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The predictive accuracy of artificial neural networks and multiple regression in the case of skewed data: exploration of some issues

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Abstract

Business organizations can be viewed as information-processing units making decisions under varying conditions of uncertainty, complexity, and fuzziness in the causal links between performance and various organizational and environmental factors. The development and use of appropriate decision-making tools has, therefore, been an important activity of management researchers and practitioners. Artificial neural networks (ANNs) are turning out to be an important addition to an organization's decision-making tool kit. A host of studies has compared the efficacy of ANNs to that of multivariate statistical methods. Our paper contributes to this stream of research by comparing the relative performance of ANN and multiple regression when the data contain skewed variables. We report results for two separate data sets; one related to individual performance and the second to firm performance. The results are used to highlight some salient issues related to the use of ANN and multiple regression models in organizational decision-making.

Keywords: Neural networks; Regression; Skewed data

1. Introduction

Increasing attention is being paid to the use of artificial neural networks (ANN) in managerial decision-making. As many managerial decision situations are fraught with variety, ambiguity and complexity (Mintzberg, Raishinghani & Theoret, 1976), ANNs are appealing as managerial decision-making aids precisely because of their expected effectiveness in such situations (Lippman, 1987). An important element in the life-cycle of an innovation (and ANN is an innovation in the field of organizational decision-making aids) is the establishment of the contingencies under and contexts in which the innovation is most effective. Hence, a stream of studies on ANNs has focused on delineating the boundaries of their usefulness (e.g. Duliba, 1991; Dutta & Shaker, 1988; Gorr, Nagin & Szczypula, 1994; Marquez & Hill, 1993; Marquez, Hill, Worthley & Remus, 1991; Sharda & Wilson, 1993). The studies reported in this paper add to this line of research. Using 'real-world' data we conduct an empirical investigation into the relative efficacy of ANNs and multiple regression when the sample data are not normally distributed, i.e. they are skewed. The effect of this contingency on the behavior of ANN and multiple regression models needs to be investigated given that reliability of multivariate statistical methods requires that data be multivariate normal.

From an organizational effectiveness view, there is a need for studies that establish the pros and cons of any innovation. Corporations tend to have a pro-innovation bias-leading them to adopt 'promising' but untested innovations (Kimberly, 1985). For example, use of labels such as "Expert" and "Intelligent" has been shown to lead to complacency as well as unthinking dependence on such systems among users (Will, 1991). Further, innovation–adoption can be disruptive because of their organization-wide consequences (Sviola, 1990). Thus, there is clearly a need for systematic investigations of the contexts and contingencies affecting the predictive accuracy of ANN models.

A number of studies have focused on investigating the relative performance of statistical and ANN methods in forecasting. These studies can be differentiated from each other on two dimensions. The first is in data types. Some studies use actual data (i.e. data from real-world) and others have used simulated data. The second dimension relates to differences in measures. Studies have used measures that are

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	Nominal/Categorical	Interval/Ratio
Real World	**1** Dutta & Shekar, 1988. (3) Yoon & Swales, 1991. (31) Salchenderger, Cinar & Nash, 1992. (20) Tam & Kiang, 1992. (25)	**2** Bansal, Kauffman & Weitz, 1993. (1) Gorr et al., 1994. (6) Duliba, 1991. (2)
Simulated	**3** Fisher & McKusick 1988. (4)	**4** Marquez et al., 1991. (12) Marquez & Hill, 1993. (11)

Fig. 1. Categorization of ANN efficacy studies.

either nominal/categorical or interval/ratio-scale. Fig. 1 provides some examples of studies in each of the cells.

There appears to be a preponderance of studies in cells one and four. If real-world data are used, usually the phenomenon is represented by a categorical variable (e.g. solvent/insolvent, bankrupt/not bankrupt, loan granted/denied, etc.). It is only when simulated data are used in the analyses that we observe the measures to be continuous/interval scale (cell 4). The two studies reported in this paper fall in cell two. Both the studies reported here use real-world data, and have variables that are measured in ratio-scale. While both studies are of organizational phenomena, they differ in their level of analysis. The first focuses on individual performance and the second on firm level performance.

In addition to differences in data type and variable measurement, our study differs from earlier ones by considering the additional dimension of variable skewness. Specifically, we investigate whether skewness in a sample's dependent variable affects the efficacy of ANN and multiple regression models. Analyses by Marquez et al. (1991) using simulated data, indicate that they do. The reliability of any statistically derived result is known to be strongly dependent on the degree to which the sample distribution is multivariate normal. Formulae for tests of statistical significance of regression coefficients are based on this assumption (Tabachnick & Fidell, 1983). To the extent that this assumption is violated, generalization of statistics-based results data beyond the sample will be highly suspect. Hence, data sets with skewed variables are particularly well suited for testing the relative efficacy of ANN and regression models.

A large proportion of studies support the use of ANN-based reasoning to deal with unstructured or semi-structured decision situations (e.g. Dutta & Shekar, 1988; Gallant, 1988; Yoon & Swales, 1991). These (and other) studies comparing ANN performance to that of multivariate statistical methods, have found ANNs to be better at prediction. However, Marquez et al. (1991) found in their simulation study that ANN-based systems perform better than regression techniques only when sample sizes are small and when variables are strongly correlated. Duliba (1991) found that an ANN model did not perform as well as regression when additional explanatory variables were introduced into the modeling. Gorr et al. (1994) noted that, for their data, although multiple regression was best overall there were no statistically significant differences in predictive accuracy across four different models. Further, they observe that

> Neither the stepwise regression nor the ANN benefited when additional model structures were incorporated (p. 31).

As skewness is a factor affecting the various models' behavior, we compare the performance of both multiple regression and ANN by deliberately choosing samples characterized by highly-skewed variables.

The paper is structured as follows: the two studies are reported next. Data set for the first study consists of a sample of MBA students where the focus is on predicting the students' graduating GPA. We conclude the paper by discussing the comparative performance of both ANN and regression models on the two data sets, suggesting guidelines for the use of ANNs for knowledge acquisition, and proposing future research directions.

2. Methodology

The same basic procedure was followed in each study: (1) use sampling without replacement of the full sample to

Table 1
Study one: prediction of student GPA

(A) *Training subsamples. Multiple regression results*

Training subsample	Skewness of GGPA	Skewness of transformed GGPA	R^2
1	−2.17	−2.75	0.19
2	−1.09	−1.33	0.08

(B) *Testing subsamples. t-tests of percentage error and absolute percentage error*

Holdout subsample	Percentage error (mean)			Absolute percentage error (mean)		
	Regression model	ANN model	Statistical significance	Regression sample	ANN model	Statistical significance
1	0.10	−0.32	$p < 0.05$	16.72	23.61	$p < 0.10$
2	0.10	0.46	$p < 0.05$	19.68	25.23	$p < 0.02$

create four (random and independent) subsamples of 50 cases each; (2) use two subsamples for training, i.e., derive regression coefficients (in the case of OLS regression) or training weights (in the case of ANN); and (3) use the other two subsamples as holdouts to make predictions and test for their accuracy. Each subsample was used only once, and only for training or testing. We did so to deliberately introduce variety into data sets particularly with respect to their degree of skewness.

For our studies, the assumption of multivariate normality implies that the sampling distributions of the dependent variable have to be normally distributed at every level of the continuous independent variables. As this condition is not testable,

> …a conservative requirement is normality of the DV (dependent variable) overall” (Tabachnick & Fidell, 1983, p. 77).

Thus, for the subsamples we created we report the dependent variables’ skewness. If the skewness was above acceptable levels in the case of the training subsamples, we used a transformed dependent variable to run the regression model. We tested various types of transformations (square root, inverse, and logarithmic) and chose that transformation which reduced skewness the most.

Testing the performance of various prediction models in existing studies fall into two categories; those measuring the central tendency of errors (equivalent to the R^2 of multiple regression) and those measuring differences in the forecasting results themselves. The former type appears to dominate among studies of ANN predictive power (Gorr et al., 1994). However, Gorr et al. (1994) point out that as the variances of mean forecast errors are often high

> “It may not be possible, …to reliably distinguish between mean accuracy even when differences in means appear relatively large” (p. 19).

The two measures that we use to test the predictive accuracy of ANN and multiple regression are based on the suggestion made by those authors (see also Makridakis and Wheelwright, 1978). The first is the percentage error defined as: ((Actual Value − Forecasted Value)/Actual Value) × 100. The second, termed the absolute percentage error, uses the absolute value of the first measure. The first measure is useful because it measures bias in a model resulting in predictions that are systematically below or above actual values. The second measure is useful to index spread of the errors (or predictive accuracy of the model).

The regression analyses were performed using SPSSX software. Brainmaker was used for the ANN models. In the case of Study One we used one hidden layer with three processing units. The input layer consisted of two variables and the output layer of one variable. For Study Two, we used one hidden layer with 10 processing units. The net was trained using the cumulative delta rule.

3. Study one: comparative analysis of prediction of MBA student performance

3.1. Data

The sample consisted of MBA students at a major northeastern university who graduated between 1988 and 1990. Data on each student’s: (i) entering GPA (EGPA); (ii) GMAT; and (iii) graduating GPA (GGPA) were obtained from the university’s student records office. Table 1 provides basic statistics of the sample. The z values for skewness of the dependent variable, GGPA, indicate that the distribution deviates significantly from assumptions of normality. For a sample of size 50, a z value in excess of 0.89 indicates rejection of normality assumptions at $p \leq 0.01$. This level of deviation from normality is strong enough to cause concerns about reliability of any statistically derived results (Tabachnick & Fidell, 1983). As shown in the table, transformations of the GGPA resulted in an increase of skewness. Hence, raw rather than transformed scores of GGPA were used to conduct regression analyses of the training samples.

3.2. Analysis

The regression model for the study is:

$$\mathrm{GGPA} = b_0 + b_1\,\mathrm{EGPA} + b_2\mathrm{GMAT} + e_0.$$

In both this and the following study, a linear regression model was used. There is no theoretical basis to expect specific forms of nonlinear relations among the variables. Attempts to specify nonlinear models would, therefore, be a guessing game. The regression model was estimated for each of the two training subsamples. Similarly, two trained networks were created using the two training subsamples. In each case, we utilized a single hidden layer due to the small number of problem inputs, and the corresponding absence of higher-level features (Gallant, 1988; Knight, 1990).

In the second stage, outputs of training were used on the two holdout subsamples to predict GGPA for each of their cases. Each subsample was used only once, i.e. training subsample one was used for prediction in holdout subsample one and training subsample 2 on holdout subsample 2. For each of the ANN and multiple regression methods, the percentage error and absolute percentage error were calculated for each case in the hold out subsamples. In the third (and final stage) of analysis, we conducted a *t*-test for differences in means (of the two error indices) across the two prediction models.

3.3. Results

Table 1(B) presents the *t*-tests results. As the percentage error indicates, bias is higher in the ANN model (statistically significant at 5% level). In the case of the regression model, the direction of bias remains constant across the two holdout subsamples. In contrast, they differ across the two models for the ANN model. Thus, with respect to bias, the regression model performs better than the ANN model. In the case of predictive accuracy, the inferences are not that unambiguous. The absolute percentage error is lower (on the average) for the regression model. However, the difference is statistically significant (at 2% level) in only one of the two holdout subsamples.

4. Study two: comparative analysis of prediction of corporate performance

4.1. Data and measures

Strategic management is concerned with the long-term survival and success of individual firms (Schendel & Hofer, 1979; Thompson & Strickland, 1990). It was hypothesized (based on a review of literature in strategic management and economics) that (i) firm factors of technological competence and product/market diversity, and (ii) industry factors of rivalry, market growth, and rate of technological change, are some of the most important variables affecting the long-term performance of firms (Nelson & Winter, 1982; Penrose, 1959; Petrov, 1982; Prahalad & Hamel, 1990; Quinn, 1992; Rosenbloom & Kantrow, 1982; Teece, 1982; Winter, 1987). In the strategic management and economics literature, we observed that long-term success is measured based on their profitability and risk. Based on a review of literature, two different profitability measures were developed. The first—Return on Invested Capital (ROIC)—is a measure of efficiency of the firm's operations. The second—Tobin's *q*, measured as the ratio of the firm's market value to the replacement value of its assets—is an indicator of the firm's effectiveness. The third performance indicator, risk—i.e. the degree to which profitability fluctuates over time (and posited to be an important goal of managers)—was measured by calculating the standard deviation of yearly ROIC over the time period spanned by the data. Thus, ROIC, Tobin's *q*, and Risk form the three performance (dependent) variables of this study. The regression model is:

$$\begin{aligned}\mathrm{Performance} = {} & \beta_0 + \beta_1\mathrm{Rivalry} + \beta_2\mathrm{Market\ Growth} \\ & + \beta_3\mathrm{Rate\ of\ Technology\ Change} \\ & + \beta_4\mathrm{Total\ Patents} + \beta_5\mathrm{Patent\ Spreads} \\ & + \beta_6\mathrm{Degree\ of\ Product/Market\ Diversity} + \varepsilon_0\end{aligned}$$

The independent variables were measured as follows:

1. Technological competence was measured in two ways:
   1.1. By the total number of patents obtained by a firm during 1973–1979.
   1.2. By calculating the spread of these patents across different technological areas that they fall in.
2. Product/market diversity was measured by looking at the spread of the firms' total sales across different industries.
3. Industry rivalry was measured using the industry's four-firm concentration ratio.
4. Market growth was measured by average yearly growth in an industry's total sales.
5. Rate of technological change was measured through a survey of executives asking them to rank the rate of introduction of product and process innovations in their business line on a scale of 1–7 ('1' being 'very slowly' to '7' being 'very rapidly').

All data were collected for the 1973–1979 period. We were restricted to this period because data for calculating firm technological competence were only available for the 1973–1979 period. We were able to obtain a sample of 200 firms for which data were available for all the variables required for the regression analysis. The time period of the

Table 2
Study two: prediction of firm performance

(A) *Training subsamples. Multiple regression results*

Training subsample	Performance variable	Skewness of performance variables: Before transformation	After transformation	R^2
1	ROIC	0.98	na	0.27
	Tobin's q	2.49	1.43	0.17
	Risk	1.71	1.67	0.31
2	ROIC	−.10	na	0.06
	Tobin's q	2.44	1.74	0.25
	Risk	2.65	2.55	0.31

(B) *Testing subsamples. t-tests of percentage error and absolute percentage error*

Holdout subsample	Performance variable	Percentage error (mean): Regression model	ANN model	Statistical significance	Absolute percentage error (mean): Regression model	ANN model	Statistical significance
1	ROIC	−2.8	−85.4	$p < 0.05$	34.7	90.0	$p < 0.01$
	Tobin's q	−14.5	−34.0	$p < 0.01$	35.6	78.0	$p < 0.05$
	Risk	−45.5	−340.0	$p < 0.01$	72.5	346.7	$p < 0.01$
2	ROIC	−.8	−86.0	$p < 0.01$	36.9	93.9	$p < 0.05$
	Tobin's q	−13.2	−150.4	$p < 0.001$	−47.8	−460.6	$p < 0.02$
	Risk	−41.8	−460.6	$p < 0.02$	82.1	915.0	$p < 0.001$

data was 1973–1979. As the sample size was only 200, we were able to construct only four subsamples of 50.

4.2. Analysis

Three different regressions were performed, one with each of the performance variables as the dependent variable. Once again, transformations were used to reduce skewness of the dependent variables. No transformations were used on ROIC as it had low skewness to start with. In the case of Tobin's q and Risk, log transformations turned out to be the best at reducing skewness. As Table 2(A) indicates, even the best transformation reduced skewness by a small portion in the case of Risk.

The comparisons of the predictive accuracy of regression and ANN proceeded in a manner similar to previous study with one difference. There is not one but four separate dependent variables.

4.3. Results

Table 2 presents details to the analyses. The R^2, varying between 0.06 and 0.31, are within the range that is usually found in social science research of this kind. The results are in favor of the regression model. Its error scores are lower that of ANN for both bias and accuracy. The differences are statistically significant at 5% (or lower) level.

5. Discussion

This paper looked at the ability of ANN procedures at solving a particular category of ill-defined problems. It concentrated on the predictive accuracy of ANNs under conditions of noisy data. This study was conducted to see whether ANN models are better than multiple regression models at prediction in samples characterized by a lack of normality.

Results of the studies that even when data have skewed dependent variables multiple regression models perform better than ANN models once appropriate transformations are applied to the skewed variables. This contrasts with other studies in this stream of research. In the case of data, where the dependent variable is categorical (e.g. bankrupt/solvent, credit granted/denied, predicted stock price above/below actual price), evidence indicates that ANN models are more accurate than multivariate statistical models such as discriminant and logistic regression. In the case of data with ratio or interval scale dependent variables, earlier studies have found such unequivocal support for ANN models (Duliba, 1991; Gorr et al., 1994; Marquez and Hill, 1993; Marquez et al., 1991). Our study was aimed at finding out whether skewness of the dependent variable could help to determine the relative accuracy of ANN and regression models. Our two studies, although very exploratory, indicate that the regression models are more accurate once the dependent variables are transformed.

One situation where ANN models are expected to perform better is that in which a large number of factors are involved with complex interactions. This could explain the superiority of the regression method in Study One, where we used only two independent variables. As the number of independent variables increases, it may be that the ability to model the complex interactions among independent variables, and not data skewness, becomes the deciding factor of in forecasting accuracy. But Study Two does not support this interpretation. This leaves us with two perplexing aspects regarding the behavior of ANN and regression models in situations characterized by skewed interval scale dependent variables.

The R^2 of multiple regression models brings into sharp relief another important aspect of this whole stream of research into the efficacy of the various expert systems and statistical methods. We observe that the R^2 in Study One are very low and not statistically significant. The simple implication of this is that the regression model is no better than any randomly-picked model and that the chosen explanation (EGPA and GMAT) have little (if any) explanatory power in accounting for the graduating GPA's variance. However, we find that prediction of GGPA based on the nonsignificant regression coefficients turn out to be more accurate than that of ANN. In such a situation, can any credence be given to the predictive power of the regression methodology? This dilemma exists not only for regression models but also for ANN models as both are based on finding a pattern of relationships in one sample and assuming the validity of the pattern in the overall population. Thus the problem of low R^2 does not lie in questioning the credibility of different pattern recognition methodologies. Rather, it is one of accepting the shortcomings that correlational studies do not establish causality in the social sciences.

5.1. Generalizability of this study's results

A possible shortcoming of the present study has to do with the nature of the sample and the variables selected as antecedents of performance. In the case of Study One, prediction of school performance is an important problem for a small set of organizations-educational institutions. Hence, generalizability to other types of organizations is questionable. Further, student scholastic performance depends on a wide variety of factors, and not just on the two considered. In fact, one can probably argue that entering GPA and GMAT are weak predictors of business school students.

In the case of Study Two, the results are quite generalizable. The problem of long-term performance is germane to almost every organization-whether they are of the for-profit or not-for-profit type. The performance objectives may vary, but the need for long-term success remains constant across all types of organizations. However, the problem of inappropriate choice of independent variables remains in the case of Study Two as well. It is a problem of every social science investigation, and methods to deal with it are beyond the scope of this paper.

The issue of the generalizability of the content of each study is not the main focus of this investigation. It is the properties, not the content, of the sample variables that are of interest. The object was to investigate the capability of two different algorithms in handling data sets that are not normally distributed. Seen in this light, we can be quite confident that the results of the two studies are applicable to any data set containing skewed variables, and thus are of wide generalizability.

6. Conclusions

The two studies conducted here are typical of a wide class of phenomena studied in organizations. Study One is an instance of an organizational behavior phenomenon at the individual level of analysis. Study Two is a typical example of phenomenon studied at the organization level of analysis. Most of the studies in management fall into one of these two levels. Seen in this perspective, results of the studies reported here ought to be given careful consideration. The results indicate that ANNs are not consistently good at prediction. There is a need for systematic empirical studies that will help determine the types of problem situations where ANNs will yield superior predictions. One way to do this is to create data sets that vary systematically on the three dimensions of: (i) number of variables; (ii) noisiness of each variable; and (iii) sample size, and then investigate the variations in each method's predictive accuracy. The simulation data set of Marquez et al. (1991) was created using only one independent variable, and hence, does not capture the efficacy of ANNs for analyzing phenomenon involving complex interacting factors.

An advantage possessed by ANNs is that they remove the guesswork involved in finding the right transformation. Linear statistical models require finding the right transformation for the variables. In contrast,

> ANNs capacity for learning and self-transformation provides an alternative to the guesswork involved in identifying the distributions and transformations required in a linear model

(Marquez et al., 1991, p. 129). Whether we want automated systems to do the learning is context dependent. For example, strategic decision-making (of which Study Two is a good instance) is one area where it may be prudent for learning to occur in managerial minds rather than in an ANN (or Expert System). Strategic issues and problem situations are open-ended, ambiguous and equivocal where all cause–effect relationships pertaining to a situation are not known. In such cases, the usefulness of ANNs and Expert Systems does not lie in providing accurate predictions. Rather it lies in the potential for exploration of 'what-if' scenarios by changing the number of factors affecting a decision situation and by varying the strength of relationships among the factors. The fact that neural networks don't provide us details of interrelationships between the nodes hinders understanding and learning by managers.

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