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**محاضرات الاحصاء ٢**

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## Best Critical Region

We consider the properties a satisfactory hypothesis test (or critical region) should possess. To introduce our investigation, we begin with a non-statistical example.

**Example:** Say that you have  $\alpha$  dollars with which to buy books. Further, suppose that you are not interested in the books themselves, but only in filling as much of your book-shelves as possible. How do you decide which books to buy? Does the following approach seem reasonable? First of all, take all the available free books. Then start choosing those books for which the cost of filling an inch of bookshelf is smallest. That is, choose those books for which the ratio  $c/w$  is a minimum, where  $w$  is the width of the book in inches and  $c$  is the cost of the book. Continue choosing books this way until you have spent the  $\alpha$  dollars.

**Definition:** uniformly most powerful critical region of size  $\alpha$  .

A test defined by a critical region  $C$  of size  $\alpha$  is a uniformly most powerful test if it is a most powerful test against each simple alternative in  $H_1$  . The critical region  $C$  is called a uniformly most powerful critical region of size  $\alpha$ .

### LIKELIHOOD RATIO TESTS

We consider a general test – construction method that is applicable when either of both of the null and alternative hypotheses – say  $H_0$  and  $H_1$  – are composite . We continue to assume that the functional form of the p. d. f. is Known . but that it depends on one or more unknown parameters . that is we assume that the p. d. f. of  $X$  is  $f(X;\theta)$ , where  $\theta$  represent one or more unknown parameters . we let  $\Omega$  denote the total parameters space – that is , the set of all possible values of the parameter  $\theta$  given by either  $H_0$  or  $H_1$  . these hypotheses will be stated as .

$$H_0: \theta \in \omega, \quad H_1: \theta \in \omega'.$$

Where  $\omega$  is a subset of  $\Omega$  and  $\omega'$  is the complement of  $\omega$  with respect to  $\Omega$  . the test will be constructed with the use of a ratio of likelihood functions that have been maximized in  $\omega$  and  $\Omega$  , respectively . in a sense , this is natural generalization of the ratio appearing in the Neyman – Pearson lemma when the two hypotheses were simple .

**Definition:**

The likelihood ratio is the quotient

$$\lambda = \frac{L(\hat{\omega})}{L(\hat{\Omega})}$$

Where  $L(\hat{\omega})$  is the maximum of the likelihood function with respect to  $\theta$  when  $\theta \in \omega$  and  $L(\hat{\Omega})$  is the maximum of the likelihood function with respect to  $\theta$  when  $\theta \in \Omega$

### **Definition:**

Consider the test of the simple null hypothesis  $H_0: \theta = \theta_0$  against the simple alternative hypothesis  $H_1: \theta = \theta_1$ . Let  $C$  be a critical region of size  $\alpha$ : that is,  $\alpha = P(C: \theta_0)$ . Then  $C$  is a best critical region of size  $\alpha$  if. For every other critical region  $D$  of size  $\alpha = P(D: \theta_0)$ . We have  $P(C: \theta_1) \geq P(D: \theta_1)$ . That is. When  $H_1: \theta = \theta_1$  is true, the probability of rejecting  $H_0: \theta = \theta_0$  with the use of the critical region  $C$  is at least as great as the corresponding probability with the use of any other critical region  $D$  of size  $\alpha$ .

Thus a best critical region of size  $\alpha$  is the critical region that has greatest power among all critical regions of size  $\alpha$ . The Neyman-Person lemma gives sufficient conditions for a best critical region of size  $\alpha$ .

### **Theorem:(Neyman- Person lemma )**

Let  $x_1, x_2, \dots, x_n$  be a random sample of size  $n$  from a distribution with pdf or pmf  $f(x: \theta)$ , where  $\theta_0$  and  $\theta_1$  are two possible values of  $\theta$ .

$$L(\theta) = L(\theta: x_1, x_2, \dots, x_n) = f(x_1: \theta) f(x_2: \theta) \dots f(x_n: \theta).$$

If there exist a positive constant  $k$  and a subset  $C$  of the sample space such that

- (a)  $P[(x_1, x_2, \dots, x_n) \in C: \theta_0] = \alpha.$
- (b)  $\frac{L(\theta_0)}{L(\theta_1)} \leq k \text{ for } (x_1, x_2, \dots, x_n) \in C. \text{ and}$
- (c)  $\frac{L(\theta_0)}{L(\theta_1)} \geq k \text{ for } (x_1, x_2, \dots, x_n) \notin C.$

Then  $C$  is a best critical region of size  $\alpha$  for testing the simple null hypothesis  $H_0: \theta = \theta_0$  against the simple alternative hypothesis  $H_1: \theta = \theta_1$ .

**Proof:** We prove the theorem when the random variables are the continuous type: for discrete – type random variables replace the integral signs by summation signs. To simplify the exposition, we shall use the following notation:

$$\int_B L(\theta) = \int B \dots \int L(\theta: x_1 x_2 \dots x_n) dx_1 dx_2 \dots dx_n.$$

Assume that there exists another critical region of size  $\alpha$ - say . D, such that.  
in this new notation

$$a = \int_C L(\theta_0) = \int_D L(\theta_0).$$

Then we have

$$\begin{aligned} 0 &= \int_C L(\theta_0) - \int_D L(\theta_0) \\ &= \int_{C \cap D} L(\theta_0) + \int_{C \cap D^c} L(\theta_0) - \int_{C \cap D} L(\theta_0) - \int_{C \cap D^c} L(\theta_0). \end{aligned}$$

Hence

$$0 = \int_{C \cap D} L(\theta_0) - \int_{C \cap D} L(\theta_0)$$

By hypothesis (b).  $kL(\theta_1) \geq L(\theta_0)$  at each point in C and therefore in  $C \cap D$ , thus .

$$k \int_{C \cap D} L(\theta_1) \geq \int_{C \cap D} L(\theta_0)$$

By hypothesis (b).  $kL(\theta_1) \leq L(\theta_0)$  at each point in C and therefore in  $C \cap D$  : thus we obtain .

$$k \int_{C \cap D} L(\theta_1) \leq \int_{C \cap D} L(\theta_0)$$

Consequently .

$$0 = \int_{C \cap D} L(\theta_0) - \int_{C \cap D} L(\theta_0) \leq (k) \{ \int_{C \cap D} L(\theta_1) - \int_{C \cap D} L(\theta_1) \}$$

That is .

$$0 \leq (k) \{ \int_{C \cap D} L(\theta_1) + \int_{C \cap D} L(\theta_1) - \int_{C \cap D} L(\theta_1) - \int_{C \cap D} L(\theta_1) \}$$

Or equivalently .

$$0 \leq (k) \{ \int_C L(\theta_1) - \int_D L(\theta_1) \}$$

Thus.

$$\int_C L(\theta_1) \geq \int_D L(\theta_1):$$

That is .  $P(C: \theta_1) \geq P(D: \theta_1)$  since that is true for every critical region D of size  $\alpha$  . C is a best critical region of size  $\alpha$ .

### **Example:**

Let  $X_1, X_2, \dots, X_n$  denote a random sample of size n from a Poisson distribution with mean  $\lambda$  A best critical region for  $H_0: \lambda = 2$  against  $H_1: \lambda = 5$  given by



$$\frac{L(2)}{L(5)} = \frac{2^{\sum_{i=1}^n x_i} e^{-2n}}{x_1! x_2! \dots x_n!} \frac{x_1! x_2! \dots x_n!}{5^{\sum_{i=1}^n x_i} e^{-5n}} \leq k.$$

This inequality can be written as

$$\left(\frac{2}{5}\right)^{\sum_{i=1}^n x_i} e^{3n} \leq k, \text{ or } \left(\sum_{i=1}^n x_i\right) \ln\left(\frac{2}{5}\right) + 3n \leq \ln k.$$

Since  $\ln(2/5) < 0$ . The latter inequality is the same as

$$\sum_{i=1}^n x_i \geq \frac{\ln k - 3n}{\ln\left(\frac{2}{5}\right)} = c.$$

If  $n = 4$  and  $c = 13$ , then

$$\alpha = P\left(\sum_{i=1}^4 x_i \geq 13; \lambda = 2\right) = 1 - 0.936 = 0.064.$$

Since  $\sum_{i=1}^4 x_i$  has a Poisson distribution with mean 8 when  $\lambda = 2$ .

Because  $\lambda$  is the quotient of nonnegative functions,  $\lambda \geq 0$ . In addition, since  $\omega \subset \Omega$ , it follows that  $L(\hat{\omega}) \leq L(\hat{\Omega})$  and hence  $\lambda \leq 1$ . thus  $0 \leq \lambda \leq 1$ . If the maximum of  $L$  in  $\omega$  is much smaller than in  $\Omega$ . It would seem that the data  $x_1, x_2, \dots, x_n$  do not support the hypothesis  $H_0: \theta \in \omega$ . that is . a small value of the ratio  $\lambda = L(\hat{\omega}) / L(\hat{\Omega})$  would lead to the rejection of  $H_0$ . In contrast, a value of the ratio  $\lambda$  that is close to 1 would support the null hypothesis  $H_0$  this reasoning leads us to the next definition.

**Definition:** To test  $H_0: \theta \in \omega$  against  $H_1: \theta \in \omega$  the critical region for the likelihood ratio test is the set of points in the sample space for which.

$\lambda = \frac{L(\hat{\omega})}{L(\hat{\Omega})} \leq k$ , Where  $0 < k < 1$  and  $k$  is selected so that the test has a desired significance level  $\alpha$ . The next example illustrates these definitions

**Example:**

Assume that weight  $X$  in ounces of a " 10- pound " bag of sugar is  $N(\mu, .5)$ . We shall test the hypothesis  $H_0: \mu = 162$  against the alternative hypothesis  $H_1: \mu \neq 162$ . Thus,  $\Omega = \{\mu: -\infty < \mu < \infty\}$  and  $\omega = \{162\}$ . To find the likelihood ratio, we need  $L(\hat{\omega})$  and  $L(\hat{\Omega})$  when  $H_0$  is true,  $\mu$  can take on only one value, namely  $\mu = 162$ . Hence  $L(\hat{\omega}) = L(162)$ . To find  $L(\hat{\Omega})$  we must find the value of  $\mu$  that maximizes  $L(\mu)$ . Recall that  $\hat{\mu} = \hat{x}$  is the maximum likelihood estimate of  $\mu$ . Then  $L(\hat{\Omega}) = L(\hat{x})$  and the likelihood ratio  $\lambda = L(\hat{\omega}) / L(\hat{\Omega})$  is given by.

$$\lambda = \frac{(10\mu)^{-\frac{n}{2}} \exp\left[-\left(\frac{1}{10}\right) \sum_{i=1}^n (x_i - 162)^2\right]}{(10\mu)^{-\frac{n}{2}} \exp\left[-\left(\frac{1}{10}\right) \sum_{i=1}^n (x_i - \hat{x})^2\right]} = \frac{\exp\left[-\left(\frac{1}{10}\right) \sum_{i=1}^n (x_i - \hat{x})^2 - \left(\frac{n}{10}\right) (\hat{x} - 162)^2\right]}{\exp\left[-\left(\frac{1}{10}\right) \sum_{i=1}^n (x_i - \hat{x})^2\right]}$$

$$= \exp \left[ -\frac{n}{10} (\underline{x} - 162)^2 \right]$$

On the one hand , a value of  $\underline{x}$  close to 162 would tend to support  $H_0$ , and in that case  $\lambda$  is close to 1 . on the other hand , an  $\underline{x}$  that differs from 162 by too much would tend to support  $H_1$ . (see Figure 1 for the graph of this likelihood ratio when  $n=5$ ). A critical region for likelihood ratio is given by  $\lambda \leq k$  , where  $k$  is selected so that the significance level of the test is  $\alpha$  . Using this criterion and simplifying the

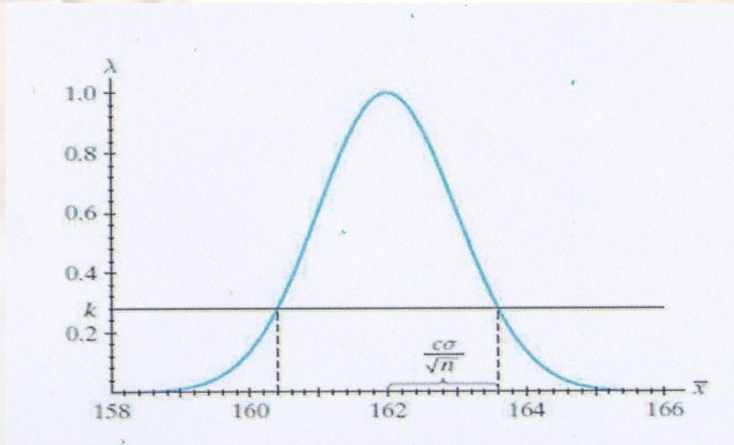


Figure 1. The likelihood ratio for testing  $H_0: \mu = 162$

Inequality as we do when we use the Neyman- Pearson lemma , we find that  $\lambda \leq k$  is equivalent to each of the following Inequalities:

$$-\left(\frac{n}{10}\right)(\underline{x} - 162)^2 \leq \ln k,$$

$$(\underline{x} - 162)^2 \geq -\left(\frac{10}{n}\right) \ln k$$

$$\frac{\{\underline{x} - 162\}}{\frac{\sqrt{5}}{\sqrt{n}}} \geq \frac{\sqrt{-\left(\frac{10}{n}\right) \ln k}}{\frac{\sqrt{5}}{\sqrt{n}}} = c$$

Since  $z = (\underline{x} - 162) / \left(\frac{\sqrt{5}}{\sqrt{n}}\right)$  is  $N(0,1)$  when  $H_0: \mu = 162$  is true. Let  $c = z_{\alpha}/2$  Thus the critical region is .

$$c = \left\{ x: \frac{|\underline{x} - 162|}{\frac{\sqrt{5}}{\sqrt{n}}} \geq c = z_{\alpha}/2 \right\}$$

To illustrate , if  $\alpha = 0.05$  then  $z_{0.025} = 1.96$ .

