What to do this week (2022/02/15, 02/17)?

Part I. Preliminaries

Part II. Parametric Inference

Part III. Nonparametric/Semi-parametric Inference Part III.1. Introduction and Overview: Motivation Part III.3. Kaplan-Meier Estimator Part III.3. Nonparametric Tests Part III.4. Cox Proportional Hazards Model Part III.4.1 Modeling Part III.4.2 Inference Part III.4.3 Extensions A Brief Summary of Part III A. Practical Example B. Talk on Survival Analysis by A.A. Tsiatis

Part IV. Advanced Topics

### Part III.4.1 Cox Proportional Hazards Model: Modeling

**Cox Proportional Hazards Model**: (Cox, JRSSB 1972) The hazard function of event time T|Z = z is

$$h(t|z) = h_0(t)e^{\beta z}, \quad t > 0$$

The conditional survivor function is

$$S(t|z) = \exp(-\int_0^t h_0(u)e^{\beta z}du) = \exp(-H_0(t)e^{\beta z}), \ t > 0$$

## Part III.4.1 Cox Proportional Hazards Model: Modeling

#### Remarks

• the hazard ratio  $h(t|Z = z_1)/h(t|Z = z_0) = e^{\beta(z_1 - z_0)}$  for all t > 0 proportional!

$$\blacktriangleright Z = \begin{cases} 1 & treatment \\ 0 & placebo \end{cases}, e^{\beta}: treatment effect$$

• 
$$Z_1 = \begin{cases} 1 & \text{treatment} \\ 0 & \text{placebo} \end{cases}$$
,  $Z_2 = \begin{cases} 1 & \text{male} \\ 0 & \text{female} \end{cases}$ ,  $\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}$ ,  
 $\mathbf{Z} = \begin{pmatrix} Z_1 \\ Z_2 \end{pmatrix}$ ,  $h(t|\mathbf{Z}) = h_0(t)e^{\beta'\mathbf{Z}}$ : relative impacts of the treatment to female and male are the same.

Often is interested to estm  $\beta$  in the Cox PH model, for comparison/evaluate/assess effect  $\ldots$   $\ldots$ 

With right-censored event times along with the covariates

$$\left\{ (U_i, \delta_i, Z_i) : i = 1, \ldots, n \right\}$$

from *n* indpt subjects and indpt censoring  $T_i \perp C_i$ 

$$L(\beta, h_0(\cdot)|data) = \prod_{i=1}^n \left(h_0(u_i)e^{\beta z_i}\right)^{\delta_i} \exp(-H_0(u_i)e^{\beta z_i})$$

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

 $\implies$  the Cox partial likelihood function (Cox, Biometrika 1975)

the Cox partial likelihood function (Cox, Biometrika 1975)

$$L_1(etaig| data) = \prod_{i=1}^n \Big(rac{e^{eta z_i}}{\sum_{l\in \mathcal{R}_i} e^{eta z_l}}\Big)^{\delta_l}$$

the risk set at time  $u_i$ :  $\mathcal{R}_i = \{j : u_j \ge u_i\}$ 

 $\implies$  the MPLE (maximum partial likelihood estimator) of  $\beta$ :

$$\hat{eta} = {\sf argmax}_{{\sf all}\,|eta} {\sf L}_1(etaig|{\sf data})$$

With some conditions, as  $n \to \infty$ 

• 
$$\hat{\beta} \rightarrow \beta$$
 a.s.  
•  $\sqrt{n}(\hat{\beta} - \beta) \rightarrow N(0, ?)$  in distn

**Example III.4.** n = 5 indpt subjects and  $Z = \begin{cases} 1 & treatment \\ 0 & placebo \end{cases}$  $(u_i, \delta_i, z_i) : (16, 1, 1), (13, 0, 0), (21, 1, 1), (11, 1, 0), (12, 1, 1)$  $\implies \hat{\beta} = \frac{1}{2} \log 2 - \log 3$ 

#### Remarks

• implementation  
• to use log 
$$L_1(\beta) = \sum_{i=1}^n \delta_i \{\beta z_i - \log(\sum_{l \in \mathcal{R}_i} e^{\beta z_l})\}$$
  
or  $U(\beta) = \partial \log L_1(\beta) / \partial \beta = \sum_{i=1}^n \delta_i \{z_i - \frac{\sum_{l \in \mathcal{R}_i} z_l e^{\beta z_l}}{\sum_{l \in \mathcal{R}_i} e^{\beta z_l}}\} = 0$   
• e.g. *R*: coxph

Remarks (cont'd)

#### interpretation

 recall likelihood, marginal likelihood, conditional likelihood, partial likelihood

the Cox partial likelihood function of β

- conditional arguments
- the marginal distn of the rank statistic when no tie, no censored observation, cfs: Kalbfleisch and Prentice (1980, 2011)

## Part III.4.2B Cox Proportional Hazards Model: Testing on $\beta$

Consider  $H_0: \beta = 0$  vs  $H_1: \beta \neq 0$ 

the partial score test

$$U(\beta) = \partial \log L_1(\beta) / \partial \beta = \sum_{i=1}^n \delta_i \left[ z_i - \frac{\sum_{l \in \mathcal{R}_i} z_l e^{\beta z_l}}{\sum_{l \in \mathcal{R}_i} e^{\beta z_l}} \right]$$

Based on  $U(\beta)/\sqrt{n} \sim AN(0,??)$  as  $n \to \infty$  with some conditions,

 $\implies$  the partial score testing procedure ...

# Part III.4.2B Cox Proportional Hazards Model: Testing on $\beta$

#### Remarks.

• e.g. when 
$$Z = \begin{cases} 1 & treatment \\ 0 & placebo \end{cases}$$

 $U(\beta)|_{\beta=0} = \sum_{l=1}^{L} \left(O_l - n_{.l} \frac{N_{1l}}{N_{.l}}\right) = O - E$ , the numerator of the logrank test statistic

- the Wald-type, using the MPLE of β and its asymptotic normality?
- the PLRT, using the structure of LRT?

To learn about the whole hazard function, to predict ... ...

Thinking ..., if  $\beta$  is known,

- ▶ at time  $V_l$ , subject j in  $\mathcal{R}_{(l)}$  with prob of failing  $h_0(V_l)e^{\beta z_j}$ ;
- the 'average' prob of failing at V<sub>l</sub> for all N<sub>l</sub> subjects in R<sub>(l)</sub> is h<sub>0</sub>(V<sub>l</sub>) ∑<sub>j∈R<sub>(l)</sub> e<sup>βz<sub>j</sub></sup>/N<sub>l</sub>;</sub>
- on the other hand, the proportion of failing at  $V_I$  is  $d_I/N_I$

Thus

$$\hat{h}_{0}(t) = \left\{ egin{array}{cc} rac{d_{l}}{\sum_{j \in \mathcal{R}_{(l)}} e^{eta^{z_{j}}}} & t = V_{l} \ 0 & otherwise \end{array} 
ight.$$

$$\hat{H}_0(t) = \int_0^t \hat{h}_0(u;\beta) du = \sum_{V_l \leq t} \hat{h}_0(V_l;\beta)$$

Finally,  $\hat{H}_0(t) = H_0(t; \hat{\beta})$  (Breslow estimator)

#### Remarks

Breslow estimator: NPMLE

uniform consistency, weak convergence

▶ If 
$$\beta = 0$$
,  $H_0(t) = H(t)$   
▶  $\hat{H}(t) = \sum_{V_l \le t} \frac{d_l}{N_l}$ : Nelson-Aalen estimator

•  $\hat{S}(t) = \exp(-\hat{H}(t))$ : Fleming-Harrington estimator, an alternative to Kaplan-Meier estimator  $\hat{S}_{KM}(t)$ 

**Example III.4.** (cont'd) n = 5 indpt subjects and  $Z = \begin{cases} 1 & treatment \\ 0 & placebo \end{cases}$ 

 $(u_i, \delta_i, z_i)$ : (16, 1, 1), (13, 0, 0), (21, 1, 1), (11, 1, 0), (12, 1, 1)

### Part III.4.3 Cox PH Model: Extensions

**III.4.3A. To include strata** e.g.  $Z = \begin{cases} 1 & treatment \\ 0 & placebo \end{cases}$ ,  $W = \begin{cases} 1 & male \\ 0 & female \end{cases}$ ,  $\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}$ To consider the Cox PH model with covariates Z, W:

$$h(t|Z,W)=h_0(t)e^{\beta_1Z+\beta_2W},$$

four hazards proportional to each other

Alternatively, stratify the subjects according to the categories of W, and consider the Cox PH model:

$$h(t|Z, W = w) = h_{w0}(t)e^{\beta Z}, w = 1, 2, ..., K$$

K pairs of proportional hazards: the same effect across different strata

Inference: in stratum 
$$k \Longrightarrow L_P^{(k)}(\beta)$$
; over all  $\prod_{k=1}^{K} L_P^{(k)}(\beta)$ 

What if different treatment effects in difference strata?

### Part III.4.3 Cox PH Model: Extensions

### III.4.3B. Time-varying (time-dependent) covariates:

e.g. air pollution level at time t: Z(t); time till an asthma attack

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

Inference: 
$$L_P(\beta) = \prod_{i=1}^n \left( \frac{e^{\beta z_i(u_i)}}{\sum_{l \in \mathcal{R}_i} e^{\beta z_l(u_i)}} \right)^{\delta_i}$$

Remarks

- interpretation of the effect of  $Z(\cdot)$  on T?
- required information of  $\{Z_i(t) : t > 0\}$ ?

### Part III.4.3 Cox Proportional Hazards Model: Extensions

#### III.4.3C. Time-varying (time-dependent) coefficient:

e.g. treatment effect at time t:  $\beta(t)$ ; time till an asthma attack

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

Inference:

- assuming a lot of ties of observed event times, or
- specifying β(t) into (i) β(t; α), (ii) a spline (piecewise-polynomial real function)

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#### Part II. Parametric Inference

#### Part III. Nonparametric/Semi-parametric Inference

- Part III.1. Introduction and Overview
- Part III.2. Kaplan-Meier Estimator
- Part III.3. Nonparametric Tests
- Part III.4. Cox Proportional Hazards Model
- ► A Summary of Part III.
  - A. Practical Example
  - B. Talk on Survival Analysis by A.A. Tsiatis

Part IV. Advanced Topics