

Reliability function of T_i in Cox-regression

For T_i : $z_{T_i}(t) = z(t; \underline{x}_i) = z_0(t) e^{\beta' \underline{x}_i}$

$\Rightarrow z(t; \underline{x}_i) = \int_0^t z(u; \underline{x}_i) du$

$= \int_0^t z_0(u) e^{\beta' \underline{x}_i} du = z_0(t) e^{\beta' \underline{x}_i}$

Thus $R(t; \underline{x}_i) = e^{-z(t; \underline{x}_i)}$
 $= e^{-z_0(t) e^{\beta' \underline{x}_i}} = R_0(t) e^{\beta' \underline{x}_i}$

Important relation valid for prop. hazards:
 If $z(t; \underline{x}) = z_0(t) g(\underline{x})$
 then $R(t; \underline{x}) = R_0(t)$

where $R_0(t) = e^{-z_0(t)}$ is reliab. function of unit with $\beta = 0$

The Estimated reliab. function of T_i :

Natural estimator $\hat{R}_i(t; \underline{x}_i) = \hat{R}_0(t) e^{\hat{\beta}' \underline{x}_i}$

so we need estimate $\hat{R}_0(t)$

Or: Since $R_0(t) = e^{-z_0(t)}$ we may also estimate $z_0(t)$.

Go through estimator of $Z_0(t)$:

Observe:

$$Z(T_i; \tilde{x}_i) = V_i \sim \text{expon}(1)$$

$$\text{so } Z_0(T_i) e^{\tilde{\beta}' \tilde{x}_i} = V_i \sim \text{expon}(1)$$

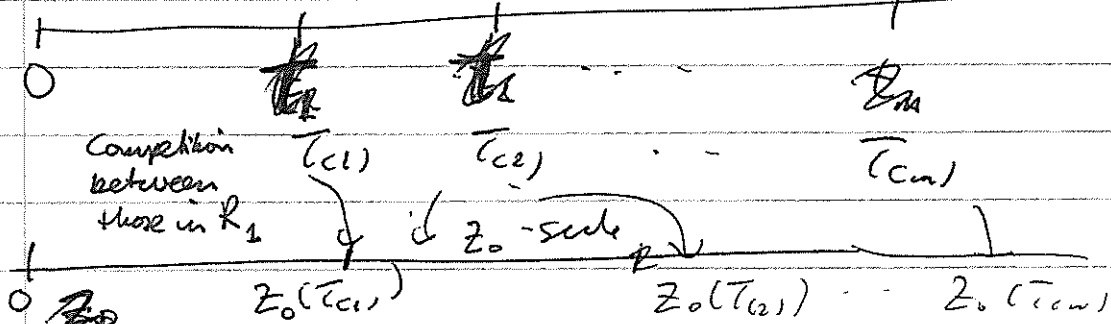
$$\text{so } Z_0(T_i) = \frac{V_i}{e^{\tilde{\beta}' \tilde{x}_i}}$$

$$\sim \text{expon}(e^{\tilde{\beta}' \tilde{x}_i})$$

[Recall $T \sim \text{expon}(a)$
 $\Rightarrow aT \sim \text{expon}(1)$
or $\frac{T}{a} \sim \text{expon}(a)$

who $\text{expon}(a): f(t) = ae^{-at}$
 $E(T) = \frac{1}{a}$

Thus - as we did for Nelson plot: Let $T_{(1)} < T_{(2)} < \dots < T_{(m)}$ be the failure times (new notation useful)



$$Z_0(T_{(1)}) = \min_{i \in R_1} Z_0(T_i)$$

$$\sim \text{expon}\left(\sum_{i \in R_1} e^{\tilde{\beta}' \tilde{x}_i}\right)$$

$$\text{So } E[Z_0(T_{(1)})] = \frac{1}{\sum_{i \in R_1} e^{\tilde{\beta}' \tilde{x}_i}}$$

Further, $Z_0(\tau_{(2)}) - Z_0(\tau_{(1)})$

= min of ~~the~~ exponential
 $\exp(-\beta' x_r)$ for each of $r \in R_2$.

$$\sim \exp\left(-\sum_{r \in R_2} e^{\beta' x_r}\right)$$

so $E[Z_0(\tau_{(2)}) - Z_0(\tau_{(1)})]$

$$= \frac{1}{\sum_{r \in R_2} e^{\beta' x_r}}$$

leading to

$$E(Z_0(\tau_{(2)})) = \frac{1}{\sum_{r \in R_1}} + \frac{1}{\sum_{r \in R_2}}$$

, etc.

Thus (Breslow - estimator) $\hat{\mu}$

$$\hat{Z}_0(t) = \sum_{t_i \leq t} \frac{1}{\sum_{r \in R_i} e^{\beta' x_r}}$$

↑ Note - β here!

[This is similar to Nelson-Oakes estimator ~~without~~]

~~without~~ when no covariates, simply
then $\beta = 0$ and we get

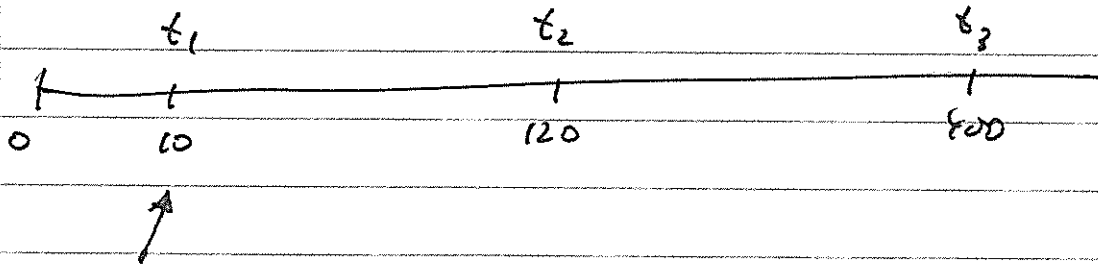
$$\sum_{t_i \in t} \frac{1}{\#R_i}$$

Also a counterpart of the M-estimator:

$$L_0(\hat{\beta}) = \prod_{i: t_i \in t} \left(1 - \frac{e^{\hat{\beta}' x_{t_i}}}{\sum_{r \in R_i} e^{\hat{\beta}' x_r}} \right)$$

$$\left[\text{For } \hat{\beta} = 0: \prod_{i: t_i \in t} \left(1 - \frac{1}{\#R_i} \right) \right]$$

In simple example:



at 10:
$$\frac{1}{e^{10\beta} + e^{3\beta} + e^{5\beta} + e^{3\beta} + e^{4\beta} + e^{\beta}} = 4.57 \cdot 10^{-4}$$

at 120:
$$\frac{1}{e^{3\beta} + e^{4\beta} + e^{\beta}} = \frac{\cancel{0.0304}}{0.0299}$$

at 400:
$$\frac{1}{e^{4\beta} + e^{\beta}} = \frac{\cancel{0.0730}}{0.0426}$$

$$\Rightarrow \hat{Z}_0(10) = 4.57 \cdot 10^{-4}$$

$$\hat{Z}_0(120) = 0.0304$$

$$\hat{Z}_0(400) = 0.0730$$

MODEL CHECKING:

Cox-Snell Residuals (Called "Generalized residual" in A&P)

Recall that

$$\begin{aligned}
 -\ln R(T_i; x_i) &= Z(T_i; x_i) \\
 &= Z_0(T_i) \cdot e^{\beta_1 x_i} \sim \text{expon}(1)
 \end{aligned}$$

Cox-Snell
Define residuals:

$$V_i = Z_0(Y_i) e^{\beta_1 x_i}$$

which is a censored set from $\text{expon}(1)$

[Some add 1 for the censored ones to have a ~~complete~~ "uncensored" set. ~~Because~~ if ~~$V \sim \text{expon}(1)$~~ then $E[V | V > y] = y + E[V] = \underline{y+1}$]

Example: A&P Fig. 3.5.

So - Cox-Snell residuals in example:

Y		\hat{F}_2	f
5	0	0	0
10	0.9593	1	1
40	0.0045	0	0
80	0.0209	0	0
120	0.3017	1	1
400	1.5567	1	1
600	0.1569	0	0

$\hat{F}_0(t_1) \cdot e^{\hat{\beta} \cdot 10} = 4.5666 \cdot 10^{-4} \cdot e^{7.65} = 0.9593$
 $\hat{F}_0(t_1) \cdot e^{\hat{\beta} \cdot 10} = 4.5666 \cdot 10^{-4} \cdot e^{3 \cdot 0.201} = 0.0045$
 $\hat{F}_0(t_2) \cdot e^{3 \cdot \hat{\beta}} = 0.0304 \cdot e^{3 \cdot 0.265} = 0.0209$
 $\hat{F}_0(t_2) \cdot e^{4 \cdot \hat{\beta}} = 0.0304 \cdot e^{4 \cdot 0.265} = 0.3017$
 $e^{\hat{\beta}}$...

Alternativ med Regressor 1:

Testing av prop. hazards-egenskapen i Cox-modellen

$$\begin{aligned} \text{dvs } \lambda(t|x) &= \lambda_0(t) g(\beta'x) \\ &= \lambda_0(t) e^{\beta'x} \\ &= \lambda_0(t) e^{\beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k} \end{aligned}$$

Detta ser ut effekten av en ökning på en enhet i ~~residual~~ kovariat x_1 ger en faktor ~~ett~~ e^{β_1} på hazardrate för alla t

Kunde tänkas att β_1 var en funktion av t , slik att ju $\beta_1(t) = 0$ för stora t , dvs kov x_1 har ingen betydelse för stora t .

Schoenfeld-residualen (3.5.2 s. 77 i A&P) definieras slik. Anta ^{för enkelhets skull} bae en kovariat x .

x_{li} - ~~estimat~~
 ↗
 verdi
 Kovariat för den enhet som faller vid t_i

$$\frac{\sum_{r \in R(t_i)} x_{lr} e^{\beta' x_{lr}}}{\sum_{r \in R(t_i)} e^{\beta' x_{lr}}}$$

↓
 Förväntat verdi på kovariat för ~~den~~ den enhet som faller vid t_i

~~Not~~ -4-

Merkelig:
~~De~~

_____ | _____
 t_i
 $R(t_i)$

↙
enhet nr. ~~k~~ ^k har en
sams. $f_k =$ feile som er

$$\frac{e^{\beta x_k}}{\sum_{k \in R(t_i)} e^{\beta x_j}}$$

Forventet kovariansverdi er

$$\sum_{k \in R(t_i)} x_k \cdot P(\text{enhet nr. } k \text{ feiler})$$

= det som står !!

Se Fig. 3.7

Ideen er at disse residuene skal ha "tyngdepunkt i 0"

~~ALL~~ -5-

SIMPLE EXAMPLE:

$t_1 = 10$: 2 fehler $x_{\text{M}} = 10$. Mean values

$$\frac{10 \cdot e^{10\hat{\beta}} + 3 \cdot e^{3\hat{\beta}} + \dots + 1 \cdot e^{\hat{\beta}}}{e^{10\hat{\beta}} + e^{3\hat{\beta}} + \dots + e^{\hat{\beta}}}$$

$$\hat{\beta} = 0.765 \quad \frac{9.7646}{\quad}$$

der Scherwed: $10 - 9.7646 = \underline{0.2354}$

$t_2 = 120$: $x_{\text{M}} = 3$

"EX" = 3.5099

Sch: $3 - 3.5099$
 $= -0.5099$

$t_3 = 400$: $x = 4$.

"EX" = 3.7254

Sch: $4 - 3.7254$
 $= 0.2746$