

Package ‘spBayesSurv’

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Type Package

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Description This package provides Bayesian model fitting for several survival models including spatial copula linear dependent Dirichlet process mixture model, anova Dirichlet process mixture model,proportional hazards model and marginal spatial proportional hazards model.

License GPL (>= 2)

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R topics documented:

spBayesSurv-package	2
anovaDDP	2
GetCurves	8
indeptCoxph	9
spCopulaCoxph	13
spCopulaDDP	18

Index	25
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spBayesSurv-package *Spatial Copula Modelling to Bayesian Survival Analysis*

Description

This package provides Bayesian model fitting for several survival models including spatial copula linear dependent Dirichlet process mixture model, anova Dirichlet process mixture model, proportional hazards model and marginal spatial proportional hazards model.

Details

Package: spBayesSurv
 Type: Package
 Version: 1.0.0
 Date: 2014-06-10
 License: GPL (>= 2)

This package provides functions for fitting several Bayesian survival models including spCopulaDDP for spatial copula linear dependent Dirichlet process mixture model, anovaDDP for anova Dirichlet process mixture, indeptCoxph for proportional hazards model, and spCopulaCox for marginal spatial proportional hazards model.

Author(s)

Haiming Zhou <zhouh@email.sc.edu> and Tim Hanson <hansont@stat.sc.edu>

References

De Iorio, M., Johnson, W. O., Mueller, P., and Rosner, G. L. (2009). Bayesian nonparametric nonproportional hazards survival modeling. *Biometrics*, 65(3), 762-771.

Zhou, H., Hanson, T. and Knapp, R. (2014+). A Spatial Copula Approach to Fully Bayesian Nonparametric Survival Analysis. In preparation for publication.

anovaDDP *Bayesian Nonparametric Nonproportional Hazards Survival Modeling*

Description

This function fits an ANOVA DDP model for survival analysis of right censored time-to-event data.

Usage

```
anovaDDP(y, delta, x=NULL, prediction, prior, mcmc, state,
         data=sys.frame(sys.parent()), na.action=na.fail, work.dir=NULL)
```

Arguments

<code>y</code>	an n by 1 vector giving the log survival times.
<code>delta</code>	an n by 1 vector indicating whether it is right censored (=0) or not (=1).
<code>x</code>	an n by p matrix of covariates without intercept. The default is NULL, indicating no covariates included.
<code>prediction</code>	a list giving the information used to obtain conditional inferences. The list includes the following elements: <code>xpred</code> giving the n by p covariates matrix, used for prediction.
<code>prior</code>	a list giving the prior information. The list includes the following parameter: <code>N</code> an integer giving the truncation of the Dirichlet process, <code>a0</code> and <code>b0</code> giving the hyperparameters for prior distribution of the precision parameter α . See Zhou, Hanson and Knapp (2014+) for more detailed hyperprior specifications.
<code>mcmc</code>	a list giving the MCMC parameters. The list must include the following elements: <code>nburn</code> an integer giving the number of burn-in scans, <code>nskip</code> an integer giving the thinning interval, <code>nsave</code> an integer giving the total number of scans to be saved, <code>ndisplay</code> an integer giving the number of saved scans to be displayed on screen (the function reports on the screen when every <code>ndisplay</code> iterations have been carried out).
<code>state</code>	a list giving the current value of the parameters. This list is used if the current analysis is the continuation of a previous analysis.
<code>data</code>	data frame.
<code>na.action</code>	a function that indicates what should happen when the data contain NAs. The default action (<code>na.fail</code>) causes <code>anovaDDP</code> to print an error message and terminate if there are any incomplete observations.
<code>work.dir</code>	working directory.

Details

This function fits an ANOVA DDP model (De Iorio et al., 2009) for survival analysis of right censored time-to-event data.

Value

The results include the MCMC chains for the parameters discussed in De Iorio et al. (2009) and Zhou, Hanson and Knapp (2014+). Use names to find out what they are.

Author(s)

Haiming Zhou <<zhouh@email.sc.edu>> and Tim Hanson <<hansont@stat.sc.edu>>

References

De Iorio, M., Johnson, W. O., Mueller, P., and Rosner, G. L. (2009). Bayesian nonparametric nonproportional hazards survival modeling. *Biometrics*, 65(3), 762-771.

Zhou, H., Hanson, T. and Knapp, R. (2014+). A Spatial Copula Approach to Fully Bayesian Non-parametric Survival Analysis. In preparation for publication.

See Also

[spCopulaDDP](#)

Examples

```
## Not run:

#####
# A simulated data: mixture of two normals
#####
rm(list=ls())
library(MASS)
library(Rcpp)
library(RcppArmadillo)
library(coda)
library(survival)
library(spBayesSurv)

## True parameters
betaT = cbind(c(3.5, 0.5), c(2.5, -1));
wT = c(0.4, 0.6);
sig2T = c(1^2, 0.5^2);
theta1 = 0.98; theta2 = 100000;

## generate coordinates:
## npred is the # of locations for prediction
n = 300; npred = 30; ntot = n + npred;
ldist = 100; wdist = 40;
s1 = runif(ntot, 0, wdist); s2 = runif(ntot, 0, ldist);
s = rbind(s1,s2);
#plot(s[1,], s[2,]);

## Covariance matrix
corT = matrix(1, ntot, ntot);
for (i in 1:(ntot-1)){
  for (j in (i+1):ntot){
    dij = sqrt(sum( (s[,i]-s[,j])^2 ));
    corT[i,j] = theta1*exp(-theta2*dij);
    corT[j,i] = theta1*exp(-theta2*dij);
  }
}

## Generate x
x = runif(ntot,-1.5,1.5);
```

```

X = cbind(rep(1,ntot), x);
p = ncol(X); # number of covariates + 1
## Generate transformed log of survival times
z = mvrnorm(1, rep(0, ntot), corT);
## The pdf of Ti:
fi = function(y, xi, w=wT){
  nw = length(w);
  ny = length(y);
  res = matrix(0, ny, nw);
  Xi = c(1,xi);
  for (k in 1:nw){
    res[,k] = w[k]*dnorm(y, sum(Xi*betaT[,k]), sqrt(sig2T[k]) )
  }
  apply(res, 1, sum)
}
## true plot
xx = seq(-2, 7, 0.01)
plot(xx, fi(xx, -1), "l", lwd=2, col=2)
lines(xx, fi(xx, 1), "l", lwd=2, col=3)
## The CDF of Ti:
Fi = function(y, xi, w=wT){
  nw = length(w);
  ny = length(y);
  res = matrix(0, ny, nw);
  Xi = c(1,xi);
  for (k in 1:nw){
    res[,k] = w[k]*pnorm(y, sum(Xi*betaT[,k]), sqrt(sig2T[k]) )
  }
  apply(res, 1, sum)
}
## The inverse for CDF of Ti
Finvsingle = function(u, xi) {
  res = uniroot(function (x) Fi(x, xi)-u, lower=-500, upper=500);
  res$root
}
Finv = function(u, xi) {sapply(u, Finvsingle, xi)};
## Generate log of survival times y
u = pnorm(z);
y = rep(0, ntot);
for (i in 1:ntot){
  y[i] = Finv(u[i], x[i]);
}
#plot(x,y);
yTrue = y;

## Censoring scheme
Centime = runif(ntot, 3.5,5);
Centime = 10000;
delta = (y<=Centime) +0 ;
sum(delta)/ntot;
cen = which(delta==0);
y[cen] = Centime[cen];

```

```

## make a data frame
dtotal = data.frame(s1=s1, s2=s2, y=y, x=x, delta=delta, yTrue=yTrue);
## Hold out npred=30 for prediction purpose
predindex = sample(1:ntot, npred);
dpred = dtotal[predindex,];
dtrain = dtotal[-predindex,];

# rename the variables
d = dtrain;n=nrow(d); n;
s = cbind(d$s1, d$s2);
y = d$y;
x = d$x;
delta =d$delta;

# Prediction settings
xpred = dpred$x;
s0 = cbind( dpred$s1, dpred$s2 );
prediction = list(spred=s0, xpred=xpred);

#####
# ANOVA DDP
#####

# Prior information
prior = list(N = 10,
             m0 = rep(0,p),
             S0 = diag(rep(1e5,p), nrow=p, ncol=p),
             Sig0 = diag(rep(1e5,p), nrow=p, ncol=p),
             k0 = 7,
             nua = 2, nub = 1,
             a0 = 1, b0 = 1);

# current state values
state <- NULL

# MCMC parameters
nburn <- 1000
nsave <- 500
nskip <- 4
ndisplay <- 100
mcmc <- list(nburn=nburn,
             nsave=nsave,
             nskip=nskip,
             ndisplay=ndisplay)

# Fit the model
res1 = anovaDDP( y = y,
                 delta =delta,
                 x = x,
                 prediction=prediction,
                 prior=prior,
                 mcmc=mcmc,
                 state=state);

```

```

par(mfrow = c(2,2))
w.save = res1$w;
Kindex = which.max(rowMeans(w.save));
traceplot(mcmc(w.save[Kindex,]), main="w")
sig2.save = res1$sigma2;
traceplot(mcmc(sig2.save[Kindex,]), main="sig2")
beta.save = res1$beta;
traceplot(mcmc(beta.save[2,Kindex,]), main="beta")
alpha.save = res1$alpha;
traceplot(mcmc(alpha.save), main="alpha")

## LPML
#cpo=CP0anovaDDP(y, delta, X, beta.save, sig2.save, w.save )$cpo;
LPML1 = sum(log(res1$cpo)); LPML1;

## MSPE
mean((dpred$yTrue-apply(res1$Ypred, 1, median))^2);

## plots
par(mfrow = c(2,2))
xnew = c(-1, 1)
xpred = cbind(xnew);
nxpred = nrow(xpred);
ygrid = seq(0,6,0.05); tgrid = exp(ygrid);
ngrid = length(ygrid);
estimates = GetCurves(res1, xpred, ygrid, CI=c(0.05, 0.95));
fhat = estimates$fhat;
Shat = estimates$Shat;
## density in y
plot(ygrid, fi(ygrid, xnew[1]), "l", lwd=2, ylim=c(0, 0.8),
      xlim=c(0,6), main="density in y")
for(i in 1:nxpred){
  lines(ygrid, fi(ygrid, xnew[i]), lwd=2)
  lines(ygrid, fhat[,i], lty=2, lwd=2, col=4);
}
## survival in y
plot(ygrid, 1-Fi(ygrid, xnew[1]), "l", lwd=2, ylim=c(0, 1),
      xlim=c(0,6), main="survival in y")
for(i in 1:nxpred){
  lines(ygrid, 1-Fi(ygrid, xnew[i]), lwd=2)
  lines(ygrid, Shat[,i], lty=2, lwd=2, col=4);
}
## density in t
plot(tgrid, fi(ygrid, xnew[1])/tgrid, "l", lwd=2, ylim=c(0, 0.15),
      xlim=c(0,100), main="density in t")
for(i in 1:nxpred){
  lines(tgrid, fi(ygrid, xnew[i])/tgrid, lwd=2)
  lines(tgrid, fhat[,i]/tgrid, lty=2, lwd=2, col=4);
}
## survival in t
plot(tgrid, 1-Fi(ygrid, xnew[1]), "l", lwd=2, ylim=c(0, 1),
      xlim=c(0,100), main="survival in t")

```

```

for(i in 1:npred){
  lines(tgrid, 1-Fi(ygrid, xnew[i]), lwd=2)
  lines(tgrid, Shat[,i], lty=2, lwd=2, col=4);
}

## End(Not run)

```

GetCurves	<i>Obtain estimated marginal density, survival, and hazard functions given covariates</i>
-----------	---

Description

This function estimates marginal density, survival, and hazard functions given covariates.

Usage

```
GetCurves(fit, xpred, ygrid, CI=c(0.05, 0.95))
```

Arguments

fit	an object obtained from functions including <code>anovaDDP</code> , <code>spCopulaDDP</code> , <code>indeptCoxph</code> and <code>spCopulaCoxph</code> .
xpred	an n by p vector of covariates matrix used for curve estimates.
ygrid	a vector of grid points (in log survival time scale) indicating where the curves will be estimated.
CI	a vector to indicate the level of credible interval, where first element indicate the lower probability.

Details

This function fits an ANOVA DDP model (De Iorio et al., 2009) for survival analysis of right censored time-to-event data.

Value

Use names to find out what they are, where `fhat` represents density, `Shat` represents survival and `Hhat` represents hazard.

Author(s)

Haiming Zhou <<zhouh@email.sc.edu>> and Tim Hanson <<hansont@stat.sc.edu>>

See Also

[anovaDDP](#), [spCopulaDDP](#), [indeptCoxph](#), [spCopulaCoxph](#)

indeptCoxph

*Bayesian Approach to Cox Proportional Hazard Model***Description**

This function fits a Cox proportional hazard model for right censored time-to-event data.

Usage

```
indeptCoxph(y, delta, x=NULL, prediction, prior, mcmc, state, RandomIntervals=F,
            data=sys.frame(sys.parent()), na.action=na.fail, work.dir=NULL)
```

Arguments

<code>y</code>	an n by 1 vector giving the survival times.
<code>delta</code>	an n by 1 vector indicating whether it is right censored (=0) or not (=1).
<code>x</code>	an n by p matrix of covariates without intercept. The default is NULL, indicating no covariates included.
<code>prediction</code>	a list giving the information used to obtain conditional inferences. The list includes the following elements: <code>xpred</code> giving the n by p covariates matrix, used for prediction.
<code>prior</code>	a list giving the prior information. The list includes the following parameter: <code>M</code> an integer giving the total number of cut points for baseline hazard. See Zhou, Hanson and Knapp (2014+) for more detailed hyperprior specifications.
<code>mcmc</code>	a list giving the MCMC parameters. The list must include the following elements: <code>nburn</code> an integer giving the number of burn-in scans, <code>nskip</code> an integer giving the thinning interval, <code>nsave</code> an integer giving the total number of scans to be saved, <code>ndisplay</code> an integer giving the number of saved scans to be displayed on screen (the function reports on the screen when every <code>ndisplay</code> iterations have been carried out).
<code>state</code>	a list giving the current value of the parameters. This list is used if the current analysis is the continuation of a previous analysis.
<code>RandomIntervals</code>	indicate if random cut points for baseline hazard is need. The default is TRUE.
<code>data</code>	data frame.
<code>na.action</code>	a function that indicates what should happen when the data contain NAs. The default action (<code>na.fail</code>) causes <code>indeptCoxph</code> to print an error message and terminate if there are any incomplete observations.
<code>work.dir</code>	working directory.

Details

This generic function fits an independent Cox PH model (Zhou, Hanson and Knapp, 2014+), for right-censored data.

Value

The results include the MCMC chains for the parameters discussed in Zhou, Hanson and Knapp (2014+). Use names to find out what they are.

Author(s)

Haiming Zhou <<zhouh@email.sc.edu>> and Tim Hanson <<hansont@stat.sc.edu>>

References

Zhou, H., Hanson, T. and Knapp, R. (2014+). A Spatial Copula Approach to Fully Bayesian Non-parametric Survival Analysis. In preparation for publication.

See Also

[spCopulaCoxph](#)

Examples

```
## Not run:

#####
# A simulated data: Cox PH
#####
rm(list=ls())
library(MASS)
library(Rcpp)
library(RcppArmadillo)
library(coda)
library(survival)
library(spBayesSurv)
## True parameters
betaT = c(-1);
theta1 = 0.98; theta2 = 100000;

## generate coordinates:
## npred is the # of locations for prediction
n = 300; npred = 30; ntot = n + npred;
ldist = 100; wdists = 40;
s1 = runif(ntot, 0, wdists); s2 = runif(ntot, 0, ldist);
s = rbind(s1,s2); #plot(s[1,], s[2,]);

## Covariance matrix
corT = matrix(1, ntot, ntot);
for (i in 1:(ntot-1)){
  for (j in (i+1):ntot){
    dij = sqrt(sum( (s[,i]-s[,j])^2 ));
    corT[i,j] = theta1*exp(-theta2*dij);
    corT[j,i] = theta1*exp(-theta2*dij);
  }
}
```

```

## Generate x
x = runif(ntot,-1.5,1.5);
## Generate transformed log of survival times
z = mvrnorm(1, rep(0, ntot), corT);
## The CDF of Ti: Lambda(t) = t^2;
Fi = function(t, xi){
  res = 1-exp(-t^3*exp(sum(xi*betaT)));
  res[which(t<0)] = 0;
  res
}
## The pdf of Ti:
fi = function(t, xi){
  res=(1-Fi(t,xi))*3*t^2*exp(sum(xi*betaT));
  res[which(t<0)] = 0;
  res
}
#integrate(function(x) fi(x, 0), -Inf, Inf)
## true plot
xx = seq(0, 10, 0.1)
plot(xx, fi(xx, -1), "l", lwd=2, col=2)
lines(xx, fi(xx, 1), "l", lwd=2, col=3)

## The inverse for CDF of Ti
Finvsingle = function(u, xi) {
  res = uniroot(function(x) Fi(x, xi)-u, lower=0, upper=5000);
  res$root
}
Finv = function(u, xi) {sapply(u, Finvsingle, xi)};
## Generate survival times t
u = pnorm(z);
t = rep(0, ntot);
for (i in 1:ntot){
  t[i] = Finv(u[i], x[i]);
}
tTrue = t; #plot(x,t);

## Censoring scheme
Centime = runif(ntot, 1, 3);
#Centime = 10000;
delta = (t<=Centime) +0 ;
sum(delta)/ntot;
cen = which(delta==0);
t[cen] = Centime[cen];

## make a data frame
dtotal = data.frame(s1=s1, s2=s2, t=t, logt=log(t), x=x, delta=delta,
                    tTrue=tTrue, logtTrue=log(tTrue));
## Hold out npred=30 for prediction purpose
predindex = sample(1:ntot, npred);
dpred = dtotal[predindex,];
dtrain = dtotal[-predindex,];

# Prediction settings

```

```

xpred = dpred$x;
s0 = cbind( dpred$s1, dpred$s2 );
prediction = list(spred=s0, xpred=xpred);

#####
# Independent Cox PH
#####
# rename the variables
d = dtrain;n=nrow(d); n;
s = cbind(d$s1, d$s2);
t = d$t;
x = d$x;
X = cbind(x);
p = ncol(X); # number of covariates
delta =d$delta;

# Initial Exp Cox PH
fit0 = survreg( Surv(t, delta) ~ x, dist="exponential", data=d );
h0 = as.vector( exp( -fit0$coefficients[1] ) );
beta = as.vector( -fit0$coefficients[-1] );
S0 = as.matrix( fit0$var[-1,-1] );

# Prior information
prior = list(M = 10,
             h0 = h0,
             r0 = 1,
             V0 = 2*as.vector( exp( -2*fit0$coefficients[1] ) *fit0$var[1,1] ),
             mu0 = as.vector( -fit0$coefficients[-1] ),
             Sig0 = diag(rep(1e5,p), nrow=p, ncol=p),
             adapter = (2.4)^2/p,
             hadapter = (2.4)^2,
             spadapter = (2.4)^2/2,
             theta0=c(1.0, 1.0, 0.5, 0.2));

# current state values
state <- list(theta = c(0.9, 1));

# MCMC parameters
nburn <- 1000
nsave <- 500
nskip <- 4
ndisplay <- 100
mcmc <- list(nburn=nburn,
             nsave=nsave,
             nskip=nskip,
             ndisplay=ndisplay)

# Fit the Cox PH model
res1 = indeptCoxph( y = t,
                   delta =delta,
                   x = x,
                   RandomIntervals=T,

```

```

        prediction=prediction,
        prior=prior,
        mcmc=mcmc,
        state=state);
par(mfrow = c(2,1))
h.save = res1$h; rowMeans(h.save);
traceplot(mcmc(h.save[2,]), main="h")
beta.save = res1$beta; rowMeans(beta.save);
traceplot(mcmc(beta.save[1,]), main="beta")
res1$ratebeta;
## LPML
LPML1 = sum(log(res1$cpo)); LPML1;
## MSPE
mean((dpred$tTrue-apply(res1$Tpred, 1, median))^2);

## plots
par(mfrow = c(2,1))
xnew = c(-1, 1)
xpred = cbind(xnew);
nxpred = nrow(xpred);
ygrid = seq(-5, 1.1, 0.05);tgrid = exp(ygrid);
ngrid = length(ygrid);
estimates = GetCurves(res1, xpred, ygrid, CI=c(0.05, 0.95));
fhat = estimates$fhat;
Shat = estimates$Shat;
## density in t
plot(tgrid, fi(tgrid, xnew[1]), "l", lwd=2, xlim=c(0,6), main="density in y")
for(i in 1:nxpred){
  lines(tgrid, fi(tgrid, xnew[i]), lwd=2)
  lines(tgrid, fhat[,i], lty=2, lwd=2, col=4);
}
## survival in t
plot(tgrid, 1-Fi(tgrid, xnew[1]), "l", lwd=2, xlim=c(0,6), main="survival in y")
for(i in 1:nxpred){
  lines(tgrid, 1-Fi(tgrid, xnew[i]), lwd=2)
  lines(tgrid, Shat[,i], lty=2, lwd=2, col=4);
}

## End(Not run)

```

Description

This function fits a spatial copula Cox PH model for survival analysis of point-referenced right censored time-to-event data.

Usage

```
spCopulaCoxph(y, delta, x=NULL, s, prediction, prior, mcmc, state, RandomIntervals=F,
              data=sys.frame(sys.parent()), na.action=na.fail, work.dir=NULL)
```

Arguments

<code>y</code>	an n by 1 vector giving the survival times.
<code>delta</code>	an n by 1 vector indicating whether it is right censored ($=0$) or not ($=1$).
<code>x</code>	an n by p matrix of covariates without intercept. The default is <code>NULL</code> , indicating no covariates included.
<code>s</code>	an n by d matrix of UMT coordinates, where d is the dimension of space.
<code>prediction</code>	a list giving the information used to obtain conditional inferences. The list includes the following elements: <code>spred</code> and <code>xpred</code> giving the n by 2 new locations and corresponding n by p covariates matrix, respectively, used for prediction .
<code>prior</code>	a list giving the prior information. The list includes the following parameter: <code>M</code> an integer giving the total number of cut points for baseline hazard. See Zhou, Hanson and Knapp (2014+) for more detailed hyperprior specifications.
<code>mcmc</code>	a list giving the MCMC parameters. The list must include the following elements: <code>nburn</code> an integer giving the number of burn-in scans, <code>nskip</code> an integer giving the thinning interval, <code>nsave</code> an integer giving the total number of scans to be saved, <code>ndisplay</code> an integer giving the number of saved scans to be displayed on screen (the function reports on the screen when every <code>ndisplay</code> iterations have been carried out).
<code>state</code>	a list giving the current value of the parameters. This list is used if the current analysis is the continuation of a previous analysis.
<code>RandomIntervals</code>	indicate if random cut points for baseline hazard is need. The default is <code>TRUE</code> .
<code>data</code>	data frame.
<code>na.action</code>	a function that indicates what should happen when the data contain NAs. The default action (<code>na.fail</code>) causes <code>spCopulaCoxph</code> to print an error message and terminate if there are any incomplete observations.
<code>work.dir</code>	working directory.

Details

This generic function fits a spatial copula Cox PH model (Zhou, Hanson and Knapp, 2014+), for (potentially) point-referenced right-censored data.

Value

The results include the MCMC chains for the parameters discussed in Zhou, Hanson and Knapp (2014+). Use names to find out what they are.

Author(s)

Haiming Zhou <<zhouh@email.sc.edu>> and Tim Hanson <<hansont@stat.sc.edu>>

References

Zhou, H., Hanson, T. and Knapp, R. (2014+). A Spatial Copula Approach to Fully Bayesian Non-parametric Survival Analysis. In preparation for publication.

See Also

[spCopulaDDP](#)

Examples

```
## Not run:

#####
# A simulated data: spatial Copula Cox PH
#####
rm(list=ls())
library(MASS)
library(Rcpp)
library(RcppArmadillo)
library(coda)
library(survival)
library(spBayesSurv)
## True parameters
betaT = c(-1);
theta1 = 0.98; theta2 = 0.1;

## generate coordinates:
## npred is the # of locations for prediction
n = 300; npred = 30; ntot = n + npred;
ldist = 100; wdists = 40;
s1 = runif(ntot, 0, wdists); s2 = runif(ntot, 0, ldist);
s = rbind(s1,s2); #plot(s[1,], s[2,]);

## Covariance matrix
corT = matrix(1, ntot, ntot);
for (i in 1:(ntot-1)){
  for (j in (i+1):ntot){
    dij = sqrt(sum( (s[,i]-s[,j])^2 ));
    corT[i,j] = theta1*exp(-theta2*dij);
    corT[j,i] = theta1*exp(-theta2*dij);
  }
}

## Generate x
x = runif(ntot,-1.5,1.5);
## Generate transformed log of survival times
z = mvrnorm(1, rep(0, ntot), corT);
## The CDF of  $T_i$ :  $\Lambda(t) = t^2$ ;
Fi = function(t, xi){
  res = 1-exp(-t^3*exp(sum(xi*betaT)));
  res[which(t<0)] = 0;
  res
}
```

```

}
## The pdf of Ti:
fi = function(t, xi){
  res=(1-Fi(t,xi))*3*t^2*exp(sum(xi*betaT));
  res[which(t<0)] = 0;
  res
}
#integrate(function(x) fi(x, 0), -Inf, Inf)
## true plot
xx = seq(0, 10, 0.1)
plot(xx, fi(xx, -1), "l", lwd=2, col=2)
lines(xx, fi(xx, 1), "l", lwd=2, col=3)

## The inverse for CDF of Ti
Finvsingle = function(u, xi) {
  res = uniroot(function (x) Fi(x, xi)-u, lower=0, upper=5000);
  res$root
}
Finv = function(u, xi) {sapply(u, Finvsingle, xi)};
## Generate survival times t
u = pnorm(z);
t = rep(0, ntot);
for (i in 1:ntot){
  t[i] = Finv(u[i], x[i]);
}
tTrue = t; #plot(x,t);

## Censoring scheme
Centime = runif(ntot, 1, 5);
#Centime = 10000;
delta = (t<=Centime) +0 ;
sum(delta)/ntot;
cen = which(delta==0);
t[cen] = Centime[cen];

## make a data frame
dtotal = data.frame(s1=s1, s2=s2, t=t, logt=log(t), x=x, delta=delta,
                    tTrue=tTrue, logtTrue=log(tTrue));
## Hold out npred=30 for prediction purpose
predindex = sample(1:ntot, npred);
dpred = dtotal[predindex,];
dtrain = dtotal[-predindex,];

# Prediction settings
xpred = dpred$x;
s0 = cbind( dpred$s1, dpred$s2 );
prediction = list(spred=s0, xpred=xpred);

#####
# spatial Copula Cox PH
#####
# rename the variables
d = dtrain;n=nrow(d); n;

```



```

s = cbind(d$s1, d$s2);
t = d$t;
x = d$x;
X = cbind(x);
p = ncol(X); # number of covariates + 1
delta =d$delta;

# Initial Exp Cox PH
fit0 = survreg( Surv(t, delta) ~ x, dist="exponential", data=d );
h0 = as.vector( exp( -fit0$coefficients[1] ) );
beta = as.vector( -fit0$coefficients[-1] );
S0 = as.matrix( fit0$var[-1,-1] );

# Prior information
prior = list(M = 10,
             h0 = h0,
             r0 = 1,
             V0 = 2*as.vector( exp( -2*fit0$coefficients[1] )*fit0$var[1,1] ),
             mu0 = as.vector( -fit0$coefficients[-1] ),
             Sig0 = diag(rep(1e5,p), nrow=p, ncol=p),
             S0 = as.matrix( fit0$var[-1,-1] ),
             adapter = 2,
             hs0 = sqrt( as.vector( exp( -2*fit0$coefficients[1] )*fit0$var[1,1] ) ),
             hadapter = (2.4)^2,
             spS0 = diag(c(2,4)),
             spadapter = (2.4)^2/2,
             theta0=c(1.0, 1.0, 0.5, 0.2));

# current state values
state <- list(theta = c(0.9, 1));

# MCMC parameters
nburn <- 1000
nsave <- 500
nskip <- 4
ndisplay <- 100
mcmc <- list(nburn=nburn,
             nsave=nsave,
             nskip=nskip,
             ndisplay=ndisplay)

# Fit the spatial Cox PH model
res2 = spCopulaCoxph( y = t,
                     delta =delta,
                     s = s,
                     x = X,
                     RandomIntervals=T,
                     prediction=prediction,
                     prior=prior,
                     mcmc=mcmc,
                     state=state);

par(mfrow = c(2,1))
h.save = res2$h; rowMeans(h.save);

```

```

traceplot(mcmc(h.save[2,]), main="h")
beta.save = res2$beta; rowMeans(beta.save);
traceplot(mcmc(beta.save[1,]), main="beta")
res2$ratebeta;
res2$ratetheta;
res2$rateh;
## LPML
LPML2 = sum(log(res2$cpo)); LPML2;
## MSPE
mean((dpred$tTrue-apply(res2$Tpred, 1, median))^2);
## plots
par(mfrow = c(2,1))
xnew = c(-1, 1)
xpred = cbind(xnew);
nxpred = nrow(xpred);
ygrid = seq(-5, 1.1, 0.05);tgrid = exp(ygrid);
ngrid = length(ygrid);
estimates = GetCurves(res2, xpred, ygrid, CI=c(0.05, 0.95));
fhat = estimates$fhat;
Shat = estimates$Shat;
## density in t
plot(tgrid, fi(tgrid, xnew[1]), "l", lwd=2, xlim=c(0,6), main="density in y")
for(i in 1:nxpred){
  lines(tgrid, fi(tgrid, xnew[i]), lwd=2)
  lines(tgrid, fhat[,i], lty=2, lwd=2, col=4);
}
## survival in t
plot(tgrid, 1-Fi(tgrid, xnew[1]), "l", lwd=2, xlim=c(0,6), main="survival in y")
for(i in 1:nxpred){
  lines(tgrid, 1-Fi(tgrid, xnew[i]), lwd=2)
  lines(tgrid, Shat[,i], lty=2, lwd=2, col=4);
}

## End(Not run)

```

spCopulaDDP

A Spatial Copula Approach to Fully Bayesian Nonparametric Survival Analysis

Description

This function fits a spatial copula survival model for survival analysis of point-referenced right censored time-to-event data.

Usage

```

spCopulaDDP(y, delta, x=NULL, s, prediction, prior, mcmc, state, FSA = TRUE, knots,
            data=sys.frame(sys.parent()), na.action=na.fail, work.dir=NULL)

```

Arguments

<code>y</code>	an n by 1 vector giving the log survival times.
<code>delta</code>	an n by 1 vector indicating whether it is right censored ($=0$) or not ($=1$).
<code>x</code>	an n by p matrix of covariates without intercept. The default is <code>NULL</code> , indicating no covariates included.
<code>s</code>	an n by d matrix of UMT coordinates, where d is the dimension of space.
<code>prediction</code>	a list giving the information used to obtain conditional inferences. The list includes the following elements: <code>spred</code> and <code>xpred</code> giving the n by 2 new locations and corresponding n by p covariates matrix, respectively, used for prediction. In addition, <code>predid</code> needs to be specified if <code>FSA=TRUE</code> .
<code>prior</code>	a list giving the prior information. The list includes the following parameter: <code>N</code> an integer giving the truncation of the Dirichlet process, <code>a0</code> and <code>b0</code> giving the hyperparameters for prior distribution of the precision parameter α . See Zhou, Hanson and Knapp (2014+) for more detailed hyperprior specifications.
<code>mcmc</code>	a list giving the MCMC parameters. The list must include the following elements: <code>nburn</code> an integer giving the number of burn-in scans, <code>nskip</code> an integer giving the thinning interval, <code>nsave</code> an integer giving the total number of scans to be saved, <code>ndisplay</code> an integer giving the number of saved scans to be displayed on screen (the function reports on the screen when every <code>ndisplay</code> iterations have been carried out).
<code>state</code>	a list giving the current value of the parameters. This list is used if the current analysis is the continuation of a previous analysis.
<code>FSA</code>	indicate if the full scale approximation is need. The default is <code>FALSE</code> .
<code>knots</code>	a list giving the knots and block ids when <code>FSA=TRUE</code> . This list includes the following parameter: <code>ss</code> an m by d matrix of UMT coordinates, where d is the dimension of space, <code>blockid</code> an n by 1 id vector indicating which block that each observation is in.
<code>data</code>	data frame.
<code>na.action</code>	a function that indicates what should happen when the data contain NAs. The default action (<code>na.fail</code>) causes <code>spCopulaDDP</code> to print an error message and terminate if there are any incomplete observations.
<code>work.dir</code>	working directory.

Details

This generic function fits a spatial copula survival model (Zhou, Hanson and Knapp, 2014+), for (potentially) point-referenced right-censored data.

Value

The results include the MCMC chains for the parameters discussed in Zhou, Hanson and Knapp (2014+). Use names to find out what they are.

Author(s)

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References

Zhou, H., Hanson, T. and Knapp, R. (2014+). A Spatial Copula Approach to Fully Bayesian Non-parametric Survival Analysis. In preparation for publication.

See Also

[anovaDDP](#)

Examples

```
## Not run:

#####
# A simulated data: mixture of two normals
#####
rm(list=ls())
library(MASS)
library(Rcpp)
library(RcppArmadillo)
library(coda)
library(survival)
library(spBayesSurv)

## True parameters
betaT = cbind(c(3.5, 0.5), c(2.5, -1));
wT = c(0.4, 0.6);
sig2T = c(1^2, 0.5^2);
theta1 = 0.98; theta2 = 0.1;

## generate coordinates:
## npred is the # of locations for prediction
n = 300; npred = 30; ntot = n + npred;
ldist = 100; wdist = 40;
s1 = runif(ntot, 0, wdist); s2 = runif(ntot, 0, ldist);
s = rbind(s1,s2);
#plot(s[1,], s[2,]);
## divide them into blocks
nldist=10; nwdist=4;
nb=nldist*nwdist; nb; # number of blocks;
coor = matrix(0, nb, 4); ## four edges for each block;
tempindex=1; lstep=ldist/nldist; wstep=wdist/nwdist;
for(i in 1:nwdist){
  for(j in 1:nldist){
    coor[tempindex,] = c((i-1)*wstep, i*wstep, (j-1)*lstep, j*lstep );
    tempindex = tempindex + 1;
  }
}
## Assign block id for each location
blockid = rep(NA,ntot);
for(i in 1:nb){
  blockid[((s1>coor[i,1])*(s1<=coor[i,2])*(s2>coor[i,3])*(s2<=coor[i,4]))==1]=i;
}
}
```

```

## Choose knots S*
nldist=15; nwdist=6;
m=nldist*nwdist; m; # number of knots;
ss = matrix(0, m, 2);
tempindex=1; lstep=ldist/nldist; wstep=wdist/nwdist;
for(i in 1:nwdist){
  for(j in 1:nldist){
    ss[tempindex,] = c( (i-1)*wstep+wstep/2, (j-1)*lstep+lstep/2);
    tempindex = tempindex + 1;
  }
}
## Covariance matrix
dnn = .Call("DistMat", s, s, PACKAGE = "spBayesSurv");
corT = theta1*exp(-theta2*dnn)+(1-theta1)*diag(ntot);

## Generate x
x = runif(ntot,-1.5,1.5);
X = cbind(rep(1,ntot), x);
p = ncol(X); # number of covariates + 1
## Generate transformed log of survival times
z = mvrnorm(1, rep(0, ntot), corT);
## The pdf of Ti:
fi = function(y, xi, w=wT){
  nw = length(w);
  ny = length(y);
  res = matrix(0, ny, nw);
  Xi = c(1,xi);
  for (k in 1:nw){
    res[,k] = w[k]*dnorm(y, sum(Xi*betaT[,k]), sqrt(sig2T[k]) )
  }
  apply(res, 1, sum)
}
## true plot
xx = seq(-2, 7, 0.01)
plot(xx, fi(xx, -1), "l", lwd=2, col=2)
lines(xx, fi(xx, 1), "l", lwd=2, col=3)
## The CDF of Ti:
Fi = function(y, xi, w=wT){
  nw = length(w);
  ny = length(y);
  res = matrix(0, ny, nw);
  Xi = c(1,xi);
  for (k in 1:nw){
    res[,k] = w[k]*pnorm(y, sum(Xi*betaT[,k]), sqrt(sig2T[k]) )
  }
  apply(res, 1, sum)
}
## The inverse for CDF of Ti
Finvsingle = function(u, xi) {
  res = uniroot(function (x) Fi(x, xi)-u, lower=-500, upper=500);
  res$root
}
Finv = function(u, xi) {sapply(u, Finvsingle, xi)};

```

```

## Generate log of survival times y
u = pnorm(z);
y = rep(0, ntot);
for (i in 1:ntot){
  y[i] = Finv(u[i], x[i]);
}
#plot(x,y);
yTrue = y;

## Censoring scheme
Centime = runif(ntot, 3.5,5);
Centime = 10000;
delta = (y<=Centime) +0 ;
sum(delta)/ntot;
cen = which(delta==0);
y[cen] = Centime[cen];

## make a data frame
dtotal = data.frame(s1=s1, s2=s2, y=y, x=x, delta=delta, yTrue=yTrue, id=blockid);
## Hold out npred=30 for prediction purpose
predindex = sample(1:ntot, npred);
dpred = dtotal[predindex,];
dtrain = dtotal[-predindex,];

# rename the variables
d = dtrain; n=nrow(d); n;
s = cbind(d$s1, d$s2);
y = d$y;
x = d$x;
delta =d$delta;

# FSA settings
knots = list(ss=ss, blockid=d$id);

# Prediction settings
xpred = dpred$x;
s0 = cbind( dpred$s1, dpred$s2 );
prediction = list(spred=s0, xpred=xpred, predid=dpred$id);

#####
# spatial copula DDP
#####
# MCMC parameters
nburn <- 1000
nsave <- 500
nskip <- 4
ndisplay <- 100
mcmc <- list(nburn=nburn,
             nsave=nsave,
             nskip=nskip,
             ndisplay=ndisplay)

# Prior information

```

```

prior = list(N = 10,
            m0 = rep(0,p),
            S0 = diag(rep(1e5,p), nrow=p, ncol=p),
            Sig0 = diag(rep(1e5,p), nrow=p, ncol=p),
            k0 = 7,
            nua = 2, nub = 1,
            a0 = 1, b0 = 1,
            spS0 = diag(c(4,4)),
            spadapter = 1,
            theta0 = c(1.0, 1.0, 0.5, 0.2));

# current state values
state <- list(theta=c(0.95, 0.5));

# Fit the model
fitspDDP = spCopulaDDP( y = y,
                      delta =delta,
                      x = x,
                      s = s,
                      prediction=prediction,
                      prior=prior,
                      mcmc=mcmc,
                      state=state,
                      FSA=FALSE,
                      knots=knots);
res = fitspDDP; remove(fitspDDP);
# trace plots
par(mfrow = c(3,2))
w.save2 = res$w;
Kindex = which.max(rowMeans(w.save2));
traceplot(mcmc(w.save2[Kindex,]), main="w")
sig2.save2 = res$sigma2;
traceplot(mcmc(sig2.save2[Kindex,]), main="sig2")
beta.save2 = res$beta;
alpha.save2 = res$alpha;
traceplot(mcmc(beta.save2[2,Kindex,]), main="beta")
traceplot(mcmc(alpha.save2), main="alpha")
theta1.save2 = res$theta1;
theta2.save2 = res$theta2
traceplot(mcmc(theta1.save2), main="theta1")
traceplot(mcmc(theta2.save2), main="theta2")

## LPML
LPML2 = sum(log(res$cpo)); LPML2;
## MSPE
mean((dpred$yTrue-apply(res$Ypred, 1, median))^2);

## plots
par(mfrow = c(2,2));
xnew = c(-1, 1);
xpred = cbind(xnew);
nxpred = nrow(xpred);
ygrid = seq(0,6.0,0.05); tgrid = exp(ygrid);

```

```

ngrid = length(ygrid);
estimates = GetCurves(res, xpred, ygrid, CI=c(0.05, 0.95));
fhat = estimates$fhat;
Shat = estimates$Shat;
## density in y
plot(ygrid, fi(ygrid, xnew[1]), "l", lwd=2, ylim=c(0, 0.8),
      xlim=c(0,6), main="density in y")
for(i in 1:nxpred){
  lines(ygrid, fi(ygrid, xnew[i]), lwd=2)
  lines(ygrid, fhat[,i], lty=2, lwd=2, col=4);
}
## survival in y
plot(ygrid, 1-Fi(ygrid, xnew[1]), "l", lwd=2, ylim=c(0, 1),
      xlim=c(0,6), main="survival in y")
for(i in 1:nxpred){
  lines(ygrid, 1-Fi(ygrid, xnew[i]), lwd=2)
  lines(ygrid, Shat[,i], lty=2, lwd=2, col=4);
}
## density in t
plot(tgrid, fi(ygrid, xnew[1])/tgrid, "l", lwd=2, ylim=c(0, 0.15),
      xlim=c(0,100), main="density in t")
for(i in 1:nxpred){
  lines(tgrid, fi(ygrid, xnew[i])/tgrid, lwd=2)
  lines(tgrid, fhat[,i]/tgrid, lty=2, lwd=2, col=4);
}
## survival in t
plot(tgrid, 1-Fi(ygrid, xnew[1]), "l", lwd=2, ylim=c(0, 1),
      xlim=c(0,100), main="survival in t")
for(i in 1:nxpred){
  lines(tgrid, 1-Fi(ygrid, xnew[i]), lwd=2)
  lines(tgrid, Shat[,i], lty=2, lwd=2, col=4);
}

## End(Not run)

```


Index

- *Topic **ANOVA DDP**
 - anovaDDP, [2](#)
 - *Topic **Bayesian nonparametric**
 - anovaDDP, [2](#)
 - spCopulaDDP, [18](#)
 - *Topic **Bayesian**
 - indeptCoxph, [9](#)
 - spCopulaCoxph, [13](#)
 - *Topic **Cox PH**
 - indeptCoxph, [9](#)
 - *Topic **Spatial copula Cox PH**
 - spCopulaCoxph, [13](#)
 - *Topic **Spatial copula**
 - spCopulaDDP, [18](#)
 - *Topic **package**
 - spBayesSurv-package, [2](#)
- anovaDDP, [2](#), [8](#), [20](#)
- GetCurves, [8](#)
- indeptCoxph, [8](#), [9](#)
- spBayesSurv (spBayesSurv-package), [2](#)
- spBayesSurv-package, [2](#)
- spCopulaCoxph, [8](#), [10](#), [13](#)
- spCopulaDDP, [4](#), [8](#), [15](#), [18](#)