

Exercise 5.1

The counting processes $N_i(t)$; $i = 1, 2, \dots, n$; have intensity processes of the form $\lambda_i(t) = Y_i(t)e^\beta$, where the $Y_i(t)$ are at risk indicators. We introduce $R_i(t) = \int_0^t Y_i(u) du$ and remember that a ‘dot’ indicates summation over i .

a) The log likelihood is

$$\begin{aligned} \ell(\beta) &= \sum_{i=1}^n \int_0^\tau \log \lambda_i(t) dN_i(t) - \int_0^\tau \lambda_i(t) dt \\ &= \sum_{i=1}^n \int_0^\tau \log \{Y_i(t)e^\beta\} dN_i(t) - \int_0^\tau Y_i(t)e^\beta dt \\ &= \beta \sum_{i=1}^n \int_0^\tau dN_i(t) - e^\beta \int_0^\tau Y_i(t) dt \\ &= \beta N_*(\tau) - e^\beta R_*(\tau). \end{aligned}$$

The score function is

$$U(\beta) = \ell'(\beta) = N_*(\tau) - e^\beta R_*(\tau)$$

The score equation $U(\beta) = 0$ is solved by

$$e^{\hat{\beta}} = \frac{N_*(\tau)}{R_*(\tau)}$$

which gives

$$\hat{\beta} = \log \left(\frac{N_*(\tau)}{R_*(\tau)} \right) = \log \hat{\nu}$$

b) The observed information is

$$I(\beta) = -U'(\beta) = e^\beta R_*(\tau)$$

and hence

$$I(\hat{\beta}) = e^{\hat{\beta}} R_*(\tau) = \frac{N_*(\tau)}{R_*(\tau)} R_*(\tau) = N_*(\tau)$$

It follows that $\hat{\beta}$ is approximately normally distributed around the true value of β with a variance that may be estimated by $1/I(\hat{\beta}) = 1/N_*(\tau)$.

c) The standard 95% confidence interval for β is

$$\hat{\beta} \pm \frac{1.96}{\sqrt{N_*(\tau)}}$$

By exponentiating both endpoints, we find that

$$\exp \left\{ \hat{\beta} \pm \frac{1.96}{\sqrt{N_*(\tau)}} \right\} = \hat{\nu} \exp \left\{ \pm \frac{1.96}{\sqrt{N_*(\tau)}} \right\}$$

is an approximate 95% confidence interval for $\nu = e^\beta$.

Exercise 5.4

The counting processes $N_i(t)$; $i = 1, 2, \dots, n$; have intensity processes of the form $\lambda_i(t) = \nu Y_i(t)$, where the $Y_i(t)$ are at risk indicators. We introduce $R_i(t) = \int_0^t Y_i(u) du$ and remember that a ‘dot’ indicates summation over i .

a) The log-likelihood is

$$\begin{aligned} \ell(\nu) &= \sum_{i=1}^n \int_0^\tau \log \lambda_i(t) dN_i(t) - \int_0^\tau \lambda_{\cdot}(t) dt \\ &= \sum_{i=1}^n \int_0^\tau \log \{\nu Y_i(t)\} dN_i(t) - \int_0^\tau \nu Y_{\cdot}(t) dt \\ &= \log \nu \int_0^\tau dN_{\cdot}(t) - \nu \int_0^\tau Y_{\cdot}(t) dt \\ &= (\log \nu) N_{\cdot}(\tau) - \nu R_{\cdot}(\tau) \end{aligned}$$

The score function is

$$U(\nu) = \ell'(\nu) = \frac{N_{\cdot}(\tau)}{\nu} - R_{\cdot}(\tau) \quad (\text{E.1})$$

b) When ν is the true value of the parameter, we know that

$$M_i(t) = N_i(t) - \int_0^t \lambda_i(t) dt = N_i(t) - \nu \int_0^t Y_i(t) dt$$

is a mean zero martingale. By aggregating over i we find that

$$M_{\cdot}(t) = N_{\cdot}(t) - \nu R_{\cdot}(t) \quad (\text{E.2})$$

is a mean zero martingale. From (E.1) we then obtain when ν is the true value of the parameter

$$U(\nu) = \frac{M_{\cdot}(\tau) + \nu R_{\cdot}(\tau)}{\nu} - R_{\cdot}(\tau) = \frac{M_{\cdot}(\tau)}{\nu} \quad (\text{E.3})$$

Now $E\{M_{\cdot}(\tau)\} = 0$ and [cf. (2.24) and (2.43) in the ABG-book]

$$\text{Var}\{M_{\cdot}(\tau)\} = E\langle M_{\cdot} \rangle(\tau) = E \left\{ \int_0^\tau \lambda_{\cdot}(t) dt \right\} = \nu E \left\{ \int_0^\tau Y_{\cdot}(t) dt \right\} = \nu E\{R_{\cdot}(\tau)\}$$

From (E.3) we then get that $E\{U(\nu)\} = 0$ and

$$\text{Var}\{U(\nu)\} = \frac{\text{Var}\{M_{\cdot}(\tau)\}}{\nu^2} = \frac{E\{R_{\cdot}(\tau)\}}{\nu}$$

when ν is the true parameter value.

c) By (E.1) the observed information is

$$I(\nu) = -U'(\nu) = \frac{N_*(\tau)}{\nu^2} \tag{E.4}$$

Using (E.2) we may write when ν is the true value of the parameter

$$I(\nu) = \frac{M_*(\tau) + \nu R_*(\tau)}{\nu^2} = \frac{M_*(\tau)}{\nu^2} + \frac{R_*(\tau)}{\nu}$$

and by taking expectations, we find $E\{I(\nu)\} = E\{R_*(\tau)\}/\nu$.