

Package ‘ddst’

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Title Data Driven Smooth Tests

Version 1.6.11

Description

Smooth tests are data driven (alternative hypothesis is dynamically selected based on data).
In this package you will find two groups of smooth of test: goodness-of-fit tests and nonparametric tests for comparing distributions.
Among goodness-of-fit tests there are tests for exponent, Gaussian, Gumbel and uniform distribution.
Among nonparametric tests there are tests for stochastic dominance, k-sample test, test with umbrella alternatives and test for change-point problems.

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Encoding UTF-8

Depends R (≥ 2.7), polynom

Imports ggplot2, orthopolynom, evd

Suggests rmutl, knitr

URL <https://pbiecek.github.io/ddst/>

BugReports <https://github.com/pbiecek/ddst/issues>

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Author Przemyslaw Biecek [aut, cre] (ORCID:
<<https://orcid.org/0000-0001-8423-1823>>),
Teresa Ledwina [aut],
Grzegorz Wylupek [aut]

Maintainer Przemyslaw Biecek <przemyslaw.biecek@gmail.com>

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ddst.againststochdom.test

Data Driven Smooth Test Against Stochastic Dominance

Description

Performs data driven smooth non-parametric two-sample test against one-sided alternatives (stochastic dominance). Suppose that we have random samples from two distributions F and G . The null hypothesis is that $F(x) < G(x)$ for some x while the alternative is that at $F(x) \geq G(x)$ for all x with strict inequality for at least one x . Detailed description of the test statistic is provided in Ledwina and Wylupek (2012).

Usage

```
ddst.againststochdom.test(
  x,
  y,
  k.N = 4,
  alpha = 0.05,
  t,
  nr = 1e+05,
  compute.cv = FALSE
)
```

Arguments

<code>x</code>	a (non-empty) numeric vector of data
<code>y</code>	a (non-empty) numeric vector of data
<code>k.N</code>	an integer specifying a level of complexity of the grid considered, only for advanced users

alpha	a significance level
t	an alpha-dependent tuning parameter in the penalty in the model selection rule
nr	an integer specifying the number of runs for a p-value and a critical value computation if any
compute.cv	a logical value indicating whether to compute a critical value corresponding to the significance level alpha or not

References

Two-sample test against one-sided alternatives. Ledwina and Wylupek (2012). <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-9469.2011.00787.x>

Examples

```
set.seed(7)
# H0 is true
x <- runif(80)
y <- runif(80)
t <- ddst.againststochdom.test(x, y, alpha = 0.05, t = 2.2, k.N = 4)
t
plot(t)

# H0 is false
# known fixed alternative
x <- runif(80)
y <- rbeta(80,4,2)
t <- ddst.againststochdom.test(x, y, alpha = 0.05, t = 2.2, k.N = 4)
t
plot(t)
```

ddst.evd.test

Data Driven Smooth Test for Extreme Value Distribution

Description

Performs data driven smooth test for composite hypothesis of extreme value distribution. Null density is given by $f(z; \gamma) = 1/\gamma_2 \exp((z - \gamma_1)/\gamma_2 - \exp((z - \gamma_1)/\gamma_2))$, $z \in R$.

Usage

```
ddst.evd.test(
  x,
  base = ddst.base.legendre,
  d.n = 10,
  c = 100,
  nr = 1e+05,
  compute.p = TRUE,
  alpha = 0.05,
```

```

compute.cv = TRUE,
...
)

```

Arguments

x	a (non-empty) numeric vector of data values
base	a function which returns an orthonormal system, possible choice: <code>ddst.base.legendre</code> for the Legendre polynomials and <code>ddst.base.cos</code> for the cosine system
d.n	an integer specifying the maximum dimension considered, only for advanced users
c	a calibrating parameter in the penalty in the model selection rule
nr	an integer specifying the number of runs for a p-value and a critical value computation if any
compute.p	a logical value indicating whether to compute a p-value or not
alpha	a significance level
compute.cv	a logical value indicating whether to compute a critical value corresponding to the significance level alpha or not
...	further arguments

Details

We model alternatives similarly as in Kallenberg and Ledwina (1997) and Janic-Wroblewska (2004) using Legendre's polynomials or cosines. For more details see: <http://www.biecek.pl/R/ddst/description.pdf>.

Value

An object of class `htest`

statistic	the value of the test statistic.
parameter	the number of choosen coordinates (k).
method	a character string indicating the parameters of performed test.
data.name	a character string giving the name(s) of the data.
p.value	the p-value for the test, computed only if <code>compute.p=TRUE</code> .

References

Hosking, J.R.M., Wallis, J.R., Wood, E.F. (1985). Estimation of the generalized extreme-value distribution by the method of probability-weighted moments. *Technometrics* 27, 251–261.

Janic-Wroblewska, A. (2004). Data-driven smooth test for extreme value distribution. *Statistics* 38, 413–426.

Janic, A. and Ledwina, T. (2008). Data-driven tests for a location-scale family revisited. *J.Statist.Theory.Pract.Specialis.*

Kallenberg, W.C.M., Ledwina, T. (1997). Data driven smooth tests for composite hypotheses: Comparison of powers. *J.Statist.Comput.Simul.* 59, 101–121.

Examples

```

library(evd)
set.seed(7)

# for given vector of 19 numbers
z <- c(13.41, 6.04, 1.26, 3.67, -4.54, 2.92, 0.44, 12.93, 6.77, 10.09,
      4.10, 4.04, -1.97, 2.17, -5.38, -7.30, 4.75, 5.63, 8.84)
## Not run:
t <- ddst.evd.test(z, compute.p = TRUE, d.n = 10)
t
plot(t)

# H0 is true
x <- -qgumbel(runif(100),-1,1)
t <- ddst.evd.test (x, compute.p = TRUE, d.n = 10)
t
plot(t)

# H0 is false
x <- rexp(80,4)
t <- ddst.evd.test (x, compute.p = TRUE, d.n = 10)
t
plot(t)

## End(Not run)

```

ddst.exp.test

*Data Driven Smooth Test for Exponentiality***Description**

Performs data driven smooth test for composite hypothesis of exponentiality. Null density is given by $f(z; \gamma) = \exp(-z/\gamma)$ for $z \geq 0$ and 0 otherwise. Modelling alternatives similarly as in Kallenberg and Ledwina (1997 a,b).

Usage

```

ddst.exp.test(
  x,
  base = ddst.base.legendre,
  d.n = 10,
  c = 100,
  nr = 1e+05,
  compute.p = TRUE,
  alpha = 0.05,
  compute.cv = TRUE,
  ...
)

```

Arguments

<code>x</code>	a (non-empty) numeric vector of data values
<code>base</code>	a function which returns an orthonormal system, possible choice: <code>ddst.base.legendre</code> for the Legendre polynomials and <code>ddst.base.cos</code> for the cosine system
<code>d.n</code>	an integer specifying the maximum dimension considered, only for advanced users
<code>c</code>	a calibrating parameter in the penalty in the model selection rule
<code>nr</code>	an integer specifying the number of runs for a p-value and a critical value computation if any
<code>compute.p</code>	a logical value indicating whether to compute a p-value or not
<code>alpha</code>	a significance level
<code>compute.cv</code>	a logical value indicating whether to compute a critical value corresponding to the significance level <code>alpha</code> or not
<code>...</code>	further arguments

Value

An object of class `htest`

<code>statistic</code>	the value of the test statistic.
<code>parameter</code>	the number of choosen coordinates (<code>k</code>).
<code>method</code>	a character string indicating the parameters of performed test.
<code>data.name</code>	a character string giving the name(s) of the data.
<code>p.value</code>	the p-value for the test, computed only if <code>compute.p=T</code> .

References

Kallenberg, W.C.M., Ledwina, T. (1997 a). Data driven smooth tests for composite hypotheses: Comparison of powers. *J.Statist.Comput.Simul.* **59**, 101–121.

Kallenberg, W.C.M., Ledwina, T. (1997 b). Data driven smooth tests when the hypothesis is composite. *J.Amer.Statist.Assoc.* **92**, 1094–1104.

Examples

```
set.seed(7)
# H0 is true
z <- rexp(80,4)
## Not run:
t <- ddst.exp.test (z, compute.p = TRUE, d.n = 10)
t
plot(t)

# H0 is false
z = rchisq(80,4)
(t = ddst.exp.test (z, compute.p = TRUE, d.n = 10))
t$p.value
```

```
plot(t)

## End(Not run)
```

ddst.forstochdom.test *Data Driven Smooth Test for Stochastic Dominance in Two Samples*

Description

Performs the data driven smooth test for detection of the stochastic ordering, as described in detail in Ledwina and Wylupek (2012). Suppose that we have random samples from two distributions F and G . The null hypothesis is that $F(x) \geq G(x)$ for all x while the alternative is that at $F(x) < G(x)$ for some x . Detailed description of the test statistic is provided in Ledwina and Wylupek (2012).

Usage

```
ddst.forstochdom.test(
  x,
  y,
  K.N = floor(log(length(x) + length(y), 2)) - 1,
  alpha = 0.05,
  t,
  nr = 1e+05,
  compute.p = TRUE,
  compute.cv = TRUE
)
```

Arguments

<code>x</code>	a (non-empty) numeric vector of data
<code>y</code>	a (non-empty) numeric vector of data
<code>K.N</code>	an integer specifying a level of complexity of the grid considered, only for advanced users
<code>alpha</code>	a significance level
<code>t</code>	an alpha-dependent tuning parameter in the penalty in the model selection rule
<code>nr</code>	an integer specifying the number of runs for a p-value and a critical value computation if any
<code>compute.p</code>	a logical value indicating whether to compute a p-value or not
<code>compute.cv</code>	a logical value indicating whether to compute a critical value corresponding to the significance level <code>alpha</code> or not

References

Nonparametric tests for stochastic ordering. Ledwina and Wylupek (2012) <doi:10.1007/s11749-011-0278-7>

Examples

```

set.seed(7)
library("rmutil", warn.conflicts = FALSE)
# 1. Pareto(1)/Pareto(1.5)
# H0 is false
x <- rpareto(50, 2, 2)
y <- rpareto(50, 1.5, 1.5)
t <- ddst.forstochdom.test(x, y, t = 2.2, K.N = 4)
t
plot(t)

# 2. Laplace(0,1)/Laplace(1,25)
# H0 is false
x <- rlaplace(50, 0, 1)
y <- rlaplace(50, 1, 25)
t <- ddst.forstochdom.test(x, y, t = 2.2, K.N = 4)
t
plot(t)

# 3. LN(0.85,0.6)/LN(1.2,0.2)
# H0 is true
x <- rlnorm(50, 0.85, 0.6)
y <- rlnorm(50, 1.2, 0.2)
t <- ddst.forstochdom.test(x, y, t = 2.2, K.N = 4)
t
plot(t)

## Not run:
# Generate distribution of test statistic
N <- 1000
samp <- replicate(N, {
  x <- runif(30)
  y <- runif(30)
  # statistics with Schwartz penalty
  ddst.forstochdom.test(x, y)$statistic
})
quantile(samp, 0.95)
plot(ecdf(samp))

## End(Not run)

```

ddst.ksample.test

Data Driven Smooth Test for k-Sample Problem

Description

Performs data driven smooth test for the classical k-sample problem. Suppose that we have random samples from k distributions F_i where $i = 1, \dots, k$. The null hypothesis is that $F_1 = \dots = F_k$ while the alternative is that at least two distributions are different. Detailed description of the test statistic is provided in Wylupek (2010).

Usage

```
ddst.ksample.test(  
  x,  
  d.N = 12,  
  c = 2.3,  
  nr = 1e+05,  
  compute.p = TRUE,  
  alpha = 0.05,  
  compute.cv = TRUE  
)
```

Arguments

x	a list of k (non-empty) numeric vectors of data
d.N	an integer specifying the maximum dimension considered, only for advanced users
c	a calibrating parameter in the penalty in the model selection rule
nr	an integer specifying the number of runs for a p-value and a critical value computation if any
compute.p	a logical value indicating whether to compute a p-value or not
alpha	a significance level
compute.cv	a logical value indicating whether to compute a critical value corresponding to the significance level alpha or not

References

Data-driven k-sample tests. Wylupek (2010) <https://www.jstor.org/stable/40586684?seq=1>

Examples

```
set.seed(7)  
# H0 is false  
x <- runif(80)  
y <- rexp(80, 1)  
z <- runif(80)  
t <- ddst.ksample.test(list(x, y, z))  
t  
plot(t)  
  
# H0 is true  
x <- runif(80)  
y <- runif(80)  
z <- runif(80)  
t <- ddst.ksample.test(list(x, y, z))  
t  
plot(t)
```

ddst.normbounded.test *Data Driven Smooth Test for Normality; Bounded Basis Functions*

Description

Performs data driven smooth test for composite hypothesis of normality Null density is given by $f(z; \gamma) = 1/(\sqrt{2\pi}\gamma_2) \exp(-(z - \gamma_1)^2/(2\gamma_2^2))$ for $z \in R$. We model alternatives similarly as in Kallenberg and Ledwina (1997 a,b) using Legendre's polynomials or cosine basis.

Usage

```
ddst.normbounded.test(
  x,
  base = ddst.base.legendre,
  d.n = 10,
  c = 100,
  compute.p = TRUE,
  alpha = 0.05,
  compute.cv = TRUE,
  ...
)
```

Arguments

x	a (non-empty) numeric vector of data values
base	a function which returns an orthonormal system, possible choice: ddst.base.legendre for the Legendre polynomials and ddst.base.cos for the cosine system
d.n	an integer specifying the maximum dimension considered, only for advanced users
c	a calibrating parameter in the penalty in the model selection rule
compute.p	a logical value indicating whether to compute a p-value or not
alpha	a significance level
compute.cv	a logical value indicating whether to compute a critical value corresponding to the significance level alpha or not
...	further arguments

Value

An object of class htest

statistic	the value of the test statistic.
parameter	the number of choosen coordinates (k).
method	a character string indicating the parameters of performed test.
data.name	a character string giving the name(s) of the data.
p.value	the p-value for the test, computed only if compute.p = TRUE.

References

- Chen, L., Shapiro, S.S. (1995). An alternative test for normality based on normalized spacings. *J. Statist. Comput. Simulation* 53, 269–288.
- Ingolot, T., Ledwina, T. (2006). Towards data driven selection of a penalty function for data driven Neyman tests. *Linear Algebra and its Appl.* **417**, 579–590.
- Janic, A. and Ledwina, T. (2008). Data-driven tests for a location-scale family revisited. *J. Statist. Theory. Pract. Special issue on Modern Goodness of Fit Methods.*
- Kallenberg, W.C.M., Ledwina, T. (1997 a). Data driven smooth tests for composite hypotheses: Comparison of powers. *J. Statist. Comput. Simul.* **59**, 101–121.
- Kallenberg, W.C.M., Ledwina, T. (1997 b). Data driven smooth tests when the hypothesis is composite. *J. Amer. Statist. Assoc.* **92**, 1094–1104.

Examples

```
set.seed(7)
# H0 is true
z <- rnorm(100)
# let's look on first 10 coordinates
d.n <- 10
t <- ddst.normbounded.test(z, compute.p = TRUE, d.n = d.n)
t
plot(t)

# H0 is false
z <- rexp(100, 1)
t <- ddst.normbounded.test(z, compute.p = TRUE, d.n = d.n)
t
plot(t)

# for Tephra data
z <- c(-1.748789, -1.75753, -1.740102, -1.740102, -1.731467, -1.765523,
      -1.761521, -1.72522, -1.80371, -1.745624, -1.872957, -1.729121,
      -1.81529, -1.888637, -1.887761, -1.881645, -1.91518, -1.849769,
      -1.755141, -1.665687, -1.764721, -1.736171, -1.736956, -1.737742,
      -1.687537, -1.804534, -1.790593, -1.808661, -1.784081, -1.729903,
      -1.711263, -1.748789, -1.772755, -1.72756, -1.71358, -1.821116,
      -1.839588, -1.839588, -1.830321, -1.807835, -1.747206, -1.788147,
      -1.759923, -1.786519, -1.726779, -1.738528, -1.754345, -1.781646,
      -1.641949, -1.755936, -1.775175, -1.736956, -1.705103, -1.743255,
      -1.82613, -1.826967, -1.780025, -1.684504, -1.751168)
t <- ddst.normbounded.test(z, compute.p = TRUE, d.n = d.n)
t
plot(t)
```

Description

Performs data driven smooth test for composite hypothesis of normality. Null density is given by $f(z; \gamma) = 1/(\sqrt{2\pi}\gamma_2) \exp(-(z - \gamma_1)^2/(2\gamma_2^2))$ for $z \in R$.

Usage

```
ddst.normubounded.test(
  x,
  d.n = 20,
  e.0,
  v.0,
  r.alpha,
  s.n.alpha,
  alpha = 0.05,
  nr = 10000,
  compute.cv = TRUE
)

ddst.normunbounded.bias(n = 100, d.n = 20, nr = 10000)
```

Arguments

x	a (non-empty) numeric vector of data values
d.n	an integer specifying the maximum dimension considered, only for advanced users
e.0	a (non-empty) numeric vector being the Monte Carlo estimate of the mean of the vector (C2; ... ;Cd.n) calculated using the function <code>ddst.normunbounded.bias()</code> \$e.0
v.0	a (non-empty) numeric vector being the Monte Carlo estimate of the variance of the vector (C2; ... ;Cd.n) calculated using the function <code>ddst.normunbounded.bias()</code> \$e.0
r.alpha	a critical value of the alpha level R.n test
s.n.alpha	a penalty in the auxiliary model selection rule
alpha	a significance level
nr	an integer specifying the number of runs for a critical value computation
compute.cv	a logical value indicating whether to compute a critical value corresponding to the significance level alpha or not
n	sample size

References

Ledwina, T., Wyłupek, G. (2015) Detection of non-Gaussianity by Ledwina and Wyłupek *Journal of Statistical Computation and Simulation* 17, 3480-3497.

Examples

```

set.seed(7)
# H0 is true
z <- rnorm(100)
# let's look on first 20 coordinates
d.n <- 20

## Not run:
# calculate finite sample corrections
# see 6.2. Composite null hypothesis H in the appendix materials
e.v <- ddst.normunbounded.bias(n = length(z))
e.v

# simulated 1-alpha quantiles, s(n, alpha) and s.o(n, alpha)
# see Table 1 in the JSCS article
s <- 4.4
r.alpha <- 2.708

t <- ddst.normubounded.test(z, d.n, e.v$e.0, e.v$v.0, r.alpha, s)
t
plot(t)

# for Tephra data
z <- c(-1.748789, -1.75753, -1.740102, -1.740102, -1.731467, -1.765523,
      -1.761521, -1.72522, -1.80371, -1.745624, -1.872957, -1.729121,
      -1.81529, -1.888637, -1.887761, -1.881645, -1.91518, -1.849769,
      -1.755141, -1.665687, -1.764721, -1.736171, -1.736956, -1.737742,
      -1.687537, -1.804534, -1.790593, -1.808661, -1.784081, -1.729903,
      -1.711263, -1.748789, -1.772755, -1.72756, -1.71358, -1.821116,
      -1.839588, -1.839588, -1.830321, -1.807835, -1.747206, -1.788147,
      -1.759923, -1.786519, -1.726779, -1.738528, -1.754345, -1.781646,
      -1.641949, -1.755936, -1.775175, -1.736956, -1.705103, -1.743255,
      -1.82613, -1.826967, -1.780025, -1.684504, -1.751168)

# calculate finite sample corrections
e.v <- ddst.normunbounded.bias(n = length(z))
e.v

s <- 3.3
so <- 3.6
r.alpha <- 2.142

t <- ddst.normubounded.test(z, d.n, e.v$e.0, e.v$v.0, r.alpha, s)
t
plot(t)

## End(Not run)

```

Description

Performs data driven smooth test for the classical two-sample problem. It is a special case of data driven test for k-samples. Detailed description of the test statistic is provided in Wylupek (2010).

Usage

```
ddst.twosample.test(
  x,
  y,
  d.N = 12,
  c = 2,
  B = 1e+05,
  compute.p = TRUE,
  alpha = 0.05,
  compute.cv = TRUE
)
```

Arguments

x	a (non-empty) numeric vector of data
y	a (non-empty) numeric vector of data
d.N	an integer specifying the maximum dimension considered, only for advanced users
c	a calibrating parameter in the penalty in the model selection rule
B	an integer specifying the number of runs for a p-value and a critical value computation if any
compute.p	a logical value indicating whether to compute a p-value or not
alpha	a significance level
compute.cv	a logical value indicating whether to compute a critical value corresponding to the significance level alpha or not

References

Data-driven k-sample tests. Wylupek (2010) <https://www.jstor.org/stable/40586684?seq=1>

Examples

```
set.seed(7)
# H0 is true
x <- runif(80)
y <- runif(80)
t <- ddst.twosample.test(x, y)
t
plot(t)

# H0 is false
x <- runif(80)
y <- rexp(80, 1)
```

```
t <- ddst.twosample.test(x, y)
t
plot(t)
```

ddst.umbrellaknownp.test

Data Driven Smooth Test for Umbrella Alternatives; Known Peak

Description

Performs data driven smooth test for so-called umbrella alternatives in k -sample problem. Suppose that we have random samples from k distributions F_i where $i = 1, \dots, k$. The null hypothesis is that there is no umbrella pattern, i.e. $F_1 \geq \dots \geq F_p \leq \dots \leq F_k$ and $F_i \neq F_j$ for some i and j . The alternative is that there is an umbrella pattern i.e. $F_1 \geq \dots \geq F_p \leq \dots \leq F_k$ and $F_i \neq F_j$ for some i and j . Detailed description of the test statistic is provided in Wylupek (2016).

Usage

```
ddst.umbrellaknownp.test(
  x,
  p,
  r.N = rep(4, length(x) - 1),
  alpha = 0.05,
  t.p,
  t.n,
  nr = 1e+05,
  compute.cv = TRUE
)
```

Arguments

<code>x</code>	a list of k (non-empty) numeric vectors of data
<code>p</code>	a peak of the umbrella pattern
<code>r.N</code>	a $(p(p-1)+2+(k-p)(k-p+1)/2)$ -dimensional vector specifying the levels of complexity of the grids considered, only for advanced users
<code>alpha</code>	a significance level
<code>t.p</code>	an α -dependent $(p(p-1)+2+(k-p)(k-p+1)/2)$ -dimensional vector of the tuning parameters in the penalties in the model selection rules T_o
<code>t.n</code>	an α -dependent $(k-1)$ -dimensional vector of the tuning parameters in the penalties in the model selection rules $T_{\tilde{o}}$
<code>nr</code>	an integer specifying the number of runs for a p-value and a critical value computation if any
<code>compute.cv</code>	a logical value indicating whether to compute a critical value corresponding to the significance level α or not

References

An automatic test for the umbrella alternatives. Wylupek (2016) <https://onlinelibrary.wiley.com/doi/abs/10.1111/sjos.12231>

Examples

```
set.seed(7)
# H0 is true
x = runif(80)
y = runif(80) + 0.2
z = runif(80)
t <- ddst.umbrellaknownp.test(list(x, y, z), p = 2, t.p = 2.2, t.n = 2.2)
t
plot(t)

# known fixed alternative
x1 = rnorm(80)
x2 = rnorm(80) + 2
x3 = rnorm(80) + 4
x4 = rnorm(80) + 3
x5 = rnorm(80) + 2
x6 = rnorm(80) + 1
x7 = rnorm(80)
t <- ddst.umbrellaknownp.test(list(x1, x2, x3, x4, x5, x6, x7), p = 3, t.p = 2.2, t.n = 2.2)
t
plot(t)

t <- ddst.umbrellaknownp.test(list(x1, x2, x3, x4, x5, x6, x7), p = 5, t.p = 2.2, t.n = 2.2)
t
plot(t)
```

```
ddst.umbrellaunknownp.test
```

Data Driven Smooth Test for Umbrella Alternatives; Unknown Peak

Description

Data Driven Smooth Test for Umbrella Alternatives; Unknown Peak

Usage

```
ddst.umbrellaunknownp.test(
  x,
  r.N = rep(4, length(x) - 1),
  alpha = 0.05,
  t.p.aux,
  t.p,
  t.n,
```

```

    nr = 1e+05,
    compute.cv = TRUE
  )

```

Arguments

<code>x</code>	a list of k (non-empty) numeric vectors of data
<code>r.N</code>	a $(p(p-1)+2+(k-p)(k-p+1)/2)$ -dimensional vector specifying the levels of complexity of the grids considered, only for advanced users
<code>alpha</code>	a significance level
<code>t.p.aux</code>	an auxiliary alpha-dependent $k \times (k - 1)$ matrix of the tuning parameters in the penalties in the model selection rules To aux employed for estimation of the peak
<code>t.p</code>	an alpha-dependent $(p(p-1)+2+(k-p)(k-p+1)/2)$ -dimensional vector of the tuning parameters in the penalties in the model selection rules T.o
<code>t.n</code>	an alpha-dependent $(k-1)$ -dimensional vector of the tuning parameters in the penalties in the model selection rules T.tilde
<code>nr</code>	an integer specifying the number of runs for a p-value and a critical value computation if any
<code>compute.cv</code>	a logical value indicating whether to compute a critical value corresponding to the significance level alpha or not

References

An automatic test for the umbrella alternatives. Wylupek (2016) <https://onlinelibrary.wiley.com/doi/abs/10.1111/sjos.12231>

Examples

```

set.seed(7)
# H0 is true
x = runif(80)
y = runif(80) + 0.2
z = runif(80)
t <- ddst.umbrellaknownp.test(list(x, y, z), p = 2, t.p = 2.2, t.n = 2.2)
t
plot(t)

# known fixed alternative
x1 = rnorm(80)
x2 = rnorm(80) + 2
x3 = rnorm(80) + 4
x4 = rnorm(80) + 3
x5 = rnorm(80) + 2
x6 = rnorm(80) + 1
x7 = rnorm(80)
t <- ddst.umbrellaknownp.test(list(x1, x2, x3, x4, x5, x6, x7), p = 3, t.p = 2.2, t.n = 2.2)
t
plot(t)

```

```
t <- ddst.umbrellaknownp.test(list(x1, x2, x3, x4, x5, x6, x7), p = 5, t.p = 2.2, t.n = 2.2)
t
plot(t)
```

ddst.uniform.test *Data Driven Smooth Test for Uniformity*

Description

Performs data driven smooth tests for simple hypothesis of uniformity on $[0,1]$. Embedding null model into the original exponential family introduced by Neyman (1937).

Usage

```
ddst.uniform.test(
  x,
  base = ddst.base.legendre,
  d.n = 10,
  c = 2.4,
  nr = 1e+05,
  compute.p = TRUE,
  alpha = 0.05,
  compute.cv = TRUE,
  ...
)
```

Arguments

x	a (non-empty) numeric vector of data
base	a function which returns an orthonormal system, possible choice: <code>ddst.base.legendre</code> for the Legendre polynomials and <code>ddst.base.cos</code> for the cosine system
d.n	an integer specifying the maximum dimension considered, only for advanced users
c	a calibrating parameter in the penalty in the model selection rule
nr	an integer specifying the number of runs for a p-value and a critical value computation if any
compute.p	a logical value indicating whether to compute a p-value or not
alpha	a significance level
compute.cv	a logical value indicating whether to compute a critical value corresponding to the significance level alpha or not
...	further arguments

Value

An object of class `htest`

<code>statistic</code>	the value of the test statistic.
<code>parameter</code>	the number of choosen coordinates (k).
<code>method</code>	a character string indicating the parameters of performed test.
<code>data.name</code>	a character string giving the name(s) of the data.
<code>p.value</code>	the p-value for the test, computed only if <code>compute.p=T</code> .

References

Inglot, T., Ledwina, T. (2006). Towards data driven selection of a penalty function for data driven Neyman tests. *Linear Algebra and its Appl.* **417**, 579–590.

Ledwina, T. (1994). Data driven version of Neyman’s smooth test of fit. *J. Amer. Statist. Assoc.* **89** 1000-1005.

Neyman, J. (1937). ‘Smooth test’ for goodness of fit. *Skand. Aktuarietidskr.* **20**, 149-199.

Examples

```
set.seed(7)
# H0 is true
z <- runif(80)
## Not run:
t <- ddst.uniform.test(z, compute.p = TRUE, d.n = 10)
t
plot(t)

# known fixed alternative
z <- rnorm(80,10,16)
t <- ddst.uniform.test(pnorm(z, 10, 16), compute.p = TRUE, d.n = 10)
t
plot(t)

# H0 is false
z <- rbeta(80,4,2)
(t <- ddst.uniform.test(z, compute.p = TRUE, d.n = 10))
t$p.value
plot(t)

## End(Not run)
```

Description

Performs data driven smooth test for upward trend in k-sample problem. Suppose that we have random samples from k distributions F_i where $i = 1, \dots, k$. The null hypothesis is that there is lack of trend, i.e. $F_1 \geq \dots \geq F_k$ and $F_i \neq F_j$ for some i and j . The alternative is that there is a trend i.e. $F_1 \geq \dots \geq F_k$ and $F_i \neq F_j$ for some i and j . This test is implemented as a special case of an umbrella test.

Usage

```
ddst.upwardtrend.test(
  x,
  r.N = rep(4, length(x) - 1),
  alpha = 0.05,
  t.p,
  t.n,
  nr = 1e+05,
  compute.cv = TRUE
)
```

Arguments

<code>x</code>	a list of k (non-empty) numeric vectors of data
<code>r.N</code>	a (k-1)-dimensional vector specifying the levels of complexity of the grids considered, only for advanced users
<code>alpha</code>	a significance level
<code>t.p</code>	an alpha-dependent (k-1)-dimensional vector of the tuning parameters in the penalties in the model selection rules T_o
<code>t.n</code>	an alpha-dependent (k-1)-dimensional vector of the tuning parameters in the penalties in the model selection rules $T_{\tilde{o}}$
<code>nr</code>	an integer specifying the number of runs for a p-value and a critical value computation if any
<code>compute.cv</code>	a logical value indicating whether to compute a critical value corresponding to the significance level alpha or not
<code>t</code>	an alpha-dependent tuning parameter in the penalty in the model selection rule

References

An automatic test for the umbrella alternatives. Wylupek (2016) <https://onlinelibrary.wiley.com/doi/abs/10.1111/sjos.12231>

Examples

```
set.seed(7)
# H0 is true
x = runif(80)
y = runif(80) + 0.2
z = runif(80) + 0.4
```

```

t <- ddst.upwardtrend.test(list(x, y, z), t.p = 2.2, t.n = 2.2)
t
plot(t)

# H0 is false
# known fixed alternative
x1 = rnorm(80)
x2 = rnorm(80) + 2
x3 = rnorm(80) + 4
x4 = rnorm(80) + 3
t <- ddst.upwardtrend.test(list(x1, x2, x3, x4), t.p = 2.2, t.n = 2.2)
t
plot(t)

```

plot.ddst.test

Plot Function fo Data Driven Tests

Description

Plots coordinates for selected test statistics

Usage

```

## S3 method for class 'ddst.test'
plot(x, ...)

```

Arguments

x	result from ddst test function
...	currently not used

Examples

```

# H0 is true
x <- runif(80)
y <- runif(80)
z <- runif(80)
t <- ddst.ksample.test(list(x, y, z))
plot(t)

```

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