Survival Analysis

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^{1.} Introduction

- Survival analysis-time to event data
- Our focus: the math of it all
- Sherry Ren will present an application

^{2.} Basics

- Time to event data
 - beginning of study -> event of interest occurs
 - example: first illegal pain pill usage -> first usage of heroin
- Useful in biostatistics

^{3.} The variables

- τ_i -> true time at which *i*th observation dies
- $C_i \rightarrow$ time at which *i*th observation is notes as censored
- $\tilde{\tau}_i \rightarrow$
 - last time at which *i*th observation is noted to be alive, whether it "died" or was censored
 - $\circ~$ minimum of ${\it C}_{i^\prime}$ point at which data is noted to be censored, and τ_i

^{4.} Survival Curve

- Denoted S(t)
- Complement of CDF: S(t) = 1 F(t)
- Represents probability of survival at every point on x-axis
- Is central object of study in survival analysis

^{5.} Hazard Function

- Represents instantaneous risk of experiencing event at time *t* among those still at risk––rate of change of survival function
- Low when survival curve isn't dropping much
- Spikes when survival function has steep decline
- Not our focus, but still useful for understanding time to event data

$$h(t) = \lim_{\Delta t o 0} rac{P\left(t \leq T < t + \Delta t | T \geq t
ight)}{\Delta t}$$

^{6.} In practice

- We have access to: $\tilde{\tau}_i$ and C_i
- $\tilde{\tau}_i$: last time at which *i*th observation was noted to be alive
- C_i: time when *i*th observation is censored
- With these, we can estimate survival curve
- Estimate options: Naive and Kaplan Meier estimators

$${ ilde au}_j = \min(au_j, c_j)$$

^{7.} Naive estimate

- Number of objects in study that haven't "died"/been censored divided by number of objects that haven't been censored at time t
- Ignores observations with censoring times preceding t
- Inspires Kaplan Meier estimator on next slide

$$\hat{S}_{ ext{naive}}(t) = rac{1}{m(t)}\sum_{k:c_k \ge t} X_k = rac{|\{1 \le k \le n \, : \, ilde{ au}_k \ge t\}|}{|\{1 \le k \le n \, : \, c_k \ge t\}|} = rac{|\{1 \le k \le n \, : \, ilde{ au}_k \ge t\}|}{m(t)}$$

^{8.} Kaplan Meier

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- Better for more censoring
- Recursive relationship $-S(t_{prev})$

$$S(t) \hspace{0.1 cm} = \hspace{0.1 cm} P(T>t)$$

$$= P(T>t|T\geq t)P(T\geq t)$$

$$= \quad \left[1 - P(T \leq t | T \geq t)
ight] P(T \geq t)$$

$$= \quad \left[1-P(T=t|T\geq t)
ight]P(T\geq t)$$

$$= \quad \left[1-P(T=t|T\geq t)
ight]P(T>t_{ ext{prev}})$$

 $= \quad \left[1 - P(T=t|T\geq t)
ight]S(t_{ ext{prev}})$

^{9.} Kaplan Meier, defined

Probability an object will be alive at time *t* One minus the proportion of events at time *t* among those at risk, multiplied by probability of survival at previous time

^{10.} Our measurements

Kaplan Meier estimate wins!



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^{12.} Thank you:)