

Solutions to exercises - Week 45

Likelihood ratio tests

- Exercises 8.3, 8.6 and 8.37.c

1

Exercise 8.3

Let Y_1, \dots, Y_m be iid Bernoulli variables with pmf

$$f(y_i | \theta) = \theta^{y_i} (1 - \theta)^{1 - y_i} \quad \text{for } y_i = 0, 1; \quad 0 < \theta < 1$$

We will test $H_0: \theta \leq \theta_0$ versus $H_1: \theta > \theta_0$

The likelihood is given by $[\mathbf{y} = (y_1, \dots, y_m)]$

$$L(\theta | \mathbf{y}) = \prod_{i=1}^m \theta^{y_i} (1 - \theta)^{1 - y_i} = \theta^{T(\mathbf{y})} (1 - \theta)^{m - T(\mathbf{y})}$$

where

$$T = T(\mathbf{y}) = \sum_{i=1}^m y_i$$

2

The unrestricted MLE for θ is $\hat{\theta} = T/m$

The MLE for θ under $H_0: \theta \leq \theta_0$ is

$$\hat{\theta}_0 = \begin{cases} T/m & \text{if } T/m \leq \theta_0 \\ \theta_0 & \text{if } T/m > \theta_0 \end{cases}$$

Thus the LRT statistic becomes

$$\lambda(\mathbf{y}) = \frac{L(\hat{\theta}_0 | \mathbf{y})}{L(\hat{\theta} | \mathbf{y})} = \begin{cases} 1 & \text{if } T/m \leq \theta_0 \\ \frac{\theta_0^T (1 - \theta_0)^{m - T}}{(T/m)^T (1 - T/m)^{m - T}} & \text{if } T/m > \theta_0 \end{cases}$$

The likelihood ratio test rejects the null hypothesis if

$$\lambda(\mathbf{y}) = \frac{\theta_0^T (1 - \theta_0)^{m - T}}{(T/m)^T (1 - T/m)^{m - T}} \leq c$$

i.e. if (by taking logarithms and multiplying by -1)

$$g(T) \stackrel{\text{def}}{=} T \log \left(\frac{T/m}{\theta_0} \right) + (m - T) \log \left(\frac{1 - T/m}{1 - \theta_0} \right) \geq -\log c$$

One may show that $g(T)$ is an increasing function of T when $T/m > \theta_0$

Hence the test rejects H_0 if $T \geq b$

4

Exercise 8.6

We have independent random variables:

$$X_1, \dots, X_n \sim \text{exponential}(\theta)$$

$$Y_1, \dots, Y_m \sim \text{exponential}(\mu)$$

We will test $H_0: \theta = \mu$ versus $H_1: \theta \neq \mu$

a) The likelihood takes the form

$$\begin{aligned} L(\theta, \mu | \mathbf{x}, \mathbf{y}) &= \prod_{i=1}^n f(x_i | \theta) \prod_{j=1}^m f(y_j | \mu) \\ &= \prod_{i=1}^n \left(\frac{1}{\theta} e^{-x_i/\theta} \right) \prod_{j=1}^m \left(\frac{1}{\mu} e^{-y_j/\mu} \right) \\ &= \frac{1}{\theta^n \mu^m} \exp \left\{ -\frac{1}{\theta} \sum_{i=1}^n x_i - \frac{1}{\mu} \sum_{j=1}^m y_j \right\} \end{aligned}$$

5

The unrestricted MLE for θ and μ are

$$\hat{\theta} = \frac{1}{n} \sum_{i=1}^n x_i \quad \hat{\mu} = \frac{1}{m} \sum_{j=1}^m y_j$$

The MLE for $\theta = \mu$ under H_0 is

$$\hat{\theta}_0 = \hat{\mu}_0 = \frac{1}{n+m} \left(\sum_{i=1}^n x_i + \sum_{j=1}^m y_j \right)$$

Thus the LRT statistic becomes

$$\lambda(\mathbf{x}, \mathbf{y}) = \frac{L(\hat{\theta}_0, \hat{\mu}_0 | \mathbf{x}, \mathbf{y})}{L(\hat{\theta}, \hat{\mu} | \mathbf{x}, \mathbf{y})} = \frac{\frac{1}{\hat{\theta}_0^n \hat{\mu}_0^m} \exp\{-(n+m)\}}{\frac{1}{\hat{\theta}^n \hat{\mu}^m} \exp\{-n-m\}} = \frac{\hat{\theta}^n \hat{\mu}^m}{\hat{\theta}_0^n \hat{\mu}_0^m}$$

6

This gives

$$\lambda(\mathbf{x}, \mathbf{y}) = \frac{(n+m)^{n+m} \left(\sum_{i=1}^n x_i \right)^n \left(\sum_{j=1}^m y_j \right)^m}{n^n m^m \left(\sum_{i=1}^n x_i + \sum_{j=1}^m y_j \right)^{n+m}}$$

The likelihood ratio test rejects the null hypothesis if $\lambda(\mathbf{x}, \mathbf{y}) \leq c$

b) The LRT statistic may be rewritten as

$$\lambda(\mathbf{x}, \mathbf{y}) = \frac{(n+m)^{n+m}}{n^n m^m} \left(\frac{\sum_{i=1}^n x_i}{\sum_{i=1}^n x_i + \sum_{j=1}^m y_j} \right)^n \left(\frac{\sum_{j=1}^m y_j}{\sum_{i=1}^n x_i + \sum_{j=1}^m y_j} \right)^m$$

If we introduce

$$T = T(\mathbf{x}, \mathbf{y}) = \frac{\sum_{i=1}^n x_i}{\sum_{i=1}^n x_i + \sum_{j=1}^m y_j}$$

we may write

$$\lambda(\mathbf{x}, \mathbf{y}) = \frac{(n+m)^{n+m}}{n^n m^m} T^n (1-T)^m$$

Rejection for $\lambda(\mathbf{x}, \mathbf{y}) \leq c$ is equivalent to rejection for $T \leq a$ or $T \geq b$, where $0 < a < b$ are constants that satisfy $a^n (1-a)^m = b^n (1-b)^m$

8

c) When H_0 is true we have:

$$\sum_{i=1}^n X_i \sim \text{gamma}(n, \theta) \quad \sum_{j=1}^m Y_j \sim \text{gamma}(m, \theta)$$

By the example on slides 19-20 for the lectures of week 35 (August 31st), we then have that

$$T = \frac{\sum_{i=1}^n X_i}{\sum_{i=1}^n X_i + \sum_{j=1}^m Y_j}$$

is beta(n, m) distributed

9

Exercise 8.37.c

Let X_1, X_2, \dots, X_n be iid $n(\theta, \sigma^2)$

We will test $H_0: \theta \leq \theta_0$ versus $H_1: \theta > \theta_0$

Consider the test that rejects H_0 when

$$\bar{X} > \theta_0 + t_{n-1, \alpha} S / \sqrt{n} \quad (*)$$

The power function of this test is

$$\beta(\theta, \sigma^2) = P_{\theta, \sigma^2} \left(\bar{X} > \theta_0 + t_{n-1, \alpha} S / \sqrt{n} \right)$$

When $\theta \leq \theta_0$ we have (with $T \sim t_{n-1}$ -distributed)

$$\begin{aligned} \beta(\theta, \sigma^2) &\leq P_{\theta, \sigma^2} \left(\bar{X} > \theta_0 + t_{n-1, \alpha} S / \sqrt{n} \right) \\ &= P_{\theta, \sigma^2} \left(\frac{\bar{X} - \theta}{S / \sqrt{n}} > t_{n-1, \alpha} \right) = P(T > t_{n-1, \alpha}) = \alpha \end{aligned}$$

10

Thus the test given by (*) has size α

We will show that the test corresponds to the LRT

The likelihood takes the form

$$L(\mu, \sigma^2 | \mathbf{x}) = (2\pi\sigma^2)^{-n/2} \exp\left\{-(1/2)\sum (x_i - \mu)^2 / \sigma^2\right\}$$

The unrestricted MLEs are given by

$$\hat{\theta} = \bar{x}$$

and

$$\hat{\sigma}^2 = \frac{1}{n} \sum (x_i - \bar{x})^2$$

11

If $\hat{\theta} = \bar{x} \leq \theta_0$, the restricted MLEs (i.e. under H_0) are the same as the unrestricted MLEs, while if $\hat{\theta} > \theta_0$ the restricted MLEs are

$$\hat{\theta}_0 = \theta_0$$

and

$$\hat{\sigma}_0^2 = \frac{1}{n} \sum (x_i - \theta_0)^2$$

Thus the LRT statistic becomes

$$\lambda(\mathbf{x}) = \begin{cases} 1 & \text{if } \bar{x} \leq \theta_0 \\ \frac{L(\theta_0, \hat{\sigma}_0^2 | \mathbf{x})}{L(\hat{\theta}, \hat{\sigma}^2 | \mathbf{x})} & \text{if } \bar{x} > \theta_0 \end{cases}$$

12

Now we have

$$\begin{aligned} \frac{L(\theta_0, \hat{\sigma}_0^2 | \mathbf{x})}{L(\hat{\theta}, \hat{\sigma}^2 | \mathbf{x})} &= \frac{(2\pi\hat{\sigma}_0^2)^{-n/2} \exp\left\{-\frac{1}{2}\sum (x_i - \theta_0)^2 / \hat{\sigma}_0^2\right\}}{(2\pi\hat{\sigma}^2)^{-n/2} \exp\left\{-\frac{1}{2}\sum (x_i - \bar{x})^2 / \hat{\sigma}^2\right\}} \\ &= \frac{(2\pi\hat{\sigma}_0^2)^{-n/2} \exp\left\{-(n/2)\right\}}{(2\pi\hat{\sigma}^2)^{-n/2} \exp\left\{-(n/2)\right\}} \\ &= \left(\frac{\hat{\sigma}^2}{\hat{\sigma}_0^2}\right)^{n/2} \\ &= \left(\frac{\sum (x_i - \bar{x})^2}{\sum (x_i - \theta_0)^2}\right)^{n/2} \end{aligned}$$

13

The likelihood ratio test rejects H_0 if (assuming $\bar{x} > \theta_0$)

$$\begin{aligned} \lambda(\mathbf{x}) &= \left(\frac{\sum (x_i - \bar{x})^2}{\sum (x_i - \theta_0)^2}\right)^{n/2} \leq c \\ \Leftrightarrow & \\ \frac{\sum (x_i - \bar{x})^2}{\sum (x_i - \theta_0)^2} &\leq c^{2/n} \\ \Leftrightarrow & \\ \frac{\sum (x_i - \bar{x})^2 + n(\bar{x} - \theta_0)^2}{\sum (x_i - \bar{x})^2} &\geq c^{-2/n} \\ \Leftrightarrow & \\ 1 + \frac{n(\bar{x} - \theta_0)^2}{\sum (x_i - \bar{x})^2} &\geq c^{-2/n} \end{aligned}$$

14

Thus (assuming $\bar{x} > \theta_0$)

$$\lambda(\mathbf{x}) \leq c \Leftrightarrow \frac{n(\bar{x} - \theta_0)^2}{\sum (x_i - \bar{x})^2} \geq c^{-2/n} - 1 = k$$

Thus the LRT rejects H_0 if

$$\frac{\bar{x} - \theta_0}{\sqrt{\sum (x_i - \bar{x})^2 / n}} \geq \sqrt{k}$$

which is equivalent to

$$\frac{\bar{x} - \theta_0}{s / \sqrt{n}} > K$$

for a suitably chosen constant K

Thus the test (*) corresponds to the LRT

15