

(P1)

ISyE 6404 - Derivation of K-M Estimator and its Variance. (in Large-Sample)

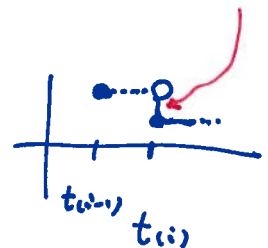
- ① ~~Likelihood of~~ data: d_i death at $t_{(i)}$
 c_i censored at $(t_{(i)}, t_{(i+1)})$
 where $t_{(1)} \leq t_{(2)} \leq \dots \leq t_{(m)}$ are the
 in cases of death-data.

② Likelihood:

i) For death-data (complete-sample):

$$p_{(i)} = \Pr(T = t_{(i)}) = S[t_{(i-1)}] - S[t_{(i)}]$$

$$\Rightarrow L = [p_{(i)}]^{d_i}$$



ii) For censored data:

$$\Rightarrow L = \Pr(T \geq t_{(i)})^{c_i} = [S(t_{(i)})]^{c_i}$$

thus,

$$L = \prod_{i=1}^m [S[t_{(i+1)}] - S[t_{(i)}]]^{d_i} [S(t_{(i)})]^{c_i}$$

indp.
cases

3

Re-formulation.

(p2)

Likelihood. (Simplification)

$$\text{Let } \pi_i = \frac{S(t_{(i)})}{S(t_{(i-1)})}$$

$$\begin{aligned} \text{Thus, } S(t_{(i)}) &= \pi_1 \cdot \pi_2 \cdots \pi_i \\ &= \frac{\cancel{S(t_{(1)})}}{1} \frac{\cancel{S(t_{(2)})}}{\cancel{S(t_{(1)})}} \cdots \frac{\boxed{S(t_{(i)})}}{\cancel{S(t_{(i-1)})}} \end{aligned} \quad \left. \begin{array}{l} \text{with} \\ S(t_{(0)}) = 1 \\ t_{(0)} = 0 \end{array} \right\}$$

@

$$\begin{aligned} \Rightarrow L &= \prod_{i=1}^n S[t_{(i-1)}] - S[t_{(i)}] \\ &= S[t_{(i-1)}] \left[1 - \frac{S[t_{(i)}]}{S[t_{(i-1)}]} \right] \\ &= (\pi_1 \cdots \pi_{i-1}) (1 - \pi_i) \end{aligned}$$

$$\begin{aligned} \Rightarrow \text{Likelihood} \equiv L &= \prod_{i=1}^n \left[(\pi_1 \pi_2 \cdots \pi_{i-1}) (1 - \pi_i) \right]^{d_i} (\pi_1 \pi_2 \cdots \pi_i)^c \\ &= \prod_{i=1}^n (1 - \pi_i)^{d_i} \boxed{\pi_i^{c_i} \cdot (\pi_1 \pi_2 \cdots \pi_{i-1})^{d_i + c_i}} \end{aligned}$$

-Eg (1)

4 Further
Reformulation of the Likelihood.

Define. $n_i = \sum_{m \geq j \geq i} (d_j + c_j)$
 \uparrow up to m .

then. (P4) shows that

Eg. (1) $\Rightarrow L = \prod_{i=1}^m (1 - \pi_i)^{d_i} \pi_i^{n_i - d_i}$

This is a "binomial likelihood" with parameters (n_i, π_i)

(~~event~~ even that all π_i are "cond. prob.")

5 Based on the "binomial likelihood",

the MLE for π_i is

$$\hat{\pi}_i = \frac{n_i - d_i}{n_i} = 1 - \frac{d_i}{n_i}$$

Next,

6

Asymptotic
variance

~~properties~~

for the ~~π_i~~ est.
 $\hat{S}(t_{(i)})$

\Downarrow

Thus,

$$\begin{aligned} \hat{S}_{KM}(t_{(i)}) &= \hat{\pi}_1 \hat{\pi}_2 \cdots \hat{\pi}_i \\ &= \prod_{i=1}^m \left(1 - \frac{d_i}{n_i}\right) \end{aligned}$$

$$L = \prod_{i=1}^m (1-\pi_i)^{d_i} \pi_i^{c_i} (\pi_1 \pi_2 \dots \pi_{i-1})^{d_i + c_i}$$

$$L^* = \prod_{i=1}^m (1-\pi_i)^{d_i} \pi_i^{n_i - d_i} \quad (p4)$$

$$m=1$$

$$i=1 \quad L = (1-\pi_1)^{d_1} \pi_1^{c_1} \cdot 1$$

$$m=1$$

$$i=1 \quad n_1 = \sum_{j=1}^m (d_j + c_j)$$

$$n_1 = d_1 + c_1$$

$$\Rightarrow n_1 - d_1 = (d_1 + c_1) - d_1 = c_1$$

$$\Rightarrow L^* = (1-\pi_1)^{d_1} \pi_1^{c_1} \quad \text{OK}$$

$$m=2$$

$$i=1 \quad L_1 = \left[(1-\pi_1)^{d_1} \pi_1^{c_1} \right] (\pi_1)^{d_1 + c_1}$$

$$i=2 \quad L_2 = (1-\pi_2)^{d_2} \pi_2^{c_2} (\pi_1)^{d_2 + c_2}$$

$$L \Rightarrow L_1 \times L_2$$

$$L = \underbrace{(1-\pi_1)^{d_1}}_{\text{red wavy}} \underbrace{(1-\pi_2)^{d_2}}_{\text{red wavy}} \underbrace{\pi_1^{c_1 + d_2 + c_2}}_{\text{red dashed}} \cdot \underbrace{\pi_2^{c_2}}_{\text{red triangles}}$$

should be correct for all other cases.

$$m=2$$

$$(i=1) \quad L_1 = (1-\pi_1)^{d_1} \pi_1^{n_1 - d_1}$$

where

$$n_1 = (d_1 + c_1) + (d_2 + c_2)$$

$$\Rightarrow n_1 - d_1 = c_1 + d_2 + c_2$$

$$(i=2) \quad L_2 = (1-\pi_2)^{d_2} \pi_2^{n_2 - d_2}$$

where

$$n_2 = d_2 + c_2$$

$$n_2 - d_2 = c_2$$

$$L_\phi = L_1 \times L_2$$

$$= \underbrace{(1-\pi_1)^{d_1}}_{\text{red wavy}} \underbrace{(1-\pi_2)^{d_2}}_{\text{red wavy}} \times \underbrace{\pi_1^{c_1 + d_2 + c_2}}_{\text{red dashed}} \underbrace{\pi_2^{c_2}}_{\text{red triangles}}$$

[6] Next, Asy. Variance for $\hat{t}_{(i)}$.
(Greenwood's procedure).

(p5)

~~Ex~~ Note that based on the Binomial (n_i, d_i) distribution.

$$\text{Var}(\hat{\pi}_i) = \frac{\pi_i(1-\pi_i)}{n_i}$$

we need to use the following Delta-method
twice to derive the asy. variance for
 $\text{Var}(\hat{S}(t_{(i)}))$

~~Ex~~ Delta-method:

Large-
sample

$$\text{Var}[f(X)] = (f'(X))^2 \text{Var}(X)$$

Now II

(p6)

Let us work on $\log \hat{S}(t_{(i)})$ first.

Denoted by, $k_i = \uparrow = \log(\hat{\pi}_1 \cdots \hat{\pi}_c)$
 $= \sum_{j=1}^i \log \hat{\pi}_j$

Since we have $\text{Var}(\pi_i)$

\swarrow
 $\text{Var}[\log(\hat{\pi}_i)] = \left(\frac{1}{(\hat{\pi}_i)} \right)^2 \text{Var}(\hat{\pi}_i)$

note

$[\log(x)]' = \frac{1}{x}$

$= \frac{1 - \pi_i}{n_i \pi_i}$

~~Next~~ $\text{Var}[\log[\hat{S}(t_{(i)})]]$
 $= \sum_{j=1}^i \frac{1 - \pi_j}{n_j \pi_j} = \sum_{j=1}^i \frac{d_j}{n_j (n_j - d_j)} \quad \text{--- Eq (3)}$

\uparrow
 This is the formula given in the first book.

Eq (10.4) $\hat{\sigma}_{km}(t_i)$

Now [2]

consider $g(x) = e^x$.

where $x = \log(\hat{S}(t_{(i)}))$

$$g'(x) = e^x$$

thus,

$$\text{Var}[e^{\log \hat{S}(t_{(i)})}] = \text{Var}(\hat{S}(t_{(i)}))$$

$$= [\hat{S}(t_{(i)})]^2 \underbrace{\text{Var}(\log(\hat{S}(t_{(i)})))}_{\text{||}}$$

|| Eq (3)

$$= [\hat{S}(t_{(i)})]^2 \sum_{j=1}^i \frac{1 - \hat{\pi}_j}{n_j \hat{\pi}_j}$$