Package ‘fdaconcur’

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Description Provides an implementation of concurrent or varying coefficient regression methods for functional data. The implementations are done for both dense and sparsely observed functional data. Pointwise confidence bands can be constructed for each case. Further, the influence of past predictor values are modeled by a smooth history index function, while the effects on the response are described by smooth varying coefficient functions, which are very useful in analyzing real data such as COVID data.
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Functional Concurrent Regression with Lag Model

Description


Usage

ConcReg_Lag(Y, X, Lag = NULL, optnsY = NULL, optnsX = NULL)

Arguments

Y
  a list which contains functional responses in the form of a list LY and the time points LT at which they are observed (i.e., list(Ly = LY, Lt = LT)).

X
  a list of lists which contains the observed functional predictors list Lxj and the time points list Ltj at which they are observed. It needs to be of the form list(list(Ly = Lx1, Lt = Lxt1), list(Ly = Lx2, Lt = Lxt2), ...).

Lag
  a length length(X) vector denoting the lags for all predictors.

optnsY
  a list of options control parameters for the response specified by list(name=value). See ‘Details’ in fdapace::FPCA.

optnsX
  a list of options control parameters for the predictors specified by list(name=value). See ‘Details’ in fdapace::FPCA.
Details

The functional concurrent regression model with lag is defined as

\[ E[Y(t)|X_1(t), \ldots, X_p(t)] = \beta_0(t) + \sum_{j=1}^{p} \beta_j(t) X_j(t - \text{Lag}[j]) \]


Value

A list of the following:

- **beta0**: a vector of \text{length(workGridY)} representing the fitted \(\beta_0(t)\)
- **beta**: A matrix for the concurrent regression effects, where rows correspond to different predictors and columns to different time points.
- **workGridY**: a vector representing the working grid for the response.
- **Lag**: a vector representing the lags for all predictors

References


Examples

```r
phi1 <- function(t) sin(pi*t / 5) / sqrt(5)
phi2 <- function(t) cos(pi*t / 5) / sqrt(5)
lambdaX <- c(10, 5)
n <- 50
N <- 101
Xi <- matrix(rnorm(2*n), nrow = n, ncol = 2)
denseLt <- list()
denseLy <- list()
t0 <- seq(0, 15, length.out = N)
for (i in 1:n) {
  denseLt[[i]] <- t0
  denseLy[[i]] <- lambdaX[1]*Xi[i, 1]*phi1(t0) + lambdaX[2]*Xi[i, 2]*phi2(t0)
}
denseX0 <- list(Ly = denseLy,Lt = denseLt)
Lag <- c(3)
t0_out <- t0[t0>=max(Lag)]
beta_1 <- function(t) 5*sin(pi*t/10)
beta_0 <- function(t) t^2/2
### functional response Y(t), t in t0_out ###
```
ConcurReg <- list()
denseLy <- list()
for (i in 1:n) {
  denseLt[[i]] <- t0_out
  denseLy[[i]] <- beta_0(t0_out) +
  denseX0$Ly[[i]][1:length(t0_out)]* beta_1(t0_out) +
  rnorm(length(t0_out), 0, 0.1)
}
denseY <- list(Ly = denseLy, Lt = denseLt)
model = ConcReg_Lag(Y=denseY, X=list(X1 = denseX0), Lag=Lag)
print(model$workGridY) # workGrid for Y between 6 to 15
plot(beta_1(model$workGridY)) # workGrid for X1 between 3 to 12
plot(beta_0(model$workGridY))
plot(model$beta[1,])
plot(model$beta0)

ConcurReg

Functional Concurrent Regression using 2D smoothing

Description

Functional concurrent regression with dense or sparse functional data for scalar or functional dependent variables. Note: function-to-scalar regression can also be handled using the VCAM function in fdapace.

Usage

ConcurReg(
  vars,
  outGrid,
  userBwMu = NULL,
  userBwCov = NULL,
  kern = "gauss",
  measurementError = FALSE,
  diag1D = "all",
  useGAM = FALSE,
  returnCov = TRUE
)

Arguments

vars A list of input functional/scalar covariates. Each field corresponds to a functional (a list) or scalar (a vector) covariate. The last entry is assumed to be the response if no entry is named 'Y'. If a field corresponds to a functional covariate, it should have two fields: 'Lt', a list of time points, and 'Ly', a list of functional values.
A vector of output time points.

A scalar/vector bandwidth used for smoothing the mean function. Each entry in the vector represents the bandwidth used for the corresponding covariate in `vars`. For the scalar covariates, you can input 0 as a placeholder. If you only input a scalar, the function will use the same bandwidth to smooth all mean functions. — a scalar/vector of positive numeric - default: NULL — if no scalar/vector value is provided, the bandwidth value for the smoothed mean function is chosen using 'GCV';

A scalar/vector bandwidth used for smoothing the auto or cross-covariances. If you use 1D smoothing for the diagonal line of the covariance (diag1D="all"), only one scalar input is needed. If you use 2D smoothing for the covariance (diag1D="none"), a vector of bandwidth is required. Each entry in the vector represents the bandwidth used for the corresponding covariate in `vars`. For the scalar covariates, you can input 0 as a placeholder. — a scalar/vector of positive numeric - default: NULL — if no scalar/vector is provided, the bandwidth value for the smoothed cross-covariance function is chosen using 'GCV';

Smoothing kernel choice, common for mu and covariance; "rect", "gauss", "epan", "gausvar", "quar" - default: "gauss".

Assume measurement error in the data; logical - default: FALSE. If TRUE the diagonal raw covariance will be removed when smoothing.

A string specifying whether to use 1D smoothing for the diagonal line of the covariance. 'none': don’t use 1D smoothing; 'all': use 1D for both auto- and cross-covariances. (default : 'all')

Use GAM smoothing instead of local linear smoothing (semi-parametric option); logical - default: FALSE.

Return the covariance surfaces, which is a four dimensional array. The first two dimensions correspond to `outGrid` and the last two correspond to the covariates and the response, i.e. (i, j, k, l) entry being Cov(X_k(t_i), X_l(t_j)); logical - default: FALSE.

If measurement error is assumed, the diagonal elements of the raw covariance will be removed. This could result in highly unstable estimate if the design is very sparse, or strong seasonality presents. WARNING! For very sparse functional data, setting measurementError = TRUE is not recommended.

A list containing the following fields:

A matrix for the concurrent regression effects, where rows correspond to different predictors and columns to different time points.

A vector containing the time-varying intercept.

A vector of the output time points.
cov  A 4-dimensional array for the (cross-)covariance surfaces, with the (i, j, k, l) entry being Cov(X_k(t_i), X_l(t_j))
R2  A vector of the time-varying R2.
n  The sample size.

References


Examples

```r
# Y(t) = beta_0(t) + beta_1(t) X_1(t) + beta_2(t) Z_2 + epsilon
#
# Settings
set.seed(1)
n <- 30
nGridIn <- 50
sparsity <- 5:10 # Sparse data sparsity
T <- round(seq(0, 1, length.out=nGridIn), 4) # Functional data support
bw <- 0.1
outGrid <- round(seq(min(T), 1, by=0.05), 2)
# Simulate functional data
mu <- T * 2 # mean function for X_1
sigma <- 1
beta_0 <- 0
beta <- rbind(cos(T), 1.5 + sin(T))
beta_2 <- 1
Z <- MASS::mvrnorm(n, rep(0, 2), diag(2))
X_1 <- Z[, 1, drop=FALSE] %*% matrix(1, 1, nGridIn) + matrix(mu, n, nGridIn, byrow=TRUE)
epsilon <- rnorm(n, sd=sigma)
Y <- matrix(NA, n, nGridIn)
for (i in seq_len(n)) {
  Y[i, ] <- beta_0 + beta[1,]*X_1[i, ] + beta[2,]*Z[i, 2] + epsilon[i]
}

# Sparsify functional data
set.seed(1)
X_1sp <- fdapace::Sparsify(X_1, T, sparsity)
set.seed(1)
Ysp <- fdapace::Sparsify(Y, T, sparsity)
vars <- list(X_1=X_1sp, Z_2=Z[, 2], Y=Ysp)
res2 <- ConcurReg(vars, outGrid, userBwMu=c(.5,0,.5), userBwCov=c(.5,0,.5), kern='gauss', measurementError=TRUE, diag1D='none', useGAM = FALSE, returnCov=TRUE)
```
Description

This package provides tools for functional concurrent regression and history index models.

Details

fdaconcur for Functional Concurrent Regression and History Index Models

Provides an implementation of concurrent or varying coefficient regression methods for functional data. The implementations are done for both dense and sparsely observed functional data. Pointwise confidence bands can be constructed for each case. Further, the influence of past predictor values are modeled by a smooth history index function, while the effects on the response are described by smooth varying coefficient functions, which are very useful in analyzing real data such as COVID data.


PACE is based on the idea that observed functional data are generated by a sample of underlying (but usually not fully observed) random trajectories that are realizations of a stochastic process. It does not rely on pre-smoothing of trajectories, which is problematic if functional data are sparsely sampled.

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See Also

Useful links:

- https://github.com/functionaldata/tFDAconcur
- Report bugs at https://github.com/functionaldata/tFDAconcur/issues
fitted_ptFCReg

Fitted functional responses from a ptFCReg object.

Description

Fitted functional responses from a ptFCReg object.

Usage

fitted_ptFCReg(object)

Arguments

object

An object of class ptFCReg, returned by ptFCReg or smPtFCRegCoef.

Value

An $n$-by-$m$ matrix, where each row corresponds to one subject, and each column corresponds to a time point in object$tGrid$.

Examples

```r
set.seed(1)
n <- 50
nGridIn <- 101
tGrid <- seq(0, 1, length.out=nGridIn) # Functional data support
muX1 <- tGrid * 2 # mean function for X_1
sigma <- 1
beta0 <- 0
beta <- rbind(cos(tGrid), 1.5 + sin(tGrid))
Z <- MASS::mvrnorm(n, rep(0, 2), diag(2))
X_1 <- Z[, 1, drop=FALSE] %*% matrix(1, 1, nGridIn) + matrix(muX1, n, nGridIn, byrow=TRUE)
epsilon <- rnorm(n, sd=sigma)
Y <- t(sapply(seq_len(n), function(i) {
  beta0 + beta[1,] * X_1[i, ] + beta[2,] * Z[i, 2] + epsilon[i]
}))
dat <- list(X1=X_1, Z1=Z[, 2], Y=Y)
res <- ptFCReg(tGrid = tGrid, dat = dat)
smres <- smPtFCRegCoef(res, bw = 2.5 / (nGridIn-1), kernel_type = 'epan')
fit_res <- stats::fitted(res)
fit_smres <- stats::fitted(smres)
```
GetCI_Dense

**Description**

Bootstrap pointwise confidence intervals for the coefficient functions in functional concurrent regression for densely observed data.

**Usage**

GetCI_Dense(dat, tGrid, level = 0.95, R = 10, bw, kernel_type)

**Arguments**

- **dat**
  A list of input functional/scalar covariates. Each field corresponds to a functional (a matrix) or scalar (a vector) variable. The last entry is assumed to be the functional response if no entry is names 'Y'. If a field corresponds to a functional variable, it should be an \( n \times m \) matrix, where each row holds the observations for one subject on the common grid \( t\text{Grid} \). If a field corresponds to a scalar covariate, it should be a vector of length \( n \).

- **tGrid**
  A vector of length \( m \) with the input time points.

- **level**
  A number taking values in \([0,1]\) determining the confidence level. Default: 0.95.

- **R**
  An integer holding the number of bootstrap replicates. Default: 999.

- **bw**
  Scalar holding the bandwidth.

- **kernel_type**
  Character holding the kernel type (see \texttt{Lwls1D} for supported kernels).

**Value**

A list containing the following fields:

- **CI_beta0**  CI for the intercept function — A data frame holding three variables: \( \text{CI\_grid} \) — the time grid where the CIs are evaluated; \( \text{CI\_beta0\_lower} \) and \( \text{CI\_beta0\_upper} \) — the lower and upper bounds of the CIs for the intercept function on \( \text{CI\_grid} \).

- **CI_beta**  A list containing CIs for the slope functions — the length of the list is same as the number of covariates. Each list contains the following fields: A data frame holding three variables: \( \text{CI\_grid} \) — the time grid where the CIs are evaluated, \( \text{CI\_beta\_j\_lower} \) and \( \text{CI\_beta\_j\_upper} \) — the lower and upper bounds of the CIs for the intercept function on \( \text{CI\_grid} \) for \( j = 1, 2, \ldots \).

- **CI_R2**  CI the time-varying \( R^2(t) \) — A data frame holding three variables: \( \text{CI\_grid} \) — the time grid where the CIs are evaluated, \( \text{CI\_R2\_lower} \) and \( \text{CI\_R2\_upper} \) — the lower and upper bounds of the CIs for the time-varying \( R^2(t) \) on \( \text{CI\_grid} \).

- **level**  The confidence level of the CIs.
GetCI_Sparse

Bootstrap pointwise confidence intervals for the coefficient functions in functional concurrent regression for sparsely observed data.

Description

Bootstrap pointwise confidence intervals for the coefficient functions in functional concurrent regression for sparsely observed data.

Usage

GetCI_Sparse(
  vars,
  outGrid = NULL,
  level = 0.95,
  R = 999,
  userBwMu = NULL,
)
userBwCov = NULL,
kern = "gauss",
measurementError = FALSE,
diag1D = "all",
useGAM = FALSE)

Arguments

vars
A list of input functional/scalar covariates. Each field corresponds to a functional (a list) or scalar (a vector) covariate. The last entry is assumed to be the response if no entry is named 'Y'. If a field corresponds to a functional covariate, it should have two fields: 'Lt', a list of time points, and 'Ly', a list of functional values.

outGrid
A vector with the output time points, which need to be within 5% and 95% of the range of functional covariates. If NULL, outGrid will be generated from 5% to 95% of the range of functional covariates with 51 grids for fitting. Default: NULL

level
A number taking values in [0,1] determining the confidence level. Default: 0.95.

R
An integer holding the number of bootstrap replicates. Default: 999.

userBwMu
A scalar/vector bandwidth used for smoothing the mean function. Each entry in the vector represents the bandwidth used for the corresponding covariate in vars. For the scalar covariates, you can input 0 as a placeholder. If you only input a scalar, the function will use the same bandwidth to smooth all mean functions. — a scalar/vector of positive numeric - default: NULL — if no scalar/vector value is provided, the bandwidth value for the smoothed mean function is chosen using 'GCV';

userBwCov
A scalar/vector bandwidth used for smoothing the auto or cross-covariances. If you use 1D smoothing for the diagonal line of the covariance (diag1D="all"), only one scalar input is needed. If you use 2D smoothing for the covariance (diag1D="none"), a vector of bandwidth is required. Each entry in the vector represents the bandwidth used for the corresponding covariate in vars. For the scalar covariates, you can input 0 as a placeholder. — a scalar/vector of positive numeric - default: NULL — if no scalar/vector is provided, the bandwidth value for the smoothed cross-covariance function is chosen using 'GCV';

kern
Smoothing kernel choice, common for mu and covariance; "rect", "gauss", "epan", "gausvar", "quar" (default: "gauss")

measurementError
Assume measurement error in the data; logical - default: FALSE. If TRUE the diagonal raw covariance will be removed when smoothing.

diag1D
A string specifying whether to use 1D smoothing for the diagonal line of the covariance. 'none': don’t use 1D smoothing; 'all': use 1D for both auto- and cross-covariances. (default : 'all')

useGAM
Use GAM smoothing instead of local linear smoothing (semi-parametric option); logical - default: FALSE.
Details

If measurement error is assumed, the diagonal elements of the raw covariance will be removed. This could result in highly unstable estimate if the design is very sparse, or strong seasonality presents. **WARNING!** For very sparse functional data, setting `measurementError = TRUE` is not recommended.

Value

A list containing the following fields:

- **CI_beta0**  CI for the intercept function — A data frame holding three variables: CIgrid — the time grid where the CIs are evaluated, CI_beta0.lower and CI_beta0.upper — the lower and upper bounds of the CIs for the intercept function on CIgrid.

- **CI_beta**  A list containing CIs for the slope functions — the length of the list is same as the number of covariates. Each list contains the following fields: A data frame holding three variables: CIgrid — the time grid where the CIs are evaluated, CI_beta_j.lower and CI_beta_j.upper — the lower and upper bounds of the CIs for the coefficient functions on CIgrid for \( j = 1, 2, \ldots \).

- **CI_R2**  CI the time-varying \( R^2(t) \) — A data frame holding three variables: CIgrid — the time grid where the CIs are evaluated, CI_R2.lower and CI_R2.upper — the lower and upper bounds of the CIs for the time-varying \( R^2(t) \) on CIgrid.

- **level**  The confidence level of the CIs.

Examples

```r
set.seed(1)
n <- 30
nGridIn <- 100
sparsity <- 5:10 # Sparse data sparsity
T <- round(seq(0, 1, length.out=nGridIn), 4) # Functional data support
bw <- 0.1
outGrid <- round(seq(min(T), 1, by=0.05), 2)
# Simulate functional data
mu <- T * 2 # mean function for X_1
sigma <- 1
beta_0 <- 0
beta <- rbind(cos(T), 1.5 + sin(T))
beta_2 <- 1
Z <- MASS::mvrnorm(n, rep(0, 2), diag(2))
X_1 <- Z[, 1, drop=FALSE] %*% matrix(1, 1, nGridIn) + matrix(mu, n, nGridIn, byrow=TRUE)
epsilon <- rnorm(n, sd=sigma)
Y <- matrix(NA, n, nGridIn)
for (i in seq_len(n)) {
  Y[i, ] <- beta_0 + beta[1,] * X_1[i, ] + beta[2,] * Z[i, 2] + epsilon[i]
}
# Sparsify functional data
set.seed(1)
```

GetCI_Sparse
X_1sp <- fdapace::Sparsify(X_1, T, sparsity)
Ysp <- fdapace::Sparsify(Y, T, sparsity)
vars <- list(X_1=X_1sp, Z_2=Z[, 2], Y=Ysp)
res <- GetCI_Sparse(vars, outGrid[-c(1,21)], level = 0.95, R = 2,
userBwMu = c(.1,.1,.1), userBwCov = c(.1,.1,.1),
kern='gauss', measurementError=TRUE, diag1D='none',
useGAM = FALSE)

historyIndexDense

Functional History Index Model

Description


Usage

historyIndexDense(Y, X, Lag = NULL, optnsY = NULL, optnsX = NULL)

Arguments

Y
a list which contains functional responses in the form of a list LY and the time points LT at which they are observed (i.e., list(Ly = LY ,Lt = LT)).

X
a list of lists which contains the observed functional predictors list Lxj and the time points list Lxj at which they are observed. It needs to be of the form list(list(Ly = Lx1,Lt = Lxt1),list(Ly = Lx2,Lt = Lxt2),...).

Lag
a length length(X) vector denoting the lags for all predictors.

optnsY
a list of options control parameters for the response specified by list(name=value). See ‘Details’ in fdapace::FPCA.

optnsX
a list of options control parameters for the predictors specified by list(name=value). See ‘Details’ in fdapace::FPCA.

Details

The functional history index model is defined as $E[Y(t)|X_1(t), \cdots, X_p(t)] = \beta_0(t) + \sum_{i=1}^p \beta_i(t) \int_0^{\Delta_i} \gamma_i(s) X_i(t-s) ds$ for $t \in \max_i \{\Delta_i\}, T] $ with a suitable $T > 0$. Write $\alpha_i(t,s) = \beta_i(t) \gamma_i(s)$. It becomes $E[Y(t)|X_1(t), \cdots, X_p(t)] = \beta_0(t) + \sum_{i=1}^p \int_0^{\Delta_i} \alpha_i(t,s) X_i(t-s) ds$. For more details we refer to Şentürk, D. and Müller, H.G., (2010). Functional varying coefficient models for longitudinal data. Journal of the American Statistical Association, 105(491), pp.1256-1264.

Value

A list of the following:

- beta0 a vector of length(workGridY) representing the fitted $\beta_0(t)$
- alpha a list of matrices with the $i$-th element representing the fitted $\alpha_i(t,s)$
- yHat an n by length(workGridY) matrix of fitted $Y_i(t)$’s.
- workGridY a vetor representing the working grid for the response.
- workGridLag a list of vectors with the $i$-th element representing the working grid in $[0, \Delta_i]$. 

\[ E[Y(t)|X_1(t), \cdots, X_p(t)] = \beta_0(t) + \sum_{i=1}^p \int_0^{\Delta_i} \alpha_i(t,s) X_i(t-s) ds \]
References


Examples

```r
set.seed(1)
### functional covariate X(t) ###
phi1 <- function(t) sin(pi*t / 5) / sqrt(5)
phi2 <- function(t) cos(pi*t / 5) / sqrt(5)
lambdaX <- c(10, 5)
n <- 150
N <- 101
Xi <- matrix(rnorm(2*n), nrow = n, ncol = 2)
denseLt <- list()
denseLy <- list()
t0 <- seq(0, 15, length.out = N)
for (i in 1:n) {
  denseLt[[i]] <- t0
  denseLy[[i]] <- lambdaX[1]*Xi[i, 1]*phi1(t0) + lambdaX[2]*Xi[i, 2]*phi2(t0)
}
denseX0 <- list(Ly = denseLy, Lt = denseLt)

### generate coefficient function gamma(u), beta(u) ###
Lag <- 5
u0 <- t0[t0<=Lag]
t0_out <- t0[t0>=Lag]
gamma_u <- function(u) sqrt(2/5) * cos(pi * u /5)
beta_1 <- function(t) 5*sin(pi*t/10)
beta_0 <- function(t) t^2/2

### functional response Y(t), t in t0_out ###
denseLt <- list()
denseLy <- list()
for (i in 1:n) {
  denseLt[[i]] <- t0_out
  Xt <- denseX0$Ly[[i]]
  Xt_u <- t(sapply((1:N)[t0>=Lag], function(j){
    rev(Xt[(j-length(u0)+1):j]) #history index for X[t-u:t]
  }))
  IntGammaXtu <- apply(Xt_u, 1, function(v){
    fdapace::trapzRcpp(u0, gamma_u(u0) * v)
  })
  denseLy[[i]] <- beta_0(t0_out) + IntGammaXtu * beta_1(t0_out) + rnorm(length(t0_out), 0, 0.1)
}
denseY <- list(Ly = denseLy, Lt = denseLt)

### functional predictor X(t) (adjust for t0_out) ###
```
```r
denseLt <- list()
denseLy <- list()
for (i in 1:n)
{
  denseLt[[i]] <- t0_out
  denseLy[[i]] <- denseX0$Ly[[i]][t0>=Lag]
}
denseX <- list(Ly = denseLy,
  Lt = denseLt)
fit <- historyIndexDense(Y = denseY, X = list(X = denseX), Lag = Lag)
fit$beta0
fit$alpha[[1]]
```

---

**historyIndexSparse**  
**Functional History Index Model**

**Description**


**Usage**

```r
historyIndexSparse(Y, X, Lag = NULL, optnsY = NULL, optnsX = NULL)
```

**Arguments**

- **Y**  
  A list which contains functional responses in the form of a list LY and the time points LT at which they are observed (i.e., list(Ly = LY, Lt = LT)).

- **X**  
  A list of lists which contains the observed functional predictors list Lxj and the time points list Ltj at which they are observed. It needs to be of the form list(list(Ly = Lx1, Lt = Lxt1), list(Ly = Lx2, Lt = Lxt2), ...).

- **Lag**  
  A length length(X) vector denoting the lags for all predictors.

- **optnsY**  
  A list of options control parameters for the response specified by list(name=value). See ‘Details’ in FPCA.

- **optnsX**  
  A list of options control parameters for the predictors specified by list(name=value). See ‘Details’ in FPCA.

**Details**

The functional history index model is defined as $E[Y(t)|X_1(t), \ldots, X_p(t)] = \beta_0(t) + \sum_{j=1}^p \beta_j(t) \int_0^{\Delta_j} \gamma_j(s) X_j(t-s) ds$ for $t \in [\max_j \{\Delta_j\}, T]$ with a suitable $T > 0$. Write $\alpha_j(t, s) = \beta_j(t) \gamma_j(s)$. It becomes $E[Y(t)|X_1(t), \ldots, X_p(t)] = \beta_0(t) + \sum_{j=1}^p \int_0^{\Delta_j} \alpha_j(t, s) X_j(t-s) ds$. For more details we refer to Şentürk, D. and Müller, H.G., (2010). Functional varying coefficient models for longitudinal data. *Journal of the American Statistical Association*, 105(491), pp.1256-1264.
Value

A list of the following:

- \( \beta_0 \): a vector of length(workGridY) representing the fitted \( \beta_0(t) \).
- \( \beta_j \): a list of vectors with the \( j \)-th element representing the fitted \( \beta_j(t) \).
- \( \gamma_j \): a list of vectors with the \( j \)-th element representing the fitted \( \gamma_j(s) \).
- workGridY: a vector representing the working grid for the response.
- workGridLag: a list of vectors with the \( j \)-th element representing the working grid in \([0, \Delta_j]\).

References


Examples

```r
set.seed(1)
### functional covariate X(t) ###
phi1 <- function(t) sin(pi*t / 5) / sqrt(5)
phi2 <- function(t) cos(pi*t / 5) / sqrt(5)
lambdaX <- c(10, 5)
n <- 150
N <- 101
Xi <- matrix(rnorm(2*n), nrow = n, ncol = 2)
denseLt <- list()
denseLy <- list()
t0 <- seq(0, 15, length.out = N)
for (i in 1:n) {
denseLt[i] <- t0
denseLy[i] <- lambdaX[1]*Xi[i, 1]*phi1(t0) + lambdaX[2]*Xi[i, 2]*phi2(t0)
}
denseX0 <- list(Ly = denseLy,Lt = denseLt)

### generate coefficient function gamma(u), beta(u) ###
Lag <- 5
u0 <- t0[t0<=Lag]
t0_out <- t0[t0>Lag]
gamma_u <- function(u) sqrt(2/5) * cos(pi * u /5)
beta_1 <- function(t) 5*sin(pi*t/10)
beta_0 <- function(t) t^2/2

### functional response Y(t), t in t0_out ###
denseLt <- list()
denseLy <- list()
for (i in 1:n) {
denseLt[i] <- t0_out
Xt <- denseX0$Ly[[i]]
```
ptFCReg

Functional concurrent regression using pointwise multiple linear regression.

Description

Functional concurrent regression using pointwise multiple linear regression.

Usage

ptFCReg(tGrid, dat)
Arguments

- **tGrid**: A vector of length \( n \) with the input time points.
- **dat**: A list of input functional/scalar covariates. Each field corresponds to a functional (a matrix) or scalar (a vector) variable. The last entry is assumed to be the functional response if no entry is names 'Y'. If a field corresponds to a functional variable, it should be an \( n \)-by-\( m \) matrix, where each row holds the observations for one subject on the common grid \( tGrid \). If a field corresponds to a scalar covariate, it should be a vector of length \( n \).

Value

A list containing the following fields:

- **beta0**: A vector containing the time-varying intercept evaluated on \( tGrid \).
- **beta**: A matrix for the concurrent regression effects, where rows correspond to different predictors and columns to different time points in \( tGrid \).
- **tGrid**: The input \( tGrid \).
- **R2**: A vector of the time-varying \( R^2(t) \), evaluated at \( t \) in \( tGrid \).
- **Ldf**: A list holding the input data, each element of which is a data frame holding the data observed at one element of \( tGrid \).

Examples

```r
set.seed(1)
n <- 50
nGridIn <- 101
tGrid <- seq(0, 1, length.out=nGridIn) # Functional data support
muX1 <- tGrid * 2 # mean function for X_1
sigma <- 1
beta0 <- 0
beta <- rbind(cos(tGrid), 1.5 + sin(tGrid))
Z <- MASS::mvrnorm(n, rep(0, 2), diag(2))
X_1 <- Z[, 1, drop=FALSE] %*% matrix(1, 1, nGridIn) + matrix(muX1, n, nGridIn, byrow=TRUE)
epsilon <- rnorm(n, sd=sigma)
Y <- sapply(seq_len(n), function(i) {
  beta0 + beta[1,] * X_1[i, ] + beta[2,] * Z[i, 2] + epsilon[i]
})
dat <- list(X1=X_1, Z1=Z[, 2], Y=Y)
res <- ptFCReg(tGrid = tGrid, dat = dat)
```

---

**smPtFCRegCoef**

Smooth the concurrent effects functions in a ptFCReg object using local linear regression. The local linear regression is implemented using the function `Lwls1D`. 
smPtFCRegCoef

Description

Smooth the concurrent effects functions in a ptFCReg object using local linear regression. The local linear regression is implemented using the function Lwls1D.

Usage

smPtFCRegCoef(object, bw, kernel_type)

Arguments

object An object of class ptFCReg returned by the function ptFCReg.
bw Scalar holding the bandwidth.
kernel_type Character holding the kernel type (see Lwls1D for supported kernels).

Value

An object of class ptFCReg, where the fields beta0 and beta hold the smoothed intercept functions and concurrent effects functions, respectively. See ptFCReg for a complete list of the fields.

Examples

set.seed(1)
n <- 50
nGridIn <- 101
tGrid <- seq(0, 1, length.out=nGridIn) # Functional data support
muX1 <- tGrid * 2 # mean function for X_1
sigma <- 1
beta0 <- 0
beta <- rbind(cos(tGrid), 1.5 + sin(tGrid))
Z <- MASS::mvrnorm(n, rep(0, 2), diag(2))
X_1 <- Z[ , 1, drop=FALSE] * matrix(1, n, nGridIn, byrow=TRUE) + matrix(muX1, n, nGridIn, byrow=TRUE)
epsilon <- rnorm(n, sd=sigma)
Y <- t(sapply(seq_len(n), function(i) {
  beta0 + beta[1,] * X_1[i, ] + beta[2,] * Z[i, 2] + epsilon[i]
}))
dat <- list(X1=X_1, Z1=Z[ , 2], Y=Y)
res <- ptFCReg(tGrid = tGrid, dat = dat)
smres <- smPtFCRegCoef(res, bw = 2.5 / (nGridIn-1), kernel_type = 'epan')
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