

EXERCISE 4 - DELTA METHOD FOR POINTWISE CI

Kaplan-Meier estimator $\hat{S}(t) = \prod_{t_j \leq t} \left[1 - \frac{\Delta N(t_j)}{Y(t_j)} \right]$

Theorem 4.8 gives us $\sqrt{m} [\hat{S}(t) - S(t)] \xrightarrow{d} S(t) \cdot W(\sigma(t))$ on $D[0, \mathcal{E}]$ where $\sigma(t) = \int_0^t \frac{\lambda(s)}{\sigma(s)} ds$
 $\mathcal{Q}(s) = P(Y_n(s) = 1) > 0$ on $[0, \mathcal{E}]$

This convergence of processes implies convergence of any finite-dimensional distribution, therefore,

for any $t \in [0, \mathcal{E}]$: $\sqrt{m} [\hat{S}(t) - S(t)] \xrightarrow{d} N(0, \hat{S}(t)\sigma(t))$

estimate by $\hat{S}(t)$

Greenwood formula: $\hat{\sigma}(t) = m \cdot \sum_{t_j \leq t} \frac{\Delta N(t_j)}{Y(t_j)(Y(t_j) - \Delta N(t_j))}$

Cramér-Gluskoby: $\sqrt{m} \frac{\hat{S}(t) - S(t)}{\hat{S}(t) \sqrt{\hat{\sigma}(t)}} = \sqrt{m} \frac{\hat{S}(t) - S(t)}{S(t) \sqrt{\sigma(t)}} \cdot \frac{S(t) \sqrt{\sigma(t)}}{\hat{S}(t) \sqrt{\hat{\sigma}(t)}} \xrightarrow{d} N(0, 1)$

Δ -Method for functions: $[0, 1] \rightarrow \mathbb{R}$ $\sqrt{m} \frac{g(\hat{S}(t)) - g(S(t))}{\hat{S}(t) \sqrt{\hat{\sigma}(t)}} \xrightarrow{d} N(0, [g'(S(t))]^2)$

Again by Cramér-Gluskoby: $\sqrt{m} \frac{g(\hat{S}(t)) - g(S(t))}{\hat{S}(t) |g'(\hat{S}(t))| \sqrt{\hat{\sigma}(t)}} \xrightarrow{d} N(0, 1)$

$1 - \alpha \leftarrow_{m \rightarrow \infty} P(|g(\hat{S}(t)) - g(S(t))| \leq \mu_{1-\frac{\alpha}{2}} \cdot \hat{S}(t) \cdot |g'(\hat{S}(t))| \cdot \sqrt{\frac{\hat{\sigma}(t)}{m}}) =$

$= P(g(\hat{S}(t)) - \mu_{1-\frac{\alpha}{2}} |g'(\hat{S}(t))| \hat{S}(t) \sqrt{\frac{\hat{\sigma}(t)}{m}} \leq g(S(t)) \leq g(\hat{S}(t)) + \mu_{1-\frac{\alpha}{2}} \hat{S}(t) |g'(\hat{S}(t))| \sqrt{\frac{\hat{\sigma}(t)}{m}})$

increasing $P(g^{-1}[g(\hat{S}(t)) - \mu_{1-\frac{\alpha}{2}} \hat{S}(t) |g'(\hat{S}(t))| \sqrt{\frac{\hat{\sigma}(t)}{m}}] \leq S(t) \leq g^{-1}[g(\hat{S}(t)) + \mu_{1-\frac{\alpha}{2}} \hat{S}(t) |g'(\hat{S}(t))| \sqrt{\frac{\hat{\sigma}(t)}{m}}])$

Choices of g : $g(y) = \log y$, $g(y) = \frac{1}{y}$, $g^{-1}(y) = \exp\{y\}$

$\exp\left\{ \log(\hat{S}(t)) \pm \mu_{1-\frac{\alpha}{2}} \frac{\hat{S}(t)}{\hat{S}(t)} \cdot \sqrt{\frac{\hat{\sigma}(t)}{m}} \right\} = \hat{S}(t) \cdot e^{\pm \mu_{1-\frac{\alpha}{2}} \sqrt{\frac{\hat{\sigma}(t)}{m}}}$

$g(y) = \log(-\log(y))$, $g(y) = \frac{1}{-\log(y)}$, $g^{-1}(y) = \exp\{-\exp\{y\}\}$

$\exp\left\{ -\exp\left\{ \log(-\log(\hat{S}(t))) \pm \mu_{1-\frac{\alpha}{2}} \frac{\hat{S}(t)}{-\hat{S}(t) \log(\hat{S}(t))} \cdot \sqrt{\frac{\hat{\sigma}(t)}{m}} \right\} \right\} = [\hat{S}(t)]^{\exp\left\{ \pm \frac{\mu_{1-\frac{\alpha}{2}} \sqrt{\frac{\hat{\sigma}(t)}{m}}}{\log(\hat{S}(t))} \right\}}$

$g(y) = \log_{1/2}(y) = \log \frac{y}{1-y}$, $g(y) = \frac{1-y}{y} \cdot \frac{(1-y)+y}{(1-y)^2} = \frac{1}{y(1-y)}$, $g^{-1}(y) = \frac{\exp\{y\}}{1+\exp\{y\}} = \frac{1}{1+\exp\{y\}}$

$\log_{1/2}^{-1}\left(\log_{1/2}(\hat{S}(t)) \pm \mu_{1-\frac{\alpha}{2}} \frac{\hat{S}(t)}{\hat{S}(t)(1-\hat{S}(t))} \cdot \sqrt{\frac{\hat{\sigma}(t)}{m}} \right) = \log_{1/2}^{-1}\left(\log_{1/2}(\hat{S}(t)) \pm \mu_{1-\frac{\alpha}{2}} \frac{\sqrt{\hat{\sigma}(t)}}{(1-\hat{S}(t)) \sqrt{m}} \right)$