

# Package ‘CoImp’

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**Title** Parametric and Non-Parametric Copula-Based Imputation Methods

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**Depends** R (>= 4.2.0), methods, stats, copula, cluster

**Imports** nnet, gtools, locfit

**Description** Copula-based imputation methods: parametric and non-parametric algorithms for missing multivariate data through conditional copulas.

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**Description**

Imputation method based on conditional copula functions.

**Usage**

```
CoImp(X, n.marg = ncol(X), x.up = NULL, x.lo = NULL, q.up = rep(0.85, n.marg),
      q.lo = rep(0.15, n.marg), type.data = "continuous", smoothing =
      rep(0.5, n.marg), plot = TRUE, model = list(normalCopula(0.5,
      dim=n.marg), claytonCopula(10, dim=n.marg), gumbelCopula(10,
      dim=n.marg), frankCopula(10, dim=n.marg), tCopula(0.5,
      dim=n.marg,...), rotCopula(claytonCopula(10,dim=n.marg),
      flip=rep(TRUE,n.marg)),...), start. = NULL, ...)
```

**Arguments**

<code>X</code>	a data matrix with missing values. Missing values should be denoted with NA.
<code>n.marg</code>	the number of variables in X.
<code>x.up</code>	a numeric vector of length <code>n.marg</code> with the upper value of each margin used in the Hit or Miss method. Specify either <code>x.up</code> xor <code>q.up</code> .
<code>x.lo</code>	a numeric vector of length <code>n.marg</code> with the lower value of each margin used in the Hit or Miss method. Specify either <code>x.lo</code> xor <code>q.lo</code> .
<code>q.up</code>	a numeric vector of length <code>n.marg</code> with the probability of the quantile used to define <code>x.up</code> for each margin. Specify either <code>x.up</code> xor <code>q.up</code> .
<code>q.lo</code>	a numeric vector of length <code>n.marg</code> with the probability of the quantile used to define <code>x.lo</code> for each margin. Specify either <code>x.lo</code> xor <code>q.lo</code> .
<code>type.data</code>	the nature of the variables in X: discrete or continuous.
<code>smoothing</code>	values for the nearest neighbour component of the smoothing parameter of the <a href="#">lp</a> function.
<code>plot</code>	logical: if TRUE plots the estimated marginal densities and a bar plot of the percentages of missing and available data for each margin.
<code>model</code>	a list of copula models to be used for the imputation, see the Details section. This should be one of normal and t (with <code>dispstr</code> as in the copula package), frank, clayton, gumbel, and rotated copulas. As in <a href="#">fitCopula</a> , itau fitting coerced tCopula to 'df.fixed=TRUE'.
<code>start.</code>	a numeric vector of starting values for the parameter optimization via <a href="#">optim</a> .
<code>...</code>	further parameters for <a href="#">fitCopula</a> , <a href="#">lp</a> and further graphical arguments.

## Details

CoImp is an imputation method based on conditional copula functions that allows to impute missing observations according to the multivariate dependence structure of the generating process without any assumptions on the margins. This method can be used independently from the dimension and the kind (monotone or non monotone) of the missing patterns.

Brief description of the approach:

1. estimate both the margins and the copula model on available data by means of the semi-parametric sequential two-step inference for margins;
2. derive conditional density functions of the missing variables given non-missing ones through the corresponding conditional copulas obtained by using the Bayes' rule;
3. impute missing values by drawing observations from the conditional density functions derived at the previous step. The Monte Carlo method used is the Hit or Miss.

The estimation approach for the copula fit is semiparametric: a range of nonparametric margins and parametric copula models can be selected by the user.

## Value

An object of S4 class "CoImp", which is a list with the following elements:

Missing.data.matrix	the original missing data matrix to be imputed.
Perc.miss	the matrix of the percentage of missing and available data.
Estimated.Model	the estimated copula model on the available data.
Estimation.Method	the estimation method used for the copula Estimated.Model.
Index.matrix.NA	matrix indices of the missing data.
Smooth.param	the smoothing parameter alpha selected on the basis of the AIC.
Imputed.data.matrix	the imputed data matrix.
Estimated.Model.Imp	the estimated copula model on the imputed data matrix.
Estimation.Method.Imp	the estimation method used for the copula Estimated.Model.Imp.

## Author(s)

F. Marta L. Di Lascio <marta.dilascio@unibz.it>, Simone Giannerini <simone.giannerini@unibo.it>

## References

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2015) "Exploring Copulas for the Imputation of Complex Dependent Data". *Statistical Methods & Applications*, 24(1), p. 159-175. DOI 10.1007/s10260-014-0287-2.

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2014) "Imputation of complex dependent data by conditional copulas: analytic versus semiparametric approach", *Book of proceedings of the 21st International Conference on Computational Statistics (COMPSTAT 2014)*, p. 491-497. ISBN 9782839913478.

Bianchi, G. Di Lascio, F.M.L. Giannerini, S. Manzari, A. Reale, A. and Ruocco, G. (2009) "Exploring copulas for the imputation of missing nonlinearly dependent data". *Proceedings of the VII Meeting Classification and Data Analysis Group of the Italian Statistical Society (Cladag)*, Editors: Salvatore Ingrassia and Roberto Rocci, Cleup, p. 429-432. ISBN: 978-88-6129-406-6.

## See Also

[NPCoImp](#), [MCAR](#), [MAR](#), [fitCopula](#), [lp](#).

## Examples

```
## generate data from a 4-variate Frank copula with different margins

set.seed(21)
n.marg <- 4
theta <- 5
copula <- frankCopula(theta, dim = n.marg)
mymvdc <- mvdc(copula, c("norm", "gamma", "beta", "gamma"), list(list(mean=7, sd=2),
list(shape=3, rate=2), list(shape1=4, shape2=1), list(shape=4, rate=3)))
n <- 20
x.samp <- copula::rMvdc(n, mymvdc)

# randomly introduce univariate and multivariate missing

perc.mis <- 0.3
set.seed(11)
miss.row <- sample(1:n, perc.mis*n, replace=TRUE)
miss.col <- sample(1:n.marg, perc.mis*n, replace=TRUE)
miss <- cbind(miss.row, miss.col)
x.samp.miss <- replace(x.samp, miss, NA)

# impute missing values

imp <- CoImp(x.samp.miss, n.marg=n.marg, smoothing = rep(0.6, n.marg), plot=TRUE,
type.data="continuous", model=list(normalCopula(0.5, dim=n.marg),
frankCopula(10, dim=n.marg), gumbelCopula(10, dim=n.marg)));

# methods show and plot

show(imp)
plot(imp)
```

```

## Not run:
## generate data from a 3-variate Clayton copula and introduce missing by
## using the MCAR function and try to impute through a rotated copula

set.seed(11)
n.marg <- 3
theta <- 5
copula <- claytonCopula(theta, dim = n.marg)
mymvdc <- mvdc(copula, c("beta", "beta", "beta"), list(list(shape1=4, shape2=1),
  list(shape1=.5, shape2=.5), list(shape1=2, shape2=3)))
n <- 50
x.samp <- copula::rMvdc(n, mymvdc)

# randomly introduce MCAR univariate and multivariate missing

perc.miss <- 0.15
setseed <- set.seed(13)
x.samp.miss <- MCAR(x.samp, perc.miss, setseed)
x.samp.miss <- x.samp.miss@"db.missing"

# impute missing values

imp <- CoImp(x.samp.miss, n.marg=n.marg, smoothing = c(0.45,0.2,0.5), plot=TRUE,
  q.lo=rep(0.1,n.marg), q.up=rep(0.9,n.marg), model=list(claytonCopula(0.5,
  dim=n.marg), rotCopula(claytonCopula(0.5,dim=n.marg))));

# methods show and plot

show(imp)
plot(imp)

## End(Not run)

```

---

CoImp-class

*Class "CoImp"*


---

### Description

A class for CoImp and its extensions

### Objects from the Class

Objects can be created by calls of the form `new("CoImp", ...)`.

### Slots

**Missing.data.matrix:** Object of class "matrix". Original missing data matrix to be imputed.

**Perc.miss:** Object of class "matrix". Missing and available data percentage for each variable.

**Estimated.Model:** Object of class "list". The list contains:

model	the copula model selected and estimated on the complete cases.
dimension	the dimension of the model.
parameter	the estimated dependence parameter of the model.
number	the index of the estimated model in the list of models given in input.

**Estimation.Method:** Object of class "character". The estimation method used for the copula model in **Estimated.Model**. Allowed methods are in [fitCopula](#).

**Index.matrix.NA:** Object of class "matrix". Matrix of row and column indexes of missing data.

**Smooth.param:** Object of class "numeric". The values of the nearest neighbor component of the smoothing parameter of the lp function.

**Imputed.data.matrix** Object of class "matrix". The imputed data matrix.

**Estimated.Model.Imp** Object of class "list". The list contains:

model	the copula model selected and estimated on the imputed cases.
dimension	the dimension of the model.
parameter	the estimated dependence parameter of the model.
number	the index of the estimated model in the list of models given in input.

**Estimation.Method.Imp** Object of class "character". The estimation method used for the copula model in **Estimated.Model.Imp**. Allowed methods are in [fitCopula](#).

## Methods

**plot** signature(x = "CoImp", y = "missing"): ...

**show** signature(object = "CoImp"): ...

## Author(s)

F. Marta L. Di Lascio <marta.dilascio@unibz.it>, Simone Giannerini <simone.giannerini@unibo.it>

## References

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2015) "Exploring Copulas for the Imputation of Complex Dependent Data". *Statistical Methods & Applications*, 24(1), p. 159-175. DOI 10.1007/s10260-014-0287-2.

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2014) "Imputation of complex dependent data by conditional copulas: analytic versus semiparametric approach", *Book of proceedings of the 21st International Conference on Computational Statistics (COMPSTAT 2014)*, p. 491-497. ISBN 9782839913478.

Bianchi, G. Di Lascio, F.M.L. Giannerini, S. Manzari, A. Reale, A. and Ruocco, G. (2009) "Exploring copulas for the imputation of missing nonlinearly dependent data". *Proceedings of the VII Meeting Classification and Data Analysis Group of the Italian Statistical Society (Cladag)*, Editors: Salvatore Ingrassia and Roberto Rocci, Cleup, p. 429-432. ISBN: 978-88-6129-406-6.

**See Also**

[NPCoImp](#), [MCAR](#), [MAR](#), [fitCopula](#).

**Examples**

```
showClass("CoImp")
```

---

MAR

*Generation of multivariate missing at random (MAR) data*

---

**Description**

Introduction of artificial missing at random (MAR) data in a given data set. Missing values are multivariate and have generic pattern.

**Usage**

```
MAR(db.complete, perc.miss = 0.3, setseed = 13, mcols = NULL, ...)
```

**Arguments**

<code>db.complete</code>	the complete data matrix.
<code>perc.miss</code>	the percentage of missing values to be generated.
<code>setseed</code>	the seed for the generation of the missing values.
<code>mcols</code>	the index of the columns in which to introduce MAR values.
<code>...</code>	further parameters for <a href="#">fitCopula</a> .

**Details**

MAR introduce artificial missing at random values in a given complete data set. Missing values are univariate and multivariate and have generic pattern.

**Value**

An object of S4 class "MAR", which is a list with the following element:

<code>perc.record.missing</code>	Object of class "numeric". A percentage value.
<code>db.missing</code>	Object of class "matrix". A data set with artificial multivariate MAR.

**Author(s)**

F. Marta L. Di Lascio <marta.dilascio@unibz.it>,  
Simone Giannerini <simone.giannerini@unibo.it>

## References

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2015) "Exploring Copulas for the Imputation of Complex Dependent Data". *Statistical Methods & Applications*, 24(1), p. 159-175. DOI 10.1007/s10260-014-0287-2.

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2014) "Imputation of complex dependent data by conditional copulas: analytic versus semiparametric approach", *Book of proceedings of the 21st International Conference on Computational Statistics (COMPSTAT 2014)*, p. 491-497. ISBN 9782839913478.

Bianchi, G. Di Lascio, F.M.L. Giannerini, S. Manzari, A. Reale, A. and Ruocco, G. (2009) "Exploring copulas for the imputation of missing nonlinearly dependent data". *Proceedings of the VII Meeting Classification and Data Analysis Group of the Italian Statistical Society (Cladag)*, Editors: Salvatore Ingrassia and Roberto Rocci, Cleup, p. 429-432. ISBN: 978-88-6129-406-6.

## See Also

[CoImp](#), [NPCoImp](#), [fitCopula](#).

## Examples

```
# generate data from a 4-variate Gumbel copula with different margins

set.seed(11)
n.marg <- 4
theta <- 5
copula <- frankCopula(theta, dim = n.marg)
mymvdc <- mvdc(copula, c("norm", "gamma", "beta", "gamma"), list(list(mean=7, sd=2),
list(shape=3, rate=2), list(shape1=4, shape2=1), list(shape=4, rate=3)))
n <- 30
x.samp <- rMvdc(n, mymvdc)

# apply MAR by introducing 30% of missing data

mar <- MAR(db.complete = x.samp, perc.miss = 0.3, setseed = 11)

mar
```

---

MAR-class

*Class "MAR"*

---

## Description

A class for MAR and its extensions

## Objects from the Class

Objects can be created by calls of the form `new("MAR", ...)`.



**Slots**

`perc.record.missing`: Object of class "numeric". A percentage value.

`db.missing`: Object of class "matrix". A data set with artificial multivariate MAR with generic pattern.

**Methods**

`show signature(object = "MAR")`: ...

**Author(s)**

F. Marta L. Di Lascio <marta.dilascio@unibz.it>, Simone Giannerini <simone.giannerini@unibo.it>

**References**

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2015) "Exploring Copulas for the Imputation of Complex Dependent Data". *Statistical Methods & Applications*, 24(1), p. 159-175. DOI 10.1007/s10260-014-0287-2.

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2014) "Imputation of complex dependent data by conditional copulas: analytic versus semiparametric approach", *Book of proceedings of the 21st International Conference on Computational Statistics (COMPSTAT 2014)*, p. 491-497. ISBN 9782839913478.

Bianchi, G. Di Lascio, F.M.L. Giannerini, S. Manzari, A. Reale, A. and Ruocco, G. (2009) "Exploring copulas for the imputation of missing nonlinearly dependent data". *Proceedings of the VII Meeting Classification and Data Analysis Group of the Italian Statistical Society (Cladag)*, Editors: Salvatore Ingrassia and Roberto Rocci, Cleup, p. 429-432. ISBN: 978-88-6129-406-6.

**See Also**

[CoImp](#), [NPCoImp](#).

**Examples**

```
showClass("MAR")
```

---

MCAR

*Generation of multivariate MCAR data*

---

**Description**

Introduction of artificial missing completely at random (MCAR) data in a given data set. Missing values are multivariate and have generic pattern.

**Usage**

```
MCAR(db.complete, perc.miss = 0.3, setseed = 13, mcols = NULL, ...)
```

**Arguments**

<code>db.complete</code>	the complete data matrix.
<code>perc.miss</code>	the percentage of missing value to be generated.
<code>setseed</code>	the seed for the generation of the missing values.
<code>mcols</code>	the index of the columns in which to introduce MCAR values.
<code>...</code>	further parameters for <code>fitCopula</code> .

**Details**

MCAR introduce artificial missing completely at random values in a given complete data set. Missing values are multivariate and have generic pattern.

**Value**

An object of S4 class "MCAR", which is a list with the following element:

`db.missing`      Object of class "matrix". A data set with artificial multivariate MCAR.

**Author(s)**

F. Marta L. Di Lascio <marta.dilascio@unibz.it>,  
Simone Giannerini <simone.giannerini@unibo.it>

**References**

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2015) "Exploring Copulas for the Imputation of Complex Dependent Data". *Statistical Methods & Applications*, 24(1), p. 159-175. DOI 10.1007/s10260-014-0287-2.

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2014) "Imputation of complex dependent data by conditional copulas: analytic versus semiparametric approach", *Book of proceedings of the 21st International Conference on Computational Statistics (COMPSTAT 2014)*, p. 491-497. ISBN 9782839913478.

Bianchi, G. Di Lascio, F.M.L. Giannerini, S. Manzari, A. Reale, A. and Ruocco, G. (2009) "Exploring copulas for the imputation of missing nonlinearly dependent data". *Proceedings of the VII Meeting Classification and Data Analysis Group of the Italian Statistical Society (Cladag)*, Editors: Salvatore Ingrassia and Roberto Rocci, Cleup, p. 429-432. ISBN: 978-88-6129-406-6.

**See Also**

`CoImp`, `NPCoImp`, `fitCopula`.

**Examples**

```
# generate data from a 4-variate Gumbel copula with different margins

set.seed(11)
n.marg <- 4
theta <- 5
```

```
copula <- frankCopula(theta, dim = n.marg)
mymvdc <- mvdc(copula, c("norm", "gamma", "beta", "gamma"), list(list(mean=7, sd=2),
list(shape=3, rate=2), list(shape1=4, shape2=1), list(shape=4, rate=3)))
n      <- 30
x.samp <- rMvdc(n, mymvdc)

# apply MCAR by introducing 30% of missing data

mcar  <- MCAR(db.complete = x.samp, perc.miss = 0.3, setseed = 11)

mcar

# same example as above but introducing missing only in the first and third column

mcar2 <- MCAR(db.complete = x.samp, perc.miss = 0.3, setseed = 11, mcols=c(1,3))

mcar2
```

---

MCAR-class

*Class "MCAR"*

---

## Description

A class for MCAR and its extensions

## Objects from the Class

Objects can be created by calls of the form `new("MCAR", ...)`.

## Slots

`db.missing`: Object of class "matrix". A data set with artificial multivariate MCAR.

## Methods

`show` signature(object = "MCAR"): ...

## Author(s)

F. Marta L. Di Lascio <marta.dilascio@unibz.it>,  
Simone Giannerini <simone.giannerini@unibo.it>

## References

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2015) "Exploring Copulas for the Imputation of Complex Dependent Data". *Statistical Methods & Applications*, 24(1), p. 159-175. DOI 10.1007/s10260-014-0287-2.

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2014) "Imputation of complex dependent data by conditional copulas: analytic versus semiparametric approach", *Book of proceedings of the 21st International Conference on Computational Statistics (COMPSTAT 2014)*, p. 491-497. ISBN 9782839913478.

Bianchi, G. Di Lascio, F.M.L. Giannerini, S. Manzari, A. Reale, A. and Ruocco, G. (2009) "Exploring copulas for the imputation of missing nonlinearly dependent data". *Proceedings of the VII Meeting Classification and Data Analysis Group of the Italian Statistical Society (Cladag)*, Editors: Salvatore Ingrassia and Roberto Rocci, Cleup, p. 429-432. ISBN: 978-88-6129-406-6.

## See Also

[CoImp](#), [NPCoImp](#).

## Examples

```
showClass("MCAR")
```

---

NPCoImp

*Non-Parametric Copula-Based Imputation Method*

---

## Description

Imputation method based on empirical conditional copula functions.

## Usage

```
NPCoImp(X, Psi=seq(0.05,0.45,by=0.05), smoothing="beta", K=7, method="gower")
```

## Arguments

X	a data matrix with missing values. Missing values should be denoted with NA.
Psi	vector of probabilities to assess the symmetry/asymmetry of the empirical conditional copula (ecc) function and find the best quantile for the imputation (see below for details).
smoothing	the character string specifying the type of smoothing of the empirical copula. Default is "beta" (empirical beta copula) but also "none" (the original empirical copula) can be used.
K	the number of data matrix rows more similar to the missing one that are used for the imputation.
method	the distance measure used for the imputation, among Euclidean, Manhattan, Canberra, Gower, and two based on the Kendall-correlation coefficient (see below for details).

## Details

NPCoImp is a non-parametric imputation method based on the empirical conditional copula function. To choose the best quantile for the imputation it assesses the (a)symmetry of the empirical conditional copula and it uses the  $K$  pseudo-observations more similar to the missing one. The NPCoImp allows the imputation of missing observations according to the multivariate dependence structure of the data generating process without any assumptions on the margins. This method can be used independently from the dimension and the kind (monotone or non monotone) of the missing patterns. Brief description of the approach:

1. estimate the empirical (beta) conditional copula of the missing observation(s) given the available ones;
2. evaluate the (a)symmetry of the empirical conditional copula around 0.5 (see the paper in the references for details);
3. select the quantile of the empirical conditional copula on the basis of its (a)symmetry. Therefore:
  - symmetry: we impute through the median of the empirical conditional copula;
  - negative asymmetry: we impute with a quantile on the left tail of the ecc (see the paper in the references for details);
  - positive asymmetry: we impute with a quantile on the right tail of the ecc (see the paper in the references for details);
4. select the  $K$  pseudo-observations closest to the imputed one and the corresponding original observations;
5. impute missing values by replacing them from the average of the original observations derived at the previous step.

## Value

An object of S4 class "NPCoImp", which is a list with the following elements:

`Imputed.matrix` the imputed data matrix.

`Selected.quantile.alpha`  
the quantile selected for the imputation and its order alpha.

`numFlat` the number of possible flat empirical conditional copulas, i.e. when ecc is always zero.

## Author(s)

F. Marta L. Di Lascio <marta.dilascio@unibz.it>, Aurora Gatto <aurora.gatto@unibz.it>

## References

Di Lascio, F.M.L, Gatto A. (202x) "A non-parametric conditional copula-based imputation method". Under review.

## See Also

[CoImp](#), [MCAR](#), [MAR](#).

**Examples**

```

## generate data from a 4-variate Frank copula with different margins

set.seed(21)
n.marg <- 4
theta <- 5
copula <- frankCopula(theta, dim = n.marg)
mymvdc <- mvdc(copula, c("norm", "gamma", "beta", "gamma"), list(list(mean=7, sd=2),
list(shape=3, rate=2), list(shape1=4, shape2=1), list(shape=4, rate=3)))
n <- 20
x.samp <- copula::rMvdc(n, mymvdc)

# randomly introduce univariate and multivariate missing

perc.mis <- 0.25
set.seed(14)
miss.row <- sample(1:n, perc.mis*n, replace=TRUE)
miss.col <- sample(1:n.marg, perc.mis*n, replace=TRUE)
miss <- cbind(miss.row, miss.col)
x.samp.miss <- replace(x.samp, miss, NA)
x.samp.miss
probs <- seq(0.05, 0.45, by=0.1)
ndist <- 7
dist.meth <- "gower"

# impute missing values
NPimp <- NPCoImp(X=x.samp.miss, Psi=probs, smoothing="beta", K=ndist,
method=dist.meth)

# methods show

show(NPimp)

## Not run:
## generate data from a 3-variate Clayton copula and introduce missing by
## using the MCAR function and try to impute through a rotated copula

set.seed(11)
n.marg <- 3
theta <- 5
copula <- claytonCopula(theta, dim = n.marg)
mymvdc <- mvdc(copula, c("beta", "beta", "beta"), list(list(shape1=4, shape2=1),
list(shape1=.5, shape2=.5), list(shape1=2, shape2=3)))
n <- 50
x.samp <- copula::rMvdc(n, mymvdc)

# randomly introduce MCAR univariate and multivariate missing

perc.miss <- 0.15
setseed <- set.seed(13)
x.samp.miss <- MCAR(x.samp, perc.miss, setseed)
x.samp.miss <- x.samp.miss@"db.missing"

```

```
probs <- seq(0.05,0.45,by=0.05)
ndist <- 7
dist.meth <- "gower"

# impute missing values

NPimp2 <- NPCoImp(X=x.samp.miss, Psi=probs, smoothing="beta", K=ndist,
                 method=dist.meth)

# methods show and plot

show(NPimp2)

## End(Not run)
```

---

NPCoImp-class

*Class "NPCoImp"*

---

### Description

A class for NPCoImp and its extensions

### Objects from the Class

Objects can be created by calls of the form `new("NPCoImp", ...)`.

### Slots

`Imputed.matrix` Object of class "matrix". The imputed data matrix.

`Selected.quantile.alpha` Object of class "vector". The quantile selected for the imputation and its order alpha.

`numFlat` Object of class "numeric". The number of possible flat empirical conditional copulas, i.e. when the function cannot be empirically estimated.

### Methods

`show` signature(object = "NPCoImp"): ...

### Author(s)

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### References

Di Lascio, F.M.L, Gatto A. (202x) "A non-parametric conditional copula-based imputation method". Under review.

**See Also**

[CoImp](#), [MCAR](#), [MAR](#).

**Examples**

```
showClass("NPCoImp")
```

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PerfMeasure	<i>Performance measures for evaluating the goodness of an imputed database</i>
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**Description**

Set of measures useful to evaluate the goodness of the used imputation method.

**Usage**

```
PerfMeasure(db.complete, db.imputed, db.missing, n.marg = 2, model =
  list(normalCopula(0.5, dim=n.marg), claytonCopula(10,
    dim=n.marg), gumbelCopula(10, dim=n.marg), frankCopula(10,
    dim=n.marg), tCopula(0.5, dim=n.marg,...),
  rotCopula(claytonCopula(10,dim=n.marg),flip=rep(TRUE,n.marg)),
  ...), ...)
```

**Arguments**

db.complete	the complete data matrix.
db.imputed	the imputed data matrix.
db.missing	the data matrix with NA data.
n.marg	the number of variables in db.complete.
model	a list of copula models to be used for the imputation. See the Details section. This should be one of normal and t (with dispstr as in the copula package), frank, clayton, gumbel, and rotated copulas. As in fitCopula, itau fitting coerced tCopula to 'df.fixed=TRUE'.
...	further parameters for <a href="#">fitCopula</a> .

**Details**

PerfMeasure computes some measures useful for evaluating the goodness of the used imputation method. PerfMeasure requires in input the imputed, the complete and the missing data matrix and gives in output five different measures of performance. See below for details



**Value**

An object of S4 class "PerfMeasure", which is a list with the following elements:

MARE	Object of class "numeric". The mean (on the replications performed) of the absolute relative error between the imputed and the corresponding original value.
RB	Object of class "numeric". The relative bias of the estimator for the dependence parameter.
RRMSE	Object of class "numeric". The relative root mean squared error of the estimator for the dependence parameter.
TID	Object of class "vector". Upper and lower tail dependence indexes for bivariate copulas. Original function is in <a href="#">tailIndex</a> .

**Author(s)**

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**References**

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2015) "Exploring Copulas for the Imputation of Complex Dependent Data". *Statistical Methods & Applications*, 24(1), p. 159-175. DOI 10.1007/s10260-014-0287-2.

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2014) "Imputation of complex dependent data by conditional copulas: analytic versus semiparametric approach", *Book of proceedings of the 21st International Conference on Computational Statistics (COMPSTAT 2014)*, p. 491-497. ISBN 9782839913478.

Bianchi, G. Di Lascio, F.M.L. Giannerini, S. Manzari, A. Reale, A. and Ruocco, G. (2009) "Exploring copulas for the imputation of missing nonlinearly dependent data". *Proceedings of the VII Meeting Classification and Data Analysis Group of the Italian Statistical Society (Cladag)*, Editors: Salvatore Ingrassia and Roberto Rocci, Cleup, p. 429-432. ISBN: 978-88-6129-406-6.

**See Also**

[CoImp](#), [NPCoImp](#), [MCAR](#), [MAR](#).

**Examples**

```
## Not run:
# generate data from a 4-variate Gumbel copula with different margins

set.seed(11)
n.marg <- 4
theta <- 5
copula <- frankCopula(theta, dim = n.marg)
mymvdc <- mvdc(copula, c("norm", "gamma", "beta", "gamma"), list(list(mean=7, sd=2),
  list(shape=3, rate=2), list(shape1=4, shape2=1), list(shape=4, rate=3)))
n <- 20
x.samp <- rMvdc(n, mymvdc)
```

```

# randomly introduce univariate and multivariate missing

perc.mis  <- 0.3
set.seed(11)
miss.row  <- sample(1:n, perc.mis*n, replace=TRUE)
miss.col  <- sample(1:n.marg, perc.mis*n, replace=TRUE)
miss      <- cbind(miss.row,miss.col)
x.samp.miss <- replace(x.samp,miss,NA)

# impute missing values

imp <- CoImp(x.samp.miss, n.marg=n.marg, smoothing=rep(0.6,n.marg), plot=TRUE,
            type.data="continuous");
imp

# apply PerfMeasure to the imputed data set

pm <- PerfMeasure(db.complete=x.samp, db.missing=x.samp.miss,
                 db.imputed=imp@"Imputed.data.matrix", n.marg=4)

pm
str(pm)

## End(Not run)

```

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PerfMeasure-class	<i>Class "PerfMeasure"</i>
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## Description

A class for PerfMeasure and its extensions

## Objects from the Class

Objects can be created by calls of the form `new("PerfMeasure", ...)`.

## Slots

**MARE:** Object of class "numeric". The mean (on the replications performed) of the absolute relative error between the imputed and the corresponding original value.

**RB:** Object of class "numeric". The relative bias of the estimator for the dependence parameter.

**RRMSE:** Object of class "numeric". The relative root mean squared error of the estimator for the dependence parameter.

**TID:** Object of class "vector". Upper and lower tail dependence indexes for bivariate copulas. Original function is in [tailIndex](#).

**Methods**

```
show signature(object = "PerfMeasure"): ...
```

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**References**

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2015) "Exploring Copulas for the Imputation of Complex Dependent Data". *Statistical Methods & Applications*, 24(1), p. 159-175. DOI 10.1007/s10260-014-0287-2.

Di Lascio, F.M.L., Giannerini, S. and Reale, A. (2014) "Imputation of complex dependent data by conditional copulas: analytic versus semiparametric approach", *Book of proceedings of the 21st International Conference on Computational Statistics (COMPSTAT 2014)*, p. 491-497. ISBN 9782839913478.

Bianchi, G. Di Lascio, F.M.L. Giannerini, S. Manzari, A. Reale, A. and Ruocco, G. (2009) "Exploring copulas for the imputation of missing nonlinearly dependent data". *Proceedings of the VII Meeting Classification and Data Analysis Group of the Italian Statistical Society (Cladag)*, Editors: Salvatore Ingrassia and Roberto Rocci, Cleup, p. 429-432. ISBN: 978-88-6129-406-6.

**See Also**

[CoImp](#), [NPCoImp](#), [MCAR](#), [MAR](#).

**Examples**

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showClass("PerfMeasure")
```

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