



Mathematical Statistics

Homework 4



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Wackerly 10.126

Suppose that X_1, X_2, \dots, X_{n_1} , Y_1, Y_2, \dots, Y_{n_2} , and W_1, W_2, \dots, W_{n_3} are independent random samples from normal distributions with respective unknown means μ_1, μ_2 , and μ_3 and common variances $\sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \sigma^2$. Suppose that we want to estimate a linear function of the means: $\theta = a_1\mu_1 + a_2\mu_2 + a_3\mu_3$. Because the maximum-likelihood estimator (MLE) of a function of parameters is the function of the MLEs of the parameters, the MLE of θ is $\hat{\theta} = a_1\bar{X} + a_2\bar{Y} + a_3\bar{W}$.

- (a) What is the standard error of the estimator $\hat{\theta}$?
- (b) What is the distribution of $\hat{\theta}$?
- (c) If the sample variances are given by S_1^2, S_2^2 , and S_3^2 , respectively, consider

$$S_p^2 = \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2 + (n_3 - 1)S_3^2}{n_1 + n_2 + n_3 - 3}.$$

- (i) What is the distribution of $(n_1 + n_2 + n_3 - 3)S_p^2/\sigma^2$?
- (ii) What is the distribution of

$$T = \frac{\hat{\theta} - \theta}{S_p \sqrt{\frac{a_1^2}{n_1} + \frac{a_2^2}{n_2} + \frac{a_3^2}{n_3}}}$$

- (d) Give a confidence interval for θ with confidence coefficient $1 - \alpha$.
- (e) Develop a test for $H_0 : \theta = \theta_0$ versus $H_1 : \theta \neq \theta_0$.

Solution

- (a) Since the samples are independent of each other, the variance of $\hat{\theta}$ is

$$\text{Var}(\hat{\theta}) = \text{Var}(a_1\bar{X} + a_2\bar{Y} + a_3\bar{W}) \tag{1}$$

$$= a_1^2 \text{Var}(\bar{X}) + a_2^2 \text{Var}(\bar{Y}) + a_3^2 \text{Var}(\bar{W}) \tag{2}$$

$$= a_1^2 \frac{\sigma^2}{n_1} + a_2^2 \frac{\sigma^2}{n_2} + a_3^2 \frac{\sigma^2}{n_3} \tag{3}$$

$$= \sigma^2 \left(\frac{a_1^2}{n_1} + \frac{a_2^2}{n_2} + \frac{a_3^2}{n_3} \right). \tag{4}$$

The standard error of $\hat{\theta}$ is

$$\text{SE}(\hat{\theta}) = \sqrt{\text{Var}(\hat{\theta})} \quad (5)$$

$$= \sigma \sqrt{\frac{a_1^2}{n_1} + \frac{a_2^2}{n_2} + \frac{a_3^2}{n_3}}. \quad (6)$$

(b) By Theorem 5.3.1 (Casella and Berger § 5.3),

$$\bar{X} \sim n \left(\mu_1, \frac{\sigma^2}{n_1} \right) \quad (7)$$

$$\bar{Y} \sim n \left(\mu_2, \frac{\sigma^2}{n_2} \right) \quad (8)$$

$$\bar{W} \sim n \left(\mu_3, \frac{\sigma^2}{n_3} \right). \quad (9)$$

Using the method of moment-generating functions, it is easy to see that

$$a_1 \bar{X} \sim n \left(a_1 \mu_1, \frac{a_1^2 \sigma^2}{n_1} \right) \quad (10)$$

$$a_2 \bar{Y} \sim n \left(a_2 \mu_2, \frac{a_2^2 \sigma^2}{n_2} \right) \quad (11)$$

$$a_3 \bar{W} \sim n \left(a_3 \mu_3, \frac{a_3^2 \sigma^2}{n_3} \right). \quad (12)$$

Thus $\hat{\theta}$ is normal with mean $a_1 \mu_1 + a_2 \mu_2 + a_3 \mu_3 = \theta$, and variance $\sigma^2 \left(\frac{a_1^2}{n_1} + \frac{a_2^2}{n_2} + \frac{a_3^2}{n_3} \right)$.

(c) (i) Notice that we can write

$$(n_1 + n_2 + n_3 - 3)S_p^2 / \sigma^2 = \frac{(n_1 - 1)S_1^2}{\sigma^2} + \frac{(n_2 - 1)S_2^2}{\sigma^2} + \frac{(n_3 - 1)S_3^2}{\sigma^2}. \quad (13)$$

By Theorem 5.3.1 (Casella and Berger § 5.3),

$$\frac{(n_1 - 1)S_1^2}{\sigma^2} \sim \chi^2(n_1 - 1) \quad (14)$$

$$\frac{(n_2 - 1)S_2^2}{\sigma^2} \sim \chi^2(n_2 - 1) \quad (15)$$

$$\frac{(n_3 - 1)S_3^2}{\sigma^2} \sim \chi^2(n_3 - 1) \quad (16)$$

Note that the above variables are independent. Now, a sum of k independent chi-squared random variables (with degrees of freedom p_i) is again a chi-squared random variable with $\sum_{i=1}^k p_i$ degrees of freedom. Thus,

$$(n_1 + n_2 + n_3 - 3)S_p^2 / \sigma^2 \sim \chi^2(n_1 + n_2 + n_3 - 3).$$

(ii) We can write

$$T = \frac{\hat{\theta} - \theta}{S_p \sqrt{\frac{a_1^2}{n_1} + \frac{a_2^2}{n_2} + \frac{a_3^2}{n_3}}} \quad (17)$$

$$= \frac{\hat{\theta} - \theta}{\sqrt{\frac{1}{n_1+n_2+n_3-3}(n_1+n_2+n_3-3)S_p^2/\sigma^2} \left(\sigma \sqrt{\frac{a_1^2}{n_1} + \frac{a_2^2}{n_2} + \frac{a_3^2}{n_3}} \right)} \quad (18)$$

$$= \left(\frac{\hat{\theta} - \theta}{\sigma \sqrt{\frac{a_1^2}{n_1} + \frac{a_2^2}{n_2} + \frac{a_3^2}{n_3}}} \right) \frac{1}{\sqrt{\frac{1}{n_1+n_2+n_3-3}(n_1+n_2+n_3-3)S_p^2/\sigma^2}}. \quad (19)$$

Note that $Z = \frac{\hat{\theta} - \theta}{\sigma \sqrt{\frac{a_1^2}{n_1} + \frac{a_2^2}{n_2} + \frac{a_3^2}{n_3}}}$ is a standard normal random variable and $X = (n_1 + n_2 + n_3 - 3)S_p^2/\sigma^2$ is a chi-squared random variable with $n_1 + n_2 + n_3 - 3$ degrees of freedom. Thus, we can write T as

$$T = \frac{Z}{\sqrt{X/(n_1 + n_2 + n_3 - 3)}} \quad (20)$$

If Z and X are independent, then T has a t distribution with $n_1 + n_2 + n_3 - 3$ degrees of freedom. To show that Z and X are independent, we only need to show that $\hat{\theta}$ and S_p^2 are independent. Now, from Theorem 5.3.1 (Casella and Berger § 5.3) we know that \bar{X} is independent of S_1^2 , \bar{Y} is independent of S_2^2 , and \bar{W} is independent of S_3^2 . Since $\hat{\theta}$ is a linear combination of \bar{X}, \bar{Y} , and \bar{W} and S_p^2 is a linear combination of S_1^2, S_2^2 , and S_3^2 , it follows that $\hat{\theta}$ and S_p^2 are independent. Therefore, Z and X are independent. Thus, $T \sim t(n_1 + n_2 + n_3 - 3)$.

(d) Since the variances of the distributions are unknown, the confidence interval for θ with confidence coefficient $1 - \alpha$ is

$$\hat{\theta} \pm t_{\alpha/2; n_1+n_2+n_3-3} S_p \sqrt{\frac{a_1^2}{n_1} + \frac{a_2^2}{n_2} + \frac{a_3^2}{n_3}}.$$

(e) The hypotheses $H_0 : \theta = \theta_0$ versus $H_a : \theta \neq \theta_0$ can be tested using the T statistic from the previous problem. Since the alternative hypothesis contains a "not equals" sign, the test will be two-sides with rejection region

$$|T| > t_{\alpha/2; n_1+n_2+n_3-3}.$$

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A merchant figures her weekly profit to be a function of three variables: retail sales (denoted by X), wholesale sales (denoted by Y), and overhead costs (denoted by W). The variables X , Y , and W are regarded as independent, normally distributed random variables with means μ_1, μ_2 , and μ_3 and variances $\sigma^2, a\sigma^2$, and $b\sigma^2$, respectively, for known constants a and b but unknown σ^2 . The merchant's expected profit per week is $\mu_1 + \mu_2 - \mu_3$. If the merchant has made independent observations of X , Y , and W for the past n weeks, construct a test of $H_0 : \mu_1 + \mu_2 - \mu_3 = k$ against the alternative $H_a : \mu_1 + \mu_2 - \mu_3 \neq k$, for a given constant k . You may specify $\alpha = 0.05$.

Solution

Let $\theta = \mu_1 + \mu_2 - \mu_3$. We can rewrite the hypotheses as $H_0 : \theta = k$ versus $H_a : \theta \neq k$. The MLE of θ is $\hat{\theta} = \bar{X} + \bar{Y} - \bar{W}$, which has a normal distribution with mean $\mu_1 + \mu_2 - \mu_3$ and variance $\frac{\sigma^2}{n}(1 + a + b)$. The distribution of $\hat{\theta} - \theta$ is normal with mean 0 and variance $\frac{\sigma^2}{n}(1 + a + b)$. Therefore, the distribution of

$$Z = \frac{\hat{\theta} - \theta}{\sigma \sqrt{\frac{1}{n}(1 + a + b)}}$$

is standard normal. Next, define

$$S_p^2 = \frac{(n-1)S_x^2 + \frac{(n-1)}{a}S_y^2 + \frac{n-1}{b}S_w^2}{3n-3},$$

where S_x^2, S_y^2 , and S_w^2 are the respective sample variances. Then

$$\chi = (3n-3)S_p^2/\sigma^2 \tag{21}$$

$$= \frac{(n-1)S_x^2}{\sigma^2} + \frac{(n-1)S_y^2}{a\sigma^2} + \frac{(n-1)S_w^2}{b\sigma^2} \tag{22}$$

has a chi-squared distribution with $3n-3$ degrees of freedom. By applying Theorem 5.3.1 (Casella and Berger § 5.3), we conclude that Z and χ are independent. So the distribution of

$$\frac{Z}{\sqrt{\chi/(3n-3)}} = \left(\frac{1}{S_p/\sigma} \right) \left(\frac{\hat{\theta} - \theta}{\sigma \sqrt{\frac{1}{n}(1 + a + b)}} \right) \tag{23}$$

$$= \frac{\hat{\theta} - \theta}{S_p \sqrt{\frac{1}{n}(1 + a + b)}} \tag{24}$$

is t with $3n-3$ degrees of freedom. So we reject H_0 if

$$\left| \frac{\hat{\theta} - \theta}{S_p \sqrt{\frac{1}{n}(1 + a + b)}} \right| > t_{0.025; 3n-3}.$$

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Wackerly 10.128

A reading exam is given to the sixth graders at three large elementary schools. The scores on the exam at each school are regarded as having normal distributions with unknown means μ_1, μ_2 , and μ_3 , respectively, and unknown common variance σ^2 ($\sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \sigma^2$). Using the data in the accompanying table on independent random samples from each school, test to see if evidence exists of a difference between μ_1 and μ_2 . Use $\alpha = 0.05$.

Solution

This problem can be solved using the theory developed in problem 10.126. Letting $\theta = \mu_1 - \mu_2 + 0\mu_3 = \mu_1 - \mu_2$, our hypothesis test becomes $H_0 : \theta = 0$ versus $H_1 : \theta \neq 0$. We will reject H_0 if the test statistic

$$T = \frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{S_p \sqrt{\frac{1}{10} + \frac{1}{10}}}$$

satisfies $|T| > t_{0.025;27} = 2.051831$. Using the data from the table, we find that

$$\bar{x} - \bar{y} = 60 - 50 \tag{25}$$

$$= 10, \tag{26}$$

and

$$S_p^2 = \frac{9(S_x^2 + S_y^2 + S_w^2)}{27} \tag{27}$$

$$= \frac{9}{27} \left(\frac{\sum x_i^2 - n\bar{x}^2}{9} + \frac{\sum y_i^2 - n\bar{y}^2}{9} + \frac{\sum w_i^2 - n\bar{w}^2}{9} \right) \tag{28}$$

$$= \frac{1}{27} [36950 - 10(60^2) + 25850 - 10(50^2) + 49900 - 10(70^2)] \tag{29}$$

$$= \frac{2700}{27} \tag{30}$$

$$= 100. \tag{31}$$

Thus,

$$T = \frac{10}{10\sqrt{2/10}} \tag{32}$$

$$= \sqrt{5} \tag{33}$$

$$\approx 2.23607. \tag{34}$$

Since $|T| = 2.23607 > 2.051831$, we reject H_0 and conclude that there is evidence supporting the hypothesis that there is a difference between μ_1 and μ_2 .

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Suppose that Y_1, Y_2, \dots, Y_n denote a random sample from the probability density function given by

$$f(y|\theta_1, \theta_2) = \begin{cases} \frac{1}{\theta_1} e^{-(y-\theta_2)/\theta_1}, & y > \theta_2 \\ 0, & \text{elsewhere.} \end{cases}$$

Find the likelihood ratio test for testing $H_0 : \theta_1 = \theta_{1,0}$ versus $H_a : \theta_1 > \theta_{1,0}$ with θ_2 unknown.

Solution

The likelihood function for the sample is

$$L(\theta_1, \theta_2|\mathbf{y}) = \prod_{i=1}^n f(y_i|\theta_1, \theta_2) \quad (35)$$

$$= \begin{cases} \left(\frac{1}{\theta_1}\right)^n \exp\left\{-\frac{1}{\theta_1} \sum_{i=1}^n (y_i - \theta_2)\right\}, & \theta_2 \leq y_{(1)} \\ 0, & \text{elsewhere} \end{cases} \quad (36)$$

The log-likelihood function for $\theta_2 < y_{(1)}$ is then

$$\mathcal{L}(\theta_1, \theta_2|\mathbf{y}) = -n \log(\theta_1) - \frac{1}{\theta_1} \sum_{i=1}^n (y_i - \theta_2). \quad (37)$$

For other values of θ_2 , it doesn't exist. Now we will use these two functions to find the MLEs of θ_1 and θ_2 (which we will denote by $\hat{\theta}_1$ and $\hat{\theta}_2$, respectively). Examining the likelihood function, we see that on the interval $-\infty < \theta_2 < y_{(1)}$, it is an increasing function of θ_2 . Thus, the MLE of θ_2 is $\hat{\theta}_2 = y_{(1)}$. To find the MLE of θ_1 , we solve

$$\frac{d}{d\theta_1} \mathcal{L}(\theta_1, \hat{\theta}_2|\mathbf{y}) = -\frac{n}{\theta_1} + \frac{1}{\theta_1^2} \sum_{i=1}^n (y_i - y_{(1)}) \quad (38)$$

$$= 0 \quad (39)$$

for θ_1 . It is easy to see that the solution is $\hat{\theta}_1 = \frac{1}{n} \sum_{i=1}^n (y_i - y_{(1)})$.

The likelihood ratio test statistic for the hypotheses in this problem is

$$\lambda_1(\mathbf{y}) = \frac{L(\theta_{1,0}, \hat{\theta}_2|\mathbf{y})}{L(\hat{\theta}_1, \hat{\theta}_2|\mathbf{y})} \quad (40)$$

$$= \left(\frac{\hat{\theta}_1}{\theta_{1,0}}\right)^n \frac{\exp\left\{-\frac{1}{\theta_{1,0}} \sum (y_i - y_{(1)})\right\}}{\exp\left\{-\frac{1}{\hat{\theta}_1} \sum (y_i - y_{(1)})\right\}} \quad (41)$$

$$= \left(\frac{\sum (y_i - y_{(1)})}{n\theta_{1,0}}\right)^n \exp\left\{-\frac{1}{\theta_{1,0}} \sum (y_i - y_{(1)}) + n\right\}. \quad (42)$$

The likelihood ratio test is to reject H_0 whenever $\lambda_1(\mathbf{y}) < c$, where $0 \leq c \leq 1$.

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Wackerly 10.130

Refer to Exercise 10.129. Find the likelihood ratio test for testing $H_0 : \theta_2 = \theta_{2,0}$ versus $H_a : \theta_2 > \theta_{2,0}$, with θ_1 unknown.

Solution

If θ_1 and θ_2 are restricted to values specified by the null hypothesis, then L is maximized when $\theta_2 = \theta_{2,0}$ and $\theta_1 = \frac{1}{n} \sum (y_i - \theta_{2,0})$. Thus, the likelihood test statistic for this hypothesis test is

$$\lambda_2(\mathbf{y}) = \frac{L\left(\frac{1}{n} \sum (y_i - \theta_{2,0}), \theta_{2,0} | \mathbf{y}\right)}{L(\hat{\theta}_1, \hat{\theta}_2 | \mathbf{y})} \quad (43)$$

$$= \left[\frac{\frac{1}{n} \sum (y_i - y_{(1)})}{\frac{1}{n} \sum (y_i - \theta_{2,0})} \right]^n \frac{\exp \left\{ -\frac{\sum (y_i - \theta_{2,0})}{\frac{1}{n} \sum (y_i - \theta_{2,0})} \right\}}{\exp \left\{ -\frac{\sum (y_i - y_{(1)})}{\frac{1}{n} \sum (y_i - y_{(1)})} \right\}} \quad (44)$$

$$= \left[\frac{\sum (y_i - y_{(1)})}{\sum (y_i - \theta_{2,0})} \right]^n \frac{\exp \{-n\}}{\exp \{-n\}} \quad (45)$$

$$= \left[\frac{\sum (y_i - y_{(1)})}{\sum (y_i - \theta_{2,0})} \right]^n. \quad (46)$$

Again, the likelihood ratio test is to reject H_0 whenever $\lambda_1(\mathbf{y}) < c$, where $0 \leq c \leq 1$.

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