

HOMEWORK 5 SUGGESTED SOLUTION

DUE DATE: 1 MAR 2017 (THU)

1. Since C is a multivariate distribution function,

$$C(u, v) \leq C(u, 1) = u, \quad C(u, v) \leq C(1, v) = v.$$

Therefore $C(u, v) \leq \min\{u, v\}$. On the other hand,

$$C(u, v) = \mathbb{P}(U \leq u, V \leq v) = \mathbb{P}(U \leq u) + \mathbb{P}(V \leq v) - \mathbb{P}(\{U \leq u\} \cup \{V \leq v\}) \geq u + v - 1.$$

Also, as C is a distribution function, $C(u, v) \geq 0$, so $C(u, v) \geq \max\{u + v - 1, 0\}$.

2. It is straightforward to see that

$$\text{sign} \left[(X_t - X_s) \left(\frac{1}{Y_t} - \frac{1}{Y_s} \right) \right] = -\text{sign} [(X_t - X_s)(Y_t - Y_s)]$$

and

$$\text{sign} \left[\left(\frac{1}{X_t} - \frac{1}{X_s} \right) \left(\frac{1}{Y_t} - \frac{1}{Y_s} \right) \right] = \text{sign} [(X_t - X_s)(Y_t - Y_s)].$$

Thus we have

$$\begin{aligned} \tau(X, 1/Y) &= -\tau(X, Y) = -0.55 \\ \tau(1/X, 1/Y) &= \tau(X, Y) = 0.55. \end{aligned}$$

3. Since Y is a monotone transformation of X (note that X is positive), any rank correlation will be 1. More rigorously, we can prove using the definitions of Kendall's τ and Spearman's ρ .

- For Kendall's τ , note that $(X_t - X_s)(Y_t - Y_s) = (X_t - X_s)(X_t^2 - X_s^2) > 0$ almost surely for $X_t, X_s \stackrel{iid}{\sim} \text{Uniform}(0, 1)$, so $\text{sign} [(X_t - X_s)(Y_t - Y_s)] = 1$ almost surely. Therefore,

$$\tau = E \{ \text{sign} [(X_t - X_s)(Y_t - Y_s)] \} = E(1) = 1.$$

- For Spearman's ρ . We can actually prove that $F(X) = G(Y)$. This is because $G(y) = P(Y \leq y) = P(X \leq \sqrt{y}) = F(\sqrt{y})$ for $0 \leq y \leq 1$. Therefore $G(Y) = F(\sqrt{Y}) = F(\sqrt{X^2}) = F(X)$. As a result, we have $\rho(X, Y) = \text{Corr}[F(X), G(Y)] = 1$.
- For Pearson's correlation, $\text{Corr}(X, Y) = 1$ if and only if $Y = aX + b$ for some $a > 0$ and $b \in \mathbb{R}$ almost surely. But obviously Y is not a linear function of X so the Pearson correlation should be less than 1. (You can also just compute the Pearson's correlation and find that it is less than 1).

4. Solution 1: Observe that

$$\exp\{-[(-\log \min(u, v))^\alpha + (-\log \min(u, v))^\alpha]^{1/\alpha}\} \leq \exp\{-[(-\log u)^\alpha + (-\log v)^\alpha]^{1/\alpha}\} \leq \min(u, v).$$

The first term can be simplified to $\exp\{2^{1/\alpha} \log \min(u, v)\} = \exp\{2^{1/\alpha}\} \min(u, v) \rightarrow \min(u, v)$ as $\alpha \rightarrow \infty$. By sandwich theorem, the result follows.

Alternative solution: If $u = v$,

$$C_\alpha(u, v) = \exp\{-2^{1/\alpha}(-\log u)\} \rightarrow u \quad \text{as } \alpha \rightarrow \infty.$$

If $u < v$, define

$$f(\alpha) := -\log C_\alpha(u, v) = [(-\log u)^\alpha + (-\log v)^\alpha]^{1/\alpha}.$$

Note that

$$\begin{aligned} \lim_{\alpha \rightarrow \infty} \log f(\alpha) &= \lim_{\alpha \rightarrow \infty} \frac{1}{\alpha} \log[(-\log u)^\alpha + (-\log v)^\alpha] \\ &= \lim_{\alpha \rightarrow \infty} \frac{(-\log u)(-\log u)^\alpha + (-\log v)(-\log v)^\alpha}{[(-\log u)^\alpha + (-\log v)^\alpha]} \\ &= \lim_{\alpha \rightarrow \infty} \frac{-\log u + (-\log v)\left(\frac{-\log v}{-\log u}\right)^\alpha}{1 + \left(\frac{-\log v}{-\log u}\right)^\alpha} \\ &= -\log u. \end{aligned}$$

The last equality follows as $-\log v < -\log u$ when $u < v$, which gives $\left(\frac{-\log v}{-\log u}\right)^\alpha \rightarrow 0$ as $\alpha \rightarrow \infty$. Hence, $C_\alpha(u, v) \rightarrow u$ as $\alpha \rightarrow \infty$. By symmetry, the case $v < u$ is the same and the required statement is proved.

5. Remark: $C_{\text{Gaussian}}(u, v) = \Phi_2(\Phi^{-1}(u), \Phi^{-1}(v))$.

(a)

$$\text{Price} = 1000000 \times e^{-0.04}(0.0346 + 0.0346 - C_{\text{Gaussian}}(0.0346, 0.0346)) = 59495.17.$$

(b)

$$\text{Price} = 1000000 \times e^{-0.04}(C_{\text{Gaussian}}(0.0346, 0.0346)) = 6991.463.$$

R Code:

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library(mvtnorm)
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C = pmvnorm(lower = c(-Inf, -Inf), upper = c(qnorm(0.0346), qnorm(0.0346)),
sigma = matrix( c(1, 0.5, 0.5, 1), 2, 2))
```

```
# (a)
```

```
price = 1000000*exp(-0.04)*(0.0346 + 0.0346 - C)
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```
# (b)
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```
price = 1000000*exp(-0.04)*C
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6. Denote F_A and F_B as the CDF of T_A and T_B . From the problem we know that the joint CDF of $(F_A(T_A), F_B(T_B))$ is the Gumbel copula with $\alpha = 2$.

$$F_A(1) = P(T_A \leq 1) = 1 - e^{-0.01} = 0.00995$$

$$F_B(1) = P(T_B \leq 1) = 1 - e^{-0.02} = 0.0198$$

$$\begin{aligned} P(T_A \leq 1, T_B \leq 1) &= P(F_A(T_A) \leq F_A(1), F_B(T_B) \leq F_B(1)) \\ &= \exp \left[- \left\{ (-\log F_A(1))^2 + (-\log F_B(1))^2 \right\}^{1/2} \right] = 0.00235 \end{aligned}$$

$$P(T_A \leq 1 \text{ or } T_B \leq 1) = P(T_A \leq 1) + P(T_B \leq 1) - P(T_A \leq 1, T_B \leq 1) = 0.0274$$

7. Fair value = expected payoff = $10^6 \times 0.00235 = 2350$.

For $\alpha = 1$, $P(T_A \leq 1, T_B \leq 1) = 0.000197$, so Fair value = 197.