# Package 'mibrr'

## November 6, 2017

Type Package

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mibrr-package

Multiple Imputation with Bayesian Regularized Regression

#### **Description**

This package implements a multiple imputation method that uses Bayesian regularized regression models as the elementary imputation methods.

#### **Details**

Index: This package was not yet installed at build time.

#### Author(s)

Kyle M. Lang [aut, crt]

Maintainer: Kyle M. Lang < k.m.lang@uvt.nl>

#### References

Lang, K. M. (2015) *MIBEN: Multiple imputation with the Bayesian elastic net* (Unpublished doctoral dissertation). University of Kansas.

Li, Q. and Lin, N. (2010) The Bayesian Elastic Net. Bayesian Analysis, 5(1), 151–170.

Park, T. and Casella, G. (2008) The Bayesian Lasso. *Journal of the American Statistical Association*, **103**, 681–686.

Zhao, Y., and Long, Q. (2013) Multiple imputation in the presence of high-dimensional data. *Statistical Methods in Medical Research*, **0**(0), 1–15.

## Examples

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ben

Bayesian Elastic Net

## Description

This function will fit the Bayesian elastic net to incomplete data.

## Usage

```
ben(data,
   у,
   Χ
                  = NULL,
    iterations
                 = c(100, 10),
    sampleSizes = list(rep(25, 2), rep(250, 2), rep(500, 2)),
   missCode
                  = NULL,
    returnConvInfo = TRUE,
    verbose
                  = TRUE,
                  = NULL,
    seed
                  = list()
    control
    )
```

## Arguments

data	A, possibly incomplete, numeric data matrix or data frame to which the BEN is to be fit.
у	The column label for the outcome variable.
X	An optional character vector giving the column labels for the predictor variables. When X = NULL the target variable is regressed onto all other variables in data.
iterations	A two-element numeric vector giving the number of iterations to employ during the MCEM approximation and tuning phases, respectively. Defaults to iterations = $c(100, 10)$ .
sampleSizes	A list containing three two-element numeric vectors giving the number of MCMC draws discarded as burn-in and retained, respectively, during the MCEM approximation, tuning, and sampling phases.  Defaults to sampleSizes = list(rep(25, 2), rep(250, 2), rep(500, 2)).
missCode	An optional integer-valued code used to flag the missing data in data. Should take a value that cannot naturally occur in data. Not needed when the missing data are coded as NA.
returnConvInfo	A logical switch: Should convergence information for the imputation model (i.e., history of the optimized penalty parameters and R-Hat values for final parameter estimates) be returned?

Defaults to returnConvInfo = TRUE.

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verbose A logical switch: Should verbose output be printed to stdout?

Defaults to verbose = TRUE.

seed An integer-valued seed for the pseudo-random number generator. When seed = NULL

R's default PRNG and seed are left alone.

control A list of control parameters for the Gibbs sampler and penalty parameter opti-

mization (see Details for more information).

#### **Details**

control is a list containing the following named elements:

**convThresh:** The R-Hat value used to judge convergence. R-Hat values < convThresh arising during the MCEM tuning phase will trigger a warning. Defaults to convThres = 1.1.

**lambda1Starts:** An optional numeric vector giving starting values for the LASSO penalty parameter,  $\lambda_1$ . Values are recycled to populate a vector with size = length(targetVars). Defaults to rep(0.5, length(targetVars)).

**lambda2Starts:** An optional numeric vector giving starting values for the ridge penalty parameter,  $\lambda_2$ . Values are recycled to populate a vector with size = length(targetVars). Defaults to rep(0.1 \* nPreds, length(targetVars)), where nPreds is the number of predictors in the model.

**usePcStarts:** A logical switch: Use the starting values for  $\lambda_1$  suggested by Park and Casella (2008)?

Defaults to usePcStarts = FALSE.

**smoothingWindow:** An integer giving the number of approximation phase  $\Lambda$  values to average over to get the starting  $\Lambda's$  for the MCEM tuning phase. Setting smoothingWindow > 1 can facilitate convergence of the MCEM tuning phase when burn-in  $\Lambda$  estimates are very noisy. Defaults to smoothingWindow = min(10, ceiling(nApprox / 10)) where nApprox is the number of MCEM approximation iterations.

**center:** A logical switch: Should the data be centered before estimating the imputation model? When center = TRUE the data centers are added back to the imputed data before the function returns.

Defaults to center = TRUE.

**scale:** A logical switch: Should the predictor data be scaled to have unit variance before estimating the imputation model? When scale = TRUE imputed data are reverted to their original scaling before the function returns.

Defaults to scale = TRUE.

**adaptScales:** A logical switch: Should the target variables' scales be actively updated as part of imputation model estimation?

Defaults to adaptScales = TRUE.

**simpleIntercept:** A logical switch: When simpleIntercept = TRUE, the mean of each intercept's posterior distribution is taken as  $\bar{y}$ , otherwise it equals  $\bar{y} - \bar{\mathbf{X}}\hat{\beta}$ .

minPredCor: The minimum correlation used by mice::quickpred when temporarily filling missing data before scaling or when filling missing data on covariates.

Defaults to minPredCor = 0.3.

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**miceIters:** The number of iterations used by the **mice** package when temporarily filling missing data before scaling or filling missing data on covariates.

Defaults to miceIters = 10.

**miceRidge:** The ridge penalty used by the **mice** package when temporarily filling missing data before scaling or filling missing data on covariates.

Defaults to miceRidge = 1e-4.

**miceMethod:** The elementary imputation method used by the **mice** package when temporarily filling missing data before scaling or filling missing data on covariates.

Defaults to miceMethod = "pmm".

**fimlStarts:** A logical switch: Should the model moments from a saturated FIML model be used to scale the target variables? When fimlStarts = TRUE, the saturated model is estimated using **lavaan**.

Defaults to fimlStarts = FALSE.

**optTraceLevel:** A non-negative integer passed to the **optimx** trace argument. See **optimx** documentation for details.

Defaults to optTraceLevel = 0.

**optCheckKkt:** A logical flag: Should the Kuhn, Jarush, Tucker optimality conditions be checked when optimizing the penalty parameters?

Defaults to optCheckKkt = TRUE.

optMethod: A character vector giving the optimization method(s) used by optimx to estimate the penalty parameters. Possible options are "Nelder-Mead", "BFGS", "CG", "L-BFGS-B", "nlm", "nlminb", "spg", "ucminf", "newuoa", "bobyqa", "nmkb", "hjkb", "Rcgmin", or "Rvmmin". When length(optMethod) > 1, optimx's follow-on optimization is employed. See the optimx documentation for details.

Defaults to optMethod = "L-BFGS-B".

**optBoundLambda:** A logical switch: Should the penalty parameters be bounded below by zero? Defaults to optBoundLambda = TRUE.

#### Value

A list containing the Gibbs samples of all model parameters and whatever additional output is requested via returnConvInfo.

#### Warning

This function is in a highly unstable *alpha* level of development. Please anticipate frequent—and dramatic—changes to the functionality and user interface.

You have been granted access to this package for evaluation purposes, only. This function is **absolutely not** ready for use in real-world analyses!

#### Author(s)

Kyle M. Lang

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#### References

Lang, K. M. (2015) *MIBEN: Multiple imputation with the Bayesian elastic net* (Unpublished doctoral dissertation). University of Kansas.

Li, Q. and Lin, N. (2010) The Bayesian Elastic Net. Bayesian Analysis, 5(1), 151–170.

## See Also

```
bl, optimx
```

#### **Examples**

bl

Bayesian LASSO

#### **Description**

This function will fit the Bayesian LASSO to incomplete data.

## Usage

```
bl(data,
  у,
                  = NULL,
   iterations
                  = c(100, 10),
                  = list(rep(25, 2), rep(250, 2), rep(500, 2)),
   sampleSizes
   missCode
   returnConvInfo = TRUE,
                  = TRUE,
   verbose
   seed
                  = NULL,
   control
                  = list()
   )
```

## **Arguments**

A, possibly incomplete, numeric data matrix or data frame to which the BL is to be fit.
 The column label for the outcome variable.
 An optional character vector giving the column labels for the predictor variables.

An optional character vector giving the column labels for the predictor variables. When X = NULL the target variable is regressed onto all other variables in data.

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iterations A two-element numeric vector giving the number of iterations to employ during

the MCEM approximation and tuning phases, respectively.

Defaults to iterations = c(100, 10).

sampleSizes A list containing three two-element numeric vectors giving the number of MCMC

draws discarded as burn-in and retained, respectively, during the MCEM approx-

imation, tuning, and sampling phases.

Defaults to sampleSizes = list(rep(25, 2), rep(250, 2), rep(500, 2)).

missCode An optional integer-valued code used to flag the missing data in data. Should

take a value that cannot naturally occur in data. Not needed when the missing

data are coded as NA.

returnConvInfo A logical switch: Should convergence information for the imputation model

(i.e., history of the optimized penalty parameters and R-Hat values for final pa-

rameter estimates) be returned?

Defaults to returnConvInfo = TRUE.

verbose A logical switch: Should verbose output be printed to stdout?

Defaults to verbose = TRUE.

seed An integer-valued seed for the pseudo-random number generator. When seed = NULL

R's default PRNG and seed are left alone.

control A list of control parameters for the Gibbs sampler and penalty parameter opti-

mization (see Details for more information).

#### **Details**

control is a list containing the following named elements:

**convThresh:** The R-Hat value used to judge convergence. R-Hat values < convThresh arising during the MCEM tuning phase will trigger a warning.

Defaults to convThres = 1.1.

**lambda1Starts:** An optional numeric vector giving starting values for the LASSO penalty parameter,  $\lambda_1$ . Values are recycled to populate a vector with size = length(targetVars). Defaults to rep(0.5, length(targetVars)).

**usePcStarts:** A logical switch: Use the starting values for  $\lambda_1$  suggested by Park and Casella (2008)?

Defaults to usePcStarts = FALSE.

**smoothingWindow:** An integer giving the number of approximation phase  $\Lambda$  values to average over to get the starting  $\Lambda's$  for the MCEM tuning phase. Setting smoothingWindow > 1 can facilitate convergence of the MCEM tuning phase when burn-in  $\Lambda$  estimates are very noisy. Defaults to smoothingWindow = min(10, ceiling(nApprox / 10)) where nApprox is the number of MCEM approximation iterations.

**center:** A logical switch: Should the data be centered before estimating the imputation model? When center = TRUE the data centers are added back to the imputed data before the function returns.

Defaults to center = TRUE.

**scale:** A logical switch: Should the predictor data be scaled to have unit variance before estimating the imputation model? When scale = TRUE imputed data are reverted to their original scaling before the function returns.

Defaults to scale = TRUE.

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**adaptScales:** A logical switch: Should the target variables' scales be actively updated as part of imputation model estimation?

Defaults to adaptScales = TRUE.

**simpleIntercept:** A logical switch: When simpleIntercept = TRUE, the mean of each intercept's posterior distribution is taken as  $\bar{y}$ , otherwise it equals  $\bar{y} - \bar{\mathbf{X}}\hat{\beta}$ .

**minPredCor:** The minimum correlation used by mice::quickpred when temporarily filling missing data before scaling or when filling missing data on covariates.

Defaults to minPredCor = 0.3.

**miceIters:** The number of iterations used by the **mice** package when temporarily filling missing data before scaling or filling missing data on covariates.

Defaults to miceIters = 10.

**miceRidge:** The ridge penalty used by the **mice** package when temporarily filling missing data before scaling or filling missing data on covariates.

Defaults to miceRidge = 1e-4.

**miceMethod:** The elementary imputation method used by the **mice** package when temporarily filling missing data before scaling or filling missing data on covariates.

Defaults to miceMethod = "pmm".

**fimlStarts:** A logical switch: Should the model moments from a saturated FIML model be used to scale the target variables? When fimlStarts = TRUE, the saturated model is estimated using **lavaan**.

Defaults to fimlStarts = FALSE.

#### Value

A list containing the Gibbs samples of all model parameters and whatever additional output is requested via returnConvInfo.

#### Warning

This function is in a highly unstable *alpha* level of development. Please anticipate frequent—and dramatic—changes to the functionality and user interface.

You have been granted access to this package for evaluation purposes, only. This function is **absolutely not** ready for use in real-world analyses!

### Author(s)

Kyle M. Lang

#### References

Lang, K. M. (2015) *MIBEN: Multiple imputation with the Bayesian elastic net* (Unpublished doctoral dissertation). University of Kansas.

Park, T. and Casella, G. (2008) The Bayesian Lasso. *Journal of the American Statistical Association*, **103**, 681–686.

Zhao, Y., and Long, Q. (2013) Multiple imputation in the presence of high-dimensional data. *Statistical Methods in Medical Research*,  $\mathbf{0}(0)$ , 1–15.

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#### See Also

ben

#### **Examples**

miben

Multiple Imputation with the Bayesian Elastic Net

## **Description**

This function implements MIBEN, a robust MICE-based multiple imputation scheme that employs the Bayesian elastic net as its elementary imputation method.

## Usage

```
miben(data,
     nImps,
     targetVars
                    = NULL,
     ignoreVars
                    = NULL,
     iterations
                    = c(100, 10),
      sampleSizes
                    = list(rep(25, 2), rep(250, 2), rep(500, 2)),
     missCode
                     = NULL,
     returnConvInfo = TRUE,
                   = FALSE,
     returnParams
     verbose
                     = TRUE,
     seed
                     = NULL,
     control
                    = list()
```

## Arguments

data An incomplete, numeric data matrix or data frame for which to create the impu-

tations.

nImps An integer giving the number of imputations to create.

targetVars An optional character vector giving the column labels for the variables to be

imputed. When targetVars = NULL, all variables not listed in ignoreVars are

imputed.

ignoreVars An optional character vector giving the column labels for those variables that

should be excluded from the imputation model (e.g., ID variables).

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iterations A two-element numeric vector giving the number of iterations to employ during

the MCEM approximation and tuning phases, respectively.

Defaults to iterations = c(100, 10).

sampleSizes A list containing three two-element numeric vectors giving the number of MCMC

draws discarded as burn-in and retained, respectively, during the MCEM approx-

imation, tuning, and sampling phases.

Defaults to sampleSizes = list(rep(25, 2), rep(250, 2), rep(500, 2)).

missCode An optional integer-valued code used to flag the missing data in data. Should

take a value that cannot naturally occur in data. Not needed when the missing

data are coded as NA.

returnConvInfo A logical switch: Should convergence information for the imputation model

(i.e., history of the optimized penalty parameters and R-Hat values for final pa-

rameter estimates) be returned?

Defaults to returnConvInfo = TRUE.

returnParams A logical switch: Should the final Gibbs samples of the imputation model's

parameters be returned?

Defaults to returnParams = FALSE.

verbose A logical switch: Should verbose output be printed to stdout?

Defaults to verbose = TRUE.

seed An integer-valued seed for the pseudo-random number generator. When seed = NULL

R's default PRNG and seed are left alone.

control A list of control parameters for the Gibbs sampler and penalty parameter opti-

mization (see Details for more information).

#### Details

control is a list containing the following named elements:

**convThresh:** The R-Hat value used to judge convergence. R-Hat values < convThresh arising during the MCEM tuning phase will trigger a warning.

Defaults to convThres = 1.1.

**lambda1Starts:** An optional numeric vector giving starting values for the LASSO penalty parameter,  $\lambda_1$ . Values are recycled to populate a vector with size = length(targetVars).

Defaults to rep(0.5, length(targetVars)).

**lambda2Starts:** An optional numeric vector giving starting values for the ridge penalty parameter,  $\lambda_2$ . Values are recycled to populate a vector with size = length(targetVars).

Defaults to rep( $0.1 \times nPreds$ , length(targetVars)), where nPreds is the number of predictors in the imputation model.

**usePcStarts:** A logical switch: Use the starting values for  $\lambda_1$  suggested by Park and Casella (2008)?

Defaults to usePcStarts = FALSE.

**smoothingWindow:** An integer giving the number of approximation phase  $\Lambda$  values to average over to get the starting  $\Lambda's$  for the MCEM tuning phase. Setting smoothingWindow > 1 can facilitate convergence of the MCEM tuning phase when burn-in  $\Lambda$  estimates are very noisy. Defaults to smoothingWindow = min(10, ceiling(nApprox / 10)) where nApprox is the number of MCEM approximation iterations.

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center: A logical switch: Should the data be centered before estimating the imputation model? When center = TRUE the data centers are added back to the imputed data before the function returns.

Defaults to center = TRUE.

**scale:** A logical switch: Should the predictor data be scaled to have unit variance before estimating the imputation model? When scale = TRUE imputed data are reverted to their original scaling before the function returns.

Defaults to scale = TRUE.

**adaptScales:** A logical switch: Should the target variables' scales be actively updated as part of imputation model estimation?

Defaults to adaptScales = TRUE.

**simpleIntercept:** A logical switch: When simpleIntercept = TRUE, the mean of each intercept's posterior distribution is taken as  $\bar{y}$ , otherwise it equals  $\bar{y} - \bar{\mathbf{X}}\hat{\beta}$ .

**minPredCor:** The minimum correlation used by mice::quickpred when temporarily filling missing data before scaling or when filling missing data on covariates.

Defaults to minPredCor = 0.3.

**miceIters:** The number of iterations used by the **mice** package when temporarily filling missing data before scaling or filling missing data on covariates.

Defaults to miceIters = 10.

miceRidge: The ridge penalty used by the mice package when temporarily filling missing data before scaling or filling missing data on covariates. Defaults to miceRidge = 1e-4.

**miceMethod:** The elementary imputation method used by the **mice** package when temporarily filling missing data before scaling or filling missing data on covariates.

Defaults to miceMethod = "pmm".

**fimlStarts:** A logical switch: Should the model moments from a saturated FIML model be used to scale the target variables? When fimlStarts = TRUE, the saturated model is estimated using **lavaan**.

Defaults to fimlStarts = FALSE.

**preserveStructure:** A logical switch: Should the data columns be returned in the same order as submitted?

Defaults to preserveStructure = TRUE.

optTraceLevel: A non-negative integer passed to the optimx trace argument. See optimx documentation for details.

Defaults to optTraceLevel = 0.

**optCheckKkt:** A logical flag: Should the Kuhn, Jarush, Tucker optimality conditions be checked when optimizing the penalty parameters?

Defaults to optCheckKkt = TRUE.

optMethod: A character vector giving the optimization method(s) used by optimx to estimate the penalty parameters. Possible options are "Nelder-Mead", "BFGS", "CG", "L-BFGS-B", "nlm", "nlminb", "spg", "ucminf", "newuoa", "bobyqa", "nmkb", "hjkb", "Rcgmin", or "Rvmmin". When length(optMethod) > 1, optimx's follow-on optimization is employed. See the optimx documentation for details.

Defaults to optMethod = "L-BFGS-B".

**optBoundLambda:** A logical switch: Should the penalty parameters be bounded below by zero? Defaults to optBoundLambda = TRUE.

#### Value

A list containing nImps imputed versions of data and whatever additional output is requested via returnConvInfo and returnParams.

## Warning

This function is in a highly unstable *alpha* level of development. Please anticipate frequent—and dramatic—changes to the functionality and user interface.

You have been granted access to this package for evaluation purposes, only. This function is **absolutely not** ready for use in real-world analyses!

## Author(s)

Kyle M. Lang

#### References

Lang, K. M. (2015) *MIBEN: Multiple imputation with the Bayesian elastic net* (Unpublished doctoral dissertation). University of Kansas.

Li, Q. and Lin, N. (2010) The Bayesian Elastic Net. Bayesian Analysis, 5(1), 151–170.

#### See Also

```
mibl, optimx
```

## **Examples**

mibl

Multiple Imputation with the Bayesian LASSO

#### **Description**

This function will implement a MICE-based multiple imputation scheme that employs the Bayesian LASSO as its elementary imputation method.

#### Usage

```
mibl(data,
    nImps,
    targetVars
                   = NULL,
    ignoreVars
                   = NULL,
    iterations
                   = c(100, 10),
                   = list(rep(25, 2), rep(250, 2), rep(500, 2)),
    sampleSizes
    missCode
                   = NULL.
    returnConvInfo = TRUE,
    returnParams = FALSE,
    verbose
                   = TRUE,
    seed
                   = NULL,
    control
                   = list()
    )
```

### **Arguments**

data An incomplete, numeric data matrix or data frame for which to create the impu-

tations.

nImps An integer giving the number of imputations to create.

targetVars An optional character vector giving the column labels for the variables to be

imputed. When targetVars = NULL, all variables not listed in ignoreVars are

imputed.

ignoreVars An optional character vector giving the column labels for those variables that

should be excluded from the imputation model (e.g., ID variables).

iterations A two-element numeric vector giving the number of iterations to employ during

the MCEM approximation and tuning phases, respectively.

Defaults to iterations = c(100, 10).

sampleSizes A list containing three two-element numeric vectors giving the number of MCMC

draws discarded as burn-in and retained, respectively, during the MCEM approx-

imation, tuning, and sampling phases.

Defaults to sampleSizes = list(rep(25, 2), rep(250, 2), rep(500, 2)).

missCode An optional integer-valued code used to flag the missing data in data. Should

take a value that cannot naturally occur in data. Not needed when the missing

data are coded as NA.

returnConvInfo A logical switch: Should convergence information for the imputation model

(i.e., history of the optimized penalty parameters and R-Hat values for final pa-

rameter estimates) be returned?

Defaults to returnConvInfo = TRUE.

returnParams A logical switch: Should the final Gibbs samples of the imputation model's

parameters be returned?

Defaults to returnParams = FALSE.

verbose A logical switch: Should verbose output be printed to stdout?

Defaults to verbose = TRUE.

seed An integer-valued seed for the pseudo-random number generator. When seed = NULL

R's default PRNG and seed are left alone.

control

A list of control parameters for the Gibbs sampler and penalty parameter optimization (see Details for more information).

#### **Details**

control is a list containing the following named elements:

convThresh: The R-Hat value used to judge convergence. R-Hat values < convThresh arising during the MCEM tuning phase will trigger a warning.</p>
Defaults to convThres = 1.1.

**lambda1Starts:** An optional numeric vector giving starting values for the LASSO penalty parameter,  $\lambda_1$ . Values are recycled to populate a vector with size = length(targetVars). Defaults to rep(0.5, length(targetVars)).

**usePcStarts:** A logical switch: Use the starting values for  $\lambda_1$  suggested by Park and Casella (2008)?

Defaults to usePcStarts = FALSE.

**smoothingWindow:** An integer giving the number of approximation phase  $\Lambda$  values to average over to get the starting  $\Lambda's$  for the MCEM tuning phase. Setting smoothingWindow > 1 can facilitate convergence of the MCEM tuning phase when burn-in  $\Lambda$  estimates are very noisy. Defaults to smoothingWindow = min(10, ceiling(nApprox / 10)) where nApprox is the number of MCEM approximation iterations.

**center:** A logical switch: Should the data be centered before estimating the imputation model? When center = TRUE the data centers are added back to the imputed data before the function returns.

Defaults to center = TRUE.

**scale:** A logical switch: Should the predictor data be scaled to have unit variance before estimating the imputation model? When scale = TRUE imputed data are reverted to their original scaling before the function returns.

Defaults to scale = TRUE.

**adaptScales:** A logical switch: Should the target variables' scales be actively updated as part of imputation model estimation?

Defaults to adaptScales = TRUE.

**simpleIntercept:** A logical switch: When simpleIntercept = TRUE, the mean of each intercept's posterior distribution is taken as  $\bar{y}$ , otherwise it equals  $\bar{y} - \bar{\mathbf{X}}\hat{\beta}$ .

**minPredCor:** The minimum correlation used by mice::quickpred when temporarily filling missing data before scaling or when filling missing data on covariates.

Defaults to minPredCor = 0.3.

**miceIters:** The number of iterations used by the **mice** package when temporarily filling missing data before scaling or filling missing data on covariates.

Defaults to miceIters = 10.

**miceRidge:** The ridge penalty used by the **mice** package when temporarily filling missing data before scaling or filling missing data on covariates.

Defaults to miceRidge = 1e-4.

**miceMethod:** The elementary imputation method used by the **mice** package when temporarily filling missing data before scaling or filling missing data on covariates.

Defaults to miceMethod = "pmm".

**fimlStarts:** A logical switch: Should the model moments from a saturated FIML model be used to scale the target variables? When fimlStarts = TRUE, the saturated model is estimated using **lavaan**.

Defaults to fimlStarts = FALSE.

**preserveStructure:** A logical switch: Should the data columns be returned in the same order as submitted?

Defaults to preserveStructure = TRUE.

#### Value

A list containing nImps imputed versions of data and whatever additional output is requested via returnConvInfo and returnParams.

#### Warning

This function is in a highly unstable *alpha* level of development. Please anticipate frequent—and dramatic—changes to the functionality and user interface.

You have been granted access to this package for evaluation purposes, only. This function is **absolutely not** ready for use in real-world analyses!

#### Author(s)

Kyle M. Lang

#### References

Lang, K. M. (2015) MIBEN: Multiple imputation with the Bayesian elastic net (Unpublished doctoral dissertation). University of Kansas.

Park, T. and Casella, G. (2008) The Bayesian Lasso. *Journal of the American Statistical Association*, **103**, 681–686.

Zhao, Y., and Long, Q. (2013) Multiple imputation in the presence of high-dimensional data. *Statistical Methods in Medical Research*, **0**(0), 1–15.

#### See Also

miben

#### **Examples**

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mibrrExampleData

Example Dataset for the MIBRR package.

## **Description**

Toy data generated as in Experiment 1 of Lang (2015).

#### Usage

```
data("mibrrExampleData")
```

#### **Format**

A data frame with 200 observations on the following 17 variables.

idNum: "Participant" ID Number.

y: Outcome Variable. Contains 20% MAR missingness.

x1-x3: Substantive predictors. Contain 20% MAR missingness.

z1-z12: Exogenous auxiliary variables. Contain 10% MCAR missingness.

#### **Details**

These data are only simulated toy data; they have no true meaning. This is one of the datasets generated as part of the Monte Carlo simulation study used to conduct Experiment 1 of my dissertation. The missingness on  $\{y, X\}$  is caused by a linear combination of two randomly selected elements of  $\{Z\}$ , and half of the elements in  $\{Z\}$  have no association with  $\{y, X\}$  (see Lang, 2015, for more details).

#### Source

Lang, K. M. (2015) *MIBEN: Multiple imputation with the Bayesian elastic net* (Unpublished doctoral dissertation). University of Kansas.

mibrrL

Print License for mibrr

## Description

Print the license under which **mibrr** is distibuted (i.e., the GPL-3).

## Usage

mibrrL()

mibrrW 17

## Value

Print the GPL-3 to stdout.

## Author(s)

Kyle M. Lang

## **Examples**

mibrrL()

mibrrW

Print Warranty Statement for mibrr

## Description

Print the sections of the GPL-3 that describe the warranty (or complete lack thereof) for mibrr.

## Usage

mibrrW()

## Value

Text giving the warranty-specific sections of the GPL-3.

## Author(s)

Kyle M. Lang

## **Examples**

mibrrW()

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predictMibrr	Generate Posterior Predictions from MIBRR Models	

#### **Description**

This function will generate posterior predictive draws form models fit using miben, mibl, ben, or bl.

### Usage

## **Arguments**

object A fitted model object returned by miben, mibl, ben, or bl.

newData A data.frame containing new predictor data from which to generate the posterior

predictions.

targetVar An optional character vector giving the column labels for the outcome variables

for which to generate posterior predictions. When targetVar = NULL

predictions are generated for all target variables contained in object.

nDraws The number of posterior predictive draws to return.

Defaults to nDraws = 0.

#### Value

A list containing the posterior predictive draws for each target variable defined in targetVar or for all target variables in object when targetVar = NULL.

#### Warning

This function is in a highly unstable *alpha* level of development. Please anticipate frequent—and dramatic—changes to the functionality and user interface.

You have been granted access to this package for evaluation purposes, only. This function is **absolutely not** ready for use in real-world analyses!

## Note

The column names of newData must contain the column names of all variables used to estimate the model represented by object.

#### Author(s)

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#### References

Lang, K. M. (2015) *MIBEN: Multiple imputation with the Bayesian elastic net* (Unpublished doctoral dissertation). University of Kansas.

## See Also

```
miben, mibl, ben, bl
```

#### **Examples**

```
data(predictData)
## Fit a Bayesian elastic net model:
benOut <- ben(data = predictData$train,</pre>
                         = "agree",
              У
                    = setdiff(colnames(predictData$train), "agree"),
              iterations = c(30, 10)
## Generate posterior predictions for 'y':
benPred <- predictMibrr(object = benOut, newData = predictData$test)</pre>
## Fit chained Bayesian elastic net models to support MI:
mibenOut <- miben(data = predictData$incomplete,</pre>
                             = 100,
                  nImps
                  iterations = c(30, 10),
                  returnParams = TRUE)
## Generate posterior predictions from elementary imputation models:
benPred <- predictMibrr(object = mibenOut, newData = predictData$test)</pre>
```

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