

Package ‘harbinger’

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Title A Unified Time Series Event Detection Framework

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Description By analyzing time series, it is possible to observe significant changes in the behavior of observations that frequently characterize events. Events present themselves as anomalies, change points, or motifs. In the literature, there are several methods for detecting events. However, searching for a suitable time series method is a complex task, especially considering that the nature of events is often unknown. This work presents Harbinger, a framework for integrating and analyzing event detection methods. Harbinger contains several state-of-the-art methods described in Salles et al. (2020) <[doi:10.5753/sbbd.2020.13626](https://doi.org/10.5753/sbbd.2020.13626)>.

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URL <https://github.com/cefet-rj-dal/harbinger>,
<https://cefet-rj-dal.github.io/harbinger/>

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detect	<i>Detect events in time series</i>
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Description

Event detection using a fitted Harbinger model

Usage

```
detect(obj, ...)
```

Arguments

obj	harbinger object
...	optional arguments.

Value

a data frame with the index of observations and if they are identified or not as an event, and their type

Examples

```
# See ?hanc_ml for an example of anomaly detection using machine learning classification
# See ?hanr_arima for an example of anomaly detection using ARIMA
# See ?hanr_fbiad for an example of anomaly detection using FBIAD
# See ?hanr_garch for an example of anomaly detection using GARCH
# See ?hanr_kmeans for an example of anomaly detection using kmeans clustering
# See ?hanr_ml for an example of anomaly detection using machine learning regression
# See ?hanr_cf_arima for an example of change point detection using ARIMA
# See ?hanr_cf_ets for an example of change point detection using ETS
# See ?hanr_cf_lr for an example of change point detection using linear regression
# See ?hanr_cf_garch for an example of change point detection using GARCH
# See ?hanr_cf_scp for an example of change point detection using the seminal algorithm
# See ?hmo_sax for an example of motif discovery using SAX
# See ?hmu_pca for an example of anomaly detection in multivariate time series using PCA
```

examples_anomalies *Time series for anomaly detection*

Description

A list of time series for anomaly detection

- simple: a simple synthetic time series
- contextual: a contextual synthetic time series
- simple: a trend synthetic time series
- trend: a simple synthetic time series
- multiple: a multiple anomalies synthetic time series
- sequence: a sequence synthetic time series
- tt: a train-test synthetic time series
- tt_warped: a warped train-test synthetic time series

#'

Usage

```
data(examples_anomalies)
```

Format

A list of time series for anomaly detection.

Source

[Harbinger package](#)

References

[Harbinger package](#)

Examples

```
data(examples_anomalies)
serie <- examples_anomalies$simple
```

examples_changepoints *Time series for change point detection*

Description

A list of time series for change point

- simple: a simple synthetic time series
- sinusoidal: a sinusoidal synthetic time series
- incremental: a incremental synthetic time series
- abrupt: a abrupt synthetic time series
- volatility: a volatility synthetic time series

#'

Usage

```
data(examples_changepoints)
```

Format

A list of time series for change point detection.

Source

[Harbinger package](#)

References

[Harbinger package](#)

Examples

```
data(examples_changepoints)
serie <- examples_changepoints$simple
```

examples_harbinger *Time series for event detection*

Description

A list of time series for event detection

- nonstationarity: a synthetic nonstationarity time series
- global_temperature_yearly: yearly global temperature of the world
- global_temperature_monthly: monthly global temperature of the world
- multidimensional: multidimensional time series with a change point
- seattle_week: Seattle weekly temperature in 2019
- seattle_daily: Seattle daily temperature in 2019

#'

Usage

```
data(examples_harbinger)
```

Format

A list of time series.

Source

[Harbinger package](#)

References

[Harbinger package](#)

Examples

```
data(examples_harbinger)
serie <- examples_harbinger$seattle_daily
```

hanct_dtw	<i>Anomaly detector using DTW</i>
-----------	-----------------------------------

Description

Anomaly detection using DTW The DTW is applied to the time series. When seq equals one, observations distant from the closest centroids are labeled as anomalies. When seq is greater than one, sequences distant from the closest centroids are labeled as discords. It wraps the tsclust presented in the dtwclust library.

Usage

```
hanct_dtw(seq = 1, centers = NA)
```

Arguments

seq	sequence size
centers	number of centroids

Value

hanct_dtw object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using simple example
dataset <- examples_anomalies$simple
head(dataset)

# setting up time series regression model
model <- hanct_dtw()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hanct_kmeans	<i>Anomaly detector using kmeans</i>
--------------	--------------------------------------

Description

Anomaly detection using kmeans The kmeans is applied to the time series. When seq equals one, observations distant from the closest centroids are labeled as anomalies. When seq is grater than one, sequences distant from the closest centroids are labeled as discords. It wraps the kmeans presented in the stats library.

Usage

```
hanct_kmeans(seq = 1, centers = NA)
```

Arguments

seq	sequence size
centers	number of centroids

Value

hanct_kmeans object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using simple example
dataset <- examples_anomalies$simple
head(dataset)

# setting up time series regression model
model <- hanct_kmeans()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hanc_ml	<i>Anomaly detector based on machine learning classification</i>
---------	--

Description

Anomaly detection using daltoolbox classification. A training and test set should be used. The training set must contain labeled events. A set of preconfigured of classification methods are described in <https://cefet-rj-dal.github.io/daltoolbox/>. They include: cla_majority, cla_dtree, cla_knn, cla_mlp, cla_nb, cla_rf, cla_svm

Usage

```
hanc_ml(model)
```

Arguments

model DALToolbox classification model

Value

hanc_ml object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using example tt
dataset <- examples_anomalies$tt
dataset$event <- factor(dataset$event, labels=c("FALSE", "TRUE"))
slevels <- levels(dataset$event)

# separating into training and test
train <- dataset[1:80,]
test <- dataset[-(1:80),]

# normalizing the data
norm <- minmax()
norm <- fit(norm, train)
train_n <- transform(norm, train)

# establishing decision tree method
model <- hanc_ml(cla_dtree("event", slevels))

# fitting the model
model <- fit(model, train_n)
```

```
# evaluating the detections during testing
test_n <- transform(norm, test)

detection <- detect(model, test_n)
print(detection[(detection$event),])
```

hanr_arima

Anomaly detector using ARIMA.

Description

Anomaly detection using ARIMA The ARIMA model adjusts to the time series. Observations distant from the model are labeled as anomalies. It wraps the ARIMA model presented in the forecast library.

Usage

```
hanr_arima()
```

Value

hanr_arima object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using simple example
dataset <- examples_anomalies$simple
head(dataset)

# setting up time series regression model
model <- hanr_arima()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

`hanr_emd`*Anomaly detector using EMD*

Description

Anomaly detection using EMD The EMD model adjusts to the time series. Observations distant from the model are labeled as anomalies. It wraps the EMD model presented in the hht library.

Usage

```
hanr_emd(noise = 0.1, trials = 5)
```

Arguments

<code>noise</code>	<code>nosie</code>
<code>trials</code>	<code>trials</code>

Value

hanr_emd object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using simple example
dataset <- examples_anomalies$simple
head(dataset)

# setting up time series emd detector
model <- hanr_emd()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

`hanr_fbiad`*Anomaly detector using FBIAD*

Description

Anomaly detector using FBIAD

Usage

```
hanr_fbiad(sw_size = 30)
```

Arguments

`sw_size` Window size for FBIAD

Value

`hanr_fbiad` object Forward and Backward Inertial Anomaly Detector (FBIAD) detects anomalies in time series. Anomalies are observations that differ from both forward and backward time series inertia [doi:10.1109/IJCNN55064.2022.9892088](https://doi.org/10.1109/IJCNN55064.2022.9892088).

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using simple example
dataset <- examples_anomalies$simple
head(dataset)

# setting up time series regression model
model <- hanr_fbiad()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

`hanr_fft`*Anomaly detector using FFT*

Description

Anomaly detection using FFT The FFT model adjusts to the time series. Observations distant from the model are labeled as anomalies. It wraps the FFT model presented in the stats library.

Usage

```
hanr_fft()
```

Value

hanr_fft object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using simple example
dataset <- examples_anomalies$simple
head(dataset)

# setting up time series fft detector
model <- hanr_fft()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

`hanr_garch`*Anomaly detector using GARCH*

Description

Anomaly detection using GARCH The GARCH model adjusts to the time series. Observations distant from the model are labeled as anomalies. It wraps the ugarch model presented in the rugarch library.

Usage

```
hanr_garch()
```

Value

hanr_garch object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using simple example
dataset <- examples_anomalies$simple
head(dataset)

# setting up time series regression model
model <- hanr_garch()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hanr_histogram

Anomaly detector using histogram

Description

Anomaly detector using histogram

Usage

```
hanr_histogram(density_threshold = 0.05)
```

Arguments

density_threshold

It is the minimum frequency for a bin to not be considered an anomaly. Default value is 5%.

Value

hanr_histogram object histogram based method to detect anomalies in time series. Bins with smaller amount of observations are considered anomalies. Values below first bin or above last bin are also considered anomalies.>.

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using simple example
dataset <- examples_anomalies$simple
head(dataset)

# setting up time series regression model
model <- hanr_histogram()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hanr_ml

Anomaly detector based on machine learning regression.

Description

Anomaly detection using daltoolbox regression The regression model adjusts to the time series. Observations distant from the model are labeled as anomalies. A set of preconfigured regression methods are described in <https://cefet-rj-dal.github.io/daltoolbox/>. They include: ts_elm, ts_conv1d, ts_lstm, ts_mlp, ts_rf, ts_svm

Usage

```
hanr_ml(model, sw_size = 15)
```

Arguments

model	DALToolbox regression model
sw_size	sliding window size

Value

hanr_ml object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using simple example
dataset <- examples_anomalies$simple
head(dataset)

# setting up time series regression model
model <- hanr_ml(ts_elm(ts_norm_gminmax(), input_size=4, nhid=3, actfun="purelin"))

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hanr_red

Anomaly and change point detector using RED

Description

Anomaly and change point detection using RED The RED model adjusts to the time series. Observations distant from the model are labeled as anomalies. It wraps the EMD model presented in the hht library.

Usage

```
hanr_red(sw_size = 30, noise = 0.001, trials = 5)
```

Arguments

sw_size	sliding window size (default 30)
noise	noise
trials	trials

Value

hanr_red object

Examples

```
library(daltoolbox)
library(zoo)

#loading the example database
data(examples_anomalies)

#Using simple example
dataset <- examples_anomalies$simple
head(dataset)

# setting up time series emd detector
model <- hanr_red()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hanr_remd

Anomaly detector using REMD

Description

Anomaly detection using REMD The EMD model adjusts to the time series. Observations distant from the model are labeled as anomalies. It wraps the EMD model presented in the forecast library.

Usage

```
hanr_remd(noise = 0.1, trials = 5)
```

Arguments

noise	nosie
trials	trials

Value

hanr_remd object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using simple example
dataset <- examples_anomalies$simple
head(dataset)

# setting up time series emd detector
model <- hanr_remd()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hanr_wavelet

Anomaly detector using Wavelet

Description

Anomaly detection using Wavelet The Wavelet model adjusts to the time series. Observations distant from the model are labeled as anomalies. It wraps the Wavelet model presented in the stats library.

Usage

```
hanr_wavelet(filter = "haar")
```

Arguments

filter Availables wavelet filters: haar, d4, la8, bl14, c6

Value

hanr_wavelet object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)
```

```
#Using simple example
dataset <- examples_anomalies$simple
head(dataset)

# setting up time series fft detector
model <- hanr_wavelet()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

han_autoencoder	<i>Anomaly detector using autoencoder</i>
-----------------	---

Description

Anomaly detector using autoencoder

Usage

```
han_autoencoder(input_size, encode_size)
```

Arguments

input_size	Establish the input size for the autoencoder anomaly detector. It is the size of the output also.
encode_size	The encode size for the autoencoder.

Value

han_autoencoder object histogram based method to detect anomalies in time series. Bins with smaller amount of observations are considered anomalies. Values below first bin or above last bin are also considered anomalies.>.

Examples

```
# setting up time series regression model
#Use the same example of hanr_fbiad changing the constructor to:
model <- han_autoencoder(3,1)
```

harbinger

Harbinger

Description

Ancestor class for time series event detection

Usage

harbinger()

Value

Harbinger object

Examples

```
# See ?hanc_ml for an example of anomaly detection using machine learning classification
# See ?hanr_arima for an example of anomaly detection using ARIMA
# See ?hanr_fbiad for an example of anomaly detection using FBIAD
# See ?hanr_garch for an example of anomaly detection using GARCH
# See ?hanr_kmeans for an example of anomaly detection using kmeans clustering
# See ?hanr_ml for an example of anomaly detection using machine learning regression
# See ?hanr_cf_arima for an example of change point detection using ARIMA
# See ?hanr_cf_ets for an example of change point detection using ETS
# See ?hanr_cf_lr for an example of change point detection using linear regression
# See ?hanr_cf_garch for an example of change point detection using GARCH
# See ?hanr_cf_scp for an example of change point detection using the seminal algorithm
# See ?hmo_sax for an example of motif discovery using SAX
# See ?hmu_pca for an example of anomaly detection in multivariate time series using PCA
```

har_eval

Evaluation of event detection

Description

Evaluation of event detection (traditional hard evaluation)

Usage

har_eval()

Value

har_eval object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

dataset <- examples_anomalies$simple
head(dataset)

# setting up time change point using GARCH
model <- hcp_garch()

# fitting the model
model <- fit(model, dataset$serie)

# making detections
detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])

# evaluating the detections
evaluation <- evaluate(har_eval(), detection$event, dataset$event)
print(evaluation$confMatrix)

# plotting the results
grf <- har_plot(model, dataset$serie, detection, dataset$event)
plot(grf)
```

har_eval_soft

Evaluation of event detection

Description

Evaluation of event detection using SoftED [doi:10.48550/arXiv.2304.00439](https://doi.org/10.48550/arXiv.2304.00439)

Usage

```
har_eval_soft(sw_size = 15)
```

Arguments

sw_size tolerance window size

Value

har_eval_soft object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using the simple
dataset <- examples_anomalies$simple
head(dataset)

# setting up time change point using GARCH
model <- hcp_garch()

# fitting the model
model <- fit(model, dataset$serie)

# making detections
detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])

# evaluating the detections
evaluation <- evaluate(har_eval_soft(), detection$event, dataset$event)
print(evaluation$confMatrix)

# plotting the results
grf <- har_plot(model, dataset$serie, detection, dataset$event)
plot(grf)
```

har_plot

Plot event detection on a time series

Description

It accepts as harbinger, a time series, a data.frame of events, a parameter to mark the detected change points, a threshold for the y-axis and an index for the time series

Usage

```
har_plot(
  obj,
  serie,
  detection,
  event = NULL,
  mark.cp = TRUE,
  ylim = NULL,
  idx = NULL,
  pointsize = 0.5,
```

```

    colors = c("green", "blue", "red", "purple")
  )

```

Arguments

obj	harbinger detector
serie	time series
detection	detection
event	events
mark.cp	show change points
ylim	limits for y-axis
idx	labels for x observations
pointsize	default point size
colors	default colors for event detection: green is TP, blue is FN, red is FP, purple means observations that are part of a sequence.

Value

A time series plot with marked events

Examples

```

library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using the time series 1
dataset <- examples_anomalies$simple
head(dataset)

# setting up time change point using GARCH
model <- hanr_arima()

# fitting the model
model <- fit(model, dataset$serie)

# making detections
detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])

# evaluating the detections
evaluation <- evaluate(har_eval_soft(), detection$event, dataset$event)
print(evaluation$confMatrix)

# plotting the results
grf <- har_plot(model, dataset$serie, detection, dataset$event)
plot(grf)

```

hcp_amoc	<i>At most one change (AMOC) method</i>
----------	---

Description

Change-point detection method that focus on identify one change point in mean/variance [doi:10.1093/biomet/57.1.1](https://doi.org/10.1093/biomet/57.1.1). It wraps the amoc implementation available in the changepoint library.

Usage

```
hcp_amoc()
```

Value

hcp_amoc object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_changepoints)

#Using simple example
dataset <- examples_changepoints$simple
head(dataset)

# setting up change point method
model <- hcp_amoc()

# fitting the model
model <- fit(model, dataset$serie)

# execute the detection method
detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hcp_binseg	<i>Binary segmentation (BinSeg) method</i>
------------	--

Description

Change-point detection method that focus on identify change points in mean/variance [doi:10.2307/2529204](https://doi.org/10.2307/2529204). It wraps the BinSeg implementation available in the changepoint library.

Usage

```
hcp_binseg(Q = 2)
```

Arguments

Q The maximum number of change-points to search for using the BinSeg method

Value

hcp_binseg object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_changepoints)

#Using simple example
dataset <- examples_changepoints$simple
head(dataset)

# setting up change point method
model <- hcp_binseg()

# fitting the model
model <- fit(model, dataset$serie)

# execute the detection method
detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hcp_cf_arima

Change Finder using ARIMA

Description

Change-point detection is related to event/trend change detection. Change Finder ARIMA detects change points based on deviations relative to ARIMA model [doi:10.1109/TKDE.2006.1599387](https://doi.org/10.1109/TKDE.2006.1599387). It wraps the ARIMA model presented in the forecast library.

Usage

```
hcp_cf_arima(sw_size = NULL)
```

Arguments

sw_size Sliding window size

Value

hcp_cf_arima object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_changepoints)

#Using simple example
dataset <- examples_changepoints$simple
head(dataset)

# setting up change point method
model <- hcp_cf_arima()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hcp_cf_ets

Change Finder using ETS

Description

Change-point detection is related to event/trend change detection. Change Finder ETS detects change points based on deviations relative to trend component (T), a seasonal component (S), and an error term (E) model [doi:10.1109/TKDE.2006.1599387](https://doi.org/10.1109/TKDE.2006.1599387). It wraps the ETS model presented in the forecast library.

Usage

```
hcp_cf_ets(sw_size = 7)
```

Arguments

sw_size Sliding window size

Value

hcp_cf_ets object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_changepoints)

#Using simple example
dataset <- examples_changepoints$simple
head(dataset)

# setting up change point method
model <- hcp_cf_ets()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hcp_cf_lr

Change Finder using LR

Description

Change-point detection is related to event/trend change detection. Change Finder LR detects change points based on deviations relative to linear regression model [doi:10.1109/TKDE.2006.1599387](https://doi.org/10.1109/TKDE.2006.1599387).

Usage

```
hcp_cf_lr(sw_size = 30)
```

Arguments

sw_size Sliding window size

Value

hcp_cf_lr object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_changepoints)

#Using simple example
dataset <- examples_changepoints$simple
head(dataset)

# setting up change point method
model <- hcp_cf_lr()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hcp_chow

Chow test method

Description

Change-point detection method that focus on identifying structural changes [doi:10.18637/jss.v007.i02](https://doi.org/10.18637/jss.v007.i02). It wraps the Fstats and breakpoints implementation available in the strucchange library.

Usage

```
hcp_chow()
```

Value

hcp_chow object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_changepoints)

#Using simple example
dataset <- examples_changepoints$simple
head(dataset)
```

```
# setting up change point method
model <- hcp_chow()

# fitting the model
model <- fit(model, dataset$serie)

# execute the detection method
detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hcp_garch

Change Finder using GARCH

Description

Change-point detection is related to event/trend change detection. Change Finder GARCH detects change points based on deviations relative to linear regression model [doi:10.1109/TKDE.2006.1599387](https://doi.org/10.1109/TKDE.2006.1599387). It wraps the GARCH model presented in the rugarch library.

Usage

```
hcp_garch(sw_size = 5)
```

Arguments

sw_size Sliding window size

Value

hcp_garch object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_changepoints)

#Using volatility example
dataset <- examples_changepoints$volatility
head(dataset)

# setting up change point method
model <- hcp_garch()

# fitting the model
model <- fit(model, dataset$serie)
```

```
detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hcp_gft

Generalized Fluctuation Test (GFT)

Description

GFT detection method focuses on identifying structural changes [doi:10.18637/jss.v007.i02](https://doi.org/10.18637/jss.v007.i02). It wraps the breakpoints implementation available in the strucchange library.

Usage

```
hcp_gft()
```

Value

hcp_chow object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_changepoints)

#Using simple example
dataset <- examples_changepoints$simple
head(dataset)

# setting up change point method
model <- hcp_gft()

# fitting the model
model <- fit(model, dataset$serie)

# execute the detection method
detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hcp_pelt	<i>Pruned exact linear time (PELT) method</i>
----------	---

Description

Change-point detection method that focus on identifying multiple exact change points in mean/variance [doi:10.1080/01621459.2012.737745](https://doi.org/10.1080/01621459.2012.737745). It wraps the BinSeg implementation available in the change-point library.

Usage

```
hcp_pelt()
```

Value

hcp_pelt object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_changepoints)

#Using simple example
dataset <- examples_changepoints$simple
head(dataset)

# setting up change point method
model <- hcp_pelt()

# fitting the model
model <- fit(model, dataset$serie)

# execute the detection method
detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hcp_red	<i>Anomaly and change point detector using RED</i>
---------	--

Description

Anomaly and change point detection using RED The RED model adjusts to the time series. Observations distant from the model are labeled as anomalies. It wraps the EMD model presented in the hht library.

Usage

```
hcp_red(  
  sw_size = 30,  
  noise = 0.001,  
  trials = 5,  
  red_cp = TRUE,  
  volatility_cp = TRUE,  
  trend_cp = TRUE  
)
```

Arguments

sw_size	sliding window size (default 30)
noise	noise
trials	trials
red_cp	red change point
volatility_cp	volatility change point
trend_cp	trend change point

Value

hcp_red object

Examples

```
library(daltoolbox)  
  
#loading the example database  
data(examples_changepoints)  
  
#Using simple example  
dataset <- examples_changepoints$simple  
head(dataset)  
  
# setting up change point method  
model <- hcp_red()  
  
# fitting the model  
model <- fit(model, dataset$serie)  
  
# execute the detection method  
detection <- detect(model, dataset$serie)  
  
# filtering detected events  
print(detection[(detection$event),])
```

hcp_scp	<i>Seminal change point</i>
---------	-----------------------------

Description

Change-point detection is related to event/trend change detection. Seminal change point detects change points based on deviations of linear regression models adjusted with and without a central observation in each sliding window <10.1145/312129.312190>.

Usage

```
hcp_scp(sw_size = 30)
```

Arguments

sw_size	Sliding window size
---------	---------------------

Value

hcp_scp object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_changepoints)

#Using simple example
dataset <- examples_changepoints$simple
head(dataset)

# setting up change point method
model <- hcp_scp()

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

`hmo_mp`*Motif discovery using Matrix Profile*

Description

Motif discovery using Matrix Profile [doi:10.32614/RJ-2020-021](https://doi.org/10.32614/RJ-2020-021)

Usage

```
hmo_mp(mode = "stamp", w, qtd)
```

Arguments

<code>mode</code>	mode of computing distance between sequences. Available options include: "stomp", "stamp", "simple", "mstomp", "scrimp", "valmod", "pmp"
<code>w</code>	word size
<code>qtd</code>	number of occurrences to be classified as motifs

Value

`hmo_mp` object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using sequence example
dataset <- examples_anomalies$sequence
head(dataset)

# setting up motif discovery method
model <- hmo_mp("stamp", 4, 3)

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hmo_sax	<i>Motif discovery using SAX</i>
---------	----------------------------------

Description

Motif discovery using SAX [doi:10.1007/s10618-007-0064-z](https://doi.org/10.1007/s10618-007-0064-z)

Usage

```
hmo_sax(a, w, qtd)
```

Arguments

a	alphabet size
w	word size
qtd	number of occurrences to be classified as motifs

Value

hmo_sax object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using sequence example
dataset <- examples_anomalies$sequence
head(dataset)

# setting up motif discovery method
model <- hmo_sax(26, 3, 3)

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

hmo_xsax

Motif discovery using xsax

Description

Motif discovery using xsax [doi:10.1007/s10618-007-0064-z](https://doi.org/10.1007/s10618-007-0064-z)

Usage

```
hmo_xsax(a, w, qtd)
```

Arguments

a	alphabet size
w	word size
qtd	number of occurrences to be classified as motifs

Value

hmo_xsax object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_anomalies)

#Using sequence example
dataset <- examples_anomalies$sequence
head(dataset)

# setting up motif discovery method
model <- hmo_xsax(37, 3, 3)

# fitting the model
model <- fit(model, dataset$serie)

detection <- detect(model, dataset$serie)

# filtering detected events
print(detection[(detection$event),])
```

`hmu_pca`*Multivariate anomaly detector using PCA*

Description

Multivariate anomaly detector using PCA [doi:10.1016/0098-3004\(93\)90090-R](https://doi.org/10.1016/0098-3004(93)90090-R)

Usage

```
hmu_pca()
```

Value

hmu_pca object

Examples

```
library(daltoolbox)

#loading the example database
data(examples_harbinger)

#Using the time series 9
dataset <- examples_harbinger$multidimensional
head(dataset)

# establishing hmu_pca method
model <- hmu_pca()

# fitting the model using the two columns of the dataset
model <- fit(model, dataset[,1:2])

# making detections
detection <- detect(model, dataset[,1:2])

# filtering detected events
print(detection[(detection$event),])

# evaluating the detections
evaluation <- evaluate(model, detection$event, dataset$event)
print(evaluation$confMatrix)
```

`mas`*Moving average smoothing*

Description

The `mas()` function returns a simple moving average smoother of the provided time series.

Usage

```
mas(x, order)
```

Arguments

<code>x</code>	A numeric vector or univariate time series.
<code>order</code>	Order of moving average smoother.

Details

The moving average smoother transformation is given by

$$(1/k) * (x[t] + x[t + 1] + \dots + x[t + k - 1])$$

where $k=order$, t assume values in the range $1:(n-k+1)$, and $n=length(x)$. See also the [ma](#) of the forecast package.

Value

Numerical time series of length $length(x)-order+1$ containing the simple moving average smoothed values.

References

R.H. Shumway and D.S. Stoffer, 2010, Time Series Analysis and Its Applications: With R Examples. 3rd ed. 2011 edition ed. New York, Springer.

Examples

```
#loading the example database
data(examples_changepoints)

#Using simple example
dataset <- examples_changepoints$simple
head(dataset)

# setting up change point method
ma <- mas(dataset$serie, 5)
```

trans_sax	SAX
-----------	-----

Description

SAX

Usage

```
trans_sax(alpha)
```

Arguments

alpha	alphabet
-------	----------

Value

obj

Examples

```
library(daltoolbox)
vector <- 1:52
model <- trans_sax(alpha = 26)
model <- fit(model, vector)
xvector <- transform(model, vector)
print(xvector)
```

trans_xsax	XSAX
------------	------

Description

XSAX

Usage

```
trans_xsax(alpha)
```

Arguments

alpha	alphabet
-------	----------

Value

obj

Examples

```
library(daltoolbox)
vector <- 1:52
model <- trans_xsax(alpha = 52)
model <- fit(model, vector)
xvector <- transform(model, vector)
print(xvector)
```


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