

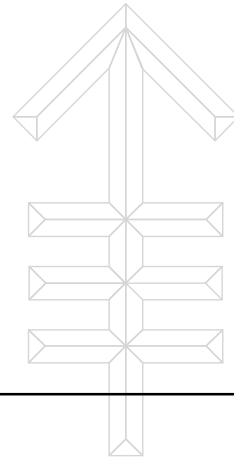


Memorial Sloan Kettering  
Cancer Center

# Survival Analysis

Chaya Moskowitz, Ph.D.  
Department of Epidemiology and Biostatistics  
Memorial Sloan Kettering Cancer Center

Financial disclosures: None



1

## Learning Objectives

- Understand what survival analysis is
- Understand when we need to use survival analysis methods
- Recognize key estimates

2

## Survival Analysis

- Statistical methods for analyzing data where the outcome is the time to an event
- Time-to-event means that we are interested in the time that elapses until the event or outcome occurs
- Examples of time-to-event outcomes:
  - Time-to-recurrence
  - Progression-free survival
  - Disease-free survival
  - Overall survival

3

## Survival Analysis Applications

- Applicable for data from single-arm clinical trials, randomized clinical trials, cohort studies, and other observational datasets
- Important for:
  - Studies where not all patients enter at the same time (staggered entry)
  - Data analyzed before all patients have experienced the outcome (censoring)

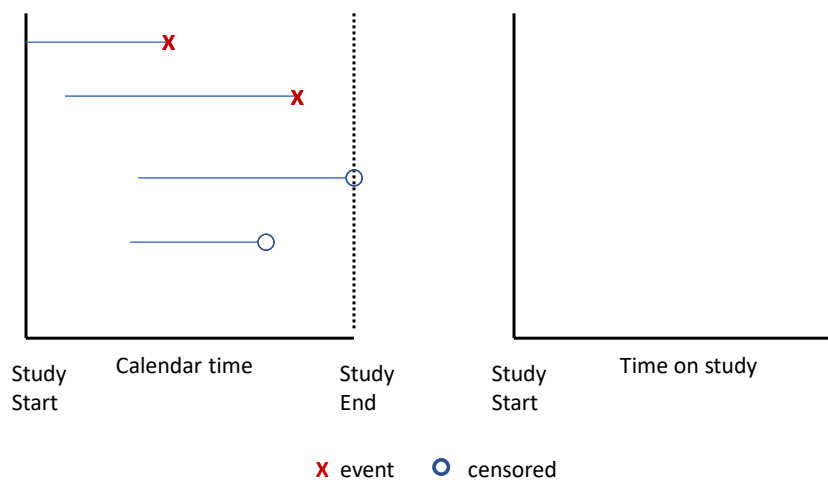
4

## Censoring

- Exact time event occurs is not known
- Different type of censoring:
  - Right censoring: event has not yet occurred
    - Most common type of censoring
    - Examples: study ends or patients are lost to follow-up
  - Interval censoring: event occurred between two time-points, but we don't know exactly when
    - Examples: outcome occurs between two scheduled follow-up visits
  - Left censoring: Event occurs before the study starts
    - Not usually found in clinical trials

5

## Survival Data Example



6

## Definitions

- Primary interest:  $T$  = the time until the event
- Instead observe:  
     $C$  = the time at which an observation is censored  
    Event status (e.g. whether the patient died or not)
- Don't throw away information on  $C$ !
- Record and give to your statistician: event status,  $T$ , and  $C$  for everyone

7

## Survival Function

- $S(t) = \text{Prob}(T > t)$
- Interpretation: Probability an individual experiences the event after time  $t$ ; probability of surviving beyond time  $t$ .
- Starts at 1 and decreases towards 0:
  - $S(t) = 1$  for  $t=0$ ,  $S(t) = 0$  for  $t=\infty$
- Non-increasing function

8

## Hazard Function

- $$h(t) = \lim_{\Delta t \rightarrow 0} \frac{\text{Prob}(t \leq T \leq \Delta t + t \mid T \geq t)}{\Delta t}$$
- Interpretation: Probability of experiencing the event in the next instant given survival without the event until time  $t$
- Also called hazard rate, instantaneous failure rate, age-specific failure rate
- Mathematically related to the survival function
- Can have many shapes but can never be negative ( $h(t) \geq 0$ )
- Hazard ratio is the ratio of two hazard functions

9

## Estimating the Survival Function

- To estimate  $S(t) = \text{Prob}(T > t)$ , why not just take the proportion of people with event times greater than  $t$ ?
  - Ignores censoring
- Two main ways:
  - Parametric estimate
    - Assumes the times-to-event follow a particular probability distribution function
  - Non-parametric estimate
    - Empirical estimate

10

## Kaplan-Meier Estimate

$$\hat{S}_{KM}(t) = \prod_{t_i \leq t} \left( 1 - \frac{D_i}{N_i} \right)$$

- $N_i$  = Number of people at risk of having the event at the  $i^{\text{th}}$  time
- $D_i$  = Number of people having the event at the  $i^{\text{th}}$  time.
- Product-Limit estimator
- Most frequently used method for estimating the survival function
- Step function with jumps at the event times

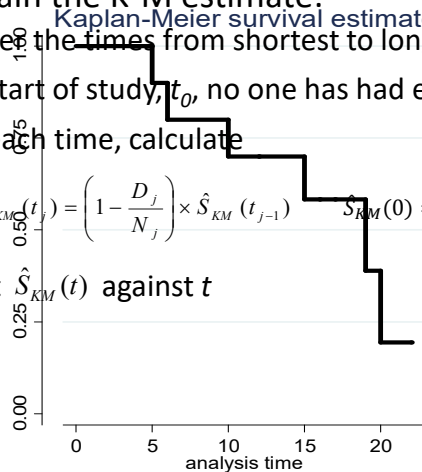
11

## Kaplan-Meier Estimate

- To obtain the K-M estimate:
  - Order the times from shortest to longest
  - At start of study,  $t_0$ , no one has had event,
  - At each time, calculate

$$\hat{S}_{KM}(t_j) = \left( 1 - \frac{D_j}{N_j} \right) \times \hat{S}_{KM}(t_{j-1}) \quad \hat{S}_{KM}(0) = 1$$

- Plot  $\hat{S}_{KM}(t)$  against  $t$



$i$	$t_i$	$D_i$	$N_i$	(1)	$\hat{S}_{KM}(t)$
0	0		10		1
1	5	1	10	$(1-1/10) \times 1$	0.90
2	6	1	9	$(1-1/9) \times .90$	0.80
3	10	1	8	$(1-1/8) \times .80$	0.70
4	12	0	---		---
5	15	1	6	$(1-1/6) \times .70$	0.58
6	16	0	---		---
7	17	0	---		---
8	19	1	3	$(1-1/3) \times .58$	0.39
9	20	1	2	$(1-1/2) \times .39$	0.19
10	22	0	---		---

12

## Caveats

- Assume probability an observation is censored is unrelated to the probability of having an event
  - Uninformative censoring
- Estimates can be unstable at the tail of the Kaplan-Meier curve when the number of patients remaining at risk gets small
- If the last observation is censored the Kaplan-Meier estimate will not reach 0.

13

## Comparing Two Survival Functions

- $H_0: S_1(t) = S_2(t)$
- Can use:
  - Log-rank test
    - Most frequently used test
    - Most powerful against consistent differences
  - Modified Wilcoxon test
    - Most powerful against early differences
- Equivalent to testing  $H_0$ : Hazard Ratio = 1.
- State in advance what test you will use
- Sample size/power depends on the number of events

14

## Time-Dependent ROC Curves

- Disease status changes over time
- ROC curves that change as a function of time
- Can define based on the survival function

Heagerty et al. *Biometrics* 2000

15

## Time-Dependent ROC Curves

- Treat sensitivity and specificity as time-dependent functions and use Bayes theorem:

$$\text{Sensitivity}(c,t) = \text{Prob}(X > c \mid D(t) = 1) = \frac{\{1 - S(t \mid X > c)\}P(X > c)}{1 - S(t)}$$

$$\text{Specificity}(c,t) = \text{Prob}(X \leq c \mid D(t) = 0) = \frac{\{1 - S(t \mid X \leq c)\}P(X \leq c)}{S(t)}$$

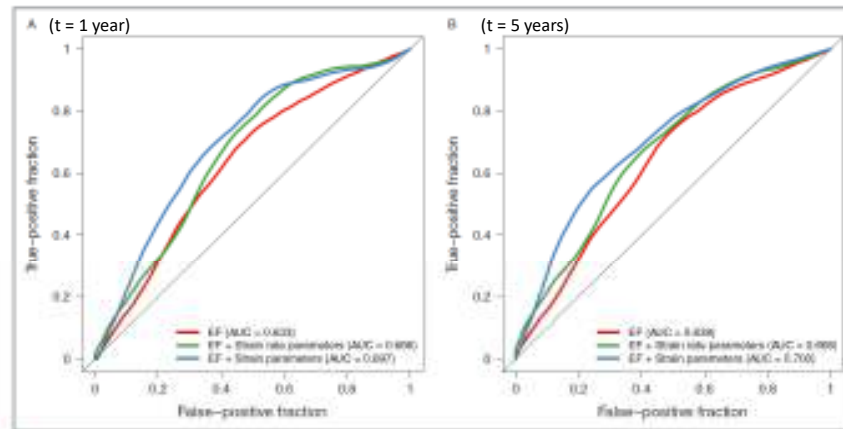
where  $X$  is the biomarker value

Heagerty et al. *Biometrics* 2000

16



## Time-Dependent ROC Curves: Example using Strain in Chronic Heart Failure



**Figure 3.** Receiver operating characteristic (ROC) curves. In comparison to EF alone, strain and EF demonstrated an improved AUC at both 1 year (0.697 versus 0.632,  $P=0.032$ ) (A) and 5 years (0.700 versus 0.638,  $P=0.014$ ) (B). In comparison to EF alone, strain rate and EF did not provide incremental value (0.666 versus 0.633,  $P=0.16$ ) at 1 year (A) and 5 years (0.684 versus 0.638,  $P=0.13$ ) (B). AUC indicates area under the ROC curve; EF, ejection fraction.

Zhang *et al.* *J Am Heart Assoc.* 2013

17

## Summary

- With time-to-event data, important to properly account for unobserved events
- When planning studies, think in terms of the number of events that will be observed
- Consider incorporating time-dependent ROC curves into planned analyses with time-to-event outcomes

18

18