School of Statistics, University of the Philippines (Diliman) Linangan ng Estadistika, Unibersidad ng Pilipinas (Diliman)

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Al-Ahmadgaid B. Asaad

Problem Set 2 | Stat 245

3.8 The following data consists of the times to relapse and death of 10 bone marrow transplant patients. In the sample patients 4 and 6 were still alive at the end of the study and patients 7-10 were alive, free of relapse at the end of the study. Suppose the time to relapse had an exponential distribution with hazard rate λ and the time to death had a Weibull distribution with parameters θ and α .

Patient	Relapse Time (months)	Death Time (months)
1	5	11
2	8	12
3	12	15
4	24	35^{+}
5	32	45
6	17	28^{+}
7	16^{+}	16^{+}
8	17^{+}	17^{+}
9	19^{+}	19^{+}
10	30+	30^{+}

- (a) Construct the likelihood for the relapse rate λ .
- (b) Construct a likelihood for the parameters θ and α .
- (c) Suppose we were only allowed to observe a patients death time if the patient relapsed. Construct the likelihood for θ and α based on this truncated sample, and compare it to the results in (b).

Solution

(a) Let X be the time to relapse, then $X \sim \text{exponential}(\lambda)$. And since the data involve here are the true lifetimes and the right censored observations, thus we have the following likelihood functions:

$$\mathcal{L} \propto \prod_{i \in D} f(x_i) \prod_{i \in R} S(C_r).$$

From Table 2.2 (refer to the book), $f(x) = \lambda \exp(-\lambda x)$, $S(x) = \exp(-\lambda x)$. So that,

$$\mathcal{L} \propto \prod_{i \in D} f(x_i) \prod_{i \in R} S(C_r)$$

$$= \prod_{i \in D} \lambda \exp(-\lambda x_i) \prod_{i \in R} \exp(-\lambda x_i)$$

$$= \lambda^{\#\{i \in D\}} \exp\left[-\lambda \sum_{i \in D} x_i\right] \times \exp\left[-\lambda \sum_{i \in R} x_i\right],$$
(1)

where $\#\{i \in D\}$ is the cardinality of the set $\{i \in D\}$. Now we take the log-likelihood function,

$$\ell = \#\{i \in D\} \log \lambda - \lambda \sum_{i \in D} x_i - \lambda \sum_{i \in R} x_i.$$

To maximize this log-likelihood function with respect to the parameter λ , we take the derivative,

$$\frac{\mathrm{d}}{\mathrm{d}\lambda}\ell = \#\{i \in D\}\frac{1}{\lambda} - \sum_{i \in D} x_i - \sum_{i \in B} x_i.$$

Now we set it to zero obtain the stationary point,

$$\frac{\mathrm{d}}{\mathrm{d}\lambda}\ell = \#\{i \in D\}\frac{1}{\lambda} - \sum_{i \in D} x_i - \sum_{i \in R} x_i \stackrel{set}{=} 0$$

$$\Rightarrow \frac{1}{\lambda} = \frac{1}{\#\{i \in D\}} \left[\sum_{i \in D} x_i + \sum_{i \in R} x_i \right]$$

$$\Rightarrow \hat{\lambda} = \frac{\#\{i \in D\}}{\left[\sum_{i \in D} x_i + \sum_{i \in R} x_i \right]}.$$

To verify if this is the maximum likelihood estimator, we take the second derivative

$$\frac{\mathrm{d}^2}{\mathrm{d}\,\lambda^2}\ell = -\#\{i \in D\}\frac{1}{\lambda^2},$$

which is negative for all λ , implying $\hat{\lambda}$ is the MLE. Now plugging-in the data, the plausible estimate of the parameter that likely explains the observations is,

$$\lambda = \frac{\#\{i \in D\}}{\sum_{i \in D} x_i + \sum_{i \in R} x_i}.$$

The $\#\{i\in D\}=6$ since there are 6 patients with uncensored lifetime. And

$$\sum_{i \in D} x_i = 5 + 8 + 12 + 24 + 32 + 17 = 98,$$

also

$$\sum_{i \in R} x_i = 16 + 17 + 19 + 30 = 82.$$

And therefore,

$$\lambda = \frac{6}{98 + 82} = \frac{1}{30}.$$

Figure 1 is the plot of the likelihood function of X.

(b) Let Y be the time to death, then $Y \sim \text{Weibull}(\theta, \alpha)$, and hence we have the following likelihood function:

$$\mathcal{L} \propto \prod_{i \in D} f(x_i) \prod_{i \in B} S(C_r).$$

The density and the survival function of Y, is given by

$$f(x) = \alpha \theta x^{\alpha - 1} \exp(-\theta x^{\alpha}), \text{ and } S(x) = \exp(-\theta x^{\alpha}),$$

respectively. So that,

$$\mathcal{L} \propto \prod_{i \in D} f(x_i) \prod_{i \in R} S(C_r)$$

$$= \prod_{i \in D} \alpha \theta x_i^{\alpha - 1} \exp(-\theta x_i^{\alpha}) \prod_{i \in R} \exp(-\theta x_i^{\alpha})$$

$$= (\alpha \theta)^{\#\{i \in D\}} \exp\left[-\theta \sum_{i \in D} x_i^{\alpha}\right] \exp\left[-\theta \sum_{i \in R} x_i^{\alpha}\right] \prod_{i \in D} x_i^{\alpha - 1}$$

where $\#\{i \in D\}$ is the cardinality of the set $\{i \in D\}$. Now we take the log-likelihood function

$$\ell = \#\{i \in D\}(\log \alpha + \log \theta) - \theta \sum_{i \in D} x_i^{\alpha} - \theta \sum_{i \in R} x_i^{\alpha} + (\alpha - 1) \sum_{i \in D} \log x_i.$$

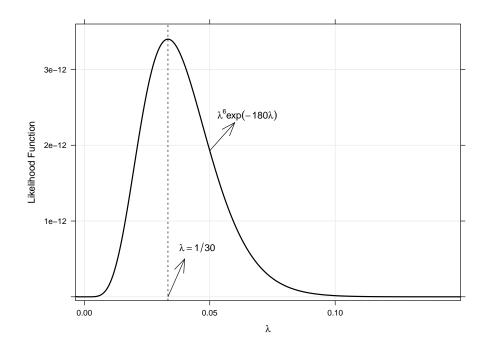


Figure 1: The likelihood function of X.

Now we take the partial derivatives with respect to both parameters,

$$\frac{\partial \ell}{\partial \theta} = \frac{\#\{i \in D\}}{\theta} - \sum_{i \in D} x_i^{\alpha} - \sum_{i \in R} x_i^{\alpha}$$

Setting this to zero to obtain the critical points, then

$$\frac{\partial \ell}{\partial \theta} = \frac{\#\{i \in D\}}{\theta} - \sum_{i \in D} x_i^{\alpha} - \sum_{i \in R} x_i^{\alpha} \stackrel{set}{=} 0$$

$$\Rightarrow \hat{\theta} = \frac{\#\{i \in D\}}{\sum_{i \in D} x_i^{\alpha} + \sum_{i \in R} x_i^{\alpha}}$$

Clearly this is the MLE for θ . Therefore, plugging the data, we have $\#\{i \in D\} = 4$ since there are four patients with exact lifetime.

$$\sum_{i \in D} x_i^{\alpha} = 11^{\alpha} + 12^{\alpha} + 15^{\alpha} + 45^{\alpha}$$

and

$$\sum_{i \in R} x_i^{\alpha} = 33^{\alpha} + 28^{\alpha} + 16^{\alpha} + 17^{\alpha} + 19^{\alpha} + 30^{\alpha}$$

So that if $\alpha = 1$, then

$$\hat{\theta} = \frac{4}{83 + 143} = \frac{2}{113} = .0177.$$

Speaking about α , the partial derivative with respect to it is,

$$\frac{\partial \ell}{\partial \alpha} = \frac{\#\{i \in D\}}{\alpha} - \theta \alpha \sum_{i \in D} x_i^{\alpha - 1} - \theta \alpha \sum_{i \in R} x_i^{\alpha - 1} + \sum_{i \in D} \log x_i \stackrel{set}{=} 0$$

In this case, there is no way to solve α . So we need to use iterative search procedure. The following are steps for Newton-Raphson iterative search:

1. Begin with a first guess $\hat{\alpha}^{(0)}$ for a root of the function $\frac{\partial \ell}{\partial \alpha}$.

$$\frac{\partial \ell}{\partial \alpha} = \frac{\#\{i \in D\}}{\alpha} - \theta \alpha \sum_{i \in D} x_i^{\alpha - 1} - \theta \alpha \sum_{i \in R} x_i^{\alpha - 1} + \sum_{i \in D} \log x_i \stackrel{set}{=} 0,$$

where θ of course is estimated by its MLE, $\hat{\theta} = \frac{\#\{i \in D\}}{\sum_{i \in D} x_i^{\alpha} + \sum_{i \in R} x_i^{\alpha}}$.

2. Solve for $\Delta \hat{\alpha}$, evaluating partial derivatives at the initial value $\hat{\alpha}^{(0)}$.

$$\frac{\partial \ell}{\partial \alpha} = \left(-\frac{\partial^2 \ell}{\partial \alpha^2}\right) (\hat{\alpha}^{(1)} - \hat{\alpha}^{(0)})$$
$$= \left(-\frac{\partial^2 \ell}{\partial \alpha^2}\right) \Delta \hat{\alpha}$$

- 3. So that $\Delta \hat{\alpha} = \hat{\alpha}^{(1)} \hat{\alpha}^{(0)} \Rightarrow \hat{\alpha}^{(1)} = \Delta \hat{\alpha} + \hat{\alpha}^{(0)}$.
- 4. Repeat Step 2, but this time evaluating partial derivatives at $\hat{\alpha}^{(1)}$, and then proceed to Step 3 to obtain the new initial value, $\hat{\alpha}^{(2)}$.

Repeat the process above, until convergence to the value of $\hat{\alpha}$. That is, if the difference between $\hat{\alpha}^{(i)}$ and $\hat{\alpha}^{(i-1)}$ is close to zero at the *i*th iteration.

The likelihood function of α and θ is plotted in Figure 2, that is plot was generated from the following equation:

$$\mathcal{L}(\alpha, \theta | \mathbf{x}) = (\alpha \theta)^4 \exp[-\theta (11^{\alpha} + \dots + 45^{\alpha} + 33^{\alpha} + \dots + 30^{\alpha})]$$
$$\times (11^{\alpha - 1} \times \dots \times 45^{\alpha - 1})$$

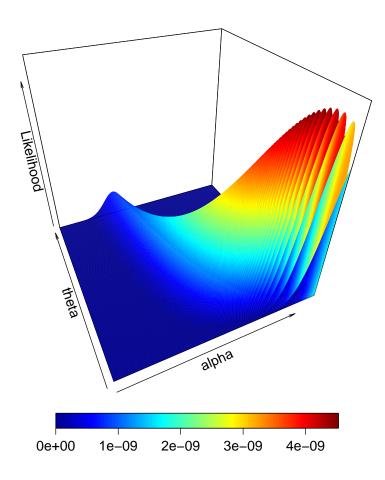


Figure 2: Likelihood Function of Y.

(c) Let Z be the time to death if the patient relapsed. From part (b), the MLE of θ is,

$$\hat{\theta} = \frac{\#\{i \in D\}}{\sum_{i \in D} x_i^{\alpha} + \sum_{i \in R} x_i^{\alpha}},$$

with the data, we have $\#\{i \in D\} = 4$, and

$$\sum_{i \in D} x_i^{\alpha} = 11^{\alpha} + 12^{\alpha} + 15^{\alpha} + 45^{\alpha}$$

and

$$\sum_{i \in R} x_i^{\alpha} = 33^{\alpha} + 28^{\alpha}.$$

Suppose $\alpha = 1$, then

$$\hat{\theta} = \frac{4}{83 + 61} = \frac{1}{36} = .0278.$$

As expected of course, the new MLE of θ is greater than the one in part (b) since the sum of the terms in the denominator is lesser with the exclusion of the patients 7 to 10, resulting to an increase in $\hat{\theta}$. The MLE of α , on the other hand, is obtain by Newton-Raphson iterative search

$$\frac{\#\{i \in D\}}{\alpha} - \theta \alpha \sum_{i \in D} x_i^{\alpha - 1} - \theta \alpha \sum_{i \in R} x_i^{\alpha - 1} + \sum_{i \in D} \log x_i \stackrel{set}{=} 0.$$

The same procedure with that in part (b) is done to obtain the value of α . Of course, the plausible value of α in explaining this sample is different from the previous one. Finally, in comparison to Figure 2 in part (b), Figure 3 is the likelihood function of the parameters given the truncated sample. Both figures were generated from the same domain, and viewed on the same perspective.

Appendix: R Codes

1. The following R codes generates Figure 1:

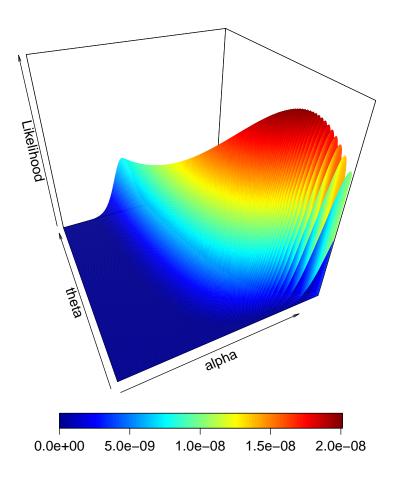


Figure 3: Likelihood Function of Z.

```
panel.text(
               .065, 2.4e-12,
              label = expression(lambda ^ 6 * exp(-180*lambda)))
          })
2. The following R codes generates Figure 2:
  install.packages("plot3D")
  x \leftarrow seq(0, 2.3, length = 300)
  y \leftarrow seq(0, .05, length = 300)
  f1 \leftarrow function(x, y) {
     (x * y) ** 4 * exp(
      - y * (11 ** x + 12 ** x + 15 ** x +
              45 ** x + 33 ** x + 28 ** x +
              16 ** x + 17 ** x + 19 ** x + 30 ** x)) *
       (11 ** (x - 1) *
        12 ** (x - 1) *
        15 ** (x - 1) *
        45 ** (x - 1))
    }
  z \leftarrow outer(x, y, f1)
  par(mai = c(.3, .3, .1, .3))
  plot3D::persp3D(x, y, z, theta = -25, phi = 35,
                    xlab = "alpha", ylab = "theta",
                    zlab = "Likelihood",
                    colkey = list(
                      side = 1,
                      length = .75,
                      dist = -0.1)
3. The following R codes generates Figure ??:
  install.packages("plot3D")
  x \leftarrow seq(0, 2.3, length = 300)
  y \leftarrow seq(0, .05, length = 300)
  f2 \leftarrow function(x, y) {
    (x * y) ** 4 * exp(
      - y * (11 ** x + 12 ** x + 15 ** x +
              45 ** x + 33 ** x + 28 ** x)) *
```