

# Package ‘psbcGroup’

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**Type** Package

**Title** Penalized Parametric and Semiparametric Bayesian Survival Models with Shrinkage and Grouping Priors

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**Description** Algorithms to implement various Bayesian penalized survival regression models including: semiparametric proportional hazards models with lasso priors (Lee et al., Int J Biostat, 2011 <[doi:10.2202/1557-4679.1301](https://doi.org/10.2202/1557-4679.1301)>) and three other shrinkage and group priors (Lee et al., Stat Anal Data Min, 2015 <[doi:10.1002/sam.11266](https://doi.org/10.1002/sam.11266)>); parametric accelerated failure time models with group/ordinary lasso prior (Lee et al. Comput Stat Data Anal, 2017 <[doi:10.1016/j.csda.2017.02.014](https://doi.org/10.1016/j.csda.2017.02.014)>).

**License** GPL (>= 2)

**Depends** LearnBayes, SuppDists, mvtnorm, survival, R (>= 3.2.3)

**LazyLoad** yes

**NeedsCompilation** yes

**Repository** CRAN

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aftGL *Function to Fit the Penalized Parametric Bayesian Accelerated Failure Time Model with Group Lasso Prior*

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### Description

Penalized parametric Bayesian accelerated failure time model with group lasso prior is implemented to analyze survival data with high-dimensional covariates.

### Usage

```
aftGL(Y, data, grpInx, hyperParams, startValues, mcmc)
```

### Arguments

Y	a data.frame containing univariate time-to-event outcomes from n subjects. It is of dimension $n \times 2$ : the columns correspond to $y, \delta$ .
data	a data.frame containing $p$ covariate vectors from n subjects. It is of dimension $n \times p$ .
grpInx	a vector of $p$ group indicator for each variable
hyperParams	a list containing hyperparameter values in hierarchical models: (nu0, sigSq0): hyperparameters for the prior of $\sigma^2$ ; (alpha0, h0): hyperparameters for the prior of $\alpha$ ; (rLam, deltaLam): hyperparameters for the prior of $\lambda^2$ .
startValues	a list containing starting values for model parameters. See Examples below.
mcmc	a list containing variables required for MCMC sampling. Components include, numReps, total number of scans; thin, extent of thinning; burninPerc, the proportion of burn-in. See Examples below.

### Value

aftGL returns an object of class aftGL.

### Author(s)

Kyu Ha Lee, Sounak Chakraborty, (Tony) Jianguo Sun

### References

Lee, K. H., Chakraborty, S., and Sun, J. (2017). Variable Selection for High-Dimensional Genomic Data with Censored Outcomes Using Group Lasso Prior. *Computational Statistics and Data Analysis*, Volume 112, pages 1-13.

### See Also

[VS](#)

**Examples**

```

# generate some survival data
set.seed(204542)

p = 20
n = 200
logHR.true <- c(rep(4, 10), rep(0, (p-10)))

CovX<-matrix(0,p,p)

for(i in 1:10){
  for(j in 1:10){
    CovX[i,j] <- 0.3^abs(i-j)
  }
}

diag(CovX) <- 1

data <- apply(rmvnorm(n, sigma=CovX, method="chol"), 2, scale)
pred <- as.vector(exp(rowSums(scale(data, center = FALSE, scale = 1/logHR.true))))

t <- rexp(n, rate = pred)
cen <- runif(n, 0, 8)
tcen <- pmin(t, cen)
di <- as.numeric(t <= cen)

n <- dim(data)[1]
p <- dim(data)[2]

Y <- data.frame(cbind(tcen, di))
colnames(Y) <- c("time", "event")

grpInx <- 1:p
K <- length(unique(grpInx))

#####
hyperParams <- list(nu0=3, sigSq0=1, alpha0=0, h0=10^6, rLam=0.5, deltaLam=2)

#####
startValues <- list(alpha=0.1, beta=rep(1,p), sigSq=1, tauSq=rep(0.4,p), lambdaSq=5,
  w=log(tcen))

#####
mcmc <- list(numReps=100, thin=1, burninPerc=0.5)

#####
fit <- aftGL(Y, data, grpInx, hyperParams, startValues, mcmc)
## Not run:
vs <- VS(fit, X=data)

## End(Not run)

```

---

aftGL_LT	<i>Function to Fit the Penalized Parametric Bayesian Accelerated Failure Time Model with Group Lasso Prior for Left-Truncated and Interval-Censored Data</i>
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---

### Description

Penalized parametric Bayesian accelerated failure time model with group lasso prior is implemented to analyze left-truncated and interval-censored survival data with high-dimensional covariates.

### Usage

```
aftGL_LT(Y, X, XC, grpInx, hyperParams, startValues, mcmcParams)
```

### Arguments

Y	Outcome matrix with three column vectors corresponding to lower and upper bounds of interval-censored data and left-truncation time
X	Covariate matrix $p$ covariate vectors from $n$ subjects. It is of dimension $n \times p$ .
XC	Matrix for confound variables: $q$ variable vectors from $n$ subjects. It is of dimension $n \times q$ .
grpInx	a vector of $p$ group indicator for each variable
hyperParams	a list containing hyperparameter values in hierarchical models: (a.sigSq, a.sigSq): hyperparameters for the prior of $\sigma^2$ ; (mu0, h0): hyperparameters for the prior of $\mu$ ; (v): hyperparameter for the prior of $\beta_C$ .
startValues	a list containing starting values for model parameters. See Examples below.
mcmcParams	a list containing variables required for MCMC sampling. Components include, numReps, total number of scans; thin, extent of thinning; burninPerc, the proportion of burn-in. See Examples below.

### Value

aftGL\_LT returns an object of class aftGL\_LT.

### Author(s)

Kyu Ha Lee, Harrison Reeder

### References

Reeder, H., Haneuse, S., Lee, K. H. (2024+). Group Lasso Priors for Bayesian Accelerated Failure Time Models with Left-Truncated and Interval-Censored Data. *under review*

**See Also**

VS

**Examples**

```

## Not run:

data(survData)
X <- survData[,c(4:5)]
XC <- NULL

n <- dim(survData)[1]
p <- dim(X)[2]
q <- 0

c0 <- rep(0, n)
yL <- yU <- survData[,1]
yU[which(survData[,2] == 0)] <- Inf
Y <- cbind(yL, yU, c0)

grpInx <- 1:p
K <- length(unique(grpInx))

#####
## Hyperparameters

a.sigSq= 0.7
b.sigSq= 0.7

mu0 <- 0
h0 <- 10^6

v = 10^6

hyperParams <- list(a.sigSq=a.sigSq, b.sigSq=b.sigSq, mu0=mu0, h0=h0, v=v)

#####
## MCMC SETTINGS

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

## Tuning parameters for specific updates
##

L.beC <- 50
M.beC <- 1
eps.beC <- 0.001

```

```

L.be <- 100
M.be <- 1
eps.be <- 0.001

mu.prop.var <- 0.5
sigSq.prop.var <- 0.01

##

mcmcParams <- list(run=list(numReps=numReps, thin=thin, burninPerc=burninPerc),
tuning=list(mu.prop.var=mu.prop.var, sigSq.prop.var=sigSq.prop.var,
L.beC=L.beC, M.beC=M.beC, eps.beC=eps.beC,
L.be=L.be, M.be=M.be, eps.be=eps.be))

#####
## Starting Values

w <- log(Y[,1])
mu <- 0.1
beta <- rep(2, p)
sigSq <- 0.5
tauSq <- rep(0.4, p)
lambdaSq <- 100
betaC <- rep(0.11, q)

startValues <- list(w=w, beta=beta, tauSq=tauSq, mu=mu, sigSq=sigSq,
lambdaSq=lambdaSq, betaC=betaC)

fit <- aftGL_LT(Y, X, XC, grpInx, hyperParams, startValues, mcmcParams)

## End(Not run)

```

---

psbcEN

---

*Function to Fit the Penalized Semiparametric Bayesian Cox Model  
with Elastic Net Prior*


---

## Description

Penalized semiparametric Bayesian Cox (PSBC) model with elastic net prior is implemented to analyze survival data with high-dimensional covariates.

## Usage

```
psbcEN(survObj, priorPara, initial, rw=FALSE, mcmcPara, num.reps,
thin, chain = 1, save = 1000)
```

**Arguments**

survObj	The list containing observed data from $n$ subjects; $t$ , $di$ , $x$
priorPara	The list containing prior parameter values; $\eta_0$ , $\kappa_0$ , $c_0$ , $r_1$ , $r_2$ , $\delta_1$ , $\delta_2$ , $s$
initial	The list containing the starting values of the parameters; $\beta$ .ini, $\lambda_1^2$ , $\lambda_2$ , $\sigma^2$ , $\tau^2$ , $h$
rw	When setting to "TRUE", the conventional random walk Metropolis Hastings algorithm is used. Otherwise, the mean and the variance of the proposal density is updated using the jumping rule described in Lee et al. (2011).
mcmcPara	The list containing the values of options for Metropolis-Hastings step for $\beta$ ; numBeta, beta.prop.var
num.reps	the number of iterations of the chain
thin	thinning
chain	the numeric name of chain in the case when running multiple chains.
save	frequency of storing the results in .Rdata file. For example, by setting "save = 1000", the algorithm saves the results every 1000 iterations.

**Details**

$t$	a vector of $n$ times to the event
$di$	a vector of $n$ censoring indicators for the event time (1=event occurred, 0=censored)
$x$	covariate matrix, $n$ observations by $p$ variables
$\eta_0$	scale parameter of gamma process prior for the cumulative baseline hazard, $\eta_0 > 0$
$\kappa_0$	shape parameter of gamma process prior for the cumulative baseline hazard, $\kappa_0 > 0$
$c_0$	the confidence parameter of gamma process prior for the cumulative baseline hazard, $c_0 > 0$
$r_1$	the shape parameter of the gamma prior for $\lambda_1^2$
$r_2$	the shape parameter of the gamma prior for $\lambda_2$
$\delta_1$	the rate parameter of the gamma prior for $\lambda_1^2$
$\delta_2$	the rate parameter of the gamma prior for $\lambda_2$
$s$	the set of time partitions for specification of the cumulative baseline hazard function
beta.ini	the starting values for $\beta$
lambda1Sq	the starting value for $\lambda_1^2$
lambda2	the starting value for $\lambda_2$
sigmaSq	the starting value for $\sigma^2$
tauSq	the starting values for $\tau^2$
$h$	the starting values for $h$
numBeta	the number of components in $\beta$ to be updated at one iteration
beta.prop.var	the variance of the proposal density for $\beta$ when rw is set to "TRUE"

**Value**

psbcEN returns an object of class psbcEN

beta.p	posterior samples for $\beta$
h.p	posterior samples for $h$
tauSq.p	posterior samples for $\tau^2$
mcmcOutcome	The list containing posterior samples for the remaining model parameters

### Note

If the prespecified value of save is less than that of num.reps, the results are saved as .Rdata file under the directory working directory/mcmcOutcome.

### Author(s)

Kyu Ha Lee, Sounak Chakraborty, (Tony) Jianguo Sun

### References

Lee, K. H., Chakraborty, S., and Sun, J. (2011). Bayesian Variable Selection in Semiparametric Proportional Hazards Model for High Dimensional Survival Data. *The International Journal of Biostatistics*, Volume 7, Issue 1, Pages 1-32.

Lee, K. H., Chakraborty, S., and Sun, J. (2015). Survival Prediction and Variable Selection with Simultaneous Shrinkage and Grouping Priors. *Statistical Analysis and Data Mining*, Volume 8, Issue 2, pages 114-127.

### Examples

```
## Not run:

# generate some survival data

set.seed(204542)

p = 20
n = 100
beta.true <- c(rep(4, 10), rep(0, (p-10)))

CovX<- diag(0.1, p)

survObj <- list()
survObj$x <- apply(rmvnorm(n, sigma=CovX, method="chol"), 2, scale)

pred <- as.vector(exp(rowSums(scale(survObj$x, center = FALSE, scale = 1/beta.true))))

t <- rexp(n, rate = pred)
cen <- runif(n, 0, 8)
survObj$t <- pmin(t, cen)
survObj$di <- as.numeric(t <= cen)

priorPara <- list()
priorPara$eta0 <- 1
```

```

priorPara$kappa0 <- 1
priorPara$c0 <- 2
priorPara$r1 <- 0.1
priorPara$r2 <- 1
priorPara$delta1 <- 0.1
priorPara$delta2 <- 1
priorPara$s <- sort(survObj$t[survObj$di == 1])
priorPara$s <- c(priorPara$s, 2*max(survObj$t)
- max(survObj$t[-which(survObj$t==max(survObj$t))]))
priorPara$J <- length(priorPara$s)

mcmcPara <- list()
mcmcPara$numBeta <- p
mcmcPara$beta.prop.var <- 1

initial <- list()
initial$beta.ini <- rep(0.5, p)
initial$lambda1Sq <- 1
initial$lambda2 <- 1
initial$sigmaSq <- runif(1, 0.1, 10)
initial$tauSq <- rexp(p, rate = initial$lambda1Sq/2)
initial$h <- rgamma(priorPara$J, 1, 1)

rw = FALSE
num.reps = 20000
chain = 1
thin = 5
save = 5

fitEN <- psbcEN(survObj, priorPara, initial, rw=FALSE, mcmcPara,
num.reps, thin, chain, save)

vs <- VS(fitEN, X=survObj$x)

## End(Not run)

```

---

psbcFL

---

*Function to Fit the Penalized Semiparametric Bayesian Cox Model  
with Fused Lasso Prior*


---

### Description

Penalized semiparametric Bayesian Cox (PSBC) model with fused lasso prior is implemented to analyze survival data with high-dimensional covariates.

### Usage

```

psbcFL(survObj, priorPara, initial, rw=FALSE, mcmcPara, num.reps,
thin, chain = 1, save = 1000)

```

**Arguments**

survObj	The list containing observed data from $n$ subjects; $t$ , $di$ , $x$
priorPara	The list containing prior parameter values; $\eta_0$ , $\kappa_0$ , $c_0$ , $r_1$ , $r_2$ , $\delta_1$ , $\delta_2$ , $s$
initial	The list containing the starting values of the parameters; $\beta$ .ini, $\lambda_1^2$ , $\lambda_2^2$ , $\sigma^2$ , $\tau^2$ , $h$ , $w^2$
rw	When setting to "TRUE", the conventional random walk Metropolis Hastings algorithm is used. Otherwise, the mean and the variance of the proposal density is updated using the jumping rule described in Lee et al. (2011).
mcmcPara	The list containing the values of options for Metropolis-Hastings step for $\beta$ ; numBeta, beta.prop.var
num.reps	the number of iterations of the chain
thin	thinning
chain	the numeric name of chain in the case when running multiple chains.
save	frequency of storing the results in .Rdata file. For example, by setting "save = 1000", the algorithm saves the results every 1000 iterations.

**Details**

$t$	a vector of $n$ times to the event
$di$	a vector of $n$ censoring indicators for the event time (1=event occurred, 0=censored)
$x$	covariate matrix, $n$ observations by $p$ variables
$\eta_0$	scale parameter of gamma process prior for the cumulative baseline hazard, $\eta_0 > 0$
$\kappa_0$	shape parameter of gamma process prior for the cumulative baseline hazard, $\kappa_0 > 0$
$c_0$	the confidence parameter of gamma process prior for the cumulative baseline hazard, $c_0 > 0$
$r_1$	the shape parameter of the gamma prior for $\lambda_1^2$
$r_2$	the shape parameter of the gamma prior for $\lambda_2^2$
$\delta_1$	the rate parameter of the gamma prior for $\lambda_1^2$
$\delta_2$	the rate parameter of the gamma prior for $\lambda_2^2$
$s$	the set of time partitions for specification of the cumulative baseline hazard function
beta.ini	the starting values for $\beta$
lambda1Sq	the starting value for $\lambda_1^2$
lambda2Sq	the starting value for $\lambda_2^2$
sigmaSq	the starting value for $\sigma^2$
tauSq	the starting values for $\tau^2$
$h$	the starting values for $h$
wSq	the starting values for $w^2$
numBeta	the number of components in $\beta$ to be updated at one iteration
beta.prop.var	the variance of the proposal density for $\beta$ when rw is set to "TRUE"

**Value**

psbcFL returns an object of class psbcFL

beta.p	posterior samples for $\beta$
h.p	posterior samples for $h$
tauSq.p	posterior samples for $\tau^2$
mcmcOutcome	The list containing posterior samples for the remaining model parameters

**Note**

If the prespecified value of save is less than that of num.reps, the results are saved as .Rdata file under the directory working directory/mcmcOutcome.

**Author(s)**

Kyu Ha Lee, Sounak Chakraborty, (Tony) Jianguo Sun

**References**

Lee, K. H., Chakraborty, S., and Sun, J. (2011). Bayesian Variable Selection in Semiparametric Proportional Hazards Model for High Dimensional Survival Data. *The International Journal of Biostatistics*, Volume 7, Issue 1, Pages 1-32.

Lee, K. H., Chakraborty, S., and Sun, J. (2015). Survival Prediction and Variable Selection with Simultaneous Shrinkage and Grouping Priors. *Statistical Analysis and Data Mining*, Volume 8, Issue 2, pages 114-127.

**Examples**

```
## Not run:

# generate some survival data

set.seed(204542)

p = 20
n = 100
beta.true <- c(rep(4, 10), rep(0, (p-10)))

CovX<- diag(0.1, p)

survObj <- list()
survObj$x <- apply(rmvnorm(n, sigma=CovX, method="chol"), 2, scale)

pred <- as.vector(exp(rowSums(scale(survObj$x, center = FALSE, scale = 1/beta.true))))

t <- rexp(n, rate = pred)
cen <- runif(n, 0, 8)
survObj$t <- pmin(t, cen)
```

```

survObj$di <- as.numeric(t <= cen)

priorPara <- list()
priorPara$eta0 <- 2
priorPara$kappa0 <- 2
priorPara$c0 <- 2
priorPara$r1 <- 0.5
priorPara$r2 <- 0.5
priorPara$delta1 <- 0.0001
priorPara$delta2 <- 0.0001
priorPara$s <- sort(survObj$t[survObj$di == 1])
priorPara$s <- c(priorPara$s, 2*max(survObj$t)
-max(survObj$t[-which(survObj$t==max(survObj$t))]))
priorPara$J <- length(priorPara$s)

mcmcPara <- list()
mcmcPara$numBeta <- p
mcmcPara$beta.prop.var <- 1

initial <- list()
initial$beta.ini <- rep(0.5, p)
initial$lambda1Sq <- 1
initial$lambda2Sq <- 1
initial$sigmaSq <- runif(1, 0.1, 10)
initial$tauSq <- rexp(p, rate = initial$lambda1Sq/2)
initial$h <- rgamma(priorPara$J, 1, 1)
initial$wSq <- rexp((p-1), rate = initial$lambda2Sq/2)

rw = FALSE
num.reps = 20000
chain = 1
thin = 5
save = 5

fitFL <- psbcFL(survObj, priorPara, initial, rw=FALSE, mcmcPara,
num.reps, thin, chain, save)
vs <- VS(fitFL, X=survObj$x)

## End(Not run)

```

---

psbcGL

---

*Function to Fit the Penalized Semiparametric Bayesian Cox Model  
with Group Lasso Prior*


---

### Description

Penalized semiparametric Bayesian Cox (PSBC) model with group lasso prior is implemented to analyze survival data with high-dimensional covariates.

**Usage**

```
psbcGL(survObj, priorPara, initial, rw=FALSE, mcmcPara, num.reps,
thin, chain = 1, save = 1000)
```

**Arguments**

survObj	The list containing observed data from $n$ subjects; $t$ , $di$ , $x$
priorPara	The list containing prior parameter values; $\eta_0$ , $\kappa_0$ , $c_0$ , $r$ , $\delta$ , $s$ , $groupInd$
initial	The list containing the starting values of the parameters; $beta.ini$ , $lambdaSq$ , $sigmaSq$ , $tauSq$ , $h$
rw	When setting to "TRUE", the conventional random walk Metropolis Hastings algorithm is used. Otherwise, the mean and the variance of the proposal density is updated using the jumping rule described in Lee et al. (2011).
mcmcPara	The list containing the values of options for Metropolis-Hastings step for $\beta$ ; $numBeta$ , $beta.prop.var$
num.reps	the number of iterations of the chain
thin	thinning
chain	the numeric name of chain in the case when running multiple chains.
save	frequency of storing the results in .Rdata file. For example, by setting "save = 1000", the algorithm saves the results every 1000 iterations.

**Details**

$t$	a vector of $n$ times to the event
$di$	a vector of $n$ censoring indicators for the event time (1=event occurred, 0=censored)
$x$	covariate matrix, $n$ observations by $p$ variables
$\eta_0$	scale parameter of gamma process prior for the cumulative baseline hazard, $\eta_0 > 0$
$\kappa_0$	shape parameter of gamma process prior for the cumulative baseline hazard, $\kappa_0 > 0$
$c_0$	the confidence parameter of gamma process prior for the cumulative baseline hazard, $c_0 > 0$
$r$	the shape parameter of the gamma prior for $\lambda^2$
$\delta$	the rate parameter of the gamma prior for $\lambda^2$
$s$	the set of time partitions for specification of the cumulative baseline hazard function
$groupInd$	a vector of $p$ group indicator for each variable
$beta.ini$	the starting values for $\beta$
$lambdaSq$	the starting value for $\lambda^2$
$sigmaSq$	the starting value for $\sigma^2$
$tauSq$	the starting values for $\tau^2$
$h$	the starting values for $h$
$numBeta$	the number of components in $\beta$ to be updated at one iteration
$beta.prop.var$	the variance of the proposal density for $\beta$ when $rw$ is set to "TRUE"

**Value**

psbcGL returns an object of class psbcGL

beta.p	posterior samples for $\beta$
h.p	posterior samples for $h$
tauSq.p	posterior samples for $\tau^2$
mcmcOutcome	The list containing posterior samples for the remaining model parameters

**Note**

To fit the PSBC model with the ordinary Bayesian lasso prior (Lee et al., 2011), groupInd needs to be set to 1:p. If the prespecified value of save is less than that of num.reps, the results are saved as .Rdata file under the directory working directory/mcmcOutcome.

**Author(s)**

Kyu Ha Lee, Sounak Chakraborty, (Tony) Jianguo Sun

**References**

Lee, K. H., Chakraborty, S., and Sun, J. (2011). Bayesian Variable Selection in Semiparametric Proportional Hazards Model for High Dimensional Survival Data. *The International Journal of Biostatistics*, Volume 7, Issue 1, Pages 1-32.

Lee, K. H., Chakraborty, S., and Sun, J. (2015). Survival Prediction and Variable Selection with Simultaneous Shrinkage and Grouping Priors. *Statistical Analysis and Data Mining*, Volume 8, Issue 2, pages 114-127.

**Examples**

```
## Not run:

# generate some survival data

set.seed(204542)

p = 20
n = 100
beta.true <- c(rep(4, 10), rep(0, (p-10)))

CovX<-matrix(0,p,p)

for(i in 1:10){
  for(j in 1:10){
    CovX[i,j] <- 0.5^abs(i-j)
  }
}

diag(CovX) <- 1
```

```

survObj <- list()
survObj$x <- apply(rmvnorm(n, sigma=CovX, method="chol"), 2, scale)

pred <- as.vector(exp(rowSums(scale(survObj$x, center = FALSE, scale = 1/beta.true))))

t <- rexp(n, rate = pred)
cen <- runif(n, 0, 8)
survObj$t <- pmin(t, cen)
survObj$di <- as.numeric(t <= cen)

priorPara <- list()
priorPara$beta0 <- 1
priorPara$kappa0 <- 1
priorPara$c0 <- 2
priorPara$r <- 0.5
priorPara$delta <- 0.0001
priorPara$s <- sort(survObj$t[survObj$di == 1])
priorPara$s <- c(priorPara$s, 2*max(survObj$t)
-max(survObj$t[-which(survObj$t==max(survObj$t))]))
priorPara$J <- length(priorPara$s)
priorPara$groupInd <- c(rep(1,10),2:11)

mcmcPara <- list()
mcmcPara$numBeta <- p
mcmcPara$beta.prop.var <- 1

initial <- list()
initial$beta.ini <- rep(0.5, p)
initial$lambdaSq <- 1
initial$sigmaSq <- runif(1, 0.1, 10)
initial$tauSq <- rexp(length(unique(priorPara$groupInd)),
rate = initial$lambdaSq/2)
initial$h <- rgamma(priorPara$J, 1, 1)

rw = FALSE
num.reps = 20000
chain = 1
thin = 5
save = 5

fitGL <- psbcGL(survObj, priorPara, initial, rw=FALSE, mcmcPara,
num.reps, thin, chain, save)
vs <- VS(fitGL, X=survObj$x)

## End(Not run)

```

---

psbcGroup

*Penalized Parametric and Semiparametric Bayesian Survival Models  
with Shrinkage and Grouping Priors*

---

## Description

The package provides algorithms for fitting penalized parametric and semiparametric Bayesian survival models with elastic net, fused lasso, and group lasso priors.

## Details

The package includes following functions:

psbcEN	The function to fit the PSBC model with elastic net prior
psbcFL	The function to fit the PSBC model with fused lasso prior
psbcGL	The function to fit the PSBC model with group lasso or Bayesian lasso prior
aftGL	The function to fit the parametric accelerated failure time model with group lasso
aftGL_LT	The function to fit the parametric accelerated failure time model with group lasso for left-truncated and interval-c

Package:	psbcGroup
Type:	Package
Version:	1.7
Date:	2024-1-9
License:	GPL (>= 2)
LazyLoad:	yes

## Author(s)

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## References

Lee, K. H., Chakraborty, S., and Sun, J. (2011). Bayesian Variable Selection in Semiparametric Proportional Hazards Model for High Dimensional Survival Data. *The International Journal of Biostatistics*, Volume 7, Issue 1, Pages 1-32.

Lee, K. H., Chakraborty, S., and Sun, J. (2015). Survival Prediction and Variable Selection with Simultaneous Shrinkage and Grouping Priors. *Statistical Analysis and Data Mining*, Volume 8, Issue 2, pages 114-127.

Lee, K. H., Chakraborty, S., and Sun, J. (2017). Variable Selection for High-Dimensional Genomic Data with Censored Outcomes Using Group Lasso Prior. *Computational Statistics and Data Analysis*, Volume 112, pages 1-13.

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survData	<i>A simulated survival dataset.</i>
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### Description

Univariate survival data.

### Usage

```
data(survData)
```

### Format

a data frame with 2000 observations on the following 4 variables.

time the time to event

event the censoring indicators for the event time; 1=event observed, 0=censored

cluster cluster numbers

cov1 the first column of covariate matrix x

cov2 the second column of covariate matrix x

### Examples

```
data(survData)
```

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VS	<i>Function to perform variable selection using SNC-BIC thresholding method</i>
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### Description

The VS is a function to perform variable selection using SNC-BIC thresholding method

### Usage

```
VS(fit, X, psiVec=seq(0.001, 1, 0.001))
```

### Arguments

fit an object of class aftGL, psbcEN, psbcFL, or psbcGL.

X a covariate matrix, n observations by p variables

psiVec a vector of candidate threshold values for the SNC step

**Author(s)**

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**References**

Lee, K. H., Chakraborty, S., and Sun, J. (2017). Variable Selection for High-Dimensional Genomic Data with Censored Outcomes Using Group Lasso Prior. *Computational Statistics and Data Analysis*, Volume 112, pages 1-13.

**See Also**

[psbcEN](#), [psbcFL](#), [psbcGL](#), [aftGL](#)

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