Nelson-Aalen & Kaplan-Meier

Basic Relations
$S(t) = \exp(-\int_0^t \alpha(s)ds)$ $\quad A(t) = \int_0^t \alpha(s)ds$ $\quad -S'(t) = \alpha(t)S(t)$ $\quad f(t) = \alpha(t)S(t)$ $\quad P(T > x|T > y) = \frac{P(T>x)}{P(T>y)} = \frac{S(x)}{S(y)}$
$\lambda(s) = \alpha(s)Y(s)$

Nelson-Aalen Non-parametric estimator of the cumulative hazard rate. $A(t) = \int_0^t \alpha(u)du$ where $\alpha(t)$ is the hazard rate at time t.

Formulas $\hat{A}(t) = \sum_{T_j \leq t} \Delta\hat{A}(T_j)$
No ties $\Delta\hat{A}(T_j) = \frac{1}{Y(T_j)}$ Rounded Ties $\Delta\hat{A}(T_j) = \sum_{k=1}^{d_j-1} \frac{1}{Y(T_j)-k}$ True Ties $\Delta\hat{A}(T_j) = \frac{d_j}{Y(T_j)}$
$\hat{\sigma}^2_{\text{N-A}}(t) = \sum_{T_j \leq t} \Delta\hat{\sigma}^2(T_j)$
No ties $\Delta\hat{\sigma}^2(T_j) = \frac{1}{Y(T_j)^2}$ Rounded Ties $\Delta\hat{\sigma}^2(T_j) = \sum_{k=1}^{d_j-1} \frac{1}{(Y(T_j)-k)^2}$ True Ties $\Delta\hat{\sigma}^2(T_j) = \frac{(Y(T_j)-d_j)d_j}{Y(T_j)^3}$

Derivation of the Nelson-Aalen Estimator. $M(t)$ is a mean-zero m.g. $H(t) = \frac{J(t)}{Y(t)}$ is predictable where $J(t) = \mathbf{1}(Y(t) > 0)$. We then get $\hat{A}(t) = \int_0^t H(s)dN(s) = \int_0^t \alpha(s)J(s)ds + \int_0^t \frac{J(s)}{Y(s)}dM(s)$. As $M(t)$ is mean-zero m.g. we then get that the Nelson-Aalen estimator is a unbiased estimator of $A^*(t) = \int_0^t \alpha(s)J(s)ds$ since $\mathbb{E}\left[\hat{A}(t) - A^*(t)\right] = 0$. $\hat{A}(t)$ is however a biased estimator of $A(t)$ since $\mathbb{E}[J(s)] = \mathbb{P}(Y(s) > 0)$. This bias is however very small.

Derivation of variance of Nelson-Aalen Estimator. Recall that $\left[\int HdM\right](t) = \int H(s)^2 dN(s)$ where we have $H(s) = \frac{J(s)}{Y(s)} \implies \left[\int HdM\right](t) = \int \left(\frac{J(s)}{Y(s)}\right)^2 dN(s) = [\hat{A} - A^*](t) \implies \hat{\sigma}^2_{\text{N-A}} = \sum_{T_j \leq t} \frac{1}{Y(T_j)}$

Delta Method CI Nelson-Aalen We have that $\hat{A}(t) \overset{\text{approx}}{\sim} N(A(t), \hat{\sigma}^2(t))$

$$g(\hat{A}(t)) \approx g(A(t)) + g'(A(t))\underbrace{(\hat{A}(t) - A(t))}_{\mathbb{E}[...]=0} \implies \mathbb{E}[g(\hat{A}(t))] \approx g(A(t)) \text{ and } \mathbb{E}[(g(\hat{A}(t)) - g(A(t))^2] \approx g'(\hat{A}(t))^2 \underbrace{\mathbb{E}[(\hat{A}(t) - A(t))^2]}_{\hat{\sigma}^2}$$

$$\implies g(\hat{A}(t)) \overset{\text{approx}}{\sim} N(g(A(t), |g'(\hat{A}(t)|\hat{\sigma})$$

Let $g(x) = \log(x)$ which then gives us $g^{-1}(x) = e^x$ and $g'(x) = \frac{1}{x}$. The interval then becomes as follows.
$g^{-1}(CI) = \exp\left\{\log(\hat{A}(t)) \pm z_{1-\alpha/2}\frac{\hat{\sigma}}{\hat{A}(t)}\right\} = \hat{A}(t)\exp\left\{\pm z_{1-\alpha/2}\frac{\hat{\sigma}}{\hat{A}(t)}\right\}$

Kaplan-Meier Non-parametric estimator of the survival function. $S(t) = e^{-A(t)}$ where $A(t)$ is the cumulative hazard rate at time t.

Formulas $\hat{S}(t) = \prod_{T_j \leq t}\left(1 - \frac{1}{Y(T_j)}\right) = \prod_{T_j \leq t}(1 - \Delta\hat{A}(T_j))$
$\hat{\tau}^2(t) = \hat{S}(t)^2 \sum_{T_j \leq t} \frac{1}{Y(T_j)^2} = \hat{S}(t)^2\hat{\sigma}^2_{\text{N-A}}$ $\quad \hat{\tau}^2(t) = \hat{S}(t)^2 \sum_{T_j \leq t} \frac{d_j}{Y(T_j)(Y(T_j)-dj)}$ (Greenwood)

Derivation of the Kaplan-Meier Estimator Recall $\mathbb{P}(T > t) \implies S(t_k|t_{k-1}) = \mathbb{P}(T > t_k|T > t_{k-1}) = \frac{S(t_k)}{S(t_{k-1})}$. Let $0 = t_0 < t_1 < \ldots < t_n$ and note that $\mathbb{P}(T > t_0) = 1$ which gives us $S(t_n) = \prod_{k=1}^n \frac{S(t_k)}{S(t_{k-1})}$. We formally we define the survival function as $S(t) = \prod_{u \leq t}(1 - dA(u))$ since $\frac{S(t_k)}{S(t_{k-1})} = dA(t_k)$ when $t_k - t_{k-1} << 1$. This gives us the estimator $\hat{S}(t) = \prod_{T_j \leq t}(1 - \Delta\hat{A}(T_J))$ as $\Delta\hat{A}(t)$ serves as an estimator for $dA(t)$.

Kaplan Meier CI $\hat{S}(t) \pm z_{1-\alpha/2}\hat{\tau}(t)$. Log-transforms (using same method as for Nelson-Aalen above) etc.

Derivation of variance of Kaplan-Meier Estimator Let $S^*(t) = \prod_{u \leq t}(1 - dA^*(t))$ where $A^*(t) = \int_0^t J(u)dA(u)$. If $\mathbb{P}(J(s) = 0) << 1$ then S^* and S are close. We measure this closeness by $\frac{\hat{S}(t)}{S^*(t)} - 1 = -\int_0^t \frac{\hat{S}(u-)}{S^*(u)}d(\hat{A} - A^*)(u)$. We then have that $\mathbb{E}\left[\frac{\hat{S}(t)}{S^*(t)}\right] = 1$. We can then repat the arguments as we do for the variance of the Nelson-Aalen estimator above. $\left[\frac{\hat{S}}{S^*} - 1\right] = \left[\int \frac{-\hat{S}}{S^*}\underbrace{d(\hat{A} - A^*)}_{dM}\right] = \{\text{Theorem}\} = \int \left(\frac{\hat{S}}{S^*}\right)^2 d[M]$. Note that M is the same mean-zero m.g. as in the Nelson-Aalen case which gives us $d[M](t) = \frac{J(t)}{Y(t)}dN(t)$. This does in turn give us that $\left[\frac{\hat{S}}{S^*} - 1\right] = \int \left(\frac{\hat{S}}{S^*}\right)^2 \frac{J}{Y^2}dN$. Now by assuming $S^* = S$ and $\hat{S}(u) \approx \hat{S}(u-)$ we get that $\text{Var}\left(\frac{\hat{S}(t)}{S(t)} - 1\right) = \hat{\sigma}^2_{\hat{S}/S-1}(t) = \int_0^t \frac{J}{Y^2}dN = \hat{\sigma}^2_{\text{N-A}}(t) \implies \hat{\sigma}^2_{\hat{S}}(t) \approx \hat{S}^2(t)\int_0^t \frac{J}{Y^2}dN = \hat{S}^2(t)\hat{\sigma}^2_{\text{N-A}}(t)$

Martingales

Definition of Martingales M is a Martingale if $E[M_t|\mathcal{F}_s] = M_s, \quad t \geq s$ and $E[|M_t|] < \infty$.

Formulas

$$(H \bullet M)_n = H_0 M_0 + H_1(M_1 - M_0) + \ldots + H_n(M_n - M_{n-1})$$

$$\langle H \bullet M \rangle_n = \sum_{i=1}^{n} H_i^2 \Delta\langle M\rangle_i \text{ where } \Delta\langle M\rangle_i = [(M_i - M_{i-1})^2|\mathcal{F}_{i-1}]$$

$$\langle H \bullet M \rangle = H^2 \bullet \langle M \rangle$$

$$\langle M \rangle_n = \sum_{i=1}^{n} \mathrm{Var}(\Delta M_i|\mathcal{F}_{i-1}) = \sum_{i=1}^{n} \mathbb{E}[(M_i - M_{i-1})^2|\mathcal{F}_{i-1}]$$

$$\left\langle \int H dM \right\rangle = \int H^2(s) d\langle M\rangle(s) = \int H^2(s)\lambda(s)ds$$

$$\Delta M_t = M_t - M_{t-1} \text{ called m.g. difference}$$

$$[H \bullet M]_n = \sum_{i=1}^{n} H_i^2 \Delta[M]_i \text{ where } \Delta[M]_i = (M_i - M_{i-1})^2$$

$$[H \bullet M] = H^2 \bullet [M]$$

$$[M]_n = \sum_{i=1}^{n} (\Delta M_i)^2 = \sum_{i=1}^{n} (M_i - M_{i-1})^2$$

$$\left[\int H dM\right] = \int H^2(s) d[M]s) = \int H^2(s) dN(s)$$

$$Cov(M_s, M_t - M_s) = 0$$

$M^2 - \langle M \rangle$ and $M^2 - [M]$ are zero mean m.g.s.

$$Var(M(t)) = E\Big(M(t)\Big)^2 = E\langle M\rangle(t) = E[M](t)$$

$$E[M_t - M_s|\mathcal{F}_s] = E[M_t|\mathcal{F}_s] - M_s = 0$$

$$E[\Delta M_t|\mathcal{F}_{t-1}] = 0$$

Doob decomposition Let X with X_0 be a general discrete time proc. and let M be def. by $M_0 = X_0 = 0$ and
$\underbrace{M_n - M_{n-1}}_{\Delta M_n} = X_n - E[X_n|\mathcal{F}_{n-1}] \implies E[\Delta M_n|\mathcal{F}_{n-1}] = 0 \implies X_n = E[X_n|\mathcal{F}_{n-1}] + \Delta M_n = \underbrace{E[X_n|\mathcal{F}_{n-1}]}_{pred.} + \underbrace{(X_n - E[X_n|\mathcal{F}_{n-1}])}_{noise}$

Frailty

Basic Relations $A(t|Z) = \int_0^t \alpha(s|Z)ds$ if proportional frailty (i.e. $\alpha(t|Z) = \alpha(t)Z$ we have $A(t|Z) = ZA(t) \implies S(t) = \exp\{-ZA(t)\}$. Consequently the piopulation survival is given by $S(t) = \mathbb{E}[S(t|Z)] = \mathbb{E}\left[\exp\{-A(t|Z)\}\right] = \mathcal{L}_Z(A(t))$ where $\mathcal{L}_Z(c)$ is the Laplace transform (i.e. $\Psi_Z(-c)$).

Population Hazard Rate $\mu(t) = \frac{-S'(t)}{S(t)} = \alpha(t)\frac{\mathcal{L}'(A(t))}{\mathcal{L}(A(t))}$ assuming proportional frailty $(\alpha(t|Z) = \alpha(t)Z$

Modelling Frailty as Power Variance Function We let $Z \sim \text{PVF}(\varphi, \nu, m)$ for $\nu, m+1, m\varphi > 0$. This gives us $\mathbb{E}[Z] = \frac{\varphi m}{\nu}$ and $\text{Var}(Z) = \frac{\varphi m}{\nu}\frac{m+1}{\nu}$. For a PVF it holds that $S(t) = \exp\left\{-\varphi\left(1 - \left(\frac{1}{1+\frac{A(t)}{\nu}}\right)^2\right)\right\}$ and $\mu(t) = \underbrace{\frac{\varphi m}{\nu}}_{\mathbb{E}[Z]}\frac{\alpha(t)}{(1+\frac{A(t)}{\nu})^{m+1}}$.

Modelling Frailty as a Gamma distribution We have that $Z \sim \Gamma(\nu, \eta), \nu, \eta > 0$. We then have $\mathbb{E}[Z]$ and $\Phi_Z(c) = \left(\frac{\nu}{\nu - c}\right)^\eta$ (see **Distriubtions** on page 6). This gives us that $\mathcal{L}_Z(c) = \frac{1}{(1+\frac{c}{\nu})^\eta}$. Common to use $\mathbb{E}[Z] = 1 \implies \nu = \eta$. This then gives us $\mathcal{L}_Z(c) = \frac{1}{(1+\frac{c}{\nu})}$. If we let $\delta = \frac{1}{\nu} = \text{Var}(Z)$ which implies $\mathcal{L}_Z(c) = \frac{1}{(1+\delta c)^{1/\delta}}$. Finally (if we assume a proportional frailty model) we get that the population survival $S(t) = \mathcal{L}_Z(A(t)) = \mathcal{L}_Z(c) = \frac{1}{(1+\delta A(t))^{1/\delta}}$ and the population hazard $\mu(t) = \frac{-S'(t)}{S(t)} = \frac{\alpha(t)}{1+\delta A(t)}$

Testing

Breslow-Estimator $\hat{A}_0(t) = \hat{A}_0(t;\hat{\beta})$ where $\hat{A}_0(t;\hat{\beta}) = \int_0^t \frac{dN_\bullet(u)}{\sum_{l=1}^n Y_l(u) r(\beta, \mathbf{x}_l)}$,
Cox prop. haz. model $\implies \alpha(t|\mathbf{x}) = \alpha_0(t) r(\beta \mathbf{x}) \implies A(t|\mathbf{x}) = A_0(t) r(\beta \mathbf{x})$

Gehan-Breslow Test $U(t_0) = \frac{Z_1(t_0)}{\sqrt{V_{11}}} \sim N(0,1)$ where $Z_1(t_0) = \int_0^{t_0} Y_2(t) dN_1(t) - \int_0^{t_0} Y_1(t) dN_2(t)$ and $V_{11}(t_0) = \int_0^{t_0} Y_1(t) Y_2(t) dN_\bullet(t)$. $H_0 : \alpha_1(t) = \alpha_2(t)$ and $H_1 : \alpha_1(t) \neq \alpha_2(t)$.
Log-rank Test $U(t_0) = \frac{Z_1(t_0)}{\sqrt{V_{11}}} \sim N(0,1)$ where $Z_1(t_0) = \int_0^{t_0} \frac{L(t)}{Y_1(t)} dN_1(t) - \int_0^{t_0} \frac{L(t)}{Y_2(t)} dN_2(t)$ where $L(t) = Y_1(t) Y(2) / Y_\bullet(t)$ and $V_{11}(t_0) = \int_0^{t_0} \frac{L(t)^2}{Y_1(t) Y_2(t)} dN_\bullet(t)$. $H_0 : \alpha_1(t) = \alpha_2(t)$ and $H_1 : \alpha_1(t) \neq \alpha_2(t)$.

See problem 5.

Cox regression Note that $r(\boldsymbol{\beta}, \mathbf{x}) = \boldsymbol{\beta}^T \mathbf{x}$.
Multiplicative model: $\alpha(t|x_1, ..., x_p) = \alpha_0(t) \exp(\beta_1 x_1 + ... + \beta_p x_p)$.
Additive model: $\alpha(t|x_1, ..., x_p) = \underbrace{\beta_0(t)}_{baseline haz.} + \beta_1 x_1 + ... + \beta_p x_p$.

Cox partial likelihood: $L(\beta) = \prod_{T_j} \frac{r(\beta, x_j)}{\sum_{i \in \mathcal{R}_j} r(\beta, x_j)}$ where $\mathcal{R}_j$ is the risk set just before event j.

LR test: $\chi^2_{LR} = 2(\log(L(\hat{\beta}) - \log(\beta_0)) \sim \chi^2(1)$

Hazard Ratio $\frac{\alpha(t|\mathbf{x}_1)}{\alpha(t|\mathbf{x}_2)}$ e.g. $\frac{\alpha(t|\mathbf{x}=(1,0))}{\alpha(t|\mathbf{x}=(0,1))} = \frac{r(\beta,(1,0))}{r(\beta,(0,1))}$. Example: Cox's proportional hazard model i.e. $\alpha(t|x) = \alpha_0(t) \exp\{\sum_j \beta_j x_j\}$. Hazard ratio example $HR_{age} = \frac{\alpha(t|age=1, sex=z)}{\alpha(t|age=0, sex=z)} = e^{\hat{\beta}_{age}}$ and $HR_{sex} = \frac{\alpha(t|age=z, sex=1)}{\alpha(t|age=z, sex=0)} = e^{\hat{\beta}_{sex}}$ where $z = 0, 1$.

Misc

Accelerated failure time models: $\log U_i = \beta^T \mathbf{x}_i + \varepsilon_i$ where $E[\varepsilon_i] = 0$ iid. $\implies S_{U_i}(u) = P(U_i > u) = P(e^{\beta^T \mathbf{x}_i + \varepsilon_i} > u) = P(\underbrace{\varepsilon_\mathbf{i}}_{w_i} > ue^{-\beta^T \mathbf{x}_i} = S_{w_i}(ue^{-\beta^T \mathbf{x}_i})$, (change of time), $\implies S'_{U_i}(u) = S'_{w_i}(ue^{-\beta^T \mathbf{x}_i})e^{-\beta^T \mathbf{x}_i} \implies \alpha_{U_i}(u) = \frac{-S'_{U_i}(u)}{S_{U_i}(u)} = \alpha_{w_i}(ue^{-\beta^T \mathbf{x}_i})ue^{-\beta^T \mathbf{x}_i}$

Likelihood With censored observations we can express the likelihood as follows. $L(\theta; t_1, ..., t_n) \prod_{i=1}^n \mathbb{P}(T = t_i)_i^\delta \mathbb{P}(T \geq t_i)^{1-\delta_i}$ where δ_i is the indicator of t_i being censored. See example below under **Examples**

Likelihood in terms of hazard rate $L(\theta) = \prod_{i \in \mathcal{D}_i} \mathbb{P}(T \in [t_i, t_i + dt; \theta)) \prod_{i \notin \mathcal{D}_i} \mathbb{P}(T \geq t_i; \theta) \approx \prod_{i \in \mathcal{D}_i} f(t_i; \theta)dt \prod_{i \notin \mathcal{D}} S(t_i; \theta)$ $\propto \prod_{i \in \mathcal{D}_i} \alpha(t_i; \theta)S(t_i; \theta) \prod_{i \notin \mathcal{D}_i} S(t_i; \theta) = \prod_{i=1}^n \alpha(t_i, \theta)^{\delta_i} S(t_i; \theta)$ where individuals with $\delta_i = 1$ belong to $\mathcal{D}_i$.

Problems, solutions and examples

Problem 1a Show $\hat{A}(t) = \int_0^t \frac{I(Y(s)>0)}{Y(s)} dN(s)$ is an unbiased estimator of $A^*(t) = \int_0^t I(Y(s) > 0)\alpha(s)ds$.
Solution $\hat{A}(t) - A^*(t) = \int_0^t \frac{I(Y(s)>0)}{Y(s)} dN(s) - \int_0^t I(Y(s) > 0)\alpha(s)ds = \int_0^t \frac{I(Y(s)>0)}{Y(s)} dN(s) - \int_0^t \frac{I(Y(s)>0)}{Y(s)} Y(s)\alpha(s)ds =$ $\int_0^t \frac{I(Y(s)>0)}{Y(s)}(dN(s) - Y(s)\alpha(s)ds) = \int_0^t \underbrace{\frac{I(Y(s) > 0)}{Y(s)}}_{\text{pred.}} \underbrace{dM(s)}_{\text{mean zero m.g}} = 0.$

Problem 1b Show $A^*(t)$ is a biased estimator of $A(t) = \int_0^t \alpha(s)ds$.
Solution $E[A^*(t)] = E[\int_0^t I(Y(s) > 0)\alpha(s)ds] \leq E[\int_0^t 1 \cdot \alpha(s)ds] = A(t)$.

Problem 1c Calculate the optional variation of $\hat{A}(t)A^*(t)$, i.e. $[\hat{A}(t)A^*(t)]$ and write this expression as a sum.
Solution $[\hat{A}(t)A^*(t)] = [\int \frac{1}{Y} dM](t) = \int_0^t \left(\frac{I(Y(s)>0)}{Y(s)}\right)^2 dN(s) = \int_0^t \frac{I(Y(s)>0)}{Y(s)^2} dN(s)$.
We also have that $Var(\hat{A}(t) - A^*(t)) = E\Big([\hat{A}(t) - A^*(t)](t)\Big)$ and thus $\hat{A}(t) - A^*(t)](t)$ is an unbiased est. of the variance.
Morover, assuming no ties $[\hat{A}(t) - A^*(t)](t) = \int_0^t \frac{I(Y(s)>0)}{Y(s)^2} dN(s) = \sum_{T_j \leq t} \frac{1}{Y(T_j)}$, which is the Nelson-Aalen estimator.

Problem 2 Let X_n be discrete time m.g. Show that $E[X_n^2]$ is non-decreasing in n.
Solution First show $M_{n+1} = X_n(X_{n+1} - X_n)$ has zero mean. $E[X_n(X_{n+1} - X_n)|\mathcal{F}_n] = X_nE[X_{n+1} - X_n|\mathcal{F}_n] = 0$. Now note that $(X_{n+1} - X_n)^2 = (X_{n+1} - X_n)(X_{n+1} - X_n) = X_{n+1}(X_n + 1 - X_n) - M_n$. We get that $E[(X_{n+1} - X_n)^2] = E[X_{n+1}(X_n + 1 - X_n) - M_n] = E[X_{n+1}(X_n + 1 - X_n)] = E[X_{n+1}^2] - E[X_{n+1}X_n] = E[X_{n+1}^2] - E[E[X_{n+1}X_n|\mathcal{F}_n]] = E[X_{n+1}^2] - E[X_n^2] \geq 0$
Problem 3 Let $T_1, ..., T_n$ i.i.d. Exp(ν). Let $c_1, ..., c_n$ be non-random censoring times and $\tilde{T}_i = \min(T_i, c_i)$. Let $D_i = 1$ if $\tilde{T}_i = T_i$. Construct the likelihood for this situation.
Solution Contribution for an observed event is $\alpha(\tilde{t}_i; \nu) \exp\{\int_0^{\tilde{t}_i} \alpha(s; \nu)ds\} = \nu \exp\{-\tilde{t}_i\nu\}$, since $\alpha(t; \nu) = \nu$. A censored event contributes to the likelihood with $S(\tilde{t}_i; \nu) = \exp\{\int_0^{\tilde{t}_i} \alpha(s; \nu)ds\} = \exp\{-\tilde{t}_i\nu\}$.
By combining these we get $L(\nu) = \prod_{i=1}^n (\alpha(\tilde{t}_i; \nu) \exp\{\int_0^{\tilde{t}_i} \alpha(s; \nu)ds\})^{D_i} (\exp\{\int_0^{\tilde{t}_i} \alpha(s; \nu)ds\})^{1-D_i} = \nu^d \exp\{-\nu r\}$, where $d = \sum_i D_i$ and $r = \sum_i \tilde{t}_i$.
Problem 4a Let $N(t)$ be a Poisson process with intensity function $\lambda(t)$. Show that $M(t) = N(t) - \int_0^t \lambda(s)ds$ is a mean zero m.g.
Solution From def. of the Po-process we know $E[N(t) - N(s)|\mathcal{F}_s] = \int_s^t \lambda(s)ds$ which follows from indep. increments property. Thus, $E[N(t) - \int_0^t \lambda(s)ds|\mathcal{F}_s] = E[N(t) - \int_0^t \lambda(s)ds - N(s) + N(s)|\mathcal{F}_s] = E[N(t) - N(s)] - \int_0^t \lambda(s)ds + N(s) = \int_s^t \lambda(s)ds - \int_0^t \lambda(s)ds + N(s) = N(s) - \int_0^s \lambda(s)ds$.

Problem 4b For $M(t)$ above, it holds that $M(t)^2 - \int_0^t \lambda(s)ds$ is a mean-zero m.g. Use this with a) to show $\lim_{h\to 0^+} \frac{1}{h}E[(M(t + h) - M(t))^2|\mathcal{F}_t] = \lambda(t)$. (i.e. $d\langle M\rangle(t) = \lambda(t)$))
Solution $E[(M(t + h) - M(t))^2|\mathcal{F}_t] = E[(M(t + h)^2|\mathcal{F}_t] - 2E[M(t + h)|\mathcal{F}_t]M(t) + M(t)^2 = E[(M(t + h)^2|\mathcal{F}_t] - M(t)$. Now using that $E[(M(t+h)^2 - \int_0^{t+h} \lambda(u)du|\mathcal{F}_t] = M(t)^2 - \int_0^t \lambda(u)du$ it follows that $E[(M(t+h) - M(t))^2|\mathcal{F}_t] = M(t)^2 - \int_0^t \lambda(u)du + \int_0^{t+h} \lambda(u)du - M(t)^2 = \int_t^{t+h} \lambda(u)du$. Desired result follows from standard calculus.
Problem 5 Show that $\int_0^{t_0} \frac{L(t)^2}{Y_1(t)Y_2(t)} dN_\bullet(t)$ is an unbiased estimator of $\langle V_{11}(t)\rangle(t_0)$ under $H_0 : \alpha_1(t) = \alpha_2(t)$.

Solution Recall $\langle Z_1\rangle(t_0) = \int_0^{t_0} \underbrace{\frac{L^2(t)}{Y_1(t)Y_2(t)}}_{=H(t)} \underbrace{Y_\bullet(t)\alpha(t)dt}_{d\Lambda_\bullet(t)}$ where $\Lambda_\bullet(t) = Y_\bullet(t)\alpha(t) = Y_1(t)\alpha(t) + Y_2(t)\alpha(t) = \Lambda_1(t) + \Lambda_2(t)$. Thus $N_\bullet = N_1(t) + N_2(t)$ is compensated by $\Lambda_\bullet(t)$. This implies $\int_0^{t_0} H(t)dM_\bullet(t) = \int_0^{t_0} H(t)(dN_\bullet - d\Lambda_\bullet(t))$ is a mean zero m.g. $\implies E[\int_0^{t_0} H(t)dM_\bullet(t)] = 0 \implies E[\underbrace{\int_0^{t_0} H(t)dN_\bullet(t)}_{V_{11}(t)}] = E[\int_0^{t_0} H(t)d\Lambda_\bullet(t)]$.

Problem 6 Assume $N_i(t); i = 1, ..., n$ have intensity processes of the form $\lambda_i(t) = Y_i(t)\alpha_0(t) \exp(\beta^T \mathbf{x_i})$ where $\mathbf{x_i} = (x_{i1}, ..., x_{ip})^T$ are fixed covariates. Let $L(\beta)$ be partial likelihood with $r(\beta^T \mathbf{x_i}) = \exp(\beta^T \mathbf{x_i})$.
a) Derive vector of score functions $\mathbf{U}(\beta) = \log L(\beta)/\partial\beta$

b) Derive observed information matrix $\mathbf{I}(\beta) = -\mathbf{U}(\beta)/\partial\beta^T$ **Solution** (ignoring bold case in solution) $L(\beta) = \prod_{T_j} \frac{r(\beta, x_{ij}(T_j))}{\sum_{\ell\in\mathcal{R}_j} r(\beta, x_\ell(T_j))} = \prod_{T_j} \frac{e^{\beta^T x_{ij}}}{\sum_{\ell\in\mathcal{R}_j} e^{\beta^T x_\ell}}$. This implies $\frac{\partial}{\partial\beta_k}\log L = \frac{\partial}{\partial\beta_k}\log\left(\prod_{T_j}\frac{e^{\beta^T x_{ij}}}{\sum_{\ell\in\mathcal{R}_j} e^{\beta^T x_\ell}}\right) = \frac{\partial}{\partial\beta_k}\sum_{T_j}\left(\beta^T x_{ij} - \log(\sum_{\ell\in\mathcal{R}_j} e^{\beta^T x_\ell})\right) = \sum_{T_j}\left((x_{ij})_k - \sum_{\ell\in\mathcal{R}_j}\frac{(x_\ell)_k e}{\sum_{\ell\in\mathcal{R}_j}}\right.$ $(U(\beta))_k$. The observed Fisher information is thus given by

$(I(\beta))_{mk} = \sum_{T_j}\frac{\sum_{\ell\in\mathcal{R}_j}(x_\ell)_m(x_\ell)_k e^{\beta^T x_\ell}}{\sum_{\ell\in\mathcal{R}_j} e^{\beta^T x_\ell}} - \sum_{T_j}\sum_{\ell\in\mathcal{R}_j}\frac{(x_\ell)_m e^{\beta^T x_\ell}}{\sum_{\ell\in\mathcal{R}_j} e^{\beta^T x_\ell}}\sum_{\ell\in\mathcal{R}_j}\frac{(x_\ell)_k e^{\beta^T x_\ell}}{\sum_{\ell\in\mathcal{R}_j} e^{\beta^T x_\ell}}$. (Note T stand for the transpose.)

Examples

Example of Nelso-Aalen Calculations (different types of ties, A_1 uses true ties whilst A_2 uses rounded ties)

t	$Y(t)$	$d(t)$	$\Delta\hat{A}_1(t)$	$\Delta\hat{\sigma}_1^2(t)$	$\Delta\hat{A}_2(t)$	$\Delta\hat{\sigma}_2^2(t)$
0.2	16	1	$\frac{1}{16}$	$\frac{(16-1)\cdot 1}{16^3}$	$\frac{1}{16}$	$\frac{1}{16^2}$
0.5	15	3	$\frac{3}{15}$	$\frac{(15-3)\cdot 3}{15^3}$	$\frac{1}{15}+\frac{1}{14}+\frac{1}{13}$	$\frac{1}{15^2}+\frac{1}{14^2}+\frac{1}{13^2}$
0.7	12	1	$\frac{1}{12}$	$\frac{(12-1)\cdot 1}{12^3}$	$\frac{1}{12}$	$\frac{1}{12^2}$
1.1	11	1	$\frac{1}{11}$	$\frac{(11-1)\cdot 1}{11^3}$	$\frac{1}{11}$	$\frac{1}{11^2}$

Example Population Hazard Rate
Let $\alpha(t|Z) = \alpha(t)Z$ where $\mathcal{L}_Z(s) = \mathbb{E}[\exp\{-sZ\}] = (1+\delta s)^{-1/\delta}$. We get that $\mathcal{L}'(s)\big|_{s=0} = -\mathbb{E}[Z] = -\frac{\mathcal{L}_Z(s)}{1+\delta}\big|_{s=0} = -1 \implies \mathbb{E}[Z] = 1$ by derivating both sides with regards to s. We can obtain the population hazard rate $\mu(t) = \alpha(t)\frac{-\mathcal{L}'_Z(A(t))}{\mathcal{L}_Z(A(t))} = \frac{\alpha(t)}{1+\delta A(t)}$. By assuming some form of $\alpha(t)$ (or $A(t)$) we can then examine the population hazard rate as $t\to\infty$.

Example of Likelihood Derivations We have $(i, t_i, \delta_i) = \{(1, 1.23, 1), (2, 1.97, 1), (3, 1.17, 0)\}$. If we assume that the times are $\text{Exp}(\nu)$ then we get $L(\nu; t_1, t_2, t_3) = \nu^2 e^{-\nu(t_1+t_2)}e^{-t_3}$.

Example of LR-test using Cox partial likelihood We have $\alpha(t;x) = \alpha_0(t)e^{\beta x}$ and $\{(T_i, \delta_i, x_i)\}_{i=1\ldots 5} = \{(1,1,1), (3,1,0), (4,0,1), (7,0,0)$ then $L(\beta) = \frac{e^\beta}{e^\beta+1+e^\beta+1+e^\beta}\cdot\frac{1}{1+e^\beta+1+e^\beta}\cdot\frac{e^\beta}{e^\beta}$. We then perform the likelihood ratio test as described under **Testing** using $\hat{\beta}$ (which we obtain using regular likelihood theory) and β_0.