STAT 855. Lifetime Data Analysis

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Part I. Preliminaries Part II. Parametric Inference Part III. Nonparametric/Semi-parametric Inference Part IV. Further Topics

What to do today (2022/01/18)?

Part I. Preliminaries

Part I.1 Introduction Part I.2 Review of Likelihood Based Approaches

Part II. Parametric Inference

Part II.1 Some Basic Concepts Part II.2 Commonly Used Parametric Distributions Part II.3 Incomplete Data Structures Part II.4 Parametric Analysis with Right-Censored Data

Part III. Nonparametric/Semi-parametric Inference

Part IV. Further Topics

Part II. Parametric Inference in LIDA

Part II.1 Some Basic Concepts

Consider continuous r.v. $T \ge 0$, time to an event

• probability density function (pdf) $f(t), t \ge 0$

• cumulative distribution function (cdf) $F(t) = P(T \le t), t \ge 0$

• survivor function
$$S(t) = P(T \ge t), t \ge 0$$

Part II.1 Some Basic Concepts Consider continuous r.v. $T \ge 0$, time to an event

hazard function

$$h(t) = \lim_{\Delta t \to 0+} \frac{P(T \in [t, t + \Delta t) | T \ge t)}{\Delta t}$$

interpretation, analytic properties, ...

• cumulative hazard function $H(t) = \int_0^t h(u) du, t \ge 0$

Exponential distribution $T \sim NE(\lambda), \lambda > 0$

$$f(t; \lambda) = \lambda \exp(-\lambda t), \ t > 0$$

(or $f(t; \theta) = \frac{1}{\theta} \exp(-t/\theta), t > 0$ with $\theta > 0$) $\blacktriangleright E(T)$



▶ h(t)

• memoryless property: P(T > a + b | T > a) = P(T > b)

the central role

Weibull distribution $T \sim Weibull(k, \theta)$:

$$f(t; \theta, k) = \frac{k}{\theta} \left(\frac{t}{\theta}\right)^{k-1} \exp\left(-(t/\theta)^k\right), \quad t > 0$$

with $\theta > 0$ and k > 0.

• $E(T) = \theta \Gamma(1 + 1/k), Var(T) = \theta^2 \left[\Gamma(1 + \frac{2}{k}) - \Gamma(1 + \frac{1}{k})^2 \right]$ • S(t)• $h(t) = \frac{k}{\theta} \left(\frac{t}{\theta} \right)^{k-1}$ • $T^k \sim NE(1/\theta)$

A translated Weibull distribution: $T \sim Weibull(k, \theta, \alpha)$:

$$f(t;\theta,k) = \frac{k}{\theta} \left(\frac{t-\alpha}{\theta}\right)^{k-1} \exp\left\{-\left(\frac{t-\alpha}{\theta}\right)^k\right\}, \quad t > \alpha$$

Part II.2 Commonly Used Parametric Distributions Gamma distribution $T \sim \Gamma(k, \theta)$:

$$f(t; \theta, k) = \frac{1}{\theta \Gamma(k)} \left(\frac{t}{\theta}\right)^{k-1} \exp\left(-t/\theta\right), \ t > 0$$

with $\theta > 0$ and k > 0. \blacktriangleright $E(T) = k\theta$, $Var(T) = k\theta^2$ \blacktriangleright S(t) \blacktriangleright h(t) ► T_1, T_2 indpt and $T_i \sim \Gamma(\alpha_i, \theta)$: $T_1 + T_2 \sim \Gamma(\alpha_1 + \alpha_2, \theta)$ $\blacktriangleright \frac{2}{\theta}T \sim \chi^2(2k)$ ι4 3 .2 .1 0 0 2 14 16 18 /ikimedia Commons

Log-normal distribution $T \sim logN(\mu, \sigma^2)$, ie $logT \sim N(\mu, \sigma^2)$:

$$T \sim rac{1}{t\sigma\sqrt{2\pi}}\expig(-rac{(logt-\mu)^2}{2\sigma^2}ig), \ t > 0$$

with $\sigma > 0$. • $E(T) = \exp(\mu + \sigma^2/2)$ • S(t)

▶ h(t)

Extreme value distribution

Gumbel distribution

►

See books on reliability, such as Lawless (2003), for more examples of parametric models for event time

Consider event time r.v. T: to make inference on its distn

When there are iid observations on *T*, ⇒ various approaches such as likelihood-based methods, especially when n >> 1

What if it is not allowed to collect iid observations from the population?

A Reliability Example: at a lab to conduct an experiment to assess the quality of a certain kind of light bulb (the distn of T, the lifetime of such light bulb?)

 \dots select *n* such light bulbs randomly, plug in them at the same time,

- wait till all of them burned out: record the lifetimes T₁,..., T_n; take them as iid observations on T
- alternatively, choosing a time c before the experiment, stop the experiment after time c elapses: only available are T_i if T_i ≤ c, i = 1,..., n ⇒ type I censoring
- or, choosing an interger r < n before the experiment, stop the experiment after r number of light bulbs burn out: only available are T₍₁₎ < T₍₂₎ < ... < T_(r). ⇒ type II censoring

Consider event time r.v. T: to make inference on its distn Let $\{T_1, \ldots, T_n\}$ be iid observations on T with the order statistics $T_{(1)} < \ldots < T_{(n)}$

- ▶ type I censoring with a predetermined time c, T_i is observed only if $T_i \leq c$ for i = 1, ..., n.
- ► type II censoring with a predetermined number r, T_i is observed only if its one of T₍₁₎,..., T_(r) for i = 1,..., n.

What if it is in a clinical trial ...

 \ldots staggered entries of the study subjects, predetermined study duration of A

▶ right-censoring Let C_i be the censoring time associated with unit i. T_i is observed if T_i ≤ C_i for i = 1,..., n

In general, the right-censored data are presented as follows:

$$\left\{ \left(U_{i},\delta_{i}
ight):i=1,\ldots,n
ight\}$$

with $U_i = \min(T_i, C_i)$ (or denoted by $T_i \wedge C_i$), and $\delta_i = I(T_i \leq C_i) = \begin{cases} 1, & T_i \leq C_i \\ 0, & otherwise \end{cases}$

Example. n = 3 and $\{(4, 1), (10, 0), (9, 1)\}$

Special Cases

- **•** type I censoring. $C_i \equiv c$ for all *i*;
- **•** type II censoring. $C_i = T_{(r)}$ for all *i*

How to make inference with right-censored data?

What to study next?

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Part II. Parametric Inference

- ▶ II.1 Some basic concepts
- II.2 Commonly used parametric distributions
- II.3 Incomplete data structures
- ▶ II.4 Parametric analysis with right-censored data

Part III. Nonparametric/Semi-parametric Inference

Part IV. Further Topics