Package ‘mBvs’

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Type Package

Title Bayesian Variable Selection Methods for Multivariate Data

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Description Bayesian variable selection methods for data with multivariate responses and multiple covariates. The package contains implementations of multivariate Bayesian variable selection methods for continuous data (Lee et al., Biometrics, 2017 <doi:10.1111/biom.12557>) and zero-inflated count data (Lee et al., Biostatistics, 2020 <doi:10.1093/biostatistics/kxy067>).

License GPL (>= 2)

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LazyLoad yes

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`mBvs-package` *Bayesian Variable Selection Methods for Multivariate Data*

Description

Bayesian variable selection methods for data with multivariate responses and multiple covariates. The package contains implementations of multivariate Bayesian variable selection methods for continuous data and zero-inflated count data.

Details

The package includes the following function:

`mvnBvs`	Bayesian variable selection for data with multivariate continuous responses
`mzipBvs`	Bayesian variable selection for conditional multivariate zero-inflated Poisson models
`mmzipBvs`	Bayesian variable selection for marginalized multivariate zero-inflated Poisson models

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Author(s)

Kyu Ha Lee, Mahlet G. Tadesse, Brent A. Coull, Jacqueline R. Starr
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References

Lee, K. H., Tadesse, M. G., Baccarelli, A. A., Schwartz J., and Coull, B. A. (2017), Multivariate Bayesian variable selection exploiting dependence structure among outcomes: application to air pollution effects on DNA methylation, *Biometrics*, Volume 73, Issue 1, pages 232-241.

Lee, K. H., Coull, B. A., Moscicki, A.-B., Paster, B. J., Starr, J. R. (2020), Bayesian variable selection for multivariate zero-inflated models: application to microbiome count data, *Biostatistics*, Volume 21, Issue 3, Pages 499-517

initiate_startValues *The function that initiates starting values*

Description

The function initiates starting values. Users are allowed to set some non-null values to starting values for a set of parameters. The function will automatically generate starting values for any parameters whose values are not specified.

Usage

```
initiate_startValues(Formula, Y, data, model = "MMZIP", B = NULL, beta0 = NULL,
V = NULL, SigmaV = NULL, gamma_beta = NULL, A = NULL, alpha0 = NULL, W = NULL,
m = NULL, gamma_alpha = NULL, sigSq_beta = NULL, sigSq_beta0 = NULL,
sigSq_alpha = NULL, sigSq_alpha0 = NULL)
```

Arguments

`Formula`	a list containing three formula objects: the first formula specifies the p_z covariates for which variable selection is to be performed in the binary component of the model; the second formula specifies the p_x covariates for which variable selection is to be performed in the count part of the model; the third formula specifies the p_0 confounders to be adjusted for (but on which variable selection is not to be performed) in the regression analysis.
`Y`	a data.frame containing q count outcomes from `n` subjects. It is of dimension $n \times q$.
`data`	a data.frame containing the variables named in the formulas in `lin.pred`.
`model`	MMZIP
`B`	starting values of B
`beta0`	starting values of β_0
`V`	starting values of B
`SigmaV`	starting values of Σ_V
`gamma_beta`	starting values of γ_β
`A`	starting values of A
`alpha0`	starting values of α_0
`W`	starting values of W
`m`	starting values of m
`gamma_alpha`	starting values of γ_α
`sigSq_beta`	starting values of σ_β^2
`sigSq_beta0`	starting values of $\sigma_{\beta_0}^2$
`sigSq_alpha`	starting values of σ_α^2
`sigSq_alpha0`	starting values of $\sigma_{\alpha_0}^2$

Value

`initiate_startValues` returns a list containing starting values that can be used for `mmzipBvs`.

Author(s)

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References

update..

See Also

`mmzipBvs`

Examples

```
## See Examples in \code{\link{mmzipBvs}}.
```

`methods` *Methods for objects of class,* `mvnBvs`*,* `mzipBvs`*, and* `mmzipBvs`*.*

Description

The `mvnBvs` class represents results from Bayesian variable selection using multivariate normal regression models. The `mzipBvs` and `mmzipBvs` classes represent results from conditional and marginalized multivariate zero-inflated regression models, respectively.

Usage

```
## S3 method for class 'mvnBvs'
print(x, digits=3, ...)
## S3 method for class 'mzipBvs'
print(x, digits=3, ...)
## S3 method for class 'mmzipBvs'
print(x, digits=3, ...)
## S3 method for class 'summ.mvnBvs'
print(x, digits=3, ...)
## S3 method for class 'summ.mzipBvs'
print(x, digits=3, ...)
## S3 method for class 'summ.mmzipBvs'
print(x, digits=3, ...)
## S3 method for class 'mvnBvs'
summary(object, digits=3, ...)
## S3 method for class 'mzipBvs'
summary(object, digits=3, ...)
## S3 method for class 'mmzipBvs'
summary(object, digits=3, ...)
```

Arguments

`x`	an object of class `mvnBvs`, `summ.mvnBvs`, `mzipBvs`, `summ.mzipBvs`, `mmzipBvs`, `summ.mmzipBvs`.
`digits`	a numeric value indicating the number of digits to display.
`object`	an object of class `mvnBvs`, `mzipBvs`, or `mmzipBvs`.
`...`	additional arguments.

See Also

`mvnBvs`, `mzipBvs`, `mmzipBvs`

`mmzipBvs` *The function to perform variable selection for marginalized multivariate zero-inflated Poisson models*

Description

The function can be used to perform variable selection for marginalized multivariate zero-inflated Poisson models.

Usage

```
mmzipBvs(Y, lin.pred, data, offset = NULL, zero_cutoff = 0.05, hyperParams,
 startValues, mcmcParams)
```

Arguments

`Y`	a data.frame containing q count outcomes from `n` subjects. It is of dimension $n \times q$.
`lin.pred`	a list containing three formula objects: the first formula specifies the p_z covariates for which variable selection is to be performed in the binary component of the model; the second formula specifies the p_x covariates for which variable selection is to be performed in the count part of the model; the third formula specifies the p_0 confounders to be adjusted for (but on which variable selection is not to be performed) in the regression analysis.
`data`	a data.frame containing the variables named in the formulas in `lin.pred`.
`offset`	an optional numeric vector with an a priori known component to be included as the linear predictor in the count part of model.
`zero_cutoff`	Response variable with proportions of zeros less than `zero.cutoff` will be removed from the binary model.
`hyperParams`	(update this) a list containing lists or vectors for hyperparameter values in hierarchical models. Components include, `rho0` (degrees of freedom for inverse-Wishart prior for Σ_V), `Psi0` (a scale matrix for inverse-Wishart prior for Σ_V), `mu_alpha0` (hyperparameter μ_{α_0} in the prior of α_0), `mu_alpha` (a numeric vector

of length q for hyperparameter μ_α in the prior of α), `mu_beta0` (hyperparameter μ_{β_0} in the prior of β_0), `mu_beta` (a numeric vector of length q for hyperparameter μ_β in the prior of β), `a_alpha0` (hyperparameter a_{α_0} in the prior of $\sigma^2_{\alpha_0}$), `b_alpha0` (hyperparameter b_{α_0} in the prior of $\sigma^2_{\alpha_0}$), `a_alpha` (hyperparameter a_α in the prior of σ^2_α), `b_alpha` (hyperparameter b_α in the prior of σ^2_α), `a_beta0` (hyperparameter a_{β_0} in the prior of $\sigma^2_{\beta_0}$), `b_beta0` (hyperparameter b_{β_0} in the prior of $\sigma^2_{\beta_0}$), `a_beta` (hyperparameter a_β in the prior of σ^2_β), `b_beta` (hyperparameter b_β in the prior of σ^2_β), `v_beta` (a numeric vector of length q for the standard deviation hyperparameter v_β of the regression parameter β prior), `omega_beta` (a numeric vector of length $p_x - p_0$ for the hyperparameter ω_β in the prior of the variable selection indicator), `v_alpha` (a numeric vector of length q for the standard deviation hyperparameter v_α of the regression parameter α prior), `omega_alpha` (a numeric vector of length $p_z - p_0$ for the hyperparameter ω_α in the prior of the variable selection indicator), See Examples below.

`startValues` a numeric vector containing starting values for model parameters. See Examples below.

`mcmcParams` (update this) a list containing variables required for MCMC sampling. Components include, `run` (a list containing numeric values for setting the overall run: `numReps`, total number of scans; `thin`, extent of thinning; `burninPerc`, the proportion of burn-in). `tuning` (a list containing numeric values relevant to tuning parameters for specific updates in Metropolis-Hastings algorithm: `beta0.prop.var`, variance of the proposal density for β_0;`beta.prop.var`, variance of the proposal density for B;`alpha.prop.var`, variance of the proposal density for A;`V.prop.var`, variance of the proposal density for V.) See Examples below.

Value

`mmzipBvs` returns an object of class `mmzipBvs`.

Author(s)

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References

update this

Examples

```
## Not run:

# loading a data set
data(simData_mzip)
Y <- simData_mzip$Y
data <- simData_mzip$X

n = dim(Y)[1]
q = dim(Y)[2]
```

```
form.bin     <- as.formula(~cov.1)
form.count    <- as.formula(~cov.1)
form.adj    <- as.formula(~1)
form <- list(form.bin, form.count, form.adj)

p_adj = dim(model.frame(form[[3]], data=data))[2]
p0 <- dim(model.frame(form[[1]], data=data))[2] + p_adj
p1 <- dim(model.frame(form[[2]], data=data))[2] + p_adj

#####################
## Hyperparameters ##

Sigma_me <- 0.5
Sigma_var <- 1
rho0 <- 2*Sigma_me^2/Sigma_var+q+3
psi0 <- Sigma_me*(rho0-q-1)

hyperParams_mmzip <- list(v_beta=rep(3, q), omega_beta=rep(0.5, p1-p_adj),
a_beta=rep(0.5, p1), b_beta=rep(0.5, p1), mu_beta0=rep(0, q), a_beta0=0.5, b_beta0=0.5,
v_alpha=rep(3, q), omega_alpha=rep(0.5, p0-p_adj),
a_alpha=rep(0.5, p0), b_alpha=rep(0.5, p0), mu_alpha0=rep(0, q), a_alpha0=0.5, b_alpha0=0.5,
rho0=rho0, Psi0=diag(psi0, q), mu_m=rep(0, q), v_m=0.5)


###################
## MCMC SETTINGS ##

run <- list(numReps=100, thin=1, burninPerc=0.5)
storage <- list(storeV=FALSE, storeW=FALSE)
vs <- list(count=TRUE, binary=TRUE)
tuning <- list(L_group=100, L_m=20, eps_group=0.00001, eps_m=0.00001,
Mvar_group=1, Mvar_m=1, beta_prop_var=0.0001, alpha_prop_var=0.0001)

mcmc_mmzip <- list(run=run, storage=storage, vs=vs, tuning=tuning)


#####################
## Starting Values

startValues_mmzip <- initiate_startValues(form, Y, data, "MMZIP")

#####################
## Other settings

offset <- data$total
zero_cutoff=0.05

######################
## Fitting the MMZIP ##
######################

fit.mmzip <- mmzipBvs(Y, form, data, offset, zero_cutoff, hyperParams_mmzip,
```

```
startValues_mmzip, mcmc_mmzip)

print(fit.mmzip)
summ.fit.mmzip <- summary(fit.mmzip); names(fit.mmzip)
summ.fit.mmzip


## End(Not run)
```

---

mvnBvs *The function to perform variable selection for multivariate normal responses*

Description

The function can be used to perform variable selection for multivariate normal responses incorporating not only information on the mean model, but also information on the variance-covariance structure of the outcomes. A multivariate prior is specified on the latent binary selection indicators to incorporate the dependence between outcomes into the variable selection procedure.

Usage

```
mvnBvs(Y, lin.pred, data, model = "unstructured", hyperParams, startValues, mcmcParams)
```

Arguments

`Y`	a data.frame containing q continuous multivariate outcomes from `n` subjects. It is of dimension $n \times q$.
`lin.pred`	a list containing two formula objects: the first formula specifies the p covariates for which variable selection is to be performed; the second formula specifies the confounders to be adjusted for (but on which variable selection is not to be performed) in the regression analysis.
`data`	a data.frame containing the variables named in the formulas in `lin.pred`.
`model`	a character that specifies the covariance structure of the model: either "unstructured" or "factor-analytic".
`hyperParams`	a list containing lists or vectors for hyperparameter values in hierarchical models. Components include, `eta` (a numeric value for the hyperparameter η that regulates the extent to which the correlation between response variables influences the prior of the variable selection indicator), `v` (a numeric vector of length q for the standard deviation hyperparameter v of the regression parameter β prior), `omega` (a numeric vector of length p for the hyperparameter ω in the prior of the variable selection indicator), `beta0` (a numeric vector of length $q+1$ for hyperparameter μ_0 and h_0 in the prior of the intercept β_0), `US` (a list containing numeric vectors for hyperparameters in the unstructured model: `US.Sigma`), `FA` (a list containing numeric vectors for hyperparameters in the factor-analytic model: `lambda` and `sigmaSq`). See Examples below.

`startValues` a numeric vector containing starting values for model parameters: `c(beta0, B, gamma, Sigma)` for the unstructured model; `c(beta0, B, gamma, sigmaSq, lambda)` for the factor-analytic model. See Examples below.

`mcmcParams` a list containing variables required for MCMC sampling. Components include, `run` (a list containing numeric values for setting the overall run: `numReps`, total number of scans; `thin`, extent of thinning; `burninPerc`, the proportion of burn-in). `tuning` (a list containing numeric values relevant to tuning parameters for specific updates in Metropolis-Hastings algorithm: `mhProp_beta_var`, variance of the proposal density for B; `mhrho_prop`, degrees of freedom of the inverse-Wishart proposal density for Σ in the unstructured model; `mhPsi_prop`, scale matrix of inverse-Wishart proposal density for Σ in the unstructured model; `mhProp_lambda_var`, variance of the proposal density for λ in the factor-analytic model.) See Examples below.

Value

`mvnBvs` returns an object of class `mvnBvs`.

Author(s)

Kyu Ha Lee, Mahlet G. Tadesse, Brent A. Coull
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References

Lee, K. H., Tadesse, M. G., Baccarelli, A. A., Schwartz J., and Coull, B. A. (2017), Multivariate Bayesian variable selection exploiting dependence structure among outcomes: application to air pollution effects on DNA methylation, *Biometrics*, Volume 73, Issue 1, pages 232-241.

Examples

```
# loading a data set
data(simData_cont)
Y <- simData_cont$Y
data <- simData_cont$X
form1 <- as.formula( ~ cov.1+cov.2)
form2 <- as.formula( ~ 1)
lin.pred <- list(form1, form2)

p  <- dim(data)[2]
p_adj  <- 0
q  <- dim(Y)[2]

#####################
## Hyperparameters ##

## Common hyperparameters
##
```

```
eta = 0.1
v = rep(10, q)
omega = rep(log(0.5/(1-0.5)), p-p_adj)
common.beta0 <- c(rep(0, q), 10^6)

## Unstructured model
##
rho0  <- q + 4
Psi0 <- diag(3, q)
US.Sigma <- c(rho0, Psi0)

## Factor-analytic model
##
FA.lam <- c(rep(0, q), 10^6)
FA.sigSq <- c(2, 1)

##
hyperParams <- list(eta=eta, v=v, omega=omega, beta0=common.beta0,
US=list(US.Sigma=US.Sigma),
FA=list(lambda=FA.lam, sigmaSq=FA.sigSq))

###################
## MCMC SETTINGS ##

## Setting for the overall run
##
numReps    <- 50
thin       <- 1
burninPerc <- 0.5

## Tuning parameters for specific updates
##
##  - those common to all models
mhProp_beta_var  <- matrix(0.5, p+p_adj, q)
##
## - those specific to the unstructured model
mhrho_prop <- 1000
mhPsi_prop <- diag(1, q)
##
## - those specific to the factor-analytic model
mhProp_lambda_var  <- 0.5

##
mcmc.US <- list(run=list(numReps=numReps, thin=thin, burninPerc=burninPerc),
                tuning=list(mhProp_beta_var=mhProp_beta_var,
                 mhrho_prop=mhrho_prop, mhPsi_prop=mhPsi_prop))

##
mcmc.FA  <- list(run=list(numReps=numReps, thin=thin, burninPerc=burninPerc),
                tuning=list(mhProp_beta_var=mhProp_beta_var,
                 mhProp_lambda_var=mhProp_lambda_var))

#####################
```

```
## Starting Values ##

##  - those common to all models
beta0 <- rep(0, q)
B <- matrix(sample(x=c(0.3, 0), size=q, replace = TRUE), p+p_adj, q)
gamma <- B
gamma[gamma != 0] <- 1
##
## - those specific to the unstructured model
Sigma <- diag(1, q)
##
## - those specific to the factor-analytic model
lambda <- rep(0.5, q)
sigmaSq <- 1

startValues    <- as.vector(c(beta0, B, gamma, Sigma))

####################################
## Fitting the unstructured model ##
####################################

fit.us <- mvnBvs(Y, lin.pred, data, model="unstructured", hyperParams,
startValues, mcmcParams=mcmc.US)

fit.us
summ.fit.us <- summary(fit.us); names(summ.fit.us)
summ.fit.us

#######################################
## Fitting the factor-analytic model ##
#######################################

startValues <- as.vector(c(beta0, B, gamma, sigmaSq, lambda))

fit.fa <- mvnBvs(Y, lin.pred, data, model="factor-analytic", hyperParams,
startValues, mcmcParams=mcmc.FA)

fit.fa
summ.fit.fa <- summary(fit.fa); names(summ.fit.fa)
summ.fit.fa
```

---

mzipBvs — *The function to perform variable selection for conditional multivariate zero-inflated Poisson models*

Description

The function can be used to perform variable selection for conditional multivariate zero-inflated Poisson models.

Usage

```
mzipBvs(Y, lin.pred, data, model = "generalized", offset = NULL, hyperParams, startValues,
 mcmcParams)
```

Arguments

`Y` a data.frame containing q count outcomes from `n` subjects. It is of dimension $n \times q$.

`lin.pred` a list containing three formula objects: the first formula specifies the p_z covariates for which variable selection is to be performed in the binary component of the model; the second formula specifies the p_x covariates for which variable selection is to be performed in the count part of the model; the third formula specifies the p_0 confounders to be adjusted for (but on which variable selection is not to be performed) in the regression analysis.

`data` a data.frame containing the variables named in the formulas in `lin.pred`.

`model` a character that specifies the type of model: A generalized multivariate Bayesian variable selection method of Lee et al.(2018) can be implemented by setting `model="generalized"`. A simpler model that assumes one common variable selection indicator ($\gamma_{j,k} = \delta_{j,k}$) and the same covariance pattern ($R = R_V$) for two model parts can be used by setting `model="restricted1"`. iii) Another simpler model that assumes the same covariance pattern ($R = R_V$) but separate variable selection indicators for the binary and count parts of the model can be implemented by setting `model="restricted2"`.

`offset` an optional numeric vector with an a priori known component to be included as the linear predictor in the count part of model.

`hyperParams` a list containing lists or vectors for hyperparameter values in hierarchical models. Components include, `rho0` (degrees of freedom for inverse-Wishart prior for Σ_V), `Psi0` (a scale matrix for inverse-Wishart prior for Σ_V), `mu_alpha0` (hyperparameter μ_{α_0} in the prior of α_0), `mu_alpha` (a numeric vector of length q for hyperparameter μ_α in the prior of α), `mu_beta0` (hyperparameter μ_{β_0} in the prior of β_0), `mu_beta` (a numeric vector of length q for hyperparameter μ_β in the prior of β), `a_alpha0` (hyperparameter a_{α_0} in the prior of $\sigma^2_{\alpha_0}$), `b_alpha0` (hyperparameter b_{α_0} in the prior of $\sigma^2_{\alpha_0}$), `a_alpha` (hyperparameter a_α in the prior of σ^2_α), `b_alpha` (hyperparameter b_α in the prior of σ^2_α), `a_beta0` (hyperparameter a_{β_0} in the prior of $\sigma^2_{\beta_0}$), `b_beta0` (hyperparameter b_{β_0} in the prior of $\sigma^2_{\beta_0}$), `a_beta` (hyperparameter a_β in the prior of σ^2_β), `b_beta` (hyperparameter b_β in the prior of σ^2_β), `v_beta` (a numeric vector of length q for the standard deviation hyperparameter v_β of the regression parameter β prior), `omega_beta` (a numeric vector of length $p_x - p_0$ for the hyperparameter ω_β in the prior of the variable selection indicator), `v_alpha` (a numeric vector of length q for the standard deviation hyperparameter v_α of the regression parameter α prior), `omega_alpha` (a numeric vector of length $p_z - p_0$ for the hyperparameter ω_α in the prior of the variable selection indicator), See Examples below.

`startValues` a numeric vector containing starting values for model parameters. See Examples below.

`mcmcParams` a list containing variables required for MCMC sampling. Components include, `run` (a list containing numeric values for setting the overall run: `numReps`, total number of scans; `thin`, extent of thinning; `burninPerc`, the proportion of burn-in). `tuning` (a list containing numeric values relevant to tuning parameters for specific updates in Metropolis-Hastings algorithm: `beta0.prop.var`, variance of the proposal density for β_0;`beta.prop.var`, variance of the proposal density for B;`alpha.prop.var`, variance of the proposal density for A;`V.prop.var`, variance of the proposal density for V.) See Examples below.

Value

`mzipBvs` returns an object of class `mzipBvs`.

Author(s)

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References

Lee, K. H., Coull, B. A., Moscicki, A.-B., Paster, B. J., Starr, J. R. (2020), Bayesian variable selection for multivariate zero-inflated models: application to microbiome count data, *Biostatistics*, Volume 21, Issue 3, Pages 499-517.

Examples

```
## Not run:
# loading a data set
data(simData_mzip)
Y <- simData_mzip$Y
data <- simData_mzip$X

n = dim(Y)[1]
q = dim(Y)[2]

form.bin     <- as.formula(~cov.1)
form.count    <- as.formula(~cov.1)
form.adj    <- as.formula(~1)
lin.pred <- list(form.bin, form.count, form.adj)

Xmat0 <- model.frame(lin.pred[[1]], data=data)
Xmat1 <- model.frame(lin.pred[[2]], data=data)
Xmat_adj <- model.frame(lin.pred[[3]], data=data)

p_adj = ncol(Xmat_adj)
p0 <- ncol(Xmat0) + p_adj
p1 <- ncol(Xmat1) + p_adj
```

```
nonz <- rep(NA, q)
for(j in 1:q) nonz[j] <- sum(Y[,j] != 0)

####################
## Hyperparameters ##

## Generalized model
##
rho0     <- q + 3 + 1
Psi0    <- diag(3, q)

mu_alpha0     <- 0
mu_alpha    <- rep(0, q)

mu_beta0    <- 0
mu_beta        <- rep(0, q)

a_alpha0    <- 0.7
b_alpha0     <- 0.7

a_alpha        <- rep(0.7, p0)
b_alpha     <- rep(0.7, p0)

a_beta0        <- 0.7
b_beta0     <- 0.7

a_beta        <- rep(0.7, p1)
b_beta         <- rep(0.7, p1)

v_beta = rep(1, q)
omega_beta = rep(0.1, p1-p_adj)
v_alpha = rep(1, q)
omega_alpha = rep(0.1, p0-p_adj)

##
hyperParams.gen <- list(rho0=rho0, Psi0=Psi0, mu_alpha0=mu_alpha0, mu_alpha=mu_alpha,
mu_beta0=mu_beta0, mu_beta=mu_beta, a_alpha0=a_alpha0, b_alpha0=b_alpha0,
a_alpha=a_alpha, b_alpha=b_alpha, a_beta0=a_beta0, b_beta0=b_beta0,
a_beta=a_beta, b_beta=b_beta, v_beta=v_beta, omega_beta=omega_beta,
v_alpha=v_alpha, omega_alpha=omega_alpha)

###################
## MCMC SETTINGS ##

## Setting for the overall run
##
numReps    <- 100
thin       <- 1
burninPerc <- 0.5

## Settings for storage
##
storeV      <-    TRUE
```

```
storeW      <-    TRUE

## Tuning parameters for specific updates
##
##  - Generalized model
beta0.prop.var    <- 0.5
alpha.prop.var    <- 0.5
beta.prop.var    <- 0.5
V.prop.var    <- 0.05

##
mcmc.gen <- list(run=list(numReps=numReps, thin=thin, burninPerc=burninPerc),
storage=list(storeV=storeV, storeW=storeW),
tuning=list(beta0.prop.var=beta0.prop.var, alpha.prop.var=alpha.prop.var,
beta.prop.var=beta.prop.var, V.prop.var=V.prop.var))

#####################
## Starting Values ##

## Generalized model
##
B <- matrix(0.1, p1, q, byrow = T)
A <- matrix(0.1, p0, q, byrow = T)

V <- matrix(rnorm(n*q, 0, 0.1), n, q)
W <- matrix(rnorm(n*q, 0, 0.1), n, q)

beta0 <- log(as.vector(apply(Y, 2, mean)))
alpha0 <- log(nonz/n / ((n-nonz)/n))

Sigma_V    <- matrix(0, q, q)
diag(Sigma_V) <- 1

R        <- matrix(0, q, q)
diag(R) <- 1

sigSq_alpha0 <- 1
sigSq_alpha <- rep(1, p0)
sigSq_beta0 <- 1
sigSq_beta <- rep(1, p1)

startValues.gen <- list(B=B, A=A, V=V, W=W, beta0=beta0, alpha0=alpha0, R=R,
sigSq_alpha0=sigSq_alpha0,
sigSq_alpha=sigSq_alpha, sigSq_beta0=sigSq_beta0, sigSq_beta=sigSq_beta, Sigma_V=Sigma_V)


###################################
## Fitting the generalized model ##
###################################
fit.gen <- mzipBvs(Y, lin.pred, data, model="generalized", offset=NULL, hyperParams.gen,
startValues.gen, mcmc.gen)

print(fit.gen)
```

```
summm.fit.gen <- summary(fit.gen); names(summ.fit.gen)
summ.fit.gen


## End(Not run)
```

---

simData_cont   *A simulated data set containing multivariate normal responses and continuous covariates*

Description

A simulated data set containing multivariate normal responses and continuous covariates

Usage

```
data("simData_cont")
```

Format

a list of two data frame objects. Components include,

`Y` a data frame for 10 multivariate normal responses from 100 observations: `Y.1-Y.10`

`X` a data frame for 2 continuous covariates from 100 observations: `cov.1-cov.2`

Examples

```
data(simData_cont)
```

---

simData_mzip   *A simulated data set containing multivariate zero-inflated count responses and a continuous covariate*

Description

A simulated data set containing multivariate zero-inflated count responses and a continuous covariate

Usage

```
data("simData_mzip")
```

Format

a list of two data frame objects. Components include,

`Y` a data frame for 10 multivariate count responses from 300 observations: `Y.1-Y.10`

`X` a data frame for a single continuous covariate from 300 observations: `cov.1`

Examples

```
data(simData_mzip)
```

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