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Improving forecasts using equally weighted predictors

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ABSTRACT

The usual procedure for developing linear models to predict any kind of target variable is to identify a subset of most important predictors and to estimate weights that provide the best possible solution for a given sample. The resulting "optimally" weighted linear composite is then used when predicting new data. This approach is useful in situations with large and reliable datasets and few predictor variables. However, a large body of analytical and empirical evidence since the 1970s shows that such optimal variable weights are of little, if any, value in situations with small and noisy datasets and a large number of predictor variables. In such situations, which are common for social science problems, including all relevant variables is more important than their weighting. These findings have yet to impact many fields. This study uses data from nine U.S. election-forecasting models whose vote-share forecasts are regularly published in academic journals to demonstrate the value of (a) weighting all predictors equally and (b) including all relevant variables in the model. Across the ten elections from 1976 to 2012, equally weighted predictors yielded a lower forecast error than regression weights for six of the nine models. On average, the error of the equal-weights models was 5% lower than the error of the original regression models. An equal-weights model that uses all 27 variables that are included in the nine models missed the final vote-share results of the ten elections on average by only 1.3 percentage points. This error is 48% lower than the error of the typical, and 29% lower than the error of the most accurate, regression model.

1. Introduction

People and organizations commonly make decisions by combining information from multiple inputs. For example, one usually weighs the pros and cons before deciding on whether or not to launch a marketing campaign, which new product to develop, or where to open a branch office. Almost 250 years ago, Benjamin Franklin suggested an approach for how to solve such problems. Franklin's friend Joseph Priestley asked for advice on whether or not to accept a job offer that would have involved moving with his family from Leeds to Wiltshire. In his response letter, written on September 19, 1772, Franklin avoided advising Priestley on what to decide. Instead, he proposed a method for how to decide. Franklin's recommendation was to list all important variables, decide which decision is favored by each variable, weight each variable by importance, and then add up the variable scores to see which decision is ultimately favored. Franklin labeled this approach "Moral Algebra, or Method of deciding doubtful Matters" (Sparks, 1844, p. 20). About half a century later, Franklin's method had another famous proponent. In 1838, Charles Darwin used the approach to help him answer a question of utmost importance: whether or not to get married (Darwin, Burkhardt, & Smith, 1986).

Franklin's moral algebra gave way to multiple regression analysis (MRA), which has become popular for solving many kinds of problems in various fields. MRA produces variable weights that yield the "optimal" (in terms of least squares) solution for a given data set. The estimated regression coefficients are then commonly used to weight the composite when predicting new (out-of-sample) data. The problem with this data fitting approach is that the resulting forecasts are not necessarily accurate. A large body of empirical and theoretical evidence since the 1970s shows that regression weights often provide *less* accurate out-of-sample forecasts than simply assigning equal weights to each variable in a linear model (Dawes, 1979; Dawes & Corrigan, 1974; Einhorn & Hogarth, 1975). These results have yet to impact many fields, including business research. Researchers rarely evaluate the quality of their models by predicting holdout data; most JBR submissions report the model fit as the only indication of a good model (Woodside, 2013).

The present study reviews the literature on the relative predictive performance of equal and regression weights and provides new evidence for U.S. presidential election forecasting, a field that is dominated by the application of MRA. The results conform to prior research, showing that equal weights perform at least as well as regression weights when predicting new data. Furthermore, including all relevant variables in an equal-weights model yields large gains in accuracy.

2. Equal and regression weights in linear models

This section reviews prior research on the relative performance of equal and regression weights and discusses the conditions under which either approach is expected to work best.

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MRA is the dominant method to develop forecasting models in many fields. Once theory is used to select the k relevant predictor variables, MRA estimates their relative impact on the target criterion. The general equation of the multiple regression model reads as:

$$y = a + \sum_{i=1}^{k} b_i x_i + e \quad (1)$$

The estimated constant a and the k "optimal" (in terms of minimized squared error) regression coefficients b_i are then used when predicting new data.

An alternative to using MRA is to assign equal weights to each variable. That is, one also relies on theory to select the variables. However, one does not let the data decide about the variables' weights. Instead, one uses prior knowledge to assess the directional effects of the variables and then standardizes (i.e., put into z-score form) and transforms all variables so that they positively correlate with the target variable. In the final step, the values of all variables are added up to calculate the single predictor variable in a simple linear regression model, hereafter, the equal-weights model:

$$y = d + g\sum_{i=1}^{k} z_i + v \quad (2)$$

where d is the estimated constant, g is the estimated coefficient of the predictor variable, and v is the error term.

As shown in Eqs. (1) and (2), the multiple regression and the equal-weights model differ in the number of parameters to be estimated. The multiple regression model estimates $k + 1$ parameters: the constant a and each variable's coefficient b_i. In contrast, the scheme for weighting the variables in the equal-weights model is determined exogenously, not relying on data. The equal-weights model is thus a special case of the multiple regression model with all b_i's $= g$. That is, the equal-weights method only needs to estimate two parameters (d and g).

2.1. Conditions for the relative accuracy of multiple regression and equal-weights models

In pre-specifying equal weights to all variables, the equal-weights method ignores any dependencies between predictor variables. As a result, the method is less flexible than MRA in explaining information available in given data. The inflexibility in weighting variables results in a bias that is mostly predictable: forecasts derived from equal-weights models tend towards predicting no effect. Thus, equal-weights models adhere to a general guideline in forecasting: "be conservative" (Armstrong, Green, & Graefe, 2015). Forecasters who rely on equal-weights models acknowledge the uncertainty in the environment (e.g., due to ambiguity about causal relationship or the existence of noisy data). Acknowledging uncertainty thus provides the theoretical rationale for the use of equal weights; the intentional introduction of bias in the model reflects the prior belief that predictions about the future in such situations are difficult (Dana, 2008).

In comparison, MRA estimates "optimal" variable weights from the data and does not incorporate prior knowledge about the plausibility of these weights or the predictability of the environment. This flexibility in estimating coefficients reduces bias and improves a model's fit to existing data. However, the gains in flexibility come at the price of overfitting. Overfitted models tend to mistake random fluctuations in the data (i.e., noise) for systematic patterns, a danger that increases in situations with much uncertainty. When patterns derived from noise are used to predict new data, the variance of forecasts increases and the model's predictive accuracy suffers.

The relative performance of multiple regression and equal-weights models for the same data then depends on the bias and variance components of the forecast error, which depend on the conditions of the forecasting problem (Gigerenzer & Brighton, 2009). Several studies provide analytical solutions for the conditions under which equal weights provide more accurate out-of-sample forecasts than regression weights (e.g., Dana, 2008; Davis-Stober, 2011; Davis-Stober, Dana, & Budescu, 2010; Einhorn & Hogarth, 1975). In general, the relative performance of equal weights increases if (1) the data are noisy and the model thus fits the data poorly (i.e., the multiple correlation coefficient R^2 is low), (2) the ratio of observations per predictor variable is low (i.e., in situations with small samples and a large number of predictor variables), and (3) the predictor variables are highly correlated.

Empirical studies yield similar conclusions. Dana and Dawes (2004) analyze the relative predictive performance of regression and equal weights for five real non-experimental social science datasets and a large number of synthetic datasets. In this study, regression weights did not yield more accurate forecasts than equal weights unless for sample sizes larger than *one hundred observations per predictor*. Only in cases in which prediction error was likely to be very small (i.e., adjusted $R^2 > .9$), regression outperformed equal weights in samples with five observations per predictor.

The conditions under which equal weights can be expected to outperform regression weights are common for many problems in the social sciences. Often, data are unreliable, predictor variables correlate with each other, and observations are scarce. The following section summarizes evidence from prior work on the relative accuracy of both methods.

2.2. Empirical evidence on the relative accuracy of multiple regression and equal-weights models

Starting at least as early as Schmidt (1971), a number of studies test the relative predictive accuracy of equal and regression weights when applied to the same data. Many of these studies analyze unit weights. Unit weights are a special case of equal weights in which each variable is assigned a value of plus or minus one, depending on the expected directional effect on the target criterion as estimated by prior knowledge.

An early review of the literature finds multiple regression to be more accurate than equal weights in three studies but less accurate in five (Armstrong, 1985, p. 208). Since then, evidence has accumulated. Czerlinski et al. (1999) test the predictive performance of regression and equal weights for 20 real-world problems in areas such as psychology, economics, biology, and medicine. Most of these tasks were collected from statistics textbooks where they were used to demonstrate the application of MRA. (In contrast to the earlier studies, the variables' directional effect was estimated from the sample data.) Ironically, equal weights provided more accurate predictions than multiple regression. Cuzán and Bundrick (2009) analyze the relative performance of equal and regression weights for forecasting U.S. presidential elections. The authors find that equal-weights versions of the Fair (2009) model and of two variations of the fiscal model (Cuzán & Heggen, 1984) outperformed two of the three regression models – and did equally well as the third – when making out-of-sample predictions.

Such findings have led researchers to conclude that the weighting of variables is secondary for the accuracy of forecasts. Once models include the relevant variables and their directional impact on the criterion is specified, the magnitudes of effects are not very important (Armstrong, 1985, p. 210; Dawes, 1979). As Dawes and Corrigan (1974, p. 105) put it in their seminal work on that topic: "The whole trick is to decide which variables to look at and then to know how to add."

3. Models for forecasting U.S. presidential elections

The development of quantitative models to predict the outcome of elections is a well-established sub-discipline of political science. Since the late 1970s, scholars have developed various versions of election forecasting models. Table 1 shows the specifications of nine models, including the variables used, their first election forecasted, the sample