## Package 'BSM2bg'

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Type P	ackage	
Title In	mplementing Bayesian Shrinkage Models Using Two Block Gibbs Samplers	
Version	1.0	
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ti	otion Two block Gibbs samplers for efficiently sampling from posterior distribuous of Bayesian group lasso, Bayesian sparse group lasso and Bayesian fused lasso moduls. The package is an implementation of Jin and Tan (2019).	
License	e GPL (>= 2)	
Import	s Rcpp (>= 1.0.3), gglasso, BSGS	
Linking	gTo Rcpp, RcppArmadillo	
NeedsC	Compilation yes	
R top	pics documented:	
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bfl	Bayesian fused Lasso	_
		_

## Description

Inference for fused lasso model by two block Gibbs sampling from the Bayesian posterior distribution.

## Usage

```
bfl(X, Y, beta, sigma2, lambda1 = 1, lambda2 = 1, alpha = 0, xi = 0, K = 10000)
```

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#### **Arguments**

Χ	a matrix of predictors, each row corresponds to one observation.
Υ	a response vector of length equal to the leading dimension (rows) of X, i.e., length(Y) == $nrow(X)$ .
beta	initial value of the regression coefficients $\beta$ , its length should equal to ncol(X).
sigma2	initial value of the variance parameter $\sigma^2$ , which should be positive.
lambda1	initial value of the penalty parameter $\lambda_1$ , which should be nonnegative.
lambda2	initial value of the penalty parameter $\lambda_2$ , which should be nonnegative.
alpha	initial value of the shape parameter for the inverse gamma prior of $\sigma^2$ .
xi	initial value of the rate parameter for the inverse gamma prior of $\sigma^2$ .
K	total number of MCMC samples to be collected.

#### **Details**

The sampling algorithm implemented by bf1 for the Bayesian fused lasso model is described in detail in Jin & Tan (2019). It samples from the joint posterior distribution of  $(\beta, \sigma^2)$  using a two block Gibbs sampler, which is defined in (3.7).

#### Value

bfl returns a list object, which contains the components listed below.

```
betas: a K*nrow(X) matrix of K samples from the (penalized) regression coefficients sigma2s: a vector of K samples of the variance parameter
```

## Author(s)

Rui Jin

#### References

Rui Jin and Aixin Tan. "Fast Markov chain Monte Carlo for high dimensional Bayesian regression models with shrinkage priors." (2019). https://arxiv.org/pdf/1903.06964.pdf

#### **Examples**

```
n <- 100
p <- 50
r <- 0.2
Xvarhalf <- diag(sqrt(1-r),p)+matrix((sqrt(1+(p-1)*r)-sqrt(1-r))/p,nrow=p,ncol=p)
X.raw <- matrix(rnorm(n*p),nrow=n,ncol=p)
X <- scale(X.raw)*sqrt(n/(n-1))
X <- matrix(as.vector(X),n,p)
beta_holder <- c(rnorm(p/10, 1, 0.1), rep(0, p/5), rnorm(p/10, 1, 0.1), rep(0, (3*p)/5))
Y.raw <- drop(X**beta_holder+rnorm(n))
Y <- Y.raw-mean(Y.raw)
beta <- rep(1, p)
sigma2 <- 1
bfl_2bg <- bfl(X, Y, beta, sigma2, lambda1 = 1, lambda2 = 1, K = 5000)</pre>
```

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	bgl	Bayesian group Lasso		
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#### **Description**

Inference for group lasso model by two block Gibbs sampling from the Bayesian posterior distribution.

## Usage

```
bgl(X, Y, group_size, beta, sigma2, lambda = 1, alpha = 0, xi = 0, K = 10000)
```

#### **Arguments**

Χ	a matrix of predictors, each row corresponds to one observation.
Υ	a response vector of length equal to the leading dimension (rows) of X, i.e., length(Y) == $nrow(X)$ .
group_size	a vector that contains the number of predictors for each group (see example below).
beta	initial value of the regression coefficients $\beta$ , its length should equal to ncol(X).
sigma2	initial value of the variance parameter $\sigma^2$ , which should be positive.
lambda	initial value of the penalty parameter $\lambda$ , which should be nonnegative.
alpha	initial value of the shape parameter for the inverse gamma prior of $\sigma^2$ .
xi	initial value of the rate parameter for the inverse gamma prior of $\sigma^2$ .
K	total number of MCMC samples to be collected.

#### **Details**

The sampling algorithm implemented by bg1 for the Bayesian group lasso model is described in detail in Jin & Tan (2019). It samples from the joint posterior distribution of  $(\beta, \sigma^2)$  using a two block Gibbs sampler, which is defined in (3.3).

## Value

bgl returns a list object, which contains the components listed below.

betas: a K\*nrow(X) matrix of K samples from the (penalized) regression coefficients sigma2s: a vector of K samples of the variance parameter

#### Author(s)

Rui Jin

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#### References

Rui Jin and Aixin Tan. "Fast Markov chain Monte Carlo for high dimensional Bayesian regression models with shrinkage priors." (2019). https://arxiv.org/pdf/1903.06964.pdf

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#### **Examples**

```
require(gglasso)
data(bardet)
group_size <- rep(5, 20)
X.raw <- bardet$x
Y.raw <- bardet$y
n <- dim(X.raw)[1]
p <- dim(X.raw)[2]
X <- scale(X.raw)*sqrt(n/(n-1))
X <- matrix(as.vector(X),n,p)
Y <- Y.raw-mean(Y.raw)
bgl_2bg<- bgl(X = X, Y = Y, group_size = group_size, beta = rep(1,p),
sigma2= 1, lambda = 0.0601 ,K = 5000)</pre>
```

bsgl

Bayesian sparse group Lasso

#### **Description**

This function perform efficient Bayesian sparse group Lasso baseded on the two block Gibbs sampler.

## Usage

```
bsgl(X, Y, group\_size, beta, sigma2, lambda1 = 1, lambda2 = 1, alpha = 0, xi = 0, K = 10000)
```

#### **Arguments**

X	a matrix of predictors, each row corresponds to one observation.
Υ	a response vector of length equal to the leading dimension (rows) of X, i.e., length(Y) == $nrow(X)$ .
group_size	a vector that contains the number of predictors for each group (see example below).
beta	initial value of the regression coefficients $\beta$ , its length should equal to nco1(X).
sigma2	initial value of the variance parameter $\sigma^2$ , which should be positive.
lambda1	initial value of the penalty parameter $\lambda_1$ , which should be nonnegative.
lambda2	initial value of the penalty parameter $\lambda_2$ , which should be nonnegative.
alpha	initial value of the shape parameter for the inverse gamma prior of $\sigma^2$ .
xi	initial value of the rate parameter for the inverse gamma prior of $\sigma^2$ .
K	total number of MCMC samples to be collected.

#### **Details**

The sampling algorithm implemented by bsg1 for the Bayesian sparse group lasso model is described in detail in Jin & Tan (2019). It samples from the joint posterior distribution of  $(\beta, \sigma^2)$  using a two block Gibbs sampler, which is defined in (3.5).

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#### Value

bsgl returns a list object, which contains the components listed below.

betas: a K\*nrow(X) matrix of K samples from the (penalized) regression coefficients sigma2s: a vector of K samples of the variance parameter

#### Author(s)

Rui Jin

Maintainer: Rui Jin <rui-jin-1@uiowa.edu>

#### References

Rui Jin and Aixin Tan. "Fast Markov chain Monte Carlo for high dimensional Bayesian regression models with shrinkage priors." (2019). https://arxiv.org/pdf/1903.06964.pdf

## **Examples**

```
require(BSGS)
data(Crisis2008BalancedData)
var.names <- colnames(Crisis2008BalancedData)[-1]</pre>
country.all <- rownames(Crisis2008BalancedData)</pre>
cov.of.interest <- colnames(Crisis2008BalancedData)[-1]</pre>
Y <- Crisis2008BalancedData[, 1]
Y \leftarrow Y - mean(Y)
X <- Crisis2008BalancedData[, -1]</pre>
dummy.variable <- cov.of.interest[lapply(apply(X, 2, unique), length) == 2]</pre>
non.dummy.X <- X[, !(colnames(X) %in% dummy.variable)]</pre>
X.normalized <- apply(non.dummy.X, 2, function(XX) (XX - mean(XX))/sd(XX))</pre>
X[, !(colnames(X) %in% dummy.variable)] <- X.normalized</pre>
n \leftarrow dim(X)[1]
p \leftarrow dim(X)[2]
group_size <- c(10, 3, 4, 2, 4, 11, 4, 1, 12)
bsgl\_2bg <- bsgl(X, Y, group\_size, rep(1, dim(X)[2]), 1, lambda1 = .104,
lambda2 = .082, K = 5000)
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