

Introduction (regression models)

Accelerated Failure Time Model (AFT model)

X : survival time

$$Y = \ln X$$

$$Y = \mu + \gamma^T Z + \sigma W \quad , W \sim \text{random error}$$

Proportional Hazards model (PH model)

$$h(x | z) = h_0(x) \exp(\beta^T z)$$

The Cox model is a special case of PH model
when $h_0(x)$ is unspecified (nonparametric)

various forms of AFT and Cox models

(1) AFT : $S(x|z) = S_0(x \exp -\gamma^T z)$

Cox : $S(x|z) = [S_0(x)]^{\exp \beta^T z}$

(2) ☆ AFT : $Y = \mu + \gamma^T Z + \sigma W$

Cox : $\ln [-\ln S(x|z)] = \beta^T z + \ln [-\ln S_0(x)]$

(3) AFT : $h(x|z) = h_0(xe^{-\gamma^T z}) \exp(-\gamma^T z)$

☆ Cox : $h(x|z) = h_0(x) \exp(\beta^T z)$

Cox model : easy to do inference but hard to interpret

△ The Cox model

Cox(1972)

$$h(t|z) = h_0(t) \exp \beta^T z$$

$h_0(t)$: Not specified → Nonparametric

$$\frac{h(t|z = \zeta_1)}{h(t|z = \zeta_0)} = \frac{h_0(t) \exp \beta^T \zeta_1}{h_0(t) \exp \beta^T \zeta_0} = \exp \beta^T (\zeta_1 - \zeta_0) \Rightarrow \text{This ratio is constant}$$

So Cox model also called PH model.

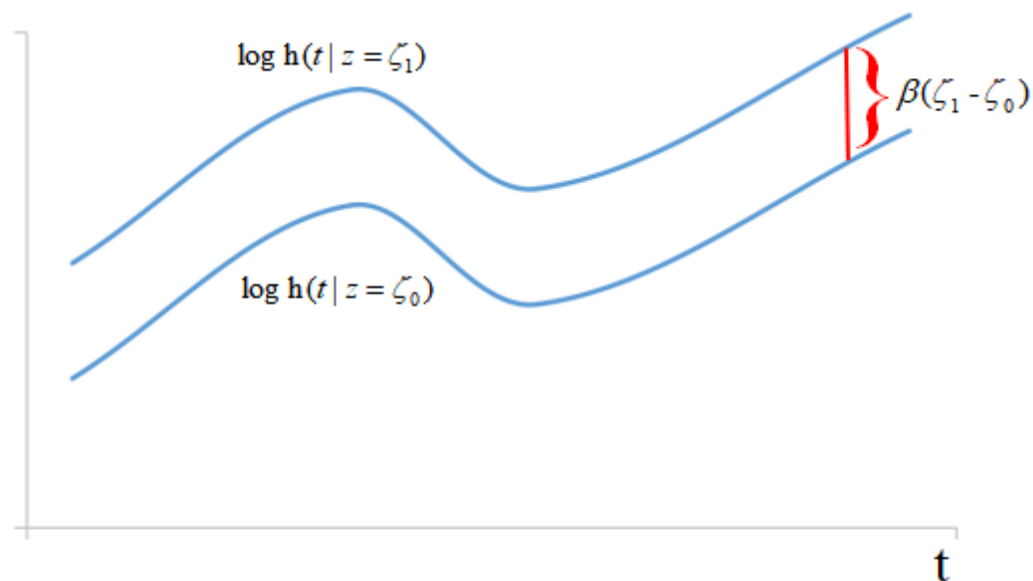
$$\zeta_1 = 1 \text{ Male}$$

$$\zeta_0 = 0 \text{ Female}$$

$$\zeta_1 - \zeta_0 = 1 \Rightarrow \exp \beta (\zeta_1 - \zeta_0) = \exp \beta$$

M relative risk to F

$$\begin{cases} \log h(t|z = \zeta_1) = \log h_0(t) + \beta \zeta_1 \\ \log h(t|z = \zeta_0) = \log h_0(t) + \beta \zeta_0 \end{cases}$$



△ Partial likelihoods for distinct event time data

Suppose that there are no ties between event times

Let $t_1 < t_2 < \dots < t_D$ denote the ordered event

and Z is a covariate.

$R(t_i)$: risk set at time t_i

(The set of all individuals who are still under study at time just prior to t_i)

$$\text{Hazard function} = \begin{cases} \frac{f(t)}{S(t)} & \text{for continuous time} \\ P(X = t | X \geq t) = \frac{P(X = t)}{P(X \geq t)} & \text{for discrete time} \end{cases}$$
$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq X \leq t + \Delta t | X > t)}{\Delta t}$$

$$\text{Likelihood function} : \begin{cases} \prod_{i=1}^n f(t_i) \\ \prod_{i=1}^n P(X = t_i) \end{cases}$$

Nonparametric methods treat time as discrete

$$\Rightarrow L(\beta) = \prod_{i=1}^n P(X_i = t_i) = \prod_{i=1}^n p(\text{individual } i \text{ die at } t_i) = \text{We can not handle this}$$



However we can handle for individual i

$$\Rightarrow p(\text{individual } i \text{ died at } t_i \mid \text{one died at } t_i)$$

$$= \frac{p(\text{individual } i \text{ died at } t_i \mid \text{Survival to } t_i)}{p(\text{one death at } t_i \mid \text{Survival to } t_i)}$$

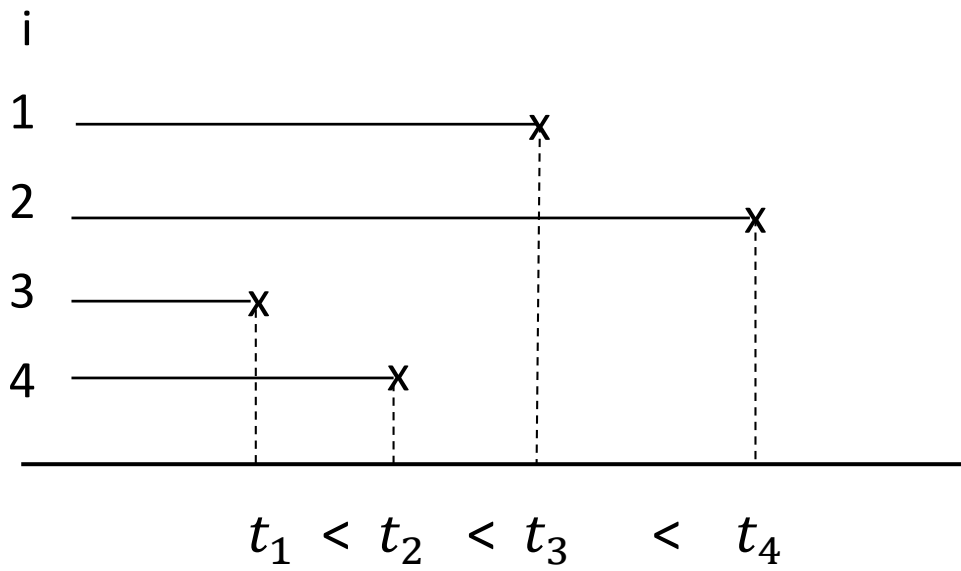
$$= \frac{h(t_i \mid z_i)}{\sum_{j \in R(t_i)} h(t_i \mid z_j)}$$

$$= \frac{\cancel{h_0(t_i)} \exp \beta z_i}{\sum_{j \in R(t_i)} \cancel{h_0(t_i)} \exp \beta z_j} = \frac{\exp \beta z_i}{\sum_{j \in R(t_i)} \exp \beta z_j}$$

$$L(\beta) = \prod_{i=1}^D \frac{\exp \beta z_i}{\sum_{j \in R(t_i)} \exp \beta z_j}$$

(We call it partial likelihood function
not full likelihood function)

Ex:



$$R(t_1) = \{ 1, 2, 3, 4 \}$$

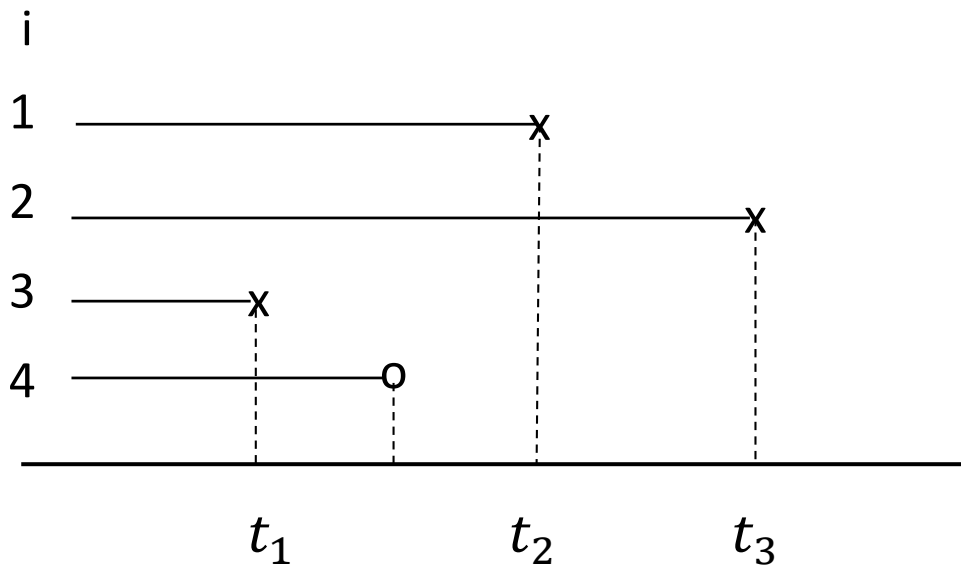
$$R(t_2) = \{ 1, 2, 4 \}$$

$$R(t_3) = \{ 1, 2 \}$$

$$R(t_4) = \{ 2 \}$$

$$L(\beta) = \frac{\exp \beta z_3}{\exp \beta z_1 + \exp \beta z_2 + \exp \beta z_3 + \exp \beta z_4} \cdot \frac{\exp \beta z_4}{\exp \beta z_1 + \exp \beta z_2 + \exp \beta z_4} \cdot \frac{\exp \beta z_1}{\exp \beta z_1 + \exp \beta z_2} \cdot \frac{\exp \beta z_2}{\exp \beta z_2}$$

Ex:



$$R(t_1) = \{ 1, 2, 3, 4 \}$$

$$R(t_2) = \{ 1, 2 \}$$

$$R(t_3) = \{ 2 \}$$

$$L(\beta) = \frac{\exp \beta z_3}{\exp \beta z_1 + \exp \beta z_2 + \exp \beta z_3 + \exp \beta z_4} \cdot \frac{\exp \beta z_1}{\exp \beta z_1 + \exp \beta z_2} \cdot \frac{\exp \beta z_2}{\exp \beta z_2}$$

Obtaining β

$$\text{Let } U(\beta) = \frac{\partial \log L(\beta)}{\partial \beta}$$

$$I(\beta) = \frac{\partial U(\beta)}{\partial \beta}$$

$$\Rightarrow \hat{\beta}^{(k+1)} = \hat{\beta}^{(k)} - I^{-1}(\hat{\beta}^{(k)})U(\hat{\beta}^{(k)})$$

Starting value $k = 0 \Rightarrow$ set $\hat{\beta}^{(0)} = c$

When $\left| \frac{\hat{\beta}^{(k+1)} - \hat{\beta}^{(k)}}{\hat{\beta}^{(k)}} \right| < \varepsilon$, stop

3 tests based on likelihood function

$$H_0: \beta = \beta_0$$

Wald test:

$$X_W^2 = (\hat{\beta} - \beta_0)^T I(\hat{\beta})(\hat{\beta} - \beta_0)$$

Score test:

$$X_S^2 = U(\beta_0)^T I(\beta_0)U(\beta_0)$$

LR test:

$$X_{LR}^2 = 2[\log L(\hat{\beta}) - \log L(\beta_0)]$$

$$n \rightarrow \infty, \begin{cases} X_W^2 \\ X_S^2 \\ X_{LR}^2 \end{cases} \rightarrow \chi_p^2$$

△ When ties are present \Rightarrow Efron(1977) , Brelow(1974) , Cox(1972)
correction

△ Testing proportional hazards

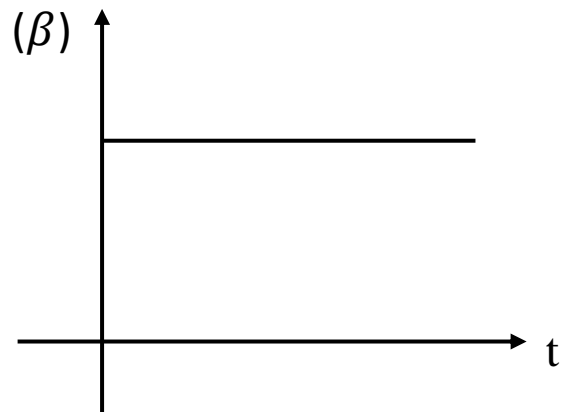
$$S(t|z) = [S_0(t)]^{\exp\beta z}$$

$$\text{Graphic} \Rightarrow \begin{cases} \log[-\log S(t|z)] = \log[-\log S_0(t)] + \beta z \\ \log H(t) = \log H_0(t) + \beta z \end{cases}$$

test Cox.zph

$$h(t|z) = h_0(t) \exp(z\beta(t))$$

$$\beta(t) = \beta \Rightarrow \text{PH holds}$$



limitation:

- ① Failure to detect non-proportionality
Ex: $\beta(t)$ quadratic shape
- ② Sample size can not be too small!

△ Strategies for nonproportional data

suppose that $\left\{ \begin{array}{l} \text{(i) cox.zph test (Schoenfeld residual plot)} \\ \text{(ii) Diagnostic technique} \end{array} \right.$

gives strong evidence of nonproportionality for one or more covariates

What should we do?

① It does not matter (little effect)

② It is not real (outliers)

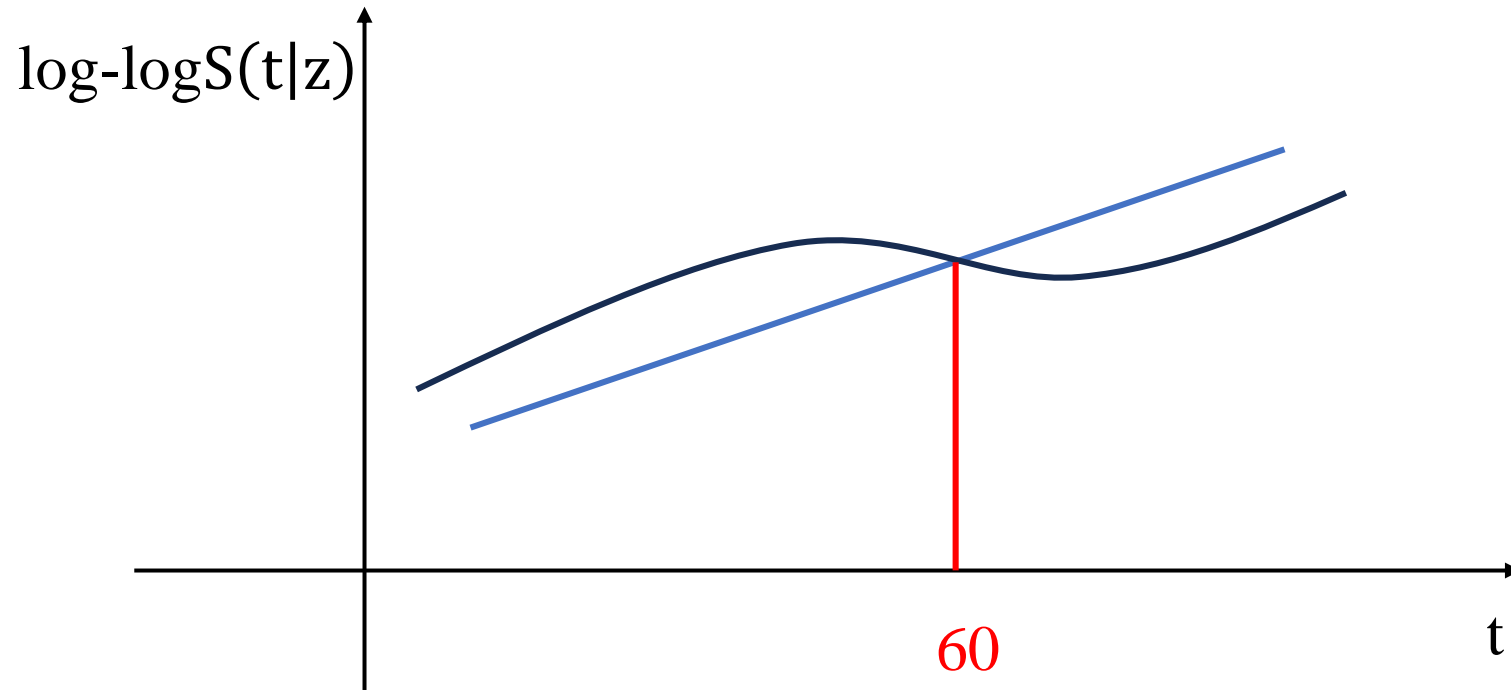
But if the proportionality is large and real, what then?

S1. Stratification:

$$h_j(t|z) = h_{0j}(t) \exp \beta z \quad , \quad j = 1, 2, \dots, s \quad \# \text{ of strata}$$

$$n_1 + n_2 + \dots + n_s = n$$

S2. Partition the time axis



$\text{coxph}(\text{Surv}(\text{time}, \text{censor}) \sim Z_1 + Z_2, \text{subset}(\text{time} < 60), \text{data} = \text{data})$

S3. Model nonproportionality by time-dependent covariates

$\beta(t)Z = \beta Z^*(t)$ limitation : need to specify functional form of $\beta(t)$ (SAS)

S4. Use a different model

Accelerated Failure Time model(AFT)

Additive hazards model ,

△ The Cox model with time-dependent covariates

Fixed covariate : $h(t|z) = h_0(t) \exp \beta z$

$$L(\beta) = \prod_{i=1}^D \frac{\exp \beta Z_i}{\sum_{j \in R(t_i)} \exp \beta Z_j}$$

Time-dependent covariates : $h(t|z(t)) = h_0(t) \exp \beta z(t)$

$$L(\beta) = \prod_{i=1}^D \frac{\exp \beta Z_i(t_i)}{\sum_{j \in R(t_i)} \exp \beta Z_j(t_i)}$$

	id	futime	status	death	trt	age	sex	day	start	stop	ascites	hepato	spiders	edema	bili
1	4	1925	2	0	1	54.74059	f	0	0	188	0	1	1	0.5	1.8
2	4	1925	2	0	1	54.74059	f	188	188	372	0	1	1	0.5	1.6
3	4	1925	2	0	1	54.74059	f	372	372	729	0	1	1	0.5	1.7
4	4	1925	2	0	1	54.74059	f	729	729	1254	0	1	1	1	3.2
5	4	1925	2	0	1	54.74059	f	1254	1254	1462	0	0	1	1	3.7
6	4	1925	2	0	1	54.74059	f	1462	1462	1824	0	1	1	1	4
7	4	1925	2	2	1	54.74059	f	1824	1824	1925	1	1	1	1	5.3