

Package: oddstream (via r-universe)

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Type Package

Title Outlier Detection in Data Streams

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Depends R (>= 3.4.0)

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Description We propose a framework that provides real time support for early detection of anomalous series within a large collection of streaming time series data. By definition, anomalies are rare in comparison to a system's typical behaviour. We define an anomaly as an observation that is very unlikely given the forecast distribution. The algorithm first forecasts a boundary for the system's typical behaviour using a representative sample of the typical behaviour of the system. An approach based on extreme value theory is used for this boundary prediction process. Then a sliding window is used to test for anomalous series within the newly arrived collection of series. Feature based representation of time series is used as the input to the model. To cope with concept drift, the forecast boundary for the system's typical behaviour is updated periodically. More details regarding the algorithm can be found in Talagala, P. D., Hyndman, R. J., Smith-Miles, K., et al. (2019) <[doi:10.1080/10618600.2019.1617160](https://doi.org/10.1080/10618600.2019.1617160)>.

BugReports <https://github.com/pridiltal/oddstream/issues>

License GPL-3

LazyData true

RoxygenNote 7.1.0

Imports pcaPP, stats, ggplot2, ks, MASS, RcppRoll, mgcv, moments, RColorBrewer, mvtsplot, tibble, reshape, dplyr, graphics, tidy, kernlab, magrittr

Encoding UTF-8

Suggests testthat, tidyverse

Repository <https://pridiltal.r-universe.dev>

RemoteUrl <https://github.com/pridiltal/oddstream>

RemoteRef HEAD

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anomalous_stream	<i>Multivariate timeseries dataset with an anomalous event.</i>
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Description

A mutivariate time series dataset with some anomalous series. These time series are with noisy signals.

Usage

```
anomalous_stream
```

Format

A data frame with 640 series each with 1459 time points.

extract_tsfeatures	<i>Extract features from a collection of time series</i>
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Description

This function extract time series features from a collection of time series. This is a modification offtsmesures function of anomalous package package .

Usage

```
extract_tsfeatures(
  y,
  normalise = TRUE,
  width = ifelse(frequency(y) > 1, frequency(y), 10),
  window = width
)
```

Arguments

y	A multivariate time serie
normalise	If TRUE, each time series is scaled to be normally distributed with mean 0 and sd 1
width	A window size for variance change, level shift and lumpiness
window	A window size for KLScore

Value

An object of class features with the following components:

mean	Mean
variance	Variance
lumpiness	Variance of annual variances of remainder
lshift	Level shift using rolling window
vchange	Variance change
linearity	Strength of linearity
curvature	Strength of curvature
spikiness	Strength of spikiness
season	Strength of seasonality
peak	Strength of peaks
trough	Strength of trough
BurstinessFF	Burstiness of time series using Fano Factor
minimum	Minimum value
maximum	Maximum value
rmeaniqmean	Ratio between interquartile mean and the arithmetic mean
moment3	Third moment
highlowmu	Ratio between the means of data that is below and upper the global mean

References

Hyndman, R. J., Wang, E., & Laptev, N. (2015). Large-scale unusual time series detection. In 2015 IEEE International Conference on Data Mining Workshop (ICDMW), (pp. 1616-1619). IEEE.

Fulcher, B. D. (2012). Highly comparative time-series analysis. PhD thesis, University of Oxford.

See Also

[find_odd_streams](#), [get_pc_space](#), [set_outlier_threshold](#), [gg_featurespace](#)

Examples

```
mvtsplot::mvtsplot(anomalous_stream, levels=8, gcol=2, norm="global")
features <- extract_tsfeatures(anomalous_stream[500:550, ])
plot.ts(features[, 1:10])
```

find_odd_streams	<i>Detect outlying series within a collection of streaming time series</i>
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Description

This function detect outlying series within a collection of streaming time series. A sliding window is used to handle streaming data. In the presence of concept drift, the forecast boundary for the system's typical behaviour can be updated periodically.

Usage

```
find_odd_streams(
  train_data,
  test_stream,
  update_threshold = TRUE,
  window_length = nrow(train_data),
  window_skip = window_length,
  concept_drift = FALSE,
  trials = 500,
  p_rate = 0.001,
  cd_alpha = 0.05
)
```

Arguments

train_data	A multivariate time series data set that represents the typical behaviour of the system.
test_stream	A multivariate streaming time series data set to be tested for outliers
update_threshold	If TRUE, the threshold value to determine outlying series is updated. The default value is set to TRUE
window_length	Sliding window size (Ideally this window length should be equal to the length of the training multivariate time series data set that is used to define the outlying threshold)

window_skip	The number of steps the window should slide forward. The default is set to window_length
concept_drift	If TRUE, The outlying threshold will be updated after each window. The default is set to FALSE
trials	Input for set_outlier_threshold function. Default value is set to 500.
p_rate	False positive rate. Default value is set to 0.001.
cd_alpha	Singnificance level for the test of non-stationarity.

Value

a list with components

out_marix	The indices of the outlying series in each window
p_value	p-value for the two sample comparison test for concept drift detection
anom_threshold	anomalous threshold

For each window a plot is also produced on the current graphic device

References

Clifton, D. A., Hugueny, S., & Tarassenko, L. (2011). Novelty detection with multivariate extreme value statistics. *Journal of signal processing systems*, 65 (3),371-389.

Duong, T., Goud, B. & Schauer, K. (2012) Closed-form density-based framework for automatic detection of cellular morphology changes. *PNAS*, 109, 8382-8387.

Talagala, P., Hyndman, R., Smith-Miles, K., Kandanaarachchi, S., & Munoz, M. (2018). Anomaly detection in streaming nonstationary temporal data (No. 4/18). Monash University, Department of Econometrics and Business Statistics.

See Also

[extract_tsfeatures](#), [get_pc_space](#), [set_outlier_threshold](#), [gg_featurespace](#)

Examples

```
#Generate training dataset
set.seed(890)
nobs = 250
nts = 100
train_data <- ts(apply(matrix(ncol = nts, nrow = nobs), 2, function(nobs){10 + rnorm(nobs, 0, 3)}))
# Generate test stream with some outlying series
nobs = 15000
test_stream <- ts(apply(matrix(ncol = nts, nrow = nobs), 2, function(nobs){10 + rnorm(nobs, 0, 3)}))
test_stream[360:1060, 20:25] = test_stream[360:1060, 20:25] * 1.75
test_stream[2550:3550, 20:25] = test_stream[2550:3550, 20:25] * 2
find_odd_streams(train_data, test_stream , trials = 100)
```

```
# Considers the first window of the data set as the training set and the remaining as
# the test stream
```

```
train_data <- anomalous_stream[1:100,]
test_stream <-anomalous_stream[101:1456,]
find_odd_streams(train_data, test_stream , trials = 100)
```

get_pc_space

Define a feature space using the PCA components of the feature matrix

Description

Define a two dimensional feature space using the first two principal components generated from the fetures matrix returned by `extract_tsfeatures`

Usage

```
get_pc_space(features, robust = TRUE, kpc = 2)
```

Arguments

features	Feature matrix returned by extract_tsfeatures
robust	If TRUE, a robust PCA will be used on the feature matrix.
kpc	Desired number of components to return.

Value

It returns a list with class 'pcattributes' containing the following components:

pcnorm	The scores of the firt kpc pricipal components
center, scale	The centering and scaling used
rotation	the matrix of variable loadings (i.e., a matrix whose columns contain the eigen-vectors). The function <code>princomp</code> returns this in the element loadings.

See Also

[PCAproj](#), [prcomp](#), [find_odd_streams](#), [extract_tsfeatures](#), [set_outlier_threshold](#), [gg_featurespace](#)

Examples

```
features <- extract_tsfeatures(anomalous_stream[1:100, 1:100])
pc <- get_pc_space(features)
```

gg_featurespace	<i>Produces a ggplot object of two dimensional feature space.</i>
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Description

Create a ggplot object of two dimensional feature space using the first two principal component returned by [get_pc_space](#).

Usage

```
gg_featurespace(object, ...)
```

Arguments

object	Object of class “pcodstream”.
...	Other plotting parameters to affect the plot.

Value

A ggplot object of two dimensional feature space.

See Also

[find_odd_streams](#), [extract_tsfeatures](#), [get_pc_space](#), [set_outlier_threshold](#)

Examples

```
features <- extract_tsfeatures(anomalous_stream[1:100, 1:100])
pc <- get_pc_space(features)
p <- gg_featurespace(pc)
p + ggplot2::geom_density_2d()
```

oddstream	<i>oddstream: A package for Outlier Detection in Data Streams</i>
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Description

Rapid advances in hardware technology have enabled a wide range of physical objects, living beings and environments to be monitored using sensors attached to them. Over time these sensors generate streams of time series data. Finding anomalous events in streaming time series data has become an interesting research topic due to its wide range of possible applications such as: intrusion detection, water contamination monitoring, machine health monitoring, etc. This package proposes a framework that provides real time support for early detection of anomalous series within a large collection of streaming time series data. By definition, anomalies are rare in comparison to a system’s typical behaviour. We define an anomaly as an observation that is very unlikely given

the forecast distribution. The proposed framework first forecasts a boundary for the system's typical behaviour using a representative sample of the typical behaviour of the system. An approach based on extreme value theory is used for this boundary prediction process. Then a sliding window is used to test for anomalous series within the newly arrived collection of series. Feature based representation of time series is used as the input to the model. To cope with concept drift, the forecast boundary for the system's typical behaviour is updated periodically. More details regarding the algorithm can be found in Talagala, P. D., Hyndman, R. J., Smith-Miles, K., et al. (2019) DOI:10.1080/10618600.2019.1617160.

Note

The name `oddstream` comes from Outlier Detection in Data STREAMs

References

Clifton, D. A., Hugueny, S., & Tarassenko, L. (2011). Novelty detection with multivariate extreme value statistics. *Journal of signal processing systems*, 65 (3),371-389.

Talagala, P. D., Hyndman, R. J., Smith-Miles, K., et al. (2019). Anomaly detection in streaming nonstationary temporal data. *Journal of Computational and Graphical Statistics*, 1-28. DOI:10.1080/10618600.2019.1617160

See Also

The core functions in this package: [find_odd_streams](#), [extract_tsfeatures](#), [get_pc_space](#), [set_outlier_threshold](#), [gg_featurespace](#)

`set_outlier_threshold` *Set a threshold for outlier detection*

Description

This function forecasts a boundary for the typical behaviour using a representative sample of the typical behaviour of a given system. An approach based on extreme value theory is used for this boundary prediction process.

Usage

```
set_outlier_threshold(pc_pcnorm, p_rate = 0.001, trials = 500)
```

Arguments

<code>pc_pcnorm</code>	The scores of the first two principal components returned by get_pc_space
<code>p_rate</code>	False positive rate. Default value is set to 0.001
<code>trials</code>	Number of trials to generate the extreme value distribution. Default value is set to 500.

Value

Returns a threshold to determine outlying series in the next window consists with a collection of time series.

References

Clifton, D. A., Hugueny, S., & Tarassenko, L. (2011). Novelty detection with multivariate extreme value statistics. *Journal of signal processing systems*, 65 (3),371-389.

Talagala, P., Hyndman, R., Smith-Miles, K., Kandanaarachchi, S., & Munoz, M. (2018). Anomaly detection in streaming nonstationary temporal data (No. 4/18). Monash University, Department of Econometrics and Business Statistics.

See Also

[find_odd_streams](#), [extract_tsfeatures](#), [get_pc_space](#), [gg_featurespace](#)

Examples

```
# Generate training dataset
set.seed(123)
nobs <- 500
nts <- 50
train_data <- ts(apply(matrix(ncol = nts, nrow = nobs), 2, function(nobs){10 + rnorm(nobs, 0, 3)}))
features <- extract_tsfeatures(train_data)
pc <- get_pc_space(features)
threshold <- set_outlier_threshold(pc$pcnorm)
threshold$threshold_fnx
```

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