Cox Proportional Hazard Model

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1 Introduction

In this note we will talk about the Cox's proportional hazards (Cox's PH) model. Suppose we observe some non-informativly right-censored data (U, δ) with covariate vector Z. That is, for subject i, the covariate vector is Z_i, survival time T_i and censoring time C_i. The observed data is (U_i, δ_i) where $U_i = \min(T_i, C_i)$ and $\delta_i = 1(T_i \leq C_i)$. Also $T_i \perp C_i | Z_i$.

And now we want to model the relationship between Z and T. One way to do that is to incorporate Z into the hazard function $h(\cdot)$, e.g.,

$$T \sim Exp(\lambda_Z) \implies h(t) = \lambda_Z \triangleq e^{\alpha+\beta Z} = \lambda_0 e^{\beta Z},$$

where $\lambda_0 = e^{\alpha}$ can be viewed as a baseline hazard. If $\beta = 0$ then Z is not associated with T.

We can generalize this idea as

$$h(t|Z) = h_0(t) \times g(Z).$$

So the hazard can be factorized and this model is sometimes called a "multiplicative intensive model" or "multiplicative hazard model" or "proportional hazard model" because this factorization implies that

$$\frac{h(t|Z = z_1)}{h(t|Z = z_2)} = \frac{g(z_1)}{g(z_2)}.$$

The hazard ratio is constant with respect to t, hence the (constant) proportional hazard. So in our previous model (the exponential survival time), the hazard ratio is

$$\frac{h(t|Z = z_1)}{h(t|Z = z_2)} = e^{\beta(z_1 - z_2)}.$$

Also this exponential form of $g(Z)$

$$h(t|Z) = h_0(t) \cdot e^{\beta Z} \tag{1}$$

is the **Cox's PH** model.

2 Estimation

(1) implies that

$$\begin{aligned}S(t|Z) =& \exp\left(-H(t|Z)\right)\\ =& \exp\left(-\int_0^t h(u|Z)\,\mathrm{d}u\right)\\ =& \exp\left(-\int_0^t h_0(t)\,\mathrm{d}u\cdot g(Z)\right)\\ =& \left(S_0(t)\right)^{g(Z)} = \left(S_0(t)\right)^{\exp(\beta Z)},\end{aligned}$$

where $S_0(t) = \exp\left(-\int_0^t h_0(u)\,\mathrm{d}u\right)$, the survival function for $Z = 0$, hence $S(t|Z = 0)$. Also remember that $f(t|Z) = h(t|Z)\,S(t|Z)$. Thus, given n independent data (u_i, δ_i, z_i), the likelihood (one can refer to our previous notes about survival analysis.) is

$$\begin{aligned}L(\beta, h_0(\cdot)) =& \prod_{i=1}^n \left(f(u_i|z_i)\right)^{\delta_i}\left(S(u_i|z_i)\right)^{1-\delta_i} = \prod_{i=1}^n h(u_i|z_i)^{\delta_i}\,S(u_i|z_i)\\ =& \prod_{i=1}^n \left(h_0(u_i)\,e^{\beta z_i}\right)^{\delta_i}\left(\exp\left(-\int_0^{u_i} h_0(t)\,\mathrm{d}t\right)\right)^{\exp(\beta z_i)} \qquad (2)\\ =& \text{function}\left(data, h_0(\cdot), \beta\right).\end{aligned}$$

If $h_0(\cdot)$ is allowed to be "arbitary", then the "parameter space " is

$$\mathcal{H}\times\mathcal{R}^p = \left\{(h(\cdot), \beta)\middle| h_0(\cdot)\geq 0, \int_0^\infty h_0(t)\,\mathrm{d}t = \infty, \beta\in\mathcal{R}^p\right\},$$

where $\int_0^\infty h_0(t)\,\mathrm{d}t = \infty$ ensures that $S_0(\infty) = 0$.

In general this likelihood is hard to maximize. And Cox proposed this idea: to factor $L(\beta, h_0(\cdot))$ as

$$L(\beta, h_0(\cdot)) = L_1(\beta)\times L_2(\beta, h_0(\cdot)),$$

where L_1 only depends on β and its maximization $(\hat{\beta})$ enjoys nice properties such as consistency and asymptotic normality while L_2 contains relatively little information about β. And this L_1 is called a **partial likelihood**.

2.1 What is $L_1(\beta)$

In this section we introduce the L_1 proposed by Cox. First let's assume there are **NO tied** nor censoring observations. And define the distinct times of failure $\tau_1 < \tau_2 < \cdots$. Denote

$$R_j = \{i|U_i \geq \tau_j\} = \text{risk set at } \tau_j,$$

and

$$Z_{(j)} = \text{value of Z for the subject who fails at } \tau_j.$$

Note that under this setting (no tie, no censor), the full likelihood (2) becomes

$$L(\beta, h_0(\cdot)) = \prod_{i=1}^n h_0(u_i)\,e^{\beta z_i}\left(\exp\left(-\int_0^{u_i} h_0(t)\,\mathrm{d}t\right)\right)^{\exp(\beta z_i)}.$$

Furthermore, we can assume $u_i = \tau_i$, i.e. the data has been sorted based on survival time. And use the KM idea, i.e. assume the survival function is **discrete** with baseline hazard value h_j at u_j. Then this likelihood becomes

$$L(\beta, h_1, \cdots, h_n) = \prod_{i=1}^{n} h_i e^{\beta z_i} \exp\left(-\sum_{j=1}^{i} h_j\right)^{\exp(\beta z_i)}. \tag{3}$$

Note that, in previous notes we have deduct that in discrete case, for any $t \in [v_j, v_{j+1})$:

$$H(t) = \sum_{i=1}^{j} h_i \qquad S(t) = \prod_{i=1}^{j} (1 - h_i).$$

Here in (3) we use the approximation that $e^{h_j} \approx 1 - h_j$ when h_j is close to 0. Then we can use the method of profile likelihood:

we can reconstruct the data from $\{\tau_j\}$, $\{R_j\}$ and $\{Z_{(j)}\}$. And L_1 is defined as

$$L_1(\beta) \triangleq \prod_j \left\{ \frac{e^{\beta Z_{(j)}}}{\sum\limits_{l \in R_j} e^{\beta Z_l}} \right\}$$

3 Inference

References