

Package ‘OpVaR’

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Type Package

Title Statistical Methods for Modeling Operational Risk

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Description Functions for modeling operational (value-at-)risk. The implementation comprises functions for modeling loss frequencies and loss severities with plain, mixed (Frigessi et al. (2012) <doi:10.1023/A:1024072610684>) or spliced distributions using Maximum Likelihood estimation and Bayesian approaches (Ergashev et al. (2013) <doi:10.21314/JOP.2013.131>). In particular, the parametrization of tail distributions includes fitting of Tukey-type distributions (Kuo and Headrick (2014) <doi:10.1155/2014/645823>). Furthermore, the package contains the modeling of bivariate dependencies between loss severities and frequencies, Monte Carlo simulation for total loss estimation as well as a closed-form approximation based on Degen (2010) <doi:10.21314/JOP.2010.084> to determine the value-at-risk.

License GPL-3

Imports evmix, VineCopula, tea, actuar, vcd, goftest, truncnorm, ReIns, MASS

Suggests knitr, rmarkdown

VignetteBuilder knitr

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OpVaR-package	<i>Statistical Methods for Modeling Operational Risk</i>
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Description

Functions for modeling operational (value-at-)risk. The implementation comprises functions for modeling loss frequencies and loss severities with plain, mixed (Frigessi et al. (2012) <doi:10.1023/A:1024072610684>) or spliced distributions using Maximum Likelihood estimation and Bayesian approaches (Ergashev et al. (2013) <doi:10.21314/JOP.2013.131>). In particular, the parametrization of tail distributions includes fitting of Tukey-type distributions (Kuo and Headrick (2014) <doi:10.1155/2014/645823>). Furthermore, the package contains the modeling of bivariate dependencies between loss severities and frequencies, Monte Carlo simulation for total loss estimation as well as a closed-form approximation based on Degen (2010) <doi:10.21314/JOP.2010.084> to determine the value-at-risk.

Details

The DESCRIPTION file:

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buildPlainSevdist	Building a sevdist object with a plain distribution
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dgh	Tukey's gh Distribution
dgpd	Generalized Pareto Distribution
dmixing	Extended Dynamic Weighted Mixture Model
dsevdist	Evaluating Plain, Spliced or Mixing Severity Distributions
dspliced	Spliced Distributions
fitDependency	Function for fitting bivariate Copulas
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fitSplicedBestFit	Fitting a spliced distribution over a given data set
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lossdat	Example loss data set
mcSim	Monte Carlo Simulation from opriskmodel objects for total loss estimation
sla	Single-Loss Approximation for Operational Value at Risk

Functions for modeling operational risk.

Author(s)

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- Tukey, J. W. (1960): The Practical Relationship between the Common Transformations of Counts of Amounts. Technical Report 36, Princeton University Statistical Techniques Research Group, Princeton.
- Zou, C. Z. et al. (2018): A Monotone Spline Interpolated Closed-Form Approximation for Operational Value-at-Risk. Working Paper (In Preparation)

 buildFreqdist

Building a freqdist object

Description

Building a freqdist object

Usage

```
buildFreqdist(freq.distr, freq.param)
```

Arguments

freq.distr	A string giving the name of the distribution. Distributions "pois" and "nbinom" are recognised.
freq.param	List of numerical values giving the parameters for the given distribution.

Details

A freqdist object with type 'plain' is generated, i.e. for a given cell the losses occur with frequency given by distribution 'distr' with parameters given by 'param'.

Author(s)

Christina Zou

See Also

The sevdist objects according to different types are built via [buildPlainSevdist](#), [buildSplicedSevdist](#) and [buildMixingSevdist](#).

Examples

```
# Poisson distributed frequency with lambda = 50
freqdist1 = buildFreqdist("pois", 50)
```

buildMixingSevdist *Building a dynamic mixture model as a sevdist object*

Description

Building a dynamic mixture model as a sevdist object

Usage

```
buildMixingSevdist(body.distr, body.param, tail.distr, tail.param, mixing.param)
```

Arguments

body.distr	A string giving the name of the body distribution.
body.param	Vector of the parameters for the given body distribution.
tail.distr	A string giving the name of the tail distribution.
tail.param	Vector of the parameters for the given tail distribution. Distributions "lgamma", "weibull", "gpd", "gh" are recognised.
mixing.param	Vector of the parameters for the given mixing distribution.

Details

A sevdist object with type 'mixing' is generated, i.e. the distribution of the severity is a dynamic mixture of the distributions 'body.distr' with parameters given by 'body.param' and 'tail.distr' with parameters given by 'tail.param' using the cdf of a mixing distribution 'mixing.distr' with parameters 'mixing.param' according to Frigessi et al. (2002).

The density $f(x)$ for a dynamic mixture model with body distribution having density g and tail distribution having density h and cumulative distribution function p of the mixing distribution is given below:

$$f(x) = C * [p(x) * g(x) + (1 - p(x)) * h(x)]$$

Author(s)

Christina Zou

References

Frigessi, A., Haug, O., & Rue, H. (2002). A dynamic mixture model for unsupervised tail estimation without threshold selection. *Extremes*, 5(3), 219-235.

Examples

```
# Create mixing sevdist object
sevdist = buildMixingSevdist("weibull", c(2,6), "gpd", c(0,4,-0.5), c(8,.8))
# Plot pdf
plot(sevdist)
```

buildPlainSevdist	<i>Building a sevdist object with a plain distribution</i>
-------------------	--

Description

Building a sevdist object with a plain distribution

Usage

```
buildPlainSevdist(distr, param)
```

Arguments

distr	A string giving the name of the distribution.
param	The parameters for the given distribution

Details

A sevdist object with type 'plain' is generated, i.e. the severity has distribution 'distr' with parameters given by 'param'.

Author(s)

Christina Zou

See Also

Other sevdist objects with type 'spliced' and 'mixing' are built via [buildSplicedSevdist](#) and [buildMixingSevdist](#).

Examples

```
# Log-gamma distributed severity with shape = 2.2 and rate = 1.2

sevdist1 = buildPlainSevdist("lgamma", c(2.2, 1.2))
plot(sevdist1)
```

`buildSplicedSevdist` *Building a sevdist object with a spliced distribution*

Description

Building a sevdist object with a spliced distribution

Usage

```
buildSplicedSevdist(body.distr, body.param, tail.distr, tail.param, thresh, weight)
```

Arguments

<code>body.distr</code>	A string giving the name of the body distribution.
<code>body.param</code>	Vector of the parameters for the given body distribution.
<code>tail.distr</code>	A string giving the name of the tail distribution. Distributions "lgamma", "weibull", "gpd", "gh" are recognised.
<code>tail.param</code>	Vector of the parameters for the given tail distribution.
<code>thresh</code>	Numeric value giving the threshold of the distribution, the severity follows a truncated 'body.distr' distribution below the threshold and a truncated 'tail.distr' distribution above the threshold.
<code>weight</code>	Numeric value in [0,1] giving the probability that the severity distribution takes values below the threshold.

Details

A sevdist object with type 'spliced' is generated, i.e. the severity has distribution 'body.distr' in the body with parameters given by 'body.param' and distribution 'tail.distr' in the tail with parameters given by 'tail.param'.

The density $f(x)$ for a spliced distribution with threshold τ , weights w , body distribution with density g and cumulative distribution function G and tail distribution with density h and cumulative distribution function H is given as below:

$$\text{If } x \leq \tau: f(x) = w * g(x)/G(\tau)$$

$$\text{If } x > \tau: f(x) = (1 - w) * h(x)/(1 - H(\tau))$$

Author(s)

Christina Zou

See Also

Other sevdist objects with type 'plain' and 'mixing' are built via [buildPlainSevdist](#) and [buildMixingSevdist](#).

Examples

```
# Spliced distributed severity with gamma distributed body with shape = 1.23, rate = 0.12
# and GPD distributed tail with shape = 716 and scale = 0.1 and threshold = 2000.
# The weight for the body is 0.8.

sevdist1 = buildSplicedSevdist("gamma", c(2.5, 0.012), "gpd", c(2000, 716, 0.1), 2000, 0.8)
plot(sevdist1)
```

dsevdist

Evaluating Plain, Spliced or Mixing Severity Distributions

Description

Functions for evaluating pdf, cdf, quantile function and random number generation given a loss severity model (sevdist object)

Usage

```
dsevdist(x, sevdist)
```

Arguments

x
sevdist

Author(s)

Marius Pfeuffer

Examples

```
##---- Should be DIRECTLY executable !! ----
##-- ==> Define data, use random,
##--or do help(data=index) for the standard data sets.

## The function is currently defined as
function(x, sevdist)
{
  if (sevdist$type == "plain")
    return(sevdist$par[[1]](x))
  if (sevdist$type == "spliced")
    return(dspliced(x, sevdist))
  if (sevdist$type == "mixing")
    return(dmixing(x, sevdist))
}
```

fitDependency

Function for fitting bivariate Copulas

Description

Function for fitting bivariate dependency between loss frequencies and severities.

Usage

```
fitDependency(cell, copula_family, method = "mle")
```

Arguments

cell	a lossdat cell
copula_family	0: independence, 1: Gaussian, 2: t, 3: Clayton, 4: Gumbel, 5: Frank, 6: Joe, see Vine Copula Package ?BiCop encoding
method	as in fitCopula of the copula package. The method "itau" should not be used as dependencies between a continuous and a discrete random variable are modeled.

Value

A BiCop object

Author(s)

Marius Pfeuffer

References

Schepsmeier et al.: VineCopula package, CRAN

Examples

```
### Fit Joe Copula
data(lossdat)
fitDependency(lossdat[[1]],6)
```

fitFreqdist	<i>Fitting the frequency distribution</i>
-------------	---

Description

Fitting the frequency distribution of operational losses

Usage

```
fitFreqdist(cell, distr)
```

Arguments

cell	A data frame giving the losses (cell\$Loss) and the user-defined period (cell\$Period) in which the loss occurred.
distr	The frequency distribution: either "pois" or "nbinom"

Details

First, the number of losses per period is counted. With the results a Poisson or Negative Binomial distribution is fitted for the number of losses per period using a Maximum Likelihood estimator.

Value

Returns a freqdist object with the given distribution fitted to the loss frequency.

Author(s)

Christina Zou

See Also

The frequency distribution is fitted using [goodfit](#) with method 'ML' from the package 'vcd'.

Examples

```
data(lossdat)
fitFreqdist(lossdat[[1]],"pois")
fitFreqdist(lossdat[[2]],"nbinom")
```

`fitMixing`*Maximum Likelihood Estimation*

Description

Maximum Likelihood Estimation for the dynamic weighted mixture model of Frigessi et al., 2002

Usage

```
fitMixing(cell, body, tail, method="L-BFGS-B", c_location0=0.75, c_scale0=2)
```

Arguments

<code>cell</code>	lossdat cell
<code>body</code>	body distribution, either gamma, lnorm or weibull
<code>tail</code>	tail distribution, either gamma, lnorm, weibull or gpd
<code>method</code>	optimization method, default is "L-BFGS-B"
<code>c_location0</code>	empirical quantile of loss severity data used for initialization of Cauchy location parameter in optimization: <code>quantile(cell\$Loss,c_location0)</code>
<code>c_scale0</code>	scaling factor for empirical standard deviation used for initialization of Cauchy scale parameter in optimization: <code>sd(cell\$Loss)/c_scale0</code>

Details

Body and tail parameters are initialized by method of moments estimators. Cauchy location is initialized by empirical 70

Value

Returns a `sevdist` object of type 'mixing' with the given body and tail distributions fitted to the loss data.

Author(s)

Marius Pfeuffer

References

Frigessi et al. *A Dynamic Mixture Model for Unsupervised Tail Estimation without Threshold Selection*, *Extremes* 5(3):219-235, 2003

Examples

```
## Not run:  
data(lossdat)  
sev=fitMixing(lossdat[[1]],"weibull","gpd")  
sev  
plot(sev,5000)  
  
## End(Not run)
```

`fitPlain`*Fit plain distribution models*

Description

Function for estimating the parameters of plain (non-spliced, non-mixing) distribution models

Usage

```
fitPlain(cell, family)
```

Arguments

<code>cell</code>	list containing the data in the component <code>cell\$Loss</code>
<code>family</code>	distribution family

Value

Returns a `sevdist` object of type 'plain' with the given distribution fitted to the loss data.

Author(s)

Marius Pfeuffer

Examples

```
data(lossdat)  
fitPlain(lossdat[[1]],"lnorm")
```

fitSpliced	<i>Estimation of the threshold, the body and the tail parameters for a spliced distribution</i>
------------	---

Description

Given a dataset with a chosen distribution for the data in the body and another distribution in the tail, the threshold, the parameters of the body and the tail distributions and the weights are estimated.

Usage

```
fitSpliced(cell, body, tail, method, thresh = NULL)
```

```
fitSplicedPar(cell, thresh, body, tail)
```

Arguments

cell	List containing the data in the component cell\$Loss
body	Distribution in the body. Can be chosen between "gamma", "lnorm", "weibull" or "erlang"
tail	Distribution in the tail. Can be chosen between "gpd", "gamma", "lnorm", "weibull" or "gh"
method	Method for the threshold estimation. In case of a GPD tail, it can be chosen between "BestFit", "Fixed", "dAMSE", "danielsson", "DK", "hall", "Himp", "HW", "mindist" or "RT"
thresh	Predetermined threshold quantile (if method="Fixed")

Details

In the spliced model, the distribution of the data is spliced into two distributions, one in the body and another in the tail. Given the threshold t , a density function d_1 for the body distribution and a density function d_2 for the tail distribution, the incidental spliced density function has the formula $d(x) = w * d_1(x)$ if $x \leq t$ and $d(x) = (1 - w) * d_2(x)$ if $x > t$. The weight w is needed to normalize the density function. The estimation of the spliced distribution consists of three steps. In the first step, the threshold given chosen body and tail distribution is estimated. For further details on the methods for the threshold estimation, see fitThreshold. In the second step, the parameters of the body and the tail distribution are obtained by maximum likelihood estimation. For the body distribution parameters, all data points are fitted to the chosen distribution. For the estimation of the parameters of the tail distribution, only the data points above the threshold are used. In the last step, the weight w is obtained by maximum likelihood estimation.

Value

Returns a sevdist object of type 'spliced' with the given body and tail distributions fitted to the loss data.

Author(s)

Christina Zou, Leonie Wicht

See Also

fitSplicedBestFit, fitThreshold

Examples

```
data(lossdat)
fitSpliced(lossdat[[3]], "gamma", "gpd", method="Fixed", thresh=2000)
```

fitSplicedBayes

Parameter Estimation for Spliced Distributions

Description

MCMC based parameter estimation for spliced distribution functions, where the body is modeled by a Weibull, gamma or log-normal distribution or Kernel density estimation for a log-normal distribution and the tail is fitted with a GPD.

Usage

```
fitSplicedBayesWeibullGPD(cell, prior, burnin=10, niter=100,
proposal_scale=evmix::fweibullgpd(cell, method="Nelder-Mead")$se,
start=evmix::fweibullgpd(cell, method="Nelder-Mead")$optim$par)
```

```
fitSplicedBayesGammaGPD(cell, prior, burnin=10, niter=100,
proposal_scale=evmix::fgammagpd(cell, method="Nelder-Mead")$se,
start=evmix::fgammagpd(cell, method="Nelder-Mead")$optim$par)
```

```
fitSplicedBayesLognormGPD(cell, prior, burnin=10, niter=100,
proposal_scale=evmix::flognormgpd(cell, method="Nelder-Mead")$se,
start=evmix::flognormgpd(cell, method="Nelder-Mead")$optim$par)
```

```
fitSplicedBayesKDEGPD(cell, prior, burnin=10, niter=100,
proposal_scale=evmix::flognormgpd(cell, method="Nelder-Mead")$se,
start=evmix::flognormgpd(cell, method="Nelder-Mead")$optim$par)
```

Arguments

cell	database for the parameter estimation
prior	parameters of the particular prior distribution
burnin	length of the burn-in-phase, standard value = 10
niter	MCMC sample size, standard value = 100
proposal_scale	respective scale values used for determining the prior distribution for each parameter
start	starting values (shapes) for the MH-algorithm steps

Details

The input contains the dataset, whose compound distribution should be fitted with the function. The second part of the input is a list with the parameters of the prior distribution. It is necessary to indicate the prior as a list containing the full parameter vector in the order `bodypar_1=c()`, `bodypar_2=c()`, `threshold=c()`, where `bodypar_1` and `bodypar_2` are the parameters of the body (Weibull: `wshape` and `wscale` as shape and scale parameter, log-norm: `mu` and `sigma`, gamma: `gshape` and `gscale` as shape and scale parameter). `threshold` is the threshold separating the distributions. `beta` and `xi` are the scale and shape parameters of the generalized Pareto distribution. Using the MH-algorithm the true parameters of the body and tail distribution should be approximated.

Value

Sevdist object containing the parameters of the target distribution.

Author(s)

Kristina Dehler, Nicole Derfuss

References

Behrens, C. N.; Lopes, H. F.; Gaman, D. (2004). Bayesian analysis of extreme events with threshold estimation. *Statistical Modelling* 4, 227-244.

Dehler, K. (2017). Bayesianische Methoden im operationellen Risiko. Master's thesis.

Ergashev, B.; Mittnik, S.; Sekeris, E. (2013). A Bayesian Approach to Extreme Value Estimation in Operational Risk Modeling. *The Journal of Operational Risk* 8(4), 55-81.

MacDonald, A.; Scarrott, C.J.; Lee, D.; Darlow, B.; Reale, M.; Russell, G. (2011). A flexible extreme value mixture model. *Computational Statistics and Data Analysis* 55(6), 2137-2157.

See Also

Read [buildSplicedSevdist](#) for further information about building sevdist objects with type "spliced". The initial parameter values are fitted using the methods from the package 'evmix', i.e. for the WeibullGPD the function [fweibullgpd](#). For the algorithm also the package 'truncnorm' is required.

Examples

```
### Example for estimating the parameters of the spliced Weibull-GPD

## Not run:

data("lossdat")
data=lossdat[[1]]$Loss

## starting values - method of moments

# Weibull distribution (shape, scale)
model <- function(x) c(F1 = x[2]*gamma(1+1/x[1])-mean(data),
F2 = x[2]^2*(gamma(1+2/x[1])-(gamma(1+1/x[1]))^2)-sd(data)^2)
```

```

weibullpar <- rootSolve::multiroot(f = model, start = c((sd(data)/mean(data))^-1.086),
mean(data)/(gamma(1+1/((sd(data)/mean(data))^-1.086))))$root

# generalized Pareto distribution (tresh, beta, xi)
thresh=quantile(data,.9) # threshold
data2=data[which(data>thresh)]
model=function(x) c(F1=thresh+x[1]/(1-x[2])-mean(data2),
F2=x[1]^2/(1-x[2])^2/(1-2*x[2])-sd(data2)^2)
gpdpar=c(thresh,rootSolve::multiroot(f=model,start=c(mean(data2),1/mean(data2)))$root)

## parameters of the prior distribution

prior <- list(xi = c(gpdpar[3],sd(data)),tau = c(quantile(data,.9),sd(data)/10),
beta = c(gpdpar[2],sd(data)),wscale = c(weibullpar[2],sd(data)),
wshape = c(weibullpar[1],sd(data)))

## estimation of (shape, scale, thresh, beta, xi)

fitSplicedBayesWeibullGPD(data, prior = prior, proposal_scale = evmix::fweibullgpd(data,
method = "Nelder-Mead", pvector = c(weibullpar[1], weibullpar[2], gpdpar[1],
gpdpar[2], gpdpar[3]))$se, start = evmix::fweibullgpd(data,
method = "Nelder-Mead", pvector = c(weibullpar[1], weibullpar[2], gpdpar[1],
gpdpar[2], gpdpar[3]))$optim$par)

## End(Not run)

```

fitSplicedBestFit *Fitting a spliced distribution over a given data set*

Description

A spliced distribution is fitted based on given loss data and required distributions for the body and the tail using a best-fit method. The function returns a sevdist object with type "spliced".

Usage

```
fitSplicedBestFit(cell, body, tail, thresh0 = 0.7, thresh.max = 0.98)
```

Arguments

cell	List containing the loss data in cell\$Loss.
body	Character string giving the name of the distribution in the body. Can be chosen between "gamma", "lnorm", "weibull" or "erlang".
tail	Character string giving the name of the distribution in the tail. Can be chosen between "gpd", "gamma", "lnorm", "weibull" or "gh".
thresh0	Initial value for the quantile of the threshold between body and tail
thresh.max	Terminal value for the quantile of the threshold between body and tail

Details

Starting with a spliced distribution with threshold given by the quantile thresh0, the respective parameters of the given body and tail distribution are fitted, as well as the weights of both parts. A list of possible thresholds is given by all loss values between all quantiles between thresh0 and thresh.max. For each of these thresholds a spliced distribution will be fitted and then the best fitting threshold with the corresponding parameters will be chosen with a Kolmogorow-Smirnov test and the result is returned in a sevdist object with type "spliced".

Author(s)

Christina Zou

See Also

fitSplicedPar, fitThreshold, fitSpliced

Examples

```
data(lossdat)
## Not run:
param<-fitSplicedBestFit(lossdat[[1]], "lnorm", "gpd")
param[[1]] ## Parameters of the body distribution
param[[2]] ## Parameters of the tail distribution

## End(Not run)
```

fitThreshold	<i>Threshold estimation for spliced distribution</i>
--------------	--

Description

Given a dataset with a chosen distribution for the data in the body and another distribution in the tail, the threshold is estimated.

Usage

```
fitThreshold(cell, body, tail, method)
```

Arguments

cell	list containing the data in the component Loss
body	list containing the data in the component Loss
tail	list containing the data in the component Loss
method	Method for the threshold estimation. In case of a GPD tail, it can be chosen between "dAMSE", "danielsson", "DK", "GH", "gomes", "hall", "Himp", "HW", "mindist", "RT"

Details

GPD tail In case of a Generalized Pareto Function in the tail, there are several methods to estimate the threshold which are based on extreme value statistics. Most of them are based on the Asymptotic Mean Squared Error (AMSE) approach. where the asymptotic squared error

$$AsyE((Hill(N, k) - gamma)^2)$$

between the true inverse tail index $gamma$ and the Hill-estimator is minimized: "dAMSE", "danielsson", "DK", "GH", "gomes", "hall", "Himp" and "HW". For further details, see tea. "RT" is a heuristic approach where the smallest order statistic k that minimizes the expression $1/k \sum_i = 1^k i^{beta} |gamma_i - median(gamma_1, \dots, gamma_k)|$ is chosen for the threshold. "mindist" minimizes the distance between the largest upper order statistics (the empirical tail) and the theoretical tail of a Pareto distribution. For further details, see tea.

Value

Returns a numeric value giving threshold fitted according the given method.

Author(s)

Christina Zou, Leonie Wicht

References

GPD Tail:

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- Hall, P. (1990) Using the Bootstrap to Estimate Mean Squared Error and Select Smoothing Parameter in Nonparametric Problems. *Journal of Multivariate Analysis*, 32, 177-203
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- Reiss, R.-D. and Thomas, M. (2007) *Statistical Analysis of Extreme Values: With Applications to Insurance, Finance, Hydrology and Other Fields*. Birkhauser, Boston.

Examples

```
data(lossdat)
fitThreshold(lossdat[[1]], method="dAMSE")
```

fitWeights*Fitting the weights of the body and the tail for a spliced distribution*

Description

Given the the weights of the spliced distribution are obtained by maximum likelihood estimation.

Usage

```
fitWeights(cell, thresh)
```

Arguments

cell	List containing the data in the component Loss
thresh	Threshold between the body and the tail.

Details

Given the threshold t , a density function $d1$ for the body distribution and a density function $d2$ for the tail distribution, the incidental spliced density function has the formula $d(x) = w * d1(x)$ if $x \leq t$ and $d(x) = (1 - w) * d2(x)$ of $x > t$. The weight w is needed to normalize the density function. It is obtained by maximum likelihood estimation. The weights depends only on the number of data points below and above the threshold, not on the distribution functions in the body and the tail.

Author(s)

Christina Zou, Leonie Wicht

See Also

fitThreshold, fitSpliced

Examples

```
data(lossdat)
thresh<-quantile(lossdat[[1]]$Loss, 0.9)
w<-fitWeights(lossdat, thresh)
```

 gh *Tukey's gh Distribution*

Description

Density, distribution function, quantile function, and random generation for Tukey's gh distribution.

Usage

```
dgh(x, A, B, g, h, log = FALSE)
pgh(q, A, B, g, h, log.p = FALSE)
qgh(q, A, B, g, h, log.p = FALSE)
rgh(n, A, B, g, h)
```

Arguments

x, q	vector of quantiles.
p	vector of probabilities.
n	number of observations.
A	location parameter.
B	scale parameter, has to be positive.
g	skewness parameter.
h	kurtosis parameter.
log, log.p	logical; if TRUE, probabilities p are given as log(p)

Details

Tukey's gh distribution with location parameter A, scale parameter B, skewness parameter g, and kurtosis parameter h is obtained by transforming a standard normal variable X by

$$T(X) = A + B \exp(h/2X^2)(\exp(gX) - 1)/g$$

if g is not equal to zero, and else by

$$T(X) = A + B \exp(h/2X^2)X.$$

Value

dgh gives the density, pgh gives the distribution function, qgh gives the quantile function, and rgh generates random deviates.

The length of the result is determined by n for rgh, and is the length of the numerical arguments for the other function.

Author(s)

Linda Moestel

References

Tukey, J. W. (1960): The Practical Relationship between the Common Transformations of Counts of Amounts. Technical Report 36, Princeton University Statistical Techniques Research Group, Princeton.

Klein, I. and Fischer, M. (2002): Symmetrical gh-transformed Distributions. in S. Mittnek and I. Klein: *Contributions to Modern Econometrics*, Kluwer Academic Publishers.

Pfaelzner, F. (2017): Einsatz von Tukey-type Verteilungen bei der Quantifizierung von operationellen Risiken. MMasterthesis Friedrich-Alexander-University Erlangen-Nueremberg.

Examples

```
##Parameters for a gh distribution
A=500
B=3
g=0.2
h=0.5

hist(rgh(n=1000,A,B,g,h))
curve(dgh(x,A,B,g,h),480,520)
curve(pgh(x,A,B,g,h),480,520)
curve(qgh(x,A,B,g,h),0,1)
```

gofest

Goodness of fit tests for severity distributions

Description

Testing the goodness-of-fit of the distributions given in a sevdist or a freqdist object to the loss data.

Usage

```
gofest(cell, object)
```

Arguments

cell	A data frame giving the losses (cell\$Loss) and the user-defined period (cell\$Period) in which the loss occurred.
object	A loss severity model (sevdist object) or a loss frequency model (freqdist object)

Details

If object is of type `sevdist`, then Anderson-Darling, Cramer-von-Mises and Kolmogorov-Smirnov test is performed on the loss data of a single cell and the respected fitted distribution given by the `sevdist` object.

If object is of type `freqdist`, then a χ^2 goodness-of-fit test will be performed.

Value

If object is of type `sevdist`, then the return is a list with the test results from all three tests: `[[1]]` Anderson-Darling, `[[2]]` Cramer-von-Mises, `[[3]]` Kolmogorow-Smirnov.

If object is of type `freqdist`, then the functions returns the result of the χ^2 test.

Refer with `$p.value` to the p-values and `$statistic` to the test statistic of each of the tests.

Author(s)

Marius Pfeuffer, Christina Zou

References

Anderson, Theodore W., and Donald A. Darling. Asymptotic theory of certain "goodness of fit" criteria based on stochastic processes. *The annals of mathematical statistics* (1952): 193-212.

Anderson, Theodore W., and Donald A. Darling. "A test of goodness of fit". *Journal of the American statistical association* 49.268 (1954): 765-769.

Birnbaum, Z. W., and Fred H. Tingey. "One-sided confidence contours for probability distribution functions". *The Annals of Mathematical Statistics* 22.4 (1951): 592-596.

Conover, William Jay, and William Jay Conover. "Practical nonparametric statistics" (1980).

Csorgo, Sandor, and Julian J. Faraway. "The exact and asymptotic distributions of Cramer-von Mises statistics". *Journal of the Royal Statistical Society. Series B (Methodological)* (1996): 221-234.

Durbin, James. "Distribution theory for tests based on the sample distribution function". *Society for Industrial and Applied Mathematics*, 1973.

See Also

We use the goodness-of-fit tests `ad.test`, `cvm.test` from the package `gofest` and `ks.test` and `chisq.test` from `stats`.

Examples

```
data("lossdat")
opriskmodel = list()
opriskmodel[[1]] = list()
opriskmodel[[1]]$freqdist = fitFreqdist(lossdat[[1]], "pois")
opriskmodel[[1]]$sevdist = fitPlain(lossdat[[1]], "gamma")

# perform test on the sevdist object
gofest(lossdat[[1]], opriskmodel[[1]]$sevdist)
```

```

# show result for e.g. only the Kolmogorow-Smirnov test
test = goftest(lossdat[[1]], opriskmodel[[1]]$sevdist)
test[[3]]$p.value
test[[3]]$statistic

# perform test on the freqdist object
goftest(lossdat[[1]], opriskmodel[[1]]$freqdist)

# the p-value is given by
goftest(lossdat[[1]], opriskmodel[[1]]$freqdist)$p.value

```

gpd

*Generalized Pareto Distribution***Description**

Density, distribution function, quantile function, and random generation for generalized Pareto distribution.

Usage

```

dgpd(x, loc, scale, shape)
pgpd(q, loc, scale, shape)
qgpd(p, loc, scale, shape)
rgpd(n, loc, scale, shape)

```

Arguments

x, q	vector of quantiles.
p	vector of probabilities.
n	number of observations.
loc	location parameter.
scale	scale parameter.
shape	shape parameter.

Details

Generalized Pareto Distribution with density

$$f(x) = 1/scale * (1 + shape * (x - loc)/scale)^{-1/shape - 1}$$

Value

dgpd gives the density, pgpd gives the distribution function, qgpd gives the quantile function, and rgpd generates random deviates.

Examples

```
dgpd(110,100,2,4) # 0.01112233
```

lossdat

Example loss data set

Description

A minimal loss data set comprising 4 cells (referring to a 2x2 business line/event type operational risk setting).

Usage

```
data("lossdat")
```

Format

The format is: List of 4 \$:'data.frame': 1965 obs. of 3 variables: ..\$ Loss : num [1:1965] 1877 1807 918 1480 1218\$ Period: num [1:1965] 1 1 1 1 1 1 1 1 1 1\$ Date : Date[1:1965], format: "2016-12-30" "2016-12-25" "2016-12-22" ... \$:'data.frame': 2025 obs. of 3 variables: ..\$ Loss : num [1:2025] 181 610 961 1312 259\$ Period: num [1:2025] 1 1 1 1 1 1 1 1 1 1\$ Date : Date[1:2025], format: "2016-12-30" "2016-12-30" "2016-12-28" ... \$:'data.frame': 1995 obs. of 3 variables: ..\$ Loss : num [1:1995] 1334 1067 1068 714 1590\$ Period: num [1:1995] 1 1 1 1 1 1 1 1 1 1\$ Date : Date[1:1995], format: "2016-12-31" "2016-12-28" "2016-12-26" ... \$:'data.frame': 1941 obs. of 3 variables: ..\$ Loss : num [1:1941] 650 847 242 513 264\$ Period: num [1:1941] 1 1 1 1 1 1 1 1 1 1\$ Date : Date[1:1941], format: "2016-12-31" "2016-12-28" "2016-12-22" ...

Details

4 cells with Losses, Time Stamp and Discrete-Time Period (referring to e.g., a quarterly or annual basis).

Source

Hypothetical, simulated example with bivariate dependencies between loss frequencies and severities

Examples

```
data(lossdat)
summary(lossdat)
```

mcSim	<i>Monte Carlo Simulation from opriskmodel objects for total loss estimation</i>
-------	--

Description

Function for conducting Monte Carlo Simulation of complete opriskmodel objects (list of cells with (1) frequency model, (2) severity model and (3) dependency model)

Usage

```
mcSim(opriskmodel, n_sim, verbose=TRUE)
VaR(mc_out, alpha)
```

Arguments

opriskmodel	an opriskmodel object
n_sim	number of simulations
mc_out	Monte Carlo simulation output
alpha	significance level for quantile/value-at-risk
verbose	verbose mode

Value

A mcsim object, which can be further processed by the VaR function to estimate empirical quantiles as value-at-risk measure

Author(s)

Marius Pfeuffer

See Also

[sla](#)

Examples

```
## Not run:
### Load Example Data Set
data(lossdat)

### Estimation of Complete Risk Model
opriskmodel1=list()
for(i in 1:length(lossdat)){
  opriskmodel1[[i]]=list()
  opriskmodel1[[i]]$freqdist=fitFreqdist(lossdat[[i]],"pois")
  opriskmodel1[[i]]$sevdist=fitPlain(lossdat[[i]],"lnorm")
}
```

```

### Cell 1: Gumbel Copula, Cell 2: Independence, Cell 3: Frank Copula, Cell 4: Independence
opriskmodel1[[1]]$dependency=fitDependency(lossdat[[1]],6)
opriskmodel1[[3]]$dependency=fitDependency(lossdat[[3]],4)

### Monte Carlo Simulation
mc_out=mcSim(opriskmodel1,100)

### Evaluation of 95
VaR(mc_out,.95)
sla(opriskmodel1,.95)

### Monte Carlo Simulation
mc_out=mcSim(opriskmodel1,100)

### Evaluation of 95
VaR(mc_out,.95)

## End(Not run)

```

Mixing

Extended Dynamic Weighted Mixture Model

Description

Implementation of the dynamic weighted mixture model of Frigessi et al., 2001

Usage

```

dmixing(x,sevdist,log=FALSE)
pmixing(q,sevdist,lower.tail=TRUE)
qmixing(p,sevdist,lower.tail=TRUE)
rmixing(n,sevdist)

```

Arguments

<code>x,q</code>	vector of quantiles
<code>p</code>	vector of probabilities.
<code>n</code>	positive integer, number of observations
<code>sevdist</code>	sevdist object
<code>log</code>	logical; if TRUE, probabilities <code>p</code> are given as $\log(p)$.
<code>lower.tail</code>	logical; if TRUE (default), probabilities are $P[X \leq x]$ otherwise, $P[X > x]$.

Details

The dynamic mixture pdf is given by $l(x)=1/r*((1-W(x))*f_1(x)+W(x)*f_2(x))$, where $W(x)$ denotes a Cauchy cdf, $f_1(x)$ and $f_2(x)$ body and tail pdfs, r is a normalizing constant.

Author(s)

Marius Pfeuffer

References

A. Frigessi et al.: *A Dynamic Mixture Model for Unsupervised Tail Estimation without Threshold Selection*, *Extremes* 5(3):219-235, 2002
 Y. Hu: *User's Guide for evmix Package in R.*, Working Paper, 2013

Examples

```
### Create mixing sevdist object
sevdist=buildMixingSevdist("weibull", c(2,6), "gpd", c(0,4,-0.5), c(8,.8))
### Evaluate pdf
dmixing(1,sevdist)
```

sla

*Single-Loss Approximation for Operational Value at Risk***Description**

Given the object opriskmodel using the single-loss approximation a list of alpha-quantiles is created for every cell in opriskmodel.

Usage

```
sla(opriskmodel, alpha, xi_low = 0.8, xi_high = 1.2, plot = FALSE)
```

Arguments

opriskmodel	Object containing the parameters for the severities and the frequencies
alpha	Level of the quantile for the total loss-process of the single-loss-approximation
xi_low	Lower interpolation-point for the spline-function, standard value = 0.8
xi_high	Upper interpolation-point for the spline-function, standard value = 1.2
plot	Plot of the interpolated correction term if xi is between xi_low and xi_high, standard value = FALSE

Details

In the first step the tailindex of the severity distribution is determined. If it does not lie in the critical zone, i.e., not between xi_low and xi_high, the closed-form single-loss approximation from Degen is used. If the tailindex lies in the critical zone, then the R-function splinefun with method "hyman" is used to create a spline with given data points xi lying in [xi_low - 0.2, xi_low] and [xi_high, xi_high + 0.2] using the value at xi = 1 as an anchor. A plot of the interpolation is provided such that user-defined adjustment of xi_low and xi_high is possible.

Author(s)

Benedikt Graswald, Jixuan Wang, Christina Zou

References

Bocker, Klaus, and Claudia Kluppelberg. "Operational VaR: a closed-form approximation." Risk-London-Rsik Magazine Limited- 18.12 (2005): 90.

Degen, Matthias. "The calculation of minimum regulatory capital using single-loss approximations." The Journal of Operational Risk 5.4 (2010): 3.

Zou, Christina Z. et al. (2018): "A Monotone Spline Interpolated Closed-Form Approximation for Operational Value-at-Risk." Working Paper (In Preparation)

Examples

```
## Not run:
#Example: SLA for the spliced log-gamma gpd model (tail-index = 0.014, no interpolation required)
opriskmodel = list()
opriskmodel[[1]] = list()
opriskmodel[[1]]$sevdist = buildSplicedSevdist("lgamma", c(1.23, 0.012),
                                               "gpd", c(200, 716, 0.014), 2000, 0.8)
opriskmodel[[1]]$freqdist = buildFreqdist("pois", 50)

#Example: SLA for the spliced log-gamma gpd model (tail-index = 0.9, interpolation performed)
opriskmodel[[2]] = list()
opriskmodel[[2]]$sevdist = buildSplicedSevdist("lgamma", c(1.23, 0.012),
                                               "gpd", c(200, 716, 0.9), 2000, 0.8)
opriskmodel[[2]]$freqdist = buildFreqdist("pois", 50)

sla(opriskmodel, alpha = 0.95)

#generate plot if interpolation was performed
sla(opriskmodel, alpha = 0.95, plot = TRUE)

## End(Not run)
```

spliced

Spliced Distributions

Description

Density, distribution function, quantile function, and random generation for Tukey's gh distribution.

Usage

```

dspliced(x, sevdist)
pspliced(q, sevdist)
qspliced(p, sevdist)
rspliced(n, sevdist)

```

Arguments

x, q	vector of quantiles.
p	vector of probabilities.
n	number of observations.
sevdist	severity distribution (sevdist) object

Details

Tukey's gh distribution with location parameter A, scale parameter B, skewness parameter g, and kurtosis parameter h is obtained by transforming a standard normal variable X by

$$T(X) = A + B \exp(h/2X^2)(\exp(gX) - 1)/g$$

if g is not equal to zero, and else by

$$T(X) = A + B \exp(h/2X^2)X.$$

Value

dgh gives the density, pgh gives the distribution function, qgh gives the quantile function, and rgh generates random deviates.

The length of the result is determined by n for rgh, and is the length of the numerical arguments for the other function.

Author(s)

Linda Moestel

References

Tukey, J. W. (1960): The Practical Relationship between the Common Transformations of Counts of Amounts. Technical Report 36, Princeton University Statistical Techniques Research Group, Princeton.

Klein, I. and Fischer, M. (2002): Symmetrical gh-transformed Distributions. in S. Mittnek and I. Klein: *Contributions to Modern Econometrics*, Kluwer Academic Publishers.

Pfaelzner, F. (2017): Einsatz von Tukey-type Verteilungen bei der Quantifizierung von operationellen Risiken. MMasterthesis Friedrich-Alexander-University Erlangen-Nueremberg.

Examples

```
##Parameters for a gh distribution
A=500
B=3
g=0.2
h=0.5

hist(rgh(n=1000,A,B,g,h))
curve(dgh(x,A,B,g,h),480,520)
curve(pgh(x,A,B,g,h),480,520)
curve(qgh(x,A,B,g,h),0,1)
```

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