

# Package: double.truncation (via r-universe)

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**Type** Package

**Title** Analysis of Doubly-Truncated Data

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**Description** Likelihood-based inference methods with doubly-truncated data are developed under various models. Nonparametric models are based on Efron and Petrosian (1999) <doi:10.1080/01621459.1999.10474187> and Emura, Konno, and Michimae (2015) <doi:10.1007/s10985-014-9297-5>. Parametric models from the special exponential family (SEF) are based on Hu and Emura (2015) <doi:10.1007/s00180-015-0564-z> and Emura, Hu and Konno (2017) <doi:10.1007/s00362-015-0730-y>. The parametric location-scale models are based on Dorre et al. (2021) <doi:10.1007/s00180-020-01027-6>.

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double.truncation-package

*Analysis of Doubly-Truncated Data*

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## Description

Likelihood-based inference methods with doubly-truncated data are developed under various models. Nonparametric models are based on Efron and Petrosian (1999) <doi:10.1080/01621459.1999.10474187> and Emura, Konno, and Michimae (2015) <doi:10.1007/s10985-014-9297-5>. Parametric models from the special exponential family (SEF) are based on Hu and Emura (2015) <doi:10.1007/s00180-015-0564-z> and Emura, Hu and Konno (2017) <doi:10.1007/s00362-015-0730-y>. The parametric location-scale models are based on Dorre et al. (2021) <doi:10.1007/s00180-020-01027-6>.

## Details

Details are seen from the references.

## Author(s)

Takeshi Emura, Ya-Hsuan Hu, Chung-Yan Huang Maintainer: Takeshi Emura <takeshiemura@gmail.com>

## References

- Dorre A, Emura T (2019) Analysis of Doubly Truncated Data, An Introduction, JSS Research Series in Statistics, Springer
- Dorre A, Huang CY, Tseng YK, Emura T (2021) Likelihood-based analysis of doubly-truncated data under the location-scale and AFT model, *Computation Stat* 36(1): 375-408
- Efron B, Petrosian V (1999). Nonparametric methods for doubly truncated data. *J Am Stat Assoc* 94: 824-834
- Emura T, Konno Y, Michimae H (2015). Statistical inference based on the nonparametric maximum likelihood estimator under double-truncation. *Lifetime Data Analysis* 21: 397-418

Emura T, Hu YH, Konno Y (2017) Asymptotic inference for maximum likelihood estimators under the special exponential family with double-truncation, Stat Pap 58 (3): 877-909

Hu YH, Emura T (2015) Maximum likelihood estimation for a special exponential family under random double-truncation, Computation Stat 30 (4): 1199-229

GoF

*Goodness-of-fit test based on the CvM and KS statistics***Description**

Goodness-of-fit test statistics are computed based on the Cramér–von Mises (CvM) and Kolmogorov–Smirnov (KS) test statistics proposed in Emura et al. (2015). P-value and critical values with significance levels of 0.01, 0.05 and 0.10 are also computed.

**Usage**

```
GoF(u.trunc, y.trunc, v.trunc, epsilon=1e-08, F0, B=500, F.plot = TRUE)
```

**Arguments**

u.trunc	lower truncation limit
y.trunc	variable of interest
v.trunc	upper truncation limit
epsilon	error tolerance for the self-consistency algorithm
F0	a function for the null distribution function
B	the number of bootstrap resamples (B=500 is the default)
F.plot	model diagnostic plot

**Details**

Details are seen from Emura et al.(2015).

**Value**

CvM	Test statistics, P-value, and critical values for the Cramér–von Mises (CvM) test
KS	Test statistics, P-value, and critical values for the Kolmogorov–Smirnov (KS) test

**Author(s)**

Takeshi Emura

**References**

Emura T, Konno Y, Michimae H (2015). Statistical inference based on the nonparametric maximum likelihood estimator under double-truncation. Lifetime Data Analysis 21: 397-418

**Examples**

```
## A data example from Efron and Petrosian (1999) ##
y.trunc=c(0.75, 1.25, 1.50, 1.05, 2.40, 2.50, 2.25)
u.trunc=c(0.4, 0.8, 0.0, 0.3, 1.1, 2.3, 1.3)
v.trunc=c(2.0, 1.8, 2.3, 1.4, 3.0, 3.4, 2.6)
F0=function(x){x/3}
GoF(u.trunc,y.trunc,v.trunc,F0=F0)
```

---

NPMLE

*Nonparametric inference based on the self-consistency method*


---

**Description**

Nonparametric maximum likelihood estimates are computed based on the self-consistency method (Efron and Petrosian 1999). The SE is computed from the asymptotic variance derived in Emura et al. (2015).

**Usage**

```
NPMLE(u.trunc, y.trunc, v.trunc,epsilon=1e-08,detail=FALSE)
```

**Arguments**

u.trunc	lower truncation limit
y.trunc	variable of interest
v.trunc	upper truncation limit
epsilon	error tolerance for the self-consistency algorithm
detail	if TRUE, show the details including the covariate matrix

**Details**

Details are seen from the references.

**Value**

f	density
F	cumulative distribution
SE	standard error
convergence	Log-likelihood, and the number of iterations
V	covariance matrix for the NPMLE

**Author(s)**

Takeshi Emura

## References

- Efron B, Petrosian V (1999). Nonparametric methods for doubly truncated data. *J Am Stat Assoc* 94: 824-834
- Emura T, Konno Y, Michimae H (2015). Statistical inference based on the nonparametric maximum likelihood estimator under double-truncation. *Lifetime Data Analysis* 21: 397-418
- Dorre A, Emura T (2019) *Analysis of Doubly Truncated Data, An Introduction*, JSS Research Series in Statistics, Springer

## Examples

```
## A data example from Efron and Petrosian (1999) ##
y.trunc=c(0.75, 1.25, 1.50, 1.05, 2.40, 2.50, 2.25)
u.trunc=c(0.4, 0.8, 0.0, 0.3, 1.1, 2.3, 1.3)
v.trunc=c(2.0, 1.8, 2.3, 1.4, 3.0, 3.4, 2.6)
NPMLE(u.trunc,y.trunc,v.trunc)
NPMLE(u.trunc,y.trunc,v.trunc,detail=TRUE)
```

---

PMLE.loglogistic

*Parametric Inference for the log-logistic model*

---

## Description

Maximum likelihood estimates (MLEs) and their standard errors (SEs) are computed for the log-logistic model based on doubly-truncated data (Dorre et al. 2021). Also computed are the likelihood value, AIC, and other quantities.

## Usage

```
PMLE.loglogistic(u.trunc, y.trunc, v.trunc, epsilon = 1e-5, D1=2, D2=2, d1=2, d2=2)
```

## Arguments

- |         |  |
|---------|--|
| u.trunc | a vector of lower truncation limits  |
| y.trunc | a vector of variables of interest  |
| v.trunc | a vector of upper truncation limits  |
| epsilon | a small positive number for the error tolerance for Newton-Raphson iterations  |
| D1      | a positive number: Randomize the initial value for a divergent iteration (the updated amount for mu is greater than D1)    |
| D2      | a positive number: Randomize the initial value for a divergent iteration (the updated amount for sigma is greater than D2) |
| d1      | a positive number: For a divergent iteration, U(-d1,d1) is added to the initial value of mu                                |
| d2      | a positive number: For a divergent iteration, U(-d2,d2) is added to the initial value of log(sigma)                        |

**Details**

A randomized Newton–Raphson algorithm (Section 3.2 of Dorre et al.(2021)) was employed to compute the MLE.

**Value**

eta	estimates
SE	standard errors
convergence	Log-likelihood, degree of freedom, AIC, the number of iterations
Score	score vector at the converged value
Hessian	Hessian matrix at the converged value

**Author(s)**

Takeshi Emura

**References**

Dorre A, Huang CY, Tseng YK, Emura T (2021) Likelihood-based analysis of doubly-truncated data under the location-scale and AFT model, *Computation Stat* 36(1): 375-408

**Examples**

```
## A data example from Efron and Petrosian (1999) ##
y.trunc=c(0.75, 1.25, 1.50, 1.05, 2.40, 2.50, 2.25)
u.trunc=c(0.4, 0.8, 0.0, 0.3, 1.1, 2.3, 1.3)
v.trunc=c(2.0, 1.8, 2.3, 1.4, 3.0, 3.4, 2.6)
PMLE.loglogistic(u.trunc,y.trunc,v.trunc)
```

---

PMLE.lognormal

*Parametric Inference for the lognormal model*

---

**Description**

Maximum likelihood estimates (MLEs) and their standard errors (SEs) are computed for the log-normal model based on doubly-truncated data (Dorre et al. 2021). Also computed are the likelihood value, AIC, and other quantities.

**Usage**

```
PMLE.lognormal(u.trunc, y.trunc, v.trunc,epsilon = 1e-5,D1=2,D2=2,d1=2,d2=2)
```

**Arguments**

u.trunc	a vector of lower truncation limits
y.trunc	a vector of variables of interest
v.trunc	a vector of upper truncation limits
epsilon	a small positive number for the error tolerance for Newton-Raphson iterations
D1	a positive number: Randomize the initial value for a divergent iteration (the updated amount for mu is greater than D1)
D2	a positive number: Randomize the initial value for a divergent iteration (the updated amount for sigma is greater than D2)
d1	a positive number: For a divergent iteration, $U(-d1,d1)$ is added to the initial value of mu
d2	a positive number: For a divergent iteration, $U(-d2,d2)$ is added to the initial value of $\log(\text{sigma})$

**Details**

A randomized Newton–Raphson algorithm (Section 3.2 of Dorre et al.(2021)) was employed to compute the MLE.

**Value**

eta	estimates
SE	standard errors
convergence	Log-likelihood, degree of freedom, AIC, the number of iterations
Score	score vector at the converged value
Hessian	Hessian matrix at the converged value

**Author(s)**

Takeshi Emura

**References**

Dorre A, Huang CY, Tseng YK, Emura T (2021) Likelihood-based analysis of doubly-truncated data under the location-scale and AFT model, *Computation Stat* 36(1): 375-408

**Examples**

```
## A data example from Efron and Petrosian (1999) ##
y.trunc=c(0.75, 1.25, 1.50, 1.05, 2.40, 2.50, 2.25)
u.trunc=c(0.4, 0.8, 0.0, 0.3, 1.1, 2.3, 1.3)
v.trunc=c(2.0, 1.8, 2.3, 1.4, 3.0, 3.4, 2.6)
PMLE.lognormal(u.trunc,y.trunc,v.trunc)
```

---

PMLE.SEF1.free	<i>Parametric inference for the one-parameter SEF model (free parameter space)</i>
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---

### Description

Maximum likelihood estimates and their standard errors (SEs) are computed. Also computed are the likelihood value, AIC, and other quantities.

### Usage

```
PMLE.SEF1.free(u.trunc, y.trunc, v.trunc,
  tau1 = min(y.trunc), tau2 = max(y.trunc), epsilon = 1e-04)
```

### Arguments

u.trunc	lower truncation limit
y.trunc	variable of interest
v.trunc	upper truncation limit
tau1	lower support
tau2	upper support
epsilon	error tolerance for Newton-Raphson

### Details

Details are seen from the references.

### Value

eta	estimates
SE	standard errors
convergence	Log-likelihood, degree of freedom, AIC, the number of iterations
Score	score at the converged value
Hessian	Hessian at the converged value

### Author(s)

Takeshi Emura

### References

Hu YH, Emura T (2015) Maximum likelihood estimation for a special exponential family under random double-truncation, *Computation Stat* 30 (4): 1199-229

Emura T, Hu YH, Konno Y (2017) Asymptotic inference for maximum likelihood estimators under the special exponential family with double-truncation, *Stat Pap* 58 (3): 877-909

Dorre A, Emura T (2019) *Analysis of Doubly Truncated Data, An Introduction*, JSS Research Series in Statistics, Springer

**Examples**

```

### Data generation: see Appendix of Hu and Emura (2015) ###
eta_true=-3
eta_u=-9
eta_v=-1
tau=10
n=300

a=u=v=y=c()

j=1
repeat{
  u1=runif(1,0,1)
  u[j]=tau+(1/eta_u)*log(1-u1)
  u2=runif(1,0,1)
  v[j]=tau+(1/eta_v)*log(1-u2)
  u3=runif(1,0,1)
  y[j]=tau+(1/eta_true)*log(1-u3)
  if(u[j]<=y[j]&&y[j]<=v[j]) a[j]=1 else a[j]=0
  if(sum(a)==n) break
  j=j+1
}
mean(a) ## inclusion probability around 0.5

v.trunc=v[a==1]
u.trunc=u[a==1]
y.trunc=y[a==1]

PMLE.SEF1.free(u.trunc,y.trunc,v.trunc)

```

---

PMLE.SEF1.negative      *Parametric inference for the one-parameter SEF model (negative parameter space)*

---

**Description**

Maximum likelihood estimates and their standard errors (SEs) are computed. Also computed are the likelihood value, AIC, and other quantities.

**Usage**

```
PMLE.SEF1.negative(u.trunc, y.trunc, v.trunc, tau1 = min(y.trunc), epsilon = 1e-04)
```

**Arguments**

u.trunc	lower truncation limit
y.trunc	variable of interest
v.trunc	upper truncation limit
tau1	lower support
epsilon	error tolerance for Newton-Raphson

**Details**

Details are seen from the references.

**Value**

eta	estimates
SE	standard errors
convergence	Log-likelihood, degree of freedom, AIC, the number of iterations
Score	score at the converged value
Hessian	Hessian at the converged value

**Author(s)**

Takeshi Emura, Ya-Hsuan Hu

**References**

Hu YH, Emura T (2015) Maximum likelihood estimation for a special exponential family under random double-truncation, *Computation Stat* 30 (4): 1199-229

Emura T, Hu YH, Konno Y (2017) Asymptotic inference for maximum likelihood estimators under the special exponential family with double-truncation, *Stat Pap* 58 (3): 877-909

Dorre A, Emura T (2019) *Analysis of Doubly Truncated Data, An Introduction*, JSS Research Series in Statistics, Springer

**Examples**

```
### Data generation: see Appendix of Hu and Emura (2015) ###
eta_true=-3
eta_u=-9
eta_v=-1
tau=10
n=300

a=u=v=y=c()

j=1
repeat{
  u1=runif(1,0,1)
  u[j]=tau+(1/eta_u)*log(1-u1)
  u2=runif(1,0,1)
  v[j]=tau+(1/eta_v)*log(1-u2)
  u3=runif(1,0,1)
  y[j]=tau+(1/eta_true)*log(1-u3)
  if(u[j]<=y[j]&&y[j]<=v[j]) a[j]=1 else a[j]=0
  if(sum(a)==n) break
  j=j+1
}
mean(a) ## inclusion probability around 0.5
```

```
v.trunc=v[a==1]
u.trunc=u[a==1]
y.trunc=y[a==1]
```

```
PMLE.SEF1.negative(u.trunc,y.trunc,v.trunc)
```

---

PMLE.SEF1.positive      *Parametric Inference for the one-parameter SEF model (positive parameter space)*

---

### Description

Maximum likelihood estimates and their standard errors (SEs) are computed. Also computed are the likelihood value, AIC, and other quantities.

### Usage

```
PMLE.SEF1.positive(u.trunc, y.trunc, v.trunc, tau2 = max(y.trunc), epsilon = 1e-04)
```

### Arguments

u.trunc	lower truncation limit
y.trunc	variable of interest
v.trunc	upper truncation limit
tau2	upper support
epsilon	error tolerance for Newton-Raphson

### Details

Details are seen from the references.

### Value

eta	estimates
SE	standard errors
convergence	Log-likelihood, degree of freedom, AIC, the number of iterations
Score	score at the converged value
Hessian	Hessian at the converged value

### Author(s)

Takeshi Emura, Ya-Hsuan Hu

## References

- Hu YH, Emura T (2015) Maximum likelihood estimation for a special exponential family under random double-truncation, *Computation Stat* 30 (4): 1199-229
- Emura T, Hu YH, Konno Y (2017) Asymptotic inference for maximum likelihood estimators under the special exponential family with double-truncation, *Stat Pap* 58 (3): 877-909
- Dorre A, Emura T (2019) *Analysis of Doubly Truncated Data, An Introduction*, JSS Research Series in Statistics, Springer

## Examples

```
#### Data generation: Appendix of Hu and Emura (2015)
eta_true=3
eta_u=1
eta_v=9
tau=10
n=300

a=u=v=y=c()

j=1
repeat{
  u1=runif(1,0,1)
  u[j]=tau+(1/eta_u)*log(u1)
  u2=runif(1,0,1)
  v[j]=tau+(1/eta_v)*log(u2)
  u3=runif(1,0,1)
  y[j]=tau+(1/eta_true)*log(u3)
  if(u[j]<=y[j]&&y[j]<=v[j]) a[j]=1 else a[j]=0
  if(sum(a)==n) break
  j=j+1
}
mean(a) ## inclusion probability around 0.5

v.trunc=v[a==1]
u.trunc=u[a==1]
y.trunc=y[a==1]

PMLE.SEF1.positive(u.trunc,y.trunc,v.trunc)
```

---

PMLE.SEF2.negative	<i>Parametric Inference for the two-parameter SEF model (negative parameter space for eta_2)</i>
--------------------	--

---

## Description

Maximum likelihood estimates and their standard errors (SEs) are computed. Also computed are the likelihood value, AIC, and other quantities. Since this is the model, estimates for the mean and SD are also computed.

**Usage**

```
PMLE.SEF2.negative(u.trunc, y.trunc, v.trunc, epsilon = 1e-04)
```

**Arguments**

u.trunc	lower truncation limit
y.trunc	variable of interest
v.trunc	upper truncation limit
epsilon	error tolerance for Newton-Raphson

**Details**

Details are seen from the references.

**Value**

eta	estimates
SE	standard errors
convergence	Log-likelihood, degree of freedom, AIC, the number of iterations
Score	score vector at the converged value
Hessian	Hessian matrix at the converged value

**Author(s)**

Takeshi Emura, Ya-Hsuan Hu

**References**

Hu YH, Emura T (2015) Maximum likelihood estimation for a special exponential family under random double-truncation, *Computation Stat* 30 (4): 1199-229

Emura T, Hu YH, Konno Y (2017) Asymptotic inference for maximum likelihood estimators under the special exponential family with double-truncation, *Stat Pap* 58 (3): 877-909

Dorre A, Emura T (2019) *Analysis of Doubly Truncated Data, An Introduction*, JSS Research Series in Statistics, Springer

**Examples**

```
### Data generation: see Appendix of Hu and Emura (2015)
n=300
eta1_true=30
eta2_true=-0.5
mu_true=30
mu_u=29.09
mu_v=30.91

a=u=v=y=c()
```

```

###generate n samples of (ui,yi,vi) subject to ui<=yi<=vi###
j=1
repeat{
  u[j]=rnorm(1,mu_u,1)
  v[j]=rnorm(1,mu_v,1)
  y[j]=rnorm(1,mu_true,1)
  if(u[j]<=y[j]&&y[j]<=v[j]) a[j]=1 else a[j]=0
  if(sum(a)==n) break ###we need n data set###
  j=j+1
}
mean(a) ### inclusion probability around 0.5 ###

v.trunc=v[a==1]
y.trunc=y[a==1]
u.trunc=u[a==1]

PMLE.SEF2.negative(u.trunc,y.trunc,v.trunc)

```

---

PMLE.SEF3.free

*Parametric Inference for the three-parameter SEF model (free parameter space for  $\eta_3$ )*


---

### Description

Maximum likelihood estimates and their standard errors (SEs) are computed. Also computed are the likelihood value, AIC, and other quantities.

### Usage

```

PMLE.SEF3.free(u.trunc, y.trunc, v.trunc,
  tau1 = min(y.trunc), tau2 = max(y.trunc),
  epsilon = 1e-04, D1=20, D2=10, D3=1, d1=6, d2=0.5)

```

### Arguments

u.trunc	lower truncation limit
y.trunc	variable of interest
v.trunc	upper truncation limit
tau1	lower support
tau2	upper support
epsilon	error tolerance for Newton-Raphson
D1	Divergence condition for $\eta_1$
D2	Divergence condition of $\eta_2$
D3	Divergence condition of $\eta_3$
d1	Range of randomization for $\eta_1$
d2	Range of randomization for $\eta_2$

**Details**

Details are seen from the references.

**Value**

eta	estimates
SE	standard errors
convergence	Log-likelihood, degree of freedom, AIC, the number of iterations
Score	score vector at the converged value
Hessian	Hessian matrix at the converged value

**Author(s)**

Takeshi Emura, Ya-Hsuan Hu

**References**

Hu YH, Emura T (2015) Maximum likelihood estimation for a special exponential family under random double-truncation, *Computation Stat* 30 (4): 1199-229

Emura T, Hu YH, Konno Y (2017) Asymptotic inference for maximum likelihood estimators under the special exponential family with double-truncation, *Stat Pap* 58 (3): 877-909

Dorre A, Emura T (2019) *Analysis of Doubly Truncated Data, An Introduction*, JSS Research Series in Statistics, Springer

**Examples**

```
## The first 10 samples of the childhood cancer data ##
y.trunc=c(6,7,15,43,85,92,96,104,108,123)
u.trunc=c(-1643,-24,-532,-1508,-691,-1235,-786,-261,-108,-120)
v.trunc=u.trunc+1825
PMLE.SEF3.free(u.trunc,y.trunc,v.trunc)
```

---

PMLE.SEF3.negative	<i>Parametric Inference for the three-parameter SEF model (negative parameter space for eta_3)</i>
--------------------	--

---

**Description**

Maximum likelihood estimates and their standard errors (SEs) are computed. Also computed are the likelihood value, AIC, and other quantities.

**Usage**

```
PMLE.SEF3.negative(u.trunc, y.trunc, v.trunc, tau1 = min(y.trunc),
  epsilon = 1e-04, D1=20, D2=10, D3=1, d1=6, d2=0.5)
```

**Arguments**

u.trunc	lower truncation limit
y.trunc	variable of interest
v.trunc	upper truncation limit
tau1	lower support
epsilon	error tolerance for Newton-Raphson
D1	Divergence condition for eta_1
D2	Divergence condition of eta_2
D3	Divergence condition of eta_3
d1	Range of randomization for eta_1
d2	Range of randomization for eta_2

**Details**

Details are seen from the references.

**Value**

eta	estimates
SE	standard errors
convergence	Log-likelihood, degree of freedom, AIC, the number of iterations
Score	score vector at the converged value
Hessian	Hessian matrix at the converged value

**Author(s)**

Takeshi Emura, Ya-Hsuan Hu

**References**

- Hu YH, Emura T (2015) Maximum likelihood estimation for a special exponential family under random double-truncation, *Computation Stat* 30 (4): 1199-229
- Emura T, Hu YH, Konno Y (2017) Asymptotic inference for maximum likelihood estimators under the special exponential family with double-truncation, *Stat Pap* 58 (3): 877-909
- Dorre A, Emura T (2019) *Analysis of Doubly Truncated Data, An Introduction*, JSS Research Series in Statistics, Springer

**Examples**

```
## The first 10 samples of the childhood cancer data ##
y.trunc=c(6,7,15,43,85,92,96,104,108,123)
u.trunc=c(-1643,-24,-532,-1508,-691,-1235,-786,-261,-108,-120)
v.trunc=u.trunc+1825
PMLE.SEF3.negative(u.trunc,y.trunc,v.trunc)
```

---

PMLE.SEF3.positive	<i>Parametric Inference for the three-parameter SEF model (positive parameter space for eta_3)</i>
--------------------	--

---

**Description**

Maximum likelihood estimates and their standard errors (SEs) are computed. Also computed are the likelihood value, AIC, and other quantities.

**Usage**

```
PMLE.SEF3.positive(u.trunc, y.trunc, v.trunc, tau2 = max(y.trunc),
  epsilon = 1e-04, D1=20, D2=10, D3=1, d1=6, d2=0.5)
```

**Arguments**

u.trunc	lower truncation limit
y.trunc	variable of interest
v.trunc	upper truncation limit
tau2	upper support
epsilon	error tolerance for Newton-Raphson
D1	Divergence condition for eta_1
D2	Divergence condition of eta_2
D3	Divergence condition of eta_3
d1	Range of randomization for eta_1
d2	Range of randomization for eta_2

**Details**

Details are seen from the references.

**Value**

eta	estimates
SE	standard errors
convergence	Log-likelihood, degree of freedom, AIC, the number of iterations
Score	score vector at the converged value
Hessian	Hessian matrix at the converged value

**Author(s)**

Takeshi Emura, Ya-Hsuan Hu

## References

Hu YH, Emura T (2015) Maximum likelihood estimation for a special exponential family under random double-truncation, *Computation Stat* 30 (4): 1199-229

Emura T, Hu YH, Konno Y (2017) Asymptotic inference for maximum likelihood estimators under the special exponential family with double-truncation, *Stat Pap* 58 (3): 877-909

Dorre A, Emura T (2019) Analysis of Doubly Truncated Data, An Introduction, *JSS Research Series in Statistics*, Springer

## Examples

```
## The first 10 samples of the childhood cancer data ##
y.trunc=c(6,7,15,43,85,92,96,104,108,123)
u.trunc=c(-1643,-24,-532,-1508,-691,-1235,-786,-261,-108,-120)
v.trunc=u.trunc+1825
PMLE.SEF3.positive(u.trunc,y.trunc,v.trunc)
```

---

PMLE.Weibull

*Parametric Inference for the Weibull model*

---

## Description

Maximum likelihood estimates (MLEs) and their standard errors (SEs) are computed for the Weibull model based on doubly-truncated data (Dorre et al. 2021). Also computed are the likelihood value, AIC, and other quantities.

## Usage

```
PMLE.Weibull(u.trunc, y.trunc, v.trunc, epsilon = 1e-5, D1=2, D2=2, d1=2, d2=2)
```

## Arguments

u.trunc	a vector of lower truncation limits
y.trunc	a vector of variables of interest
v.trunc	a vector of upper truncation limits
epsilon	a small positive number for the error tolerance for Newton-Raphson iterations
D1	a positive number: Randomize the initial value for a divergent iteration (the updated amount for mu is greater than D1)
D2	a positive number: Randomize the initial value for a divergent iteration (the updated amount for sigma is greater than D2)
d1	a positive number: For a divergent iteration, $U(-d1, d1)$ is added to the initial value of mu
d2	a positive number: For a divergent iteration, $U(-d2, d2)$ is added to the initial value of $\log(\text{sigma})$

**Details**

A randomized Newton–Raphson algorithm (Section 3.2 of Dorre et al.(2021)) was employed to compute the MLE.

**Value**

eta	estimates
SE	standard errors
convergence	Log-likelihood, degrees of freedom, AIC, the number of iterations
Score	score vector at the converged value
Hessian	Hessian matrix at the converged value

**Author(s)**

Takeshi Emura

**References**

Dorre A, Huang CY, Tseng YK, Emura T (2021) Likelihood-based analysis of doubly-truncated data under the location-scale and AFT model, *Computation Stat* 36(1): 375-408

**Examples**

```
## A data example from Efron and Petrosian (1999) ##
y.trunc=c(0.75, 1.25, 1.50, 1.05, 2.40, 2.50, 2.25)
u.trunc=c(0.4, 0.8, 0.0, 0.3, 1.1, 2.3, 1.3)
v.trunc=c(2.0, 1.8, 2.3, 1.4, 3.0, 3.4, 2.6)
PMLE.Weibull(u.trunc,y.trunc,v.trunc)
```

---

simu.Weibull

*Simulating doubly-truncated data from the Weibull model*

---

**Description**

A data frame is generated by simulated data from the Weibull model.

**Usage**

```
simu.Weibull(n,mu,sigma,delta)
```

**Arguments**

n	sample size
mu	location parameter
sigma	scale parameter
delta	a positive parameter controlling the inclusion probability

**Details**

The data are generated from the random vector  $(U, Y, V)$  subject to the inclusion criterion  $U \leq Y \leq V$ . The random vector are defined as  $U = \mu - \delta + \sigma * W$ ,  $Y = \mu + \sigma * W$ , and  $V = \mu + \delta + \sigma * W$ , where  $P(W > w) = \exp(-\exp(w))$ . See Section 5.1 of Dorre et al. (2021) for details. The inclusion probability is  $P(U \leq Y \leq V)$ .

**Value**

u	lower truncation limits
y	log-transformed lifetimes
v	upper truncation limits

**Author(s)**

Takeshi Emura

**References**

Dorre A, Huang CY, Tseng YK, Emura T (2021) Likelihood-based analysis of doubly-truncated data under the location-scale and AFT model, *Computation Stat* 36(1): 375-408

**Examples**

```
## A simulation from Dorre et al.(2021) ##  
simu.Weibull(n=100,mu=5,sigma=2,delta=2.08)  
  
Dat=simu.Weibull(n=100,mu=5,sigma=2,delta=2.08)  
PMLE.Weibull(Dat$u,Dat$y,Dat$v)
```

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