Example of Independence (Slud piecewise)

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The pairwise example in Slud's paper

The joint distribution is:

$$f(t,s) = \begin{cases} f_1(t)f_C(s) & (t \le s) \\ f_C(s)\frac{S_1(s)}{S_2(s)}f_2(t) & (t > s) \end{cases}$$

Let

•
$$f_1(t) = \exp(-t), S_1(s) = \exp(-x)$$

•
$$f_C(s) = \exp(-s), S_C(s) = \exp(-s)$$

•
$$f_2(t) = \rho \exp(-\rho t)$$
, $S_2(s) = |exp(-\rho t)|$

•
$$\rho(t) = \frac{h_2(t)}{h_1(t)} = \rho$$
, which is a constant.

Then

$$f(t,s) = \begin{cases} \exp(-t-s) & (t \le s) \\ \rho \exp(-\rho t + (\rho-2)s) & (t > s) \end{cases}$$

And

$$f(t) = \frac{2\rho - 2}{\rho - 2} \exp(-2t) - \frac{\rho}{\rho - 2} \exp(-\rho t)$$
$$S(t) = \frac{\rho - 1}{\rho - 2} \exp(-2t) - \frac{1}{\rho - 2} \exp(-\rho t)$$
$$\psi(t) = \exp(-2t)$$

$$S_{x}(x) = P(X = T \land C > x) = P(T > x, C > x) = P(T > C > x) + P(C > T > x)$$

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$$= \int_{x}^{\infty} \int_{x}^{t} f(t, s) ds dt + \int_{x}^{\infty} \int_{x}^{s} f(t, s) dt ds$$

$$= \int_{x}^{\infty} \int_{x}^{t} \rho \exp(-\rho t + (\rho - 2)s) ds dt + \int_{x}^{\infty} \int_{x}^{t} \exp(-t - s) dt ds$$

$$= \int_{x}^{\infty} \rho \left(\frac{\exp(-2t)}{\rho - 2} - \frac{\exp(\rho x - 2x - \rho t)}{\rho - 2}\right) dt + \int_{x}^{\infty} \exp(-x - s) ds$$

$$= \frac{\rho}{\rho - 2} \frac{\rho - 2}{2\rho} \exp(-2x) + \frac{\exp(-2x)}{2\rho}$$

$$= \exp(-2x)$$

Therefore,

$$S_H(t) = S_x(t) = \exp(-2t), \lambda_H(t) = 2$$
, (consistent to previous notation))

Then the m() function is

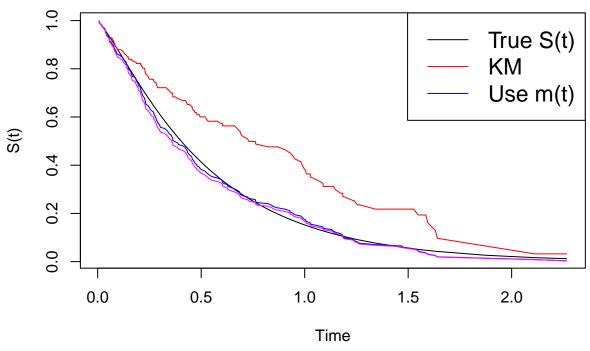
$$m(t) = \frac{\lambda_F(t)}{\lambda_H(t)} = \frac{\frac{\frac{2\rho - 2}{\rho - 2}\exp(-2t) - \frac{\rho}{\rho - 2}\exp(-\rho t)}{\frac{\rho - 1}{\rho - 2}\exp(-2t) - \frac{1}{\rho - 2}\exp(-\rho t)}}{2} = \frac{(2\rho - 2)\exp(-2t) - \rho\exp(-\rho t)}{2(\rho - 1)\exp(-2t) - 2\exp(-\rho t)}$$

And from the above formula, we can know that when $\rho = 1$, $m(t) = \frac{1}{2}$.

Let's an add parameter in the m(t) function:

$$m_{\theta}(t) = \frac{\lambda_F(t)}{\lambda_H(t)} = \frac{(2\theta - 2)\exp(-2t) - \theta\exp(-\theta t)}{2(\theta - 1)\exp(-2t) - 2\exp(-\theta t)}$$

Then we could estimate the θ by calulating the MLE. Since it is hard to solve the $\hat{\theta}$, Newton Raphson method is applied.



mean(abs(fit_km\$surv - S(fit_km\$time)))

[1] 0.1183952

mean(abs(sest - S(fit_km\$time)))

[1] 0.0156356

mean(abs(sest_est - S(fit_km\$time)))

[1] 0.0253022