## Univariate Extreme Value Theory

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#### Introduction

Block Maxima Method

$$M_n = max\{X_1, \dots, X_n\}, \text{ for } n \to \infty$$

 $M_n$  follows a Generalised Extreme Value (GEV) distribution

Peak over Threshold Method

... for a very large threshold u\_

follows a Generalised Pareto distribution (GPD)

# Block maxima approach

#### Model Formulation

The model focuses on the statistical behaviour of  $M_n = max\{X_1, \dots, X_n\}$ , where  $X_1, \dots, X_n$  is a sequence of i.i.d. random variables with distribution function F.

$$Pr(M_n \le x) = Pr(X_1 \le x) \dots Pr(X_n \le x) = F^n(x)$$

So we look at the behaviour of  $F^n$  as  $n \to \infty$ .

But for any  $z < z^+$ , where  $z^+$  is the upper end-point of F,  $F^n \to 0$  as  $n \to \infty$ , so the distribution of  $M_n$  degenerates to a point mass on  $z^+$ .

==> Linear normalization:

$$M_n^* = \frac{M_n - b_n}{a_n}$$
, for sequences of constants  $\{a_n > 0\}$  and  $\{b_n\}$ 

### Extremal Types Theorem

**Theorem :** If there exist sequences of constants  $\{a_n > 0\}$  and  $\{b_n\}$  such that

$$Pr\{(M_n - b_n)/a_n \le z\} \to G(z) \quad \text{as } n \to \infty$$

where G is a non-degenerate distribution function, then G belongs to one of the following families:

$$\begin{split} &\mathrm{I}: G(z) &= \exp\left\{-\exp\left[-\left(\frac{z-b}{a}\right)\right]\right\}, \quad -\infty < z < \infty; \\ &\mathrm{II}: G(z) &= \left\{\begin{array}{ll} 0, & z \leq b, \\ \exp\left\{-\left(\frac{z-b}{a}\right)^{-\alpha}\right\}, & z > b; \end{array}\right. \\ &\mathrm{III}: G(z) &= \left\{\begin{array}{ll} \exp\left\{-\left[-\left(\frac{z-b}{a}\right)^{\alpha}\right]\right\}, & z < b, \\ 1, & z \geq b, \end{array}\right. \end{split}$$

for a > 0 (scale parameter), b (location parameter) and, in the the case of families II and III,  $\alpha > 0$  (shape parameter).

• The families labeled I, II and III are known as

I: Gumbel

II: Fréchet

III: Weibull

families, and are collectively called extreme value distributions.

• These three types of extreme value distributions are the only possible limits for the distributions of the  $M_n^*$  regardless of the distribution F for the population.

### The Generalised Extreme Value (GEV) Distribution

$$G(z) = \exp\left\{-\left[1 + \xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\},$$

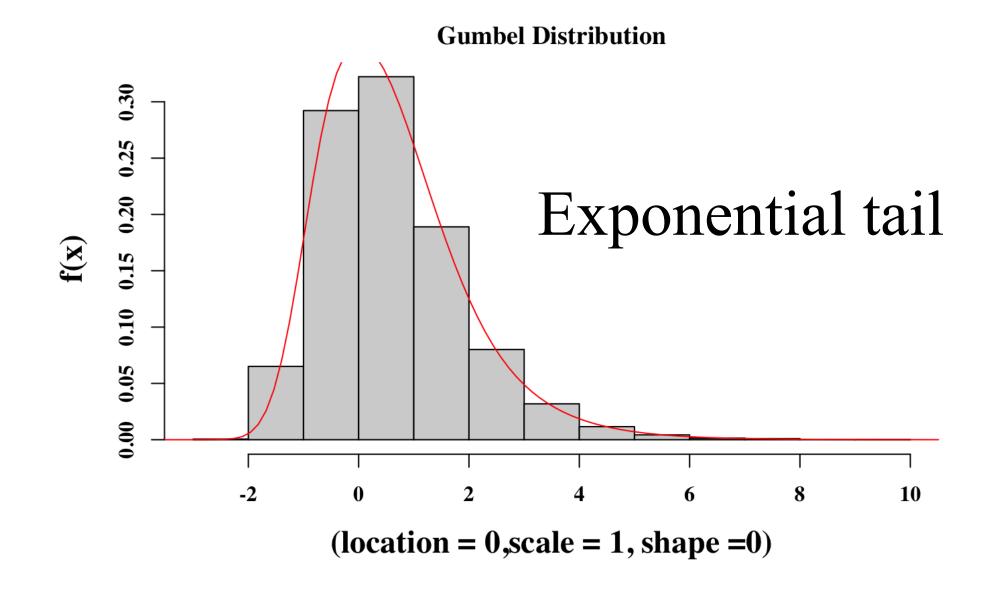
defined on  $\{z: 1 + \xi(z - \mu)/\sigma > 0\}$ , where  $-\infty < \mu < \infty, \sigma > 0$  and  $-\infty < \xi < \infty$ .

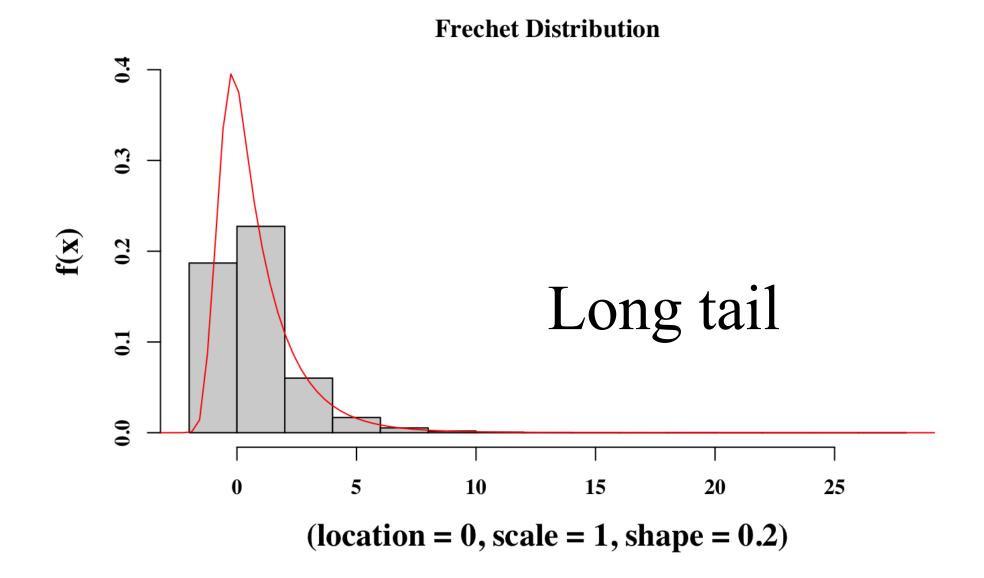
I (Gumbel):  $\xi = 0$  (interpreted as  $\xi \to 0$ )

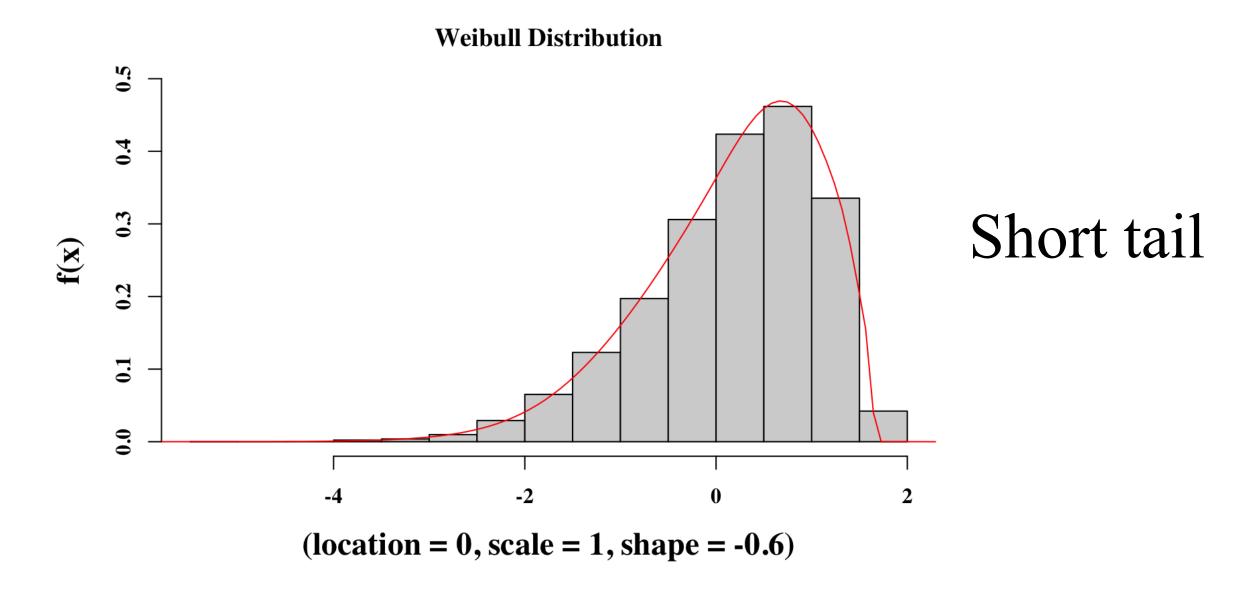
II (Fréchet) :  $\xi > 0$ 

III (Weibull) :  $\xi < 0$ 

 $\xi$  determines the nature of the tail distribution.







#### Inference for the GEV Distribution

#### Choice of block size:

- Small block size => approximation by the model is likely to be poor leading to bias in estimation and extrapolation
- Large block size => generates few block maxima, leading to large estimation variance

Pragmatic considerations often lead to the adoption of blocks of length one year.

### Parameter estimation by maximum likelihood

Let  $X_1, ... X_n$  be independent variables with the GEV distribution. The log-likelihood for the GEV parameters when  $\xi \neq 0$  is

$$\ell(\mu, \sigma, \xi) = -m \log \sigma - (1 + 1/\xi) \sum_{i=1}^{m} \log \left[ 1 + \xi \left( \frac{z_i - \mu}{\sigma} \right) \right] - \sum_{i=1}^{m} \left[ 1 + \xi \left( \frac{z_i - \mu}{\sigma} \right) \right]^{-1/\xi}$$

provided that  $1 + \xi(z_i - \mu)\sigma^{-1} > 0$  for i = 1,...,m.

The log-likelihood for the GEV parameters when  $\xi = 0$  is

$$\ell(\mu, \sigma) = -m \log \sigma - \sum_{i=1}^{m} \left( \frac{z_i - \mu}{\sigma} \right) - \sum_{i=1}^{m} \exp \left\{ -\left( \frac{z_i - \mu}{\sigma} \right) \right\}$$

#### Return Levels

Estimates of extreme quantiles of the maximum distribution are obtained by inverting the GEV distribution function:

$$z_{p} = \begin{cases} \mu - \frac{\sigma}{\xi} \left[ 1 - \{ -\log(1-p) \}^{-\xi} \right], & \text{for } \xi \neq 0, \\ \mu - \sigma \log\{ -\log(1-p) \}, & \text{for } \xi = 0, \end{cases}$$

where  $G(z_p) = 1 - p$ .

 $=>z_p$  is the return level associated with the return period 1/p

**Return level plot**:  $z_p$  plotted against  $log y_p$  where  $y_p = -log(1-p)$ .

Return level plot is convenient for model presentation and validation.

## Threshold models

#### Model Formulation

We can also see as extreme events as those that exceed some high threshold u.

Let  $X_1, \ldots X_n$  be a sequence of i.i.d. random variables with distribution function F.

A description of the stochastic behaviour of extreme events is given by the conditional probability:

$$Pr\{X > u + y \mid X > u\} = \frac{1 - F(u + y)}{1 - F(u)}, \quad y > 0$$

### The generalized Pareto distribution

**Theorem :** Let  $M_n = max\{X_1, \dots, X_n\}$ , where  $X_1, \dots X_n$  is a sequence of i.i.d. random variables with distribution function F. Suppose that F satisfies the extreme value theorem so that for large n,

 $Pr\{(M_n \le z) \approx G(z), \text{ where G is an extreme value distribution.}$ 

Then, for large enough u, the distribution function of (X - u) conditional on X > u is approximately

$$H(y) = 1 - \left(1 + \frac{\xi y}{\tilde{\sigma}}\right)^{-1/\xi}$$

defined on  $\{y: y > 0 \& (1 + \xi y/\tilde{\sigma}) > 0\}$ , where  $\tilde{\sigma} = \sigma + \xi(u - \mu)$ .

The family of distributions defined is called the generalized Pareto family.

## Duality between GEV and generalised Pareto families

The shape parameter  $\xi$  is dominant in determining the behaviour of the generalised Pareto distribution:

• 
$$\xi = 0$$
:  $H(y) = 1 - exp(-\frac{y}{\tilde{\sigma}}), y > 0$  (corresponds to exponential distribution)

- $\xi > 0$ : no upper limit
- $\xi < 0$ : upper bound of  $u \frac{\tilde{\sigma}}{\xi}$

### Threshold Selection (Mean residual life plot)

The mean of the generalised Pareto distribution given  $\xi < 1$ , with threshold  $u_0$ :  $E(X - u_0 | X > u_0) = \frac{\sigma_{u_0}}{1 - \xi}$ 

The generalised Pareto distribution should also valid for all thresholds  $u > u_0$ :

$$E(X - u \mid X > u) = \frac{\sigma_u}{1 - \xi}$$

$$= \frac{\sigma_{u_0} + \xi u}{1 - \xi}$$

So E(X - u | X > U) is a linear function of u.

$$\left\{ \left(u, \frac{1}{n_u} \sum_{i=1}^{n_u} (x_{(i)} - u)\right) : u < x_{\max} \right\},\,$$

where  $x_{(1)}, \ldots, x_{(n_u)}$  are the observations that exceed the threshold u, are the points of the mean residual life plot.

### Parameter estimation by maximum likelihood

Let  $y_1, \ldots, y_k$  be k excesses of a threshold u. The log-likelihood for the generalised Pareto distribution parameters when  $\xi \neq 0$  is

$$\ell(\sigma, \xi) = -k \log \sigma - (1 + 1/\xi) \sum_{i=1}^{k} \log(1 + \xi y_i/\sigma),$$

provided that  $1 + \sigma^{-1}\xi y_i > 0$  for i = 1,...,k.

The log-likelihood for the generalised Pareto distribution parameters when  $\xi = 0$  is

$$\ell(\sigma) = -k \log \sigma - \sigma^{-1} \sum_{i=1}^{k} y_i.$$

# EVT in wildfire modeling

#### Models for fire sizes

Distribution of fire sizes tend to be heavy tailed:

Pareto distribution

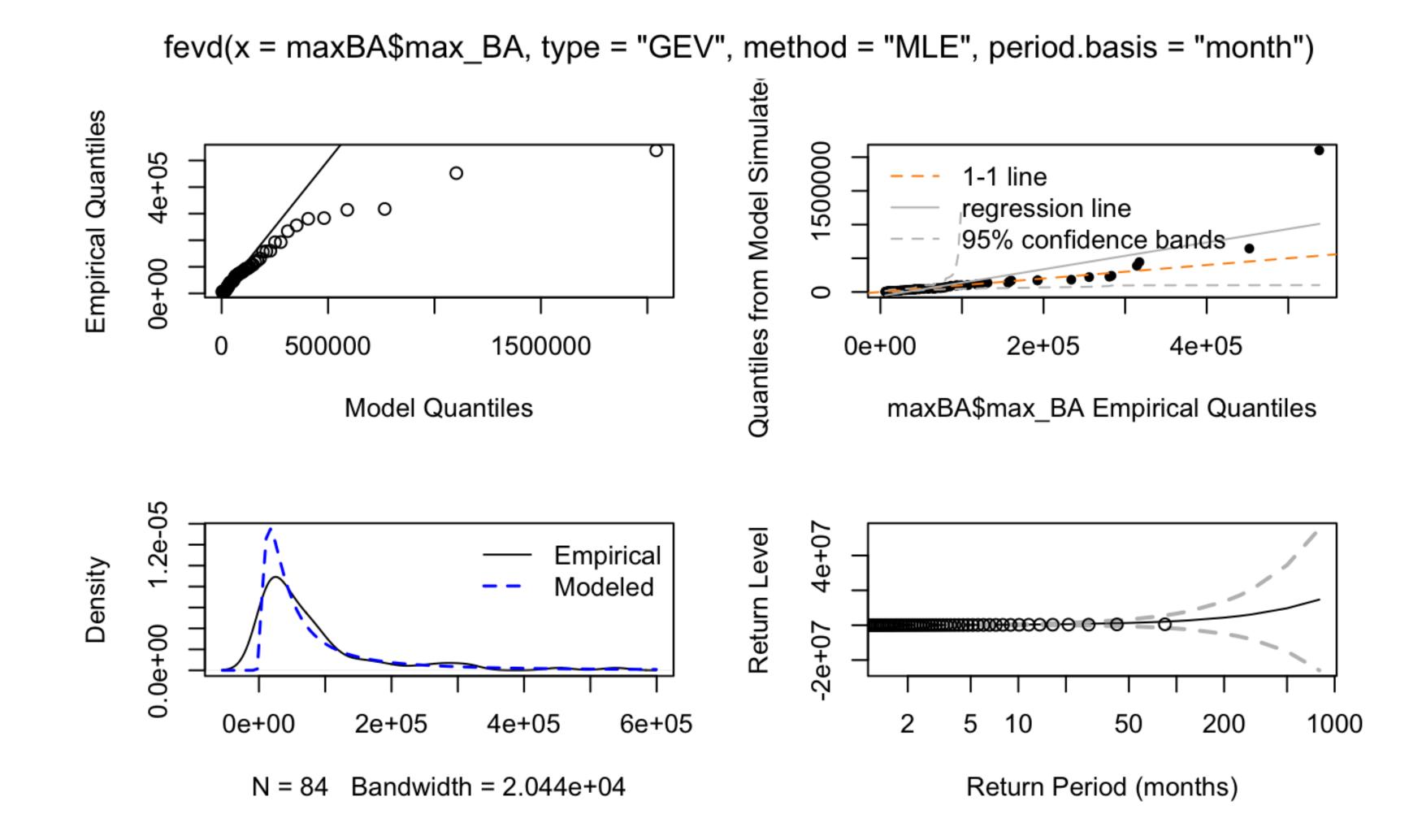
$$F(x) = 1 - (\beta/x)^{\eta}, \quad \beta \le x < \infty$$

• Tapered Pareto distribution (smaller exponential tails; otherwise similar to the Pareto distribution)

$$F(x) = 1 - (\beta/x)^{\eta} exp(\frac{\beta - x}{\theta}), \quad \beta \le x < \infty$$

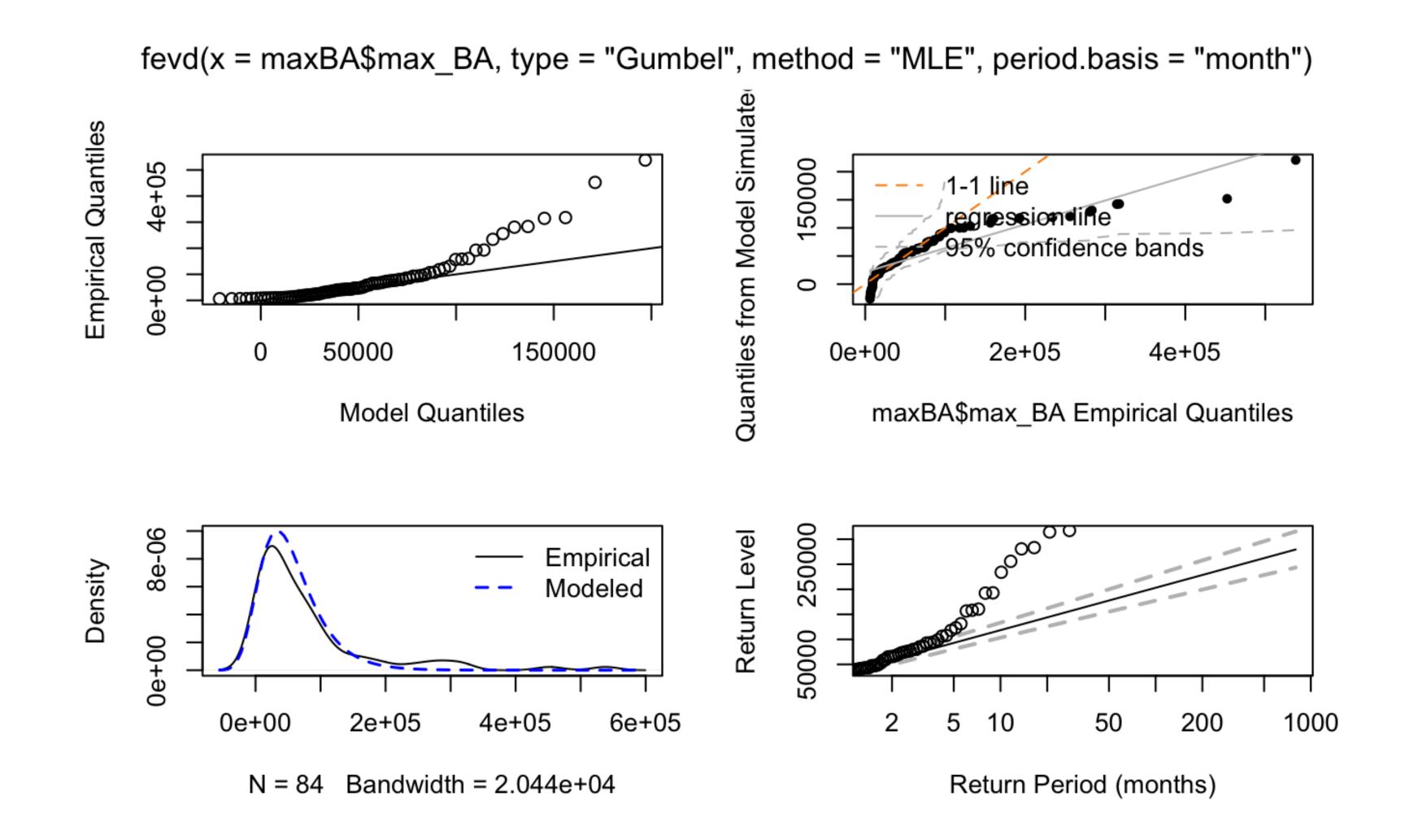
### Block maxima: GEV on monthly maxima of BA (odd years)

Library "extRemes" "fevd" function



### Block maxima: Gumbel on monthly maxima of BA (odd years)

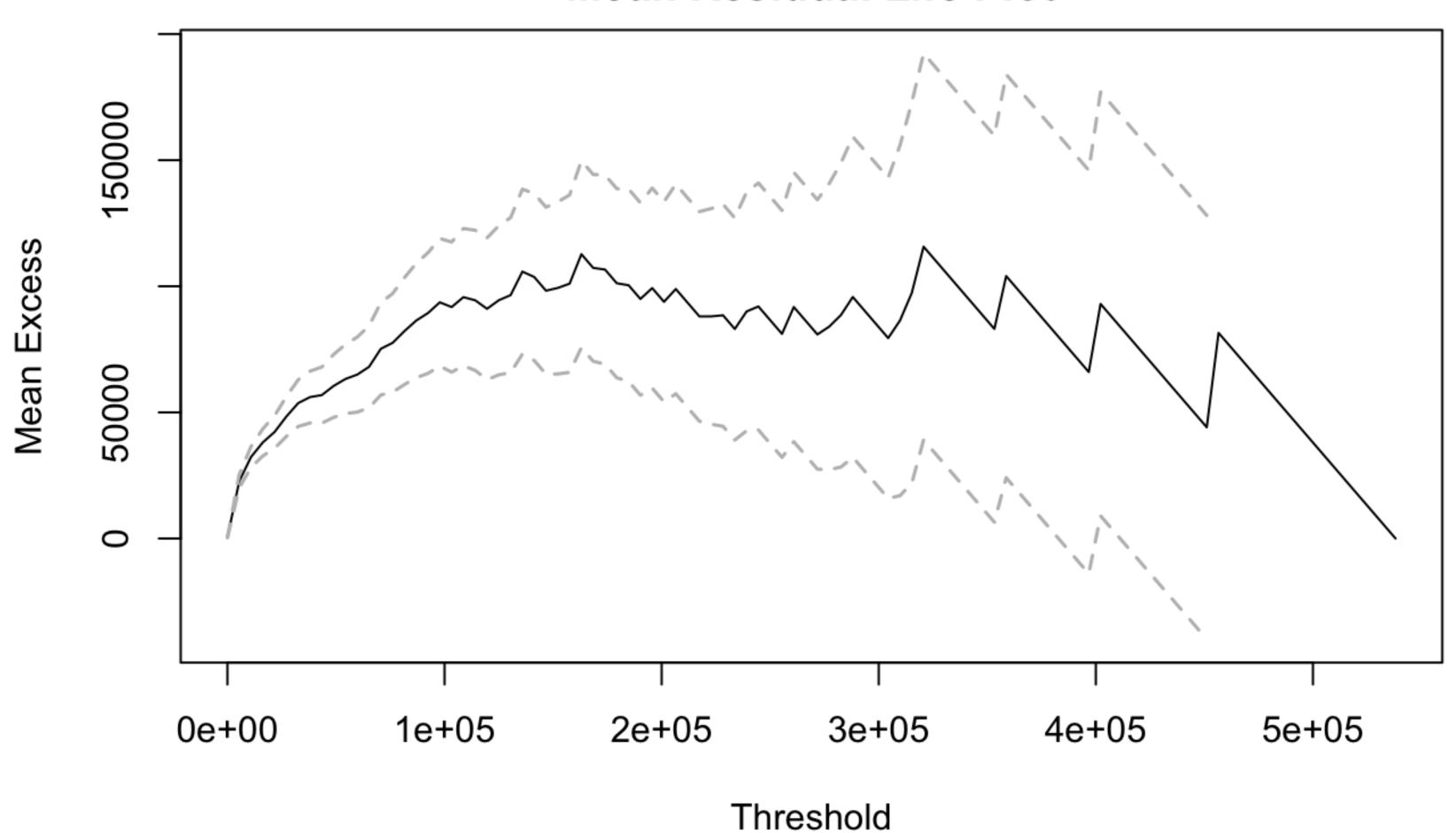
Library "extRemes" "fevd" function



### Mean Residual Life Plot of BA (odd years and BA > 0)

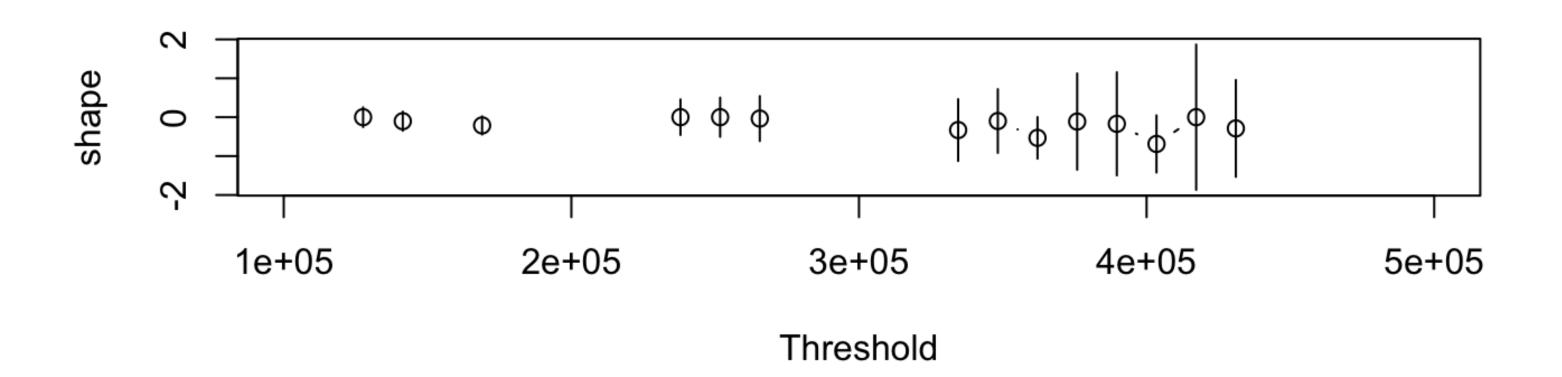
Library "extRemes" "mrlplot" function

#### **Mean Residual Life Plot**

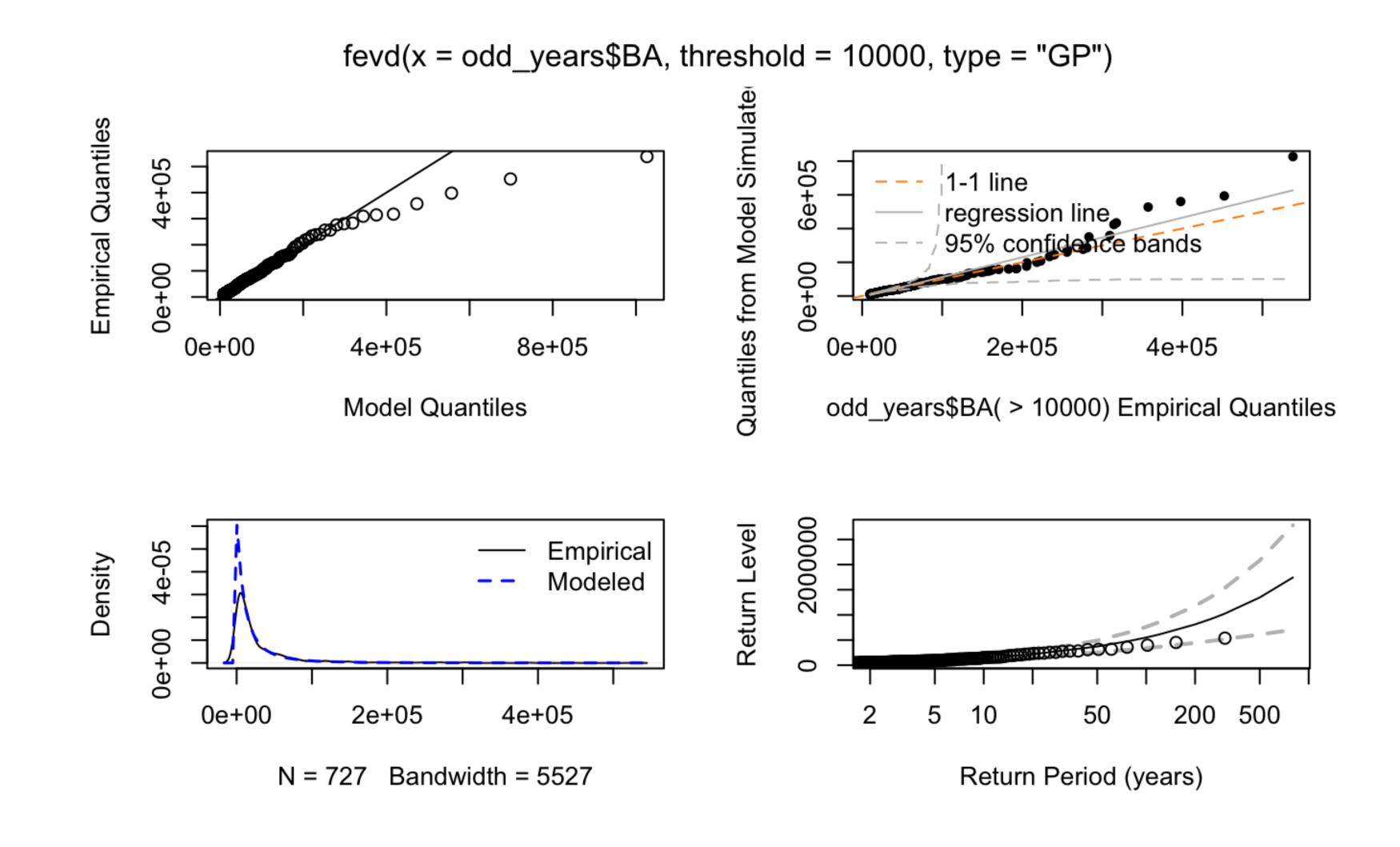


## Threshold range plot (odd years and BA > 0)





#### Fitting generalised Pareto distribution with threshold of 10000:



#### Resources

Coles, Stuart. An Introduction to Statistical Modeling of Extreme Values. Springer, 2011.

Gilleland E, Katz RW (2016). "extRemes 2.0: An Extreme Value Analysis Package in R." *Journal of Statistical Software*, **72**(8), 1–39. doi: <u>10.18637/jss.v072.i08</u>.