Package ‘QBAsyDist’

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Description Provides the local polynomial maximum likelihood estimates for the location and scale functions as well as the semiparametric quantile estimates in the generalized quantile-based asymmetric distributional setting. These functions are useful for any member of the generalized quantile-based asymmetric family of distributions.
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## Description

Density, cumulative distribution function, quantile function and random sample generation from the quantile-based asymmetric exponential power distribution (AEPD) studied in Gijbels et al. (2019b). An alternative form of the density AEPD is also studied in Komunjer (2007).
Usage

dAEPD(y, mu, phi, alpha, p)
pAEPD(q, mu, phi, alpha, p)
qAEPD(beta, mu, phi, alpha, p)
rAEPD(n, mu, phi, alpha, p)

Arguments

y, q These are each a vector of quantiles.
mu This is the location parameter $\mu$.
phi This is the scale parameter $\phi$.
alpha This is the index parameter $\alpha$.
p This is the shape parameter, which must be positive.
beta This is a vector of probabilities.
n This is the number of observations, which must be a positive integer that has length 1.

Value

dAEPD provides the density, pAEPD provides the cumulative distribution function, qAEPD provides the quantile function, and rAEPD generates a random sample from the quantile-based asymmetric exponential power distribution.

References


Examples

# Quantile-based asymmetric exponential power distribution
# Density
rnum<-rnorm(100)
dAEPD(y=rnum,mu=0,phi=1,alpha=.5,p=2)

# Distribution function
pAEPD(q=rnum,mu=0,phi=1,alpha=.5,p=2)

# Quantile function
beta<-c(0.25,0.5,0.75)
qAEPD(beta=beta,mu=0,phi=1,alpha=.5,p=2)
# random sample generation
rAEPD(n=100,mu=0,phi=1,alpha=.5,p=2)

<table>
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<th>Quantile-based asymmetric Laplace distribution</th>
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**Description**

Density, cumulative distribution function, quantile function and random sample generation for the quantile-based asymmetric Laplace distribution (ALaD) discussed in Yu and Zhang (2005) and Gijbels et al. (2019a).

**Usage**

\[
\text{dALaD}(y, \mu, \phi, \alpha) \\
\text{pALaD}(q, \mu, \phi, \alpha) \\
\text{qALaD}(\beta, \mu, \phi, \alpha) \\
\text{rALaD}(n, \mu, \phi, \alpha)
\]

**Arguments**

- **y, q** These are each a vector of quantiles.
- **mu** This is the location parameter \( \mu \).
- **phi** This is the scale parameter \( \phi \).
- **alpha** This is the index parameter \( \alpha \).
- **beta** This is a vector of probabilities.
- **n** This is the number of observations, which must be a positive integer that has length 1.

**Value**

\text{dALaD} provides the density, \text{pALaD} provides the cumulative distribution function, \text{qALaD} provides the quantile function, and \text{rALaD} generates a random sample from the quantile-based asymmetric Laplace distribution. The length of the result is determined by \( n \) for \text{rALaD}, and is the maximum of the lengths of the numerical arguments for the other functions.

**References**


ALoD

See Also
dQBAD, pQBAD, qQBAD, rQBAD

Examples

```r
# Density
rnum<-rnorm(100)
dALaD(y=rnum,mu=0,phi=1,alpha=.5)

# Distribution function
pALaD(q=rnum,mu=0,phi=1,alpha=.5)

# Quantile function
beta<-c(0.25,0.5,0.75)
qALaD(beta=beta,mu=0,phi=1,alpha=.5)

# random sample generation
rALaD(n=100,mu=0,phi=1,alpha=.5)
```

**ALoD**

*Quantile-based asymmetric logistic distribution*

### Description

Density, cumulative distribution function, quantile function and random sample generation from the quantile-based asymmetric logistic distribution (ALoD) proposed in Gijbels et al. (2019a).

### Usage

```r
dALoD(y, mu, phi, alpha)
pALoD(q, mu, phi, alpha)
qALoD(beta, mu, phi, alpha)
rALoD(n, mu, phi, alpha)
```

### Arguments

- `y, q`: These are each a vector of quantiles.
- `mu`: This is the location parameter $\mu$.
- `phi`: This is the scale parameter $\phi$.
- `alpha`: This is the index parameter $\alpha$.
- `beta`: This is a vector of probabilities.
- `n`: This is the number of observations, which must be a positive integer that has length 1.
Value

dALoD provides the density, pALoD provides the cumulative distribution function, qALoD provides the quantile function, and rALoD generates a random sample from the quantile-based asymmetric logistic distribution. The length of the result is determined by n for rALoD, and is the maximum of the lengths of the numerical arguments for the other functions.

References


See Also

dQBAD, pQBAD, qQBAD, rQBAD

Examples

```r
# Quantile-based asymmetric logistic distribution (ALoD)
# Density
rnum <- rnorm(100)
dALoD(y = rnum, mu = 0, phi = 1, alpha = 0.5)

# Distribution function
pALoD(q = rnum, mu = 0, phi = 1, alpha = 0.5)

# Quantile function
beta <- c(0.25, 0.5, 0.75)
qALoD(beta = beta, mu = 0, phi = 1, alpha = 0.5)

# random sample generation
rALoD(n = 100, mu = 0, phi = 1, alpha = 0.5)
```

AND

Quantile-based asymmetric normal distribution

Description

Density, cumulative distribution function, quantile function and random sample generation from the quantile-based asymmetric normal distribution (AND) introduced in Gijbels et al. (2019a).

Usage

dAND(y, mu, phi, alpha)
pAND(q, mu, phi, alpha)
qAND(beta, mu, phi, alpha)

rAND(n, mu, phi, alpha)

**Arguments**

- **y, q**: These are each a vector of quantiles.
- **mu**: This is the location parameter \( \mu \).
- **phi**: This is the scale parameter \( \phi \).
- **alpha**: This is the index parameter \( \alpha \).
- **beta**: This is a vector of probabilities.
- **n**: This is the number of observations, which must be a positive integer that has length 1.

**Value**

\( d\text{AND} \) provides the density, \( p\text{AND} \) provides the cumulative distribution function, \( q\text{AND} \) provides the quantile function, and \( r\text{AND} \) generates a random sample from the quantile-based asymmetric normal distribution.

**References**


**See Also**

\( d\text{QBAD}, p\text{QBAD}, q\text{QBAD}, r\text{QBAD} \)

**Examples**

```r
# Quantile-based asymmetric normal distribution (AND)
# Density
rnum<-rnorm(100)
dAND(y=rnum, mu=0, phi=1, alpha=.5)

# Distribution function
pAND(q=rnum, mu=0, phi=1, alpha=.5)

# Quantile function
beta<-c(0.25, 0.5, 0.75)
qAND(beta=beta, mu=0, phi=1, alpha=.5)

# Random sample generation
rAND(n=100, mu=0, phi=1, alpha=.5)
```
ATD
Quantile-based asymmetric Student’s-t distribution

Description
Density, cumulative distribution function, quantile function and random sample generation from the quantile-based asymmetric Student’s-t distribution (ATD) proposed in Gijbels et al. (2019a).

Usage
\begin{align*}
dATD(y, \mu, \phi, \alpha, \nu) \\
pATD(q, \mu, \phi, \alpha, \nu) \\
qATD(beta, \mu, \phi, \alpha, \nu) \\
rATD(n, \mu, \phi, \alpha, \nu)
\end{align*}

Arguments
\begin{align*}
y, q & \quad \text{These are each a vector of quantiles.} \\
\mu & \quad \text{This is the location parameter } \mu. \\
\phi & \quad \text{This is the scale parameter } \phi. \\
\alpha & \quad \text{This is the index parameter } \alpha. \\
\nu & \quad \text{This is the degrees of freedom parameter } \nu, \text{ which must be positive.} \\
\beta & \quad \text{This is a vector of probabilities.} \\
n & \quad \text{This is the number of observations, which must be a positive integer that has length 1.}
\end{align*}

Value
\begin{itemize}
\item \texttt{dATD} provides the density, \texttt{pATD} provides the cumulative distribution function, \texttt{qATD} provides the quantile function, and \texttt{rATD} generates a random sample from the quantile-based asymmetric Student’s-t distribution. The length of the result is determined by \texttt{n} for \texttt{rATD}, and is the maximum of the lengths of the numerical arguments for the other functions.
\end{itemize}

References

See Also
\texttt{dQBAD, pQBAD, qQBAD, rQBAD}
Examples

# Quantile-based asymmetric Student's-t distribution (ATD)
# Density
rnum<-rnorm(100)
dATD(rnum,mu=0,phi=1,alpha=0.5,nu=10)

# Distribution function
pATD(rnum,mu=0,phi=1,alpha=0.5,nu=10)

# Quantile function
beta<-c(0.25,0.5,0.75)
qATD(beta=beta,mu=0,phi=1,alpha=.5,nu=10)

# random sample generation
rATD(n=100,mu=0,phi=1,alpha=.5,nu=10)

---

**bone.data**  
*Dataset concerning the actual measurements of bone density in adolescents*

Description


Usage

bone.data

Format

A data frame with 485 rows and 4 variables:

- **idnum**  ID of adolescent.
- **age**  Age of adolescent.
- **gender**  Gender of adolescent.
- **spnbmd**  Relative Change in the actual measurements of bone density (BMD).

References

Examples

data(bone.data)
y=bone.data$spnbmd
x=bone.data$age
plot(x,y)

GAD

Generalized quantile-based asymmetric family

Description

Density, cumulative distribution function, quantile function and random sample generation from the
generalized quantile-based asymmetric family of densities defined in Gijbels et al. (2019b).

Usage

dGAD(y, eta, phi, alpha, f, g)
pGAD(q, eta, phi, alpha, F, g)
qGAD(beta, eta, phi, alpha, F, g, QF = NULL, lower = -Inf,
   upper = Inf)
rGAD(n, eta, phi, alpha, F, g, lower = -Inf, upper = Inf, QF = NULL)

Arguments

y, q
These are each a vector of quantiles.
eta
This is the location parameter $\eta$.
phi
This is the scale parameter $\phi$.
alpha
This is the index parameter $\alpha$.
f
This is the reference density function $f$ which is a standard version of a unimodal
and symmetric around 0 density.
g
This is the “link” function. The function $g$ is to be differentiated. Therefore, $g$
must be written as a function. For example, g<-function(y){log(y)} for log link
function.
F
This is the cumulative distribution function $F$ of the unimodal and symmetric
around 0 reference density function $f$.
beta
This is a vector of probabilities.
QF
This is the quantile function of the reference density $f$.
lower
This is the lower limit of the domain (support of the random variable) $f_\alpha(y; \eta, \phi)$,
default -Inf.
upper
This is the upper limit of the domain (support of the random variable) $f_\alpha(y; \eta, \phi)$,
default Inf.
n
This is the number of observations, which must be a positive integer that has
length 1.
GAD

References


Examples

# Example 1: Let F be a standard normal cumulative distribution function then
f_N<-function(s){dnorm(s, mean = 0, sd = 1)} # density function of N(0,1)
F_N<-function(s){pnorm(s, mean = 0, sd = 1)} # distribution function of N(0,1)
QF_N<-function(beta){qnorm(beta, mean = 0, sd = 1, lower.tail = TRUE, log.p = FALSE)}

# For identity link function
g_id<-function(y)(y)
# For log-link function
g_log<-function(y)(log(y))

rnum<-rnorm(100)
beta=c(0.25,0.50,0.75)

# Density
dGAD(y=rnorm(100),eta=10,phi=1,alpha=0.5,f=f_N,g=g_id) # For identity link
dGAD(y=rexp(100,0.1),eta=10,phi=1,alpha=0.5,f=f_N,g=g_log) # For log-link

# Distribution function
pGAD(q=rnorm(100),eta=0,phi=1,alpha=.5,F=F_N,g=g_id) # For identity link
pGAD(q=rexp(100,0.1),eta=10,phi=1,alpha=.5,F=F_N,g=g_log) # For log-link

# Quantile function
qGAD(beta=beta,eta=0,phi=1,alpha=0.5,F=F_N,g=g_id) # For identity link
qGAD(beta=beta,eta=10,phi=1,alpha=0.5,F=F_N,g=g_log,lower = 0, upper = Inf) # For log-link

# random sample generation
rGAD(n=100,eta=0,phi=1,alpha=0.5,F=F_N,g=g_id ,lower = -Inf, upper = Inf,QF=NULL) # For identity link
rGAD(n=100,eta=10,phi=1,alpha=0.5,F=F_N,g=g_log ,lower =0, upper = Inf,QF=NULL) # For log-link

# Example 2: Let F be a standard Laplace cumulative distribution function then
f_La<-function(s){0.5*exp(-abs(s))} # density function of Laplace(0,1)
F_La<-function(s){0.5+0.5*sign(s)*(1-exp(-abs(s)))} # distribution function of Laplace(0,1)
QF_La<-function(beta){-sign(beta-0.5)*log(1-2*abs(beta-0.5))}

# For identity link function
g_id<-function(y)(y)
# For log-link function
g_log<-function(y)(log(y))

beta=c(0.25,0.50,0.75)

# Density
dGAD(y=rnorm(100),eta=10,phi=1,alpha=0.5,f=f_La,g=g_id) # For identity-link
dGAD(y=rexp(100,0.1),eta=10,phi=1,alpha=0.5,f=f_La,g=g_log) # For log-link

dGAD(y=rexp(100,0.1),eta=10,phi=1,alpha=0.5,f=f_La,g=g_log) # For log-link

# Distribution function
pGAD(q=rnum,eta=0,phi=1,alpha=.5,F=F_La,g=g_id) # For identity-link
pGAD(q=rexp(100,0.1),eta=10,phi=1, alpha=.5,F=F_La,g=g_log) # For log-link

# Quantile function
qGAD(beta=beta,eta=0,phi=1,alpha=0.5,F=F_La,g=g_id,lower = -Inf, upper = Inf) # For identity link
qGAD(beta=beta,eta=10,phi=1,alpha=0.5,F=F_La,g=g_log,lower = 0, upper = Inf) # For log-link

# random sample generation
rGAD(n=100,eta=0,phi=1,alpha=.5,F=F_La,g=g_id) # For identity link
rGAD(n=100,eta=10,phi=1,alpha=.5,F=F_La,g=g_log ,lower =0, upper = Inf,QF=NULL) # For log-link

---

**GTEF**  
*Generalized tick-exponential family*

**Description**
Density, cumulative distribution function, quantile function and random sample generation from the generalized tick-exponential family (GTEF) of densities discussed in Gijbels et al. (2019b).

**Usage**
- \( dGTEF(y, \text{eta}, \phi, \text{alpha}, p, g) \)
- \( pGTEF(q, \text{eta}, \phi, \text{alpha}, p, g) \)
- \( qGTEF(beta, \text{eta}, \phi, \text{alpha}, p, g, \text{lower} = -\text{Inf}, \text{upper} = \text{Inf}) \)
- \( rGTEF(n, \text{eta}, \phi, \text{alpha}, p, g, \text{lower} = -\text{Inf}, \text{upper} = \text{Inf}) \)

**Arguments**
- \( y, q \): These are each a vector of quantiles.
- \( \text{eta} \): This is the location parameter \( \eta \).
- \( \phi \): This is the scale parameter \( \phi \).
- \( \text{alpha} \): This is the index parameter \( \alpha \).
- \( p \): This is the shape parameter, which must be positive.
- \( g \): This is the "link" function. The function \( g \) is to be differentiated. Therefore, \( g \) must be written as a function. For example, \( g<-\text{function}(y)\{\log(y)\} \) for log link function.
- \( \text{beta} \): This is a vector of probabilities.
- \( \text{lower} \): This is the lower limit of the domain (support of the random variable) \( f^\alpha_y(y; \eta, \phi) \), default -\( \text{Inf} \).
upper  This is the upper limit of the domain (support of the random variable) $f^\beta_y(y; \eta, \phi)$, default Inf.

n  This is the number of observations, which must be a positive integer that has length 1.

Value

dGTEF provides the density, pGTEF provides the cumulative distribution function, qGTEF provides the quantile function, and rGTEF generates a random sample from the generalized tick-exponential family of densities. The length of the result is determined by \texttt{n} for \texttt{rGTEF}, and is the maximum of the lengths of the numerical arguments for the other functions.

References


Examples

```r
# For identity link function
y=rnorm(100)
g_id<-function(y){y}
dGTEF(y,eta=0,phi=1,alpha=0.5,p=2,g=g_id)

# cumulative distribution function
pGTEF(q=y,eta=10,phi=1,alpha=0.5,p=2,g=g_id)

# Quantile function
beta=c(0.25,0.5,0.75)
qGTEF(beta=beta,eta=10,phi=1,alpha=0.5,p=2,g=g_id)

# random sample generation
rGTEF(n=100,eta=10,phi=1,alpha=.5,p=2,g=g_id,lower = -Inf, upper = Inf)

# For log link function
y=rexp(100)
g_log<-function(y){log(y)}
dGTEF(y,eta=10,phi=1,alpha=0.5,p=2,g=g_log)

# cumulative distribution function
pGTEF(q=y,eta=10,phi=1,alpha=0.5,p=2,g=g_log)

# Quantile function
beta=c(0.25,0.5,0.75)
qGTEF(beta=beta,eta=10,phi=1,alpha=0.5,p=2,g=g_log,lower = 0, upper = Inf)

# random sample generation
rGTEF(n=100,eta=10,phi=1,alpha=.5,p=2,g=g_log,lower = 0, upper = Inf)
```
**Hurricane**

*Hurricane dataset for the North Atlantic region (up to 2017).*

**Description**

This is a dataset of the strongest hurricanes in the North Atlantic region. The dataset is a clean up version of the dataset Al which is available in the HURDAT package.

**Usage**

`Hurricane`

**Format**

A data frame with 1831 rows and 3 variables:

- **Year**  Year of the tropical cyclone occurrence (up to 2017)
- **Key**  Unique key identifying the tropical cyclone. Formatted like AABBBCCC where AA is Basin, BB is YearNum and CC is Year
- **WmaxST**  Maximum Wind Speed (in knots per hour) of the strongest hurricanes in the North Atlantic region

**Examples**

```r
data(Hurricane)
y=Hurricane$WmaxST
x=Hurricane$Year
plot(x,y)
```

**LocomotorPerfor**

*Data on locomotor performance in small and large terrestrial mammals.*

**Description**

A detailed description of these data is available in Iriarte-Diaz (2002). This dataset is also used in Gijbels et al. (2019c). For $n = 142$ species of mammals measurements on their body length, body mass (in kg) and maximum relative running speed were recorded. The maximum relative running speed measurement takes into account the body length of the mammals, and was obtained by dividing the maximum speed of the mammal species by its body length.
LogLikAEPD

**Usage**

LocomotorPerfor

**Format**

A data frame with 142 rows and 2 variables:

- **Body_Mass** The body mass of \( n = 142 \) species of mammals.
- **MRRS** The maximum relative running speed measurement takes into account the body length of the mammals, and was obtained by dividing the maximum speed of the mammal species by its body length.

**References**


**Examples**

```r
data(LocomotorPerfor)
y=log(LocomotorPerfor$MRRS)
x=log(LocomotorPerfor$Body_Mass)
plot(x,y)
```

---

**LogLikAEPD**

*Log-likelihood function for the quantile-based asymmetric exponential power distribution (AEPD) of distributions.*

**Description**

Log-Likelihood function \( \ell_n(\mu, \phi, \alpha, p) = \ln[L_n(\mu, \phi, \alpha, p)] \) in the quantile-based asymmetric exponential power distribution (AEPD) of densities defined in Gijbels et al. (2019b).

**Usage**

LogLikAEPD(y, mu, phi, alpha, p)

**Arguments**

- \( y \) This is a vector of quantiles.
- \( \mu \) This is the location parameter \( \mu \).
- \( \phi \) This is the scale parameter \( \phi \).
- \( \alpha \) This is the index parameter \( \alpha \).
- \( p \) This is the shape parameter, which must be positive.
LogLikAE PD provides the realized value of the Log-likelihood function of the quantile-based asymmetric exponential power distribution.

References


Examples

# Example
y<-rnorm(100)
LogLikAE PD(rexp(100,0.1),mu=10,phi=1,alpha=0.5,p=2)

Value

LogLikAE PD provides the realized value of the Log-likelihood function of the quantile-based asymmetric Laplace distribution.

Description

Log-Likelihood function $\ell_n(\mu, \phi, \alpha) = \ln[L_n(\mu, \phi, \alpha)]$ of the quantile-based asymmetric Laplace distribution discussed in Gijbels et al. (2019a).

Usage

LogLikAE PD(y, mu, phi, alpha)

Arguments

y This is a vector of quantiles.
mu This is the location parameter $\mu$.
phi This is the scale parameter $\phi$.
alpha This is the index parameter $\alpha$.

Value

LogLikAE PD provides the value of the Log-likelihood function of the quantile-based asymmetric Laplace distribution.
LogLikALoD

References


Examples

```r
# Example
y<-rnorm(100)
LogLikALaD(y,mu=0,phi=1,alpha=0.5)
```

-----

LogLikALoD  Log-likelihood function for the quantile-based asymmetric logistic distribution.

Description

The log-likelihood function $\ell_n(\mu, \phi, \alpha) = \ln[L_n(\mu, \phi, \alpha)]$ in the quantile-based asymmetric logistic distribution is presented in Gijbels et al. (2019a).

Usage

```r
LogLikALoD(y, mu, phi, alpha)
```

Arguments

- `y` This is a vector of quantiles.
- `mu` This is the location parameter $\mu$.
- `phi` This is the scale parameter $\phi$.
- `alpha` This is the index parameter $\alpha$.

Value

`LogLikALoD` provides the value of the Log-likelihood function of the quantile-based asymmetric logistic distribution.

References


Examples

```r
# Example
y<-rnorm(100)
LogLikALaD(y,mu=0,phi=1,alpha=0.5)
```
LogLikAND

---

Log-likelihood function for the quantile-based asymmetric normal distribution.

### Description

The log-likelihood function $\ell_n(\mu, \phi, \alpha) = \ln[L_n(\mu, \phi, \alpha)]$ in the quantile-based asymmetric normal distribution is presented in Gijbels et al. (2019a).

### Usage

```r
LogLikAND(y, mu, phi, alpha)
```

### Arguments

- `y` This is a vector of quantiles.
- `mu` This is the location parameter $\mu$.
- `phi` This is the scale parameter $\phi$.
- `alpha` This is the index parameter $\alpha$.

### Value

`LogLikAND` provides the value of the Log-likelihood function of the quantile-based asymmetric normal distribution.

### References


### Examples

```r
# Example
y <- rnorm(100)
LogLikAND(y, mu=0, phi=1, alpha=0.5)
```
LogLikATD

Log-likelihood function for the quantile-based asymmetric Student’s-t distribution.

Description

The log-likelihood function \( \ell_n(\mu, \phi, \alpha, \nu) = \ln[L_n(\mu, \phi, \alpha, \nu)] \) and parameter estimation of \( \theta = (\mu, \phi, \alpha, \nu) \) in the quantile-based asymmetric Student’s-t distribution by using the maximum likelihood estimation are discussed in Gijbels et al. (2019a).

Usage

\[
\text{LogLikATD}(y, \text{mu}, \text{phi}, \text{alpha}, \text{nu})
\]

Arguments

- \( y \) This is a vector of quantiles.
- \( \text{mu} \) This is the location parameter \( \mu \).
- \( \text{phi} \) This is the scale parameter \( \phi \).
- \( \text{alpha} \) This is the index parameter \( \alpha \).
- \( \text{nu} \) This is the degrees of freedom parameter \( \nu \), which must be positive.

Value

\text{LogLikATD} provides the value of the Log-likelihood function of the quantile-based asymmetric Student’s-t distribution.

References


Examples

\[
# Example
y<-rnorm(100)
\text{LogLikATD}(y, \text{mu}=0, \text{phi}=1, \text{alpha}=0.5, \text{nu}=10)
\]
Description

Log-Likelihood function $\ell_n(\eta, \phi, \alpha) = \ln[L_n(\eta, \phi, \alpha)]$ in the three parameter generalized quantile-based asymmetric family of densities defined in Gijbels et al. (2019b).

Usage

```
LogLikGAD(y, eta, phi, alpha, f, g)
```

Arguments

- `y`: This is a vector of quantiles.
- `eta`: This is the location parameter $\eta$.
- `phi`: This is the scale parameter $\phi$.
- `alpha`: This is the index parameter $\alpha$.
- `f`: This is the reference density function $f$ which is a standard version of a unimodal and symmetric around 0 density.
- `g`: This is the "link" function. The function $g$ is to be differentiated. Therefore, $g$ must be written as a function. For example, `g<-function(y){log(y)}` for log link function.

Value

`LogLikGAD` provides the realized value of the Log-likelihood function of the generalized quantile-based asymmetric family of distributions.

References


Examples

```
# Example 1: Let F be a standard normal cumulative distribution function then
f_N<-function(s){dnorm(s, mean = 0, sd = 1)} # density function of N(0,1)
y<-rnorm(100)
g_id<-function(y){y}
g_log<-function(y){log(y)}
LogLikGAD(y, eta=0, phi=1, alpha=0.5, f=f_N, g=g_id) # For identity-link
LogLikGAD(rexp(100,0.1), eta=10, phi=1, alpha=0.5, f=f_N, g=g_log) # For log-link
```
LogLikGTEF

Log-likelihood function for the generalized tick-exponential family (GTEF) of distributions.

Description

Log-Likelihood function $\ell_n(\eta, \phi, \alpha, p) = \ln[L_n(\eta, \phi, \alpha, p)]$ in the generalized tick-exponential family of densities discussed in Gijbels et al. (2019b).

Usage

LogLikGTEF(y, eta, phi, alpha, p, g)

Arguments

y
This is a vector of quantiles.

eta
This is the location parameter $\eta$.

phi
This is the scale parameter $\phi$.

alpha
This is the index parameter $\alpha$.

p
This is the shape parameter, which must be positive.

g
This is the "link" function. The function $g$ is to be differentiated. Therefore, $g$ must be written as a function. For example, g<-function(y){log(y)} for log link function.

Value

LogLikGAD provides the realized value of the Log-likelihood function of the generalized quantile-based asymmetric family of distributions.

References

Examples

```r
# Examples
y <- rnorm(100)
g_id <- function(y) {y}
g_log <- function(y) {log(y)}
LogLikGTEF(y, eta=0, phi=1, alpha=0.5, p=2, g=g_id) # For identity-link
LogLikGTEF(rexp(100, 0.1), eta=10, phi=1, alpha=0.5, p=2, g=g_log) # For log-link
```

LogLikQBAD

Log-likelihood function for the quantile-based asymmetric family of distributions.

Description

Log-Likelihood function \( \ell_n(\mu, \phi, \alpha) = \ln[L_n(\mu, \phi, \alpha)] \) in the three parameter quantile-based asymmetric family of densities defined in Section 3.2 of Gijbels et al. (2019a).

Usage

```r
LogLikQBAD(y, mu, phi, alpha, f)
```

Arguments

- `y`: This is a vector of quantiles.
- `mu`: This is the location parameter \( \mu \).
- `phi`: This is the scale parameter \( \phi \).
- `alpha`: This is the index parameter \( \alpha \).
- `f`: This is the reference density function \( f \) which is a standard version of a unimodal and symmetric around 0 density.

Value

LogLikQBAD provides the realized value of the Log-likelihood function of quantile-based asymmetric family of distributions.

References

**Examples**

# Example 1: Let $F$ be a standard normal cumulative distribution function then

```r
f_N<-function(s){dnorm(s, mean = 0, sd = 1)} # density function of $N(0,1)$
y<-rnorm(100)
LogLikQBAD(y,mu=0,phi=1,alpha=0.5,f=f_N)
```

# Example 2: Let $F$ be a standard Laplace cumulative distribution function then

```r
f_La<-function(s){0.5*exp(-abs(s))} # density function of Laplace($0,1$)
LogLikQBAD(y,mu=0,phi=1,alpha=0.5,f=f_La)
```

---

**LRTest**

*Likelihood ratio test to test for symmetry.*

**Description**

The likelihood ratio test to test for symmetry, in the context of a framework of quantile-based asymmetric family of densities is discussed in Gijbels et al. (2019d).

**Usage**

```r
LRTest(y, f)
```

**Arguments**

- `y` This is a vector of quantiles.
- `f` This is the reference density function $f$ which is a standard version of a unimodal and symmetric around 0 density.

**Value**

The likelihood ratio test statistic with $P$-value.

**References**


**Examples**

# Example: Let $F$ be a standard normal cumulative distribution function then

```r
f_N<-function(s){dnorm(s, mean = 0, sd = 1)} # density function of $N(0,1)$
rnum=rnorm(100)
LRTest(rnum,f=f_N)
```
**mleAEPD**

Maximum likelihood estimation (MLE) for the quantile-based asymmetric exponential power distribution.

---

**Description**

The log-likelihood function $\ell_n(\mu, \phi, \alpha, p) = \ln[L_n(\mu, \phi, \alpha, p)]$ and parameter estimation of $\theta = (\mu, \phi, \alpha, p)$ in the three parameter quantile-based asymmetric exponential power distribution by using the maximum likelihood estimation are discussed in Gijbels et al. (2019b).

**Usage**

mleAEPD(y)

**Arguments**

y

This is a vector of quantiles.

**Value**

The maximum likelihood estimate of parameter $\theta = (\mu, \phi, \alpha, p)$ of the quantile-based asymmetric exponential power distribution.

**References**


**Examples**

```r
# Example
rnum=rnorm(100)
mleAEPD(rnum)
```

---

**mleALaD**

Maximum likelihood estimation (MLE) for the quantile-based asymmetric Laplace distribution.

---

**Description**

The log-likelihood function $\ell_n(\mu, \phi, \alpha) = \ln[L_n(\mu, \phi, \alpha)]$ and parameter estimation of $\theta = (\mu, \phi, \alpha)$ in the quantile-based asymmetric Laplace distribution by using the maximum likelihood estimation are discussed in Gijbels et al. (2019a). See also in Yu and Zhang (2005). The linear programing (LP) algorithm is used to obtain a solution to the maximization problem. The LP algorithm can be found in Koenker (2005). See also mleALD in the Package ald.
Usage

mleALoD(y)

Arguments

y 
This is a vector of quantiles.

Value

The maximum likelihood estimate of parameter $\theta = (\mu, \phi, \alpha)$ of the quantile-based asymmetric Laplace distribution.

References


Examples

```r
## Example:
y = rnorm(100)
mleALoD(y)
```

---

*mleALoD*  
Maximum likelihood estimation (MLE) for the quantile-based asymmetric logistic distribution.

Description

The log-likelihood function $\ell_n(\mu, \phi, \alpha) = \ln[L_n(\mu, \phi, \alpha)]$ and parameter estimation of $\theta = (\mu, \phi, \alpha)$ in the quantile-based asymmetric logistic distribution by using the maximum likelihood estimation are discussed in Gijbels et al. (2019a).

Usage

mleALoD(y)

Arguments

y 
This is a vector of quantiles.
mleAND

Value

The maximum likelihood estimate of parameter $\theta = (\mu, \phi, \alpha)$ of the quantile-based asymmetric family of distributions.

References


Examples

```r
# Example
rnum=rnorm(100)
mleALoD(rnum)
```

Description

The log-likelihood function $\ell_n(\mu, \phi, \alpha) = \ln[L_n(\mu, \phi, \alpha)]$ and parameter estimation of $\theta = (\mu, \phi, \alpha)$ in the asymmetric normal distribution by using the maximum likelihood estimation are discussed in Gijbels et al. (2019a).

Usage

```r
mleAND(y, alpha = NULL)
```

Arguments

- `y` This is a vector of quantiles.
- `alpha` This is the index parameter $\alpha$.

Value

The maximum likelihood estimate of parameter $\theta = (\mu, \phi, \alpha)$ of the quantile-based asymmetric normal distribution.

References

Examples

```r
# Maximum likelihood estimation
y=rnorm(100)
mleATD(y)
mleATD(y, alpha=0.5)
```

---

**mleATD**  
*Maximum likelihood estimation (MLE) for the quantile-based asymmetric Student’s-t distribution.*

**Description**

The log-likelihood function \( \ell_n(\mu, \phi, \alpha, \nu) = \ln[L_n(\mu, \phi, \alpha, \nu)] \) and parameter estimation of \( \theta = (\mu, \phi, \alpha, \nu) \) in the quantile-based asymmetric Student’s-t distribution. by using the maximum likelihood estimation are discussed in Gijbels et al. (2019a).

**Usage**

```r
mleATD(y)
```

**Arguments**

- `y`  
  This is a vector of quantiles.

**Value**

The maximum likelihood estimate of parameter \( \theta = (\mu, \phi, \alpha, \nu) \) of the quantile-based asymmetric Student’s-t distribution.

**References**


**Examples**

```r
# Example
y=rnorm(20)
mleATD(y)
```
mleGAD

Maximum likelihood estimation (MLE) for the generalized quantile-based asymmetric family of distributions (GAD).

Description

The log-likelihood function \( \ell_n(\eta, \phi, \alpha) = \ln[L_n(\eta, \phi, \alpha)] \) and parameter estimation of \( \theta = (\eta, \phi, \alpha) \) in the three parameter generalized quantile-based asymmetric family of densities by using the maximum likelihood estimation are discussed in Gijbels et al. (2019b).

Usage

mleGAD(y, f, g, lower = -Inf, upper = Inf)

Arguments

y
This is a vector of quantiles.
f
This is the reference density function \( f \) which is a standard version of a unimodal and symmetric around 0 density.
g
This is the "link" function. The function \( g \) is to be differentiated. Therefore, \( g \) must be written as a function. For example, \( g<-function(y){log(y)} \) for log link function.
lower
This is the lower limit of the domain (support of the random variable) \( f_{\alpha}^g(y; \eta, \phi) \), default -Inf.
upper
This is the upper limit of the domain (support of the random variable) \( f_{\alpha}^g(y; \eta, \phi) \), default Inf.

Value

The maximum likelihood estimate of parameter \( \theta = (\eta, \phi, \alpha) \) of the generalized quantile-based asymmetric family of densities

References


Examples

# Example 1: Let \( F \) be a standard normal cumulative distribution function then
f_N<-function(s){dnorm(s, mean = 0, sd = 1)} # density function of N(0,1)
y<-rnorm(100)
g_id<-function(y){y}
g_log<-function(y){log(y)}
mleGAD(y,f=f_N,g=g_id) # For identity-link
mleGAD(rexp(100,0.1), f=f_N, g=g_log, lower = 0, upper = Inf) # For log-link

# Example 2: Let F be a standard Laplace cumulative distribution function then
f_La<-function(s){0.5*exp(-abs(s))} # density function of Laplace(0,1)
mleGAD(y,f=f_La,g=g_id) # For identity-link
mleGAD(rexp(100,0.1),f=f_La,g=g_log,lower = 0, upper = Inf) # For log-link

---

### mleGTEF

Maximum likelihood estimation (MLE) for the generalized tick-exponential family (GTEF) of distributions.

---

#### Description

The log-likelihood function \( \ell_n(\eta, \phi, \alpha, p) = \ln[L_n(\eta, \phi, \alpha, p)] \) and parameter estimation of \( \theta = (\eta, \phi, \alpha, p) \) in the generalized tick-exponential family of distributions by using the maximum likelihood estimation are discussed in Gijbels et al. (2019b).

#### Usage

mleGTEF(y, g, lower = -Inf, upper = Inf)

#### Arguments

- **y**: This is a vector of quantiles.
- **g**: This is the "link" function. The function \( g \) is to be differentiated. Therefore, \( g \) must be written as a function. For example, \( g <- \text{function}(y) \{ \log(y) \} \) for log link function.
- **lower**: This is the lower limit of the domain (support of the random variable) \( f^\phi_{\alpha}(y; \eta, \phi) \), default -Inf.
- **upper**: This is the upper limit of the domain (support of the random variable) \( f^\phi_{\alpha}(y; \eta, \phi) \), default Inf.

#### Value

The maximum likelihood estimate of parameter \( \theta = (\eta, \phi, \alpha, p) \) of the generalized tick-exponential family of distributions.

#### References

mleQBAD

Maximum likelihood estimation (MLE) for the quantile-based asymmetric family of distributions.

Description

The log-likelihood function $\ell_n(\mu, \phi, \alpha) = \ln[L_n(\mu, \phi, \alpha)]$ and parameter estimation of $\theta = (\mu, \phi, \alpha)$ in the three parameter quantile-based asymmetric family of densities by using the maximum likelihood estimation are discussed in Section 3.2 of Gijbels et al. (2019a).

Usage

mleQBAD(y, f, alpha = NULL)

Arguments

y This is a vector of quantiles.

f This is the reference density function $f$ which is a standard version of a unimodal and symmetric around 0 density.

alpha This is the index parameter $\alpha$.

Value

The maximum likelihood estimate of parameter $\theta = (\mu, \phi, \alpha)$ of the quantile-based asymmetric family of densities

References


Examples

# Example 1: Let F be a standard normal cumulative distribution function then
f_N<-function(s){dnorm(s, mean = 0, sd = 1)} # density function of N(0,1)
rnum=rnorm(100)
mleQBAD(rnum,f=f_N)
mleQBAD(rnum,f=f_N,alpha=.5)
# Example 2: Let $F$ be a standard Laplace cumulative distribution function then
f_La<-function(s){0.5*exp(-abs(s))} # density function of Laplace(0,1)
mleQBAD(rnum,f=f_La)
mleQBAD(rnum,f=f_La,alpha=.5)

momALaD

**Method of moments (MoM) estimation for the quantile-based asymmetric Laplace distribution.**

**Description**

Parameter estimation in the quantile-based asymmetric Laplace distribution by using method of moments is studied in Gijbels et al. (2019a).

**Usage**

momALaD(y, alpha = NULL)

**Arguments**

- **y**
  - This is a vector of quantiles.
- **alpha**
  - This is the index parameter $\alpha$. If $\alpha$ is unknown, the it should be NULL which is default option. In this case, the sample skewness will be used to estimate $\alpha$. If $\alpha$ is known, then the value of $\alpha$ has to be specified in the function.

**Value**

momALaD provides the method of moments estimates of the unknown parameters of the distribution.

**References**


**Examples**

# Example
y=rnorm(100)
momALaD(y=y, alpha=0.5) # If alpha is known with alpha=0.5
momALaD(y=y) # If alpha is unknown
**momALoD**

*Method of moments (MoM) estimation for the quantile-based asymmetric logistic distribution.*

### Description

Parameter estimation in the quantile-based asymmetric logistic distribution by using method of moments are studied in Gijbels et al. (2019a).

### Usage

```r
momALoD(y, alpha = NULL)
```

### Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>y</td>
<td>This is a vector of quantiles.</td>
</tr>
<tr>
<td>alpha</td>
<td>This is the index parameter $\alpha$. If $\alpha$ is unknown, indicate NULL which is the default option. In this case, the sample skewness will be used to estimate $\alpha$. If $\alpha$ is known, then the value of $\alpha$ has to be specified in the function.</td>
</tr>
</tbody>
</table>

### Value

`momALoD` provides the method of moments estimates of the unknown parameters of the distribution.

### References


### Examples

```r
# Example
y=rnorm(100)
momALoD(y=y, alpha=0.5) # If alpha is known with alpha=0.5
momALoD(y=y) # If alpha is unknown
```
**momAND**

---

Method of moments (MoM) estimation for the quantile-based asymmetric normal distribution.

---

**Description**

Parameter estimation in the quantile-based asymmetric normal distribution by using method of moments are discussed in Gijbels et al. (2019a).

**Usage**

```r
momAND(y, alpha = NULL)
```

**Arguments**

- `y` This is a vector of quantiles.
- `alpha` This is the index parameter \( \alpha \). If \( \alpha \) is unknown, indicate NULL which is the default option. In this case, the sample skewness will be used to estimate \( \alpha \). If \( \alpha \) is known, then the value of \( \alpha \) has to be specified in the function.

**Value**

`momAND` provides the method of moments estimates of the unknown parameters of the distribution.

**References**


**Examples**

```r
# Example
y=rnorm(100)
momAND(y=y, alpha=0.5) # If alpha is known with alpha=0.5
momAND(y=y) # If alpha is unknown
```
**momATD**

*Method of moments (MoM) estimation for the quantile-based asymmetric Student’s-t distribution.*

**Description**

Parameter estimation in the quantile-based asymmetric Student’s-t distribution by using method of moments are discussed in Gijbels et al. (2019a). We here used the first four sample moments to estimate parameter \( \theta = (\mu, \phi, \alpha, \nu) \) under the assumption that the first four population moments exist, which needs to assume \( \nu > 4 \).

**Usage**

```r
momATD(y, alpha = NULL)
```

**Arguments**

- `y` This is a vector of quantiles.
- `alpha` This is the index parameter \( \alpha \). If \( \alpha \) is unknown, indicate NULL which is the default option. In this case, the sample skewness will be used to estimate \( \alpha \). If \( \alpha \) is known, then the value of \( \alpha \) has to be specified in the function.

**Value**

`momATD` provides the method of moments estimates of the unknown parameters of the distribution.

**References**


**Examples**

```r
# Example
y=rnorm(100)
momATD(y=y, alpha=0.5) # If alpha is known with alpha=0.5
momATD(y=y) # If alpha is unknown
```
momemtALaD

Moments estimation for the quantile-based asymmetric Laplace distribution.

Description
Mean, variance, skewness, kurtosis and moments about the location parameter (i.e., \( \alpha \)th quantile) of the quantile-based asymmetric Laplace distribution studied in Gijbels et al. (2019a) useful for quantile regression with location parameter equal to \( \mu \), scale parameter \( \phi \) and index parameter \( \alpha \).

Usage
meanALaD(mu, phi, alpha)
varALaD(mu, phi, alpha)
skewALaD(alpha)
kurtALaD(alpha)
momentALaD(phi, alpha, r)

Arguments
mu This is the location parameter \( \mu \).
phi This is the scale parameter \( \phi \).
alpha This is the index parameter \( \alpha \).
r This is a value which is used to calculate \( r \)th moment about \( \mu \).

Value
meanALaD provides the mean, varALaD provides the variance, skewALaD provides the skewness, kurtALaD provides the kurtosis, and momentALaD provides the \( r \)th moment about the location parameter \( \mu \) of the quantile-based asymmetric Laplace distribution.

References

Examples
# Example
meanALaD(mu=0,phi=1,alpha=0.5)
varALaD(mu=0,phi=1,alpha=0.5)
skewALaD(alpha=0.5)
kurtALoD(alpha=0.5)
momentALoD(phi=1, alpha=0.5, r=1)

| momentALoD | Moments estimation for the quantile-based asymmetric logistic distribution. |

Description

Mean, variance, skewness, kurtosis and moments about the location parameter (i.e., αth quantile) of the quantile-based asymmetric logistic distribution defined in Gijbels et al. (2019a) useful for quantile regression with location parameter equal to \( \mu \), scale parameter \( \phi \) and index parameter \( \alpha \).

Usage

meanALoD(mu, phi, alpha)
varALoD(mu, phi, alpha)
skewALoD(alpha)
kurtALoD(alpha)
momentALoD(phi, alpha, r)

Arguments

mu | This is the location parameter \( \mu \).
phi | This is the scale parameter \( \phi \).
alpha | This is the index parameter \( \alpha \).
r | This is a value which is used to calculate the \( r \)th moment about \( \mu \).

Value

meanALoD provides the mean, varALoD provides the variance, skewALoD provides the skewness, kurtALoD provides the kurtosis, and momentALoD provides the \( r \)th moment about the location parameter \( \mu \) of the quantile-based asymmetric logistic distribution.

References

Examples

# Example
meanALoD(mu=0,phi=1,alpha=0.5)
varALoD(mu=0,phi=1,alpha=0.5)
skewALoD(alpha=0.5)
kurtALoD(alpha=0.5)
momentALoD(phi=1,alpha=0.5,r=1)

Description

Mean, variance, skewness, kurtosis and moments about the location parameter (i.e., α-th quantile) of the quantile-based asymmetric normal distribution introduced in Gijbels et al. (2019a) useful for quantile regression with location parameter equal to μ, scale parameter φ and index parameter α.

Usage

meanAND(mu, phi, alpha)
varAND(mu, phi, alpha)
skewAND(alpha)
kurtAND(alpha)
momentAND(phi, alpha, r)

Arguments

mu
phi
alpha
r

This is the location parameter μ.
This is the scale parameter φ.
This is the index parameter α.
This is a value which is used to calculate r-th moment about μ.

Value

meanAND provides the mean, varAND provides the variance, skewAND provides the skewness, kurtAND provides the kurtosis, and momentAND provides the r-th moment about the location parameter μ of the quantile-based asymmetric normal distribution.
References


Examples

# Example
meanAND(mu=0, phi=1, alpha=0.5)
varAND(mu=0, phi=1, alpha=0.5)
skewAND(alpha=0.5)
kurtAND(alpha=0.5)
momentAND(phi=1, alpha=0.5, r=1)

\---

**momentATD**

Moments estimation for the quantile-based asymmetric Student’s-t distribution.

Description

Mean, variance, skewness, kurtosis and moments about the location parameter (i.e., \(\alpha\)th quantile) of the quantile-based asymmetric Student’s-t distribution defined in Gijbels et al. (2019a) useful for quantile regression with location parameter equal to \(\mu\), scale parameter \(\phi\) and index parameter \(\alpha\).

Usage

meanATD(mu, phi, alpha, nu)
varATD(mu, phi, alpha, nu)
skewATD(alpha, nu)
kurtATD(alpha, nu)
momentATD(phi, alpha, nu, r)

Arguments

- **mu**: This is the location parameter \(\mu\).
- **phi**: This is the scale parameter \(\phi\).
- **alpha**: This is the index parameter \(\alpha\).
- **nu**: This is the degrees of freedom parameter \(\nu\), which must be positive.
- **r**: This is a value which is used to calculate the \(r\)th moment \((r \in \{1, 2, 3, 4\})\) about \(\mu\).
Value

meanATD provides the mean, varATD provides the variance, skewATD provides the skewness, kurtATD provides the kurtosis, and momentATD provides the rth moment about the location parameter $\mu$ of the quantile-based asymmetric Student’s-t distribution.

References


Examples

# Example
meanATD(mu=0,phi=1,alpha=0.5,nu=10)
varATD(mu=0,phi=1,alpha=0.5,nu=10)
skewATD(alpha=0.5,nu=10)
kurtATD(alpha=0.5,nu=10)
momentATD(phi=1,alpha=0.5,nu=10,r=1)

---

momentQBAD  Moment estimation for the quantile-based asymmetric family of distributions.

Description

Mean, variance, skewness, kurtosis and moments about the location parameter (i.e., $\alpha$th quantile) of the quantile-based asymmetric family of densities defined in Gijbels et al. (2019a) useful for quantile regression with location parameter equal to $\mu$, scale parameter $\phi$ and index parameter $\alpha$.

Usage

mu_k(f, k)
gamma_k(f, k)
meanQBAD(mu, phi, alpha, mu_1)
varQBAD(mu, phi, alpha, mu_1, mu_2)
skewQBAD(alpha, mu_1, mu_2, mu_3)
kurtQBAD(alpha, mu_1, mu_2, mu_3, mu_4)
momentQBAD(phi, alpha, f, r)
Arguments

- \( f \): This is the reference density function \( f \) which is a standard version of a unimodal and symmetric around 0 density.
- \( k \): This is an integer value \((k = 1, 2, 3, \ldots)\) for calculating \( \mu_k = \int_0^\infty 2s^k f(s) ds \)
  and \( \gamma_k = \int_0^\infty s^{k-1} \left( \frac{f'(s)}{f(s)} \right)^2 ds \).
- \( \mu \): This is the location parameter \( \mu \).
- \( \phi \): This is the scale parameter \( \phi \).
- \( \alpha \): This is the index parameter \( \alpha \).
- \( \mu_1 \): This is the quantity \( \int_0^\infty 2sf(s) ds \).
- \( \mu_2 \): This is the quantity \( \int_0^\infty 2s^2 f(s) ds \).
- \( \mu_3 \): This is the quantity \( \int_0^\infty 2s^3 f(s) ds \).
- \( \mu_4 \): This is the quantity \( \int_0^\infty 2s^4 f(s) ds \).
- \( r \): This is a value which is used to calculate the \( r \)th moment about \( \mu \).

Value

\( \mu_k \) provides the quantity \( \int_0^\infty 2s^k f(s) ds \), \( \gamma_k \) provides the quantity \( \int_0^\infty s^{k-1} \left( \frac{f'(s)}{f(s)} \right)^2 ds \), \text{meanQBAD} provides the mean, \text{varQBAD} provides the variance, \text{skewQBAD} provides the skewness, \text{kurtQBAD} provides the kurtosis, and \text{momentQBAD} provides the \( r \)th moment about the location parameter \( \mu \) of the asymmetric family of distributions.

References


Examples

```
# Example 1: Let F be a standard normal cumulative distribution function then
f_N<-function(s){dnorm(s, mean = 0, sd = 1)} # density function of N(0,1)
mu_k(f=f_N,k=1)
gamma_k(f=f_N,k=1)
mu.1_N=sqrt(2/pi)
mu.2_N=1
mu.3_N=2*sqrt(2/pi)
mu.4_N=4
meanQBAD(mu=0,phi=1,alpha=0.5,mu_1=mu.1_N)
varQBAD(mu=0,phi=1,alpha=0.5,mu_1=mu.1_N,mu_2=mu.2_N)
skewQBAD(alpha=0.5,mu_1=mu.1_N,mu_2=mu.2_N,mu_3=mu.3_N)
kurtQBAD(alpha=0.5,mu_1=mu.1_N,mu_2=mu.2_N,mu_3=mu.3_N,mu_4=mu.4_N)
momentQBAD(phi=1,alpha=0.5,f=f_N,r=1)
```

```
# Example 2: Let F be a standard Laplace cumulative distribution function then
f_La<-function(s){0.5*exp(-abs(s))} # density function of Laplace(0,1)
mu_k(f=f_La,k=1)
```
momQBAD

\[ \gamma_k(f=f_{La}, k=1) \]
\[ \mu_{1,La}=1 \]
\[ \mu_{2,La}=2 \]
\[ \mu_{3,La}=6 \]
\[ \mu_{4,La}=24 \]
\[ \text{meanQBAD}(\mu=0, \phi=1, \alpha=0.5, \mu_1=\mu_{1,La}) \]
\[ \text{varQBAD}(\mu=0, \phi=1, \alpha=0.5, \mu_1=\mu_{1,La}, \mu_2=\mu_{2,La}) \]
\[ \text{skewQBAD}(\alpha=0.5, \mu_1=\mu_{1,La}, \mu_2=\mu_{2,La}, \mu_3=\mu_{3,La}) \]
\[ \text{kurtQBAD}(\alpha=0.5, \mu_1=\mu_{1,La}, \mu_2=\mu_{2,La}, \mu_3=\mu_{3,La}, \mu_4=\mu_{4,La}) \]
\[ \text{momentQBAD}(\phi=1, \alpha=0.5, f=f_{La}, r=1) \]

---

momQBAD

Method of moments (MoM) estimation for the quantile-based asymmetric family of distributions.

Description

Parameter estimation in the quantile-based asymmetric family of densities by using method of moments are discussed in Section 3.1 of Gijbels et al. (2019a).

Usage

\[ \text{momQBAD}(y, f, \alpha = \text{NULL}) \]

Arguments

- **y** This is a vector of quantiles.
- **f** This is the reference density function \( f \) which is a standard version of a unimodal and symmetric around 0 density.
- **alpha** This is the index parameter \( \alpha \). If \( \alpha \) is unknown, indicate NULL which is default option. In this case, the sample skewness will be used to estimate \( \alpha \). If \( \alpha \) is known, then the value of \( \alpha \) has to be specified in the function.

Value

momQBAD provides the method of moments estimates of the unknown parameters of the distribution.

References

Examples

# Example 1: Let $F$ be a standard normal cumulative distribution function then
f_N<-function(s){dnorm(s, mean = 0, sd = 1)} # density function of $N(0,1)$
y=rnorm(100)
momQBAD(y=y,f=f_N,alpha=0.5) # If alpha is known with alpha=0.5
momQBAD(y=y,f=f_N) # If alpha is unknown

# Example 2: Let $F$ be a standard Laplace cumulative distribution function then
f_La<-function(s){0.5*exp(-abs(s))} # density function of $Laplace(0,1)$
momQBAD(y=y,f=f_La,alpha=0.5) # If alpha is known with alpha=0.5
momQBAD(y=y,f=f_La) # If alpha is unknown

NLRTest

Nonparametric likelihood ratio test to test for symmetry.

Description

The nonparametric likelihood ratio test to test for symmetry is discussed in Gijbels et al. (2019d).

Usage

NLRTest(y, f = NULL, F = NULL, QF = NULL, method = c("smooth", "parametric"), nboot = 500)

Arguments

y
This is a vector of quantiles.
f
This is the reference density function $f$ which is a standard version of a unimodal and symmetric around 0 density.
F
This is the cumulative distribution function $F$ of a unimodal and symmetric around 0 reference density function $f$.
QF
This is the quantile function of the reference density $f$.
method
The method to be used for drawing bootstrap samples. The default method is a smooth bootstrap procedure. The density function $f$, the cumulative distribution function $F$ and the quantile function $QF$ are required for parametric bootstrap procedure. If $QF$ is not given, then the numerical $QF$ will be used.
nboot
The number of bootstrap samples desired. The default number is 500.

Value

The nonparametric likelihood ratio test statistic with bootstrap $P$-value.

References

Examples

# Example 1: Let F be a standard normal cumulative distribution function then
f_N<-function(s){dnorm(s, mean = 0, sd = 1)} # density function of N(0,1)
F_N<-function(s){pnorm(s, mean = 0, sd = 1)} # distribution function of N(0,1)
QF_N<-function(beta){qnorm(beta, mean = 0, sd = 1, lower.tail = TRUE, log.p = FALSE)}

# Example: STRength dataset
my.sample<-c(1.901,2.132,2.203,2.228,2.257,2.350,2.361,2.396,2.397, 
2.445,2.454,2.474,2.518,2.522,2.525,2.532,2.575,2.614,2.616, 
2.618,2.624,2.659,2.675,2.738,2.740,2.856,2.917,2.928,2.937, 
2.937,2.977,2.996,3.030,3.125,3.139,3.145,3.220,3.223,3.235, 
4.027,4.225,4.395,5.020)

NLRTest(my.sample,f=NULL,F=NULL,QF=NULL,method=c("smooth"),nboot=500)
NLRTest(my.sample,f=f_N,F=F_N,QF=QF_N,method=c("parametric"),nboot=500)
NLRTest(my.sample,f=f_N,F=F_N,QF=NULL,method=c("parametric"),nboot=500)

QBAD

Quantile-based asymmetric family of distributions

Description

Density, cumulative distribution function, quantile function and random sample generation from the quantile-based asymmetric family of densities defined in Gijbels et al. (2019a).

Usage

dQBAD(y, mu, phi, alpha, f)
pQBAD(q, mu, phi, alpha, F)
qQBAD(beta, mu, phi, alpha, F, QF = NULL)
rQBAD(n, mu, phi, alpha, F, QF = NULL)

Arguments

y, q
These are each a vector of quantiles.
mu
This is the location parameter \( \mu \).
phi
This is the scale parameter \( \phi \).
alpha
This is the index parameter \( \alpha \).
f
This is the reference density function \( f \) which is a standard version of a unimodal and symmetric around 0 density.
This is the cumulative distribution function $F$ of a unimodal and symmetric around 0 reference density function $f$.

This is a vector of probabilities.

This is the quantile function of the reference density $f$.

This is the number of observations, which must be a positive integer that has length 1.

**Value**

$dQBAD$ provides the density, $pQBAD$ provides the cumulative distribution function, $qQBAD$ provides the quantile function, and $rQBAD$ generates a random sample from the quantile-based asymmetric family of distributions. The length of the result is determined by $n$ for $rQBAD$, and is the maximum of the lengths of the numerical arguments for the other functions.

**References**


**Examples**

```r
# Example 1: Let F be a standard normal cumulative distribution function then
f_N <- function(s) {dnorm(s, mean = 0, sd = 1)}  # density function of N(0,1)
F_N <- function(s) {pnorm(s, mean = 0, sd = 1)}  # distribution function of N(0,1)
QF_N <- function(beta) {qnorm(beta, mean = 0, sd = 1, lower.tail = TRUE, log.p = FALSE)}
rnum <- rnorm(100)
beta <- c(0.25, 0.50, 0.75)

# Density
dQBAD(y = rnum, mu = 0, phi = 1, alpha = .5, f = f_N)

# Distribution function
pQBAD(q = rnum, mu = 0, phi = 1, alpha = .5, F = F_N)

# Quantile function
qQBAD(beta = beta, mu = 0, phi = 1, alpha = .5, F = F_N, QF = QF_N)

# random sample generation
rQBAD(n = 100, mu = 0, phi = 1, alpha = .5, F = F_N, QF = QF_N)

# Example 2: Let F be a standard Laplace cumulative distribution function then
f_La <- function(s) {0.5*exp(-abs(s))}  # density function of Laplace(0,1)
F_La <- function(s) {0.5 + 0.5*sign(s)*(1-exp(-abs(s)))}  # distribution function of Laplace(0,1)
QF_La <- function(beta) {-sign(beta - 0.5)*log(1-2*abs(beta - 0.5))}
rnum <- rnorm(100)
beta <- c(0.25, 0.50, 0.75)
```

```r
# Density
dQBAD(y = rnum, mu = 0, phi = 1, alpha = .5, f = f_La)

# Distribution function
pQBAD(q = rnum, mu = 0, phi = 1, alpha = .5, F = F_La)

# Quantile function
qQBAD(beta = beta, mu = 0, phi = 1, alpha = .5, F = F_La, QF = QF_La)

# random sample generation
rQBAD(n = 100, mu = 0, phi = 1, alpha = .5, F = F_La, QF = QF_La)
```
# Density
dQBAD(y=rnum, mu=0, phi=1, alpha=.5, F=F_La)

# Distribution function
pQBAD(q=rnum, mu=0, phi=1, alpha=.5, F=F_La)

# Quantile function
qQBAD(beta=c(0.25, 0.50, 0.75), mu=0, phi=1, alpha=.5, F=F_La, QF=QF_La)
qQBAD(beta=c(0.25, 0.50, 0.75), mu=0, phi=1, alpha=.5, F=F_La)

# random sample generation
rQBAD(n=100, mu=0, phi=1, alpha=.5, F=F_La, QF=QF_La)
rQBAD(n=100, mu=0, phi=1, alpha=.5, F=F_La)

---

**SemiQRegALaD**

*Semiparametric quantile regression in quantile-based asymmetric Laplace distributional settings.*

**Description**

The local polynomial technique is used to estimate location and scale function of the quantile-based asymmetric Laplace distribution discussed in Gijbels et al. (2019c). The semiparametric quantile estimation technique is used to estimate $\beta$th conditional quantile function in quantile-based asymmetric Laplace distributional setting discussed in Gijbels et al. (2019b) and Gijbels et al. (2019c).

**Usage**

```r
locpolALaD_x0(x, y, p1 = 1, p2 = 1, h, alpha = 0.5, x0, tol = 1e-08)

locpolALaD(x, y, p1 = 1, p2 = 1, h, alpha = 0.5, m = 101)

SemiQRegALaD(beta, x, y, p1 = 1, p2 = 1, h, alpha = NULL, m = 101)
```

**Arguments**

- **x**: This a conditioning covariate.
- **y**: The is a response variable.
- **p1**: This is the order of the Taylor expansion for the location function (i.e., $\mu(X)$) in local polynomial fitting technique. The default value is 1.
- **p2**: This is the order of the Taylor expansion for the log of scale function (i.e., $\ln[\phi(X)]$) in local polynomial fitting technique. The default value is 1.
- **h**: This is the bandwidth parameter $h$. 
alpha This is the index parameter $\alpha$ of the quantile-based asymmetric Laplace density. The default value is 0.5 in the code `locpolALaD_x0` and code `locpolALaD`. The default value of $\alpha$ is NULL in the code `SemiQRegALaD`. In this case, the $\alpha$ will be estimated based on the residuals of local linear mean regression.

$x_0$ This is a grid-point $x_0$ at which the function is to be estimated.

tol the desired accuracy. See details in `optimize`.

$m$ This is the number of grid points at which the functions are to be evaluated. The default value is 101.

beta This is a specific probability for estimating $\beta$th quantile function.

Value

The code `locpolALaD_x0` provides the realized value of the local maximum likelihood estimator of $\tilde{\theta}_{rj}(x_0)$ for $(r \in \{1, 2\}; j = 1, 2, ..., p_r)$ with the estimated approximate asymptotic bias and variance at the grind point $x_0$ discussed in Gijbels et al. (2019c).

The code `locpolALaD` provides the realized value of the local maximum likelihood estimator of $\tilde{\theta}_{r0}(x_0)$ for $(r \in \{1, 2\})$ with the estimated approximate asymptotic bias and variance at all $m$ grind points $x_0$ discussed in Gijbels et al. (2019c).

The code `SemiQRegALaD` provides the realized value of the $\beta$th conditional quantile estimator by using semiparametric quantile regression technique discussed in Gijbels et al. (2019b) and Gijbels et al. (2019c).

References


Examples

data(Hurricane)
locpolALaD_x0(Hurricane$Year, Hurricane$WmaxST, p1=1, p2=1, h=2.18, alpha=0.16, x0=median(Hurricane$Year))

data(Hurricane)
locpolALaD(Hurricane$Year, Hurricane$WmaxST, p1=1, p2=1, h=2.18, alpha=0.16)

## For Hurricane Data
data(Hurricane)
Hurricane<-Hurricane[which(Hurricane$Year>1970),]

plot(Hurricane$Year, Hurricane$WmaxST)
SemiQRegALaD

h=2.181082
alpha=0.1649765
gridPoints=101

fit_ALaD <- locpolALaD(Hurricane$Year, Hurricane$WmaxST, p1=1,p2=1,h=h, alpha=alpha, m = gridPoints)
str(fit_ALaD)

par(mgp=c(2,4,0),mar=c(5,4,4,1)+0.01)

# For phi plot
plot(fit_ALaD$x0,exp(fit_ALaD$theta_20),ylab=expression(widehat(phi)(x[0])),xlab="Year",
type="l",font.lab=2,cex.lab=1.5,bty="l",cex.axis=1.5,lwd =3)
## For theta2 plot
plot(fit_ALaD$x0,fit_ALaD$theta_20,ylab=expression(bold(widehat(theta[2]))(x[0])),
xlab="Year",type="l",col=c(1), lty=1, font.lab=1,cex.lab=1.5,bty="l",cex.axis=1.3,lwd =3)

#### Estimated Quantile lines by ALaD
par(mgp=c(2.5, 1, 0),mar=c(5,4,4,1)+0.01)
# X11()

plot(Hurricane$Year, Hurricane$WmaxST, xlab = "Year",ylim=c(20,210),
ylab = "Maximum Wind Speed",font.lab=1,cex.lab=1.3,bty="l",pch=20,cex.axis=1.3)
lines(fit_ALaD$x0,fit_ALaD$theta_10, type=quotesingle.Var
col=c(4),lty=1,lwd =3)
lines(fit_ALaD$x0,SemiQRegALaD(beta=0.50,Hurricane$Year, Hurricane$WmaxST,
p1=1,p2=1, h=h, alpha=alpha, m=gridPoints)$fit_beta_ALaD,type=quotesingle.Var
col=c(1),lty=1,lwd =3)
lines(fit_ALaD$x0,SemiQRegALaD(beta=0.90,Hurricane$Year, Hurricane$WmaxST,
p1=1,p2=1, h=h, alpha=alpha, m=gridPoints)$fit_beta_ALaD,type=quotesingle.Var
col=c(14),lty=1,lwd =3)
lines(fit_ALaD$x0,SemiQRegALaD(beta=0.95,Hurricane$Year, Hurricane$WmaxST,
p1=1,p2=1, h=h, alpha=alpha, m=gridPoints)$fit_beta_ALaD,type=quotesingle.Var
col=c(19),lty=1,lwd =3)

# Add local linear mean regression line
library(locpol)

fit_mean<-locpol(WmaxST~Year, data=Hurricane,kernel=gaussK,deg=1,
xeval=NULL,xevalLen=101)

lines(fit_mean$lpFit[,1], fit_mean$lpFit[,2],type='l',col=c(2),lty=1,lwd =3)

axis(2, at = c(25, 75, 125,175),cex.axis=1.3)

legend("topright", legend = c(expression(beta==0.1650), expression(beta==0.50),
"Mean line",expression(beta==0.90), expression(beta==0.95)), col = c(4,1,2,14,19),
lty=c(1,1,1,1,1), inset = 0, lwd = 3,cex=1.2)
SemiQRegAND

Semiparametric quantile regression in quantile-based asymmetric normal distributional settings.

Description

The local polynomial technique is used to estimate location and scale function of the quantile-based asymmetric normal distribution discussed in Gijbels et al. (2019c). The semiparametric quantile estimation technique is used to estimate $\beta$th conditional quantile function in quantile-based asymmetric normal distributional setting discussed in Gijbels et al. (2019b) and Gijbels et al. (2019c).

Usage

locpolAND_x0(x, y, p1 = 1, p2 = 1, h, alpha = 0.5, x0, tol = 1e-08)
locpolAND(x, y, p1, p2, h, alpha, m = 101)
SemiQRegAND(beta, x, y, p1 = 1, p2 = 1, h, alpha = NULL, m = 101)

Arguments

x This a conditioning covariate.
y The is a response variable.
p1 This is the order of the Taylor expansion for the location function (i.e., $\mu(X)$) in local polynomial fitting technique. The default value is 1.
p2 This is the order of the Taylor expansion for the log of scale function (i.e., $\ln[\phi(X)]$) in local polynomial fitting technique. The default value is 1.
h This is the bandwidth parameter $h$.
alpha This is the index parameter $\alpha$ of the quantile-based asymmetric normal density. The default value is 0.5 in the codes code locpolAND_x0 and code locpolAND. The default value of $\alpha$ is NULL in the code SemiQRegAND. In this case, $\alpha$ will be estimated based on the residuals from local linear mean regression.
x0 This is a grid-point $x_0$ at which the function is to be estimated.
tol the desired accuracy. See details in optimize.
m This is the number of grid points at which the functions are to be evaluated. The default value is 101.
beta This is a specific probability for estimating $\beta$th quantile function.

Value

The code locpolAND_x0 provides the realized value of the local maximum likelihood estimator of $\hat{\theta}_{rj}(x_0)$ for $(r \in \{1,2\}; j = 1,2,\ldots,p_r)$ with the estimated approximate asymptotic bias and variance at the grind point $x_0$ discussed in Gijbels et al. (2019c).
The code `locpolAND` provides the realized value of the local maximum likelihood estimator of $\hat{\theta}_r(x_0)$ for $r \in \{1, 2\}$ with the estimated approximate asymptotic bias and variance at all $m$ grind points $x_0$ discussed in Gijbels et al. (2019c).

The code `SemiQRegAND` provides the realized value of the $\beta$th conditional quantile estimator by using semiparametric quantile regression technique discussed in Gijbels et al. (2019b) and Gijbels et al. (2019c).

References


Examples

```r
data(LocomotorPerfor)
x=log(LocomotorPerfor$Body_Mass)
y=log(LocomotorPerfor$MRRS)
h_ROT = 0.9030372
locpolAND_x0(x, y, p1=1, p2=1, h=h_ROT, alpha=0.50, x0=median(x))

data(LocomotorPerfor)
x=log(LocomotorPerfor$Body_Mass)
y=log(LocomotorPerfor$MRRS)
h_ROT = 0.9030372
locpolAND(x, y, p1=1, p2=1, h=h_ROT, alpha=0.50)

# Data
data(LocomotorPerfor)
x=log(LocomotorPerfor$Body_Mass)
y=log(LocomotorPerfor$MRRS)
h_ROT = 0.9030372
gridPoints=101
alpha=0.5937
plot(x,y)
# location and scale functions estimation at the grid point x0
gridPoints=101
fit_AND <- locpolAND(x, y, p1=1, p2=1, h=h_ROT, alpha=alpha, m = gridPoints)
par(mgp=c(2,.4,0),mar=c(5,4,4,1)+0.01)
# For phi plot
plot(fit_AND$x0,exp(fit_AND$theta_20),ylab=expression(widehat(phi)(x[0])),
xlab="log(Body mass)",type="l",font.lab=2,cex.lab=1.5,
bty="l",cex.axis=1.5,lwd =3)
```
For theta2 plot
plot(fit_AND$x0,fit_AND$theta_20,ylab=expression(bold(widehat(theta[2]))(x[0]))),
xlab="log(Body mass)",type="l",col=c(1), lty=1, font.lab=1, cex.lab=1.5,
bty="l",cex.axis=1.3,lwd =3)

par(mgp=c(2.5, 1, 0),mar=c(5,4,4,1)+0.01)
# X11(width=7, height=7)
plot(x,y, ylim=c(0,4.5),xlab = "log(Body mass (kg))",
ylab = "log(Maximum relative running speed)",font.lab=1.5,
cex.lab=1.5,bty="l",pch=20,cex.axis=1.5)
lines(fit_AND$x0,fit_AND$theta_10, type='1',col=c(4),lty=6,lwd =3)
lines(fit_AND$x0,SemiQRegAND(beta=0.50,x, y,
p1=1,p2=1, h=h_ROT,alpha=alpha,m=gridPoints)$fit_beta_AND,
type='1',col=c(1),lty=5,lwd =3)
lines(fit_AND$x0,SemiQRegAND(beta=0.10,x, y,
p1=1,p2=1, h=h_ROT,alpha=alpha,m=gridPoints)$fit_beta_AND,type='1',col=c(19),lty=2,lwd =3)
legend("topright", legend = c(expression(beta==0.10),
expression(beta==0.50), expression(beta==0.5937),
expression(beta==0.90)), col = c(19,1,4,14), lty=c(2,5,6,4),
adj = c(.07, 0.5),, inset = c(0.05, +0.01), lwd = 3,cex=1.2)

SemiQRegGALaD

SemiQRegGALaD
Semiparametric quantile regression in generalized Laplace distributional settings.

Description

The local polynomial technique is used to estimate location and scale functions of the quantile-based asymmetric Laplace distribution as discussed in Gijbels et al. (2019c). Using these estimates, the quantile function of the generalized asymmetric Laplace distribution will be estimated. A detailed study can be found in Gijbels et al. (2019b).

Usage

SemiQRegGALaD(beta, x, y, p1 = 1, p2 = 1, h, alpha = NULL, g,
lower = -Inf, upper = Inf, m = 101)

Arguments

beta This is a specific probability for estimating $\beta$th quantile function.
This is a conditioning covariate.

The is a response variable.

This is the order of the Taylor expansion for the location function \( i.e., \mu(X) \) in local polynomial fitting technique. The default value is 1.

This is the order of the Taylor expansion for the log of scale function \( i.e., \ln[\phi(X)] \) in local polynomial fitting technique. The default value is 1.

This is the bandwidth parameter \( h \).

This is the index parameter \( \alpha \) of the generalized asymmetric Laplace density. The default value of \( \alpha \) is NULL in the code \texttt{SemiQRegGALaD}. In this case, the \( \alpha \) will be estimated based on the residuals form local linear mean regression.

This is the "link" function. The function \( g \) is to be differentiated. Therefore, \( g \) must be written as a function. For example, \( g<-\text{function}(y)\{\log(y)\} \) for log link function.

This is the lower limit of the domain (support of the random variable) \( f_\alpha^g(y; \eta, \phi) \), default \(-\text{Inf}\).

This is the upper limit of the domain (support of the random variable) \( f_\alpha^g(y; \eta, \phi) \), default \( \text{Inf} \).

This is the number of grid points at which the functions are to be evaluated. The default value is 101.

The code \texttt{SemiQRegGALaD} provides the realized value of the \( \beta \)th conditional quantile estimator by using semiparametric quantile regression technique discussed in Gijbels et al. (2019b) and Gijbels et al. (2019c).

**References**


**Examples**

data(LocomotorPerfor)
x=log(LocomotorPerfor$Body_Mass)
y=LocomotorPerfor$MRRS

# For log-link function
g_log<-\text{function}(y)\{\log(y)\}
h_ROT = \ 0.9030372
fit<-\text{SemiQRegGALaD}(beta=0.90, x, y, p1=1, p2=1, h=h_ROT, g=g_log, lower=0)
SemiQRegGAND

plot(x, y)
lines(fit$x0, fit$qf_g)

SemiQRegGAND

Semiparametric quantile regression in generalized normal distributional settings.

Description

The local polynomial technique is used to estimate location and scale function of the quantile-based asymmetric normal distribution discussed in Gijbels et al. (2019b) and Gijbels et al. (2019c). Using these estimates, the quantile function of the generalized asymmetric normal distribution will be estimated. A detailed study can be found in Gijbels et al. (2019b).

Usage

SemiQRegGAND(beta, x, y, p1 = 1, p2 = 1, h, alpha = NULL, g, lower = -Inf, upper = Inf, m = 101)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>beta</td>
<td>This is a specific probability for estimating $\beta$th quantile function.</td>
</tr>
<tr>
<td>x</td>
<td>This is a conditioning covariate.</td>
</tr>
<tr>
<td>y</td>
<td>The is a response variable.</td>
</tr>
<tr>
<td>p1</td>
<td>This is the order of the Taylor expansion for the location function (i.e., $\mu(X)$) in local polynomial fitting technique. The default value is 1.</td>
</tr>
<tr>
<td>p2</td>
<td>This is the order of the Taylor expansion for the log of scale function (i.e., $\ln[\phi(X)]$) in local polynomial fitting technique. The default value is 1.</td>
</tr>
<tr>
<td>h</td>
<td>This is the bandwidth parameter $h$.</td>
</tr>
<tr>
<td>alpha</td>
<td>This is the index parameter $\alpha$ of the generalized asymmetric normal density. The default value of $\alpha$ is NULL in the code SemiQRegGAND. In this case, the $\alpha$ will be estimated based on the residuals from local linear mean regression.</td>
</tr>
<tr>
<td>g</td>
<td>This is the &quot;link&quot; function. The function $g$ is to be differentiated. Therefore, $g$ must be written as a function. For example, $g&lt;-function(y){log(y)}$ for log link function.</td>
</tr>
<tr>
<td>lower</td>
<td>This is the lower limit of the domain (support of the random variable) $f_{\alpha}(y; \eta, \phi)$, default -Inf.</td>
</tr>
<tr>
<td>upper</td>
<td>This is the upper limit of the domain (support of the random variable) $f_{\alpha}(y; \eta, \phi)$, default Inf.</td>
</tr>
<tr>
<td>m</td>
<td>This is the number of grid points at which the functions are to be evaluated. The default value is 101.</td>
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The code \texttt{SemiQRegGAND} provides the realized value of the $\beta$th conditional quantile estimator by using semiparametric quantile regression technique discussed in Gijbels et al. (2019b) and Gijbels et al. (2019c).

\textbf{References}


\textbf{Examples}

```r
data(LocomotorPerfor)
x=log(LocomotorPerfor$Body_Mass)
y=LocomotorPerfor$MRRS

# For log-link function
g_log<-function(y){log(y)}
h_ROT = 0.9030372
fit<-SemiQRegGAND(beta=0.5,x,y,p1=1,p2=1,h=h_ROT,g=g_log,lower=0)
plot(x,y)
lines(fit$x0,fit$qf_g)
```
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