# Package 'SetTest'

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**Type** Package

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

**Version** 0.2.0

**Author** Hong Zhang and Zheyang Wu

**Maintainer** Hong Zhang <hzhang@wpi.edu>

**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.

**License** GPL-2

**LazyData** TRUE

**RoxygenNote** 6.0.1

**NeedsCompilation** no

**Repository** CRAN

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# R topics documented:

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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](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](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 $\epsilon$ 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 $\mu$ 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 $\epsilon$ 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 $\mu$ 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](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 $\epsilon$ 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 $\mu$ 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](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](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](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](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](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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