# Package 'SurvSparse'

October 31, 2023

Type Package				
<b>Fitle</b> Survival Analysis with Sparse Longitudinal Covariates				
Version 0.1				
Description Survival analysis with sparse longitudinal covariates under right censoring scheme. Different hazards models are involved. Please cite the manuscripts corresponding to this package: Sun, Z. et al. (2022) <doi:10.1007 s10985-022-09548-6="">, Sun, Z. and Cao, H. (2023) <arxiv:2310.15877> and Sun, D. et al. (2023) <arxiv:2308.15549></arxiv:2308.15549></arxiv:2310.15877></doi:10.1007>				
License GPL-3				
Encoding UTF-8				
Imports splines, stats, dplyr, MASS, nloptr, nleqslv, tibble,foreach, gaussquad, tidyr, purrr				
RoxygenNote 7.2.3				
NeedsCompilation no				
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Repository CRAN				
<b>Date/Publication</b> 2023-10-31 17:30:02 UTC				
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2 add.haz

add.haz	Additive hazards model with sparse longitudinal covariates

## Description

Regression analysis of additive hazards model with sparse longitudinal covariates. Three different weighting schemes are provided to impute the missing values.

## Usage

```
add.haz(data, n, tau, h, method)
```

## Arguments

-		
	data	An object of class tibble. The structure of the tibble must be: tibble(id = id, $X$ = failure time, covariates = observation for covariates, obs_times = observation times, delta = censoring indicator).
	n	An object of class integer. The sample size.
	tau	An object of class numeric. The pre-specified time endpoint.
	h	An object of class vector. If use auto bandwidth selection, the structure of the vector must be: $h = c$ (the maximum bandwidth, the minimum bandwidth, the number of bandwidth divided). If use fixed bandwidth, h is the chosen bandwidth.
	method	An object of class integer. If use weighted LVCF, method = 1. If use half kernel, $method = 2$ . If use full kernel, $method = 3$ .

## Value

a list with the following elements:

est The estimation for the corresponding parameters.

se The estimation for the standard error of the estimated parameters.

## References

```
Sun, Z. et al. (2022) <doi:10.1007/s10985-022-09548-6>
```

## Examples

```
library(gaussquad)
library(dplyr)
library(nleqslv)
library(MASS)
n=500
lqrule64 <- legendre.quadrature.rules(64)[[64]]
simdata <- function(alpha,beta ) {</pre>
```

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```
cen=1
nstep=20
Sigmat_z <- exp(-abs(outer(1:nstep, 1:nstep, "-")) / nstep)</pre>
z <- c(mvrnorm( 1, c(1: nstep)/2, Sigmat_z ))</pre>
left_time_points <- (0:(nstep - 1)) / nstep</pre>
z_fun <- stepfun(left_time_points, c(0,z ))</pre>
lam_fun <- function(tt) { alpha(tt)+beta*z_fun(tt)}</pre>
u <- runif(1)</pre>
fail_time <- nleqslv( 0 , function(ttt)</pre>
 legendre.quadrature(lam_fun,
                    lower = 0,
                    upper = ttt,
                    lqrule64) + log(u))$x
X <- min(fail_time, cen)</pre>
obs=rpois(1,5)+1
tt= sort(runif(obs, min = 0, max = 1))
obs_times <- tt[which(tt<=cen)]
if (length(obs_times) == 0)
 obs_times <- cen
 covariates_obscov <-z_fun(obs_times)</pre>
 return( tibble(X = X,delta = fail_time < cen,</pre>
 covariates = covariates_obscov,obs_times = obs_times, censoring = cen ) ) }
data <- replicate(n, simdata(alpha = function(tt) tt, 1 ),</pre>
               simplify = FALSE ) %>% bind_rows(.id = "id")
add.haz(data,n,1,n^(-0.5),3)
```

trans.haz

Transformed hazards model with sparse longitudinal covariates

## **Description**

Statistical inference on transformed hazards model with sparse longitudinal covariates. Kernel-weighted log-likelihood and sieve maximum log-likelihood estimation are combined to conduct statistical inference on the hazards function.

## Usage

```
trans.haz(data, n, nknots, norder, tau, s, h)
```

## **Arguments**

data	An object of class tibble. The structure of the tibble must be: tibble(id = id, X = failure time, covariates = observation for covariates, obs_times = observation times, delta = censoring indicator).
n	An object of class integer. The sample size.
nknots	An object of class integer. The number of knots for B-spline.
norder	An object of class integer. The order of B-spline.

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An object of class numeric. The maximum follow-up time.

An object of class numeric. The parameter for Box-Cox transformation.

An object of class vector. If use auto bandwidth selection, the structure of the vector must be: h = c(the maximum bandwidth, the minimum bandwidth, the number of bandwidth divided). If use fixed bandwidth, h is the chosen bandwidth.

#### Value

a list with the following elements:

est The estimation for the corresponding parameters.

se The estimation for the standard error of the estimated parameters.

#### References

```
Sun, D. et al. (2023) <arXiv:2308.15549>
```

## **Examples**

```
library(dplyr)
library(gaussquad)
library(nleqslv)
library(MASS)
n=200
lgrule64 <- legendre.quadrature.rules(64)[[64]]</pre>
simdata <- function( beta ) {</pre>
cen=1
nstep=20
Sigmat_z <- exp(-abs(outer(1:nstep, 1:nstep, "-")) / nstep)</pre>
z \leftarrow 2*(pnorm(c(mvrnorm(1, rep(0,20), Sigmat_z)))-0.5)
left_time_points <- (0:(nstep - 1)) / nstep</pre>
z_{fun} \leftarrow stepfun(left_{time_points}, c(0,z))
h_fun <- function(x) { beta * z_fun(x) }</pre>
lam_fun <- function(tt) 2 * exp(h_fun(tt))</pre>
u \leftarrow runif(1)
fail_time <- nleqslv(0, function(ttt)</pre>
legendre.quadrature(lam_fun, lower = 0,upper = ttt, lqrule64) + log(u))$x
X <- min(fail_time, cen)</pre>
obs=rpois(1, 5)+1
tt= sort(runif(obs, min = 0, max = 1))
obs_times <- tt[which(tt<=cen)]
if (length(obs_times) == 0)
 obs_times <- cen
 covariates_obscov <-z_fun(obs_times)</pre>
 return( tibble(X = X,delta = fail_time < cen,</pre>
 covariates = covariates_obscov,obs_times = obs_times, censoring = cen ) )
  }
beta=1
```

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```
data <- replicate( n, simdata( beta ), simplify = FALSE ) %>% bind_rows(.id = "id") trans.haz(data,n,3,3,1,s=0,n^{(-0.35)})
```

tv.co.Cox

Multiplicative hazards model with sparse longitudinal covariates

## **Description**

Regression analysis of multiplicative hazards model with sparse longitudinal covariates. The kernel weighting approach is employed to impute the missing value and localize the estimating equation. A wild bootstrap-based simultaneous confidence band for the nonparametric function is also provided.

## Usage

```
tv.co.Cox(data, n, 1, times, bd, scb)
```

## Arguments

data	An object of class tibble. The structure of the tibble must be: tibble(id = id, X = failure time, covariates = observation for covariates, obs_times = observation times, delta = censoring indicator).
n	An object of class integer. The sample size.
1	An object of class vector. The selection vector. For example, for the p dimensional regression coefficient function, if we want to construct simultaneous confidence band for the first regression coefficient function, we can take $l=c(1,0,,0)$ .
times	An object of class vector. The interest time.
bd	An object of class vector. If use auto bandwidth selection, the structure of the vector must be: bd=c(the maximum bandwidth, the minimum bandwidth, the number of bandwidth divided). If use fixed bandwidth, bd is the chosen bandwidth.
scb	An object of class vector. If need to construct the simultaneous confidence band, the structure of the vector must be: c(desirable confidence level, repeat times). Otherwise, scb=0.

## Value

a list with the following elements:

The estimation for the corresponding parameters.

The estimation for the standard error of the estimated parameters.

The quantile used to construct simultaneous confidence band.

## References

```
Sun, Z. and Cao, H. (2023) <arXiv:2310.15877>
```

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## **Examples**

```
library(dplyr)
library(gaussquad)
library(MASS)
library(nleqslv)
n=500
0.5*(t+0.5)^2
lqrule64 <- legendre.quadrature.rules(64)[[64]]</pre>
simdata <- function( beta ) {</pre>
cen=1
nstep=20
Sigmat_z <- exp(-abs(outer(1:nstep, 1:nstep, "-")) / nstep)</pre>
z <-c(mvrnorm(1, rep(0,20), Sigmat_z))
left_time_points <- (0:(nstep - 1)) / nstep</pre>
z_fun <- stepfun(left_time_points, c(0,z ))</pre>
h_{fun} \leftarrow function(x) \{ beta(x) * z_{fun}(x) \}
lam_fun <- function(tt) 2 * exp(h_fun(tt))</pre>
u <- runif(1)
fail_time <- nleqslv(0, function(ttt)</pre>
legendre.quadrature(lam_fun, lower = 0,upper = ttt, lqrule64) + log(u))$x
X <- min(fail_time, cen)</pre>
obs=rpois(1, 5)+1
tt= sort(runif(obs, min = 0, max = 1))
obs_times <- tt[which(tt<=cen)]
if (length(obs_times) == 0)
 obs_times <- cen
 covariates_obscov <-z_fun(obs_times)</pre>
 return( tibble(X = X,delta = fail_time < cen,</pre>
 covariates = covariates_obscov,obs_times = obs_times ) ) }
data <- replicate( n, simdata( beta ), simplify = FALSE ) %>% bind_rows(.id = "id")
tv.co.Cox(data,n,1,0.2,bd=c(n^{-0.4},n^{-0.4}),scb=0)
```

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