

Dependence of non-continuous random variables

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Outline

The “continuous” vs. “non-continuous” case: typical fallacies

Dependence of non-continuous random variables

Concordance measures for non-continuous random variables

Problems & References

Some Theory Behind

Motivation

Consider

- Two possibly **dependent** loss types and

$N_i(T)$ = **number** of losses of type i within the year T

- **Dependence structures** of the pair of **non continuous** random variables

$$(N_1(T), N_2(T))$$

Other examples

- **Counting random variables** like claim/loss frequencies or number of defaults in a portfolio
- **Variables with jumps** like losses censored by a certain threshold

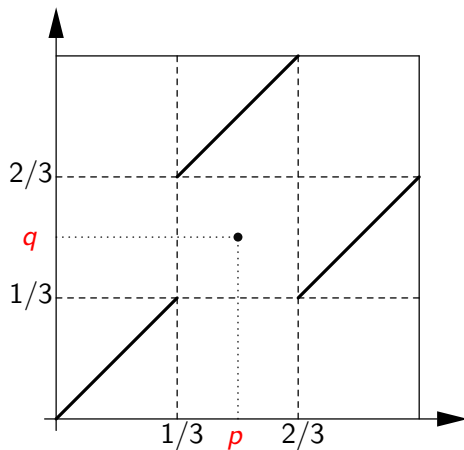
Distributions with continuous marginals

- Notation: $(X, Y) \sim F$ with marginals F_1 and F_2

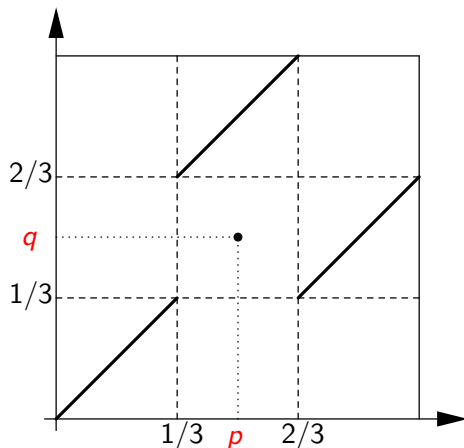
F_1 and F_2 continuous

1. There exists a **unique** copula \mathcal{C} such that $F(x, y) = \mathcal{C}(F_1(x), F_2(y))$ (Sklar's theorem)
 2. Modeling of the marginals and the copula can be done **separately**
 3. \mathcal{C} captures dependence properties which are **invariant** under a.s. strictly increasing transformations of the marginals
 4. Scale and translation invariant measures of dependence are functions of **\mathcal{C} alone**
- ⇒ **\mathcal{C} is the (scale and location invariant) dependence structure**

Pathological Example



Pathological Example



- $(p, q) \in [0, 1/3] \times [0, 1/3]$:
perfect positive dependence
- $(p, q) = (1/\sqrt{3}, 1/\sqrt{3})$:
independence
- $(p, q) \in [2/3, 1] \times [2/3, 1]$:
perfect negative dependence

Further Pitfalls

- The **copula** is **not unique**; i.e. several **possible copulas** exist
- The **dependence structures of F** are generally **not the same** as the dependence structures of the possible copulas

$$F(x, y) \leq F^*(x, y) \quad \forall x, y \in \mathbb{R} \not\Rightarrow C(u, v) \leq C^*(u, v) \quad \forall u, v \in [0, 1]$$

- Possible copulas **remain invariant** under strictly **increasing** and continuous transformations, but **do not** necessarily **change in the same way** as the unique copula in the “continuous” case if at least one of the transformations is **decreasing**
- **Weak convergence** of F_n does **not imply** the **point-wise convergence** of the corresponding **possible copulas**
- Any **measure of association** which depends only on the copula of F is **a constant**

Kendall's Tau and Spearman's rho in the "Non-Continuous" Case?

"Naive" Idea: *work with some of the non unique fitting copula*

But: fitting copulas can differ **considerably**.

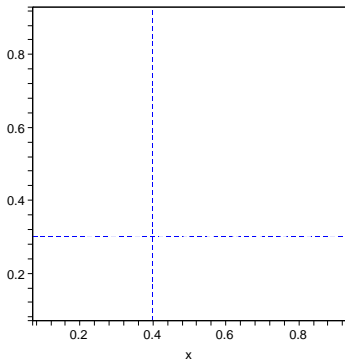
- For **independent** Bernoulli random variables X and Y
 - ▶ $\tau(X, Y) \in [-3/4, 3/4]$
 - ▶ $\rho(X, Y) \in [-13/16, 13/16]$
- for **comonotonic** Bernoulli random variables X and Y
 - ▶ $\tau(X, Y) \in [0, 1]$
 - ▶ $\rho(X, Y) \in [1/2, 1]$

Because: Difference between the **probability of concordance and discordance** $\neq 4 \int C(u, v) dC^*(u, v) - 1$

Some Starting Points

- Investigation of the **family of possible copulas** corresponding to a **fixed bivariate distribution**
 - ▶ In particular search for a **suitable extension strategy** which would produce a copula capturing the dependence structures of the joint distribution function
- Investigation of **possible bivariate distributions** obtained from a **fixed copula** and marginals which follow some specified distribution (up to parameters), such as Poisson, binomial or Bernoulli

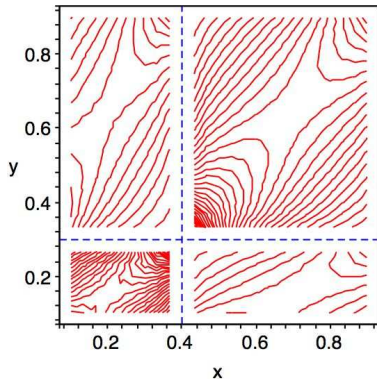
Extension Strategy: Examples



Subcopula for Bernoulli marginals:

$$P[X = 0] = 0.4, P[Y = 0] = 0.3$$

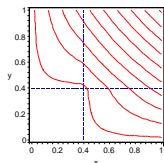
$$P[X = 0, Y = 0] = 0.2.$$



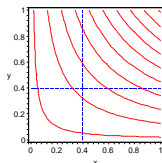
Extension by a Gauss copula with
parameter $\rho = 0.6$.

The "Standard" Extension Strategy

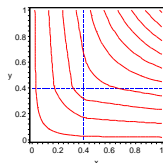
$$C(0.4, 0.4) = 0$$



$$C(0.4, 0.4) = 0.16$$



$$C(0.4, 0.4) = 0.3$$



The Standard Extension \mathcal{C}_S

- The standard extension copula of Schweizer and Sklar
- \mathcal{C}_S corresponds to the linear interpolation of the unique subcopula as well as the unique copula of the smoothed jdf

Some Selected Properties of \mathcal{C}_S

Pros

- X and Y are **independent** if and only if \mathcal{C}_S is the independence copula
- (X^*, Y^*) **more concordant** than (X, Y) if and only if $\mathcal{C}_S(u, v) \leq \mathcal{C}_S^*(u, v)$ for all $u, v \in [0, 1]$
- \mathcal{C}_S reacts on **monotone transformations** of the marginals as the unique copula in the “continuous” case

Cons

- If X and Y are **perfect monotonic dependent**, \mathcal{C}_S does **not** coincide with the **Fréchet-Hoeffding bounds**
- **Weak convergence** does **not** imply the **point-wise convergence** of the \mathcal{C}_S 's

Towards Kendall's Tau and Spearman's Rho

Difference between the probabilities of concordance and discordance equals $4 \int \mathcal{C}_S(u, v) d\mathcal{C}_S^*(u, v) - 1$

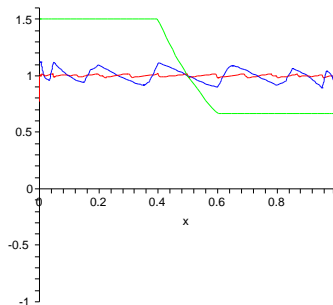
Consider

- Kendall's tau: $\tilde{\tau}(\mathcal{C}_S) = 4 \int_0^1 \int_0^1 \mathcal{C}_S(u, v) d\mathcal{C}_S(u, v) - 1$
- Spearman's rho: $\tilde{\rho}(\mathcal{C}_S) = 12 \int_0^1 \int_0^1 [\mathcal{C}_S(u, v) - uv] du dv$

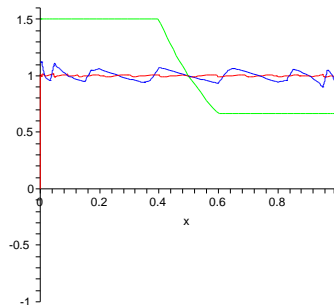
However

- $\tilde{\tau}$ and $\tilde{\rho}$ do not reach the bounds 1 and -1
- Exact bounds of $\tilde{\tau}$ and $\tilde{\rho}$ are complicated and do not have the same absolute value

Exact Bounds for Kendall's Tau and Spearman's Rho



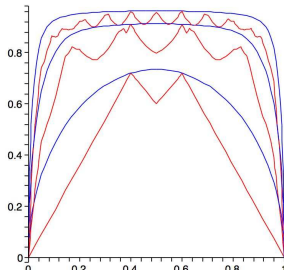
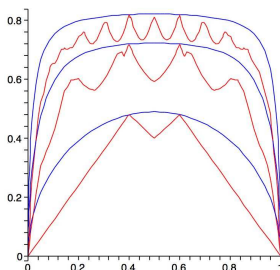
$|\tilde{\tau}(\mathcal{M}_S)/\tilde{\tau}(\mathcal{W}_S)|$ for Binomial distributions $F_1 = \mathcal{B}(n, 0.4)$ and $F_2 = \mathcal{B}(n, x)$ with $n = 1, 4$ and 10 .



$|\tilde{\rho}(\mathcal{M}_S)/\tilde{\rho}(\mathcal{W}_S)|$ for Binomial distributions $F_1 = \mathcal{B}(n, 0.4)$ and $F_2 = \mathcal{B}(n, x)$ with $n = 1, 4$ and 10 .

Less Sharp Bounds for Kendall's Tau and Spearman's Rho

1. $|\tilde{\tau}(X, Y)| \leq \sqrt{1 - E \Delta F_1(X)} \sqrt{1 - E \Delta F_2(Y)}$. The bounds are attained if $Y = T(X)$ a.s. where T is a **strictly** monotone and **continuous** transformation on the range of X .
2. $|\tilde{\rho}(X, Y)| \leq \sqrt{1 - E \Delta F_1(X)^2} \sqrt{1 - E \Delta F_2(Y)^2}$. The bounds are attained if $Y = T(X)$ a.s. where T is a **strictly** monotone and **continuous** transformation on the range of X .



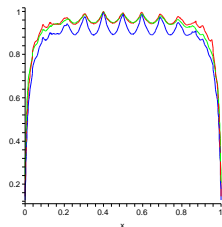
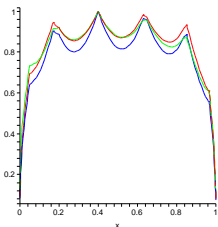
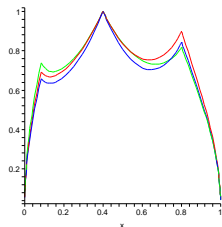
Kendall's Tau and Spearman's Rho for Non-Continuous Random Variables

$$\tau(X, Y) = \frac{4 \int_0^1 \int_0^1 C_S(u, v) dC_S(u, v) - 1}{\sqrt{[1 - E \Delta F_1(X)][1 - E \Delta F_2(Y)]}}$$

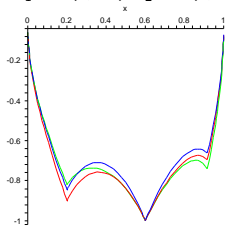
$$\rho(X, Y) = \frac{12 \left(\int_0^1 \int_0^1 (C_S(u, v) - uv) du dv \right)}{\sqrt{[1 - E \Delta F_1(X)]^2 [1 - E \Delta F_2(Y)]^2}}$$

- τ and ρ satisfy (modified) **axioms of concordance measures**
- **Bounds** are **attained** if $X \stackrel{\text{a.s.}}{=} T(Y)$ for T **continuous** and **strictly** monotone
- τ and ρ are the **sample versions** for **empirical distributions**

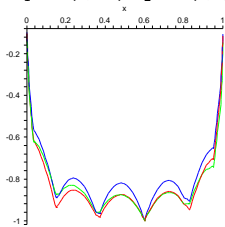
τ , ρ and ϱ for Binomial Distributions



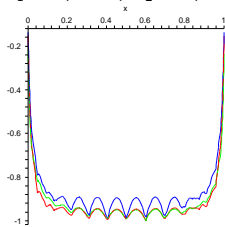
$$F_1 = \mathcal{B}(2, 0.4), F_2 = \mathcal{B}(2, x).$$



$$F_1 = \mathcal{B}(4, 0.4), F_2 = \mathcal{B}(4, x).$$



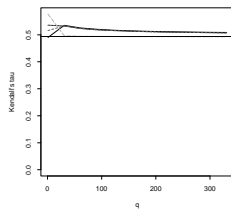
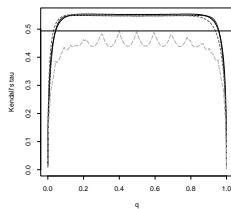
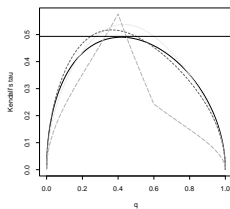
$$F_1 = \mathcal{B}(10, 0.4), F_2 = \mathcal{B}(10, x).$$



Some Problems





- Modeling:** dependence properties of a family

$$\mathcal{H} = \{\mathcal{C}(F, G) : F \in \mathcal{F}, G \in \mathcal{G}\}$$



Kendall's tau for binomial marginals and a Gauss copula (solid line), Frank copula (short-dashed line), Gumbel copula (dotted line), and Fréchet copula (long-dashed line).

References

-  [M. Denuit and P. Lambert, 2005](#)
Constraints on concordance measures in bivariate discrete data
-  [W. Hoeffding, 1940](#)
Maßstabinvariante Korrelationstheorie für diskontinuierliche Verteilungen
-  [A. Marshall, 1996](#)
Copulas, marginals and joint distributions
-  [J. Nešlehová, 2004](#)
Dependence of non-continuous random variables

Some Theory Behind: Dependence Structure in the Non-Continuous Case

In the continuous case: \mathcal{C} is the cdf. of the **transformed** vector $(F_1(X), F_2(Y))$.

Idea: In the non-continuous case, use a **different transformation** of the marginals:

$$\psi(x, u) := P[X < x] + uP[X = x] = F(x-) + u\Delta F(x)$$

Result: for a random vector (U, V) with uniform marginals which is independent of (X, Y) , $(\psi(X, U), \psi(Y, V))$ has **uniform marginals** and the corresponding **unique copula** is a **possible copula** of (X, Y) .

Moreover: different dependence structure of (U, V) leads to different possible copulas of (X, Y) .