Package ‘parody’

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Title Parametric And Resistant Outlier DYtection

Version 1.66.0

Description Provide routines for univariate and multivariate outlier detection
with a focus on parametric methods, but support for some
methods based on resistant statistics.

Depends R (>= 3.5.0), tools, utils

Suggests knitr, BiocStyle, testthat, rmarkdown

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VignetteBuilder knitr

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Contents

box.scale — *calibrated scaling inlier multiplier radius for various outlier detection approaches*

Description

calibrated scaling inlier multiplier radius for various outlier detection approaches

Usage

```
box.scale(n, alpha=0.05)
```

Arguments

n	n
alpha	alpha

Author(s)

Vince Carey <stvjc@channing.harvard.edu>

Examples

```
box.scale(20)
```

bushfire — *satellite data on bushfire scars*

Description

satellite data on bushfire scars

Usage

```
data(bushfire)
```

Format

The format is: num [1:38, 1:5] 111 113 113 110 101 93 92 94 94 100 ...

Details

Satellite measurements on five frequency bands corresponding to each of 38 pixels.

Source

Maronna RA and Yohai VJ (1995) JASA 90:330.

Examples

```
data(bushfire)
mv.calout.detect(bushfire)
```

---

calout.detect *interface to modular calibrated outlier detection system*

Description

Various classical and resistant outlier detection procedures are provided in which the outlier misclassification rate for Gaussian samples is fixed over a range of sample sizes.

Usage

```
calout.detect(x, alpha = 0.05, method = c("GESD", "boxplot", "medmad",
    "shorth", "hybrid"), k = ((length(x)%%2) * floor(length(x)/2) +
    (1 - (length(x)%%2)) * (length(x)/2 - 1)), scaling, ftype,
    location, scale, gen.region = function(x, location, scale,
        scaling, alpha) {
        g <- scaling(length(x), alpha)
        location(x) + c(-1, 1) * g * scale(x)
    })
```

Arguments

`x`	data vector, NAs not allowed
`alpha`	outlier mislabeling rate for Gaussian samples
`method`	one of c("GESD", "boxplot", "medmad", "shorth"); the first selects generalized extreme studentized deviate (Rosner, 1983); the second selects calibrated boxplot rules; the third selects the method of Hampel in which the sample median is used for location estimation, and the median absolute deviation is used for scale; and the fourth selects Rousseeuw's rule, with the midpoint of the shortest half sample used as location estimator, and the length of this shortest half sample used as scale estimator. An important characteristic of the GESD procedure is that the critical values for outlier labeling are calibrated to preserve the overall Type I error rate of the procedure given that there will be k tests, whether or not any outliers are present in the data.
`k`	for GESD, the prespecified upper limit on the number of outliers suspected in the data; defaults to "half" the sample size.
`scaling`	for resistant methods, scaling is a sample-size dependent function that tells how many multiples of the scale estimate should be laid off on each side of the location estimate to demarcate the inlier region; see Davies and Gather (1993) for the general formulation. The main contribution of this program consists in the development of scaling functions that "calibrate" outlier detection in Gaussian

samples. The scaling function is assumed to take two arguments, n and alpha, and it should return a real number.

If method=="boxplot", the default value scaling=box.scale will confine the probability of erroneous detection of one or more outliers in a pure Gaussian sample to alpha. The use of scaling=function(n,alpha) 1.5 gives the standard boxplot outlier labeling rule.

If method=="medmad", the use of scaling=hamp.scale.4 will confine the outlier mislabeling rate to alpha; whereas the use of scaling=function(n,alpha) 5.2 gives Hampel's rule (Davies and Gather, 1993, p. 790).

If method=="shorth", the default value scaling=shorth.scale will confine the outlier mislabeling rate to alpha.

`ftype` The type of "fourth" calculation; the standard definition of the fourth uses 0.5 * floor((n + 3)/2) to obtain the sortile of the fourth value; Hoaglin and Iglewicz (1987) give an "ideal" definition of the fourth which reduces the dependence of boxplot-based outlier detection performance (in small samples) on the quantity n mod 4.

`location` a function on a vector returning a location estimate

`scale` a function on a vector returning a scale estimate

`gen.region` a function of x, location, scale, scaling, alpha that returns the inlier region as a 2-vector

Value

a list with components ind (indices of outliers in the input vector) val (values of these components) and outlier.region, which is only defined for the resistant methods.

References

Davies and Gather (1993 JASA), Rousseeuw and Leroy (1988 Stat Neer), Rosner (1983 Technom), Hoaglin and Iglewicz (1987 JASA), Carey, Walters, Wager and Rosner (1997 Technom)

Examples

```
lead <- c(83, 70, 62, 55, 56, 57, 57, 58, 59, 50, 51, 52, 52, 52, 54, 54, 45, 46, 48,
        48, 49, 40, 40, 41, 42, 42, 44, 44, 35, 37, 38, 38, 34, 13, 14)

calout.detect(lead,alpha=.05,method="boxplot",ftype="ideal")
calout.detect(lead,alpha=.05,method="GESD",k=5)
calout.detect(lead,alpha=.05,method="medmad",scaling=hamp.scale.3)
calout.detect(lead,alpha=.05,method="shorth")
```

mv.calout.detect *calibrated multivariate outlier detection*

Description

interface to a parametric multivariate outlier detection algorithm

Usage

```
mv.calout.detect(x, k = min(floor((nrow(x) - 1)/2), 100), Ci = C.unstr,
    lamfun = lams.unstr, alpha = 0.05, method = c("parametric",
        "rocke", "kosinski.raw", "kosinski.exch")[1], ...)
```

Arguments

`x`	data matrix
`k`	upper bound on number of outliers; defaults to just less than half the sample size
`Ci`	function computing Ci, the covariance determinant ratio excluding row i. At present, sole option is `C.unstr` (Caroni and Prescott 1992 Appl Stat).
`lamfun`	function computing lambda, the critical values for Ci
`alpha`	false outlier labeling rate
`method`	string identifying algorithm to use
`...`	reserved for future use

Details

bushfire is a dataset distributed by Kosinski to illustrate his method.

Value

a list with components

`inds`	indices of outlying rows
`vals`	values of outlying rows
`k`	input parameter k
`alpha`	input parameter alpha

Author(s)

VJ Carey

References

C. Caroni and P. Prescott, Journal of the Royal Statistical Society. Series C (Applied Statistics), Vol. 41, No. 2 (1992), pp. 355-364

Examples

```
data(tcost)
mv.calout.detect(tcost)
data(bushfire)
mv.calout.detect(bushfire)
```

---

shorth *one-dimensional MVE (min. vol. ellipsoid)*

Description

generalized length of shortest-half sample

Usage

```
shorth(x, Alpha=0.5)
```

Arguments

`x`	data vector, no NAs
`Alpha`	minimum fraction of data to be covered by scale estimator. if Alpha == 0.5, the `shorth` is calculated

Value

a list, say L, with components

`shorth`	a 2-vector with endpoints of the shortest Alpha-sample
`length.shorth`	see previous return component `L$shorth[2]-L$shorth[1]`
`midpt.shorth`	mean(L[["shorth"]])
`meanshorth`	mean of values in the shorth, studied by Andrews et al (1972) as a location estimator
`correction.parity.dep`	correction factor to be applied to achieve approximate unbiasedness and diminish small-sample parity dependence; `L["shorth"]] * L[["correction"]]` is approximately unbiased for the Gaussian standard deviation, for 0 < Alpha < 1.
`bias.correction.gau.5`	correction factor to be applied along with correction.parity.dep when Alpha = .5; empirically derived bias correction useful for 10 < N < 2000 and possibly beyond. To use, divide: `(L[["shorth"]] * L[["correction"]] / L[["bias.corr"]])` is approximately unbiased for Gaussian standard deviation, when Alpha=.5.
`Alpha`	coverage fraction used

References

Rousseeuw and Leroy, Stat Neer (1988), Gruebel, Ann Stat (1988)

tcost — *Data on milk transportation costs, from Johnson and Wichern, Applied Multivariate Statistical Analysis, 3rd edition*

Description

Multivariate data on milk transportation costs

Usage

```
data(tcost)
```

Format

The format is: num [1:36, 1:3] 16.44 7.19 9.92 4.24 11.2 ...

- attr(*, "dimnames")=List of 2

..$: chr [1:36] "1" "2" "3" "4" ...

..$: chr [1:3] "fuel" "repair" "capital"

Details

Extract from Johnson and Wichern example dataset on milk transportation.

Source

Johnson and Wichern, Applied Multivariate Statistical Analysis, 3rd edition, p263

Examples

```
data(tcost)
mv.calout.detect(tcost)
```

tukeyor — *calibrated outlier region based on various algorithms*

Description

calibrated outlier region based on various algorithms

Usage

```
tukeyor(x, alpha=0.05, g=box.scale(length(x), alpha = alpha), ftype="ideal")
```

Arguments

`x`	x
`alpha`	alpha
`g`	g
`ftype`	ftype

Author(s)

Vince Carey <stvjc@channing.harvard.edu>

Examples

```
data(tcost)
apply(tcost, 2, tukeyor)
```

Index