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A Short Course on Extreme Value Statistics in Applications

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The Bivariate ACER Method



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Bivariate Extreme Value Distributions

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Our goal is to accurately determine empirically the joint distribution function of the extreme value vector $(M_{X,N}, M_{Y,N})$, where $M_{X,N} = \max \{X_j; j = 1, \dots, N\}$, and with a similar definition of $M_{Y,N}$. Specifically, we want to estimate

$P(\xi, \eta) = \text{Prob} (M_{X,N} \leq \xi, M_{Y,N} \leq \eta)$ accurately for large values of ξ and η .



Bivariate Extreme Value Distributions

By transformation of variables, any other marginal distribution can be obtained from the standard Fréchet distribution

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Now, it follows that $\text{Prob}(M_{x,N} \leq z) = \exp(-N/z)$, or, equivalently, $\text{Prob}(M_{x,N}/N \leq z) = \exp(-1/z)$, $z > 0$. The same result applies to $M_{y,N}$.



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Hence, to obtain standard univariate results for each margin, we should consider the re-scaled vector,

$$M_N^* = (M_{x,N}^*, M_{y,N}^*) = (M_{x,N}/N, M_{y,N}/N).$$



Bivariate Extreme Value Distributions

Then if,

$$\text{Prob}(M_{x,N}^* \leq x, M_{y,N}^* \leq y) \rightarrow G(x, y), \text{ as } N \rightarrow \infty,$$

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Here

$$V(x, y) = \int_0^1 2 \max\left(\frac{w}{x}, \frac{1-w}{y}\right) dH(w),$$

where H is a distribution function on $[0, 1]$ satisfying the mean value constraint

$$\int_0^1 w dH(w) = 1/2.$$



Bivariate Extreme Value Distributions

For any GEV marginal, it is only necessary to transform the marginals from standard Fréchet to the required members of the GEV family. Specifically, by defining,

$$\tilde{x} = \left\{ 1 + \gamma_x \left(\frac{x - \mu_x}{\sigma_x} \right) \right\}^{1/\gamma_x} \quad \text{and} \quad \tilde{y} = \left\{ 1 + \gamma_y \left(\frac{y - \mu_y}{\sigma_y} \right) \right\}^{1/\gamma_y},$$

it follows that the complete set of bivariate asymptotic extreme value distributions is determined by distribution functions of the form,

$$G(x, y) = \exp\{-V(\tilde{x}, \tilde{y})\},$$



Cascade of Approximations

We introduce the non-exceedance event

$\mathcal{C}_{kj}(\xi, \eta) = \{X_{j-1} \leq \xi, Y_{j-1} \leq \eta, \dots, X_{j-k+1} \leq \xi, Y_{j-k+1} \leq \eta\}$ for $1 \leq k \leq j \leq N+1$. Then, from the definition of $P(\xi, \eta)$ it follows that,

$$\begin{aligned} P(\xi, \eta) &= \text{Prob}(\mathcal{C}_{N+1, N+1}(\xi, \eta)) \\ &= \text{Prob}(X_N \leq \xi, Y_N \leq \eta \mid \mathcal{C}_{NN}(\xi, \eta)) \cdot \text{Prob}(\mathcal{C}_{NN}(\xi, \eta)) \\ &= \prod_{j=2}^N \text{Prob}(X_j \leq \xi, Y_j \leq \eta \mid \mathcal{C}_{jj}(\xi, \eta)) \cdot \text{Prob}(\mathcal{C}_{22}(\xi, \eta)). \end{aligned}$$



Cascade of Approximations

The following representation applies for a suitably chosen k ,

$$P(\xi, \eta) \approx \exp \left\{ - \sum_{j=k}^N (\alpha_{kj}(\xi; \eta) + \beta_{kj}(\eta; \xi) - \gamma_{kj}(\xi, \eta)) \right\}; \quad \xi, \eta \rightarrow \infty,$$

where we have used the notation

$$\alpha_{kj}(\xi; \eta) = \text{Prob}(X_j > \xi \mid \mathcal{C}_{kj}(\xi, \eta)),$$

$$\beta_{kj}(\eta; \xi) = \text{Prob}(Y_j > \eta \mid \mathcal{C}_{kj}(\xi, \eta)) \text{ and}$$

$$\gamma_{kj}(\xi, \eta) = \text{Prob}(X_j > \xi, Y_j > \eta \mid \mathcal{C}_{kj}(\xi, \eta)).$$



Cascade of Approximations

The k 'th order bivariate ACER function is given by,

$$\mathcal{E}_k(\xi, \eta) = \frac{1}{N - k + 1} \sum_{j=k}^N (\alpha_{kj}(\xi; \eta) + \beta_{kj}(\eta; \xi) - \gamma_{kj}(\xi, \eta)); \quad k = 1, 2, \dots$$

Hence, when $N \gg k$, we may write

$$P(\xi, \eta) \approx \exp \{ - (N - k + 1) \mathcal{E}_k(\xi, \eta) \}; \quad \xi, \eta \rightarrow \infty.$$



Bivariate Extreme Value Copulas

The Gumbel logistic:

$$\mathcal{G}_k(\xi, \eta) = \left[(\varepsilon_k^x(\xi))^m + (\varepsilon_k^y(\eta))^m \right]^{\frac{1}{m}}.$$



Bivariate Extreme Value Copulas

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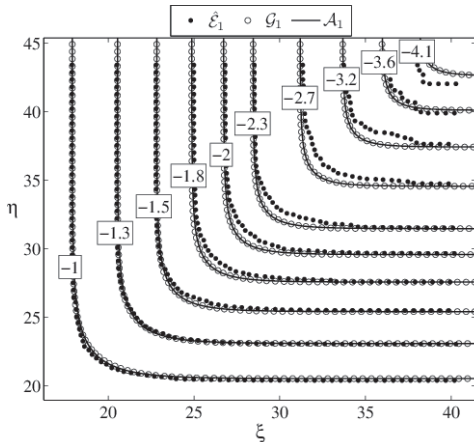
$$\mathcal{G}_k(\xi, \eta) = \left[(\varepsilon_k^x(\xi))^m + (\varepsilon_k^y(\eta))^m \right]^{\frac{1}{m}}.$$

The Asymmetric logistic:

$$\begin{aligned} \mathcal{A}_k(\xi, \eta) = & \left[(\phi \varepsilon_k^x(\xi))^m + (\theta \varepsilon_k^y(\eta))^m \right]^{\frac{1}{m}} \\ & + (1 - \phi) \varepsilon_k^x(\xi) + (1 - \theta) \varepsilon_k^y(\eta). \end{aligned}$$

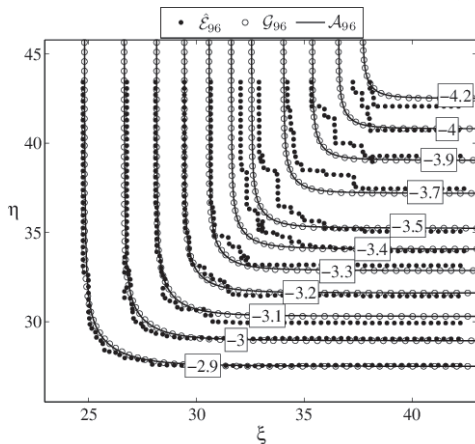


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