

$X_1$  depends on  $X_2$ 

### Multiple Regression Equation:

When the values of one variable, are associated with or influenced by other variable, method of Least Square can be used to measure <sup>the</sup> relationship in terms of an equation, which is of the form

$$X_1 = a + b_{12} X_2$$

Sometimes there is interrelation between many variables and the value of one variable may be influenced by many other, e.g., the yield of crop per acre say ( $X_1$ ) depends upon quality of seed ( $X_2$ ), fertility of soil ( $X_3$ ), fertilizer used ( $X_4$ ), weather conditions ( $X_5$ ) and so on. Whenever we are interested in studying the joint effect of a group of variables upon a variable not included in that group, one study is that of multiple correlation and multiple regression.

Let us consider a distribution involving three random variables  $X_1$ ,  $X_2$  and  $X_3$  in which the variable  $X_1$  depends on the values of  $X_2$  and  $X_3$ . The equation of multiple regression of  $X_1$  on  $X_2$  and  $X_3$  is of the form.

$$X_1 = a + b_{12.3} X_2 + b_{13.2} X_3 \quad -(1)$$

## Multiple Correlation:

The simple correlation between dependent variable and the joint effect of all independent variables on dependent variable is called as multiple correlation.

In a trivariate case, having dependent variable  $X_1$  and independent variables  $X_2$  and  $X_3$  and containing  $N$  observations. The multiple correlations are

$$R_{1.23}^2 = \frac{\gamma_{12}^2 + \gamma_{13}^2 - 2\gamma_{12}\gamma_{13}\gamma_{23}}{1 - \gamma_{23}^2}$$

Similarly

$$R_{2.31}^2 = \frac{\gamma_{23}^2 + \gamma_{21}^2 - 2\gamma_{12}\gamma_{23}\gamma_{31}}{1 - \gamma_{31}^2}$$

and

$$R_{3.12}^2 = \frac{\gamma_{31}^2 + \gamma_{32}^2 - 2\gamma_{12}\gamma_{23}\gamma_{31}}{1 - \gamma_{12}^2}$$

The coefficients of regressions,  $b$ 's we are determined by the principle of LS's criterion, by minimising the sum of the squared of the residuals.

$$S = \sum X_{1.23}^2 = \sum (X_1 - \hat{X}_1)^2$$

error of the estimate or residual

$$= \sum (X_1 - a - b_{12.3}X_2 - b_{13.2}X_3)^2 \quad (1)$$

The normal equations are obtained by differentiating equation (1) with respect to  $a$ ,  $b_{12.3}$  and  $b_{13.2}$ , we have

$$\frac{\partial S}{\partial a} = 2 \sum (X_1 - a - b_{12.3}X_2 - b_{13.2}X_3)(-1) = 0$$

$$\frac{\partial S}{\partial b_{12.3}} = 2 \sum (X_1 - a - b_{12.3}X_2 - b_{13.2}X_3)(-X_2) = 0$$

$$\frac{\partial S}{\partial b_{13.2}} = 2 \sum (X_1 - a - b_{12.3}X_2 - b_{13.2}X_3)(-X_3) = 0$$

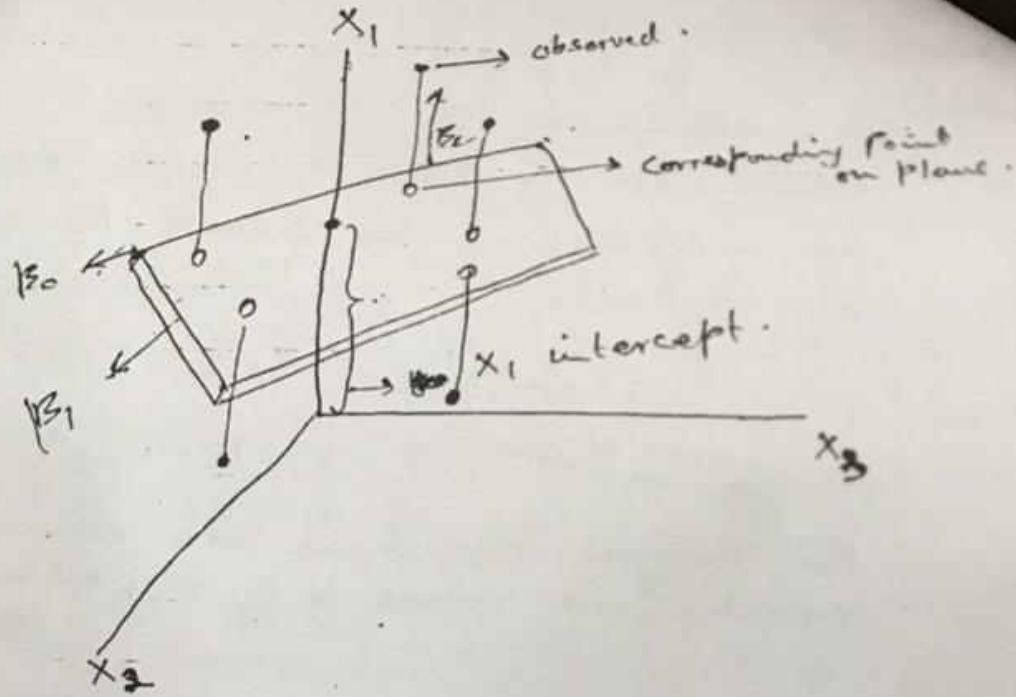
$$\Rightarrow \begin{aligned} \sum (X_1 - a - b_{12.3}X_2 - b_{13.2}X_3) &= 0 \\ \sum X_2 (X_1 - a - b_{12.3}X_2 - b_{13.2}X_3) &= 0 \\ \sum X_3 (X_1 - a - b_{12.3}X_2 - b_{13.2}X_3) &= 0 \end{aligned}$$

$$\begin{aligned} \Rightarrow \sum X_{1.23} &= 0 & - & (i) \\ \sum X_2 X_{1.23} &= 0 & - & (ii) \\ \sum X_3 X_{1.23} &= 0 & - & (iii) \end{aligned}$$

We assume that the variables  $X_1$ ,  $X_2$ , and  $X_3$  have been measured from their respective means, so that.

$$\text{Eq}(i) \quad E(X_1) = E(X_2) = E(X_3) = 0$$

gives  $a = 0 \rightarrow$



$$\hat{x}_1 = \alpha + b_{12.3}x_2 + b_{13.2}x_3.$$

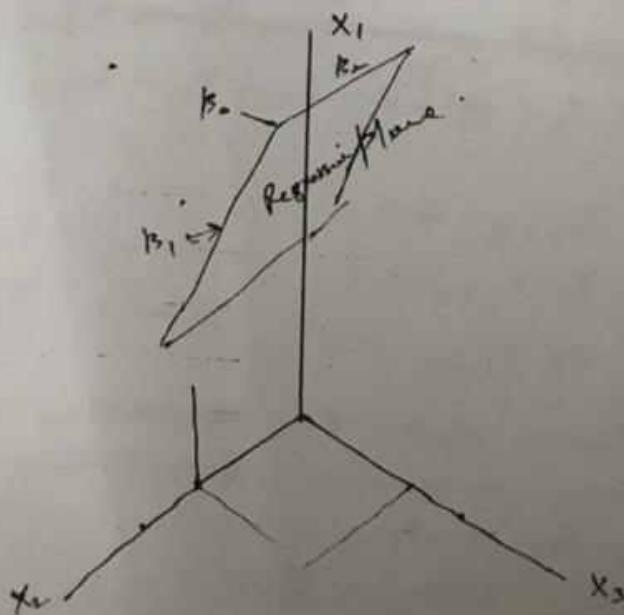
$\hat{x}_1$  is the estimated values

$\alpha$  is the intercept

$b_{12.3}$  and  $b_{13.2}$  slopes associated with  $x_2$  and  $x_3$ .

$x_2$  and  $x_3$  are independent variables

$x_1$  is dependent variable.



and exp(ii) and (iii) gives

$$\begin{aligned} \sum X_1 X_2 - b_{12 \cdot 3} \sum X_2^2 - b_{13 \cdot 2} \sum X_2 X_3 &= 0 \\ \sum X_1 X_3 - b_{12 \cdot 3} \sum X_2 X_3 - b_{13 \cdot 2} \sum X_3^2 &= 0 \end{aligned} \quad (3)$$

Since  $X_i$ 's are measured from their respective means, we have

$$\sigma_i^2 = \frac{1}{N} \sum X_i^2$$

and

$$\text{Cov}(X_i, X_j) = \frac{1}{N} \sum X_i X_j$$

and

$$\gamma_{ij} = \frac{\text{Cov}(X_i, X_j)}{\sigma_i \sigma_j}$$

Hence from exp (3), we get

$$\begin{aligned} N \text{Cov}(X_1, X_2) - Nb_{12 \cdot 3} \sigma_2^2 - N b_{13 \cdot 2} \text{Cov}(X_2, X_3) &= 0 \\ N \text{Cov}(X_1, X_3) - Nb_{12 \cdot 3} \text{Cov}(X_2, X_3) - Nb_{13 \cdot 2} \sigma_3^2 &= 0 \end{aligned}$$

$$\Rightarrow \text{Cov}(X_1, X_2) - b_{12 \cdot 3} \sigma_2^2 - b_{13 \cdot 2} \text{Cov}(X_2, X_3) = 0$$

$$\text{Cov}(X_1, X_3) - b_{12 \cdot 3} \text{Cov}(X_2, X_3) - b_{13 \cdot 2} \sigma_3^2 = 0$$

$$\begin{aligned} \gamma_{12} \sigma_1 \sigma_2 - b_{12 \cdot 3} \sigma_2^2 - b_{13 \cdot 2} \gamma_{23} \sigma_2 \sigma_3 &= 0 \\ \gamma_{13} \sigma_1 \sigma_3 - b_{12 \cdot 3} \gamma_{23} \sigma_2 \sigma_3 - b_{13 \cdot 2} \sigma_3^2 &= 0 \end{aligned} \quad (4)$$

Since there are two equations and two unknowns using cramer's rule we have

$$\begin{aligned} \gamma_{12} \sigma_1 - b_{12 \cdot 3} \sigma_2 - b_{13 \cdot 2} \gamma_{23} \sigma_3 &= 0 \\ \gamma_{13} \sigma_1 - b_{12 \cdot 3} \gamma_{23} \sigma_2 - b_{13 \cdot 2} \sigma_3 &= 0 \end{aligned} \quad (5)$$

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$$w_{12} = - \begin{vmatrix} \gamma_{11} & \gamma_{13} \\ \gamma_{31} & \gamma_{33} \end{vmatrix}, \quad w_{13} = - \begin{vmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{31} & \gamma_{32} \end{vmatrix}, \quad w_{21} = - \begin{vmatrix} \gamma_{21} & \gamma_{23} \\ \gamma_{31} & \gamma_{33} \end{vmatrix}$$

If we use

$$W = \begin{vmatrix} 1 & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & 1 & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{vmatrix} \quad \text{--- (8)}$$

and  $w_{ij}$  is the cofactor of the element in the  $i$ th and  $j$ th column of  $W$ , we have from equation (6) and (7)

$$b_{12,3} = -\frac{\sigma_1}{\sigma_2} \cdot \frac{w_{12}}{w_{11}} \quad \text{and} \quad b_{13,2} = -\frac{\sigma_1}{\sigma_3} \cdot \frac{w_{13}}{w_{11}}$$

Substituting this value in eq (1) when  $a = 0$ , we get  
=> the equation of the plane of regression of  $X_1$  on  $X_2$  and  $X_3$

$$X_1 = -\frac{\sigma_1}{\sigma_2} \cdot \frac{w_{12}}{w_{11}} X_2 - \frac{\sigma_1}{\sigma_3} \cdot \frac{w_{13}}{w_{11}} X_3$$

$$\frac{X_1}{\sigma_1} w_{11} + \frac{X_2}{\sigma_2} w_{12} + \frac{X_3}{\sigma_3} w_{13} = 0 \quad \text{--- (10)}$$

Similarly the other two regression equations

regression equation  $X_2$  on  $X_1$  and  $X_3$  is

$$\frac{X_2}{\sigma_2} w_{22} + \frac{X_3}{\sigma_3} w_{23} + \frac{X_1}{\sigma_1} w_{21} = 0$$

and the regression equation  $X_3$  on  $X_1$  and  $X_2$  is

$$\frac{X_3}{\sigma_3} w_{33} + \frac{X_1}{\sigma_1} w_{31} + \frac{X_2}{\sigma_2} w_{32} = 0$$

and in terms of original values the regression equation  $X_1$  on  $X_2$  and  $X_3$  is

$$\frac{x_1 - \bar{x}_1}{\sigma_1} w_{11} + \frac{x_2 - \bar{x}_2}{\sigma_2} w_{12} + \frac{x_3 - \bar{x}_3}{\sigma_3} w_{13} = 0$$

and

regression equation  $X_2$  on  $X_1$  and  $X_3$  is

$$\frac{x_2 - \bar{x}_2}{\sigma_2} w_{22} + \frac{x_3 - \bar{x}_3}{\sigma_3} w_{23} + \frac{x_1 - \bar{x}_1}{\sigma_1} w_{21} = 0$$

Regression equation  $X_3$  on  $X_1$  and  $X_2$  is

$$\frac{x_3 - \bar{x}_3}{\sigma_3} w_{33} + \frac{x_1 - \bar{x}_1}{\sigma_1} w_{31} + \frac{x_2 - \bar{x}_2}{\sigma_2} w_{32} = 0.$$

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$$\begin{vmatrix} 1 & \gamma_{12} & \gamma_{13} \\ \gamma_{12} & 1 & \gamma_{23} \\ \gamma_{13} & \gamma_{23} & 1 \end{vmatrix}$$

$$\begin{aligned} \gamma_{12} \sigma_1 &= b_{12 \cdot 3} \sigma_2 + b_{13 \cdot 2} \gamma_{23} \sigma_3 \\ \gamma_{13} \sigma_1 &= b_{12 \cdot 3} \gamma_{23} \sigma_2 + b_{13 \cdot 2} \sigma_3 \end{aligned} \quad ] \quad (5)$$

$$b_{12 \cdot 3} = \frac{\begin{vmatrix} \gamma_{12} \sigma_1 & \gamma_{23} \sigma_3 \\ \gamma_{13} \sigma_1 & \sigma_3 \end{vmatrix}}{\begin{vmatrix} \sigma_2 & \gamma_{23} \sigma_3 \\ \gamma_{23} \sigma_2 & \sigma_3 \end{vmatrix}} = \frac{\sigma_1}{\sigma_3} \cdot \frac{\begin{vmatrix} \gamma_{12} & \gamma_{13} \\ \gamma_{13} & 1 \end{vmatrix}}{\begin{vmatrix} 1 & \gamma_{23} \\ \gamma_{23} & 1 \end{vmatrix}}$$

$$b_{12 \cdot 3} = \frac{\sigma_1}{\sigma_2} \left( \frac{\gamma_{12} - \gamma_{13} \gamma_{23}}{1 - \gamma_{23}^2} \right) \quad (6)$$

Similarly, we get -

$$b_{13 \cdot 2} = \frac{\begin{vmatrix} \sigma_2 & \gamma_{12} \sigma_1 \\ \gamma_{23} \sigma_2 & \gamma_{13} \sigma_1 \end{vmatrix}}{\begin{vmatrix} \sigma_2 & \gamma_{23} \sigma_3 \\ \gamma_{23} \sigma_2 & \sigma_3 \end{vmatrix}} = \frac{\sigma_1}{\sigma_3} \cdot \frac{\begin{vmatrix} 1 & \gamma_{12} \\ \gamma_{23} & \gamma_{13} \end{vmatrix}}{\begin{vmatrix} 1 & \gamma_{13} \\ \gamma_{12} & 1 \end{vmatrix}}$$

$$b_{13 \cdot 2} = \frac{\sigma_1}{\sigma_3} \left( \frac{\gamma_{13} - \gamma_{12} \gamma_{23}}{1 - \gamma_{23}^2} \right) \quad (7)$$

### Partial Correlation Coefficient:

Sometimes the correlation between two variables  $x_1$  and  $x_2$  may be partly due to the correlation of a third variable  $x_3$  with both  $x_1$  and  $x_2$ . In such a situation one may want to know what the correlation between  $x_1$  and  $x_2$  would be if the linear effect of  $x_3$  on each of  $x_1$  and  $x_2$  were eliminated. This correlation is called as partial correlation.

The linear regression equations

$$\begin{aligned}x_1 \text{ on } x_3 \text{ is } & X_1 = b_{13} X_3 \\x_2 \text{ on } x_3 \text{ is } & X_2 = b_{23} X_3\end{aligned}$$

Removing the linear effect of  $x_3$  from  $x_1$  and  $x_2$  we get the residuals

$$\begin{aligned}X_{1 \cdot 3} &= X_1 - b_{13} X_3 \\X_{2 \cdot 3} &= X_2 - b_{23} X_3\end{aligned}$$

The correlation between  $X_1$  and  $X_2$  after eliminating the linear effect of  $X_3$  is

$$\gamma_{12 \cdot 3} = \frac{\text{Cov}(X_{1 \cdot 3}, X_{2 \cdot 3})}{\sqrt{\text{Var}(X_{1 \cdot 3}) \text{Var}(X_{2 \cdot 3})}}$$

We have

$$\text{Cov}(X_{1 \cdot 3}, X_{2 \cdot 3}) = \frac{1}{n} \sum X_{1 \cdot 3} X_{2 \cdot 3}$$

Since  $X$ 's are measured from their respective means

$$\begin{aligned}&= \frac{1}{n} \sum [(X_1 - b_{13} X_3)(X_2 - b_{23} X_3)] \\&= \frac{1}{n} \sum [X_1 X_2 - b_{13} X_2 X_3 - b_{23} X_1 X_3 + b_{13} b_{23} X_3^2] \\&= \frac{1}{n} \sum X_1 X_2 - b_{13} \cdot \frac{1}{n} \sum X_2 X_3 - b_{23} \cdot \frac{1}{n} \sum X_1 X_3 + b_{13} b_{23} \cdot \frac{1}{n} \sum X_3^2 \\&\text{Cov}(X_{1 \cdot 3}, X_{2 \cdot 3}) = \gamma_{12} \sigma_1 \sigma_2 - b_{13} \gamma_{23} \sigma_2 \sigma_3 - b_{23} \gamma_{13} \sigma_1 \sigma_3 + b_{13} b_{23} \sigma_3^2\end{aligned}$$

We know that

$$b_{13} = \gamma_{13} \frac{\sigma_1}{\sigma_3} \quad \text{and} \quad b_{23} = \gamma_{23} \frac{\sigma_2}{\sigma_3}$$

$$\begin{aligned}\therefore \text{Cov}(X_{1 \cdot 3}, X_{2 \cdot 3}) &= \gamma_{12} \sigma_1 \sigma_2 - \gamma_{13} \frac{\sigma_1}{\sigma_3} \cdot \gamma_{23} \frac{\sigma_2}{\sigma_3} \sigma_3 \sigma_3 - \gamma_{23} \frac{\sigma_2}{\sigma_3} \cdot \gamma_{13} \frac{\sigma_1}{\sigma_3} \sigma_3 \sigma_3 + \gamma_{13} \frac{\sigma_1}{\sigma_3} \cdot \gamma_{23} \frac{\sigma_2}{\sigma_3} \sigma_3 \sigma_3 \\&= \gamma_{12} \sigma_1 \sigma_2 - \gamma_{13} \gamma_{23} \sigma_1 \sigma_2 - \gamma_{23} \gamma_{13} \sigma_1 \sigma_2 + \gamma_{13} \sigma_1 \sigma_2 \cdot \gamma_{23} \sigma_3 \sigma_3\end{aligned}$$

$$\boxed{\text{Cov}(X_{1 \cdot 3}, X_{2 \cdot 3}) = (\gamma_{12} - \gamma_{13} \gamma_{23}) \sigma_1 \sigma_2}$$

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$$\begin{aligned}
 \text{Var}(X_{1.3}) &= \frac{1}{n} \sum X_{1.3}^2 = \frac{1}{n} \sum X_{1.3} \cdot X_{1.3} = \frac{1}{n} \sum x_1 x_{1.3} \\
 &= \frac{1}{n} \sum x_1 (x_1 - b_{13} x_3) \\
 &= \frac{1}{n} \sum x_1^2 - b_{13} \cdot \frac{1}{n} \sum x_1 x_3 \\
 &= \sigma_1^2 - b_{13} \gamma_{13} \sigma_1 \sigma_3 \quad \rightarrow \text{Cov}(x_1, x_3) \\
 &= \sigma_1^2 - \gamma_{13} \frac{\sigma_1}{\sigma_3} \cdot \gamma_{13} \sigma_1 \sigma_3 \\
 \boxed{\text{Var}(X_{1.3}) = \sigma_1^2 (1 - \gamma_{13}^2)}
 \end{aligned}$$

Similarly,

$$\boxed{\text{Var}(X_{2.3}) = \sigma_2^2 (1 - \gamma_{23}^2)}$$

Hence

$$\begin{aligned}
 \gamma_{12.3} &= \frac{\text{Cov}(X_{1.3}, X_{2.3})}{\sqrt{\text{Var}(X_{1.3}) \text{Var}(X_{2.3})}} = \frac{(\gamma_{12} - \gamma_{12} \gamma_{23}) \sigma_1 \sigma_2}{\sqrt{(1 - \gamma_{13}^2) \cdot \sigma_2^2 (1 - \gamma_{23}^2)}} \\
 \boxed{\gamma_{12.3} = \frac{(\gamma_{12} - \gamma_{12} \gamma_{23})}{\sqrt{(1 - \gamma_{13}^2) (1 - \gamma_{23}^2)}}}
 \end{aligned}$$

Similarly

$$\boxed{\gamma_{13.2} = \frac{(\gamma_{13} - \gamma_{12} \gamma_{23})}{\sqrt{(1 - \gamma_{12}^2) (1 - \gamma_{23}^2)}}}$$

and

$$\boxed{\gamma_{23.1} = \frac{(\gamma_{23} - \gamma_{12} \gamma_{13})}{\sqrt{(1 - \gamma_{12}^2) (1 - \gamma_{13}^2)}}}$$

### Test of Significance.

To test the null hypothesis that  $H_0: \rho_{12.3} = 0$ , we may calculate

$$t = \frac{\gamma_{12.3}}{\sqrt{1 - \gamma_{12.3}^2}} \cdot \sqrt{n-3}$$

with  $n-3$  d.f.

### Multiple Correlation Coefficient:

The simple correlation between dependent variable and the joint effect of all independent variables on dependent variable is called as multiple correlation coefficient.

In a trivariate distribution, having dependent variable, and independent variable  $X_2$  and  $X_3$  and containing  $n$  observations. The simple correlation is

$$R_{1.23} = \frac{\text{Cov}(X_1, e_{1.23})}{\sqrt{\text{Var}(X_1) \text{Var}(e_{1.23})}} = \frac{\sum X_1 e_{1.23}}{\sqrt{\sum X_1^2 \sum e_{1.23}^2}}$$

where,

$$e_{1.23} = b_{12.3} X_2 + b_{13.2} X_3$$

$$\text{and } X_{1.23} = X_1 - b_{12.3} X_2 - b_{13.2} X_3 \\ = X_1 - e_{1.23}$$

We assume that all  $X$ 's are measured from their respective mean.

$$\Rightarrow E(X) = 0 \Rightarrow E(e_{1.23}) = 0 \text{ and } E(X_{1.23}) = 0$$

$$\sum X_1 e_{1.23}$$

$$= \sum X_1 (X_1 - X_{1.23})$$

$$= \sum X_1^2 - \sum X_1 X_{1.23}$$

$$= \sum X_1^2 - \sum X_{1.23}^2$$

$$= n \sigma_i^2 - n \sigma_{1.23}^2$$

$$\boxed{\sum e_{1.23} = n(\sigma_i^2 - \sigma_{1.23}^2)}$$

$$\boxed{\sum X_1^2 = n \sigma_i^2}$$

$$\sum e_{1.23}^2 = \sum (X_1 - X_{1.23})^2$$

$$= \sum (X_1^2 - 2X_1 X_{1.23} + X_{1.23}^2)$$

$$= \sum X_1^2 - 2 \sum X_1 X_{1.23} + \sum X_{1.23}^2$$

$$= \sum X_1^2 - 2 \sum X_{1.23}^2 + \sum X_{1.23}^2$$

$$= \sum X_1^2 - \sum X_{1.23}^2$$

$$= n \sigma_i^2 - n \sigma_{1.23}^2$$

$$\boxed{\sum e_{1.23}^2 = n(\sigma_i^2 - \sigma_{1.23}^2)}$$

$$\begin{aligned} \sum X_{1.23} &= \sum X_{1.23} (X_1 - b_{12.3} X_2 - b_{13.2} X_3) \\ &= \sum X_1 X_{1.23} - b_{12.3} \sum X_2 X_{1.23} - b_{13.2} \sum X_3 X_{1.23} \end{aligned}$$

In multiple regression analysis, normal equations

$$\left. \begin{aligned} \sum X_{1.23} &= 0 \\ \sum X_2 X_{1.23} &= 0 \\ \sum X_3 X_{1.23} &= 0 \end{aligned} \right\} \Rightarrow \boxed{\sum X_{1.23}^2 = \sum X_1 X_{1.23}}$$

$$R_{1.23} = \frac{n(\sigma_i^2 - \sigma_{1.23}^2)}{\sqrt{[n \sigma_i^2][n(\sigma_i^2 - \sigma_{1.23}^2)]}}$$

$$= \frac{n(\sigma_i^2 - \sigma_{1.23}^2)}{n \sigma_i \sqrt{(\sigma_i^2 - \sigma_{1.23}^2)}}$$

$$= \frac{\sqrt{\sigma_i^2 - \sigma_{1.23}^2}}{\sigma_i}$$

$$= \sqrt{\frac{\sigma_i^2 - \sigma_{1.23}^2}{\sigma_i^2}} = \sqrt{1 - \frac{\sigma_{1.23}^2}{\sigma_i^2}}$$

$$\boxed{R_{1.23}^2 = 1 - \frac{\sigma_{1.23}^2}{\sigma_i^2}} = \boxed{1 - \frac{\sum e_{1.23}^2}{\sum X_1^2} = R_{1.23}^2}$$

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$$W = \begin{vmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{vmatrix} = \begin{vmatrix} 1 & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & 1 & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & 1 \end{vmatrix} = (1 - \gamma_{23}^2) - \gamma_{12}(\gamma_{11} - \gamma_{12}\gamma_{22}) + \gamma_{13}(\gamma_{12}\gamma_{23} - \gamma_{21})$$
$$= 1 - \gamma_{23}^2 - \gamma_{12}^2 + \gamma_{12}\gamma_{13}\gamma_{23} + \gamma_{13}\gamma_{23}\gamma_{12} - \gamma_{12}^2$$

$$W_{11} = \begin{vmatrix} \gamma_{12} & \gamma_{13} \\ \gamma_{32} & \gamma_{33} \end{vmatrix} = \begin{vmatrix} 1 & \gamma_{13} \\ \gamma_{32} & 1 \end{vmatrix}$$
$$W = 1 - \gamma_{12}^2 - \gamma_{13}^2 - \gamma_{23}^2 + 2\gamma_{12}\gamma_{13}\gamma_{23}$$

$$W_{11} = 1 - \gamma_{23}^2$$

$$R_{1,23}^2 = 1 - \frac{W}{W_{11}} = 1 - \frac{1 - \gamma_{12}^2 - \gamma_{13}^2 - \gamma_{23}^2 + 2\gamma_{12}\gamma_{13}\gamma_{23}}{1 - \gamma_{23}^2}$$
$$= 1 - \frac{(1 - \gamma_{23}^2) - \gamma_{12}^2 - \gamma_{13}^2 + 2\gamma_{12}\gamma_{13}\gamma_{23}}{1 - \gamma_{23}^2}$$
$$= 1 - 1 + \frac{\gamma_{12}^2 + \gamma_{13}^2 - 2\gamma_{12}\gamma_{13}\gamma_{23}}{1 - \gamma_{23}^2}$$

$$R_{1,23}^2 = \frac{\gamma_{12}^2 + \gamma_{13}^2 - 2\gamma_{12}\gamma_{13}\gamma_{23}}{1 - \gamma_{23}^2}$$

Similarly

$$R_{2,31}^2 = 1 - \frac{W}{W_{22}} = \frac{\gamma_{23}^2 + \gamma_{21}^2 - 2\gamma_{12}\gamma_{23}\gamma_{21}}{1 - \gamma_{21}^2}$$

$$R_{3,12}^2 = 1 - \frac{W}{W_{33}} = \frac{\gamma_{21}^2 + \gamma_{32}^2 - 2\gamma_{12}\gamma_{23}\gamma_{31}}{1 - \gamma_{12}^2}$$

PRACTICAL 9

PROBLEM: A collector of antique clocks believes that the price received for the clock at an antique auction increases with the age of the clocks and with the number of bidders. The following model is suggested:

$$X_1 = \beta_0 + \beta_1 X_2 + \beta_2 X_3 + \epsilon$$

where  $X_1$  = Auction Price  $X_3$  = Age of clock (years)  $X_2$  = no. of bidders  
A sample of 32 auction prices of grandfather clocks, along with their ages and the number of bidders, is given below:

Age $X_3$	Number of bidders $X_2$	Auction Price $X_1$	Age $X_3$	Number of bidders $X_2$	Auction Price $X_1$
127	13	1235	170	14	2131
115	12	1080	182	9	1550
127	7	845	162	11	1884
150	9	1522	184	10	2041
156	6	1047	143	6	854
192	11	979	159	9	1483
156	12	822	108	14	1055
132	10	1253	175	8	1545
137	9	1297	108	6	729
113	9	946	179	9	1792
137	15	1713	111	15	1175
117	11	1024	187	8	1593
137	8	1147	111	7	755
153	6	1092	115	7	744
117	13	1152	194	5	1356
126	10	1336	168	7	1262

- a) Fit the regression model  $X_1$  on  $X_2$  and  $X_3$ .
- b) Is there evidence to indicate that the overall model is useful? Test at 5% level of significance.
- c) Construct the regression model in terms of correlations. The correlation matrix is

$$\begin{matrix} & X_1 & X_2 \\ X_1 & 1 & 0.39464 \\ X_2 & 0.39464 & 1 \\ X_3 & 0.73023 & -0.25375 \end{matrix}$$

- d) Calculate the multiple correlation coefficient  $R_{1,2,3}$  of  $X_1$  on  $X_2$  and  $X_3$ .
- e) Estimate the Auction Price ( $X_1$ ) if an antique clock of Age ( $X_3$ ) 150 years passes through 16 bidders ( $X_2$ ).
- f) Plot the observed and fitted values on the same graph paper and comment on the results.