

Review of: "Decoding the Correlation Coefficient: A Window into Association, Fit, and Prediction in Linear Bivariate Relationships"

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Potential competing interests: No potential competing interests to declare.

comments for *Qeios* by H. D. Vinod on Hosseini's [Decoding the Correlation Coefficient: A Window into Association, Fit, and Prediction in Linear Bivariate Relationships](#)

This is an introductory paper about the simplest bivariate linear regression $Y=a+bX$, where $r(X, Y)$ is the simple correlation coefficient between the two variables. The regression coefficients are "a," the intercept, and "b," the slope. The coefficient of determination R^2 (R-squared) is identical if we regress Y on X or flip the model and regress X on Y . However, the identical R^2 values upon flipping hold only under linearity and do not hold if the relation is nonlinear (non-parametric kernel). The simple correlation $r(X, Y)$ is the square root of R^2 , where the square root sign is that of the covariance of X and Y , $cov(X, Y)$ only in bivariate linear regressions.

If we standardize X and Y such that each has mean zero and unit standard deviation ($SD_x=1$, $SD_y=1$), then the intercept "a" disappears from the standardized data model, and the slope "b" becomes the correlation $r(X, Y)$. Such a conversion of the slope is an algebraic fact. Hence verify that the slope is: $b=r (SD_y/SD_x)$ as correctly stated by the author. However, some comments regarding forecasting are incorrect.

The author correctly acknowledges the potential implications of correlations for causality. However, causality from passively observed data is a profound subject that requires a study of kernel regressions using flipped models and three criteria. A free R software package called **generalCorr** has simple R commands to compute causal directions and strengths between variables, even allowing for control variables. For theory, see Vinod (2017), "Generalized Correlation and Kernel Causality with Applications in Development Economics," in *Communications in Statistics - Simulation and Computation Volume 46, issue 6, 2017*, DOI link: <http://dx.doi.org/10.1080/03610918.2015.1122048>

There are dozens of published applications of Vinod's causality methods, including Allen & Hooper (2018). Generalized correlation measures of causality and forecasts of the VIX using nonlinear models. *Sustainability* 10 (8), 2695. <https://doi.org/10.3390/su10082695>. <https://www.mdpi.com/2071-1050/10/8/2695>

A more recent application of Vinod's methods is in Fonseca, et al. (2023). Assessing causality among topics and sentiments: The case of the G20 discussion on Twitter. *Journal of Information Science*, pages 1-16. <https://doi.org/10.1177/01655515231160034>

The assertions in Hosseini's paper are not intended to be applicable to even a slightly more general linear model where we have two regressors (X and Z), $Y=a+bX+cZ$. The new slope coefficients (b and c) then become so-called *partial* correlation coefficients adjusted by suitable ratios of standard deviations. See an open-access paper, Vinod (2022), "Kernel regression coefficients for practical significance," *Journal of Risk and Financial Management* 15(1), pp.1-13. <https://doi.org/10.3390/jrfm15010032>