

Frequently Asked Questions

1. Can we use multiple correlation when we have two variables?

Answer:

Multiple correlation is used when there is tri-variate or multivariate distribution. When there are two variables, we use total correlation coefficient given by Karl Pearson.

2. Give an example for multiple correlation coefficient.

Answer:

If there is interrelation between many variables and the value of one variable may be influenced by many others, example, the yield of crop per acre, say X_1 depends upon quality of seed say X_2 , fertility of soil, say X_3 , fertilizer used say X_4 , irrigation facilities say X_5 , weather conditions say X_6 and so on, then we use multiple correlation coefficient.

3. What do you mean by multiple correlation coefficient.

Answer:

In tri-variate distribution in which each of the variables X_1 , X_2 , and X_3 has N observations, the multiple correlation coefficient between X_1 on X_2 and X_3 is, usually denoted by $R_{1.23}$ is the simple correlation coefficient between X_1 and the joint effect of X_2 and X_3 on X_1 . In other words $R_{1.23}$ is the correlation coefficient between X_1 and its estimated value as given by the plane of regression of X_1 on X_2 and X_3 .

4. Give an expression for multiple correlation coefficient in terms of total correlation coefficients.

Answer:

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

5. Derive an expression for multiple correlation coefficient.

Answer:

In tri-variate distribution in which each of the variables X_1 , X_2 , and X_3 has N observations, the multiple correlation coefficient between X_1 on X_2 and X_3 is, usually denoted by $R_{1.23}$ is the simple correlation coefficient between X_1 and the joint effect of X_2 and X_3 on X_1 . In other words $R_{1.23}$ is the correlation coefficient between X_1 and its estimated value as given by the plane of regression of X_1 on X_2 and X_3 namely,

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

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

$$\text{Implies, } e_{1.23} = X_1 - X_{1.23}.$$

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

$$E(X_{1.23}) = 0 \text{ and } E(e_{1.23}) = 0. \text{ (Since } E(X_i) = 0; i = 1, 2, 3).$$

$$\text{By definition, } R_{1.23} = \frac{\text{Cov}(X_1, e_{1.23})}{\sqrt{V(X_1)V(e_{1.23})}}$$

$$\begin{aligned}
\text{Cov}(X_1, e_{1.23}) &= E[\{X_1 - E(X_1)\}\{e_{1.23} - E(e_{1.23})\}] \\
&= E(X_1 e_{1.23}) = \frac{1}{N} \sum X_1 e_{1.23} = \frac{1}{N} \sum X_1 (X_1 - X_{1.23}) \\
&= \frac{1}{N} \sum X_1^2 - \frac{1}{N} \sum X_1 X_{1.23} = \frac{1}{N} \sum X_1^2 - \frac{1}{N} \sum X_{1.23}^2 = \sigma_1^2 - \sigma_{1.23}^2
\end{aligned}$$

Also,

$$\begin{aligned}
V(e_{1.23}) &= E(e_{1.23}^2) = \frac{1}{N} \sum e_{1.23}^2 = \frac{1}{N} \sum (X_1 - X_{1.23})^2 = \frac{1}{N} \sum (X_1^2 + X_{1.23}^2 - 2X_1 X_{1.23}) \\
&= \frac{1}{N} \sum X_1^2 + \frac{1}{N} \sum X_{1.23}^2 - \frac{2}{N} \sum X_1 X_{1.23} = \frac{1}{N} \sum X_1^2 + \frac{1}{N} \sum X_{1.23}^2 - \frac{2}{N} \sum X_{1.23}^2 \\
&= \sigma_1^2 - \sigma_{1.23}^2
\end{aligned}$$

Substituting in $R_{1.23}$ we get,

$$R_{1.23} = \frac{\sigma_1^2 - \sigma_{1.23}^2}{\sqrt{\sigma_1^2(\sigma_1^2 - \sigma_{1.23}^2)}} \Rightarrow R_{1.23}^2 = \frac{\sigma_1^2 - \sigma_{1.23}^2}{\sigma_1^2} = 1 - \frac{\sigma_{1.23}^2}{\sigma_1^2} \Rightarrow 1 - R_{1.23}^2 = \frac{\sigma_{1.23}^2}{\sigma_1^2}$$

6. Give an expression for multiple correlation coefficient in terms of partial and total correlation coefficient.

Answer:

$$1 - R_{1.23}^2 = (1 - r_{12}^2)(1 - r_{13.2}^2)$$

7. Write the properties of Multiple Correlation coefficient.

Answer:

- Multiple correlation coefficient measures the closeness of the association between the observed values and the expected values of a variable obtained from the multiple linear regression of that variable on other variables.
- Multiple correlation coefficient between observed values and expected values when the expected values are calculated from a linear relation of the variables determined by the method of least square, is always greater than that where expected values are calculated from any other linear combination of the variables.
- Since $R_{1.23}$ is the simple correlation between X_1 and $e_{1.23}$, it must lie between - 1 and +1. But $R_{1.23}$ is a non-negative quantity, $0 \leq R_{1.23} \leq 1$.
- If $R_{1.23} = 1$ then association is perfect and all the regression residuals are zero, and as such $\sigma_{1.23}^2 = 0$. In this case, since $X_1 = e_{1.23}$, the predicted value of X_1 , the multiple linear regression equation of X_1 on X_2 and X_3 may be said to be a perfect prediction formula.
- If $R_{1.23} = 0$ then all total and partial correlations involving X_1 are zero. So X_1 is completely uncorrelated with all the other variables in this case and the multiple regression equation fails to throw any light on the value of X_1 when X_2 and X_3 are known.
- $R_{1.23}$ is not less than any total correlation coefficient. i.e., $R_{1.23} > r_{12}$ or r_{13} or r_{23} .

8. Show that $1 - R_{1.23}^2 = (1 - r_{12}^2)(1 - r_{13.2}^2)$.

Answer:

$$\text{We know that } 1 - R_{1.23}^2 = 1 - \frac{r_{12}^2 + r_{13}^2 - 2r_{12}r_{13}r_{23}}{1 - r_{23}^2} = \frac{1 - r_{12}^2 - r_{23}^2 - r_{13}^2 + 2r_{12}r_{13}r_{23}}{1 - r_{23}^2}$$

$$\text{Also } 1 - r_{13.2}^2 = 1 - \frac{(r_{13}^2 + r_{12}r_{23})^2}{(1 - r_{12}^2)(1 - r_{23}^2)} = \frac{1 - r_{12}^2 - r_{23}^2 - r_{13}^2 + 2r_{12}r_{13}r_{23}}{(1 - r_{12}^2)(1 - r_{23}^2)}$$

$$\Rightarrow 1 - R_{1.23}^2 = (1 - r_{12}^2)(1 - r_{13.2}^2)$$

9. From result in question No. 7, deduce that, $R_{1.23} \geq r_{12}$

Answer:

Since $|r_{13.2}| \leq 1$, we have,

$$1 - R_{1.23}^2 \leq 1 - r_{12}^2 \text{ implies, } R_{1.23} \geq r_{12}$$

10. From result in question No. 7, deduce that $R_{1.23}^2 = r_{12}^2 + r_{13}^2$ if $r_{23} = 0$.

Answer:

$$\text{We have } r_{13.2}^2 = \frac{(r_{13}^2 + r_{12}r_{23})^2}{\sqrt{(1 - r_{12}^2)(1 - r_{23}^2)}} = \frac{r_{13}^2}{\sqrt{(1 - r_{12}^2)}}, \text{ if } r_{23} = 0.$$

$$\text{Therefore } 1 - R_{1.23}^2 = (1 - r_{12}^2) \left[1 - \frac{r_{13}^2}{1 - r_{12}^2} \right] = 1 - r_{12}^2 - r_{13}^2$$

$$\text{Hence } R_{1.23}^2 = r_{12}^2 + r_{13}^2, \text{ if } r_{23} = 0$$

11. Using expression for multiple correlation coefficient in terms of partial and

$$\text{total correlation coefficients, deduce that } 1 - R_{1.23}^2 = \frac{(1 - \rho)(1 + 2\rho)}{(1 + \rho)} \text{ provided}$$

all coefficients of zero order are equal to ρ .

Answer

Here we have given, $r_{12} = r_{13} = r_{23} = \rho$. Therefore,

$$r_{13.2} = \frac{\rho - \rho^2}{\sqrt{(1 - \rho^2)(1 - \rho^2)}} = \frac{\rho(1 - \rho)}{(1 - \rho^2)} = \frac{\rho}{1 + \rho^2}. \text{ Hence we get,}$$

$$1 - R_{1.23}^2 = (1 - \rho^2) \left[1 - \frac{\rho^2}{(1 + \rho^2)} \right] = \frac{(1 - \rho)(1 + 2\rho)}{(1 + \rho)}$$

12. If $R_{1.23} = 0$, X_1 is uncorrelated with any of other variables, i.e., $r_{12} = r_{13} = 0$.

Answer:

Let us consider the expression for multiple correlation coefficient in terms of partial and total correlation coefficient. If $R_{1.23} = 0$, we get,

$$1 = (1 - r_{12}^2)(1 - r_{13.2}^2)$$

Since $0 \leq r_{12}^2 \leq 1$ and $0 \leq r_{13.2}^2 \leq 1$, will hold if and only if $r_{12} = 0$ and $r_{13.2} = 0$.

$$\Rightarrow \frac{r_{13} - r_{12}r_{23}}{\sqrt{(1-r_{12}^2)(1-r_{23}^2)}} = 0 \Rightarrow r_{13} = 0$$

Now, $r_{13.2} = 0$,

If $R_{1.23} = 0$ then $r_{12} = r_{13} = 0$. i.e., X_1 is uncorrelated with any of other variables

13. Give generalised form of multiple correlation coefficient.

Answer:

In the case of n variables X_1, X_2, \dots, X_n , the multiple correlation coefficients of X_1 on $X_2, X_3 \dots X_n$ is usually denoted by $R_{1.23\dots n}$, is the correlation coefficient between X_1 and $e_{1.23\dots n} = X_1 - X_{1.23\dots n}$

$$\therefore R_{1.23\dots n} = \frac{\text{Cov}(X_1, e_{1.23\dots n})}{\sqrt{V(X_1)V(e_{1.23\dots n})}}$$

$$\begin{aligned} \text{Cov}(X_1, e_{1.23\dots n}) &= \frac{1}{N} \sum X_1 e_{1.23\dots n} = \frac{1}{N} \sum X_1 (X_1 - X_{1.23\dots n}) \\ &= \frac{1}{N} \sum X_1^2 - \frac{1}{N} \sum X_1 X_{1.23\dots n} = \frac{1}{N} \sum X_1^2 - \frac{1}{N} \sum X_{1.23\dots n}^2 = \sigma_1^2 - \sigma_{1.23\dots n}^2 \end{aligned}$$

$$\begin{aligned} \text{Also, } V(e_{1.23\dots n}) &= \frac{1}{N} \sum e_{1.23\dots n}^2 = \frac{1}{N} \sum (X_1 - X_{1.23\dots n})^2 = \frac{1}{N} \sum (X_1^2 + X_{1.23\dots n}^2 - 2X_1 X_{1.23\dots n}) \\ &= \frac{1}{N} \sum X_1^2 + \frac{1}{N} \sum X_{1.23\dots n}^2 - 2 \frac{1}{N} \sum X_1 X_{1.23\dots n} \\ &= \frac{1}{N} \sum X_1^2 + \frac{1}{N} \sum X_{1.23\dots n}^2 - \frac{2}{N} \sum X_{1.23\dots n}^2 = \sigma_1^2 - \sigma_{1.23\dots n}^2 \end{aligned}$$

Therefore

$$R_{1.23\dots n} = \frac{\sigma_1^2 - \sigma_{1.23\dots n}^2}{\sqrt{\sigma_1^2(\sigma_1^2 - \sigma_{1.23\dots n}^2)}} = \left(\frac{\sigma_1^2 - \sigma_{1.23\dots n}^2}{\sigma_1^2} \right)^{1/2}$$

$$R_{1.23\dots n}^2 = 1 - \frac{\sigma_{1.23\dots n}^2}{\sigma_1^2} = 1 - \frac{\omega}{\omega_{11}}$$

14. Write the expressions for the multiple correlation coefficient, $R_{2.13}$ and $R_{3.12}$.

Answer:

$$R_{2.13}^2 = \frac{r_{21}^2 + r_{23}^2 - 2r_{21}r_{23}r_{13}}{1 - r_{13}^2} \text{ and } R_{3.12}^2 = \frac{r_{13}^2 + r_{12}^2 - 2r_{12}r_{13}r_{23}}{1 - r_{12}^2}$$

15. From the data relating to the yield of dry bark (X_1), height (X_2) and girth (X_3) for 18 cinchona plants, the following correlation coefficients were obtained. $r_{12} = 0.77$; $r_{13} = 0.72$ and $r_{23} = 0.52$.

Find the multiple correlation coefficient $R_{1.23}^2$

Answer:

$$R_{1.23}^2 = \frac{r_{12}^2 + r_{13}^2 - 2r_{12}r_{13}r_{23}}{1 - r_{23}^2} = \frac{(0.77)^2 + (0.72)^2 - 2(0.77 \times 0.72 \times 0.52)}{1 - 0.52^2} = 0.7334$$

Therefore $R_{1.23} = \text{square root } (0.7334) = 0.8564$, since multiple correlation coefficient is non-negative.