears as both main effect and quadratic effect in the complete-data model.

Usage

mice.impute.quadratic(y, ry, x, ...)

Arguments

y
Incomplete data vector of length n

ry
Vector of missing data pattern (FALSE=missing, TRUE=observed)

x
Matrix (n x p) of complete covariates.

... Other named arguments.

Details

This implements polynomial combination method. First, the polynomial combination $Z = Y \beta_1 + Y^2 \beta_2$ is formed. $SZ$ is imputed by predictive mean matching, followed by a decomposition of the imputed data $SZ$ into components $SY$ and $Y^2S$. See Van Buuren (2012, pp. 139-141) and Vink et al (2012) for more details. The method ensures that 1) the imputed data for $SY$ and $Y^2S$ are mutually consistent, and 2) that provides unbiased estimates of the regression weights in a complete-data linear regression that use both $SY$ and $Y^2S$.

Value

A vector of length nmis with imputations.
Note

There are two situations to consider. If only the linear term $Y$ is present in the data, calculate the quadratic term $YY$ after imputation. If both the linear term $Y$ and the the quadratic term $YY$ are variables in the data, then first impute $Y$ by calling `mice.impute.quadratic()` on $Y$, and then impute $YY$ by passive imputation as `meth["YY"] <- ~I(Y^2)`. See example section for details. Generally, we would like $YY$ to be present in the data if we need to preserve quadratic relations between $YY$ and any third variables in the multivariate incomplete data that we might wish to impute.

Author(s)

Gerko Vink (University of Utrecht), <g.vink@uu.nl>

References


See Also

`mice.impute.pmm`

Examples

```r
require(lattice)

# Create Data
B1=.5
B2=.5
X<-rnorm(1000)
XX<-X^2
e<-rnorm(1000, 0, 1)
Y <- B1*X+B2*XX+e
dat <- data.frame(x=X, xx=XX, y=Y)

# Impose 25 percent MCAR Missingness
dat[0 == rbinom(1000, 1, 1-.25), 1:2] <- NA

# Prepare data for imputation
ini <- mice(dat, maxit=0)
meth <- c("quadratic", "~I(x^2)", "")
pred <- ini$pred
pred[,"xx"] <- 0

# Impute data
imp <- mice(dat, meth=meth, pred=pred)

# Pool results
pool(with(imp, lm(y~x+xx)))
```
mice.impute.rf

Imputation by random forests

Description

Imputes univariate missing data using random forests.

Usage

mice.impute.rf(y, ry, x, ntree = 10, ...)

Arguments

y
Numeric vector with incomplete data

ry
Response pattern of y (TRUE = observed, FALSE = missing)

x
Design matrix with length(y) rows and p columns containing complete covariates.

ntree
The number of trees to grow. The default is 10.

... Other named arguments passed down to randomForest() and randomForest::randomForest.default.

Details

Imputation of y by random forests. The method calls randomForest() which implements Breiman’s random forest algorithm (based on Breiman and Cutler’s original Fortran code) for classification and regression. See Appendix A.1 of Doove et al. (2014) for the definition of the algorithm used. An alternative implementation was independently developed by Shah et al (2014), and is available in the package CALIBERfimpute. Simulations by Shah (Feb 13, 2014) suggested that the quality of the imputation for 10 and 100 trees was identical, so mice 2.22 changed the default number of trees from ntree = 100 to ntree = 10.

Value

Numeric vector of length sum(!ry) with imputations

Author(s)

Lisa Doove, Stef van Buuren, Elise Dusseldorp, 2012
**References**


**See Also**

mice, mice.impute.cart, randomForest, mice.impute.rfcat, mice.impute.rfcont

**Examples**

```r
library("lattice")
imp <- mice(nhanes2, meth = "rf", ntree = 3)
plot(imp)
```

---

**mice.impute.ri**  
*Imputation by the random indicator method for nonignorable data*

**Description**

Imputes univariate missing data using the random indicator method. This method estimates an offset between the distribution of the observed and missing data using an algorithm that iterates over the response model and the imputation model.

**Usage**

```r
mice.impute.ri(y, ry, x, ri.maxit = 10, ...)
```

**Arguments**

- `y`  
  Incomplete data vector of length n
- `ry`  
  Vector of missing data pattern (FALSE=missing, TRUE=observed)
- `x`  
  Matrix (n x p) of complete covariates.
- `ri.maxit`  
  Number of inner iterations
- `...`  
  Other named arguments passed down to .norm.draw()

**Value**

A vector of length nmis with imputations.
Author(s)
Shahab Jolani (University of Utrecht) <s.jolani@uu.nl>

References

mice.impute.sample  Imputation by simple random sampling

Description
Imputes a random sample from the observed y data

Usage
mice.impute.sample(y, ry, x = NULL, ...)

Arguments
y  Incomplete data vector of length n
ry  Vector of missing data pattern (FALSE=missing, TRUE=observed)
x  Matrix (n x p) of complete covariates.
...  Other named arguments.

Details
This function takes a simple random sample from the observed values in y, and returns these as imputations.

Value
A vector of length nmis with imputations.

Author(s)
Stef van Buuren, Karin Groothuis-Oudshoorn, 2000

References
mice.mids

Multivariate Imputation by Chained Equations (Iteration Step)

Description

Takes a mids object, and produces a new object of class mids.

Usage

mice.mids(obj, maxit = 1, diagnostics = TRUE, printFlag = TRUE, ...)

Arguments

obj An object of class mids, typically produces by a previous call to mice() or mice.mids()
maxit The number of additional Gibbs sampling iterations.
diagnostics A Boolean flag. If TRUE, diagnostic information will be appended to the value of the function. If FALSE, only the imputed data are saved. The default is TRUE.
printFlag A Boolean flag. If TRUE, diagnostic information during the Gibbs sampling iterations will be written to the command window. The default is TRUE.
... Named arguments that are passed down to the elementary imputation functions.

Details

This function enables the user to split up the computations of the Gibbs sampler into smaller parts. This is useful for the following reasons:

- RAM memory may become easily exhausted if the number of iterations is large. Returning to prompt/session level may alleviate these problems.
- The user can compute customized convergence statistics at specific points, e.g. after each iteration, for monitoring convergence. - For computing a 'few extra iterations'.

Note: The imputation model itself is specified in the mice() function and cannot be changed with mice.mids. The state of the random generator is saved with the mids object.

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000

References


See Also

complete, mice, set.seed, mids
Examples

imp1 <- mice(nhanes,maxit=1)
imp2 <- mice.mids(imp1)

# yields the same result as
imp <- mice(nhanes,maxit=2)

# for example:
#
# > imp$imp$bmi[1,]
# 1 2 3 4 5
# 1 30.1 35.3 33.2 35.3 27.5
# > imp2$imp$bmi[1,]
# 1 2 3 4 5
# 1 30.1 35.3 33.2 35.3 27.5
#

mice.theme

Set the theme for the plotting Trellis functions

Description

The mice.theme() function sets default choices for Trellis plots that are built into mice.

Usage

mice.theme(transparent = TRUE, alpha.fill = 0.3)

Arguments

transparent A logical indicating whether alpha-transparancy is allowed. The default is TRUE.
alpha.fill A numerical values between 0 and 1 that indicates the default alpha value for fills.

Value

mice.theme() returns a named list that can be used as a theme in the functions in lattice. By default, the mice.theme() function sets transparent <- TRUE if the current device .Device supports semi-transparent colors.

Author(s)

Stef van Buuren 2011
Description

The `mids` object contains a multiply imputed data set. The `mids` object is generated by the `mice()` and `mice.mids()` functions. The `mids` class of objects has methods for the following generic functions: `print`, `summary`, `plot`.

Slots

.Data: Object of class "list" containing the following slots:

call: The call that created the object.
data: A copy of the incomplete data set.
m: The number of imputations.
nmis: An array containing the number of missing observations per column.
imp: A list of `ncol(data)` components with the generated multiple imputations. Each part of the list is a `nmis[j]` by `m` matrix of imputed values for variable `j`.
method: A vector of strings of length(`ncol(data)`) specifying the elementary imputation method per column.
predictorMatrix: A square matrix of size `ncol(data)` containing integers specifying the predictor set.
visitSequence: The sequence in which columns are visited.
post: A vector of strings of length `ncol(data)` with commands for post-processing
seed: The seed value of the solution.
iteration: Last Gibbs sampling iteration number.
lastSeedValue: The most recent seed value.
chainMean: A list of `m` components. Each component is a `length(visitSequence)` by `maxit` matrix containing the mean of the generated multiple imputations. The array can be used for monitoring convergence. Note that observed data are not present in this mean.
chainVar: A list with similar structure of `chainMean`, containing the covariances of the imputed values.
loggedEvents: A `data.frame` with six columns containing warnings, corrective actions, and other inside info.
pad: A list containing various settings of the padded imputation model, i.e. the imputation model after creating dummy variables. Normally, this list is only useful for error checking. List members are `pad$data` (data padded with columns for factors), `pad$predictorMatrix` (predictor matrix for the padded data), `pad$method` (imputation methods applied to the padded data), the vector `pad$visitSequence` (the visit sequence applied to the padded data), `pad$post` (post-processing commands for padded data) and `categories` (a matrix containing descriptive information about the padding operation).
loggedEvents: A matrix with six columns containing a record of automatic removal actions. It is NULL if no action was made. At initialization the program does the following three actions: 1. A variable that contains missing values, that is not imputed and that is used as a predictor is removed, 2. a constant variable is removed, and 3. a collinear variable is removed. During iteration, the program does the following actions: 1. one or more variables that are linearly dependent are removed (for categorical data, a ‘variable’ corresponds to a dummy variable), and 2. proportional odds regression imputation that does not converge and is replaced by polyreg. Column it is the iteration number at which the record was added, im is the imputation number, co is the column number in the data, dep is the name of the name of the dependent variable, meth is the imputation method used, and out is a (possibly long) character vector with the names of the altered or removed predictors.

Note

Many of the functions of the mice package do not use the S4 class definitions, and instead rely on the S3 list equivalent oldClass(obj) <= "mids".

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000

References


See Also

mice, mira, mipo

mids2mplus

Export mids object to Mplus

Description

Converts a mids object into a format recognized by Mplus, and writes the data and the Mplus input files

Usage

mids2mplus(imp, file.prefix = "imp", path = getwd(), sep = \\
"\t", dec = \\
".", silent = FALSE)
Arguments

- **imp**: The imp argument is an object of class mids, typically produced by the mice() function.
- **file.prefix**: A character string describing the prefix of the output data files.
- **path**: A character string containing the path of the output file. By default, files are written to the current R working directory.
- **sep**: The separator between the data fields.
- **dec**: The decimal separator for numerical data.
- **silent**: A logical flag stating whether the names of the files should be printed.

Details

This function automates most of the work needed to export a mids object to Mplus. The function writes the multiple imputation datasets, the file that contains the names of the multiple imputation data sets and an Mplus input file. The Mplus input file has the proper file names, so in principle it should run and read the data without alteration. Mplus will recognize the data set as a multiply imputed data set, and do automatic pooling in procedures where that is supported.

Value

The return value is NULL.

Author(s)

Gerko Vink, 2011.

See Also

mids, mids2spss

---

**mids2spss** 

Export mids object to SPSS

Description

Converts a mids object into a format recognized by SPSS, and writes the data and the SPSS syntax files.

Usage

mids2spss(imp, filedat = "midsdata.txt", filesps = "readmids.sps", path = getwd(), sep = "\t", dec = ".", silent = FALSE)
Arguments

imp  The imp argument is an object of class mids, typically produced by the mice() function.

fイルdat  A character string describing the name of the output data file.

filesps  A character string describing the name of the output syntax file.

path  A character string containing the path of the output file. The value in path is appended to fﾑイルdat and fﾑイルlesps. By default, files are written to the current R working directory. If path=NULL then no file path appending is done.

sep  The separator between the data fields.

dec  The decimal separator for numerical data.

silent  A logical flag stating whether the names of the files should be printed.

Details

This function automates most of the work needed to export a mids object to SPSS. It uses a modified version of writeForeignSPSS() from the foreign package. The modified version allows for a choice of the field and decimal separators, and makes some improvements to the formatting, so that the generated syntax file is amenable to the INCLUDE statement in SPSS.

Below are some things to pay attention to.

The SPSS syntax file has the proper file names and separators set, so in principle it should run and read the data without alteration. SPSS is more strict than R with respect to the paths. Always use the full path, otherwise SPSS may not be able to find the data file.

Factors in R translate into categorical variables in SPSS. The internal coding of factor levels used in R is exported. This is generally acceptable for SPSS. However, when the data are to be combined with existing SPSS data, watch out for any changes in the factor levels codes. The read.spss() in package foreign for reading .sav uses its own internal numbering scheme 1, 2, 3, ... for the levels of a factor. Consequently, changes in factor code can cause discrepancies in factor level when re-imported to SPSS. The solution is to manually recode the factor level in SPSS.

SPSS will recognize the data set as a multiply imputed data set, and do automatic pooling in procedures where that is supported. Note however that pooling is an extra option only available to those who licence the MISSING VALUES module. Without this licence, SPSS will still recognize the structure of the data, but not do any pooling.

Value

The return value is NULL.

Author(s)

Stef van Buuren, dec 2010.

See Also

mids
Description

The \texttt{mipo} object is generated by the \texttt{pool} function from a link\{\texttt{mira-class}\} object. The \texttt{mipo} class of objects has methods for the following generic functions: \texttt{print}, \texttt{summary}.

Slots

\texttt{.Data}: Object of class "list" containing the following slots:

- \texttt{call}: The call that created the \texttt{mipo} object.
- \texttt{call1}: The call that created the \texttt{mira} object that was used in \texttt{call}.
- \texttt{call2}: The call that created the \texttt{mids} object that was used in \texttt{call1}.
- \texttt{data}: A copy of the incomplete data set.
- \texttt{nmis}: An array containing the number of missing observations per column.
- \texttt{m}: Number of multiple imputations.
- \texttt{qhat}: An \(m \times npar\) matrix containing the complete data estimates for the \(npar\) parameters of the \(m\) complete data analyses.
- \texttt{u}: An \(m \times npar \times npar\) array containing the variance-covariance matrices of the estimates of the \(m\) complete data analyses.
- \texttt{qbar}: The average of complete data estimates. The multiple imputation estimate.
- \texttt{ubar}: The average of the variance-covariance matrix of the complete data estimates.
- \texttt{b}: The between imputation variance-covariance matrix for the estimates.
- \texttt{t}: The total variance-covariance matrix for the estimates.
- \texttt{r}: Relative increases in variance due to missing data.
- \texttt{dfcom}: Degrees of freedom in the hypothetically complete data: the sample size minus the number of free parameters.
- \texttt{df}: Degrees of freedom associated with the t-statistics.
- \texttt{fmi}: Fraction of missing information.
- \texttt{lambda}: Proportion of the variation attributable to the missing data: \((b+b/m)/t\).

Note

The functions of the \texttt{mice} package do not use the S4 class definitions, and instead rely on the S3 list equivalent \texttt{oldClass(obj) <- "mipo"}.

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000
References


See Also

`pool, mids, mira`

---

**mira-class**

* Multiply imputed repeated analyses (mira)

**Description**

The `mira` object is generated by the `with.mids()` function. The `as.mira()` function takes the results of repeated complete-data analysis stored as a list, and turns it into a `mira` object that can be pooled. Pooling requires that `coef()` and `vcov()` methods are available for fitted object. The `mira` class of objects has methods for the following generic functions: `print`, `summary`.

**Slots**

`#` Object of class "list" containing the following slots:

- `.call`: The call that created the object.
- `.call1`: The call that created the `mids` object that was used in `.call`.
- `.nmis`: An array containing the number of missing observations per column.
- `.analyses`: A list of `m` components containing the individual fit objects from each of the `m` complete data analyses.

**Note**

Many of the functions of the `mice` package do not use the S4 class definitions, and instead rely on the S3 list equivalent `oldClass(obj) <- "mira"`.

**Author(s)**

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000

**References**


**See Also**

`with.mids, mids, mipo`
Cumulative hazard rate or Nelson-Aalen estimator

Description

Calculates the cumulative hazard rate (Nelson-Aalen estimator)

Usage

nelsonaalen(data, timevar, statusvar)

Arguments

data           A data frame containing the data.
timevar        The name of the time variable in data.
statusvar      The name of the event variable, e.g. death in data.

Details

This function is useful for imputing variables that depend on survival time. White and Royston (2009) suggested using the cumulative hazard to the survival time $H_0(T)$ rather than $T$ or $\log(T)$ as a predictor in imputation models. See section 7.1 of Van Buuren (2012) for an example.

Value

A vector with $\text{nrow(data)}$ elements containing the Nelson-Aalen estimates of the cumulative hazard function.

Author(s)

Stef van Buuren, 2012

References


Examples

```r
require(MASS)
leuk$status <- 1  # no censoring occurs in leuk data (MASS)
ch <- nelsonaalen(leuk, time, status)
plot(x = leuk$time, y = ch, ylab='Cumulative hazard', xlab='Time')
```

### See example on http://www.engineeredsoftware.com/Imar/pe_cum_hazard_function.htm
time <- c(43, 67, 92, 94, 149, rep(149,7))
status <- c(rep(1.5), rep(0.7))
eng <- data.frame(time, status)
ch <- nelsonaalen(eng, time, status)
plot(x = time, y = ch, ylab='Cumulative hazard', xlab='Time')

---

nhanes  

**NHANES example - all variables numerical**

**Description**

A small data set with non-monotone missing values.

**Format**

A data frame with 25 observations on the following 4 variables.

- **age**  Age group (1=20-39, 2=40-59, 3=60+)
- **bmi**  Body mass index (kg/m**2**)  
- **hyp**  Hypertensive (1=no, 2=yes)
- **chl**  Total serum cholesterol (mg/dL)

**Details**

A small data set with all numerical variables. The data set nhanes2 is the same data set, but with age and hyp treated as factors.

**Source**


**See Also**

nhanes2

**Examples**

```r
imp <- mice(nhanes)  # create 5 imputed data sets
complete(imp)         # print the first imputed data set
```
**Description**

A small data set with non-monotone missing values.

**Format**

A data frame with 25 observations on the following 4 variables.

- **age**: Age group (1=20-39, 2=40-59, 3=60+)
- **bmi**: Body mass index (kg/m^2)
- **hyp**: Hypertensive (1=no, 2=yes)
- **chl**: Total serum cholesterol (mg/dL)

**Details**

A small data set with missing data and mixed numerical and discrete variables. The data set `nhanes` is the same data set, but with all data treated as numerical.

**Source**


**See Also**

- `nhanes`

**Examples**

```r
imp <- mice(nhanes2)  # create 5 imputed data sets
complete(imp)          # print the first imputed data set
```

---

**norm.draw**

*Draws values of beta and sigma by Bayesian linear regression*

**Description**

This function draws random values of beta and sigma under the Bayesian linear regression model as described in Rubin (1987, p. 167). This function can be called by user-specified imputation functions.
Usage

\texttt{norm.draw(y, ry, x, ridge = 1e-05, \ldots)}

Arguments

\begin{itemize}
  \item \texttt{y} \quad \text{Incomplete data vector of length \textit{n}}
  \item \texttt{ry} \quad \text{Vector of missing data pattern (FALSE=missing, TRUE=observed)}
  \item \texttt{x} \quad \text{Matrix (\textit{n} x \textit{p}) of complete covariates.}
  \item \texttt{ridge} \quad \text{A small numerical value specifying the size of the ridge used. The default value ridge = 1e-05 represents a compromise between stability and unbiasedness. Decrease ridge if the data contain many junk variables. Increase ridge for highly collinear data.}
  \item \ldots \quad \text{Other named arguments.}
\end{itemize}

Value

A list containing components \texttt{coef} (least squares estimate), \texttt{beta} (drawn regression weights) and \texttt{sigma} (drawn value of the residual standard deviation).

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2000

References


\begin{itemize}
  \item \texttt{pattern} \quad \textit{Datasets with various missing data patterns}
\end{itemize}

Description

Four simple datasets with various missing data patterns

Format

\begin{itemize}
  \item \texttt{list("pattern1"')} \quad \text{Data with a univariate missing data pattern}
  \item \texttt{list("pattern2"')} \quad \text{Data with a monotone missing data pattern}
  \item \texttt{list("pattern3"')} \quad \text{Data with a file matching missing data pattern}
  \item \texttt{list("pattern4"')} \quad \text{Data with a general missing data pattern}
\end{itemize}

Details

Van Buuren (2012) uses these four artificial datasets to illustrate various missing data patterns.
plot.mids

Source


Examples

```
require(lattice)
require(MASS)

pattern4

data <- rbind(pattern1, pattern2, pattern3, pattern4)
mdpat <- cbind(expand.grid(rec = 8:1, pat = 1:4, var = 1:3), r=as.numeric(as.vector(is.na(data))))

types <- c("Univariate","Monotone","File matching","General")

plot <- levelplot(r~var+rec|as.factor(pat), data=mdpat,
  as.table=TRUE, aspect="iso",
  shrink=c(0.9),
  col.regions = mdc(1:2),
  colorkey=FALSE,
  scales=list(draw=FALSE),
  xlab="", ylab="",
  between = list(x=1,y=0),
  strip = strip.custom(bg = "grey95", style = 1,
    factor.levels = types))

print(plot)

md.pattern(pattern4)
p <- md.pairs(pattern4)
p

### proportion of usable cases
p$mr/(p$mr+p$mm)

### outbound statistics
p$rm/(p$rm+p$rr)

fluxplot(pattern2)
```

---

**plot.mids**  
*Plot the trace lines of the MICE algorithm*

Description

Trace line plots, also called stream plots or history plots, portray the value of an estimate against the iteration number. The estimate can be anything that you can calculate, but typically are chosen as parameter of scientific interest. The plot method for a mids object plots the mean and standard deviation of the imputed (not observed) values against the iteration number for each of the $m$
replications. By default, the function plot the development of the mean and standard deviation for each incomplete variable. On convergence, the streams should intermingle and be free of any trend.

Usage

```r
## S3 method for class 'mids'
plot(x, y = NULL, theme = mice.theme(), layout = c(2, 3),
     type = "l", col = 1:10, lty = 1, ...)
```

Arguments

- `x`: An object of class `mids`
- `y`: A formula that specifies which variables, stream and iterations are plotted. If omitted, all streams, variables and iterations are plotted.
- `theme`: The trellis theme to applied to the graphs. The default is `mice.theme()`.
- `layout`: A vector of length 2 given the number of columns and rows in the plot. The default is `c(2, 3)`.
- `type`: Parameter type of `panel.xyplot`.
- `col`: Parameter col of `panel.xyplot`.
- `lty`: Parameter lty of `panel.xyplot`.
- `...`: Extra arguments for `xyplot`.

Value

An object of class "trellis".

Author(s)

Stef van Buuren 2011

See Also

`mice`, `mids`, `xyplot`

---

**pool**

*Multiple imputation pooling*

Description

Pools the results of m repeated complete data analysis

Usage

```r
pool(object, method = "smallsample")
```
Arguments

object  An object of class mira, produced by with.mids() or as.mira()

method  A string describing the method to compute the degrees of freedom. The default value is "smallsample", which specifies the is Barnard-Rubin adjusted degrees of freedom (Barnard and Rubin, 1999) for small samples. Specifying a different string produces the conventional degrees of freedom as in Rubin (1987).

Details

The function averages the estimates of the complete data model, computes the total variance over the repeated analyses, and computes the relative increase in variance due to nonresponse and the fraction of missing information. The function relies on the availability of

1. the estimates of the model, typically present as 'coefficients' in the fit object
2. an appropriate estimate of the variance-covariance matrix of the estimates per analyses (estimated by vcov).

The function pools also estimates obtained with lme() and lmer(), BUT only the fixed part of the model.

Value

An object of class mipo, which stands for 'multiple imputation pooled outcome'.

Author(s)

Stef van Buuren, Karin Groothuis-Oudshoorn, 2009

References


See Also

with.mids, as.mira, vcov
Examples

# which vcov methods can R find
methods(vcov)

#
imp <- mice(nhanes)
fit <- with(data=imp,exp=lm(bmi~hyp+chl))
pool(fit)

#Call: pool(object = fit)
#
#Pooled coefficients:
#(Intercept)    hyp    chl
#  22.01313   -1.45578  0.03459
#
#Fraction of information about the coefficients missing due to nonresponse:
#(Intercept)    hyp    chl
#  0.29571    0.05639  0.38759

# summary(pool(fit))
# est  se   t df Pr(>|t|)  lo 95 hi 95 missing
#(Intercept) 22.01313  4.94086  4.4553  12.016 0.000783 11.24954 32.77673  NA
#hyp         -1.45578  2.26789 -0.6419  20.613 0.528006 -6.17752  3.26596   8
#chl          0.03459  0.02829  1.2228  9.347 0.251332 -0.02904  0.09022  10
#
# fmi
#(Intercept) 0.29571
#hyp         0.05639
#chl         0.38759
#

pool.compare

Compare two nested models fitted to imputed data

Description

Compares two nested models after m repeated complete data analysis

Usage

pool.compare(fit1, fit0, data = NULL, method = "Wald")

Arguments

fit1
An object of class 'mira', produced by with.mids().

fit0
An object of class 'mira', produced by with.mids(). The model in fit0 should be a submodel of fit1. Moreover, the variables of the submodel should be the first variables of the larger model and in the same order as in the submodel.

data
In case of method 'likelihood' it is necessary to pass also the original mids object to the data argument. Default value is NULL, in case of method='Wald'.

method

A string describing the method to compare the two models. Two kind of comparisons are included so far: 'Wald' and 'likelihood'.

Details

The function is based on the article of Meng and Rubin (1992). The Wald-method can be found in paragraph 2.2 and the likelihood method can be found in paragraph 3. One could use the Wald method for comparison of linear models obtained with e.g. `lm` in `with.mids()`. The likelihood method should be used in case of logistic regression models obtained with `glm()` in `with.mids()`. It is assumed that `fit1` contains the larger model and the model in `fit0` is fully contained in `fit1`. In case of `method='Wald'`, the null hypothesis is tested that the extra parameters are all zero.

Value

A list containing several components. Component `call` is that call to the `pool.compare` function. Component `call1` is the call that created `fit1`. Component `call0` is the call that created the imputations. Component `call01` is the call that created `fit0`. Component `call02` is the call that created the imputations. Components `method` is the method used to compare two models: 'Wald' or 'likelihood'. Component `nmis` is the number of missing entries for each variable. Component `m` is the number of imputations. Component `qhat1` is a matrix, containing the estimated coefficients of the `m` repeated complete data analyses from `fit1`. Component `qhat0` is a matrix, containing the estimated coefficients of the `m` repeated complete data analyses from `fit0`. Component `ubar1` is the mean of the variances of `fit1`, formula (3.1.3), Rubin (1987). Component `ubar0` is the mean of the variances of `fit0`, formula (3.1.3), Rubin (1987). Component `qbar1` is the pooled estimate of `fit1`, formula (3.1.2) Rubin (1987). Component `qbar0` is the pooled estimate of `fit0`, formula (3.1.2) Rubin (1987). Component `dm` is the test statistic. Component `rm` is the relative increase in variance due to nonresponse, formula (3.1.7), Rubin (1987). Component `df1`: `df1 = under the null hypothesis it is assumed that `dm` has an F distribution with `(df1,df2)` degrees of freedom. Component `df2`: `df2`. Component `pvalue` is the P-value of testing whether the larger model is statistically different from the smaller submodel.

Author(s)

Karin Groothuis-Oudshoorn and Stef van Buuren, 2009

References


See Also

`lm.mids`, `glm.mids`, `vcov`,
### Examples

```r
### To compare two linear models:
imp <- mice(nhanes2)
mi1 <- with(data=imp, expr=lm(bmi~age+hyp+chl))
mi0 <- with(data=imp, expr=lm(bmi~age+hyp))
pc <- pool.compare(mi1, mi0, method='Wald')
pc$svalue
# [1] 0.000293631
#

### Comparison of two general linear models (logistic regression).
## Not run:
imp <- mice(boys, maxit=2)
fit0 <- with(imp, glm(gen$levels(gen)[1] ~ hgt+hc,family=binomial))
fit1 <- with(imp, glm(gen$levels(gen)[1] ~ hgt+hc+reg,family=binomial))
pool.compare(fit1, fit0, method='likelihood', data=imp)
## End(Not run)
```

---

### Description

Pools $R^2$ of $m$ repeated complete data models.

### Usage

```r
pool.r.squared(object, adjusted = FALSE)
```

### Arguments

- **object**: An object of class 'mira', produced by `lm.mids` or `with.mids` with `lm` as modelling function.
- **adjusted**: A logical value. If adjusted=TRUE then the adjusted $R^2$ is calculated. The default value is FALSE.

### Details

The function pools the coefficients of determination $R^2$ or the adjusted coefficients of determination ($R^2_a$) obtained with the `lm` modelling function. For pooling it uses the Fisher $z$-transformation.

### Value

Returns a 1x4 table with components. Component est is the pooled $R^2$ estimate. Component lo95 is the 95% lower bound of the pooled $R^2$. Component hi95 is the 95% upper bound of the pooled $R^2$. Component fmi is the fraction of missing information due to nonresponse.
**pool.scalar**

### Author(s)

Karin Groothuis-Oudshoorn and Stef van Buuren, 2009

### References


### See Also

*pool.pool.scalar*

### Examples

```r
imp<-mice(nhanes)

fit<-lm.mids(chl~age+hyp+bmi,imp)
pool.r.squared(fit)
pool.r.squared(fit,adjusted=TRUE)

#fit<-lm.mids(chl~age+hyp+bmi,imp)
#
# pool.r.squared(fit)
#
# est  lo 95  hi 95  fmi
# R^2 0.5108041 0.1479687 0.7791927 0.3024413
#
# pool.r.squared(fit,adjusted=TRUE)
#
# est  lo 95  hi 95  fmi
# adj R^2 0.4398066 0.08251427 0.743172 0.3404165
#
```

---

**pool.scalar**

*Multiple imputation pooling: univariate version*

### Description

Pools univariate estimates of m repeated complete data analysis

### Usage

```
pool.scalar(Q, U, n = 99999, k = 1, method = "smallsample")
```
Arguments

- **Q**: A vector of univariate estimates of \( m \) repeated complete data analyses.
- **U**: A vector containing the corresponding \( m \) variances of the univariate estimates.
- **n**: A number providing the sample size. If nothing is specified, a large sample \( n = 99999 \) is assumed.
- **k**: A number indicating the number of parameters to be estimated. By default, \( k = 1 \) is assumed.
- **method**: A string indicating the method to calculate the degrees of freedom. If `method = "smallsample"` (the default) then the Barnard-Rubin adjustment for small degrees of freedom is used. Otherwise, the method from Rubin (1987) is used.

Details

The function averages the univariate estimates of the complete data model, computes the total variance over the repeated analyses, and computes the relative increase in variance due to nonresponse and the fraction of missing information.

Value

Returns a list with components. Component \( m \) is the number of imputations. Component \( \hat{q} \) contains the \( m \) univariate estimates of repeated complete data analyses. Component \( u \) contains the corresponding \( m \) variances of the univariate estimates. Component \( \bar{q} \) is the pooled univariate estimate, formula (3.1.2) Rubin (1987). Component \( \bar{u} \) is the mean of the variances (i.e. the pooled within-imputation variance), formula (3.1.3) Rubin (1987). Component \( b \) is the between-imputation variance, formula (3.1.4) Rubin (1987). Component \( t \) is the total variance of the pooled estimated, formula (3.1.5) Rubin (1987). Component \( r \) is the relative increase in variance due to nonresponse, formula (3.1.7) Rubin (1987). Component \( df \) is the degrees of freedom for \( t \) reference distribution, formula (3.1.6) Rubin (1987) or method of Barnard-Rubin (1999) (if `method = "smallsample"`). Component \( fmi \) is the fraction missing information due to nonresponse, formula (3.1.10) Rubin (1987). Component \( \lambda \) is the proportion of variation due to nonresponse, formula (2.24) Van Buuren (2012).

Author(s)

Karin Groothuis-Oudshoorn and Stef van Buuren, 2009

References


See Also

`pool`
Examples

```r
imp <- mice(hanes)
m <- imp$m
Q <- rep(NA, m)
U <- rep(NA, m)
for (i in 1:m) {
    Q[i] <- mean(complete(imp, i)$bmi)
    U[i] <- var(complete(imp, i)$bmi) / nrow(hanes) # (standard error of estimate)^2
}
pool.scalar(Q, U, method = "rubin")  # Rubin 1987
pool.scalar(Q, U, n = nrow(hanes), k = 1)  # Barnard-Rubin 1999
```

Description

Hox pupil popularity data with some missing popularity scores

Format

A data frame with 2000 rows and 7 columns:

- **pupil**: Pupil number within school
- **school**: School number
- **popular**: Pupil popularity with 848 missing entries
- **sex**: Pupil gender
- **texp**: Teacher experience (years)
- **const**: Constant intercept term
- **teachpop**: Teacher popularity

Details

The original, complete dataset was generated by Joop Hox as an example of well-behaved multilevel data set. The distributed data contains missing data in pupil popularity.

Source


Examples

```r
popmis[1:3,]
```
Description
Subset of data from the POPS study, a national, prospective study on preterm children, including all liveborn infants <32 weeks gestational age and/or <1500 g from 1983 (n = 1338).

Format
pops is a data frame with 959 rows and 86 columns. pops_pred is the 86 by 86 binary predictor matrix used for specifying the multiple imputation model.

Details
The data set concerns of subset of 959 children that survived up to the age of 19 years.
Hille et al (2005) divided the 959 survivors into three groups: Full responders (examined at an outpatient clinic and completed the questionnaires, n = 596), postal responders (only completed the mailed questionnaires, n = 109), non-responders (did not respond to any of the mailed requests or telephone calls, or could not be traced, n = 254).

Compared to the postal and non-responders, the full response group consists of more girls, contains more Dutch children, has higher educational and social economic levels and has fewer handicaps. The responders form a highly selective subgroup in the total cohort.

Multiple imputation of this data set has been described in Hille et al (2007) and Van Buuren (2012), chapter 8.

Source

Examples
pops <- data(pops)
Description

Data from Potthoff-Roy (1964) with repeated measures on dental fissures.

Format

tbs is a data frame with 27 rows and 6 columns:

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>id</td>
<td>Person number</td>
</tr>
<tr>
<td>sex</td>
<td>Sex M/F</td>
</tr>
<tr>
<td>d8</td>
<td>Distance at age 8 years</td>
</tr>
<tr>
<td>d10</td>
<td>Distance at age 10 years</td>
</tr>
<tr>
<td>d12</td>
<td>Distance at age 12 years</td>
</tr>
<tr>
<td>d14</td>
<td>Distance at age 14 years</td>
</tr>
</tbody>
</table>

Details

This data set is the famous Potthoff-Roy data, used to demonstrate MANOVA on repeated measure data. Potthoff and Roy (1964) published classic data on a study in 16 boys and 11 girls, who at ages 8, 10, 12, and 14 had the distance (mm) from the center of the pituitary gland to the pteryomaxillary fissure measured. Changes in pituitary-ptyeryomaxillary distances during growth is important in orthodontic therapy. The goals of the study were to describe the distance in boys and girls as simple functions of age, and then to compare the functions for boys and girls. The data have been reanalyzed by many authors including Jennrich and Schluchter (1986), Little and Rubin (1987), Pinheiro and Bates (2000), Verbeke and Molenberghs (2000) and Molenberghs and Kenward (2007). See Chapter 9 of Van Buuren (2012) for a challenging exercise using these data.

Source


Examples

```r
# create missing values at age 10 as in Little and Rubin (1987)

phr <- potthoffroy
idmis <- c(3,6,9,10,13,16,23,24,27)
phr[idmis, 4] <- NA
```
print.mids

Description

Print a mids object
Print a mira object
Print a mipo object

Usage

## S3 method for class 'mids'
print(x, ...)

## S3 method for class 'mira'
print(x, ...)

## S3 method for class 'mipo'
print(x, ...)

Arguments

x Object of class mids, mira or mipo
...

Other parameters passed down to print.default()

Value

NULL

NULL

NULL

See Also

mids
mira
mipo
quickpred

Quick selection of predictors from the data

Description

Selects predictors according to simple statistics

Usage

quickpred(data, mincor = 0.1, minpuc = 0, include = '', exclude = '', method = "pearson")

Arguments

data Matrix or data frame with incomplete data.

mincor A scalar, numeric vector (of size ncol(data)) or numeric matrix (square, of size ncol(data)) specifying the minimum threshold(s) against which the absolute correlation in the data is compared.

minpuc A scalar, vector (of size ncol(data)) or matrix (square, of size ncol(data)) specifying the minimum threshold(s) for the proportion of usable cases.

include A string or a vector of strings containing one or more variable names from names(data). Variables specified are always included as a predictor.

exclude A string or a vector of strings containing one or more variable names from names(data). Variables specified are always excluded as a predictor.

method A string specifying the type of correlation. Use 'pearson' (default), 'kendall' or 'spearman'. Can be abbreviated.

Details

This function creates a predictor matrix using the variable selection procedure described in Van Buuren et al.~(1999, p.~687–688). The function is designed to aid in setting up a good imputation model for data with many variables.

Basic workings: The procedure calculates for each variable pair (i.e. target-predictor pair) two correlations using all available cases per pair. The first correlation uses the values of the target and the predictor directly. The second correlation uses the (binary) response indicator of the target and the values of the predictor. If the largest (in absolute value) of these correlations exceeds mincor, the predictor will be added to the imputation set. The default value for mincor is 0.1.

In addition, the procedure eliminates predictors whose proportion of usable cases fails to meet the minimum specified by minpuc. The default value is 0, so predictors are retained even if they have no usable case.

Finally, the procedure includes any predictors named in the include argument (which is useful for background variables like age and sex) and eliminates any predictor named in the exclude argument. If a variable is listed in both include and exclude arguments, the include argument takes precedence.
Advanced topic: `mincor` and `minpuc` are typically specified as scalars, but vectors and squares matrices of appropriate size will also work. Each element of the vector corresponds to a row of the predictor matrix, so the procedure can effectively differentiate between different target variables. Setting a high values for can be useful for auxiliary, less important, variables. The set of predictor for those variables can remain relatively small. Using a square matrix extends the idea to the columns, so that one can also apply cellwise thresholds.

**Value**

A square binary matrix of size `ncol(data)`.

**Author(s)**

Stef van Buuren, Aug 2009

**References**


**See Also**

`mice`, `mids`

**Examples**

```r
# default: include all predictors with absolute correlation over 0.1
quickpred(nhanes)

# all predictors with absolute correlation over 0.4
quickpred(nhanes, mincor=0.4)

# include age and bmi, exclude chl
quickpred(nhanes, mincor=0.4, inc=c('age','bmi'), exc='chl')

# only include predictors with at least 30% usable cases
quickpred(nhanes, minpuc=0.3)

# use low threshold for bmi, and high thresholds for hyp and chl
pred <- quickpred(nhanes, mincor=c(0,0.1,0.5,0.5))
pred

# use it directly from mice
imp <- mice(nhanes, pred=quickpred(nhanes, minpuc=0.25, include='age'))
```
**rbind.mids**

Rowwise combination of a mids object.

**Description**

Append mids objects by rows

**Usage**

```r
rbind.mids(x, y, ...) # Add more arguments if needed
```

**Arguments**

- **x**: A mids object.
- **y**: A mids object or a data.frame, matrix, factor or vector.
- **...**: Additional data.frame, matrix, vector or factor. These can be given as named arguments.

**Details**

This function combines two mids objects rowwise into a single mids object or combines a mids object and a vector, matrix, factor or data frame rowwise into a mids object. The number of columns in the (incomplete) data x$data and y (or y$data if y is a mids object) should be equal. If y is a mids object then the number of imputations in x and y should be equal.

**Value**

An S3 object of class mids

**Note**

Component call is a vector, with first argument the mice() statement that created x and second argument the call to rbind.mids(). Component data is the rowwise combination of the (incomplete) data in x and y. Component m is equal to x$m. Component nmis is an array containing the number of missing observations per column, defined as x$nmis + y$nmis. Component imp is a list of nvar components with the generated multiple imputations. Each part of the list is a nmis[j] by m matrix of imputed values for variable j. If y is a mids object then imp[[j]] equals rbind(x$imp[[j]], y$imp[[j]]); otherwise the original data of y will be copied into this list, including the missing values of y then y is not imputed. Component method is a vector of strings of length(nvar) specifying the elementary imputation method per column defined as x$method. Component predictorMatrix is a square matrix of size ncol(data) containing the predictor set defined as x$predictorMatrix. Component visitSequence is the sequence in which columns are visited, defined as x$visitSequence. Component seed is the seed value of the solution, x$seed. Component iteration is the last Gibbs sampling iteration number, x$iteration. Component lastSeedValue is the most recent seed value, x$lastSeedValue Component chainMean is set to NA. Component chainVar is set to NA. Component pad is set to x$pad, a list containing various settings of the padded imputation model, i.e. the imputation model after creating dummy variables. Component loggedEvents is set to x$loggedEvents.
Author(s)

Karin Groothuis-Oudshoorn, Stef van Buuren, 2009

References


See Also

cbind.mids, ibind.mids

---

selfreport  Self-reported and measured BMI

Description

Dataset containing height and weight data (measured, self-reported) from two studies.

Format

A data frame with 2060 rows and 15 variables:

src  Study, either krul or mgg (factor)
id  Person identification number
pop  Population, all NL (factor)
age  Age of respondent in years
sex  Sex of respondent (factor)
hm  Height measured (cm)
wmm  Weight measured (kg)
hr  Height reported (cm)
wr  Weight reported (kg)
prg  Pregnancy (factor), all Not pregnant
edu  Educational level (factor)
etn  Ethnicity (factor)
web  Obtained through web survey (factor)
bm  BMI measured (kg/m2)
br  BMI reported (kg/m2)
Details

This dataset combines two datasets: krul data (Krul, 2010) (1257 persons) and the mgg data (Van Keulen 2011; Van der Klauw 2011) (803 persons). The krul dataset contains height and weight (both measures and self-reported) from 1257 Dutch adults, whereas the mgg dataset contains self-reported height and weight for 803 Dutch adults. Section 7.3 in Van Buuren (2012) shows how the missing measured data can be imputed in the mgg data, so corrected prevalence estimates can be calculated.

Source


Examples

md.pattern(selfreport[,c("age","sex","hm","hr","wm","wr")])

### FIMD Section 7.3.5 Application

bmi <- function(h,w){return(w/(h/100)^2)}
init <- mice(selfreport,maxit=0)
meth <- init$meth
meth["bm"] <- "-bmi(hm,wm)"
pred <- init$pred
pred[,c("src","id","web","bm","br")] <- 0
imp <- mice(selfreport, pred=pred, meth=meth, seed=66573, maxit=2, m=1)
## imp <- mice(selfreport, pred=pred, meth=meth, seed=66573, maxit=20, m=10)

### Like FIMD Figure 7.6

cd <- complete(imp, 1)
xy <- xy.coords(cd$bm, cd$br-cd$bm)
plot(xy,col=mdc(2),xlab="Measured BMI",ylab="Reported - Measured BMI",xlim=c(17,45),ylim=c(-5,5), type="n",lwd=0.7)
polygon(x=c(30,20,30),y=c(0,10,0),col="grey95",border=NA)
polygon(x=c(30,40,30),y=c(0,-10,-10),col="grey95",border=NA)
abline(0,0,lty=2,lwd=0.7)
squeeze <- cd$src="krul"

idx <- xyc$[idx]; xyc <- xyc[idx]; xyc$y <- xyc$[idx]

yx <- yx; yxs$ <- yx$[!idx]; yxs$y <- yx$[!idx]

points(xyc, col=mdc(1), cex=0.7)

points(yx, col=mdc(2), cex=0.7)

lines(lowess(xyc), col=mdc(4), lwd=2)

lines(lowess(yx), col=mdc(5), lwd=2)

text(1:4, x=c(40, 28, 20, 32), y=c(4, 4, -4, -4), cex=3)

box(lwd=1)

---

**squeeze**

*Squeeze the imputed values to be within specified boundaries.*

---

**Description**

This function replaces any values in \( x \) that are lower than \( \text{bounds}[1] \) by \( \text{bounds}[1] \), and replaces any values higher than \( \text{bounds}[2] \) by \( \text{bounds}[2] \).

**Usage**

\[
\text{squeeze}(x, \text{bounds} = c(\min(x[r]), \max(x[r])), r = \text{rep}(\text{TRUE}, \text{length}(x)))
\]

**Arguments**

- **x**: A numerical vector with values
- **bounds**: A numerical vector of length 2 containing the lower and upper bounds. By default, the bounds are to the minimum and maximum values in \( x \).
- **r**: A logical vector of length \( \text{length}(x) \) that is used to select a subset in \( x \) before calculating automatic bounds.

**Value**

A vector of length \( \text{length}(x) \).

**Author(s)**

Stef van Buuren, 2011.
Description

Plotting methods for imputed data using lattice. stripplot produces one-dimensional scatterplots. The function automatically separates the observed and imputed data. The functions extend the usual features of lattice.

Usage

```
# S3 method for class 'mids'
stripplot(x, data, na.groups = NULL, groups = NULL,
          as.table = TRUE, theme = mice.theme(), allow.multiple = TRUE,
          outer = TRUE,
          drop.unused.levels = lattice.getOption("drop.unused.levels"),
          panel = lattice.getOption("panel.stripplot"),
          default.prepanel = lattice.getOption("prepanel.default.stripplot"),
          jitter.data = TRUE, horizontal = FALSE, ..., subscripts = TRUE,
          subset = TRUE)
```

Arguments

- `x`: A mids object, typically created by mice() or mice.mids().
- `data`: Formula that selects the data to be plotted. This argument follows the lattice rules for formulas, describing the primary variables (used for the per-panel display) and the optional conditioning variables (which define the subsets plotted in different panels) to be used in the plot.
  - The formula is evaluated on the complete data set in the long form. Legal variable names for the formula include names(x$data) plus the two administrative factors .imp and .id.
  - **Extended formula interface:** The primary variable terms (both the LHS y and RHS x) may consist of multiple terms separated by a `+` sign, e.g., `y1 + y2 ~ x | a * b`. This formula would be taken to mean that the user wants to plot both `y1 ~ x | a * b` and `y2 ~ x | a * b`, but with the `y1 ~ x` and `y2 ~ x` in separate panels. This behavior differs from standard lattice. Only combine terms of the same type, i.e. only factors or only numerical variables. Mixing numerical and categorical data occasionally produces odds labeling of vertical axis.
  - For convinience, in stripplot() and bwplot the formula `y~.imp` may be abbreviated as `y`. This applies only to a single `y`, and does not (yet) work for `y1+y2~.imp`.
- `na.groups`: An expression evaluating to a logical vector indicating which two groups are distinguished (e.g. using different colors) in the display. The environment in which this expression is evaluated in the response indicator is na(x$data).
The default `na.group = NULL` constrasts the observed and missing data in the LHS `y` variable of the display, i.e. groups created by `is.na(y)`. The expression `y1 & y2` creates groups by `is.na(y1) & is.na(y2)`, and `y1 | y2` creates groups as `is.na(y1) | is.na(y2)`, and so on.

**groups**

This is the usual `groups` arguments in *lattice*. It differs from `na.groups` because it evaluates in the completed data `data.frame(complete(x, "long", inc=TRUE))` (as usual), whereas `na.groups` evaluates in the response indicator. See `xyplot` for more details. When both `na.groups` and `groups` are specified, `na.groups` takes precedence, and `groups` is ignored.

**theme**

A named list containing the graphical parameters. The default function `mice.theme` produces a short list of default colors, line width, and so on. The extensive list may be obtained from `trellis.par.get()`. Global graphical parameters like `col` or `cex` in high-level calls are still honored, so first experiment with the global parameters. Many setting consists of a pair. For example, `mice.theme` defines two symbol colors. The first is for the observed data, the second for the imputed data. The theme settings only exist during the call, and do not affect the trellis graphical parameters.

**jitter.data**

See `panel.xyplot`.

**horizontal**

See `xyplot`.

**as.table**

See `xyplot`.

**panel**

See `xyplot`.

**default.prepanel**

See `xyplot`.

**outer**

See `xyplot`.

**allow.multiple**

See `xyplot`.

**drop.unused.levels**

See `xyplot`.

**subscripts**

See `xyplot`.

**subset**

See `xyplot`.

... Further arguments, usually not directly processed by the high-level functions documented here, but instead passed on to other functions.

### Details

The argument `na.groups` may be used to specify (combinations of) missingness in any of the variables. The argument groups can be used to specify groups based on the variable values themselves. Only one of both may be active at the same time. When both are specified, `na.groups` takes precedence over `groups`.

Use the `subset` and `na.groups` together to plots parts of the data. For example, select the first imputed data set by by `subset=imp=1`.

Graphical parameters like `col`, `pch` and `cex` can be specified in the arguments list to alter the plotting symbols. If `length(col)==2`, the color specification to define the observed and missing groups. `col[1]` is the color of the 'observed' data, `col[2]` is the color of the missing or imputed data.
A convenient color choice is col=mdc(1:2), a transparent blue color for the observed data, and a transparent red color for the imputed data. A good choice is col=mdc(1:2), pch=20, cex=1.5. These choices can be set for the duration of the session by running mice.theme().

Value

The high-level functions documented here, as well as other high-level Lattice functions, return an object of class "trellis". The update method can be used to subsequently update components of the object, and the print method (usually called by default) will plot it on an appropriate plotting device.

Note

The first two arguments (x and data) are reversed compared to the standard Trellis syntax implemented in lattice. This reversal was necessary in order to benefit from automatic method dispatch.

In mice the argument x is always a mids object, whereas in lattice the argument x is always a formula.

In mice the argument data is always a formula object, whereas in lattice the argument data is usually a data frame.

All other arguments have identical interpretation.

Author(s)

Stef van Buuren

References


See Also

mice, xyplot, densityplot, bwplot, Lattice for an overview of the package, as well as stripplot, panel.stripplot, print.trellis, trellis.par.set

Examples

```r
require(lattice)

imp <- mice(boys, maxit=1)

### stripplot, all numerical variables
### Not run: stripplot(imp)

### same, but with improved display
### Not run: stripplot(imp, col=c("grey",mdc(2)),pch=c(1,20))
```
### distribution per imputation of height, weight and bmi
### labeled by their own missingness
## Not run: stripplot(imp, hgt+wgt+bmi~imp, cex=c(2,4), pch=c(1,20), jitter=FALSE,
layout=c(3,1))
## End(Not run)

### same, but labeled with the missingness of wgt (just four cases)
## Not run: stripplot(imp, hgt+wgt+bmi~imp, na=wgt, cex=c(2,4), pch=c(1,20), jitter=FALSE,
layout=c(3,1))
## End(Not run)

### distribution of age and height, labeled by missingness in height
### most height values are missing for those around
### the age of two years
### some additional missings occur in region WEST
## Not run: stripplot(imp, age+hgt~imp|reg, hgt, col=c(hcl(0,0,40,0.2), mdc(2)),pch=c(1,20))

### heavily jitted relation between two categorical variables
### labeled by missingness of gen
### aggregated over all imputed data sets
## Not run: stripplot(imp, gen-phb, factor=2, cex=c(8,1), hor=TRUE)

### circle fun
stripplot(imp, gen-.imp, na = wgt, factor = 2, cex = c(8.6),
         hor = FALSE, outer = TRUE, scales = "free", pch = c(1,19))

---

**summary.mira**

*Summary of a mira object*

**Description**

Summary of a mira object

Summary of a mipo object

Summary of a mids object

**Usage**

## S3 method for class 'mira'
summary(object, ...)

## S3 method for class 'mipo'
summary(object, ...)

## S3 method for class 'mids'
summary(object, ...)
supports.transparent

Arguments

object  
A mira object

...  
Other parameters passed down to print() and summary()

Value

NULL

A table containing summary statistics of the pooled analysis

NULL

See Also

mira
mipo
mids

supports.transparent  Supports semi-transparent foreground colors?

Description

This function is used by mdc() to find out whether the current device supports semi-transparent foreground colors.

Usage

supports.transparent()

Details

The function calls the function dev.capabilities() from the package grDevices. The function return FALSE if the status of the current device is unknown.

Value

TRUE or FALSE

See Also

mdc.dev.capabilities

Examples

supports.transparent()
Terneuzen birth cohort

Description

Data of subset of the Terneuzen Birth Cohort data on child growth.

Format

`tbs` is a data frame with 3951 rows and 11 columns:

- **id**: Person number
- **occ**: Occasion number
- **nocc**: Number of occasions
- **first**: Is this the first record for this person? (TRUE/FALSE)
- **typ**: Type of data (all observed)
- **age**: Age (years)
- **sex**: Sex 1=M, 2=F
- **hgt.z**: Height Z-score
- **wgt.z**: Weight Z-score
- **bmi.z**: BMI Z-score
- **ao**: Adult overweight (0=no, 1=yes)

`tbcNtarget` is a data frame with 2612 rows and 3 columns:

- **id**: Person number
- **ao**: Adult overweight (0=no, 1=yes)
- **bmi.z.jv**: BMI Z-score as young adult (18-29 years)

Details

This `tbc` data set is a random subset of persons from a much larger collection of data from the Terneuzen Birth Cohort. The total cohort comprises of 2604 unique persons, whereas the subset in `tbc` covers 306 persons. The `tbcNtarget` is an auxiliary data set containing two outcomes at adult age. For more details, see De Kroon et al (2008, 2010, 2011). The imputation methodology is explained in Chapter 9 of Van Buuren (2012).

Source


**Examples**

```r
data <- tbc
md.pattern(data)
```

---

**version**

*Echoes the package version number*

---

**Description**

Echoes the package version number

**Usage**

```r
version(pkg = "mice")
```

**Arguments**

- **pkg**
  
  A character vector with the package name.

**Value**

A character vector containing the package name, version number and installed directory.

**Author(s)**

Stef van Buuren, Oct 2010

**Examples**

```r
version()
version("base")
```
Walking disability data

Description

Two items YA and YB measuring walking disability in samples A, B and E.

Format

A data frame with 890 rows on the following 5 variables:

- sex Sex of respondent (factor)
- age Age of respondent
- YA Item administered in samples A and E (factor)
- YB Item administered in samples B and E (factor)
- src Source: Sample A, B or E (factor)

Details

Example dataset to demonstrate imputation of two items (YA and YB). Item YA is administered to sample A and sample E, item YB is administered to sample B and sample E, so sample E acts as a bridge study. Imputation using a bridge study is better than simple equating or than imputation under independence.

Item YA corresponds to the HAQ8 item, and item YB corresponds to the GAR9 items from Van Buuren et al (2005). Sample E (as well as sample B) is the Euridiss study (n=292), sample A is the ERGOPLUS study (n=306).

See Van Buuren (2012) chapter 7 for more details on the imputation methodology.

References


Examples

```r
md.pattern(walking)

micemill <- function(n) {
  for (i in 1:n) {
    imp <- mice.mids(imp) # global assignment
    cors <- with(imp, cor(as.numeric(YA),
                           as.numeric(YB),
                           method="kendall"))
    tau <- rbind(tau, getfit(cors, s=TRUE)) # global assignment
  }
}
```r
plotit <- function()
  matplot(x=1:nrow(tau), y=tau,
          ylab=expression(paste("Kendall's ", tau)),
          xlab="Iteration", type="l", lwd=1,
          lty=1:10, col="black")

  tau <- NULL
  imp <- mice(walking, max=0, m=10, seed=92786)
  pred <- imp$pred
  pred[,c("src","age","sex")] <- 0
  imp <- mice(walking, max=0, m=3, seed=92786, pred=pred)
  micemill(5)
  plotit()

# to get figure 7.8 van Buuren (2012) use m=10 and micemill(20)
```

---

**windspeed**  
*Subset of Irish wind speed data*

**Description**

Subset of Irish wind speed data

**Format**

A data frame with 433 rows and 6 columns containing the daily average wind speeds within the period 1961-1978 at meteorological stations in the Republic of Ireland. The data are a random sample from a larger data set.

- RochePt  Roche Point
- Rosslare  Rosslare
- Shannon  Shannon
- Dublin  Dublin
- Clones  Clones
- MalinHead  Malin Head

**Details**

The original data set is much larger and was analyzed in detail by Haslett and Raftery (1989). Van Buuren et al (2006) used this subset to investigate the influence of extreme MAR mechanisms on the quality of imputation.
References


Examples

windspeed[1:3,]

with.mids Evaluate an expression in multiple imputed datasets

Description

Performs a computation of each of imputed datasets in data.

Usage

## S3 method for class 'mids'
with(data, expr, ...)

Arguments

data An object of type mids, which stands for 'multiply imputed data set', typically created by a call to function mice().

expr An expression with a formula object, with the response on the left of a ~ operator, and the terms, separated by + operators, on the right. See the documentation of lm and formula for details.

... Additional parameters passed to expr

Value

A list object of S3 class mira

Author(s)

Karin Oudshoorn, Stef van Buuren 2009-2012

References

xyplot.mids

See Also

mids, mira, pool, pool.compare, pool.r.squared

Examples

imp <- mice(nhanes2)
fit1 <- with(data=imp, exp=lm(bmi~age+hyp+chl))
fit2 <- with(data=imp, exp=glm(hyp~age+bmi+chl, family=binomial))
anova.imp <- with(data=imp, exp=anova(lm(bmi~age+hyp+chl)))

xyplot.mids Scatterplot of observed and imputed data

Description

Plotting methods for imputed data using lattice. xyplot() produces a conditional scatterplots. The function automatically separates the observed (blue) and imputed (red) data. The function extends the usual features of lattice.

Usage

## S3 method for class 'mids'
xyplot(x, data, na.groups = NULL, groups = NULL,
as.table = TRUE, theme = mice.theme(), allow.multiple = TRUE,
outer = TRUE,
drop.unused.levels = latticegetOption("drop.unused.levels"), ...,
subscripts = TRUE, subset = TRUE)

Arguments

x A mids object, typically created by mice() or mice.mids().
data Formula that selects the data to be plotted. This argument follows the lattice rules for formulas, describing the primary variables (used for the per-panel display) and the optional conditioning variables (which define the subsets plotted in different panels) to be used in the plot.

The formula is evaluated on the complete data set in the long form. Legal variable names for the formula include names(x$data) plus the two administrative factors .imp and .id.

Extended formula interface: The primary variable terms (both the LHS y and RHS x) may consist of multiple terms separated by a ‘+’ sign, e.g., y1 + y2 ~ x | a * b. This formula would be taken to mean that the user wants to plot both y1 ~ x | a * b and y2 ~ x | a * b, but with the y1 ~ x and y2 ~ x in separate panels. This behavior differs from standard lattice. Only combine terms of the same type, i.e. only factors or only numerical variables. Mixing numerical and categorical data occasionally produces odds labeling of vertical axis.
The argument `na.groups` may be used to specify (combinations of) missingness in any of the variables. The argument `groups` can be used to specify groups based on the variable values themselves. Only one of both may be active at the same time. When both are specified, `na.groups` takes precedence over `groups`.

Use the `subset` and `na.groups` together to plot parts of the data. For example, select the first imputed data set by `subset=imp==1`.

Graphical parameters like `col`, `pch` and `cex` can be specified in the arguments list to alter the plotting symbols. If `length(col)==2`, the color specification to define the observed and missing groups. `col[1]` is the color of the ‘observed’ data, `col[2]` is the color of the missing or imputed data. A convenient color choice is `col=mdc(1:2)`, a transparent blue color for the observed data, and a transparent red color for the imputed data. A good choice is `col=mdc(1:2)`, `pch=20`, `cex=1.5`. These choices can be set for the duration of the session by running `mice.theme()`.

Details

The argument `na.groups` may be used to specify (combinations of) missingness in any of the variables. The argument `groups` can be used to specify groups based on the variable values themselves. Only one of both may be active at the same time. When both are specified, `na.groups` takes precedence over `groups`.

Use the `subset` and `na.groups` together to plot parts of the data. For example, select the first imputed data set by `subset=imp==1`.

Graphical parameters like `col`, `pch` and `cex` can be specified in the arguments list to alter the plotting symbols. If `length(col)==2`, the color specification to define the observed and missing groups. `col[1]` is the color of the ‘observed’ data, `col[2]` is the color of the missing or imputed data. A convenient color choice is `col=mdc(1:2)`, a transparent blue color for the observed data, and a transparent red color for the imputed data. A good choice is `col=mdc(1:2)`, `pch=20`, `cex=1.5`. These choices can be set for the duration of the session by running `mice.theme()`.
Value

The high-level functions documented here, as well as other high-level Lattice functions, return an object of class "trellis". The update method can be used to subsequently update components of the object, and the print method (usually called by default) will plot it on an appropriate plotting device.

Note

The first two arguments (x and data) are reversed compared to the standard Trellis syntax implemented in lattice. This reversal was necessary in order to benefit from automatic method dispatch.

In mice the argument x is always a mids object, whereas in lattice the argument x is always a formula.

In mice the argument data is always a formula object, whereas in lattice the argument data is usually a data frame.

All other arguments have identical interpretation.

Author(s)

Stef van Buuren

References


See Also

mice, stripplot, densityplot, bwplot, Lattice for an overview of the package, as well as xyplot, panel.xyplot, print.trellis, trellis.par.set

Examples

require(lattice)

imp <- mice(boys, maxit=1)

### xyplot: scatterplot by imputation number
### observe the erroneous outlying imputed values
### (caused by imputing hgt from bmi)
xyplot(imp, hgt-age Imp, pch=c(1,20),cex=c(1,1.5))

### same, but label with missingness of wgt (four cases)
xyplot(imp, hgt-age Imp, na.group=wgt, pch=c(1,20),cex=c(1,1.5))
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