

Package ‘HotDeckImputation’

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Title Hot Deck Imputation Methods for Missing Data

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Description Hot deck imputation methods to resolve missing data.

License GPL-3

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HotDeckImputation-package	2
impute.CPS_SEQ_HD	3
impute.mean	5
impute.NN_HD	6
impute.SEQ_HD	10
match.d_r_odd	12
match.d_r_vam	13
reweight.data	14
Index	16

HotDeckImputation-package

Hot Deck Imputation Methods for Missing Data

Description

This package provides hot deck imputation methods to resolve missing data. Methods provided are popular in survey methodology, mostly used in the context of large national statistics, but are also finding their way to data mining due to their computational simplicity. A key aspect of this package is the implementation of the commonly advocated donor-limit.

Details

Package: HotDeckImputation
Type: Package
Version: 1.1.0
Date: 2014-10-21
License: GPL-3

HotDeckImputation is the ever expanding implementation of hot deck imputation methods, such as the nearest neighbor, the CPS-sequential and random hot deck. The package aims to be comprehensive in the functionality provided, covering key aspects of hot deck imputation not found elsewhere.

Currently implemented functions include:

Nearest neighbor hot deck imputation.

Sequential hot deck imputation.

CPS sequential hot deck imputation.

Development requests are welcome.

Author(s)

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References

Andridge, R.R. and Little, R.J.A. (2010) A Review of Hot Deck Imputation for Survey Non-response. *International Statistical Review*. **78**, 40–64.

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impute.CPS_SEQ_HD

CPS Sequential Hot-Deck Imputation

Description

Resolves missing data by the CPS sequential Hot-Deck Imputation.

Usage

```
impute.CPS_SEQ_HD(DATA = NULL, covariates = NULL, initialvalues = 0,
                 navalues = NA, modifyinplace = TRUE)
```

Arguments

DATA	Data containing missing values. Should be a matrix of numbers.
covariates	Vector containing the covariates (columns that should be used to create the imputation classes). If <code>is.null(covariates) length(covariates)==0</code> this function defaults to <code>impute.SEQ_HD</code> . See Section: Note for further Details.
initialvalues	The initial values for the start-up process of the imputation. Should be "integer" and <code>length(initialvalues)==1 length(initialvalues)==dim(DATA)[2]</code> . The default of 0 is not normally a good value.
navalues	NA code for each variable that should be imputed. Should be "integer" and <code>length(initialvalues)==1 length(initialvalues)==dim(DATA)[2]</code> . Default is R's NA value.
modifyinplace	Should DATA be modified in place? (See the Section: Warning.) If not, a copy is made.

Details

This function imputes the missing values in any variable by creating imputation classes and then replicating the most recently observed value in the class and variable. Imputation classes are created by the adjustment cell method.

Value

An imputed data matrix the same size as the input DATA.

Warning

If `modifyinplace == FALSE` DATA or rather the variable supplied is edited directly! This is significantly faster if the data set is large.

Note

This is a very fast imputation method. Only one pass of the data is needed. With the use of proper covariates, data may be missing MAR. Covariates should be complete (not missing data). If not, NA will be used for building classes. This may or may not be appropriate for the data. The presence of missing values in the covariates is not checked.

Author(s)

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References

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Joenssen, D.W. (2015) Hot-Deck-Verfahren zur Imputation fehlender Daten – Auswirkungen des Donor-Limits. Ilmenau: Ilmedia. [in German, Dissertation]

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See Also

[impute.SEQ_HD](#), [impute.mean](#), [impute.NN_HD](#)

Examples

```
#Set the random seed to an arbitrary number
set.seed(421)
```

```
n<-1000
m<-3
pmiss<-.1
```

```

#Generate matrix of random integers and 2 binary covariates
Y<-cbind(matrix(sample(0:1,replace=TRUE,size=n*2),nrow=n),
  matrix(sample(0:9,replace=TRUE,size=n*m),nrow=n))

#generate missing values, MCAR, in all but the first two columns
Y[,-c(1,2)][sample(1:length(Y[,-c(1,2)]),
  size=floor(pmiss*length(Y[,-c(1,2)])))]<-NA

#perform the sequential imputation Y within the
#classes created by cross-classifying variables 1 and 2
impute.CPS_SEQ_HD(DATA=Y,covariates=c(1,2),initialvalues=0, navalues=NA, modifyinplace = FALSE)

####an example highlighting the modifyinplace option
#using cbind to show the results of the function and the intial data next to another
cbind(impute.CPS_SEQ_HD(DATA=Y,covariates=c(1,2),initialvalues=0,
  navalues=NA, modifyinplace = FALSE),Y)
#notice that columns 8-10 (representing Y) still have missing data

#same procedure, except modifyinplace is set to TRUE
cbind(impute.CPS_SEQ_HD(DATA=Y,covariates=c(1,2),initialvalues=0,
  navalues=NA, modifyinplace = TRUE),Y)
#notice that columns 8-10 (representing Y) are identical to columns 3-5,
#Y has (and any Variables pointing to the same object have) been directly modified.

```

impute.mean

Attribute Wise Mean Imputation

Description

This function imputes the column mean of the complete cases for the missing cases. Utilized by impute.NN_HD as a method for dealing with missing values in distance calculation.

Usage

```
impute.mean(DATA = NULL)
```

Arguments

DATA Data with missing values.

Value

Returns an imputed data matrix with the same dimensions as DATA.

Author(s)

Dieter William Joenssen <Dieter.Joenssen@googlemail.com>

References

- Little, R.J.A and Rubin, D.B. (2002) *Statistical Analysis with Missing Data*. Hoboken: Wiley.
- Joensuu, D.W. (2015) Hot-Deck-Verfahren zur Imputation fehlender Daten – Auswirkungen des Donor-Limits. Ilmenau: Ilmedia. [in German, Dissertation]

See Also

[impute.NN_HD](#)

Examples

```
#Set the random seed to an arbitrary number
set.seed(421)

#Generate matrix of random integers
Y<-matrix(sample(0:9,replace=TRUE,size=6*3),nrow=6)

#generate 6 missing values, MCAR, in all but the first row
Y[-1,][sample(1:12,size=6)]<-NA

#Impute the colMeans of Y
impute.mean(DATA=Y)
```

impute.NN_HD

The Nearest Neighbor Hot Deck Algorithms

Description

A comprehensive function that performs nearest neighbor hot deck imputation. Aspects such as variable weighting, distance types, and donor limiting are implemented. New concepts such as the optimal distribution of donors are also available.

Usage

```
impute.NN_HD(DATA = NULL, distance = "man", weights = "range", attributes = "sim",
  comp = "rw_dist", donor_limit = Inf, optimal_donor = "no",
  list_donors_recipients = NULL, diagnose = NULL)
```

Arguments

DATA	Data containing missing values. Must either be data.frame, then factors and strings will be recoded using model.matrix or Will be coerced by data.matrix.
distance	Distance type to use when searching for the nearest neighbor. See the details section for options.
weights	Weights by which the variables should be scaled. See the details section for options.

attributes	Determines how attributes should be handled. Currently only "sim", meaning donor and recipient pools are disjoint, is implemented.
comp	Defines the compensation of missing values for distance calculation. See the details section for options.
donor_limit	Limits how often a donor may function as such. See the details section for options.
optimal_donor	Defines how the optimal donor is found when a donor limit is used. See the details section for options.
list_donors_recipients	Option for manually specifying the donor and recipient pools via a list with components "donors" and "recipients".
diagnose	Option to recover the generated distances and donor-recipient matches. See details section for usage.

Details

argument: distance can be defined as:

- *numeric matrix*, donors x recipients distance matrix
- *numeric length = 1*, Minkovski parameter
- *string length = 1*, distance metric to be used:
 - "man", Manhattan distance
 - "eukl", Euclidean distance
 - "tscheb", Chebyshev distance
 - "mahal", Mahalanobis distance (covariance matrix calculated after missing data compensation, incompatible with comp="rw_dist")

argument: weights can be defined as:

- *string length = 1*, reweighting type "range", "sd", "var", or "none"
- *numeric length = 1*, one numeric weight for all variables
- *string vector*, like option 1, only different type for each variable (not implemented)
- *numeric vector*, like option 2, only different numeric weight for each variable
- *list*, mixture of options 3 and 4 (not implemented)

argument: comp can be defined as:

- "rw_dist", total distance is reweighted by number of distances that may be computed
- "mean", mean imputation is performed before distance calculation
- "rseq", random hot deck imputation, each variable sequentially (uses impute.SEQ_HD)
- "rsim", random hot deck imputation, each variable simultaneously (not implemented)

argument: donor_limit is a single number interpreted by its range:

- (0,1), dynamic donor limit, i.e., .5 means any 1 donor may serve up to 50% of all recipients, rounded up if fractional

- $[1, Inf)$, static donor limit, i.e., 2 means any 1 donor may serve up to 2 recipients, fractional parts discarded
- Inf , no donor limit

argument: optimal_donor is a single string interpreted by its value:

- "no", donor-recipient matching is performed in order by which the recipients appear in the data (fastest)
- "rand", donor-recipient matching is performed in a random recipient-order
- "mmin", donor-recipient matching is performed by the matrix minimum method (sequence independent)
- "modifvam", donor-recipient matching is performed by a modified (only columns considered) Vogel's approximation method (sequence independent)
- "vam", donor-recipient matching is performed by the Vogel's approximation method (sequence independent)
- "odd", donor-recipient matching is performed via the optimal donor distribution method (sequence independent, best results)

argument: diagnose should be:

- NULL, no diagnostics will be returned.
- *character string*, desired variable name under which the diagnostics will be saved to .GlobalEnv. The following character strings will however default to NULL with a warning: "if", "else", "repeat", "while", "function", "for", "in", "next", "break", "TRUE", "FALSE", "NULL", "Inf", "NaN", "NA", "NA_integer_", "NA_real_", "NA_complex_", "NA_character_", "c", "q", "s", "t", "C", "D", "F", "I", "T"
- *anything else*, defaults to NULL with a warning.

Should be a character string of the desired variable name which will be created in .GlobalEnv

Value

An imputed data matrix the same size as the input DATA. If the diagnose option is used correctly, a list containing the following components will be created in the workspace:

distances the donor-recipient distance matrix used for matching

list_donors_recipients
 the resultant recipient-donor matches

Author(s)

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References

- Andridge, R.R. and Little, R.J.A. (2010) A Review of Hot Deck Imputation for Survey Non-response. *International Statistical Review*. **78**, 40–64.
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See Also

[impute.mean](#), [match.d_r_vam](#), [reweight.data](#)

Examples

```
#Set the random seed to an arbitrary number
set.seed(421)

#Generate random integer matrix size 10x4
Y<-matrix(sample(x=1:100,size=10*4),nrow=10)

#remove 5 values, ensuring one complete covariate and 5 donors
Y[-c(1:5),-1][sample(1:15,size=5)]<-NA

#Impute using various different (arbitrarily chosen) settings
impute.NN_HD(DATA=Y,distance="man",weights="var")

impute.NN_HD(DATA=Y,distance=2,weights=rep(.5,4),donor_limit=2,optimal_donor="mmin")

impute.NN_HD(DATA=Y,distance="eukl",weights=.25,comp="mean",donor_limit=1,
  optimal_donor="odd")

#Recover some diagnostics
```

```

impute.NN_HD(DATA=Y,distance="eukl",weights=.25,comp="mean",donor_limit=1,
  optimal_donor="odd",diagnose = "diagnostics")
# look at the diagnostics
diagnostics

```

impute.SEQ_HD	<i>Sequential Hot-Deck Imputation</i>
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Description

Resolves missing data by sequential Hot-Deck Imputation.

Usage

```

impute.SEQ_HD(DATA = NULL, initialvalues = 0, navalues = NA,
  modifyinplace = TRUE)

```

Arguments

DATA	Data containing missing values. Should be a matrix of integers.
initialvalues	The initial values for the start-up process of the imputation. Should be "integer" and <code>length(initialvalues)==1 length(initialvalues)==dim(DATA)[2]</code> . The default of 0 is not normally a good value.
navalues	NA code for each variable that should be imputed. Should be "integer" and <code>length(initialvalues)==1 length(initialvalues)==dim(DATA)[2]</code> . Default is R's NA value.
modifyinplace	Should DATA be modified in place? (See the Section: Warning.) If not, a copy is made.

Details

This function imputes the missing values in any variable by replicating the most recently observed value in that variable.

Value

An imputed data matrix the same size as the input DATA.

Warning

If `modifyinplace == FALSE` DATA or rather the variable supplied is edited directly! This is significantly faster if the data set is large.

Note

This is by far the fastest imputation method. Only one pass of the data is needed. However, no covariate information is used, thus only leads to good results if the data are missing MCAR.

Author(s)

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References

Hanson, R.H. (1978) The Current Population Survey: Design and Methodology. *Technical Paper No. 40*. U.S. Bureau of the Census.

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See Also

[impute.CPS_SEQ_HD](#), [impute.mean](#), [impute.NN_HD](#)

Examples

```
#Set the random seed to an arbitrary number
set.seed(421)

n<-1000
m<-5
pmiss<-.1

#Generate matrix of random integers
Y<-matrix(sample(0:9,replace=TRUE,size=n*m),nrow=n)

#generate 6 missing values, MCAR, in all but the first row
Y[-1,][sample(1:length(Y[-1,]),size=floor(pmiss*length(Y[-1,])))]<-NA

#perform the sequential imputation Y
impute.SEQ_HD(DATA=Y,initialvalues=0, navalues=NA, modifyinplace = FALSE)

####an example highlighting the modifyinplace option
#using cbind to show the results of the function and the initial data next to another
cbind(impute.SEQ_HD(DATA=Y,initialvalues=0, navalues=NA, modifyinplace = FALSE),Y)
#notice that columns 6-10 (representing Y) still have missing data

#same procedure, except modifyinplace is set to TRUE
cbind(impute.SEQ_HD(DATA=Y,initialvalues=0, navalues=NA, modifyinplace = TRUE),Y)
#notice that columns 6-10 (representing Y) are identical to columns 1-5,
#Y has (and any Variables pointing to the same object have) been directly modified.
```

`match.d_r_odd`*Donor-Recipient Matching via Optimal Donor Distribution Method*

Description

A function that performs the optimal donor distribution method. GLPK is used to find the optimal solution to the integer program.

Usage

```
match.d_r_odd(distance = NULL, recipients=NULL, donors=NULL, donor_limit=NULL)
```

Arguments

<code>distance</code>	A distance matrix of dimensions $\text{length}(\text{donors}) * \text{length}(\text{recipients})$
<code>recipients</code>	A vector of object (row) numbers from the original data matrix, indicating which objects require imputation.
<code>donors</code>	A vector of object (row) numbers from the original data matrix, indicating which objects may be used for imputation.
<code>donor_limit</code>	A vector of $\text{length}(\text{donors})$ detailing how often any one donor may be used.

Value

A matrix of dimensions $\text{length}(\text{recipients}) * 2$. The first column, named `recipients`, is equivalent to `recipients`. The second column, named `donors`, contains the donor that is matched to any of the recipients.

Author(s)

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References

- Domschke, W. (1995) *Logistik: Transport*. Munich: Oldenbourg. [in German]
- Joenssen, D.W. (2015) Donor Limited Hot Deck Imputation: A Constrained Optimization Problem. In: B. Lausen, S. Krolak-Schwerdt, and M. Böhmer (Eds.): *Data Science, Learning by Latent Structures, and Knowledge Discovery. Studies in Classification, Data Analysis and Knowledge Organization*, pages 319–328. Berlin/Heidelberg: Springer.
- Joenssen, D.W. (2015) Hot-Deck-Verfahren zur Imputation fehlender Daten – Auswirkungen des Donor-Limits. Ilmenau: Ilmedia. [in German, Dissertation]

See Also

[impute.NN_HD](#), [match.d_r_vam](#)

Examples

```

#Set the random seed to an arbitrary number
set.seed(421)

#Set up a random distance matrix
ndonor=20
nrecip=20
distance<-matrix(sample(1:100,replace=TRUE,size=ndonor*nrecip),nrow=ndonor,ncol=nrecip)
#Name donors and recipients
donors<-1:nrow(distance)
recipients<-(nrow(distance)+1):(nrow(distance)+ncol(distance))
colnames(distance)<-recipients
rownames(distance)<-donors
#Set up the donor limit variable
donor_limit<-rep(1,length(donors))

#perform the matching
match.d_r_odd(distance=distance,recipients=recipients,donors=donors,
donor_limit=donor_limit)

```

match.d_r_vam

Donor-Recipient Matching via Vogel's Approximation Method

Description

A function that performs Vogel's approximation method. A heuristic to reduce the total sum of donor-recipient distances.

Usage

```
match.d_r_vam(distance = NULL, recipients=NULL, donors=NULL, donor_limit=NULL)
```

Arguments

distance	A distance matrix of dimensions $\text{length}(\text{donors}) * \text{length}(\text{recipients})$
recipients	A vector of object (row) numbers from the original data matrix, indicating which objects require imputation.
donors	A vector of object (row) numbers from the original data matrix, indicating which objects may be used for imputation.
donor_limit	A vector of $\text{length}(\text{donors})$ detailing how often any one donor may be used.

Value

A matrix of dimensions $\text{length}(\text{recipients}) * 2$. The first column, named recipients, is equivalent to recipients. The second column, named donors, contains the donor that is matched to any of the recipients.

Author(s)

Dieter William Joenssen <Dieter.Joenssen@googlemail.com>

References

- Domschke, W. (1995) *Logistik: Transport*. Munich: Oldenbourg. [in German]
- Joenssen, D.W. (2015) Donor Limited Hot Deck Imputation: A Constrained Optimization Problem. In: B. Lausen, S. Krolak-Schwerdt, and M. Böhmer (Eds.): *Data Science, Learning by Latent Structures, and Knowledge Discovery. Studies in Classification, Data Analysis and Knowledge Organization*, pages 319–328. Berlin/Heidelberg: Springer.
- Joenssen, D.W. (2015) Hot-Deck-Verfahren zur Imputation fehlender Daten – Auswirkungen des Donor-Limits. Ilmenau: Ilmedia. [in German, Dissertation]

See Also

[impute.NN_HD](#)

Examples

```
#Set the random seed to an arbitrary number
set.seed(421)

#Set up a random distance matrix
ndonor=20
nrecip=20
distance<-matrix(sample(1:100,replace=TRUE,size=ndonor*nrecip),nrow=ndonor,ncol=nrecip)
#Name donors and recipients
donors<-1:nrow(distance)
recipients<-(nrow(distance)+1):(nrow(distance)+ncol(distance))
colnames(distance)<-recipients
rownames(distance)<-donors
#Set up the donor limit variable
donor_limit<-rep(1,length(donors))

#perform the matching
match.d_r_vam(distance=distance,recipients=recipients,donors=donors,
donor_limit=donor_limit)
```

reweight.data

Reweight Variables

Description

Reweighting function to preprocess a data matrix prior to Minkovski distance calculation.

Usage

```
reweight.data(DATA = NULL, weights = NULL, minkovski_factor = 1)
```

Arguments

`DATA` Data that should be reweighted.
`weights` Numeric vector with length equal to the number of variables in `DATA`.
`minkovski_factor` The desired Minkovski parameter that will be used for calculating the distances.

Value

Returns a data matrix with the same dimensions as `DATA`.

Author(s)

Dieter William Joenssen <Dieter.Joenssen@googlemail.com>

See Also

[impute.NN_HD](#)

Examples

```
#Set the random seed to an arbitrary number
set.seed(421)

#Generate matrix of random integers
Y<-matrix(sample(0:9,replace=TRUE,size=6*3),nrow=6)

#choose variable variances
Weights<-1/apply(X=Y,MARGIN=2,FUN=var)

#reweight data for faster Euclidean distance calculation
reweight.data(DATA = Y, weights = Weights, minkovski_factor = 2)
```

Index

*Topic **NA**

- HotDeckImputation-package, 2
- impute.CPS_SEQ_HD, 3
- impute.mean, 5
- impute.NN_HD, 6
- impute.SEQ_HD, 10

*Topic **impute**

- impute.CPS_SEQ_HD, 3
- impute.SEQ_HD, 10

*Topic **manip**

- HotDeckImputation-package, 2
- impute.CPS_SEQ_HD, 3
- impute.mean, 5
- impute.NN_HD, 6
- impute.SEQ_HD, 10
- reweight.data, 14

*Topic **multivariate**

- HotDeckImputation-package, 2
- impute.CPS_SEQ_HD, 3
- impute.NN_HD, 6
- impute.SEQ_HD, 10

*Topic **optimize**

- impute.CPS_SEQ_HD, 3
- impute.NN_HD, 6
- impute.SEQ_HD, 10
- match.d_r_odd, 12
- match.d_r_vam, 13

*Topic **package**

- HotDeckImputation-package, 2

HotDeckImputation

(HotDeckImputation-package), 2

HotDeckImputation-package, 2

impute.CPS_SEQ_HD, 3, 11

impute.mean, 4, 5, 9, 11

impute.NN_HD, 4, 6, 6, 11, 12, 14, 15

impute.SEQ_HD, 4, 10

match.d_r_odd, 12

match.d_r_vam, 9, 12, 13

reweight.data, 9, 14