# Package 'UAHDataScienceO'

February 20, 2025

Type Package
<b>Title</b> Educational Outlier Detection Algorithms with Step-by-Step Tutorials
Version 1.0.0
Maintainer Andriy Protsak Protsak <andriy.protsak@edu.uah.es></andriy.protsak@edu.uah.es>
<b>Description</b> Provides implementations of some of the most important outlier detection algorithms. Includes a tutorial mode option that shows a description of each algorithm and provides a step-by-step execution explanation of how it identifies outliers from the given data with the specified input parameters. References include the works of Azzedine Boukerche, Lining Zheng, and Omar Alfandi (2020) <doi:10.1145 3381028="">, Abir Smiti (2020) <doi:10.1016 j.cosrev.2020.100306="">, and Xiaogang Su, Chih-Ling Tsai (2011) <doi:10.1002 widm.19="">.</doi:10.1002></doi:10.1016></doi:10.1145>
License MIT + file LICENSE
Encoding UTF-8
RoxygenNote 7.3.2
VignetteBuilder knitr
Suggests knitr, rmarkdown
NeedsCompilation no
Author Andres Missiego Manjon [aut],  Juan Jose Cuadrado Gallego [aut]  ( <a href="https://orcid.org/0000-0001-8178-5556">https://orcid.org/0000-0001-8178-5556</a> ),  Andriy Protsak Protsak [aut, cre],  Universidad de Alcala de Henares [cph]
Repository CRAN
<b>Date/Publication</b> 2025-02-20 17:20:08 UTC
Contents
boxandwhiskers

2 boxandwhiskers

	DBSCAN_method	5
	euclidean_distance	6
	knn	6
	lof	7
	mahalanobis_distance	8
	mahalanobis_method	9
	manhattan_dist	10
	mean_outliersLearn	11
	quantile_outliersLearn	11
	sd_outliersLearn	12
	transform_to_vector	13
	$z\_score\_method \dots \dots$	14
Indov		15
Index		15

boxandwhiskers

**Box And Whiskers** 

## Description

This function implements the box & whiskers algorithm to detect outliers

## Usage

```
boxandwhiskers(data, d, learn)
```

## Arguments

data	Input data.
d	Degree of outlier or distance at which an event is considered an outlier
learn	if TRUE the tutorial mode is activated (the algorithm will include an explanation detailing the theory behind the outlier detection algorithm and a step by step explanation of how is the data processed to obtain the outliers following the theory mentioned earlier)

#### Value

Numeric vector containing the indices of detected outliers.

#### Author(s)

Andres Missiego Manjon

```
inputData = t(matrix(c(3,2,3.5,12,4.7,4.1,5.2,4.9,7.1,6.1,6.2,5.2,14,5.3),2,7,dimnames=list(c("r","d"))) inputData = data.frame(inputData) boxandwhiskers(inputData,2,FALSE) # Can be set to TRUE
```

compare\_multivariate\_methods

Compare Multivariate Outlier Detection Methods

#### **Description**

Compares multiple multivariate outlier detection methods on the same dataset

#### Usage

```
compare_multivariate_methods(data, methods, params)
```

#### **Arguments**

data Input dataset (must be a data.frame)

methods Vector of method names to compare. Available methods are: "lof", "dbscan",

"knn", "mahalanobis"

params List of parameters for each method. Must contain named lists:

• lof: list(K=numeric, threshold=numeric)

• dbscan: list(max\_distance\_threshold=numeric, min\_pts=numeric)

• knn: list(d=numeric, K=numeric)

• mahalanobis: list(alpha=numeric)

#### Value

None, produces a visualization matrix comparing the outliers detected by each method.

#### Author(s)

Andriy Protsak

```
inputData = t(matrix(c(3,2,3.5,12,4.7,4.1,5.2,
4.9,7.1,6.1,6.2,5.2,14,5.3),2,7,dimnames=list(c("r","d")))
inputData = data.frame(inputData)
methods = c("lof", "dbscan", "knn", "mahalanobis")
params = list(
    lof = list(K=3, threshold=0.5),
    dbscan = list(max_distance_threshold=4, min_pts=3),
    knn = list(d=3, K=2),
    mahalanobis = list(alpha=0.7)
)
compare_multivariate_methods(inputData, methods, params)
```

compare\_univariate\_methods

Compare Univariate Outlier Detection Methods

#### **Description**

Compares univariate outlier detection methods on the flattened dataset

#### Usage

```
compare_univariate_methods(data, methods, params)
```

#### **Arguments**

data Input dataset (must be a data.frame)

methods Vector of method names to compare. Available methods are: "z\_score", "boxand-

whiskers"

params List of parameters for each method. Must contain named lists:

• z\_score: list(d=numeric)

• boxandwhiskers: list(d=numeric)

#### Value

None, produces a visualization matrix comparing the outliers detected by each method.

#### Author(s)

Andriy Protsak

```
inputData = t(matrix(c(3,2,3.5,12,4.7,4.1,5.2,
4.9,7.1,6.1,6.2,5.2,14,5.3),2,7,dimnames=list(c("r","d")))
inputData = data.frame(inputData)
methods = c("z_score", "boxandwhiskers")
params = list(
    z_score = list(d=2),
    boxandwhiskers = list(d=2)
)
compare_univariate_methods(inputData, methods, params)
```

DBSCAN\_method 5

DDCCXN	method
DDSCAN	ille criou

DBSCAN method

## Description

Outlier detection method using DBSCAN

#### Usage

```
DBSCAN_method(inputData, max_distance_threshold, min_pts, learn)
```

## Arguments

inputData

Input Data (must be a data.frame)

max\_distance\_threshold

This is used to calculate the distance between all the points and check if the euclidean distance is less than the max\_distance\_threshold parameter to decide

if add it to the neighbors or not

min\_pts

the minimum number of points to form a dense region

learn

if TRUE the tutorial mode is activated (the algorithm will include an explanation detailing the theory behind the outlier detection algorithm and a step by step explanation of how is the data processed to obtain the outliers following the

theory mentioned earlier)

#### Value

Numeric vector containing the indices of detected outliers.

#### Author(s)

Andres Missiego Manjon

```
inputData = t(matrix(c(3,2,3.5,12,4.7,4.1,5.2,
4.9,7.1,6.1,6.2,5.2,14,5.3),2,7,dimnames=list(c("r","d")));
inputData = data.frame(inputData);
eps = 4;
min_pts = 3;
DBSCAN_method(inputData, eps, min_pts, FALSE); #Can be set to TRUE
```

6 knn

euclidean\_distance

euclidean\_distance

#### Description

This function calculates the euclidean distance between 2 points. They must have the same number of dimensions

#### Usage

```
euclidean_distance(p1, p2)
```

#### **Arguments**

Done of the points that will be used by the algorithm with N dimensions

p2 The other point that will be used by the algorithm with N dimensions

#### Value

Euclidean Distance calculated between the two N-dimensional points

#### Author(s)

Andres Missiego Manjon

#### **Examples**

```
inputData = t(matrix(c(3,2,3.5,12,4.7,4.1,5.2,
4.9,7.1,6.1,6.2,5.2,14,5.3),2,7,dimnames=list(c("r","d")));
inputData = data.frame(inputData);
point1 = inputData[1,];
point2 = inputData[4,];
distance = euclidean_distance(point1, point2);
```

knn

knn

#### **Description**

This function implements the knn algorithm for outlier detection

#### Usage

```
knn(data, d, K, learn)
```

lof 7

#### **Arguments**

data Input Data (must be a data.frame)

d Degree of outlier or distance at which an event is considered an outlier

K Nearest neighbor for which an event must have a degree of outlier to be considered an outlier

learn if TRUE the tutorial mode is activated (the algorithm will include an explanation detailing the theory behind the outlier detection algorithm and a step by step

detailing the theory behind the outlier detection algorithm and a step by step explanation of how is the data processed to obtain the outliers following the

theory mentioned earlier)

#### Value

Numeric vector containing the indices of detected outliers.

#### Author(s)

Andres Missiego Manjon

#### **Examples**

```
inputData = t(matrix(c(3,2,3.5,12,4.7,4.1,5.2,
4.9,7.1,6.1,6.2,5.2,14,5.3),2,7,dimnames=list(c("r","d")))
inputData = data.frame(inputData)
knn(inputData,3,2,FALSE) #Can be changed to TRUE
```

lof lof

#### Description

Local Outlier Factor algorithm to detect outliers

## Usage

```
lof(inputData, K, threshold, learn)
```

#### **Arguments**

inputData Input Data (must be a data.frame)

K This number represents the nearest neighbor to use to calculate the density of

each point. This value is chosen arbitrarily and is responsibility of the data

scientist/user to select a number adequate to the dataset.

threshold Value that is used to classify the points comparing it to the calculated ARDs

of the points in the dataset. If the ARD is smaller, the point is classified as an

outliers. If not, the point is classified as a normal point (inlier)

8 mahalanobis\_distance

learn

if TRUE the tutorial mode is activated (the algorithm will include an explanation detailing the theory behind the outlier detection algorithm and a step by step explanation of how is the data processed to obtain the outliers following the theory mentioned earlier)

#### Value

Numeric vector containing the indices of detected outliers.

#### Author(s)

Andres Missiego Manjon

#### **Examples**

```
inputData = t(matrix(c(3,2,3.5,12,4.7,4.1,5.2,4.9,7.1,6.1,6.2,5.2,14,5.3),2,7,dimnames=list(c("r","d")));inputData = data.frame(inputData);
lof(inputData,3,0.5,FALSE) #Can be changed to TRUE
```

mahalanobis\_distance
mahalanobis\_distance

## Description

Calculates the mahalanobis\_distance given the input data

#### Usage

```
mahalanobis_distance(value, sample_mean, sample_covariance_matrix)
```

## Arguments

value Point to calculate the mahalanobis\_distance

sample\_mean Sample mean
sample\_covariance\_matrix

Sample Covariance Matrix

#### Value

Mahalanobis distance associated to the point

#### Author(s)

Andres Missiego Manjon

mahalanobis\_method 9

#### **Examples**

```
inputData = t(matrix(c(3,2,3.5,12,4.7,4.1,5.2,
4.9,7.1,6.1,6.2,5.2,14,5.3),2,7,dimnames=list(c("r","d")));
inputData = data.frame(inputData);
inputData = as.matrix(inputData);
sampleMeans = c();
for(i in 1:ncol(inputData)){
    column = inputData[,i];
    calculatedMean = sum(column)/length(column);
    print(sprintf("Calculated mean for column %d: %f", i, calculatedMean))
    sampleMeans = c(sampleMeans, calculatedMean);
}
covariance_matrix = cov(inputData);
distance = mahalanobis_distance(inputData[3,], sampleMeans, covariance_matrix);
```

mahalanobis\_method

mahalanobis\_method

#### Description

Detect outliers using the Mahalanobis Distance method

#### Usage

```
mahalanobis_method(inputData, alpha, learn)
```

#### **Arguments**

inputData Input Data dataset that will be processed (with or not the step by step explana-

tion) to obtain the underlying outliers. It must be a data.frame type.

alpha Significance level alpha. This value indicates the proportion that it is expected

to be outliers out of the dataset. It has to be in the range from 0 to 1

learn if TRUE the tutorial mode is activated (the algorithm will include an explanation

detailing the theory behind the outlier detection algorithm and a step by step explanation of how is the data processed to obtain the outliers following the

theory mentioned earlier)

#### Value

Numeric vector containing the indices of detected outliers.

#### Author(s)

Andres Missiego Manjon

10 manhattan\_dist

#### **Examples**

```
inputData = t(matrix(c(3,2,3.5,12,4.7,4.1,5.2, 4.9,7.1,6.1,6.2,5.2,14,5.3),2,7,dimnames=list(c("r","d")))); inputData = data.frame(inputData); mahalanobis_method(inputData, 0.7, FALSE); #Can be set to TRUE
```

manhattan\_dist

manhattan\_dist

## Description

Calculates the manhattan distance between two 2D points

#### Usage

```
manhattan_dist(A, B)
```

## Arguments

A One of the 2D points

B The other 2D point

#### Value

Manhattan distance calculated between point A and B

#### Author(s)

Andres Missiego Manjon

```
distance = manhattan_dist(c(1,2), c(3,4));
```

mean\_outliersLearn 11

mean\_outliersLearn

mean\_outliersLearn

#### **Description**

Calculates the mean of the given data vector

#### Usage

```
mean_outliersLearn(data)
```

#### **Arguments**

data

Input Data that will be processed to calculate the mean. It must be a vector

#### Value

Mean of the input data

## Author(s)

Andres Missiego Manjon

#### **Examples**

```
mean = mean\_outliersLearn(c(2,3,2.3,7.8));
```

```
quantile_outliersLearn
```

quantile\_outliersLearn

## Description

Function that obtains the 'v' quantile

#### Usage

```
quantile_outliersLearn(data, v)
```

#### **Arguments**

data Input Data

Goes from 0 to 1 (e.g. 0.25). Indicates the quantile that wants to be obtained

12 sd\_outliersLearn

#### Value

Quantile v calculated

#### Author(s)

Andres Missiego Manjon

#### **Examples**

```
q = quantile\_outliersLearn(c(12,2,3,4,1,13), 0.60)
```

 $sd\_outliersLearn$ 

 $sd\_outliersLearn$ 

## Description

Calculates the standard deviation of the input data given the mean.

#### Usage

```
sd_outliersLearn(data, mean)
```

#### **Arguments**

data Input Data that will be used to calculate the standard deviation. Must be a vector

mean Mean of the input data vector of the function.

#### Value

Standard Deviation of the input data

#### Author(s)

Andres Missiego Manjon

```
inputData = c(1,2,3,4,5,6,1);
mean = sum(inputData)/length(inputData);
sd = sd_outliersLearn(inputData, mean);
```

transform\_to\_vector 13

transform\_to\_vector transform\_to\_vector

#### **Description**

Transform any type of data to a vector

#### Usage

```
transform_to_vector(data)
```

#### **Arguments**

data

Input data that will be transformed into a vector

#### Value

Data formatted as a vector

#### Author(s)

Andres Missiego Manjon

```
numeric_data = c(1, 2, 3)
character_data = c("a", "b", "c")
logical_data = c(TRUE, FALSE, TRUE)
factor_data = factor(c("A", "B", "A"))
integer_data = as.integer(c(1, 2, 3))
complex_data = complex(real = c(1, 2, 3), imaginary = c(4, 5, 6))
list_data = list(1, "apple", TRUE)
data_frame_data = data.frame(x = c(1, 2, 3), y = c("a", "b", "c"))
transformed_numeric = transform_to_vector(numeric_data)
transformed_character = transform_to_vector(character_data)
transformed_logical = transform_to_vector(logical_data)
transformed_factor = transform_to_vector(factor_data)
transformed_integer = transform_to_vector(integer_data)
transformed_complex = transform_to_vector(complex_data)
transformed_list = transform_to_vector(list_data)
transformed_data_frame = transform_to_vector(data_frame_data)
```

z\_score\_method

|--|--|

## Description

This function implements the outlier detection algorithm using standard deviation and mean

## Usage

```
z_score_method(data, d, learn)
```

## Arguments

data	Input Data that will be processed with or without the tutorial mode activated
d	Degree of outlier or distance at which an event is considered an outlier
learn	if TRUE the tutorial mode is activated (the algorithm will include an explanation detailing the theory behind the outlier detection algorithm and a step by step explanation of how is the data processed to obtain the outliers following the theory mentioned earlier)

#### Value

Numeric vector containing the indices of detected outliers.

## Author(s)

Andres Missiego Manjon

```
\label{eq:continuous} \begin{split} & inputData = t(matrix(c(3,2,3.5,12,4.7,4.1,5.2,\\ & 4.9,7.1,6.1,6.2,5.2,14,5.3),2,7, dimnames=list(c("r","d")))) \\ & inputData = data.frame(inputData) \\ & z\_score\_method(inputData,2,FALSE) \ \#Can \ be \ changed \ to \ TRUE \end{split}
```

## **Index**

```
boxandwhiskers, 2

compare_multivariate_methods, 3
compare_univariate_methods, 4

DBSCAN_method, 5

euclidean_distance, 6

knn, 6

lof, 7

mahalanobis_distance, 8

mahalanobis_method, 9

manhattan_dist, 10

mean_outliersLearn, 11

quantile_outliersLearn, 11

sd_outliersLearn, 12

transform_to_vector, 13

z_score_method, 14
```