Package ‘SLFPCA’
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Title Sparse Logistic Functional Principal Component Analysis
Version 2.0
Description Implementation for sparse logistic functional principal component analysis (SLF-PCA). SLFPCA is specifically developed for functional binary data, and the estimated eigenfunction can be strictly zero on some sub-intervals, which is helpful for interpretation. The crucial function of this package is SLFPCA().
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GenBinaryFD Generate binary functional data
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Description

Generate binary functional data through latent process.
Usage

GenBinaryFD(n, interval, sparse, regular, meanfun, score, eigfd)

Arguments

n An integer denoting the number of sample size.
interval A vector of length two denoting the supporting interval.
sparse A vector denoting the possible numbers of observation size. The elements are
chosen with equal chance. The length of sparse must be one if regular = TRUE.
regular Logical; If TRUE, the observation grids are equally-spaced.
meanfun A function for the mean.
score A n by npc matrix containing the FPC scores, where npc is the number of
FPCs.
eigfd A list containing functional objects for the eigenfunctions.

Value

A list containing the following components:

Lt A list of n vectors, where n is the sample size. Each entry contains the obser-
vation time in ascending order for each subject.
Lx A list of n vectors, where n is the sample size. Each entry contains vales of the
latent process of each subject at the observation time correspond to
Lt.
Ly A list of n vectors, where n is the sample size. Each entry contains the binary
measurements of each subject at the observation time correspond to Lt.

Examples

n <- 100
npc <- 2
interval <- c(0, 10)
gridequal <- seq(0, 10, length.out = 51)
basis <- fda::create.bspline.basis(c(0, 10), nbasis = 13, norder = 4,
breaks = seq(0, 10, length.out = 11))
meanfun <- function(t){2 * sin(pi * t/5)/sqrt(5)}
lambda_1 <- 3^2 #the first eigenvalue
lambda_2 <- 2^2 #the second eigenvalue
score <- cbind(rnorm(n, 0, sqrt(lambda_1)), rnorm(n, 0, sqrt(lambda_2)))
eigfun <- list()
eigfun[[1]] <- function(t){cos(pi * t/5)/sqrt(5)}
eigfun[[2]] <- function(t){sin(pi * t/5)/sqrt(5)}
eigfd <- list()
for(i in 1:npc){
    eigfd[[i]] <- fda::smooth.basis(gridequal, eigfun[[i]](gridequal), basis)$fd
}
DataNew <- GenBinaryFD(n, interval, sparse = 8:12, regular = FALSE,
meanfun = meanfun, score, eigfd)
Sparse logistic functional principal component analysis (SLFPCA) for binary data. The estimated eigenfunctions from SLFPCA can be strictly zero on some sub-intervals, which is helpful for interpretation.

Usage

SLFPCA(
  Ly, 
  Lt, 
  interval, 
  npc, 
  L_list, 
  norder, 
  kappa_theta, 
  sparse_pen, 
  nRegGrid = 51, 
  bwmu_init = 0.5, 
  bwcov_init = 1, 
  stepmu, 
  mucand_num = 100, 
  itermax = 100, 
  tol = 0.5
)

Arguments

Ly A list of n vectors, where n is the sample size. Each entry contains the binary measurements of each subject at the observation time correspond to Lt.

Lt A list of n vectors, where n is the sample size. Each entry contains the observation time in ascending order for each subject.

interval A vector of length two denoting the supporting interval.

npc An integer denoting the number of FPCs.

L_list A vector denoting the candidates for the number of B-spline basis functions.

norder An integer denoting the order of the using B-spline basis, which is one higher than their degree.

kappa_theta A vector denoting the smoothing parameters for eigenfunctions, the optimal tuning parameter is chosen from them.

sparse_pen A vector denoting the sparseness parameters for eigenfunctions, the optimal tuning parameter is chosen from them.
nRegGrid  An integer denoting the number of equally spaced time points in the supporting interval. The eigenfunctions and mean function are estimated at these equally spaced time points first, before transforming into functional data object. (default: 51)

bwmu_init  A scalar denoting the bandwidth for mean function estimation in the setting of initial values. (default: 0.5)

bwcov_init  A scalar denoting the bandwidth for covariance function estimation in the setting of initial values. (default: 1)

stepmu  A scalar denoting the length between each considered smoothing parameter for mean function. For selection of smoothing parameter for mean function, we start from zero and increase the value until GCV score begins increasing.

mucand_num  An integer denoting the maximum number of the considered smoothing parameter for mean function. (default: 100)

itermax  An integer denoting the maximum number of iterations. (default: 100)

tol  A scalar. When difference of the loglikelihood functions between two consecutive iteration is less than \( \text{tol} \), the convergence is supposed to be reached. (default: 0.5)

Value

A list containing the following components:

- mufd  A functional data object for the mean function estimate.
- eigfd_list  A list containing npc functional data objects, which are the eigenfunction estimates.
- score  A \( n \) by \( \text{npc} \) matrix containing the estimates of the FPC scores, where \( n \) is the sample size.
- kappa.mu  A scalar denoting the selected smoothing parameter for mean function.
- kappa.theta  A scalar denoting the selected smoothing parameter for eigenfunctions.
- sparse.pen  A scalar denoting the selected sparseness parameter for eigenfunctions.
- L_select  A scalar denoting the selected number of B-spline basis functions.
- EBICscore  A vector denoting the selected EBIC scores corresponding to different numbers of B-spline basis functions in \( L_{\text{list}} \).

References


Examples

#Generate data
n <- 100
npc <- 1
interval <- c(0, 10)
gridequal <- seq(0, 10, length.out = 51)
basis <- fda::create.bspline.basis(c(0, 10), nbasis = 13, norder = 4, 
   breaks = seq(0, 10, length.out = 11))
meanfun <- function(t){2 * sin(pi * t/5)/sqrt(5)}
lambda_1 <- 3^2 # the first eigenvalue
score <- cbind(rnorm(n, 0, sqrt(lambda_1)))
eigfun <- list()
eigfun[[1]] <- function(t){cos(pi * t/5)/sqrt(5)}
eigfd <- list()
for(i in 1:npc){
eigfd[[i]] <- fda::smooth.basis(gridequal, eigfun[[i]](gridequal), basis)$fd
}
DataNew <- GenBinaryFD(n, interval, sparse = 8:12, regular = FALSE, 
   meanfun = meanfun, score, eigfd)
SLFPCA_list <- SLFPCA(DataNew$Ly, DataNew$Lt, interval, npc, L_list = 13, 
   norder = 4, kappa_theta = 0.2, sparse_pen = 0, 
   nRegGrid = 51, stepmu = 0.005)
plot(SLFPCA_list$eigfd_list[[1]])
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