EXTREME DISTRIBUTION FUNCTIONS OF COPULAS

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In this paper we study some properties of the distribution function of the random variable C(X,Y) when the copula of the random pair (X,Y) is M (respectively, W) – the copula for which each of X and Y is almost surely an increasing (respectively, decreasing) function of the other –, and C is any copula. We also study the distribution functions of M(X,Y) and W(X,Y) given that the joint distribution function of the random variables X and Y is any copula.

Keywords: copula, diagonal section, distribution function, Lipschitz condition, opposite diagonal section, ordering, Spearman's footrule

AMS Subject Classification: 60E05, 62H05, 62E10

1. INTRODUCTION

Let H_1 and H_2 be two bivariate distribution functions with common continuous onedimensional margins F and G – the distribution functions considered are taken to be right-continuous. Let (X,Y) be a random pair – all the random variables considered are defined on the same probability space (Ω, \mathcal{F}, P) – whose joint distribution function is H_2 , and let $\langle H_1|H_2\rangle(X,Y)$ denote the random variable $H_1(X,Y)$. The H_2 distribution function of H_1 , which we denote by $(H_1|H_2)$, is given by

$$(H_1|H_2)(t) = \Pr[\langle H_1|H_2\rangle(X,Y) \le t]$$

= $\mu_{H_2}(\{(x,y) \in \mathbb{R}^2 \mid H_1(x,y) \le t\}), t \in [0,1],$

where μ_{H_2} denotes the measure on \mathbb{R}^2 induced by H_2 [7, 12]. In this paper we study some properties of the distribution function of the random variable $H_1(X,Y)$ when each variable of the random pair (X,Y) is almost surely an increasing (respectively, decreasing) function of the other.

Since our methods involve the concept of a copula, we review this notion and some of its properties. A (bivariate) copula is the restriction to $[0,1]^2$ of a continuous (bivariate) distribution function whose margins are uniform on [0,1]. The importance of copulas stems largely from the observation that the joint distribution H of the random pair (X,Y) with respective margins F and G can be expressed by H(x,y) = C(F(x), G(y)), for all $(x,y) \in [-\infty, \infty]^2$, where C is a copula that is

uniquely determined on Range $F \times \text{Range } G$ (Sklar's Theorem) [17, 18]. Let Π denote the copula for independent random variables, i. e., $\Pi(u, v) = uv$ for all $(u, v) \in [0, 1]^2$. For a complete survey on copulas, see [11].

By Sklar's Theorem, if C_1 and C_2 are two copulas and (U,V) is a pair of uniform [0,1] random variables with copula C_2 , and $\langle C_1|C_2\rangle(U,V)$ denotes the random variable $C_1(U,V)$ – written $\langle C_1|C_2\rangle$ when the meaning is clear –, then the C_2 distribution function of C_1 is given by

$$\begin{array}{lcl} (C_1|C_2)(t) & = & \Pr[\langle C_1|C_2\rangle(U,V) \leq t] \\ & = & \mu_{C_2}(\{(u,v) \in [0,1]^2 \,|\, C_1(u,v) \leq t\}), \ t \in [0,1]. \end{array}$$

Every copula C of the random pair (X,Y) satisfies the following inequalities:

$$\max(u + v - 1, 0) = W(u, v) \le C(u, v) \le M(u, v)$$
$$= \min(u, v), \ \forall \ (u, v) \in [0, 1]^2.$$

M (respectively, W) is the copula for which each of X and Y is almost surely an increasing (respectively, decreasing) function of the other.

In the sequel, we shall use the following notation: For any pair of random variables X and Y with respective distribution functions F and G, " \leq_{st} " denotes the stochastic inequality, i. e., $X \leq_{st} Y$ if, and only if, $F \geq G$; and $X \stackrel{d}{=} Y$ denotes the equality in distribution.

Distribution functions of copulas are employed – among other purposes – to construct orderings on the set of copulas (see [12]). If C, C_1 and C_2 are copulas, two of those orderings are: (a) C_1 is C-larger than C_2 if $\langle C_1|C\rangle \geq_{st} \langle C_2|C\rangle$; and (b) C_1 is C-larger in measure than C_2 if $\langle C|C_1\rangle \geq_{st} \langle C|C_2\rangle$. As a consequence, two equivalences are given, namely: (c) C_1 is C-equivalent to C_2 (written $C_1 \equiv_C C_2$) if $\langle C_1|C\rangle \stackrel{d}{=} \langle C_2|C\rangle$; and (d) C_1 is C-equivalent in measure to C_2 if $\langle C|C_1\rangle \stackrel{d}{=} \langle C|C_2\rangle$.

It is known that if F is a right-continuous distribution function such that $F(0^-) = 0$ and $F(t) \ge t$ for all t in [0,1], then there exists a copula C such that (C|C)(t) = F(t) for all t in [0,1] (see [13, 16]). We now wonder whether this result can be generalized (in some sense) to other distribution functions of copulas. To be exact: if C_0 is a copula, and F is a distribution function such that $(M|C_0)(t) \le F(t) \le (W|C_0)(t)$ for all t in [0,1], does there exist a copula C such that $(C|C_0)(t) = F(t)$ for all t in [0,1]? The answer is affirmative when $C_0 = M$. We will also provide some additional properties of the distributions (C|M) and (C|W) for any copula C.

2. THE M DISTRIBUTION FUNCTION OF A COPULA

The diagonal section δ_C of a copula C is the function given by $\delta_C(t) = C(t,t)$ for all t in [0,1]. A diagonal is a function $\delta \colon [0,1] \longrightarrow [0,1]$ which satisfies the following properties:

(i)
$$\delta(1) = 1$$
,

(ii) $\delta(t) \le t$ for all t in [0, 1],

(iii) $0 \le \delta(t') - \delta(t) \le 2(t'-t)$ for all t, t' in [0,1] such that $t \le t'$ – i.e., δ is increasing and 2-Lipschitz.

The diagonal section of any copula is a diagonal; and for any diagonal δ , there always exist copulas whose diagonal section is δ [5] (see also [4, 14, 15]): for instance, the Bertino copula B_{δ} [6], which is given by

$$B_{\delta}(u, v) = \min(u, v) - \min(s - \delta(s) | \min(u, v)$$

 $\leq s \leq \max(u, v), (u, v) \in [0, 1]^{2}.$

The diagonal section δ_C of a copula C is the restriction to [0,1] of the distribution function of $\max(U,V)$, whenever (U,V) is a random pair distributed as C. Let $\delta_C^{(-1)}$ denote the *cadlag* inverse of δ_C , i.e., $\delta_C^{(-1)}(t) = \sup\{u \in [0,1] \mid \delta_C(u) \leq t\}$ for t in [0,1].

The following result gives a (partial) answer to the question posed at the end of Section 1.

Theorem 1. Let F be a right-continuous distribution function such that $F(0^-) = 0$, $F(t) \ge t$ for all t in [0,1], and $F'(t) \ge 1/2$ for almost every t in [0,1]. Then there exists a copula C such that (C|M)(t) = F(t) for all t in [0,1].

Proof. We know that $\delta_C^{(-1)}$ is the restriction to the interval [0,1] of a distribution function with support on [0,1] and such that $(M|M)(t) \leq (C|M)(t) \leq (W|M)(t)$ for all t in [0,1]. Since

$$(C|M)(t) = \delta_C^{(-1)}(t), \ \forall \ t \in [0,1]$$

(see [12]), and δ_C is 2-Lipschitz, we have that $\delta_C^{(-1)}$ must be a strictly increasing function (not necessarily continuous) whose derivative is greater or equal to 1/2 for almost every point in [0,1]. Since the Bertino copula B_{δ} associated with δ satisfies $(B_{\delta}|M)(t) = \delta^{(-1)}(t) = F(t)$ for all t in [0,1] (see [12]), this completes the proof. \square

If C_1 and C_2 are two copulas, then we say that $C_1 \equiv_M C_2$ if $(C_1|M)(t) = (C_2|M)(t)$ for all t in [0,1]. The next example provides a class in this equivalence relation which contains more than one copula.

Example 1. Let C be the copula given by $C(u,v) = \max(0, u+v-1, \min(u,v-1/2))$, $(u,v) \in [0,1]^2$. C is a shuffle of Min [9], whose mass is spread uniformly on two line segments on $[0,1]^2$: one joining the points (0,1/2) and (1/2,1), and the second one joining the points (1/2,1/2) and (1,0). Then it is easy to verify that (C|M)(t) = (W|M)(t) = (1+t)/2 for all t in [0,1].

As a consequence of Theorem 1, we have the following

Corollary 2. Each equivalence class of the equivalence relation \equiv_M on the set of copulas contains a unique Bertino copula.

Consider Spearman's footrule coefficient [19], whose population version for a random pair (X, Y) with copula C, is given by

$$\varphi_C = 1 - 3 \int_0^1 \int_0^1 |u - v| \, dC(u, v)$$

(see [11]). In terms of the M distribution function of the copula C, this measure can be rewritten as

$$\varphi_C = 4 - 6 \int_0^1 (C|M)(t) dt$$

(see [12]). Given two copulas C_1 and C_2 , $\langle C_1|M\rangle \leq_{st} \langle C_2|M\rangle$ implies that $\varphi_{C_1} \leq \varphi_{C_2}$. However, the converse result is not true in general, as the following example shows.

Example 2. Let C be the shuffle of Min given by $C(u,v) = \min(u,v,\max(1/3,u+v-2/3))$, $(u,v) \in [0,1]^2$. Its mass is spread uniformly on three line segments in $[0,1]^2$: one joining the points (0,0) and (1/3,1/3), another one joining the points (1/3,2/3) and (2/3,1/3), and the third one joining the points (2/3,2/3) and (1,1). Then we have $(\Pi|M)(t) = \sqrt{t}$ for all t in [0,1], and (C|M)(t) = 2/3 if $t \in [1/3,2/3]$ and (C|M)(t) = t otherwise. Thus, $\varphi_{\Pi} = 0 < 2/3 = \varphi_{C}$, but $(\Pi|M)(1/3) \simeq 0.577 < 0.67 \simeq (C|M)(1/3)$.

The "M-larger" ordering has several applications. For example, if (U_i, V_i) are two uniform [0, 1] random variables with copula C_i , i = 1, 2, then C_1 is M-larger than C_2 if, and only if, the order statistics of U_1 and V_1 are stochastically "inside" the interval determined by the order statistics of U_2 and V_2 [12]. The next result shows the relationship between the M-larger and the M-larger in measure orderings. To this end, we first note that, for any pair (U, V) of random variables with associated copula C, the C distribution function of M is given by

$$(M|C)(t) = \Pr[\min(U, V) \le t] = \Pr[U \le t] + \Pr[U > t, V \le t]$$
$$= t + \int_{t}^{1} \Pr[V \le t | U = u] du = t + \int_{t}^{1} \frac{\partial C}{\partial u}(u, t) du$$
$$= t + t - C(t, t) = 2t - \delta_{C}(t)$$

for every t in [0,1].

Proposition 3. Let C_1 and C_2 be two copulas. Then $\langle M|C_1\rangle \leq_{st} \langle M|C_2\rangle$ if, and only if, $\langle C_1|M\rangle \leq_{st} \langle C_2|M\rangle$.

Proof. Let δ_{C_1} and δ_{C_2} be the respective diagonal sections of C_1 and C_2 . Then C_1 is M-larger in measure than C_2 if, and only if, $2t - \delta_{C_1}(t) \leq 2t - \delta_{C_2}(t)$ for all t

in
$$[0,1]$$
, i.e., $\delta_{C_2} \leq \delta_{C_1}$, which is equivalent to $\delta_{C_1}^{(-1)} \leq \delta_{C_2}^{(-1)}$, that is, $(C_1|M)(t) \leq (C_2|M)(t)$ for all t in $[0,1]$.

As a consequence of Proposition 3, the M-equivalence in measure coincides with the M-equivalence. We now show that the equality $\langle M|C\rangle \stackrel{d}{=} \langle C|M\rangle$ only holds when C=M.

Proposition 4. Let C be a copula. Then $\langle M|C\rangle \stackrel{d}{=} \langle C|M\rangle$ if, and only if, C=M.

Proof. Suppose $\langle M|C\rangle \stackrel{d}{=} \langle C|M\rangle$, i.e., $2t-\delta_C(t)=\delta_C^{(-1)}(t)$ for all t in [0,1]. Thus, $\delta_C^{(-1)}(t)=\sup\{u\in[0,1]\,|\,\delta_C(u)\leq t\}\leq 2t$ for all t in [0,1], which implies that $\delta_C(t)\geq t/2$ for all t in [0,1]. Hence, $2t-\delta_C^{(-1)}(t)\geq t/2$ for all t in [0,1], i.e., $\delta_C^{(-1)}(t)\leq 3t/2$ for all t in [0,1], which implies that $\delta_C(t)\geq 2t/3$ for all t in [0,1]. After n iterations, we have that $\delta_C(t)\geq nt/(n+1)$ for all t in [0,1]. Therefore, if n tends to infinity, we have that $\delta_C(t)\geq t$, and hence, $\delta_C(t)=t$ for all t in [0,1]. Thus, we obtain that C=M; otherwise, if there exists a point (u,v) in $[0,1]^2$ such that C(u,v)< M(u,v) with $u\leq v$ (the case $u\geq v$ is similar), then $C(u,u)\leq C(u,v)< M(u,v)=u$, that is, there exists u in [0,1] such that $\delta_C(u)< u$, which is absurd. The converse is trivial, completing the proof.

Let C_1 and C_2 be two copulas. We say that C_1 is df-larger than C_2 if $\langle C_1|C_1\rangle \geq_{st}$ $\langle C_2|C_2\rangle$ [2, 12, 13]. The following example shows that the df-larger and the M-larger orderings are not comparable.

Example 3.

- (a) Consider the copulas Π and the shuffle of Min given by $C(u,v) = \min(u,v,\max(0,u-0.3,v-0.612,u+v-0.912)), (u,v) \in [0,1]^2$, whose mass is spread on three line segments in $[0,1]^2$: one joining the points (0,0.612) and (0.3,0.912), the second one joining the points (0.3,0) and (0.912,0.612), and the third one joining the points (0.912,0.912) and (1,1). For every t in [0,1], we have $(\Pi|\Pi)(t) = t t \ln t, (\Pi|M)(t) = \sqrt{t}, (C|C)(t) = \max(t,\min(2t,t+0.3,0.912))$, and $(C|M)(t) = \max(t,\min(t+0.3,(t+0.912)/2))$ for all t in [0,1]. Then, it is easy to check that $\langle \Pi|\Pi \rangle \leq_{st} \langle C|C \rangle$; however, we have $(\Pi|M)(0) = 0 < 0.3 = (C|M)(0)$ and $(\Pi|M)(0.912) \simeq 0.955 > 0.912 = (C|M)(0.912)$.
- (b) Consider now the copulas Π and A = (M+W)/2 recall that the convex linear combination of two copulas is again a copula. The mass distribution of A is spread uniformly on two line segments in $[0,1]^2$: one connecting the points (0,0) to (1,1), and the second one connecting (0,1) to (1,0). Then, for every t in [0,1], we have $(A|A)(t) = \min(3t,(2+t)/3)$ and $(A|M)(t) = \min(2t,(2t+1)/3)$. Thus, it is easy to verify that $\langle \Pi|M\rangle \leq_{st} \langle A|M\rangle$; but $(\Pi|\Pi)(0.25) \simeq 0.5966 < 0.75 = (A|A)(0.25)$ and $(\Pi|\Pi)(0.75) \simeq 0.9658 > 0.9167 = (A|A)(0.75)$.

3. THE W DISTRIBUTION FUNCTION OF A COPULA

The opposite diagonal section ω_C of a copula C is the function given by $\omega_C(t) = C(t, 1-t)$ for all t in [0,1]. An opposite diagonal is a function $\omega \colon [0,1] \longrightarrow [0,1]$ which satisfies the following properties:

- (i) $\omega(1) = 0$.
- (ii) $\omega(t) \leq \min(t, 1-t)$ for all t in [0, 1],
- (iii) $\omega(t') \omega(t) \le t' t$ for all t, t' in [0, 1] such that $t \le t' i$. e., ω is 1-Lipschitz.

The opposite diagonal section of any copula is an opposite diagonal; and for any opposite diagonal ω , there exist copulas whose opposite diagonal section is ω : for instance, the copula J_{ω} given by

$$J_{\omega}(u,v) = \max\left(0, u + v - 1, \frac{u + v - 1 + \omega(u) + \omega(1 - v)}{2}\right)$$

for all (u, v) in $[0, 1]^2$ (see [3]).

The following result provides a probabilistic interpretation of the opposite diagonal section of a copula (in the sequel, we will denote the distribution function of a random variable X either by df(X) or a letter such as F).

Proposition 5. Let (U, V) be a pair of random variables with associated copula C. Then

$$\omega_C(t) = \frac{1}{2} \cdot (\Pr[\min(U, 1 - V) \le t < \max(U, 1 - V)]).$$

Proof. The copula C' associated with the random pair (U, 1 - V) is given by C'(u, v) = u - C(u, 1 - v) for every (u, v) in $[0, 1]^2$ (see [11]). Then we have that

$$\begin{split} \mathrm{df}(\min(U,1-V))(t) &= \Pr[\min(U,1-V) \leq t] \\ &= \Pr[U \leq t] + \Pr[1-V \leq t] - \Pr[U \leq t, 1-V \leq t] \\ &= t+t-C'(t,t) = t+C(t,1-t) = t+\omega_C(t), \end{split}$$

and

$$df(\max(U, 1 - V))(t) = \Pr[\max(U, 1 - V) \le t] = \Pr[U \le t, 1 - V \le t]$$

= $C'(t, t) = t - C(t, 1 - t) = t - \omega_C(t).$

whence the result easily follows.

Let (U, V) be a random pair with copula C. The W distribution function of C is given by

$$(C|W)(t) = \Pr[C(U,V) \le t] = \Pr[C(U,1-U) \le t] = \Pr[\omega_C(U) \le t]$$

= $\lambda(\{u \in [0,1] | \omega_C(u) \le t\}),$

where λ denotes the Lebesgue measure in \mathbb{R} .

Distribution functions of copulas are also employed in constructing new measures of association. Thus, for instance, given a copula C, it seems reasonable to obtain a measure χ_C – in the same sense than Spearman's footrule coefficient φ_C – based on the W distribution function of C, and given by the linear expression

$$\chi_C = a \int_0^1 (C|W)(t) dt + b$$

where a and b are two real numbers. If we consider $\chi_W = -1$ and $\chi_\Pi = 0$ for this measure – for the Spearman's footrule coefficient we have $\varphi_M = 1$, $\varphi_\Pi = 0$, and $\varphi_W = -1/2$ –, since $(\Pi|W)(t) = 1 - \sqrt{\max(0, 1 - 4t)}$ and $(M|W)(t) = \min(2t, 1)$ for all t in [0, 1], then we obtain

$$\chi_C = 5 - 6 \int_0^1 (C|W)(t) dt.$$

The coefficient χ_C can be also written as

$$\chi_C = 6 \int_0^1 C(t, 1-t) dt - 1 = 3 \int_0^1 \int_0^1 |1-u-v| dC(u, v) - 1.$$

This coefficient – which first appeared in this last form in [1] – satisfies $\chi_M = 1/2$. Observe also that the population version γ_C of the known *Gini's rank correlation coefficient* [8, 10, 11] of a copula C can be written as $\gamma_C = 2(\varphi_C + \chi_C)/3$.

Unlike the relationship between the M-larger and the M-larger in measure orderings, there is no analogue to Proposition 3 for the W-larger and the W-larger in measure orderings, as the next example shows. The example also provides a class in the equivalence relation \equiv_W – recall that if C_1 and C_2 are two copulas, then $C_1 \equiv_W C_2$ if $(C_1|W)(t) = (C_2|W)(t)$ for all t in [0,1] – which contains more than one copula. First note that, if (U,V) is a random pair with copula C, then the C distribution function of W is given by

$$(W|C)(t) = \Pr[U+V-1 \le t] = \Pr[U \le t] + \Pr[U > t, V \le 1+t-U]$$
$$= t + \int_t^1 \Pr[V \le 1+t-u \,|\, U=u] \,\mathrm{d}u$$
$$= t + \int_t^1 \frac{\partial C}{\partial u}(u, 1+t-u) \,\mathrm{d}u$$

for every t in [0,1].

Example 4. Let C be the shuffle of Min given by $C(u, v) = \min(u, v, \max(1/2, u + v - 1))$, $(u, v) \in [0, 1]^2$. Its mass is spread uniformly on two line segments in $[0, 1]^2$: one joining the points (0, 0) and (1/2, 1/2), and the second one joining the points (1/2, 1) and (1, 1/2). Then it is easy to verify that $(C|W)(t) = (M|W)(t) = \min(2t, 1)$ for all t in [0, 1]. But, on the other hand, we have (W|C)(t) = 1/2 if $t \in [0, 1/2)$ and (W|C)(t) = 1 if $t \in [1/2, 1]$, and (W|M)(t) = (1 + t)/2.

Hence, (W|C)(1/4) = 1/2 < 5/8 = (W|M)(1/4) and (W|C)(3/4) = 1 > 7/8 = (W|M)(3/4).

To see the "utility" of the C distribution function of W, where C is the copula of the random pair (U,V), we provide the following result, which describes the relationship between this distribution function and the distribution function of the random variable U+V. In what follows, we will use some notation. Let f be a real function defined on [a,b] (or on a dense subset of [a,b], including a and b) having only removable or jump discontinuities. Then ℓ^+f and ℓ^-f are the functions defined on [a,b] via $\ell^+f(x)=f(x^+)$ and $\ell^-f(x)=f(x^-)$, where $f(x^+)$ (respectively, $f(x^-)$) denotes the limit – if it exists – by the right (respectively, left) of f in x. Let \hat{C} denote the survival copula of C, i. e., $\hat{C}(u,v)=u+v-1+C(1-u,1-v)$ for every $(u,v)\in[0,1]^2$ (see [11]).

Proposition 6. Let (U, V) be a pair of random variables with associated copula C. Then we have

$$df(U+V)(t) = \begin{cases} \ell^{+}(1-(W|\hat{C})(1-t)), & \text{if } t \in [0,1] \\ (W|C)(t-1), & \text{if } t \in [1,2]. \end{cases}$$

Proof. Let $t \in [0,1]$. Then we have

$$df(U+V)(t) = \mu_C(\{(u,v) \in [0,1]^2 \mid u+v \leq t\})$$

$$= \mu_C(\{(u,v) \in [0,1]^2 \mid (1-u) + (1-v) - 1 \geq 1 - t\})$$

$$= \mu_C(\{(1-u',1-v') \in [0,1]^2 \mid u'+v'-1 \geq 1 - t\})$$

$$= \mu_{\hat{C}}(\{(u',v') \in [0,1]^2 \mid u'+v'-1 \geq 1 - t\})$$

$$= \mu_{\hat{C}}(\{(u',v') \in [0,1]^2 \mid W(u',v') \geq 1 - t\})$$

$$= 1 - \mu_{\hat{C}}(\{(u',v') \in [0,1]^2 \mid W(u',v') < 1 - t\})$$

$$= 1 - \ell^-((W|\hat{C})(1-t))$$

$$= \ell^+(1 - (W|\hat{C})(1-t)).$$

where we have done the transformations u' = 1 - u, v' = 1 - v. On the other hand, for every $t \in [1, 2]$, we have

$$\begin{split} (W|C)(t) &= \mu_C(\{(u,v) \in [0,1]^2 \mid u+v-1 \le t\}) \\ &= \mu_C(\{(u,v) \in [0,1]^2 \mid u+v \le t+1\}) \\ &= \mathrm{df}(U+V)(t+1), \end{split}$$

which completes the proof.

ACKNOWLEDGEMENT

This work was supported by the Ministerio de Educación y Ciencia (Spain) and FEDER, under research project MTM2006-12218.

(Received May 12, 2008.)

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