University of Waterloo

An Introduction to Survival Analysis

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- Definitions
- Example

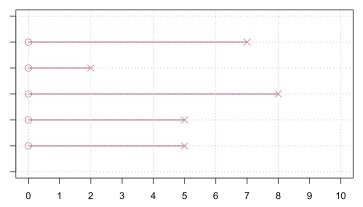
4 Cox PH Model

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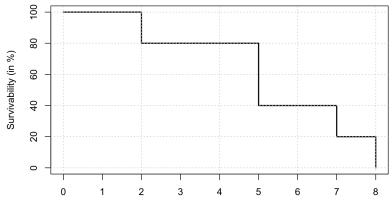
Measuring Survival Time (From Cancer Diagnosis)



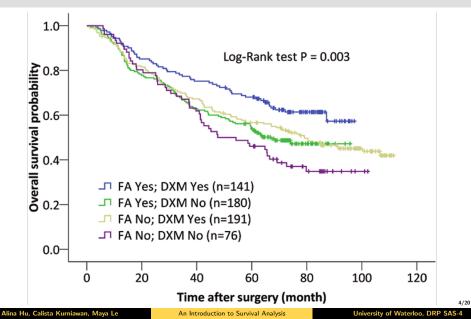
Measuring Survival Time (From Cancer Diagnosis)



Visualization (Kaplan-Meier Curve)



Time Since Diagnosis



Introduction to Survival Analysis

Definition

- Survival analysis is a branch of statistics that measures the time until an event occurs.
- **Survival time** is the particular variable of interest.
 - Solution $E \times posure \rightarrow Event$
 - Ex. Time of cancer diagnosis to death
- Survival Analysis doesn't have to just be involved with death, but in the same lens of cancer, it could be the time of complete remission to relapse

Censoring

Definition

- Censoring occurs when we don't know the exact time to event.
- We don't delete these observations
 - Make a note that the result was censored.
- Different types of censoring
 - Right censoring
 - Left Censoring
 - Interval censoring

Right Censoring

Definition

- Time to the event is GREATER than some value x
 - $t_i > x$
- Study: Estimating survival time after diagnosis of pancreatic cancer (Wahutu, 2016)
 - Consider: Patients still alive at the end of the study; Patients who are lost to follow up

Interval Censoring

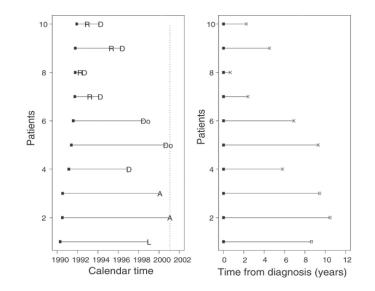
Definition

- Fine to event is BETWEEN 2 values x_1 and x_2
 - > $x_1 < t_i < x_2$
- Study: Oral lesion occurrence in immunosuppressed children (Rodrigues, 2018)
 - > Consider: Lesion occurrence is identified by a specialist at regular checkups

Left Censoring

Definition

- Time to the event is LESS than some value x
 - $t_i < x$
- Study: Age at menarche cohort study (Wohlfahrt-Veje, 2016)
 - Consider: Young women enrolled in the study who have already begun menstruating



Important Functions

Functions of interest

- Survival function: S(t) = P(T > t)
- > Hazard function: h(t) represents the instantaneous risk of occurrence of the event given the history

Kaplan-Meier Survival Curves

Purpose

A useful non-parametric way to estimate the survival function. We calculating using the formula

$$S(t_j) = S(t_{j-1}) \left(1 - \frac{d_j}{n_j} \right)$$

Where d_j is the number of deaths at time t_j and n_j is the number of subjects at risk.

Assumptions

- 1. Random censoring
- 2. Non-informative censoring
- 3. Independence of censoring
- 4. Survival probabilities do not change over time
- 5. No competing risks

Example: Calculating KM Curves By Hand for Lung Cancer Trial

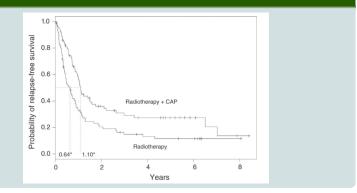
Figure 1

ladiotherapy (<i>n</i> =86)		Radiotherapy+CAP (<i>n</i> =78)			
Survival times (days) Kaplan-Meler survivor function S(t)		Survival times (days)	Kaplan-Meier survivor function S(t)		
18	1 × (1-1/86)=0.988	9	1 × (1-1/78)=0.987		
23*	S(18) × (1-0/85)=0.988	22	S(18) × (1-1/77)=0.974		
25	S(23) × (1-1/84)=0.977	35	S(22) × (1-1/76)=0.962		
27	S(25) × (1-1/83)=0.965	53	S(35) × (1-1/75)=0.949		
28	S(27) × (1-1/82)=0.953	76	S(53) × (1-1/74)=0.936		
30	S(28) × (1-1/81)=0.941	81	S(76) × (1-1/73)=0.923		
36	S(30) × (1-1/80)=0.930	94	S(81) × (1-1/72)=0.910		
45	S(36) × (1-1/79)=0.918	97	S(94) × (1-1/71)=0.897		
55	S(45) × (1-1/78)=0.906	103	S(97) × (1-1/70)=0.885		
56	S(55) × (1-1/77)=0.894	114	S(103) × (1-1/69)=0.872		
57	S(56) × (1-3/76)=0.859	115	S(114) × (1-1/68)=0.859		
57	S(56) × (1-3/76)=0.859	121 ^a	S(115) × (1-0/67)=0.859		
57	S(56) × (1-3/76)=0.859	126	S(121) × (1-1/66)=0.846		

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Example: Comparing KM Curves

Figure 2



Observations

- Overall, Radiotherapy+CAP has a higher survival probability
- The Radiotherapy+CAP group has greater median survival time

Log-Rank Test

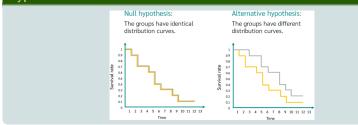
Purpose

A non-parametric test statistic used to compare two survival curves (independent from each other) by calculating

$$\chi^{2} = \sum_{i=1}^{g} \frac{(O_{i} - E_{i})^{2}}{E_{i}}$$

where O_i is the observed number of events and E_i is the total expected number of events in each group i.

Hypothesis



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An Introduction to Survival Analysis

Back to Cancer Research Example

Log Rank Test for Lung Cancer Trial

	Radiotherapy (n =86) Radiotherapy + CAP (n =78)		
Number of relapses (O _i)	70	54	
Median survival time(years) (95% CI)	0.64 (0.45-0.87)	1.10 (0.96–1.59)	
Expected number of relapses (E;)	53.4	70.6	
Hazard ratio (95% Cl)	0.58 (0.41-0.83)		
Logrank test	χ ² =9.1, 1 df, P<0.002		
Logram test χ^{-y_1} , 1 dt, 7-0002 df=degree of freedom: CAP=cytoxan, doxonubicin and platinum-based chemotherapy.			

Observations

- Log rank test yields a χ^2 value of 9.1 on 1 degree of freedom (P<0.002)
- Hazard Ratio of 0.58 indicates that there is 42% less risk of relapse at any point in time among patients surviving in the combination treatment group compared to those treated with radiotherapy alone
- Indication is present that the combination treatment is more effective than radiotherapy treatment

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The Cox Propotional Hazard model

Definition

$h(t, \mathbf{X}) = h_0(t) e^{\sum_{i=1}^p \beta_i X_i}$

 $\mathbf{X} = (X_1, X_2, \dots, X_p)$ explanatory/predictor variables

An expression for the hazard at time t for an individual with a given specification of a set of explanatory variables denoted by X.

Product of Two Quantities

$$h_0(t) \times e^{\sum_{i=1}^p \beta_i X_i}$$

$h_0(t)$		$e^{\sum_{i=1}^{p} \beta_i X_i}$				
Baseline hazard		Exponential				
	Involves $t \mbox{ but not } X\mbox{'s}$	Involves X 's but not t (X 's are time-independent)				

Semi-Parametric Nature

What does semi-parametric mean?

- Combines parametric and non-parametric components.
- The baseline hazard, $h_0(t)$, is an unspecified function (non-parametric).
- The relationship between the covariates and the hazard rate is expressed parametrically.

Why is this important?

- The Cox PH model is a "robust" model, so that the results from using the Cox model will closely approximate the results for the correct parametric model.
- This property makes the Cox PH Model more flexible than fully parametric models while still allowing meaningful interpretation.

Interpretation

Hazard Ratio (HR)

$$\widehat{HR} = \frac{\widehat{h}(t, \mathbf{X}^*)}{\widehat{h}(t, \mathbf{X})}$$

Measures the relative risk of an event for different covariate levels.

Interval Estimation

Large sample 95% confidence interval:

$$\exp\left[\hat{\beta}_1 \pm 1.96\sqrt{\mathsf{Var}(\hat{\beta}_1)}\right]$$

where

$$s_{\hat{\beta}_1} = \sqrt{\mathsf{Var}(\hat{\beta}_1)}$$

Cox PH Model Ovarian Dataset Example

Table 1 Hazard ratios from the Cox PH model for the ovarian dataset

From: Survival Analysis Part II: Multivariate data analysis - an introduction to concepts and methods

	Univariate analysis			Multivariate analysis				
Covariate	Coefficient (b _i)	HR [exp(b∂]	95% CI	P -value	Coefficient (b _i)	HR [exp(b∂)	95% CI	P -value
FIGO stage	0.809	2.24	(2.03-2.48)	<0.001	0.731	2.08	(1.82-2.37)	<0.001
Histology				<0.001				<0.001
Serous	(0.000)	(1.00)			(0.000)	(1.00)		
Mucinous	-0.727	0.48	(0.38-0.61)		-0.422	0.66	(0.500.85)	
Endometroid	-1.162	0.31	(0.22-0.45)		0.198	1.22	(0.80-1.85)	
Clear cell	-0.343	0.71	(0.52-0.97)		0.342	1.41	(0.99-2.00)	
Adenocarcinoma	0.119	1.13	(0.74-1.72)		0.501	1.65	(0.91-2.99)	
Undifferentiated	0.390	1.48	(0.81-2.70)		0.746	2.11	(1.03-4.29)	
Mixed mesodermal	0.614	1.85	(1.28-2.66)		0.789	2.20	(1.45–3.35)	
Grade				<0.001				<0.001
1	(0.000)	(1.00)			(0.000)	(1.00)		
2	1.116	3.05	(1.90-4.91)		0.885	2.42	(1.40-4.19)	
3	1.650	5.20	(3.31-8.18)		0.885	2.42	(1.40-4.18)	
Absence of ascites	-0.798	0.45	(0.37-0.55)	<0.001	-0.396	0.67	(0.54-0.84)	<0.001
Age (per 5-year increase)	0.153	1.17	(1.12–1.21)	<0.001	0.133	1.14	(1.09–1.19)	<0.001

HR=hazard ratio, CI=confidence interval.

References



Log rank test tutorial.

Survival analysis: Self learning book.



M. J. Bradburn, T. G. Clark, S. B. Love, and D. G. Altman. Survival analysis part ii: Multivariate data analysis – an introduction to concepts and methods.

Nature.

T. G. Clark, M. J. Bradburn, S. B. Love, and D. G. Altman. Survival analysis part i: Basic concepts and first analyses. *Nature*.