

# Rank-based Estimation under Asymptotic Dependence and Independence, with Applications to Spatial Extremes

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# Extreme value theory

- Extrapolate outside the range of data and estimate properties of the underlying distribution *beyond the observed regions*
- Given 50 years of rainfall data, EVT finds
  - the 1-in-100-years rainfall (or even 1-in-10 000 years)
  - the probability of at least  $x$ mm rainfall ( $x$  larger than anything observed)
- Mathematically, EVT uses largest data points to estimate the whole tail of one (or multiple) random variable(s)

# Tail dependence

- Typical problem:  $(X, Y) = (\text{rainfall at location 1, rainfall at location 2})$
- Estimate

$$\mathbb{P}(X \geq u, Y \geq v),$$

for large (unobserved) values  $u, v$

- Univariate methods  $\Rightarrow$  estimation of marginal tails of  $X$  and  $Y$
- Dependence structure in tail regions

# Tail dependence

- Copula-based approach: represent the tail dependence structure by

$$R(x, y) := \lim_{t \downarrow 0} t^{-1} \mathbb{P}(F_1(X) \geq 1 - tx, F_2(Y) \geq 1 - ty),$$

$F_1$  and  $F_2$  are marginal d.f. of  $X$ ,  $Y$

- Extrapolation: limit allows to write

$$\mathbb{P}(F_1(X) \geq 1 - tx, F_2(Y) \geq 1 - ty) \approx tR(x, y)$$

- So estimation of  $R \Rightarrow$  estimation of far tail probabilities

# Asymptotic independence

- What if  $X$  and  $Y$  are independent? Then  $R(x, y) = 0$
- Many distributions satisfy  $R(x, y) = 0$  (*asymptotically independent*)
- Example:  $(X, Y)$  is jointly Normal with correlation  $\rho \in (-1, 1)$
- Modelling/inference based on  $R \Rightarrow$  cannot distinguish different asympt. independent distributions

# Alternative tail representation: the function $c$

- Instead of  $R$ , we consider the function

$$c(x, y) := \lim_{t \downarrow 0} q(t)^{-1} \mathbb{P}(F_1(X) \geq 1 - tx, F_2(Y) \geq 1 - ty)$$

- $q$  is chosen so that the limit is non-trivial
- As opposed to  $R$ ,  $c$  has non-trivial form whether  $X, Y$  are asympt. independent or dependent
- Examples:
  - $X$  and  $Y$  are independent:  $c(x, y) = xy$
  - $X$  and  $Y$  are Normal with correlation  $\rho$ :  $c(x, y) = (xy)^{1/(1+\rho)}$

# Non-parametric estimation (unfeasible)

- (iid) observations  $(X_1, Y_1), \dots, (X_n, Y_n)$
- Wish to estimate

$$c(x, y) := \lim_{t \downarrow 0} q(t)^{-1} \mathbb{P}(F_1(X) \geq 1 - tx, F_2(Y) \geq 1 - ty)$$

- For a small  $t_n > 0$ ,

$$\hat{c}_n(x, y) := q(t_n)^{-1} \frac{1}{n} \sum_{i=1}^n \mathbb{1} \left\{ \hat{F}_1(X_i) \geq 1 - t_n x, \hat{F}_2(Y_i) \geq 1 - t_n y \right\},$$

where  $\hat{F}_j$  are the empirical d.f.

# Parametric method

- Suppose  $c = c_{\theta_0} \in \{c_\theta : \theta \in \Theta\}$
- Estimate  $\theta_0$  by

$$(\hat{\theta}, \hat{\sigma}) := \arg \min_{\theta, \sigma} \left\| \sigma \int g c_\theta - q(t_n) \int g \hat{c}_n \right\|,$$

for a weight function  $g : [0, \infty)^2 \rightarrow \mathbb{R}^p$

- If  $\hat{c}_n \approx c$ , hopefully  $\hat{\theta} \approx \theta_0$  and  $\hat{\sigma} \approx q(t_n)$



# Spatial tail dependence

- Typical problem:  $\{X(s) : s \in \mathbb{R}^2\}$  = rainfall over a spatial domain
- Simultaneous estimation of marginal tails of  $X(s)$
- Given observations at  $d$  locations, estimate

$$\mathbb{P}(F_s(X(s)) \geq 1 - tx(s), \text{ for each } s \in \mathcal{S}), \quad (*)$$

for small  $t$  and finite collection of locations  $\mathcal{S}$

- Locations  $\mathcal{S}$  potentially unobserved
- Spatial tail dependence model: probabilities  $(*)$  for all collections  $\mathcal{S}$

# Spatial tail dependence

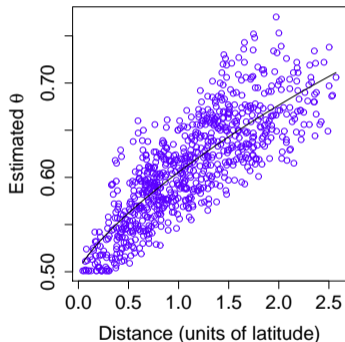
- Key: popular models are identifiable by finite number of pairwise prob.

$$\mathbb{P}(F_{s_1}(X(s_1)) \geq 1 - tx(s_1), F_{s_2}(X(s_2)) \geq 1 - tx(s_2))$$

- Spatial model ( $\theta_{\text{spatial}}$ )  $\Rightarrow$  Bivariate model for each pair ( $\theta_{\text{pair}}(\theta_{\text{spatial}})$ )
- Bivariate methodology  $\Rightarrow$  Estimator  $\hat{\theta}_{\text{pair}}$  for each pair
- Fit spatial model via least squares:

$$\hat{\theta}_{\text{spatial}} := \arg \min_{\theta_{\text{spatial}}} \sum_{\text{pair} \in \text{observed pairs}} \|\theta_{\text{pair}}(\theta_{\text{spatial}}) - \hat{\theta}_{\text{pair}}\|^2$$

# Rainfall over Victoria region (AUS), 1967-2017



- 40 locations  $\Rightarrow$  780 pairs
- Fractal inverted Brown–Resnick process
- Pairwise parameter depends on Euclidean distance
- Blue dots =  $\hat{\theta}_{\text{pair}}$ , black curve = fitted spatial model

# Thanks for your attention! Questions?

Lalancette, M., S. Engelke, and S. Volgushev (2021). [Rank-based estimation under asymptotic dependence and independence, with applications to spatial extremes](#). *Ann. Stat.*, to appear.

Other contributions in the paper:

- Novel examples of (bivariate and spatial) tail models
- Asymptotic theory for all (bivariate and spatial) estimators
- Simulation studies