## Another generalization of bivariate FGM distributions

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Let H(x, y) be the bivariate cdf of (X, Y), with univariate marginals F(x), G(y)and supports [a, b], [c, d], respectively. Throughout this abstract, x and y in H(x, y), F(x), G(y), as well as u and v in C(u, v), where  $0 \le u, v \le 1$ , will be suppressed. We write  $H \in \mathcal{F}(F, G)$ , where  $\mathcal{F}(F, G)$  is the family of cdf's with marginals F, G.

The Farlie-Gumbel-Morgenstern (FGM) family is  $H_{\theta} = FG[1 + \theta(1 - F)(1 - G)]$ ,  $-1 \le \theta \le 1$ , and the corresponding copula is  $C_{\theta} = uv[1 + \theta(1 - u)(1 - v)]$ ,  $-1 \le \theta \le 1$ . This family is frequently used in theory and applications. This motivated to study proper extensions in [2] and [1].

Let  $\Phi, \Psi$  be two univariate cdf's with the same supports [a, b], [c, d]. Suppose that the Radon-Nykodim derivatives  $d\Phi/dG, d\Psi/dG$  exist. We define the bivariate cdf

$$H = FG + \lambda(F - \Phi)(G - \Psi).$$

This cdf reduces to the classic FGM for  $\Phi = F^2$ ,  $\Psi = G^2$ , and has interesting properties:

- 1.  $H \in \mathcal{F}(F,G)$  for  $\lambda$  belonging to an interval depending on  $d\Phi/dG$ ,  $d\Psi/dG$ .
- 2. H suggests the congugate family  $H_* \in \mathcal{F}(\Phi, \Psi)$ .
- 3. Define  $a_1 = 1 d\Phi/dF$ ,  $b_1 = 1 d\Psi/dG$ . Then  $E[a_1(X)] = E[b_1(Y)] = 0$  and  $E[a_1^2(X)] = \alpha 1$ ,  $E[b_1^2(Y)] = \beta 1$ , where  $\alpha = \int_a^b (\frac{d\Phi}{dF})^2 dF$ ,  $\beta = \int_c^d (\frac{d\Psi}{dG})^2 dG$ .
- 4. The first canonical correlation is  $\rho_1 = \lambda \sqrt{(\alpha 1)(\beta 1)}$  and Pearson contingency coefficient is  $\phi^2 = \rho_1^2$ .
- 5. Spearman's rho and Kendall's tau are  $\rho_S = 12\lambda(\frac{1}{2} F_{\Phi})(\frac{1}{2} G_{\Psi})$  and  $\tau = 8\lambda(\frac{1}{2} F_{\Phi})(\frac{1}{2} G_{\Psi})$ , where  $F_{\Phi} = \int_a^b \Phi dF$ ,  $\Phi_F = \int_c^d F d\Phi$ .

The geometric dimensionality of a bivariate cdf is defined and discussed. Then we introduce the following generalized FGM

$$\begin{aligned} H &= FG + \lambda_1 (F - \Phi) (G - \Psi) \\ &+ \lambda_2 [(\frac{1}{2}F^2 + (F_{\Phi} - \frac{1}{2})F - F_{\Phi}(x)] [(\frac{1}{2}G^2 + (G_{\Psi} - \frac{1}{2})G - G_{\Psi}(y)], \end{aligned}$$

where  $F_{\Phi}(x) = \int_{a}^{x} \Phi(t) dF(t)$ ,  $G_{\Psi}(y) = \int_{c}^{y} \Psi(t) dG(t)$ . This  $H \in \mathcal{F}(F, G)$  is diagonal and two-dimensional. Finally we study how to approximate any cdf by a member of this family.

## References

- Cuadras, C. M. (2008). Constructing copula functions with weighted geometric means. Journal of Statistical Planning and Inference 139, 3766–3772.
- [2] Rodríguez-Lallena, J. A., Úbeda-Flores, M. (2004). A new class of bivariate copulas. *Statistics & Probability Letters* 66, 315–325.