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Experiment No-03

Topic- FITTING OF MULTIPLE LINEAR REGRESSION MODEL.

Problem- The following arrangement of the sum of squares and sum of product corrected for mean, each being based on 28 observations.

$$\begin{matrix} & \begin{pmatrix} x_1 & x_2 & x_3 & y \end{pmatrix} \\ \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} & \begin{pmatrix} 10.458 & 0.238 & 7.032 & 1.379 \\ & 1.316 & -0.268 & 2.198 \\ & & 16.047 & 0.368 \\ & & & 4.244 \end{pmatrix} \end{matrix}$$

- 1) Fit a regression model of the form

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$$

- 2) Test for the significance of the multiple correlation coefficient of Y on (X₁, X₂, X₃).

Also construct the 95% confidence interval for each of the regression coefficient.

Theory-

(1) Suppose we are to fit a regression model of the form-

$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p + \varepsilon$ where Y is the dependent variables, X_i 's are independent variables ($i=1,2,3, \dots, p$) and β_i 's are the regression coefficient ($i=1,2,3, \dots, p$). Let us further suppose that there are 'n' observations under each of the 'p-variable' and Y. Therefore, for the i^{th} observation, we have-

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_p X_{pi} + \varepsilon_i ; i = 1,2,3, \dots, n \quad \dots\dots\dots(1)$$

Here it is assume that-

$$E(\varepsilon_i) = 0$$
$$E(\varepsilon_i, \varepsilon_j) = \begin{cases} 0 & ; i \neq j \\ \sigma^2 & ; i = j \end{cases} \quad i, j = 1,2,3, \dots, n$$

Also, $\varepsilon_i \sim$ Normal distribution with mean 0 and variance σ^2

Taking sum over all the 'n' observation on equation (1) and dividing by 'n' we get—

$$\frac{1}{n} \sum_{i=1}^n Y_i = \frac{n\beta_0}{n} + \beta_1 \frac{1}{n} \sum_{i=1}^n X_{1i} + \beta_2 \frac{1}{n} \sum_{i=1}^n X_{2i} + \dots + \beta_p \frac{1}{n} \sum_{i=1}^n X_{pi} + \frac{1}{n} \sum_{i=1}^n \varepsilon_i$$
$$\Rightarrow \bar{Y} = \beta_0 + \beta_1 \bar{X}_1 + \beta_2 \bar{X}_2 + \dots + \beta_p \bar{X}_p + \bar{\varepsilon} \quad \dots\dots\dots(2)$$

Subtracting eqn (2) from each of the 'n' equation in (1), we get-

$$\Rightarrow Y_i - \bar{Y} = (\beta_0 - \beta_0) + \beta_1 (X_{1i} - \bar{X}_1) + \beta_2 (X_{2i} - \bar{X}_2) + \dots + \beta_p (X_{pi} - \bar{X}_p) + (\varepsilon_i - \bar{\varepsilon})$$
$$\Rightarrow Y_i = \beta_1 (X_{1i} - \bar{X}_1) + \beta_2 (X_{2i} - \bar{X}_2) + \dots + \beta_p (X_{pi} - \bar{X}_p) + (\varepsilon_i - \bar{\varepsilon})$$
$$\Rightarrow y_i = \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_p x_{pi} + \varepsilon_i \quad ; i = 1,2,3, \dots, n \quad \dots\dots\dots(3)$$

Where x_{ki} denote deviation of the i^{th} observation under k^{th} variable from its mean,

$$k=1,2,3, \dots, p \quad \text{and} \quad i=1,2,3, \dots, n$$

The 'n' equations in no (3) may be written in the matrix form as-

$$\underset{\sim}{Y} = \underset{\sim}{X} \underset{\sim}{\beta} + \underset{\sim}{\varepsilon}$$

Where,

$$\underset{\sim}{Y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}_{n \times 1}, \quad \underset{\sim}{X} = \begin{pmatrix} x_{11} & x_{21} & \cdots & x_{p1} \\ x_{12} & x_{22} & \cdots & x_{p2} \\ \vdots & \vdots & & \vdots \\ x_{1n} & x_{2n} & \cdots & x_{pn} \end{pmatrix}_{n \times p}, \quad \underset{\sim}{\beta} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{pmatrix}_{p \times 1}, \quad \underset{\sim}{\varepsilon} = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_p \end{pmatrix}_{p \times 1}$$

The least square estimates of $\hat{\beta}$ is given by-

$$\hat{\beta} = (\underset{\sim}{X}'\underset{\sim}{X})^{-1} \underset{\sim}{X}'\underset{\sim}{Y} = \begin{pmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \vdots \\ \hat{\beta}_p \end{pmatrix}_{p \times 1}$$

Where,

$$\underset{\sim}{X}'\underset{\sim}{X} = \begin{pmatrix} \sum_{i=1}^n x_{1i}^2 & \sum_{i=1}^n x_{1i}x_{2i} & \cdots & \sum_{i=1}^n x_{1i}x_{pi} \\ \sum_{i=1}^n x_{2i}x_{1i} & \sum_{i=1}^n x_{2i}^2 & \cdots & \sum_{i=1}^n x_{2i}x_{pi} \\ \vdots & \vdots & & \vdots \\ \sum_{i=1}^n x_{pi}x_{1i} & \sum_{i=1}^n x_{pi}x_{2i} & \cdots & \sum_{i=1}^n x_{pi}^2 \end{pmatrix}, \text{ and } \underset{\sim}{X}'\underset{\sim}{Y} = \begin{pmatrix} \sum_i x_{1i}y_i \\ \sum_i x_{2i}y_i \\ \vdots \\ \sum_i x_{pi}y_i \end{pmatrix}$$

The required multiple linear regression model to be fitted is -

$$Y = \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \cdots + \hat{\beta}_p X_p$$

(2) Here the null hypothesis to be tested is -

H₀: The multiple correlation coefficient of Y on (X₁, X₂, X₃) is zero.

Under H₀ the test statistic is-

$$F = \frac{R^2}{1-R^2} \left(\frac{n-p-1}{p} \right) \sim F(p, n-p-1)$$

Where, R is the multiple correlation coefficient of a variable with the other 'p' variables in a random sample of size 'n' from a (p+1) variate distribution.

$$R^2 = 1 - \left[\frac{\sum_{i=1}^n y_i^2 - \hat{\beta}'(X'X)\hat{\beta}}{\sum_{i=1}^n y_i^2} \times \frac{(n-1)}{(n-p)} \right]$$

The calculated value is compared with the tabulated value and conclusion are drawn accordingly.

Confidence Interval Contraction-

Suppose in a regression model $\tilde{Y} = \tilde{X}\tilde{\beta} + \tilde{\varepsilon}$, \tilde{X} has full rank 'p' and $\tilde{\varepsilon}$ is distributed as $N_w(0, \sigma^2 I_n)$. The simultaneous 100(1- α)% confidence interval for β_i is given by -

$$\hat{\beta}_i \pm \left(\sqrt{\text{Var}(\hat{\beta}_i)} \times \sqrt{p \times F_{p, n-p}(\alpha)} \right)$$

Where $\text{Var}(\hat{\beta}_i)$ is the diagonal element of $[s^2(X'X)^{-1}]$ corresponding to β_i and

$s^2 = \frac{\tilde{\varepsilon}'\tilde{\varepsilon}}{n-p}$ and $F_{p, n-p}(\alpha)$ is the upper 100(1- α)th percentile of the F distribution with p and (n-p) d.f.

The program for finding the solution to the given problem is-

$$X'X = \begin{matrix} & \begin{pmatrix} x_1 & x_2 & x_3 \end{pmatrix} \\ \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} & \begin{pmatrix} 10.458 & 0.238 & 7.032 \\ 0.238 & 0.316 & -0.268 \\ 7.03 & -0.268 & 16.047 \end{pmatrix} \end{matrix}, \text{ and } X'Y = \begin{matrix} & \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \\ \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} & \begin{pmatrix} 1.379 \\ 2.198 \\ 0.368 \end{pmatrix} \end{matrix}$$

R Program-

```
XX=array(c(10.458,0.238,7.032,0.238,1.316,-0.268,7.032,-0.268,16.047),dim=c(3,3))
```

```
XX
```

```
XY=array(c(1.379,2.198,0.368),dim=c(3,1))
```

```
XY
```

```
XX_inv=solve(XX)
```

```
B=(XX_inv)%*%(XY)
```

```
B
```

```
den=4.244
```

```
num=den-(t(B)%*%(XX)%*%B)
```

```
n=28
```

```
p=3
```

```
R_sqr=1-((num/den)*((n-1)/(n-p)))
```

```
R_sqr
```

```
F_cal=( R_sqr/(1- R_sqr))*((n-p-1)/p)
```

```
F_cal
```

```
F_tab=qf(1-0.05,3,24)
```

```
F_tab
```

```
EE=num
```

```
S_sqr=EE/(n-p)
```

```
V=S_sqr[1,1]*(XX_inv)
```

```
V
```

```
V_B=array(c(sqrt(V[1,1]), sqrt(V[2,2]), sqrt(V[3,3])),dim=c(3,1))
```

$T2 = \sqrt{p \cdot qf(0.05, 3, 25)}$

$LCL = B - (V_B \cdot T2)$

LCL

$UCL = B + (V_B \cdot T2)$

UCL

#We write the following program to get the pair (LCL, UCL) for Beta1, Beta2 and Beta3

CONF_INTRVL=mat.or.vec(3,2)

for (i in 1:3){

CONF_INTRVL[i,1]=c(LCL[i])

CONF_INTRVL[i,2]=c(UCL[i])}

CONF_INTRVL

#Result from the R-Programming-

#F_cal=57.7116

#F_tab=3.008787

#THE VALUE OF REGRESSION COEFFICIENTS ARE-

#Beta1=0.08521572

#Beta2=1.65750420

#Beta3=0.01327190

#AND CONFIDENCE INTERVAL FOR Beta1, Beta2 AND Beta3 IS GIVEN BY-

0.05499460 0.11543684

1.58583258 1.72917582

-0.01111644 0.03766024

Result and Conclusion-

- (i) The required multiple linear regression model to be fitted is -

$$Y = 0.08521572X_1 + 1.65750420X_2 + 0.01327190X_3$$

- (ii) Since the calculated value of F (i.e. cal F=57.7116) is greater than the tabulated value of F (i.e. tab F=3.008787). Therefore we reject our null hypothesis & we conclude that the multiple correlation coefficient of Y on (X_1 , X_2 , X_3) is not equal to zero.

The 95% confidence interval for β_i are given below-

For β_1 is = (0.05499460, 0.11543684)

For β_2 is = (1.58583258, 1.72917582)

For β_3 is = (-0.01111644, 0.03766024)