

# Package ‘RobLox’

October 12, 2022

**Version** 1.2.0

**Date** 2019-04-02

**Title** Optimally Robust Influence Curves and Estimators for Location and Scale

**Description** Functions for the determination of optimally robust influence curves and estimators in case of normal location and/or scale.

**Depends** R(>= 3.4), stats, distrMod(>= 2.8.0), RobAStBase(>= 1.2.0)

**Imports** methods, lattice, RColorBrewer, Biobase, RandVar(>= 1.2.0), distr(>= 2.8.0)

**Suggests** MASS

**ByteCompile** yes

**License** LGPL-3

**Encoding** latin1

**URL** <http://robast.r-forge.r-project.org/>

**LastChangedDate** {`$LastChangedDate`: 2019-04-02 21:10:23 +0200 (Di, 02. Apr 2019) `$`}

**LastChangedRevision** {`$LastChangedRevision`: 1215 `$`}

**VCS/SVNRevision** 1214

**NeedsCompilation** no

**Author** Matthias Kohl [cre, cph],  
Peter Ruckdeschel [aut, cph]

**Maintainer** Matthias Kohl <Matthias.Kohl@stamats.de>

**Repository** CRAN

**Date/Publication** 2019-04-11 06:45:19 UTC

## R topics documented:

RobLox-package	2
finiteSampleCorrection	4

rlOptIC	5
rlsOptIC.AL	6
rlsOptIC.An1	8
rlsOptIC.An2	10
rlsOptIC.AnMad	11
rlsOptIC.BM	12
rlsOptIC.Ha3	13
rlsOptIC.Ha4	14
rlsOptIC.HaMad	16
rlsOptIC.Hu1	17
rlsOptIC.Hu2	18
rlsOptIC.Hu2a	19
rlsOptIC.Hu3	20
rlsOptIC.HuMad	21
rlsOptIC.M	22
rlsOptIC.MM2	24
rlsOptIC.Tu1	25
rlsOptIC.Tu2	26
rlsOptIC.TuMad	27
roblox	28
rowRoblox and colRoblox	31
rsOptIC	34
showdown	35

## Index 38

---

RobLox-package	<i>Optimally robust influence curves and estimators for location and scale</i>
----------------	--

---

## Description

Functions for the determination of optimally robust influence curves and estimators in case of normal location and/or scale.

## Details

Package:	RobLox
Version:	1.2.0
Date:	2019-04-02
Depends:	R(>= 3.4), stats, distrMod(>= 2.8.0), RobAStBase(>= 1.2.0)
Imports:	methods, lattice, RColorBrewer, Biobase, RandVar(>= 1.2.0), distr(>= 2.8.0)
Suggests:	MASS
ByteCompile:	yes
License:	LGPL-3
URL:	<a href="http://robast.r-forge.r-project.org/">http://robast.r-forge.r-project.org/</a>
VCS/SVNRevision:	1214

## Package versions

Note: The first two numbers of package versions do not necessarily reflect package-individual development, but rather are chosen for the RobAStXXX family as a whole in order to ease updating "depends" information.

## Author(s)

Matthias Kohl <matthias.kohl@stamats.de>

## References

M. Kohl (2005). Numerical Contributions to the Asymptotic Theory of Robustness. Dissertation. University of Bayreuth. Rieder, H. (1994) *Robust Asymptotic Statistics*. New York: Springer. Rieder, H., Kohl, M. and Ruckdeschel, P. (2008). The Costs of not Knowing the Radius. *Statistical Methods and Applications* **17**(1) 13-40. Extended version: <http://r-kurs.de/RRlong.pdf>

M. Kohl, P. Ruckdeschel, and H. Rieder (2010). Infinitesimally Robust Estimation in General Smoothly Parametrized Models. *Statistical Methods and Application*, **19**(3):333-354.

## See Also

[RobAStBase-package](#)

## Examples

```
library(RobLox)
ind <- rbinom(100, size=1, prob=0.05)
x <- rnorm(100, mean=ind*3, sd=(1-ind) + ind*9)
roblox(x)
res <- roblox(x, eps.lower = 0.01, eps.upper = 0.1, returnIC = TRUE)
estimate(res)
confint(res)
confint(res, method = symmetricBias())
pIC(res)
## don't run to reduce check time on CRAN
## Not run:
checkIC(pIC(res))
Risks(pIC(res))
Infos(pIC(res))
plot(pIC(res))
infoPlot(pIC(res))

## End(Not run)
## row-wise application
ind <- rbinom(200, size=1, prob=0.05)
X <- matrix(rnorm(200, mean=ind*3, sd=(1-ind) + ind*9), nrow = 2)
rowRoblox(X)
```

---

`finiteSampleCorrection`*Function to compute finite-sample corrected radii*

---

**Description**

Given some radius and some sample size the function computes the corresponding finite-sample corrected radius.

**Usage**

```
finiteSampleCorrection(r, n, model = "locsc")
```

**Arguments**

<code>r</code>	asymptotic radius (non-negative numeric)
<code>n</code>	sample size
<code>model</code>	has to be "locsc" (for location and scale), "loc" (for location) or "sc" (for scale), respectively.

**Details**

The finite-sample correction is based on empirical results obtained via simulation studies.

Given some radius of a shrinking contamination neighborhood which leads to an asymptotically optimal robust estimator, the finite-sample empirical MSE based on contaminated samples was minimized for this class of asymptotically optimal estimators and the corresponding finite-sample radius determined and saved.

The computation is based on the saved results of these Monte-Carlo simulations.

**Value**

Finite-sample corrected radius.

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

Rieder, H. (1994) *Robust Asymptotic Statistics*. New York: Springer.

Rieder, H., Kohl, M. and Ruckdeschel, P. (2008) The Costs of not Knowing the Radius. *Statistical Methods and Applications* 17(1) 13-40. Extended version: <http://r-kurs.de/RRlong.pdf>

**See Also**

[roblox](#), [rowRoblox](#), [colRoblox](#)

**Examples**

```
finiteSampleCorrection(n = 3, r = 0.001, model = "locsc")
finiteSampleCorrection(n = 10, r = 0.02, model = "loc")
finiteSampleCorrection(n = 250, r = 0.15, model = "sc")
```

---

r1OptIC

*Computation of the optimally robust IC for AL estimators*


---

**Description**

The function `r1OptIC` computes the optimally robust IC for AL estimators in case of normal location and (convex) contamination neighborhoods. The definition of these estimators can be found in Rieder (1994) or Kohl (2005), respectively.

**Usage**

```
r1OptIC(r, mean = 0, sd = 1, bUp = 1000, computeIC = TRUE)
```

**Arguments**

<code>r</code>	non-negative real: neighborhood radius.
<code>mean</code>	specified mean.
<code>sd</code>	specified standard deviation.
<code>bUp</code>	positive real: the upper end point of the interval to be searched for the clipping bound <code>b</code> .
<code>computeIC</code>	logical: should IC be computed. See details below.

**Details**

If `'computeIC'` is `'FALSE'` only the Lagrange multipliers `'A'`, `'a'`, and `'b'` contained in the optimally robust IC are computed.

**Value**

If `'computeIC'` is `'TRUE'` an object of class `"ContIC"` is returned, otherwise a list of Lagrange multipliers

<code>A</code>	standardizing constant
<code>a</code>	centering constant; always <code>'= 0'</code> is this symmetric setup
<code>b</code>	optimal clipping bound

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Rieder, H. (1994) *Robust Asymptotic Statistics*. New York: Springer.

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[ContIC-class](#), [roblox](#)

**Examples**

```
IC1 <- rlsOptIC(r = 0.1)
distrExOptions("ErelativeTolerance" = 1e-12)
checkIC(IC1)
distrExOptions("ErelativeTolerance" = .Machine$double.eps^0.25) # default
Risks(IC1)
cent(IC1)
clip(IC1)
stand(IC1)
plot(IC1)
```

---

rlsOptIC.AL

*Computation of the optimally robust IC for AL estimators*

---

**Description**

The function `rlsOptIC.AL` computes the optimally robust IC for AL estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Section 8.2 of Kohl (2005).

**Usage**

```
rlsOptIC.AL(r, mean = 0, sd = 1, A.loc.start = 1, a.sc.start = 0,
            A.sc.start = 0.5, bUp = 1000, delta = 1e-6, itmax = 100,
            check = FALSE, computeIC = TRUE)
```

**Arguments**

<code>r</code>	non-negative real: neighborhood radius.
<code>mean</code>	specified mean.
<code>sd</code>	specified standard deviation.
<code>A.loc.start</code>	positive real: starting value for the standardizing constant of the location part.

a.sc.start	real: starting value for centering constant of the scale part.
A.sc.start	positive real: starting value for the standardizing constant of the scale part.
bUp	positive real: the upper end point of the interval to be searched for the clipping bound b.
delta	the desired accuracy (convergence tolerance).
itmax	the maximum number of iterations.
check	logical: should constraints be checked.
computeIC	logical: should IC be computed. See details below.

### Details

The Lagrange multipliers contained in the expression of the optimally robust IC can be accessed via the accessor functions `cent`, `clip` and `stand`. If `'computeIC'` is `'FALSE'` only the Lagrange multipliers `'A'`, `'a'`, and `'b'` contained in the optimally robust IC are computed.

### Value

If `'computeIC'` is `'TRUE'` an object of class `"ContIC"` is returned, otherwise a list of Lagrange multipliers

A	standardizing matrix
a	centering vector
b	optimal clipping bound

### Author(s)

Matthias Kohl <Matthias.Kohl@stamats.de>

### References

- Rieder, H. (1994) *Robust Asymptotic Statistics*. New York: Springer.
- Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

### See Also

[ContIC-class](#), [roblox](#)

### Examples

```
IC1 <- rlsOptIC.AL(r = 0.1, check = TRUE)
distrExOptions("ErelativeTolerance" = 1e-12)
checkIC(IC1)
distrExOptions("ErelativeTolerance" = .Machine$double.eps^0.25) # default
Risks(IC1)
cent(IC1)
clip(IC1)
stand(IC1)
```

```

## don't run to reduce check time on CRAN
## Not run:
plot(IC1)
infoPlot(IC1)

## k-step estimation
## better use function roblox (see ?roblox)
## 1. data: random sample
ind <- rbinom(100, size=1, prob=0.05)
x <- rnorm(100, mean=0, sd=(1-ind) + ind*9)
mean(x)
sd(x)
median(x)
mad(x)

## 2. Kolmogorov(-Smirnov) minimum distance estimator (default)
## -> we use it as initial estimate for one-step construction
(est0 <- MDEstimator(x, ParamFamily = NormLocationScaleFamily()))

## 3.1 one-step estimation: radius known
IC1 <- rlsOptIC.AL(r = 0.5, mean = estimate(est0)[1], sd = estimate(est0)[2])
(est1 <- oneStepEstimator(x, IC1, est0))

## 3.2 k-step estimation: radius known
## Choose k = 3
(est2 <- kStepEstimator(x, IC1, est0, steps = 3L))

## 4.1 one-step estimation: radius unknown
## take least favorable radius r = 0.579
## cf. Table 8.1 in Kohl(2005)
IC2 <- rlsOptIC.AL(r = 0.579, mean = estimate(est0)[1], sd = estimate(est0)[2])
(est3 <- oneStepEstimator(x, IC2, est0))

## 4.2 k-step estimation: radius unknown
## take least favorable radius r = 0.579
## cf. Table 8.1 in Kohl(2005)
## choose k = 3
(est4 <- kStepEstimator(x, IC2, est0, steps = 3L))

## End(Not run)

```

**Description**

The function `rlsOptIC.An1` computes the optimally robust IC for An1 estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Subsection 8.5.3 of Kohl (2005).

**Usage**

```
rlsOptIC.An1(r, aUp = 2.5, delta = 1e-06)
```

**Arguments**

r	non-negative real: neighborhood radius.
aUp	positive real: the upper end point of the interval to be searched for a.
delta	the desired accuracy (convergence tolerance).

**Details**

The optimal value of the tuning constant  $a$  can be read off from the slot Infos of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Andrews, D.F., Bickel, P.J., Hampel, F.R., Huber, P.J., Rogers, W.H. and Tukey, J.W. (1972) *Robust estimates of location*. Princeton University Press.

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[IC-class](#)

**Examples**

```
IC1 <- rlsOptIC.An1(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
## don't run to reduce check time on CRAN
## Not run:
plot(IC1)
infoPlot(IC1)

## End(Not run)
```

---

`rlsOptIC.An2`*Computation of the optimally robust IC for An2 estimators*

---

**Description**

The function `rlsOptIC.An2` computes the optimally robust IC for An2 estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Subsection 8.5.3 of Kohl (2005).

**Usage**

```
rlsOptIC.An2(r, a.start = 1.5, k.start = 1.5, delta = 1e-06, MAX = 100)
```

**Arguments**

<code>r</code>	non-negative real: neighborhood radius.
<code>a.start</code>	positive real: starting value for a.
<code>k.start</code>	positive real: starting value for k.
<code>delta</code>	the desired accuracy (convergence tolerance).
<code>MAX</code>	if a or k are beyond the admitted values, MAX is returned.

**Details**

The computation of the optimally robust IC for An2 estimators is based on `optim` where `MAX` is used to control the constraints on a and k. The optimal values of the tuning constants a and k can be read off from the slot `Infos` of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Andrews, D.F., Bickel, P.J., Hampel, F.R., Huber, P.J., Rogers, W.H. and Tukey, J.W. (1972) *Robust estimates of location*. Princeton University Press.

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[IC-class](#)

**Examples**

```
IC1 <- rlsOptIC.An2(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

`rlsOptIC.AnMad`*Computation of the optimally robust IC for AnMad estimators*

---

**Description**

The function `rlsOptIC.AnMad` computes the optimally robust IC for AnMad estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. These estimators were considered in Andrews et al. (1972). A definition of these estimators can also be found in Subsection 8.5.3 of Kohl (2005).

**Usage**

```
rlsOptIC.AnMad(r, aUp = 2.5, delta = 1e-06)
```

**Arguments**

<code>r</code>	non-negative real: neighborhood radius.
<code>aUp</code>	positive real: the upper end point of the interval to be searched for a.
<code>delta</code>	the desired accuracy (convergence tolerance).

**Details**

The optimal value of the tuning constant `a` can be read off from the slot `Infos` of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Andrews, D.F., Bickel, P.J., Hampel, F.R., Huber, P.J., Rogers, W.H. and Tukey, J.W. (1972) *Robust estimates of location*. Princeton University Press.

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**[IC-class](#)**Examples**

```
IC1 <- rlsOptIC.AnMad(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

 rlsOptIC.BM

---

*Computation of the optimally robust IC for BM estimators*


---

**Description**

The function `rlsOptIC.BM` computes the optimally robust IC for BM estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. These estimators were proposed by Bednarski and Mueller (2001). A definition of these estimators can also be found in Section 8.4 of Kohl (2005).

**Usage**

```
rlsOptIC.BM(r, bL.start = 2, bS.start = 1.5, delta = 1e-06, MAX = 100)
```

**Arguments**

<code>r</code>	non-negative real: neighborhood radius.
<code>bL.start</code>	positive real: starting value for $b_{loc}$ .
<code>bS.start</code>	positive real: starting value for $b_{sc,0}$ .
<code>delta</code>	the desired accuracy (convergence tolerance).
<code>MAX</code>	if $b_{loc}$ or $b_{sc,0}$ are beyond the admitted values, MAX is returned.

**Details**

The computation of the optimally robust IC for BM estimators is based on `optim` where MAX is used to control the constraints on  $b_{loc}$  and  $b_{sc,0}$ . The optimal values of the tuning constants  $b_{loc}$ ,  $b_{sc,0}$ ,  $\alpha$  and  $\gamma$  can be read off from the slot `Infos` of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

## References

- Bednarski, T and Mueller, C.H. (2001) Optimal bounded influence regression and scale M-estimators in the context of experimental design. *Statistics*, **35**(4): 349–369.
- Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

## See Also

[IC-class](#)

## Examples

```
IC1 <- rlsOptIC.BM(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

rlsOptIC.Ha3

*Computation of the optimally robust IC for Ha3 estimators*

---

## Description

The function `rlsOptIC.Ha3` computes the optimally robust IC for Ha3 estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Subsection 8.5.2 of Kohl (2005).

## Usage

```
rlsOptIC.Ha3(r, a.start = 0.25, b.start = 2.5, c.start = 5,
             delta = 1e-06, MAX = 100)
```

## Arguments

<code>r</code>	non-negative real: neighborhood radius.
<code>a.start</code>	positive real: starting value for a.
<code>b.start</code>	positive real: starting value for b.
<code>c.start</code>	positive real: starting value for c.
<code>delta</code>	the desired accuracy (convergence tolerance).
<code>MAX</code>	if a or b or c are beyond the admitted values, MAX is returned.

## Details

The computation of the optimally robust IC for Ha3 estimators is based on `optim` where `MAX` is used to control the constraints on a, b and c. The optimal values of the tuning constants a, b and c can be read off from the slot `Infos` of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[IC-class](#)

**Examples**

```
IC1 <- rlsOptIC.Ha3(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
## don't run to reduce check time on CRAN
## Not run:
plot(IC1)
infoPlot(IC1)

## End(Not run)
```

---

rlsOptIC.Ha4

*Computation of the optimally robust IC for Ha4 estimators*

---

**Description**

The function `rlsOptIC.Ha4` computes the optimally robust IC for Ha4 estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Subsection 8.5.2 of Kohl (2005).

**Usage**

```
rlsOptIC.Ha4(r, a.start = 0.25, b.start = 2.5, c.start = 5,
             k.start = 1, delta = 1e-06, MAX = 100)
```

**Arguments**

r	non-negative real: neighborhood radius.
a.start	positive real: starting value for a.
b.start	positive real: starting value for b.
c.start	positive real: starting value for c.
k.start	positive real: starting value for k.
delta	the desired accuracy (convergence tolerance).
MAX	if a or b or c or k are beyond the admitted values, MAX is returned.

**Details**

The computation of the optimally robust IC for Ha4 estimators is based on `opt im` where MAX is used to control the constraints on a, b, c and k. The optimal values of the tuning constants a, b, c and k can be read off from the slot Infos of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Marazzi, A. (1993) *Algorithms, routines, and S functions for robust statistics*. Wadsworth and Brooks / Cole.

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[IC-class](#)

**Examples**

```
IC1 <- rlsOptIC.Ha4(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

rlsOptIC.HaMad

*Computation of the optimally robust IC for HuMad estimators*


---

### Description

The function `rlsOptIC.HuMad` computes the optimally robust IC for HuMad estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. These estimators were considered in Andrews et al. (1972). A definition of these estimators can also be found in Subsection 8.5.2 of Kohl (2005).

### Usage

```
rlsOptIC.HaMad(r, a.start = 0.25, b.start = 2.5, c.start = 5,
               delta = 1e-06, MAX = 100)
```

### Arguments

<code>r</code>	non-negative real: neighborhood radius.
<code>a.start</code>	positive real: starting value for a.
<code>b.start</code>	positive real: starting value for b.
<code>c.start</code>	positive real: starting value for c.
<code>delta</code>	the desired accuracy (convergence tolerance).
<code>MAX</code>	if a or b or c are beyond the admitted values, MAX is returned.

### Details

The computation of the optimally robust IC for HaMad estimators is based on `optim` where `MAX` is used to control the constraints on a, b and c. The optimal values of the tuning constants a, b, and c can be read off from the slot `Infos` of the resulting IC.

### Value

Object of class "IC"

### Author(s)

Matthias Kohl <Matthias.Kohl@stamats.de>

### References

Andrews, D.F., Bickel, P.J., Hampel, F.R., Huber, P.J., Rogers, W.H. and Tukey, J.W. (1972) *Robust estimates of location*. Princeton University Press.

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**[IC-class](#)**Examples**

```
IC1 <- rlsOptIC.HaMad(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

`rlsOptIC.Hu1`*Computation of the optimally robust IC for Hu1 estimators*

---

**Description**

The function `rlsOptIC.Hu1` computes the optimally robust IC for Hu1 estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. These estimators were proposed by Huber (1964), Proposal 2. A definition of these estimators can also be found in Subsection 8.5.1 of Kohl (2005).

**Usage**

```
rlsOptIC.Hu1(r, kUp = 2.5, delta = 1e-06)
```

**Arguments**

<code>r</code>	non-negative real: neighborhood radius.
<code>kUp</code>	positive real: the upper end point of the interval to be searched for <code>k</code> .
<code>delta</code>	the desired accuracy (convergence tolerance).

**Details**

The optimal value of the tuning constant `k` can be read off from the slot `Infos` of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Huber, P.J. (1964) Robust estimation of a location parameter. *Ann. Math. Stat.* **35**: 73–101.  
Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**[IC-class](#)**Examples**

```
IC1 <- rlsOptIC.Hu1(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

 rlsOptIC.Hu2

---

*Computation of the optimally robust IC for Hu2 estimators*


---

**Description**

The function `rlsOptIC.Hu2` computes the optimally robust IC for Hu2 estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. These estimators were proposed in Example 6.4.1 of Huber (1981). A definition of these estimators can also be found in Subsection 8.5.1 of Kohl (2005).

**Usage**

```
rlsOptIC.Hu2(r, k.start = 1.5, c.start = 1.5, delta = 1e-06, MAX = 100)
```

**Arguments**

<code>r</code>	non-negative real: neighborhood radius.
<code>k.start</code>	positive real: starting value for <code>k</code> .
<code>c.start</code>	positive real: starting value for <code>c</code> .
<code>delta</code>	the desired accuracy (convergence tolerance).
<code>MAX</code>	if <code>k1</code> or <code>k2</code> are beyond the admitted values, <code>MAX</code> is returned.

**Details**

The computation of the optimally robust IC for Hu2 estimators is based on `optim` where `MAX` is used to control the constraints on `k` and `c`. The optimal values of the tuning constants `k` and `c` can be read off from the slot `Infos` of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

- Huber, P.J. (1981) *Robust Statistics*. New York: Wiley.
- Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[IC-class](#)

**Examples**

```
IC1 <- rlsOptIC.Hu2a(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

 rlsOptIC.Hu2a

---

*Computation of the optimally robust IC for Hu2a estimators*


---

**Description**

The function `rlsOptIC.Hu2a` computes the optimally robust IC for Hu2a estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. These estimators are a simple modification of Huber (1964), Proposal 2 where we, in addition, admit a clipping from below. The definition of these estimators can be found in Subsection 8.5.1 of Kohl (2005).

**Usage**

```
rlsOptIC.Hu2a(r, k1.start = 0.25, k2.start = 2.5, delta = 1e-06, MAX = 100)
```

**Arguments**

<code>r</code>	non-negative real: neighborhood radius.
<code>k1.start</code>	positive real: starting value for <code>k1</code> .
<code>k2.start</code>	positive real: starting value for <code>k2</code> .
<code>delta</code>	the desired accuracy (convergence tolerance).
<code>MAX</code>	if <code>k1</code> or <code>k2</code> are beyond the admitted values, <code>MAX</code> is returned.

**Details**

The computation of the optimally robust IC for Hu2a estimators is based on `optim` where `MAX` is used to control the constraints on `k1` and `k2`. The optimal values of the tuning constants `k1` and `k2` can be read off from the slot `Infos` of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Huber, P.J. (1964) Robust estimation of a location parameter. *Ann. Math. Stat.* **35**: 73–101.  
 Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[IC-class](#)

**Examples**

```
IC1 <- rlsOptIC.Hu2a(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

 rlsOptIC.Hu3

---

*Computation of the optimally robust IC for Hu3 estimators*


---

**Description**

The function `rlsOptIC.Hu3` computes the optimally robust IC for Hu3 estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Subsection 8.5.1 of Kohl (2005).

**Usage**

```
rlsOptIC.Hu3(r, k.start = 1, c1.start = 0.1, c2.start = 0.5,
             delta = 1e-06, MAX = 100)
```

**Arguments**

<code>r</code>	non-negative real: neighborhood radius.
<code>k.start</code>	positive real: starting value for <code>k</code> .
<code>c1.start</code>	positive real: starting value for <code>c1</code> .
<code>c2.start</code>	positive real: starting value for <code>c2</code> .
<code>delta</code>	the desired accuracy (convergence tolerance).
<code>MAX</code>	if <code>k</code> or <code>c1</code> or <code>c2</code> are beyond the admitted values, <code>MAX</code> is returned.

**Details**

The computation of the optimally robust IC for Hu2 estimators is based on `optim` where `MAX` is used to control the constraints on `k`, `c1` and `c2`. The optimal values of the tuning constants `k`, `c1` and `c2` can be read off from the slot `Infos` of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Huber, P.J. (1981) *Robust Statistics*. New York: Wiley.

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[IC-class](#)

**Examples**

```
IC1 <- rlsOptIC.Hu3(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

rlsOptIC.HuMad

*Computation of the optimally robust IC for HuMad estimators*

---

**Description**

The function `rlsOptIC.HuMad` computes the optimally robust IC for HuMad estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. These estimators were proposed by Andrews et al. (1972), p. 12. A definition of these estimators can also be found in Subsection 8.5.1 of Kohl (2005).

**Usage**

```
rlsOptIC.HuMad(r, kUp = 2.5, delta = 1e-06)
```

**Arguments**

r	non-negative real: neighborhood radius.
kUp	positive real: the upper end point of the interval to be searched for k.
delta	the desired accuracy (convergence tolerance).

**Details**

The optimal value of the tuning constant k can be read off from the slot Infos of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

- Andrews, D.F., Bickel, P.J., Hampel, F.R., Huber, P.J., Rogers, W.H. and Tukey, J.W. (1972) *Robust estimates of location*. Princeton University Press.
- Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[IC-class](#)

**Examples**

```
IC1 <- rlsOptIC.HuMad(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

rlsOptIC.M

*Computation of the optimally robust IC for M estimators*

---

**Description**

The function `rlsOptIC.M` computes the optimally robust IC for M estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Section 8.3 of Kohl (2005).

**Usage**

```
rlsOptIC.M(r, ggLo = 0.5, ggUp = 1.5, a1.start = 0.75, a3.start = 0.25,  
           bUp = 1000, delta = 1e-05, itmax = 100, check = FALSE)
```

**Arguments**

r	non-negative real: neighborhood radius.
ggLo	non-negative real: the lower end point of the interval to be searched for $\gamma$ .
ggUp	positive real: the upper end point of the interval to be searched for $\gamma$ .
a1.start	real: starting value for $\alpha_1$ .
a3.start	real: starting value for $\alpha_3$ .
bUp	positive real: upper bound used in the computation of the optimal clipping bound b.
delta	the desired accuracy (convergence tolerance).
itmax	the maximum number of iterations.
check	logical. Should constraints be checked.

**Details**

The optimal values of the tuning constants  $\alpha_1$ ,  $\alpha_3$ , b and  $\gamma$  can be read off from the slot Infos of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Huber, P.J. (1981) *Robust Statistics*. New York: Wiley.

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[IC-class](#)

**Examples**

```
IC1 <- rlsOptIC.M(r = 0.1, check = TRUE)
distrExOptions("ErelativeTolerance" = 1e-12)
checkIC(IC1, NormLocationScaleFamily())
distrExOptions("ErelativeTolerance" = .Machine$double.eps^0.25)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

rlsOptIC.MM2

*Computation of the optimally robust IC for MM2 estimators*


---

**Description**

The function `rlsOptIC.MM2` computes the optimally robust IC for MM2 estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. These estimators are based on a proposal of Fraiman et al. (2001), p. 206. A definition of these estimators can also be found in Section 8.6 of Kohl (2005).

**Usage**

```
rlsOptIC.MM2(r, c.start = 1.5, d.start = 2, delta = 1e-06, MAX = 100)
```

**Arguments**

<code>r</code>	non-negative real: neighborhood radius.
<code>c.start</code>	positive real: starting value for <code>c</code> .
<code>d.start</code>	positive real: starting value for <code>d</code> .
<code>delta</code>	the desired accuracy (convergence tolerance).
<code>MAX</code>	if <code>a</code> or <code>k</code> are beyond the admitted values, <code>MAX</code> is returned.

**Details**

The computation of the optimally robust IC for MM2 estimators is based on `optim` where `MAX` is used to control the constraints on `c` and `d`. The optimal values of the tuning constants `c` and `d` can be read off from the slot `Infos` of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

## References

Fraiman, R., Yohai, V.J. and Zamar, R.H. (2001) Optimal robust M-estimates of location. *Ann. Stat.* **29**(1): 194–223.

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

## See Also

[IC-class](#)

## Examples

```
IC1 <- rlsOptIC.MM2(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

rlsOptIC.Tu1

*Computation of the optimally robust IC for Tu1 estimators*

---

## Description

The function `rlsOptIC.Tu1` computes the optimally robust IC for Tu1 estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Subsection 8.5.4 of Kohl (2005).

## Usage

```
rlsOptIC.Tu1(r, aUp = 10, delta = 1e-06)
```

## Arguments

<code>r</code>	non-negative real: neighborhood radius.
<code>aUp</code>	positive real: the upper end point of the interval to be searched for a.
<code>delta</code>	the desired accuracy (convergence tolerance).

## Details

The optimal value of the tuning constant `a` can be read off from the slot `Infos` of the resulting IC.

## Value

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Beaton, A.E. and Tukey, J.W. (1974) The fitting of power series, meaning polynomials, illustrated on band-spectroscopic data. *Discussions. Technometrics* **16**: 147–185.

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[IC-class](#)

**Examples**

```
IC1 <- rlsOptIC.Tu1(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

rlsOptIC.Tu2

*Computation of the optimally robust IC for Tu2 estimators*

---

**Description**

The function `rlsOptIC.Tu2` computes the optimally robust IC for Tu2 estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Subsection 8.5.4 of Kohl (2005).

**Usage**

```
rlsOptIC.Tu2(r, a.start = 5, k.start = 1.5, delta = 1e-06, MAX = 100)
```

**Arguments**

<code>r</code>	non-negative real: neighborhood radius.
<code>a.start</code>	positive real: starting value for a.
<code>k.start</code>	positive real: starting value for k.
<code>delta</code>	the desired accuracy (convergence tolerance).
<code>MAX</code>	if a or k are beyond the admitted values, MAX is returned.

**Details**

The computation of the optimally robust IC for Tu2 estimators is based on `optim` where `MAX` is used to control the constraints on `a` and `k`. The optimal values of the tuning constant `a` and `k` can be read off from the slot `Infos` of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Beaton, A.E. and Tukey, J.W. (1974) The fitting of power series, meaning polynomials, illustrated on band-spectroscopic data. *Discussions. Technometrics* **16**: 147–185.

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[IC-class](#)

**Examples**

```
IC1 <- rlsOptIC.Tu2(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

rlsOptIC.TuMad

*Computation of the optimally robust IC for TuMad estimators*

---

**Description**

The function `rlsOptIC.TuMad` computes the optimally robust IC for TuMad estimators in case of normal location with unknown scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Subsection 8.5.4 of Kohl (2005).

**Usage**

```
rlsOptIC.TuMad(r, aUp = 10, delta = 1e-06)
```

**Arguments**

r	non-negative real: neighborhood radius.
aUp	positive real: the upper end point of the interval to be searched for a.
delta	the desired accuracy (convergence tolerance).

**Details**

The optimal value of the tuning constant  $a$  can be read off from the slot Infos of the resulting IC.

**Value**

Object of class "IC"

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

- Beaton, A.E. and Tukey, J.W. (1974) The fitting of power series, meaning polynomials, illustrated on band-spectroscopic data. *Discussions. Technometrics* **16**: 147–185.
- Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[IC-class](#)

**Examples**

```
IC1 <- rlsOptIC.TuMad(r = 0.1)
checkIC(IC1)
Risks(IC1)
Infos(IC1)
plot(IC1)
infoPlot(IC1)
```

---

roblox

*Optimally robust estimator for location and/or scale*

---

**Description**

The function `roblox` computes the optimally robust estimator and corresponding IC for normal location and/or scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Rieder (1994) or Kohl (2005), respectively.

**Usage**

```
roblox(x, mean, sd, eps, eps.lower, eps.upper, initial.est, k = 1L,
      fsCor = TRUE, returnIC = FALSE, mad0 = 1e-4, na.rm = TRUE)
```

**Arguments**

<code>x</code>	vector <code>x</code> of data values, may also be a matrix or <code>data.frame</code> with one row, respectively one column/(numeric) variable.
<code>mean</code>	specified mean.
<code>sd</code>	specified standard deviation which has to be positive.
<code>eps</code>	positive real ( $0 < \text{eps} \leq 0.5$ ): amount of gross errors. See details below.
<code>eps.lower</code>	positive real ( $0 \leq \text{eps.lower} \leq \text{eps.upper}$ ): lower bound for the amount of gross errors. See details below.
<code>eps.upper</code>	positive real ( $\text{eps.lower} \leq \text{eps.upper} \leq 0.5$ ): upper bound for the amount of gross errors. See details below.
<code>initial.est</code>	initial estimate for mean and/or sd. If missing median and/or MAD are used.
<code>k</code>	positive integer. <code>k</code> -step is used to compute the optimally robust estimator.
<code>fsCor</code>	logical: perform finite-sample correction. See function <a href="#">finiteSampleCorrection</a> .
<code>returnIC</code>	logical: should IC be returned. See details below.
<code>mad0</code>	scale estimate used if computed MAD is equal to zero
<code>na.rm</code>	logical: if TRUE, the estimator is evaluated at <code>complete.cases(x)</code> .

**Details**

Computes the optimally robust estimator for location with scale specified, scale with location specified, or both if neither is specified. The computation uses a `k`-step construction with an appropriate initial estimate for location or scale or location and scale, respectively. Valid candidates are e.g. median and/or MAD (default) as well as Kolmogorov(-Smirnov) or von Mises minimum distance estimators; cf. Rieder (1994) and Kohl (2005).

If the amount of gross errors (contamination) is known, it can be specified by `eps`. The radius of the corresponding infinitesimal contamination neighborhood is obtained by multiplying `eps` by the square root of the sample size.

If the amount of gross errors (contamination) is unknown, try to find a rough estimate for the amount of gross errors, such that it lies between `eps.lower` and `eps.upper`.

In case `eps.lower` is specified and `eps.upper` is missing, `eps.upper` is set to 0.5. In case `eps.upper` is specified and `eps.lower` is missing, `eps.lower` is set to 0.

If neither `eps` nor `eps.lower` and/or `eps.upper` is specified, `eps.lower` and `eps.upper` are set to 0 and 0.5, respectively.

If `eps` is missing, the radius-minimax estimator in sense of Rieder et al. (2008), respectively Section 2.2 of Kohl (2005) is returned.

In case of location, respectively scale one additionally has to specify `sd`, respectively `mean` where `sd` and `mean` have to be a single number.

For sample size  $\leq 2$ , median and/or MAD are used for estimation.

If `eps = 0`, mean and/or `sd` are computed. In this situation it's better to use function [MLEstimator](#).

**Value**

Object of class "kStepEstimate".

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

Rieder, H. (1994) *Robust Asymptotic Statistics*. New York: Springer.

Rieder, H., Kohl, M. and Ruckdeschel, P. (2008) The Costs of not Knowing the Radius. *Statistical Methods and Applications* 17(1) 13-40. Extended version: <http://r-kurs.de/RRlong.pdf>

M. Kohl, P. Ruckdeschel, and H. Rieder (2010). Infinitesimally Robust Estimation in General Smoothly Parametrized Models. *Statistical Methods and Application*, **19**(3):333-354.

**See Also**

[ContIC-class](#), [rlOptIC](#), [rsOptIC](#), [rlsOptIC.AL](#), [kStepEstimate-class](#), [roptest](#)

**Examples**

```
ind <- rbinom(100, size=1, prob=0.05)
x <- rnorm(100, mean=ind*3, sd=(1-ind) + ind*9)

## amount of gross errors known
res1 <- roblox(x, eps = 0.05, returnIC = TRUE)
estimate(res1)
## don't run to reduce check time on CRAN
## Not run:
confint(res1)
confint(res1, method = symmetricBias())
pIC(res1)
checkIC(pIC(res1))
Risks(pIC(res1))
Infos(pIC(res1))
plot(pIC(res1))
infoPlot(pIC(res1))

## End(Not run)

## amount of gross errors unknown
res2 <- roblox(x, eps.lower = 0.01, eps.upper = 0.1, returnIC = TRUE)
estimate(res2)
## don't run to reduce check time on CRAN
## Not run:
confint(res2)
confint(res2, method = symmetricBias())
pIC(res2)
```

```

checkIC(pIC(res2))
Risks(pIC(res2))
Infos(pIC(res2))
plot(pIC(res2))
infoPlot(pIC(res2))

## End(Not run)

## estimator comparison
# classical optimal (non-robust)
c(mean(x), sd(x))

# most robust
c(median(x), mad(x))

# optimally robust (amount of gross errors known)
estimate(res1)

# optimally robust (amount of gross errors unknown)
estimate(res2)

# Kolmogorov(-Smirnov) minimum distance estimator (robust)
(ks.est <- MDEstimator(x, ParamFamily = NormLocationScaleFamily()))

# optimally robust (amount of gross errors known)
roblox(x, eps = 0.05, initial.est = estimate(ks.est))

# Cramer von Mises minimum distance estimator (robust)
(CvM.est <- MDEstimator(x, ParamFamily = NormLocationScaleFamily(), distance = CvMDist))

# optimally robust (amount of gross errors known)
roblox(x, eps = 0.05, initial.est = estimate(CvM.est))

```

---

rowRoblox and colRoblox

*Optimally robust estimation for location and/or scale*

---

## Description

The functions `rowRoblox` and `colRoblox` compute optimally robust estimates for normal location and/or scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Rieder (1994) or Kohl (2005), respectively.

## Usage

```

rowRoblox(x, mean, sd, eps, eps.lower, eps.upper, initial.est, k = 1L,
          fsCor = TRUE, mad0 = 1e-4, na.rm = TRUE)
colRoblox(x, mean, sd, eps, eps.lower, eps.upper, initial.est, k = 1L,
          fsCor = TRUE, mad0 = 1e-4, na.rm = TRUE)

```

**Arguments**

<code>x</code>	matrix or data.frame of (numeric) data values.
<code>mean</code>	specified mean. See details below.
<code>sd</code>	specified standard deviation which has to be positive. See also details below.
<code>eps</code>	positive real ( $0 < \text{eps} \leq 0.5$ ): amount of gross errors. See details below.
<code>eps.lower</code>	positive real ( $0 \leq \text{eps.lower} \leq \text{eps.upper}$ ): lower bound for the amount of gross errors. See details below.
<code>eps.upper</code>	positive real ( $\text{eps.lower} \leq \text{eps.upper} \leq 0.5$ ): upper bound for the amount of gross errors. See details below.
<code>initial.est</code>	initial estimate for mean and/or sd. If missing median and/or MAD are used.
<code>k</code>	positive integer. k-step is used to compute the optimally robust estimator.
<code>fsCor</code>	logical: perform finite-sample correction. See function <code>finiteSampleCorrection</code> .
<code>mad0</code>	scale estimate used if computed MAD is equal to zero
<code>na.rm</code>	logical: if TRUE, the estimator is evaluated at <code>complete.cases(x)</code> .

**Details**

Computes the optimally robust estimator for location with scale specified, scale with location specified, or both if neither is specified. The computation uses a k-step construction with an appropriate initial estimate for location or scale or location and scale, respectively. Valid candidates are e.g. median and/or MAD (default) as well as Kolmogorov(-Smirnov) or Cram\`er von Mises minimum distance estimators; cf. Rieder (1994) and Kohl (2005). In case package Biobase from Bioconductor is installed as is suggested, median and/or MAD are computed using function `rowMedians`.

These functions are optimized for the situation where one has a matrix and wants to compute the optimally robust estimator for every row, respectively column of this matrix. In particular, the amount of cross errors is assumed to be constant for all rows, respectively columns.

If the amount of gross errors (contamination) is known, it can be specified by `eps`. The radius of the corresponding infinitesimal contamination neighborhood is obtained by multiplying `eps` by the square root of the sample size.

If the amount of gross errors (contamination) is unknown, try to find a rough estimate for the amount of gross errors, such that it lies between `eps.lower` and `eps.upper`.

In case `eps.lower` is specified and `eps.upper` is missing, `eps.upper` is set to 0.5. In case `eps.upper` is specified and `eps.lower` is missing, `eps.lower` is set to 0.

If neither `eps` nor `eps.lower` and/or `eps.upper` is specified, `eps.lower` and `eps.upper` are set to 0 and 0.5, respectively.

If `eps` is missing, the radius-minimax estimator in sense of Rieder et al. (2008), respectively Section 2.2 of Kohl (2005) is returned.

In case of location, respectively scale one additionally has to specify `sd`, respectively `mean` where `sd` and `mean` can be a single number, i.e., identical for all rows, respectively columns, or a vector with length identical to the number of rows, respectively columns.

For sample size  $\leq 2$ , median and/or MAD are used for estimation.

If `eps = 0`, mean and/or `sd` are computed.

**Value**

Object of class "kStepEstimate".

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

- Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.
- Rieder, H. (1994) *Robust Asymptotic Statistics*. New York: Springer.
- Rieder, H., Kohl, M. and Ruckdeschel, P. (2008) The Costs of not Knowing the Radius. *Statistical Methods and Applications* 17(1) 13-40. Extended version: <http://r-kurs.de/RRlong.pdf>
- M. Kohl, P. Ruckdeschel, and H. Rieder (2010). Infinitesimally Robust Estimation in General Smoothly Parametrized Models. *Statistical Methods and Application*, **19**(3):333-354.

**See Also**

[roblox, kStepEstimate-class](#)

**Examples**

```
ind <- rbinom(200, size=1, prob=0.05)
X <- matrix(rnorm(200, mean=ind*3, sd=(1-ind) + ind*9), nrow = 2)
rowRoblox(X)
rowRoblox(X, k = 3)
rowRoblox(X, eps = 0.05)
rowRoblox(X, eps = 0.05, k = 3)

X1 <- t(X)
colRoblox(X1)
colRoblox(X1, k = 3)
colRoblox(X1, eps = 0.05)
colRoblox(X1, eps = 0.05, k = 3)

X2 <- rbind(rnorm(100, mean = -2, sd = 3), rnorm(100, mean = -1, sd = 4))
rowRoblox(X2, sd = c(3, 4))
rowRoblox(X2, eps = 0.03, sd = c(3, 4))
rowRoblox(X2, sd = c(3, 4), k = 4)
rowRoblox(X2, eps = 0.03, sd = c(3, 4), k = 4)

X3 <- cbind(rnorm(100, mean = -2, sd = 3), rnorm(100, mean = 1, sd = 2))
colRoblox(X3, mean = c(-2, 1))
colRoblox(X3, eps = 0.02, mean = c(-2, 1))
colRoblox(X3, mean = c(-2, 1), k = 4)
colRoblox(X3, eps = 0.02, mean = c(-2, 1), k = 4)
```

rsOptIC

*Computation of the optimally robust IC for AL estimators***Description**

The function rsOptIC computes the optimally robust IC for AL estimators in case of normal scale and (convex) contamination neighborhoods. The definition of these estimators can be found in Rieder (1994) or Kohl (2005), respectively.

**Usage**

```
rsOptIC(r, mean = 0, sd = 1, bUp = 1000, delta = 1e-06, itmax = 100, computeIC = TRUE)
```

**Arguments**

r	non-negative real: neighborhood radius.
mean	specified mean.
sd	specified standard deviation.
bUp	positive real: the upper end point of the interval to be searched for the clipping bound b.
delta	the desired accuracy (convergence tolerance).
itmax	the maximum number of iterations.
computeIC	logical: should IC be computed. See details below.

**Details**

If 'computeIC' is 'FALSE' only the Lagrange multipliers 'A', 'a', and 'b' contained in the optimally robust IC are computed.

**Value**

If 'computeIC' is 'TRUE' an object of class "ContIC" is returned, otherwise a list of Lagrange multipliers

A	standardizing constant
a	centering constant
b	optimal clipping bound

**Author(s)**

Matthias Kohl <Matthias.Kohl@stamats.de>

**References**

Rieder, H. (1994) *Robust Asymptotic Statistics*. New York: Springer.  
 Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.

**See Also**

[ContIC-class](#), [roblox](#)

**Examples**

```
IC1 <- rsOptIC(r = 0.1)
distrExOptions("ErelativeTolerance" = 1e-12)
checkIC(IC1)
distrExOptions("ErelativeTolerance" = .Machine$double.eps^0.25) # default
Risks(IC1)
cent(IC1)
clip(IC1)
stand(IC1)
plot(IC1)
```

---

 showdown

---

*Estimator Showdown by Monte-Carlo Study.*


---

**Description**

The function `showdown` can be used to perform Monte-Carlo studies comparing a competitor with `rmx` estimators in case of normal location and scale. In addition, maximum likelihood (ML) estimators (mean and sd) and median and MAD are computed. The comparison is based on the empirical MSE.

**Usage**

```
showdown(n, M, eps, contD, seed = 123, estfun, estMean, estSd,
         eps.lower = 0, eps.upper = 0.05, steps = 3L, fsCor = TRUE,
         plot1 = FALSE, plot2 = FALSE, plot3 = FALSE)
```

**Arguments**

<code>n</code>	integer; sample size, should be at least 3.
<code>M</code>	integer; Monte-Carlo replications.
<code>eps</code>	amount of contamination in $[0, 0.5]$ .
<code>contD</code>	object of class "UnivariateDistribution"; contaminating distribution.
<code>seed</code>	random seed.
<code>estfun</code>	function to compute location and scale estimator; see details below.
<code>estMean</code>	function to compute location estimator; see details below.
<code>estSd</code>	function to compute scale estimator; see details below.
<code>eps.lower</code>	used by <code>rmx</code> estimator.
<code>eps.upper</code>	used by <code>rmx</code> estimator.
<code>steps</code>	integer; steps used for estimator construction.

fsCor	logical; use finite-sample correction.
plot1	logical; plot cdf of ideal and real distribution.
plot2	logical; plot 20 (or M if $M < 20$ ) randomly selected samples.
plot3	logical; generate boxplots of the results.

### Details

Normal location and scale with mean = 0 and sd = 1 is used as ideal model (without restriction due to equivariance).

Since there is no estimator which yields reliable results if 50 percent or more of the observations are contaminated, we use a modification where we re-simulate all samples including at least 50 percent contaminated data.

If `estfun` is specified it has to compute and return a location and scale estimate (vector of length 2). One can also specify the location and scale estimator separately by using `estMean` and `estSd` where `estMean` computes and returns the location estimate and `estSd` the scale estimate.

We use function `rowRoblox` for the computation of the `rmx` estimator.

### Value

Data.frame including empirical MSE (standardized by sample size  $n$ ) and `relMSE` with respect to the `rmx` estimator.

### Author(s)

Matthias Kohl <Matthias.Kohl@stamats.de>

### References

- Kohl, M. (2005) *Numerical Contributions to the Asymptotic Theory of Robustness*. Bayreuth: Dissertation.
- Rieder, H. (1994) *Robust Asymptotic Statistics*. New York: Springer.
- Rieder, H., Kohl, M. and Ruckdeschel, P. (2008) The Costs of not Knowing the Radius. *Statistical Methods and Applications* 17(1) 13-40. Extended version: <http://r-kurs.de/RRlong.pdf>
- M. Kohl, P. Ruckdeschel, and H. Rieder (2010). Infinitesimally Robust Estimation in General Smoothly Parametrized Models. *Statistical Methods and Application*, **19**(3):333-354.

### See Also

[rowRoblox](#)

### Examples

```
library(MASS)
## compare with Huber's Proposal 2
showdown(n = 20, M = 100, eps = 0.02, contD = Norm(mean = 3, sd = 3),
         estfun = function(x){ unlist(hubers(x)) },
         plot1 = TRUE, plot2 = TRUE, plot3 = TRUE)
```

```
## compare with Huber M estimator with MAD scale
showdown(n = 20, M = 100, eps = 0.02, contD = Norm(mean = 3, sd = 3),
  estfun = function(x){ unlist(huber(x)) },
  plot1 = TRUE, plot2 = TRUE, plot3 = TRUE)
```

# Index

- \* **Monte-Carlo study**
  - showdown, [35](#)
- \* **finite-sample correction**
  - finiteSampleCorrection, [4](#)
- \* **influence curve**
  - rlOptIC, [5](#)
  - rlsOptIC.AL, [6](#)
  - rlsOptIC.An1, [8](#)
  - rlsOptIC.An2, [10](#)
  - rlsOptIC.AnMad, [11](#)
  - rlsOptIC.BM, [12](#)
  - rlsOptIC.Ha3, [13](#)
  - rlsOptIC.Ha4, [14](#)
  - rlsOptIC.HaMad, [16](#)
  - rlsOptIC.Hu1, [17](#)
  - rlsOptIC.Hu2, [18](#)
  - rlsOptIC.Hu2a, [19](#)
  - rlsOptIC.Hu3, [20](#)
  - rlsOptIC.HuMad, [21](#)
  - rlsOptIC.M, [22](#)
  - rlsOptIC.MM2, [24](#)
  - rlsOptIC.Tu1, [25](#)
  - rlsOptIC.Tu2, [26](#)
  - rlsOptIC.TuMad, [27](#)
  - roblox, [28](#)
  - rowRoblox and colRoblox, [31](#)
  - rsOptIC, [34](#)
- \* **normal location and scale**
  - finiteSampleCorrection, [4](#)
  - rlsOptIC.AL, [6](#)
  - rlsOptIC.An1, [8](#)
  - rlsOptIC.An2, [10](#)
  - rlsOptIC.AnMad, [11](#)
  - rlsOptIC.BM, [12](#)
  - rlsOptIC.Ha3, [13](#)
  - rlsOptIC.Ha4, [14](#)
  - rlsOptIC.HaMad, [16](#)
  - rlsOptIC.Hu1, [17](#)
  - rlsOptIC.Hu2, [18](#)
  - rlsOptIC.Hu2a, [19](#)
  - rlsOptIC.Hu3, [20](#)
  - rlsOptIC.HuMad, [21](#)
  - rlsOptIC.M, [22](#)
  - rlsOptIC.MM2, [24](#)
  - rlsOptIC.Tu1, [25](#)
  - rlsOptIC.Tu2, [26](#)
  - rlsOptIC.TuMad, [27](#)
  - roblox, [28](#)
  - rowRoblox and colRoblox, [31](#)
- \* **normal location**
  - finiteSampleCorrection, [4](#)
  - rlOptIC, [5](#)
  - roblox, [28](#)
  - rowRoblox and colRoblox, [31](#)
- \* **normal scale**
  - finiteSampleCorrection, [4](#)
  - roblox, [28](#)
  - rowRoblox and colRoblox, [31](#)
  - rsOptIC, [34](#)
- \* **package**
  - RobLox-package, [2](#)
- \* **robust**
  - finiteSampleCorrection, [4](#)
  - rlOptIC, [5](#)
  - rlsOptIC.AL, [6](#)
  - rlsOptIC.An1, [8](#)
  - rlsOptIC.An2, [10](#)
  - rlsOptIC.AnMad, [11](#)
  - rlsOptIC.BM, [12](#)
  - rlsOptIC.Ha3, [13](#)
  - rlsOptIC.Ha4, [14](#)
  - rlsOptIC.HaMad, [16](#)
  - rlsOptIC.Hu1, [17](#)
  - rlsOptIC.Hu2, [18](#)
  - rlsOptIC.Hu2a, [19](#)
  - rlsOptIC.Hu3, [20](#)
  - rlsOptIC.HuMad, [21](#)
  - rlsOptIC.M, [22](#)

- rlsOptIC.MM2, 24
- rlsOptIC.Tu1, 25
- rlsOptIC.Tu2, 26
- rlsOptIC.TuMad, 27
- roblox, 28
- rowRoblox and colRoblox, 31
- rsOptIC, 34
- showdown, 35

colRoblox, 5

colRoblox (rowRoblox and colRoblox), 31

finiteSampleCorrection, 4, 29, 32

MLEstimator, 29

r1OptIC, 5, 30

rlsOptIC.AL, 6, 30

rlsOptIC.An1, 8

rlsOptIC.An2, 10

rlsOptIC.AnMad, 11

rlsOptIC.BM, 12

rlsOptIC.Ha3, 13

rlsOptIC.Ha4, 14

rlsOptIC.HaMad, 16

rlsOptIC.Hu1, 17

rlsOptIC.Hu2, 18

rlsOptIC.Hu2a, 19

rlsOptIC.Hu3, 20

rlsOptIC.HuMad, 21

rlsOptIC.M, 22

rlsOptIC.MM2, 24

rlsOptIC.Tu1, 25

rlsOptIC.Tu2, 26

rlsOptIC.TuMad, 27

RobLox (RobLox-package), 2

roblox, 5–7, 28, 33, 35

RobLox-package, 2

roptest, 30

rowRoblox, 5, 36

rowRoblox (rowRoblox and colRoblox), 31

rowRoblox and colRoblox, 31

rsOptIC, 30, 34

showdown, 35