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ARTIFICIAL INTELLIGENCE IN HELPING AUDITORS TO EVALUATE CLIENT FINANCIAL VIABILITY

Susan WILSON, Associate Professor, PhD, CIPA

Department of Accounting, College of Business, Butler University

Nelli AMARFII-RAILEAN, leturer,

Economy Department, State University „A. Russo"

Continuitatea activității este unul din principiile generale de care trebuie să se țină cont la formularea opiniei de audit. Ca parte a procesului de audit, auditorul trebuie să exprime opinia privind capacitatea întreprinderii de a continua activitatea sa într-un viitor previzibil. Tradițional, conform prevederilor standardelor internaționale de audit, opinia auditorului este bază pe un sistem prestabilit de indicatori financiari și operativi, care, în esența au menirea unui barametru al viabilității financiare viitoare a agentului economic. În funcție de dimensiunile acestor indicatori agentul economic poate fi atribuit unei din categoriile: financiar stabil sau instabil, sentință de care în mare măsură depinde capacitatea agentului economic de a-și continua activitatea și de a păstra relațiile cu creditorii, investitorii și clienții în viitor.

Acest studiu analizează posibilitatea utilizării inteligenței artificiale (Artificial Neural Networks) ca alternativă metodelor tradiționale statistice în evaluarea viabilității financiare a clientului. Modelul „canalelor nervoase" (ANN) este utilizat pe larg în domeniul biologiei, însă ultimele lucrări ale autorilor americani recomandă utilizarea acestui model în diagnoza financiară, considerîndu-l mai eficient decît metodele statistice tradiționale în prognozarea rezultatelor activității economico-financiare a agenților economici.

Lucrarea dată explică modalitățile și avantajul utilizării acestui model în fundamentarea deciziei auditorului privind viabilitatea financiară a clientului său în contextul respectării principiului continuității activității.

Subject Areas: Artificial Intelligence, Auditor Judgment, Decision Support, and Financial Distress.

Auditors, as part of the audit process, must express an opinion as to whether the audited client will continue as a going concern over the next year. The going concern assumption is that a business will continue to operate for an indefinite period. The Statements of Auditing Standards (SAS) No. 58 *(Reports on Audited Financial Statements)* (AICPA, 1988b) and No. 59 *(The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern)* (AICPA, 1988c) require auditors to form a judgment and to state their opinion regarding this assumption.

Evaluating financial viability and expressing an opinion about a client's financial health is not easy because auditors do not examine 100% of a client's records. Records can be incomplete or inadequate, and the data provided are subject to uncertainties (about, for example, a firm's future ability to finance its operations or interest rate changes). If auditors issue an opinion indicating that a client will remain financially healthy, but the client fails soon after, the auditors could be held liable for losses suffered by the stockholders and creditors (in the form of a decline in market value of stocks or decline in the value of assets). Conversely, if auditors express doubts about the continued financial viability of a client, this could destabilize the client financially, leading perhaps to revocation of lines of credit by suppliers and other creditors; again, the auditors could be held liable for losses.

The literature indicates auditors do issue inappropriate opinions regarding a client's solvency (Altman & McGough, 1974; Menon & Schwartz, 1987; Koh, 1991). Menon and Schwartz, for example, reported that in a sample of 147 firms filing for bankruptcy, auditors had identified financial viability problems and expressed a negative going concern opinion only in 63 cases. Researchers who have experimented with financial opinion distress models and statistical techniques to improve the tools available to auditors evaluating the financial viability of audit clients include Altman (1968); Altman, Haldeman, and Narayanan (1977); Ohlson (1980); Hamer (1983); Jones (1987); Hopwood, McKeown, and Mutchler (1989); Gilbert, Menon, and Schwartz (1990); Mutchler and Williams (1990); Bell (1991); Hooks (1992); Boritz and Kennedy (1995); and Etheridge and Sriram (1996,1997).

Logit and multivariate discriminant analysis (MDA) are the two most frequently used techniques in financial distress modeling studies (Sinkey, 1975; Altman et al., 1977; Martin, 1977; Ohlson, 1980; Jones, 1987; and Gilbert et al., 1990). Both logit and MDA provide reliable outputs with fewer classification or prediction errors for classifying a holdout sample of firms as failed or healthy. These techniques are complex, however, and also suffer other limitations, requiring researchers to seek other techniques.

A nonparametric technique that researchers find useful is Artificial Neural Networks, or ANNs (Parker & Abramowicz, 1989; Bell, 1991; Liang, Chandler, Han, & Roan, 1992; Fanning & Cogger, 1994; and Etheridge & Sriram, 1997). Backpropagation is the most common ANN for financial distress modeling. Several recent studies in accounting have used backpropagation ANNs to categorize firms as failed or nonfailed, with varying degrees of success (Bell, Ribar, & Verchio, 1990; Tarn & Kiang, 1992; and Klersey & Dugan, 1994). Most of these studies found that backpropagation ANNs performed at least as well as traditional statistical techniques in categorizing firms.

For auditors, the costs of incorrectly classifying a failed bank as solvent (Type I error) or incorrectly classifying a solvent bank as failed (Type II error) are not equal. Costs, in this context, refer to the probabilistic increase in liability that auditors might incur if they incorrectly assess the financial health of an audited client. Research indicates that auditors consider incorrectly judging a failed firm as solvent (Type I error) to be costlier than incorrectly judging a solvent firm as failed (Type II error).

EVALUATING FINANCIAL VIABILITY

Auditing standards require that auditors express an opinion regarding the client's continued financial viability. Auditors are rightfully careful in this regard. If they express unwarranted doubts about the continued financial viability of a client, the firm's creditors are likely to deny credit, the firm's stock value may decline, and investors will lose confidence in the firm. The firm could be forced into financial failure because users of the firm's financial statements may react to the auditor's report as if the firm had already failed. This reaction to the auditor's report is known as a self-fulfilling prophecy. Yet, if auditors fail to express doubts regarding the future financial viability of a failing client, they could be held liable for negligence as well as losses suffered by creditors and stockholders.

Because the consequences of indicating that a client may fail are so telling (a negative going concern opinion), auditors presumably express such an opinion only when they are certain of a client's near bankruptcy. Then again, the low percentage of negative going concern opinions may be attributed to the failure of auditors to recognize an impending financial failure.

To evaluate a client's financial condition, auditors rely on the audit evidence and also on various analytical techniques. The auditing standards SAS 56 (AICPA, 1998a) and SAS 59 (AICPA, 1998c) require that auditors use analytical techniques to gather sufficient evidence while making an informed decision regarding the future financial viability of audit clients. These analytical techniques include both financial distress models and statistical techniques. As Kida (1984, p. 147) pointed out, "Discussions with audit partners revealed that prediction models are ... used in actual going concern decisions."

Researchers and practitioners have long been interested in the use of prediction models and statistical techniques to improve the audit decision process.

Most of these studies use financial ratios as variables to model financial viability, and use bankruptcy as a surrogate variable for financial problems. The financial ratio variables usually provide high prediction rates. Some studies have used nonfinancial variables, including management turnover or financial market-related variables, client size, or reorganization. These studies do not find that the inclusion of nonfinancial ratios improves prediction rates significantly.

The sample of firms typically used consists of a matched pair of failed and healthy firms, with financial ratio data for each firm. A set of firm characteristics, usually financial ratios considered relevant for evaluating financial health, is obtained for one or more years. The sample firms are then split into training and holdout samples, and the training sample is used to develop the financial distress models.

The model is constructed one year later, after it is known whether the firm is still a going concern. The model is tested on the holdout sample of firms. For statistical purposes, the value for each characteristic is used to define a hyperplane such that firms above the hyperplane are going concerns and those below the hyperplane are not. The performance is evaluated according to the number of correct predictions of failed and healthy firms in the holdout sample.Most financial distress studies use either logit or MDA as the statistical technique, both to test the financial distress models and to predict the failed and healthy firms in the holdout sample. Both these techniques are assumed to perform reliably if they correctly classify most of the firms in the holdout sample (low misclassification errors). These are complex techniques, however, and have some limitations that raise questions about their reliability as statistical techniques.

Unlike logit or multivariate discriminant analysis, ANNs have certain attributes that make them more attractive as modeling techniques. ANNs do not require the data to be multivariate normal or have equal covariance matrices, or maintain a log-linear relationship among independent variables. They have attributes that make them more attractive as statistical techniques. They are good at pattern recognition. That is, from the underlying data, ANNs learn data patterns (variable relationships) and their association with financial failure or health. In turn, they use these patterns and relationships to classify new firms as either failed or healthy. ANNs also accommodate numerous variables, without the detraction of multicollinearity. Because they are nonlinear procedures, ANNs also are more versatile and robust than linear statistical techniques, and can use both quantitative and qualitative cues.

ANNs have some limitations, too. ANNs require significant training time and computer resources.

ANNs are computer-based techniques that process data in a parallel manner. They are trained to learn the relationships among variables and use this learning to recognize the presence or absence of similar patterns in other data. They perform even when the data are incomplete or noisy. ANNs are composed of a large number of highly connected, simple processing elements, or neurons. The processing elements in ANNs are organized into layers: each layer with numerous processing elements and different functions. The processing elements in each layer are also connected to the processing elements in the preceding and the successive layers, and sometimes even to the processing elements in the same layer. Each processing element processes the data it receives from its input connections, and then provides a signal to the other processing elements through its output connections.

The strength of a connection between two processing elements is represented by a weight (value) that can vary depending on the strength of the signals received from other processing elements, among other things. Weights normally have values in the range of -1 to +1. A weight of -1 indicates that the connection is strongly inhibiting or that a signal received through that connection is unlikely to initiate a signal of its own. A weight with a value of +1 is strongly excitative in nature, meaning that a signal from this connection is likely to induce a processing element to transmit its own signal.

If a processing element has more than one connection, the weights from those connections will be stored in a vector. For example, if a processing element has input connections from 100 other processing elements, then the strength of each connection will be represented by one weight in a vector of 100 weights. The vectors of weights associated with a processing element are sometimes called the "adaptive coefficients" of a processing element. These weights are adaptive in the sense that they can change in response to new stimuli.

Typically, the first layer in an ANN is the input layer. Its purpose is to accept inputs. The input layer processing elements then transmit signals to the second layer in the ANN, the hidden layer, where most of the learning takes place. After processing the signals from the input layer, the processing elements in the hidden layer transmit signals to the output layer. The processing elements in the output layer, after further processing the signals from the hidden layer, produce a result for the user.

The key component that controls the functions of an ANN is a group of mathematical functions that include the summation function, the transfer function, and the learning law. Remember that a processing element receives input through its connections (these inputs can be either positive or negative). The summation function, when it receives the input, converts it to a single value, then sums the products of the input multiplied by their respective weights (the weights represent the strength of the connections). The transfer function then determines the output of the processing element, depending on the result of the summation function. Because the transfer functions are nonlinear, it is possible to use the ANNs for a wide range of problems. The learning law helps in revising the adaptive coefficients as a function of the input values or as a function of the feedback value. Revising or modifying the adaptive coefficients helps the ANN to learn.

Improvements in training are monitored by observing the change in mean-squared error. The objective is to minimize the mean-squared error. The term "error" refers to the difference between predicted result and actual result. For example, for a set of learning cases, an error occurs when the output values from the ANN for a case (such as the prediction of failure or nonfailure) do not conform to the actual values of the case (whether a firm failed or not). The learning law defines how weights are changed to reduce the number of times the ANN output does not conform to the actual output. Once it is trained, the ANN is ready to be tested on a holdout sample.

ANN AND FINANCIAL HEALTH EVALUATION - AN ILLUSTRATION

The auditor, before using the ANN, must obtain sufficient data on a group of firms that includes both failed (firms that filed for bankruptcy) and healthy firms. It is critical that the auditor obtain data on firms that are representative of the firms to which the ANN will be applied. Failure to do so can lead to incorrect decisions. The failed and healthy firms may be selected and matched on the basis of revenue assets, or industrial classification code (SIC code). The auditor must obtain relevant financial ratio data on each failed and healthy firm to use as input data.

Suppose the auditor chooses three financial ratios as input data: return on equity, working capital ratio (current assets over current liabilities), and return on assets. Data on these three financial ratios must be included for every healthy and failed firm included in the sample. Once the data are ready, they can be separated into training and holdout samples. The training sample can be used initially to train the ANN, and the holdout sample is used to test the ANN.

The ANN, during training, learns the relationships between the independent variables (financial ratios) and the dependent variable (failed or healthy). Assigning weights to the financial ratios and associating them with a failed or healthy firm is part of the ANN training. The ANN begins to associate certain ratio relationships with a failed or a healthy firm. By constantly adjusting the weights, the ANN learning can be improved. That is, the ANN begins too consistently produce the known output (failed or healthy) from the given inputs.

Once an ANN is trained, it is ready for testing on the holdout sample. The ANN uses financial ratios on unidentified firms and places them into failed or healthy categories. By comparing the predicted categories to the actual categories, the error rates and ANN performance can be determined.

Auditors may not use the ANN output identifying a client as healthy or failing as the sole reason to express an opinion on the client's financial status. If the audit evidence overwhelmingly points to a financially healthy client or to a financially weak client, the auditors will have only limited use for the ANN. At the most, they may use the ANN output as one more document to support their opinion.

When there are significant uncertainties surrounding a client's financial status or when there are lingering concerns about the financial health of a client, for the auditors, the ANN can be a useful audit tool. If the ANN identifies the client as healthy, an auditor can use it to reinforce and support the evaluation of the client. If the ANN identifies the client as failing, an auditor can use the ANN output as a factor to collect more audit evidence and to investigate the client further before expressing an opinion.

DISCUSSION AND CONCLUSIONS

We pursued this study with two objectives: (1) to discuss how auditors can use nonparametric ANNs as analytical techniques during a going concern evaluation, and (2) to compare the performance of ANN techniques in terms of error rates and relative costs. As a secondary objective, we also evaluate the suitability of the backpropagation ANN for a classification problem.

When the relative cost ratios are low, the probabilistic neural network and the backpropagation perform well in our tests. As the relative cost ratios increase, the categorical learning network performs better than either the backpropagation ANN or probabilistic neural network. Auditors performing a going concern evaluation would choose a categorical learning network over backpropagation or probabilistic neural network in order to minimize the costs associated with an incorrect assessment of a client's financial health.

Backpropagation network is frequently used in financial distress and other classification studies. While by its architecture it is more suited for prediction problems than classification problems, it appears to have performed reasonably accurately in classifying failed and nonfailed firmss. It has low estimated overall error rates and also lower estimated relative costs than probabilistic neural network, a network that, by its architecture, is better suited for classification problems.

The contribution of this study is, nevertheless, to introduce auditors to the value of ANNs with respect to going concern evaluations. Our results highlight the importance of error rates and show how different ANNs can reduce or increase the costs of misclassification.

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