

# Return Curves Estimation

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## 1 Introduction

This vignette provides complementary information to the R Documentation for the `ReturnCurves` package. It summarises the key methodologies implemented in the package and is heavily based on the works of Murphy-Barltrop et al. [2023] and Murphy-Barltrop et al. [2024]; for full details we refer the user to these articles.

The `ReturnCurves` package aims at estimating the  $p$ -probability return curve [Murphy-Barltrop et al., 2023] for small  $p > 0$ , while implementing pointwise and smooth approaches to estimate the so called angular dependence function first introduced by Wadsworth and Tawn [2013].

```
library(ReturnCurves)
```

To illustrate the functionality of the package, we use ... *data need to find better data yet*

```
set.seed(321)
data <- cbind(rnorm(1000), rnorm(1000))
```

## 2 Marginal transformation

The estimation of the angular dependence function and/or of the return curve is implemented for a bivariate vector  $(X_E, Y_E)$  marginally distributed as standard exponential, i.e.  $X_E, Y_E \sim \text{Exp}(1)$ . Thus, the original data  $(X, Y)$  needs to be marginally transformed, which is achieved via the probability integral transform. We follow the procedure of Coles and Tawn [1991] where the empirical cumulative distribution function  $\tilde{F}$  is fitted below a threshold  $u$ , and a generalised Pareto distribution (GPD) is fitted above, giving the following estimate of the marginal cumulative distribution function (cdf) of  $X$  or  $Y$  :

$$\hat{F}(z) = \begin{cases} 1 - (1 - \tilde{F}(u)) \left[1 + \xi \frac{z-u}{\sigma}\right]_+^{-1/\xi}, & \text{if } z > u, \\ \tilde{F}(z), & \text{if } z \leq u, \end{cases} \quad (1)$$

where  $\hat{\sigma}$  and  $\hat{\xi}$  are the estimated scale and shape parameters of the GPD. Exponential margins are obtained by applying  $-\log(1 - \hat{F}(\cdot))$  to each margin, where  $\hat{F}(\cdot)$  is estimated separately for each margin.

This is done with the function `margtransf` which takes a matrix containing the original data, a vector of the marginal quantiles used to fit the GPD and a boolean value `constrainedshape` which decides whether  $\xi > -1$  if set to `TRUE` (Default), or  $\xi \in \mathbb{R}$  if set to `FALSE` as inputs.

Function `margtransf` returns an object of S4 class `margtrasnf.class` with six attributes:

- `data`: matrix with the data on the original margins
- `qmarg`: vector of marginal quantiles used to fit the GPD
- `constrainedshape`: whether  $\xi > -1$  or  $\xi \in \mathbb{R}$
- `parameters`: matrix containing parameters  $(\sigma, \xi)$
- `thresh`: vector containing threshold  $u$  above which the GPD is fitted
- `dataexp`: matrix with the data on standard exponential margins

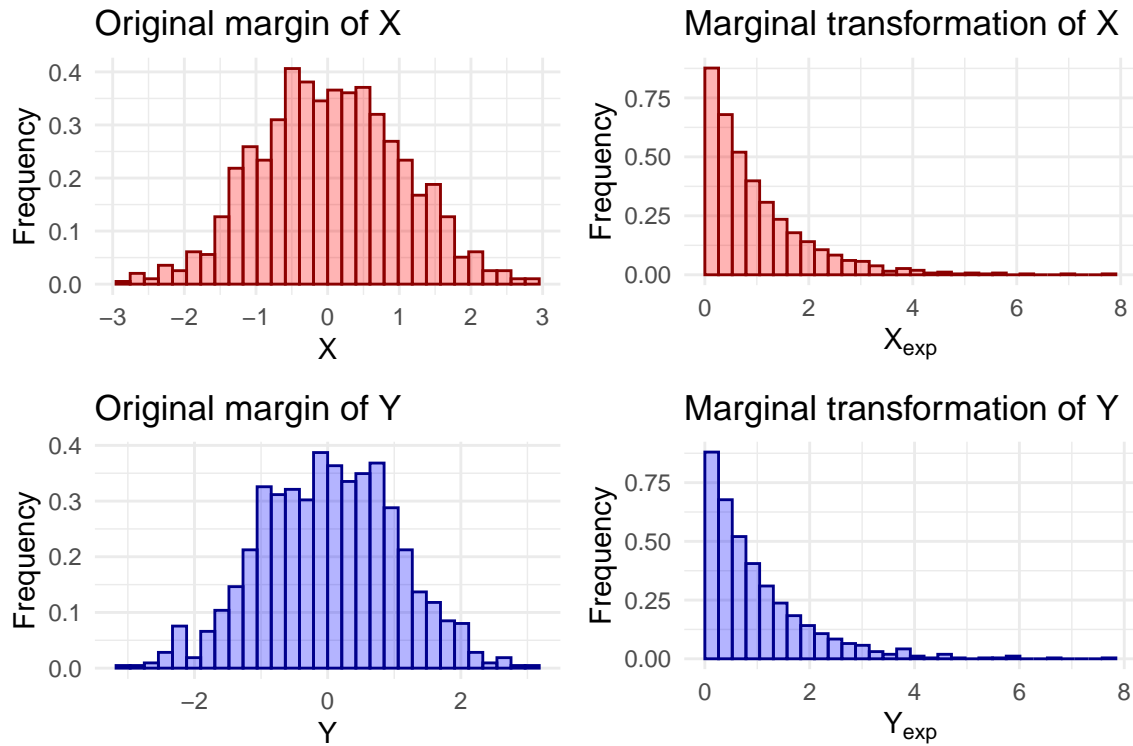
```
# qmarg and constrainedshape set to the default values
expdata <- margtransf(data = data, qmarg = rep(0.95, 2), constrainedshape = T)

# attributes of the S4 object
str(expdata)
#> Formal class 'margtransf.class' [package "ReturnCurves"] with 6 slots
#> ..@ data          : num [1:1000, 1:2] 1.705 -0.712 -0.278 -0.12 -0.124 ...
#> ..@ qmarg         : num [1:2] 0.95 0.95
#> ..@ constrainedshape: logi TRUE
#> ..@ parameters    : num [1:2, 1:2] 0.505 -0.303 0.398 -0.104
#> ..@ thresh        : num [1:2] 1.65 1.69
#> ..@ dataexp       : num [1:1000, 1:2] 3.101 0.266 0.489 0.602 0.599 ...

# head of the data on standard exponential margins
head(expdata@dataexp)
#>      [,1]      [,2]
#> [1,] 3.1008831 0.06500483
#> [2,] 0.2662680 0.09971547
#> [3,] 0.4887599 2.43141796
#> [4,] 0.6024795 0.69414668
#> [5,] 0.5988365 3.55115450
#> [6,] 0.8974876 0.13911280
```

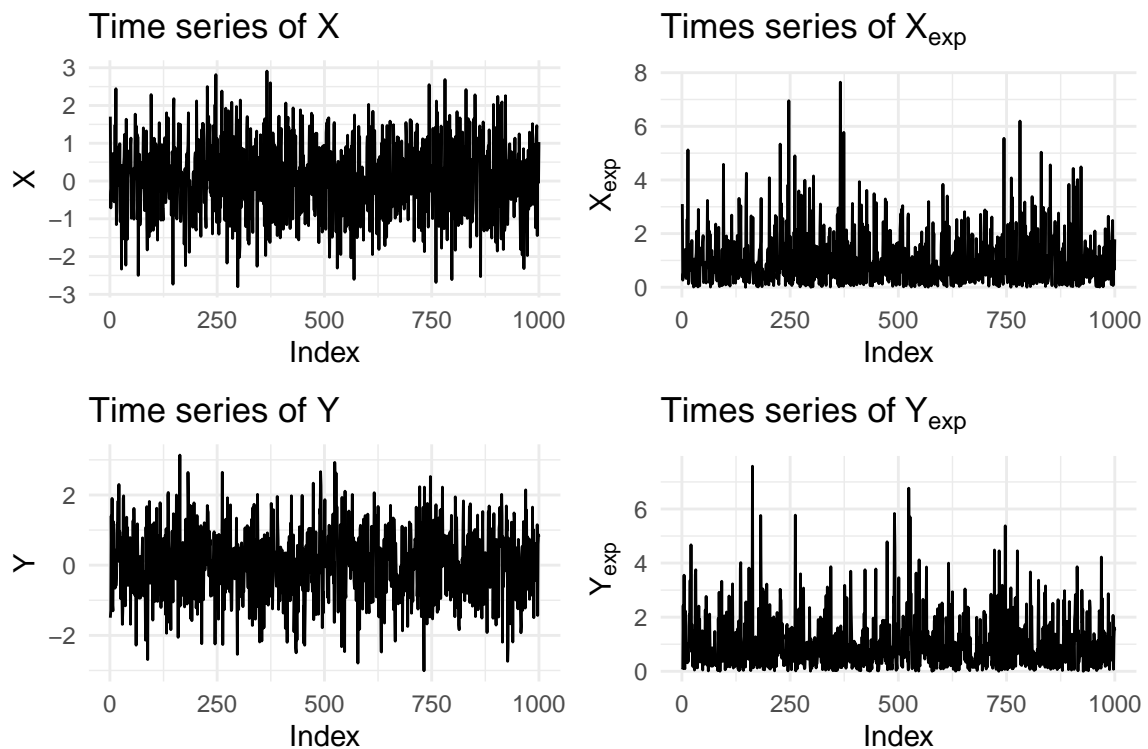
It is possible to plot an S4 object of `margtrasnf.class` with `plot`. By setting argument `which = "hist"`, histograms of each variable on original and standard exponential margins can be seen:

```
plot(expdata, which = "hist")
```



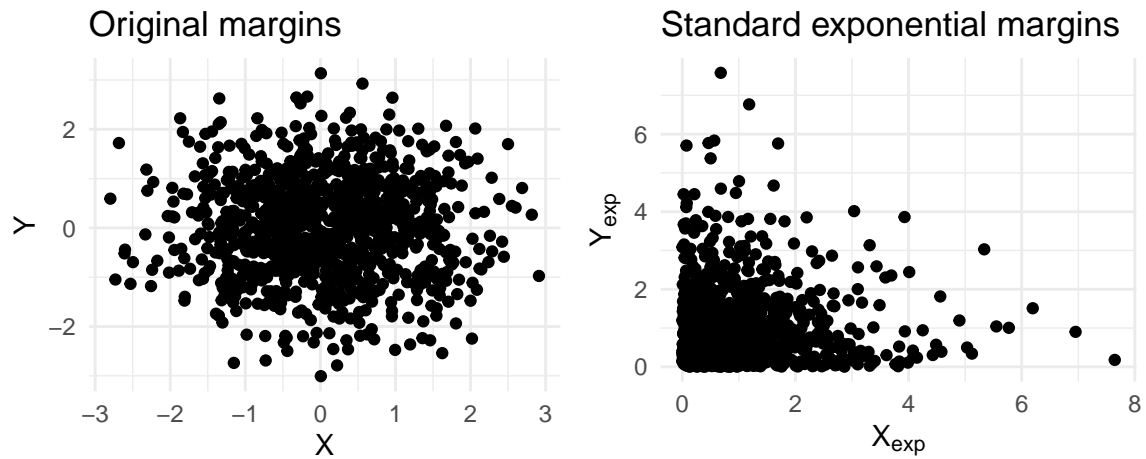
To visualise the time series of each variable on original and standard exponential margins, we need to set `which = "ts"`:

```
plot(expdata, which = "ts")
```



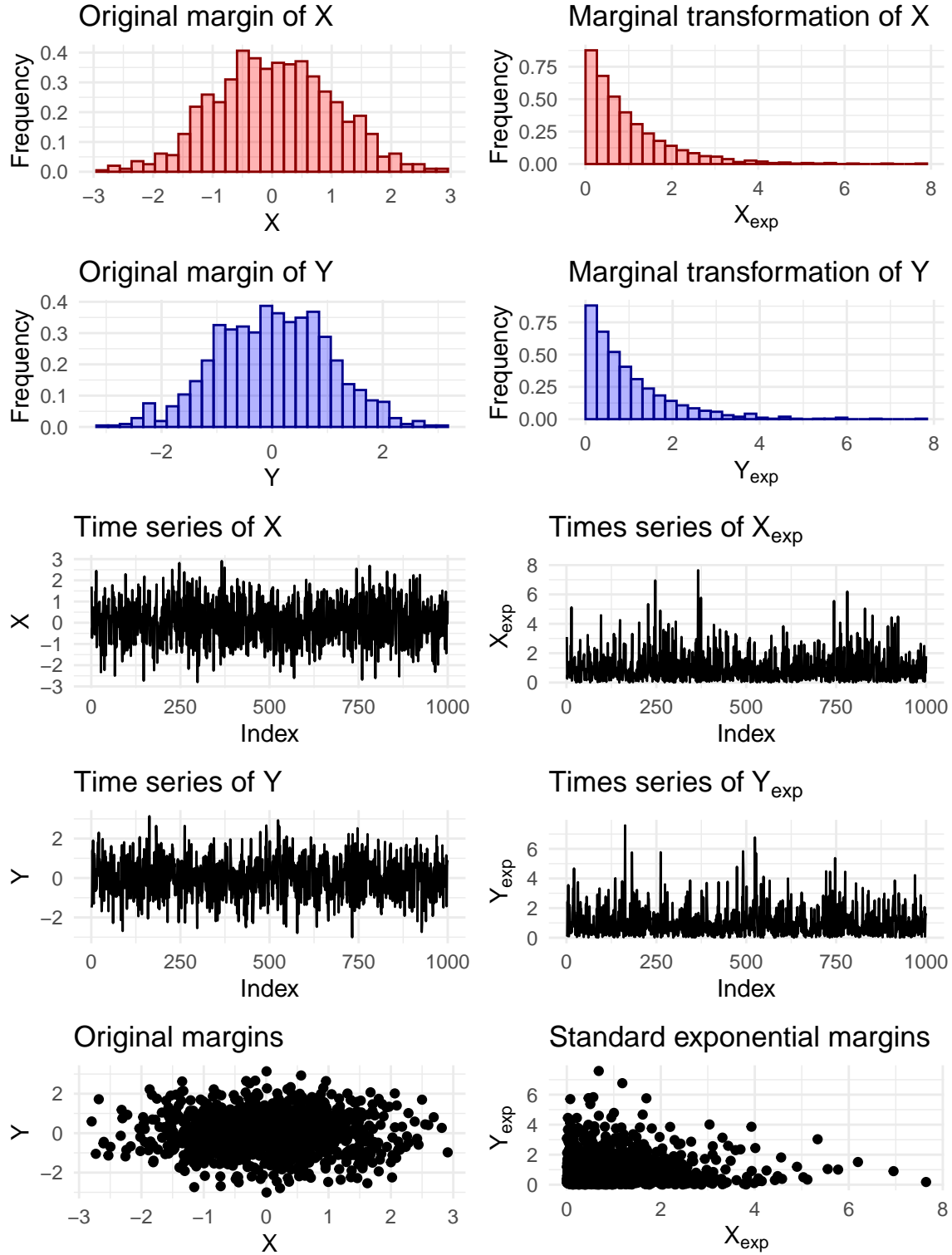
The joint distribution on original and standard exponential margins can be access with `which = "joint"`:

```
plot(expdata, which = "joint")
```



Finally, it is possible to plot all these together by setting `which = "all"`, which is the default for this argument.

```
plot(expdata, which = "all") # or just plot(expdata)
```



### 3 Estimation of the angular dependence function

In bivariate extremes, interest may lie in studying regions where both variables are extreme or where only one is extreme. A few methods, such as the one introduced by Wadsworth and Tawn [2013], aim at characterising

the joint tail behaviour in both scenarios are available in the literature. Given standard exponentially distributed variables  $X_E$  and  $Y_E$  and a slowly varying function  $\mathcal{L}(\cdot; \omega)$  at infinity, the joint tail behaviour of  $(X_E, Y_E)$  is captured through  $\lambda(\omega)$  via the assumption

$$\Pr(X_E > \omega u, Y_E > (1 - \omega)u) = \mathcal{L}(e^u; \omega) e^{-\lambda(\omega)u} \quad \text{as } u \rightarrow \infty,$$

which can be rewritten as

$$\Pr\left(\min\left\{\frac{X_E}{\omega}, \frac{Y_E}{1 - \omega}\right\}\right) = \mathcal{L}(e^u; \omega) e^{-\lambda(\omega)u} \quad \text{as } u \rightarrow \infty, \quad (2)$$

where  $\omega \in [0, 1]$  and  $\lambda(\omega) \geq \max\{\omega, 1 - \omega\}$  is called the angular dependence function (ADF). In the case of asymptotic dependence (see, e.g., Coles et al. [1999]),  $\lambda(\omega) = \max\{\omega, 1 - \omega\}$  for all  $\omega \in [0, 1]$ .

Lastly, defining a min-projection variable at  $\omega$ ,  $T_\omega = \min\left\{\frac{X_E}{\omega}, \frac{Y_E}{1 - \omega}\right\}$ , equation (2) implies that

$$\Pr(T_\omega > u + t \mid T_\omega > u) = \frac{\mathcal{L}(e^{u+t}; \omega)}{\mathcal{L}(e^u; \omega)} e^{-\lambda(\omega)t} \rightarrow e^{-\lambda(\omega)t} \quad \text{as } u \rightarrow \infty, \quad (3)$$

for any  $\omega \in [0, 1]$  and  $t > 0$ . In other words, for all  $\omega \in [0, 1]$  and, as  $u_\omega \rightarrow \infty$ ,  $T_\omega^1 := (T_\omega - u_\omega \mid T_\omega > u_\omega) \sim \text{Exp}(\lambda(\omega))$ . Estimation of the ADF can be done in different ways; Murphy-Barltrop et al. [2024] present a few.

For the `ReturnCurves` package, two approaches are implemented: a pointwise estimator using the Hill estimator [Hill, 1975],  $\hat{\lambda}_H$ , and a smoother estimator based on Bernstein-Bézier polynomials estimated via composite likelihood methods,  $\hat{\lambda}_{CL}$ . For the latter, Murphy-Barltrop et al. [2024] propose using a family of Bernstein-Bézier polynomials to improve the estimation of the ADF. Given  $k \in \mathbb{N}$ , it is assumed that  $\lambda(\omega) = \lambda(\omega; \beta)$  can be represented by the following family of functions:

$$\mathcal{B}_k^* = \left\{ (1 - \omega)^k + \sum_{i=1}^{k-1} \beta_i \binom{k}{i} \omega^i (1 - \omega)^{k-i} + \omega^k =: f(\omega) \mid \omega \in [0, 1], \right. \\ \left. \beta \in [0, \infty)^{k-1} \text{ such that } f(\omega) \geq \max\{\omega, 1 - \omega\} \right\}. \quad (4)$$

As  $T_\omega^1$  is exponentially distributed when  $u_\omega \rightarrow \infty$ , the parameter vector  $\beta$  can be estimated using a composite likelihood function defined as

$$\mathcal{L}_C(\beta) = \left[ \prod_{\omega \in \Omega} \lambda(\omega; \beta)^{|t_\omega^1|} \right] \exp \left\{ - \sum_{\omega \in \Omega} \sum_{t_\omega^1 \in \mathbf{t}_\omega^1} \lambda(\omega; \beta) t_\omega \right\}, \quad (5)$$

where  $|t_\omega^1|$  represents the cardinality of set  $\mathbf{t}_\omega^1 := \{t_\omega - u_\omega \mid t_\omega \in \mathbf{t}_\omega, t_\omega > u_\omega\}$  for some large values  $u_\omega$ , and  $\Omega$  is a finite subset spanning the interval  $[0, 1]$ . The estimator of the ADF through composite likelihood methods is given by  $\lambda(\cdot; \hat{\beta}_{CL})$  where  $\hat{\beta}_{CL}$  maximises equation (5).

Finally, Murphy-Barltrop et al. [2024] showed that incorporating knowledge of the conditional extremes [Heffernan and Tawn, 2004] parameters  $\alpha_{y|x}$  and  $\alpha_{x|y}$  improves the estimation of the ADF. In particular, the authors show that, in order to satisfy theoretical properties of  $\lambda(\omega)$ ,  $\lambda(\omega) = \max\{\omega, 1 - \omega\}$  for all  $\omega \in [0, \alpha_{x|y}^1] \cup [\alpha_{y|x}^1, 1]$  with  $\alpha_{x|y}^1 = \alpha_{x|y}/(1 + \alpha_{x|y})$  and  $\alpha_{y|x}^1 = 1/(1 + \alpha_{y|x})$ . Thus, after estimating the conditional extremes parameters  $\alpha_{y|x}$  and  $\alpha_{x|y}$  through maximum likelihood estimation, we can set  $\lambda(\omega) = \max\{\omega, 1 - \omega\}$  for  $\omega \in [0, \hat{\alpha}_{x|y}^1] \cup [\hat{\alpha}_{y|x}^1, 1]$ . Then, for the Hill estimator,  $\lambda(\omega) = \hat{\lambda}_H$  for  $\omega \in [\hat{\alpha}_{x|y}^1, \hat{\alpha}_{y|x}^1]$ . For the composite likelihood estimator, a rescaling of equation (4) is needed to ensure continuity at  $\hat{\alpha}_{x|y}^1$  and  $\hat{\alpha}_{y|x}^1$ , as defined

below:

$$\mathcal{B}_k^1 = \left\{ (1 - \hat{\alpha}_{x|y}^1) \left( 1 - \frac{v - \hat{\alpha}_{x|y}^1}{\hat{\alpha}_{y|x}^1 - \hat{\alpha}_{x|y}^1} \right)^k + \sum_{i=1}^{k-1} \beta_i \binom{k}{i} \left( \frac{v - \hat{\alpha}_{x|y}^1}{\hat{\alpha}_{y|x}^1 - \hat{\alpha}_{x|y}^1} \right)^i \left( 1 - \frac{v - \hat{\alpha}_{x|y}^1}{\hat{\alpha}_{y|x}^1 - \hat{\alpha}_{x|y}^1} \right)^{k-i} + \hat{\alpha}_{y|x}^1 \left( \frac{v - \hat{\alpha}_{x|y}^1}{\hat{\alpha}_{y|x}^1 - \hat{\alpha}_{x|y}^1} \right)^k =: f(v) \mid v \in [\hat{\alpha}_{x|y}^1, \hat{\alpha}_{y|x}^1], \beta \in [0, \infty)^{k-1} \text{ such that } f(v) \geq \max\{v, 1 - v\} \right\}.$$

$\lambda(\omega) = \lambda(\omega; \beta)$  is assumed to be represented by an element of  $\mathcal{B}_k^1$  on  $[\hat{\alpha}_{x|y}^1, \hat{\alpha}_{y|x}^1]$ . Finally, the estimators used for estimation are processed in order to satisfy theoretical conditions on  $\lambda$  as identified in Murphy-Barltrop et al. [2024].

Estimation of the ADF can be done using the function `adf_est` which takes as inputs:

- an S4 object of class `margtransf.class` representing the marginal transformation of the data,
- a sequence of rays `w` in  $[0, 1]$ ,
- a string `method` indicating which estimator to get,  $\lambda_H$  or  $\lambda_{CL}$ ,
- and a boolean value `constrained` which decides whether to incorporate conditional extremes parameters  $\alpha_{y|x}$  and  $\alpha_{x|y}$  in the estimation.

Additional arguments can be defined outside of the default values; these include marginal quantiles for the min-projection variable  $T^1$ , marginal quantiles to fit the conditional extremes method if `constrained=T`, the polynomial degree  $k$ , the initial values for  $\beta$  for the composite maximum likelihood procedure, and the convergence tolerance; this increases the probability of the function converging to its global maximum rather than getting stuck at a local maximum.

Function `adf_est` returns an object of S4 class `adf_est.class` with ten attributes, where the first nine are the inputs of the function and the last is a vector `adf` containing the estimates of  $\lambda(\omega)$ .

```
# Estimation using Hill estimator without conditional extremes parameters
whill <- seq(0, 1, by = 0.001)
## q and constrained are set to the default values here
lambdah <- adf_est(margdata = expdata, w = whill, method = "hill",
                  q = 0.95, constrained = F)

# Estimation using Hill estimator with conditional extremes parameters
## q and qalphas are set to the default values
lambdah2 <- adf_est(margdata = expdata, w = whill, method = "hill", q = 0.95,
                  qalphas = rep(0.95, 2), constrained = T)

# Estimation using CL method without conditional extremes parameters
## w, q and constrained are set to the default values here
lambdac1 <- adf_est(margdata = expdata, w = seq(0, 1, by = 0.01), method = "cl",
                  q = 0.95, constrained = F)

# Estimation using CL method with conditional extremes parameters
## w, q and qalphas are set to the default values
lambdac12 <- adf_est(margdata = expdata, w = seq(0, 1, by = 0.01), method = "cl",
                  q = 0.95, qalphas = rep(0.95, 2), constrained = T)

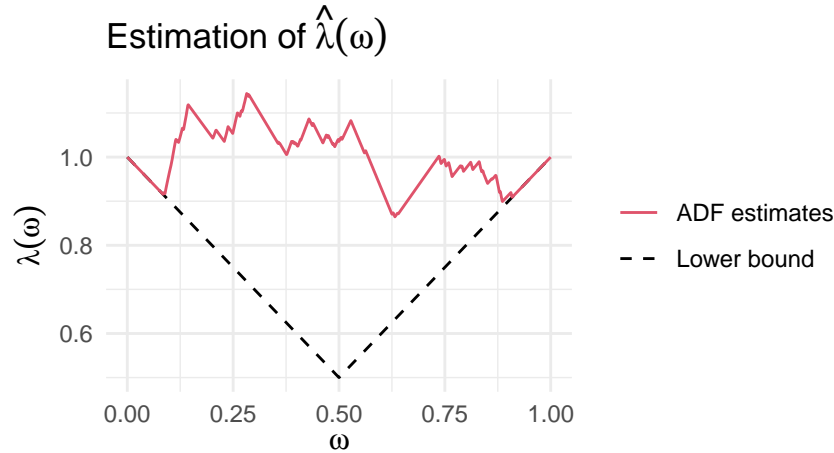
# attributes of the S4 object
str(lambdah)
#> Formal class 'adf_est.class' [package "ReturnCurves"] with 11 slots
#> ..@ dataexp      : num [1:1000, 1:2] 3.101 0.266 0.489 0.602 0.599 ...
#> ..@ w           : num [1:1001] 0 0.001 0.002 0.003 0.004 0.005 0.006 0.007 0.008 0.009 ...
```

```
#> ..@ method      : chr "hill"
#> ..@ q            : num 0.95
#> ..@ qalphas      : num [1:2] 0.95 0.95
#> ..@ k            : num 7
#> ..@ constrained: logi FALSE
#> ..@ tol          : num 1e-04
#> ..@ par_init     : num [1:6] 0 0 0 0 0 0
#> ..@ interval     : num [1:2] 0 1
#> ..@ adf          : num [1:1001] 1 0.999 0.998 0.997 0.996 0.995 0.994 0.993 0.992 0.991 ...

# head of the vector with adf estimates for the first estimator
head(lambdah@adf)
#> [1] 1.000 0.999 0.998 0.997 0.996 0.995
```

It is possible to plot an S4 object of `adf_est.class` with `plot`, where a comparison of the estimated ADF and its lower bound,  $\max\{\omega, 1 - \omega\}$ , is shown.

```
# plot of the ADF estimation based on the unconstrained Hill estimator
plot(lambdah)
```



### 3.1 Goodness-of-fit of the angular dependence function

After estimation of the ADF, it is important to assess its goodness-of-fit. Noting that  $T_\omega^1 = (T_\omega - u_\omega \mid T_\omega > u_\omega) \sim \text{Exp}(\lambda(\omega)) \Leftrightarrow \lambda(\omega)T_\omega^1 \sim \text{Exp}(1)$ , we can investigate whether there is agreement between model and empirical exponential quantiles, or not. This is done in the `ReturnCurves` package through QQ plots by plotting points  $(F_E^{-1}(i/(n+1)), T_{(i)}^1)$ , where  $F_E^{-1}$  denotes the inverse of the cumulative distribution of a standard exponential distribution and  $T_{(i)}^1$  is the  $i$ -th ordered increasing statistic,  $i = 1, \dots, n$ . The uncertainty of the empirical quantiles is quantified using a bootstrap approach. If temporal dependence is present in the data, a block bootstrap approach should be used (`blocksize > 1`).

The assessment of the goodness-of-fit of  $\lambda(\omega)$  can be done using the function `adf_gof` which takes an S4 object of class `adf_est.class`, ray  $\omega$  to be considered, the size of the blocks for the bootstrap procedure and the corresponding number of samples, and the significance level  $\alpha$  for the tolerance intervals as inputs. In turn, it returns an S4 object of class `adf_gof.class` with an extra attribute, `gof`, containing a list with the model and empirical quantiles, and the lower and upper bounds of the tolerance interval.

We note that this function is implemented to evaluate the fit at a single ray  $\omega$ ; therefore, we recommend repeating the procedure for a few rays to have a better representation. In addition, if the ray provided by the user was not used for the estimation of the ADF, then the closest  $\omega$  in the grid is used instead.



```

# Goodness of fit of the adf for three rays w
rays <- c(0.25, 0.5, 0.75)
## blocksize, nboot and alpha are set to the default values
gofh <- sapply(rays, adf_gof, adf = lambdah, blocksize = 1, nboot = 250, alpha = 0.05)

# attributes of the S4 object
str(gofh[[1]])
#> Formal class 'adf_gof.class' [package "ReturnCurves"] with 6 slots
#> ..@ adf      :Formal class 'adf_est.class' [package "ReturnCurves"] with 11 slots
#> .. .. ..@ dataexp      : num [1:1000, 1:2] 3.101 0.266 0.489 0.602 0.599 ...
#> .. .. ..@ w            : num [1:1001] 0 0.001 0.002 0.003 0.004 0.005 0.006 0.007 0.008 0.009 ...
#> .. .. ..@ method      : chr "hill"
#> .. .. ..@ q            : num 0.95
#> .. .. ..@ qalphas     : num [1:2] 0.95 0.95
#> .. .. ..@ k            : num 7
#> .. .. ..@ constrained: logi FALSE
#> .. .. ..@ tol          : num 1e-04
#> .. .. ..@ par_init     : num [1:6] 0 0 0 0 0 0
#> .. .. ..@ interval     : num [1:2] 0 1
#> .. .. ..@ adf          : num [1:1001] 1 0.999 0.998 0.997 0.996 0.995 0.994 0.993 0.992 0.991 ...
#> ..@ ray        : num 0.25
#> ..@ blocksize: num 1
#> ..@ nboot      : num 250
#> ..@ alpha      : num 0.05
#> ..@ gof        :List of 4
#> .. ..$ model    : num [1:50] 0.0198 0.04 0.0606 0.0817 0.1032 ...
#> .. ..$ empirical: num [1:50] 0.026 0.054 0.112 0.126 0.141 ...
#> .. ..$ lower    : num [1:50] 0.026 0.026 0.026 0.026 0.054 ...
#> .. ..$ upper    : num [1:50] 0.112 0.141 0.235 0.283 0.302 ...

# head of the list elements of slot gof
head(gofh[[1]]@gof$model)
#> [1] 0.01980263 0.04000533 0.06062462 0.08167803 0.10318424 0.12516314
head(gofh[[1]]@gof$empirical)
#> [1] 0.02601951 0.05395085 0.11152974 0.12629937 0.14122529 0.21832026
head(gofh[[1]]@gof$lower)
#> [1] 0.02601951 0.02601951 0.02601951 0.02601951 0.05395085 0.11152974
head(gofh[[1]]@gof$upper)
#> [1] 0.1115297 0.1412253 0.2351376 0.2831817 0.3022290 0.3205085

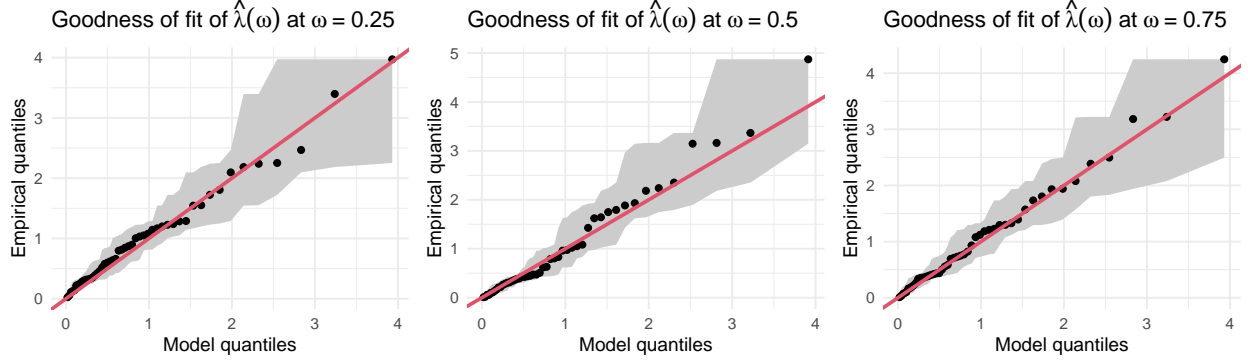
```

As before, it is possible to plot an S4 object of `adf_gof.class` with `plot`, where the QQ-plot with the model and empirical quantiles are shown. The points should lie close to the line  $y = x$ ; for a good fit and agreement between these quantile, line  $y = x$  should mainly lie within the  $(1 - \alpha)\%$  tolerance intervals.

```

library(gridExtra)
grid.arrange(plot(gofh[[1]]), plot(gofh[[2]]), plot(gofh[[3]]), ncol = 3)

```



## 4 Estimation of the return curve

Given a probability  $p$  and the joint survivor function  $\Pr(X > x, Y > y)$  of the bivariate vector  $(X, Y)$ , the  $p$ -probability return curve is defined as

$$\text{RC}(p) := \{(x, y) \in \mathbb{R}^2 : \Pr(X > x, Y > y) = p\}. \quad (6)$$

The interest lies in values of  $p$  close to 0 as these are the ones characterising rare joint exceedances events. Given any point  $(x, y) \in \text{RC}(p)$ , the event  $\{X > x, Y > y\}$  is expected to happen once each return period  $1/p$ , on average. This is equivalent to having an expected value of  $np$  points in the region  $(x, \infty) \times (y, \infty)$  in a sample size of  $n$  from  $(X, Y)$ .

Since the probability  $p$  is close to 0, methods that can accurately capture the behaviour of the joint tail are necessary in order to realistically extrapolate and estimate  $\text{RC}(p)$  for values of  $p$  outside of the observation period. Murphy-Barltrop et al. [2023] consider a couple of methods to achieve this, one of which uses the ADF  $\lambda(\omega)$  given in equation (2) to characterise the joint tail behaviour.

Estimation of  $\text{RC}(p)$  is done with standard exponentially distributed variables; therefore, the first step is to transform the original data onto standard exponential margins using equation (1), and then, after estimation of  $\text{RC}(p)$ , back transform them onto the original margins. Estimates of  $\text{RC}(p)$  are obtained through estimates of  $t$  and  $u$  from equation (3), and rays  $\omega$ . In particular, the value of  $t > 0$  can be obtained by first estimating  $u$  as the  $(1 - p^*)$ -th quantile of  $T_\omega$  where  $p^* > p$  is a small probability, and then ensuring that  $\Pr(T_\omega > t + u) = p$ . Since  $u$  is estimated as the  $(1 - p^*)$ -th quantile of  $T_\omega$ , we have that  $\Pr(T_\omega > u) = p^*$ ; thus,

$$p = \Pr(T_\omega > t + u) = \Pr(T_\omega > u) \Pr(T_\omega > t + u \mid T_\omega > u) = p^* e^{-\hat{\lambda}(\omega)t},$$

which leads to  $t = -\log(p/p^*)/\hat{\lambda}(\omega)$ . Finally, the estimates of the return curve  $\hat{\text{RC}}(p)$  can be obtained by setting  $(x, y) := (\omega(t + u), (1 - \omega)(t + u))$ .

In the **ReturnCurves** package, estimation of the return curve is done through function **rc\_est** which shares the same inputs as function **adf\_est** with an additional argument **p** representing the curve survival probability. This probability value should be smaller than  $1 - q$ , where  $q$  is the quantile for the min-projection variables  $T_\omega^1$ , and, when applicable, smaller than  $1 - q_\alpha$ , where  $q_\alpha$  are the quantiles used in the conditional extremes method.

Function **rc\_est** returns an S4 object of class **rc\_est.class** with twelve attributes, where the last slot **rc** contains a matrix with the estimates of the return curve on the original margins.

```
n <- dim(data)[1]
prob <- 10/n
# Estimation using Hill estimator without conditional extremes parameters
whill <- seq(0, 1, by = 0.001)
## q and constrained are set to the default values here
rch <- rc_est(margdata = expdata, w = whill, p = prob, method = "hill",
```

```

q = 0.95, constrained = F)

# Estimation using Hill estimator with conditional extremes parameters
## q and qalphas are set to the default values
rch2 <- rc_est(margdata = expdata, w = whill, p = prob, method = "hill", q = 0.95,
              qalphas = rep(0.95, 2), constrained = T)

# Estimation using CL method without conditional extremes parameters
## w, q and constrained are set to the default values here
rccl <- rc_est(margdata = expdata, w = seq(0, 1, by = 0.01), p = prob, method = "cl",
              q = 0.95, constrained = F)

# Estimation using CL method with conditional extremes parameters
## w, q and qalphas are set to the default values
rccl2 <- rc_est(margdata = expdata, w = seq(0, 1, by = 0.01), p = prob, method = "cl",
              q = 0.95, qalphas = rep(0.95, 2), constrained = T)

# attributes of the S4 object
str(rch)
#> Formal class 'rc_est.class' [package "ReturnCurves"] with 13 slots
#> ..@ data      : num [1:1000, 1:2] 1.705 -0.712 -0.278 -0.12 -0.124 ...
#> ..@ qmarg     : num [1:2] 0.95 0.95
#> ..@ w         : num [1:1001] 0 0.001 0.002 0.003 0.004 0.005 0.006 0.007 0.008 0.009 ...
#> ..@ p         : num 0.01
#> ..@ method    : chr "hill"
#> ..@ q         : num 0.95
#> ..@ qalphas   : num [1:2] 0.95 0.95
#> ..@ k         : num 7
#> ..@ constrained: logi FALSE
#> ..@ tol       : num 0.001
#> ..@ par_init  : num [1:6] 0 0 0 0 0 0
#> ..@ interval  : num [1:2] 0 1
#> ..@ rc        : num [1:1001, 1:2] -2.8 -2.56 -2.3 -2.08 -1.97 ...

# head of the vector with adf estimates for the first estimator
head(rch@rc)
#>      [,1]      [,2]
#> [1,] -2.797440 2.275493
#> [2,] -2.560148 2.269500
#> [3,] -2.299140 2.262939
#> [4,] -2.083273 2.262939
#> [5,] -1.967764 2.262939
#> [6,] -1.873685 2.262939

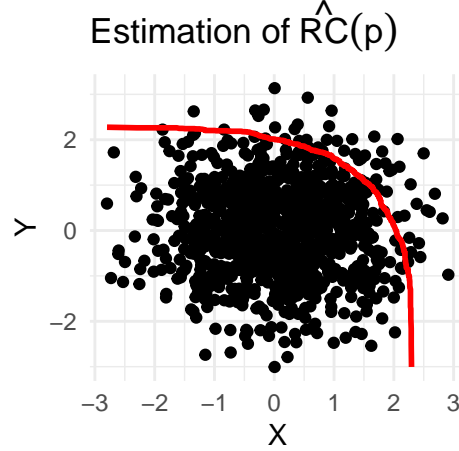
```

It is possible to plot an S4 object of `rc_est.class` with `plot`, where the original data is plotted with the estimated line for the return curve  $\hat{RC}(p)$ .

```

# plot of the ADF estimation based on the unconstrained Hill estimator
plot(rch)

```



#### 4.1 Uncertainty of the return curve estimates

Murphy-Barltrop et al. [2023] propose a procedure to assess the uncertainty of the return curve estimates. For large positive  $m \in \mathbb{N}$ , let

$$\Theta := \left\{ \frac{\pi(m+1-j)}{2(m+1)} \mid 1 \leq j \leq m \right\}, \quad (7)$$

define a set of angles. For each  $\theta \in \Theta$ , the line  $L_\theta := \{(x, y) \in \mathbb{R}_+^2 \mid \tan(\theta) > 0\}$  intersects the estimated  $\hat{RC}(p)$  exactly once, i.e.,  $\{(\hat{x}_\theta, \hat{y}_\theta)\} := \hat{RC}(p) \cap L_\theta$  where  $(\hat{x}_\theta, \hat{y}_\theta) \in \hat{RC}(p)$ . Moreover, let  $\hat{d}_\theta := (\hat{x}_\theta^2 + \hat{y}_\theta^2)^{1/2}$  denote the  $L_2$ -norm of the point estimate.

Uncertainty in the return curve estimates is quantified using the distribution of  $\hat{d}_\theta$  at each angle  $\theta \in \Theta$  as follows: for  $k = 1, \dots, \text{nboot}$ :

1. Bootstrap the original data set; when temporal dependence is present, a block bootstrap should be used.
2. For each  $\theta \in \Theta$ , obtain  $\hat{d}_{\theta,k}$  for the corresponding return curve estimate.

Finally, given  $\theta \in \Theta$ , empirical estimates of the mean, median and  $(1 - \alpha)\%$  confidence intervals for  $\hat{d}_\theta$  can be obtained using the sample of  $\hat{d}_{\theta,k}$ . These are available through function `rc_unc`, which takes as inputs:

- **retcurve**: an S4 object of class `rc_est.class` containing the return curve estimates,
- **blocksize**: size of blocks for the block bootstrap procedure; if no temporal dependence is present, then set `blocksize = 1`,
- **nboot**: number of bootstrap samples to be taken,
- **nangles**: number of angles  $m$ ,
- **alpha**: significance level to compute the  $(1 - \alpha)\%$  confidence intervals.

Function `rc_unc` returns an S4 object of class `rc_unc.class` with six attributes, where the last slot `unc` contains a list with

- **median**: a vector containing the empirical estimates of the median return curve
- **mean**: a vector containing the empirical estimates of the mean return curve
- **lower**: a vector containing the lower bound of the confidence interval
- **upper**: a vector containing the upper bound of the confidence interval

For simplicity, just the uncertainty of the return curve obtained using the unconstrained Hill estimator is computed here.

```
# blocksize, nangles and alpha set to default
# nboot set to 100 for computational time < 5s
```

```

rch_unc <- rc_unc(rch, blocksize = 1, nboot = 100, nangles = 150, alpha = 0.05)

# attributes of the S4 object
str(rch_unc)
#> Formal class 'rc_unc.class' [package "ReturnCurves"] with 6 slots
#> ..@ retcurve :Formal class 'rc_est.class' [package "ReturnCurves"] with 13 slots
#> .. .. ..@ data      : num [1:1000, 1:2] 1.705 -0.712 -0.278 -0.12 -0.124 ...
#> .. .. ..@ qmargin   : num [1:2] 0.95 0.95
#> .. .. ..@ w         : num [1:1001] 0 0.001 0.002 0.003 0.004 0.005 0.006 0.007 0.008 0.009 ...
#> .. .. ..@ p         : num 0.01
#> .. .. ..@ method    : chr "hill"
#> .. .. ..@ q         : num 0.95
#> .. .. ..@ qalphas   : num [1:2] 0.95 0.95
#> .. .. ..@ k         : num 7
#> .. .. ..@ constrained: logi FALSE
#> .. .. ..@ tol       : num 0.001
#> .. .. ..@ par_init   : num [1:6] 0 0 0 0 0 0
#> .. .. ..@ interval   : num [1:2] 0 1
#> .. .. ..@ rc         : num [1:1001, 1:2] -2.8 -2.56 -2.3 -2.08 -1.97 ...
#> ..@ blocksize: num 1
#> ..@ nboot     : num 100
#> ..@ nangles   : num 150
#> ..@ alpha     : num 0.05
#> ..@ unc       :List of 4
#> .. ..$ median: num [1:150, 1:2] -2.74 -2.69 -2.63 -2.58 -2.52 ...
#> .. .. ..- attr(*, "dimnames")=List of 2
#> .. .. .. ..$ : chr [1:150] "50%" "50%" "50%" "50%" ...
#> .. .. .. ..$ : NULL
#> .. ..$ mean : num [1:150, 1:2] -2.74 -2.69 -2.63 -2.58 -2.52 ...
#> .. ..$ lower : num [1:150, 1:2] -2.74 -2.69 -2.64 -2.58 -2.53 ...
#> .. .. ..- attr(*, "dimnames")=List of 2
#> .. .. .. ..$ : chr [1:150] "2.5%" "2.5%" "2.5%" "2.5%" ...
#> .. .. .. ..$ : NULL
#> .. ..$ upper : num [1:150, 1:2] -2.74 -2.68 -2.63 -2.57 -2.51 ...
#> .. .. ..- attr(*, "dimnames")=List of 2
#> .. .. .. ..$ : chr [1:150] "97.5%" "97.5%" "97.5%" "97.5%" ...
#> .. .. .. ..$ : NULL

# head of the list elements of slot unc
head(rch_unc@unc$median)
#>      [,1]      [,2]
#> 50% -2.742524 2.272356
#> 50% -2.687627 2.270863
#> 50% -2.632740 2.269283
#> 50% -2.577874 2.267126
#> 50% -2.522998 2.265119
#> 50% -2.467979 2.265119
head(rch_unc@unc$mean)
#>      [,1]      [,2]
#> [1,] -2.742432 2.281187
#> [2,] -2.687452 2.279277
#> [3,] -2.632504 2.276845
#> [4,] -2.577555 2.274800

```

```

#> [5,] -2.522557 2.273586
#> [6,] -2.467499 2.272795
head(rch_unc@unc$lower)
#>      [,1]      [,2]
#> 2.5% -2.744281 2.103411
#> 2.5% -2.691119 2.103049
#> 2.5% -2.637941 2.102687
#> 2.5% -2.584766 2.101588
#> 2.5% -2.531622 2.099461
#> 2.5% -2.478347 2.099226
head(rch_unc@unc$upper)
#>      [,1]      [,2]
#> 97.5% -2.740098 2.505498
#> 97.5% -2.682821 2.501814
#> 97.5% -2.625497 2.501292
#> 97.5% -2.568185 2.499856
#> 97.5% -2.510861 2.498252
#> 97.5% -2.453450 2.497592

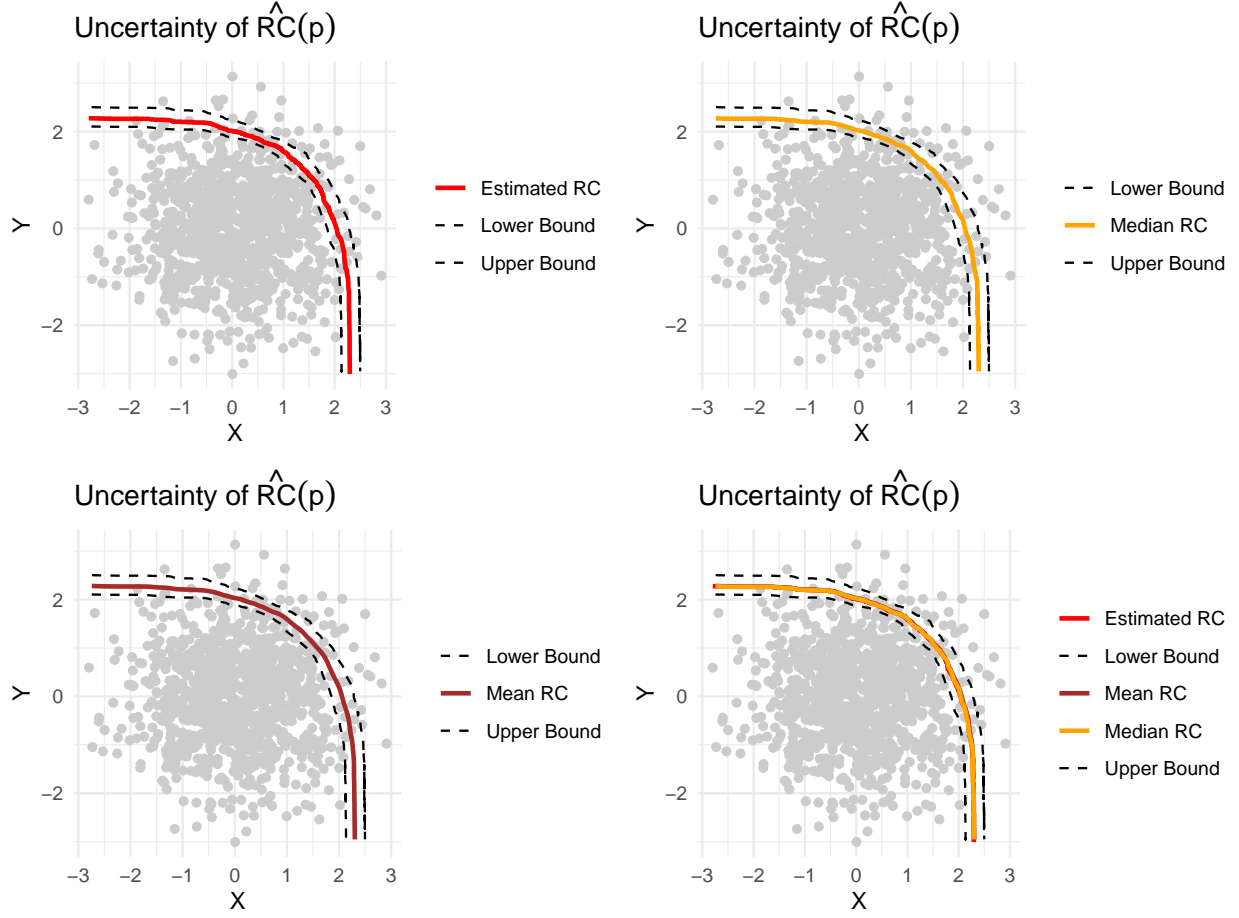
```

It is possible to plot an instance of the S4 class `rc_unc.class` with function `plot`; this takes the S4 object and an extra argument `which` as inputs. If `which = "rc"` (default), then the estimated return curve is plotted, setting `which = "median"` shows the empirical median estimates of the return curve, while setting `which = "mean"` shows the empirical mean estimates of the return curve. All plots show the uncertainty associated with the estimated return curve in dashed lines. Finally, by setting `which = "all"`, plots the estimated return curve, the empirical median and mean estimates and the associated uncertainty.

```

library(gridExtra)
grid.arrange(plot(rch_unc, which = "rc"), plot(rch_unc, which = "median"),
              plot(rch_unc, which = "mean"), plot(rch_unc, which = "all"), nrow = 2)

```



## 4.2 Goodness-of-fit of the return curve estimates

It is important to assess the goodness-of-fit of the return curve estimates, given that the true return curve is unknown in reality. This is implemented in the `ReturnCurves` package based on the approach proposed by Murphy-Barltrop et al. [2023].

Given the return curve  $RC(p)$ , the probability of lying in a survival region  $(x, \infty) \times (y, \infty)$  is  $p$ . Given the same set of angles  $\Theta$  as in equation (7), for each  $\theta_j \in \Theta$ , the empirical probability  $\hat{p}_j$  of lying in  $(\hat{x}_{\theta_j}, \infty) \times (\hat{y}_{\theta_j}, \infty)$ , where  $(\hat{x}_{\theta_j}, \hat{y}_{\theta_j})$  is the corresponding point in  $\hat{RC}(p)$ , is given by the proportion of points in that region. The goodness-of-fit of the estimated return curve is then assessed via a bootstrap procedure; for each angle  $\theta_j \in \Theta$ , the original data set is bootstrapped and empirical probability estimates  $\hat{p}_j$  are obtained. When temporal dependence is present in the data, a block bootstrap approach should be taken and the size of the blocks must be defined. We note that for each  $j$ , `nboot` empirical probabilities are estimated and, so the median and the  $(1 - \alpha)\%$  pointwise confidence intervals for the probabilities are obtained by taking the 50%,  $(\alpha/2)\%$  and  $(1 - \alpha/2)\%$  quantiles of the set of empirical probabilities for each  $j$ , respectively.

The goodness-of-fit for an estimated return curve is implemented through function `rc_gof`. This shares the same input arguments as the `rc_unc` function and returns an S4 object with six attributes with the last slot `gof` containing a list with

- **median**: a vector with the median of the empirical probabilities,
- **lower**: a vector with the lower bound of the confidence interval,
- **upper**: a vector with the upper bound of the confidence interval.

For simplicity, just the goodness-of-fit of the return curve obtained using the unconstrained Hill estimator is

computed here.

```
# blocksize, nboot, nangles and alpha set to default
rch_gof <- rc_gof(rch, blocksize = 1, nboot = 250, nangles = 150, alpha = 0.05)

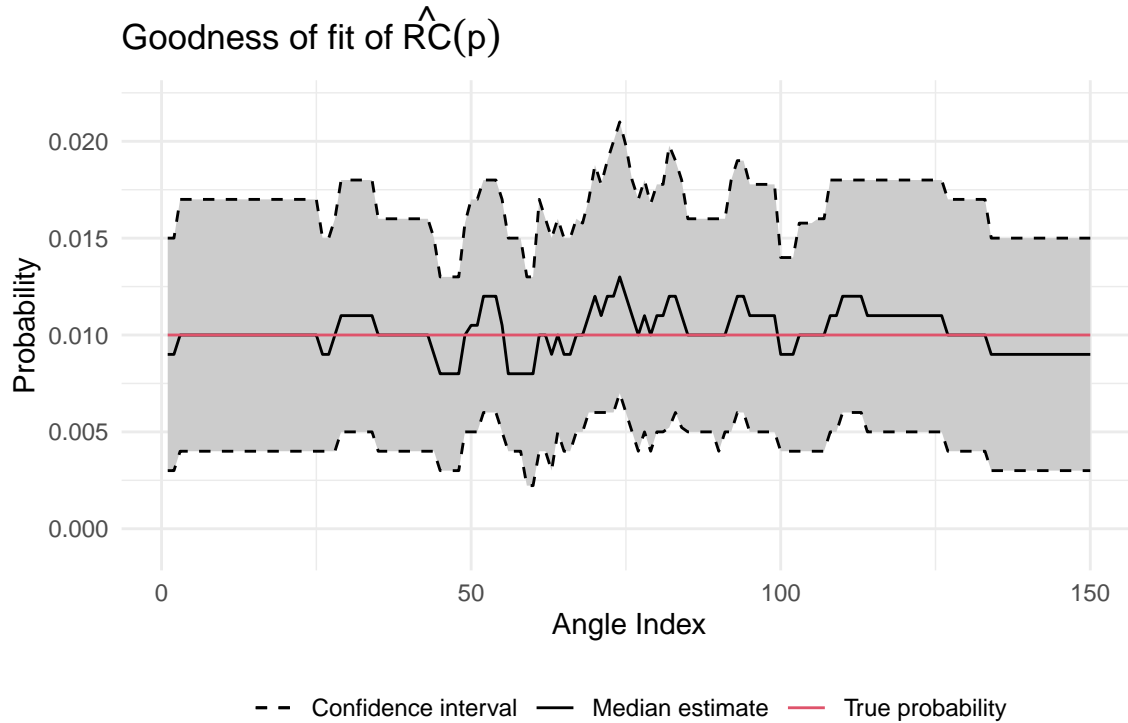
# attributes of the S4 object
str(rch_gof)
#> Formal class 'rc_gof.class' [package "ReturnCurves"] with 5 slots
#> ..@ retcurve :Formal class 'rc_est.class' [package "ReturnCurves"] with 13 slots
#> .. .. ..@ data      : num [1:1000, 1:2] 1.705 -0.712 -0.278 -0.12 -0.124 ...
#> .. .. ..@ qmarg     : num [1:2] 0.95 0.95
#> .. .. ..@ w         : num [1:1001] 0 0.001 0.002 0.003 0.004 0.005 0.006 0.007 0.008 0.009 ...
#> .. .. ..@ p         : num 0.01
#> .. .. ..@ method    : chr "hill"
#> .. .. ..@ q         : num 0.95
#> .. .. ..@ qalphas   : num [1:2] 0.95 0.95
#> .. .. ..@ k         : num 7
#> .. .. ..@ constrained: logi FALSE
#> .. .. ..@ tol       : num 0.001
#> .. .. ..@ par_init  : num [1:6] 0 0 0 0 0 0
#> .. .. ..@ interval  : num [1:2] 0 1
#> .. .. ..@ rc        : num [1:1001, 1:2] -2.8 -2.56 -2.3 -2.08 -1.97 ...
#> ..@ blocksize: num 1
#> ..@ nboot     : num 250
#> ..@ alpha     : num 0.05
#> ..@ gof       :List of 3
#> .. ..$ median: Named num [1:150] 0.009 0.009 0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.01 ...
#> .. .. ..- attr(*, "names")= chr [1:150] "50%" "50%" "50%" "50%" ...
#> .. ..$ lower : Named num [1:150] 0.003 0.003 0.004 0.004 0.004 0.004 0.004 0.004 0.004 0.004 0.004 ...
#> .. .. ..- attr(*, "names")= chr [1:150] "2.5%" "2.5%" "2.5%" "2.5%" ...
#> .. ..$ upper : Named num [1:150] 0.015 0.015 0.017 0.017 0.017 0.017 0.017 0.017 0.017 0.017 0.017 ...
#> .. .. ..- attr(*, "names")= chr [1:150] "97.5%" "97.5%" "97.5%" "97.5%" ...

# head of the list elements of slot gof
head(rch_gof@gof$median)
#> 50% 50% 50% 50% 50% 50%
#> 0.009 0.009 0.010 0.010 0.010 0.010
head(rch_gof@gof$lower)
#> 2.5% 2.5% 2.5% 2.5% 2.5% 2.5%
#> 0.003 0.003 0.004 0.004 0.004 0.004
head(rch_gof@gof$upper)
#> 97.5% 97.5% 97.5% 97.5% 97.5% 97.5%
#> 0.015 0.015 0.017 0.017 0.017 0.017
```

It is possible to plot an instance of the S4 class `rc_gof.class` with function `plot`, where a comparison between the true probability  $p$  (in red) and the empirical median estimates (in black) is shown. Ideally,  $p$  should be contained in the confidence region, shaded in grey. Finally, in practice, the value of  $p$  should be within the range of the data and not too extreme, given the nature of empirical probabilities.

```
plot(rch_gof)
```





## References

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