# **Extremes on Phase-Type Distributions**

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# Summary

- Univariate results
- Bivariate results
- Examples
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#### Introduction: Univariate Maxima

Let  $X_1, X_2, \ldots$  be *iid* r.vs with common *df F*.

**Fisher-Tippett Theorem:** Let  $U^n = \max(X_i, i = 1, ..., n)$ . If there exist a r.v U with nondegenerate df G and *normalizing constants*  $a_n > 0$ ,  $b_n$  such that  $a_n U^n + b_n \xrightarrow{w} U$ , then G belongs to the type of one of the following

$$\Phi_{\alpha}(x) = \exp(-x^{-\alpha}), \quad x > 0 \Rightarrow G \text{ is of Fréchet type}$$
  

$$\Psi_{\alpha}(x) = \exp(-(-x)^{\alpha}), \quad x \le 0 \Rightarrow G \text{ is of Weibull type}$$
  

$$\Lambda(x) = \exp(-e^{-x}), \quad x \in \Re \Rightarrow G \text{ is of Gumbel type}$$

where  $\alpha > 0$ , and we write  $F \in MaxDA(G)$ .

#### Introduction: Univariate Minima

Let  $L^n = \min(X_i, i = 1, ..., n)$ . If there exist a r.v L with nondegenerate df G and normalizing constants  $a_n > 0$ ,  $b_n$  such that  $a_n L^n + b_n \xrightarrow{w} L$ , then G belongs to the type of one of the following

$$\Phi_{\alpha}^{*}(x) = 1 - \exp(-(-x)^{-\alpha}), \quad x < 0 \Rightarrow G \text{ is of type I}$$
$$\Psi_{\alpha}^{*}(x) = 1 - \exp(-x^{\alpha}), \quad x \ge 0 \Rightarrow G \text{ is of type II}$$
$$\Lambda^{*}(x) = 1 - \exp(-e^{x}), \quad x \in \Re \Rightarrow G \text{ is of type III}$$

where  $\alpha > 0$ , and we write  $F \in MinDA(G)$ .

### Univariate Phase-Type Distribution

Let  $\{Y(t), t \ge 0\}$  be a CTMC with state space  $\xi = \{\Delta, 1, \dots, d\}$ , initial distribution  $\beta = (0, \alpha)$ , and infinitesimal generator

$$\mathbf{Q} = \left(\begin{array}{cc} \mathbf{0} & \mathbf{0} \\ \mathbf{-Ae} & \mathbf{A} \end{array}\right)$$

Then the nonnegative random variable X of the time until absorption into

state  $\Delta$  is  $PH(\alpha, \mathbf{A}, d)$ .

$$\overline{F}(x) = \Pr(Y(x) \notin \{\Delta\}) = \alpha e^{\mathbf{A}x} \mathbf{e}, \quad x \ge 0.$$

#### Maxima: Univariate Case

The matrix **A** has a real dominant eigenvalue  $-\eta$ , not necessarily unique, such that for all complex eigenvalues  $\lambda$ , Re( $\lambda$ ) <  $-\eta$ .

1. if  $-\eta$  is a simple eigenvalue of **A** then

$$e^{\mathbf{A}x} = e^{-\eta x} (\mathbf{M} + \mathbf{O}(1)), \ as \ x \to \infty$$

2. if  $-\eta$  has algebric multiplicity l, then there exists  $k \in [0, l-1]$ 

$$e^{\mathbf{A}x} = x^k e^{-\eta x} (\mathbf{M} + \mathbf{O}(1)), \ as \ x \to \infty,$$

where k + 1 is the maximal order of Jordan blocks corresponding to  $-\eta$ , called the index of  $-\eta$ .

Let X be a  $PH(\alpha, \mathbf{A}, d)$  random variable. Then  $F \in MaxDA(\Lambda)$  with normalizing constants

$$a_n = \frac{1}{\eta}, b_n = \frac{\log nc + k \log \log n - k \log \eta}{\eta}, \text{ where } c = \alpha \mathbf{Me} > 0.$$

#### Minima: Univariate Case

Let X is  $PH(\alpha, \mathbf{A}, d)$ . Then m is the minimum number of transitions needed for the underlying CTMC to be absorbed if and only if

$$-lpha \mathbf{A}^m \mathbf{e} > 0$$
 and when  $m \geq 2, \ -lpha \mathbf{A}^\ell \mathbf{e} = 0, \ \ell = 1, \dots m-1.$ 

Let X be a  $PH(\alpha, \mathbf{A}, d)$ . Then  $F \in MinDA(\Psi_m^*)$  with normalizing constants

$$a_n = \left(\frac{m!}{nc}\right)^{1/m}, \quad b_n = 0,$$

where  $c = -\alpha \mathbf{A}^m \mathbf{e}$ .

## Multivariate Phase-Type Distribution

- { $Y(t), t \ge 0$ } is a CTMC with finite state space  $\xi = \{\Delta, 1, \dots, d\}$ , initial distribution  $\beta = (0, \alpha)$  and infinitesimal generator **Q**
- ξ<sub>i</sub>, i = 1,..., p, are nonempty stochastically closed subsets of the state space ξ such that ∩<sup>p</sup><sub>i=1</sub> ξ<sub>i</sub> = {Δ}, and

$$\xi = (\bigcup_{i=1}^{p} \xi_i) \bigcup_{i=1}^{p} \xi_i \text{ for some subset } \xi_0 \subset \xi \text{ with } \xi_0 \bigcap \xi_i = \emptyset, i = 1, \dots, p$$

•  $X_i = \inf\{t \ge 0 : Y(t) \in \xi_i\}, i = 1, ..., p$ 

The joint distribution of  $(X_1, \ldots, X_p)$  is called a MPH random vector with representation  $(\alpha, \mathbf{A}, \xi, \xi_1, \ldots, \xi_p)$ . Thus, a MPH distribution is a joint distribution of first passage times to various overlapping subsets of the state space  $\xi$ .

#### Multivariate Phase-Type Distribution (cont'd)

For  $0 \leq x_p \leq \cdots \leq x_1$ 

$$\bar{F}(x_1,\ldots,x_p) = \alpha e^{\mathbf{A}x_p} \mathbf{g}_p e^{\mathbf{A}(x_{p-1}-x_p)} \mathbf{g}_{p-1} \cdots e^{\mathbf{A}(x_1-x_2)} \mathbf{g}_1 \mathbf{e},$$

where, for k = 1, ..., p,  $\mathbf{g}_k$  is a  $d \times d$  diagonal matrix whose *i*th diagonal entry, for i = 1, ..., d, equals 1 if  $i \in \xi \setminus \xi_k$  and 0 otherwise.

The random variable  $X_i$  represents the first passage time of the CTMC into  $\xi_i$ . This implies that  $X_i$  is univariate PH distributed with representation  $(\alpha_{\xi \setminus \xi_i}, \mathbf{A}_{\xi \setminus \xi_i}, d + 1 - |\xi_i|)$ 

 $\bar{F}$ 

$$\mathbf{A} = \left( \begin{array}{ccc} \mathbf{A}_0 & \mathbf{B}_1 & \mathbf{B}_2 \\ \mathbf{0} & \mathbf{A}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{A}_2 \end{array} \right),$$

where,  $\mathbf{A}_i$  represents the subgenerator for states in  $\xi_i \setminus \{\Delta\}$ , and  $\mathbf{B}_i$  represents the matrix of transition intensities from states in  $\xi_0$  to states in  $\xi_i \setminus \{\Delta\}$ .

Example: Marshall-Olkin df has subgenerator

$$\mathbf{A} = \begin{pmatrix} -\lambda_{12} - \lambda_1 - \lambda_2 & \lambda_1 & \lambda_2 \\ 0 & -\lambda_{12} - \lambda_2 & 0 \\ 0 & 0 & -\lambda_{12} - \lambda_1 \end{pmatrix}$$
$$(x, y) = \exp\{-\lambda_1 x - \lambda_2 y - \lambda_{12} \max(x, y)\}$$

## Multivariate Maxima/Minima

Let  $\mathbf{X}^{(1)} = (X_1^{(1)}, \dots, X_p^{(1)}), \mathbf{X}^{(2)} = (X_1^{(2)}, \dots, X_p^{(2)}), \dots$  be iid random vectors with common distribution *F*, and let  $\mathbf{U}^{(n)}$  be a random vector with *j*th component

$$U_j^{(n)} = \max(X_j^{(i)}, i = 1, \dots n).$$

If there exist  $\mathbf{a}^{(n)}$ ,  $\mathbf{b}^{(n)} \in \Re^p$  and  $\mathbf{U}$  with df G such that

$$\mathbf{a}^{(n)}\mathbf{U}^{(n)} + \mathbf{b}^{(n)} \stackrel{w}{\to} \mathbf{U},$$

then  $F \in MaxDA(G)$ .

**Theorem 1** Let *F* be the distribution function of a bivariate PH distribution with representation  $(\alpha, \mathbf{A}, \xi, \xi_1, \xi_2)$ , and  $m_i$  be the minimum number of transitions required in order to enter  $\xi_i$ . Then the limiting distribution of the componentwise minima is given by

• Case 1: 
$$m_1 = m_2 = m$$

$$\bar{G}(x_1, x_2) = \exp\left\{-x_1^m - x_2^m + c \min\left(\frac{x_1^m}{c_1}, \frac{x_2^m}{c_2}\right)\right\},\$$
  
where  $c_i = -\alpha A^{m_i} g_i e$ ,  $i = 1, 2$ , and  $c = -\alpha A^m e$ .

• Case 2:  $m_1 \neq m_2$ 

$$\bar{G}(x_1, x_2) = \exp(-x^{m_1} - x^{m_2})$$

**Theorem 2** Let *F* be the distribution function of a bivariate PH distribution with representation  $(\alpha, \mathbf{A}, \xi, \xi_1, \xi_2)$ . Then the limiting distribution of the componentwise maxima has the following form:

$$G(x_1, x_2) = \begin{cases} e^{-e^{-x_1}} e^{-e^{-x_2}} \exp\left\{\frac{e^{-x_1}}{c_1} \alpha \mathbf{M}_1 e^{\mathbf{A}(x_2 + \log c_2 - x_1 - \log c_1)\eta^{-1}} \mathbf{g}_2 \mathbf{e}\right\}, \\ \text{if } x_1 + \log c_1 \le x_2 + \log c_2 \\ e^{-e^{-x_1}} e^{-e^{-x_2}} \exp\left\{\frac{e^{-x_2}}{c_2} \alpha \mathbf{M}_2 e^{\mathbf{A}(x_1 + \log c_1 - x_2 - \log c_2)\eta^{-1}} \mathbf{g}_1 \mathbf{e}\right\}, \\ \text{if } x_2 + \log c_2 \le x_1 + \log c_1 \end{cases}$$

if  $\eta_1 = \eta_2 = \eta$  and  $k_1 = k_2 = k$ , where  $c_i = \alpha M_i e > 0$  for i = 1, 2.

For any other case we have independence, and

$$G(x_1, x_2) = \exp(-e^{-x_1})\exp(-e^{-x_2})$$

#### Pickands' representation

In the bivariate case, if  $F \in MaxDA(G)$ 

$$G(x,y) = \exp\left\{\log(G_1(x)G_2(y))A\left(\frac{\log G_1(x)}{\log(G_1(x)G_2(y))}\right)\right\},\$$

where A is the Pickands' representation function, which is a convex function on [0, 1] such that  $\max(t, 1 - t) \le A(t) \le 1$ .

$$A(t) = \begin{cases} 1 - \frac{1-t}{c_2} \alpha \mathbf{M}_2 e^{\mathbf{A}_{\eta}^1 \log \frac{c_1}{c_2} \frac{1-t}{t}} \mathbf{g}_1 \mathbf{e}, & \text{if } 0 \le t \le \frac{c_1}{c_1 + c_2} \\ 1 - \frac{t}{c_1} \alpha \mathbf{M}_1 e^{\mathbf{A}_{\eta}^1 \log \frac{c_2}{c_1} \frac{t}{1-t}} \mathbf{g}_1 \mathbf{e}, & \text{if } \frac{c_1}{c_1 + c_2} \le t \le 1 \end{cases}$$

# Example 1

$$\alpha = (1, 0, 0), \quad \mathbf{A} = \begin{pmatrix} -a & p & q \\ 0 & -b & 0 \\ 0 & 0 & -c \end{pmatrix}, \quad a < \min(b, c), p + q \le a,$$

$$A(t) = \begin{cases} 1 - t + \left(\frac{b-a}{(c-a)(b+p-a)}\right)^{1-\frac{c}{a}}q(c+q-a)^{-\frac{c}{a}}t^{\frac{c}{a}}(1-t)^{1-\frac{c}{a}}, & 0 \le t \le \frac{c_1}{c_1+c_2} \\ t + \left(\frac{c-a}{(b-a)(q+c-a)}\right)^{1-\frac{b}{a}}p(p+b-a)^{-\frac{b}{a}}t^{1-\frac{b}{a}}(1-t)^{\frac{b}{a}}, & \frac{c_1}{c_1+c_2} \le t \le 1 \end{cases}$$

If 
$$p = q = 0$$
, then  $A(t) = \max(t, 1 - t)$ 

# Example 1 (a)



 $(a, b, c, p, q) = (2, 3, 3, 0, 0) \rightarrow \text{solid line}$  $(a, b, c, p, q) = (2, 3, 3, 1, 1) \rightarrow \text{long-dashed line}$  $(a, b, c, p, q) = (2, 2.1, 2.1, 1, 1) \rightarrow \text{short-dashed line}$ 

# Example 1 (b)



 $(a, b, c, p, q) = (2, 2.1, 3, 1, 1) \rightarrow \text{solid line}$  $(a, b, c, p, q) = (2, 3, 2.5, 0.1, 1) \rightarrow \text{long-dashed line}$  $(a, b, c, p, q) = (2, 3, 3, 1, 0.1) \rightarrow \text{short-dashed line}$ 

# Example 2

$$\alpha = (p, 1 - p, 0, 0), \ 0 \le p \le 1,$$

$$\mathbf{A} = \begin{pmatrix} -5 & 0 & 1 & 2 \\ 0 & -5 & 2 & 0 \\ 0 & 0 & -7 & 0 \\ 0 & 0 & 0 & -6 \end{pmatrix},$$

$$A(t) = \begin{cases} 1 - t + 2^{\frac{4}{5}} p (1 + 2p)^{-\frac{6}{5}} (4 - p)^{\frac{1}{5}} t^{\frac{6}{5}} (1 - t)^{-\frac{1}{5}}, & 0 \le t \le \frac{2 + 4p}{6 + 3p} \\ t + 2^{\frac{2}{5}} (2 - p) (4 - p)^{-\frac{7}{5}} (1 + 2p)^{\frac{2}{5}} t^{-\frac{2}{5}} (1 - t)^{\frac{7}{5}}, & \frac{2 + 4p}{6 + 3p} \le t \le 1 \end{cases}$$

# Example 2 (cont'd)



 $p = 0 \rightarrow \text{solid line}$  $p = 0.5 \rightarrow \text{long-dashed line}$  $p = 1 \rightarrow \text{short-dashed line}$ 

### **Conclusions**

- for bivariate maxima, a flexible Pickands' representation is obtained
- for minima, the bivariate exponential Marshall-Olkin df arises in the limit
- simpler to see in the bivariate case, but our results can be extended to higher dimensions