

Package ‘PCA4TS’

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Title Segmenting Multiple Time Series by Contemporaneous Linear Transformation

Version 0.1

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Description To seek for a contemporaneous linear transformation for a multivariate time series such that the transformed series is segmented into several lower-dimensional subseries, and those subseries are uncorrelated with each other both contemporaneously and serially.

Depends R (>= 3.1.1)

Imports tseries

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permutationFDR *Permutation Using the FDR Method*

Description

The permutation is determined by grouping the components of a multivariate series X into q groups, where q and the cardinal numbers of those groups are also unknown.

Usage

```
permutationFDR(X, Vol = FALSE, Beta, m = NULL)
```

Arguments

X	a data matrix used to find the grouping mechanism with n rows and p columns, where n is the sample size and p is the dimension of the time series.
Vol	logical. If FALSE (the default), then prewhiten each series by fitting a univariate AR model with the order between 0 and 5 determined by AIC. If TRUE, then prewhiten each volatility process using GARCH(1,1) model.
Beta	the error rate in FDR
m	a positive constant used to calculate the maximum cross correlation over the lags between $-m$ and m . If m is not specified, the default constant $10 * \log_{10}(n/p)$ will be used.

Details

See Chang et al. (2014) for the permutation step and more information.

Value

An object of class "permutationFDR" is a list containing the following components:

NoGroups	number of groups with at least two components series
Nos_of_Members	number of members in each of groups with at least two members
Groups	indices of components in each of groups with at least two members
Pvalues	Pvalue for multiple test H_0 for each of $p(p-1)/2$ pairs in ascending order
NoConnectedPairs	number of connected pairs
Xpre	the prewhitened data with $n - R$ rows and p columns

Note

This is the second step for segmentation by grouping the transformed time series. The first step is to seek for a contemporaneous linear transformation of the original series, see [segmentTS](#).

Author(s)

Jinyuan Chang, Bin Guo and Qiwei Yao

References

Chang, J., Guo, B. and Yao, Q. (2014). Segmenting Multiple Time Series by Contemporaneous Linear Transformation: PCA for Time Series. Available at <http://arxiv.org/abs/1410.2323>

See Also

[segmentTS](#), [permutationMax](#)

Examples

```
## Example 1 (Example 5 of Chang et al.(2014)).
## p=6, x_t consists of 3 independent subseries with 3, 2 and 1 components.

p=6;n=1500
# Generate x_t
X=mat.or.vec(p,n)
x=arima.sim(model=list(ar=c(0.5, 0.3), ma=c(-0.9, 0.3, 1.2,1.3)),n=n+2,sd=1)
for(i in 1:3) X[i,]=x[i:(n+i-1)]
x=arima.sim(model=list(ar=c(0.8, -0.5),ma=c(1,0.8,1.8) ),n=n+1,sd=1)
for(i in 4:5) X[i,]=x[(i-3):(n+i-4)]
x=arima.sim(model=list(ar=c(-0.7, -0.5), ma=c(-1, -0.8)),n=n,sd=1)
X[6,]=x
# Generate y_t
A=matrix(runif(p*p, -3, 3), ncol=p)
Y=A%*%X
Y=t(Y)
Trans=segmentTS(Y, k0=5)
# The transformed series z_t
Z=Trans$X
# Plot the cross correlogram of x_t and y_t
Z=data.frame(Z)
names(Z)=c("Z1", "Z2", "Z3", "Z4", "Z5", "Z6")
# The cross correlogram of z_t shows 3-2-1 block pattern
acfZ=acf(Z, plot=FALSE)
plot(acfZ, max.mfrow=6, xlab='', ylab='', mar=c(1.8,1.3,1.6,0.5),
      oma=c(1,1.2,1.2,1), mgp=c(0.8,0.4,0),cex.main=1)
# Identify the permutation mechanism
permutation=permutationFDR(Z,Beta=10^(-8))
permutation$Groups

## Example 2 (Example 6 of Chang et al.(2014)).
## p=20, x_t consists of 5 independent subseries with 6, 5, 4, 3 and 2 components.

p=20;n=3000
# Generate x_t
X=mat.or.vec(p,n)
x=arima.sim(model=list(ar=c(0.5, 0.3), ma=c(-0.9, 0.3, 1.2,1.3)),n.start=500,n=n+5,sd=1)
```

```

for(i in 1:6) X[i,]=x[(i-1):(n+i-1)]
x=arima.sim(model=list(ar=c(-0.4,0.5),ma=c(1,0.8,1.5,1.8)),n.start=500,n=n+4,sd=1)
for(i in 7:11) X[i,]=x[(i-6):(n+i-7)]
x=arima.sim(model=list(ar=c(0.85,-0.3),ma=c(1,0.5,1.2)), n.start=500,n=n+3,sd=1)
for(i in 12:15) X[i,]=x[(i-11):(n+i-12)]
x=arima.sim(model=list(ar=c(0.8,-0.5),ma=c(1,0.8,1.8)),n.start=500,n=n+2,sd=1)
for(i in 16:18) X[i,]=x[(i-15):(n+i-16)]
x=arima.sim(model=list(ar=c(-0.7,-0.5),ma=c(-1,-0.8)),n.start=500,n=n+1,sd=1)
for(i in 19:20) X[i,]=x[(i-18):(n+i-19)]
# Generate y_t
A=matrix(runif(p*p, -3, 3), ncol=p)
Y=A%*%X
Y=t(Y)
Trans=segmentTS(Y, k0=5)
# The transformed series z_t
Z=Trans$X
# Identify the permutation mechanism
permutation=permutationFDR(Z,Beta=10^(-200))
permutation$Groups

```

permutationMax

Permutation Using the Maximum Cross Correlation Method

Description

The permutation is determined by grouping the components of a multivariate series X into q groups, where q and the cardinal numbers of those groups are also unknown.

Usage

```
permutationMax(X, Vol = FALSE, m = NULL)
```

Arguments

X	a data matrix used to find the grouping mechanism with n rows and p columns, where n is the sample size and p is the dimension of the time series.
Vol	logical. If FALSE (the default), then prewhiten each series by fitting a univariate AR model with the order between 0 and 5 determined by AIC. If TRUE, then prewhiten each volatility process using GARCH(1,1) model.
m	a positive constant used to calculate the maximum cross correlation over the lags between $-m$ and m . If m is not specified, the default constant $10 * \log_{10}(n/p)$ will be used.

Details

See Chang et al. (2014) for the permutation step and more information.

Value

An object of class "permutationMax" is a list containing the following components:

NoGroups	number of groups with at least two components series
Nos_of_Members	number of members in each of groups with at least two members
Groups	indices of components in each of groups with at least two members
maxcorr	maximum correlation (over lags) of $p(p-1)/2$ pairs in descending order
corrRatio	ratios of successive values from maxcorr
NoConnectedPairs	number of connected pairs
Xpre	the prewhitened data with $n - R$ rows and p columns

Note

This is the second step for segmentation by grouping the transformed time series. The first step is to seek for a contemporaneous linear transformation of the original series, see [segmentTS](#).

Author(s)

Jinyuan Chang, Bin Guo and Qiwei Yao

References

Chang, J., Guo, B. and Yao, Q. (2014). Segmenting Multiple Time Series by Contemporaneous Linear Transformation: PCA for Time Series. Available at <http://arxiv.org/abs/1410.2323>

See Also

[segmentTS](#), [permutationFDR](#)

Examples

```
## Example 1 (Example 5 of Chang et al.(2014)).
## p=6, x_t consists of 3 independent subseries with 3, 2 and 1 components.

p=6;n=1500
# Generate x_t
X=mat.or.vec(p,n)
x=arima.sim(model=list(ar=c(0.5, 0.3), ma=c(-0.9, 0.3, 1.2,1.3)),n=n+2,sd=1)
for(i in 1:3) X[i,]=x[i:(n+i-1)]
x=arima.sim(model=list(ar=c(0.8,-0.5),ma=c(1,0.8,1.8) ),n=n+1,sd=1)
for(i in 4:5) X[i,]=x[(i-3):(n+i-4)]
x=arima.sim(model=list(ar=c(-0.7, -0.5), ma=c(-1, -0.8)),n=n,sd=1)
X[6,]=x
# Generate y_t
A=matrix(runif(p*p, -3, 3), ncol=p)
Y=A%%X
Y=t(Y)
Trans=segmentTS(Y, k0=5)
```

```

# The transformed series z_t
Z=Trans$X
# Plot the cross correlogram of x_t and y_t
Z=data.frame(Z)
names(Z)=c("Z1", "Z2", "Z3", "Z4", "Z5", "Z6")
# The cross correlogram of z_t shows 3-2-1 block pattern
acfZ=acf(Z, plot=FALSE)
plot(acfZ, max.mfrow=6, xlab='', ylab='', mar=c(1.8,1.3,1.6,0.5),
      oma=c(1,1.2,1.2,1), mgp=c(0.8,0.4,0),cex.main=1)
# Identify the permutation mechanism
permutation=permutationMax(Z)
permutation$Groups

## Example 2 (Example 6 of Chang et al.(2014)).
## p=20, x_t consists of 5 independent subseries with 6, 5, 4, 3 and 2 components.

p=20;n=3000
# Generate x_t
X=mat.or.vec(p,n)
x=arima.sim(model=list(ar=c(0.5, 0.3), ma=c(-0.9, 0.3, 1.2,1.3)),n.start=500,n=n+5,sd=1)
for(i in 1:6) X[i,]=x[i:(n+i-1)]
x=arima.sim(model=list(ar=c(-0.4,0.5),ma=c(1,0.8,1.5,1.8)),n.start=500,n=n+4,sd=1)
for(i in 7:11) X[i,]=x[(i-6):(n+i-7)]
x=arima.sim(model=list(ar=c(0.85,-0.3),ma=c(1,0.5,1.2)), n.start=500,n=n+3,sd=1)
for(i in 12:15) X[i,]=x[(i-11):(n+i-12)]
x=arima.sim(model=list(ar=c(0.8,-0.5),ma=c(1,0.8,1.8)),n.start=500,n=n+2,sd=1)
for(i in 16:18) X[i,]=x[(i-15):(n+i-16)]
x=arima.sim(model=list(ar=c(-0.7, -0.5), ma=c(-1, -0.8)),n.start=500,n=n+1,sd=1)
for(i in 19:20) X[i,]=x[(i-18):(n+i-19)]
# Generate y_t
A=matrix(runif(p*p, -3, 3), ncol=p)
Y=A%*%X
Y=t(Y)
Trans=segmentTS(Y, k0=5)
# The transformed series z_t
Z=Trans$X
# Identify the permutation mechanism
permutation=permutationMax(Z)
permutation$Groups

```

returns

Daily returns of six stocks

Description

The data contains the daily returns of the stocks of Bank of America Corporation, Dell Inc., JP-Morgan Chase Co., FedEx Corporation, McDonald's Corp. and American International Group in 2 January 2002 – 10 July 2008.

Usage

```
data("returns")
```

Examples

```
data(returns)

# Time series plots of the returns

Y=returns
names(Y)=c("Y1", "Y2", "Y3", "Y4", "Y5", "Y6")
location=c(1, 253, 505, 757, 1009, 1260, 1511)
year=c(2002, 2003, 2004, 2005, 2006, 2007, 2008)

par(mfrow=c(6,1),mar=c(2,2,0.5,1),cex=0.5, mgp = c(1.4, 0.6, 0))
plot(Y[,1],type='l',lty=1,xlab='',ylab='',col="blue",xaxt="n")
axis(1, at=location, labels=year, col.axis='brown')
plot(Y[,2],type='l',lty=1,xlab='',ylab='',col="blue",xaxt="n")
axis(1, at=location, labels=year, col.axis='brown')
plot(Y[,3],type='l',lty=1,xlab='',ylab='',col="blue",xaxt="n")
axis(1, at=location, labels=year, col.axis='brown')
plot(Y[,4],type='l',lty=1,xlab='',ylab='',col="blue",xaxt="n")
axis(1, at=location, labels=year, col.axis='brown')
plot(Y[,5],type='l',lty=1,xlab='',ylab='',col="blue",xaxt="n")
axis(1, at=location, labels=year, col.axis='brown')
plot(Y[,6],type='l',lty=1,xlab='',ylab='',col="blue",xaxt="n")
axis(1, at=location, labels=year, col.axis='brown')
```

segmentTS

Segment Multivariate Time Series

Description

Calculate linear transformation of the p -variate time series y_t such that the transformed series $x_t=By_t$ is segmented into several lower-dimensional subseries, and those subseries are uncorrelated with each other both contemporaneously and serially.

Usage

```
segmentTS(Y, k0, thresh = FALSE, tuning.vec = 2, K = 5)
```

Arguments

Y a data matrix with n rows and p columns, where n is the sample size and p is the dimension of the time series.

k0 a positive integer specified to calculate W_y . See (2.5) in Chang et al. (2014).

thresh logical. If FALSE (the default), no thresholding will be applied. If TRUE, a thresholding method will be applied first to estimate W_y , see (3.4) and (3.5) in Chang et al. (2014).

tuning.vec the value of thresholding parameter λ . The thresholding level is specified by

$$u = \lambda(\log p/n)^{(1/2)}.$$

Default value is 2. If tuning.vec is a vector, then a cross validation method proposed in Cai and Liu (2011) will be used to choose the best tuning parameter.

K the number of folders used in the cross validation, the default is 5. It is required when thresh is TRUE.

Details

When p is small, thresholding is not required. However, when p is large, it is necessary to use the thresholding method, see more information in Chang et al. (2014).

Value

An object of class "segmentTS" is a list containing the following components:

B the p by p transformation matrix such that $x_t = B y_t$

X the transformed series with n rows and p columns

Note

This is the first step to transform the time series. The second step is grouping the transformed time series, see [permutationMax](#), [permutationFDR](#).

Author(s)

Jinyuan Chang, Bin Guo and Qiwei Yao

References

Chang, J., Guo, B. and Yao, Q. (2014). *Segmenting Multiple Time Series by Contemporaneous Linear Transformation: PCA for Time Series*. Available at <http://arxiv.org/abs/1410.2323>.

Cai, T. and Liu, W. (2011). *Adaptive thresholding for sparse covariance matrix estimation*. Journal of the American Statistical Association 106: 672-684.

See Also

[permutationMax](#), [permutationFDR](#).

Examples

```

## Example 1 (Example 5 of Chang et al.(2014)).
## p=6, x_t consists of 3 independent subseries with 3, 2 and 1 components.

p=6;n=1500
# Generate x_t
X=mat.or.vec(p,n)
x=arima.sim(model=list(ar=c(0.5, 0.3), ma=c(-0.9, 0.3, 1.2,1.3)),n=n+2,sd=1)
for(i in 1:3) X[i,]=x[i:(n+i-1)]
x=arima.sim(model=list(ar=c(0.8,-0.5),ma=c(1,0.8,1.8) ),n=n+1,sd=1)
for(i in 4:5) X[i,]=x[(i-3):(n+i-4)]
x=arima.sim(model=list(ar=c(-0.7, -0.5), ma=c(-1, -0.8)),n=n,sd=1)
X[6,]=x
# Generate y_t
A=matrix(runif(p*p, -3, 3), ncol=p)
Y=A%*%X
Y=t(Y)
Trans=segmentTS(Y, k0=5)
# The transformed series z_t
Z=Trans$X
# Plot the cross correlogram of z_t and y_t
Y=data.frame(Y);Z=data.frame(Z)
names(Y)=c("Y1","Y2","Y3","Y4","Y5","Y6")
names(Z)=c("Z1","Z2","Z3","Z4","Z5","Z6")
# The cross correlogram of y_t shows no block pattern
acfY=acf(Y)
# The cross correlogram of z_t shows 3-2-1 block pattern
acfZ=acf(Z)

## Example 2 (Example 6 of Chang et al.(2014)).
## p=20, x_t consists of 5 independent subseries with 6, 5, 4, 3 and 2 components.

p=20;n=3000
# Generate x_t
X=mat.or.vec(p,n)
x=arima.sim(model=list(ar=c(0.5, 0.3), ma=c(-0.9, 0.3, 1.2,1.3)),n.start=500,n=n+5,sd=1)
for(i in 1:6) X[i,]=x[i:(n+i-1)]
x=arima.sim(model=list(ar=c(-0.4,0.5),ma=c(1,0.8,1.5,1.8)),n.start=500,n=n+4,sd=1)
for(i in 7:11) X[i,]=x[(i-6):(n+i-7)]
x=arima.sim(model=list(ar=c(0.85,-0.3),ma=c(1,0.5,1.2)), n.start=500,n=n+3,sd=1)
for(i in 12:15) X[i,]=x[(i-11):(n+i-12)]
x=arima.sim(model=list(ar=c(0.8,-0.5),ma=c(1,0.8,1.8)),n.start=500,n=n+2,sd=1)
for(i in 16:18) X[i,]=x[(i-15):(n+i-16)]
x=arima.sim(model=list(ar=c(-0.7, -0.5), ma=c(-1, -0.8)),n.start=500,n=n+1,sd=1)
for(i in 19:20) X[i,]=x[(i-18):(n+i-19)]
# Generate y_t
A=matrix(runif(p*p, -3, 3), ncol=p)
Y=A%*%X
Y=t(Y)
Trans=segmentTS(Y, k0=5)
# The transformed series z_t
Z=Trans$X

```

```

# Plot the cross correlogram of x_t and y_t
Y=data.frame(Y);Z=data.frame(Z)
namesY=NULL;namesZ=NULL
for(i in 1:p)
{
  namesY=c(namesY,paste0("Y",i))
  namesZ=c(namesZ,paste0("Z",i))
}
names(Y)=namesY;names(Z)=namesZ
# The cross correlogram of y_t shows no block pattern
acfY=acf(Y, plot=FALSE)
plot(acfY, max.mfrow=6, xlab='', ylab='', mar=c(1.8,1.3,1.6,0.5),
      oma=c(1,1.2,1.2,1), mgp=c(0.8,0.4,0),cex.main=1)
# The cross correlogram of z_t shows 6-5-4-3-2 block pattern
acfZ=acf(Z, plot=FALSE)
plot(acfZ, max.mfrow=6, xlab='', ylab='', mar=c(1.8,1.3,1.6,0.5),
      oma=c(1,1.2,1.2,1), mgp=c(0.8,0.4,0),cex.main=1)
# Identify the permutation mechanism
permutation=permutationMax(Z)
permutation$Groups

```

segmentVOL

Segment Multivariate Volatility Processes

Description

Calculate linear transformation of the p -variate volatility processes y_t such that the transformed volatility process $x_t=By_t$ can be segmented into q lower-dimensional processes, and there exist no *conditional* cross correlations across those q processes.

Usage

```
segmentVOL(Y, k0)
```

Arguments

Y a data matrix with n rows and p columns, where n is the sample size and p is the dimension of the time series.

$k0$ a positive integer specified to calculate Wy .

Value

An object of class "segmentVOL" is a list containing the following components:

B the p by p transformation matrix such that $x_t=By_t$

X the transformed series with n rows and p columns

Author(s)

Jinyuan Chang, Bin Guo and Qiwei Yao

References

Chang, J., Guo, B. and Yao, Q. (2014). *Segmenting Multiple Time Series by Contemporaneous Linear Transformation: PCA for Time Series*. Available at <http://arxiv.org/abs/1410.2323>.

See Also

[segmentTS](#)

Examples

```
## Example 7 of Chang et al.(2014)
## Segmenting the returns of the 6 stocks

require(tseries)
data(returns)
Y=returns
n=dim(Y)[1]; p=dim(Y)[2]
# Carry out the transformation procedure
Trans=segmentVOL(Y,5)
X_0=data.frame(Trans$X)
X_1=X_0
# The ACF plot of the residuals after prewhitening the transformed data by GARCH(1,1)
nanum=rep(0,p)
for(j in 1:p) {options( warn = -1 )
  t=garch(X_1[,j], order = c(1,1),trace=FALSE)
  X_1[,j]=t$residuals
  a=X_1[,j]
  nanum[j]=length(a[is.na(X_1[,j])]) }
X=X_1[(max(nanum)+1):n,]
colnames(X)=c("X1", "X2", "X3", "X4", "X5", "X6")
t=acf(X,plot=FALSE)
plot(t, max.mfrow=6, xlab='', ylab='', mar=c(1.8,1.3,1.6,0.5),
      oma=c(1,1.2,1.2,1), mgp=c(0.8,0.4,0),cex.main=1.0,ylim=c(0,1))
# Identify the permutation mechanism
permutation=permutationMax(X_0,Vol=TRUE)
permutation$Groups
options( warn = 0)
```

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