Package ‘ShrinkageBayesGlm’

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Type Package

Title Bayesian Shrinkage Prior with Categorical, Count and Zero-Inflated Data

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Description Utilizes Bayesian shrinkage priors and Polya-gamma data augmentation for variable selection with categorical, count and zero-inflated responses. The models involved are multinomial regression, logistic regression, negative binomial regression, and zero-inflated negative binomial regression.

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Encoding UTF-8

LazyData true

RoxygenNote 7.1.2

Suggests testthat (>= 3.0.0)

Config/testthat/edition 3

R topics documented:

`dirichlet_laplace_logistic_mc` *Logistic regression with Dirichlet Laplace prior*

Description

Logistic regression with Dirichlet Laplace prior

Usage

```
dirichlet_laplace_logistic_mc(Y, X, mc_length, a, beta_start)
```

Arguments

`Y`	The binary response variable
`X`	The design matrix
`mc_length`	no. of MCMC iterations
`beta_start`	initial parameters

Value

sample_beta: posterior samples of the coefficients beta

W_all: posterior samples of the latent variable

shi_all: posterior samples of the hyper-parameters

phi_all: posterior samples of the hyper-parameters

tau_sq_all: posterior samples of the hyper-parameters

`dirichlet_laplace_mlogit_mc` *Multinomial logistic regression with Dirichlet Laplace prior*

Description

Multinomial logistic regression with Dirichlet Laplace prior

Usage

```
dirichlet_laplace_mlogit_mc(
  y,
  X,
  n = rep(1, nrow(as.matrix(y))),
  m.0 = array(0, dim = c(ncol(X), ncol(y))),
  sigma = array(0, dim = c(ncol(X), ncol(X), ncol(y))),
  samp = 1000,
  burn = 500,
  a = 0.8
)
```

Arguments

`y`	The categorical variable with more than two classes
`X`	The design matrix
`n`	sample size
`m.0`	initial mean parameters mostly zero, a matrix of dimension P*J-1, p=no. of variables, J=no. of categorical classes
`sigma`	initial variance covariance matrix of dimension P*P*J-1
`samp`	no. of MCMC samples, generally 1000
`burn`	burnin samples, generally 500

Value

sample_beta: posterior samples of the coefficients beta

w: posterior samples of the latent variable

`dirichlet_laplace_negative_binomial_mc`

Negative Binomial regression with Dirichlet Laplace prior

Description

Negative Binomial regression with Dirichlet Laplace prior

Usage

```
dirichlet_laplace_negative_binomial_mc(
  Y,
  X,
  h,
  mc_length,
  a,
  starting_beta = NULL
)
```

Arguments

`Y`	The count response
`X`	The design matrix
`h`	The number of failures in negative binomial regression
`mc_length`	no. of MCMC samples
`starting_beta`	initial parameters

Value

sample_beta: posterior samples of the coefficients beta

W_all: posterior samples of the latent variable

shi_all: posterior samples of the hyper-parameters

phi_all: posterior samples of the hyper-parameters

tau_sq_all: posterior samples of the hyper-parameters

Examples

```
dirichlet_laplace_negative_binomial_mc(Y=Y,X=X,h=h,mc_length=1000,a=0.8,starting_beta=NULL)
```

`dirichlet_laplace_zinb_mc` *Zero-inflated Negative Binomial Regression with Dirichlet Laplace prior*

Description

Zero-inflated Negative Binomial Regression with Dirichlet Laplace prior

Usage

```
dirichlet_laplace_zinb_mc(
  X = X,
  y = Y,
  mc_length = mc_length,
  a = a,
  burnin = burnin,
  thin = thin
)
```

Arguments

X	design matrix
y	zero-inflated count response
mc_length	no. of MCMC iterations
burnin	burnin
thin	thinning parameter, generally set to 1

Value

Alpha: posterior samples of Alpha parameter

Beta: posterior samples of Beta parameter

R or R2: posterior samples of R parameter

shi_all: posterior samples of hyper-parameter of the prior for Beta

fi_all:posterior samples of hyper-parameter of the prior for Beta

tau_sq_all:posterior samples of hyper-parameter of the prior for Beta

shi_all1: posterior samples of hyper-parameter of the prior for Alpha

fi_all1:posterior samples of hyper-parameter of the prior for Alpha

tau_sq_all1:posterior samples of hyper-parameter of the prior for Alpha

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double_pareto_logistic_mc *Logistic Regression with Double Pareto Prior*

Description

Logistic Regression with Double Pareto Prior

Usage

```
double_pareto_logistic_mc(Y, X, mc_length, beta_start)
```

Arguments

`Y`	The binary response variable
`X`	The design matrix
`mc_length`	no. of MCMC iterations
`beta_start`	initial parameters

Value

sample_beta: posterior samples of the coefficients beta

W_all: posterior samples of the latent variable

lambda_sq_all: posterior samples of the local parameter in the shrinkage prior

tau_sq_all: posterior samples of the global parameter in the shrinkage prior

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double_pareto_mlogit_mc *Multinomial logistic regression with Double Pareto prior*

Description

Multinomial logistic regression with Double Pareto prior

Usage

```
double_pareto_mlogit_mc(
  y,
  X,
  n = rep(1, nrow(as.matrix(y))),
  m.0 = array(0, dim = c(ncol(X), ncol(y))),
  sigma = array(0, dim = c(ncol(X), ncol(X), ncol(y))),
  samp = 1000,
  burn = 500
)
```

Arguments

`y`	The categorical variable with more than two classes
`X`	The design matrix
`n`	sample size
`m.0`	initial mean parameters mostly zero, a matrix of dimension P*J-1, p=no. of variables, J=no. of categorical classes
`sigma`	initial variance covariance matrix of dimension P*P*J-1
`samp`	no. of MCMC samples, generally 1000
`burn`	burnin samples, generally 500

Value

sample_beta: posterior samples of the coefficients beta

w: posterior samples of the latent variable

`double_pareto_negative_binomial_mc`
Negative Binomial regression with Double Pareto prior

Description

Negative Binomial regression with Double Pareto prior

Usage

```
double_pareto_negative_binomial_mc(Y, X, h, mc_length, starting_beta = NULL)
```

Arguments

`Y`	The count response
`X`	The design matrix
`h`	The number of failures in negative binomial regression
`mc_length`	no. of MCMC samples
`starting_beta`	initial parameters

Value

sample_beta: posterior samples of the coefficients beta

W_all: posterior samples of the latent variable

lambda_sq_all: posterior samples of the local parameter in the shrinkage prior

tau_sq_all: posterior samples of the global parameter in the shrinkage prior

double_pareto_zinb_mc *Zero-inflated Negative Binomial Regression with Double Pareto prior*

Description

Zero-inflated Negative Binomial Regression with Double Pareto prior

Usage

```
double_pareto_zinb_mc(
  y = y,
  X = X,
  mc_length = mc_length,
  burnin = burnin,
  thin = 1
)
```

Arguments

`y`	zero-inflated count response
`X`	design matrix
`mc_length`	no. of MCMC iterations
`burnin`	burnin
`thin`	thinning parameter, generally set to 1

Value

Alpha: posterior samples of Alpha parameter

Beta: posterior samples of Beta parameter

R or R2: posterior samples of R parameter

lambda_sq_all: posterior samples of hyper-parameter of the prior for Beta

tau_sq_all:posterior samples of hyper-parameter of the prior for Beta

lambda_sq_all1:posterior samples of hyper-parameter of the prior for Alpha

tau_sq_all1: posterior samples of hyper-parameter of the prior for Alpha

horseshoe_logistic_mc *Logistic regression with Horseshoe prior*

Description

Logistic regression with Horseshoe prior

Usage

```
horseshoe_logistic_mc(Y, X, mc_length, beta_start)
```

Arguments

`Y`	The binary response variable
`X`	The design matrix
`mc_length`	no. of MCMC iterations
`beta_start`	initial parameters

Value

sample_beta: posterior samples of the coefficients beta

W_all: posterior samples of the latent variable

xi_all: posterior samples of hyper-parameter

gamma_all: posterior samples of hyper-parameter

lambda_all: posterior samples of local parameter in the shrinkage prior

tau_sq_all: posterior samples of global parameter in the shrinkage prior

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`horseshoe_mlogit_mc` *Multinomial logistic regression with Horseshoe prior*

Description

Multinomial logistic regression with Horseshoe prior

Usage

```
horseshoe_mlogit_mc(
  y,
  X,
  n = rep(1, nrow(as.matrix(y))),
  m.0 = array(0, dim = c(ncol(X), ncol(y))),
  sigma = array(0, dim = c(ncol(X), ncol(X), ncol(y))),
  samp = 1000,
  burn = 500
)
```

Arguments

`y`	The categorical variable with more than two classes
`X`	The design matrix
`n`	sample size
`m.0`	initial mean parameters mostly zero, a matrix of dimension P*J-1, p=no. of variables, J=no. of categorical classes
`sigma`	initial variance covariance matrix of dimension P*P*J-1
`samp`	no. of MCMC samples, generally 1000
`burn`	burnin samples, generally 500

Value

sample_beta: posterior samples of the coefficients beta

w: posterior samples of the latent variable `horseshoe_negative_binomial_mc` *Negative Binomial regression with Horseshoe prior*

Description

Negative Binomial regression with Horseshoe prior

Usage

```
horseshoe_negative_binomial_mc(Y, X, h, mc_length, starting_beta = NULL)
```

Arguments

`Y`	The count response
`X`	The design matrix
`h`	The number of failures in negative binomial regression
`mc_length`	no. of MCMC samples
`starting_beta`	initial parameters #' @export list of posterior samples of the parameters

Value

sample_beta: posterior samples of the coefficients beta

W_all: posterior samples of the latent variable

xi_all: posterior samples of hyper-parameter

gamma_all: posterior samples of hyper-parameter

lambda_all: posterior samples of local parameter in the shrinkage prior

tau_sq_all: posterior samples of global parameter in the shrinkage prior

`horseshoe_zinb_mc` *Zero-inflated Negative Binomial Regression with Horseshoe prior*

Description

Zero-inflated Negative Binomial Regression with Horseshoe prior

Usage

```
horseshoe_zinb_mc(
  X = X,
  y = Y,
  mc_length = mc_length,
  burnin = burnin,
  thin = thin
)
```

Arguments

`X`	design matrix
`y`	zero-inflated count response
`mc_length`	no. of MCMC iterations
`burnin`	burnin
`thin`	thinning parameter, generally set to 1

Value

Alpha: posterior samples of Alpha parameter

Beta: posterior samples of Beta parameter

R or R2: posterior samples of R parameter

xi: posterior samples of hyper-parameter of the prior for Beta

gamma:posterior samples of hyper-parameter of the prior for Beta

lambda:posterior samples of hyper-parameter of the prior for Beta

tausq: posterior samples of hyper-parameter of the prior for Beta

xi1:posterior samples of hyper-parameter of the prior for Alpha

gamma1:posterior samples of hyper-parameter of the prior for Alpha

lambda1:posterior samples of hyper-parameter of the prior for Alpha

tausq1:posterior samples of hyper-parameter of the prior for Alpha

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