

## △ Accelerated Failure Time model

survival time :  $X$  , covariate  $Z$

$$Y = \ln X$$

$$Y = \mu + \gamma Z + \varepsilon \quad (\varepsilon = \sigma W)$$

△  $\varepsilon$  : unspecified (nonparametric)

- 1. An attractive alternative model to cox model
- 2. Direct physical interpretation

Estimation : By ① rank estimate

② Generalized Estimating equation

Note that :  $\gamma : +$  then  $Z \uparrow \Rightarrow Y \uparrow$  (help survival)

$-$  then  $Z \uparrow \Rightarrow Y \downarrow$  (hurt survival)

## 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

## △ Clustered survival time

Breast cancer v.s. mutation of BRCA gene (Ashkenazi Jewish population)  
risk

- ① Cluster
- ② Frailty
- ③ Mixed effect Cox model

$$h_{ij}(t_{ij}) = h_0(t_{ij}) \cdot w_i \cdot e^{z_{ij}\beta}$$

$$w \sim \frac{w^{\frac{1}{\theta}-1} e^{-\frac{w}{\theta}}}{\Gamma\left(\frac{1}{\theta}\right) \theta^{\frac{1}{\theta}}}$$

gamma distribution

# Competing risk

Multiple events

① Simplistic method

treat other event time as censor

△ However this method is questionable !

This censor is not independent !!

△ Cause-specific hazards and cumulative incidence functions

K distinct causes of death

one can experience at most one of K causes of death

$$\begin{aligned} \text{Cause-specific} &\Rightarrow F_j(t) = P(T \leq t, C = j) = \int_0^t h_j(u) S(u) du \\ \text{CDF} &F_j(\infty) = P(C = j) \end{aligned}$$

- The cause-specific hazard of  $j$ th cause

$$h_j(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t < T < t + \Delta t, C = j | T > t)}{\Delta t}$$

$$\Rightarrow h(t) = \sum_{j=1}^k h_j(t)$$

- $D$  ordered event times  $\Rightarrow t_1 < t_2 < \dots < t_D$

$$\hat{h}(t_i) = \frac{d_i}{n_i} \quad \Leftrightarrow \quad \hat{h}(t_i) = \frac{\sum_{k=1}^{\bar{k}} d_{ik}}{n_i}$$

$$\hat{h}_k(t_i) = \frac{d_{ik}}{n_i}$$

$$\hat{F}_k(t) = \sum_{t_i \leq t} \hat{S}(t_{i-1}) \hat{h}_k(t_i) \quad \Leftarrow$$

Cumulative incidence  
function

Common way to display: stacked plot

## Ex: Prostate cancer data

$$n = 14294 \begin{cases} 0 \text{ censored} \\ 1 \text{ death from prostate cancer} \\ 2 \text{ death from other cancer} \end{cases}$$

Need install mstate package and use “Cuminc” command

Consider Age 80+ population

- Regression methods for cause-specific hazards

special challenges  $\Rightarrow$  It's difficult to define precisely the hazard function on which the covariate should operate.

simple method (Putter et.al.(2007)) treat other events as censored

vice versa!!

Fine and Gray

$$\overline{h}_k(t) = - \frac{d \log(1-F_k(t))}{dt}$$

$$\overline{h}_k(t|z) = \overline{h}_{0k}(t)e^{z\beta}$$

Use Fine and Gray method  $\Rightarrow$  package “cmprsk” command “crr”.

Consider  $T_2$  stage patients in prostate cancer data.

- Run R codes to see the example.

Other causes:

- grade poor risk ratio **0.126** (Fine and gray) vs. **0.281** (Putter et al.)

Prostate cancer :

- grade poor risk ratio **1.132** vs. **1.22**

## Recurrent event (ordered event)

① AG (Andersen-Gill)

$$Y_i(t)\lambda_0(t)\exp(X_i(t)\beta)$$

Poisson process

② WLW (Wei , Lin and Weissfeld)

$$Y_{ij}(t)\lambda_{0j}(t)\exp(X_i(t)\beta_j)$$

jth event

③ Conditional model (PWP , Prentice , William & Peterson)

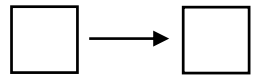
similar to AG but effect for events may be difficult.



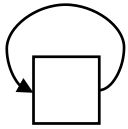
Ex : One has event on 10,30,42

	Interval	Stratum
AG	(0,10]	1
	(10,30]	1
	(30,42]	1
WLW	(0,10]	1
	(0,30]	2
	(0,42]	3
PWP	(0,10]	1
	(10,30]	2
	(30,42]	3

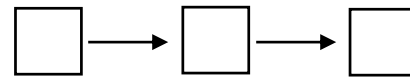
Time to first event



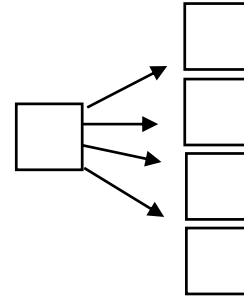
AG



Conditional(PWP)



WLW



Ex : Smith has experienced his second event on day 32.

Who are the subjects at risk when Smith has his second event ?

AG : All subjects who were under observation on day 32.

WLW : All subjects who were under observation on day 32 , and have not yet had a second event.

PWP : All subjects who were under observation on day 32, have not yet had a second event , and have experienced a first event.

PWP

t	coef	exp(coef)	se(coef)	robustse	z	Pr(> z )
tx	-0.41836	0.658129	0.304194	0.293599	-1.425	0.154
num	0.11421	1.120987	0.053999	0.051294	2.227	0.026
size	-0.00745	0.992576	0.073207	0.063265	-0.118	0.906
tx:strata(int erval)interv al=2	-0.03349	0.967067	0.500317	0.552349	-0.061	0.952
tx:strata(int erval)interv al=3	0.350949	1.420415	0.667693	0.501027	0.7	0.484
tx:strata(int erval)interv al=4	0.622714	1.86398	0.749012	0.591132	1.053	0.292
tx:strata(int erval)interv al=5	NA	NA		0	0NA	NA

Event 1	-0.41836
Recurrent Event 2	-0.4519
Recurrent Event 2	-0.0674
Recurrent Event 2	0.2044

WLW

	coef	exp(coef)	se(coef)	robustse	z	Pr(> z )
tx	-0.44654	0.63984	0.30522	0.29072	-1.536	0.12454
num	0.15686	1.16983	0.05244	0.05089	3.082	0.00205 **
size	0.01421	1.01431	0.07029	0.0654	0.217	0.82801
tx:strata(int erval)interv al=2	0.13506	1.14461	0.49823	0.4969	0.272	0.78577
tx:strata(int erval)interv al=3	0.44582	1.56177	0.56088	0.60339	0.739	0.45999
tx:strata(int erval)interv al=4	0.50452	1.65619	0.65574	0.649	0.777	0.43693
tx:strata(int erval)interv al=5	NA	NA	0	0	NA	NA

Event 1	-0.4465
Recurrent Event 2	-0.3115
Recurrent Event 2	-0.0001
Recurrent Event 2	0.0987