Package ‘alphastable’

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Title Inference for Stable Distribution

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Description

Developed to perform the tasks given by the following. 1-computing the probability density function and distribution function of a univariate stable distribution; 2- generating from univariate stable, truncated stable, multivariate elliptically contoured stable, and bivariate strictly stable distributions; 3- estimating the parameters of univariate symmetric stable, skew stable, Cauchy, multivariate elliptically contoured stable, and multivariate strictly stable distributions; 4- estimating the parameters of the mixture of symmetric stable and mixture of Cauchy distributions.

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Encoding UTF-8

LazyData true

Depends R(>= 3.4.0)

Imports mvtnorm, nnls, stabledist, nlme

Suggests Matrix, fBasics, FMStable, RUnit, Rmpfr, sfsmisc

RoxygenNote 6.0.1

NeedsCompilation no

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R topics documented:

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mdstab.elliptical *mdstab.elliptical*

Description

computes the probability density function of a d-dimensional elliptically contoured stable distribution at a given point in R^{d}, see Teimouri et al. (2018).

Usage

```
mdstab.elliptical(x, alpha, Sigma, Mu)
```

Arguments

x	vector of real values in R^d
alpha	tail index parameter
Sigma	d by d positive definite dispersion matrix
Mu	location vector in R^d

Value

a numeric value

Note

mdstab.elliptical() computes the probability density function of an d-dimensional elliptically contoured stable distribution using either asymptotic series or Monte Carlo approximation.

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Teimouri, M., Rezakhah, S., and Mohammadpour, A. (2018). Parameter estimation using the EM algorithm for symmetric stable random variables and sub-Gaussian random vectors, Journal of Statistical Theory and Applications, 17(3),1-20.

Examples

```
# In the following example, we compute the pdf of a two-dimensional elliptically contoured
# stable distribution with parameters alpha=1.3, Sigma=matrix(c(1,.5,.5,1),2,2), and mu=(0,0)^T.
library("stabledist")
mdstab.elliptical(c(5,5),1.2,matrix(c(1,0.5,0.5,1),2,2),c(0,0))
```

`mfitstab.elliptical` *mfitstab.elliptical*

Description

estimates the parameters of a d-dimensional elliptically contoured stable distribution, see Teimouri et al. (2018).

Usage

```
mfitstab.elliptical(yy, alpha0, Sigma0, Mu0)
```

Arguments

`yy`	vector of d-dimensional realizations
`alpha0`	initial value of the tail index parameter to start the EM algorithm
`Sigma0`	initial value of the dispersion matrix to start the EM algorithm
`Mu0`	initial value of the location vector to start the EM algorithm

Value

`alpha`	estimated value of the tail index parameter
`Sigma`	estimated value of the dispersion matrix
`Mu`	estimated value of the location vector

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Teimouri, M., Rezakhah, S., and Mohammadpour, A. (2018). Parameter estimation using the EM algorithm for symmetric stable random variables and sub-Gaussian random vectors, Journal of Statistical Theory and Applications, 17(3),1-20,

Examples

```
# Here we follow for applying the EM algorithm to Z=(x1, x2)^T using the
# initial values alpha0=1, Sigma0=matrix(c(0.75,0.25,0.25,0.75),2,2), and
# Mu0=(0.5,0.5)^T.
library("stabledist")
x1<-urstab(100,1.2,0,1,2,0)
x2<-urstab(100,1.2,0,0.5,2,0)
z<-cbind(x1,x2)
mfitstab.elliptical(z,1,matrix(c(0.75,0.25,0.25,0.75),2,2),c(0.5,0.5))
```

`mfitstab.ustat` *mfitstab.ustat*

Description

estimates the parameters of a strictly bivariate stable distribution using approaches proposed by Mohammadi et al. (2015)<doi.org/10.1007/s00184-014-0515-7> and Teimouri et al. (2017)<doi.org/10.1155/2017/3483827>. The estimated parameters are tail index and discretized spectral measure on `m` equidistant points located on unit sphere in `R^2`.

Usage

```
mfitstab.ustat(u,m,method=method)
```

Arguments

`u`	an `n` by 2 vector of observations
`m`	number of masses located on unit circle in `R^2`
`method`	integer values 1 or 2, respectively, corresponds to the method given by Teimouri et al. (2017) and Mohammadi et al. (2015)

Value

`alpha`	estimated value of tail index
`mass`	estimated value of discrete spectral measure

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Mohammadi, M., Mohammadpour, A., and Ogata, H. (2015). On estimating the tail index and the spectral measure of multivariate alpha-stable distributions, Metrika, 78(5), 549-561.

Nolan. J. P. (2013). Multivariate elliptically contoured stable distributions: theory and estimation, Computational Statistics, 28(5), 2067-2089.

Teimouri, M., Rezakhah, S., and Mohammadpour, A. (2017). U-Statistic for multivariate stable distributions, Journal of Probability and Statistics, https://doi.org/10.1155/2017/3483827.

Examples

```
# Here, for example, we are interested to estimate the parameters of a bivariate
# stable distribution. For this, two sets of n=400 iid realizations which are
# assumed to distributed jointly as a strictly bivariate stable distribution with
# tail index alpha=1.2 are simulated. Considering m=4, masses of the discrete spectral
# measure are addressed by s_j=(cos(2*pi(j-1)/m), sin (2*pi(j-1)/m)); for j=1,...,4.
library("nnls")
x1<-urstab(400,1.2,-0.50,1,0,0)
x2<-urstab(400,1.2,0.50,0.5,0,0)
z<-cbind(x1,x2)
mfitstab.ustat(z,4,1)
```

`mrstab` *mrstab*

Description

generates `iid` realizations from bivariate stable vectors using the methodology proposed by Modarres and Nolan (1994).

Usage

```
mrstab(n, m, alpha, Gamma, Mu)
```

Arguments

`n`	sample size
`m`	number of masses
`alpha`	tail index parameter
`Gamma`	vector of masses
`Mu`	location vector

Value

a vector of `n` numeric values

Note

`mrstab()` assumes that masses are located at unit sphere with addresses `s_j=(cos(2*pi(j-1)/m), sin(2*pi(j-1)/m))`; for `j=1,...,4`.

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Modarres, R. and Nolan, J. P. (1994). A method for simulating stable random vectors, Computational Statistics, 9(1), 11-19.

Examples

```
# We use the following command to simulate n=200 iid vectors from a two-dimensional stable
# distribution with alpha=1.3, with a vector of 4 masses as gamma=(0.1,0.5,0.5,0.1)^T,
# and mu=(0,0)^T.
library("stabledist")
mrstab(200,4,1.3,c(0.1,0.5,0.5,0.1),c(0,0))
```

---

mrstab.elliptical *mrstab.elliptical*

Description

generates iid realizations from d-dimensional elliptically contoured stable distribution, see Nolan (2013) <doi.org/10.1007/s00180-013-0396-7>.

Usage

```
mrstab.elliptical(n, alpha, Sigma, Mu)
```

Arguments

n	sample size
alpha	tail index parameter
Sigma	d by d positive definite dispersion matrix
Mu	location vector in R^d

Details

`mrstab.elliptical()` needs to install the `mvtnorm` package

Value

an n by d matrix of numeric values

Note

`mrstab.elliptical()` generates iid realizations from d-dimensional elliptically contoured stable distribution based on definitions given by Nolan (2013) and Samorodnitsky and Taqqu (1994)

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Nolan. J. P. (2013). Multivariate elliptically contoured stable distributions: theory and estimation, Computational Statistics, 28(5), 2067-2089.

Samorodnitsky, G. and Taqqu, M. S. (1994). Stable Non-Gaussian Random Processes: Stochastic Models and Infinite Variance, Chapman and Hall, London.

Examples

```
# In the following example, we simulate n=200 iid vectors of a two-dimensional elliptically
# contoured stable distribution with parameters alpha=1.3, Sigma=matrix(c(1,.5,.5,1),2,2),
# and mu=(0,0)^T.
library("mvtnorm")
library("stabledist")
mrstab.elliptical(200,1.3,matrix(c(1,.5,.5,1),ncol=2,nrow=2),c(0,0))
```

`udstab` *udstab*

Description

computes the probability density function (pdf) of the univariate stable distribution based on formulas given by Nolan (1997) <doi.org/10.1080/15326349708807450> and asymptotic series, see Teimouri and Amindavar (2008).

Usage

```
udstab(x, alpha, beta, sigma, mu, param)
```

Arguments

`x`	point at which the pdf is computed
`alpha`	tail index parameter
`beta`	skewness parameter
`sigma`	scale parameter
`mu`	location parameter
`param`	kind of parameterization; must be 0 or 1 for `S_0` and `S_1` parameterizations, respectively

Value

a numeric value

Note

`udstab()` computes the pdf of univariate stable distribution using asymptotic series within their convergence regions. For points outside of convergence regions, the pdf is computed using `stabledist` package based on formulas given by Nolan (1997). So, to compute the pdf using the `upstab()` we may need to install `stabledist` package.

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Nolan, J. P. (1997). Numerical calculation of stable densities and distribution functions, Communications in statistics-Stochastic models, 13(4), 759-774.

Teimouri, M. and Amindavar, H. (2008). A novel approach to calculate stable densities, Proceedings of the World Congress on Engineering, 1, 710-714.

Examples

```
# In the following, we compute the pdf of a univariate stable distribution at point 2
# with parameters alpha=1.2, beta=0.9, sigma=1, and mu=0 in S_{0} parameterization.
library("stabledist")
udstab(2,1.2,0.9,1,0,1)
```

---

ufitstab.cauchy *ufitstab.cauchy*

Description

estimates the parameters of the Cauchy distribution. Given the initial values of the skewness, scale, and location parameters, it uses the EM algorithm to estimate the parameters of the Cauchy distribution.

Usage

```
ufitstab.cauchy(y, beta0, sigma0, mu0, param)
```

Arguments

`y`	vector of observations
`beta0`	initial value of skewness parameter to start the EM algorithm
`sigma0`	initial value of scale parameter to start the EM algorithm
`mu0`	initial value of location parameter to start the EM algorithm
`param`	kind of parameterization; must be 0 or 1 for `S_0` and `S_1` parameterizations, respectively

Details

Generally the EM algorithm seeks for the ML estimations when the log-likelihood function is not tractable mathematically. This is done by considering an extra missing (or latent) variable when the conditional expectation of the complete data log-likelihood given observed data and a guess of unknown parameter(s) is maximized. So, first we look for a stochastic representation. The representation given by the following proposition is valid for Cauchy distribution. Suppose `Y~S_0(1,beta,sigma,mu)` and `T~S_{1}(1,1,1,0)` (here `S_0` and `S_1` refer to parameterizations `S_0` and `S_1`, respectively). Then `Y=sigma*(1-|beta|)*N/Z+sigma*beta*T+mu` where `N~Z~N(0,1)`. The random variables `N`, `Z`, and `T` are mutually independent.

Value

`beta`	estimated value of the skewness parameter
`sigma`	estimated value of the scale parameter
`mu`	estimated value of the location parameter

Note

The set of data considered here is large recorded intensities (in Richter scale) of the earthquake at seismometer locations in western North America between 1940 and 1980, see Davidian and Giltinan (1995). Among the features, we focus on the 182 distances from the seismological measuring station to the epicenter of the earthquake (in km) as the variable of interest. This set of data can be found in package `nlme`. We note that `ufitstab.cauchy()` is robust with respect to the initial values.

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Davidian, M. and Giltinan, D.M. (1995). Nonlinear Mixed Effects Models for Repeated Measurement Data, Chapman and Hall.

Examples

```
# In the following example, using the initial values beta_0=0.5, sigma_0=5, and mu_0=10,
# we apply the EM algorithm to estimate the parameters of Cauchy distribution fitted to
# the earthquake data given by the vector y.
y<-c(7.5,  8.8,   8.9,   9.4,   9.7,   9.7,   10.5,  10.5,  12.0,  12.2,  12.8,  14.6,
     14.9,  17.6,  23.9,  25.0,  2.9,   3.2 ,  7.6,   17.0,  8.0,   10.0,  10.0,  8.0,
     19.0,  21.0,  13.0,  22.0,  29.0,  31.0,  5.8,   12.0,  12.1,  20.5,  20.5,  25.3,
     35.9,  36.1,  36.3,  38.5,  41.4,  43.6,  44.4,  46.1,  47.1,  47.7,  49.2,  53.1,
     4.0,   10.1,  11.1,  17.7,  22.5,  26.5,  29.0,  30.9,  37.8,  48.3,  62.0,  50.0,
     16.0,  62.0,  1.2,   1.6,   9.1,   3.7,   5.3,   7.4,   17.9,  19.2,  23.4,  30.0,
     38.9,  10.8,  15.7,  16.7,  20.8,  28.5,  33.1,  40.3,  8.0,   32.0,  30.0,  31.0,
     16.1,  63.6,  6.6,   9.3,   13.0,  17.3,  105.0, 112.0, 123.0, 5.0,   23.5,  26.0,
     0.5,   0.6,   1.3,   1.4,   2.6,   3.8,   4.0,   5.1,   6.2,   6.8,   7.5,   7.6,
     8.4,   8.5,   8.5,   10.6,  12.6,  12.7,  12.9,  14.0,  15.0,  16.0,  17.7,  18.0,
     22.0,  22.0,  23.0,  23.2,  29.0,  32.0,  32.7,  36.0,  43.5,  49.0,  60.0,  64.0,
```

```
     105.0, 122.0, 141.0, 200.0, 45.0,  130.0, 147.0, 187.0, 197.0, 203.0, 211.0, 17.0,
     19.6,  20.2,  21.1,  88.0,  91.0,  12.0,  148.0, 42.0,  85.0,  21.9,  24.2,  66.0,
     87.0,  23.4,  24.6,  25.7,  28.6,  37.4,  46.7,  56.9,  60.7,  61.4,  62.0,  64.0,
     82.0,  107.0, 109.0, 156.0, 224.0, 293.0, 359.0, 370.0, 25.4,  32.9,  92.2,  45.0,
     145.0, 300.0)
library("stabledist")
ufitstab.cauchy(y,0.5,5,10,0)
```

ufitstab.cauchy.mix *ufitstab.cauchy.mix*

Description

estimates the parameters of a k-component mixture of Cauchy distributions. Assuming that k is known, given the vector of initial values of entire parameter space, it uses the EM algorithm to estimate the parameters of the k-component mixture of Cauchy distributions.

Usage

```
ufitstab.cauchy.mix(y, k, omega0, beta0, sigma0, mu0)
```

Arguments

y	vector of observations
k	number of components
omega0	initial value for weight vector to start the EM algorithm
beta0	initial value for skewness vector to start the EM algorithm
sigma0	initial value for scale vector to start the EM algorithm
mu0	initial value for location vector to start the EM algorithm

Details

Generally the EM algorithm seeks for the ML estimations when the log-likelihood function is not tractable mathematically. This is done by considering an extra missing (or latent) variable when the conditional expectation of the complete data log-likelihood given observed data and a guess of unknown parameter(s) is maximized. So, first we look for a stochastic representation. The representation given by the following proposition is valid for Cauchy distribution. Suppose `Y~ S_{0}(1,beta,sigma,mu)` and `T~S_{1}(1,1,1,0)` (here `S_0` and `S_1` refer to parameterizations `S_0` and `S_1`, respectively). Then `Y=sigma*(1-|beta|)*N/Z+sigma*beta*T+mu` where `N~Z~N(0,1)`. The random variables `N`, `Z`, and `P` are mutually independent.

Value

omega-bar	a k-component vector of estimated values for the weight vector
beta-bar	a k-component vector of estimated values for the skewness vector
sigma-bar	a k-component vector of estimated values for the scale vector
mu-bar	a k-component vector of estimated values for the location vector

Note

We use the survival times in days of 72 guinea pigs infected with different doses of tubercle bacilli, see Bjerkedal (1960). We note that the EM algorithm is robust with respect to the initial values.

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Bjerkedal, T. (1960) Acquisition of resistance in guinea pigs infected with different doses of virulent tubercle bacilli, American Journal of Epidemiology, 72, 130-148.

Examples

```
# In the following, we give an example that fits a two-component mixture of Cauchy distributions
# to the survival times (in days) of 72 guinea pigs through the EM algorithm. For this, the initial
# values are: omega_0=(0.65,0.35), sigma_0=(20,50), beta_0=(0.20,0.05), and mu_0=(95,210).
library("stabledist")
y<-c(10,33,44,56,59,72,74,77,92,93,96,100,100,102,105,107,107,108,108,108,
     109,112,121,122,122,124,130,134,136,139,144,146,153,159,160,163,163,
     168,171,172,176,113,115,116,120,183,195,196,197,202,213,215,216,222,
     230,231,240,245,251,253,254,255,278,293,327,342,347,361,402,432,458,
     555)
ufitstab.cauchy.mix(y,2,c(0.65,0.35),c(0.20,0.05),c(20,50),c(95,210))
```

`ufitstab.skew` *ufitstab.skew*

Description

using the EM algorithm, it estimates the parameters of skew stable distribution.

Usage

```
ufitstab.skew(y, alpha0, beta0, sigma0, mu0, param)
```

Arguments

`y`	vector of observations
`alpha0`	initial value of tail index parameter to start the EM algorithm
`beta0`	initial value of skewness parameter to start the EM algorithm
`sigma0`	initial value of scale parameter to start the EM algorithm
`mu0`	initial value of location parameter to start the EM algorithm
`param`	kind of parameterization; must be 0 or 1 for `S_0` and `S_1` parameterizations, respectively

Details

For any skew stable distribution we give a new representation by the following. Suppose `Y~ S_{0}(alpha, beta, sigma, mu)`, `P~ S_{1}(alpha/2,1,(cos(pi*alpha/4))^(2/alpha),0)`, and `V~ S_{1}(alpha,1,1,0)`. Then, `Y=eta*(2P)^(1/2)*N+theta*V+ mu-lambda`, where `eta=sigma*(1-|beta|)^(1/alpha)` `theta=sigma*sign(beta)*|beta|^(1/alpha)`, `lambda=sigma*beta*tan(pi*alpha/2)`, and `N~N(0,1)` follows a skew stable distribution. All random variables `N`, `P`, and `V` are mutually independent.

Value

`alpha`	estimated value of the tail index parameter
`beta`	estimated value of the skewness parameter
`sigma`	estimated value of the scale parameter
`mu`	estimated value of the location parameter

Note

Daily price returns of Abbey National shares between 31/7/91 and 8/10/91 (including `n=50` business days). By assuming that `p_{t}` denotes the price at `t`-th day, the price return at `t`-th day is defined as `(p_{t-1}-p_{t})/p_{t-1}`; for `t=2,...,n`, see Buckle (1995). We note that the EM algorithm is robust with respect to the initial values.

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Buckle, D. J. (1995). Bayesian inference for stable distributions, Journal of the American Statistical Association, 90(430), 605-613.

Examples

```
# For example, We use the daily price returns of Abbey National shares. Using the initial
# values as alpha_{0}=0.8, beta_{0}=0, sigma_{0}=0.25, and mu_{0}=0.25.
price<-c(296,296,300,302,300,304,303,299,293,294,294,293,295,287,288,297,
         305,307,304,303,304,304,309,309,309,307,306,304,300,296,301,298,
         295,295,293,292,307,297,294,293,306,303,301,303,308,305,302,301,
         297,299)
x<-c()
n<-length(price)
for(i in 2:n){x[i]<-(price[i-1]-price[i])/price[i-1]}
library("stabledist")
ufitstab.skew(x[2:n],0.8,0,0.25,0.25,1)
```

ufitstab.sym *ufitstab.sym*

Description

estimates the parameters of a symmetric stable distribution through the EM algorithm, see Teimouri et al. (2018).

Usage

```
ufitstab.sym(yy, alpha0, sigma0, mu0)
```

Arguments

yy	a vector of observations
alpha0	initial value for the tail index parameter
sigma0	initial values for the scale parameter
mu0	initial values for the location parameter

Value

alpha	estimated value of the tail index parameter
sigma	estimated value of the scale parameter
mu	estimated value of the location parameter

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Teimouri, M., Rezakhah, S., and Mohammadpour, A. (2018). Parameter estimation using the EM algorithm for symmetric stable random variables and sub-Gaussian random vectors, Journal of Statistical Theory and Applications, 17(3),1-20.

Examples

```
# By the following example, we apply the EM algorithm to n=50 iid realization of symmetric
# stable distribution with parameters alpha=1.2, sigma=1, and mu=1. The initial values
# are alpha_0=1.2, sigma_0=1, and mu_0=1.
library("stabledist")
y<-urstab(50,1.2,0,1,1,0)
ufitstab.sym(y,1.2,1,1)
```

ufitstab.sym.mix *ufitstab.sym.mix*

Description

estimates the parameters of a k-component mixture of symmetric stable distributions, Teimouri et al. (2018) <doi.org/10.1080/03610918.2017.1288244>. Having k and given the vector of initial values of entire parameter space, it uses some type of the EM algorithm (ECME) to estimate the parameters of mixture of symmetric stable distributions.

Usage

```
ufitstab.sym.mix(yy, k, omega0, alpha0, sigma0, mu0)
```

Arguments

yy	vector of observations
k	number of components
omega0	vector of initial values for weights
alpha0	vector of initial values for tail indices
sigma0	vector of initial values for scale parameters
mu0	vector of initial values for location parameters

Value

omega-bar	a k-component vector of estimated values for the weight vector
alpha-bar	a k-component vector of estimated values for the tail index vector
sigma-bar	a k-component vector of estimated values for the scale vector
mu-bar	a k-component vector of estimated values for the location vector
membership	a k by n matrix whose entries are 1 and 0; for i-th row, if j-th column is one; then i-th observation belongs to the j-th component

Note

The set of data, used here, is the velocities of 82 distant galaxies, diverging from our own galaxy, called here galaxy. These data are available at `https://people.maths.bris.ac.uk/mapjg/mixdata`. We note that `ufitstab.sym.mix()` is robust with respect to the initial values.

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Teimouri, M., Rezakhah, S., and Mohammadpour, A. (2018). EM algorithm for symmetric stable mixture model, Communications in Statistics-Simulation and Computation, 47(2), 582-604.

Examples

```
# In what follows, we apply the EM algorithm to estimate the parameters of the
# mixture of symmetric stable distributions. For this, the initial values for
# fitting a three-component mixture of symmetric stable distribution to the
# galaxy data are: (0.1,0.35,0.55) for weight vector, (1.2,1.2,1.2) for tail
# index vector, (1,1,1) for scale vector, and (8,20,22) for the location vector.
galaxy<-c(9.172,9.350,9.483,9.558,9.775,10.227,10.406,16.084,16.170,18.419,
          18.552,18.600,18.927,19.052,19.070,19.330,19.343,19.349,19.440,
          19.473,19.529,19.541,19.547,19.663,19.846,19.856,19.863,19.914,
          19.918,19.973,19.989,20.166,20.175,20.179,20.196,20.215,20.221,
          20.415,20.629,20.795,20.821,20.846,20.875,20.986,21.137,21.492,
          21.701,21.814,21.921,21.960,22.185,22.209,22.242,22.249,22.314,
          22.374,22.495,22.746,22.747,22.888,22.914,23.206,23.241,23.263,
          23.484,23.538,23.542,23.666,23.706,23.711,24.129,24.285,24.289,
          24.366,24.717,24.990,25.633,26.960,26.995,32.065,32.789,34.279)
library("stabledist")
ufitstab.sym.mix(galaxy,3,c(0.1,0.35,0.55),c(1.2,1.2,1.2),c(1,1,1),c(8,20,22))
```

`ufitstab.ustat` *ufitstab.ustat*

Description

estimates the tail index and scale parameters of a symmetric and zero-location stable distribution using U-statistic proposed by Fan (2006) <DOI: 10.1080/03610920500439992>.

Usage

```
ufitstab.ustat(x)
```

Arguments

`x`	vector of observations

Value

`alpha`	estimated value of the tail index parameter
`sigma`	estimated value of the scale parameter

Note

The `ufitstab.ustat()` must be applied to a symmetric and zero-location stable distribution.

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Fan, Z. (2006). Parameter estimation of stable distributions, Communications in Statistics-Theory and Methods, 35(2), 245-255.

Examples

```
# We are estimating the parameters of a symmetric stable distribution. For this, firstly,
# we simulate a sample of n=100 iid realizations from stable distribution in S_1 parameterization
# with parameters alpha=1.2, beta=0, sigma=1, and mu=0.
x<-urstab(100,1.2,0,1,0,1)
ufitstab.ustat(x)
```

`upstab` *upstab*

Description

computes the cumulative distribution function (cdf) of the univariate stable distribution based on formulas given by Nolan (1997) <doi.org/10.1080/15326349708807450> and asymptotic series, see Teimouri and Amindavar (2008).

Usage

```
upstab(x, alpha, beta, sigma, mu, param)
```

Arguments

`x`	point at which the cdf is computed
`alpha`	tail index parameter
`beta`	skewness parameter
`sigma`	scale parameter
`mu`	location parameter
`param`	kind of parameterization; must be 0 or 1 for `S_0` and `S_1` parameterizations, respectively

Value

a numeric value

Note

`upstab()` computes the cdf of univariate stable distribution using asymptotic series within their convergence regions. For points outside of convergence regions, the cdf is computed using `stabledist` package based on formulas given by Nolan (1997). So, to compute the cdf using the `upstab()` we may need to install `stabledist` package.

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Nolan, J. P. (1997). Numerical calculation of stable densities and distribution functions, Communications in statistics-Stochastic models, 13(4), 759-774.

Teimouri, M. and Amindavar, H. (2008). A novel approach to calculate stable densities, Proceedings of the World Congress on Engineering, 1, 710-714.

Examples

```
# In the following, we compute the cdf of a univariate stable distribution at point 2
# with parameters alpha=1.2, beta=0.9, sigma=1, and mu=0 in S_{0} parameterization.


upstab(2,1.2,0.9,1,0,1)
```

---

urstab *urstab*

Description

simulates `iid` realizations from univariate stable distribution based on formulas given by Chambers et al. (1976) <DOI: 10.1080/01621459.1976.10480344> and Weron (1996) <doi.org/10.1016/0167-7152(95)00113-1>.

Usage

```
urstab(n,alpha,beta,sigma,mu,param)
```

Arguments

`n`	sample size
`alpha`	tail index parameter
`beta`	skewness parameter
`sigma`	scale parameter
`mu`	location parameter
`param`	kind of parameterization must; be 0 or 1 for `S_0` and `S_1` parameterizations, respectively

Value

a vector of `n` numeric values

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Chambers, J. M., Mallows, C. L., and Stuck, B. W. (1976). A method for simulating stable random variables, Journal of the american statistical association, 71(354), 340-344.

Weron, R. (1996). On the Chambers-Mallows-Stuck method for simulating skewed stable random variables, Statistics & probability letters, 28(2), 165-171.

Examples

```
# By the following example, we simulate n=200 iid realizations from univariate stable
# distribution with parameters alpha=1.2, beta=0.5, sigma=2, and mu=0 in S_0 parameterization.
x <- urstab(200, 1.2, 0.5, 2, 0, 0)
```

---

urstab.trunc *urstab.trunc*

Description

using the methodology given by Soltan and Shirvani (2010), Shirvani and Soltani (2013) for simulating `iid` truncated stable random variable, it simulates truncated stable realizations.

Usage

```
urstab.trunc(n, alpha, beta, sigma, mu, a, b, param)
```

Arguments

`n`	sample size
`alpha`	tail index parameter
`beta`	skewness parameter
`sigma`	scale parameter
`mu`	location parameter
`a`	lower bound of truncation
`b`	upper bound of truncation
`param`	kind of parameterization; must be 0 or 1 for `S_0` and `S_1` parameterizations, respectively

Value

a vector of `n` numeric values

Author(s)

Mahdi Teimouri, Adel Mohammadpour, and Saralees Nadarajah

References

Shirvani, A. and Soltani, A. R. (2013). A characterization for truncated Cauchy random variables with nonzero skewness parameter, Computational Statistics, 28(3), 1011-1016.

Soltani, A. R. and Shirvani, A. (2010). Truncated stable random variables: characterization and simulation, Computational Statistics, 25(1), 155-161.

Teimouri, M. and Nadarajah, S. (2013). On simulating truncated stable random variables, Computational Statistics, 28(5), 2367-2377.

Teimouri, M. and Nadarajah, S. (2017). On simulating truncated skewed Cauchy random variables, Communications in Statistics-Simulation and Computation, 46(2), 1318-1321.

Examples

```
# We simulate n=200 iid realizations from truncated stable distribution with parameters
# alpha=1.3, beta=0.5, sigma=2, and mu=0 which is truncated over (-5,5) in S_0 parameterization.
urstab.trunc(200,1.3,0.5,2,0,-5,5,0)
```

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