

# 7 Copulas and dependence

7.1 Copulas

7.2 Dependence concepts and measures

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## 7.1 Copulas

- We now look more closely at modelling the dependence among the components of a random vector  $\mathbf{X} \sim F$  (risk-factor changes).
- **In short:**  $F$  “=” marginal dfs  $F_1, \dots, F_d$  “+” dependence structure  $C$
- **Advantages:**
  - ▶ Most natural in a static distributional context (no time dependence; apply, e.g. to residuals of an ARMA-GARCH model)
  - ▶ Copulas allow us to understand and study dependence independently of the margins (first part of Sklar’s Theorem; see later)
  - ▶ Copulas allow for a bottom-up approach to multivariate model building (second part of Sklar’s Theorem; see later). This is often useful for constructing tailored  $F$ , e.g. when we have more information about the margins than  $C$  or for stress testing purposes.

## 7.1.1 Basic properties

### Definition 7.1 (Copula)

A *copula*  $C$  is a df with  $U(0, 1)$  margins.

### Characterization

$C : [0, 1]^d \rightarrow [0, 1]$  is a copula if and only if

1)  $C$  is *grounded*, that is,

$$C(u_1, \dots, u_d) = 0 \text{ if } u_j = 0 \text{ for at least one } j \in \{1, \dots, d\}.$$

2)  $C$  has standard *uniform* univariate *margins*, that is,

$$C(1, \dots, 1, u_j, 1, \dots, 1) = u_j \text{ for all } u_j \in [0, 1] \text{ and } j \in \{1, \dots, d\}.$$

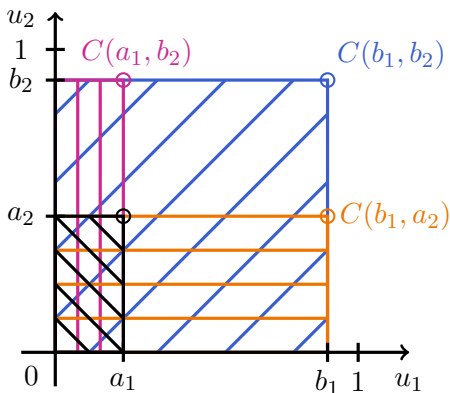
3)  $C$  is *d-increasing*, that is, for all  $\mathbf{a}, \mathbf{b} \in [0, 1]^d$ ,  $\mathbf{a} \leq \mathbf{b}$ ,

$$\Delta_{(\mathbf{a}, \mathbf{b}]} C = \sum_{\mathbf{i} \in \{0, 1\}^d} (-1)^{\sum_{j=1}^d i_j} C(a_1^{i_1} b_1^{1-i_1}, \dots, a_d^{i_d} b_d^{1-i_d}) \geq 0.$$

Equivalently (if existent): density  $c(\mathbf{u}) \geq 0$  for all  $\mathbf{u} \in (0, 1)^d$ .

2-increasingness explained in a picture:

$$\begin{aligned}\Delta_{(a,b]}C &= C(b_1, b_2) - C(b_1, a_2) - C(a_1, b_2) + C(a_1, a_2) \\ &= \mathbb{P}(U \in (a, b]) \stackrel{!}{\geq} 0\end{aligned}$$



$\Rightarrow \Delta_{(a,b]}C$  is the **probability of** a random vector  $U \sim C$  to be in  $(a, b]$ .

## Preliminaries

### Lemma 7.2 (Probability transformation)

Let  $X \sim F$ ,  $F$  continuous. Then  $F(X) \sim U(0, 1)$ .

*Idea of the proof.*  $\mathbb{P}(F(X) \leq u) = \mathbb{P}(F^{\leftarrow}(F(X)) \leq F^{\leftarrow}(u)) = \mathbb{P}(X \leq F^{\leftarrow}(u)) = F(F^{\leftarrow}(u)) = u$ ,  $u \in [0, 1]$ ; more details in the appendix.  $\square$

Note that  $F$  needs to be **continuous** (otherwise  $F(X)$  would not reach all intervals  $\subseteq [0, 1]$ ).

### Lemma 7.3 (Quantile transformation)

Let  $U \sim U(0, 1)$  and  $F$  be any df. Then  $X = F^{\leftarrow}(U) \sim F$ .

*Proof.*  $\mathbb{P}(F^{\leftarrow}(U) \leq x) \stackrel{(G15)}{=} \mathbb{P}(U \leq F(x)) = F(x)$ ,  $x \in \mathbb{R}$ .  $\square$

Probability and quantile transformations are the key to all applications involving copulas. They allow us to go from  $\mathbb{R}^d$  to  $[0, 1]^d$  and back.

# Sklar's Theorem

## Theorem 7.4 (Sklar's Theorem)

- 1) For any df  $F$  with margins  $F_1, \dots, F_d$ , there exists a copula  $C$  such that

$$F(x_1, \dots, x_d) = C(F_1(x_1), \dots, F_d(x_d)), \quad \mathbf{x} \in \mathbb{R}^d. \quad (26)$$

$C$  is uniquely defined on  $\prod_{j=1}^d \text{ran } F_j$  and given by

$$C(u_1, \dots, u_d) = F(F_1^{\leftarrow}(u_1), \dots, F_d^{\leftarrow}(u_d)), \quad \mathbf{u} \in \prod_{j=1}^d \text{ran } F_j.$$

- 2) Conversely, given any copula  $C$  and univariate dfs  $F_1, \dots, F_d$ ,  $F$  defined by (26) is a df with margins  $F_1, \dots, F_d$ .

*Proof.*

- 1) **Proof for continuous  $F_1, \dots, F_d$  only.** Let  $\mathbf{X} \sim F$  and define  $U_j = F_j(X_j)$ ,  $j \in \{1, \dots, d\}$ . By the probability transformation,  $U_j \sim U(0, 1)$  (continuity!),  $j \in \{1, \dots, d\}$ , so the df  $C$  of  $\mathbf{U}$  is a copula. Since  $F_j \uparrow$  on  $\text{ran } X_j$ , (G13) implies that  $X_j = F_j^{\leftarrow}(F_j(X_j)) = F_j^{\leftarrow}(U_j)$ ,  $j \in \{1, \dots, d\}$ . Therefore,

$$\begin{aligned} F(\mathbf{x}) &= \mathbb{P}(X_j \leq x_j \ \forall j) = \mathbb{P}(F_j^{\leftarrow}(U_j) \leq x_j \ \forall j) \stackrel{\text{(G15)}}{=} \mathbb{P}(U_j \leq F_j(x_j) \ \forall j) \\ &= C(F_1(x_1), \dots, F_d(x_d)), \quad \mathbf{x} \in \mathbb{R}^d. \end{aligned}$$

Hence  $C$  is a copula and satisfies (26).

(G14) implies that  $F_j(F_j^{\leftarrow}(u_j)) = u_j$  for all  $u_j \in \text{ran } F_j$ , so

$$\begin{aligned} C(u_1, \dots, u_d) &= C(F_1(F_1^{\leftarrow}(u_1)), \dots, F_d(F_d^{\leftarrow}(u_d))) \\ &\stackrel{(26)}{=} F(F_1^{\leftarrow}(u_1), \dots, F_d^{\leftarrow}(u_d)), \quad \mathbf{u} \in \prod_{j=1}^d \text{ran } F_j. \end{aligned}$$

2) For  $U \sim C$ , define  $\mathbf{X} = (F_1^{\leftarrow}(U_1), \dots, F_d^{\leftarrow}(U_d))$ . Then

$$\begin{aligned}\mathbb{P}(\mathbf{X} \leq \mathbf{x}) &= \mathbb{P}(F_j^{\leftarrow}(U_j) \leq x_j \ \forall j) \underset{\text{(GI5)}}{=} \mathbb{P}(U_j \leq F_j(x_j) \ \forall j) \\ &= C(F_1(x_1), \dots, F_d(x_d)), \quad \mathbf{x} \in \mathbb{R}^d.\end{aligned}$$

Therefore,  $F$  defined by (26) is a df (that of  $\mathbf{X}$ ), with margins  $F_1, \dots, F_d$  (obtained by the quantile transformation).  $\square$

### Example 7.5 (Bivariate Bernoulli distribution)

Let  $(X_1, X_2)$  follow a bivariate Bernoulli distribution with  $\mathbb{P}(X_1 = k, X_2 = l) = 1/4$ ,  $k, l \in \{0, 1\}$ .  $\Rightarrow \mathbb{P}(X_j = k) = 1/2$ ,  $k \in \{0, 1\}$ ,  $\text{ran } F_j = \{0, 1/2, 1\}$ ,  $j \in \{1, 2\}$ . Any copula with  $C(1/2, 1/2) = 1/4$  satisfies (26) (e.g.  $C(u_1, u_2) = \Pi(u_1, u_2)$  or the diagonal copula  $C(u_1, u_2) = \min\{u_1, u_2, (\delta(u_1) + \delta(u_2))/2\}$  with  $\delta(u) = u^2$ ).

- A copula model for  $\mathbf{X}$  means  $F(\mathbf{x}) = C(F_1(x_1), \dots, F_d(x_d))$  for some (parametric) copula  $C$  and (parametric) marginals  $F_1, \dots, F_d$ .
- $\mathbf{X}$  (or  $F$ ) with margins  $F_1, \dots, F_d$  has copula  $C$  if (26) holds.



## Invariance principle

### Lemma 7.6 (Core of the invariance principle)

Let  $X_j \sim F_j$ ,  $F_j$  continuous,  $j \in \{1, \dots, d\}$ . Then

$$\mathbf{X} \text{ has copula } C \iff (F_1(X_1), \dots, F_d(X_d)) \sim C.$$

*Proof.* See the appendix. □

### Theorem 7.7 (Invariance principle)

Let  $\mathbf{X} \sim F$  with continuous margins  $F_1, \dots, F_d$  and copula  $C$ . If  $T_j \uparrow$  on  $\text{ran } X_j$  for all  $j$ , then  $(T_1(X_1), \dots, T_d(X_d))$  (also) has copula  $C$ .

*Proof.* W.l.o.g. assume  $T_j$  to be right-continuous at its at most countably many discontinuities (since  $X_j$  is continuously distributed, we only change  $T_j(X_j)$  on a null set). Since  $T_j \uparrow$  on  $\text{ran } X_j$  and  $X_j$  is continuously distributed,  $T_j(X_j)$  is continuously distributed and we have

$$\begin{aligned}
 F_{T_j(X_j)}(x) &= \mathbb{P}(T_j(X_j) \leq x) = \mathbb{P}(T_j(X_j) < x) \stackrel{(G15)}{=} \mathbb{P}(X_j < T_j^{\leftarrow}(x)) \\
 &= \mathbb{P}(X_j \leq T_j^{\leftarrow}(x)) = F_j(T_j^{\leftarrow}(x)), \quad x \in \mathbb{R}.
 \end{aligned}$$

This implies that  $\mathbb{P}(F_{T_j(X_j)}(T_j(X_j)) \leq u_j \forall j)$  equals

$$\mathbb{P}(F_j(T_j^{\leftarrow}(T_j(X_j))) \leq u_j \forall j) \stackrel{(G13)}{=} \mathbb{P}(F_j(X_j) \leq u_j \forall j) \stackrel{\text{L.7.6}}{=} \underset{\text{"only if"}}{C(\mathbf{u})}.$$

The claim follows from the if part (" $\Leftarrow$ ") of Lemma 7.6. □

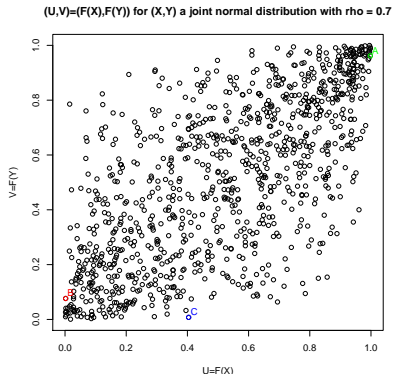
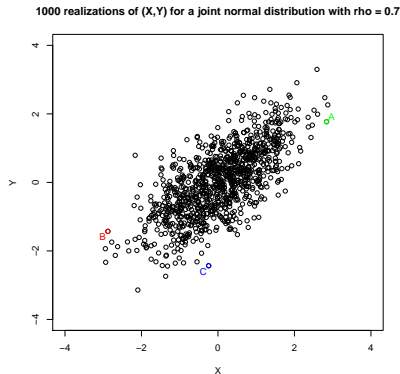
## Interpretation of Sklar's Theorem (and the invariance principle)

- 1) Part 1) of Sklar's Theorem allows one to **decompose any df  $F$  into its margins and a copula**. This, together with the invariance principle, allows one to **study dependence independently of the margins via the margin-free  $\mathbf{U} = (F_1(X_1), \dots, F_d(X_d))$  instead of  $\mathbf{X} = (X_1, \dots, X_d)$**  (they both have the same copula!). This is interesting for statistical applications, e.g. **parameter estimation** or **goodness-of-fit**.
- 2) Part 2) allows one to **construct flexible multivariate distributions** for particular applications.

## Visualizing the first part of Sklar's Theorem

**Left:** Scatter plot of  $n = 1000$  samples from  $(X_1, X_2) \sim N_2(\mathbf{0}, P)$ , where  $P = \begin{pmatrix} 1 & 0.7 \\ 0.7 & 1 \end{pmatrix}$ . We mark three points A, B, C.

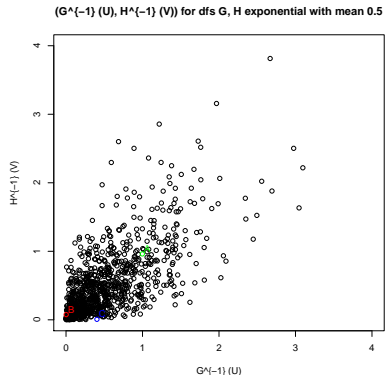
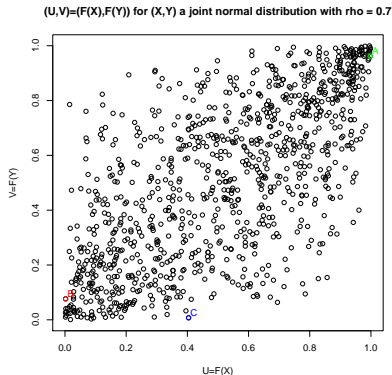
**Right:** Scatter plot of the corresponding Gauss copula (after applying the df  $\Phi$  of  $N(0, 1)$ ). Note how A, B, C change.



## Visualizing the second part of Sklar's Theorem

**Left:** Same Gauss copula scatter plot as before. Apply marginal Exp(2)-quantile functions ( $F_j^{-1}(u) = -\log(1-u)/2$ ,  $j \in \{1, 2\}$ ).

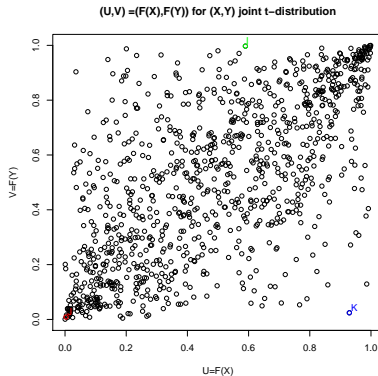
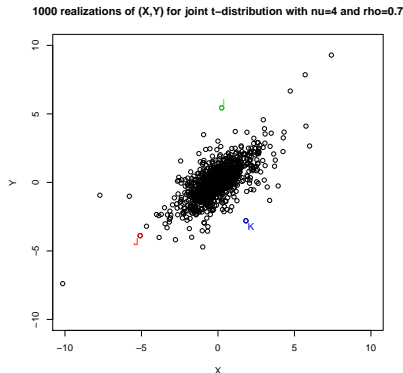
**Right:** The corresponding transformed random variates. Again, note the three points A, B, C.



## Visualizing the first part of Sklar's Theorem

**Left:** Scatter plot of  $n = 1000$  samples from  $(X_1, X_2) \sim t_2(4, \mathbf{0}, P)$ , where  $P = \begin{pmatrix} 1 & 0.7 \\ 0.7 & 1 \end{pmatrix}$ . We mark three points I, J, K.

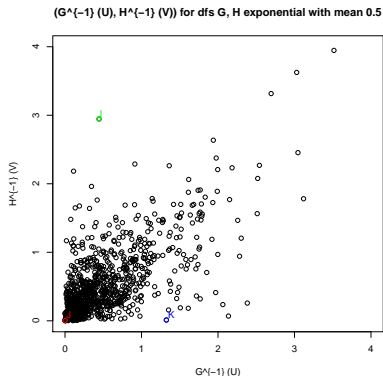
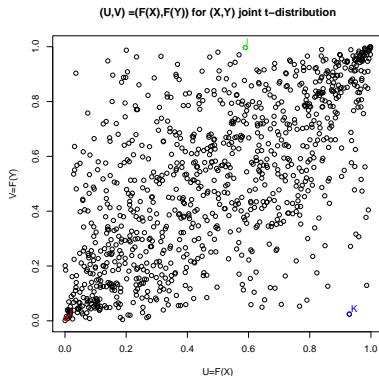
**Right:** Scatter plot of the corresponding  $t_4$  copula (after applying the df  $t_4$ ). Note how A, B, C change.



## Visualizing the second part of Sklar's Theorem

**Left:** Same  $t_4$  copula scatter plot as before. Apply marginal Exp(2)-quantile functions ( $F_j^{-1}(u) = -\log(1-u)/2$ ,  $j \in \{1, 2\}$ ).

**Right:** The corresponding transformed random variates. Again, note the three points I, J, K.



## Fréchet–Hoeffding bounds

### Theorem 7.8 (Fréchet–Hoeffding bounds)

Let  $W(\mathbf{u}) = \max\{\sum_{j=1}^d u_j - d + 1, 0\}$  and  $M(\mathbf{u}) = \min_{1 \leq j \leq d} \{u_j\}$ .

1) For any  $d$ -dimensional copula  $C$ ,

$$W(\mathbf{u}) \leq C(\mathbf{u}) \leq M(\mathbf{u}), \quad \mathbf{u} \in [0, 1]^d.$$

2)  $W$  is a copula if and only if  $d = 2$ .

3)  $M$  is a copula for all  $d \geq 2$ .

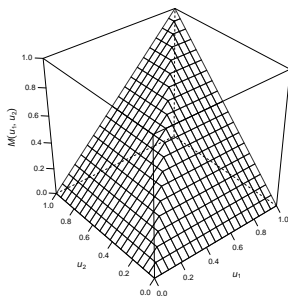
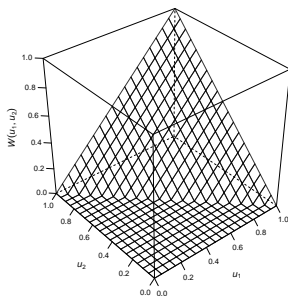
*Proof.* See the appendix. □

■ It is easy to verify that, for  $U \sim U(0, 1)$ ,

▶  $(U, \dots, U) \sim M$ ;

▶  $(U, 1 - U) \sim W$ .

- Plot of  $W, M$  for  $d = 2$  (compare with  $(U, 1 - U) \sim W$ ,  $(U, U) \sim M$ )



- The Fréchet–Hoeffding bounds correspond to perfect dependence (negative for  $W$ ; positive for  $M$ ); see Proposition 7.14 later.
- The Fréchet–Hoeffding bounds lead to bounds for any df  $F$ , via

$$\max\left\{\sum_{j=1}^d F_j(x_j) - d + 1, 0\right\} \leq F(\mathbf{x}) \leq \min_{1 \leq j \leq d} \{F_j(x_j)\}.$$

We will use them later to derive bounds for the correlation coefficient.



## 7.1.2 Examples of copulas

- *Fundamental copulas*: important special copulas;
- *Implicit copulas*: extracted from known  $F$  via Sklar's Theorem;
- *Explicit copulas*: have simple closed-form expressions and follow construction principles of copulas.

### Fundamental copulas

- $\Pi(\mathbf{u}) = \prod_{j=1}^d u_j$  is the *independence copula* since  $C(F_1(x_1), \dots, F_d(x_d)) \stackrel{\text{Sklar}}{=} F(\mathbf{x}) \stackrel{\text{ind.}}{=} \prod_{j=1}^d F_j(x_j)$  if and only if  $C(\mathbf{u}) = \Pi(\mathbf{u})$  (now replace  $x_j$  by  $F_j^{\leftarrow}(u_j)$  and apply (GI4)). Therefore,  $X_1, \dots, X_d$  are independent if and only if their copula is  $\Pi$ .
- The Fréchet–Hoeffding bound  $W$  is the *countermonotonicity copula*. It is the df of  $(U, 1 - U)$ . If  $X_1, X_2$  are perfectly negatively dependent ( $X_2$  is a.s. a strictly decreasing function in  $X_1$ ), their copula is  $W$ .

- The Fréchet–Hoeffding bound  $M$  is the *comonotonicity copula*. It is the df of  $(U, \dots, U)$ . If  $X_1, \dots, X_d$  are perfectly positively dependent ( $X_2, \dots, X_{d-1}$  are a.s. strictly increasing functions in  $X_1$ ), their copula is  $M$ .

## Implicit copulas

*Elliptical copulas* are implicit copulas arising from elliptical distributions via Sklar's Theorem. The two most prominent parametric families in this class are the *Gauss copula* and the *t copula*.

## Gauss copulas

- Consider (w.l.o.g.)  $\mathbf{X} \sim N_d(\mathbf{0}, P)$ . The *Gauss copula* (family) is given by

$$\begin{aligned} C_P^{\text{Ga}}(\mathbf{u}) &= \mathbb{P}(\Phi(X_1) \leq u_1, \dots, \Phi(X_d) \leq u_d) \\ &= \Phi_P(\Phi^{-1}(u_1), \dots, \Phi^{-1}(u_d)) \end{aligned}$$

where  $\Phi_P$  is the df of  $N_d(\mathbf{0}, P)$  and  $\Phi$  the df of  $N(0, 1)$ .

- $P = I_d \Rightarrow C = \Pi$ ; and  $P = J_d = \mathbf{1}\mathbf{1}' \Rightarrow C = M$ ;  
 $d = 2$  and  $\rho = P_{12} = -1 \Rightarrow C = W$ .
- Sklar's Theorem  $\Rightarrow$  The density of  $C(\mathbf{u}) = F(F_1^{\leftarrow}(u_1), \dots, F_d^{\leftarrow}(u_d))$  is

$$c(\mathbf{u}) = \frac{f(F_1^{\leftarrow}(u_1), \dots, F_d^{\leftarrow}(u_d))}{\prod_{j=1}^d f_j(F_j^{\leftarrow}(u_j))}, \quad \mathbf{u} \in (0, 1)^d.$$

In particular, the density of  $C_P^{\text{Ga}}$  is

$$c_P^{\text{Ga}}(\mathbf{u}) = \frac{1}{\sqrt{\det P}} \exp\left(-\frac{1}{2} \mathbf{x}'(P^{-1} - I_d) \mathbf{x}\right), \quad (27)$$

where  $\mathbf{x} = (\Phi^{-1}(u_1), \dots, \Phi^{-1}(u_d))$ .

## $t$ copulas

- Consider (w.l.o.g.)  $\mathbf{X} \sim t_d(\nu, \mathbf{0}, P)$ . The  $t$  copula (family) is given by

$$\begin{aligned} C_{\nu, P}^t(\mathbf{u}) &= \mathbb{P}(t_\nu(X_1) \leq u_1, \dots, t_\nu(X_d) \leq u_d) \\ &= t_{\nu, P}(t_\nu^{-1}(u_1), \dots, t_\nu^{-1}(u_d)) \end{aligned}$$

where  $t_{\nu,P}$  is the df of  $t_d(\nu, \mathbf{0}, P)$  and  $t_\nu$  the df of the univariate  $t$  distribution with  $\nu$  degrees of freedom.

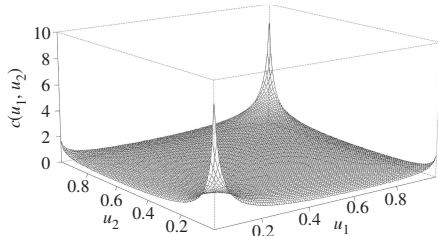
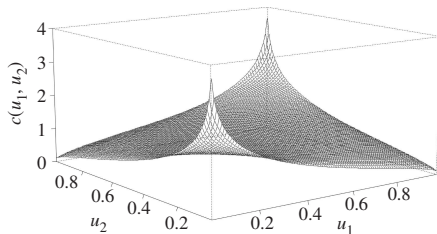
- $P = J_d = \mathbf{1}\mathbf{1}' \Rightarrow C = M$ ; and  $d = 2$  and  $\rho = P_{12} = -1 \Rightarrow C = W$ . However,  $P = I_d \Rightarrow C \neq \Pi$  (unless  $\nu = \infty$  in which case  $C_{\nu,P}^t = C_P^{\text{Ga}}$ ).
- Sklar's Theorem  $\Rightarrow$  The density of  $C_{\nu,P}^t$  is

$$c_{\nu,P}^t(\mathbf{u}) = \frac{\Gamma((\nu + d)/2)}{\Gamma(\nu/2)\sqrt{\det P}} \left( \frac{\Gamma(\nu/2)}{\Gamma((\nu + 1)/2)} \right)^d \frac{(1 + \mathbf{x}'P^{-1}\mathbf{x}/\nu)^{-(\nu+d)/2}}{\prod_{j=1}^d (1 + x_j^2/\nu)^{-(\nu+1)/2}},$$

for  $\mathbf{x} = (t_\nu^{-1}(u_1), \dots, t_\nu^{-1}(u_d))$ .

- For more details, see Demarta and McNeil (2005).
- For scatter plots, see the visualization of Sklar's Theorem above. Note the difference in the tails: The smaller  $\nu$ , the more mass is concentrated in the joint tails.

Perspective plots of the densities of  $C_{\rho=0.3}^{\text{Ga}}$  (left) and  $C_{4,\rho=0.3}^t(\mathbf{u})$  (right).



Advantages and drawbacks of elliptical copulas (see later, too):

### Advantages:

- Modelling pairwise dependencies (comparably flexible)
- Density available
- Sampling (typically) simple

### Drawbacks:

- Typically,  $C$  is not explicit
- Radially symmetric (so the same lower/upper tail behaviour)

# Explicit copulas

*Archimedean copulas* are copulas of the form

$$C(\mathbf{u}) = \psi(\psi^{-1}(u_1) + \cdots + \psi^{-1}(u_d)), \quad \mathbf{u} \in [0, 1]^d,$$

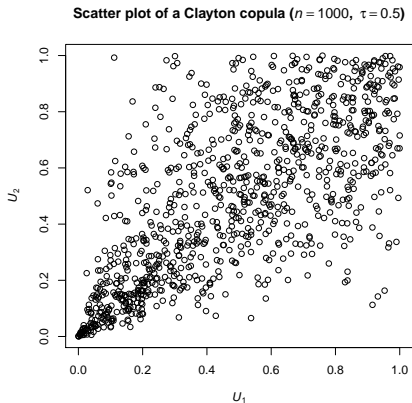
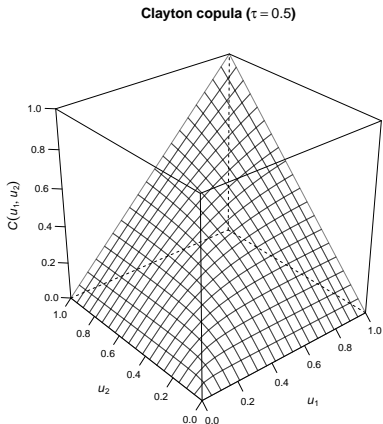
where the (*Archimedean*) *generator*  $\psi : [0, \infty) \rightarrow [0, 1]$  is  $\downarrow$  on  $[0, \inf\{t : \psi(t) = 0\}]$  and satisfies  $\psi(0) = 1$ ,  $\psi(\infty) = \lim_{t \rightarrow \infty} \psi(t) = 0$ ; we set  $\psi^{-1}(0) = \inf\{t : \psi(t) = 0\}$ . The set of all generators is denoted by  $\Psi$ . If  $\psi(t) > 0$ ,  $t \in [0, \infty)$ , we call  $\psi$  *strict*.

## Examples

- **Clayton copula:** Obtained for  $\psi(t) = (1+t)^{-1/\theta}$ ,  $t \in [0, \infty)$ ,  $\theta \in (0, \infty)$   
 $\Rightarrow C_\theta^c(\mathbf{u}) = (u_1^{-\theta} + \cdots + u_d^{-\theta} - d + 1)^{-1/\theta}$ . For  $\theta \downarrow 0$ ,  $C \rightarrow \Pi$ ; and for  $\theta \uparrow \infty$ ,  $C \rightarrow M$ .
- **Gumbel copula:** Obtained for  $\psi(t) = \exp(-t^{1/\theta})$ ,  $t \in [0, \infty)$ ,  $\theta \in [1, \infty)$   
 $\Rightarrow C_\theta^g(\mathbf{u}) = \exp(-((- \log u_1)^\theta + \cdots + (- \log u_d)^\theta)^{1/\theta})$ . For  $\theta = 1$ ,  $C = \Pi$ ; and for  $\theta \rightarrow \infty$ ,  $C \rightarrow M$ .

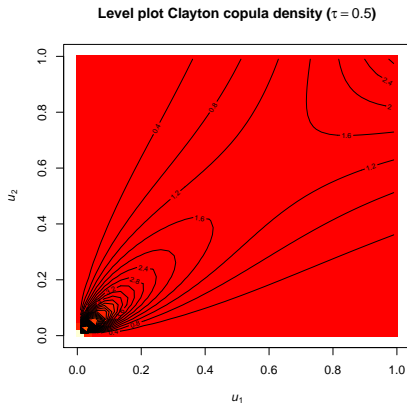
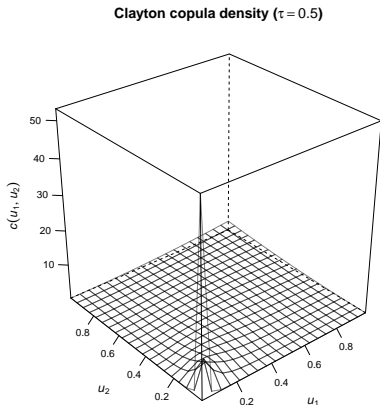
**Left:** Plot of a bivariate **Clayton copula** (Kendall's tau 0.5; see later).

**Right:** Corresponding **scatter plot** (sample size  $n = 1000$ )



**Left:** Plot of the corresponding density.

**Right:** Level plot of the density (with heat colors).

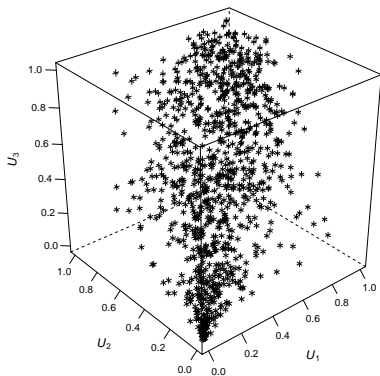




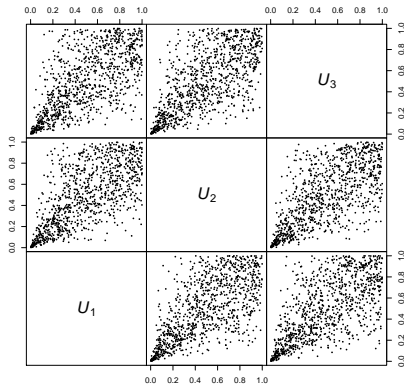
**Left:** Cloud plot of a trivariate Clayton copula (sample size  $n = 1000$ ; Kendall's tau 0.5).

**Right:** Corresponding scatter plot matrix.

Clayton copula cloud plot ( $n = 1000$ ,  $\tau = 0.5$ )

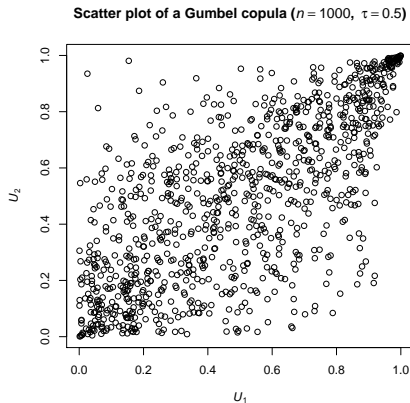
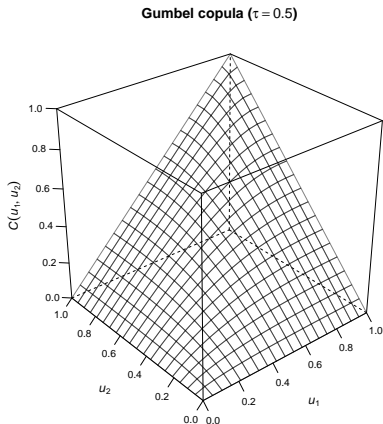


Scatter plot matrix of a Clayton copula ( $n = 1000$ ,  $\tau = 0.5$ )



**Left:** Plot of a bivariate **Gumbel copula** (Kendall's tau 0.5).

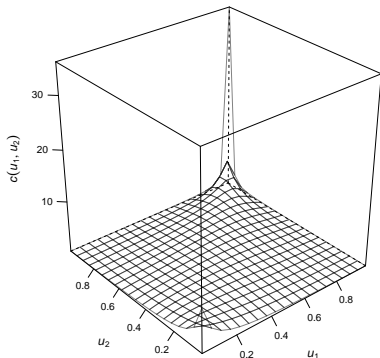
**Right:** Corresponding **scatter plot** (sample size  $n = 1000$ )



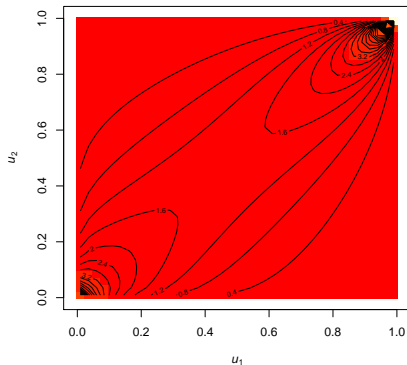
**Left:** Plot of the corresponding density.

**Right:** Level plot of the density (with heat colors).

Gumbel copula density ( $\tau = 0.5$ )



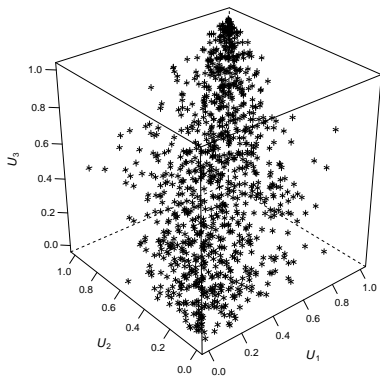
Level plot Gumbel copula density ( $\tau = 0.5$ )



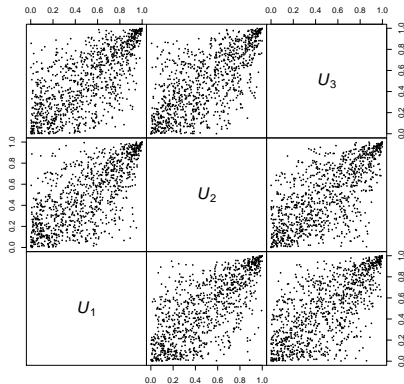
**Left:** Cloud plot of a trivariate Gumbel copula (sample size  $n = 1000$ ; Kendall's tau 0.5).

**Right:** Corresponding scatter plot matrix.

Gumbel copula cloud plot ( $n = 1000$ ,  $\tau = 0.5$ )



Scatter plot matrix of a Gumbel copula ( $n = 1000$ ,  $\tau = 0.5$ )



## Advantages and drawbacks of Archimedean copulas (see later, too):

### Advantages:

- Typically **explicit** (if  $\psi^{-1}$  is available)
- Useful in calculations: **Properties** can typically be expressed **in terms of  $\psi$**
- **Densities** of various examples available
- **Sampling** often simple
- **Not restricted to radial symmetry**

### Drawbacks:

- All margins of the same dimension are equal (symmetry or **exchangeability**; see later)
- Often used only with a small **number of parameters** (some extensions available, but still less than  $d(d-1)/2$ )

### 7.1.3 Meta distributions

- *Fréchet class*: Class of all dfs  $F$  with given marginal dfs  $F_1, \dots, F_d$ ;  
*Meta- $C$  models*: All dfs  $F$  with the same given copula  $C$ .
- **Example**: A meta-Gauss model is a multivariate df  $F$  with Gauss copula  $C$  and some margins  $F_1, \dots, F_d$ .

### 7.1.4 Simulation of copulas and meta distributions

#### Sampling implicit copulas

Due to their construction via Sklar's Theorem, implicit copulas can be sampled via Lemma 7.6.

##### Algorithm 7.9 (Simulation of implicit copulas)

- 1) Sample  $\mathbf{X} \sim F$ , where  $F$  is a df with continuous margins  $F_1, \dots, F_d$ .
- 2) Return  $\mathbf{U} = (F_1(X_1), \dots, F_d(X_d))$  (probability transformation).

## Example 7.10

- Sampling **Gauss copulas**  $C_P^{\text{Ga}}$ :

- 1) Sample  $\mathbf{X} \sim N_d(\mathbf{0}, P)$  ( $\mathbf{X} \stackrel{d}{=} A\mathbf{Z}$  for  $AA' = P$ ,  $\mathbf{Z} \sim N_d(\mathbf{0}, I_d)$ ).
- 2) Return  $\mathbf{U} = (\Phi(X_1), \dots, \Phi(X_d))$ .

- Sampling  **$t_\nu$  copulas**  $C_{\nu, P}^t$ :

- 1) Sample  $\mathbf{X} \sim t_d(\nu, \mathbf{0}, P)$  ( $\mathbf{X} \stackrel{d}{=} \sqrt{W}A\mathbf{Z}$  for  $W = \frac{1}{V}$ ,  $V \sim \Gamma(\frac{\nu}{2}, \frac{\nu}{2})$ ).
- 2) Return  $\mathbf{U} = (t_\nu(X_1), \dots, t_\nu(X_d))$ .

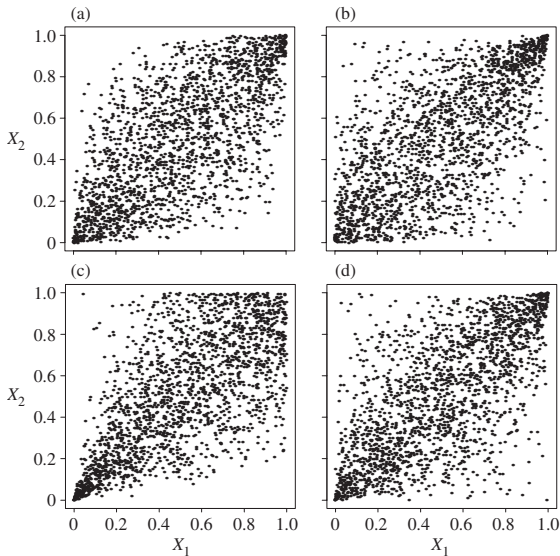
## Sampling meta distributions

Meta- $C$  distributions can be sampled via Sklar's Theorem, Part 2).

### Algorithm 7.11 (Sampling)

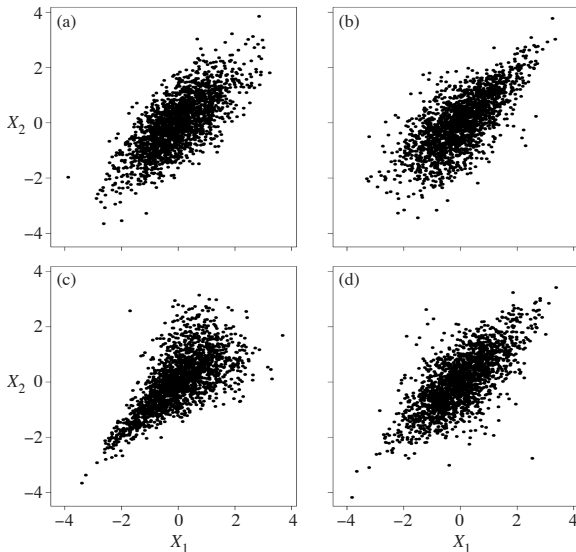
- 1) Sample  $\mathbf{U} \sim C$ .
- 2) Return  $\mathbf{X} = (F_1^{\leftarrow}(U_1), \dots, F_d^{\leftarrow}(U_d))$  (**quantile transformation**).

2000 samples from (a):  $C_{\rho=0.7}^{\text{Ga}}$ ; (b):  $C_{\theta=2}^{\text{G}}$ ; (c):  $C_{\theta=2.2}^{\text{C}}$ ; (d):  $C_{\nu=4, \rho=0.71}^t$





... transformed to  $N(0, 1)$  margins; all have linear correlation  $\approx 0.7$ !



## A general sampling algorithm

For a general copula  $C$  (without further information), the only known sampling algorithm is the *conditional distribution method*; see Embrechts et al. (2003) and Hofert (2010, p. 41).

### Theorem 7.12 (Conditional distribution method)

If  $C$  is a  $d$ -dimensional copula and  $U' \sim U(0, 1)^d$ , let

$$U_1 = U'_1,$$

$$U_2 = C^{\leftarrow}(U'_2 | U_1),$$

$$\vdots$$

$$U_d = C^{\leftarrow}(U'_d | U_1, \dots, U_{d-1}).$$

Then  $U \sim C$ .

This typically involves numerical root-finding and the following result.

### Theorem 7.13 (Schmitz (2003))

Let  $C$  be a  $d$ -dimensional copula which admits, for  $d \geq 3$ , continuous partial derivatives w.r.t. the first  $d - 1$  arguments. Then

$$C(u_j | u_1, \dots, u_{j-1}) = \frac{D_{j-1, \dots, 1} C^{(1, \dots, j)}(u_1, \dots, u_j)}{D_{j-1, \dots, 1} C^{(1, \dots, j-1)}(u_1, \dots, u_{j-1})}$$

for a.e.  $u_1, \dots, u_{j-1} \in [0, 1]$ , where the superscripts denote the corresponding marginal copulas and  $D_{j-1, \dots, 1}$  the differential operator w.r.t. the first  $j - 1$  components.

- For  $d = 2$  one obtains that  $C(u_2 | u_1) = D_1 C(u_1, u_2)$  for a.e.  $u_1 \in [0, 1]$ .
- For most well-known copula families, the conditional distribution method is neither simple to apply nor fast  $\Rightarrow$  Efficient sampling algorithms are typically family-specific.

## 7.1.5 Further properties of copulas

### Survival copulas

- If  $U \sim C$ , then  $\mathbf{1} - U \sim \hat{C}$ , the *survival copula* of  $C$ .
- $\hat{C}$  can be expressed as

$$\hat{C}(\mathbf{u}) = \sum_{J \subseteq \{1, \dots, d\}} (-1)^{|J|} C((1 - u_1)^{I_J(1)}, \dots, (1 - u_d)^{I_J(d)})$$

in terms of its corresponding copula (essentially an application of the *Poincaré–Sylvester sieve formula*). For  $d = 2$ ,

$$\begin{aligned}\hat{C}(u_1, u_2) &= 1 - (1 - u_1) - (1 - u_2) + C(1 - u_1, 1 - u_2) \\ &= -1 + u_1 + u_2 + C(1 - u_1, 1 - u_2).\end{aligned}$$

- If  $C$  admits a density,  $\hat{c}(\mathbf{u}) = c(\mathbf{1} - \mathbf{u})$ .
- If  $\hat{C} = C$ ,  $C$  is called *radially symmetric*. Check that  $W$ ,  $\Pi$ , and  $M$  are radially symmetric.

- One can show: If  $X_j$  is symmetrically distributed about  $a_j$ ,  $j \in \{1, \dots, d\}$ , then  $\mathbf{X}$  is radially symmetric about  $\mathbf{a}$  if and only if  $C = \hat{C}$ .
- Sklar's Theorem can also be formulated for survival functions. In this case, the main part reads

$$\bar{F}(\mathbf{x}) = \hat{C}(\bar{F}_1(x_1), \dots, \bar{F}_d(x_d)),$$

where  $F(\mathbf{x}) = \mathbb{P}(\mathbf{X} > \mathbf{x})$  with corresponding marginal survival functions  $\bar{F}_1, \dots, \bar{F}_d$  (with  $\bar{F}_j(x) = \mathbb{P}(X_j > x)$ ).

⇒ Survival copulas combine marginal survival functions to joint survival functions. Note that  $\hat{C}$  is a df, whereas  $\bar{F}$  and  $\bar{F}_1, \dots, \bar{F}_d$  are not!

## Copula densities

- By **Sklar's Theorem**, if  $F_j$  has density  $f_j$ ,  $j \in \{1, \dots, d\}$ , and  $C$  has density  $c$ , then the density  $f$  of  $F$  satisfies

$$f(\mathbf{x}) = c(F_1(x_1), \dots, F_d(x_d)) \prod_{j=1}^d f_j(x_j) \quad (28)$$

As seen before, we can recover  $c$  via

$$c(\mathbf{u}) = \frac{f(F_1^{-1}(u_1), \dots, F_d^{-1}(u_d))}{f_1(F_1^{-1}(u_1)) \cdots f_d(F_d^{-1}(u_d))}.$$

- It follows from (28) that the **log-density** splits into

$$\log f(\mathbf{x}) = \log c(F_1(x_1), \dots, F_d(x_d)) + \sum_{j=1}^d \log f_j(x_j).$$

which **allows for a two-stage estimation** (**marginal** and **copula parameters**); see Section 7.5.

## Exchangeability

- $X$  is *exchangeable* if

$$(X_1, \dots, X_d) \stackrel{d}{=} (X_{\pi(1)}, \dots, X_{\pi(d)})$$

for any permutation  $(\pi(1), \dots, \pi(d))$  of  $(1, \dots, d)$ .

- A copula  $C$  is *exchangeable* if it is the df of an exchangeable  $U$  with  $U(0, 1)$  margins. This holds if only if  $C(u_1, \dots, u_d) = C(u_{\pi(1)}, \dots, u_{\pi(d)})$  for all possible permutations of arguments, i.e. if  $C$  is *symmetric*.
- Exchangeable/symmetric copulas are useful for approximate modelling homogeneous portfolios.
- **Examples:**
  - ▶ Archimedean copulas
  - ▶ Elliptical copulas (such as Gauss/ $t$ ) for equicorrelated  $P$  (i.e.  $P = \rho J_d + (1 - \rho)I_d$  for  $\rho \geq -1/(d - 1)$ ); in particular,  $d = 2$

## 7.2 Dependence concepts and measures

*Measures of association/dependence* are scalar measures which **summarize the dependence in terms of a single number**. There are better and worse examples of such measures, which we will study in this section.

### 7.2.1 Perfect dependence

$X_1, X_2$  are *countermonotone* if  $(X_1, X_2)$  has copula  $W$ .

$X_1, \dots, X_d$  are *comonotone* if  $(X_1, \dots, X_d)$  has copula  $M$ .

#### Proposition 7.14 (Perfect dependence)

- 1)  $X_2 = T(X_1)$  a.s. with decreasing  $T(x) = F_2^{\leftarrow}(1 - F_1(x))$  (countermonotone) **if and only if**  $C(u_1, u_2) = W(u_1, u_2)$ ,  $u_1, u_2 \in [0, 1]$ .
- 2)  $X_j = T_j(X_1)$  a.s. with increasing  $T_j(x) = F_j^{\leftarrow}(F_1(x))$ ,  $j \in \{2, \dots, d\}$  (comonotone), **if and only if**  $C(\mathbf{u}) = M(\mathbf{u})$ ,  $\mathbf{u} \in [0, 1]^d$ .

*Proof.* See the appendix. □



### Proposition 7.15 (Comonotone additivity)

Let  $\alpha \in (0, 1)$  and  $X_j \sim F_j$ ,  $j \in \{1, \dots, d\}$ , be comontone. Then  $F_{X_1 + \dots + X_d}^{\leftarrow}(\alpha) = F_1^{\leftarrow}(\alpha) + \dots + F_d^{\leftarrow}(\alpha)$ ; see the appendix for a proof.

## 7.2.2 Linear correlation

For two random variables  $X_1$  and  $X_2$  with  $\mathbb{E}(X_j^2) < \infty$ ,  $j \in \{1, 2\}$ , the (*linear* or *Pearson's*) *correlation coefficient*  $\rho$  is defined by

$$\rho(X_1, X_2) = \frac{\text{cov}(X_1, X_2)}{\sqrt{\text{var } X_1} \sqrt{\text{var } X_2}} = \frac{\mathbb{E}((X_1 - \mathbb{E}X_1)(X_2 - \mathbb{E}X_2))}{\sqrt{\mathbb{E}((X_1 - \mathbb{E}X_1)^2)} \sqrt{\mathbb{E}((X_2 - \mathbb{E}X_2)^2)}}.$$

### Proposition 7.16 (Hoeffding's identity)

Let  $X_j \sim F_j$ ,  $j \in \{1, 2\}$ , be two random variables with  $\mathbb{E}(X_j^2) < \infty$ ,  $j \in \{1, 2\}$ , and joint distribution function  $F$ . Then

$$\text{cov}(X_1, X_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (F(x_1, x_2) - F_1(x_1)F_2(x_2)) dx_1 dx_2.$$

## Classical properties and drawbacks of linear correlation

Let  $X_1$  and  $X_2$  be two random variables with  $\mathbb{E}(X_j^2) < \infty$ ,  $j \in \{1, 2\}$ .

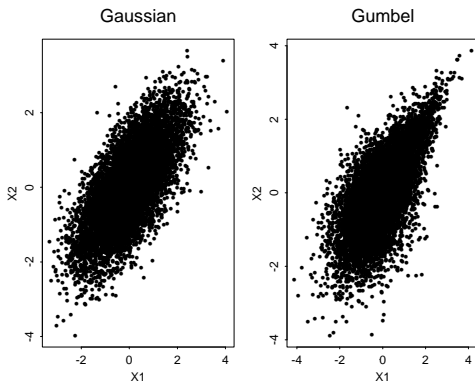
Note that  $\rho$  depends on the marginal distributions! In particular, second moments have to exist (not the case, e.g. for  $X_1, X_2 \stackrel{\text{ind.}}{\sim} F(x) = 1 - x^{-3}!$ )

- $|\rho| \leq 1$ . Furthermore,  $|\rho| = 1$  if and only if there are constants  $a \in \mathbb{R} \setminus \{0\}, b \in \mathbb{R}$  with  $X_2 = aX_1 + b$  a.s. with  $a \geq 0$  if and only if  $\rho = \pm 1$ . This discards other strong functional dependence such as  $X_2 = X_1^2$ , for example.
- If  $X_1$  and  $X_2$  are independent, then  $\rho = 0$ . However, the converse is not true in general; see Example 7.17 below.
- $\rho$  is invariant under strictly increasing linear transformations on  $\text{ran } X_1 \times \text{ran } X_2$  but not invariant under strictly increasing functions in general. To see this, consider  $(X_1, X_2) \sim N_2(\mathbf{0}, P)$  with  $P_{12} = \rho$ . Then  $\rho(X_1, X_2) = \rho$ , but  $\rho(F_1(X_1), F_2(X_2)) = \frac{6}{\pi} \arcsin(\rho/2)$ .

# Correlation fallacies

## Fallacy 1: $F_1$ , $F_2$ , and $\rho$ uniquely determine $F$

This is true for bivariate elliptical distributions, but wrong in general. The following samples both have  $N(0, 1)$  margins and correlation  $\rho = 0.7$ , yet come from different (copula) models:



Another example is this.

### Example 7.17 (Uncorrelated $\nRightarrow$ independent)

- Consider the two risks

$$X_1 = Z \quad (\text{Profit \& Loss Country A}),$$

$$X_2 = ZV \quad (\text{Profit \& Loss Country B}),$$

where  $V, Z$  are independent with  $Z \sim N(0, 1)$  and  $\mathbb{P}(V = -1) = \mathbb{P}(V = 1) = 1/2$ . Then  $X_2 \sim N(0, 1)$  and  $\rho(X_1, X_2) = \text{cov}(X_1, X_2) = \mathbb{E}(X_1 X_2) \underset{\text{ind.}}{=} \mathbb{E}(V)\mathbb{E}(Z^2) = 0$ , but  $X_1$  and  $X_2$  are not independent (in fact,  $V$  switches between counter- and comonotonicity).

- Consider  $(X'_1, X'_2) \sim N_2(\mathbf{0}, I_2)$ . Both  $(X'_1, X'_2)$  and  $(X_1, X_2)$  have  $N(0, 1)$  margins and  $\rho = 0$ , but the copula of  $(X'_1, X'_2)$  is  $\Pi$  and the copula of  $(X_1, X_2)$  is  $C(\mathbf{u}) = 0.5W(\mathbf{u}) + 0.5M(\mathbf{u})$ .

## Fallacy 2: Given $F_1, F_2$ , any $\rho \in [-1, 1]$ is attainable

This is true for elliptically distributed  $(X_1, X_2)$  with  $\mathbb{E}(R^2) < \infty$  (as then  $\text{corr } \mathbf{X} = P$ ), but wrong in general:

- If  $F_1$  and  $F_2$  are not of the same type (no linearity),  $\rho(X_1, X_2) = 1$  is not attainable (recall that  $|\rho| = 1$  if and only if there are constants  $a \in \mathbb{R} \setminus \{0\}, b \in \mathbb{R}$  with  $X_2 = aX_1 + b$  a.s.).
- Hoeffding's identity

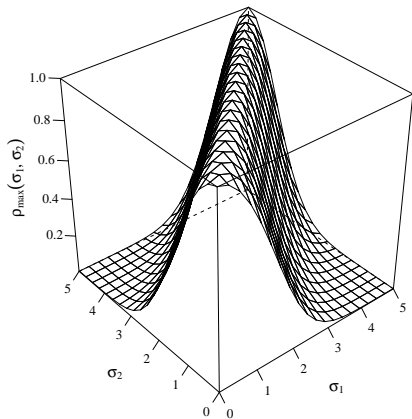
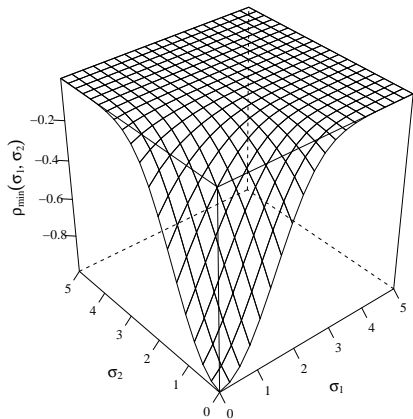
$$\text{cov}(X_1, X_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (C(F_1(x_1), F_2(x_2)) - F_1(x_1)F_2(x_2)) dx_1 dx_2.$$

implies bounds on attainable  $\rho$ :

$$\rho \in [\rho_{\min}, \rho_{\max}] \quad (\rho_{\min} \text{ is attained for } C = W, \rho_{\max} \text{ for } C = M).$$

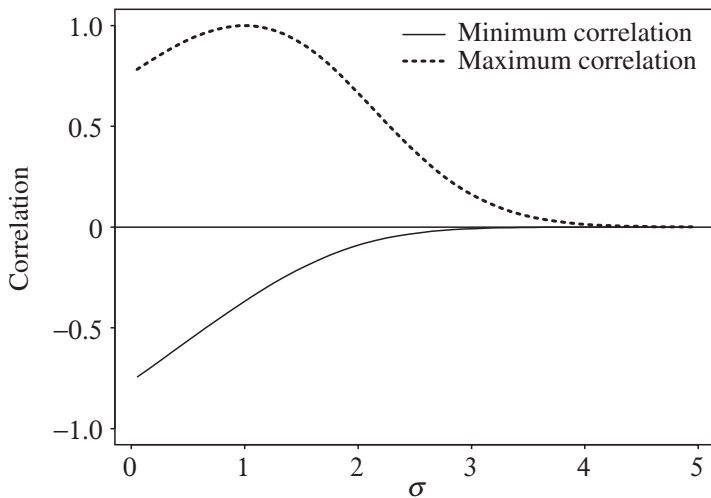
### Example 7.18 (Bounds for a model with $\text{LN}(0, \sigma_j^2)$ margins)

Let  $X_j \sim \text{LN}(0, \sigma_j^2)$ ,  $j \in \{1, 2\}$ . One can show that minimal ( $\rho_{\min}$ ; left) and maximal ( $\rho_{\max}$ ; right) correlations are given as follows.



For  $\sigma_1^2 = 1$ ,  $\sigma_2^2 = 16$  one has  $\rho \in [-0.0003, 0.0137]!$

Specifically, let  $X_1 \sim \text{LN}(0, 1)$  and  $X_2 \sim \text{LN}(0, \sigma^2)$ . Now let  $\sigma$  vary and plot  $\rho_{\min}$  and  $\rho_{\max}$  against  $\sigma$ :



### Fallacy 3: $\rho$ maximal (i.e. $C = M$ ) $\Rightarrow \text{VaR}_\alpha(X_1 + X_2)$ maximal

- This is true if  $(X_1, X_2)$  is elliptically distributed (since the maximal  $\rho = 1$  implies that  $X_1, X_2$  are comonotone,  $\text{VaR}_\alpha$  is subadditive (see later;  $\Rightarrow$  additivity provides the largest possible bound), and  $\text{VaR}_\alpha$  is comonotone additive (see Proposition 7.15).
- Any superadditivity example  $\text{VaR}_\alpha(X_1 + X_2) > \text{VaR}_\alpha(X_1) + \text{VaR}_\alpha(X_2)$  (the right-hand side is  $\text{VaR}_\alpha(X_1 + X_2)$  under comonotonicity, which gives maximal correlation) serves as a counterexample; see Section 2.3.5.

## 7.2.3 Rank correlation

Rank correlation coefficients are...

- ... always defined;
- ... invariant under strictly increasing transformations of the random variables (hence only depend on the underlying copula).



## Kendall's tau and Spearman's rho

### Definition 7.19 (Kendall's tau)

Let  $X_j \sim F_j$  with  $F_j$  continuous,  $j \in \{1, 2\}$ . Let  $(X'_1, X'_2)$  be an independent copy of  $(X_1, X_2)$ . *Kendall's tau* is defined by

$$\begin{aligned}\rho_\tau &= \mathbb{E}(\text{sign}((X_1 - X'_1)(X_2 - X'_2))) \\ &= \mathbb{P}((X_1 - X'_1)(X_2 - X'_2) > 0) - \mathbb{P}((X_1 - X'_1)(X_2 - X'_2) < 0),\end{aligned}$$

where  $\text{sign}(x) = I_{(0, \infty)}(x) - I_{(-\infty, 0)}(x)$  (so  $-1$  for  $x < 0$ ,  $0$  for  $x = 0$  and  $1$  for  $x > 0$ ).

By definition, Kendall's tau is the probability of *concordance* minus the probability of *discordance*.

### Proposition 7.20 (Formula for Kendall's tau)

Let  $X_j \sim F_j$  with  $F_j$  continuous,  $j \in \{1, 2\}$ , and copula  $C$ . Then

$$\rho_\tau = 4 \int_0^1 \int_0^1 C(u_1, u_2) dC(u_1, u_2) - 1.$$

*Proof.* See the appendix. □

An estimator of  $\rho_\tau$  is provided by the sample version of Kendall's tau

$$r_n^\tau = \frac{1}{\binom{n}{2}} \sum_{1 \leq i_1 < i_2 \leq n} \text{sign}((X_{i_1 1} - X_{i_2 1})(X_{i_1 2} - X_{i_2 2})). \quad (29)$$

### Definition 7.21 (Spearman's rho)

Let  $X_j \sim F_j$  with  $F_j$  continuous,  $j \in \{1, 2\}$ . Spearman's rho is defined by  $\rho_S = \rho(F_1(X_1), F_2(X_2))$ .

## Proposition 7.22 (Formula for Spearman's rho)

Let  $X_j \sim F_j$  with  $F_j$  continuous,  $j \in \{1, 2\}$ , and copula  $C$ . Then

$$\rho_S = 12 \int_0^1 \int_0^1 C(u_1, u_2) du_1 du_2 - 3.$$

*Proof.* By Hoeffding's identity, we have  $\rho_S(X_1, X_2) = \rho(F_1(X_1), F_2(X_2)) = 12 \int_0^1 \int_0^1 (C(u_1, u_2) - u_1 u_2) du_1 du_2 = 12 \int_0^1 \int_0^1 C(u_1, u_2) du_1 du_2 - 3$ .  $\square$

- An estimator  $r_n^S$  is given by the sample correlation computed from componentwise (scaled) ranks (i.e. marginal empirical dfs) of the data.
- For  $\kappa = \rho_\tau$  and  $\kappa = \rho_S$ , Embrechts et al. (2002) show that  $\kappa = \pm 1$  if and only if  $X_1, X_2$  are co-/countermonotonic.
- **Fallacy 1** ( $F_1, F_2, \rho$  uniquely determine  $F$ ) is not solved by replacing  $\rho$  by rank correlation coefficients  $\kappa$  (it is easy to construct several copulas with the same Kendall's tau, e.g. via Archimedean copulas).

- **Fallacy 2** (For  $F_1, F_2$ , any  $\rho \in [-1, 1]$  is attainable) is solved. Take

$$F(x_1, x_2) = \lambda W(F_1(x_1), F_2(x_2)) + (1 - \lambda) M(F_1(x_1), F_2(x_2)).$$

This is a model with  $\rho_S = \tau \rho_\tau = 1 - 2\lambda$  (choose  $\lambda$  as desired).

- **Fallacy 3** ( $C = M$  implies  $\text{VaR}_\alpha(X_1 + X_2)$  maximal) is also not solved by rank correlation coefficients  $\kappa = 1$ : Although  $\kappa = 1$  corresponds to  $C = M$ , this copula does not necessarily provide the largest  $\text{VaR}_\alpha(X_1 + X_2)$ ; see our superadditivity examples.
- Also, in general,  $\kappa = 0$  does not imply independence.
- Nevertheless, rank correlations are useful to summarize dependence, to parameterize copula families to make dependence comparable and for copula parameter calibration or estimation.

## 7.2.4 Coefficients of tail dependence

**Goal:** Measure **extremal dependence**, i.e. dependence in the **joint tails**.

### Definition 7.23 (Tail dependence)

Let  $X_j \sim F_j$ ,  $j \in \{1, 2\}$ , be continuously distributed random variables. Provided that the limits exist, the **lower tail-dependence coefficient**  $\lambda_l$  and **upper tail-dependence coefficient**  $\lambda_u$  of  $X_1$  and  $X_2$  are defined by

$$\lambda_l = \lim_{u \downarrow 0} \mathbb{P}(X_2 \leq F_2^{\leftarrow}(u) \mid X_1 \leq F_1^{\leftarrow}(u)),$$

$$\lambda_u = \lim_{u \uparrow 1} \mathbb{P}(X_2 > F_2^{\leftarrow}(u) \mid X_1 > F_1^{\leftarrow}(u)).$$

If  $\lambda_l \in (0, 1]$  ( $\lambda_u \in (0, 1]$ ), then  $(X_1, X_2)$  is **lower (upper) tail dependent**.  
If  $\lambda_l = 0$  ( $\lambda_u = 0$ ), then  $(X_1, X_2)$  is **lower (upper) tail independent**.

As (conditional) probabilities, we clearly have  $\lambda_l, \lambda_u \in [0, 1]$ .

- Tail dependence is a copula property, since

$$\begin{aligned} \mathbb{P}(X_2 \leq F_2^{\leftarrow}(u) \mid X_1 \leq F_1^{\leftarrow}(u)) &= \frac{\mathbb{P}(X_1 \leq F_1^{\leftarrow}(u), X_2 \leq F_2^{\leftarrow}(u))}{\mathbb{P}(X_1 \leq F_1^{\leftarrow}(u))} \\ &= \frac{F(F_1^{\leftarrow}(u), F_2^{\leftarrow}(u))}{F_1(F_1^{\leftarrow}(u))} \stackrel{\text{Sklar}}{\underset{\text{(GI4)}}{=}} \frac{C(u, u)}{u}, \quad u \in (0, 1), \text{ so } \lambda_1 = \lim_{u \downarrow 0} \frac{C(u, u)}{u}. \end{aligned}$$

- If  $u \mapsto C(u, u)$  is differentiable in a neighborhood of 0 and the limit exists, then  $\lambda_1 = \lim_{u \downarrow 0} \frac{d}{du} C(u, u)$  (l'Hôpital's Rule).
- If  $C$  is totally differentiable in a neighborhood of 0 and the limit exists, then  $\lambda_1 = \lim_{u \downarrow 0} (D_1 C(u, u) + D_2 C(u, u))$  (Chain Rule).
- If  $C$  is symmetric,  $\lambda_1 = 2 \lim_{u \downarrow 0} D_1 C(u, u)$ . By Theorem 7.13,  $\lambda_1 = 2 \lim_{u \downarrow 0} \mathbb{P}(U_2 \leq u \mid U_1 = u)$  for  $(U_1, U_2) \sim C$ . Combined with any continuous df  $F$  and  $(X_1, X_2) = (F^{\leftarrow}(U_1), F^{\leftarrow}(U_2))$ , one has

$$\lambda_1 = 2 \lim_{x \downarrow -\infty} \mathbb{P}(X_2 \leq x \mid X_1 = x) \stackrel{\text{if density}}{=} 2 \lim_{x \downarrow -\infty} \int_{-\infty}^x f_{X_2 \mid X_1=x}(x_2) dx_2. \quad (30)$$

- Similarly as above, for the upper tail-dependence coefficient,

$$\begin{aligned}\lambda_u &= \lim_{u \uparrow 1} \frac{1 - 2u + C(u, u)}{1 - u} = \lim_{u \downarrow 0} \frac{\hat{C}(u, u)}{u} \\ &= \lim_{u \uparrow 1} \frac{2(1 - u) - (1 - C(u, u))}{1 - u} = 2 - \lim_{u \uparrow 1} \frac{1 - C(u, u)}{1 - u}.\end{aligned}$$

- For all **radially symmetric copulas** (e.g. the bivariate  $C_P^{\text{Ga}}$  and  $C_{\nu, P}^t$  copulas), we have  $\lambda_l = \lambda_u =: \lambda$ .
- For **Archimedean copulas with strict  $\psi$** , a substitution and l'Hôpital's Rule show:

$$\begin{aligned}\lambda_l &= \lim_{u \downarrow 0} \frac{\psi(2\psi^{-1}(u))}{u} = \lim_{t \rightarrow \infty} \frac{\psi(2t)}{\psi(t)} = 2 \lim_{t \rightarrow \infty} \frac{\psi'(2t)}{\psi'(t)}, \\ \lambda_u &= 2 - \lim_{u \uparrow 1} \frac{1 - \psi(2\psi^{-1}(u))}{1 - u} = 2 - \lim_{t \downarrow 0} \frac{1 - \psi(2t)}{1 - \psi(t)} = 2 - 2 \lim_{t \downarrow 0} \frac{\psi'(2t)}{\psi'(t)}.\end{aligned}$$

**Clayton:**  $\lambda_l = 2^{-1/\theta}$ ,  $\lambda_u = 0$ ; **Gumbel:**  $\lambda_l = 0$ ,  $\lambda_u = 2 - 2^{1/\theta}$

## 7.3 Normal mixture copulas

... are the **copulas of multivariate normal** (mean-) **variance mixtures**  $\mathbf{X} \stackrel{d}{=} \boldsymbol{\mu} + \sqrt{\mathbf{W}} \mathbf{A} \mathbf{Z}$  ( $\mathbf{X} \stackrel{d}{=} \mathbf{m}(W) + \sqrt{W} \mathbf{A} \mathbf{Z}$ ); e.g. Gauss,  $t$  copulas.

### 7.3.1 Tail dependence

#### Coefficients of tail dependence

Let  $(X_1, X_2)$  be distributed according to a normal variance mixture and assume (w.l.o.g.) that  $\boldsymbol{\mu} = (0, 0)$  and  $\mathbf{A} \mathbf{A}' = \mathbf{P} = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$ . In this case,  $F_1 = F_2$  and  $C$  is symmetric and radially symmetric. We thus obtain that

$$\lambda \stackrel{\text{radial}}{=} \lambda \stackrel{\text{symm.}}{=} \lambda \stackrel{\text{symm.}}{=} \lambda \stackrel{(30)}{=} 2 \lim_{x \downarrow -\infty} \mathbb{P}(X_2 \leq x \mid X_1 = x).$$

#### Example 7.24 ( $\lambda$ for the Gauss and $t$ copula)

- Considering the bivariate  $N(\mathbf{0}, \mathbf{P})$  density, one can show (via  $f_{X_2|X_1}(x_2 \mid x_1) = \frac{f_{X_1, X_2}(x_1, x_2)}{f_{X_1}(x_1)}$ ) that  $X_2 \mid X_1 = x \sim N(\rho x, 1 - \rho^2)$ . This implies that



$\lambda = 2 \lim_{x \downarrow -\infty} \mathbb{P}(X_2 \leq x \mid X_1 = x) = 2 \lim_{x \downarrow -\infty} \Phi\left(\frac{x(1-\rho)}{\sqrt{1-\rho^2}}\right) = I_{\{\rho=1\}}$   
 (essentially **no tail dependence**).

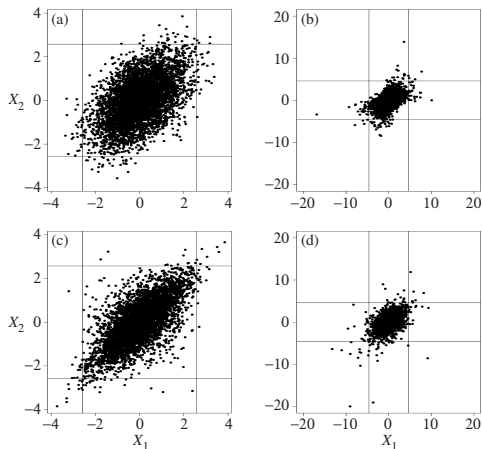
- For  $C_{\nu, P}^t$ , one can show that  $X_2 \mid X_1 = x \sim t_{\nu+1}\left(\rho x, \frac{(1-\rho^2)(\nu+x^2)}{\nu+1}\right)$  and thus  $\mathbb{P}(X_2 \leq x \mid X_1 = x) = t_{\nu+1}\left(\frac{x-\rho x}{\sqrt{\frac{(1-\rho^2)(\nu+x^2)}{\nu+1}}}\right)$ . Hence

$$\lambda = 2t_{\nu+1}\left(-\sqrt{\frac{(\nu+1)(1-\rho)}{1+\rho}}\right) \quad (\text{tail dependence}).$$

$\nu$	$\rho = -0.5$	$\rho = 0$	$\rho = 0.5$	$\rho = 0.9$	$\rho = 1$
$\infty$	0	0	0	0	1
10	0.00	0.01	0.08	0.46	1
4	0.01	0.08	0.25	0.63	1
2	0.06	0.18	0.39	0.72	1

What drives tail dependence of normal variance mixtures is  $W$ . If  $W$  has a power tail, we get tail dependence, otherwise not.

# Joint quantile exceedance probabilities



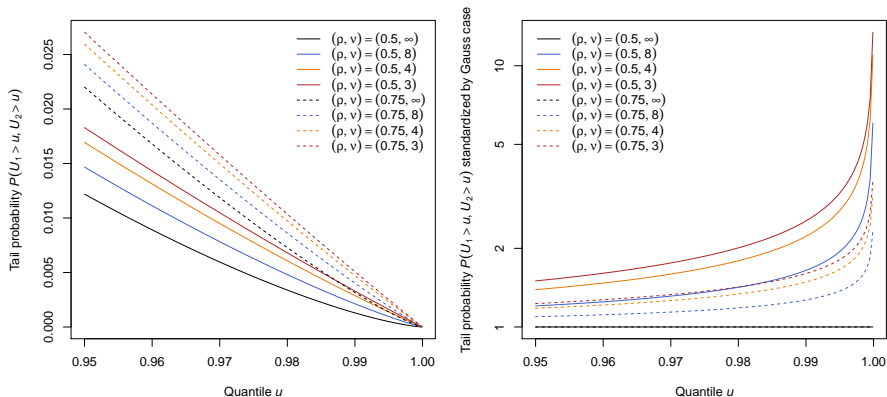
5000 samples from

- (a)  $N_2(\mathbf{0}, P = (\frac{1}{\rho} \begin{pmatrix} \rho & 1 \\ 1 & \rho \end{pmatrix}))$ ,  $\rho = 0.5$ ;
- (b)  $C_\rho^{\text{Ga}}$  with  $t_4$  margins (same dependence as in (a));
- (c)  $C_{4,\rho}^t$  with  $N(0, 1)$  margins;
- (d)  $t_2(4, \mathbf{0}, P)$  (same dependence as in (c)).

Lines denote 0.005- and 0.995-quantiles.

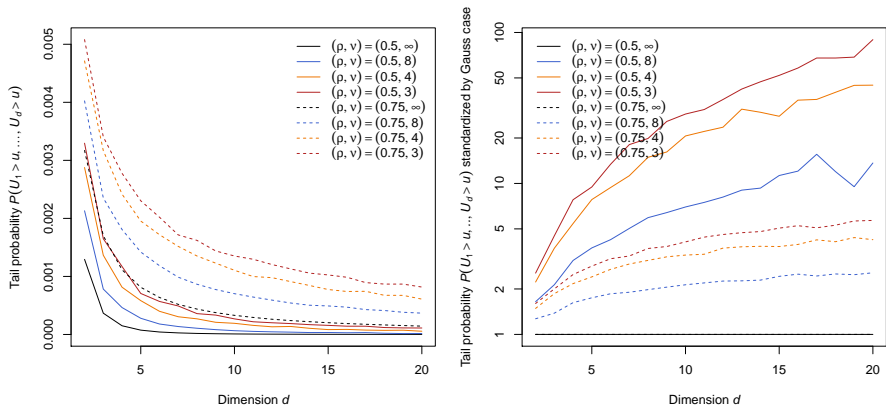
Note the different number of points in the bivariate tails (all models have the same Kendall's tau!)

# Joint tail probabilities $\mathbb{P}(U_1 > u, U_2 > u)$ for $d = 2$



- **Left:** The higher  $\rho$  or the smaller  $\nu$ , the larger  $\mathbb{P}(U_1 > u, U_2 > u)$ .
- **Right:**  $u \mapsto \frac{\mathbb{P}(U_1 > u, U_2 > u)}{\mathbb{P}(V_1 > u, V_2 > u)} \underset{\text{symm.}}{\stackrel{\text{radial}}{=}} \frac{C_{\nu, \rho}^t(u, u)}{C_{\rho}^{\text{Ga}}(u, u)}$

# Joint tail probabilities $\mathbb{P}(U_1 > u, \dots, U_d > u)$ for $u = 0.99$



- Homogeneous  $P$  (off-diagonal entry  $\rho$ ). Note the MC randomness.
- **Left:** Clear, less mass in corners in higher dimensions.
- **Right:**  $d \mapsto \frac{\mathbb{P}(U_1 > u, \dots, U_d > u)}{\mathbb{P}(V_1 > u, \dots, V_d > u)} \underset{\text{symm.}}{\text{radial}} \frac{C_{\nu, \rho}^t(u, \dots, u)}{C_{\rho}^{\text{Ga}}(u, \dots, u)}$  for  $u = 0.99$ .

### Example 7.25 (Joint tail probabilities: an interpretation)

- Consider 5 daily returns  $\mathbf{X} = (X_1, \dots, X_5)$  with pairwise correlations (all)  $\rho = 0.5$ . However, we are unsure about the best joint model.
- If the copula of  $\mathbf{X}$  is  $C_{\rho=0.5}^{\text{Ga}}$ , the probability that on any day all 5 returns lie below their  $u = 0.01$  quantiles is

$$\mathbb{P}(X_1 \leq F_1^{\leftarrow}(u), \dots, X_5 \leq F_5^{\leftarrow}(u)) = \mathbb{P}(U_1 \leq u, \dots, U_5 \leq u) \\ \approx_{\text{MC error}} 7.48 \times 10^{-5}.$$

In the long run such an event will happen once every  $1/7.48 \times 10^{-5} \approx 13\,369$  trading days on average ( $\approx$  once every 51.4 years; assuming 260 trading days in a year).

- If the copula of  $\mathbf{X}$  is  $C_{\nu=4, \rho=0.5}^t$ , however, such an event will happen approximately 7.68 times more often, i.e.  $\approx$  once every 6.7 years. This gets worse the larger  $d$ !

## 7.3.2 Rank correlations

### Proposition 7.26 (Spearman's rho for normal variance mixtures)

Let  $\mathbf{X} \sim M_2(\mathbf{0}, P, \hat{F}_W)$  with  $\mathbb{P}(\mathbf{X} = \mathbf{0}) = 0$ ,  $\rho = P_{12}$ . Then

$$\rho_S = \frac{6}{\pi} \mathbb{E} \left( \arcsin \frac{W\rho}{\sqrt{(W + \tilde{W})(W + \bar{W})}} \right),$$

for  $W, \tilde{W}, \bar{W} \stackrel{\text{ind.}}{\sim} F_W$  with Laplace–Stieltjes transform  $\hat{F}_W$ . For Gauss copulas,  $\rho_S = \frac{6}{\pi} \arcsin(\frac{\rho}{2})$ .

*Proof.* See the appendix. □

### Proposition 7.27 (Kendall's tau for elliptical distributions)

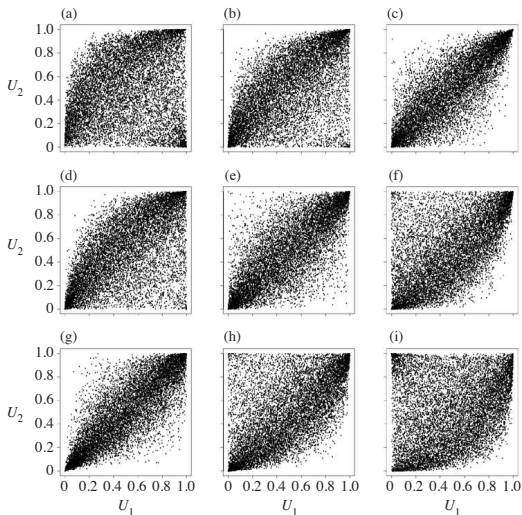
Let  $\mathbf{X} \sim E_2(\mathbf{0}, P, \psi)$  with  $\mathbb{P}(\mathbf{X} = \mathbf{0}) = 0$ ,  $\rho = P_{12}$ . Then  $\rho_\tau = \frac{2}{\pi} \arcsin \rho$ .

*Proof.* See the appendix. □

### 7.3.3 Skewed normal mixture copulas

- *Skewed normal mixture copulas* are the copulas of normal mixture distributions which are not elliptical, e.g. the *skewed  $t$  copula*  $C_{\nu, P, \gamma}^t$  is the copula of a generalized hyperbolic distribution; see McNeil et al. (2015, Sections 6.2.3 and 7.3.3) for more details.
- It can be sampled as other implicit copulas; see Algorithm 7.9 (the evaluation of the margins requires numerical integration of a skewed  $t$  density).
- The main advantage of such a copula over  $C_{\nu, P}^t$  is its radial asymmetry (e.g. for modelling  $\lambda_l \neq \lambda_u$ )

10 000 samples from  $C_{\nu=5, \rho=0.8, \gamma=0.8(I_{\{i<2\}}-I_{\{i>2\}}, I_{\{j>2\}}-I_{\{j<2\}})}$ :



(a)  $\gamma = (0.8, -0.8)$

(b)  $\gamma = (0.8, 0)$

(c)  $\gamma = (0.8, 0.8)$

(d)  $\gamma = (0, -0.8)$

(e)  $\gamma = (0, 0)$

(f)  $\gamma = (0, 0.8)$

(g)  $\gamma = (-0.8, -0.8)$

(h)  $\gamma = (-0.8, 0)$

(i)  $\gamma = (-0.8, 0.8)$



### 7.3.4 Grouped normal mixture copulas

- *Grouped normal mixture copulas* are copulas which attach together a set of normal mixture copulas, e.g. a *grouped  $t$  copula* is the copula of

$$\mathbf{X} = (\sqrt{W_1}Y_1, \dots, \sqrt{W_1}Y_{s_1}, \dots, \sqrt{W_S}Y_{s_1+\dots+s_{S-1}+1}, \dots, \sqrt{W_S}Y_d)$$

for  $(W_1, \dots, W_S) \sim M(\text{IG}(\frac{\nu_1}{2}, \frac{\nu_1}{2}), \dots, \text{IG}(\frac{\nu_S}{2}, \frac{\nu_S}{2}))$  and  $\mathbf{Y} \sim N_d(\mathbf{0}, P)$  (so  $\mathbf{Y} \stackrel{d}{=} A\mathbf{Z}$  as before); see Demarta and McNeil (2005) for details.

- Clearly, the marginals are  $t$  distributed, hence

$$\mathbf{U} = (t_{\nu_1}(X_1), \dots, t_{\nu_1}(X_{s_1}), \dots, t_{\nu_S}(X_{s_1+\dots+s_{S-1}+1}), \dots, t_{\nu_S}(X_d))$$

follows a *grouped  $t$  copula*. This is straightforward to simulate.

- It can be fitted with pairwise inversion of Kendall's tau.
- If  $S = d$ , grouped  $t$  copulas are also known as *generalized  $t$  copulas*; see Luo and Shevchenko (2010).

## 7.4 Archimedean copulas

Recall that an (Archimedean) generator  $\psi$  is a function  $\psi : [0, \infty) \rightarrow [0, 1]$  which is  $\downarrow$  on  $[0, \inf\{t : \psi(t) = 0\}]$  and satisfies  $\psi(0) = 1$ ,  $\psi(\infty) = \lim_{t \rightarrow \infty} \psi(t) = 0$ ; the set of all generators is denoted by  $\Psi$ .

### 7.4.1 Bivariate Archimedean copulas

#### Theorem 7.28 (Bivariate Archimedean copulas)

For  $\psi \in \Psi$ ,  $C(u_1, u_2) = \psi(\psi^{-1}(u_1) + \psi^{-1}(u_2))$  is a copula if and only if  $\psi$  is convex.

- For a strict and twice-continuously differentiable  $\psi$ , one can show that

$$\rho_\tau = 1 - 4 \int_0^\infty t(\psi'(t))^2 dt = 1 + 4 \int_0^1 \frac{\psi^{-1}(t)}{(\psi^{-1}(t))'} dt.$$

- If  $\psi$  is strict,  $\lambda_l = 2 \lim_{t \rightarrow \infty} \frac{\psi'(2t)}{\psi'(t)}$  and  $\lambda_u = 2 - 2 \lim_{t \downarrow 0} \frac{\psi'(2t)}{\psi'(t)}$ .

- The most widely used one-parameter Archimedean copulas are:

Family	$\theta$	$\psi(t)$	$V \sim F = \mathcal{LS}^{-1}(\psi)$
A	$[0, 1)$	$(1 - \theta)/(\exp(t) - \theta)$	Geo( $1 - \theta$ )
C	$(0, \infty)$	$(1 + t)^{-1/\theta}$	$\Gamma(1/\theta, 1)$
F	$(0, \infty)$	$-\log(1 - (1 - e^{-\theta}) \exp(-t))/\theta$	Log( $1 - e^{-\theta}$ )
G	$[1, \infty)$	$\exp(-t^{1/\theta})$	$S(1/\theta, 1, \cos^{\theta}(\pi/(2\theta)), I_{\{\theta=1\}}; 1)$
J	$[1, \infty)$	$1 - (1 - \exp(-t))^{1/\theta}$	Sibuya( $1/\theta$ )

Family	$\rho_{\tau}$	$\lambda_l$	$\lambda_u$
A	$1 - 2(\theta + (1 - \theta)^2 \log(1 - \theta))/(3\theta^2)$	0	0
C	$\theta/(\theta + 2)$	$2^{-1/\theta}$	0
F	$1 + 4(D_1(\theta) - 1)/\theta$	0	0
G	$(\theta - 1)/\theta$	0	$2 - 2^{1/\theta}$
J	$1 - 4 \sum_{k=1}^{\infty} 1/(k(\theta k + 2)(\theta(k - 1) + 2))$	0	$2 - 2^{1/\theta}$

## 7.4.2 Multivariate Archimedean copulas

$\psi$  is *completely monotone (c.m.)* if  $(-1)^k \psi^{(k)}(t) \geq 0$  for all  $t \in (0, \infty)$  and all  $k \in \mathbb{N}_0$ . The set of all c.m. generators is denoted by  $\Psi_\infty$ .

### Theorem 7.29 (Kimberling (1974))

If  $\psi \in \Psi$ ,  $C(\mathbf{u}) = \psi\left(\sum_{j=1}^d \psi^{-1}(u_j)\right)$  is a copula  $\forall d$  if and only if  $\psi \in \Psi_\infty$ .

Bernstein's Theorem characterizes all  $\psi \in \Psi_\infty$ .

### Theorem 7.30 (Bernstein (1928))

$\psi(0) = 1$ ,  $\psi$  c.m. if and only if  $\psi(t) = \mathbb{E}(\exp(-tV))$  for  $V \sim G$  with  $V \geq 0$  and  $G(0) = 0$ .

We thus use the notation  $\psi = \hat{G}$ .

### Proposition 7.31 (Stochastic representation, related properties)

Let  $\psi \in \Psi_\infty$  with  $V \sim G$  such that  $\hat{G} = \psi$  and let  $E_1, \dots, E_d \stackrel{\text{ind.}}{\sim} \text{Exp}(1)$  be independent of  $V$ . Then

- 1) The survival copula of  $\mathbf{X} = (\frac{E_1}{V}, \dots, \frac{E_d}{V})$  is Archimedean (with  $\psi$ ).
- 2)  $\mathbf{U} = (\psi(X_1), \dots, \psi(X_d)) \sim C$  and the  $U_j$ 's are conditionally independent given  $V$  with  $\mathbb{P}(U_j \leq u \mid V = v) = \exp(-v\psi^{-1}(u))$ .

*Proof.*

- 1) The joint survival function of  $\mathbf{X}$  is given by

$$\begin{aligned}\bar{F}(\mathbf{x}) &= \mathbb{P}(X_j > x_j \ \forall j) = \int_0^\infty \mathbb{P}(E_j/V > x_j \ \forall j \mid V = v) dG(v) \\ &= \int_0^\infty \mathbb{P}(E_j > vx_j \ \forall j) dG(v) = \int_0^\infty \prod_{j=1}^d \exp(-vx_j) dG(v) \\ &= \int_0^\infty \exp\left(-v \sum_{j=1}^d x_j\right) dG(v) = \psi\left(\sum_{j=1}^d x_j\right).\end{aligned}$$

The  $j$ th marginal survival function is thus (set  $x_k = 0 \ \forall k \neq j$ )  
 $\bar{F}_j(x_j) = \mathbb{P}(X_j > x_j) = \psi(x_j)$  ( $\downarrow$  and continuous) and therefore  
 $\hat{C}(\mathbf{u}) = \bar{F}(\bar{F}_1^{\leftarrow}(u_1), \dots, \bar{F}_d^{\leftarrow}(u_d)) = \psi(\sum_{j=1}^d \psi^{-1}(u_j))$ .

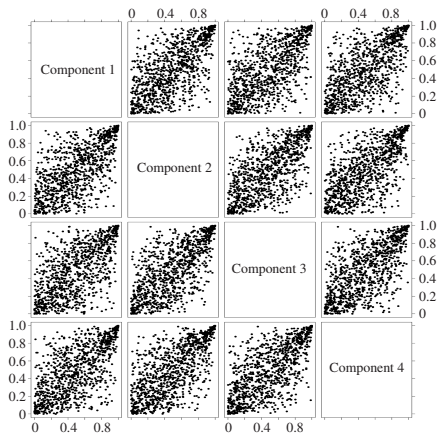
- 2)  $\mathbb{P}(\mathbf{U} \leq \mathbf{u}) = \mathbb{P}(X_j > \psi^{-1}(u_j) \ \forall j) \stackrel{1)}{=} \psi(\sum_{j=1}^d \psi^{-1}(u_j))$ . Conditional independence is clear by construction and  $\mathbb{P}(U_j \leq u \mid V = v) = \mathbb{P}(X_j > \psi^{-1}(u) \mid V = v) = \mathbb{P}(E_j > v\psi^{-1}(u)) = \exp(-v\psi^{-1}(u))$ .  $\square$

We call all Archimedean copulas with  $\psi \in \Psi_\infty$  *LT-Archimedean copulas*.

### Algorithm 7.32 (Marshall and Olkin (1988))

- 1) Sample  $V \sim G$  (df corresponding to  $\psi$ ).
- 2) Sample  $E_1, \dots, E_d \stackrel{\text{ind.}}{\sim} \text{Exp}(1)$  independently of  $V$ .
- 3) Return  $\mathbf{U} = (\psi(E_1/V), \dots, \psi(E_d/V))$  (conditional independence).

1000 samples of a 4-dim. Gumbel copula ( $\rho_\tau = 0.5$ ;  $\lambda_u \approx 0.5858$ )



- For fixed  $d$ , c.m. can be relaxed to  $d$ -monotonicity; see McNeil and Nešlehová (2009).
- Various non-exchangeable extensions to Archimedean copulas exist.

## 7.5 Fitting copulas to data

- Let  $\mathbf{X}, \mathbf{X}_1, \dots, \mathbf{X}_n$  be independent random vectors with **df**  $F$ , continuous **margins**  $F_1, \dots, F_d$  and **copula**  $C$ . We assume we have data  $\mathbf{x}_1, \dots, \mathbf{x}_n$ , interpreted as realizations of  $\mathbf{X}_1, \dots, \mathbf{X}_n$ ; in what follows we work with the latter.
- Assume
  - ▶  $F_j = F_j(\cdot; \boldsymbol{\theta}_{0,j})$  for some  $\boldsymbol{\theta}_{0,j} \in \Theta_j$ ,  $j \in \{1, \dots, d\}$ ;  
( $F_j(\cdot; \boldsymbol{\theta}_j)$  continuous  $\forall \boldsymbol{\theta}_j \in \Theta_j$ ,  $j \in \{1, \dots, d\}$ )
  - ▶  $C = C(\cdot; \boldsymbol{\theta}_{0,C})$  for some  $\boldsymbol{\theta}_{0,C} \in \Theta_C$ .

Thus  $F$  has the true but unknown parameter vector  $\boldsymbol{\theta}_0 = (\boldsymbol{\theta}'_{0,C}, \boldsymbol{\theta}'_{0,1}, \dots, \boldsymbol{\theta}'_{0,d})'$  to be estimated.

- Here, we focus particularly on  $\boldsymbol{\theta}_{0,C}$ . Whenever necessary, we assume that the margins  $F_1, \dots, F_d$  and the copula  $C$  are absolutely continuous with corresponding densities  $f_1, \dots, f_d$  and  $c$ , respectively.



- We assume the chosen copula to be appropriate (w.r.t. symmetry, tail dependence etc.).

## 7.5.1 Method-of-moments using rank correlation

- We focus on one-parameter copulas here, i.e.  $\theta_{0,C} = \theta_0$ .
- For  $d = 2$ , Genest and Rivest (1993) suggested estimating  $\theta_{0,C}$  by solving  $\rho_\tau(\theta_C) = r_n^\tau$  w.r.t.  $\theta_C$ , i.e.

$$\hat{\theta}_{n,C}^{\text{IKTE}} = \rho_\tau^{-1}(r_n^\tau), \quad (\text{inversion of Kendall's tau estimator (IKTE)})$$

where  $\rho_\tau(\cdot)$  denotes Kendall's tau as a function in  $\theta$  and  $r_n^\tau$  is the sample version of Kendall's tau (computed via (29) from  $\mathbf{X}_1, \dots, \mathbf{X}_n$  or pseudo-observations  $U_1, \dots, U_n$ ; see later).

- The standardized dispersion matrix  $P$  for elliptical copulas can be estimated via *pairwise inversion of Kendall's tau*; see McNeil et al. (2015, Example 7.56). If  $r_{n,j_1j_2}^\tau$  denotes the sample version of Kendall's tau for data pair  $(j_1, j_2)$ , then  $\hat{P}_{n,j_1j_2}^{\text{IKTE}} = \sin(\frac{\pi}{2} r_{n,j_1j_2}^\tau)$ ; see Proposition 7.27.

For obtaining a proper correlation matrix  $P$  (positive semi-definite), see Higham (2002).

- ▶ For Gauss copulas, it is preferable to use Spearman's rho based on

$$\rho_S \stackrel{\text{Prop. 7.26}}{=} \frac{6}{\pi} \arcsin \frac{\rho}{2} \approx \rho.$$

The latter approximation error is comparably small, so that the matrix of pairwise sample versions of Spearman's rho is an estimator for  $P$ .

- ▶ For  $t$  copulas,  $\hat{P}_n^{\text{IKTE}}$  can be used to estimate  $P$  and then  $\nu$  can be estimated via its MLE based on  $\hat{P}_n^{\text{IKTE}}$ .

## 7.5.2 Forming a pseudo-sample from the copula

- $X_1, \dots, X_n$  (as good as) never has  $U(0, 1)$  margins. For applying the “copula approach” we thus need *pseudo-observations* from  $C$ .
- In general, we take  $\hat{U}_i = (\hat{U}_{i1}, \dots, \hat{U}_{id}) = (\hat{F}_1(X_{i1}), \dots, \hat{F}_d(X_{id}))$ ,  $i \in \{1, \dots, n\}$ , where  $\hat{F}_j$  denotes an estimator of  $F_j$ ; see Lemma 7.6. Note

that  $\hat{U}_1, \dots, \hat{U}_n$  are typically neither independent (even if  $X_1, \dots, X_n$  are) nor perfectly  $U(0, 1)$ .

■ Possible choices for  $\hat{F}_j$ :

- 1) Non-parametric estimators with scaled empirical dfs (to avoid density evaluation on the boundary of  $[0, 1]^d$ ), so

$$\hat{U}_{ij} = \frac{n}{n+1} \hat{F}_{n,j}(X_{ij}) = \frac{R_{ij}}{n+1}, \quad (31)$$

where  $R_{ij}$  denotes the rank of  $X_{ij}$  among all  $X_{1j}, \dots, X_{nj}$ .

- 2) Parametric estimators (such as Student  $t$ , Pareto, etc.; typically if  $n$  is small). In this case, one often still uses (31) for estimating  $\theta_{0,C}$  (to keep the error due to misspecification of the margins small).
- 3) EVT-based. Bodies are modelled empirically; tails semiparametrically via GPD.

## 7.5.3 Maximum likelihood estimation

### The (classical) maximum likelihood estimator

- By Sklar's Theorem, the density of  $F$  is given by

$$f(x; \theta_0) = c(F_1(x_1; \theta_{0,1}), \dots, F_d(x_d; \theta_{0,d}); \theta_{0,C}) \prod_{j=1}^d f_j(x_j; \theta_{0,j}).$$

- The log-likelihood based on  $\mathbf{X}_1, \dots, \mathbf{X}_n$  is thus

$$\begin{aligned} \ell(\theta; \mathbf{X}_1, \dots, \mathbf{X}_n) &= \sum_{i=1}^n \ell(\theta; \mathbf{X}_i) \\ &= \sum_{i=1}^n \ell_C(\theta_C; F_1(X_{i1}; \theta_1), \dots, F_d(X_{id}; \theta_d)) + \sum_{i=1}^n \sum_{j=1}^d \ell_j(\theta_j; X_{ij}), \end{aligned}$$

where

$$\ell_C(\theta_C; u_1, \dots, u_d) = \log c(u_1, \dots, u_d; \theta_C)$$

$$\ell_j(\theta_j; x) = \log f_j(x; \theta_j), \quad j \in \{1, \dots, d\}.$$

- The *maximum likelihood estimator (MLE)* of  $\theta_0$  is

$$\hat{\theta}_n^{\text{MLE}} = \underset{\theta \in \Theta}{\operatorname{argsup}} \ell(\theta; \mathbf{X}_1, \dots, \mathbf{X}_n).$$

This optimization is typically done by numerical means. Note that this can be quite demanding, especially in high dimensions.

## The inference functions for margins estimator

- Joe and Xu (1996) suggested the *two-step estimation approach*:

**Step 1:** For  $j \in \{1, \dots, d\}$ , estimate  $\theta_{0,j}$  by its MLE  $\hat{\theta}_{n,j}^{\text{MLE}}$ .

**Step 2:** Estimate  $\theta_{0,C}$  by

$$\hat{\theta}_{n,C}^{\text{IFME}} = \underset{\theta_C \in \Theta_C}{\operatorname{argsup}} \ell(\theta_C, \hat{\theta}_{n,1}^{\text{MLE}}, \dots, \hat{\theta}_{n,d}^{\text{MLE}}; \mathbf{X}_1, \dots, \mathbf{X}_n).$$

The *inference functions for margins estimator (IFME)* of  $\theta_0$  is thus

$$\hat{\theta}_n^{\text{IFME}} = (\hat{\theta}_{n,C}^{\text{IFME}}, \hat{\theta}_{n,1}^{\text{MLE}}, \dots, \hat{\theta}_{n,d}^{\text{MLE}})$$

- This is typically much easier to compute than  $\hat{\theta}_n^{\text{MLE}}$  while providing good results; see Joe and Xu (1996) or Kim et al. (2007).
- $\hat{\theta}_n^{\text{IFME}}$  can also be used as initial value for computing  $\hat{\theta}_n^{\text{MLE}}$ .
- In terms of likelihood equations,  $\hat{\theta}_n^{\text{IFME}}$  compares to  $\hat{\theta}_n^{\text{MLE}}$  as follows:

$$\hat{\theta}_n^{\text{MLE}} \text{ solves } \left( \frac{\partial}{\partial \theta_C} \ell, \frac{\partial}{\partial \theta_1} \ell, \dots, \frac{\partial}{\partial \theta_d} \ell \right) = \mathbf{0},$$

$$\hat{\theta}_n^{\text{IFME}} \text{ solves } \left( \frac{\partial}{\partial \theta_C} \ell, \frac{\partial}{\partial \theta_1} \ell_1, \dots, \frac{\partial}{\partial \theta_d} \ell_d \right) = \mathbf{0},$$

where

$$\ell = \ell(\boldsymbol{\theta}; \mathbf{X}_1, \dots, \mathbf{X}_n),$$

$$\ell_j = \ell_j(\boldsymbol{\theta}_j; X_{1j}, \dots, X_{nj}) = \sum_{i=1}^n \ell_j(\boldsymbol{\theta}_j; X_{ij}).$$

### Example 7.33 (A computationally convincing example)

Suppose  $X_j \sim N(\mu_j, \sigma_j^2)$ ,  $j \in \{1, \dots, d\}$ , for  $d = 100$ , and  $C$  has (just) one parameter.

- MLE requires to solve a 201-dimensional optimization problem.
- IFME only requires 100 optimizations in two dimensions and 1 one-dimensional optimization.

If the marginals are estimated parametrically one often still uses the pseudo-observations built from the marginal empirical dfs to estimate  $\theta_{0,C}$  (see MPLE below) in order to avoid misspecification of the margins (if  $n$  is sufficiently large).

## The maximum pseudo-likelihood estimator

- The *maximum pseudo-likelihood estimator (MPLE)*, introduced by Genest et al. (1995), works similarly to  $\hat{\theta}_n^{\text{IFME}}$ , but estimates the margins non-parametrically:

**Step 1:** Compute rank-based pseudo-observations  $\hat{U}_1, \dots, \hat{U}_n$ .

**Step 2:** Estimate  $\theta_{0,C}$  by

$$\hat{\theta}_{n,C}^{\text{MPLE}} = \underset{\theta_C \in \Theta_C}{\operatorname{argsup}} \sum_{i=1}^n \ell_C(\theta_C; \hat{U}_{i1}, \dots, \hat{U}_{id}) = \underset{\theta_C \in \Theta_C}{\operatorname{argsup}} \sum_{i=1}^n \log c(\hat{U}_i; \theta_C).$$

- Genest and Werker (2002) show that  $\hat{\theta}_{n,C}^{\text{MPLE}}$  is not asymptotically efficient in general.
- Kim et al. (2007) compare  $\hat{\theta}_n^{\text{MLE}}$ ,  $\hat{\theta}_n^{\text{IFME}}$ , and  $\hat{\theta}_{n,C}^{\text{MPLE}}$  in a simulation study ( $d = 2$  only!) and argue in favor of  $\hat{\theta}_{n,C}^{\text{MPLE}}$  overall, especially w.r.t. robustness against misspecification of the margins; but see Embrechts and Hofert (2013b) for  $d \gg 2$ .



### Example 7.34 (Fitting the Gauss copula)

- The (copula-related) log-likelihood  $\ell_C$  is

$$\ell_C(P; \hat{U}_1, \dots, \hat{U}_n) = \sum_{i=1}^n \ell_C(P; \hat{U}_i) \stackrel{\text{Eq. (27)}}{=} \sum_{i=1}^n \log c_P^{\text{Ga}}(\hat{U}_i).$$

For maximization over all correlation matrices  $P$ , we can use the Cholesky factor  $A$  as reparameterization and maximize over all lower triangular matrices  $A$  with 1s on the diagonal; still this is  $\mathcal{O}(d^2)$ .

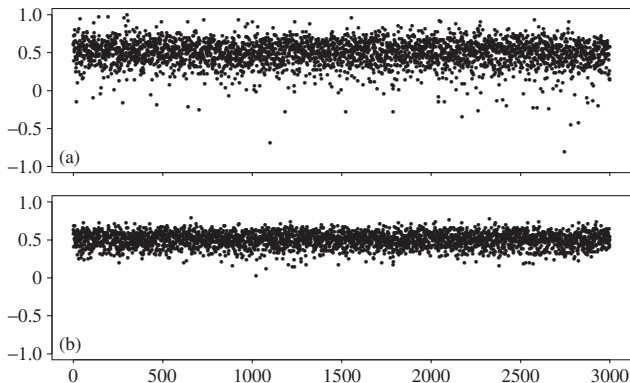
- Alternatively, use pairwise inversion of Spearman's rho or Kendall's tau.

### Example 7.35 (Fitting the $t$ copula)

- For small  $d$ , maximize the likelihood over all correlation matrices (as for the Gauss copula case) and the d.o.f.  $\nu$ .
- For moderate/larger  $d$ , do:
  - 1) Estimate  $P$  via pairwise inversion of Kendall's tau (see above).
  - 2) Plug  $\hat{P}$  into the likelihood and maximize it w.r.t.  $\nu$  to obtain  $\hat{\nu}_n$ .

### Example 7.36 (Correlation estimation for heavy-tailed data)

Consider  $n = 3000$  realizations of independent samples of size 90 from  $t_2(3, \mathbf{0}, (\frac{1}{0.5} \ 0.5))$  ( $\Rightarrow$  linear correlation  $\rho = 0.5$ ). Shall we estimate  $\rho$  via the sample correlation (estimates are shown in (a)) or via inversion of Kendall's tau (shown in (b))? The variance of the latter is smaller:



Estimation is only one side of the coin. The other is *goodness-of-fit* (i.e. to find out whether our estimated model indeed represents the given data well) and *model selection* (i.e. to decide which model is best among all adequate fitted models). Goodness-of-fit can be (computationally) challenging, particularly for large  $d$ . See the appendix for a graphical approach.

## 7.6 A copulas-based proof of subadditivity of ES

### Proposition 7.37 (Subadditivity of ES)

$$\text{ES}_\alpha(L) = \frac{\sup_{\{\tilde{Y} \sim B(1, 1-\alpha)\}} \mathbb{E}(L\tilde{Y})}{1-\alpha}, \text{ which, trivially, is subadditive.}$$

*Proof.* Let  $L = F_L^\leftarrow(U)$  for  $U \sim U(0, 1)$  and  $Y = I_{\{U > \alpha\}} \sim B(1, 1 - \alpha)$ . Then  $\text{ES}_\alpha(L) = \frac{1}{1-\alpha} \int_\alpha^1 F_L^\leftarrow(u) du = \frac{1}{1-\alpha} \int_0^1 F_L^\leftarrow(u) I_{\{u > \alpha\}} \cdot 1 du = \frac{1}{1-\alpha} \mathbb{E}(F_L^\leftarrow(U) I_{\{U > \alpha\}}) = \frac{1}{1-\alpha} \mathbb{E}(LY)$ . Note that  $L$  and  $Y$  are comontone, so that for any other  $\tilde{Y} \sim B(1, 1 - \alpha)$ , Hoeffding's identity implies that  $\mathbb{E}(L\tilde{Y}) \leq \mathbb{E}(LY)$ . Hence  $\text{ES}_\alpha(L) = \frac{\sup_{\{\tilde{Y} \sim B(1, 1-\alpha)\}} \mathbb{E}(L\tilde{Y})}{(1-\alpha)}$ . From this representation,  $\text{ES}_\alpha$  is easily seen to be subadditive.  $\square$

This is also the shortest proof according to Embrechts and Wang (2015). An elementary proof is given in the appendix.