

Partial correlation

In the case of multivariate data say, x_1, x_2, \dots, x_p we may be interested to study of the degree to which two variables say x_1 and x_2 may be said to be related when the influence of the other $(p-2)$ variables x_3, x_4, \dots, x_p is eliminated from both of them.

Now if $x_{1.34\dots p}$ and $x_{2.34\dots p}$ are the estimated value of x_1 and x_2 respectively and the errors are

$$e_{1.34\dots p} = x_1 - x_{1.34\dots p}$$

$$\text{and } e_{2.34\dots p} = x_2 - x_{2.34\dots p}$$

then the product moment correlation between $e_{1.34\dots p}$ and $e_{2.34\dots p}$ is known as the partial correlation between x_1 and x_2 and is denoted by,

$$r_{12.34\dots p} = \frac{\text{COV}(e_{1.34\dots p}, e_{2.34\dots p})}{\sqrt{\text{Var}(e_{1.34\dots p}) \text{Var}(e_{2.34\dots p})}}$$

Here we have

$$\sum_{i=3}^p e_{1.34\dots p} = \sum_{i=3}^p e_{2.34\dots p} = 0 \quad \text{--- (1)}$$

$$\sum_{i=3}^p x_i \cdot e_{1.34\dots p} = \sum_{i=3}^p x_i \cdot e_{2.34\dots p} = 0 \quad \text{for } i=3, 4, \dots, p$$

[From least square equations]

$$\text{Var}(e_{1.34\dots p}) = \sigma_1^2 \frac{R^{(2)}}{R_{11}^{(2)}}$$

$$\text{and } \text{Var}(e_{2.34\dots p}) = \sigma_2^2 \frac{R^{(1)}}{R_{22}^{(1)}}$$

where sum is taken over all possible values of the variables]

Where $R^{(1)}$ is the determinant obtain from

$$R = \begin{pmatrix} \gamma_{11} & \gamma_{12} & \dots & \gamma_{1p} \\ \gamma_{21} & \gamma_{22} & \dots & \gamma_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{p1} & \gamma_{p2} & \dots & \gamma_{pp} \end{pmatrix} \text{ p x p}$$

by eliminating the 1st row and 1st column. While $R_{ij}^{(1)}$ is the cofactor of γ_{ij} in $R^{(1)}$ and $R_{ij}^{(2)}$ are similarly define.

$$\text{Now, } \text{Cov}(e_{1.34 \dots p}, e_{2.34 \dots p})$$

$$= \frac{1}{n} \sum (e_{1.34 \dots p} \cdot e_{2.34 \dots p})$$

$$= \frac{1}{n} \sum \left\{ (x_1 - \bar{x}_1) + \frac{\sigma_1}{\sigma_3} \frac{R_{13}^{(2)}}{R_{11}^{(2)}} (x_3 - \bar{x}_3) + \dots + \frac{\sigma_1}{\sigma_p} \frac{R_{1p}^{(2)}}{R_{11}^{(2)}} (x_p - \bar{x}_p) \right\} \times e_{2.34 \dots p}$$

$$= \frac{1}{n} \sum \left[(x_1 - \bar{x}_1) e_{2.34 \dots p} \right] \quad [\text{from } (*)]$$

$$= \frac{1}{n} \sum (x_1 - \bar{x}_1) \left\{ (x_2 - \bar{x}_2) + \frac{\sigma_2}{\sigma_3} \frac{R_{23}^{(1)}}{R_{22}^{(1)}} (x_3 - \bar{x}_3) + \dots + \frac{\sigma_2}{\sigma_p} \frac{R_{2p}^{(1)}}{R_{22}^{(1)}} (x_p - \bar{x}_p) \right\}$$

$$= \sigma_{12} \sigma_1 \sigma_2 + \frac{R_{23}^{(1)}}{R_{22}^{(1)}} \sigma_{13} \sigma_1 \sigma_2 + \dots + \frac{R_{2p}^{(1)}}{R_{22}^{(1)}} \sigma_{1p} \sigma_1 \sigma_2$$

$$= \frac{\sigma_1 \sigma_2}{R_{22}^{(1)}} \left[\sigma_{12} R_{22}^{(1)} + \sigma_{13} R_{23}^{(1)} + \dots + \sigma_{1p} R_{2p}^{(1)} \right]$$

Now, $\sigma_{12} R_{22}^{(1)} + \sigma_{13} R_{23}^{(1)} + \dots + \sigma_{1p} R_{2p}^{(1)}$ is the determinant obtained from $R^{(1)}$ by replacing the first row with $\sigma_{12}, \sigma_{13}, \dots, \sigma_{1p}$ i.e. (-1) th the cofactor of γ_{12} i.e. $-R_{12}$.

Now since, $R^{(1)} = R_{11}$, $R^{(2)} = R_{22}$ and $R_{11}^{(2)} = R_{22}^{(1)}$

$$\text{Hence } \sigma_{12.34 \dots p} = \frac{-\sigma_1 \sigma_2 \frac{R_{12}}{R_{22}^{(1)}}}{\sigma_1 \sigma_2 \sqrt{\frac{R_{11}^{(2)}}{\sigma_1^2} \times \frac{R_{22}^{(1)}}{\sigma_2^2}}} = - \frac{R_{12}}{\sqrt{R_{22} R_{11}}}$$