Nonparametric estimation of extreme risks from heavy-tailed distributions

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joint work with

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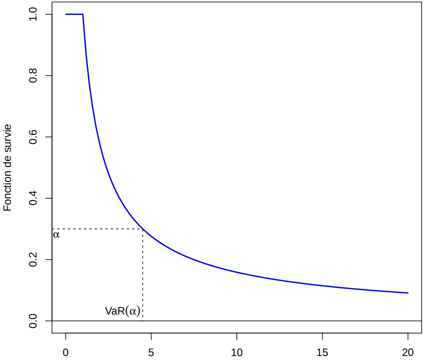
The Value-at-Risk

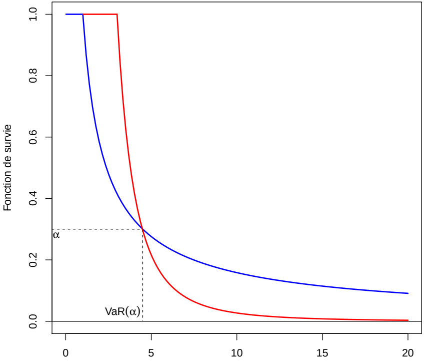
Let $Y \in \mathbb{R}$ be a random loss variable. The Value-at-Risk of level $\alpha \in (0,1)$ denoted by $\mathrm{VaR}(\alpha)$ is the α-quantile of the survival function $\bar{F}(x) = P(Y > x)$

$$\mathrm{VaR}(\alpha) := \overline{F}^{-1}(\alpha) = \inf\{t, \overline{F}(t) \le \alpha\}$$



Drawback of the Value-at-Risk

Consider Y_1 and Y_2 two random loss variables with associated survival functions $\overline{F}_1$ and $\overline{F}_2$.

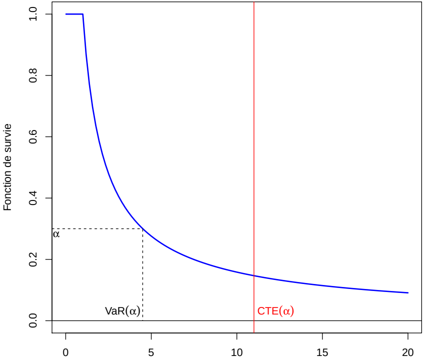


Random variables with light tail probabilities and with heavy tail probabilities may have the same VaR(α). This is one of the main criticisms against the VaR, Embrechts et al. [1997].

The Conditional Tail Expectation

The Conditional Tail Expectation of level $\alpha \in (0,1)$ denoted by CTE(α) is defined by

$$\text{CTE}(\alpha) := \mathbb{E}(Y|Y > \text{VaR}(\alpha)).$$



The CTE takes into account the whole information contained in the upper part of the tail distribution.

Some risk measures

- Let $Y \in \mathbb{R}$ be a random loss variable. The Value-at-Risk of level $\alpha \in (0,1)$ is the α-quantile defined by

$$\mathrm{VaR}(\alpha) := \overline{F}^{-1}(\alpha),$$

where $\overline{F}^{-1}$ is the (generalized) inverse of the survival function of Y.

- The Conditional Tail Expectation of level $\alpha \in (0,1)$ is defined by

$$\mathrm{CTE}(\alpha) := \mathbb{E}(Y | Y > \mathrm{VaR}(\alpha)).$$

- The Conditional-Value-at-Risk of level $\alpha \in (0,1)$ introduced by Rockafellar et Uryasev [2000] is defined by

$$\mathrm{CVaR}_\lambda(\alpha) := \lambda \mathrm{VaR}(\alpha) + (1-\lambda)\mathrm{CTE}(\alpha),$$

with $0 \leq \lambda \leq 1$.

- The Conditional Tail Variance of level $\alpha \in (0,1)$ introduced by Valdez [2005] is defined by

$$\mathrm{CTV}(\alpha) := \mathbb{E}((Y - \mathrm{CTE}(\alpha))^2 | Y > \mathrm{VaR}(\alpha)).$$

A new risk measure : the Conditional Tail Moment

The first goal of this work is to unify the definitions of the previous risk measures. To this end, the Conditional Tail Moment of level $\alpha \in (0,1)$ is introduced :

$$\mathrm{CTM}_a(\alpha) := \mathbb{E}(Y^a | Y > \mathrm{VaR}(\alpha)),$$

where $a \geq 0$ is such that the moment of order a of Y exists.

All the previous risk measures of level α can be rewritten as

$$\begin{aligned} \mathrm{CTE}(\alpha) &= \mathrm{CTM}_1(\alpha), \\ \mathrm{CVaR}(\alpha) &= \lambda \mathrm{VaR}(\alpha) + (1-\lambda)\mathrm{CTM}_1(\alpha), \\ \mathrm{CTV}(\alpha) &= \mathrm{CTM}_2(\alpha) - \mathrm{CTM}_1^2(\alpha). \end{aligned}$$

$\Longrightarrow$ All the risk measures depend on the VaR and the CTM_a.

Extreme losses and regression case

Our second aim is to estimate these risk measures in case of extreme losses and in the case where a covariate $X \in \mathbb{R}^p$ is recorded simultaneously with Y.

1. The fixed level $\alpha \in (0,1)$ is replaced by a sequence $\alpha_n \underset{n \to \infty}{\longrightarrow} 0$.
2. Denoting by $\overline{F}(.|x)$ the conditional survival distribution function of Y given $X = x$, the Regression Value-at Risk is defined by :

$$\mathrm{RVaR}(\alpha_n|x) := \overline{F}^{-1}(\alpha_n|x) = \inf\{t, \overline{F}(t|x) \le \alpha_n\},$$

and the Regression Conditional Tail Moment of order a is defined by :

$$\mathrm{RCTM}_a(\alpha_n|x) := \mathbb{E}(Y^a|Y > \mathrm{RVaR}(\alpha_n|x), X = x),$$

where $a > 0$ is such that the moment of order a of Y exists.

Extreme regression risk measures

This yields the following risk measures :

$$\begin{aligned}
\mathrm{RCTE}(\alpha_n|x) &= \mathrm{RCTM}_1(\alpha_n|x),\\
\mathrm{RCVaR}_\lambda(\alpha_n|x) &= \lambda \mathrm{RVaR}(\alpha_n|x) + (1-\lambda)\mathrm{RCTM}_1(\alpha_n|x),\\
\mathrm{RCTV}_n(\alpha_n|x) &= \mathrm{RCTM}_2(\alpha_n|x) - \mathrm{RCTM}_1^2(\alpha_n|x).
\end{aligned}$$

$\Longrightarrow$ All the risk measures depend on the RVaR and the RCTM_a.

The conditional moment of order $a \geq 0$ of Y given $X = x$ is defined by

$$\varphi_a(y|x) = \mathbb{E}\left(Y^a \mathbb{I}\{Y > y\}|X = x\right),$$

where $\mathbb{I}\{.\}$ is the indicator function. Since $\varphi_0(y|x) = \overline{F}(y|x)$, it follows

$$\begin{aligned}
\mathrm{RVaR}(\alpha_n|x) &= \varphi_0^{-1}(\alpha_n|x),\\
\mathrm{RCTM}_a(\alpha_n|x) &= \frac{1}{\alpha_n}\varphi_a(\varphi_0^{-1}(\alpha_n|x)|x).
\end{aligned}$$

Goal : estimate $\varphi_a(.|x)$ and $\varphi_a^{-1}(.|x)$.

Inference

Estimator of $\varphi_a(.|x)$:

We propose to use a classical kernel estimator given by

$$\widehat{\varphi}_{a,n}(y|x) = \sum_{i=1}^{n} K\left(\frac{x - X_i}{h_n}\right) Y_i^a \mathbb{I}\{Y_i > y\} \Big/ \sum_{i=1}^{n} K\left(\frac{x - X_i}{h_n}\right).$$

- h_n is a sequence called the window-width such that $h_n \to 0$ as $n \to \infty$,
- K is a bounded density on $\mathbb{R}^p$ with support included in the unit ball of $\mathbb{R}^p$.

Estimator of $\varphi_a^{-1}(.|x)$:

Since $\hat{\varphi}_{a,n}(.|x)$ is a non-increasing function, an estimator of $\varphi_a^{-1}(\alpha|x)$ can be defined for $\alpha \in (0, 1)$ by

$$\hat{\varphi}_{a,n}^{-1}(\alpha|x) = \inf\{t, \hat{\varphi}_{a,n}(t|x) < \alpha\}.$$

Heavy-tail assumptions

(F.1) The conditional survival distribution function of Y given $X = x$ is assumed to be heavy-tailed *i.e.* for all $\lambda > 0$,

$$\lim_{y \to \infty} \frac{\overline{F}(\lambda y|x)}{\overline{F}(y|x)} = \lambda^{-1/\gamma(x)}.$$

In this context, $\gamma(.)$ is a positive function of the covariate x and is referred to as the conditional tail index since it tunes the tail heaviness of the conditional distribution of Y given $X = x$.

Condition **(F.1)** also implies that for $a \in [0, 1/\gamma(x))$, $\mathrm{RCTM}_a(.|x)$ exists, and for all $y > 0$,

$$\mathrm{RCTM}_a(1/y|x) = y^{a\gamma(x)} \ell_a(y|x),$$

where for x fixed, $\ell_a(.|x)$ is a slowly-varying function *i.e.* for all $\lambda > 0$,

$$\lim_{y \to \infty} \frac{\ell_a(\lambda y|x)}{\ell_a(y|x)} = 1.$$

Heavy-tail assumptions

(F.2) $\ell_a(.|x)$ is normalized for all $a \in [0, 1/\gamma(x))$.

In such a case, the Karamata representation of the slowly-varying function can be written as

$$\ell_a(y|x) = c_a(x) \exp\left(\int_1^y \frac{\varepsilon_a(u|x)}{u} du \right),$$

where $c_a(.)$ is a positive function and $\varepsilon_a(y|x) \to 0$ as $y \to \infty$.

(F.3) $|\varepsilon_a(.|x)|$ is continuous and ultimately non-increasing for all $a \in [0, 1/\gamma(x))$.

Regularity assumptions

A Lipschitz condition on the probability density function g of X is also required :

(L) There exists a constant $c_g > 0$ such that $|g(x) - g(x')| \leq c_g d(x, x')$.

where $d(x, x')$ is the Euclidean distance between x and x'.

Finally, for $y > 0$ and $\xi > 0$, the largest oscillation of the conditional moment of order $a \in [0, 1/\gamma(x))$ is defined by

$$\omega(x, y, a, \xi, h_n) = \sup \left\{ \left| \frac{\varphi_a(z|x)}{\varphi_a(z|x')} - 1 \right|, \; z \in [(1-\xi)y, (1+\xi)y], \; x' \in B(x, h_n) \right\},$$

where $B(x, h_n)$ denotes the ball centred at x with radius h_n.

Main result

Theorem 1 :

Suppose **(F.1)**, **(F.2)** and **(L)** hold. Let

- $0 \le a_1 < a_2 < \cdots < a_J$,
- $x \in \mathbb{R}^p$ such that $g(x) > 0$ and $0 < \gamma(x) < 1/(2a_J)$,
- $\alpha_n \to 0$ and $nh_n^p \alpha_n \to \infty$ as $n \to \infty$,
- $\xi > 0$ such that $\sqrt{nh_n^p \alpha_n}\,(h_n \vee \max_a \omega(x, \mathrm{RVaR}(\alpha_n|x), a, \xi, h_n)) \to 0$,

Then,

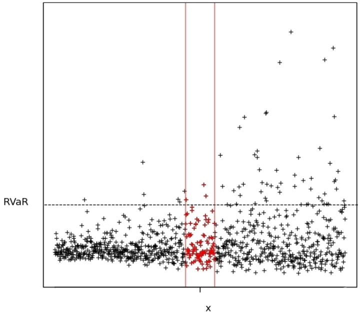
$$\sqrt{nh_n^p \alpha_n}\left\{\left(\frac{\widehat{\mathrm{RCTM}}_{a_j,n}(\alpha_n|x)}{\mathrm{RCTM}_{a_j}(\alpha_n|x)} - 1\right)_{j\in\{1,\dots,J\}}, \left(\frac{\widehat{\mathrm{RVaR}}_n(\alpha_n|x)}{\mathrm{RVaR}(\alpha_n|x)} - 1\right)\right\}$$

is asymptotically Gaussian, centered, with covariance matrix $\|K\|_2^2\gamma^2(x)\Sigma(x)/g(x)$ where

$$\Sigma(x) = \left(\begin{array}{c|c} \frac{a_i a_j(2-(a_i+a_j)\gamma(x))}{(1-(a_i+a_j)\gamma(x))} & \begin{array}{c} a_1 \\ \vdots \\ a_J \end{array} \\ \hline a_1 \cdots a_J & 1 \end{array}\right).$$

Conditions on the sequences α_n and h_n

$nh_n^p\alpha_n \to \infty$: Necessary and sufficient condition for the almost sure presence of at least one point in the region $B(x,h_n) \times [\mathrm{RVaR}(\alpha_n|x), +\infty)$ of $\mathbb{R}^p \times \mathbb{R}$.



$\sqrt{nh_n^p\alpha_n}\,(h_n \vee \max_a \omega(x, \mathrm{RVaR}(\alpha_n|x), a, \xi, h_n)) \to 0$: The biais induced by the smoothing is negligible compared to the standard-deviation.

Consequences

Suppose the assumptions of Theorem 1 hold. Then, if $0 < \gamma(x) < 1/2$,

$$\sqrt{nh_n^p \alpha_n}\left(\frac{\widehat{\mathrm{RCTE}}_n(\alpha_n|x)}{\mathrm{RCTE}(\alpha_n|x)} - 1\right) \xrightarrow{d} \mathcal{N}\left(0, \frac{2(1-\gamma(x))\gamma^2(x)}{1-2\gamma(x)}\frac{\|K\|_2^2}{g(x)}\right)$$

$$\sqrt{nh_n^p \alpha_n}\left(\frac{\widehat{\mathrm{RCVaR}}_{\lambda,n}(\alpha_n|x)}{\mathrm{RCVaR}_\lambda(\alpha_n|x)} - 1\right) \xrightarrow{d} \mathcal{N}\left(0, \frac{\gamma^2(x)(\lambda^2+2-2\lambda-2\gamma(x))}{1-2\gamma(x)}\frac{\|K\|_2^2}{g(x)}\right)$$

The $\mathrm{RCTV}(\alpha_n|x)$ estimator involves the computation of a second order moment, it requires the stronger condition $0 < \gamma(x) < 1/4$,

$$\sqrt{nh_n^p \alpha_n}\left(\frac{\widehat{\mathrm{RCTV}}_n(\alpha_n|x)}{\mathrm{RCTV}(\alpha_n|x)} - 1\right) \xrightarrow{d} \mathcal{N}\left(0, V_{\gamma(x)}\frac{\|K\|_2^2}{g(x)}\right),$$

where

$$V_{\gamma(x)} = \frac{8(1-\gamma(x))(1-2\gamma(x))(1+2\gamma(x)+3\gamma^2(x))}{(1-3\gamma(x))(1-4\gamma(x))}.$$

Illustration on a simulated dataset

A sample $\{(X_i, Y_i), i = 1, \dots, n\}$ of size $n = 1000$ is generated. The covariate X is uniform on $[0, 1]$. The conditional distribution of $Y|X = x$ is chosen in the Hall class :

$$\overline{F}(y|x) = y^{-1/\gamma(x)} \underbrace{a(1 + by^{\rho/\gamma(x)})}_{\ell(y|x)}$$

with $a = 1/2$, $b = 1$, $\rho = -1$ and conditional tail index function

$$x \in [0, 1] \to \gamma(x) = \frac{1}{2}\left(\frac{1}{10} + \sin(\pi x)\right)\left(\frac{11}{10} - \frac{1}{2}\exp\left(64\left(x - \frac{1}{2}\right)^2\right)\right).$$

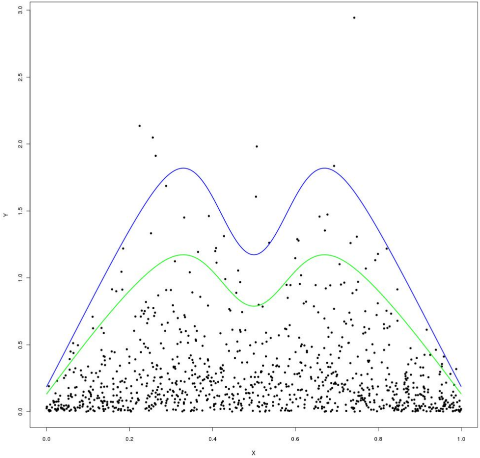
We have chosen a bi-quadratic kernel

$$K(u) \propto (1 - u^2)^2 \mathbb{I}_{\{|u| \leq 1\}}$$

with smoothing parameter $h_n = 0.1$.

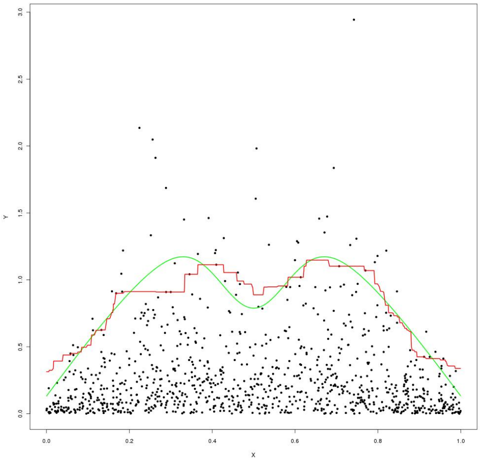
Our goal if to estimate $\text{RCTE}(\alpha_n|x)$ and $\text{RVaR}(\alpha_n|x)$ with $\alpha_n = 0.05$.

Theoretical RCTE($\alpha_n|x$) and RVaR($\alpha_n|x$)



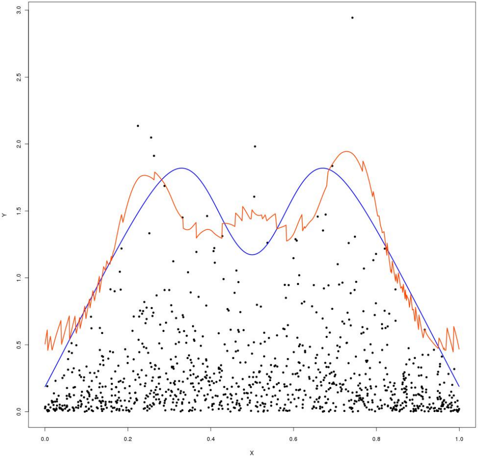
Theoretical RCTE($\alpha_n|x$) and RVaR($\alpha_n|x$) with a logarithmic scale.

Theoretical and estimated RVaR($\alpha_n|x$)



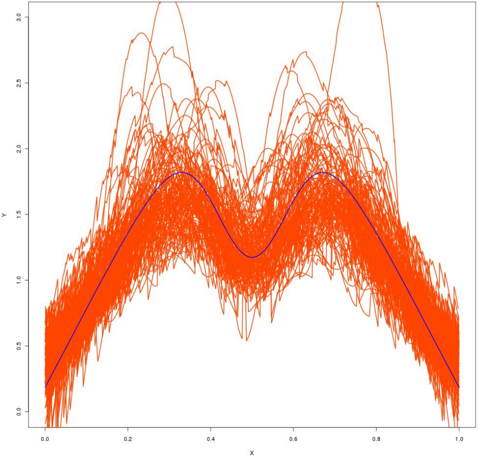
Theoretical and estimated RVaR($\alpha_n|x$) with a logarithmic scale.

Theoretical and estimated RCTE($\alpha_n|x$)



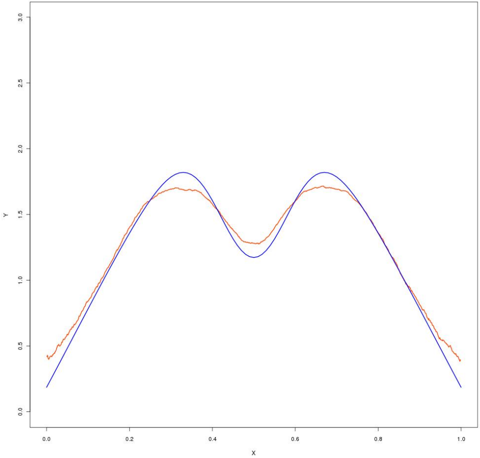
Theoretical and estimated RCTE($\alpha_n|x$) with a logarithmic scale.

100 replications and theoretical RCTE($\alpha_n|x$)



Theoretical and estimated RCTE($\alpha_n|x$) with a logarithmic scale.

Theoretical RCTE($\alpha_n|x$) and mean of the 100 estimated RCTE($\alpha_n|x$)



Theoretical and estimated RCTE($\alpha_n|x$) with a logarithmic scale.

A Weissman type estimator

- In Theorem 1, the condition $nh_n^p\alpha_n \to \infty$ provides a lower bound on the level of the risk measure to estimate.
- This restriction is a consequence of the use of a kernel estimator which cannot extrapolate beyond the maximum observation in the ball $B(x, h_n)$.
- In consequence, α_n must be an order of an extreme quantile within the sample.

Definition

Let us consider $(\alpha_n)_{n\geq 1}$ and $(\beta_n)_{n\geq 1}$ two positive sequences such that $\alpha_n \to 0$, $\beta_n \to 0$ and $0 < \beta_n < \alpha_n$. A kernel adaptation of Weissman's estimator [1978] is given by

$$\widehat{\mathrm{RCTM}}^{W}_{a,n}(\beta_n|x) = \widehat{\mathrm{RCTM}}_{a,n}(\alpha_n|x) \underbrace{\left(\frac{\alpha_n}{\beta_n}\right)^{a\hat{\gamma}_n(x)}}_{\text{extrapolation}}$$

Extrapolation

Theorem 2 :

Suppose the assumptions of Theorem 1 hold together with **(F.3)**. Let $\hat{\gamma}_n(x)$ be an estimator of the conditional tail index such that

$$\sqrt{nh_n^p\alpha_n}(\hat{\gamma}_n(x) - \gamma(x)) \xrightarrow{d} \mathcal{N}\left(0, v^2(x)\right),$$

with $v(x) > 0$. If, moreover $(\beta_n)_{n\geq 1}$ is a positive sequence such that $\beta_n \to 0$ and $\beta_n/\alpha_n \to 0$ as $n \to \infty$, then

$$\frac{\sqrt{nh_n^p\alpha_n}}{\log(\alpha_n/\beta_n)}\left(\frac{\widehat{\mathrm{RCTM}}^W_{a,n}(\beta_n|x)}{\mathrm{RCTM}_a(\beta_n|x)} - 1\right) \xrightarrow{d} \mathcal{N}\left(0, (av(x))^2\right).$$

The condition $\beta_n/\alpha_n \to 0$ allows us to extrapolate and choose a level β_n arbitrarily small.

Estimation of the conditional tail index

- Without covariate : Hill [1975]

Let $(k_n)_{n\geq 1}$ be a sequence of integers such that $k_n \in \{1 \dots n\}$. The Hill estimator is given by

$$\hat{\gamma}_{n,\alpha_n} = \frac{1}{k_n - 1} \sum_{i=1}^{k_n - 1} \log Z_{n-i+1,n} - \log Z_{n-k_n+1,n},$$

where $Z_{1,n} \leq \cdots \leq Z_{n,n}$ are the order statistics associated with i.i.d. random variables $Z_1, \dots, Z_n$ and $\alpha_n = k_n/n$.

- With a covariate :

A kernel version of the Hill estimator is given by

$$\hat{\gamma}_{n,\alpha_n}(x) = \sum_{j=1}^{J} (\log \widehat{\mathrm{RVaR}}_n(\tau_j \alpha_n | x) - \log \widehat{\mathrm{RVaR}}_n(\tau_1 \alpha_n | x)) \Bigg/ \sum_{j=1}^{J} \log(\tau_1/\tau_j),$$

where $J \geq 1$ and $(\tau_j)_{j\geq 1}$ is a decreasing sequence of weights.

Extrapolation

The asymptotic normality of $\hat{\gamma}_{n,\alpha_n}(x)$ has been established by Daouia et al. [2011] .

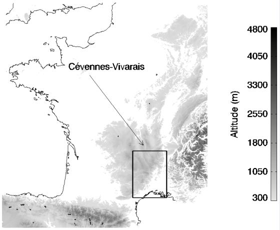
As a consequence, replacing $\widehat{\mathrm{RVaR}}_n$ by $\widehat{\mathrm{RVaR}}_n^W$ and $\widehat{\mathrm{RCTM}}_{a,n}$ by $\widehat{\mathrm{RCTM}}_{a,n}^W$ provides (asymptotically Gaussian) estimators for all the risk measures considered in this talk, and for arbitrarily small levels.

In particular, since $\mathrm{RCTE}(\alpha_n|x) = \mathrm{RCTM}_1(\alpha_n|x)$, we obtain

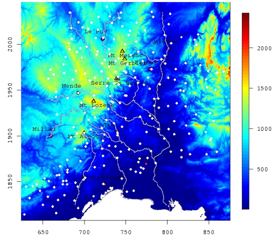
$$\widehat{\mathrm{RCTE}}_n^W(\beta_n|x) = \widehat{\mathrm{RCTE}}_n(\alpha_n|x)\left(\frac{\alpha_n}{\beta_n}\right)^{\hat{\gamma}_n(x)}.$$

Daily rainfalls in the Cévennes-Vivarais region (France)

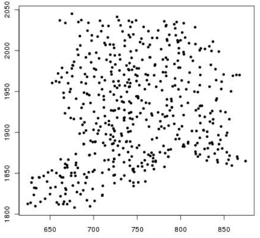
France



Cévennes-Vivarais region



Raingauge stations



- 523 raingauge stations, daily rainfall measures (in mm) during 1958–2000.
- Estimation of risk measures associated to return periods of 100 years.

A cross validation procedure to choose h_n and α_n : Step 1

- Double loop on $\mathcal{H} = \{h_i; i = 1, \ldots, M\}$ and on $\mathcal{A} = \{\alpha_j; j = 1, \ldots, R\}$.
- Loop on all raingauge stations $\{x_t; t = 1, \ldots, N\}$.

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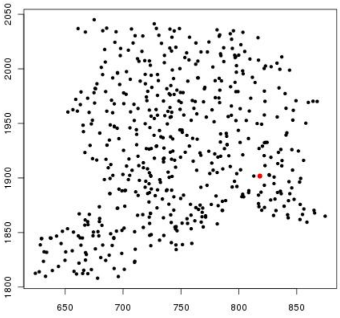
Consider one raingauge station x_t



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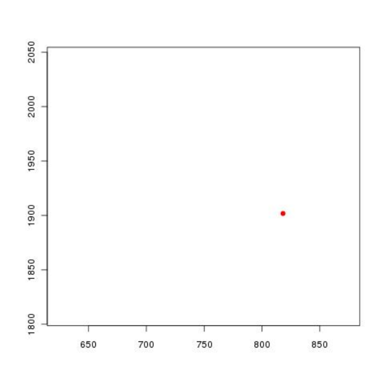
Remove all other raingauge stations



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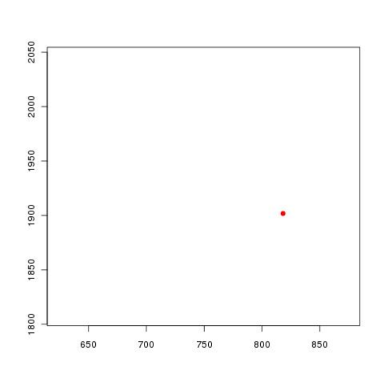

- Estimate $\gamma > 0$ using the classical Hill estimator.
- It only depends on α_j.

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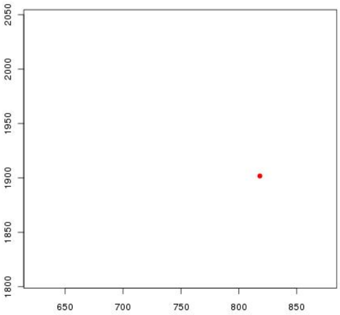
Remove all other raingauge stations

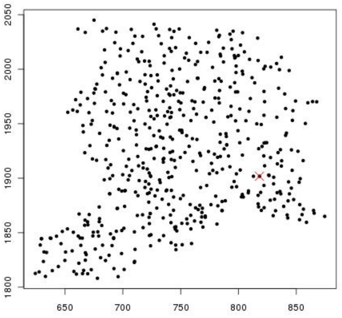


- Estimate $\gamma > 0$ using the classical Hill estimator.
- It only depends on α_j.

$\Longrightarrow$ We obtain $\hat{\gamma}_{n,t,\alpha_j}$

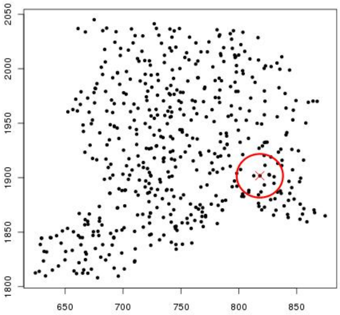
A cross validation procedure to choose h_n and α_n : Step 2

Remove the station x_t



A cross validation procedure to choose h_n and α_n : Step 2

Work in $B(x_t, h_i) \setminus \{x_t\}$



A cross validation procedure to choose h_n and α_n : Step 2

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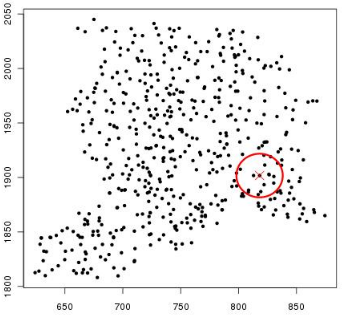

- Estimate $\gamma(x) > 0$ using the kernel version of the Hill estimator.
- It depends on α_j and on h_i.

A cross validation procedure to choose h_n and α_n : Step 2

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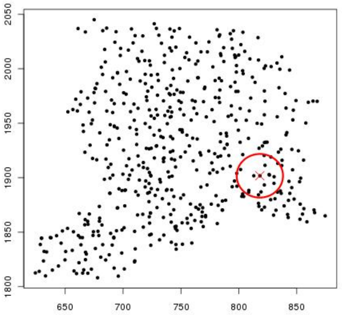
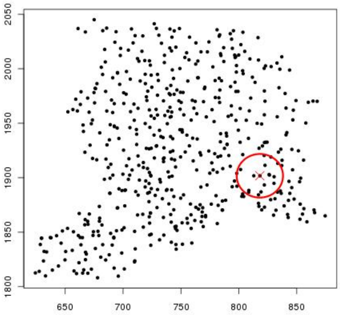


- Estimate $\gamma(x) > 0$ using the kernel version of the Hill estimator.
- It depends on α_j and on h_i.

$\Longrightarrow$ We obtain $\hat{\gamma}_{n,h_i,\alpha_j}(x_t)$

A cross validation procedure to choose h_n and α_n : Step 2

Work in $B(x_t, h_i) \setminus \{x_t\}$



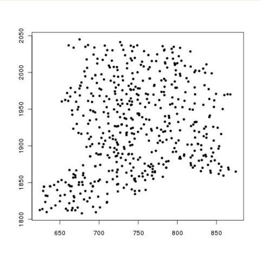
- Estimate $\gamma(x) > 0$ using the kernel version of the Hill estimator.
- It depends on α_j and on h_i.

$\Longrightarrow$ We obtain $\hat{\gamma}_{n,h_i,\alpha_j}(x_t)$

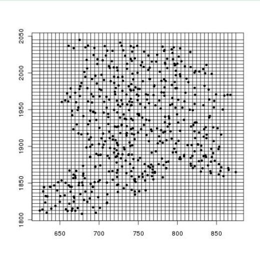
$$(h_{emp}, \alpha_{emp}) = \underset{(h_i,\alpha_j)\in\mathcal{H}\times\mathcal{A}}{\arg\min}\ \text{median}\{(\hat{\gamma}_{n,t,\alpha_j} - \hat{\gamma}_{n,h_i,\alpha_j}(x_t))^2, t \in \{1,\ldots,N\}\}.$$

Computation of $\widehat{\mathrm{RVaR}}_n^W$ and $\widehat{\mathrm{RCTE}}_n^W$

523 Stations



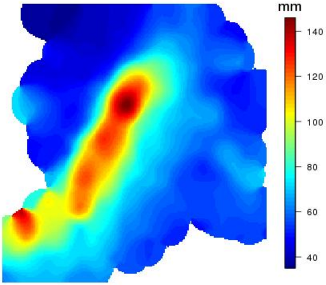
Regular grid : 200×200



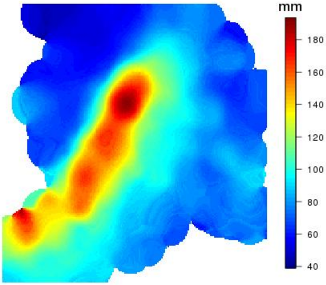
- Two dimensional covariate X =(latitude, longitude).
- Bi-quadratic kernel : $K(x) \propto (1 - \|x\|^2)^2 \mathbb{I}_{\{\|x\| \leq 1\}}$.
- Harmonic sequence of weights : $(\tau_j)_{j \in \{1,\ldots,9\}} = 1/j$.
- Results of the procedure $(h_{emp}, \alpha_{emp}) = (24, 1/(3 \times 365.25))$.

Estimated risk measures for a return period of 3 years

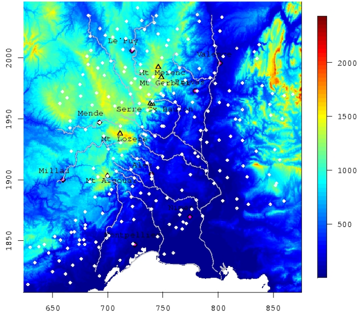
$\widehat{\mathrm{RVaR}}_n(1/(3 \times 365.25)|x)$

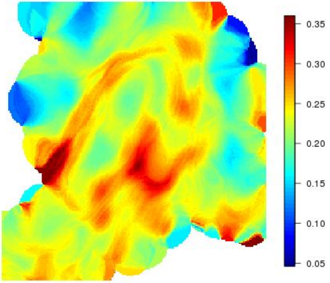


$\widehat{\mathrm{RCTE}}_n(1/(3 \times 365.25)|x)$

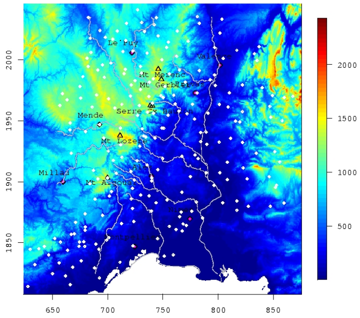


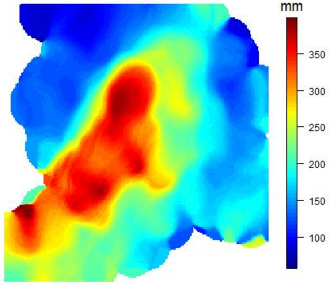
Estimated conditional tail index



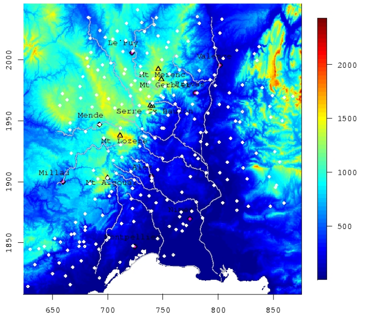


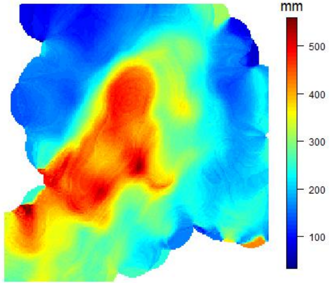
$\widehat{\mathrm{RVaR}}_n^W(1/(100 \times 365.25)|x)$: 100-year return level





$\widehat{\mathrm{RCTE}}_n^W(1/(100 \times 365.25)|x)$ above the 100-year return level





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