

Package ‘ppcc’

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Title Probability Plot Correlation Coefficient Test

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Description Calculates the Probability Plot Correlation Coefficient (PPCC) between a continuous variable X and a specified distribution. The corresponding composite hypothesis test that was first introduced by Filliben (1975) <doi:10.1080/00401706.1975.10489279> can be performed to test whether the sample X is element of either the Normal, log-Normal, Exponential, Uniform, Cauchy, Logistic, Generalized Logistic, Gumbel (GEVI), Weibull, Generalized Extreme Value, Pearson III (Gamma 2), Mielke's Kappa, Rayleigh or Generalized Logistic Distribution. The PPCC test is performed with a fast Monte-Carlo simulation.

Depends R(>= 3.0.0)

Suggests VGAM (>= 1.0), nortest(>= 1.0)

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| ppcc-package | <i>Goodness-of-Fit Tests using the Probability Plot Correlation Coefficient</i> |
|--------------|---|

Description

The function `ppccTest` performs the Probability Plot Correlation Coefficient test for various continuous distribution functions.

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| ppccTest | <i>Probability Plot Correlation Coefficient Test</i> |
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Description

Performs the Probability Plot Correlation Coefficient Test of Goodness-of-Fit

Usage

```
ppccTest(
  x,
  qfn = c("qnorm", "qlnorm", "qunif", "qexp", "qcauchy", "qlogis", "qgumbel",
    "qweibull", "qpearson3", "qgev", "qkappa2", "qrayleigh", "qglogis"),
  shape = NULL,
  ppos = NULL,
  mc = 10000,
  ...
)
```

Arguments

| | |
|--------------------|---|
| <code>x</code> | a numeric vector of data values; NA values will be silently ignored. |
| <code>qfn</code> | a character vector naming a valid quantile function |
| <code>shape</code> | numeric, the shape parameter for the relevant distribution, if applicable; defaults to NULL |
| <code>ppos</code> | character, the method for estimating plotting point positions, default's to NULL, see Details for corresponding defaults and <code>ppPositions</code> for available methods |
| <code>mc</code> | numeric, the number of Monte-Carlo replications, defaults to 10000 |
| <code>...</code> | further arguments, currently ignored |

Details

Filliben (1975) suggested a probability plot correlation coefficient test to test a sample for normality. The ppcc is defined as the product moment correlation coefficient between the ordered data $x_{(i)}$ and the order statistic medians M_i ,

$$r = \frac{\sum_{i=1}^n (x_{(i)} - \bar{x}) (M_i - \bar{M})}{\sqrt{\sum_{i=1}^n (x_{(i)} - \bar{x})^2 \sum_{j=1}^n (M_j - \bar{M})^2}},$$

whereas the ordered statistic medians are related to the quantile function of the standard normal distribution, $M_i = \phi^{-1}(m_i)$. The values of m_i are estimated by plotting-point position procedures (see [ppPositions](#)).

In this function the test is performed by Monte-Carlo simulation:

1. Calculate quantile-quantile \hat{r} for the ordered sample data x and the specified qfn distribution (with shape, if applicable) and given ppos.
2. Draw n (pseudo) random deviates from the specified qfn distribution, where n is the sample size of x .
3. Calculate quantile-quantile r_i for the random deviates and the specified qfn distribution with given ppos.
4. Repeat step 2 and 3 for $i = \{1, 2, \dots, mc\}$.
5. Calculate $S = \sum_{i=1}^n \text{sgn}(\hat{r} - r_i)$ with sgn the sign-function.
6. The estimated p -value is $p = S/mc$.

The probability plot correlation coefficient is invariant for location and scale. Therefore, the null hypothesis is a composite hypothesis, e.g. $H_0 : X \in N(\mu, \sigma)$, $\mu \in R$, $\sigma \in R_{>0}$. Furthermore, distributions with one (additional) specified shape parameter can be tested.

The magnitude of \hat{r} depends on the selected method for plotting-point positions (see [ppPositions](#)) and the sample size. Several authors extended Filliben's method to assess the goodness-of-fit to other distributions, whereas theoretical quantiles were used as opposed to Filliben's medians.

The default plotting positions (see [ppPositions](#)) depend on the selected qfn.

Distributions with none or one single scale parameter that can be tested:

| Argument | Function | Default ppos | Reference |
|-----------|-------------|--------------|------------------------|
| qunif | Uniform | Weibull | Vogel and Kroll (1989) |
| qexp | Exponential | Gringorton | |
| qgumbel | Gumbel | Gringorton | Vogel (1986) |
| qrayleigh | Rayleigh | Gringorton | |

Distributions with location and scale parameters that can be tested:

| Argument | Function | Default ppos | Reference |
|----------|------------|--------------|-----------------------------|
| qnorm | Normal | Blom | Looney and Gullledge (1985) |
| qlnorm | log-Normal | Blom | Vogel and Kroll (1989) |
| qcauchy | Cauchy | Gringorton | |

qlogis Logistic Blom

If Blom's plotting position is used for qnorm, then the ppcc-test is related to the Shapiro-Francia normality test (Royston 1993), where $W' = r^2$. See `sf.test` and `example(ppccTest)`.

Distributions with additional shape parameters that can be tested:

| Argument | Function | Default pppos | Reference |
|-----------|------------------------|---------------|---------------------------|
| qweibull | Weibull | Gringorton | |
| qpearson3 | Pearson III | Blom | Vogel and McMartin (1991) |
| qgev | GEV | Cunane | Chowdhury et al. (1991) |
| qkappa2 | two-param. Kappa Dist. | Gringorton | |
| qglogis | Generalized Logistic | Gringorton | |

If `qfn = qpearson3` and `shape = 0` is selected, the `qnorm` distribution is used. If `qfn = qgev` and `shape = 0`, the `qgumbel` distribution is used. If `qfn = qglogis` and `shape = 0` is selected, the `qglogis` distribution is used.

Value

a list with class 'htest'

Note

As the `pvalue` is estimated through a Monte-Carlo simulation, the results depend on the selected seed (see `set.seed`) and the total number of replicates (`mc`).

The default of `mc = 10000` re-runs is sufficient for testing the composite hypothesis on levels of $\alpha = [0.1, 0.05]$. If a level of $\alpha = 0.01$ is desired, than larger sizes of re-runs (e.g. `mc = 100000`) might be required.

References

- J. U. Chowdhury, J. R. Stedinger, L.-H. Lu (1991), Goodness-of-Fit Tests for Regional Generalized Extreme Value Flood Distributions, *Water Resources Research* 27, 1765–1776.
- J. J. Filliben (1975), The Probability Plot Correlation Coefficient Test for Normality, *Technometrics* 17, 111–117.
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- S. W. Looney, T. R. Gullett (1985), Use of Correlation Coefficient with Normal Probability Plots, *The American Statistician* 39, 75–79.
- P. W. Mielke (1973), Another family of distributions for describing and analyzing precipitation data. *Journal of Applied Meteorology* 12, 275–280.
- P. Royston, P. (1993), A pocket-calculator algorithm for the Shapiro-Francia test for non-normality: an application to medicine. *Statistics in Medicine* 12, 181-184.

R. M. Vogel (1986), The Probability Plot Correlation Coefficient Test for the Normal, Lognormal, and Gumbel Distributional Hypotheses, *Water Resources Research* 22, 587–590.

R. M. Vogel, C. N. Kroll (1989), Low-flow frequency analysis using probability-plot correlation coefficients, *Journal of Water Resources Planning and Management* 115, 338–357.

R. M. Vogel, D. E. McMartin (1991), Probability Plot Goodness-of-Fit and Skewness Estimation Procedures for the Pearson Type 3 Distribution, *Water Resources Research* 27, 3149–3158.

See Also

[qqplot](#), [qqnorm](#), [ppoints](#), [ppPositions](#), [Normal](#), [Lognormal](#), [Uniform](#), [Exponential](#), [Cauchy](#), [Logistic](#), [qgumbel](#), [Weibull](#), [qgev](#).

Examples

```
## Filliben (1975, p.116)
## Note: Filliben's result was 0.98538
## decimal accuracy in 1975 is assumed to be less than in 2017
x <- c(6, 1, -4, 8, -2, 5, 0)
set.seed(100)
ppccTest(x, "qnorm", ppos="Filliben")
## p between .75 and .9
## see Table 1 of Filliben (1975, p.113)
##
set.seed(100)
## Note: default plotting position for
## qnorm is ppos="Blom"
ppccTest(x, "qnorm")
## p between .75 and .9
## see Table 2 of Looney and Gulledge (1985, p.78)
##
##
set.seed(300)
x <- rnorm(30)
qn <- ppccTest(x, "qnorm")
qn
## p between .5 and .75
## see Table 2 for n = 30 of Looney and Gulledge (1985, p.78)
##
## Compare with Shapiro-Francia test
if(require(nortest)){
  sn <- sf.test(x)
  print(sn)
  W <- sn$statistic
  rr <- qn$statistic^2
  names(W) <- NULL
  names(rr) <- NULL
  print(all.equal(W, rr))
}
ppccTest(x, "qunif")
ppccTest(x, "qlnorm")
old <- par()
```

```

par(mfrow=c(1,3))
xlab <- "Theoretical Quantiles"
ylab <- "Empirical Quantiles"
qqplot(x = qnorm(ppPositions(30, "Blom")),
       y = x, xlab=xlab, ylab=ylab, main = "Normal q-q-plot")
qqplot(x = qunif(ppPositions(30, "Weibull")),
       y = x, xlab=xlab, ylab=ylab, main = "Uniform q-q-plot")
qqplot(x = qlnorm(ppPositions(30, "Blom")),
       y = x, xlab=xlab, ylab=ylab, main = "log-Normal q-q-plot")
par(old)
##
if (require(VGAM)){
set.seed(300)
x <- rgumbel(30)
gu <- ppccTest(x, "qgumbel")
print(gu)
1000 * (1 - gu$statistic)
}
##
## see Table 2 for n = 30 of Vogel (1986, p.589)
## for n = 30 and Si = 0.5, the critical value is 16.9
##
set.seed(200)
x <- runif(30)
un <- ppccTest(x, "qunif")
print(un)
1000 * (1 - un$statistic)
##
## see Table 1 for n = 30 of Vogel and Kroll (1989, p.343)
## for n = 30 and Si = 0.5, the critical value is 10.5
##
set.seed(200)
x <- rweibull(30, shape = 2.5)
ppccTest(x, "qweibull", shape=2.5)
ppccTest(x, "qweibull", shape=1.5)
##
if (require(VGAM)){
set.seed(200)
x <- rgev(30, shape = -0.2)
ev <- ppccTest(x, "qgev", shape=-0.2)
print(ev)
1000 * (1 - ev$statistic)
##
## see Table 3 for n = 30 and shape = -0.2
## of Chowdhury et al. (1991, p.1770)
## The tabulated critical value is 80.
}

```

Description

Calculates plotting point positions according to different authors

Usage

```
ppPositions(
  n,
  method = c("Gringorton", "Cunane", "Filliben", "Blom", "Weibull", "ppoints")
)
```

Arguments

`n` numeric, the sample size
`method` a character string naming a valid method (see Details)

Details

The following methods can be selected:

"Gringorton" the plotting point positions are calculated as

$$m_i = (i - 0.44) / (n + 0.12)$$

"Cunane" the plotting point positions are calculated as

$$m_i = (i - 0.4) / (n + 0.2)$$

"Blom" the plotting point positions are calculated as

$$m_i = (i - 0.3175) / (n + 0.25)$$

"Filliben" the order statistic medians are calculated as:

$$m_i = \begin{cases} 1 - 0.5^{1/n} & i = 1 \\ (i - 0.3175) / (n + 0.365) & i = 2, \dots, n - 1 \\ 0.5^{1/n} & i = n \end{cases}$$

"ppoints" R core's default plotting point positions are calculated (see [ppoints](#)).

Value

a vector of class numeric that contains the plotting positions

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