

STAT 6390: Analysis of Survival Data

Textbook coverage: Chapter 3

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Parametric regression models

- Previously, we learned to fit parametric regression model with the form

$$Y = \log(T) = \alpha + X'\beta + \epsilon, \quad (1)$$

with `survreg`.

- The following table gives some of the common distributions in `survreg`.

dist in <code>survreg</code>	Distribution of T	Distribution of ϵ
exponential	exponential	extreme values
weibull	Weibull	extreme values
loglogistic	log-logistic	logistic
lognormal	log-normal	normal

- Here, models are named for the distribution of T , not ϵ .
- Different distributions assume different shapes for the hazard function.
- See Chapter 2.2 of Kalbfleisch and Prentice (2011) for more comprehensive discussion.

The proportional hazards model

- In the previous note, we note that the hazard at time t for an individual can be written as

$$\lambda(t; x) = \lambda \cdot r(X'\beta)$$

under the exponential assumption.

- To generalize this, we could consider modeling the hazard function

$$h(t; x) = h_0(t)r(X'\beta), \quad (2)$$

where $h_0(t)$ is an unspecified function.

- We assume X is time independent.
- In (2) is the product of two functions:
 - $h_0(t)$ characterizes how the hazard function changes as a function of time
 - $r(X'\beta)$ characterizes how the hazard function changes as a function of subject covariates.
- $h_0(t)$ is referred to as the **baseline hazard function** when $r(X'\beta)$ is parameterized such that $r(0) = 1$.

Hazard ratio

- Under the model (2), the ratio of the hazard function for two subject with covariate x_1 and x_0 is

$$\text{HR}(t; x_1, x_0) = \frac{h(t; x_1)}{h(t; x_0)} = \frac{r(x_1' \beta)}{r(x_0' \beta)}. \quad (3)$$

- This implies that the hazard ratio (HR) depends only on the function $r(X' \beta)$ and does not require the actual form of $h_0(t)$.
- This gives the *proportional hazard* assumption.

The Cox model

- Cox (1992) is the first to propose model (2) with $r(X'\beta) = e^{X'\beta}$.
- With $r(X'\beta) = e^{X'\beta}$, (2) reduces to

$$h(t; x) = h_0(t)e^{X'\beta}, \quad (4)$$

and the hazard ratio $HR(t; x_1, x_0)$ becomes $e^{(x_1 - x_0)'\beta}$.

- Equivalently, the log hazard ratio is $(x_1 - x_0)'\beta$.

The Cox model

- Suppose we have a “continuous” covariate x_k , which corresponds to β_k .
- Holding other covariate values at constant, then the log hazard ratio

$$\log \{HR(t, x_k + 1, x_k)\} = \log \{h(t, x_k + 1)\} - \log \{h(t, x_k)\} = \beta_k.$$

- β_k is the increase in log-hazard with one unit increase in x_k at any time.
- e^{β_k} is the hazard ratio associated with one unit increase in x_k .
- If x_k is a “categorical” covariate and can only takes on two possible values, 0 and 1, then β_k is the difference in log-hazard between the two groups.

The Cox model

- From the definition of hazard function, we have

$$P(t \leq T < t + dt | T \geq t, x) \approx h(t|x)dt.$$

- This implies

$$\frac{P(t \leq T < t + dt | T \geq t, x_k + 1)}{P(t \leq T < t + dt | T \geq t, x_k)} \approx e^{\beta_k}.$$

- Thus, e^{β_k} can be loosely interpreted in terms of conditional probabilities of dying.

The Cox model

- Since β characterizes the covariate effect, the main focus of the inference procedure is to estimate β and test $H_0 : \beta = 0$.
- As in many other regression model, we will also diagnostics procedure.
- The baseline hazard function, $h_0(t)$, can be treated as a nuisance parameter.

Complete likelihood

- Recall the likelihood we derived in note 3:

$$L = \prod_{i=1}^n \{f_T(t_i)\}^{\Delta_i} \cdot \{S_T(t_i)\}^{1-\Delta_i} = \prod_{i=1}^n \{h_T(t_i)\}^{\Delta_i} \cdot S_T(t_i). \quad (5)$$

- If T has hazard function (4), then

$$h_T(t) = h_0(t)e^{X'\beta} \text{ and } S_T(t) = \exp\left\{-H_0(t)e^{X'\beta}\right\},$$

where $H_0(t) = \int_0^t h_0(u) du$.

- The complete likelihood can be obtained by plugging the above into (5).
- The maximization of the likelihood would requires solving for the unknown parameter β and unspecified baseline hazard at t_i 's.

Partial likelihood

- Consider the *conditional probability* the i th individual fails at t_i , given the risk set at t_i :

$$\begin{aligned} & P(\text{the } i\text{th individual dies} | \text{one death at } t_i) \\ &= \frac{P(\text{the } i\text{th individual dies} | \text{survival to } t_i)}{P(\text{one death at } t_i | \text{survival to } t_i)} \\ &= \frac{h_i(t; x)}{\sum_{j:t_j \geq t_i} h_j(t; x)} = \frac{e^{X_i' \beta}}{\sum_{j:t_j \geq t_i} e^{X_j' \beta}}, \end{aligned}$$

where the last equality follows from the Cox model assumption.

- The *partial likelihood* is formed by multiplying these conditional probabilities:

$$L_p(\beta) = \prod_{i=1}^n \left(\frac{e^{X_i' \beta}}{\sum_{j:t_j \geq t_i} e^{X_j' \beta}} \right)^{\Delta_i} \quad (6)$$

Partial likelihood

- The expression in (6) assumes no ties and excludes terms with $\Delta_i = 0$.
- A different approach to derive (6) is to consider the complete likelihood (5), and decompose it to

$$\begin{aligned}
 L &= \prod_{i=1}^n \{h_T(t_i)\}^{\Delta_i} \cdot S_T(t_i) \\
 &= \prod_{i=1}^n \left(\frac{h_i(t_i)}{\sum_{j:t_j \geq t_i} h_j(t_i)} \right)^{\Delta_i} \cdot \left(\sum_{j:t_j \geq t_i} h_j(t_i) \right)^{\Delta_i} \cdot S_T(t_i) \\
 &:= \prod_{i=1}^n L_1 \cdot L_2 \cdot L_3,
 \end{aligned}$$

where L_1 reduces to the partial likelihood in (6).

Partial likelihood

- Cox (1975) argues that L_1 carries “most” of the information about β .
- Cox (1975) also argues that L_2 and L_3 carry information about $\lambda_0(t)$.
- Cox (1975) suggested treating $L_p(\beta)$ as a regular likelihood function and making inference on β accordingly.
- The maximum partial likelihood estimator (MPLE) of β gives an unbiased estimator for β .
- The information matrix based on $L_p(\beta)$ can be used to derive standard error for the MPLE.

Partial likelihood

- Suppose (for now) that we only have one type of covariate, e.g, $p = 1$.
- For the ease of notation, we will right $j \in R(t_i)$ instead of $j : t_j \geq t_i$ to denote the index j is from the risk set.
- The log of the partial likelihood, $\log\{L_p(\beta)\}$ has the form

$$\ell_p(\beta) = \sum_{i=1}^n \Delta_i \left[X_i \beta - \log \left\{ \sum_{j \in R(t_i)} e^{X_j \beta} \right\} \right].$$

- The first derivative gives the *score function*:

$$\frac{d\ell_p}{d\beta} = \sum_{i=1}^n \Delta_i \left[X_i - \left\{ \frac{\sum_{j \in R(t_i)} X_j e^{X_j \beta}}{\sum_{j \in R(t_i)} e^{X_j \beta}} \right\} \right]. \quad (7)$$

Partial likelihood

- Notice that the fraction in the summation can be expressed as

$$\frac{\sum_{j \in R(t_i)} X_j e^{X_j \beta}}{\sum_{j \in R(t_i)} e^{X_j \beta}} = \sum_{j \in R(t_i)} \frac{X_j e^{X_j \beta}}{\sum_{k \in R(t_i)} e^{X_k \beta}} = \sum_{j \in R(t_i)} X_j \cdot \omega_{ij}(\beta),$$

where $\omega_{ij}(\beta) = \frac{e^{X_j \beta}}{\sum_{k \in R(t_i)} e^{X_k \beta}}.$

- $\omega_{ij}(\beta)$ can be seen as the conditional probability of death at t_i .
- This implies $\bar{X}_i = \sum_{j \in R(t_i)} X_j \cdot \omega_{ij}(\beta)$ is like a weighted average of X over all the individuals in the risk set at t_i .
- This further reduced (7) to

$$\sum_{i=1}^n \Delta_i (X_i - \bar{X}_i), \quad (8)$$

a familiar $\sum (O_i - E_i)$ form!

Partial likelihood

- The second derivative is

$$\frac{d^2 \ell_p}{d\beta^2} = - \sum_{i=1}^n \Delta_i \sum_{j \in R(t_i)} w_{ij}(\beta) \cdot (X_j - \bar{X})^2.$$

- Then $\hat{\text{Var}}(\hat{\beta}) = I(\hat{\beta})^{-1}$, where $I(\beta) = -\frac{d^2 \ell_p}{d\beta^2}$.

Link to counting process

- To emphasize \bar{X}_i in (8) depends on β and time (e.g., t_i), we use the notation $\bar{X}_i(\beta, t)$.
- Equation (8) can be expressed in the form of a stochastic integral with respect to $dN_i(t)$:

$$U(\beta, t) = \sum_{i=1}^n \Delta_i \{X_i - \bar{X}_i(\beta, t)\} = \sum_{i=1}^n \int_0^t \{X_i - \bar{X}_i(\beta, u)\} dN_i(u) \quad (9)$$

Link to counting process

- Recall that when we study counting process for survival data, we have defined the zero-mean martingale

$$M_i(t) = N_i(t) - \Lambda_i(t) = N_i(t) - \int_0^t \lambda_i(u) du,$$

where the intensity function has the form $\lambda_i(u) = h_i(u) Y_i(u)$ and $Y_i(u) = I(\tilde{T}_i \geq u)$.

- We also stated that

$$dM_i(t) = dN_i(t) - d\Lambda_i(t)$$

has conditional expectation zero.

- Under the Cox model assumption, we have $h_i(u) = h_0(u)e^{x_i\beta}$ and $M_i(t)$ is

$$M_i(t) = N_i(t) - \int_0^t Y_i(u) h_0(u) e^{x_i\beta} du.$$

Link to counting process

- Under the Cox assumption, we have

$$\sum_{i=1}^n \int_0^t \{X_i - \bar{X}_i(\beta, u)\} d\Lambda(u) = 0.$$

- Thus, we can rewrite (9) as

$$U(\beta, t) = \sum_{i=1}^n \int_0^t \{X_i - \bar{X}_i(\beta, u)\} dM_i(u),$$

which is a sum of stochastic integral of predictable vector process.

- This also implies $U(\beta, t)$ is a zero-mean martingale.
- Asymptotic properties for $\hat{\beta}$ can then be derived using martingale theories.

Estimating $H_0(t)$

- The Nelson-Aalen estimator for $\Lambda_0(t)$ is then

$$\hat{H}_0(\beta, t) = \sum_{i: t_i \leq t} \frac{dN(t_i)}{\sum_{j=1}^n Y_j(t) e^{X_j \beta}} \quad (10)$$

- The Nelson-Aalen estimator can also be derived by fixing β in the complete likelihood (5).
- Under the Cox assumption, we have

$$\begin{aligned} L(h; \beta) &= \prod_{i=1}^n \{h_T(t_i)\}^{\Delta_i} \cdot S_T(t_i) \\ &= \prod_{i=1}^n \{h_0(t_i) e^{X_i \beta}\}^{\Delta_i} \cdot \exp \{-H_0(t_i) e^{X_i \beta}\}. \end{aligned} \quad (11)$$

Estimating $H_0(t)$

- The likelihood (11) is maximized at $h_0(t)$ at event times, e.g., $h_0(t_{(1)}), \dots, h_0(t_{(n)})$.
- Suppose there is a total of D events, and let $h_{0i} = h_0(t_{(i)})$, for $i = 1, \dots, D$.
- Then $H_0(t) = \sum_{i:t_{(i)} \leq t} h_0(t_{(i)}) = \sum_{i:t_{(i)} \leq t} h_{0i}$, and

$$L(h; \beta) = \left[\prod_{i=1}^D h_{0i} e^{X_i \beta} \right] \cdot \exp \left\{ \sum_{i=1}^n e^{X_i \beta} \sum_{j:t_{(j)} \leq t_i} h_{0j} \right\}.$$

- The likelihood (11) is proportional to

$$L(h; \beta) \propto \prod_{i=1}^D h_{0i} \cdot \exp \left\{ -h_{0i} \sum_{j \in R(t_{(i)})} e^{X_j \beta} \right\}$$

Estimating $H_0(t)$

- Maximizing the log of $L(h; \beta)$ yields

$$\hat{h}_{0i} = \frac{1}{\sum_{j \in R(t_{(i)})} e^{x_j \beta}}, \text{ and}$$

$$\hat{H}(t) = \sum_{i; t_i \leq t} \frac{1}{\sum_{j \in R(t_{(i)})} e^{x_j \beta}},$$

which is equivalent to (10) when there is no tie.

- Of more interesting is that when plugging $\hat{H}(t)$ into (11) gives the partial likelihood of (6).

Reference

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