

Parameter estimation for C_R^{Ga} , $C_{\nu,R}^t$, C_θ^{Cl} and C_θ^{Gu}

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$$\begin{aligned}(\rho_\tau)_{ij} &= \rho_\tau(X_{k,i}, X_{k,j}) \\ &= P((X_{k,i} - X_{l,i})(X_{k,j} - X_{l,j}) > 0) - P((X_{k,i} - X_{l,i})(X_{k,j} - X_{l,j}) < 0) \\ &= E(\text{sign}((X_{k,i} - X_{l,i})(X_{k,j} - X_{l,j}))).\end{aligned}$$

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Standard empirical estimator of Kendalls Tau:

$$(\widehat{\rho_\tau})_{ij} = \binom{n}{2}^{-1} \sum_{1 \leq k < l \leq n} \text{sign}((X_{k,i} - X_{l,i})(X_{k,j} - X_{l,j})).$$

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- ▶ Compute the spectral decomposition $\hat{R} = \Gamma \Lambda \Gamma^T$ of \hat{R} , where Λ is a diagonal matrix, containing the eigenvalues of \hat{R} on the diagonal, and Γ is an orthogonal matrix with the eigenvectors of \hat{R} in its columns.

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- ▶ Compute $\tilde{R} = \Gamma\tilde{\Lambda}\Gamma^T$. \tilde{R} is symmetric and positive definite but not necessarily a correlation matrix; the diagonal elements \hat{R}_{ii} might be unequal 1.

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- ▶ Compute $\tilde{R} = \Gamma\tilde{\Lambda}\Gamma^T$. \tilde{R} is symmetric and positive definite but not necessarily a correlation matrix; the diagonal elements \tilde{R}_{ii} might be unequal 1.
- ▶ Set $R^* := D\tilde{R}D$ where D is a diagonal matrix with $D_{k,k} = 1/\sqrt{\tilde{R}_{k,k}}$.

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for $k = 1, 2, \dots, n$ (see Genest und Rivest 1993).

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- ▶ a non-parametric estimation method;
 \hat{F}_i is the empirical distribution function $\hat{F}_i(x) = \frac{1}{n+1} \sum_{t=1}^n I_{\{X_{t,i} \leq x\}}$,
 $1 \leq i \leq d$.

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$$L(\xi; \hat{U}_1, \hat{U}_2, \dots, \hat{U}_n) = \prod_{k=1}^n c_{\xi, R}^t(\hat{U}_k)$$

and $c_{\xi, R}^t$ is the density of the t -copula $C_{\xi, R}^t$.

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This implies

$$\begin{aligned} \ln L(\xi; \hat{U}_1, \hat{U}_2, \dots, \hat{U}_n) = \\ \sum_{k=1}^n \ln g_{\xi, R}(t_{\xi}^{-1}(\hat{U}_{k,1}), \dots, t_{\xi}^{-1}(\hat{U}_{k,d})) - \sum_{k=1}^n \sum_{j=1}^d \ln g_{\xi}(t_{\xi}^{-1}(\hat{U}_{k,j})), \end{aligned}$$

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where $g_{\xi, R}$ is the cumulative density function of a d -dimensional standard t -distribution with ξ degrees of freedom and correlation matrix R , and g_{ξ} is the density function of a univariate standard t -distribution with ξ degrees of freedom.