

**Quantifying the correlation of
bivariate survival times by means of
a novel self-consistency approach**

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Contents

- Practical relevance
- Current approaches
- Novel Iterative Multiple Imputation approach
(‘self-consistency’)
- Three case studies
- Comparative empirical investigations

Practical relevance

- Correlations within pairs of possibly censored survival times are of interest in the analysis of :
 - Survival-type endpoints in studies of twins
 - Times till failure of paired organs
 - Surrogate survival-type endpoints
- Quantification by Kendall's τ or Spearman's r_s

Estimating correlations under censoring

- Fully non-parametric approaches based on the Kaplan-Meier estimate on the plane (i.e., for a bivariate survival function)
 - ‘finite region’ estimates of correlation, if bivariate survival function does not drop to zero.
- Semiparametric approaches have a
 - non-parametric component* – transformation of survival times to survival probabilities, using Kaplan-Meier – and a
 - parametric component* – a parametric bivariate distribution is fitted over the whole range of transformed times
 - ‘infinite region’ estimates of correlation (better interpretable, but extrapolation)

Copula approach (1)

Copula: bivariate parametric distribution with uniform margins U and V . Time $T_1 \rightarrow U$, time $T_2 \rightarrow V$.

A single parameter θ governs degree of correlation:

Clayton $(u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}$

Gumbel $\exp\left\{-\left[(-\log u)^\theta + (-\log v)^\theta\right]^{1/\theta}\right\}$

Frank $-\frac{1}{\theta} \log\left\{1 + \frac{[\exp(-\theta u) - 1][\exp(-\theta v) - 1]}{[\exp(-\theta) - 1]}\right\}$

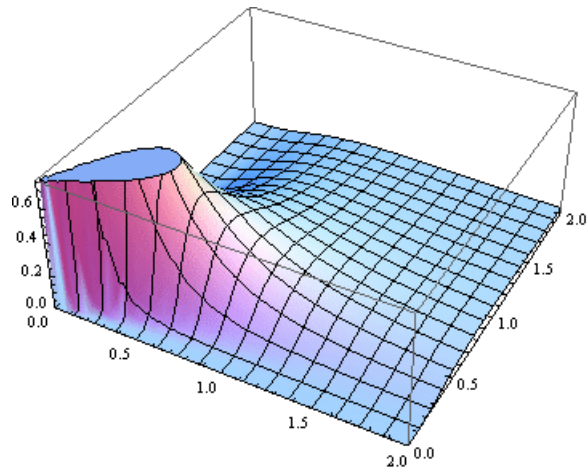
Normal $\int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta^2}} \exp\left[-\frac{s_1^2 - 2\theta s_1 s_2 + s_2^2}{2(1-\theta^2)}\right] ds_1 ds_2$

Bivariate
distribution
functions

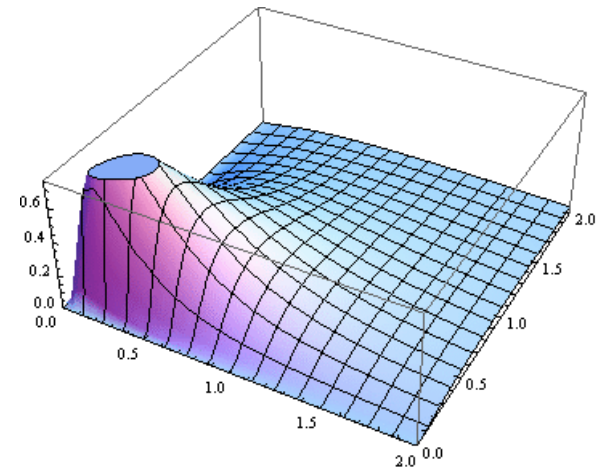
Copula approach (2)

Densities of copulas for $r_s=0.6$, lognormal marginal survival

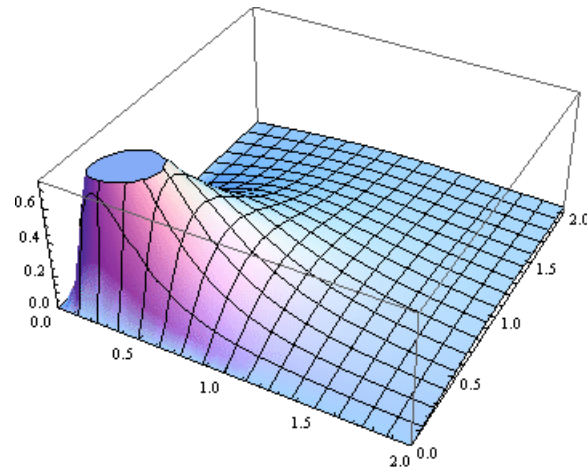
Clayton



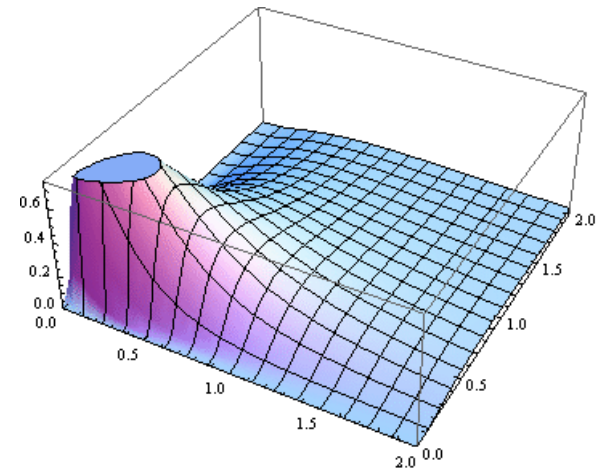
Gumbel



Frank



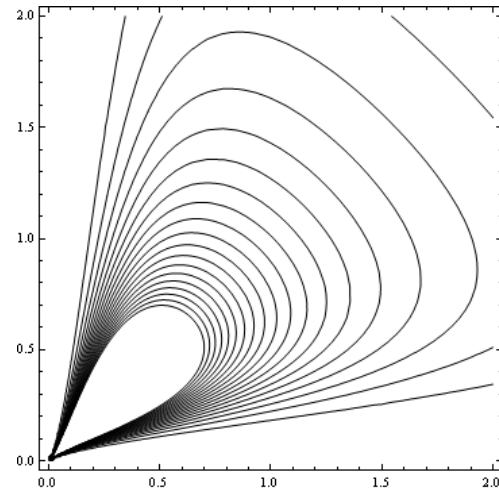
Normal



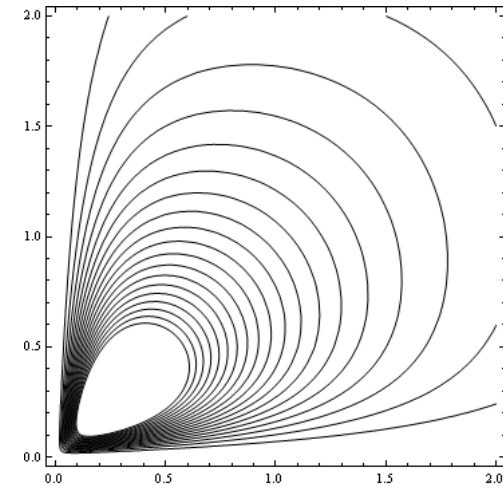
Copula approach (3)

Contour plots of copulas for $r_s = 0.6$

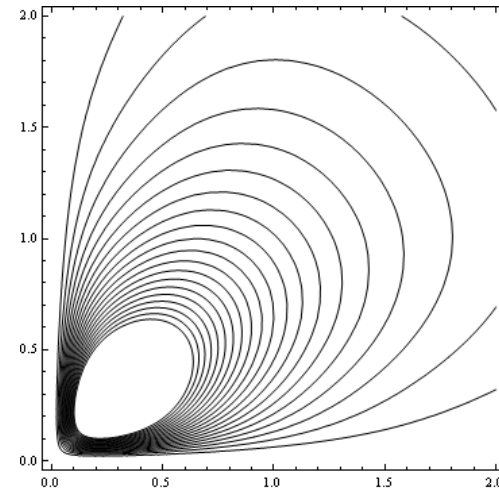
Clayton



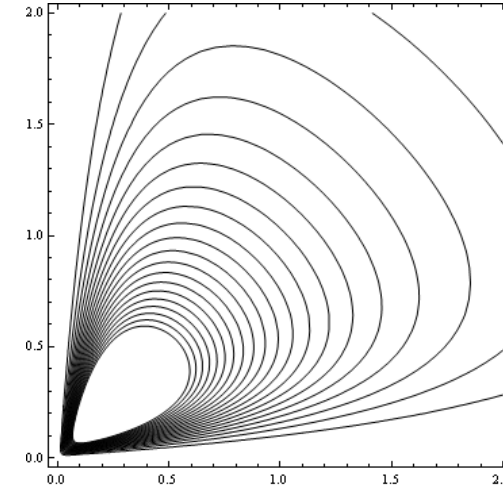
Gumbel



Frank



Normal



Iterative Multiple Imputation, IMI (Self-consistency approach)

Principle steps of algorithm:

1. Transform T_1 and T_2 to normal deviates N_1 and N_2

$$N_1 = \Phi^{-1}(S(T_1)) \quad N_2 = \Phi^{-1}(S(T_2))$$

normal copula idea

2. Obtain a starting value r_0 of the Pearson correlation from uncensored pairs (N_1, N_2)

normal scores Spearman

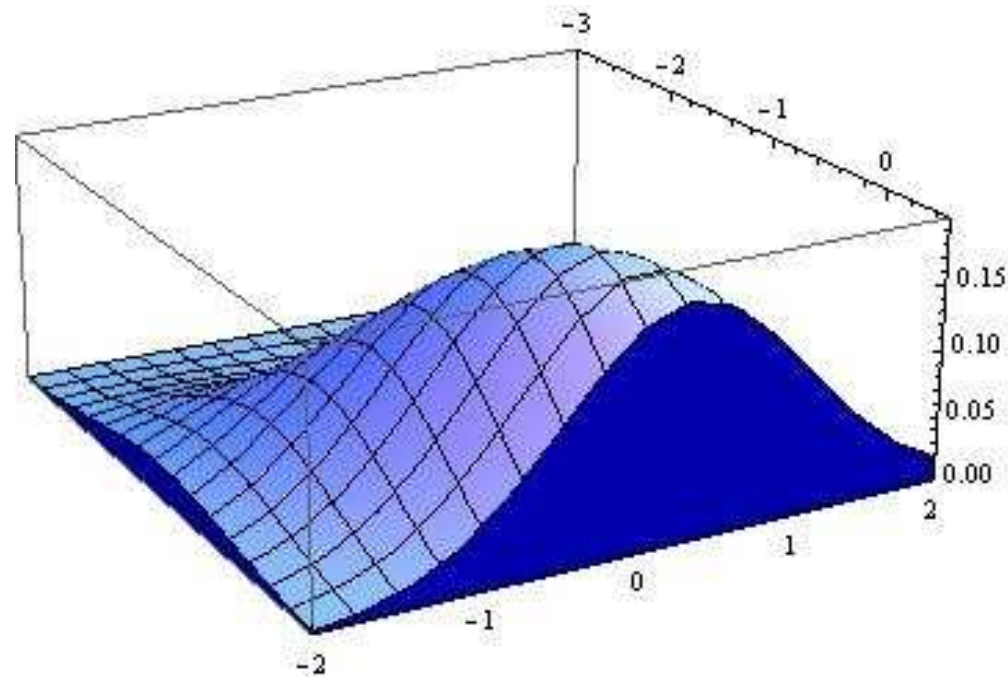
Iterative Multiple Imputation, IMI (2)

3. Produce M data sets with ‘uncensored’ N_1 and N_2 :
 - uncensored N_1 and N_2 are copied to each data set
 - censored N_1 and/or N_2 are made ‘uncensored’ by imputation, conditional on the censoring values N_1 and N_2 and using conditional normal distributions:
e.g., $N_1 : N\left(r_0 N_2, (1 - r_0^2)\right)$
 - with both N_1 and N_2 censored a few MCMC steps are required.

Iterative Multiple Imputation, IMI (2a)

Conditional normal distributions:

$$N_1 : N(r_0 N_2, (1 - r_0^2))$$



Iterative Multiple Imputation, IMI (3)

4. For each of the M data sets obtain r_1 from all, now 'uncensored' N_1 and N_2 .
5. For each of the M data sets update the imputed N_1 and/or N_2 using r_1 .
6. The iterative process of **updating** N_1 and/or N_2 and then **updating** r is repeated until convergence of r within each data set.
7. The reported value of r is the average from the M data sets.

Iterative Multiple Imputation, IMI (4)

95% Confidence intervals for r :

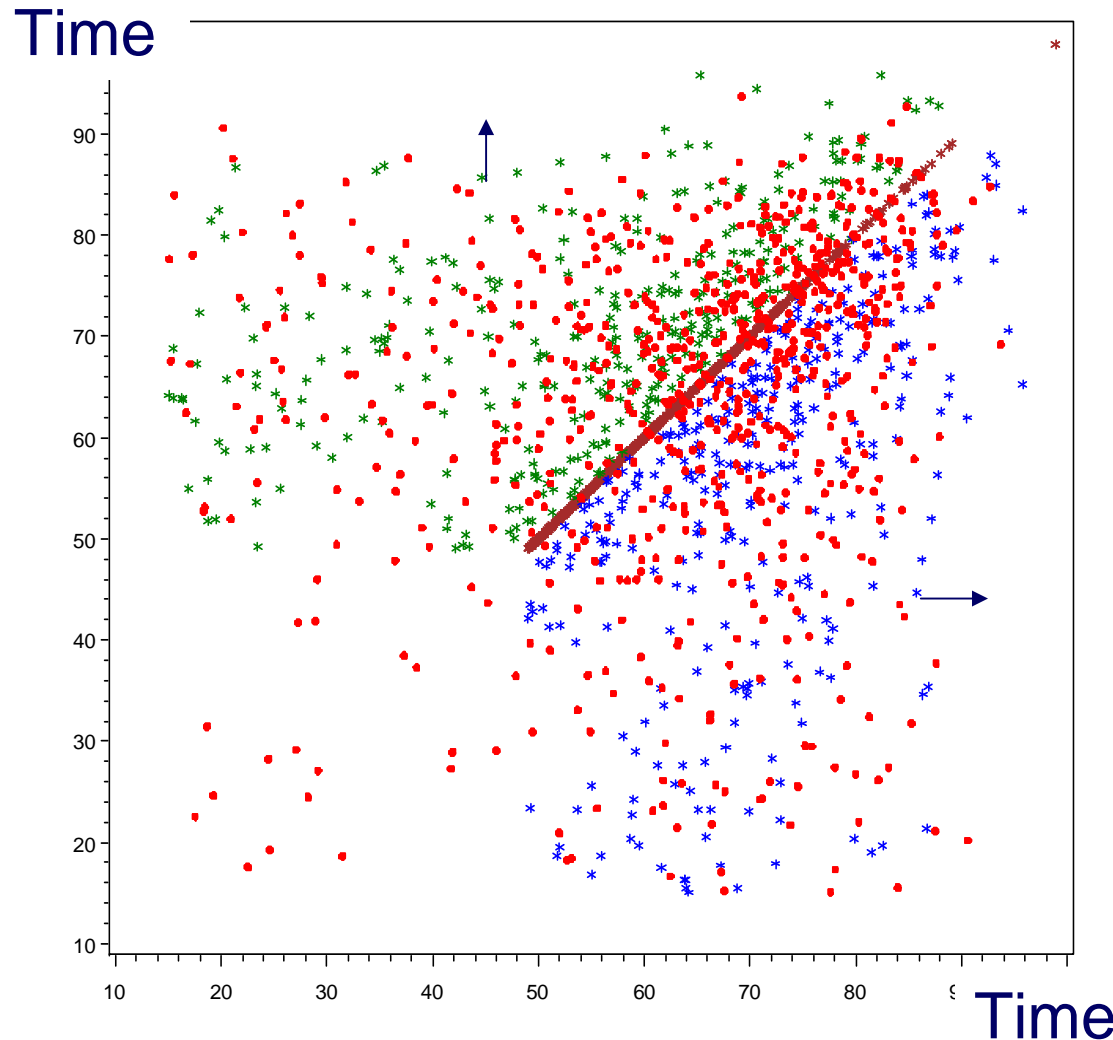
$$\left[\tanh(\varphi \pm 1.96 SE(\varphi)) \right]$$

where $\varphi = \tanh^{-1}(r)$

and $SE(\varphi)$ is obtained from the ‘within’ and ‘between’ data sets variance of φ (Rubin, 1987)

Example 1

Danish Twin Survival Study (male, monozygotic)
(n = 1366, % censored times = 61)



Spearman correlations:

Copulas:

Clayton: $r_S = 0.10$

Gumbel: $r_S = 0.22$ ←

Frank: $r_S = 0.20$

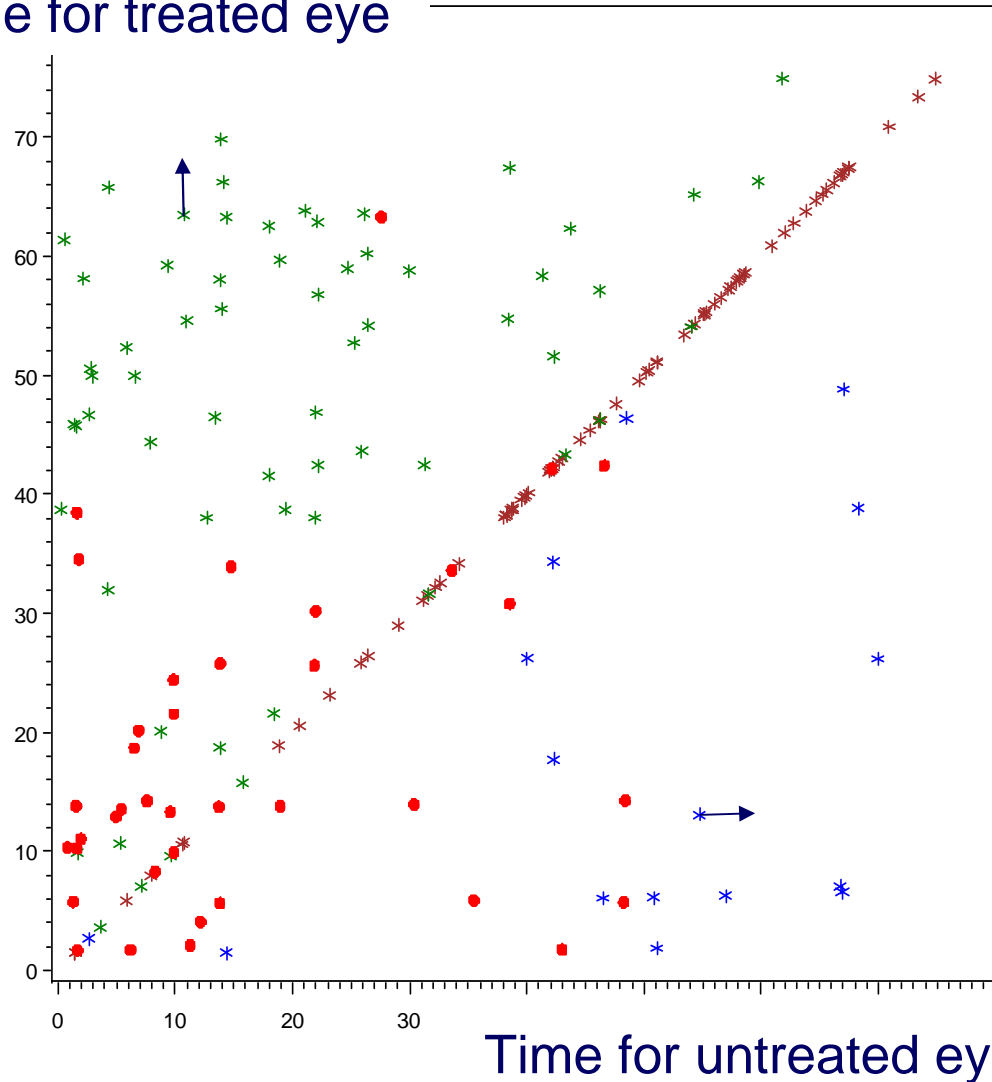
Normal: $r_S = 0.18$

IMI: $r_S = 0.22$

Example 2

Diabetic Retinopathy Study (n = 197, % censored times = 61)

Time for treated eye



Spearman correlations:

Copulas:

Clayton: $r_S = 0.22$

Gumbel: $r_S = 0.42$

Frank: $r_S = 0.37$ ←

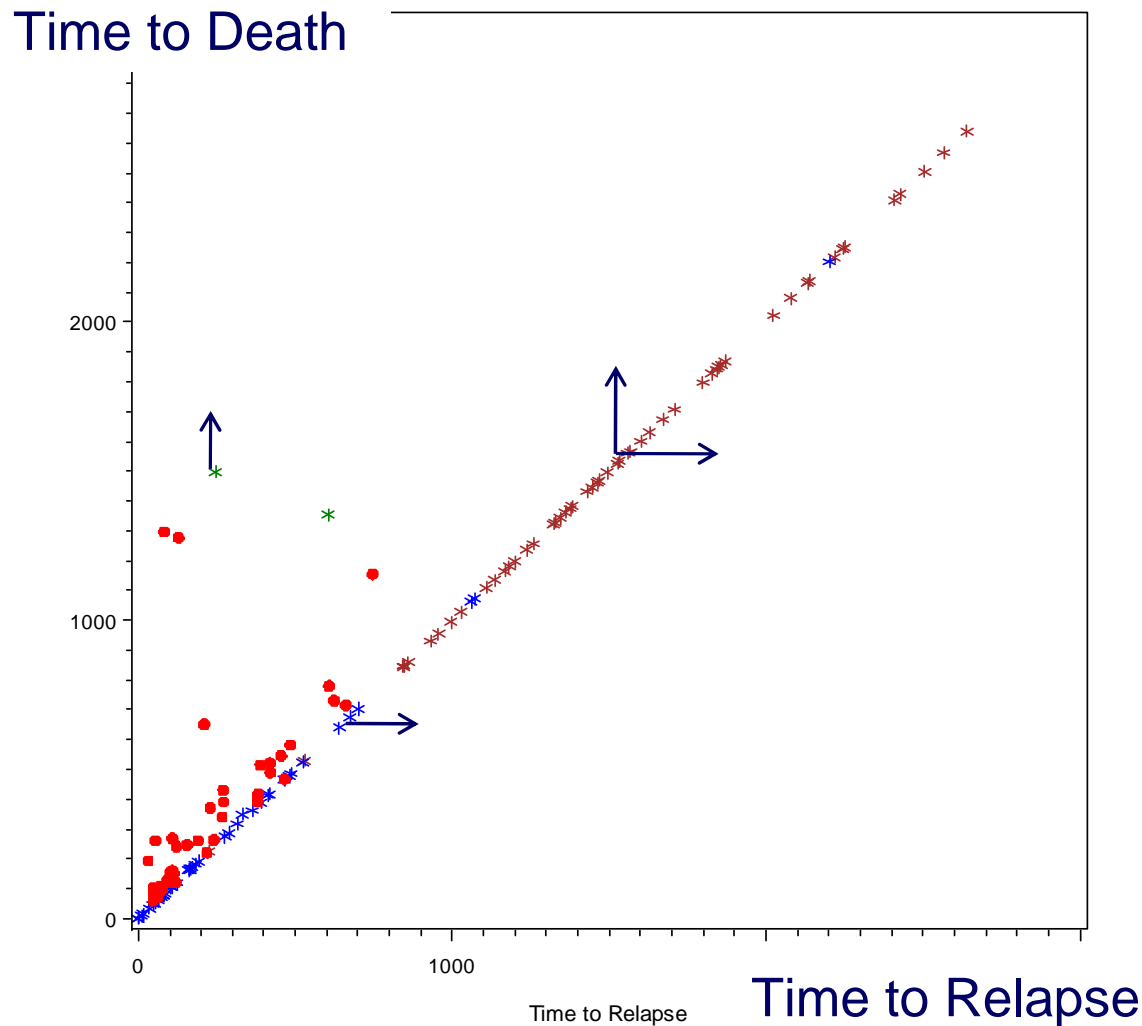
Normal: $r_S = 0.35$

IMI: $r_S = 0.35$

Example 3

Bone Marrow Transplant Study

(n = 137, % censored: 41 (death) / 69 (relapse))



Spearman correlations:

Copulas:

Clayton: $r_S = 0.62$

Gumbel: $r_S = 0.83$ ←

Frank: $r_S = 0.80$

Normal: $r_S = 0.79$

IMI: $r_S = 0.85$

Bivariate - exponential survival times

Entries: IMI / Normal Copula

r (population)	%cens = 30	%cens = 60	%cens = 90
0.0	0.00 / 0.00	0.00 / 0.00	0.00 / 0.02
0.3	0.30 / 0.28	0.30 / 0.28	0.30 / 0.29
0.6	0.60 / 0.58	0.60 / 0.58	0.60 / 0.56
0.9	0.90 / 0.89	0.90 / 0.90	0.90 / 0.89

$N = 10.000$

Gumbel survival times

Entries: IMI / Normal Copula

<i>r</i> (population)	%cens = 30	%cens = 60	%cens = 90
0.0	0.00 / 0.00	0.00 / 0.00	0.00 / 0.00
0.3	0.30 / 0.29	0.27 / 0.26	0.22 / 0.23
0.6	0.60 / 0.58	0.56 / 0.54	0.50 / 0.48
0.9	0.89 / 0.88	0.88 / 0.86	0.84 / 0.83

$N = 10.000$

Clayton survival times

Entries: IMI / Normal Copula

<i>r</i> (population)	%cens = 30	%cens = 60	%cens = 90
0.0	0.00 / 0.00	0.00 / 0.00	0.00 / 0.00
0.3	0.36 / 0.35	0.42 / 0.42	0.57 / 0.57
0.6	0.67 / 0.66	0.75 / 0.75	0.88 / 0.87
0.9	0.93 / 0.92	0.97 / 0.96	0.97 / 0.99

$N = 10.000$

Concluding remarks

- Normal copula has been considered as unsuitable for censored survival data and/or intractable – neither is the case as we have shown.
- In the examples IMI was always close to the copula chosen.
- We recommend either the semiparametric copula approach, choosing a certain copula by its max lik, or the IMI approach.
- The procedures discussed have been implemented in SAS-macros and R- functions and will be available for download from our website.