Package ‘SetTest’

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Type Package

Title Group Testing Procedures for Signal Detection and Goodness-of-Fit

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Description It provides cumulative distribution function (CDF), quantile, p-value, statistical power calculator and random number generator for a collection of group-testing procedures, including the Higher Criticism tests, the one-sided Kolmogorov-Smirnov tests, the one-sided Berk-Jones tests, the one-sided phi-divergence tests, etc. The input are a group of p-values. The null hypothesis is that they are i.i.d. Uniform(0,1). In the context of signal detection, the null hypothesis means no signals. In the context of the goodness-of-fit testing, which contrasts a group of i.i.d. random variables to a given continuous distribution, the input p-values can be obtained by the CDF transformation. The null hypothesis means that these random variables follow the given distribution. For reference, see Hong Zhang, Jiashun Jin and Zheyang Wu. ``Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases'', submitted.

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R topics documented:

`pbj` *CDF of Berk-Jones statitic under the null hypothesis.*

Description

CDF of Berk-Jones statitic under the null hypothesis.

Usage

```
pbj(q, M, k0, k1, onesided = FALSE)
```

Arguments

`q`	- quantile, must be a scalar.
`M`	- correlation matrix of input statistics (of the input p-values).
`k0`	- search range starts from the k0th smallest p-value.
`k1`	- search range ends at the k1th smallest p-value.
`onesided`	- TRUE if the input p-values are one-sided.

Value

The left-tail probability of the null distribution of B-J statistic at the given quantile.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Donoho, David; Jin, Jiashun. "Higher criticism for detecting sparse heterogeneous mixtures". Annals of Statistics 32 (2004).

3. Berk, R.H. & Jones, D.H. Z. "Goodness-of-fit test statistics that dominate the Kolmogorov statistics". Wahrscheinlichkeitstheorie verw Gebiete (1979) 47: 47.

See Also

`stat.bj` for the definition of the statistic.

Examples

```
pval <- runif(10)
bjstat <- stat.phi(pval, s=1, k0=1, k1=10)$value
pbj(q=bjstat, M=diag(10), k0=1, k1=10)
```

`phc` *CDF of Higher Criticism statitic under the null hypothesis.*

Description

CDF of Higher Criticism statitic under the null hypothesis.

Usage

```
phc(q, M, k0, k1, LS = F, ZW = F, onesided = FALSE)
```

Arguments

`q`	- quantile, must be a scalar.
`M`	- correlation matrix of input statistics (of the input p-values).
`k0`	- search range starts from the k0th smallest p-value.
`k1`	- search range ends at the k1th smallest p-value.
`LS`	- if LS = T, then method of Li and Siegmund (2015) will be implemented (for independence case only).
`ZW`	- if ZW = T, then approximation method of Zhang and Wu will be implemented.
`onesided`	- TRUE if the input p-values are one-sided.

Value

The left-tail probability of the null distribution of HC statistic at the given quantile.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Donoho, David; Jin, Jiashun. "Higher criticism for detecting sparse heterogeneous mixtures". Annals of Statistics 32 (2004).

3. Li, Jian; Siegmund, David. "Higher criticism: p-values and criticism". Annals of Statistics 43 (2015).

See Also

`stat.hc` for the definition of the statistic.

Examples

```
pval <- runif(10)
hcstat <- stat.phi(pval, s=2, k0=1, k1=5)$value
phc(q=hcstat, M=diag(10), k0=1, k1=10)
```

`power.bj` *Statistical power of Berk and Jones test.*

Description

Statistical power of Berk and Jones test.

Usage

```
power.bj(alpha, n, beta, method = "gaussian-gaussian", eps = 0, mu = 0,
  df = 1, delta = 0)
```

Arguments

`alpha`	- type-I error rate.
`n`	- dimension parameter, i.e. the number of input statitics to construct B-J statistic.
`beta`	- search range parameter. Search range = (1, beta*n). Beta must be between 1/n and 1.
`method`	- different alternative hypothesis, including mixtures such as, "gaussian-gaussian", "gaussian-t", "t-t", "chisq-chisq", and "exp-chisq". By default, we use Gaussian mixture.
`eps`	- mixing parameter of the mixture.
`mu`	- mean of non standard Gaussian model.
`df`	- degree of freedom of t/Chisq distribution and exp distribution.
`delta`	- non-cenrality of t/Chisq distribution.

Details

We consider the following hypothesis test,

$$H_0 : X_i \sim F, H_a : X_i \sim G$$

Specifically, $F = F_0$ and $G = (1 - \epsilon)F_0 + \epsilon F_1$, where ϵ is the mixing parameter, F_0 and F_1 is speified by the "method" argument:

"gaussian-gaussian": F_0 is the standard normal CDF and $F = F_1$ is the CDF of normal distribution with μ defined by mu and $\sigma = 1$.

"gaussian-t": F_0 is the standard normal CDF and $F = F_1$ is the CDF of t distribution with degree of freedom defined by df.

"t-t": F_0 is the CDF of t distribution with degree of freedom defined by df and $F = F_1$ is the CDF of non-central t distribution with degree of freedom defined by df and non-centrality defined by delta.

"chisq-chisq": F_0 is the CDF of Chisquare distribution with degree of freedom defined by df and $F = F_1$ is the CDF of non-central Chisquare distribution with degree of freedom defined by df and non-centrality defined by delta.

"exp-chisq": F_0 is the CDF of exponential distribution with parameter defined by df and $F = F_1$ is the CDF of non-central Chisqaure distribution with degree of freedom defined by df and non-centrality defined by delta.

Value

Power of BJ test.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Donoho, David; Jin, Jiashun. "Higher criticism for detecting sparse heterogeneous mixtures". Annals of Statistics 32 (2004).

3. Jager, Leah; Wellner, Jon A. "Goodness-of-fit tests via phi-divergences". Annals of Statistics 35 (2007).

4. Berk, R.H. & Jones, D.H. Z. "Goodness-of-fit test statistics that dominate the Kolmogorov statistics". Wahrscheinlichkeitstheorie verw Gebiete (1979) 47: 47.

See Also

`stat.bj` for the definition of the statistic.

Examples

```
power.bj(0.05, n=10, beta=0.5, eps = 0.1, mu = 1.2)
```

`power.hc` *Statistical power of Higher Criticism test.*

Description

Statistical power of Higher Criticism test.

Usage

```
power.hc(alpha, n, beta, method = "gaussian-gaussian", eps = 0, mu = 0,
  df = 1, delta = 0)
```

Arguments

`alpha`	- type-I error rate.
`n`	- dimension parameter, i.e. the number of input statitics to construct Higher Criticism statistic.
`beta`	- search range parameter. Search range = (1, beta*n). Beta must be between 1/n and 1.
`method`	- different alternative hypothesis, including mixtures such as, "gaussian-gaussian", "gaussian-t", "t-t", "chisq-chisq", and "exp-chisq". By default, we use Gaussian mixture.
`eps`	- mixing parameter of the mixture.
`mu`	- mean of non standard Gaussian model.
`df`	- degree of freedom of t/Chisq distribution and exp distribution.
`delta`	- non-cenrality of t/Chisq distribution.

Details

We consider the following hypothesis test,

$$H_0 : X_i \sim F, H_a : X_i \sim G$$

Specifically, $F = F_0$ and $G = (1 - \epsilon)F_0 + \epsilon F_1$, where ϵ is the mixing parameter, F_0 and F_1 is speified by the "method" argument:

"gaussian-gaussian": F_0 is the standard normal CDF and $F = F_1$ is the CDF of normal distribution with μ defined by mu and $\sigma = 1$.

"gaussian-t": F_0 is the standard normal CDF and $F = F_1$ is the CDF of t distribution with degree of freedom defined by df.

"t-t": F_0 is the CDF of t distribution with degree of freedom defined by df and $F = F_1$ is the CDF of non-central t distribution with degree of freedom defined by df and non-centrality defined by delta. "chisq-chisq": F_0 is the CDF of Chisquare distribution with degree of freedom defined by df and $F = F_1$ is the CDF of non-central Chisquare distribution with degree of freedom defined by df and non-centrality defined by delta.

"exp-chisq": F_0 is the CDF of exponential distribution with parameter defined by df and $F = F_1$ is the CDF of non-central Chisqaure distribution with degree of freedom defined by df and non-centrality defined by delta.

Value

Power of HC test.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Donoho, David; Jin, Jiashun. "Higher criticism for detecting sparse heterogeneous mixtures". Annals of Statistics 32 (2004).

See Also

stat.hc for the definition of the statistic.

Examples

```
power.hc(0.05, n=10, beta=0.5, eps = 0.1, mu = 1.2)
```

---

power.phi *Statistical power of phi-divergence test.*

Description

Statistical power of phi-divergence test.

Usage

```
power.phi(alpha, n, s, beta, method = "gaussian-gaussian", eps = 0,
  mu = 0, df = 1, delta = 0)
```

Arguments

alpha	- type-I error rate.
n	- dimension parameter, i.e. the number of input statitics to construct phi-divergence statistic.
s	- phi-divergence parameter. s = 2 is the higher criticism statitic.s = 1 is the Berk and Jones statistic.
beta	- search range parameter. Search range = (1, beta*n). Beta must be between 1/n and 1.
method	- different alternative hypothesis, including mixtures such as, "gaussian-gaussian", "gaussian-t", "t-t", "chisq-chisq", and "exp-chisq". By default, we use Gaussian mixture.
eps	- mixing parameter of the mixture.
mu	- mean of non standard Gaussian model.
df	- degree of freedom of t/Chisq distribution and exp distribution.
delta	- non-cenrality of t/Chisq distribution.

Details

We consider the following hypothesis test,

$$H_0 : X_i \sim F, H_a : X_i \sim G$$

Specifically, $F = F_0$ and $G = (1 - \epsilon)F_0 + \epsilon F_1$, where ϵ is the mixing parameter, F_0 and F_1 is speified by the "method" argument:

"gaussian-gaussian": F_0 is the standard normal CDF and $F = F_1$ is the CDF of normal distribution with μ defined by mu and $\sigma = 1$.

"gaussian-t": F_0 is the standard normal CDF and $F = F_1$ is the CDF of t distribution with degree of freedom defined by df.

"t-t": F_0 is the CDF of t distribution with degree of freedom defined by df and $F = F_1$ is the CDF of non-central t distribution with degree of freedom defined by df and non-centrality defined by delta.

"chisq-chisq": F_0 is the CDF of Chisquare distribution with degree of freedom defined by df and $F = F_1$ is the CDF of non-central Chisquare distribution with degree of freedom defined by df and non-centrality defined by delta.

"exp-chisq": F_0 is the CDF of exponential distribution with parameter defined by df and $F = F_1$ is the CDF of non-central Chisqaure distribution with degree of freedom defined by df and non-centrality defined by delta.

Value

Power of phi-divergence test.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Donoho, David; Jin, Jiashun. "Higher criticism for detecting sparse heterogeneous mixtures". Annals of Statistics 32 (2004).

See Also

`stat.phi` for the definition of the statistic.

Examples

```
#If the alternative hypothesis Gaussian mixture with eps = 0.1 and mu = 1.2:#
power.phi(0.05, n=10, s=2, beta=0.5, eps = 0.1, mu = 1.2)
```

---

pphi — *calculate the left-tail probability of phi-divergence under general correlation matrix.*

Description

calculate the left-tail probability of phi-divergence under general correlation matrix.

Usage

```
pphi(q, M, k0, k1, s = 2, t = 30, onesided = FALSE)
```

Arguments

`q`	- quantile, must be a scalar.
`M`	- correlation matrix of input statistics (of the input p-values).
`k0`	- search range starts from the k0th smallest p-value.
`k1`	- search range ends at the k1th smallest p-value.
`s`	- the phi-divergence test parameter.
`t`	- numerical truncation parameter.
`onesided`	- TRUE if the input p-values are one-sided.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

Examples

```
M = toeplitz(1/(1:10)*(-1)^(0:9)) #alternating polynomial decaying correlation matrix
pphi(q=2, M=M, k0=1, k1=5, s=2)
pphi(q=2, M=diag(10), k0=1, k1=5, s=2)
```

`pphi.omni` *calculate the left-tail probability of omnibus phi-divergence statistics under general correlation matrix.*

Description

calculate the left-tail probability of omnibus phi-divergence statistics under general correlation matrix.

Usage

```
pphi.omni(q, M, K0, K1, S, t = 30, onesided = FALSE)
```

Arguments

`q`	- quantile, must be a scalar.
`M`	- correlation matrix of input statistics (of the input p-values).
`K0`	- vector of search range starts (from the k0th smallest p-value).
`K1`	- vector of search range ends (at the k1th smallest p-value).
`S`	- vector of the phi-divergence test parameters.
`t`	- numerical truncation parameter.
`onesided`	- TRUE if the input p-values are one-sided.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

Examples

```
M = matrix(0.3,10,10) + diag(1-0.3, 10)
pphi.omni(0.05, M=M, K0=rep(1,4), K1=rep(5,4), S=c(-1,0,1,2))
```

---

qbj — *Quantile of Berk-Jones statitic under the null hypothesis.*

Description

Quantile of Berk-Jones statitic under the null hypothesis.

Usage

```
qbj(p, M, k0, k1, onesided = FALSE)
```

Arguments

`p`	- a scalar left probability that defines the quantile.
`M`	- correlation matrix of input statistics (of the input p-values).
`k0`	- search range starts from the k0th smallest p-value.
`k1`	- search range ends at the k1th smallest p-value.
`onesided`	- TRUE if the input p-values are one-sided.

Value

Quantile of BJ statistics.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Donoho, David; Jin, Jiashun. "Higher criticism for detecting sparse heterogeneous mixtures". Annals of Statistics 32 (2004).

3. Berk, R.H. & Jones, D.H. Z. "Goodness-of-fit test statistics that dominate the Kolmogorov statistics". Wahrscheinlichkeitstheorie verw Gebiete (1979) 47: 47.

See Also

`stat.bj` for the definition of the statistic.

Examples

```
## The 0.05 critical value of BJ statistic when n = 10:
qbj(p=.95, M=diag(10), k0=1, k1=5, onesided=FALSE)
```

---

qhc — *Quantile of Higher Criticism statitics under the null hypothesis.*

Description

Quantile of Higher Criticism statitics under the null hypothesis.

Usage

```
qhc(p, M, k0, k1, onesided = FALSE, LS = F, ZW = F)
```

Arguments

`p`	- a scalar left probability that defines the quantile.
`M`	- correlation matrix of input statistics (of the input p-values).
`k0`	- search range starts from the k0th smallest p-value.
`k1`	- search range ends at the k1th smallest p-value.
`onesided`	- TRUE if the input p-values are one-sided.
`LS`	- if LS = T, then method of Li and Siegmund (2015) will be implemented.When n and q is very large, approximation method is prefered.
`ZW`	- if ZW = T, then approximation method of Zhang and Wu will be implemented.

Value

Quantile of HC statistics.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Donoho, David; Jin, Jiashun. "Higher criticism for detecting sparse heterogeneous mixtures". Annals of Statistics 32 (2004).

3. Li, Jian; Siegmund, David. "Higher criticism: p-values and criticism". Annals of Statistics 43 (2015).

See Also

`stat.hc` for the definition of the statistic.

Examples

```
## The 0.05 critical value of HC statistic when n = 10:
qhc(p=.95, M=diag(10), k0=1, k1=5, onesided=FALSE)
```

qphi — *Quantile of phi-divergence statitic under the null hypothesis.*

Description

Quantile of phi-divergence statitic under the null hypothesis.

Usage

```
qphi(p, M, k0, k1, s = 2, onesided = FALSE)
```

Arguments

`p`	- a scalar left probability that defines the quantile.
`M`	- correlation matrix of input statistics (of the input p-values).
`k0`	- search range starts from the k0th smallest p-value.
`k1`	- search range ends at the k1th smallest p-value.
`s`	- the phi-divergence test parameter.
`onesided`	- TRUE if the input p-values are one-sided.

Value

Quantile of phi-divergence statistics.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Donoho, David; Jin, Jiashun. "Higher criticism for detecting sparse heterogeneous mixtures". Annals of Statistics 32 (2004).

See Also

`stat.phi` for the definition of the statistic.

Examples

```
## The 0.05 critical value of HC statistic when n = 10:
qphi(p=.95, M=diag(10), k0=1, k1=5, s=2, onesided=FALSE)
```

`stat.bj` *Construct Berk and Jones (BJ) statitics.*

Description

Construct Berk and Jones (BJ) statitics.

Usage

```
stat.bj(p, k0 = 1, k1 = NA)
```

Arguments

`p`	- vector of input p-values.
`k0`	- search range left end parameter. Default k0 = 1.
`k1`	- search range right end parameter. Default k1 = 0.5*number of input p-values.

Details

Let $p_{(i)}, i = 1, ..., n$ be a sequence of ordered p-values, the Berk and Jones statistic

$$BJ = \sqrt{2n} \max_{1 \leq i \leq \lfloor \beta n \rfloor} (-1)^j \sqrt{i/n * \log(i/n/p_{(i)}) + (1 - i/n) * \log((1 - i/n)/(1 - p_{(i)}))}$$

and when $p_{(i)} > i/n$, $j = 1$, otherwise $j = 0$.

Value

value - BJ statistic constructed from a vector of p-values.

location - the order of the p-values to obtain BJ statistic.

stat - vector of marginal BJ statistics.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Jager, Leah; Wellner, Jon A. "Goodness-of-fit tests via phi-divergences". Annals of Statistics 35 (2007).

3. Berk, R.H. & Jones, D.H. Z. "Goodness-of-fit test statistics that dominate the Kolmogorov statistics". Wahrscheinlichkeitstheorie verw Gebiete (1979) 47: 47.

Examples

```
stat.bj(runif(10))
#When the input are statistics#
stat.test = rnorm(20)
p.test = 1 - pnorm(stat.test)
stat.bj(p.test, k0 = 2, k1 = 20)
```

stat.hc *Construct Higher Criticism (HC) statitics.*

Description

Construct Higher Criticism (HC) statitics.

Usage

```
stat.hc(p, k0 = 1, k1 = NA)
```

Arguments

p	- vector of input p-values.
k0	- search range left end parameter. Default k0 = 1.
k1	- search range right end parameter. Default k1 = 0.5*number of input p-values.

Details

Let $p_{(i)}, i = 1, ..., n$ be a sequence of ordered p-values, the higher criticism statistic

$$HC = \sqrt{n} \max_{1 \leq i \leq \lfloor \beta n \rfloor} [i/n - p_{(i)}] / \sqrt{p_{(i)}(1 - p_{(i)})}$$

Value

value - HC statistic constructed from a vector of p-values.

location - the order of the p-values to obtain HC statistic.

stat - vector of marginal HC statistics.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Donoho, David; Jin, Jiashun. "Higher criticism for detecting sparse heterogeneous mixtures". Annals of Statistics 32 (2004).

Examples

```
stat.hc(runif(10))
#When the input are statistics#
stat.test = rnorm(20)
p.test = 1 - pnorm(stat.test)
stat.hc(p.test, k0 = 1, k1 = 10)
```

stat.phi *Construct phi-divergence statitics.*

Description

Construct phi-divergence statitics.

Usage

```
stat.phi(p, s, k0 = 1, k1 = NA)
```

Arguments

p	- vector of input p-values.
s	- phi-divergence parameter. s = 2 is the higher criticism statitic.s = 1 is the Berk and Jones statistic.
k0	- search range left end parameter. Default k0 = 1.
k1	- search range right end parameter. Default k1 = 0.5*number of input p-values.

Details

Let $p_{(i)}, i = 1, ..., n$ be a sequence of ordered p-values, the phi-divergence statistic

$$PHI = \sqrt{2n}/(s - s^2) \max_{1 \leq i \leq \lfloor \beta n \rfloor} (-1)^j \sqrt{1 - (i/n)^s (p_{(i)})^s - (1 - i/n)^{(1-s)} * (1 - p_{(i)})^{(1-s)}}$$

and when $p_{(i)} > i/n$, $j = 1$, otherwise $j = 0$.

Value

value - phi-divergence statistic constructed from a vector of p-values.

location - the order of the p-values to obtain phi-divergence statistic.

stat - vector of marginal phi-divergence statistics.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Jager, Leah; Wellner, Jon A. "Goodness-of-fit tests via phi-divergences". Annals of Statistics 35 (2007).

Examples

```
stat.phi(runif(10), s = 2)
#When the input are statistics#
stat.test = rnorm(20)
p.test = 1 - pnorm(stat.test)
stat.phi(p.test, s = 0.5, k0 = 2, k1 = 5)
```

stat.phi.omni — *calculate the omnibus phi-divergence statistics under general correlation matrix.*

Description

calculate the omnibus phi-divergence statistics under general correlation matrix.

Usage

```
stat.phi.omni(p, M, K0 = rep(1, 4), K1 = rep(length(M[1, ]), 4), S = c(-1,
  0, 1, 2), t = 30, onesided = FALSE)
```

Arguments

p	- input pvalues.
M	- correlation matrix of input statistics (of the input p-values).
K0	- vector of search range starts (from the k0th smallest p-value).
K1	- vector of search range ends (at the k1th smallest p-value).
S	- vector of the phi-divergence test parameters.
t	- numerical truncation parameter.
onesided	- TRUE if the input p-values are one-sided.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

Examples

```
M = toeplitz(1/(1:10)*(-1)^(0:9)) #alternating polynomial decaying correlation matrix
stat.phi.omni(runif(10), M=M, K0=rep(1,4), K1=rep(5,4), S=c(-1,0,1,2))
```

test.bj — *Multiple comparison test using Berk and Jones (BJ) statitics.*

Description

Multiple comparison test using Berk and Jones (BJ) statitics.

Usage

```
test.bj(prob, M, k0, k1, onesided = FALSE)
```

Arguments

`prob`	- vector of input p-values.
`M`	- correlation matrix of input statistics (of the input p-values).
`k0`	- search range starts from the k0th smallest p-value.
`k1`	- search range ends at the k1th smallest p-value.
`onesided`	- TRUE if the input p-values are one-sided.

Value

pvalue - the p-value of the Berk-Jones test.

bjstat - the Berk-Jones statistic.

location - the order of the input p-values to obtain BJ statistic.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Jager, Leah; Wellner, Jon A. "Goodness-of-fit tests via phi-divergences". Annals of Statistics 35 (2007).

3. Berk, R.H. & Jones, D.H. Z. "Goodness-of-fit test statistics that dominate the Kolmogorov statistics". Wahrscheinlichkeitstheorie verw Gebiete (1979) 47: 47.

See Also

`stat.bj` for the definition of the statistic.

Examples

```
test.bj(runif(10), M=diag(10), k0=1, k1=10)
#When the input are statistics#
stat.test = rnorm(20)
p.test = 2*(1 - pnorm(abs(stat.test)))
test.bj(p.test, M=diag(20), k0=1, k1=10)
```

---

test.hc — *Multiple comparison test using Higher Criticism (HC) statitics.*

Description

Multiple comparison test using Higher Criticism (HC) statitics.

Usage

```
test.hc(prob, M, k0, k1, LS = F, ZW = F, onesided = FALSE)
```

Arguments

prob	- vector of input p-values.
M	- correlation matrix of input statistics (of the input p-values).
k0	- search range starts from the k0th smallest p-value.
k1	- search range ends at the k1th smallest p-value.
LS	- if LS = T, then method of Li and Siegmund (2015) will be implemented.When n and q is very large, approximation method is prefered.
ZW	- if ZW = T, then approximation method of Zhang and Wu will be implemented.
onesided	- TRUE if the input p-values are one-sided.

Value

pvalue - The p-value of the HC test.

hcstat - HC statistic.

location - the order of the input p-values to obtain HC statistic.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Donoho, David; Jin, Jiashun. "Higher criticism for detecting sparse heterogeneous mixtures". Annals of Statistics 32 (2004).

3. Li, Jian; Siegmund, David. "Higher criticism: p-values and criticism". Annals of Statistics 43 (2015).

See Also

stat.hc for the definition of the statistic.

Examples

```
pval.test = runif(10)
test.hc(pval.test, M=diag(10), k0=1, k1=10)
test.hc(pval.test, M=diag(10), k0=1, k1=10, LS = TRUE)
test.hc(pval.test, M=diag(10), k0=1, k1=10, ZW = TRUE)
#When the input are statistics#
stat.test = rnorm(20)
p.test = 2*(1 - pnorm(abs(stat.test)))
test.hc(p.test, M=diag(20), k0=1, k1=10)
```

test.phi — *Multiple comparison test using phi-divergence statitics.*

Description

Multiple comparison test using phi-divergence statitics.

Usage

```
test.phi(prob, M, k0, k1, s = 2, onesided = FALSE)
```

Arguments

prob	- vector of input p-values.
M	- correlation matrix of input statistics (of the input p-values).
k0	- search range starts from the k0th smallest p-value.
k1	- search range ends at the k1th smallest p-value.
s	- phi-divergence parameter. s = 2 is the higher criticism statitic.s = 1 is the Berk and Jones statistic.
onesided	- TRUE if the input p-values are one-sided.

Value

pvalue - The p-value of the phi-divergence test.

phistat - phi-diergence statistic.

location - the order of the input p-values to obtain phi-divergence statistic.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

2. Jager, Leah; Wellner, Jon A. "Goodness-of-fit tests via phi-divergences". Annals of Statistics 35 (2007).

See Also

stat.phi for the definition of the statistic.v

Examples

```
test.phi(runif(10), M=diag(10), s = 0.5, k0=1, k1=10)
#When the input are statistics#
stat.test = rnorm(20)
p.test = 2*(1 - pnorm(abs(stat.test)))
test.phi(p.test, M=diag(20), s = 0.5, k0=1, k1=10)
```

`test.phi.omni` *calculate the right-tail probability of omnibus phi-divergence statistics under general correlation matrix.*

Description

calculate the right-tail probability of omnibus phi-divergence statistics under general correlation matrix.

Usage

```
test.phi.omni(prob, M, K0, K1, S, onesided = FALSE)
```

Arguments

`prob`	- vector of input p-values.
`M`	- correlation matrix of input statistics (of the input p-values).
`K0`	- vector of search range starts (from the k0th smallest p-value).
`K1`	- vector of search range ends (at the k1th smallest p-value).
`S`	- vector of the phi-divergence test parameters.
`onesided`	- TRUE if the input p-values are one-sided.

References

1. Hong Zhang, Jiashun Jin and Zheyang Wu. "Distributions and Statistical Power of Optimal Signal-Detection Methods In Finite Cases", submitted.

Examples

```
M = matrix(0.3,10,10) + diag(1-0.3, 10)
test.phi.omni(runif(10), M=M, K0=rep(1,4), K1=rep(5,4), S=c(-1,0,1,2))
```

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