

Application of Fuzzy Logic to Fraud Detection

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INTRODUCTION

In light of recent reporting of the failures of some of the major publicly-held companies in the U.S. (e.g., Enron & WorldCom), it has become increasingly important that management, auditors, analysts, and regulators be able to assess and identify fraudulent financial reporting. The Enron and WorldCom failures illustrate that financial reporting fraud could have disastrous consequences both for stockholders and employees. These recent failures have not only adversely affected the U.S. accounting profession but have also raised serious questions about the credibility of financial statements. KPMG (2003) reports seven broad categories of fraud experienced by U.S. businesses and governments: employee fraud (60%), consumer fraud (32%), third-party fraud (25%), computer crime (18%), misconduct (15%), medical/insurance fraud (12%), and financial reporting fraud (7%). Even though it occurred with least frequency, the average cost of financial reporting fraud was the highest, at \$257 million, followed by the cost of medical/insurance fraud (average cost of \$33.7 million).

Statistical methods, expert reasoning, and data mining may be used to achieve the objective of identifying financial reporting fraud. One way that a company can justify its financial health is by developing a database of financial and non-financial variables to evaluate the risk of fraud. These variables may help determine if the company has reached a stress level susceptible to fraud, or the variables may identify fraud indicators. There are a number of methods of analysis that may be used in fraud determination. Fuzzy logic is one method of analyzing financial and non-financial statement data. When applied to fraud detection, a fuzzy logic program clusters the information into various fraud risk categories. The clusters identify variables that are used as input in a statistical model. Expert reasoning is then applied to interpret the responses to questions about financial and non-financial conditions that may indicate fraud. The responses provide information for variables that can be developed continuously over the life of the company. This article summarizes the specifics of fraud detection modeling and presents the features and critical issues of fuzzy logic when applied for that purpose.

BACKGROUND

Fraud Detection

The problem of fraudulent financial reporting is not limited to the U.S. In 2002, the Dutch retailer, Ahold, disclosed losses of \$500 million related to accounting at its U.S. subsidiary (Arnold, 2003). Recently, Parmalat, an Italian firm, declared insolvency as a result of fraudulent financial reporting. The CEO of Parmalat has been accused of mishandling \$10 billion and of hiding losses in offshore funds and bank accounts. The scandal at Parmalat could also have serious consequences for the company's auditor (Gallani & Trofimov, 2004).

The auditor's responsibility for fraud detection in the U.S. has been defined in Statement on Auditing Standards No. 99, *Fraud Detection in a GAAS Audit* (AICPA, 2002). This statement has four key provisions (Lanza, 2002): (1) increased emphasis on professional skepticism, (2) frequent discussion among audit team personnel regarding the risk of misstatement due to fraud, (3) random audit testing of locations, accounts, and balances, and (4) procedures to test for management override of controls. Auditors are discouraged from placing too much reliance on client representation and are required to maintain a skeptical attitude throughout the audit. The standard encourages auditors to engage in frequent discussion among engagement personnel regarding the risk of material misstatement due to fraud. SAS 99 also requires auditors to inquire of management and others not directly involved with fraud, perform analytical procedures, and conduct necessary tests to assess management override of controls. Finally, auditors are advised to evaluate the risk of fraud and steps taken by the client to mitigate the risk of fraud.

The U.S. Congress in 2002 passed the Sarbanes-Oxley Act, which spells out a number of steps firms must take to minimize fraudulent financial reporting. This legislation requires the principal executive officer and the principal financial officer of publicly traded companies to certify the appropriateness of the financial statements and disclosures in each quarterly and annual report that their company issues. These officers are also responsible for establishing and maintaining internal controls within the company. Further, they must disclose to auditors and the audit committee of

the board of directors any fraud, whether or not material, involving management or employees who have a significant role in defining or implementing internal controls. As this law goes into effect, evaluation and reporting of a company's internal controls and financial statements in order to detect fraud becomes even more critical, and must be on-going.

Prior research shows that various kinds of decision aids may be used to assist the auditor in detecting financial reporting fraud. Bell, Szykowny, and Willingham (1993) used bivariate and cascaded logit to assess the likelihood of management fraud. Their model achieved within-sample correct classification of 97% on the fraud observations and 75% on the non-fraud observations. Hansen, McDonald, Messier, and Bell (1996) used a generalized qualitative response model to predict management fraud. They reported 89.3% predictive accuracy over 20 trials. Bell and Carcello (2000) developed a logistic regression model as a decision aid to assist in the auditor's fraud decision. Auditors may also use an expert system as a decision aid to assist in fraud determination. Eining, Jones, and Loebbecke (1997) examined the effect that the use of an expert system has on auditor decision-making ability in detecting fraud. Their research showed that in allowing the interaction between the auditor and the system, the expert systems that have been used to assist auditors in complex decision processes often give results that are more accurate and consistent. Similarly, Whitecotton and Butler (1998) found that allowing decision makers to select information for the decision aid increases decision aid reliance. Fuzzy clustering may also be used as a decision aid for an auditor to detect fraudulent financial reporting (Lenard & Alam, 2004).

Fuzzy Clustering

When available data does not suggest a clear answer, decision makers often look for patterns or groups in the underlying data to make a decision (Alam, Booth, Lee, & Thordarson, 2000). While discriminant analysis and logistic regression assign observations to groups that were defined in advance, cluster analysis is the art of finding groups in data (Kaufman & Rousseeuw, 1990). Fuzzy set theory, introduced by Zadeh (1965), attempts to classify subjective reasoning (e.g., a human description of "good", "very good", or "not so good") and assigns degrees of possibility in reaching conclusions (Lenard, Alam, & Booth, 2000). As opposed to hard clustering, where there is a clear-cut decision for each object, fuzzy clustering allows for ambiguity in the data by showing where a solution is not clearly represented in any one category or cluster. Fuzzy clustering shows the degree to which (in terms of a percentage) an item "belongs" to a cluster of data. In other words, a data item may belong "partially" in each of several categories. The strength of fuzzy analysis is this ability to model partial categorizations.

Lau, Wong, and Pun (1999) used neural networks and fuzzy modeling to control a plastic injection-molding machine. They suggested that the neural network and fuzzy technology complement each other and offset the pitfalls of computationally intelligent technologies. Alam et al. (2000) used a combination of fuzzy clustering and self-organizing neural networks, and were successful in identifying potentially failing banks. Ahn, Cho, and Kim (2000) reported results using these technologies to predict business failure, and stressed the importance of these predictions as useful in aiding decision makers. Lenard et al. (2000) used fuzzy clustering to identify two different categories of bankruptcy. Companies placed in the second bankrupt category exhibited more extreme values in terms of the financial ratios used in the study. Companies either showed much better results (such as a high current ratio) than would be expected for a company facing bankruptcy, or the companies showed very poor results, such as a much higher debt ratio than any of the other bankrupt companies in the data sample. Lenard and Alam (2004) operationalized a fuzzy logic model for fraud detection in an Excel spreadsheet. By using the fuzzy logic model to develop clusters for different statements representing red flags in the detection of fraud, non-financial data was included with financial statement variables for the analysis. The overall prediction accuracy for the model was 86.7%.

Nolan (1998) used expert fuzzy classification and found that fuzzy technology enables one to perform approximate reasoning, as when a student assignment is graded as "very good", or "not so good", and improves performance in three ways. First, performance is improved through efficient numerical representation of vague terms, because the fuzzy technology can numerically show representation of a data item in a particular category. The second way performance is enhanced is through increased range of operation in ill-defined environments, which is the way that fuzzy methodology can show partial membership of data elements in one or more categories that may not be clearly defined in traditional analysis. Finally, performance is increased because the fuzzy technology has decreased sensitivity to "noisy" data, or outliers. Ammar, Wright, and Selden (2000) used a multilevel fuzzy rule-based system to rank state financial management. The authors used fuzzy set theory to represent imprecision in evaluated information and judgments. Pathak, Viyarthi, and Summers (2003) developed a fuzzy logic based system for auditors to identify fraud in settled claimed insurance. They believe that their system was able to cut costs by detecting fraudulent filings.

CRITICAL ISSUES OF FUZZY LOGIC

The fuzzy clustering procedure used by Lenard et al. (2000) and Lenard and Alam (2004) is called FANNY (Kaufman & Rousseeuw, 1990). The program FANNY uses "fuzzi-

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