Package ‘ExtremeRisks’

May 7, 2020

Version 0.0.3

Date 2020-05-05

Title Extreme Risk Measures

Author Simone Padoan [cre, aut],
Gilles Stupfler [aut]

Maintainer Simone Padoan <simone.padoan@unibocconi.it>

Imports evd, mvtnorm, copula

Depends R (>= 3.5.0)

Description A set of procedures for estimating risks related to extreme events via risk measures such as expectile, value-at-risk, etc. is provided. Estimation methods for univariate independent observations and temporal dependent observations are available. The statistical inference is performed through parametric and non-parametric estimators. Inferential procedures such as confidence intervals and hypothesis testing are obtained by exploiting the asymptotic theory. Adapts the methodologies derived in Padoan and Stupfler (2020) <arxiv:2004.04078>, Daouia et al. (2018) <doi:10.1111/rssb.12254>, Drees (2000) <doi
reira (2006) <doi:10.1007/0-387-34471-3>, de Haan et al. (2016) <doi:10.1007/s00780-015-0287-6>.

URL mypage.unibocconi.it/simonepadoan/

NeedsCompilation yes

Repository CRAN

Repository/R-Forge/Project extremerisks

Repository/R-Forge/Revision 12

Repository/R-Forge/DateTimeStamp 2020-05-05 10:42:39

Date/Publication 2020-05-07 10:20:02 UTC

R topics documented:

`dowjones` *Negative log-returns of DOW JONES.*

Description

Series of negative log-returns of the U.S. stock market index Dow Jones.

Format

A $8784 * 2$ data frame.

Details

From the series of n = 8785 closing prices S_t, $t = 1, 2, ...$, for the Dow Jones stock market index, recorded from January 29, 1985 to December 12, 2019, the series of negative log-returns.

$X_{t+1} = -\log(S_{t+1}/S_t), \quad 1 \leq t \leq n-1$

is available. Hence the dataset (negative log-returns) contains 8784 observations.

`EBTailIndex` *Expectile Based Tail Index Estimation*

Description

Computes a point estimate of the tail index based on the Expectile Based (EB) estimator.

Usage

```
EBTailIndex(data, tau, est=NULL)
```

Arguments

`data`	A vector of $(1 \times n)$ observations.
`tau`	A real in $(0, 1)$ specifying the intermediate level τ_n. See **Details**.
`est`	A real specifying the estimate of the expectile at the intermediate level `tau`.

Details

For a dataset `data` of sample size n, the tail index γ of its (marginal) distribution is estimated using the EB estimator:

$$\hat{\gamma}_n^E = \left(1 + \frac{\hat{\bar{F}}_n(\tilde{\xi}_{\tau_n})}{1-\tau_n}\right)^{-1},$$

where $\hat{\bar{F}}_n$ is the empirical survival function of the observations, $\tilde{\xi}_{\tau_n}$ is an estimate of the τ_n-*th* expectile. The observations can be either independent or temporal dependent. See Padoan and Stupfler (2020) and Daouia et al. (2018) for details.

- The so-called intermediate level `tau` or τ_n is a sequence of positive reals such that $\tau_n \to 1$ as $n \to \infty$. Practically, $\tau_n \in (0, 1)$ is the ratio between the empirical mean distance of the τ_n-*th* expectile from the smaller observations and the empirical mean distance of of the τ_n-*th* expectile from all the observations. An estimate of τ_n-*th* expectile is computed and used in turn to estimate γ.
- The value `est`, if provided, is meant to be an esitmate of the τ_n-*th* expectile which is used to estimate γ. On the contrary, if `est=NULL`, then the routine `EBTailIndex` estimate first the τ_n-*th* expectile expectile and then use it to estimate γ.

Value

An estimate of the tain index γ.

Author(s)

Simone Padoan, `<simone.padoan@unibocconi.it>`, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, `<gilles.stupfler@ensai.fr>`, http://ensai.fr/en/equipe/stupfler-gilles/

References

Padoan A.S. and Stupfler, G. (2020). Extreme expectile estimation for heavy-tailed time series. *arXiv e-prints* arXiv:2004.04078, http://arxiv.org/abs/2004.04078.

Daouia, A., Girard, S. and Stupfler, G. (2018). Estimation of tail risk based on extreme expectiles. *Journal of the Royal Statistical Society: Series B*, **80**, 263-292.

See Also

HTailIndex, MomTailIndex, MLTailIndex,

Examples

```
# Tail index estimation based on the Expectile based estimator obtained with data
# simulated from an AR(1) with 1-dimensional Student-t distributed innovations

tsDist <- "studentT"
tsType <- "AR"

# parameter setting
corr <- 0.8
df <- 3
par <- c(corr, df)

# Big- small-blocks setting
bigBlock <- 65
smallblock <- 15

# Intermediate level (or sample tail probability 1-tau)
tau <- 0.97

# sample size
ndata <- 2500

# Simulates a sample from an AR(1) model with Student-t innovations
data <- rtimeseries(ndata, tsDist, tsType, par)

# tail index estimation
gammaHat <- EBTailIndex(data, tau)
gammaHat
```

`estExpectiles` *High Expectile Estimation*

Description

Computes a point and interval estimate of the expectile at the intermediate level.

Usage

```
estExpectiles(data, tau, method="LAWS", tailest="Hill", var=FALSE, varType="asym-Dep-Adj",
              bigBlock=NULL, smallBlock=NULL, k=NULL, alpha=0.05)
```

Arguments

`data`	A vector of $(1 \times n)$ observations.
`tau`	A real in $(0, 1)$ specifying the intermediate level τ_n. See **Details**.
`method`	A string specifying the method used to estimate the expecile. By default `est="LAWS"` specifies the use of the direct LAWS estimator. See **Details**.

tailest	A string specifying the type of tail index estimator. By default `tailest="Hill"` specifies the use of Hill estimator. See **Details**.
var	If `var=TRUE` then an estimate of the variance of the expectile estimator is computed.
varType	A string specifying the asymptotic variance to compute. By default `varType="asym-Dep-Adj"` specifies the variance estimator for serial dependent observations implemented with a suitable adjustment. See **Details**.
bigBlock	An interger specifying the size of the big-block used to estimaste the asymptotic variance. See **Details**.
smallBlock	An interger specifying the size of the small-block used to estimaste the asymptotic variance. See **Details**.
k	An integer specifying the value of the intermediate sequence k_n. See **Details**.
alpha	A real in $(0, 1)$ specifying the confidence level $(1-\alpha)100\%$ of the approximate confidence interval for the expecile at the intermedite level.

Details

For a dataset `data` of sample size n, an estimate of the τ_n*-th* expectile is computed. Two estimators are available: the so-called direct Least Asymmetrically Weighted Squares (LAWS) and indirect Quantile-Based (QB). The definition of the QB estimator depends on the estimation of the tail index γ. Here, γ is estimated using the Hill estimation (see HTailIndex) or in alternative using the the expectile based estimator (see EBTailIndex). The observations can be either independent or temporal dependent. See Section 3.1 in Padoan and Stupfler (2020) for details.

- The so-called intermediate level `tau` or τ_n is a sequence of positive reals such that $\tau_n \to 1$ as $n \to \infty$. Practically, $\tau_n \in (0, 1)$ is the ratio between *N* (Numerator) and *D* (Denominator). Where *N* is the empirical mean distance of the τ_n*-th* expectile from the observations smaller than it, and *D* is the empirical mean distance of τ_n*-th* expectile from all the observations.
- If `method='LAWS'`, then the expectile at the intermediate level τ_n is estimated applying the direct LAWS estimator. Instead, If `method='QB'` the indirect QB esimtator is used to estimate the expectile. See Section 3.1 in Padoan and Stupfler (2020) for details.
- When the expectile is estimated by the indirect QB esimtator (`method='QB'`), an estimate of the tail index γ is needed. If `tailest='Hill'` then γ is estimated using the Hill estimator (see also HTailIndex). If `tailest='ExpBased'` then γ is estimated using the expectile based estimator (see EBTailIndex). See Section 3.1 in Padoan and Stupfler (2020) for details.
- `k` or k_n is the value of the so-called intermediate sequence k_n, $n = 1, 2, \ldots$. Its represents a sequence of positive integers such that $k_n \to \infty$ and $k_n/n \to 0$ as $n \to \infty$. Practically, when `method='LAWS'` and `tau=NULL`, k_n specifies by $\tau_n = 1 - k_n/n$ the intermediate level of the expectile. Instead, when `method='QB'`, if `tailest="Hill"` then the value k_n specifies the number of `k`+1 larger order statistics to be used to estimate γ by the Hill estimator and if `tau=NULL` then it also specifies by $\tau_n = 1 - k_n/n$ the confidence level τ_n of the quantile to estimate. Finally, if `tailest="ExpBased"` and `tau=NULL` then it also specifies by $\tau_n = 1 - k_n/n$ the intermediate level expectile based esitmator of γ (see EBTailIndex).
- If `var=TRUE` then the asymptotic variance of the expecile estimator is computed. With independent observations the asymptotic variance is computed by the formula Theorem 3.1 of Padoan and Stupfler (2020). This is achieved through `varType="asym-Ind"`. With serial

dependent observations the asymptotic variance is estimated by the formula in Theorem 3.1 of Padoan and Stupfler (2020). This is achieved through `varType="asym-Dep"`. In this latter case the computation of the asymptotic variance is based on the "big blocks seperated by small blocks" techinque which is a standard tools in time series, see Leadbetter et al. (1986). See also Section C.1 in Appendix of Padoan and Stupfler (2020). The size of the big and small blocks are specified by the parameters `bigblock` and `smallblock`, respectively. Still with serial dependent observations, If `varType="asym-Dep-Adj"`, then the asymptotic variance is estimated using formula (C.79) in Padoan and Stupfler (2020), see Section C.1 of the Appendix for details.

- Given a small value $\alpha \in (0,1)$ then an asymptotic confidence interval for the τ_n-*th* expectile, with approximate nominal confidence level $(1-\alpha)100\%$ is computed. See Sections 3.1 and C.1 in the Appendix of Padoan and Stupfler (2020).

Value

A list with elements:

- `ExpctHat`: an estimate of the τ_n-*th* expecile;
- `VarExpHat`: an estimate of the asymptotic variance of the expectile estimator;
- `CIExpct`: an estimate of the approximate $(1-\alpha)100\%$ confidence interval for τ_n-*th* expecile.

Author(s)

Simone Padoan, <simone.padoan@unibocconi.it>, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, <gilles.stupfler@ensai.fr>, http://ensai.fr/en/equipe/stupfler-gilles/

References

Padoan A.S. and Stupfler, G. (2020). Extreme expectile estimation for heavy-tailed time series. *arXiv e-prints* arXiv:2004.04078, http://arxiv.org/abs/2004.04078.

Daouia, A., Girard, S. and Stupfler, G. (2018). Estimation of tail risk based on extreme expectiles. *Journal of the Royal Statistical Society: Series B*, **80**, 263-292.

Leadbetter, M.R., Lindgren, G. and Rootzen, H. (1989). Extremes and related properties of random sequences and processes. *Springer*.

See Also

HTailIndex, EBTailIndex, predExpectiles, extQuantile

Examples

```
# Extreme expectile estimation at the intermediate level tau obtained with
# 1-dimensional data simulated from am AR(1) with Student-t innovations

tsDist <- "studentT"
tsType <- "AR"

# parameter setting
corr <- 0.8
```

```
df <- 3
par <- c(corr, df)

# Big- small-blocks setting
bigBlock <- 65
smallBlock <- 15

# Intermediate level (or sample tail probability 1-tau)
tau <- 0.99

# sample size
ndata <- 2500

# Simulates a sample from an AR(1) model with Student-t innovations
data <- rtimeseries(ndata, tsDist, tsType, par)

# High expectile (intermediate level) estimation
expectHat <- estExpectiles(data, tau, var=TRUE, bigBlock=bigBlock, smallBlock=smallBlock)
expectHat$ExpctHat
expectHat$CIExpct
```

`estExtLevel` *Extreme Level Estimation*

Description

Estimates the expectile's extreme level corresponding to a quantile's extreme level.

Usage

```
estExtLevel(alpha_n, data=NULL, gammaHat=NULL, VarGamHat=NULL, tailest="Hill", k=NULL,
        var=FALSE, varType="asym-Dep", bigBlock=NULL, smallBlock=NULL, alpha=0.05)
```

Arguments

`alpha_n`	A real in $(0, 1)$ specifying the extreme level α_n for the quantile. See **Details**.
`data`	A vector of $(1 \times n)$ observations to be used to estimate the tail index in the case it is not provided. By default `data=NULL` specifies that no data are given.
`gammaHat`	A real specifying an estimate of the tail index. By default `gammaHat=NULL` specifies that no estimate is given. See **Details**.
`VarGamHat`	A real specifying an estimate of the variance of the tail index estimate. By default `VarGamHat=NULL` specifies that no estimate is given. See **Details**.
`tailest`	A string specifying the type of tail index estimator to be used. By default `tailest="Hill"` specifies the use of Hill estimator. See **Details**.
`k`	An integer specifying the value of the intermediate sequence k_n. See **Details**.
`var`	If `var=TRUE` then an estimate of the variance of the extreme level estimator is computed.

varType	A string specifying the asymptotic variance to compute. By default `varType="asym-Dep"` specifies the variance estimator for serial dependent observations. See **Details**.
bigBlock	An interger specifying the size of the big-block used to estimaste the asymptotic variance. See **Details**.
smallBlock	An interger specifying the size of the small-block used to estimaste the asymptotic variance. See **Details**.
alpha	A real in $(0, 1)$ specifying the confidence level $(1-\alpha)100\%$ of the approximate confidence interval for the expecile at the intermedite level.

Details

For a given extreme level α_n for the α_n-*th* quantile, an estimate of the extreme level $\tau_n'(\alpha_n)$ is computed such that $\xi_{\tau_n'(\alpha_n)} = q_{\alpha_n}$. The estimator is defined by

$\hat{\tau}_n'(\alpha_n) = 1 - (1-\alpha_n)\frac{\hat{\gamma}_n}{1-\hat{\gamma}_n}$

where $\hat{\gamma}_n$ is a consistent estimator of the tail index γ. If a value for the parameter `gammaHat` is given, then such a value is used to compute $\hat{\tau}_n'$. If `gammaHat` is `NULL` and a dataset is provided through the parameter `data`, then the tail index γ is estimated by a suitable estimator $\hat{\gamma}_n$. See Section 6 in Padoan and Stupfler (2020) for more details.

- If `VarGamHat` is specified, i.e. the variance of the tail index estimator, then the variance of the extreme level estimator $\hat{\tau}_n'$ is computed by using such value.
- When estimating the tail index, if `tailest='Hill'` then γ is estimated using the Hill estimator (see also HTailIndex). If `tailest='ML'` then γ is estimated using the Maximum Likelihood estimator (see MLTailIndex). If `tailest='ExpBased'` then γ is estimated using the expectile based estimator (see EBTailIndex). If `tailest='Moment'` then γ is estimated using the moment based estimator (see MomTailIndex). See Padoan and Stupfler (2020) for details.
- `k` or k_n is the value of the so-called intermediate sequence k_n, $n = 1, 2, \ldots$. Its represents a sequence of positive integers such that $k_n \to \infty$ and $k_n/n \to 0$ as $n \to \infty$. Practically, when `tailest="Hill"` then the value k_n specifies the number of `k`$+1$ larger order statistics to be used to estimate γ by the Hill estimator. See MLTailIndex, EBTailIndex and MomTailIndex for the other estimators.
- If `var=TRUE` then the asymptotic variance of the extreme level estimator is computed by applying the delta method, i.e.
  $Var(\tau_n') = Var(\hat{\gamma}_n) * (\alpha_n - 1)^2/(1-\hat{\gamma}_n)^4$
  where $Var(\hat{\gamma}_n$ is provided by `VarGamHat` or is estimated when esitmating the tail index through `tailest='Hill'` and `tailest='ML'`. See HTailIndex and MLTailIndex for details on how the variance is computed.
- Given a small value $\alpha \in (0, 1)$ then an asymptotic confidence interval for the extreme level, $\tau_n'(\alpha_n)$, with approximate nominal confidence level $(1-\alpha)100\%$ is computed.

Value

A list with elements:

- `tauHat`: an estimate of the extreme level τ_n';
- `tauVar`: an estimate of the asymptotic variance of the extreme level estimator $\hat{\tau}_n'(\alpha_n)$;
- `tauCI`: an estimate of the approximate $(1-\alpha)100\%$ confidence interval for the extreme level $\tau_n'(\alpha_n)$.

Author(s)

Simone Padoan, <simone.padoan@unibocconi.it>, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, <gilles.stupfler@ensai.fr>, http://ensai.fr/en/equipe/stupfler-gilles/

References

Padoan A.S. and Stupfler, G. (2020). Extreme expectile estimation for heavy-tailed time series. *arXiv e-prints* arXiv:2004.04078, http://arxiv.org/abs/2004.04078.

Daouia, A., Girard, S. and Stupfler, G. (2018). Estimation of tail risk based on extreme expectiles. *Journal of the Royal Statistical Society: Series B*, **80**, 263-292.

See Also

estExpectiles, predExpectiles, extQuantile

Examples

```
# Extreme level estimation for a given quantile's extreme level alpha_n
# obtained with 1-dimensional data simulated from an AR(1) with Student-t innovations

tsDist <- "studentT"
tsType <- "AR"

# parameter setting
corr <- 0.8
df <- 3
par <- c(corr, df)

# Big- small-blocks setting
bigBlock <- 65
smallBlock <- 15

# quantile's extreme level
alpha_n <- 0.999

# sample size
ndata <- 2500

# Simulates a sample from an AR(1) model with Student-t innovations
data <- rtimeseries(ndata, tsDist, tsType, par)

# expectile's extreme level estimation
tau1Hat <- estExtLevel(alpha_n, data, var=TRUE, k=150, bigBlock=bigBlock,
                       smallBlock=smallBlock)
tau1Hat
```

expectiles *Expectile Computation*

Description

Computes the true expectile for some families of parametric models.

Usage

```
expectiles(par, tau, tsDist="gPareto", tsType="IID", trueMethod="true",
           estMethod="LAWS", nrep=1e+05, ndata=1e+06, burnin=1e+03)
```

Arguments

`par`	A vector of $(1 \times p)$ parameters of the time series parametric family. See **Details**.
`tau`	A real in $(0, 1)$ specifying the level τ of the expectile to be computed. See **Details**.
`tsDist`	A string specifying the parametric family of the innovations distribution. By default `tsDist="gPareto"` specifies a Pareto family of distributions. See **Details**.
`tsType`	A string specifying the type of time series. By default `tsType="IID"` specifies a sequence of independent and indentically distributed random variables. See **Details**.
`trueMethod`	A string specifying the method used to computed the expecile. By default `trueMethod="true"` specifies that the true analytical expression to computed the expectile is used. See **Details**.
`estMethod`	A string specifying the method used to estimate the expecile. By default `est="LAWS"` specifies the use of the direct LAWS estimator. See **Details**.
`nrep`	A positive interger specifying the number of simulations to use for computing an approximation of the expectile. See **Details**.
`ndata`	A positive interger specifying the number of observations to genreated for each simulation. See **Details**.
`burnin`	A positive interger specifying the number of initial observations to discard from the simulated sample.

Details

For a parametric family of time series models or a parametric family of distributions (for the case of independent observations) the τ*-th* expectile (or expectile of level `tau`) is computed.

- There are two methods to compute the τ*-th* expectile. For the Generalised Pareto and Student-*t* parametric families of distributions, the analytical epxression of the expectile is available. This is used to compute the τ*-th* expectile if the parameter `trueMethod="true"` is specified. For most of parametric family of distributions or parametric families of time series models the analytical epxression of the expectile is not available. In this case an approximate value of the τ*-th* expectile is computed via a Monte Carlo method if the parameter trueMethod=="approx" is specified. In particular, ndata observations from a family of time series models (e.g. tsType="AR" and tsDist="studentT") or a sequence of independent and indentically distributed random variables with common family of distributions (e.g. tsType="IID" and tsDist="gPareto") are simulated nrep times. For each simulation the τ-*th* expectile is estimate by the estimation method specified by estMethod. The mean of such estimate provides an approximate value of the τ-*th* expectile. The available estimator to esitmate the expecile are the direct LAWS (estMethod="LAWS") and the indirect QB (estMethod="QB"), see estExpectiles for details. The available families of distributions are: Generalised Pareto (tsDist="gPareto"), Student-*t* (tsDist="studentT") and Frechet (tsDist="Frechet"). The available classes of time series with parametric innovations families of distributions are specified in rtimeseries.

Value

The τ-*th* expectile.

Author(s)

Simone Padoan, <simone.padoan@unibocconi.it>, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, <gilles.stupfler@ensai.fr>, http://ensai.fr/en/equipe/stupfler-gilles/

References

Padoan A.S. and Stupfler, G. (2020). Extreme expectile estimation for heavy-tailed time series. *arXiv e-prints* arXiv:2004.04078, http://arxiv.org/abs/2004.04078.

See Also

rtimeseries

Examples

```
# Derivation of the true tau-th expectile for the Pareto distribution
# via accurate simulation

# parameter value
par <- c(1, 0.3)

# Intermediate level (or sample tail probability 1-tau)
tau <- 0.99

trueExp <- expectiles(par, tau)
trueExp


# tau-th expectile of the AR(1) with Student-t innovations
tsDist <- "studentT"
tsType <- "AR"

# Approximation via Monte Carlo methods
trueMethod <- "approx"
```

```
# parameter setting
corr <- 0.8
df <- 3
par <- c(corr, df)

# Intermediate level (or sample tail probability 1-tau)
tau <- 0.99

trueExp <- expectiles(par, tau, tsDist, tsType, trueMethod)
trueExp
```

ExpectMES *Marginal Expected Shortfall Expectile Based Estimation*

Description

Computes a point and interval estimate of the Marginal Expected Shortfall (MES) using an expectile based approach.

Usage

```
ExpectMES(data, tau, tau1, method="LAWS", var=FALSE, varType="asym-Dep", bias=FALSE,
          bigBlock=NULL, smallBlock=NULL, k=NULL, alpha_n=NULL, alpha=0.05)
```

Arguments

data	A vector of $(1 \times n)$ observations.
tau	A real in $(0, 1)$ specifying the intermediate level τ_n. See **Details**.
tau1	A real in $(0, 1)$ specifying the extreme level τ'_n. See **Details**.
method	A string specifying the method used to estimate the expecile. By default `est="LAWS"` specifies the use of the LAWS based estimator. See **Details**.
var	If `var=TRUE` then an estimate of the asymptotic variance of the MES estimator is computed.
varType	A string specifying the type of asymptotic variance to compute. By default `varType="asym-Dep"` specifies the variance estimator for serial dependent observations. See **Details**.
bias	A logical value. By default `bias=FALSE` specifies that no bias correction is computed. See **Details**.
bigBlock	An interger specifying the size of the big-block used to estimaste the asymptotic variance. See **Details**.
smallBlock	An interger specifying the size of the small-block used to estimaste the asymptotic variance. See **Details**.
k	An integer specifying the value of the intermediate sequence k_n. See **Details**.

`alpha_n`	A real in $(0, 1)$ specifying the quantile's extreme level to be use in order to estimate the expectile's extreme level.
`alpha`	A real in $(0, 1)$ specifying the confidence level $(1 - \alpha)100\%$ of the approximate confidence interval for the expecile at the intermedite level.

Details

For a dataset `data` of sample size n, an estimate of the τ'_n*-th* MES is computed. The estimation of the MES at the extreme level `tau1` (τ'_n) is indeed meant to be a prediction. Two estimators are available: the so-called Least Asymmetrically Weighted Squares (LAWS) based estimator and the Quantile-Based (QB) estimator. The definition of both estimators depends on the estimation of the tail index γ. Here, γ is estimated using the Hill estimation (see HTailIndex for details). The observations can be either independent or temporal dependent. See Section 4 in Padoan and Stupfler (2020) for details.

- The so-called intermediate level `tau` or τ_n is a sequence of positive reals such that $\tau_n \to 1$ as $n \to \infty$. See predExpectiles for details.
- The so-called extreme level `tau1` or τ'_n is a sequence of positive reals such that $\tau'_n \to 1$ as $n \to \infty$. See predExpectiles for details.
- When `method='LAWS'`, then the τ'_n*-th* MES is estimated using the LAWS based estimator. When `method='QB'`, the expectile is instead estimated using the QB esimtator. See Sectino 4 in Padoan and Stupfler (2020) and in particular Corollary 4.3 and 4.4 for details. The definition of both estimators depend on the estimation of the tail index γ. In particular, the tail index γ is estimated using the Hill estimator (see HTailIndex).
- If `var=TRUE` then an esitmate of the asymptotic variance of the tau'_n*-th* MES is computed. Notice that the estimation of the asymptotic variance **is only available** when γ is estimated using the Hill estimator (see HTailIndex). With independent observations the asymptotic variance is estimated by $\hat{\gamma}^2$, see Corollary 4.3 in Padoan and Stupfler (2020). This is achieved through `varType="asym-Ind"`. With serial dependent observations the asymptotic variance is estimated by the formula in Corollary 4.3 of Padoan and Stupfler (2020). This is achieved through `varType="asym-Dep"`. See Section 4 adn 5 in Padoan and Stupfler (2020) for details. In this latter case the computation of the serial dependence is based on the "big blocks seperated by small blocks" techinque which is a standard tools in time series, see e.g. Leadbetter et al. (1986). The size of the big and small blocks are specified by the parameters `bigBlock` and `smallBlock`, respectively.
- If `bias=TRUE` then γ is estimated using formula (4.2) of Haan et al. (2016). This is used by the LAWS and QB estimators. Furthermore, the τ'_n*–th* quantile is estimated using the formula in page 330 of de Haan et al. (2016). This provides a bias corrected version of the Weissman estimator. This is used by the QB estimator. However, in this case the asymptotic variance is not estimated using the formula in Haan et al. (2016) Theorem 4.2. Instead, for simplicity the asymptotic variance is estimated by the formula in Corollary 3.8, with serial dependent observations, and $\hat{\gamma}^2$ with independent observation (see e.g. de Drees 2000, for the details).
- `k` or k_n is the value of the so-called intermediate sequence k_n, $n = 1, 2, \ldots$. Its represents a sequence of positive integers such that $k_n \to \infty$ and $k_n/n \to 0$ as $n \to \infty$. Practically, when `tau=NULL` and `method='LAWS'`, then $\tau_n = 1 - k_n/n$ is the intermediate level of the expectile to be stimated. k_n also specifies the number of `k`+1 larger order statistics used in the definition of the Hill estimator (see HTailIndex for detail). Differently, When `tau=NULL` and `method='QB'`, then $\tau_n = 1 - k_n/n$ is the intermediate level of the quantile to be stimated.

- If the quantile's extreme level is provided by `alpha_n`, then expectile's extreme level tau'_n is replaced by $tau'_n(\alpha_n)$ which is estimated by the method described in Section 6 of Padoan and Stupfler (2020). See estExtLevel for details.
- Given a small value $\alpha \in (0,1)$ then an estimate of an asymptotic confidence interval for tau'_n-*th* expectile, with approximate nominal confidence level $(1-\alpha)100\%$, is computed. The confidence intervals are computed exploiting formula in Corollary 4.3, 4.4 and Theorem 6.2 of Padoan and Stupfler (2020) and (46) in Drees (2003). See Sections 4-6 in Padoan and Stupfler (2020) for details. When `biast=TRUE` confidence intervals are computed in the same way but after correcting the tail index estimate by an estimate of the bias term, see formula (4.2) in de Haan et al. (2016) for details.

Value

A list with elements:

- `HatXMES`: an estimate of the τ'_n-*th* expectile based MES;
- `VarHatXMES`: an estimate of the asymptotic variance of the expectile based MES estimator;
- `CIHatXMES`: an estimate of the approximate $(1-\alpha)100\%$ confidence interval for τ'_n-*th* MES.

Author(s)

Simone Padoan, <simone.padoan@unibocconi.it>, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, <gilles.stupfler@ensai.fr>, http://ensai.fr/en/equipe/stupfler-gilles/

References

Padoan A.S. and Stupfler, G. (2020). Extreme expectile estimation for heavy-tailed time series. *arXiv e-prints* arXiv:2004.04078, http://arxiv.org/abs/2004.04078.

Daouia, A., Girard, S. and Stupfler, G. (2018). Estimation of tail risk based on extreme expectiles. *Journal of the Royal Statistical Society: Series B*, **80**, 263-292.

de Haan, L., Mercadier, C. and Zhou, C. (2016). Adapting extreme value statistics to

nancial time series: dealing with bias and serial dependence. *Finance and Stochastics*, **20**, 321-354.

Drees, H. (2003). Extreme quantile estimation for dependent data, with applications to finance. *Bernoulli*, **9**, 617-657.

Drees, H. (2000). Weighted approximations of tail processes for

β-mixing random variables. *Annals of Applied Probability*, **10**, 1274-1301.

Leadbetter, M.R., Lindgren, G. and Rootzen, H. (1989). Extremes and related properties of random sequences and processes. *Springer*.

See Also

QuantMES, HTailIndex, predExpectiles, extQuantile

Examples

```
# Marginl Expected Shortfall expectile based estimation at the extreme level
# obtained with 2-dimensional data simulated from an AR(1) with bivariate
# Student-t distributed innovations

tsDist <- "AStudentT"
tsType <- "AR"
tsCopula <- "studentT"

# parameter setting
corr <- 0.8
dep <- 0.8
df <- 3
par <- list(corr=corr, dep=dep, df=df)

# Big- small-blocks setting
bigBlock <- 65
smallBlock <- 15

# quantile's extreme level
alpha_n <- 0.999

# sample size
ndata <- 2500

# Simulates a sample from an AR(1) model with Student-t innovations
data <- rbtimeseries(ndata, tsDist, tsType, tsCopula, par)


# Extreme MES expectile based estimation
MESHat <- ExpectMES(data, NULL, NULL, var=TRUE, k=150, bigBlock=bigBlock,
                    smallBlock=smallBlock, alpha_n=alpha_n)
MESHat
```

---

extQuantile *Value-at-Risk (VaR) or Extreme Quantile (EQ) Estimation*

Description

Computes a point and interval estimate of the VaR based on the Weissman estimator.

Usage

```
extQuantile(data, tau, tau1, var=FALSE, varType="asym-Dep", bias=FALSE, bigBlock=NULL,
             smallBlock=NULL, k=NULL, alpha=0.05)
```

Arguments

`data`	A vector of $(1 \times n)$ observations.
`tau`	A real in $(0, 1)$ specifying the intermediate level τ_n. See **Details**.
`tau1`	A real in $(0, 1)$ specifying the extreme level τ'_n. See **Details**.
`var`	If `var=TRUE` then an estimate of the asymptotic variance of the VaR estimator is computed.
`varType`	A string specifying the type of asymptotic variance to compute. By default `varType="asym-Dep"` specifies the variance estimator for serial dependent observations. See **Details**.
`bias`	A logical value. By default `biast=FALSE` specifies that no bias correction is computed. See **Details**.
`bigBlock`	An interger specifying the size of the big-block used to estimaste the asymptotic variance. See **Details**.
`smallBlock`	An interger specifying the size of the small-block used to estimaste the asymptotic variance. See **Details**.
`k`	An integer specifying the value of the intermediate sequence k_n. See **Details**.
`alpha`	A real in $(0, 1)$ specifying the confidence level $(1 - \alpha)100\%$ of the approximate confidence interval for the VaR.

Details

For a dataset `data` of sample size n, the VaR or EQ, correspoding to the extreme level `tau1`, is computed by applying the Weissman estimator. The definition of the Weissman estimator depends on the estimation of the tail index γ. Here, γ is estimated using the Hill estimation (see HTailIndex). The observations can be either independent or temporal dependent (see e.g. de Haan and Ferreira 2006; Drees 2003; de Haan et al. 2016 for details).

- The so-called intermediate level `tau` or τ_n is a sequence of positive reals such that $\tau_n \to 1$ as $n \to \infty$. Practically, $(1 - \tau_n) \in (0, 1)$ is a small proportion of observations in the observed data sample that exceed the tau_n-*th* empirical quantile. Such proportion of observations is used to estimate the tau_n-*th* quantile and γ.
- The so-called extreme level `tau1` or τ'_n is a sequence of positive reals such that $\tau'_n \to 1$ as $n \to \infty$. The value $(1 - tau'_n) \in (0, 1)$ is meant to be a small tail probability such that $(1 - \tau'_n) = 1/n$ or $(1 - \tau'_n) < 1/n$. It is also assumed that $n(1 - \tau'_n) \to C$ as $n \to \infty$, where C is a positive finite constant. The value C is the expected number of exceedances of the τ'_n-*th* quantile. Typically, $C \in (0, 1)$ which means that it is expected that there are no observations in a data sample exceeding the quantile of level $(1 - \tau'_n)$.
- If `var=TRUE` then an esitmate of the asymptotic variance of the tau'_n-*th* quantile is computed. With independent observations the asymptotic variance is estimated by the formula $\hat{\gamma}^2$ (see e.g. de Drees 2000, 2003, for details). This is achieved through `varType="asym-Ind"`. With serial dependent data the asymptotic variance is estimated by the formula in 1288 in Drees (2000). This is achieved through `varType="asym-Dep"`. In this latter case the computation of the serial dependence is based on the "big blocks seperated by small blocks" techinque which is a standard tools in time series, see e.g. Leadbetter et al. (1986). The size of the big and small blocks are specified by the parameters `bigBlock` and `smallBlock`, respectively. With

serial dependent data the asymptotic variance can also be estimated by formula (32) of Drees (2003). This is achieved through `varType="asym-Alt-Dep"`.

- If `bias=TRUE` then an estimate of the τ_n'–*th* quantile is computed using the formula in page 330 of de Haan et al. (2016), which provides a bias corrected version of the Weissman estimator. However, in this case the asymptotic variance is not estimated using the formula in Haan et al. (2016) Theorem 4.2. Instead, for simplicity standard formula in Drees (2000) page 1288 is used.
- `k` or k_n is the value of the so-called intermediate sequence k_n, $n = 1, 2, \ldots$. Its represents a sequence of positive integers such that $k_n \to \infty$ and $k_n/n \to 0$ as $n \to \infty$. Practically, the value k_n specifies the number of `k`+1 larger order statistics to be used to estimate the τ_n-*th* empirical quantile and γ. The intermediate level τ_n can be seen defined as $\tau_n = 1 - k_n/n$.
- Given a small value $\alpha \in (0, 1)$ then an estimate of an asymptotic confidence interval for tau_n'-*th* quantile, with approximate nominal confidence level $(1 - \alpha)100\%$, is computed. The confidence intervals are computed exploiting the formulas (33) and (46) of Drees (2003). When `biast=TRUE` confidence intervals are computed in the same way but after correcting the tail index estimate by an estimate of the bias term, see formula (4.2) in de Haan et al. (2016) for details. Furthermore, in this case with serial dependent data the asymptotic variance is estimated using the formula in Drees (2000) page 1288.

Value

A list with elements:

- `ExtQHat`: an estimate of the VaR or τ_n'-*th* quantile;
- `VarExQHat`: an estimate of the asymptotic variance of the VaR estimator;
- `CIExtQ`: an estimate of the approximate $(1 - \alpha)100\%$ confidence interval for the VaR.

Author(s)

Simone Padoan, <simone.padoan@unibocconi.it>, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, <gilles.stupfler@ensai.fr>, http://ensai.fr/en/equipe/stupfler-gilles/

References

Padoan A.S. and Stupfler, G. (2020). Extreme expectile estimation for heavy-tailed time series. *arXiv e-prints* arXiv:2004.04078, http://arxiv.org/abs/2004.04078.

de Haan, L., Mercadier, C. and Zhou, C. (2016). Adapting extreme value statistics to

nancial time series: dealing with bias and serial dependence. *Finance and Stochastics*, **20**, 321-354.

de Haan, L. and Ferreira, A. (2006). Extreme Value Theory: An Introduction. *Springer-Verlag*, New York.

Drees, H. (2000). Weighted approximations of tail processes for

β-mixing random variables. *Annals of Applied Probability*, **10**, 1274-1301.

Drees, H. (2003). Extreme quantile estimation for dependent data, with applications to finance. *Bernoulli*, **9**, 617-657.

Leadbetter, M.R., Lindgren, G. and Rootzen, H. (1989). Extremes and related properties of random sequences and processes. *Springer*.

See Also

HTailIndex, EBTailIndex, estExpectiles

Examples

```
# Extreme quantile estimation at the level tau1 obtained with 1-dimensional data
# simulated from an AR(1) with univariate Student-t distributed innovations

tsDist <- "studentT"
tsType <- "AR"

# parameter setting
corr <- 0.8
df <- 3
par <- c(corr, df)

# Big- small-blocks setting
bigBlock <- 65
smallBlock <- 15

# Intermediate level (or sample tail probability 1-tau)
tau <- 0.97
# Extreme level (or tail probability 1-tau1 of unobserved quantile)
tau1 <- 0.9995

# sample size
ndata <- 2500

# Simulates a sample from an AR(1) model with Student-t innovations
data <- rtimeseries(ndata, tsDist, tsType, par)

# VaR (extreme quantile) estimation
extQHat1 <- extQuantile(data, tau, tau1, TRUE, bigBlock=bigBlock, smallBlock=smallBlock)
extQHat1$ExtQHat
extQHat1$CIExtQ

# VaR (extreme quantile) estimation with bias correction
extQHat2 <- extQuantile(data, tau, tau1, TRUE, bias=TRUE, bigBlock=bigBlock, smallBlock=smallBlock)
extQHat2$ExtQHat
extQHat2$CIExtQ
```

`HTailIndex` *Hill Tail Index Estimation*

Description

Computes a point and interval estimate of the tail index based on the Hill's estimator.

Usage

```
HTailIndex(data, k, var=FALSE, varType="asym-Dep", bias=FALSE, bigBlock=NULL,
          smallBlock=NULL, alpha=0.05)
```

Arguments

`data`	A vector of $(1 \times n)$ observations.
`k`	An integer specifying the value of the intermediate sequence k_n. See **Details**.
`var`	If `var=TRUE` then an estimate of the variance of the tail index estimator is computed.
`varType`	A string specifying the asymptotic variance to compute. By default `varType="asym-Dep"` specifies the variance estimator for serial dependent observations. See **Details**.
`bias`	A logical value. By default `biast=FALSE` specifies that no bias correction is computed. See **Details**.
`bigBlock`	An interger specifying the size of the big-block used to estimaste the asymptotic variance. See **Details**.
`smallBlock`	An interger specifying the size of the small-block used to estimaste the asymptotic variance. See **Details**.
`alpha`	A real in $(0, 1)$ specifying the confidence level $(1-\alpha)100\%$ of the approximate confidence interval for the tail index.

Details

For a dataset `data` of sample size n, the tail index γ of its (marginal) distribution is computed by applying the Hill estimator. The observations can be either independent or temporal dependent.

- `k` or k_n is the value of the so-called intermediate sequence k_n, $n = 1, 2, \ldots$. Its represents a sequence of positive integers such that $k_n \to \infty$ and $k_n/n \to 0$ as $n \to \infty$. Practically, the value k_n specifies the number of `k`+1 larger order statistics to be used to estimate γ.
- If `var=TRUE` then an estimate of the asymptotic variance of the Hill estimator is computed. With independent observations the asymptotic variance is estimated by the formula $\hat{\gamma}^2$, see Theorem 3.2.5 of de Haan and Ferreira (2006). This is achieved through `varType="asym-Ind"`. With serial dependent observations the asymptotic variance is estimated by the formula in 1288 in Drees (2000). This is achieved through `varType="asym-Dep"`. In this latter case the serial dependence is estimated by exploiting the "big blocks seperated by small blocks" technique which is a standard tools in time series, see Leadbetter et al. (1986). See also formula (11) in Drees (2003). The size of the big and small blocks are specified by the parameters `bigBlock` and `smallBlock`, respectively.
- If `bias=TRUE` then an estimate of the bias term of the Hill estimator is computed implementing using formula (4.2) in de Haan et al. (2016). However, in this case the asymptotic variance is not estimated using the formula in Haan et al. (2016) Theorem 4.1. Instead for simplicity standard formulas have been used (see de Haan and Ferreira 2006 Theorem 3.2.5 and Drees 2000 page 1288).
- Given a small value $\alpha \in (0, 1)$ then an estimate of an asymptotic confidence interval for γ, with approximate nominal confidence level $(1-\alpha)100\%$, is computed. The confidence intervals are computed exploiting the formulas in de Haan and Ferreira (2006) Theorem 3.2.5

and Drees (2000) page 1288. When `biast=TRUE` the confidence intervals are computed in the same way but after correcting the tail index estimate by an estimate of the bias term, see formula (4.2) in de Haan et al. (2016) for details.

Value

A list with elements:

- `gammaHat`: an estimate of tail index γ;
- `VarGamHat`: an estimate of the asymptotic variance of the Hill estimator;
- `BiasGamHat`: an estimate of bias term of the Hill estimator;
- `AdjExtQHat`: the adjustment to correct the Weissman estimator of an extreme quantile.

Author(s)

Simone Padoan, <simone.padoan@unibocconi.it>, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, <gilles.stupfler@ensai.fr>, http://ensai.fr/en/equipe/stupfler-gilles/

References

Padoan A.S. and Stupfler, G. (2020). Extreme expectile estimation for heavy-tailed time series. *arXiv e-prints* arXiv:2004.04078, http://arxiv.org/abs/2004.04078.

de Haan, L., Mercadier, C. and Zhou, C. (2016). Adapting extreme value statistics to

nancial time series: dealing with bias and serial dependence. *Finance and Stochastics*, **20**, 321-354.

de Haan, L. and Ferreira, A. (2006). Extreme Value Theory: An Introduction. *Springer-Verlag*, New York.

Drees, H. (2000). Weighted approximations of tail processes for

β-mixing random variables. *Annals of Applied Probability*, **10**, 1274-1301.

Leadbetter, M.R., Lindgren, G. and Rootzen, H. (1989). Extremes and related properties of random sequences and processes. *Springer*.

See Also

MLTailIndex, MomTailIndex, EBTailIndex

Examples

```
# Tail index estimation based on the Hill estimator obtained with
# 1-dimensional data simulated from an AR(1) with univariate Student-t
# distributed innovations

tsDist <- "studentT"
tsType <- "AR"

# parameter setting
corr <- 0.8
df <- 3
par <- c(corr, df)
```

```
# Big- small-blocks setting
bigBlock <- 65
smallBlock <- 15

# Number of larger order statistics
k <- 150

# sample size
ndata <- 2500

# Simulates a sample from an AR(1) model with Student-t innovations
data <- rtimeseries(ndata, tsDist, tsType, par)

# tail index estimation
gammaHat1 <- HTailIndex(data, k, TRUE, bigBlock=bigBlock, smallBlock=smallBlock)
gammaHat1$gammaHat
gammaHat1$CIgamHat

# tail index estimation with bias correction
gammaHat2 <- HTailIndex(data, 2*k, TRUE, bias=TRUE, bigBlock=bigBlock, smallBlock=smallBlock)
gammaHat2$gammaHat-gammaHat2$BiasGamHat
gammaHat2$CIgamHat
```

`MLTailIndex` *Maximum Likelihood Tail Index Estimation*

Description

Computes a point and interval estimate of the tail index based on the Maximum Likelihood (ML) estimator.

Usage

```
MLTailIndex(data, k, var=FALSE, varType="asym-Dep", bigBlock=NULL,
            smallBlock=NULL, alpha=0.05)
```

Arguments

`data`	A vector of $(1 \times n)$ observations.
`k`	An integer specifying the value of the intermediate sequence k_n. See **Details**.
`var`	If `var=TRUE` then an estimate of the asymptotic variance of the tail index estimator is computed.
`varType`	A string specifying the asymptotic variance to compute. By default `varType="asym-Dep"` specifies the variance estimator for serial dependent observations. See **Details**.
`bigBlock`	An interger specifying the size of the big-block used to estimaste the asymptotic variance. See **Details**.

smallBlock An interger specifying the size of the small-block used to estimaste the asymptotic variance. See **Details**.

alpha A real in $(0,1)$ specifying the confidence level $(1-\alpha)100\%$ of the approximate confidence interval for the tail index.

Details

For a dataset `data` of sample size n, the tail index γ of its (marginal) distribution is computed by applying the ML estimator. The observations can be either independent or temporal dependent.

- `k` or k_n is the value of the so-called intermediate sequence k_n, $n = 1, 2, \ldots$. Its represents a sequence of positive integers such that $k_n \to \infty$ and $k_n/n \to 0$ as $n \to \infty$. Practically, the value k_n specifies the numer of `k`+1 larger order statistics to be used to estimate γ.
- If `var=TRUE` then the asymptotic variance of the Hill estimator is computed. With independent observations the asymptotic variance is estimated by the formula in Theorem 3.4.2 of de Haan and Ferreira (2006). This is achieved through `varType="asym-Ind"`. With serial dependent observations the asymptotic variance is estimated by the formula in 1288 in Drees (2000). This is achieved through `varType="asym-Dep"`. In this latter case the serial dependence is estimated by exploiting the "big blocks seperated by small blocks" techinque which is a standard tools in time series, see Leadbetter et al. (1986). See also formula (11) in Drees (2003). The size of the big and small blocks are specified by the parameters `bigBlock` and `smallBlock`, respectively.
- Given a small value $\alpha \in (0,1)$ then an asymptotic confidence interval for the tail index, with approximate nominal confidence level $(1-\alpha)100\%$ is computed.

Value

A list with elements:

- `gammaHat`: an estimate of tail index γ;
- `VarGamHat`: an estimate of the variance of the ML estimator;
- `CIgamHat`: an estimate of the approximate $(1-\alpha)100\%$ confidence interval for γ.

Author(s)

Simone Padoan, <simone.padoan@unibocconi.it>, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, <gilles.stupfler@ensai.fr>, http://ensai.fr/en/equipe/stupfler-gilles/

References

Padoan A.S. and Stupfler, G. (2020). Extreme expectile estimation for heavy-tailed time series. *arXiv e-prints* arXiv:2004.04078, http://arxiv.org/abs/2004.04078.

Drees, H. (2000). Weighted approximations of tail processes for

β-mixing random variables. *Annals of Applied Probability*, **10**, 1274-1301.

de Haan, L. and Ferreira, A. (2006). Extreme Value Theory: An Introduction. *Springer-Verlag*, New York.

Leadbetter, M.R., Lindgren, G. and Rootzen, H. (1989). Extremes and related properties of random sequences and processes. *Springer*.

See Also

HTailIndex, MomTailIndex, EBTailIndex

Examples

```
# Tail index estimation based on the Maximum Likelihood estimator obtained with
# 1-dimensional data simulated from an AR(1) with univariate Student-t
# distributed innovations

tsDist <- "studentT"
tsType <- "AR"

# parameter setting
corr <- 0.8
df <- 3
par <- c(corr, df)

# Big- small-blocks setting
bigBlock <- 65
smallBlock <- 15

# Number of larger order statistics
k <- 150

# sample size
ndata <- 2500

# Simulates a sample from an AR(1) model with Student-t innovations
data <- rtimeseries(ndata, tsDist, tsType, par)

# tail index estimation
gammaHat <- MLTailIndex(data, k, TRUE, bigBlock=bigBlock, smallBlock=smallBlock)
gammaHat$gammaHat
gammaHat$CIgamHat
```

MomTailIndex *Moment based Tail Index Estimation*

Description

Computes a point estimate of the tail index based on the Moment Based (MB) estimator.

Usage

```
MomTailIndex(data, k)
```

Arguments

data	A vector of $(1 \times n)$ observations.
k	An integer specifying the value of the intermediate sequence k_n. See **Details**.

Details

For a dataset `data` of sample size n, the tail index γ of its (marginal) distribution is computed by applying the MB estimator. The observations can be either independent or temporal dependent. For details see de Haan and Ferreira (2006).

- `k` or k_n is the value of the so-called intermediate sequence k_n, $n = 1, 2, \ldots$. Its represents a sequence of positive integers such that $k_n \to \infty$ and $k_n/n \to 0$ as $n \to \infty$. Practically, the value k_n specifies the number of `k`+1 larger order statistics to be used to estimate γ.

Value

An estimate of the tail index γ.

Author(s)

Simone Padoan, <simone.padoan@unibocconi.it>, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, <gilles.stupfler@ensai.fr>, http://ensai.fr/en/equipe/stupfler-gilles/

References

de Haan, L. and Ferreira, A. (2006). Extreme Value Theory: An Introduction. *Springer-Verlag*, New York.

See Also

HTailIndex, MLTailIndex, EBTailIndex

Examples

```
# Tail index estimation based on the Moment estimator obtained with
# 1-dimensional data simulated from an AR(1) with univariate Student-t
# distributed innovations

tsDist <- "studentT"
tsType <- "AR"

# parameter setting
corr <- 0.8
df <- 3
par <- c(corr, df)

# Big- small-blocks setting
bigBlock <- 65
smallblock <- 15

# Number of larger order statistics
k <- 150

# sample size
ndata <- 2500
```

```
# Simulates a sample from an AR(1) model with Student-t innovations
data <- rtimeseries(ndata, tsDist, tsType, par)

# tail index estimation
gammaHat <- MomTailIndex(data, k)
gammaHat
```

---

predExpectiles *Extreme Expectile Estimation*

Description

Computes a point and interval estimate of the expectile at the extreme level (Expectile Prediction).

Usage

```
predExpectiles(data, tau, tau1, method="LAWS", tailest="Hill", var=FALSE,
               varType="asym-Dep", bias=FALSE, bigBlock=NULL, smallBlock=NULL,
               k=NULL, alpha_n=NULL, alpha=0.05)
```

Arguments

`data`	A vector of $(1 \times n)$ observations.
`tau`	A real in $(0, 1)$ specifying the intermediate level τ_n. See **Details**.
`tau1`	A real in $(0, 1)$ specifying the extreme level τ_n'. See **Details**.
`method`	A string specifying the method used to estimate the expecile. By default `est="LAWS"` specifies the use of the LAWS based estimator. See **Details**.
`tailest`	A string specifying the tail index estimator. By default `tailest="Hill"` specifies the use of Hill estimator. See **Details**.
`var`	If `var=TRUE` then an estimate of the asymptotic variance of the expectile estimator is computed.
`varType`	A string specifying the type of asymptotic variance to compute. By default `varType="asym-Dep"` specifies the variance estimator for serial dependent observations. See **Details**.
`bias`	A logical value. By default `bias=FALSE` specifies that no bias correction is computed. See **Details**.
`bigBlock`	An interger specifying the size of the big-block used to estimaste the asymptotic variance. See **Details**.
`smallBlock`	An interger specifying the size of the small-block used to estimaste the asymptotic variance. See **Details**.
`k`	An integer specifying the value of the intermediate sequence k_n. See **Details**.
`alpha_n`	A real in $(0, 1)$ specifying the quantile's extreme level to be use in order to estimate the expectile's extreme level.
`alpha`	A real in $(0, 1)$ specifying the confidence level $(1 - \alpha)100\%$ of the approximate confidence interval for the expecile at the intermedite level.

Details

For a dataset `data` of sample size n, an estimate of the τ_n'*-th* expectile is computed. The estimation of the expectile at the extreme level `tau1` (τ_n') is indeed meant to be a prediction. Two estimators are available: the so-called Least Asymmetrically Weighted Squares (LAWS) based estimator and the Quantile-Based (QB) estimator. The definition of both estimators depends on the estimation of the tail index γ. Here, γ is estimated using the Hill estimation (see HTailIndex for details) or in alternative using the the expectile based estimator (see EBTailIndex). The observations can be either independent or temporal dependent. See Section 3.2 in Padoan and Stupfler (2020) for details.

- The so-called intermediate level `tau` or τ_n is a sequence of positive reals such that $\tau_n \to 1$ as $n \to \infty$. Practically, $\tau_n \in (0, 1)$ is the ratio between *N* (Numerator) and *D* (Denominator). Where *N* is the empirical mean distance of the τ_n*-th* expectile from the observations smaller than it, and *D* is the empirical mean distance of τ_n*-th* expectile from all the observations.
- The so-called extreme level `tau1` or τ_n' is a sequence of positive reals such that $\tau_n' \to 1$ as $n \to \infty$. The value $(1 - tau_n') \in (0, 1)$ is meant to be a small tail probability such that $(1 - \tau_n') = 1/n$ or $(1 - \tau_n') < 1/n$. It is also assumed that $n(1 - \tau_n') \to C$ as $n \to \infty$, where C is a positive finite constant. Typically, $C \in (0, 1)$ so it is expected that there are no observations in a data sample that are greater than the expectile at the extreme level τ_n'.
- When `method='LAWS'`, then the τ_n'*-th* expectile is estimated using the LAWS based estimator. When `method='QB'`, the expectile is instead estimated using the QB esimtator. The definition of both estimators depend on the estimation of the tail index γ. When `tailest='Hill'` then γ is estimated using the Hill estimator (see HTailIndex). When `tailest='ExpBased'`, then γ is estimated using the expectile based estimator (see EBTailIndex). See Section 3.2 in Padoan and Stupfler (2020) for details.
- If `var=TRUE` then an esitmate of the asymptotic variance of the tau_n'*-th* expectile is computed. Notice that the estimation of the asymptotic variance **is only available** when γ is estimated using the Hill estimator (see HTailIndex). With independent observations the asymptotic variance is estimated by $\hat{\gamma}^2$, see the remark below Theorem 3.5 in Padoan and Stupfler (2020). This is achieved through `varType="asym-Ind"`. With serial dependent observations the asymptotic variance is estimated by the formula in Throrem 3.5 of Padoan and Stupfler (2020). This is achieved through `varType="asym-Dep"`. See Section 3.2 in Padoan and Stupfler (2020) for details. In this latter case the computation of the serial dependence is based on the "big blocks seperated by small blocks" techinque which is a standard tools in time series, see e.g. Leadbetter et al. (1986). The size of the big and small blocks are specified by the parameters `bigBlock` and `smallBlock`, respectively.
- If `bias=TRUE` then γ is estimated using formula (4.2) of Haan et al. (2016). This is used by the LAWS and QB estimators. Furthermore, the τ_n'*–th* quantile is estimated using the formula in page 330 of de Haan et al. (2016). This provides a bias corrected version of the Weissman estimator. This is used by the QB estimator. However, in this case the asymptotic variance is not estimated using the formula in Haan et al. (2016) Theorem 4.2. Instead, for simplicity the asymptotic variance is estimated by the formula in Corollary 3.8, with serial dependent observations, and $\hat{\gamma}^2$ with independent observation (see e.g. de Drees 2000, for the details).
- `k` or k_n is the value of the so-called intermediate sequence k_n, $n = 1, 2, \ldots$. Its represents a sequence of positive integers such that $k_n \to \infty$ and $k_n/n \to 0$ as $n \to \infty$. Practically, when `tau=NULL` and `method='LAWS'`, then $\tau_n = 1 - k_n/n$ is the intermediate level of the expectile to be stimated. The latter is also used to estimate the tail index when `tailest='ExpBased'`. Instead, if `tailest='Hill'`, then k_n specifies the number of `k`+1 larger order statistics used

in the definition of the Hill estimator. Differently, When `tau=NULL` and `method='QB'`, then $\tau_n = 1 - k_n/n$ is the intermediate level of the quantile to be stimated and of the expectile to be stimated when `tailest='ExpBased'`. Instead, when `tailest='Hill'` it is the numer of `k`+1 larger order statistics used in the definition of the Hill estimator.

- If quantile's extreme level is provided by `alpha_n`, then expectile's extreme level $tau'_n(\alpha_n)$ is replaced by $tau'_n(\alpha_n)$ which is esitmated using the method described in Section 6 of Padoan and Stupfler (2020). See estExtLevel for details.
- Given a small value $\alpha \in (0, 1)$ then an estimate of an asymptotic confidence interval for tau'_n-*th* expectile, with approximate nominal confidence level $(1 - \alpha)100\%$, is computed. The confidence intervals are computed exploiting formula (10) and (11) in Padoan and Stupfler (2020) and (46) in Drees (2003). See Section 5 in Padoan and Stupfler (2020) for details. When `biast=TRUE` confidence intervals are computed in the same way but after correcting the tail index estimate by an estimate of the bias term, see formula (4.2) in de Haan et al. (2016) for details.

Value

A list with elements:

- `EExpcHat`: an estimate of the τ'_n-*th* expecile;
- `VarExtHat`: an estimate of the asymptotic variance of the expectile estimator;
- `CIExpct`: an estimate of the approximate $(1-\alpha)100\%$ confidence interval for τ'_n-*th* expecile.

Author(s)

Simone Padoan, <simone.padoan@unibocconi.it>, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, <gilles.stupfler@ensai.fr>, http://ensai.fr/en/equipe/stupfler-gilles/

References

Padoan A.S. and Stupfler, G. (2020). Extreme expectile estimation for heavy-tailed time series. *arXiv e-prints* arXiv:2004.04078, http://arxiv.org/abs/2004.04078.

Daouia, A., Girard, S. and Stupfler, G. (2018). Estimation of tail risk based on extreme expectiles. *Journal of the Royal Statistical Society: Series B*, **80**, 263-292.

de Haan, L., Mercadier, C. and Zhou, C. (2016). Adapting extreme value statistics to

nancial time series: dealing with bias and serial dependence. *Finance and Stochastics*, **20**, 321-354.

Drees, H. (2003). Extreme quantile estimation for dependent data, with applications to finance. *Bernoulli*, **9**, 617-657.

Drees, H. (2000). Weighted approximations of tail processes for

β-mixing random variables. *Annals of Applied Probability*, **10**, 1274-1301.

Leadbetter, M.R., Lindgren, G. and Rootzen, H. (1989). Extremes and related properties of random sequences and processes. *Springer*.

See Also

HTailIndex, EBTailIndex, estExpectiles, extQuantile

Examples

```
# Extreme expectile estimation at the extreme level tau1 obtained with
# 1-dimensional data simulated from an AR(1) with univariate
# Student-t distributed innovations

tsDist <- "studentT"
tsType <- "AR"

# parameter setting
corr <- 0.8
df <- 3
par <- c(corr, df)

# Big- small-blocks setting
bigBlock <- 65
smallBlock <- 15

# Intermediate level (or sample tail probability 1-tau)
tau <- 0.95
# Extreme level (or tail probability 1-tau1 of unobserved expectile)
tau1 <- 0.9995

# sample size
ndata <- 2500

# Simulates a sample from an AR(1) model with Student-t innovations
data <- rtimeseries(ndata, tsDist, tsType, par)

# Extreme expectile estimation
expectHat1 <- predExpectiles(data, tau, tau1, var=TRUE, bigBlock=bigBlock,
                         smallBlock=smallBlock)
expectHat1$EExpcHat
expectHat1$CIExpct
# Extreme expectile estimation with bias correction
tau <- 0.80
expectHat2 <- predExpectiles(data, tau, tau1, "QB", var=TRUE, bias=TRUE, bigBlock=bigBlock,
 smallBlock=smallBlock)
expectHat2$EExpcHat
expectHat2$CIExpct
```

QuantMES *Marginal Expected Shortfall Quantile Based Estimation*

Description

Computes a point and interval estimate of the Marginal Expected Shortfall (MES) using a quantile based approach.

Usage

```
QuantMES(data, tau, tau1, var=FALSE, varType="asym-Dep", bias=FALSE, bigBlock=NULL,
          smallBlock=NULL, k=NULL, alpha=0.05)
```

Arguments

`data`	A vector of $(1 \times n)$ observations.
`tau`	A real in $(0, 1)$ specifying the intermediate level τ_n. See **Details**.
`tau1`	A real in $(0, 1)$ specifying the extreme level τ'_n. See **Details**.
`var`	If `var=TRUE` then an estimate of the asymptotic variance of the MES estimator is computed.
`varType`	A string specifying the type of asymptotic variance to compute. By default `varType="asym-Dep"` specifies the variance estimator for serial dependent observations. See **Details**.
`bias`	A logical value. By default `bias=FALSE` specifies that no bias correction is computed. See **Details**.
`bigBlock`	An interger specifying the size of the big-block used to estimaste the asymptotic variance. See **Details**.
`smallBlock`	An interger specifying the size of the small-block used to estimaste the asymptotic variance. See **Details**.
`k`	An integer specifying the value of the intermediate sequence k_n. See **Details**.
`alpha`	A real in $(0, 1)$ specifying the confidence level $(1 - \alpha)100\%$ of the approximate confidence interval for the expecile at the intermedite level.

Details

For a dataset `data` of sample size n, an estimate of the τ'_n*-th* MES is computed. The estimation of the MES at the extreme level `tau1` (τ'_n) is indeed meant to be a prediction. Estimates are obtained through the quantile based estimator defined in page 12 of Padoan and Stupfler (2020). Such an estimator depends on the estimation of the tail index γ. Here, γ is estimated using the Hill estimation (see HTailIndex for details). The observations can be either independent or temporal dependent. See Section 4 in Padoan and Stupfler (2020) for details.

- The so-called intermediate level `tau` or τ_n is a sequence of positive reals such that $\tau_n \to 1$ as $n \to \infty$. See predExpectiles for details.
- The so-called extreme level `tau1` or τ'_n is a sequence of positive reals such that $\tau'_n \to 1$ as $n \to \infty$. See predExpectiles for details.
- If `var=TRUE` then an esitmate of the asymptotic variance of the tau'_n*-th* MES is computed. Notice that the estimation of the asymptotic variance **is only available** when γ is estimated using the Hill estimator (see HTailIndex). With independent observations the asymptotic variance is estimated by $\hat{\gamma}^2$, see Corollary 4.3 in Padoan and Stupfler (2020). This is achieved through `varType="asym-Ind"`. With serial dependent observations the asymptotic variance is estimated by the formula in Corollary 4.2 of Padoan and Stupfler (2020). This is achieved through `varType="asym-Dep"`. See Section 4 and 5 in Padoan and Stupfler (2020) for details. In this latter case the computation of the serial dependence is based on the "big blocks seperated by small blocks" techinque which is a standard tools in time series, see e.g. Leadbetter et

al. (1986). The size of the big and small blocks are specified by the parameters `bigBlock` and `smallBlock`, respectively.

- If `bias=TRUE` then γ is estimated using formula (4.2) of Haan et al. (2016). This is used by the LAWS and QB estimators. Furthermore, the τ'_n*–th* quantile is estimated using the formula in page 330 of de Haan et al. (2016). This provides a bias corrected version of the Weissman estimator. This is used by the QB estimator. However, in this case the asymptotic variance is not estimated using the formula in Haan et al. (2016) Theorem 4.2. Instead, for simplicity the asymptotic variance is estimated by the formula in Corollary 3.8, with serial dependent observations, and $\hat{\gamma}^2$ with independent observation (see e.g. de Drees 2000, for the details).
- `k` or k_n is the value of the so-called intermediate sequence k_n, $n = 1, 2, \ldots$. Its represents a sequence of positive integers such that $k_n \to \infty$ and $k_n/n \to 0$ as $n \to \infty$. k_n specifies the number of `k`$+1$ larger order statistics used in the definition of the Hill estimator (see HTailIndex for details).
- If the quantile's extreme level is provided by `alpha_n`, then expectile's extreme level tau'_n is replaced by $tau'_n(\alpha_n)$ which is estimated by the method described in Section 6 of Padoan and Stupfler (2020). See estExtLevel for details.
- Given a small value $\alpha \in (0, 1)$ then an estimate of an asymptotic confidence interval for tau'_n*-th* expectile, with approximate nominal confidence level $(1 - \alpha)100\%$, is computed. The confidence intervals are computed exploiting formula in Corollary 4.2, Theorem 6.2 of Padoan and Stupfler (2020) and (46) in Drees (2003). See Sections 4-6 in Padoan and Stupfler (2020) for details. When `biast=TRUE` confidence intervals are computed in the same way but after correcting the tail index estimate by an estimate of the bias term, see formula (4.2) in de Haan et al. (2016) for details.

Value

A list with elements:

- `HatQMES`: an estimate of the τ'_n*-th* quantile based MES;
- `VarHatQMES`: an estimate of the asymptotic variance of the quantile based MES estimator;
- `CIHatQMES`: an estimate of the approximate $(1 - \alpha)100\%$ confidence interval for τ'_n*-th* MES.

Author(s)

Simone Padoan, <simone.padoan@unibocconi.it>, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, <gilles.stupfler@ensai.fr>, http://ensai.fr/en/equipe/stupfler-gilles/

References

Padoan A.S. and Stupfler, G. (2020). Extreme expectile estimation for heavy-tailed time series. *arXiv e-prints* arXiv:2004.04078, http://arxiv.org/abs/2004.04078.

Daouia, A., Girard, S. and Stupfler, G. (2018). Estimation of tail risk based on extreme expectiles. *Journal of the Royal Statistical Society: Series B*, **80**, 263-292.

de Haan, L., Mercadier, C. and Zhou, C. (2016). Adapting extreme value statistics to

nancial time series: dealing with bias and serial dependence. *Finance and Stochastics*, **20**, 321-354.

Drees, H. (2003). Extreme quantile estimation for dependent data, with applications to finance. *Bernoulli*, **9**, 617-657.

Drees, H. (2000). Weighted approximations of tail processes for

β-mixing random variables. *Annals of Applied Probability*, **10**, 1274-1301.

Leadbetter, M.R., Lindgren, G. and Rootzen, H. (1989). Extremes and related properties of random sequences and processes. *Springer*.

See Also

ExpectMES, HTailIndex, predExpectiles, extQuantile

Examples

```
# Marginl Expected Shortfall quantile based estimation at the extreme level
# obtained with 2-dimensional data simulated from an AR(1) with bivariate
# Student-t distributed innovations


tsDist <- "AStudentT"
tsType <- "AR"
tsCopula <- "studentT"

# parameter setting
corr <- 0.8
dep <- 0.8
df <- 3
par <- list(corr=corr, dep=dep, df=df)

# Big- small-blocks setting
bigBlock <- 65
smallBlock <- 15

# quantile's extreme level
tau1 <- 0.9995

# sample size
ndata <- 2500

# Simulates a sample from an AR(1) model with Student-t innovations
data <- rbtimeseries(ndata, tsDist, tsType, tsCopula, par)


# Extreme MES expectile based estimation
MESHat <- QuantMES(data, NULL, tau1, var=TRUE, k=150, bigBlock=bigBlock,
                   smallBlock=smallBlock)
MESHat
```

`rbtimeseries` *Simulation of Two-Dimensional Temporally Dependent Observations*

Description

Simulates samples from parametric families of bivariate time series models.

Usage

```
rbtimeseries(ndata, dist="studentT", type="AR", copula="Gumbel", par, burnin=1e+03)
```

Arguments

`ndata`	A positive interger specifying the number of observations to simulate.
`dist`	A string specifying the parametric family of the innovations distribution. By default `dist="studentT"` specifies a Student-*t* family of distributions. See **Details**.
`type`	A string specifying the type of time series. By default `type="AR"` specifies a linear Auto-Regressive time series. See **Details**.
`copula`	A string specifying the type copula to be used. By default `copula="Gumbel"` specifies the Gumbel copula. See **Details**.
`par`	A list of p parameters to be specified for the bivariate time series parametric family. See **Details**.
`burnin`	A positive interger specifying the number of initial observations to discard from the simulated sample.

Details

For a time series class (`type`), with a parametric family (`dist`) for the innovations, a sample of size `ndata` is simulated. See for example Brockwell and Davis (2016).

- The available categories of bivariate time series models are: Auto-Regressive (`type="AR"`), Auto-Regressive and Moving-Average (`type="ARMA"`), Generalized-Autoregressive-Conditional-Heteroskedasticity (`type="GARCH"`) and Auto-Regressive.
- With AR(1) times series the available families of distributions for the innovations and the dependence structure (copula) are:
  - Student-*t* (`dist="studentT"` and `copula="studentT"`) with marginal parameters (equal for both distributions): $\phi \in (-1, 1)$ (autoregressive coefficient), $\nu > 0$ (degrees of freedom) and dependence parameter $dep \in (-1, 1)$. The parameters are specified as `par <-list(corr,df,dep)`;
  - Asymmetric Student-*t* (`dist="AStudentT"` and `copula="studentT"`) with marginal parameters (equal for both distributions): $\phi \in (-1, 1)$ (autoregressive coefficient), $\nu > 0$ (degrees of freedom) and dependence parameter $dep \in (-1, 1)$. The paraters are specified as `par <-list(corr,df,dep)`. Note that in this case the tail index of the lower and upper tail of the first marginal are different, see Padoan and Stupfler (2020) for details;
- With ARMA(1,1) times series the available families of distributions for the innovations and the dependence structure (copula) are:
  - symmetric Pareto (`dist="double-Pareto"` and `copula="Gumbel"` or `copula="Gaussian"`) with marginal parameters (equal for both distributions): $\phi \in (-1, 1)$ (autoregressive coefficient), $\sigma > 0$ (scale), $\alpha > 0$ (shape), θ (movingaverage coefficient), and dependence

parameter dep ($dep > 0$ if copula="Gumbel" or $dep \in (-1, 1)$ if copula="Gaussian"). The parameters are specified as par <-list(corr,scale,shape,smooth,dep).

- symmetric Pareto (dist="double-Pareto" and copula="Gumbel" or copula="Gaussian") with marginal parameters (equal for both distributions): $\phi \in (-1, 1)$ (autoregressive coefficient), $\sigma > 0$ (scale), $\alpha > 0$ (shape), θ (movingaverage coefficient), and dependence parameter dep ($dep > 0$ if copula="Gumbel" or $dep \in (-1, 1)$ if copula="Gaussian"). The parameters are specified as par <-list(corr,scale,shape,smooth,dep). Note that in this case the tail index of the lower and upper tail of the first marginal are different, see Padoan and Stupfler (2020) for details;

• With ARCH(1)/GARCH(1,1) time series the distribution of the innovations are symmetric Gaussian (dist="Gaussian") or asymmetric Gaussian dist="AGaussian". In both cases the marginal parameters (equal for both distributions) are: α_0, α_1, β. In the asymmetric Gaussian case the tail index of the lower and upper tail of the first marginal are different, see Padoan and Stupfler (2020) for details. The available copulas are: Gaussian (copula="Gaussian") with dependence parameter $dep \in (-1, 1)$, Student-*t* (copula="studentT") with dependence parameters $dep \in (-1, 1)$ and $\nu > 0$ (degrees of freedom), Gumbel (copula="Gumbel") with dependence parameter $dep > 0$. The parameters are specified as par <-list(alpha0,alpha1,beta,dep) or par <-list(alpha0,alpha1,beta,dep,df).

Value

A vector of $(2 \times n)$ observations simulated from a specified bivariate time series model.

Author(s)

Simone Padoan, <simone.padoan@unibocconi.it>, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, <gilles.stupfler@ensai.fr>, http://ensai.fr/en/equipe/stupfler-gilles/

References

Brockwell, Peter J., and Richard A. Davis. (2016). Introduction to time series and forecasting. *Springer*.

Padoan A.S. and Stupfler, G. (2020). Extreme expectile estimation for heavy-tailed time series. *arXiv e-prints* arXiv:2004.04078, http://arxiv.org/abs/2004.04078.

See Also

rtimeseries, expectiles

Examples

```
# Data simulation from a 2-dimensional AR(1) with bivariate Student-t distributed
# innovations, with one marginal distribution whose lower and upper tail indices
# that are different

tsDist <- "AStudentT"
tsType <- "AR"
tsCopula <- "studentT"

# parameter setting
```

```
corr <- 0.8
dep <- 0.8
df <- 3
par <- list(corr=corr, dep=dep, df=df)

# sample size
ndata <- 2500

# Simulates a sample from an AR(1) model with Student-t innovations
data <- rbtimeseries(ndata, tsDist, tsType, tsCopula, par)

# Extreme expectile estimation
plot(data, pch=21)
plot(data[,1], type="l")
plot(data[,2], type="l")
```

---

rtimeseries *Simulation of One-Dimensional Temporally Dependent Observations*

Description

Simulates samples from parametric families of time series models.

Usage

```
rtimeseries(ndata, dist="studentT", type="AR", par, burnin=1e+03)
```

Arguments

ndata	A positive interger specifying the number of observations to simulate.
dist	A string specifying the parametric family of the innovations distribution. By default `dist="studentT"` specifies a Student-*t* family of distributions. See **Details**.
type	A string specifying the type of time series. By default `type="AR"` specifies a linear Auto-Regressive time series. See **Details**.
par	A vector of $(1 \times p)$ parameters to be specified for the univariate time series parametric family. See **Details**.
burnin	A positive interger specifying the number of initial observations to discard from the simulated sample.

Details

For a time series class (`type`) with a parametric family (`dist`) for the innovations, a sample of size `ndata` is simulated. See for example Brockwell and Davis (2016).

- The available categories of time series models are: Auto-Regressive (`type="AR"`), Auto-Regressive and Moving-Average (`type="ARMA"`), Generalized-Autoregressive-Conditional-Heteroskedasticity (`type="GARCH"`) and Auto-Regressive and Moving-Maxima (`type="ARMAX"`).
- With AR(1) and ARMA(1,1) times series the available families of distributions for the innovations are:
  - Student-*t* (`dist="studentT"`) with parameters: $\phi \in (-1, 1)$ (autoregressive coefficient), $\nu > 0$ (degrees of freedom) specified by `par=c(corr,df)`;
  - symmetric Frechet (`dist="double-Frechet"`) with parameters $\phi \in (-1, 1)$ (autoregressive coefficient), $\sigma > 0$ (scale), $\alpha > 0$ (shape), θ (movingaverage coefficient), specified by `par=c(corr,scale,shape,smooth)`;
  - symmetric Pareto (`dist="double-Pareto"`) with parameters $\phi \in (-1, 1)$ (autoregressive coefficient), $\sigma > 0$ (scale), $\alpha > 0$ (shape), θ (movingaverage coefficient), specified by `par=c(corr,scale,shape,smooth)`.

  With ARCH(1)/GARCH(1,1) time series the Gaussian family of distributions is available for the innovations (`dist="Gaussian"`) with parameters, $\alpha_0, \alpha_1, \beta$ specified by `par=c(alpha0,alpha1,beta)`. Finally, with ARMAX(1) times series the Frechet families of distributions is available for the innovations (`dist="Frechet"`) with parameters, $\phi \in (-1, 1)$ (autoregressive coefficient), $\sigma > 0$ (scale), $\alpha > 0$ (shape) specified by `par=c(corr,scale,shape)`.

Value

A vector of $(1 \times n)$ observations simulated from a specified time series model.

Author(s)

Simone Padoan, <simone.padoan@unibocconi.it>, http://mypage.unibocconi.it/simonepadoan/;
Gilles Stupfler, <gilles.stupfler@ensai.fr>, http://ensai.fr/en/equipe/stupfler-gilles/

References

Brockwell, Peter J., and Richard A. Davis. (2016). Introduction to time series and forecasting. *Springer*.

Padoan A.S. and Stupfler, G. (2020). Extreme expectile estimation for heavy-tailed time series. *arXiv e-prints* arXiv:2004.04078, http://arxiv.org/abs/2004.04078.

See Also

expectiles

Examples

```
# Data simulation from a 1-dimensional AR(1) with univariate Student-t
# distributed innovations

tsDist <- "studentT"
tsType <- "AR"

# parameter setting
corr <- 0.8
```

```
df <- 3
par <- c(corr, df)

# sample size
ndata <- 2500

# Simulates a sample from an AR(1) model with Student-t innovations
data <- rtimeseries(ndata, tsDist, tsType, par)

# Graphic representation
plot(data, type="l")
acf(data)
```

---

sp500 *Negative log-returns of S\&P 500.*

Description

Series of negative log-returns of the U.S. stock market index Standard and Poor 500.

Format

A $8784 * 2$ data frame.

Details

From the series of n = 8785 closing prices S_t, $t = 1, 2, ...$, for the Standard and Poor 500 stock market index, recorded from January 29, 1985 to December 12, 2019, the series of negative log-returns.

$X_{t+1} = -\log(S_{t+1}/S_t), \quad 1 \leq t \leq n - 1$

is available. Hence the dataset (negative log-returns) contains 8784 observations.

Index