Package ‘ecp’

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R topics documented:

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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

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")

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**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 x d matrix containing the length T time series with d-dimensional observations.
membre  Initial membership vector for the time series.
alpha  Moment index used for determining the distance between and within clusters.
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 `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.

merged  A (T-1) x 2 matrix indicating which segments were merged at each step of the agglomerative procedure.
fit  Vector showing the progression of the penalized goodness-of-fit statistic.
progression  A T x (T+1) matrix showing the progression of the set of change points.
cluster  The estimated cluster membership vector.
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

## 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 = rmult2(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)
```

---

**e.cp3o**

*CHANGE POINTS ESTIMATION BY PRUNED OBJECTIVE (VIA E-STATISTIC)*

**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.

- **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)

Nicholas A. James, Wenyu Zhang

References


See Also


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.
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, Wenyu Zhang

References

See Also


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
```
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).

k
Number of change point locations to estimate, suppressing permutation based testing. If k=NULL then only the statistically significant estimated change points are returned.

min.size
Minimum number of observations between change points.

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

Details

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.

Value

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.

Author(s)

Nicholas A. James

References


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.lvl=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.lvl=0.05,R=499,k=NULL,min.size=30,alpha=1)
```

---

**kcpa**

*Kernel Change Point Analysis*

**Description**

An algorithm for multiple change point analysis that uses the 'kernel trick' and dynamic programming.

**Usage**

`kcpa(X, L, C)`

**Arguments**

- `X` A T x d matrix containing the length T time series with d-dimensional observations.
- `L` The maximum number of change points.
- `C` The constant used to penalize the inclusion of additional change points in the fitted model.

**Details**

Segments are found through the use of dynamic programming and the kernel trick.

**Value**

If the algorithm determines that the best fit is obtained through using k change points then the returned value is an array of length k, containing the change point locations.
**ks.cp3o**

**Author(s)**
Nicholas A. James

**References**

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**ks.cp3o**  
CHANGE POINTS ESTIMATION BY PRUNED OBJECTIVE (VIA KOLMOGOROV-SMIRNOV STATISTIC)

**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**
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.
- **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


See Also


Examples

```r
set.seed(400)
x = matrix(c(rnorm(100), rnorm(100, 3), rnorm(100, 0, 2)))
y = ks.cp3o(Z=x, K=7, minsize=30, verbose=FALSE)
# View estimated change point locations
y$estimates
```

ks.cp3o_delta

CHANGE POINTS ESTIMATION BY PRUNED OBJECTIVE (VIA
KOLMOGOROV-SMIRNOV STATISTIC)

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.
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.
- **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


See Also


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
```
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