### Biost 572 Presentation 1

Introduction, Motivation

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### Chapter 20

Application of Time-to-Event Methods in the Assessment of Safety in Clinical Trials

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Adapted from the book:

Design and Analysis of Clinical Trials with Time-to-Event Endpoints

Edited by Karl E . Peace

Chapman and Hall/CRC 2009

### Beta-Blocker Heart Attack Trial

- Group et al. (1982)
- Propranolol vs Placebo
- Primary endpoint: All cause mortality
  - Propranolol 7% mortality (135 deaths)
  - ▶ Placebo showed 9.5% mortality (183 deaths).
- Crude incidences of various AEs was observed to be higher in Propranolol arm
- Time-to-event analysis suggested evidence of shorter time to first AE i.e bronchospasm/fatigue (Davis et al., 1987)

# Literature Review: Moore and van der Laan (2009)

#### Parametric framework

- Covariate adjustment in linear models can provide gains in precision over unadjusted estimate (Biost 514/515/570)
- Adjusting in logistic regression often does not buy you improvements in precision (Robinson and Jewell, 1991; Hernández et al., 2006)

#### Estimating equations framework

- Estimation of nuisance parameters
- "Lack of criterion for selecting candidate solutions when there are multiple roots in parameter of interest"

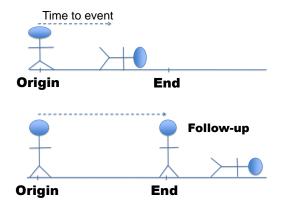
### Focus of the paper: Discrete failure time

#### Objectives

- Estimation of treatment specific survival at a fixed end point
- Exploits important (pre-specified) covariates to improve efficiency in treatment specific survival at fixed end point
- Provide a consistent estimator in the presence of informative censoring

"**Ultimate**" goal: Difference in survival probabilities between treatments adjusting for pre-specified covariates of interest.

### Introduction to Time-to-event outcomes



**Event of Interest**: Death/Infection/AE

Right censored data: Non-ignorable missing data.

**Informative censoring** 

### Brief Review: Survivor/Hazard function

$$S(t) = Pr(T > t) = 1 - F(t)$$

 F(t) is the fraction of the population whose event time has been observed by time t.

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{\Pr[t \le T < t + \Delta t | T \ge t]}{\Delta t}$$

Conditional probability per unit time (Hazard rate).

### Brief Review: Survival Analysis

Cox (1972) Proportional Hazards Regression

$$\lambda(t|A, \mathbf{W}) = \lambda_0(t) \exp(\beta_1 A + \boldsymbol{\beta}_W^T \mathbf{W})$$

Cox PH allows us to adjust for baseline covariates with  ${\bf W}$  Assumptions of Cox-PH

- Non-informative censoring
- Proportional hazards (odds) assumptions
- Large sample size\*

**Solution:** Biost 515/537 Cox-PH with robust standard errors.

# Setup: Discrete Version (Zhang and Gilbert, 2010)

$$\lambda(t_j) = \Pr(T = t_j | T > t_{j-1})$$

T\*: "True" failure time (Unobserved due to discrete follow-up)

$$T = t_j$$
 if  $T^* \in [t_{j-1}, t_j)$  with  $t_j$  for  $j = 1, \dots, 10$ .

 $\widetilde{T} = min(T, C)$ : where C is our censoring time.

 $\Delta = I(T \leq C)$ : Indicator of subject **not** being censored

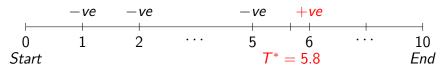
 $A \in \{0,1\}$ : Treatment indicator

**W**: Observed covariates

#### Discrete failure time

If someone develops an infection during the study

$$\cdots \quad \widetilde{T} = min(6, +\infty) = 6 \text{ with } \Delta = 1$$



If someone develops an infection after the study ended

$$\cdots$$
  $\widetilde{T} = min(11.5, 10) = 10$  with  $\Delta = 0$ 

$$-ve$$
  $-ve$   $-ve$   $+ve$ 
 $0$   $1$   $2$   $\cdots$   $9$   $10$   $10.5$ 
 $Start$   $End$   $T^*$ 

## Scientific questions: Setup based on the paper

Having observed the data  $O = (\mathbf{W}, A, \widetilde{T}, \Delta) \sim P_O$  where  $P_O$  is the data generating mechanism.

$$P_O o \Psi_1(p_O)(t_k) = \Pr(T_1 > t_k) = E_0(S_0(t_k|A=1, \mathbf{W}))$$

$$P_O o \Psi_0(p_O)(t_k) = \Pr(T_0 > t_k) = E_1(S_0(t_k|A=0,\mathbf{W}))$$

We might be interested in the following treatment effect at  $t_k$ 

$$\mathsf{P}_0 \rightarrow \Psi_{\mathsf{AD}}(\mathsf{p}_0)(\mathsf{t}_\mathsf{k}) = \mathsf{Pr}(\mathsf{T}_1 > \mathsf{t}_\mathsf{k}) - \mathsf{Pr}(\mathsf{T}_0 > \mathsf{t}_\mathsf{k})$$

### Proposed method & Author's claims

$$\textbf{P}_{\textbf{O}} \rightarrow \Psi_{\textbf{AD}}(\textbf{p}_{\textbf{O}})(\textbf{t}_{\textbf{k}}) = \text{Pr}(\textbf{T}_{\textbf{1}} > \textbf{t}_{\textbf{k}}) - \text{Pr}(\textbf{T}_{\textbf{0}} > \textbf{t}_{\textbf{k}})$$

- "Target" the parameter of interest directly
- Targeted MLE: borrow useful information from parametric models and overcome drawbacks of estimating equations.
- "Doubly robust"
  - Robust to model mis-specification
  - Overcomes the problem of informative censoring
- Simulations on weak/strong covariate in combination with random censoring and informative censoring.

#### What is to come

- Introduction to targeted MLE for survival outcomes
- Estimation algorithm
- Test the coded algorithm on a "toy" dataset
- Test with the proposed simulation in the paper

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