Chapter 4.19
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