



AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

Setat.

Netherlands school of economics.

ECONOMETRIC INSTITUTE

GIANNINI FOUNDATION OF
AGRICULTURAL ECONOMICS

WITHDRAWN

SEP 21 1977

A CHARACTERIZATION OF MULTIDIMENSIONAL
EXTREME-VALUE DISTRIBUTIONS

L. de HAAN

Erasmus

REPORT 7617/S

ECONOMETRIC INSTITUTE

A CHARACTERIZATION OF MULTIDIMENSIONAL EXTREME-VALUE DISTRIBUTIONS

LAURENS DE HAAN

RAPPORT no. 7617/S

ERASMUS UNIVERSITY ROTTERDAM, P.O. BOX 1738, ROTTERDAM, THE NETHERLANDS

A characterization of multidimensional
extreme-value distributions

Laurens de Haan

1. Introduction. One can ask to what extent there is an analogue in extreme-value theory of the preponderant role which the normal distribution plays in the limit theory for partial sums of i.i.d. summands. In this note we prove a characterization of multidimensional extreme-value distributions similar to a well known characterization of the multivariate normal law. The characterization of the normal law using the independence of certain linear combinations of independent random variables fails to have an analogue for sample maxima.

2. The result. It is well known (Lukacs and Laha [8] th. 2.1.4) that every linear combination of the components of a p -dimensional random vector has a univariate normal distribution if and only if the random vector has a p -variate normal df. We prove the following analogue for extreme-value distributions (for information about multidimensional extreme-value distributions we refer to [3] and [5]).

Theorem. Let $X = (X_1, X_2, \dots, X_p)$ be a random vector with non-negative components and $\alpha > 0$. X has a p -variate extreme value distribution with for some $b_1, \dots, b_p > 0$, $P\{X_k \leq x\} = \exp -(b_k x)^{-\alpha} = \phi_\alpha(b_k x)$ for $k = 1, 2, \dots, p$ if and only if every random variable Y of the form

$$Y = \max (a_1 X_1, a_2 X_2, \dots, a_p X_p)$$

with $a_k > 0$ ($k = 1, 2, \dots, p$) is a multiple of a random variable with df ϕ_α .

Proof. By considering $(X_1^{1/\alpha}, X_2^{1/\alpha}, \dots, X_p^{1/\alpha})$ it is clear that it is sufficient to prove the case $\alpha = 1$.

First suppose that X has a p -variate extreme value distribution with the mentioned marginals. Denoting the df of X by $G(x_1, x_2, \dots, x_p)$ one then has (Geffroy [3] Ch. VI, p. 167 sqq)

$$(1) \quad G(ax_1, ax_2, \dots, ax_p) = G^a(x_1, x_2, \dots, x_p)$$

for all

$a, x_1, x_2, \dots, x_p > 0$. Now $P\{Y \leq x\} = P\{a_1 X_1 \leq x, \dots, a_p X_p \leq x\} = G(a_1^{-1}x, \dots, a_p^{-1}x)$. By (1) the righthand side equals

$$G^{1/x}(a_1^{-1}, a_2^{-1}, \dots, a_p^{-1}) = \exp - \frac{-\log G(a_1^{-1}, a_2^{-1}, \dots, a_p^{-1})}{x}$$

As $0 < G(a_1^{-1}, \dots, a_p^{-1}) < 1$ for all $a_1 > 0, \dots, a_p > 0$ (Balkema and Resnick [1] th. 3 and its cor. 2), the distribution of Y is of type Φ_1 .

Conversely suppose Y satisfies the conditions of the theorem for all positive a_1, a_2, \dots, a_p . Then G satisfies

$$G(a_1^{-1}x, \dots, a_p^{-1}x) = \exp - \frac{c(a_1, \dots, a_p)}{x}$$

for $x > 0$ where $c(a_1, \dots, a_p)$ is positive. It follows that

$$G(a_1^{-1}x, a_2^{-1}x, \dots, a_p^{-1}x) = G^{1/x}(a_1^{-1}, a_2^{-1}, \dots, a_p^{-1})$$

which (Geffroy, loc. cit.) implies that G is a p -variate extreme value distribution with all marginals of type Φ_1 . \square

Remark. By applying the transformations

$$(T_1, T_2, \dots, T_p) = (\alpha^{-1} \log X_1, \alpha^{-1} \log X_2, \dots, \alpha^{-1} \log X_p)$$

and

$$(S_1, S_2, \dots, S_p) = (-X_1^{-1}, -X_2^{-1}, \dots, -X_p^{-1})$$

one gets from the theorem characterizations of the extreme value distributions with marginals $\exp(-e^{-x})$ and $\exp(-x)^\alpha$ respectively, which are the two other classes of one-dimensional extreme value distributions given by Gnedenko [4].

Example. Let E_n ($n = 0, \pm 1, \pm 2, \dots$) be independent random variables with df Φ_1 . Suppose that the sequence $\{X_n\}_{n=-\infty}^{+\infty}$ of random variables satisfies

$$X_{n+1} = \max(\rho X_n, E_n)$$

for some ρ ($0 < \rho < 1$) and $n = 0, \pm 1, \pm 2, \dots$ (cf. Helland and Nilsen [6]).

It is easily checked that then $X_n = \max_{j=0,1,2,\dots} \rho^j E_{n-j}$ and hence

$Y = \max(a_1 X_{n+1}, a_2 X_{n+2}, \dots, a_p X_{n+p})$ satisfies the conditions of the theorem for any n and positive p . One could thus call the distribution of $\{X_n\}_{n=-\infty}^{\infty}$ an infinite-dimensional extreme value distribution.

The statement of the theorem can be extended to the domain of attraction of the extreme-value distributions: the random vector $X = (X_1, X_2, \dots, X_p)$ is in the domain of symmetric attraction of a simple extreme value distribution (for explanation of the terms "symmetric" and "simple" see de Haan and Resnick [5] section 3) if and only if every Y of the form given in the theorem is in the domain of attraction of Φ_1 .⁺)

3. Other characterizations. We wish to add some remarks about possible other characterizations. There are two famous characterizations of the normal distribution by means of properties of linear combinations of independent random variables: one involves the existence of two stochastically independent linear combinations and the other the existence of two different linear combinations with the same probability distribution (Chapters 5 and

⁺) These properties can be formulated as properties of multidimensional regularly varying functions i.e. measurable positive functions $h(x_1, \dots, x_p)$ such that $\{h(t, t, \dots, t)\}^{-1} h(tx_1, tx_2, \dots, tx_p)$ converges to a positive limit as $t \rightarrow \infty$ for any positive x_1, x_2, \dots, x_p . The limit function $g(x_1, x_2, \dots, x_p)$ then satisfies for $a, x_1, x_2, \dots, x_p > 0$ $g(ax_1, ax_2, \dots, ax_p) = a^\rho g(x_1, x_2, \dots, x_p)$ where ρ is a real constant. It follows from the above that h is regularly varying as a multivariate function if and only if for any positive a_1, a_2, \dots, a_p the function $h(ta_1, ta_2, \dots, ta_p)$ is regularly varying as a univariate function of t .

8 of Lukacs and Laha [8] respectively). The second characterization (due mainly to Marcinkiewicz and Linnik) has an analogue in extreme value theory due also to Linnik (see [7] section 2.6): the property characterizes a much wider class than the extreme value distributions.

We shall now consider a possible analogue of the first characterization of the normal distribution. A simple argument shows that a characterization of this sort is impossible in extreme value theory:

Let X_1, X_2, \dots, X_p be independent positive random variables and suppose that for non-negative numbers $a_1, a_2, \dots, a_p, b_1, b_2, \dots, b_p$ the random variables

$$Y_1 = \max (a_1 X_1, a_2 X_2, \dots, a_p X_p)$$

and

$$Y_2 = \max (b_1 X_1, b_2 X_2, \dots, b_p X_p)$$

are independent. Let G_i be the distribution function of X_i for $i = 1, 2, \dots, p$. Then for all $x, y > 0$

$$H(x, y) = P\{Y_1 \leq x, Y_2 \leq y\} = G_1(\min(\frac{x}{a_1}, \frac{y}{b_1})) \dots G_p(\min(\frac{x}{a_p}, \frac{y}{b_p}))$$

so that for $y^{-1}x < \min(b_1^{-1}a_1, b_2^{-1}a_2, \dots, b_p^{-1}a_p)$ the df $H(x, y)$ does not depend on y . So independence of Y_1 and Y_2 is possible only if the latter minimum is zero i.e. only in the trivial case that Y_1 and Y_2 are based on disjoint subsets of the X 's.

We finish with the following remark. Let again X_1, X_2, \dots, X_p be independent, but let now $P\{X_i \leq x\} = \exp(-1/x)$ for $x > 0$. Let $A = (a_{ij})_{i,j=1}^p$ be a matrix with non-negative elements and define $Y_i = \max(a_{i1} X_1, a_{i2} X_2, \dots, a_{ip} X_p)$ for $i = 1, 2, \dots, p$. The joint distribution of (Y_1, Y_2, \dots, Y_p) then is a p -dimensional extreme-value distribution but one of special type, namely the measure occurring in the standard representation for such functions (see [5] section 2) is concentrated in p points. These points are taken as the column vectors of a conjugate matrix A^* of A in an interesting

paper on the kind of matrix algebra that is relevant here by Cuninghame-Green [2].

Acknowledgement. A question by Bruce Brown of La Trobe University prompted me to this investigation.

References

1. Balkema, A.A. and S.I. Resnick (1976). Max-infinite divisibility. Technical report 76-12, Department of Mathematics, University of Amsterdam.
2. Cuninghame-Green, R.A. (1976). Projections in minimax algebra. *Mathematical Programming* 10, 111-123.
3. Geffroy, J. (1958). Contributions à la théorie des valeurs extrêmes. *Publ. de l'Inst. Statist. de l'Un. de Paris* 7, 37-121 and 8, 1-185.
4. Gnedenko, B.V. (1943). Sur la distribution limite du terme maximum d'une série aléatoire. *Ann. Math.* 44, 423-453.
5. Haan, L. de and S.I. Resnick (1976). Limit theory for multivariate sample extremes. Technical report 80, Department of Statistics, Stanford University.
6. Helland, I.S. and T.S. Nilsen (1975). On a general random exchange model. Technical report, Mathematics Institute, University of Bergen.
7. Kagan, A.M., Y.V. Linnik and C.R. Rao (1973). Characterization problems in mathematical statistics. Wiley, New York.
8. Lukacs, E and R.G. Laha (1964). Applications of characteristic functions. Griffin, London.

