MULTIPLE LINEAR REGRESSION VIEWPOINTS
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The Beta or Not the Beta: What is the Research Question?

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Abstract

The present article discusses the interpretability of beta weights in terms of their definition, technical aspects and the research philosophy guiding the use of multiple regression. The major conclusion is that variable importance and variable ordering can not be ascertained by examining beta weights. Additionally, it is recommended that discussion of variables as a group without identification of singular variable importance would more appropriately match the multivariate purpose of multiple regression.

Introduction

Cohen and Cohen, (1975, p. 79) say that one important problem in multiple linear regression is not straight forward - that of defining the contribution of each independent variable. They suggest that substantive reasoning and precise formulation of the research question are critical in utilization of statistical methodology. Discussion of the inability to interpret a beta weight in terms of identifying best or most important variable(s) in a regression equation seems to center on 3 issues: their definition with respect to purpose in multiple regression, their stability as a parameter estimate, and an understanding of the research question posed when using multiple regression (Brown and Tracz, 1990). The first two issues will only be briefly highlighted since they are generally well covered in major textbooks on the topic.

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Definition

Beta is the partial regression coefficient when all variables are standardized. Its square is the proportion of variance shared with the dependent variable that is independent of the remaining independent variables (Cohen and Cohen, p. 92). (Thorndike 1978, p. 152) presents the equation:

$$S^2_{zy}=\beta^2_{x_1}+\beta^2_{x_2}+2\beta_{x_1}\beta_{x_2}r_{x_1x_2}$$

(ß = Beta)

showing the variance predicted in standard score form and noting that the squared beta weights reflect the relative importance of the independent variables, pointing out that the $ß^2$ is not a proportion of variance, but relative contribution. However, Cohen and Cohen (1975, p. 95) show a similar formula:

$$R^2=\Sigma\beta^2_i+2\Sigma\beta_i\beta_j r_{ij}$$

(ß = beta)

saying that the above formula and its variations <u>only appear</u> to partition portions accounted for uniquely noting that any $ß_i$ and r_{yi} may be of opposite sign (suppression) and that $ß_i$ $ß_j$ r_{ij} may be negative precluding use of this equation as a variance partitioning procedure.

Edwards (1984, p. 107) says that if the test of a regression coefficient for a given variable is significant, then that variable when entered last in a regression would result in a significant increase in the regression sum of squares. A variation of that definition by Edwards suggests that if all other independent variables are held constant except X, the b (unstandardized) is the amount that the dependent variable increases with each unit of the independent variable.

Pedhazur (1982, p. 63) notes that testing a given beta weight is like testing incremental changes in R^2 for a given independent variable. Similarly, Huberty (1989) notes that the difference of incremental squared multiple correlations is precisely the square of the semi-partial correlation between the criterion and any predictor with the remaining predictors partialled. He states that it is clear from this relationship that a variable ordering cannot not be accomplished via the beta values.

Technical

The instability of beta weights (bouncing betas as they are often called) is well documented. Stevens (1986, p. 98) indicates that the desirable property of least squares regression is the unbiased, minimum variance estimator of the population beta that will not be consistently high or low but will bounce above or below.

The test for the beta asks if it is different from zero while controlling for the effects of other variables (Pedhazer, 1986, p. 59), but because the denominator in the test reflects other variables, the higher the intercorrelations, the larger the standard error. Situations exist where a significant R^2 exists with no significant betas or a non-significant beta for a given variable, but a significant correlation between the variable and the dependent variable. Huberty (1989) notes that use of the squared values of the standardized regression coefficients to assess variable importance is generally eschewed by methodologists due to the unreliable effects of multicollinearity.

Huberty also notes that sample specificity is a major issue in beta interpretation and that although a large ratio of sample size to response variables is preferred, such does not ensure valid generalizations. For path analysis, Pedhazur (1982, p. 628) warns the coefficients are sample specific and cannot be used for comparisons or generalizations across populations.

Pedhazur (1982, p. 247) says that it is the scale free property of the beta that leads researchers to treat them as an indicator of the relative importance of the variables for which they are associated. However, the magnitude of the beta reflects not only the presumed effect of the variable in question, but also the variance/covariance of the other variables in the model.

Research Philosophy

The research question being asked in multiple regression and the singular importance of variables presents an incongruity. Huberty (1989) says the idea of relative variable importance in a multivariate context is not clear and that there is little consensus of the meaning of relative variable importance existing among social and behavioral science methodologists. He goes on to say that the fundamental reason for conducting multivariate analysis is the study of a system of variables rather than univariate relations. For research, Huberty states that variable importance depends on the collection of variables studied, including all relevant variables while excluding irrelevant ones and that interdependence among variables makes the concept of variable importance very questionable and fruitless. Darlington (1968) echoes that thought in stating that independent contribution to variance makes little sense when variables are intercorrelated. Edwards (1984) finds no satisfactory method for determining the relative contribution of independent variables to the regression sum of squares when intercorrelation exists. Stevens (1986, p. 99) indicates that discussing the unique contribution of a given independent variable is generally meaningless if the predictors are correlated. Multicollinearity is a problem that makes the importance of a given predictor difficult because of confounded effects among the variables.

The concept of control of variables enters the discussion of research design since partialling is considered in the definition of a beta weight. But, Pedhazur (1982) argues that controlling variables only has meaning if grounded in theory. With little theoretical consideration among the pattern of variables, controlling the variance of one variable to examine the effects of other variables may amount to distortion of reality and misleading results. He refers to the concept of studying the effect of one variable on another by holding one constant via regression analysis as an "air of fantasy" (p. 225). In experimental research, Pedhazur notes that if independent variables can be manipulated and control of extraneous variables is reasonably done, then conclusions of the direct effects of one variable on another can be made. In regression, the equations reflect the average relations between a dependent and independent variable and not necessarily the process by which the independent variable effects the dependent variable. He points to an example from the Coleman study that having versus not having a language lab in a school may be different from removing a lab from a school. To draw a similar type of conclusion from regression research based on a beta weight interpretation must be done with a much care. He notes that it has been argued that to find out what happens to a system when you interfere with it, you must interfere with it.

Summary

None of the major texts or papers reviewed suggested the use of beta weights for purposes of identifying the most important variables. In fact, there were little or no suggestions for interpreting beta weights at all for reasons of definition, instability, sample specificity, specification errors, and most importantly, the incongruity of the general purpose of multiple correlation and the singling out of individual variables.

It appears that interpretation has come about among some researchers by paralleling experimental designs' congruity with the ANOVA in the context of multiple regression. That is, if factorial design (with ANOVA, as a statistical tool), can isolate independent contribution to explaining variance in the outcome variable (even if independence is forced by equalizing cell sizes) then attempts are made to apply the same "logic" to correlational design and multiple regression. Typically, one reads a research statement such as, "the focus of this study was to see if variable Y (dependent) can be explained by a combination of variables X1, X2, . . . (independent)." However, after analysis, the discussion usually includes statements such as ". . . the overall R^2 was .xx with X2 being the best predictor and X1 not being important because of its small beta weight." No caveats are expressed and very often the relationships among the variables are ignored.

The question now becomes what can be said with respect to beta weights following the completion of a multiple correlational analysis. For interpretive purposes, Pedhazur (1982, p. 247) suggests reporting the beta, the b weight and the standard deviation of all variables with discussion of issues that may be a factor. Huberty recommends data exploration including variable screening before inclusion in a model and cross validation. The discussion of the variables as a set with no speculation of univocal importance would more appropriately follow the multivariate purpose of multiple regression. Of course, specifying models to be tested based on theory to untangle complex relationships is preferred.

Pedhazur (1982, p. 65) points to the frustration of trying to identify the relative importance of variables since there is more than one answer to the question and the ambiguity of some problems is not entirely able to be solved. He notes that beta weights have "great appeal because they hold the promise for unraveling complex phenomena" (p. 221), but they are unstable and require many conditions for interpretation. He goes on to say that the absence of a model precludes any meaningful interpretation of coefficients. "No amount of fancy statistical acrobatics will undo the harm that may result using an ill conceived theory" (p. 230).

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