Package ‘StempCens’

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Description

It estimates the parameters of a censored or missing data in spatio-temporal models using the SAEM algorithm (Delyon et al., 1999). This algorithm is a stochastic approximation of the widely used EM algorithm and an important tool for models in which the E-step does not have an analytic form. Besides the expressions obtained to estimate the parameters to the proposed model, we include the calculations for the observed information matrix using the method developed by Louis (1982). To examine the performance of the fitted model, case-deletion measure are provided.

Details

The functions provided are:
- **CovarianceM**: computes the spatio-temporal covariance matrix for balanced data.
- **EffectiveRange**: computes the effective range for an isotropic spatial correlation function.
- **EstStempCens**: returns the maximum likelihood estimates of the unknown parameters.
- **PredStempCens**: performs spatio-temporal prediction in a set of new spatial locations for fixed time points.
- **CrossStempCens**: performs cross-validation, which measure the performance of the predictive model on new test dataset.
- **DiagStempCens**: returns measures and graphics for diagnostic analysis.

Author(s)

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References


CovarianceM


---

**Description**

It computes the spatio-temporal covariance matrix for balanced data, i.e., when we have the same temporal indexes per location. To compute the spatial correlation it provides 5 functions: exponential, gaussian, matern, spherical and power exponential. To compute the temporal correlation is used an autocorrelation function of an AR(1) process.

**Usage**

CovarianceM(phi, rho, tau2, sigma2, distSpa, disTemp, kappa, type.S)

**Arguments**

phi value of the spatial scaling parameter.

rho value of the time scaling parameter.

tau2 value of the the nugget effect parameter.

sigma2 value of the partial sill.

distSpa \( n \times n \) spatial distance matrix without considering repetitions.

disTemp \( T \times T \) temporal distance matrix without considering repetitions.

kappa parameter for all spatial covariance functions. In the case of exponential, gaussian and spherical function \( \kappa \) is equal to zero. For the power exponential function \( \kappa \) is a number between 0 and 2. For the matern correlation function is upper than 0.

type.S type of spatial correlation function: 'exponential' for exponential, 'gaussian' for gaussian, 'matern' for matern, 'pow.exp' for power exponential and 'spherical' for spherical function, respectively. See the analytical form of these functions in EffectiveRange.

**Value**

The function returns the \( n \times n \times T \) spatio-temporal covariance matrix for balanced data.

**Author(s)**

Katherine L. Valeriano, Victor H. Lachos and Larissa A. Matos
Examples

```r
# Initial parameter values
phi <- 5; rho <- 0.45
tau2 <- 0.80; sigma2 <- 2

# Simulating data
n1 <- 10  # Number of spatial locations
n2 <- 5   # Number of temporal index
set.seed(1000)
x.co <- round(runif(n1,0,10),5)  # X coordinate
y.co <- round(runif(n1,0,10),5)  # Y coordinate
coord <- cbind(x.co,y.co)         # Cartesian coordinates without repetitions
time <- as.matrix(seq(1,n2))     # Time index without repetitions

# Covariance matrix
Ms <- as.matrix(dist(coord))     # Spatial distances
Mt <- as.matrix(dist(time))      # Temporal distances
Cov <- CovarianceM(phi,rho,tau2,sigma2,distSpa=Ms,disTemp=Mt,kappa=0,type.S="exponential")
```

---

**CrossStempCens**

*Cross-Validation in spatio-temporal model with censored/missing responses*

**Description**

This function performs cross-validation in spatio-temporal model with censored/missing responses, which measure the performance of the predictive model on new test dataset. The cross-validation method for assessing the model performance is validation set approach (or data split).

**Usage**

```r
CrossStempCens(Pred.StempCens, yObs.pre)
```

**Arguments**

- **Pred.StempCens**: an object of class `Pred.StempCens` given as output by the `PredStempCens` function.
- **yObs.pre**: a vector of the observed responses, the test data.

**Value**

- **Bias**: bias prediction error.
- **Mspe**: mean squared prediction error.
- **Rmspe**: root mean squared prediction error.
- **Mae**: mean absolute error.

**Author(s)**

Katherine L. Valeriano, Victor H. Lachos and Larissa A. Matos
CrossStempCens

See Also

EstStempCens, PredStempCens

Examples

## Not run:
# Initial parameter values
beta <- c(-1,1.50)
phi <- 5; rho <- 0.6
tau2 <- 0.80; sigma2 <- 2
# Simulating data
n1 <- 7  # Number of spatial locations
n2 <- 5  # Number of temporal index
set.seed(400)
x.co <- round(runif(n1,0,10),9)  # X coordinate
y.co <- round(runif(n1,0,10),9)  # Y coordinate
coord <- cbind(x.co,y.co)  # Cartesian coordinates without repetitions
coord2 <- cbind(rep(x.co,each=n2),rep(y.co,each=n2))  # Cartesian coordinates with repetitions
time <- as.matrix(seq(1,n2))  # Time index without repetitions
time2 <- as.matrix(rep(time,n1))  # Time index with repetitions
x1 <- rexp(n1*n2,2)
x2 <- rnorm(n1*n2,2,1)
x <- cbind(x1,x2)
media <- x%*%beta
# Covariance matrix
Ms <- as.matrix(dist(coord))  # Spatial distances
Mt <- as.matrix(dist(time))  # Temporal distances
Cov <- CovarianceM(phi,rho,tau2,sigma2,Ms,Mt,0,"gaussian")
# Data
require(mvtnorm)
y <- as.vector(rmvnorm(1,mean=as.vector(media),sigma=Cov))
data <- data.frame(coord2,time2,y,x)
names(data) <- c("x.coord","y.coord","time","yObs","x1","x2")
# Splitting the dataset
local.est <- coord[c(1,2,4,5,6),]
data.est <- data[ data$x.coord%in%local.est[,1] & data$y.coord%in%local.est[,2],]
data.valid <- data[ data$x.coord%in%coord[c(3,7),1] & data$y.coord%in%coord[c(3,7),2],]
# Censored
perc <- 0.20
y <- data.est$yObs
aa <- sort(y); bb <- aa[1:(perc*nrow(data.est))]
cutof <- bb[perc*nrow(data.est)]
cc <- matrix(1,nrow(data.est),1)*(y<=cutof)
y[cc==1] <- cutof
data.est <- data.frame(data.est[-c(4,5,6)],y,cc,data.est[,c(5,6)])
names(data.est) <- c("x.coord","y.coord","time","yObs","censored","x1","x2")

# Estimation
y <- data.est$yObs
x <- cbind(data.est$x1,data.est$x2)
cc <- data.est$censored
time2 <- as.data.frame(data.est$time)
coord2 <- data.est[,1:2]
LI <- y; LI[cc==1] <- -Inf        # Left-censored
LS <- y
est_teste <- EstStempCens(y, x, cc, time2, coord2, LI, LS, init.phi=3.5, init.rho=0.5,
init.tau2=1,type.Data="balanced", method="nlminb", kappa=0,
type.S="gaussian", IMatrix=FALSE, M=20, perc=0.25, MaxIter=300,
pc=0.20)

# Prediction
locPre <- data.valid[,1:2]
timePre <- as.data.frame(data.valid$time)
xPre <- cbind(data.valid$x1,data.valid$x2)
pre_teste <- PredStempCens(est_teste, locPre, timePre, xPre)
class(pre_teste)

# Cross-validation
cross_teste <- CrossStempCens(pre_teste, data.valid$yObs)
cross_teste$Mspe # MSPE
## End(Not run)

---

**DiagStempCens**

*Diagnostic in spatio-temporal model with censored/missing responses*

**Description**

Return measures and graphics for diagnostic analysis in spatio-temporal model with censored/missing responses.

**Usage**

DiagStempCens(Est.StempCens, type.diag = "individual", diag.plot = TRUE, ck)

**Arguments**

- **Est.StempCens** an object of class Est.StempCens given as output by the `EstStempCens` function. In the `EstStempCens` function, `IMatrix` must be `TRUE`.
- **type.diag** type of diagnostic: 'individual' is related when one observation is deleted, 'time' is related when an entire time is deleted, 'location' is related when an entire location is deleted and 'all' the three cases ('individual', 'time' and 'location'). By default `type.diag` is individual.
- **diag.plot** TRUE or FALSE. It indicates if diagnostic plots must be showed. By default = TRUE.
- **ck** the value for `ck` considered in the benchmark value for the index plot: \( \text{mean}(GD) + ck \times \text{sd}(GD) \), where `GD` is the vector with all values of the diagnostic measures.
DiagStempCens

Details
This function uses the case deletion approach to study the impact of deleting one or more observations from the dataset on the parameters estimates, using the ideas of Cook (1977) and Zhu et al. (2001). The measure is defined by

$$GD_i(\theta^*) = (\theta^* - \theta^*[i])' [-Q^*(\theta|\theta^*)] (\theta^* - \theta^*[i]), i = 1, ..., m,$$

where $\theta^*$ is the estimate of $\theta$ using the complete data, $\theta^*[i]$ are the estimates obtained after deletion of the i-th observation (or group of observations) and $Q^*(\theta|\theta^*)$ is the Hessian matrix.

We can eliminate an observation, an entire location or an entire time index.

Value
The function returns a list with the diagnostic measures.

If type.diag == individual | time | location: GD is a data.frame with the index value of the observation and the GD measure.

If type.diag == all: GDind is a data.frame with the index value of the observation and the GD measure for individual.
GDtime is a data.frame with the time index value and the GD measure for time.
GDloc is a data.frame with the side index value and the GD measure for location.

Author(s)
Katherine L. Valeriano, Victor H. Lachos and Larissa A. Matos

See Also
EstStempCens

Examples
```r
## Not run:
# Initial parameter values
beta <- c(-1,1.5)
phi <- 3; rho <- 0.40
tau2 <- 1; sigma2 <- 2
# Simulating data
n1 <- 5    # Number of spatial locations
n2 <- 5    # Number of temporal index
set.seed(98765)
x.co <- round(runif(n1,0,10),9)  # X coordinate
y.co <- round(runif(n1,0,10),9)  # Y coordinate
coord <- cbind(x.co,y.co)        # Cartesian coordinates without repetitions
coord2 <- cbind(rep(x.co,each=n2),rep(y.co,each=n2)) # Cartesian coordinates with repetitions
time <- as.matrix(seq(1,n2))    # Time index without repetitions
time2 <- as.matrix(rep(time,n1)) # Time index with repetitions
x1 <- rexp(n1*n2,2)
x2 <- rnorm(n1*n2,2,1)
x <- cbind(x1,x2)
media <- x%*%beta
```
# Covariance matrix
Ms <- as.matrix(dist(coord))  # Spatial distances
Mt <- as.matrix(dist(time))  # Temporal distances
Cov <- CovarianceM(phi, rho, tau2, sigma2, Ms, Mt, 0, "exponential")

# Data
require(mvtnorm)
y <- as.vector(rmvnorm(1, mean=as.vector(media), sigma=Cov))
perc <- 0.20
aa <- sort(y); bb <- aa[((1-perc)*n1*n2+1):(n1*n2)]; cutoff <- bb[1]
cc <- matrix(1, (n1*n2), 1) * (y >= cutoff)
y[cc == 1] <- cutoff
y[17] <- abs(y[17]) + 2 * sd(y)
LI <- y
LS <- y; LS[cc == 1] <- Inf  # Right-censored

# Estimation
set.seed(74689)
est <- EstStempCens(y, x, cc, time2, coord2, LI, LS, init.phi=2.5, init.rho=0.5, init.tau2=0.8,
                     type.Data="balanced", method="nlminb", kappa=0, type.S="exponential",
                     IMatrix=TRUE, lower.lim=c(0.01, -0.99, 0.01), upper.lim=c(30, 0.99, 20), M=20,
                     perc=0.25, MaxIter=300, pc=0.20)

# Diagnostic
set.seed(12345)
diag <- DiagStempCens(est, type.diag="time", diag.plot = TRUE, ck=1)
## End(Not run)

---

EffectiveRange

**Effective range for some spatial correlation functions**

**Description**

It computes the effective range for an isotropic spatial correlation function, which is commonly defined to be the distance from which the correlation becomes small, typically below 0.05.

**Usage**

EffectiveRange(cor = 0.05, phi, kappa = 0, Sp.model = "exponential")

**Arguments**

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>cor</td>
<td>effective correlation to check for. By default = 0.05.</td>
</tr>
<tr>
<td>phi</td>
<td>spatial scaling parameter.</td>
</tr>
<tr>
<td>kappa</td>
<td>smoothness parameter, required by the matern and power exponential functions. By default = 0.0.</td>
</tr>
<tr>
<td>Sp.model</td>
<td>type of spatial correlation function: 'exponential' for exponential, 'gaussian' for gaussian, 'matern' for matern, 'pow.exp' for power exponential and 'spherical' for spherical function, respectively. By default = exponential.</td>
</tr>
</tbody>
</table>
The available isotropic spatial correlation functions are:

**Exponential:** \( \text{Corr}(d) = \exp(-d/\phi) \),

**Gaussian:** \( \text{Corr}(d) = \exp(-(d/\phi)^2) \),

**Matern:** \( \text{Corr}(d) = 1/(2^{(\kappa - 1)}\Gamma(\kappa))(d/\phi)^{\kappa}K_\kappa(d/\phi) \),

**Power exponential:** \( \text{Corr}(d) = \exp(-(d/\phi)^\kappa) \),

**Spherical:** \( \text{Corr}(d) = 1 - 1.5d/\phi + 0.5(d/\phi)^3 \),

where \( d \) is the Euclidean distance between two observations, \( \phi \) is the spatial scaling parameter, \( \Gamma(.) \) is the gamma function, \( \kappa \) is the smoothness parameter and \( K_\kappa(.) \) is the modified Bessel function of the second kind of order \( \kappa \).

The function returns the effective range, i.e., the approximate distance from which the spatial correlation is lower than \( \text{cor} \).

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phi <- 164.60
range1 <- EffectiveRange(0.05, phi, kappa=0, Sp.model="exponential")
range2 <- EffectiveRange(0.05, phi, kappa=1, Sp.model="pow.exp")
# Note that these functions are equivalent.

---

**EstStempCens**

ML estimation in spatio-temporal model with censored/missing responses

Return the maximum likelihood estimates of the unknown parameters of spatio-temporal model with censored/missing responses. The estimates are obtained using SAEM algorithm. The function also computes the observed information matrix using the method developed by Louis (1982). The types of censoring considered are left, right, interval or missing values.

EstStempCens(
  y,
  x,
  cc,
  time,
)
coord, LI, LS, init.phi, init.rho, init.tau2, tau2.fixo = FALSE, 
type.Data = "balanced", method = "nlminb", kappa = 0, 
type.S = "exponential", IMatrix = TRUE, lower.lim = c(0.01, -0.99, 0.01), 
upper.lim = c(30, 0.99, 20), M = 20, perc = 0.25, 
MaxIter = 300, pc = 0.2, error = 1e-06
)

Arguments

y       a vector of responses.
x       a matrix or vector of covariates.
cc      a vector of censoring indicators. For each observation: 1 if censored/missing and 0 if non-censored/non-missing.
time    a vector of time.
coord   a matrix of coordinates of the spatial locations.
LI      lower limit of detection. For each observation: if non-censored/non-missing = y, if left-censored/missing = -Inf or = LOD if right/interval-censored.
LS      upper limit of detection. For each observation: if non-censored/non-missing = y, if right-censored/missing = Inf or = LOD if left/interval-censored.
init.phi initial value of the spatial scaling parameter.
init.rho initial value of the time scaling parameter.
init.tau2 initial value of the nugget effect parameter.
tau2.fixo TRUE or FALSE. Indicate if the nugget effect ($\tau^2$) parameter must be fixed. By default = FALSE.
type.Data type of the data: 'balanced' for balanced data and 'unbalanced' for unbalanced data. By default = balanced.
method optimization method used to estimate ($\phi$, $\rho$ and $\tau^2$): 'optim' for the function \texttt{optim} and 'nlminb' for the function \texttt{nlminb}. By default = \texttt{nlminb}.
kappa parameter for all spatial covariance functions. In the case of exponential, gaussian and spherical function $\kappa$ is equal to zero. For the power exponential function $\kappa$ is a number between 0 and 2. For the matern correlation function is upper than 0.
The spatio-temporal Gaussian model is given by:

\[ Y(s_i, t_j) = \mu(s_i, t_j) + Z(s_i, t_j) + \epsilon(s_i, t_j), \]

where the deterministic term \( \mu(s_i, t_j) \) and the stochastic terms \( Z(s_i, t_j), \epsilon(s_i, t_j) \) can depend on the observed spatio-temporal indexes for \( Y(s_i, t_j) \). We assume \( Z \) is normally distributed with zero-mean and covariance matrix \( \Sigma_z = \sigma^2 \Omega_{\phi \rho} \), where \( \sigma^2 \) is the partial sill, \( \Omega_{\phi \rho} \) is the spatio-temporal correlation matrix, \( \phi \) and \( \rho \) are the spatial and time scaling parameters; \( \epsilon(s_i, t_j) \) is an independent and identically distributed measurement error with \( E[\epsilon(s_i, t_j)] = 0 \), variance \( \text{Var}[\epsilon(s_i, t_j)] = \tau^2 \) (the nugget effect) and \( \text{Cov}[\epsilon(s_i, t_j), \epsilon(s_k, t_l)] = 0 \) for all \( s_i \neq s_k \) or \( t_j \neq t_l \).

In particular, we define \( \mu(s_i, t_j) \), the mean of the stochastic process as

\[ \mu(s_i, t_j) = \sum_{k=1}^{p} x_k(s_i, t_j) \beta_k, \]

where \( x_1(s_i, t_j), ..., x_p(s_i, t_j) \) are known functions of \( (s_i, t_j) \), and \( \beta_1, ..., \beta_p \) are unknown parameters to be estimated. Equivalently, in matrix notation, we have the spatio-temporal linear model as follows:

\[ Y = X\beta + Z + \epsilon, \]

\[ Z \sim N(0, \sigma^2 \Omega_{\phi \rho}), \]

\[ \epsilon \sim N(0, \tau^2 I_m). \]

Therefore the spatio-temporal process, \( Y \), has normal distribution with mean \( E[Y] = X\beta \) and variance \( \Sigma = \sigma^2 \Omega_{\phi \rho} + \tau^2 I_m \). We assume that \( \Sigma \) is non-singular and \( X \) has full rank.

The estimation process was computed via SAEM algorithm initially proposed by Delyon et al. (1999).
m.results A list given by:

theta     final estimation of $\theta = (\beta, \sigma^2, \tau^2, \phi, \rho)$.
Theta     estimated parameters in all iterations, $\theta = (\beta, \sigma^2, \tau^2, \phi, \rho)$.
beta      estimated $\beta$.
sigma2     estimated $\sigma^2$.
tau2       estimated $\tau^2$.
phi        estimated $\phi$.
rho        estimated $\rho$.
Eff.range  estimated effective range.
PsiInv     estimated $\Psi^{-1}$, where $\Psi = \Sigma/\sigma^2$.
Cov        estimated $\Sigma$.
SAEMy      stochastic approximation of the first moment for the truncated normal distribution.
SAEMyy     stochastic approximation of the second moment for the truncated normal distribution.
Hessian    Hessian matrix, the negative of the conditional expected second derivative matrix given the observed values.
Louis      the observed information matrix using the Louis’ method.
loglik     log likelihood for SAEM method.
AIC        Akaike information criteria.
BIC        Bayesian information criteria.
AICcorr    corrected AIC by the number of parameters.
iteration  number of iterations needed to convergence.

Author(s)
Katherine L. Valeriano, Victor H. Lachos and Larissa A. Matos

Examples

## Not run:
# Simulating data
# Initial parameter values
beta <- c(-1,1.50)
phi <- 5; rho <- 0.45
tau2 <- 0.80; sigma2 <- 1.5
n1 <- 5  # Number of spatial locations
n2 <- 5  # Number of temporal index
set.seed(1000)
x.coord <- round(runif(n1,0,10),9)  # X coordinate
y.coord <- round(runif(n1,0,10),9)  # Y coordinate
coord <- cbind(x.coord,y.coord)      # Cartesian coordinates without repetitions
coord2 <- cbind(rep(x.coord,each=n2),rep(y.coord,each=n2)) # Cartesian coordinates with repetitions
time <- as.matrix(seq(1,n2))        # Time index without repetitions
time2 <- as.matrix(rep(time,n1))  # Time index with repetitions
x1 <- rexp(n1*n2,2)
x2 <- rnorm(n1*n2,2,1)
x <- cbind(x1,x2)
media <- x%*%beta
# Covariance matrix
Ms <- as.matrix(dist(coord))  # Spatial distances
Mt <- as.matrix(dist(time))  # Temporal distances
Cov <- CovarianceM(phi,rho,tau2,sigma2,Ms,Mt,1.5,"matern")
# Data
require(mvtnorm)
y <- as.vector(rmvnorm(1,mean=as.vector(media),sigma=Cov))
perc <- 0.20
aa <- sort(y); bb <- aa[1:(perc*n1*n2)]; cutof <- bb[perc*n1*n2]
cc <- matrix(1,(n1*n2),1)*(y<=cutof)
y[cc==1] <- cutof
LI <- y; LI[cc==1] <- -Inf  # Left-censored
LS <- y
# Estimation
est_teste <- EstStempCens(y, x, cc, time2, coord2, LI, LS, init.phi=3.5,
init.rho=0.5, init.tau2=0.7, tau2.fixo=FALSE, kappa=1.5,
type.S="matern", IMatrix=TRUE, M=20, perc=0.25,
MaxIter=300, pc=0.2)
## End(Not run)

---

PredStempCens  

**Prediction in spatio-temporal model with censored/missing responses**

**Description**

This function performs spatio-temporal prediction in a set of new S spatial locations for fixed time points.

**Usage**

`PredStempCens(Est.StempCens, locPre, timePre, xPre)`

**Arguments**

- **Est.StempCens** an object of class `Est.StempCens` given as output by the `EstStempCens` function.
- **locPre** a matrix of coordinates for which prediction is performed.
- **timePre** the time point vector for which prediction is performed.
- **xPre** a matrix of covariates for which prediction is performed.
**Value**

The function returns an object of class `Pred.StempCens` which is a list given by:

- `predValues` predicted values.
- `VarPred` predicted covariance matrix.

**Author(s)**

Katherine L. Valeriano, Victor H. Lachos and Larissa A. Matos

**See Also**

`EstStempCens`

**Examples**

```r
## Not run:
# Initial parameter values
beta <- c(-1,1.50)
phi <- 5; rho <- 0.60
tau2 <- 0.80; sigma2 <- 2
# Simulating data
n1 <- 17  # Number of spatial locations
n2 <- 5   # Number of temporal index
set.seed(12345)
x.co <- round(runif(n1,0,10),9)  # X coordinate
y.co <- round(runif(n1,0,10),9)  # Y coordinate
coord <- cbind(x.co,y.co)         # Cartesian coordinates without repetitions
coord2 <- cbind(rep(x.co,each=n2),rep(y.co,each=n2)) # Cartesian coordinates with repetitions
time <- as.matrix(seq(1,n2))     # Time index without repetitions
time2 <- as.matrix(rep(time,n1)) # Time index with repetitions
x1 <- rexp(n1*n2,2)
x2 <- rnorm(n1*n2,2,1)
x <- cbind(x1,x2)
media <- x%*%beta
# Covariance matrix
Ms <- as.matrix(dist(coord))  # Spatial distances
Mt <- as.matrix(dist(time))  # Temporal distances
Cov <- CovarianceM(phi,rho,tau2,sigma2,Ms,Mt,0.50,"pow.exp")
# Data
require(mvtnorm)
y <- as.vector(rmvnorm(1,mean=as.vector(media),sigma=Cov))
data <- data.frame(coord2,time2,y,x)
names(data) <- c("x.coord","y.coord","time","yObs","x1","x2")
# Splitting the dataset
local.est <- coord[-c(4,13),]
data.est <- data[data$x.coord%in%local.est[,1]&data$y.coord%in%local.est[,2],]
data.valid <- data[data$x.coord%in%coord[c(4,13),1]&data$y.coord%in%coord[c(4,13),2],]
# Censored
perc <- 0.10
y <- data.est$yObs
```

aa <- sort(y); bb <- aa[1:((perc*nrow(data.est)))]
cutoff <- bb[(perc*nrow(data.est))]
cc <- matrix(1,nrow(data.est),1)*(y<=cutoff)
y[cc==1] <- cutoff
data.est <- cbind(data.est[-c(4,5,6)],y,cc,data.est[,c(5,6)])

# Estimation
y <- data.est$yObs
x <- cbind(data.est$x1,data.est$x2)
cc <- data.est$censored
time2 <- matrix(data.est$time)
coord2 <- data.est[,1:2]
LI <- y; LI[cc==1] <- -Inf  # Left-censored
LS <- y
est_teste <- EstStempCens(y, x, cc, time2, coord2, LI, LS, init.phi=3.5,
                          init.rho=0.5, init.tau2=1, kappa=0.5, type.S="pow.exp",
                          IMatrix=FALSE, M=20, perc=0.25, MaxIter=300, pc=0.20)
class(est_teste)

# Prediction
locPre <- data.valid[,1:2]
timePre <- matrix(data.valid$time)
xPre <- cbind(data.valid$x1,data.valid$x2)
pre_teste <- PredStempCens(est_teste, locPre, timePre, xPre)
library(ggplot2)
Model <- rep(c("y Observed","y Predicted"),each=10)
station <- rep(rep(c("Station 1", "Station 2"),each=5),times=2)
xcoord1 <- rep(seq(1:5),4)
ycoord1 <- c(data.valid$yObs,pre_teste$predValues)
data2 <- data.frame(Model,station,xcoord1,ycoord1)
ggplot(data=data2,aes(x=xcoord1,y=ycoord1)) + geom_line(aes(color=Model)) +
facett_wrap(station~.,nrow=2) + labs(x="",y="") + theme(legend.position="bottom")
## End(Not run)
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