

Package ‘galts’

October 13, 2022

Type Package

Title Genetic Algorithms and C-Steps Based LTS (Least Trimmed Squares) Estimation

Version 1.3.1

Date 2017-11-24

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Description Includes the `ga.lts()` function that estimates LTS (Least Trimmed Squares) parameters using genetic algorithms and C-steps. `ga.lts()` constructs a genetic algorithm to form a basic subset and iterates C-steps as defined in Rousseeuw and van-Driessen (2006) to calculate the cost value of the LTS criterion. OLS (Ordinary Least Squares) regression is known to be sensitive to outliers. A single outlying observation can change the values of estimated parameters. LTS is a resistant estimator even the number of outliers is up to half of the data. This package is for estimating the LTS parameters with lower bias and variance in a reasonable time. Version ≥ 1.3 includes the function `medmad` for fast outlier detection in linear regression.

Depends `genalg`, `DEoptim`

Repository CRAN

License GPL

LazyLoad yes

Date/Publication 2017-11-24 10:49:11 UTC

NeedsCompilation no

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galts-package	<i>Genetic algorithms and C-steps based LTS (Least Trimmed Squares) estimation</i>
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Description

This package includes the `ga.lts` function that estimates LTS (Least Trimmed Squares) parameters using genetic algorithms and C-steps. `ga.lts()` constructs a genetic algorithm to form a basic subset and iterates C-steps as defined in Rousseeuw and van-Driessen (2006) to calculate the cost value of the LTS criterion. OLS (Ordinary Least Squares) regression is known to be sensitive to outliers. A single outlying observation can change the values of estimated parameters. LTS is a resistant estimator even the number of outliers is up to half of the data. This package is for estimating the LTS parameters with lower bias and variance in a reasonable time.

Details

Package:	galts
Type:	Package
Version:	1.1
Date:	2011-02-04
License:	GPL
LazyLoad:	yes

Author(s)

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References

Rousseeuw, P. J., van Driessen, K. (2006). Computing LTS Regression for Large Data Sets ,Data Mining and Knowledge Discovery, 12, 29-45.

Satman, M.,H. (2012). A Genetic Algorithm Based Modification on the LTS Algorithm for Large Data Sets, Communications in Statistics - Simulation and Computation, Vol 41, Issue 5, pp. 644-652.

Examples

```
# Data generating process
x1 <- rnorm(100)
x2 <- rnorm(100)
e <- rnorm(100)
```

```

# Setting betas to 5
y <- 5 + 5 * x1 + 5 * x2 + e

# Contaminate the data on the dimension of X's randomly
# This is the maximum contamination rate that the LTS can cope with.
outlyings <- sample(1:100, 48)
x1[outlyings] <- 10
x2[outlyings] <- 10

# Estimating LTS with ga (Default optimization method)
lts <- ga.lts(y ~ x1 + x2, popsize = 40, iters = 2, lower = -20, upper = 20)
print(lts)

#Estimating LTS with differential evolution
lts <- ga.lts(y ~ x1 + x2, popsize = 40, iters = 2, lower = -20, upper = 20, method = "de")
print(lts)

```

ga.lts	<i>Function for estimating the LTS (Least Trimmed Squares) regression parameters using genetic algorithms.</i>
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Description

This function estimates the LTS (Least Trimmed Squares) regression parameters using genetic algorithms. LTS is a robust regression estimator with high breakdown property. LTS is a resistant estimator even the number of outliers is up to half of the data. However, calculating LTS estimator is computationally expensive. `ga.lts()` uses evolutionary algorithms (genetic algorithms by default, optionally differential evolution) to construct a basic subset and iterates C-steps as defined in Rousseeuw and van-Driessen (2006). Despite lower time efficiency of the `ga.lts()`, estimations have lower mean square errors, as a result of lower biases and lower variances.

Usage

```
ga.lts(formula, h = NULL, iters = 2, popsize = 50, lower, upper,
csteps = 2, method = "ga", verbose = FALSE)
```

Arguments

formula	Dependent ~ Independents style formula as same in <code>lm()</code> and <code>glm()</code> .
h	User defined variable to define the majority of the data. Default is $\text{floor}(n/2) + \text{floor}((p+1)/2)$ where n is the number of observations and p is the number of parameters to estimate
iters	Number of generations of the evolutionary algorithm. This variable can be kept larger if the precision is more important than the computation time. Default is 2.

popsize	Number of candidates (chromosomes) in the population of evolutionary algorithm. Default is 50.
lower	Lower bound for the initial estimates of the parameters.
upper	Upper bound for the initial estimates of the parameters.
csteps	Number of C-steps to be performed for each candidate solution. Default is 2.
method	A string variable for the evolutionary algorithm. 'ga' for the genetic algorithms and 'de' for the differential evolution. Default is 'ga'
verbose	A boolean variable for printing the current status of algorithms to screen. Default is FALSE.

Value

coefficients	A vector of estimated parameters
crit	LTS criterion value for the reported coefficients
method	Name of the method used in the optimization process

Author(s)

Mehmet Hakan Satman

References

- Rousseeuw, P. J., van Driessen, K. (2006). Computing LTS Regression for Large Data Sets ,Data Mining and Knowledge Discovery, 12, 29-45.
- Satman, M.,H. (2012). A Genetic Algorithm Based Modification on the LTS Algorithm for Large Data Sets, Communications in Statistics - Simulation and Computation, Vol 41, Issue 5, pp. 644-652.

Examples

```
# Data generating process
x1 <- rnorm(100)
x2 <- rnorm(100)
e <- rnorm(100)

# Setting betas to 5
y <- 5 + 5 * x1 + 5 * x2 + e

# Contaminate the data on the dimension of X's randomly
# This is the maximum contamination rate that the LTS can cope with.
outlyings <- sample(1:100, 48)
x1[outlyings] <- 10
x2[outlyings] <- 10

# Estimating LTS with ga (Default optimization method)
lts <- ga.lts(y ~ x1 + x2, popsize = 40, iters = 2, lower = -20, upper = 20)
print(lts)
```

```
# Estimating LTS with differential evolution
lts <- ga.lts(y ~ x1 + x2, popsize = 40, iters = 2, lower = -20, upper = 20, method = "de")
print(lts)
```

medmad

Function for detecting regression outliers

Description

A method for detecting regression outliers.

Usage

```
medmad(formula, h=NULL, csteps=20)
```

Arguments

formula	Dependent ~ Independents style formula as same in lm() and glm().
h	User defined variable to define the majority of the data. Default is $\text{floor}(n/2) + \text{floor}((p+1)/2)$ where n is the number of observations and p is the number of parameters to estimate
csteps	Number of C-steps to be performed for each candidate solution. Default is 2.

Value

coefficients	A vector of estimated parameters
crit	LTS criterion value for the reported coefficients
residuals	Calculated residuals from the final estimate of model

Author(s)

Mehmet Hakan Satman

Examples

```
n <- 100
x1 <- rnorm(n,0,10)
x2 <- rnorm(n,0,10)
x3 <- rnorm(n,0,10)
x4 <- rnorm(n,0,10)
e <- rnorm(n)
x <- cbind(1, x1, x2, x3, x4)
p <- 5
betas <- rep(5,p)
c <- 0.20
h <- n - n*c
y <- 5 + 5*x1 + 5*x2 + 5*x3 + 5*x4 + e
```

```
x1[(h + 1):n] <- rnorm(n-h, 100, 10)
x2[(h + 1):n] <- rnorm(n-h, 100, 10)
x3[(h + 1):n] <- rnorm(n-h, 100, 10)
x4[(h + 1):n] <- rnorm(n-h, 100, 10)

mm <- medmad(formula = y ~ x1 + x2 + x3 + x4, csteps = 10)
```

medmad.cov

Function for robust covariance matrix estimation.

Description

Function for robust covariance matrix estimation.

Usage

```
medmad.cov(data)
```

Arguments

data Row matrix of data

Value

varcov Covariance matrix

Author(s)

Mehmet Hakan Satman

Examples

```
n <- 100
c <- 0.20
h <- n - n*c
x1 <- rnorm(n,0,10)
x2 <- rnorm(n,0,10)
x3 <- rnorm(n,0,10)
x4 <- rnorm(n,0,10)
x1[(h + 1):n]<-rnorm(n-h, 100, 10)
x2[(h + 1):n]<-rnorm(n-h, 100, 10)
x3[(h + 1):n]<-rnorm(n-h, 100, 10)
x4[(h + 1):n]<-rnorm(n-h, 100, 10)
mat <- medmad.cov(cbind(x1, x2, x3, x4))
print (mat)
```

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