# Chapter 9 Refinements of Semi-parametric PHM 

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## §9.2 Time-dependent covariates

- $Z$ : baseline/fixed, not changing over time; most common. $Z(t)$ : time-dependent or time-varying covariate, e.g. weight, BMI, blood pressure, health or trt status at time $t$.
- PHM and PL:

$$
\begin{gathered}
h(t \mid Z(t))=h_{0}(t) \exp \left(Z(t)^{\prime} \beta\right) \\
L(\beta)=\prod_{i=1}^{D} L_{i}=\prod_{i=1}^{D} \frac{\exp \left(Z_{(i)}(t)^{\prime} \beta\right)}{\sum_{j \in R\left(t_{i}\right)} \exp \left(Z_{(j)}(t)^{\prime} \beta\right)} .
\end{gathered}
$$

- Example: $n=4 ; Z(t)$ : smoking status at $t$.
obs 1: $Z(t)=1$ for $0 \leq t<2 ; Z(t)=0$ for $t \geq 2$; event at $t=5$. obs $2: Z(t)=0$ for $0 \leq t<4 ; Z(t)=1$ for $t \geq 4 ;$ event at $t=6$.
obs 3: $Z(t)=0$ up to an event at $t=1$.
obs 4: $Z(t)=1$ up to an event at $t=3$.
$L_{1}=\frac{\exp (0 * \beta)}{\exp (0 * \beta)+\exp (1 * \beta)+\exp (0 * \beta)+\exp (1 * \beta)}$.

$$
\begin{aligned}
L_{2} & =\frac{\exp (1 * \beta)}{\exp (1 * \beta)+\exp (0 * \beta)+\exp (1 * \beta)} \\
L_{3} & =\frac{\exp (0 * \beta)}{\exp (0 * \beta)+\exp (1 * \beta)} \\
L_{4} & =\frac{\exp (1 * \beta)}{\exp (1 * \beta)}=1
\end{aligned}
$$

- Example 9.1: SAS

DFS: disease-free survival, min(disease recurrence, death).
Dan Sargent's paper: in colon-cancer trials, the outcome is

1) 5-yr survival as the current practice;
2) 3-yr DFS as the new proposed one.
$Z_{a}=0$ if $t<$ time at which aGVHD occurs; $=1 \mathrm{o} / \mathrm{w}$.
$Z_{c}=0$ if $t<$ time at which cGVHD occurs; $=1 \mathrm{o} / \mathrm{w}$.
$Z_{p}=0$ if $t<$ time at the platelets recovered; $=1 \mathrm{o} / \mathrm{w}$.

- An application: check the PH assumption.
- Consider a simple example: a binary $Z=0$ or 1 , indicating one of the two groups.
PHM: $h(t \mid Z)=h_{0}(t) \exp \left(Z \beta_{1}\right) \Longrightarrow$
$\frac{h(t \mid \operatorname{Grp} 1)}{h(t \mid \operatorname{Grp} 0)}=\exp \left(\beta_{1}\right)$, constant $!$
- Now, consider an alternative model:
$h(t \mid Z)=h_{0}(t) \exp \left(Z \beta_{1}+Z g(t) \beta_{2}\right) \Longrightarrow$ $\frac{h(t \mid \operatorname{Grp} 1)}{h(t \mid \operatorname{Grp} 0)}=\exp \left(\beta_{1}+g(t) \beta_{2}\right)$, time-varying $\left(\right.$ if $\left.\beta_{2}=0\right)$ !
- Checking a PHM: add a time-dependent covariate, e.g. $Z \times \log (t)$, and see whether its coefficient is significant! not a general GOF test: depending on the true and specified $g(t)$; you used this type of tests often...
- Example 9.2: SAS


## §9.3 Stratified PHM

- Consider two binary covariates: $Z_{1}$ indicating trt grp, $Z_{2}$ indicating male grp.
PHM: $h\left(t \mid Z_{1}, Z_{2}\right)=h_{0}(t) \exp \left(Z_{1} \beta_{1}+Z_{2} \beta_{2}\right) \Longrightarrow$
$\frac{h\left(t \mid t r t, Z_{2}\right)}{\left.h(t c t) Z_{2}\right)}=\exp \left(\beta_{1}\right)$,
$\frac{h\left(t Z_{1}, M\right)}{h\left(t \mid Z_{1}, F\right)}=\exp \left(\beta_{2}\right)$. -again constant and PH!
- How about if 1) PH assumption may not hold for $Z_{2}$ while holds for $Z_{1}$ and 2) only $\beta_{1}$ is of interest?
- 1) fix the problem, e.g., by ...; 2) use a stratified PHM:
$h\left(t \mid Z_{1}, Z_{2}\right)=h_{0}\left(t \mid Z_{2}\right) \exp \left(Z_{1} \beta_{1}\right)$
- Implications:
$h\left(t \mid Z_{1}, M\right)=h_{0, M}(t) \exp \left(Z_{1} \beta_{1}\right)$,
$h\left(t \mid Z_{1}, F\right)=h_{0, F}(t) \exp \left(Z_{1} \beta_{1}\right)$,
and there is no restriction/assumption on the relationship between the two baseline hazards; e.g.,
$h\left(t \mid Z_{1}, M\right) / h\left(t \mid Z_{1}, F\right)=h_{0, M}(t) / h_{0, F}(t)$ may or may not be a constant!
On the other hand, $\frac{h\left(t \mid t r t, Z_{2}\right)}{h\left(t \mid c t l, Z_{2}\right)}=\exp \left(\beta_{1}\right)$, still a PHM!
- Summary: to adjust for a confounder, 1) put it in a regression model; or 2) treat it as a stratifier.
A key difference: 1) may require a stronger modeling assumption.
- How to estimate $\beta$ ?
- Method 1: analogous to M-H method,

1) fit a PHM for each stratum: using $L^{(h)}(\beta)$ based on the data in stratum $h \Longrightarrow \hat{\beta}^{(h)}$;
2) combine $\hat{\beta}^{(h)}$ 's, e.g., by $\ldots$

Prior to 2), may conduct a homogeneity test on $H_{0}$ : $\beta^{(1)}=\beta^{(2)}=\ldots ;$ why and how?

- Method 2: under the homogeneity assumption, use $L(\beta)=\prod_{h} L^{(h)}(\beta)$.
- Example 9.1b: SAS


## §9.4 Left-truncated and right-censored data

- Channing House data:

Age 1: age at the entry;
Age 2: age at the end of study or death.
Covariate: gender.

- Recall how we dealt with LT-RC'ed data:

One sample problem: modify K-M or N-A estimator; how?
K-sample problem: modify generalized rank tests; how?
Regression with PHM: modify PL; how?

- LT-RT'ed data: $\left(Y_{j}, T_{j}, \delta_{j}, Z_{j}\right), j=1, \ldots, n$.
- PHM: $h(t \mid Z)=h_{0}(t) \exp \left(Z^{\prime} \beta\right)$.
- Modification: $R\left(t_{i}\right)=\left\{j: Y_{j}<t_{i} \leq T_{j}\right\}$;

PL remains the same with the new $R\left(t_{i}\right)$.

- MPLE

$$
\begin{aligned}
& \hat{\beta}=\operatorname{argmax}_{\beta} \prod_{i=1}^{D} \frac{\exp \left(Z_{i(i)}^{\prime} \beta\right)}{\sum_{j \in R\left(t_{i}\right)} \exp \left(Z_{j}^{\prime} \beta\right)}, \\
& \hat{H}_{0}(t)=\sum_{t_{i} \leq t}, \begin{array}{c}
d_{i} \\
\sum_{j \in R\left(t_{i}\right)} \exp \left(Z_{j}^{\prime} \beta\right)
\end{array}
\end{aligned}
$$

- Example 9.4: SAS
- Another use of the counting process notation:

Code time-dependent covariates: e.g., how to input the data with time-dependnet smoking status in the example on p.2? Any issue with multiple "observations" from the same subject?

