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

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

with `survreg`.

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

`dist` in `survreg`	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
$$h(t; x) = h_0(t) r(X'\beta), \tag{2}$$
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

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

- 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

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

  and the hazard ratio $\mathrm{HR}(t; x_1, x_0)$ 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

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

- 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

$$\mathrm{P}(t \leq T < t + \mathrm{d}t | T \geq t, x) \approx h(t|x)\mathrm{d}t.$$

- This implies

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

- 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:

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

- 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 $H_0(t) = \int_0^t h_0(u)\,\mathrm{d}u$.
- 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 ith individual fails at t_i, given the risk set at t_i:

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

where the last equality follows from the Cox model assumption.

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

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

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

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

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*:

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

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 $\omega_{ij}(\beta) = \frac{e^{X_j\beta}}{\sum_{k\in R(t_j)} e^{X_k\beta}}$.
- $\omega_{ij}(\beta)$ can be seem as the conditional probability of death at t_j.
- 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

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

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

Partial likelihood

- The second derivative is

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

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

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 $\mathrm{d}N_i(t)$:

$$U(\beta, t) = \sum_{i=1}^{n} \Delta_i \left\{X_i - \bar{X}_i(\beta, t)\right\} = \sum_{i=1}^{n} \int_0^t \left\{X_i - \bar{X}_i(\beta, u)\right\} \mathrm{d}N_i(u) \qquad (9)$$

Link to counting process

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

$$M_i(t) = N_i(t) - \Lambda_i(t) = N_i(t) - \int_0^t \lambda_i(u)\,\mathrm{d}u,$$

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

$$\mathrm{d}M_i(t) = \mathrm{d}N_i(t) - \mathrm{d}\Lambda_i(t)$$

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

$$M_i(t) = N_i(t) - \int_0^t Y_i(u)h_0(u)e^{X_i\beta}\,\mathrm{d}u.$$

Link to counting process

- Under the Cox assumption, we have

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

- Thus, we can rewrite (9) as

$$U(\beta, t) = \sum_{i=1}^{n} \int_0^t \left\{X_i - \bar{X}_i(\beta, u)\right\} \mathrm{d}M_i(u),$$

  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 $\Lambda_0(t)$

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

$$\hat{\Lambda}_0(\beta, t) = \sum_{i; t_i \geq t} \frac{\mathrm{d}N(t_i)}{\sum_{j=1}^{n} Y_j(t) e^{X_j \beta}}$$

Reference

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