Package ‘EDFtest’

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Description This repository contains software for the calculation of goodness-of-fit test statistics and their P-values. The three statistics computed are the Empirical Distribution function statistics called Cramer-von Mises, Anderson-Darling, and Watson statistics. The statistics and their P-values can be used to assess an assumed distribution. The following distributions are available: Uniform, Normal, Gamma, Logistic, Laplace, Weibull, Extreme Value, and Exponential.
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EDFtest-package

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EDFtest-package

EDFtest: Goodness-of-fit Tests based on Empirical Distribution Function

Description

EDFtest provides software for the calculation of goodness-of-fit test statistics and their P-values. The three statistics computed are the Empirical Distribution function statistics called Cramér-von Mises, Anderson-Darling, and Watson statistic.

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Authors:

- Richard Lockhart
- Li Yao

References


AD

See Also

Useful links:

- https://github.com/LiYao-sfu/EDFtest
- Report bugs at https://github.com/LiYao-sfu/EDFtest/issues

AD

Anderson-Darling statistic

Description

Compute the Anderson-Darling goodness-of-fit statistic $A^2$ for an i.i.d sample, x, to test for the given distribution with parameters unknown. Estimate parameters by ML using EDFtest MLE function by default.

Usage

AD.uniform(x, parameter = estimate.uniform(x))
AD.normal(x, parameter = estimate.normal(x))
AD.gamma(x, parameter = estimate.gamma(x))
AD.logistic(x, parameter = estimate.logistic(x))
AD.laplace(x, parameter = estimate.laplace(x))
AD.weibull(x, parameter = estimate.weibull(x))
AD.extremevalue(x)
AD.exp(x, parameter = estimate.exp(x))
AD(z)

Arguments

x A random sample.
parameter Parameters of the given distribution, MLE by default.
z A standard uniform random sample.

Value

Anderson-Darling statistic of the given sample.
See Also

estimate for estimating distribution parameters by ML; CvM for calculating Cramér-von Mises statistic; Watson for calculating Watson statistic; AD.pvalue for calculating P-value of Anderson-Darling statistic.

Examples

```r
x0 <- runif(n = 100, min = -1, max = 1)
AD.uniform(x0)

x1 <- rnorm(n = 100, mean = 0, sd = 1)
AD.normal(x1)

x2 <- rgamma(n = 100, shape = 1, scale = 1)
AD.gamma(x2)

x3 <- rlogis(n = 100, location = 0, scale = 1)
AD.logistic(x3)

x4 <- rmutil::rlaplace(n = 100, m = 0, s = 1)
AD.laplace(x4)

x5 <- rweibull(n = 100, shape = 1, scale = 1)
AD.weibull(x5)

x5_log <- log(x5)
AD.extremevalue(x5_log)

x6 <- rexp(n = 100, rate = 1/2)
AD.exp(x6)
```

P-value of Anderson-Darling statistic

Description

Compute the P-value of the given Anderson-Darling statistic $A^2$ using `imhof` function in `CompQuadForm`.

Usage

```r
AD.uniform.pvalue(a, neig = 100, verbose = FALSE)
AD.normal.pvalue(a, neig = 100, verbose = FALSE)
AD.gamma.pvalue(a, shape, neig = 100, verbose = FALSE)
AD.logistic.pvalue(a, neig = 100, verbose = FALSE)
AD.laplace.pvalue(a, neig = 100, verbose = FALSE)
```
AD.pvalue

AD.weibull.pvalue(a, neig = 100, verbose = FALSE)

AD.extremevalue.pvalue(a, neig = 100, verbose = FALSE)

AD.exp.pvalue(a, neig = 100, verbose = FALSE)

Arguments

a
  Anderson-Darling statistic $A^2$ with a given distribution.

neig
  Number of eigenvalues used for imhof.

verbose
  Logical; if TRUE, print warning messages.

shape
  The shape parameter of Gamma distribution.

Details

Parameters must be estimated by maximum likelihood (ML) in order for the P-values computed here to be asymptotically valid. They are computed using the fact that when parameters are estimated by maximum likelihood and the null hypothesis is true, the asymptotic distribution of the GOF statistic is the distribution of an infinite weighted sum of weighted chi-square random variables on 1 degree of freedom. The weights are eigenvalues of an integral equation. They depend on the distribution being tested, the statistic being used, and in some cases on the actual parameter values. These weights are then computed approximately by discretization of the integral equation; when that equation depends on one or more parameter values we use the MLE in the equation.

Some notes on the specific distributions: For the Normal, Logistic, Laplace, Extreme Value, Weibull and Exponential distributions, the limiting distributions do not depend on the parameters. For the Gamma distribution, the shape parameter affects the limiting distribution. The tests remain asymptotically valid when the MLE is used to approximate the limit distribution.

The Exponential distribution is a special case of the Weibull and Gamma families arising when the shape is known to be 1. Knowing a parameter and therefore not estimating it affects the distribution of the test statistic and the functions provided for the Exponential distribution allow for this.

If a data set $X_1,...,X_n$ follows the Weibull distribution then $Y_1 = \log(X_1), \ldots, Y_n = \log(X_n)$ follows the Extreme Value distribution and vice versa. The two procedures give identical test statistics and P-values, in principal.

Some of the models have more than one common parametrization. For the Exponential, Gamma, and Weibull distributions, some writers use a rate parameter and some use the scale parameter which is the inverse of the rate. Our code uses the scale parameter.

For the Laplace distribution, some writers use the density $f(x) = \exp(-|x - \mu|/\beta)/(2\beta)$ in which $\beta$ is a scale parameter. Others use the standard deviation $\sigma = \beta/\sqrt{2}$. Our code uses the scale parameter.

For the Uniform distribution, we offer code for the two parameter Uniform distribution on the range $\theta_1$ to $\theta_2$. These are estimated by the sample minimum and sample maximum. The probability integral transforms of the remaining $n-2$ points are then tested for uniformity on the range 0 to 1. This procedure is justified because the these probability integral transforms have exactly this distribution if the original data had a uniform distribution over any interval.
It is not unusual to test the hypothesis that a sample follows the standard uniform distribution on \([0,1]\). In this case the parameters should not be estimated. Instead use \(AD(z)\) or \(CvM(z)\) or Watson(z) to compute the statistic values and then get P-values from \(AD\.uniform\.pvalue(a)\) or \(CvM\.uniform\.pvalue(w)\) or \(Watson\.uniform\.pvalue(u)\) whichever is wanted.

**Value**

P-value of the Anderson-Darling statistic.

**See Also**

\(AD\) for calculating Anderson-Darling statistic; \(CvM\.pvalue\) for calculating P-value of Cramér-von Mises statistic; \(Watson\.pvalue\) for calculating P-value of Watson statistic.

**Examples**

\[
x0=\text{runif}(n=100,\min=-1,\max=1) \\
asq0 = AD\.uniform(x0) \\
AD\.uniform\.pvalue(asq0)
\]

\[
x1=\text{rnorm}(n=100,\text{mean}=0,\text{sd}=1) \\
asq1 = AD\.normal(x1) \\
AD\.normal\.pvalue(asq1)
\]

\[
x2=\text{rgamma}(n=100,\text{shape}=1,\text{scale}=1) \\
asq2 = AD\.gamma(x2) \\
AD\.gamma\.pvalue(asq2,1)
\]

\[
x3=\text{rlogis}(n=100,\text{location}=0,\text{scale}=1) \\
asq3 = AD\.logistic(x3) \\
AD\.logistic\.pvalue(asq3)
\]

\[
x4=\text{rmutil::rlaplace}(n=100,\text{m}=0,\text{s}=1) \\
asq4 = AD\.laplace(x4) \\
AD\.laplace\.pvalue(asq4)
\]

\[
x5=\text{rweibull}(n=100,\text{shape}=1,\text{scale}=1) \\
asq5 = AD\.weibull(x5) \\
AD\.weibull\.pvalue(asq5) \\
x5_log=\log(x5) \\
AD\.extremevalue\.pvalue(AD\.extremevalue(x5_log))
\]

\[
x6=\text{rexp}(n=100,\text{rate}=1/2) \\
asq6 = AD\.exp(x6) \\
AD\.exp\.pvalue(asq6)
\]
CvM  

Cramer-von Mises statistic

Description

Compute the Cramér-von Mises goodness-of-fit statistic $W^2$ for an i.i.d. sample, $x$, to test for the given distribution with parameters unknown. Estimate parameters by ML using \texttt{EDFtest} MLE function by default.

Usage

\begin{align*}
\text{CvM.uniform}(x, \text{parameter} = \text{estimate.uniform}(x)) \\
\text{CvM.normal}(x, \text{parameter} = \text{estimate.normal}(x)) \\
\text{CvM.gamma}(x, \text{parameter} = \text{estimate.gamma}(x)) \\
\text{CvM.logistic}(x, \text{parameter} = \text{estimate.logistic}(x)) \\
\text{CvM.laplace}(x, \text{parameter} = \text{estimate.laplace}(x)) \\
\text{CvM.weibull}(x, \text{parameter} = \text{estimate.weibull}(x)) \\
\text{CvM.extremevalue}(x) \\
\text{CvM.exp}(x, \text{parameter} = \text{estimate.exp}(x)) \\
\text{CvM(z)}
\end{align*}

Arguments

\begin{itemize}
\item \texttt{x} A random sample.
\item \texttt{parameter} Parameters of the given distribution, MLE by default.
\item \texttt{z} A standard uniform random sample.
\end{itemize}

Value

Cramér-von Mises statistic of the given sample.

See Also

\texttt{estimate} for estimating distribution parameters by ML; \texttt{AD} for calculating Anderson-Darling statistic; \texttt{Watson} for calculating Watson statistic; \texttt{CvM.pvalue} for calculating P-value of Cramér-von Mises statistic.
Examples

\[
\begin{align*}
  x_0 &= \text{runif}(n=100, \text{min}=-1, \text{max}=1) \\
  \text{CvM.uniform}(x_0) \\
  x_1 &= \text{rnorm}(n=100, \text{mean}=0, \text{sd}=1) \\
  \text{CvM.normal}(x_1) \\
  x_2 &= \text{rgamma}(n=100, \text{shape}=1, \text{scale}=1) \\
  \text{CvM.gamma}(x_2) \\
  x_3 &= \text{rlogis}(n=100, \text{location}=0, \text{scale}=1) \\
  \text{CvM.logistic}(x_3) \\
  x_4 &= \text{rmutil::rlaplace}(n=100, m=0, s=1) \\
  \text{CvM.laplace}(x_4) \\
  x_5 &= \text{rweibull}(n=100, \text{shape}=1, \text{scale}=1) \\
  \text{CvM.weibull}(x_5) \\
  x_5\_\log &= \log(x_5) \\
  \text{CvM.extremevalue}(x_5\_\log) \\
  x_6 &= \text{rexp}(n=100, \text{rate}=1/2) \\
  \text{CvM.exp}(x_6)
\end{align*}
\]

CvM.pvalue

**P-value of Cramer-von Mises statistic**

Description

Compute the P-value of the given Cramér-von Mises statistic \( W^2 \) using *imhof* function in *CompQuadForm*.

Usage

\[
\begin{align*}
  \text{CvM.uniform.pvalue}(w, \text{neig} = 100, \text{verbose} = \text{FALSE}) \\
  \text{CvM.normal.pvalue}(w, \text{neig} = 100, \text{verbose} = \text{FALSE}) \\
  \text{CvM.gamma.pvalue}(w, \text{shape}, \text{neig} = 100, \text{verbose} = \text{FALSE}) \\
  \text{CvM.logistic.pvalue}(w, \text{neig} = 100, \text{verbose} = \text{FALSE}) \\
  \text{CvM.laplace.pvalue}(w, \text{neig} = 100, \text{verbose} = \text{FALSE}) \\
  \text{CvM.weibull.pvalue}(w, \text{neig} = 100, \text{verbose} = \text{FALSE}) \\
  \text{CvM.extremevalue.pvalue}(w, \text{neig} = 100, \text{verbose} = \text{FALSE}) \\
  \text{CvM.exp.pvalue}(w, \text{neig} = 100, \text{verbose} = \text{FALSE})
\end{align*}
\]
Arguments

- **w**: Cramér-von Mises statistic \( W^2 \) with a given distribution.
- **neig**: Number of eigenvalues used for \( \text{imhof} \).
- **verbose**: Logical; if TRUE, print warning messages.
- **shape**: The shape parameter of Gamma distribution.

Details

Parameters must be estimated by maximum likelihood (ML) in order for the P-values computed here to be asymptotically valid. They are computed using the fact that when parameters are estimated by maximum likelihood and the null hypothesis is true, the asymptotic distribution of the GOF statistic is the distribution of an infinite weighted sum of weighted chi-square random variables on 1 degree of freedom. The weights are eigenvalues of an integral equation. They depend on the distribution being tested, the statistic being used, and in some cases on the actual parameter values. These weights are then computed approximately by discretization of the integral equation; when that equation depends on one or more parameter values we use the MLE in the equation.

Some notes on the specific distributions: For the Normal, Logistic, Laplace, Extreme Value, Weibull and Exponential distributions, the limiting distributions do not depend on the parameters. For the Gamma distribution, the shape parameter affects the limiting distribution. The tests remain asymptotically valid when the MLE is used to approximate the limit distribution.

The Exponential distribution is a special case of the Weibull and Gamma families arising when the shape is known to be 1. Knowing a parameter and therefore not estimating it affects the distribution of the test statistic and the functions provided for the Exponential distribution allow for this.

If a data set \( X_1, \ldots, X_n \) follows the Weibull distribution then \( Y_1 = \log(X_1), \ldots, Y_n = \log(X_n) \) follows the Extreme Value distribution and vice versa. The two procedures give identical test statistics and P-values, in principal.

Some of the models have more than one common parametrization. For the Exponential, Gamma, and Weibull distributions, some writers use a rate parameter and some use the scale parameter which is the inverse of the rate. Our code uses the scale parameter.

For the Laplace distribution, some writers use the density \( f(x) = \exp(-|x-\mu|/\beta)/(2\beta) \) in which \( \beta \) is a scale parameter. Others use the standard deviation \( \sigma = \beta/\sqrt{2} \). Our code uses the scale parameter.

For the Uniform distribution, we offer code for the two parameter Uniform distribution on the range \( \theta_1 \) to \( \theta_2 \). These are estimated by the sample minimum and sample maximum. The probability integral transforms of the remaining \( n-2 \) points are then tested for uniformity on the range 0 to 1. This procedure is justified because the these probability integral transforms have exactly this distribution if the original data had a uniform distribution over any interval.

It is not unusual to test the hypothesis that a sample follows the standard uniform distribution on \([0,1]\). In this case the parameters **should not** be estimated. Instead use \( \text{AD}(z) \) or \( \text{CvM}(z) \) or \( \text{Watson}(z) \) to compute the statistic values and then get P-values from \( \text{AD.uniform.pvalue}(a) \) or \( \text{CvM.uniform.pvalue}(w) \) or \( \text{Watson.uniform.pvalue}(u) \) whichever is wanted.

Value

P-value of the given Cramér-von Mises statistic.
See Also

*CvM* for calculating Cramér-von Mises statistic; *AD.pvalue* for calculating P-value of Anderson-Darling statistic; *Watson.pvalue* for calculating P-value of Watson statistic.

Examples

```r
x0=runif(n=100, min=-1, max=1)
wsq0 = CvM.uniform(x0)
CvM.uniform.pvalue(wsq0)

x1=rnorm(n=100, mean=0, sd=1)
wsql = CvM.normal(x1)
CvM.normal.pvalue(wsql)

x2=rgamma(n=100, shape=1, scale=1)
wsq2 = CvM.gamma(x2)
CvM.gamma.pvalue(wsq2)

x3=rlogis(n=100, location=0, scale=1)
wsql3 = CvM.logistic(x3)
CvM.logistic.pvalue(wsql3)

x4= rmutil::rlaplace(n=100, m=0, s=1)
wsq4 = CvM.laplace(x4)
CvM.laplace.pvalue(wsq4)

x5=rweibull(n=100, shape=1, scale=1)
wsq5 = CvM.weibull(x5)
CvM.weibull.pvalue(wsq5)
x5_log=log(x5)
CvM.extremevalue.pvalue(CvM.extremevalue(x5_log))

x6=rexp(n=100, rate=1/2)
wsql6 = CvM.exp(x6)
CvM.exp.pvalue(wsql6)
```

---

**estimate**  
*MLE for univariate sample*

**Description**

Estimate parameters of various distributions by the method of maximum likelihood. The following families are available: Normal(location=\(\mu\), scale=\(\sigma^2\)), Gamma(shape=\(\alpha\), scale=\(\beta\)), Logistic(location=\(\mu\), scale=s), Laplace(location=\(\mu\), scale=b), Weibull(shape=\(\alpha\), scale=\(\beta\)), and Exponential(scale=\(\theta\)).

**Usage**

```
estimate.uniform(x)
```
estimate.normal(x)
estimate.gamma(x, use.rate = FALSE)
estimate.logistic(x, eps = 1e-07, verbose = FALSE)
estimate.laplace(x, use.sd = FALSE)
estimate.weibull(x, eps = 1e-07)
estimate.exp(x, use.rate = FALSE)

Arguments

x A random sample.
use.rate Logical; if TRUE use the rate instead of the scale.
eps Stopping criterion, 1e-7 by default.
verbose Logical; if TRUE, print estimates in each iteration.
use.sd Logical; if TRUE use the sd instead of the scale for Laplace distribution.

Value

Estimated parameters of the assumed distribution by MLE.

Examples

x0=runif(n=100,min=-1,max=1)
estimate.uniform(x0)
x1=rnorm(n=100,mean=0,sd=1)
estimate.normal(x1)
x2=rgamma(n=100,shape=1,scale=1)
estimate.gamma(x2)
x3=rlogis(n=100,location=0,scale=1)
estimate.logistic(x3)
x4= rmutil::rlaplace(n=100,m=0,s=1)
estimate.laplace(x4)
x5=rweibull(n=100,shape=1,scale=1)
estimate.weibull(x5)
x6=rexp(n=100,rate=1/2)
estimate.exp(x6,use.rate=TRUE)
Description
This function takes in an i.i.d. random sample, use MLE to estimate parameters of the assumed
distribution, compute probability integral transforms, and computes Cramér-von Mises, Anderson-
Darling and Watson statistics and their P-values using \texttt{imhof} function in \texttt{CompQuadForm}.

Usage
\begin{verbatim}
gof.uniform(x, print = FALSE, verbose = FALSE) 
gof.normal(x, print = FALSE, verbose = FALSE) 
gof.gamma(x, print = FALSE, verbose = FALSE) 
gof.logistic(x, print = FALSE, verbose = FALSE) 
gof.laplace(x, print = FALSE, verbose = FALSE) 
gof.weibull(x, print = FALSE, verbose = FALSE) 
gof.extremevalue(x, print = FALSE, verbose = FALSE) 
gof.exp(x, print = FALSE, verbose = FALSE) 
\end{verbatim}

Arguments
\begin{itemize}
\item \texttt{x} \hfill A random sample.
\item \texttt{print} \hfill Logical; if TRUE print both statistics and P-values; if FALSE the results are returned invisibly.
\item \texttt{verbose} \hfill verbose Logical; if TRUE, print warning messages.
\end{itemize}

Details
Parameters must be estimated by maximum likelihood (ML) in order for the P-values computed here
to be asymptotically valid. They are computed using the fact that when parameters are estimated
by maximum likelihood and the null hypothesis is true, the asymptotic distribution of the GOF
statistic is the distribution of an infinite weighted sum of weighted chi-square random variables on
1 degree of freedom. The weights are eigenvalues of an integral equation. They depend on the
distribution being tested, the statistic being used, and in some cases on the actual parameter values.
These weights are then computed approximately by discretization of the integral equation; when
that equation depends on one or more parameter values we use the MLE in the equation.

Some notes on the specific distributions: For the Normal, Logistic, Laplace, Extreme Value, Weibull
and Exponential distributions, the limiting distributions do not depend on the parameters. For the
Gamma distribution, the shape parameter affects the limiting distribution. The tests remain asymptotically valid when the MLE is used to approximate the limit distribution.

The Exponential distribution is a special case of the Weibull and Gamma families arising when the shape is known to be 1. Knowing a parameter and therefore not estimating it affects the distribution of the test statistic and the functions provided for the Exponential distribution allow for this.

If a data set $X_1,\ldots,X_n$ follows the Weibull distribution then $Y_1 = \log(X_1), \ldots, Y_n = \log(X_n)$ follows the Extreme Value distribution and vice versa. The two procedures give identical test statistics and P-values, in principal.

Some of the models have more than one common parametrization. For the Exponential, Gamma, and Weibull distributions, some writers use a rate parameter and some use the scale parameter which is the inverse of the rate. Our code uses the scale parameter.

For the Laplace distribution, some writers use the density $f(x) = \exp(-|x - \mu|/\beta)/(2\beta)$ in which $\beta$ is a scale parameter. Others use the standard deviation $\sigma = \beta/\sqrt{2}$. Our code uses the scale parameter.

For the Uniform distribution, we offer code for the two parameter Uniform distribution on the range $\theta_1$ to $\theta_2$. These are estimated by the sample minimum and sample maximum. The probability integral transforms of the remaining n-2 points are then tested for uniformity on the range 0 to 1. This procedure is justified because these probability integral transforms have exactly this distribution if the original data had a uniform distribution over any interval.

It is not unusual to test the hypothesis that a sample follows the standard uniform distribution on $[0,1]$. In this case the parameters should not be estimated. Instead use $AD(z)$ or $CvM(z)$ or $Watson(z)$ to compute the statistic values and then get P-values from $AD.uniform.pvalue(a)$ or $CvM.uniform.pvalue(w)$ or $Watson.uniform.pvalue(u)$ whichever is wanted.

Value

Cramér-von Mises, Anderson-Darling and Watson statistics and their P-values.

See Also

gof.sandwich for general distributions using Sandwich estimation of covariance function; gof.bootstrap for generic functions using bootstrap method.

Examples

```r
x0=runif(n=100,min=-1,max=1)
gof.uniform(x0,print=FALSE)

x1=rnorm(n=100,mean=0,sd=1)
gof.normal(x1)

x2=rgamma(n=100,shape=1,scale=1)
gof.gamma(x2)

x3=rlogis(n=100,location=0,scale=1)
gof.logistic(x3)

x4=rmutil::rlaplace(n=100,m=0,s=1)
```
gof.laplace(x4)

x5=rweibull(n=100,shape=1,scale=1)
gof.weibull(x5)
x5_log=log(x5)
gof.extremevalue(x5_log)

x6=rexp(n=100,rate=1/2)
gof.exp(x6)

---

gof.bootstrap  
Generic GOF tests based on EDF using bootstrap

Description
This function takes in an i.i.d. random sample, use MLE to estimate parameters of the assumed distribution, compute probability integral transforms, and computes Cramér-von Mises, Anderson-Darling and Watson statistics and their P-values using bootstrap method.

Usage

gof.uniform.bootstrap(x, M = 10000)
gof.normal.bootstrap(x, M = 10000)
gof.gamma.bootstrap(x, M = 10000)
gof.logistic.bootstrap(x, M = 10000)
gof.laplace.bootstrap(x, M = 10000)
gof.weibull.bootstrap(x, M = 10000)
gof.extremevalue.bootstrap(x, M = 10000)
gof.exp.bootstrap(x, M = 10000)

Arguments

x  A random sample.
M  Number of bootstrap, 10000 by default.

Value
Cramér-von Mises, Anderson-Darling and Watson statistics and their P-values.
gof.sandwich

See Also

gof.sandwich for general distributions using Sandwich estimation of covariance function; gof for
generic functions using imhof function.

Examples

```r
x0=runif(n=100,min=-1,max=1)
gof.uniform.bootstrap(x0,M=100)

x1=rnorm(n=100,mean=0,sd=1)
gof.normal.bootstrap(x1,M=100)

x2=rgamma(n=100,shape=1,scale=1)
gof.gamma.bootstrap(x2,M=100)

x3=rlogis(n=100,location=0,scale=1)
gof.logistic.bootstrap(x3,M=100)

x4=rmutil::rlaplace(n=100,m=0,s=1)
gof.laplace.bootstrap(x4,M=100)

x5=rweibull(n=100,shape=1,scale=1)
gof.weibull.bootstrap(x5,M=100)
x5_log=log(x5)
gof.extremevalue.bootstrap(x5_log,M=100)

x6=rexp(n=100,rate=1/2)
gof.exp.bootstrap(x6,M=100)
```

---

gof.sandwich

**GOF tests for general distributions using Sandwich estimation of covariance function**

Description

This function tests the hypothesis that data y come from distribution Fdist with unknown parameter
values theta. Estimates of theta must be provided in thetahat.

Usage

gof.sandwich(y, x = NULL, Fdist, thetahat, Score, m = max(n, 100), ...)

Arguments

- `y` A random sample or the response of regression problem.
- `x` The matrix of covariates.
- `Fdist` User supplied function to compute probability integral transform of y.
- `thetahat` Parameter estimates by MLE.
Score
User supplied function to compute 3 components of the score function an n by
p matrix with entries partial log f(y_i,θ)/ partial theta_j.

m
Eigenvalues are extracted for an m by m grid of the covariance function.

... Other inputs passed to Fdist and Score when needed.

Details
It uses a large sample approximation to the limit distribution based on the use of the score function
components to estimate the Fisher information and the limiting covariance function of the empirical
process.
The estimates thetahat should be roots of the likelihood equations.

Value
Cramér-von Mises, Anderson-Darling and Watson statistics and their P-values.

See Also
gof for generic functions using imhof function; gof.bootstrap for generic functions using boot-
strap method.

Examples
sample = rnorm(n=100,mean=0,sd=1)
mle = estimate.normal(sample)
cdf.normal.user = function(x,theta){
  pnorm(x,mean=theta[1],sd=theta[2])
}
score.normal.user = function(x,theta){
  sig=theta[2]
  mu=theta[1]
  s.mean= (x-mu)/sig
  s.sd= s.mean^2/sig-length(x)/sig
  cbind(s.mean/sig,s.sd)
}
output = gof.sandwich(y=sample,Fdist=cdf.normal.user,thetahat=mle,Score=score.normal.user,m=100)
output

Watson
Watson statistic

Description
Compute the Watson goodness-of-fit statistic $U^2$ for an i.i.d. sample, x, to test for the given dis-
tribution with parameters unknown. Estimate parameters by ML using EDFtest MLE function by
default.
Usage

Watson.uniform(x, parameter = estimate.uniform(x))
Watson.normal(x, parameter = estimate.normal(x))
Watson.gamma(x, parameter = estimate.gamma(x))
Watson.logistic(x, parameter = estimate.logistic(x))
Watson.laplace(x, parameter = estimate.laplace(x))
Watson.weibull(x, parameter = estimate.weibull(x))
Watson.extremevalue(x)
Watson.exp(x, parameter = estimate.exp(x))
Watson(z)

Arguments

x          A random sample.
parameter  Parameters of the given distribution, MLE by default.
z          A standard uniform random sample.

Value

Watson statistic of the given sample.

See Also

estimate for estimating distribution parameters by ML; CvM for calculating Cramér-von Mises statistic; AD for calculating Anderson-Darling statistic; Watson.pvalue for calculating P-value of Watson statistic.

Examples

x0=runif(n=100,min=-1,max=1)
Watson.uniform(x0)

x1=rnorm(n=100,mean=0,sd=1)
Watson.normal(x1)

x2=rgamma(n=100,shape=1,scale=1)
Watson.gamma(x2)

x3=rlogis(n=100,location=0,scale=1)
Watson.logistic(x3)
x4 = rmultil::rlaplace(n=100, m=0, s=1)
Watson.laplace(x4)

x5 = rweibull(n=100, shape=1, scale=1)
Watson.weibull(x5)
x5_log = log(x5)
Watson.extremevalue(x5_log)

x6 = rexp(n=100, rate=1/2)
Watson.exp(x6)

Watson.pvalue

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<tr>
<th></th>
<th>P-value of Watson statistic</th>
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**Description**

Compute the P-value of the given Watson statistic $U^2$ using `imhof` function in CompQuadForm.

**Usage**

Watson.uniform.pvalue(u, neig = 100, verbose = FALSE)

Watson.normal.pvalue(u, neig = 100, verbose = FALSE)

Watson.gamma.pvalue(u, shape, neig = 100, verbose = FALSE)

Watson.logistic.pvalue(u, neig = 100, verbose = FALSE)

Watson.laplace.pvalue(u, neig = 100, verbose = FALSE)

Watson.weibull.pvalue(u, neig = 100, verbose = FALSE)

Watson.extremevalue.pvalue(u, neig = 100, verbose = FALSE)

Watson.exp.pvalue(u, neig = 100, verbose = FALSE)

**Arguments**

- **u**: Watson statistic $U^2$ with a given distribution.
- **neig**: Number of eigenvalues used for `imhof()`.
- **verbose**: Logical; if TRUE, print warning messages.
- **shape**: The shape parameter of Gamma distribution.
Details

Parameters must be estimated by maximum likelihood (ML) in order for the P-values computed here to be asymptotically valid. They are computed using the fact that when parameters are estimated by maximum likelihood and the null hypothesis is true, the asymptotic distribution of the GOF statistic is the distribution of an infinite weighted sum of weighted chi-square random variables on 1 degree of freedom. The weights are eigenvalues of an integral equation. They depend on the distribution being tested, the statistic being used, and in some cases on the actual parameter values. These weights are then computed approximately by discretization of the integral equation; when that equation depends on one or more parameter values we use the MLE in the equation.

Some notes on the specific distributions: For the Normal, Logistic, Laplace, Extreme Value, Weibull and Exponential distributions, the limiting distributions do not depend on the parameters. For the Gamma distribution, the shape parameter affects the limiting distribution. The tests remain asymptotically valid when the MLE is used to approximate the limit distribution.

The Exponential distribution is a special case of the Weibull and Gamma families arising when the shape is known to be 1. Knowing a parameter and therefore not estimating it affects the distribution of the test statistic and the functions provided for the Exponential distribution allow for this.

If a data set \( X_1, \ldots, X_n \) follows the Weibull distribution then \( Y_1 = \log(X_1), \ldots, Y_n = \log(X_n) \) follows the Extreme Value distribution and vice versa. The two procedures give identical test statistics and P-values, in principal.

Some of the models have more than one common parametrization. For the Exponential, Gamma, and Weibull distributions, some writers use a rate parameter and some use the scale parameter which is the inverse of the rate. Our code uses the scale parameter.

For the Laplace distribution, some writers use the density 
\[
    f(x) = \frac{\exp(-|x-\mu|/\beta)}{(2\beta)}
\]
in which \( \beta \) is a scale parameter. Others use the standard deviation \( \sigma = \beta/\sqrt{2} \). Our code uses the scale parameter.

For the Uniform distribution, we offer code for the two parameter Uniform distribution on the range \( \theta_1 \) to \( \theta_2 \). These are estimated by the sample minimum and sample maximum. The probability integral transforms of the remaining \( n-2 \) points are then tested for uniformity on the range 0 to 1. This procedure is justified because the these probability integral transforms have exactly this distribution if the original data had a uniform distribution over any interval.

It is not unusual to test the hypothesis that a sample follows the standard uniform distribution on \([0,1]\). In this case the parameters should not be estimated. Instead use \( AD(z) \) or \( CvM(z) \) or \( Watson(z) \) to compute the statistic values and then get P-values from \( AD\.uniform\.pvalue(a) \) or \( CvM\.uniform\.pvalue(w) \) or \( Watson\.uniform\.pvalue(u) \) whichever is wanted.

Value

P-value of the given Watson statistic.

See Also

Watson for calculating Watson statistic; CvM\.pvalue for calculating P-value of Cramér-von Mises statistic; AD\.pvalue for calculating P-value of Anderson-Darling statistic.
Examples

```r
x0 = runif(n=100, min=-1, max=1)
usq0 = Watson.uniform(x0)
Watson.uniform.pvalue(usq0)

x1 = rnorm(n=100, mean=0, sd=1)
usq1 = Watson.normal(x1)
Watson.normal.pvalue(usq1)

x2 = rgamma(n=100, shape=1, scale=1)
usq2 = Watson.gamma(x2)
Watson.gamma.pvalue(usq2, 1)

x3 = rlogis(n=100, location=0, scale=1)
usq3 = Watson.logistic(x3)
Watson.logistic.pvalue(usq3)

x4 = rmutil::rlaplace(n=100, m=0, s=1)
usq4 = Watson.laplace(x4)
Watson.laplace.pvalue(usq4)

x5 = rweibull(n=100, shape=1, scale=1)
usq5 = Watson.weibull(x5)
Watson.weibull.pvalue(usq5)
x5_log = log(x5)
Watson.extremevalue.pvalue(Watson.extremevalue(x5_log))

x6 = rexp(n=100, rate=1/2)
usq6 = Watson.exp(x6)
Watson.exp.pvalue(usq6)
```
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