Package ‘ecp’
December 15, 2017

Type Package
Title Non-Parametric Multiple Change-Point Analysis of Multivariate Data
Version 3.1.0
Date 2017-12-01
Author Nicholas A. James, Wenyu Zhang and David S. Matteson
Maintainer Wenyu Zhang <wzRUX@cornell.edu>
Description Implements various procedures for finding multiple change-points. Two methods make use of dynamic programming and pruning, with no distributional assumptions other than the existence of certain absolute moments in one method. Hierarchical and exact search methods are included. All methods return the set of estimated change-points as well as other summary information.
License GPL (>= 2)
Depends R (>= 3.00), Rcpp
Suggests mvtnorm, MASS, combinat, R.rsp
LinkingTo Rcpp
NeedsCompilation yes
Repository CRAN
VignetteBuilder R.rsp
Date/Publication 2017-12-15 12:14:35 UTC

R topics documented:

  ACGH .............................................................. 2
  DJIA ............................................................. 3
  e.agglo .......................................................... 3
  e.cp3o ............................................................ 5
  e.cp3o_delta ....................................................... 7
  e.divisive ........................................................ 8
  ks.cp3o ........................................................... 10
  ks.cp3o_delta ..................................................... 11
**ACGH**

**Bladder Tumor Micro-Array Data**

**Description**

Micro-array data for 43 different individuals with a bladder tumor.

**Usage**

`data(ACGH)`

**Format**

A list with the following components.

- `data`: The micro-array data for 43 individuals. This information is stored in a 2215 by 43 matrix.
- `individual`: A numeric vector indicating which individuals' micro-array data are present.

**Source**

Bleakley K., Vert J.-P. (2011), The group fused Lasso for multiple change-point detection


**References**

Bleakley K., Vert J.-P. (2011), The group fused Lasso for multiple change-point detection


**Examples**

```r
data(ACGH, package="ecp")
```
DJIA

_Dow Jones Industrial Average Index_

Description
The weekly log returns for the Dow Jones Industrial Average index from April 1990 to January 2012.

Usage
data(DJIA)

Format
A list with the following components.
dates: A character vector of dates associated with each observation in the returns series.
index: Weekly log returns from April 1990 to January 2012 of the DOW 30 index.
market: Weekly log returns from April 1990 to January 2012, for the companies in the DOW 30 apart from Kraft.

Source
http://research.stlouisfed.org/fred2/series/DJIA/downloaddata

References

Examples
data(DJIA, package="ecp")

e.agglo

ENERGY AGGLOMERATIVE

Description
An agglomerative hierarchical estimation algorithm for multiple change point analysis.

Usage
e.agglo(X, member=1:nrow(X), alpha=1, penalty=function(cps){0})
Arguments

\[ x \]  A \( T \times d \) matrix containing the length \( T \) time series with \( d \)-dimensional observations.

\[ \text{member} \]  Initial membership vector for the time series.

\[ \text{alpha} \]  Moment index used for determining the distance between and within clusters.

\[ \text{penalty} \]  Function used to penalize the obtained goodness-of-fit statistics. This function takes as its input a vector of change point locations (cps).

Details

Homogeneous clusters are created based on the initial clustering provided by the \text{member} argument. In each iteration, clusters are merged so as to maximize a goodness-of-fit statistic. The computational complexity of this method is \( O(T^2) \), where \( T \) is the number of observations.

Value

Returns a list with the following components.

\[ \text{merged} \]  A \((T-1) \times 2\) matrix indicating which segments were merged at each step of the agglomerative procedure.

\[ \text{fit} \]  Vector showing the progression of the penalized goodness-of-fit statistic.

\[ \text{progression} \]  A \( T \times (T+1) \) matrix showing the progression of the set of change points.

\[ \text{cluster} \]  The estimated cluster membership vector.

\[ \text{estimates} \]  The location of the estimated change points.

Author(s)

Nicholas A. James

References


See Also

e.divisive
Examples

```r
set.seed(100)
mem = rep(c(1,2,3,4),times=c(10,10,10,10))
x = as.matrix(c(rnorm(10,0,1),rnorm(20,2,1),rnorm(10,-1,1)))
y = e.agglo(X=x,member=mem,alpha=1,penalty=function(cp,Xts) 0)
y$estimates
```

```r
# Not run:
# Multivariate spatio-temporal example
# You will need the following packages:
# mvtnorm, combinat, and MASS
library(mvtnorm); library(combinat); library(MASS)
set.seed(2013)
lambda = 1500 #overall arrival rate per unit time
muA = c(-7,-7); muB = c(0,0); muC = c(5.5,0)
covA = 25*diag(2)
covB = matrix(c(9,0,0,1),2)
covC = matrix(c(9,.9,.9,.9),2)
time.interval = matrix(c(0,1,3,4,5,1,3,4,5,7),4,2)
#mixing coefficients
mixing.coef = rbind(c(1/3,1/3,1/3),c(.2,.5,.3), c(.35,.3,.35),
c(.2,.3,.5))
stppData = NULL
for(i in 1:4){
  count = rpois(1, lambda* diff(time.interval[i,]))
  Z = rmult(z2(n = count, p = mixing.coef[i,]))
  S = rbind(rmvnorm(Z[1],muA,covA), rmvnorm(Z[2],muB,covB),
             rmvnorm(Z[3],muC,covC))
  X = cbind(rep(i,count), runif(n = count, time.interval[i,1],
                            time.interval[i,2]), S)
  stppData = rbind(stppData, X[order(X[,2]),])
}
member = as.numeric(cut(stppData[,2], breaks = seq(0,7,by=1/12)))
output = e.agglo(X=stppData[,3:4],member=member,alpha=1,
                 penalty=function(cp,Xts) 0)
```

## End(Not run)

---

**Description**

An algorithm for multiple change point analysis that uses dynamic programming and pruning. The E-statistic is used as the goodness-of-fit measure.
Usage

e.cp3o(Z, K=1, minsize=30, alpha=1, verbose=FALSE)

Arguments

Z  A T x d matrix containing the length T time series with d-dimensional observations.
K  The maximum number of change points.
minsize  The minimum segment size.
alpha  The moment index used for determining the distance between and within segments.
verbose  A flag indicating if status updates should be printed.

Details

Segmentations are found through the use of dynamic programming and pruning. For long time series, consider using e.cp3o_delta.

Value

The returned value is a list with the following components.

time  The total amount to time take to estimate the change point locations.
number  The estimated number of change points.
estimates  The location of the change points estimated by the procedure.
gofM  A vector of goodness of fit values for differing number of change points. The first entry corresponds to when there is only a single change point, the second for when there are two, and so on.
cpLoc  The list of locations of change points estimated by the procedure for different numbers of change points up to K.

Author(s)

Nicholas A. James

References


**Examples**

```r
set.seed(400)
x1 = matrix(c(rnorm(50),rnorm(50,3)))
y1 = e.cp3o(z=x1, K=2, minsize=30, alpha=1, verbose=FALSE)
#View estimated change point locations
y1$estimates
```

---

**Description**

An algorithm for multiple change point analysis that uses dynamic programming and pruning. The E-statistic is used as the goodness-of-fit measure.

**Usage**

```r
e.cp3o_delta(Z, K=1, delta=29, alpha=1, verbose=FALSE)
```

**Arguments**

- `Z` A T x d matrix containing the length T time series with d-dimensional observations.
- `K` The maximum number of change points.
- `delta` The window size used to calculate the complete portion of our approximate test statistic. This also corresponds to one less than the minimum segment size.
- `alpha` The moment index used for determining the distance between and within segments.
- `verbose` A flag indicating if status updates should be printed.

**Details**

Segmentations are found through the use of dynamic programming and pruning. Between-segment distances are calculated only using points within a window of the segmentation point. The computational complexity of this method is $O(KT^2)$, where $K$ is the maximum number of change points, and $T$ is the number of observations.

**Value**

The returned value is a list with the following components.

- `number` The estimated number of change points.
- `estimates` The location of the change points estimated by the procedure.
e.divisive

A vector of goodness of fit values for differing number of change points. The first entry corresponds to when there is only a single change point, the second for when there are two, and so on.

cpLoc

The list of locations of change points estimated by the procedure for different numbers of change points up to K.

time

The total amount to time take to estimate the change point locations.

Author(s)

Nicholas A. James

References


Examples

```
set.seed(400)
x1 = matrix(c(rnorm(100),rnorm(100,3),rnorm(100,0,2)))
y1 = e.cp3o_delta(Z=x1, K=7, delta=29, alpha=1, verbose=FALSE)
#View estimated change point locations
y1$estimates
```

e.divisive

ENERGY DIVISIVE

Description

A divisive hierarchical estimation algorithm for multiple change point analysis.

Usage

e.divisive(X, sig.lvl=.05, R=199, k=NULL, min.size=30, alpha=1)

Arguments

X

A T x d matrix containing the length T time series with d-dimensional observations.

sig.lvl

The level at which to sequentially test if a proposed change point is statistically significant.

R

The maximum number of random permutations to use in each iteration of the permutation test. The permutation test p-value is calculated using the method outlined in Gandy (2009).
Number of change point locations to estimate, suppressing permutation based testing. If k=NULL then only the statistically significant estimated change points are returned.

Minimum number of observations between change points.

The moment index used for determining the distance between and within segments.

Segments are found through the use of a binary bisection method and a permutation test. The computational complexity of this method is $O(kT^2)$, where $k$ is the number of estimated change points, and $T$ is the number of observations.

The returned value is a list with the following components.

- **k.hat**: The number of clusters within the data created by the change points.
- **order.found**: The order in which the change points were estimated.
- **estimates**: Locations of the statistically significant change points.
- **considered.last**: Location of the last change point, that was not found to be statistically significant at the given significance level.
- **permutations**: The number of permutations performed by each of the sequential permutation test.
- **cluster**: The estimated cluster membership vector.
- **p.values**: Approximate p-values estimated from each permutation test.

Nicholas A. James


See Also
e.agglo

Examples

```r
set.seed(100)
x1 = matrix(c(rnorm(100), rnorm(100, 3), rnorm(100, 0, 2)))
y1 = e.divisive(X=x1, sig.lv1=0.05, R=199, k=NULL, min.size=30, alpha=1)
x2 = rbind(MASS::mvrnorm(100, c(0, 0), diag(2)),
            MASS::mvrnorm(100, c(2, 2), diag(2)))
y2 = e.divisive(X=x2, sig.lv1=0.05, R=499, k=NULL, min.size=30, alpha=1)
```

### Description

An algorithm for multiple change point analysis that uses dynamic programming and pruning. The Kolmogorov-Smirnov statistic is used as the goodness-of-fit measure.

### Usage

```r
ks.cp3o(Z, K=1, minsize=30, verbose=FALSE)
```

### Arguments

- **Z**: A T x d matrix containing the length T time series with d-dimensional observations.
- **K**: The maximum number of change points.
- **minsize**: The minimum segment size.
- **verbose**: A flag indicating if status updates should be printed.

### Details

Segmentations are found through the use of dynamic programming and pruning. For long time series, consider using `ks.cp3o_delta`.

### Value

The returned value is a list with the following components.

- **number**: The estimated number of change points.
- **estimates**: The location of the change points estimated by the procedure.
- **gofM**: A vector of goodness of fit values for differing number of change points. The first entry corresponds to when there is only a single change point, the second for when there are two, and so on.
The list of locations of change points estimated by the procedure for different numbers of change points up to K.

The total amount of time taken to estimate the change point locations.

Author(s)

Wenyu Zhang

References


Examples

```r
set.seed(400)
x = matrix(c(rnorm(100), rnorm(100, 3), rnorm(100, 0, 2)))
y = ks.cp3o_delta(x, K=7, minsize=30, verbose=FALSE)
# View estimated change point locations
y$estimates
```

Description

An algorithm for multiple change point analysis that uses dynamic programming and pruning. The Kolmogorov-Smirnov statistic is used as the goodness-of-fit measure.

Usage

```r
ks.cp3o_delta(Z, K=1, minsize=30, verbose=FALSE)
```

Arguments

- `Z`: A T x d matrix containing the length T time series with d-dimensional observations.
- `K`: The maximum number of change points.
- `minsize`: The minimum segment size. This is also the window size used to calculate between-segment distances.
- `verbose`: A flag indicating if status updates should be printed.

Details

Segmentations are found through the use of dynamic programming and pruning. Between-segment distances are calculated only using points within a window of the segmentation point.
Value

The returned value is a list with the following components.

- **number**: The estimated number of change points.
- **estimates**: The location of the change points estimated by the procedure.
- **gofM**: A vector of goodness of fit values for differing number of change points. The first entry corresponds to when there is only a single change point, the second for when there are two, and so on.
- **cpLoc**: The list of locations of change points estimated by the procedure for different numbers of change points up to K.
- **time**: The total amount to time take to estimate the change point locations.

Author(s)

Wenyu Zhang

References


Examples

```r
set.seed(400)
x = matrix(c(rnorm(100), rnorm(100, 3), rnorm(100, 0, 2)))
y = ks.cp3o_delta(Z=x, K=7, minsize=30, verbose=FALSE)
#View estimated change point locations
y$estimates
```
Index

*Topic agglomerative
  e.agglo, 3
*Topic datasets
  ACGH, 2
  DJIA, 3
*Topic divisive
  e.divisive, 8
*Topic dynamic
  e.cp3o, 5
  e.cp3o_delta, 7
  ks.cp3o, 10
  ks.cp3o_delta, 11
*Topic hierarchical
  e.agglo, 3
  e.divisive, 8
*Topic pruning
  e.cp3o, 5
  e.cp3o_delta, 7
  ks.cp3o, 10
  ks.cp3o_delta, 11

ACGH, 2

DJIA, 3

e.agglo, 3, 10
e.cp3o, 5
e.cp3o_delta, 7
e.divisive, 4, 8

ks.cp3o, 10
ks.cp3o_delta, 11